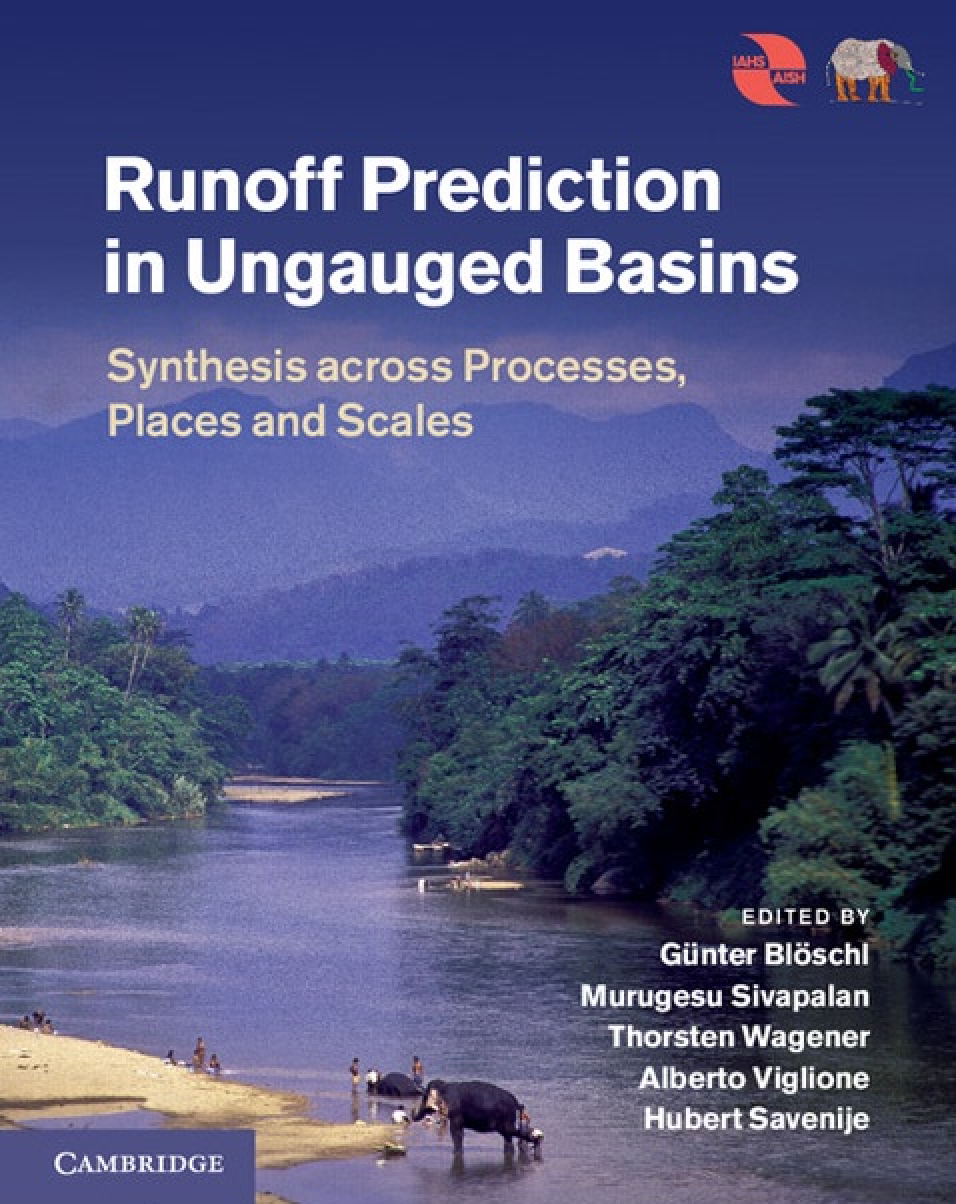

Runoff Prediction in Ungauged Basins

Synthesis across Processes, Places and Scales

EDITED BY
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CAMBRIDGE

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Predicting water runoff in the mostly ungauged water catchment areas of the world is vital to practical applications such as the design of drainage infrastructure and flooding defences, for runoff forecasting and for catchment management tasks such as water allocation and climate impact analysis.

This important new book synthesises decades of rigorous analytical research from around the world, forming a holistic approach to catchment hydrology, and providing a one-stop resource for hydrologists in both developed and developing countries. It brings together results from individual location-based studies with comparative analysis along gradients of climate and landscape features. Topics include data for runoff regionalisation and the prediction of runoff hydrographs, flow duration curves, flow paths and residence times, annual and seasonal runoff, and floods.

Illustrated with many case studies, and including a final chapter on recommendations for researchers and practitioners, this book is written by expert international authors involved in the prestigious International Association of Hydrological Sciences (IAHS) Predictions in Ungauged Basins (PUB) initiative. It is a key resource for academic researchers in the fields of hydrology, hydrogeology, ecology, geography, soil science, and environmental and civil engineering, and professionals working with water runoff in ungauged water basins.

Günter Blöschl is Professor of Hydrology, Director of the Centre for Water Resource Systems, and Head of the Institute of Hydraulic Engineering and Water Resources Management at the Vienna University of Technology. He has published extensively on subjects related to hydrology and water resources and served as an editor and associate editor for ten of the best scientific journals in the field. Professor Blöschl has been elected Fellow of the American Geophysical Union and the German Academy of Science and Engineering, has chaired the International Association of Hydrological Sciences (IAHS) Predictions in Ungauged Basins (PUB) initiative, and has been elected President of the European Geosciences Union. Recently he has been awarded the prestigious Advanced Grant of the European Research Council (ERC).

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Foreword

Prediction in ungauged basins: context, challenges, opportunities

Society increasingly looks to science for predictions, or at least explanations, of events, resources and hazards. Examples appear continually in government committee hearings, serious newspapers and television channels, and international re-insurance industries, to choose one commercial example. This expectation is particularly obvious in the case of water. People are nervous about (for example) water shortages, crop-threatening droughts, floods, water chemistry and pricing. Hydrologists would be wise to improve the capacity and reliability of their predictions to respond to this societal need.

Prediction is commonly thought of as a fundamental capability of science. Observations and understanding, conceptualised as explanatory theories, allow predictions, which then can be tested to refute or increase confidence in the original theory. In hydrology, the quality of these tests does not typically match up with tests in some other sciences that apply laboratory-tested principles and models to the environment. We have much to learn from disciplines, such as atmospheric science, physical oceanography and astrophysics, that have been successful at applying laboratory-tested principles at large scales in complex environments. Although it is true that hydrology has to contend with the interactions of more media (rock, soil, vegetation, engineered structures) than do the disciplines mentioned, there are still intellectual traditions, organisational approaches, analytical methods, and technologies to be learned from them in order to test the generality of landscape-scale hydrological theories.

Empirical investigation, including experimentation, is another fundamental tool of science. Hydrological investigations are conducted in a wide variety of environments – with diverse climates, topography, soils, land cover and manipulation by humans. They also occur at a wide range of temporal and spatial scales, and involve single or multiple processes. It is difficult to organise the vast amount of information from these studies into coherent theories. Diverse results are then seen as contradictory or at least leading to so much confusion that prediction is impossible. Yet, it should not be surprising that results from different locations differ in magnitude, even in the absence or presence of certain processes. Theories predict such a result, and allow organised interpretation and resolution of differences in measured magnitudes. Yet the bulk of the hydrological literature comprises a conceptually disordered resource of 'unique' descriptions, single-process studies and methods, but few attempts at organisation through the medium of broadly applicable, quantitative theory, or even conceptually organised descriptive summaries, that would facilitate both understanding and prediction. This is the 'fragmentation' problem, which the Predictions in Ungauged Basins (PUB) initiative has reduced to an encouraging degree, as this book illustrates.

There is a resilient meta-hypothesis in hydrological science that quantitative theories of linked hydrological processes at landscape scale, implemented and tested in a transparent and rigorous manner, could leverage the extensive body of environmental measurements into more reliable predictions. This is an interesting and challenging, if still unproven, idea. Such a development would require improvements in the conduct of both modelling and empirical investigations – a trajectory assessed in this book for the specific case of runoff predictions in ungauged basins (and by extension, unrecorded conditions in monitored locations).

The first attempt at promulgating general hydrological theory, based on fluid mechanics and thermodynamics, was Eagleson's 1970 book *Dynamic Hydrology*, followed by his suite of papers in *Water Resources Research* (1978) laying out a statistical dynamic formulation of various linked components of a land-surface water budget. Earlier attempts to develop theories of single processes, such as the work of Darcy, Richards, Horton, Theis, Toth, Penman and Monteith, had pointed the way, but Eagleson provided a guide for integration. More recent contributions by many people have illuminated ways of dealing with the representation of processes at a wide range of scales, and with the unwelcome fact that many material properties important in hydrology exhibit large, but crudely measured and poorly understood spatial variations.

The current book is an assessment of progress in combining models with new data-collection and processing tools to make predictions of streamflow, and therefore of associated hydrological fluxes such as evaporation and groundwater storage changes. It embraces the scientific approach of making a model-based prediction and then testing it, and recording the errors in an objective manner. Such a strategy measures progress in skill development and facilitates judicious assessment of the reliability of predictions. This is not common in hydrology, where calibration routinely hides uncertainties in process representation, landscape and material properties, and spatial variability of atmospheric events. However, the global survey of prediction methods indicates that tested, integrative modelling of biophysically controlled hydrological mechanisms is still a minority activity in catchment-scale streamflow predictions. Most predictions still consist of summaries, calibrations and extrapolations of strictly empirical information.

The local, empirically focused approach has obvious utility for making certain kinds of predictions within the interpolated range of measurements, although many hydrologists have emphasised the degree to which uncertainties debilitate the use of such predictions, even in that range. The approach is even more unreliable when it is applied to the important domains that society cares about, which lie outside of monitored localities (the ungauged basin), outside of the recorded range of 'possible' events, and in conditions of climate and land cover that may not yet exist but are anticipated. For these (true) prediction challenges, according to the meta-hypothesis, there would be value if we had methods based on a sound scientific platform of mechanistic understanding and rigorous testing. We would then know *how well* we could predict, and we would be able to agree on critical uncertainties, and to focus scientific research and technological innovation on them. But we are unlikely to select either of these foci if most hydrological predictions continue to be pragmatically ad hoc, not rigorously tested and compared, and aimed at generating locally acceptable solutions, rather than transferable hydrological understanding. The PUB initiative has made progress in overcoming these parochial vices.

It is often said that the urgent applicability of hydrological knowledge to human affairs encourages short cuts and discourages exploitation of the best practices of science. Although this may be understandable in specific applications under limitations of time and resources, there is no fundamental reason why the subsidised research community needs to limit its investigations in the same way. The research community is free to address the meta-hypothesis that rigorously formulated biophysical process models could assimilate new and better landscape measurements to yield predictions tested in the same way that some other environmental sciences achieve. This would not require that a prediction be correct at the first attempt, and it would allow an incorrect prediction to be explained by investigating whether the form of a mechanistic representation or the value of a critical parameter were accurate, rather than calibrating the prediction against measured output and announcing success. The book assesses progress in this direction.

Making this suggestion is not to argue against current hydrological practice. Much of it is required for urgent policy and management (remember that José Ortega y Gasset said, 'Life cannot wait until the sciences have explained the universe scientifically.'). Nevertheless, given the widespread dissatisfaction with hydrologists' ability to predict flood discharges or water yields in ungauged basins or those expected to result from climate change and other anthropogenic disturbances, surely there is an argument to be made for some investment in a different, more distinctively scientific strategy on the part of some hydrologists. The results could generate a higher-yielding strategy for the discipline.

The global organisation of the PUB initiative has also fostered an intermediate approach to organising the diversity of knowledge and approaches to runoff prediction, even for conditions and scales for which rigorous mechanistic models are not yet formulated, or at least parameterised, adequately for reliable predictions. This approach involves comparative hydrology – comparing results and the success of prediction methods at representing hydrological outcomes for different regions and scales. The strategy, referred to in the book as hydrological synthesis, is a formal way of comparing hydrological experience in diverse circumstances (I would say through the interpretation of available theory wherever possible), and is a welcome approach to ordering hydrological knowledge. Hydrological synthesis converts the disordered body of case study results into a gradually expanding sample of geographical range (or 'parameter space') that can be compared and interpolated. It raises questions about how regional differences and the general behaviour of hydrological response result from the nature of landscape–atmosphere interactions over time scales ranging from seconds to landform evolution time. The compilation of responses and predictions produces insights about which factors are critical controls on hydrological response at various scales. It also indicates the progress made in prediction at each scale, and the hydrological uncertainties requiring resolution. Synthesis through comparison of results and localities also encourages the use of information on patterns of hydrological landscape features, such as topography, soil and plant communities, to choose prediction methods, to group useful information and to apply results. These patterns are strongly correlated because they have evolved interactively, and the associations between them tend to limit the variability of hydrological response into clusters and trends, albeit with a still-unwelcome (for prediction) degree of variability. However, the PUB strategy has successfully organised knowledge, yielded transferable generalisations, and highlighted hypotheses for further investigation, as the book documents.

The fluid mechanical and thermodynamic theories of biophysical mechanisms at various scales needed for improving predictions are more securely developed and tested, at least at laboratory scale, than is the other part of the hydrological prediction problem – which is to attach these theories to the very complex boundaries and material properties of landscape features. The need to choose temporal and spatial resolutions for making these connections leads to challenging uncertainties about the operations of the mechanistic theories themselves. Although the problem is often characterised as a need for better *parameterisation* (which in hydrological modelling usually means some form of averaging of response to a stimulus), or for higher-*resolution* modelling with the same equations, there is often a need for better *formulation* in the sense of representing better *how* a process works, or even *which* process is working. For example, the volume and timing of runoff into a channel could be calculated as (a) the result of overland flow from a long contributing area with variable abstraction of water from the flow and a high surface resistance or (b) of unsaturated and then saturated subsurface flow from a shorter contributing area with different forms of flow resistance and water storage along the flow path. One could calibrate either representation against measurements of rainfall and runoff from a catchment. However, extrapolations of resulting predictions based on the inaccurate formulation to much larger rainstorms, snowmelt, drier initial conditions, timber harvest or other reasonably likely conditions would not be reliable. The unreliability could lead directly to misinformation if the prediction were required to predict not simply runoff but also soil-moisture patterns and evaporation, erosion, water quality, land management or effective pollution regulation (for example). This problem of improving process formulation, as it relates to hydrological prediction at landscape scale, needs to be tackled systematically through field measurement campaigns, modelling 'experiments' and syntheses of the kind documented here that search for environmental patterns and extend knowledge beyond individual case studies. The attractiveness of the challenge is that it invites new discoveries, based on new forms of measurement at a still-unsampled range of scales, as well as improvements in technology and physical and mathematical technique.

The landscape-features side of the problem is also an essential and attractive research target, but it also is challenging. Critical quantities vary in complicated, irregular and wide-ranging ways, and for some of them there is no agreed-upon measurement method. An extra impediment arises because the disciplines that have studied these features have attracted fewer scientists with an appetite for quantitative, theory-based generalisation. Thus, we have relatively few high-quality measurements of hydrological landscape properties and few quantitative theories of how coherent patterns and random variations develop in the first place, or how they differ from place to place. Technological developments have occurred in the measurement of surface hydrological properties, such as topography and albedo, and new data-processing methods for analysing and representing patterns are being employed. But the measurement and useful representation of subsurface material properties and geometry remains a serious impediment to prediction. Modelling the co-evolution of landscape patterns is beginning to develop, which should constrain the number and types of patterns that need to be considered for hydrological prediction.

In addition, field scientists need to engage with the task of theory-building in order to make useful measurements of critical properties that would encourage coherent progress in hydrological prediction. Field studies need to be designed and reported in a manner consistent with theoretical generalisation and hypothesis testing. The task of field studies is not only to report on exceptional circumstances (although these extend the sampling of geographical conditions), but to gradually extend understanding in a coherent and replicable manner. Often, reports that are portrayed as defying conventional wisdom turn out, at least qualitatively, to be physically reasonable and even predictable when extant theory is applied to the local circumstance. The strategy of hydrological synthesis – a formal way of comparing hydrological experience in diverse circumstances (I would say through the interpretation of available theory, wherever possible) – emphasised in this book is a welcome approach to ordering hydrological knowledge and setting an agenda for new discoveries and generalisations.

The book expresses an enduring aspiration of the community that established the International Association of Scientific Hydrology (since renamed as International Association of Hydrological Sciences). It re-focuses the goal of one branch of that community on a distinctively scientific approach to understanding and utilising hydrology at a time when technological advances in measurement and computation are becoming available for creative exploitation in the service of humankind. This is an exciting prospect.

Thomas Dunne

Preface

Sustainable management of river basins requires a variety of tools that can generate runoff predictions over a range of time and space scales. The most widely used predictive tools for runoff are essentially data-driven, i.e., they are estimated from gauged data. Unfortunately, in most catchments around the world runoff is not gauged. In any given region, in any part of the world, only a small fraction of the catchments possess a stream gauge where runoff is gauged. All other catchments have no stream gauge, and are therefore ungauged, and yet runoff information is needed almost everywhere people live for a multitude of management purposes.

Lack of universal theories or equations applicable directly at the catchment scale has led to a plethora of models being developed and used for predicting runoff. These models differ markedly in their model concepts and structure, their parameters, and the inputs they use. They also differ in terms of what dominant processes they represent, and the scales at which they make predictions. Most models are developed by people with different disciplinary backgrounds, while benefiting from local observations, experiences and practices, which are influenced by local climate conditions and catchment characteristics. Consequently, they tend to have unique features not applicable in other places: every hydrological research group around the world seemingly studies a different object: their local catchment. The net result has been considerable fragmentation, a 'cacophony', and a dissipation of effort that is not conducive to further advances.

The Decade on Predictions in Ungauged Basins (PUB) launched by the International Association of Hydrological Sciences (IAHS) in 2003 was aimed at achieving major advances in the capacity to make predictions in ungauged basins, through harnessing improved understanding of climatic and landscape controls on hydrological processes. The future vision of PUB was indeed to help make a transformation 'from cacophony to a harmonious melody'. One of the clear tasks that the PUB initiative set out to achieve was to address the fragmentation of modelling approaches through *comparative evaluation*: 'Classify model performances in terms of time and space scales, climate, data requirements and type of application, and explore reasons for the model performances in terms of hydrological insights and climate–soil–vegetation–topography controls.' This book has completed such a comparative evaluation, which is one of its major highlights.

However, PUB also had a higher ambition. It was felt that focusing on a grand problem such as PUB, which needed to draw heavily on new fundamental and theoretical advances in hydrology and associated earth system sciences to address the immediate problem-solving needs of society, had the potential benefit of enabling hydrology to meet both its scientific and its societal obligations. In other words, PUB was also seen as the vehicle to advance and revitalise the science of hydrology. Indeed, over the past decade, the PUB community has made huge strides in advancing both predictive capability and fundamental understanding of hydrological processes, working together in a concerted and coordinated manner. The PUB effort has helped to challenge long-held assumptions and question common paradigms, and has increased the constructive dialogue between different sub-disciplines and schools of thought.

So, as PUB comes to an official close, this book represents one contribution to PUB, which can be seen as another important step both in the development of PUB and in the growth of hydrology as a holistic earth science. This book does not even pretend to document all of the advances and contributions that the PUB community has achieved. These are substantial and should not go unnoticed, and will be documented in some other form. This book is mainly and explicitly focused on a synthesis of runoff predictions in ungauged basins, organised across processes, places and scales. This synthesis attempts to place current practice, experience and prediction uncertainty of a range of prediction methods in an ordered way, so that new insights can be gained not only about the methods themselves but also about how runoff variability changes across processes, places and scales. We believe we have succeeded in bringing some order to the disorder, to the extent of at least partially helping to transition 'from cacophony to a harmonious melody', even if it meant asking new questions that only future research can answer. We believe that this is a positive development both for predictions and for the science. This is also reflected in the organisation of the book, as one whole, internally self-consistent tome, with one coherent theme, rather than a collection of chapters that focus on several different PUB themes that one could equally well produce under the circumstances. We had to make a choice about the organisation of the book in our quest for the 'harmony'; we hope that it made a difference, since there was a clear price we had to pay for achieving this harmony.

The book started as a PUB benchmark report, but over time metamorphosed into a synthesis, mainly building on a comparative assessment of thousands of studies from all around the world, with predictive uncertainty assessed along the axes of processes, places and scales, and interpreted hydrologically. The literature on the current state of the art of runoff predictions, in terms of the various signatures, was reviewed by over 130 contributing authors, and organised into several chapters. The painstaking effort of comparative assessment was carried out by several able assistants in Vienna, who toiled hard to do the analyses and generate new insights from them, with the support of several of the book contributors as well as the cooperation of scores of the original study authors, who provided the data sources needed for the assessment. All of the chapters went through numerous (countless) revisions by the contributors themselves, and then by the editors, as part of the overall synthesis effort.

The evolution of both the outlines and the contents of the book over the past three years or more was a process unto itself, confusing and confounding editors and contributors alike as it moved along, crystallising into its present shape only in the final few months. In other words, the editorial process was a co-evolutionary process, no less a complex system than the catchment that is the subject of our study. In that sense, the 'blind men and the elephant' metaphor applies to the book just as it does to the PUB initiative. Some messages that appear in the synthesis chapter were not there at the beginning, or were only vaguely there, and emerged through the process of writing the book. In that sense, the synthesis did serve its purpose. However, we are humble enough to admit that the book is not the end, but only the end of a beginning, and we remain blind men, still blind to the true reality that is catchment hydrology. Hopefully, there is a broader vision that challenges the narrow vision that has helped us to shape this book.

Readers will not fail to notice scores of photographs of real catchments in colour throughout the book. Our decision to include them is a tribute to the late Vit Klemeš, former President of the IAHS, and comes from our determination that catchments henceforth be seen as inimitable objects that are alive, and not just defined by the techniques and abstractions we may use, from time to time, to analyse them. In a series of papers, Klemeš emphasised the primacy of process understanding over techniques in hydrological research. Techniques are certainly needed for predictions in ungauged basins, but the focus in this book – as in much of the PUB initiative – has been on the hydrology, with the techniques playing an essential but supporting role. It is the hydrological interpretation of the patterns that various analysis techniques and models produced that takes centre stage in this book.

The contents of the book, in a sense, reflect the lessons learned from the diversity offered by nature's own experiments, as expressed through the thousands of studies surveyed in this book. Through its comparative performance assessment of methods across processes, places and scales, the book takes an approach to generalisation through learning from the differences and similarities between catchments around the world. It throws light on the status of PUB at the present moment and can serve as a benchmark against which future progress can be judged. Along the way, the book has also come out with a new scientific framework that can potentially guide future efforts aimed at improving runoff predictions in ungauged basins and at advancing the science of hydrology. This proposed new framework has centred on a higher-level synthesis of what we can learn from individual places with generalised understanding gained from comparing the differences between places, thus benefiting from legacies of co-evolution. Maybe this is too esoteric to include in a book on predictions, or maybe it will trigger new ways of doing things; only time will tell.

This book is aimed at hydrologists, earth and environmental scientists with an interest in water, especially early career scientists, aspiring graduate students and practitioners, as well as hydrology teachers. Yet it is not a textbook, manual, handbook nor even a monograph. It puts predictions in a new light, it makes catchment hydrology more coherent and exciting, and runoff variability and water balance more holistic. Perhaps the book can serve as a ready reference for students and new entrants to hydrology wanting to get a sense of the holistic nature of catchment water balance, and to imagine new and innovative ways to make runoff predictions. We hope that, in the long run, it will change the way hydrology is taught, researched and practised.

The book owes its genesis to the IAHS Predictions in Ungauged Basin initiative. We are truly grateful to the IAHS for having the wisdom and courage to start such a 10-year global effort, and for bringing the hydrological community together globally on such a daunting task. We could not have completed this book without the underlying community support that IAHS managed to pull together. Indeed, the synthesis presented in the book is built on the collective experience, inputs and insights of a large number of researchers around the world, and is therefore truly a grassroots effort, even if the grass roots are no longer visible. We as editors hope that, in spite of the challenges and frustrations faced along the way, it has been a worthwhile effort and that the final product reflects well on the best intentions and profound wisdom of the hydrology community, and the high ambitions of the PUB

initiative. We are grateful to Kuniyoshi Takeuchi for having the foresight to launch the initiative and to him and subsequent Presidents (Arthur Askew and Gordon Young), and Secretary-General Pierre Hubert, for providing unconditional support to the PUB initiative generally, and to this book project in particular. We are also grateful to Jeff McDonnell and John Pomeroy, the other two PUB Chairs, for leading PUB during their terms in a way that the PUB spirit never wavered, and PUB continued to make progress towards its goals.

We would like to profusely thank the 130 contributors, including coordinating contributors, for their efforts at pulling together material for the various chapters, and for putting up with us as we continually edited the material to the point that, very truly, not one sentence that any author contributed remains intact in the book. We thank them all for having faith in the editors to the end, in spite of the obvious frustrations. Special thanks to Magdalena Rogger, Thomas Nester, Jürgen Komma, Juraj Parajka, Jose Luis Salinas, Emanuele Baratti, Rasmiaditya Silasari, Patrick Hogan and Gemma Carr for the invaluable assistance they rendered towards the comparative assessment exercise, redrawing of the figures, editing, proofreading and overall project management. Without their efforts, this book would never have seen the light of day. We would also like to acknowledge the financial support of the Austrian Academy of Sciences through the Predictions in Ungauged Basins project, and the US National Science Foundation through the Hydrologic Synthesis project, and the institutional support of our respective employers, especially Vienna University of Technology and the University of Illinois, for making available considerable resources to enable us to work together over extended periods. We are grateful to Thomas Dunne for being willing to write a foreword to the book; the PUB initiative benefited from Tom's wisdom during its formative stages, and it is gratifying that he followed the initiative to its end and was able to read the book and offer wise thoughts once again to potential readers. Finally, we would like to extend our thanks to our respective families for putting up with our long absences, in both body and spirit, over the three years that it took to complete this book.

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M. Sivapalan
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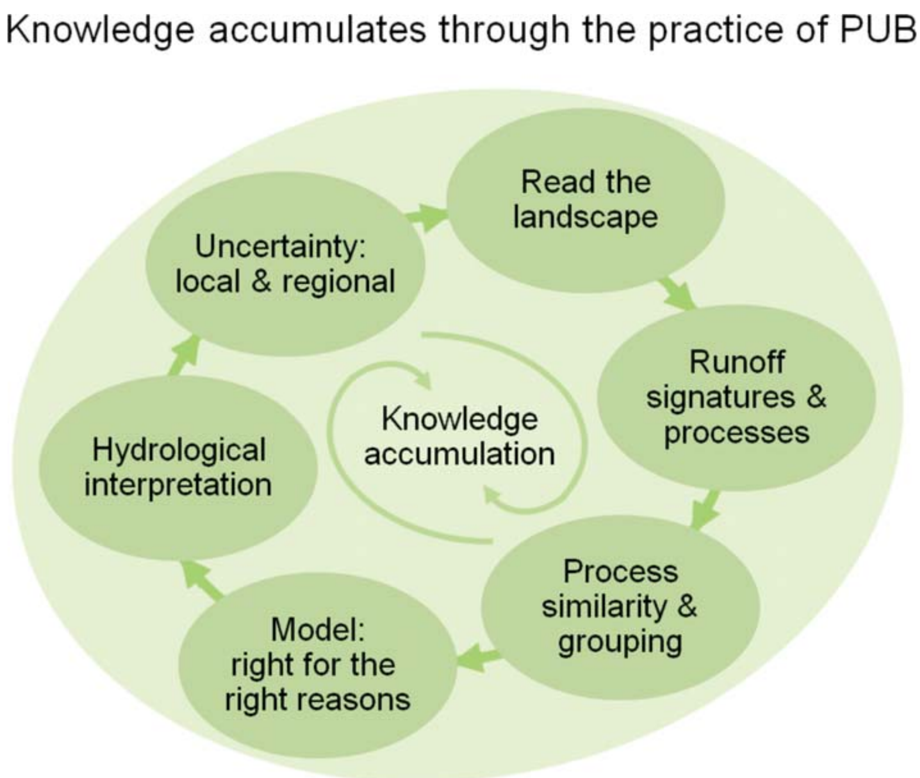
H. H. G. Savenije
(Editors)

Abstract

This book is devoted to predicting runoff in ungauged basins (PUB), i.e., predicting runoff at those locations where no runoff data are available. It aims at a synthesis of research on predictions of runoff in ungauged basins across processes, places and scales as a response to the dilemma of fragmentation in hydrology. It takes a comparative approach to learning from the differences and similarities between catchments around the world. The book also provides a comparative performance assessment (in the form of blind testing) of methods that are being used for predictions in ungauged basins, interpreted in a hydrologically meaningful way. It therefore throws light on the status of PUB at the present moment and can serve as a benchmark against which future progress on PUB can be judged. In so doing, the book has also come out with a new scientific framework that can guide the advances that are needed to underpin PUB and to advance the science of hydrology as a whole. The synthesis presented in the book is built on the collective experience of a large number of researchers around the world inspired by the PUB initiative of the International Association of Hydrological Sciences, which makes it truly a community effort. It has provided insights into the scientific, technical and societal factors that contribute to PUB. On the basis of the synthesis presented in this book, recommendations are made on the predictive, scientific and community aspects of PUB and of hydrology as a whole.


Knowledge accumulates through the practice of PUB
Read the landscape
Runoff signatures & processes
Process similarity & grouping
Model: right for the right reasons
Hydrological interpretation
Uncertainty: local & regional
Knowledge accumulation

1 Introduction

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1.1 Why we need runoff predictions

During the February 2007 Zambezi River flood, Paulo Zucula, the director of Mozambique's National Institute for Disaster Management, was trying to contain the disaster along the river: 'The evacuated people have been in camps for over a week without proper feeding … they are isolated and we can't go there by road, so we have to airlift some of them and drop food,' he said. Some 90 000 people were made homeless by the flood. According to an Oxfam worker, about 1000 people a day were arriving at the camps even without any shelter being provided. The government had learned the lessons of the previous 2001 flood, however, during which about 700 people died. This time it promptly launched missions by boat and helicopter to evacuate people from affected areas. But they were rapidly running short of food for the people in the 33 temporary camps, which also lacked tents, medicine and clean water.

In January 2008 a major flood again struck the Zambezi. This time some 50 000 people in Mozambique were displaced by the flood. 'Property and infrastructure is again being wrecked but we are more worried about the people,' said Paulo Zucula. The flood in the Zambezi valley was in fact worse than the floods of February 2007, and the authorities were forced to evacuate areas where the victims of earlier floods had been resettled.

What has this disaster got to do with runoff Predictions in Ungauged Basins (PUB)? A lot! The hydrology of the Zambezi valley in Mozambique is strongly affected by the presence of the Cahora Bassa Dam (see Figure 1.1). This dam, designed to release about 1900 m^3/s through its turbines for hydropower generation, has a limited flood release capacity. In order to deal with major flooding, it has to lower its reservoir level substantially before the onset of the flood season each year. It is a perpetual trade-off between the economic value of hydropower generation, the risk of flood damage and the risk of dam failure. What makes the operation of the dam even more complicated is that large parts of the upstream catchment of the Zambezi are literally ungauged. Runoff in the main stream of the Zambezi River may be governed by the upstream Kariba Dam, from where warnings are issued whenever they open the flood gates, but the operators have no knowledge of the inflow from the intermediate catchment, of which the Luangwa with its 50 000 km^2 is the largest. The Luangwa is completely ungauged. As a result, operators sometimes have to open the floodgates and discharge more water than would be necessary, with the benefit of hindsight. Better runoff predictions in the Luangwa could reduce flood releases, increase hydropower production, improve flood warning, and reduce downstream damage and suffering.

In Chapter 11, a case study by Hessel Winsemius shows that, even in an ungauged basin such as the Luangwa, much can be done in terms of improved flood predictions. Figure 1.2 is a screen dump of the online model that Winsemius developed for the Luangwa River basin, completely based on remotely sensed data (mostly precipitation and meteorological information). The model has been

Figure 1.1. The Cahora Bassa Dam, Mozambique, spilling through one of the eight flood gates.

* Coordinating contributor

Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales, ed. Günter Blöschl, Murugesu Sivapalan, Thorsten Wagener, Alberto Viglione and Hubert Savenije. Published by Cambridge University Press.

Table 1.1. *Need for runoff predictions in ungauged basins*

Hydrological problem	Water management purpose
How much water do we have?	Water allocation, long-term planning, groundwater recharge
When do we have water?	Water supply and hydropower production, planning of restoration measures
For how long do we have water?	Ecological purposes, hydropower potential, industrial and domestic water supply, irrigation
How dry will it be?	Environmental flows for ecological stream health, drought management, river restoration, assessing dilution of effluents
How high will the flood be?	Design of spillways, culverts, dams, dam removal, levees, reservoir management, river restoration, risk management
What are the dynamics of runoff?	All of the above plus water quality (sediments, nutrients) predictions

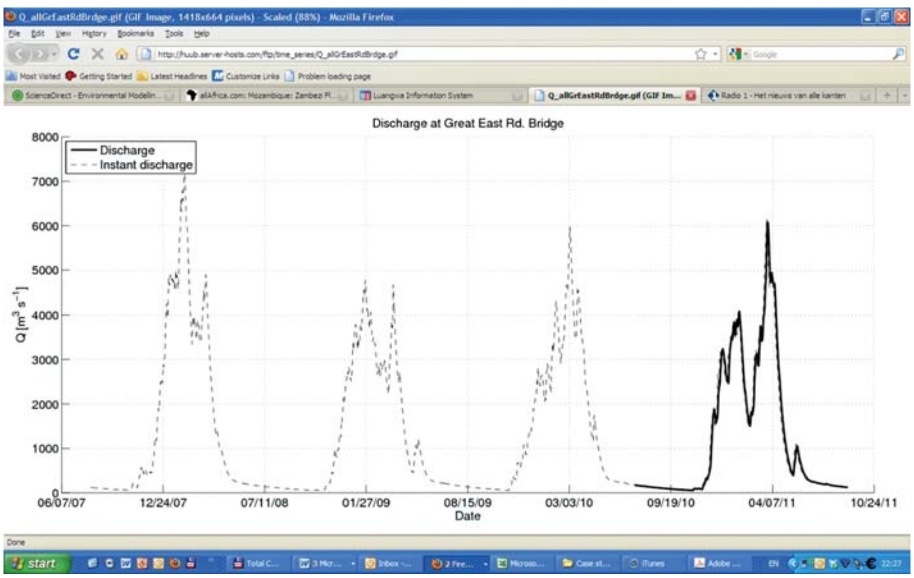

Figure 1.2. The online model that predicts runoff from the Luangwa River basin into the Zambezi, just upstream from Cahora Bassa Reservoir.

operational since 2009 and gives hourly updates of runoff estimates. The runoff is very substantial compared to the average outflow of the Cahora Bassa Dam, and so these predictions can indeed make a difference between life and death, early warning and forced displacement. It shows the direct relevance of PUB for society.

The challenges in the routine management of the Cahora Bassa Reservoir demonstrate the importance of runoff predictions for reservoir management, but there are many other purposes for which runoff predictions are needed. Flood predictions are needed for the design of spillways, culverts, dams, levees, reservoir management, river restoration and risk management. Low flow predictions are needed for determining environmental flows for ecological stream health, drought management, river restoration and assessing the dilution of discharges into a stream. Table 1.1 illustrates the range of problems for which runoff predictions in the context of integrated water resources and risk management are needed. All of them have direct societal relevance (Carr *et al.*, 2012). Clearly, runoff predictions are important to a large part of humanity.

Unfortunately, in most catchments around the world, runoff is not measured. In any given region, in any part of the world, only a fraction of the catchments possess a stream gauge where water levels are gauged, which are then transformed into runoff, i.e., the volume of water per unit time that flows through a cross-section of a stream. All the other catchments have no stream gauge, and so are ungauged, and yet runoff information is needed almost everywhere people live for the multitude of purposes outlined above.

The only recourse is therefore to predict runoff in these catchments or locations using alternative data, or information or knowledge. How one can predict runoff for these ungauged catchments and how well one can do this are the subject matter of this book.

1.2 Runoff predictions in ungauged basins are difficult

So, how can one predict runoff at the catchment scale? Unfortunately, there are currently no universal theories or equations applicable for predicting runoff at the catchment scale. Most of the knowledge we have of processes that occur within the catchment has been derived at the 'point' or laboratory scale (Dooge, 1986; Blöschl, 2005b). The equations of flow of water are essentially valid at the laboratory scale. Similarly, theories of infiltration we currently use are point-scale equations, and overland flow is clearly defined at the hydrodynamic scale, developed in hydraulic laboratories where turbulent processes are very well researched. The challenge for predictions is to move from the well-researched point-scale equations to the catchment scale, something termed the upscaling problem. One way of addressing the upscaling problem is to divide the catchment into smaller elements, which are small enough to apply these point-scale equations, and then assemble these pieces together to form a model of the entire catchment to make the required runoff predictions. This approach could work, in principle – geometrically the catchment can be easily decomposed into sufficiently uniform elements. This so-called reductionist approach is then the most logical way of building predictive models. For estimating runoff in ungauged catchments the approach will then lead to a form of distributed process-based hydrological models that solve the governing equations for mass, momentum and energy in a spatially explicit way, drawing on as much laboratory-scale process understanding as possible. In this book we will call this the Newtonian approach, as the essence of such models is based on Newtonian physics or mechanics.

The Newtonian approach has numerous strengths. First and foremost, it is based on cause-and-effect relationships. If you change an input or a parameter of the model at some location, there is a clearly defined response of the runoff to this change. This is very important for many applications, in particular for those related to change prediction. Land use change effects can be directly simulated by these types of models and, similarly, the approach lends itself naturally for climate impact analyses. Second, these models are spatially explicit and have the potential to represent processes within the catchment in much detail, such as spatial patterns in the infiltration characteristics, the exact channel shape or the presence of any hydraulic structures. Again, there is considerable benefit in the spatial representation, as any detailed knowledge one may have about the catchment can be fully exploited. Third, the underlying equations, such as Darcy's law or Manning's equation are known to work at the laboratory scale for a wide range of flow conditions, so it should be possible to extrapolate them to a wide range of hydrological situations, such as under much higher precipitation. The underlying equations are universal, so should be applicable everywhere at all times. This is appealing since it will generate generalisable knowledge. Also, there are many examples from sister disciplines, such as the atmospheric sciences and river hydraulics, where distributed models are the universal currency.

However, there are three problems with the Newtonian approach for predicting catchment runoff. When subdividing the catchment into computational units, it is necessary to characterise the system through which the water flows for every single element. In principle, this may appear to be a trivial task, but in practice it turns out to be very difficult. In essence, the medium through which the water flows is unknown. It is difficult to identify the spatial (and depth) distribution of the flow parameters, such as the hydraulic conductivity that describes how easily water moves through a medium such as soil or rock. The runoff estimated by the models is usually very sensitive to these parameters, and even a small change will produce a big change in runoff. It is not feasible to measure these parameters everywhere in a catchment, even in a research catchment, let alone in routine applications needed in water resources management, where almost always there are strict resource and time limitations. Second, even if we were able to characterise parameters such as hydraulic conductivity and roughness for every pixel within a catchment, computational resources currently do not allow us to actually use laboratory-scale computational elements – at least a trillion elements would be needed for a catchment of practical interest. Because of this, the elements or building blocks of distributed processes-based hydrological models are usually much larger, at least tens of metres. This leads to the problem of quantifying the flow processes within such elements, i.e., how to parameterise the effects of subgrid variability. This parameterisation is not very well understood either. Preferential flow phenomena may lead to flow dynamics that are very different from those at the laboratory scale. Third, many of the processes controlling catchment runoff are in fact not physical processes but chemical and biological processes. For example, soil chemical processes may strongly affect the infiltration characteristics. Biological activity of earth worms and plants may alter the hydraulic conductivity considerably. Stream–aquifer interactions are often controlled by biological activity at their interface and transpiration is, of course, a biologically driven process. So, while the flow processes *per se* are physical phenomena, they are controlled by many other processes that cannot be quantified by means of Newtonian physics.

Because of these issues, distributed process-based hydrological models often tend to produce biased results when applied to real catchments. To reduce bias in the runoff predictions, at least some of the model parameters need to be calibrated to runoff data. However, this is of course not possible in ungauged basins.

A number of alternative methods have therefore been developed and have been the methods of choice in practical applications for a long time. These alternatives involve the use of runoff data from gauged catchments in a region, and models for ungauged catchments that strongly build on these runoff data. These can be statistical models or simple process models of a conceptual kind, without recourse to Newtonian physics. However, these models are centred on the notion of similarity between the gauged and the ungauged catchments. These types of models acknowledge that, even though there are no runoff data in the catchment of interest, runoff data do exist in other, similar catchments, and these can be transferred in some way in space to help make runoff predictions in the ungauged basins.

1.3 Fragmentation in hydrology

Because distributed process-based hydrological models are not the only method of making runoff predictions in ungauged basins, a plethora of other methods have been developed that are based on the notion of similarity. There is no one standard method of runoff predictions in ungauged basins, rather there are literally hundreds of different methods. They differ by their model structure, their parameters, and by the inputs they use. They also differ in what processes they represent. Depending on the environments, the relative role of snow processes, runoff generation processes and transpiration processes may differ, as may the factors that control them. Some of the differences between the models are directly related to the differences in climate and catchment characteristics. Also, historically, hydrologists have had less incentive than researchers in other disciplines in the earth sciences to collaborate with colleagues around the world, as the land surface is organised into separate river basins, and there is little water exchange across them. Unlike meteorology, for example, a single catchment can be studied with much success in isolation. As hydrologists we do not have a single object of study as, say, a physicist who studies the structure of a particular atom. All physicists around the world may study the hydrogen atom and the models they come up with relate to the same common object – one hydrogen atom. In contrast, every hydrological research group around the world is studying a different object, i.e., a different catchment with different response characteristics. This is a fundamental difference that hydrology must face up to.

All of these factors, collectively, have contributed to the fragmentation of hydrology at various levels.

Processes: Different processes in hydrology have often been dealt with separately, and therefore hydrologists have often looked at flow characteristics at different time scales in an independent way. The annual water yield is usually studied independently of knowledge of low flows of the catchment of interest; floods are often studied independently of knowledge of the seasonal flow patterns within catchments; and flow duration curves are studied separately. Is there a deeper connection between these processes? What is needed is a simultaneous treatment of these processes at different time scales.

Places: As each research group has tended to analyse their own catchments, over the years tremendous understanding of runoff processes has been developed for individual places, but transferring this to other places has been hard. Models are often tailor-made to a particular catchment and it is hard to reason why a particular model structure or model parameters should be preferred over others. Different schools of thought have developed their own favourite methods for different environments and purposes, e.g., statistical versus causal methods or physically based versus conceptual models. Generalising the findings of how well the models work and why has been notoriously difficult.

Scales: Research has been performed over a huge range of scales, and connecting them has caused tremendous difficulties. This is known as the scale problem in hydrology (Blöschl and Sivapalan, 1995). When upscaling laboratory-scale infiltration equations to the catchment scale, assumptions need to be made about the natural hydrological variability and how it is organised (Blöschl, 2001). Similarly, routing equations at a plot scale may differ from those at the hillslope scale. This situation has been exacerbated by the spectrum of disciplines involved, including engineers, geologists, soil scientists and meteorologists, each of them with different worldviews of at what scales processes should be conceptualised.

Current textbooks on hydrology propagate the same fragmented vision of hydrology, organised by process, and written in the form of recipes, e.g., ten different formulas for estimating infiltration, potential evaporation, and so on. The situation is literally analogous to 'a cacophony of noises … not a harmonious melody' (Sivapalan, 1997; Sivapalan *et al*., 2003b). This fragmentation can be best illustrated by the famous Indian legend of the 'six blind men and the elephant'. By touching different parts of the body of an elephant, these blind men are trying to figure out for themselves what an elephant may look like, but have no other way of 'seeing' it. Each of them tries to make inferences about the elephant by touching one body part of the elephant: it seems like a wall to the blind man that touches the side of the elephant, a spear to the one who feels the tusk, a snake to the one who handles the trunk, a tree to the one who feels the leg, a fan to the one who

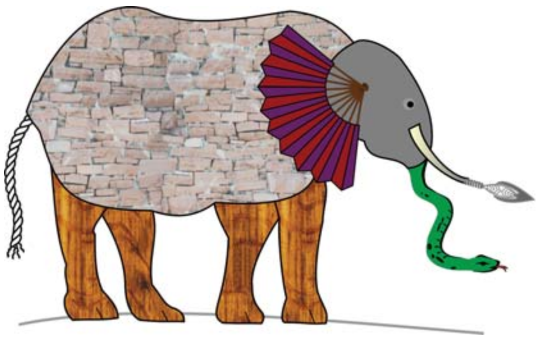

Figure 1.3. Fragmentation in hydrology: similar to the six blind men, a fragmented approach to hydrology makes it difficult to see the full pattern of catchment processes. From Sivapalan *et al.* (2003b), © Jason Hunt.

touches the ear, and a rope to the one who touches the tail (Figure 1.3). The experiences and interpretations of the six blind men are different, which makes it difficult for them to come up with a collective understanding and agree on the true nature of the beast they are trying to 'visualise'. A verse of John Godfrey Saxe's (1816–87) version of this famous Indian legend clearly brings out this confusion:

And so these men of Indostan
Disputed loud and long,
Each in his own opinion
Exceeding stiff and strong,
Though each was partly in the right,
And all were in the wrong!

Perhaps catchment hydrology is in a similar state. Like the six blind men, hydrologists too are often partly in the right but they continue to fail to grasp the holistic picture of the catchment, the object of their study. There is a clear and urgent need to develop a unified vision of hydrology at the catchment scale that overcomes the limitations that arise from their narrow perspectives. What is needed is a synthesis that helps to broaden their perspectives, and to go beyond what is perceived by an individual researcher or group.

1.4 The Prediction in Ungauged Basins initiative: a response to the challenge of fragmentation

About a decade ago, a new global initiative was launched by the hydrological community, under the aegis of the International Association of Hydrological Sciences (IAHS). Called Prediction in Ungauged Basins (PUB), one of the motivations of this grassroots initiative was to overcome the fragmentation in catchment hydrology (Sivapalan *et al*., 2003b; SSG, 2003). The idea was to bring the scientific community together to use PUB to advance the collective understanding in hydrology, just as the six blind men in the Indian legend might have joined forces to enlighten themselves about the elephant to seek wisdom from other sources. The PUB initiative has been guided by a number of overarching principles to help reach its goals (Figure 1.4). First and foremost, the initiative was about real hydrological processes in real catchments, embracing a multitude of processes, places and scales. If real progress was to be made in overcoming the fragmentation, a diverse population of real catchments in different regions and at different scales had to be examined. A diverse range of processes and a diverse range of data and approaches had to be brought together, all focusing on the common science problem of predictions in ungauged basins. By making different catchments and methods comparable, the aim was to synthesise existing knowledge and create new knowledge, and in this way help improve the predictive abilities and reduce uncertainty. Comparability of diverse places, methods and applications was considered the key to the unification or synthesis needed to transcend the fragmentation and make fundamental progress in hydrology.

It was thus clear that to overcome the fragmentation the community had to be brought together. The PUB initiative was therefore designed as a global community effort, indeed a grassroots movement, consisting of a network of scientists from around the world, and inclusive of all interests. A balance of researchers interested in fundamental research as well as in what is immediately useful was considered valuable, as for any other relevant facets of the prediction problem. The benefits to be gained were clear: greater coherence of the science agenda, coordination of the research activities and a stimulus for the excitement of hydrological research. The PUB initiative has been a truly international effort, with contributors from every continent focusing on the issue of predictions in ungauged basins, leading to a network of concerned scientists.

Over the past decade, the IAHS PUB initiative has been the catalyst for a range of research activities organised around six cross-cutting themes, and executed through a large number of national, regional and global PUB working groups. These PUB themes are: (i) catchment similarity and classification, (ii) conceptualisation of process heterogeneity, (iii) uncertainty analysis and model diagnostics, (iv) new data collection approaches, (v) new hydrological theory and (vi) new modelling approaches. These themes are reflected in the frontispiece to this book, and figure prominently in the guide to PUB best practice that appears in Chapter 13 (Recommendations). The PUB research activities have contributed substantially to the literature, leading to significant advances in the various programs of PUB.

Guiding Principles Behind PUB Science and Implementation Plan

A number of key principles naturally arise from the broad community objectives presented before, and have guided the development of the science and implementation plan of PUB. Special gratitude to Dunne (1998) for the inspiration it provided.

- In view of its societal obligations, PUB will focus on real hydrologic phenomena, such as floods, droughts, eutrophication of receiving waters, degradation of natural ecosystems, effects of climatic variability and change and/or land use changes etc. (after Dunne, 1998*);
- In being essentially a science initiative, PUB will mainly seek to advance fundamental knowledge of hydrological processes, even to the extent of going beyond the immediate problem solving needs or the community interest of the present time (after Dunne, 1998*);
- PUB will constantly focus attention on what is not known, indeed it will gain energy from its own uncertainties, emphasizing the need for empirical exploration and explicit attempts to validate or falsify new ideas (after Dunne, 1998*);
- PUB emphasizes learning from data from selected basins in different biomes or hydro-climatic regions, demonstrating the value of data and the need for future data requirements, and should not be seen as an alternative to data collection;
- PUB will be obligatorily be self-critical, and will include within it a strong element focused on continual assessment of its own progress, with the predictive uncertainty being used as the measure of progress (after Dunne, 1998*);
- PUB is necessarily integrative, will avoid and indeed overcome the fragmentation of approaches that has bedeviled hydrology in the past, and rather will seek convergence of a variety of approaches towards common objectives, also profiting from lateral perspectives into ancillary sciences (after Dunne, 1998*);
- Develop a hydrological prediction system that is capable of assessing the errors or uncertainty in model predictions, quantifying the different sources of the uncertainty – parameter estimates, climatic inputs and model structure – and constraining these uncertainties by making the best use of the information available from other sites and of measurement programs implemented at the site of interest.

*Dunne, T. (1998). Wolman Lecture: Hydrologic science .... in landscapes ....on a planet ... in the future. In: *Hydrologic Science: Taking Stock and Looking Ahead*, National Academy Press, Washington, D.C., 138p.

Figure 1.4. Guiding principles of the PUB Science Plan, SSG (2003), p. 47.

Work on this book also developed as a community effort and reflects all of the principles that have underpinned the PUB initiative (Figure 1.4). The book itself is an outcome of a strongly felt need to synthesise the state of the art of prediction in ungauged basins, and to carry out a comparative performance assessment of a range of prediction methods being used for the various runoff signatures. Since the book is focused on a synthesis of current prediction methods, it cannot possibly do justice to the enormous contributions of the range of activities that have been carried out under each of the six PUB themes. However, while the book is a contribution to PUB in its own right, its overall organisation has been inspired by the concepts and clarity of thinking engendered by the PUB initiative. In particular, the six PUB themes are reflected in the book in a cross-cutting way, and the outcomes reflect the progress that has been achieved over the past 10 years towards improved predictions in ungauged basins.

1.5 What this book aims to achieve: synthesis across processes, places and scales

This book is specifically devoted to predicting runoff in ungauged basins, i.e., at those locations where no runoff data are available. It will assess, on a comprehensive, objective, open and transparent basis, the state of hydrological predictions in the absence of data, and identify what are the prediction challenges of the future.

It will accomplish this assessment through a synthesis across processes, places and scales, as a response to the challenge of fragmentation in catchment hydrology. In this way it will strive to bring together research on predictions of runoff in ungauged basins that has so far been disparate. One of the goals of the proposed synthesis is to bring order to what otherwise looks like disorder, to identify connections where none existed, and in this way generate new ideas and novel approaches to advance the science of hydrology, and improve the practice of hydrological predictions. There are three levels of synthesis pursued in this book (Blöschl, 2006), as described below.

1.5.1 Synthesis across processes

It appears that hydrologists have, so far, too often looked at individual runoff processes in isolation. It seems likely that there is a connection between floods and low flows, between the long-term behaviour of catchments and their short-term behaviour. The philosophy adopted in this book is that catchments are similar to whole organisms or ecosystems. The different parts are connected because they are themselves a result of process interactions and feedbacks over a wide range of time scales, from seconds of rainsplash processes on the land surface to millennia of landscape evolution processes. While individual parts of the system can be studied in isolation with considerable success, even more progress can be made holistically if the interactions of the parts are also studied. If catchments are viewed as being similar to organisms, then there is perhaps also an analogy with how to study them to understand how the organisms function.

A medical doctor has many different options for studying the state and functioning of a patient: taking the pulse, checking the breathing, ordering blood tests and so on. Ultimately, however, a doctor is not interested in one particular reading, say, the blood pressure alone, but in what the combination of all these diverse pieces of information reveals about the health of the patient. Just as with the doctor example, the idea of this book is to diagnose catchments in several different ways to understand their state and functioning (Figure 1.5).

In the case of catchments, taking the pulse, checking the breathing and making blood tests will be analogous to exploring the different characteristics of runoff variability, which in this book we define as runoff signatures. We call them 'signatures' to reflect the fact that they are the result of the functioning of the same catchment 'organism' and will therefore reveal some aspect of their state and internal dynamics. In this sense, signatures are response patterns. They emerge as complex catchment systems develop through co-evolution of climate, soils, vegetation and topography in natural landscapes. This is a major point of departure from their previous treatment in the literature. This point is exploited in a major way in Chapter 2, as the framework for the synthesis adopted in this book. The signatures are of course complementary, just as the medical tests on a human being are complementary. They represent different views of the internal dynamics and external manifestations of the same catchment organism, and so they can be used to construct a composite picture of the system functioning. The signatures are therefore a key vehicle for the synthesis we want to achieve.

Figure 1.5. Synthesis across processes by diagnosing catchment functioning through runoff signatures. Partly based on Frisbee *et al.* (2011).

In this book the runoff signatures are viewed in such a way that runoff variability can be broken up into several components, each of them a manifestation of catchment functioning, albeit at different time scales, and each of them meaningful and representative of a certain class of applications of societal relevance.

- Annual runoff is a reflection of the competition of water and energy at the catchment scale in the interplay of climate, vegetation and soils.
- Seasonal runoff also reflects interaction between water and energy availability, but in addition catchment storage becomes very important and changes the character of runoff.
- Flow duration curve is the distribution function of runoff that forms a more complex signature linking short-term and long-term processes.
- Low flows result from the interplay between the dynamics of climate with geology, where persistence and long-term processes are of key importance.
- Floods are a reflection of catchment processes at the upper extreme and result from the interplay of weather, soils, topography and geology in a highly dynamic way.
- Hydrographs are the complex result of all these processes and are the most detailed signature of how a catchment behaves.

It is recognised in this book that these different runoff signatures need to be looked at simultaneously and in a consistent way, similarly to how a doctor examines a patient from different perspectives at the same time and in a consistent way. A consistent and coherent treatment of these signatures is therefore one of the cornerstones of this book.

1.5.2 Synthesis across places

Overcoming the fragmentation across places is particularly difficult as catchments are indeed tremendously different. The approach adopted in this book to synthesise across places is built on the notion of 'similarity'. As a central theme throughout the book, this notion of hydrological similarity is used to compare different catchments and landscape units, to learn from their similarities and differences. We look at different places at the same time. Again, the analogy with the medical doctor is appropriate here. The medical profession has two options to understand a patient's medical condition, how the condition can be inferred from particular symptoms, to predict the future evolution of that person's health and to decide on any treatment. The first option is to look at this particular patient in much detail, including biopsy or surgery, to identify exactly the root cause of the symptoms. The second option is to pool the findings from many patients and to learn from their case histories. The crucial step is then to transfer the knowledge obtained from the large group of people to the particular person being treated. Each human being is different, but there are many common characteristics. Doctors pool together the information from many people and analyse the differences and the similarities. How will cancer evolve for a given state of the body? Clearly, doctors will resort to the case histories of thousands of patients around the world to make a prediction for that particular patient. The two options are complementary, and the medical profession has adopted a combination of these two approaches ever since the profession organised itself, if not before.

Hydrology could operate in a similar fashion. We could pool the information on many catchments together, and analyse their differences and similarities. How will runoff evolve for a given state of the catchment? Clearly, a viable path towards synthesis is to resort to the case histories of thousands of catchments around the world to make a prediction for a particular catchment. Similarity is the foundation of this synthesis, and is therefore a key theme of the book.

Hydrological similarity will help bring order to the current cacophony of catchment processes, models and data setups that bedevil the science today. Similarity is therefore the natural vehicle to organise the synthesis so as to assist towards holistic understanding of hydrological processes everywhere. Hydrological similarity will also help runoff prediction in ungauged basins, since it can help exploit the knowledge of hydrological processes at various levels of detail. To assist with predictions we therefore need to learn from what everybody has learned around the world, and pool together the wisdom and experience from many countries and the diversity of approaches. The concept of similarity makes different places comparable, and in this way assists in the generalisation of the understanding gained from one catchment to the collective understanding of how different catchments function under different conditions.

It is recognised in this book that a critically important part of synthesis across places is therefore a comparative assessment of how well different methods for runoff predictions work in ungauged basins. A consistent and coherent assessment of the performance of methods is therefore another of the cornerstones of this book.

1.5.3 Synthesis across scales

Hydrological processes occur at all scales, from microscopic water flow in soil pores to global-scale interactions of soil moisture and climate. Consequently, hydrological analysis has been performed at many scales, from the

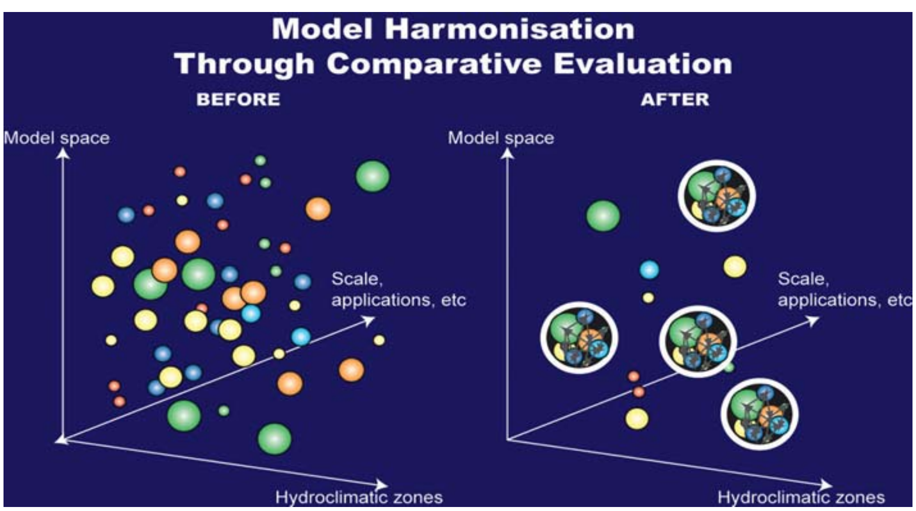

Figure 1.6. Harmonisation of process understanding and models through comparative evaluation across places (taken from PUB Science Plan, see SSG, 2003). The figure depicts the synthesis (harmonisation) that can be achieved through organising the activities and outcomes along the axes of climate, scale and methods, which has been the motivation behind this book.

laboratory to the global scale. The goal in this book is to predict runoff at the catchment scale. This necessarily involves integration across spatial scales in some way. There are two strategies for approaching this scale problem to assist with making runoff predictions. The first is the upward or mechanistic approach. It is strongly based on laboratory experiments and involves an upscaling to the catchment scale, often by spatially explicit, distributed modelling approaches. While causal controls can be analysed very well by this approach, it is difficult to represent all catchment-scale process interactions. The second is the downward or holistic approach. It is strongly based on behaviour observed at the catchment scale, often based on lumped statistical methods or conceptual rainfall–runoff models. While these types of approaches do have the ability to capture process interactions at the catchment scale – if this information is represented in the data – identifying causality may be very difficult. The two approaches typically deal with scale issues in different ways. For example, in the upward mechanistic approach of rainfall–runoff modelling, measured point rainfall is distributed across the catchments and then routed explicitly across hillslopes and along the stream network to obtain flood peaks of catchments of different sizes. In contrast, in the downward statistical approach of regional flood frequency analysis a scaling relationship is usually established between flood peak and catchment area that embodies all processes in a holistic way. In both approaches, in practice, model parameters are usually calibrated in some way in order to reduce bias. Biases tend to change significantly with location but tend not to change much over the time scales we are interested in because much of the bias is related to unknown subsurface characteristics. Calibration therefore has the potential to increase the accuracy of runoff predictions. However, it is clear that if one calibrates parameters to compensate for the real uncertainty, this is likely to be a ‘quick fix’, which may jeopardise the physical realism of the model and therefore its predictive capability in ungauged basins.

This book takes a view that transcends any particular approach. We do not assume the primacy of either of the two prediction approaches. Of course, if hydrological information were to be available everywhere, and all the time, the upward approach would be preferred. But it never is. In fact this is the *raison d’être* proffered for the downward approach. We view runoff processes as space-time patterns of hydrological variability. Any approach is an *approximate* representation of this variability. The organisation of catchments into a stream network leaves an imprint on runoff response, turning them into organised entities, and the aim of runoff predictions is to connect the process to the pattern. Each of the two approaches connects process and pattern in different ways. In the book we are therefore inclusive of all these approaches. In our considered view these approaches need to be compared both in terms of their characteristics and in terms of their performance when applied to real catchments around the world. As the methods have different strengths and weaknesses, the choice of method is an interesting and important issue, and there will be many cases where it may be wise to use methods that combine the strengths of both approaches and minimise their weaknesses.

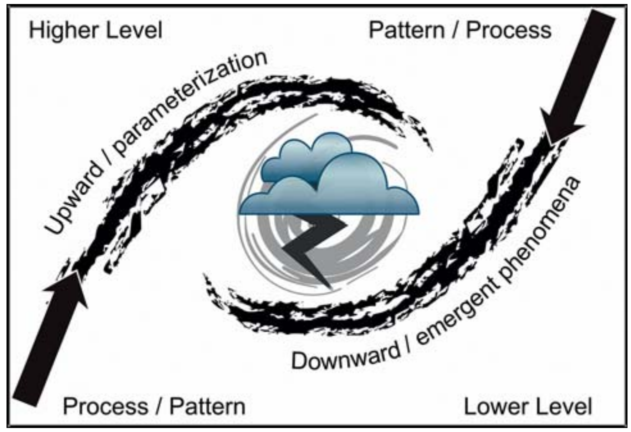

Figure 1.7. Reconciliation of downward and upward approaches – break or transition from a reliance on averaging and parameterisation of lower-level features to a culture of discovery and explanation of emergent phenomena at the higher level. From Sivapalan (2005).

1.6 How to read the book and what to get out of it

How is the synthesis across processes, places and scales reflected in the organisation of the book? Synthesis along these three axes has in fact been the guiding principle in the structuring of the book.

Synthesis across processes is reflected in the way that the book is organised around runoff signatures. Each of the Chapters 5 to 10 deals with one runoff signature – from annual runoff to runoff hydrographs. The commonality of structure of each chapter acknowledges that signatures have common causes in the way catchments function hydrologically. The signatures are simply different manifestations of the same spectrum of catchment processes, so a coherent and consistent treatment contributes to a synthesis across processes.

Synthesis across places is reflected in the way that hydrological similarity is one of the recurring themes of the book, also reflecting one of the key PUB themes (i.e., *catchment similarity and classification*). Hydrological similarity appears explicitly in Chapters 5 to 10 as a vehicle to advance understanding and predictions, through its role in regionalisation of models and parameters. Hydrological similarity also appears explicitly in the comparative assessment of the performance of runoff predictions in ungauged basins around the world in each of these six chapters.

Synthesis across scales is reflected in the fact that statistical methods and process-based methods are treated in a consistent way throughout Chapters 5 to 10. Statistical methods and process-based methods represent different approaches to deal with scale issues that arise in predicting runoff in ungauged basins. Statistical methods usually are lumped or holistic representations of the entire catchment system, or many catchments, based on the behaviour observed at the catchment scale. They are therefore typically representative of the downward approach. Process-based methods, in contrast, are mechanistic methods based on a causal understanding of water flow at the process scale, and are therefore more representative of the upward approach. A common structure in these chapters has been adopted for comparability of the statistical and process-based methods, which may help in understanding the similarities and differences in how they bridge the scales.

Chapter 2 presents and articulates the synthesis framework used in the book. As data are the doorway to enhanced understanding and improved predictions, Chapter 3 is devoted to the specific data needed for making predictions in ungauged basins (and reflecting the PUB theme of *new data collection approaches*). Chapter 4 deals with the key issues of flow paths and storage in catchments, and lays the foundations of the general process insights used in the remaining chapters (and reflecting the PUB theme of *conceptualisation of process heterogeneity*). Much of what controls runoff is in the subsurface, so understanding these flow paths and storage-related processes is particularly important for predictions in ungauged basins. Chapters 5 to 10 are the main chapters of the book, each of them dealing with one runoff signature. The structure of each chapter is almost identical, where first the practical needs of the particular signature and its societal relevance are highlighted; in the next section, the process interactions that underpin the signature are reviewed, including how these can be used to define hydrological similarity. The following two sections review statistical and process-based methods for predictions in ungauged basins (reflecting the PUB theme of *new modelling approaches*). Again, wherever possible and reasonable, the types of methods are organised in a similar way across all chapters. Chapters 5 to 10 all close with a comparative assessment of the performance of methods of runoff predictions in ungauged basins around the world, based both on a literature review and on dedicated comparative analysis of numerous data sets that underpinned many of these historical studies. The performance assessment is carried out through a cross-validation of model predictions in over 20 000 catchments, which represents one measure of predictive uncertainty: it reflects the PUB theme focused on *uncertainty analysis and model diagnostics*. Chapter 11 contains several case studies from around the world. The purpose here is to highlight the societal relevance of predictions in ungauged basins in different contexts, and to demonstrate that many of the methods presented in the book actually work for purposes that are important to society. Finally, Chapter 12 synthesises the findings of the previous chapters, and undertakes a yet higher level synthesis to generate profound conclusions and implications for hydrological science, and recommendations for hydrological practice, as summarised in Chapter 13.

2 A synthesis framework for runoff prediction in ungauged basins

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2.1 Catchments are complex systems

2.1.1 Co-evolution of catchment characteristics

Landscapes present amazing patterns that appear to be ubiquitous at any scale one looks. At the pore scale, microbes colonise soil particles and form biofilms that alter water flow paths and water–sediment contact time, thus affecting geochemical weathering and the nucleation of secondary minerals. Biogeochemical alteration of the mineral–water interface results in stable particle aggregates allowing the fast movement of water in interconnected flow paths. At the patch scale, rills form in response to rain-splash erosive action and overland flow redistributes important nutrients and carbon that affect soil properties, such as infiltration capacity. Vegetation responds to this spatial variability in water and nutrient availability to form clusters characteristic of the dominant flow processes. At the hillslope scale, clear patterns emerge in soil characteristics as a result of the interplay of water and carbon movement, erosion, soil formation and both vegetation and animal action. At the landscape scale, the interplay of land uplifting and erosion–deposition processes generates landforms that feed back to ecological and pedological processes. At the same time, climate interacts with vegetation, soils and landforms through hydrological processes to produce large-scale vegetation patterns. It stands to reason that the co-evolution of climate, vegetation and soils at the landscape scale leads to specific ways of hydrological partitioning that are reflected in runoff records. The satellite image of the landscape in the Channel Country in south-western Queensland shown in Figure 2.1 illustrates the complexity of the landscape patterns where an intricate network of riverbeds has evolved in the alluvial fans made mostly of clays (Baker, 1986). Many of the challenges highlighted in Chapter 1 could be addressed if these landscape patterns could be connected quantitatively to catchment hydrological response.

Taken from biology, the concept of co-evolution refers to the process of reciprocal evolutionary change between interacting species, driven by natural selection (Thompson, 1994). In the case of catchments, co-evolution implies a process of reciprocal evolutionary change of soils, vegetation and topography, mediated by material and energy fluxes, in response to fast climate dynamics and slow geological processes (Figure 2.2). The patterns that emerge reflect the legacy of past processes, their interconnections over a long period of time leading to the complex spatial patterns that we see in the landscape today (Sivapalan, 2005). These spatial patterns are also responsible for the temporal patterns in runoff response, but the connection between these spatial and temporal patterns is still poorly

Figure 2.1. Channel Country in south-western Queensland, Australia, as a false-colour composite image of Landsat 7's ETM+ sensor on 10 January 2000. http://earthobservatory.nasa.gov/IOTD/view.php?id=3346.

* Coordinating contributor

Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales, ed. Günter Blöschl, Murugesu Sivapalan, Thorsten Wagener, Alberto Viglione and Hubert Savenije. Published by Cambridge University Press.

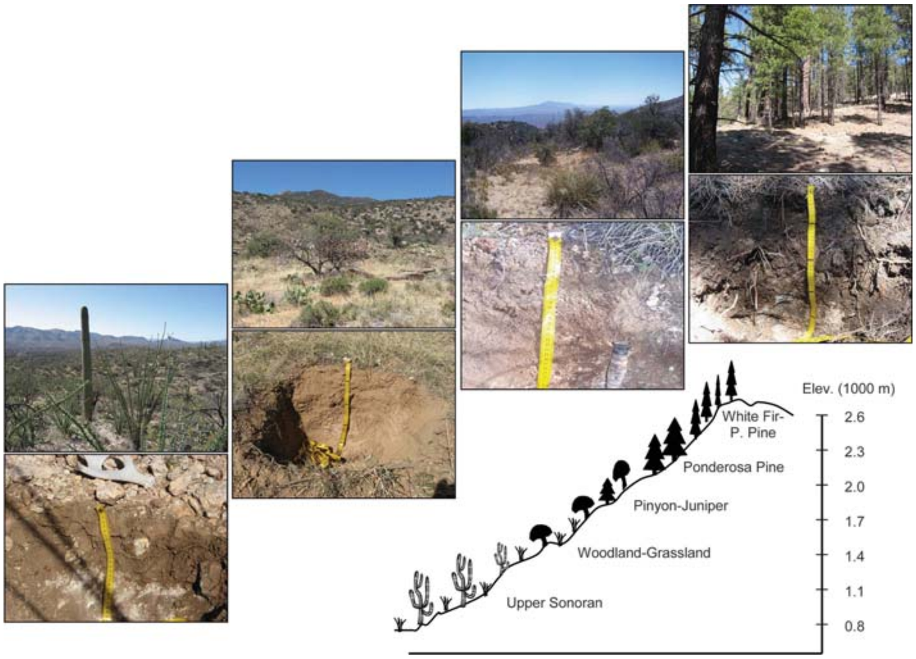

Figure 2.2. Soil–ecosystem evolution along a climate gradient in the south-western USA. From Rasmussen (2008).

understood. Jefferson *et al*. (2010) present an example of this in Oregon, USA, i.e., the net effects of co-evolution and hydrology in the basalt landscape in the Oregon Cascade Range. They showed how dominant runoff processes differ in catchments formed on lava flows that have different ages. Younger catchments exhibit subdued response to precipitation as most water infiltrates and percolates into the permeable bedrock, recharging deep aquifers that generate runoff through permanent springs. Older catchments, on the other hand, have deeper soils with shallow clay layers that create impeding layers, blocking infiltrated water from recharging the aquifers and instead cause shallow subsurface flow that quickly enters the channel network during rain events. At the landscape scale, this change in dominant flow processes causes more incision and a higher drainage density. This, in a nutshell, is the process of co-evolution as it applies to hydrology. Humans often play an important role in altering landscape characteristics, wherein their activities in some environments depend on water availability and through their actions they also affect the water availability (Sivapalan *et al*., 2012). The co-evolution of processes that have led to landscape patterns and their relationship to temporal and spatial patterns of hydrological response is a key to a broader understanding of hydrological response, including that under human-induced changes.

Because of the coupling between different processes across many spatial and temporal scales, catchments are complex systems (Rihani, 2002; Raupach, 2005; Kumar, 2007; Blöschl and Merz, 2010). These are systems with a large number of strongly interdependent variables at many space and time scales. Complex systems are different from simple systems that contain a small number of dimensions only, such as simple mechanical systems. Simple systems are predictable in a deterministic sense and have limited complexity. Complex systems are also different from random systems with a very large number of dimensions, such as a gas. Random systems are predictable in a statistical sense and the tracers may be complex at the molecular scale, but as one goes up in scale the variability averages out (Dooge, 1986).

A simple illustration of the difference between simple systems and complex systems is presented in Figure 2.3, in relation to flood processes and flood estimation in Austria. The left panel on Figure 2.3 illustrates a traditional reductionist way of relating precipitation and catchment time scales to the flood time scale. The flood response time is the sum of storm duration and catchment response time. But in real catchments these three time scales are not independent (Figure 2.3, right panel) and the interplay amongst them can be interpreted differently at different time scales, from hours to millennia. The events that produce the maximum annual floods are those for which the storm duration is close to the concentration time of the catchment, because the catchment-response time scales filter the distribution of all storms to produce the distribution of flood-producing storms. This is the reasoning behind the rational method for flood estimation and it applies at the event scale. At the seasonal time scale, flood characteristics tend to be closely related to the seasonal water balance and, conversely, runoff event types affect the seasonal water balance through rainfall and snowmelt. At the time scale of decades, however, the flow paths as well as soil moisture affect erosion during floods and soil evolution (modulated by differences in geology),

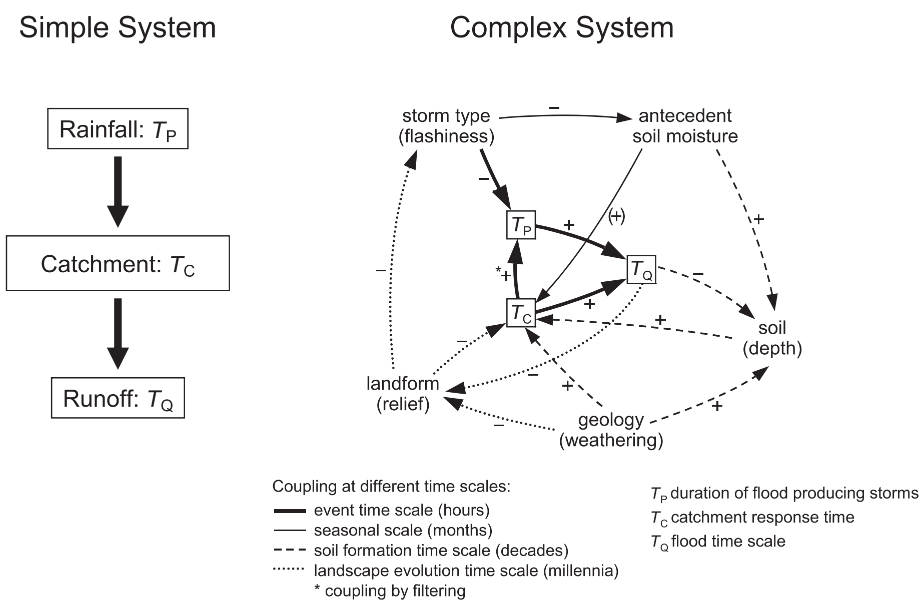

Figure 2.3. Simple and complex system representation of the time scales of floods and their process controls. Interactions of the processes at different time scales have been gleaned from comparative hydrology. From Gaál *et al*. (2012).

while soil depth and permeability affect flow paths and therefore the flood response at the event scale. Even at the landscape evolution time scale there are further interactions. Gaál *et al*. (2012) illustrated how the comparison of catchments of contrasting characteristics can help to recognise the combined effect and interplay of flood processes on the landscape. They showed, for example, one catchment whose form has adapted to the flashiness of floods by producing efficient drainage networks, which in turn enhance the flashiness of the flood response. In other catchments, tortuous drainage networks have evolved, which in turn retard the flood response and impede the evolution of an efficient drainage network.

Complex systems are notoriously difficult to understand, and exhibit inherent limits to their predictability (Blöschl and Zehe, 2005; Kumar, 2011). The complex interactions and feedbacks of the various component processes occurring within a catchment make it difficult to connect cause and effect in a straightforward manner, thus presenting a significant challenge to predictions in ungauged basins. On the other hand, an important feature of complex systems, as outlined above, is their tendency to generate emergent patterns. Depending on the scale at which one looks, the patterns the system produces may be different. If one zooms in, one set of patterns emerges. If one zooms out, a new set of patterns emerges. Looking at emergent patterns, one cannot easily find causal connections between the patterns at different scales. In the catena example above, it is not trivial to explain how the interactions of local-scale processes led to catena patterns at the hillslope scale and further organised patterns around the river network at the catchment scale. The evolution of these patterns is the result of the interaction of several component processes at a range of space and time scales, producing patterns at many space scales (Figure 2.2). Yet the fact that catchments as complex systems create interesting spatial and temporal patterns offers opportunities that can be exploited to advance predictions.

2.1.2 Signatures: a manifestation of co-evolution

Spatial patterns such as those presented in Figures 2.1 and 2.2 are readily observable, and they contribute to observed temporal patterns of hydrological response produced by catchments. Most importantly, the observed runoff response of a catchment constitutes an interesting, complex temporal pattern of water fluxes, which are the result of the collective behaviour of a great number of components of the catchment, including the effects of the landscape patterns.

When looking at the catchment behaviour in an aggregate way, one can identify typical holistic characteristics of the catchment response, something termed 'catchment functioning' by Black (1997), by analogy with a similar term used in ecology (Jax, 2005). The collective or holistic response of the catchment resulting from the component processes can be expressed in terms of holistic behaviour such as partitioning, transmission, storage and release of water, energy and matter (Black, 1997; McDonnell *et al*., 2007; Wagener *et al*., 2007). Partitioning refers to the separation of water, energy and matter into different pathways at or near the land surface through processes including interception, infiltration and surface runoff. Storage refers to actions of the catchment to retain water, energy and matter in different parts of the catchment and over very different time scales. Storage can include snow and ice, interception, soil moisture, aquifers, water bodies and also vegetation. Transmission refers to the fluxes of water, energy and matter through the catchment. These fluxes are strongly dependent on the connectivity between the different parts of the catchment and will significantly vary over time in many cases, depending on the moisture state of the system. Finally, release refers to the mechanisms by which water, energy and matter are released from the catchment through atmospheric, surface and subsurface fluxes. Fluxes of water, energy and matter include evaporation, transpiration, channel flow, sediment transport and groundwater exchange.

The co-evolution of climate, vegetation, landscape and soils, through the self-organised landscape patterns it tends to produce, gives rise to evident fingerprints on the catchment runoff responses. Since the structure of the landscape determines the heterogeneity and organisation of pathways that water can follow, and associated residence times, these also govern the richness of the catchment's hydrological responses. This includes the emergent connectivity of pathways, the appearance of thresholds and tipping points, all leading to a holistic response that is harder to prescribe *a priori*, let alone predict on the basis of traditional simple system approaches. Indeed, Knighton and Nanson (2001) have documented complex patterns of event-scale runoff variability at a range of time and space scales for the Channel Country of Australia, including Lake Eyre, which overlaps with the geographic region presented earlier in Figure 2.1. The work raises interesting questions about how the amazingly complex spatial patterns shown in Figure 2.1 are mirrored in the runoff variability, and whether it can be explained hydrologically to enable predictions. Understanding these connections is particularly important when humans increasingly become a major part of this co-evolutionary system, with the possibility of generation of new emergent dynamics hitherto unobserved (Winder *et al*., 2005; Kallis, 2007).

In this book, following Jothityangkoon *et al*. (2001) and Eder *et al*. (2003), the temporal patterns of the observed runoff response of catchments, when viewed at different time scales, are termed runoff 'signatures', and deemed emergent patterns. We term them 'signatures' because they are considered as reflections of the overall functioning of the catchments, including the co-evolutionary features of the catchments' surface and subsurface architecture. The spatial signatures (or fingerprints) of catchments, such as soil catena, stream network topology and soil moisture patterns, are all intimately related to the temporal patterns of runoff at different time scales, and the focus here is on advancing and exploiting our understanding of their interrelationships.

Runoff variability at any location is a temporal continuum covering a wide range of time scales, but the characteristics one sees depend on the temporal scale one chooses to look at. This is because catchments exhibit the characteristics of complex systems, so different patterns emerge at different time scales. At time scales of seconds one may recognise the effects of turbulence and wave action in the runoff. At time scales of millennia, if such data were available as in the case of Jefferson *et al*. (2010), one would recognise long-term climate and landscape evolution trends. There may be several emergent patterns in the time domain and they are all inter-connected because they are all the result of the same complex system and co-evolutionary processes.

Depending on the collective behaviour of the catchment processes and the underlying drivers, the runoff signatures may differ. Therefore they can be seen as windows that enable us to look into the catchment dynamics at different time scales. They help us to understand the system holistically. Signatures provide insights into catchment processes, and are thus outward manifestations of the internal dynamics of the catchment. The runoff signatures examined in this book are annual runoff, seasonal runoff, flow duration curves, low flows, floods and runoff hydrographs (Figure 2.4). In a preface to a special journal issue on the downward approach to hydrological prediction, Sivapalan *et al*. (2003a) said, inter alia:

> The Budyko curve, inter-annual and mean monthly variability of water balance, flow duration curves, and the spatial organisation of these signatures … are the key signatures that embody the hydrological organisation or hidden order, and a quest for identifying them seems promising.

For example, annual runoff is a reflection of the catchment dynamics at relatively long time scales, which is particularly evident in the between-year variability of annual runoff. Seasonal runoff reflects the within-year variability, i.e., how the catchment organises itself at the sub-annual time scale. The flow duration curve represents the full spectrum of variability in terms of flow magnitudes. Low flows focus on the low end of that spectrum, and so provide a window into catchment dynamics when there is little water in the system, and floods are at the opposite end, when there is much water in the system. Hydrographs are the complex combination of all of these signatures. They are the most detailed signatures of how catchments respond to water and energy inputs.

In this book, the signatures are the starting point for making runoff predictions in ungauged basins as they are the manifestations of the catchment functioning at different time scales. They are also the focal point of the predictions, and predictions of all the signatures in ungauged basins are reviewed in this book in their own right. In fact, they are fully consistent with the time scales at which runoff predictions in ungauged basins are needed from a societal perspective, as illustrated in Table 1.1.

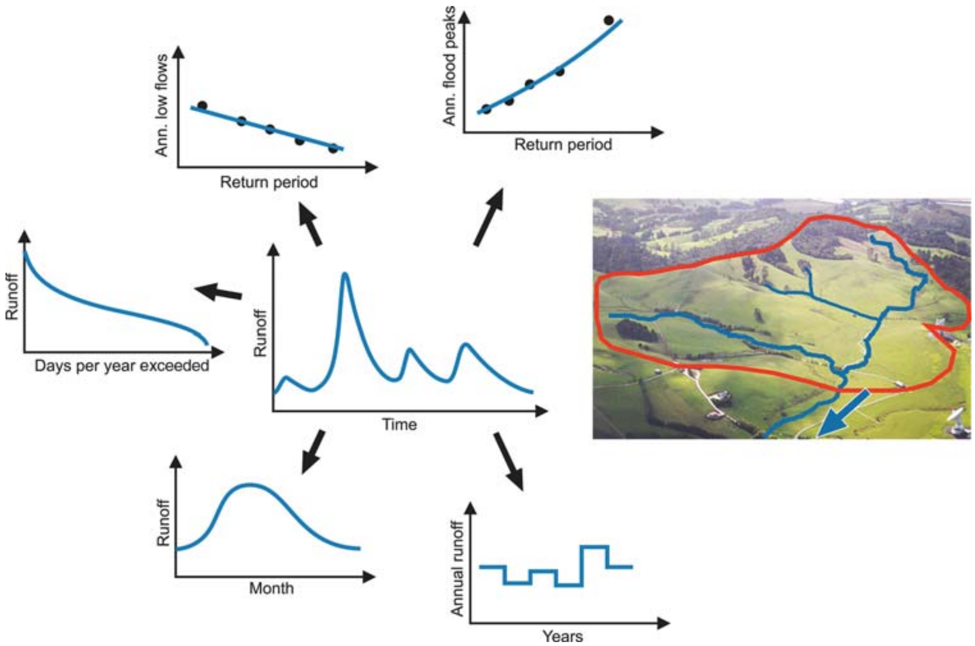

Figure 2.4. Runoff signatures examined in this book. Clockwise from bottom right: annual runoff, seasonal runoff, flow duration curves, low flows, floods and runoff hydrographs. Photo: R. Young.

2.2 Comparative hydrology and the Darwinian approach

2.2.1 Generalisation through comparative hydrology

One way of learning from the runoff signature patterns is to build models based on Newtonian mechanics that can represent the component processes in a particular catchment in considerable detail. These models can then be used to perform simulations over several years (or decades) to see whether they match the patterns observed in natural catchments (e.g., Carrillo *et al*., 2011). Similar detailed mechanistic models can also be built to simulate hydrological processes over shorter time scales in order to predict rainfall–runoff response in ungauged basins. The strength of these mechanistic models is that the causality of the component processes can be represented in a deterministic way and in much detail, although it is inherently much more difficult to represent well the feedbacks between different processes acting at a range of time scales. It is this aspect of complex systems that contributes to their limited predictability. Modelling the interactions and feedbacks between different processes acting within catchments may be improved if we better understand the effects of co-evolution of climate, vegetation, landform and soils on catchment functioning.

Instead of studying a particular catchment in much detail, an alternative approach may be to examine many catchments at the same time and study the emergent patterns in a comparative way. Here, the purpose is to develop *generalisations* beyond individual catchments by learning from differences between many catchments that are deemed legacies of co-evolution. There is a lot of potential for this type of comparative analysis. Figure 2.5 illustrates the idea for regions in Australia with different precipitation availability. Under sufficiently arid conditions (a), almost all precipitation evaporates, and hydrological processes are essentially vertical, producing sparse vegetation organised in spotty spatial patterns. As precipitation availability increases (b and c), horizontal flow processes become increasingly important and perennial vegetation emerges in close association with the drainage network structure. At even higher precipitation rates (d and e) canopies begin to close and woody vegetation occupies most of the catchment, but there may yet be differences in the species between drainage lines and the uplands. Process-based models of the Newtonian type could also produce these patterns, but it is unclear how to parameterise these models across climate gradients to reflect changes in dominant hydrological processes that help generate the spatial patterns. By doing comparative analysis across these diverse regions, i.e., exploiting the differences in the patterns, one may be able to infer the controls on the landscape processes at the long time scales of vegetation adaptation, and build appropriate models that reflect such controls.

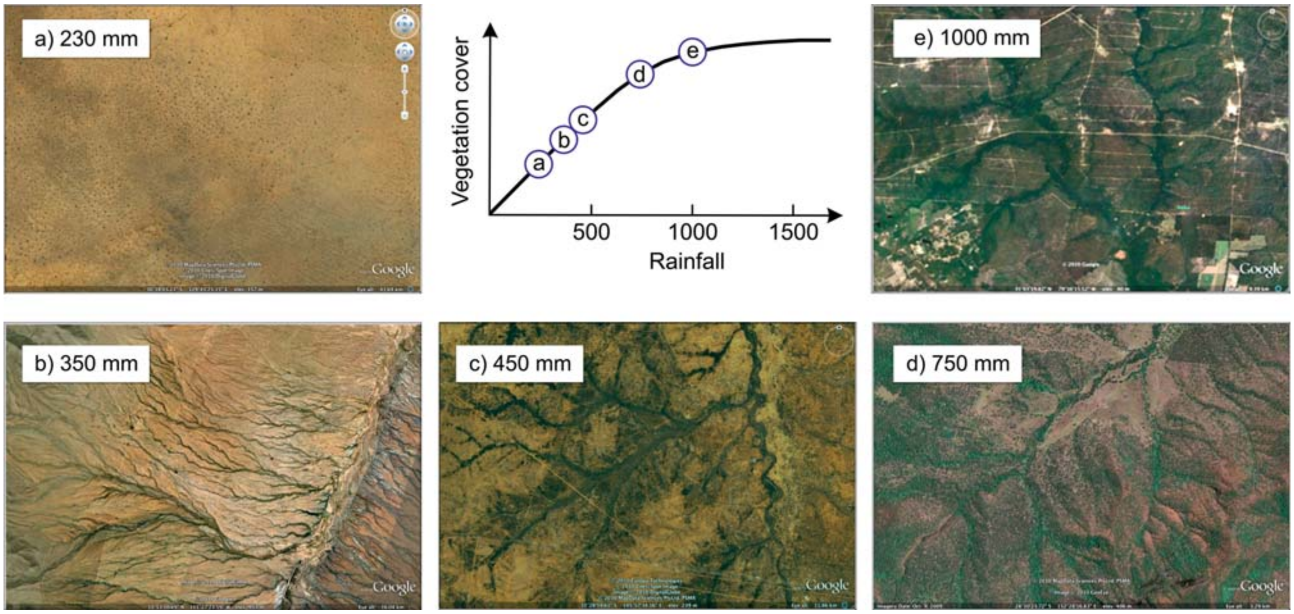

Figure 2.5. Vegetation patterns for different regions in Australia with annual precipitation ranging from 230 to 1000 mm. From Thompson *et al*. (2011).

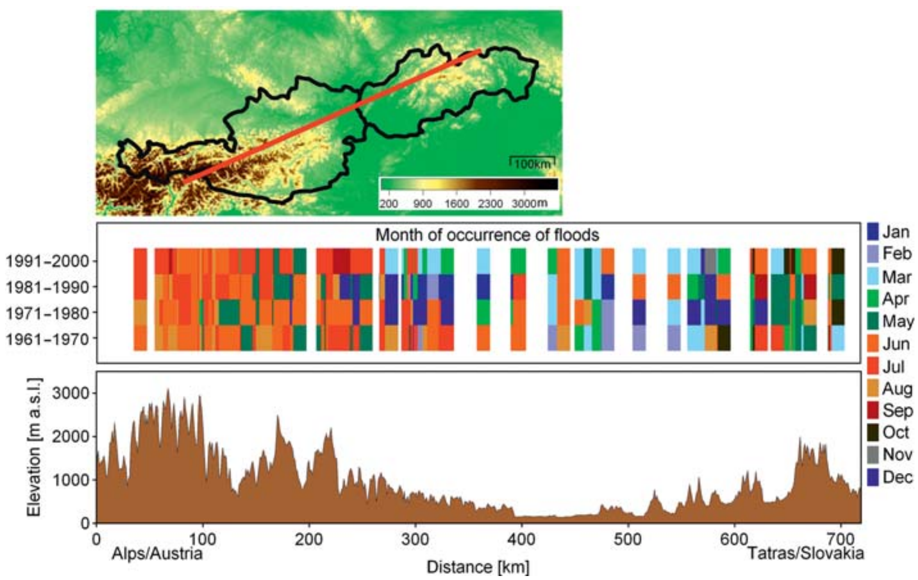

Figure 2.6. Season (month) of the occurrence of floods along a transect Austria–Slovakia in the decades of the period 1961–2000. Bottom panel shows the elevation of the transect. From Parajka *et al*. (2009a).

Figure 2.6 shows another example to illustrate what can be learned through comparing and contrasting many catchments; knowledge that is impossible to obtain otherwise. It presents, along a transect across Austria and Slovakia, the time of the year that floods have occurred, revealing interesting differences and similarities, even though most of the precipitation occurs in summer in the entire region. In the Alpine catchments in the west, floods are summer-dominated, while in the lowland catchments in the centre of the cross-section, winter floods dominate. This is because of the seasonal interplay of soil moisture dynamics and flood generation processes. In summer, the lowland soils tend to be very dry, while in winter they are much wetter, thus favouring flood occurrence. It is also interesting to see how winter floods move further up in elevation as the climate gets warmer (at location 300 km).

The approach of analysing many catchments in a synoptic way, as in the two previous examples, has been termed 'comparative hydrology' by Falkenmark and Chapman (1989). Rather than modelling a single catchment in detail, the idea here is to compare many catchments with contrasting characteristics in order to understand the process controls of the catchments viewed as complex systems. Falkenmark and Chapman (1989, p. 12) summarised their approach as follows:

> The term 'comparative hydrology' was coined to describe the study of the character of hydrological processes as influenced by climate and the nature of the earth's surface and subsurface. Emphasis is placed on understanding the interactions between hydrology and the ecosystem, and determining to what extent hydrological predictions may be transferred from one area to another.

They note, however (p. 9):

> It should be remembered that the book represents no more than a first effort to draw attention to the field of comparative hydrology, and we sincerely hope that by doing so, further research in the field will be stimulated. In our understanding, comparative hydrology should develop into a basically analytical science. The heavy descriptive content in the late sections of this textbook should therefore be accepted as an infant disease, as few analytical studies stressing similarities and differences between hydrological zones are yet available.

The present book builds on the comparative hydrology approach of Falkenmark and Chapman, and attempts to do so in a quantitative way to generalise beyond individual catchments.

One of the strengths of comparative hydrology is that it allows the examination of processes in a more *holistic* way than does normal modelling. In a model, only those processes and scales actually represented in the model can be analysed, while in the comparative hydrology approach we can see the summary effect and interplay of all relevant processes if the data from the catchments of contrasting characteristics are compared. Also, the comparative hydrology approach provides an opportunity to exploit multiple development histories. Different catchments have evolved in different ways as a result of different climates and geologies and that historical legacy is apparent at one time in many places. This concept can be illustrated by the example of the medical doctor in Figure 1.5. Instead of dissecting each patient to look inside the body for the cause of a reported ailment, the doctor may choose to look around the world to see the case histories of a larger population of people with similar ailments before prescribing a treatment.

The comparative approach used for generalisation can be deemed a Darwinian approach. Charles Darwin conducted a comparative analysis of wildlife and fossils that he had collected during his world trip, and came up with the principle of natural selection by being able to generalise the patterns he saw in the record he assembled. As Sivapalan *et al*. (2011a, p. 5) put it in a hydrological context:

> The Darwinian approach values holistic understanding of the behaviour of the given landscape. It embraces the history of a given place, including those features that are relics of historical events, as central to understanding both its present and its future. The Darwinian approach gains predictive power by connecting a given site to several sites located along critical gradients. Laws in the Darwinian approach will seek to explain patterns of variability and commonality across several sites.

The Darwinian approach therefore contrasts sharply with the Newtonian approach, which remains the dominant paradigm in physics, and even in hydrology, and builds on the application of universal laws (Harte, 2002). The Darwinian approach, on the other hand, is the dominant paradigm in ecology and emphasises patterns and the history of the place. Much of the insight and power of the Darwinian approach comes from comparing similar and dissimilar places and then attempting to generalise, just as Darwin learned by comparing species from around the world. The Newtonian approach generalises by discovering universal laws governing particular processes through experimentation and mathematical derivations, whereas the Darwinian approach generalises through discovering patterns through comparative analyses across places and seeking explanations of how they came about.

How then does the comparative hydrology approach *help* in the synthesis across processes, places and scales, the focus of this book? We consider each catchment as a result of nature's myriad experiments. Each catchment represents a sample, a distinct outcome, one of an infinite variety, but resulting from a combination of the same co-evolutionary earth system processes, and underpinned by common, yet unknown, organising principles: water flow processes, land-forming processes and life-sustaining processes. But these same organising principles may manifest themselves in different ways in different climates and geologies, so they may look randomly different. The comparative hydrology approach may be a useful framework to study these apparently random (or unique) catchments as a way to develop common understanding.

Just as a jigsaw puzzle looks random at first, once it starts to fall into place it begins to reveal interesting patterns and indeed connections. In other words, the goal of comparative hydrology is to ultimately bring order into what otherwise looks disordered, to find new connections where none existed, and it will therefore be the hallmark of the synthesis we propose. The comparative hydrology approach will bring order into a diversity of hydrological processes, just the way Darwin found order amongst otherwise different species, or the way the periodic table of chemical elements brought order to a seemingly unrelated collection of elements. The comparative hydrology approach will bring order into the diversity across places,

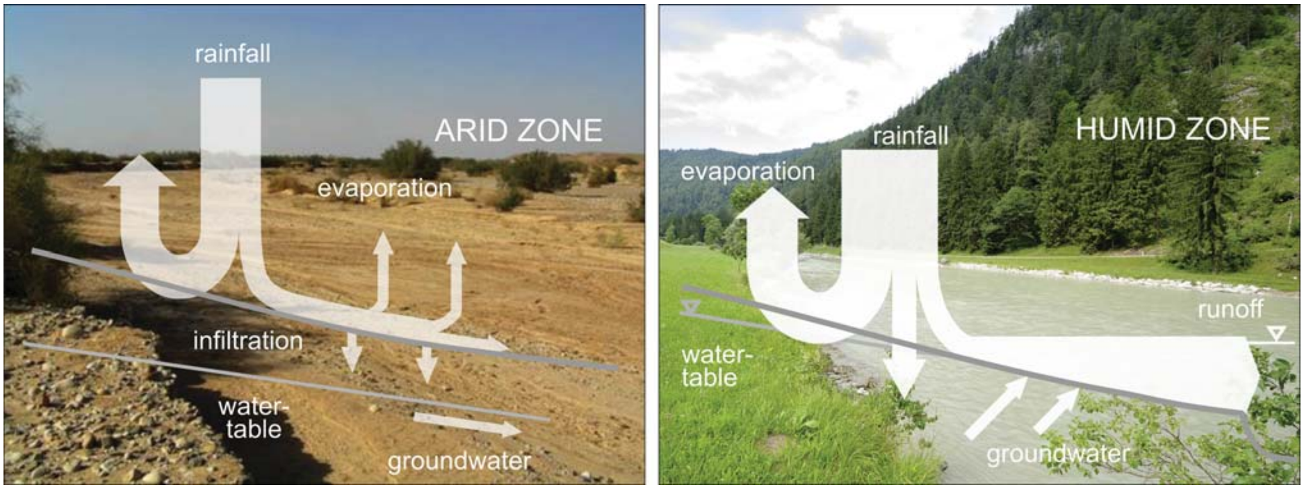

Figure 2.7. Runoff generation and surface water–groundwater interactions under typical arid and humid conditions. After Erhard-Cassegrain and Margat (1979) in Falkenmark and Chapman (1989). Photos: (left) O. Dahan, (right) P. Haas.

as it will help find patterns along spatial gradients of climate and landscape characteristics. And the comparative hydrology approach will bring order into the diversity across scales as the land surface is organised into catchments of all sizes, nested within each other, and different properties may then emerge at different scales that can be studied, interpreted and explained by the approach. Bronowski (1956, p. 23) brilliantly described this natural, otherwise normal, scientific process in the following words:

> All science is the search for unity in hidden likenesses …The progress of science is the discovery at each step of a new order which gives unity to what had long seemed unlike … For order does not display itself of itself; if it can be said to be there at all, it is not there for the mere looking … order must be discovered and, in a deep sense, it must be created. What we see, as we see it, is mere disorder.

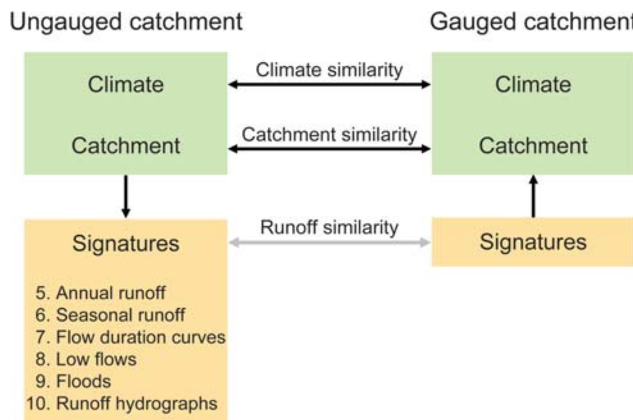

Figure 2.8. Prediction of runoff signatures in ungauged basins through climate, catchment and runoff similarity (the numbers in the box refer to the various chapters of this book).

2.2.2 Hydrological similarity

The success of the comparative hydrology approach hinges on the concepts of similarity and dissimilarity. If one compares many catchments, some of them will appear more similar with respect to a particular characteristic and this similarity will guide the interpretation of the different emergent patterns. Catchments can be considered hydrologically similar, in a general way, if they filter climate variability in similar fashion, as expressed by their (scaled) hydrological signatures. This similarity may be brought about by similar trajectories of co-evolution of climate, vegetation, soils and landscape. The concept of similarity and dissimilarity of processes is illustrated in Figure 2.7. In arid catchments, there is relatively little precipitation, much of which evaporates, and there is little infiltration (and which is highly episodic) down to a deep aquifer. Part of the stream reaches will be losing reaches, with flow in the river infiltrating through the river bed to recharge the underlying aquifer. In contrast, in a humid catchment precipitation will be higher, and infiltration will be less episodic. Part of the stream reaches will be gaining reaches, where the groundwater recharges the streamflow.

Hydrological similarity in terms of similarity of processes is difficult to identify in a real-world setting as only partial knowledge of the hydrological processes is available. Based on the rationale that runoff is the result of the interplay of climate and catchment processes, one can therefore split up the more generic similarity into runoff similarity, climate similarity and catchment similarity (Figure 2.8). The comparative hydrology approach then consists of learning from the similarities and differences of catchments in terms of their climate, catchment characteristics and runoff signatures. The underlying assumption is that catchments that are similar with respect to climate and catchment characteristics will also behave similarly in a hydrological sense. This assumption can be tested in gauged catchments, where one can learn from relating the runoff signatures to climate and catchment characteristics. One can then use the concept of similarity to transpose what one has learned in gauged catchments in order to predict runoff in ungauged basins.

Climate similarity
Climate similarity, in the context of this book, entails similarity in climate characteristics that are relevant for hydrology. Climate classification schemes such as those by Köppen (1936) and Thornthwaite (1931) define regions through a combination of mean annual precipitation, air temperature and their seasonal variability. Budyko (1974) and L'vovich (1979) developed long-term average relationships between measures of water and energy availability in various regions. A typical index of this kind is the aridity index, which is the ratio of annual potential evaporation and annual precipitation. Those catchments with aridity indices larger than unity are deemed water-limited, and those with an aridity index smaller than unity are energy-limited. If the aridity indices are similar, the catchments are deemed similar with respect to the relative availability of water and energy. Catchment characteristics, such as soils, topography and vegetation, puzzlingly only play a secondary role in this partitioning, which is suggestive of their co-evolution. Climate similarity can also be defined as similarity in the inter-annual variability of precipitation if one is interested in the long-term fluctuations of runoff. Climate similarity can further be defined as similarity in the extreme rainfall and its seasonality if one is interested in floods, and in terms of dry spells and of their seasonality if one is interested in droughts and low flows. The relative importance of snow processes can be very relevant for hydrological similarity, and these can be indexed by air temperature and/or catchment elevation.

Comparative hydrology sometimes discovers similarity indices and predictors that contradict or defy process interpretations. This may be because they represent several, not one, factors that contribute to the explanation of a variable of interest, and so mask the process interpretation. An example is mean annual precipitation, which happens to be a powerful similarity index for flood peak, for example. It becomes a useful similarity index not only because of its direct effect on runoff generation at the event scale but also through its indirect effect on longer-term soil moisture availability and still longer term landscape, soil and vegetation evolution processes. In other words, the value of mean annual precipitation as a climate similarity index for floods goes beyond the event scale causality, and reflects the net effects of co-evolutionary processes.

Catchment similarity
Catchment similarity, in the context of this book, entails similarity in those catchment characteristics that control runoff processes (McDonnell and Woods, 2004). From a catchment functioning perspective these are processes that control the partitioning, transmission, storage and release of water, so similarity relates to similarity in one or more of these functions. Catchment characteristics that relate to partitioning include the infiltration properties of soils, such as hydraulic conductivity, which is often estimated with the use of pedo-transfer functions from soil texture. They also include vegetation indices, often as a proxy of evaporation at seasonal or annual time scales. Catchment characteristics that relate to transmission are those that represent flow paths in some way. One example is the topographic wetness index (upslope contributing area divided by the local surface topographic slope) that provides similarity of the competition between hillslope recharge and drainage (Kirkby, 1978). Catchment characteristics that relate to storage are geology and soil properties such as soil depth. Also, area is sometimes used as an indicator of catchment storage, as larger catchments tend to be more groundwater dominated with deeper flow paths and more active storage availability.

Many of the catchment processes occur below the surface, so similarity is difficult to quantify unambiguously. Co-evolutionary indices related to interacting catchment processes are therefore particularly important. The classic index is stream network density (stream length per area). The rationale behind the use of stream network density as a similarity index is that the stream network is itself a result of the co-evolution of the landscape, soil and vegetation, subject to the climate and geology in a particular region (Abrahams, 1984; Wang and Wu, 2012). Drainage densities tend to be the result of water availability (precipitation – evaporation), infiltration characteristics of the surface soils and the drainage characteristics of the underlying geology, which together determine how much runoff is generated and the fraction of surface runoff, and the armouring provided by the presence of vegetation. In this way, the drainage density is a holistic index combining a range of processes at a multitude of time scales, and thus reflects the overall catchment functioning. Hydrology clearly exhibits many similarities with geomorphology (de Boer, 1992). In a review of predictive modelling in geomorphology, Haff (1996) states, inter alia:

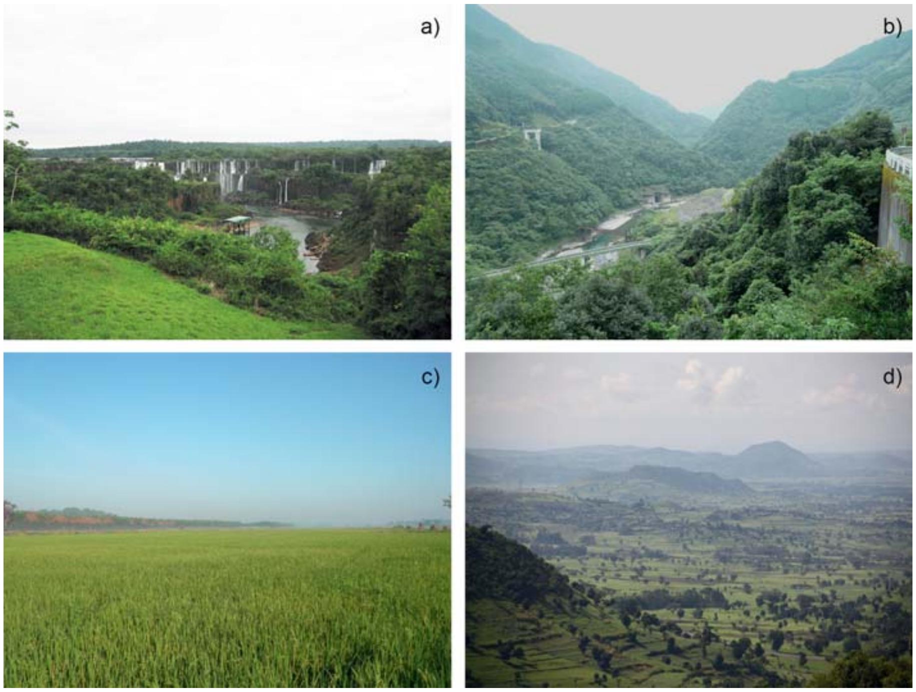

Figure 2.9. Climate and catchment similarities and dissimilarities: (a) wet flat forest at Iguazu, mean annual precipitation $P_A = 1880$ mm/yr; (b) wet steep forest in the Kuma River in Japan, $P_A = 1990$ mm/yr; (c) wet flat rice paddy at the Irrawaddy River basin in Myanmar, $P_A = 2500$ mm/yr. Photos: Y. Tachikawa; (d) Semien Mountains in Ethiopia, $P_A = 1100$ mm/yr. Photo: A. Eder.

> In geomorphic systems, 'empirical' variables that are found to be useful for prediction may in fact be related to emergent variables of the system. In such cases, searching for emergent variables, and the constitutive rules that connect them, should be a central focus of activity of geomorphological science, … rather than scaling up the results of well-controlled laboratory-scale studies.

The photographs in Figure 2.9 show examples of how different landscapes under similar total annual rainfall have co-evolved differently.

Xu *et al*. (2012) have found a Budyko-type relationship between the ratio of deep-rooted vegetation to total vegetation cover across Australia, which is also governed by the same ratio of water and energy. It stands to reason that we can make progress in understanding other seemingly simple catchment responses, such as the baseflow recession, by focusing on the role of climate, vegetation, soil and landform interactions in governing this emergent simplicity. This is the rationale behind the organisation of the book.

Runoff similarity

In the case of runoff similarity, the interest resides in how similar or dissimilar the characteristics of runoff are. Within the framework of signatures as emergent patterns, runoff similarity can therefore be defined as similarity in the runoff signatures. If one is interested in the long-term hydrological behaviour, catchments would be considered similar if their 'annual runoff signature' does not differ much. This may be the long-term mean runoff (expressed as a fraction of precipitation) or, alternatively, the variability of annual runoff between years (expressed in terms of, say, elasticity). If one is interested in floods, catchments may be considered similar if their flood signatures, such as the flood frequency curve, exhibit similarities. Similarity does not necessarily imply that all the signatures are identical. Typically, similarity rests on scaled variables (Wagener *et al*., 2007). For example, the flood frequency curves scaled by the mean annual flood may be considered the characteristic by which similar catchments should not differ much. Two catchments could be similar in all signatures (which may be rare), but they could be considered similar in terms of one signature, say, low flow, but dissimilar in terms of others such as floods. This means the runoff similarity may depend on the signature one is interested in. In other words, given the diversity of nature, one cannot expect there to be 'perfect' similarity.

Indices of runoff similarity require runoff data to be available. For the case of ungauged basins, runoff data clearly are not available. The similarity approach then uses the similarity of climate and catchment characteristics in order to infer hydrological similarity in an approximate way, and help predict runoff in ungauged basins.

2.2.3 Catchment grouping: exploiting the similarity concept for PUB

Hydrological similarity between catchments can be exploited in two ways for runoff predictions in ungauged basins:

- to assist in the understanding of hydrological processes;
- to transfer information from gauged to ungauged locations.

Understanding of hydrological processes: Once the hydrological similarity or dissimilarity of catchments has been identified (for a particular purpose) the catchments can be grouped to reflect the similarity. These groups can then be used for classifying catchments. The power of classification can perhaps be best illustrated by the periodic table of chemical elements credited to Dmitri Mendeleev. Before Mendeleev's classification, the reactions of chemical elements must have appeared chaotic and confusing. Mendeleev's periodic table not only enabled him to better understand the behaviour of various chemical elements (e.g., on the basis of their atomic number) but he was also able to 'predict' characteristics of chemical elements that were then unknown. In a similar fashion, classification can be used in hydrology for organising catchments, simplifying relationships and generalising findings. These may help with process-based models, in particular to find out what types of models to use. This type of classification/grouping may also assist with assessing our predictive ability, e.g., in what kind of catchment is our predictive ability higher or lower. Ultimately this will assist with the generalisation issue that has haunted hydrologists since the science began.

Transferring information from gauged to ungauged locations

From a more practical point of view, similarity can be used to transfer information from gauged to ungauged locations. In a first step, catchments (or landscape units) are identified that are similar in terms of the climate and/or the catchment characteristics chosen and are grouped together. Usually some index is chosen that quantifies what makes two catchments similar in terms of climate (such as similar mean annual precipitation, P_A) and catchment characteristics (such as mean catchment elevation, Z). A distance measure then defines the similarity or dissimilarity between two catchments. A typically used distance measure is the Euclidian distance. In the examples above, the Euclidian distance is $D^2 = (P_{A,i} - P_{A,j})^2 + (Z_i - Z_j)^2$ (in fact, the indices could be scaled to make P_A and Z dimensionless, and in this way give them equal power). The important point here is that the distance D is small if the catchments are similar with respect to their catchment/climate characteristics. The catchments are then grouped into similar regions on the basis of minimising the distance measure D. The over-riding idea of grouping usually is that within the group the catchments should be as similar as possible, but the averages of the different groups should be as different as possible. This is illustrated in Figure 2.10a

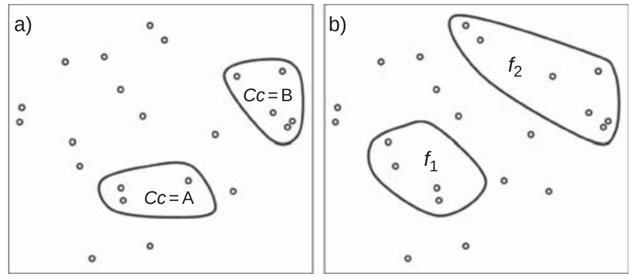

Figure 2.10. Map of an imaginary country where catchments (indicated as points) are grouped into regions. (a) Grouping into regions with similar catchment characteristics, Cc; (b) grouping into regions where the regionalisation methods f_1 and f_2 (such as the regression equations) are similar.

where the catchment characteristics within each of the two regions are similar, but are different between the regions. There is a trade-off between the number of groups and the homogeneity within the group, the more groups one forms the more homogeneous each of them will be, but a larger number of groups entails a relatively smaller number of catchments per group. There are numerous methods available for identifying homogeneous groups, including cluster analysis and other multivariate statistical methods (see e.g., Cressie, 1991; Arabie *et al*., 1996). This grouping step breaks up the landscape into a mosaic of units that may or may not be contiguous. The rationale is that, if the climate/catchment characteristics are similar, the hydrological processes will also be similar. In a second step, this grouping is then exploited for regionalisation. For example, the grouping can be used to transfer the flow duration curve scaled by the mean annual flow from gauged to ungauged basins on the basis of the assumption that these scaled curves will be identical in the entire homogeneous region. Similarly, scaled flood frequency curves (i.e., growth curves) can be transferred from gauged to ungauged catchments based on similar assumptions.

Sometimes, however, one is not interested in finding groups of catchments that are most similar in terms of their climate/catchment characteristics but in terms of their mapping functions, i.e., the models that estimate runoff from climate and catchment characteristics. The mapping functions can be regressions between catchment characteristics (such as elevation) and runoff signatures (such as mean annual runoff). The mapping functions can also be process-based rainfall–runoff methods. The important difference from the previous approach is that now we are not interested in finding regions that are homogeneous in terms of, say, mean annual runoff, but in terms of the regionalisation method, i.e., implying that the same, say, regression model applies to all catchments within a region, but a different model applies in different regions. This is illustrated in

Figure 2.10b. The runoff signature S_Q (such as mean annual runoff) is estimated from climate characteristics, Cl, and catchment characteristics, Cc, based on a model f (which can be a regression, a rainfall–runoff model, etc.). The model will then differ between the regions, i.e., in region 1, the $S_Q = f_1\ (Cc, Cl)$, in region 2, the $S_Q = f_2\ (Cc, Cl)$. Instead of Cc and Cl that were similar in the previous approach, now it is f_1, f_2 etc. that are similar within a group. In some instances, the model f is process-based using balance equations based on Newtonian mechanics. In other instances the model f does not resolve the processes in detail but exploits the co-evolution of catchments. For example, even if the runoff processes are not known in detail, a regression between stream network density and mean annual floods can give excellent results. However, the relationship between stream network density and mean annual floods may differ fundamentally between regions. In one region the low stream network density may be due to karst, in another region the low stream network density may be due to sandy soils, and in still another region it may be due to low precipitation. In these three regions the functional relationships, f, between stream network density and mean annual floods will be different. Identifying groups with similar regionalisation methods is less straightforward than those with similar catchment characteristics and, often, iterative methods are used.

Finally, the grouping of catchments is sometimes done on the basis of runoff. This may be useful as a first regionalisation step. However, to transfer the runoff signatures to ungauged catchments some sort of allocation rule is needed, i.e., information about what group a particular ungauged catchment belongs to. Allocation rules can, again, be estimated from runoff data and then used for climate and catchment characteristics in the ungauged catchments.

2.3 From comparative hydrology to predictions in ungauged basins

2.3.1 Statistical methods of predictions in ungauged basins

There are two fundamentally different types of methods available for estimating runoff in ungauged basins. The first are statistical methods. In these methods the runoff signatures of interest are assumed to be random variables. Typically, the statistical methods are not based on balance equations of mass, momentum and energy. Instead, they consist of simple linear (or non-linear) relationships between runoff, and climate and catchment characteristics. The model structure is usually assumed *a priori*. The model parameters, however, are usually estimated from the data in the region of interest. In this book, the statistical methods have been assembled into three groups:

Regression methods: In a regression method, the runoff signature $\hat{y}$ of interest (for example, the flood discharge of a given probability) is estimated from catchment and/or climate characteristics x_i with sampling error ε:

$$\hat{y} = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \varepsilon + \eta$$

where there are i different characteristics, β_i are the model parameters (i.e., regression coefficients) and η is the model error. Many techniques are available to estimate the model parameters for the linear model (e.g., Mendenhall and Sincich, 2011). There are two options: use one regression model for the entire domain of interest (termed global regression); or subdivide the domain into regions (according to Figure 2.10b) and apply separate regression models for each region (termed regional regression). From a hydrological perspective it is important that the regression coefficients be interpreted hydrologically. This is because such interpretations increase the likelihood that the equation also applies to the ungauged catchments that have not been used in estimating the coefficients. The regression equations are very simple representations of otherwise complex process relationships. These may, in particular, involve co-evolutionary aspects of the catchment. The interpretation of the coefficient is therefore not necessarily mechanistic but may be based on a broader reasoning of the co-evolution of landscapes, climate, soils and vegetation.

Index methods: Index methods are based on some scaled property of the catchment. For example, the flow duration curve can be scaled by the mean annual flow. The index method then assumes that the scaled flow duration curve is uniform within a region as identified above. Another example is the Budyko curve method, where the ratio of mean annual actual evaporation to mean annual precipitation is expressed as a function of the aridity index, the ratio of mean annual potential evaporation and mean annual precipitation. The index methods reflect some underlying hydrological principle that is not inferred from the data but from hydrological reasoning.

Geostatistical methods: The geostatistical methods exploit the correlation of runoff signatures in space. In the geostatistical approach the runoff signature of interest in the ungauged catchment is assumed to be a weighted mean of the runoff signatures in the neighbouring catchments. The weights are estimated on the basis of the spatial correlations of the runoff signatures and the relative locations of the catchments and/or the stream network. The geostatistical approach goes beyond simple spatial distance measures as they account for spatial correlations that will differ between processes and regions (e.g., longer spatial distances for low flows than for floods), and the so-called declustering property of geostatistics, i.e., the ability to give less weight to observations that are close to each other because they are correlated, so contain less information about the random variable. For clarity, in Chapters 5 and 6 simple methods based on spatial proximity are also discussed within the geostatistics section, since there are practical similarities in the procedures of mapping with the geostatistical method, even though, strictly speaking, no random variables are involved.

Estimation from short runoff records: While this book is about runoff predictions in ungauged basins, there may be instances where a short runoff record is indeed available. The record may be too short to estimate the runoff signatures to a level of accuracy that is sufficient for the problem at hand. However, together with information from other catchments in the region and the use of regionalisation methods, it may be possible to exploit the information that is contained in the short runoff records. Runoff information from a neighbouring catchment is usually used to account for the temporal variability in the runoff signatures in the poorly gauged catchment of interest as a result of the runoff records in that catchment being too short.

2.3.2 Process-based methods of predictions in ungauged basins

A second type of methods for estimating runoff in ungauged basins is process-based methods. Process-based methods are normally based on some combination of balance equations of mass, momentum and energy. Most of them are deterministic methods, i.e., without random elements. However, there are some combinations of process-based methods with statistical methods. The model structure, in most instances, is assumed *a priori*, based on a conceptual understanding of the hydrological processes operating at the catchment scale. For the case of predicting runoff hydrographs, several methods include models that are based on an understanding of hydrological processes obtained at the laboratory scale. Examples are models that use the Richards equations for estimating infiltration and subsurface water movement. Model parameters for the first type of conceptual models are usually inferred from parameters that have been found by calibration to runoff in neighbouring catchments. Model parameters for the second type of models that are based on laboratory-scale governing equations are usually inferred from field data and similarity assumptions. In this book, the process-based methods have been assembled into three groups:

Derived distribution methods: In this type of approach, the runoff signatures (such as floods) are estimated from precipitation signatures (such as rainfall statistics). The appealing feature of the derived distribution approach is that the rainfall–runoff relationship can be formulated directly in terms of probabilities, often in an analytical way, which makes for a clear model structure. However, the model parameters may not be easy to identify in ungauged basins.

Methods based on continuous rainfall–runoff models: All the signatures (annual runoff, seasonal runoff, flow duration curve, low flows, floods) in ungauged basins can be estimated in a straightforward way if runoff hydrographs are available in that catchment over a sufficiently long period. One way of estimating these signatures therefore is first to estimate hydrographs in ungauged basins and then to extract the signatures from them. If the focus is on a particular signature, special considerations in rainfall–runoff modelling may apply, e.g., one may strive to represent low flows particularly well by the rainfall–runoff model, if one is interested in low flows in ungauged basins. This method hinges on the accuracy of runoff modelling in ungauged basins, which often justifies the use of alternative methods.

Methods that exploit proxy data: While no runoff data are available in ungauged basins, there may be other data available that may contain useful information about the runoff signatures. This method strives to make use of such data as flood marks, vegetation patterns, and a range of remote sensing products on hydrological variables such as snow and soil moisture.

2.4 Assessment of predictions in ungauged basins

2.4.1 Comparative assessment as a means of synthesis

In the comparative hydrology approach, the idea is to learn from the similarities and differences between catchments in different places, and to interpret these in terms of underlying climate–landscape–human controls. In a quantitative science such as hydrology, learning comes from hypothesis testing, and the hypotheses in the context of PUB are runoff predictions in ungauged basins. Testing the predictions against independent data demonstrates that the understanding of the system is real. Assessing the predictions of runoff is therefore a scientific exercise and we can learn from the performance of such predictions. A comparative assessment provides a much wider richness of insights than testing a model at a single place. One place has only one history, whereas many places have multiple histories and hence can contribute much to our understanding.

Assessing how well the runoff predictions perform is a particularly important and interesting exercise because the predictive uncertainties tend to be large relative to the magnitude of the runoff to be predicted. The uncertainties are due to many reasons. Hydrological processes have enormous spatio-temporal variability, which is difficult to capture. Runoff data are only collected at a few points in the stream network, and in data-poor regions any stream gauge may be far from the ungauged basin of interest. Also, there may be uncertainties in the collected data. Predictive errors of models, both statistical and process-based, arise from data uncertainties, model structure uncertainties and model parameter uncertainties. Assessment of the performance provides an estimate of the total uncertainty to be expected if 'blind testing' or cross-validation is performed. This uncertainty estimation is complementary to other methods of estimating uncertainty, such as Monte Carlo methods.

There are numerous additional insights that can potentially be gained by a comparative assessment of the performance of methods for predicting runoff in ungauged basins:

- Understanding where particular methods work best, and why, will provide insights into the co-evolution context for a wide range of processes and process interactions across scales.
- Understanding what factors control the performance will provide an opportunity to generalise the conclusions drawn from individual studies.
- It will provide researchers and practitioners with useful information about the prediction performance they can expect for a particular environment with specific climate and catchment characteristics, specific data availability and a particular model type.
- Comparative assessment may therefore provide guidance on what methods to choose in a particular environment.
- It will also shed light on the value of data for predictions in ungauged basins that goes beyond the needs of a particular case study.
- Finally, identifying the various controls on the performance of estimating runoff in ungauged basins will also provide a benchmark to guide future progress on predictions of runoff in ungauged basins. This strategy will also provide a vehicle to generalise the benchmarking assessment beyond one individual study.

All of these contribute to the synthesis of predictions in ungauged basins across processes, places and scales.

To achieve this objective, a comparative assessment has been conducted, as part of the PUB initiative, which has been clustered into three main groups:

(1) Analysing the process controls on the model performance. A number of climate and catchment characteristics have been identified. A large number of catchments and modelling studies around the world have then been organised according to these climate and catchment characteristics, with a view to learning from their differences and similarities in performance in a general way. The following climate characteristics have been used in the book:
    - Aridity (the ratio of potential evaporation and precipitation on a long-term basis, averaged across the catchment). This is an indicator of the competition between energy and water affecting the water balance and therefore all runoff signatures.
    - Air temperature (long-term average air temperature, averaged across the catchment). In cold regions this is an indicator of the role of snow processes, which will, again, affect all runoff signatures. Air temperature is also related to aridity, so it is not a fully independent variable.
    - Elevation (average topographic elevation within the catchment). This is a composite indicator including a range of processes that are related to elevation, such as long-term precipitation and hence soil moisture availability, and air temperature. In some environments there will also be a relationship between elevation and aridity and elevation and snow processes.
    - Catchment area. Depending on the runoff signature examined this is an indicator of the degree of aggregation of catchment processes related to scale effects; as an indicator of storage within the catchment; and as an indicator of the amount of rainfall data that is available for runoff estimation in ungauged basins, since larger catchments tend to contain a large number of rain gauges.

(2) Analysing the predictive performance for different types of methods. The methods of estimating runoff in ungauged basins have been grouped into statistical and process-based, and each of them further subdivided. Rather than evaluating specific models the focus has been on generic model types, to be able to generalise beyond a specific method. An essential part of the synthesis is to go beyond individual models and focus on generic model types. For statistical methods, the model types include regressions (both global regression and regional regression), index methods and geostatistical methods. Process-based methods for most signatures are much more difficult to benchmark because there is much less literature available for them, with the exception of runoff hydrographs. In Chapter 10, a range of methods for estimating the parameters of process-based rainfall–runoff models have been compared, as this is an important aspect of such models.

(3) Analysing data availability. The quality of runoff predictions in ungauged basins depends not only on the hydrological setting and the regionalisation method but also, importantly, on the data that are available for the regionalisation. The final aspect of comparison therefore

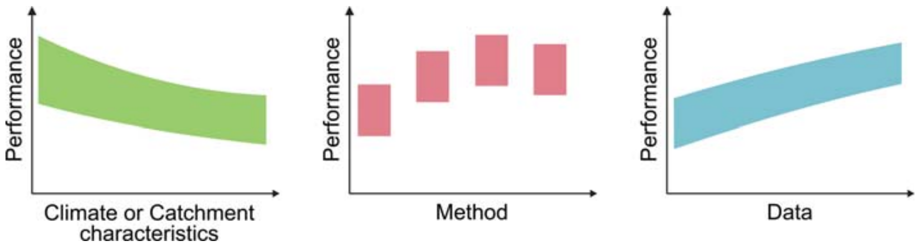

Figure 2.11. Analysis of performance of a particular runoff signature (such as annual runoff, the flow duration curve etc.) with respect to the controls.

examines the number of stream gauges available in a particular study as an index to characterise data availability.

The three types of comparative analyses of the predictive performance of estimating runoff signatures are illustrated schematically in Figure 2.11. The comparative assessment figures have been colour-coded throughout the book to highlight the different nature of these three types of comparative assessment.

2.4.2 Performance measures

The focus of this book is on predictions of runoff in ungauged basins. In order to assess the performance of the predictive methods, predicted runoff signatures in ungauged basins need to be compared to observed runoff signatures. This type of assessment is most often achieved by a split sample technique, breaking a data set into two parts, using one for estimation of the model parameters and the remainder for the assessment of the predictions (Klemeš, 1986b). This means that the model used to estimate runoff in the ungauged basins does not use runoff information from that basin. The catchment is treated as ungauged. Only after the runoff prediction has been made are the runoff observations used for the assessment. However, local observations of climate and catchment characteristics can be used in the catchment of interest. This procedure allows for an independent cross-validation of each methodology used to provide predictions in ungauged basins, rather than enabling just a goodness of fit of a particular regionalisation method. Often, it is useful to perform this cross-validation for all catchments in a region. In this case, a leave-one-out strategy is adopted where, first, one of the catchments is treated as ungauged and the runoff signatures estimated from runoff from the other catchments in the region as well as the climate and catchment characteristics. The model's predictive ability is then tested on the catchment that was left out. The procedure is then repeated for all catchments within the region in turn, allowing for a full cross-validation and optimal use of all available data.

In each case, the model performance is assessed by comparing predicted runoff signatures in the catchments treated as ungauged basins with the observed runoff signatures. The difference is then a measure of the model performance. This 'blind testing' gives an estimate of the total uncertainty to be expected. It includes all the uncertainty components including input data uncertainty, model uncertainty and parameter uncertainty (Wagener and Montanari, 2011). As a consequence, understanding the performance in a generalised way is a step towards reducing the uncertainty of the model predictions beyond individual case studies.

As the differences between predictions and observations are available for many catchments and (depending on the signature) for many points in time, it is useful to characterise them by statistical metrics or performance measures to better compare different process controls, prediction methods and data availability settings. A number of statistical metrics are commonly used in the literature and these are summarised in Tables 2.1 and 2.2. There are a number of groups of performance measures:

- Measures of bias are indicators of whether the average of the differences between predictions and observations is close to zero. Bias can be positive and negative and a bias of zero implies perfect prediction with respect to bias. It is an important aspect of model performance since it describes the mass balance error of runoff.
- Measures of random errors are indicators of spread of the differences of predicted and observed runoff signatures. A random error of zero implies perfect predictions with respect to random errors. An example is the root mean square error which has the same units as the runoff signatures that are being compared.
- Correlation coefficients denote the strength of the association between predicted and observed runoff signatures. There are two types here (r^2 and R^2). r^2 describes what fraction of the data variability can be explained by a linear relationship with the predictions. A correlation of 1 implies perfect linear association of the observed and predicted pattern although the mean and the variability can be quite different from those of the data. R^2 describes what fraction of the data variability can be explained by the predictions themselves. R^2 of 1 implies that the predictions and the observations are identical.

Table 2.1. *Main performance measures used to evaluate the signatures in Chapters 5–10. For definition of Level 1 and Level 2 assessments see Section 2.4.3. For description of performance measures see Table 2.2. Runoff signatures are as follows:* Q*: runoff,* q*: specific runoff,* Q_{100}*: 100 yr flood runoff,* Q_{95}*: low flow that is exceeded 95% of time*

	Level 1	Level 2	Type of variability analysed
Chapter 5 Annual runoff	r^2 of Q, q, log Q, log q	NE, ANE of mean runoff	spatial
Chapter 6 Seasonal runoff	NSE, r^2 for each month	NE, ANE of range, NSE	temporal and spatial
Chapter 7 Flow duration curves	ANE of quantiles, proportion of NSE < 0.75 (NSE of quantiles)	NE, ANE of slope	temporal
Chapter 8 Low flows	R^2, r^2 RRMSE of q_{95}	NE, ANE of q_{95}	spatial
Chapter 9 Floods	RMSNE of q_{100}	NE, ANE of q_{100}	spatial
Chapter 10 Runoff hydrographs	NSE	NSE	temporal

- Model efficiencies are a composite measure of bias and random error. A Nash and Sutcliffe model efficiency (NSE) of unity implies perfect predictions, smaller values of NSE mean less perfect predictions (Nash and Sutcliffe, 1970).

Note that some of the measures are performance measures, where 1 denotes perfect performance, while others are error measures, where 0 represents perfect performance. In the assessment plots of Chapters 5–9, performance measures have been plotted upwards, while error measures have been plotted downwards on the vertical axis.

Most performance measures can be calculated either on the basis of runoff (m^3/s) or on the basis of specific runoff (($m^3/s)/km^2$). Runoff signatures tend to produce much higher correlations for runoff than for specific runoff because area is always an important predictor of runoff due to mass balance considerations.

In addition to the quantitative performance measures, qualitative reasoning can be used to help understand how close the runoff predictions are to the real-world system, i.e., how realistic the model predictions are. This aspect might have to include extensive hydrological reasoning. One example is the interpretation of the coefficients in the regression equations. If they match the understanding one has of the hydrological system, they can be considered more realistic, and one would expect that they can then be extrapolated more reliably to ungauged basins. Another example is the degree to which runoff models in ungauged basins represent the flow paths with the basin of interest.

2.4.3 Level 1 and Level 2 assessments

In order to perform the comparative assessment of runoff predictions in ungauged basins, a two step process has been adopted:

Level 1 assessment: In a first step, a literature survey was performed. Publications in the international refereed literature were scrutinised for results of the predictive performance of runoff. This analysis was conducted for all the signatures: annual runoff, seasonal runoff, flow duration curves, low flows, floods, and runoff hydrographs. The Level 1 assessment is a meta analysis of prior studies performed by the hydrological community. The advantage of this type of meta-analysis is that a wide range of environments, climates and hydrological processes can be covered that go beyond what can be reasonably achieved by a single study. It is a comparative assessment that synthesises the results from the available international literature. However, the level of detail of the information provided is often limited. The results in the literature were almost always reported in an aggregated way, i.e. as average or median performance over the study region or part of the study region.

Level 2 assessment: To complement the Level 1 assessment, a second assessment step was performed, termed Level 2 assessment. In this step, some of the authors of the publications from Level 1 were approached with a request to provide data on their runoff predictions *for individual ungauged basins*. The data they provided included information on the catchment and climate characteristics, on the method used, the data availability, and predictive performance. As in Level 1, the cross-validation performance for ungauged basins was analysed; however, information on individual catchments was now available. The overall number of catchments involved was smaller than in the Level 1 assessment, so the spectrum of hydrological processes covered in the assessment was narrower. However, the amount of information available on predicting runoff signatures in particular catchments was much higher. Level 1 and Level 2 are therefore complementary steps, as illustrated in Fig. 2.12.

2.5 Summary of key points

- Catchments are complex systems that have evolved through a process of reciprocal evolutionary change of soils, vegetation and topography, mediated by water fluxes, in response to long-term climate dynamics and

Table 2.2. *Performance measures used in the comparative assessment and symbols*

Symbol	Name	Estimator	Meaning	Value for perfect performance	How it relates to other measures
r^2	Coefficient of determination (squared correlation coefficient)	$r^2 = \frac{\left(\sum(\hat{Q}_i-\overline{\hat{Q}})(Q_i-\overline{Q})\right)^2}{\sum(\hat{Q}_i-\overline{\hat{Q}})^2\sum(Q_i-\overline{Q})^2}$	Degree of linear association. 1 for perfect positive association, 0 if no linear correlation	1	Random error after scaling with a linear relationship
R^2	Coefficient of determination	$R^2 = 1-\frac{\sum(\hat{Q}_i-Q_i)^2}{\sum(Q_i-\overline{Q})^2}$	1 for perfect prediction, 0 if prediction is no better than the average of the observed data, negative value would be worse.	1	Composite measure of bias and random error
RMSNE	root mean square normalised error	$\mathrm{RMSNE} = \sqrt{\frac{1}{n}\sum\left(\frac{\hat{Q}_i-Q_i}{Q_i}\right)^2}$	0 for perfect prediction, larger for poorer predictions.	0	Composite measure of bias and random error
RRMSE	relative root mean square error	$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum(\hat{Q}_i-Q_i)^2}}{\overline{Q}}$	0 for perfect prediction, larger for poorer predictions.	0	Composite measure of bias and random error
NE	normalised error	$\mathrm{NE}_i = \frac{\hat{Q}_i-Q_i}{Q_i}$	Difference between prediction and observation, scaled by the observation. 0 for a perfect prediction at one location, larger or smaller for poorer predictions.	0	$\mathrm{Var}(\mathrm{NE}_i) = \mathrm{RMSNE}^2$ if prediction unbiased, i.e., $\sum\left(\frac{\hat{Q}_i-Q_i}{Q_i}\right) = 0$
ANE	absolute normalised error	$\mathrm{ANE}_i = \left\lvert\frac{\hat{Q}_i-Q_i}{Q_i}\right\rvert$	Absolute difference between prediction and observation, scaled by the observation. 0 for a perfect prediction at one location, larger for poorer predictions.	0	
NSE	Nash and Sutcliffe model efficiency	$\mathrm{NSE} = 1-\frac{\sum(\hat{Q}_t-Q_t)^2}{\sum(Q_t-\overline{Q})^2}$	1 for perfect prediction, 0 if prediction is no better than the average of the observed data, negative for poorer predictions.	1	Composite measure of bias and random error

$\hat{Q}_i$: estimated runoff signature at location i, $\hat{Q}_t$: estimated runoff signature at time t, Q: corresponding observed runoff, $\overline{Q}$: average observed runoff in time (or space).

geological processes. The interactions and feedbacks between these components have contributed to the generation of the diversity of interesting patterns that we see in natural catchments.

- Hydrological response signatures are the outward manifestation of the operation of these complex systems. They thus provide a window into the dynamic catchment behaviour at a range of time scales. They help us to understand the catchment system holistically.
- Comparing many catchments with contrasting characteristics in a synoptic way, defined as 'comparative hydrology', will help understand the controls of the behaviour of catchments viewed as complex systems. The resulting idea is to learn from the similarities and differences between catchments in different places, and to interpret these in terms of underlying climate–landscape–human controls.
- Hydrological similarity can be defined in terms of climate, catchment characteristics or runoff signatures.

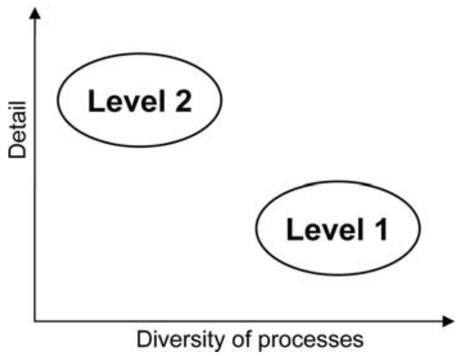

Figure 2.12. Definition of Level 1 and Level 2 assessments. Detail relates to the amount of information available on predicting runoff signatures in a particular catchment, such as the predictive errors and catchment/climate characteristics. Diversity of processes relates to the spectrum of hydrological processes covered in the comparative assessment, from a small diversity if only a few regions are examined to a large diversity if many regions worldwide are examined.

Understanding hydrological similarity is the basis for our ability to predict runoff in ungauged basins, extrapolating from gauged to ungauged basins within a homogeneous region, based on either statistical or process-based methods.

- Runoff predictions in ungauged basins are associated with considerable uncertainty. Assessing the performance of the predictions will give an estimate of the total uncertainty to be expected, including data, model and parameter uncertainties. This method of uncertainty estimation is complementary to other methods such as Monte Carlo simulations.
- Comparative assessment of the performance of runoff predictions amongst a range of methods, and in many ungauged basins around the world, will give generalised estimates of the predictive uncertainty and a generalised understanding of the factors controlling it. In this way it will shed light on the co-evolution of catchments. It will provide guidance on what methods to choose in particular environments and why, and will thus provide a benchmark to guide any future progress on predictions of runoff in ungauged basins.
- A comparative assessment (blind testing) of the predictions of runoff signatures (annual runoff, seasonal runoff, flow duration curve, low flows, floods and runoff hydrographs) in ungauged basins is performed in this book, as part of a synthesis across processes, places and scales, at two different levels. The Level 1 assessment is a meta-analysis from the extensive published literature. The Level 2 assessment is a more detailed analysis of numerous individual catchments from around the world, selected from the studies reported in the literature. In each case, predictive performance is analysed in a comparative way as a function of climate and catchment characteristics, the prediction method and data availability.

3 A data acquisition framework for runoff prediction in ungauged basins

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3.1 Why do we need data?

Most river basins around the world are ungauged; indeed, only a few are gauged. Therefore, when runoff is required at any ungauged river or catchment, it is estimated through some kind of extrapolation from a gauged site to that ungauged site, which is not straightforward. This is the whole *raison d'etre* of the PUB initiative. One way or another, this extrapolation requires data of many kinds.

Extrapolation from gauged to ungauged catchments requires a model of some kind, be it statistical, process-based or a combination thereof. Implementation of models needs data – all types of models need data to implement at the ungauged location; indeed, all models gain legitimacy from data as part of the validation process. Normally, and certainly throughout this book, we consider data of three different kinds: runoff data (in gauged locations), climate (input) data and catchment characteristics data.

Statistical models attempt to build statistical (e.g., regression) relationships between runoff at gauged locations and associated climate and catchment data, which can then be extrapolated for predictions in ungauged basins with the use of local climate and catchment data. Process-based models do the same, except that they benefit from the use of universal balance laws (mass balance, momentum balance etc.), but they too need all three kinds of data (runoff, climate and catchment) at gauged locations for calibration/validation/conditioning, and climate and catchment data at the ungauged locations where predictions are needed.

However, one should not be fooled into thinking that the data are just inputs to a model, in the sense of 'grist to the mill'. Data have hydrological context, and contain hydrological content. The data relating to runoff, climate and catchment collected from any one place, interpreted by a trained hydrologist, and informed by prior knowledge from outside the place, can reveal a lot about the hydrology of the place; it can inform what models we should choose, and it can help us interpret, condition and reject the predictions made by a model.

Hence, data are more than just input to a model. The value of data becomes paramount when one begins to accept the notion that catchments are complex systems, reflecting the co-evolution of climate, soils, topography and vegetation, and the patterns one sees in the landscape structure and the runoff response (e.g., signatures) are emergent patterns, and reflect more than the mere balance equations that are embedded in many of today's process-based models. Therefore, there is value and much to be learned from the combination of runoff, climate and catchment data, a learning process that we have called '*reading the landscape*'. Data will be the ultimate source of the understanding that is embedded in all the models because, when understood properly, they reflect the co-evolution that is common to all catchments.

We can thus summarise the need for data in three categories: (i) data needed to read and understand the landscape in a hydrological context; (ii) data needed to develop regression relationships that will be used in statistical models; and (iii) data needed for process-based models, such as climatic forcing and parameter values, data to assist with model development (inference from rainfall–runoff data), and to calibrate or validate models developed elsewhere.

The starting point for any PUB study therefore has to include an assessment of available data and the information that can be derived from this data. This activity includes the need for catchment interpretation based on the available database and the time frame of the study. Depending on the application and the resources available, runoff prediction in ungauged basins is generally based on different data acquisition strategies, ranging from global data sets of typically low resolution to local and regional data sources of varying availability and accuracy followed by field observations/assessment of local system characteristics. If the resources are available, the most accurate runoff predictions can be obtained by utilising very local data describing the specific characteristics and behaviour of the system. The input data requirement will be dependent on the nature of

* Coordinating contributor

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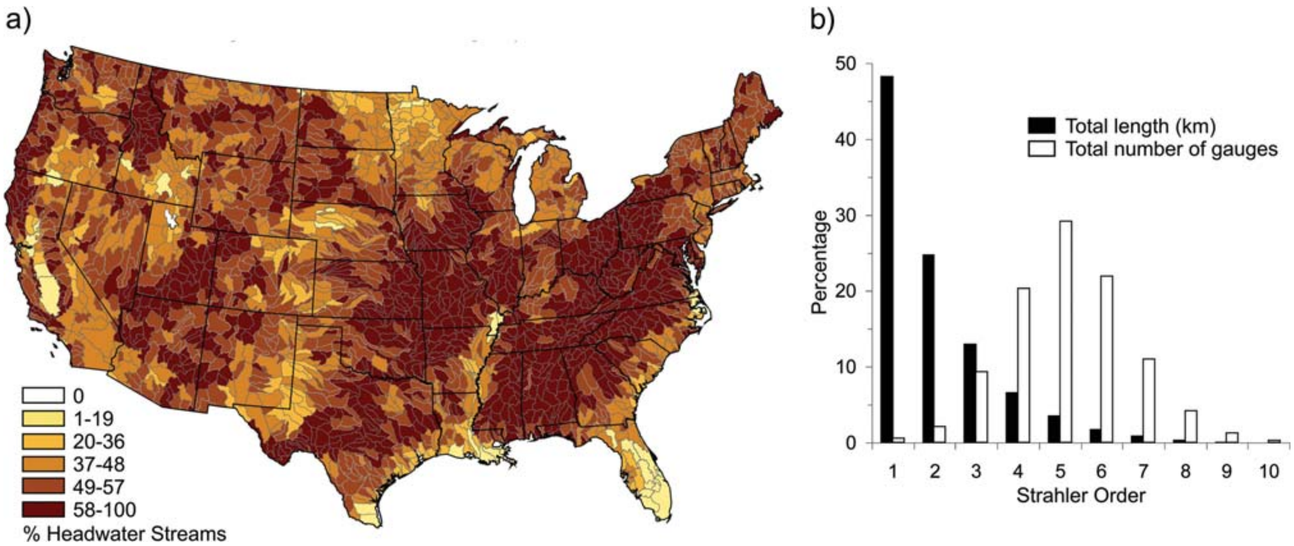

Figure 3.1. (a) Spatial distribution of headwater stream length as a percentage of total stream length in the USA. From Nadeau and Rains (2007). (b) Distributions of stream length and stream gauges against stream order in the USA. From Poff *et al*. (2006).

the runoff prediction desired. While global or regional data will be useful for annual runoff prediction, more intensive local data will be needed for hydrograph prediction.

The objectives of this chapter are to provide an assessment of the data available for PUB, and to provide some initial guidance on how this data might be acquired. These data products can often be estimated from global or national data sets, but their availability at higher resolution or as a directly measured or observed product from regional to local scales can enhance data quality and therefore PUB. Some data sources and observations can be direct (e.g., model input parameters or forcing) or indirect (e.g., likely runoff dynamics interpreted from regionalisation, similar catchments, or experience). Indirect data or observation can provide qualitative information and aid in model selection and evaluation. Auxiliary data types and higher resolution information become increasingly important at short time scales and smaller spatial extents. The following sections provide an overview of hydrological landscape interpretation based on hierarchical data from the global to regional to local scales that provide a general and practical pathway to PUB. The introduction of this acquisition framework is followed by a discussion of the main data sources (separated by hydrological variables) from global to local scale. In addition, three case studies illustrate the hierarchical data acquisition strategy discussed here.

3.2 A hierarchy of data acquisition

Most river basins around the world are ungauged. Interestingly, this lack of data often increases with decreasing catchment sizes. Figure 3.1 shows an example of the data bias towards larger scales with respect to the US stream gauge network (see discussion in Wagener and Montanari, 2011). At what spatial scale this lack of data becomes a problem for decision-making varies from country to country. A general consequence, however, is that data scarcity is a major issue even for highly developed (and therefore often highly monitored countries). At the global scale, data sources are primarily limited to remote sensing and global climate models, notwithstanding aggregated products such as global soil maps. In the last few decades new satellite sensors have also made available useful measurements across large areas. These global products, together with regional and local observations and landscape interpretation, can provide data corroboration and validation and a hierarchy of inputs for hydrological modelling and runoff estimates. Paradoxically, the data requirements to achieve accurate simulations increase with decreasing temporal and spatial scale of prediction. This is because at small spatial scales runoff tends to be more tightly linked to details of landscape structure and climate forcing and exhibits greater space-time variability, thereby hampering parameter regionalisation and scaling (Wood *et al*., 1988). At greater spatial scales, much system heterogeneity is subsumed and averaged, often leading to simpler catchment response to climate forcing (Sivapalan, 2003a). Therefore, data needs and the value or information content of data products from global data sets to local observations for runoff prediction are scale dependent. Indeed, the issue of data adequacy and availability, in the context of natural variability present across regions of the world, will be a recurring theme throughout this book, including in the assessment of the performance of prediction methods.

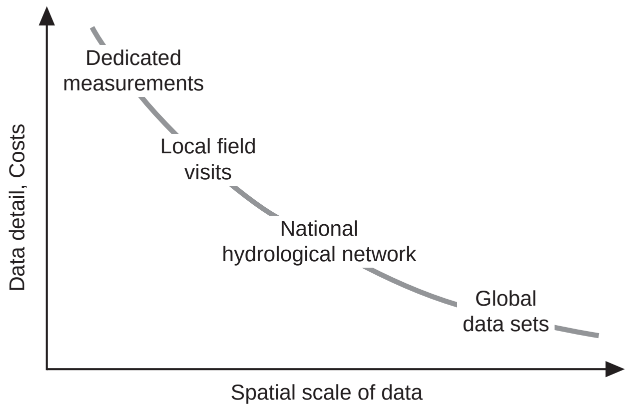

Figure 3.2. Hierarchy of data acquisition: dedicated measurements provide detailed information at high costs over small spatial scales; global data sets provide more generalised information at lower costs to the individual user.

A hydrologist has a number of options to approach the problem if runoff is to be predicted in a particular ungauged catchment. Typically, the choice of data acquisition depends on time and other resources available (Figure 3.2). Data sets at the global scale provide the context and bounds on hydrological behaviour and runoff potential via basic climatology. Numerous global data sets that are of relevance to predicting runoff in ungauged basins exist that can be downloaded at no or little cost to the user. In many instances, this broad-scale information will not suffice to predict runoff with the required accuracy or the required spatial and temporal resolution, so the hydrologist will acquire hydrological data from any hydrological network that is operated by the national or state authorities. This usually involves more effort of data quality checking and predictive methods than when only using the global data sets. If more time and resources are available the hydrologist will make a field visit to assess the hydrological landscape based on his/her expert knowledge. Local characteristics of climate forcing and internal catchment characteristics provide insights into likely catchment water storage, surface partitioning and internal redistribution, and release of water to runoff and evaporation. Finally, if time and financial resources are even larger, one could clearly collect some short-term measurements or even install a stream gauge and other hydrological equipment to get a better understanding of the catchment response. This means that acquiring information for estimating runoff from ungauged catchments can follow a hierarchical approach, depending on resource availability.

The prediction methods presented in Chapters 5–10 that follow make use of the data acquired at a range of scales, from proxy data at the local scale to global-scale data sets. The remotely and locally observed catchment characteristics can be combined for catchment regionalisation and/or qualitative description for *a-priori* model selection in the context of PUB. What data are acquired specifically depends on the system under study, e.g., whether it is located in an arid or in a humid region, and on the purpose of the predictions. For example, if we are interested in predicting low flow characteristics then taking a few selected runoff measurements during low flow conditions might be most helpful, while we might be interested in indicators of historical flood levels such as flood marks for inundation mapping. The following four-point discussion provides an example of hierarchical data acquisition, moving from globally available to locally specific data.

3.2.1 Assessment based on global data sets

A catchment located anywhere in the world will have an annual and seasonal climatology characterised by a given precipitation regime and a basic energy balance. This broad-scale context is often discussed in terms of the annual water balance and a climatic index. The well-known Budyko (1974) diagram represents this as the ratio of mean annual evaporation to mean annual precipitation versus the ratio of mean annual potential evaporation to mean annual precipitation, thereby relating a metric of the mean annual water balance to a climatic aridity or dryness index (Figure 3.3). The location of a given catchment on this general relationship or curve represents the relative degree of water versus energy limitation and can inform the coarse interpretation of the controls on catchment runoff. While valuable, this type of broad-scale assessment does not include internal catchment characteristics that can influence runoff dynamics nor shorter-term climate and weather forcing that lead to dynamic hydrology and storm runoff, but rather provides a starting point for more localised assessment.

3.2.2 Assessment based on national hydrological network and national surveys

Every country will have some type of national hydrological network, even though the spatial coverage of such gauging networks might vary widely (Figure 3.4). The density of the stream gauge network in the regional vicinity around the basin of interest at least partially defines what approach to PUB can be utilised. The denser the network, the more likely it is that a statistical approach to transferring hydrological information will be successful. The need for a more process-based modelling strategy increases with the distance between measurement points. One would generally seek any runoff and meteorological data available locally or regionally. The available database is then analysed with respect to annual water balance, seasonality, storm behaviour, variability etc., which will

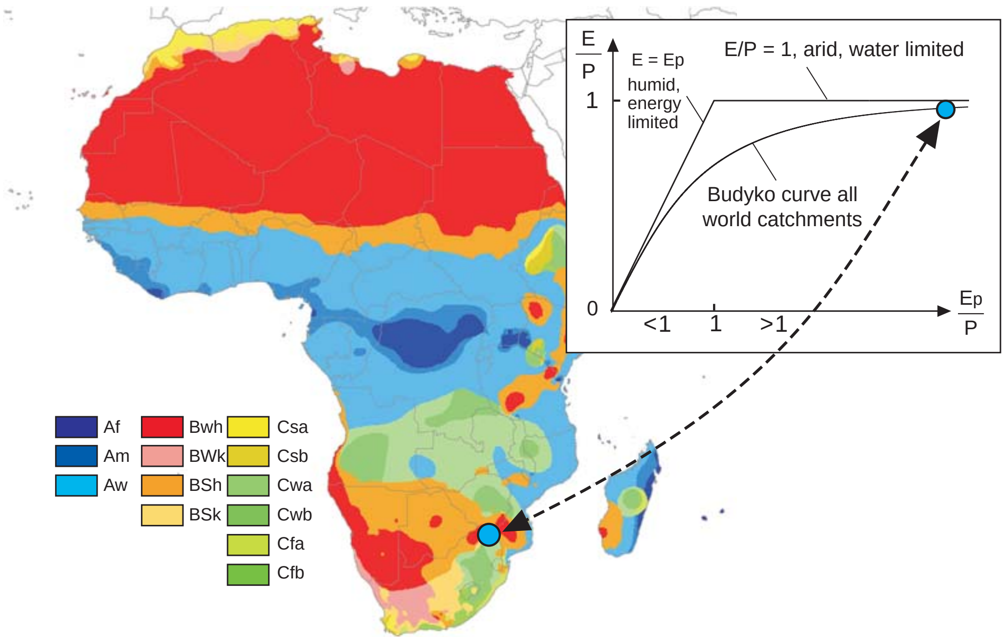

Figure 3.3. Placing a catchment in its climatic regime enables a first-order assessment of its energy and water balance at coarse time scales. (Left) Revised Koeppen classification with location of Olifants basin in Southern Africa marked as a dot on map. From Peel *et al*. (2007). (Right) Budyko curve showing the relationship between evaporation index (E/P) and aridity index (E_P/P).

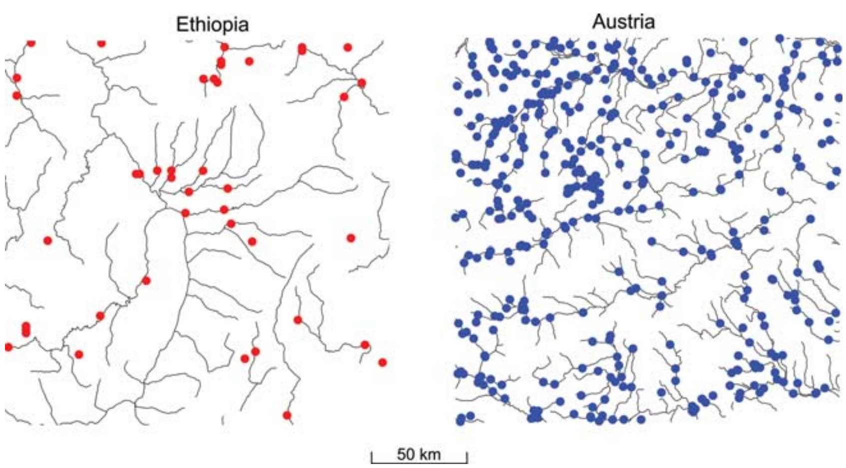

Figure 3.4. National stream gauge networks in Ethiopia and Austria.

be the main activity for many large-scale studies (especially at national scale).

Typically, there will also be information on the physical characteristics of the catchment that can be used for system characterisation. Topographic maps can be used to ascertain catchment size, shape, morphology and drainage density. Soil information including depth and texture, as well as surface characteristics, can be gained from maps and translated into hydrologically relevant information, e.g., through using pedo-transfer functions. Many countries will also possess maps on eco-regions (or land use or vegetation cover) and on geology, which can be used for a first-order assessment of catchment characteristics. It is important to remember that these maps will not be able to fully describe the extent of natural variability that is likely in specific locations. Local observations will be necessary to utilise vegetation patterns as indicators of moisture stability and landscape heterogeneity (including erosional patterns) that can inform the nature of water redistribution processes.

3.2.3 Assessment based on local field visits including reading the landscape

Despite the high value of remotely sensed observations and analyses, the relative strength of different hydrological processes and dominant runoff generation mechanisms

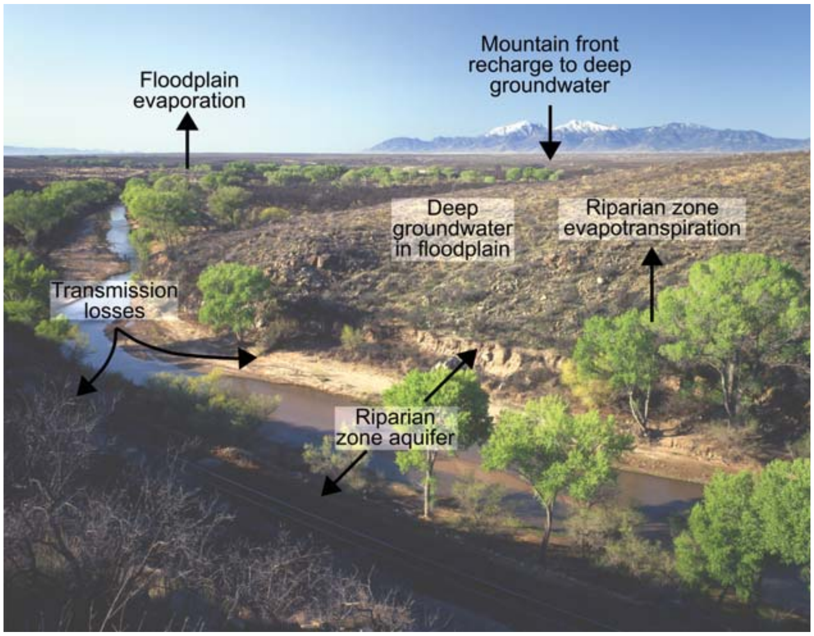

Figure 3.5. Hydrological interpretation of landscape features. Photo: © SAHRA at University of Arizona.

are not easily inferred from topography and surface characteristics alone. Where possible, field reconnaissance and expert judgement can be invaluable for hydrological assessment and, when coupled with remote analyses, allow for more skilled interpretation and reading of the hydrological landscape (Figure 3.5). Field visits allow for comparison of the PUB catchment to similar gauged catchments or heavily researched and more completely understood catchments, thereby allowing transfer of the ‘hydrological knowledge library’ individuals or teams possess from previous experience. This remotely sensed and field visit derived similarity analysis relies on experience-derived intuition and expert judgement. Interviews with those possessing local knowledge and experienced interpretation of the landscape can help determine or select appropriate models and representation of dominant hydrological processes operating in a catchment to improve PUB.

Bedrock geological characteristics (e.g., weathering depth, porosity, faults, dip direction, etc.) and soil depths provide information about the likelihood and magnitude of subsurface storage and geological and soil zone contributions to runoff. Additionally, catchment slope and flow path lengths, in connection with forcing information, can be used to infer likely runoff responsiveness (flashiness of the hydrological system). Vegetation characteristics both reflect and modify long-term hydrological dynamics. For example, dry upland vegetation and wet alluvial vegetation imply deeper groundwater and flow paths that could sustain runoff during low precipitation time periods. They also suggest transient soil moisture availability in the upland environment. A landscape with wet vegetation types across most landscape positions indicates widely available water and a more stable soil moisture regime. Vegetation type, while a function of many complex ecological and environmental variable interactions, can be used as an indicator of soil moisture stability/instability and rooting depth water availability. For example, Mediterranean vegetation indicates seasonally available water, while sagebrush can indicate low or non-growing seasonal water availability.

Stream channel characteristics can also help infer catchment runoff dynamics. Catchment drainage density can be an indicator of climate and geology. The connection between cross-section form and river runoff can result in a high degree of temporal and spatial regularity as expressed in the at-a-site and downstream hydraulic geometry relationships (Mejia and Reed, 2011). Scoured channels and floodplains indicate high flows and runoff magnitude, while streambed sediment characteristics and morphology can inform estimation of stream power and runoff magnitude when coupled with stream slope measures (Trevisani *et al.*, 2010). Bankfull runoff estimation can be used as an indicator of the size of peak runoff, whereas in-channel and near-channel vegetation persistence/species can inform interpretation of likely flow stability and riparian corridor water table dynamics.

Runoff mechanisms can also be inferred by combining previously described remote and local observations. Erosional features across landscape positions can indicate the magnitude, frequency and spatial extent of overland flow. Locations of overland flow indicators can also suggest infiltration excess or saturated overland flow processes.

Figure 3.6. Spot measurement of runoff in Alaska. Photo: M. Gooseff.

Deep soils and weathered or fractured bedrocks coupled with lower catchment slope can indicate deeper, less flashy, subsurface flow generated runoff while less permeable bedrock, shallow soils and steep slopes can promote transient subsurface flow.

The spatial organisation and distribution of vegetation offer further indication concerning patterns of water availability. Spatial structures in vegetation are known to naturally arise in response to water availability (Caylor *et al.*, 2004; Rietkerk *et al.*, 2004; Scanlon *et al.*, 2007) at least in arid or semi-arid environments. Because of the two-way coupling between water availability and the presence of vegetation (as a driver of local partitioning), vegetation spatial organisation is hypothesised to be both a control and a signature of hydrological processes, although the strength of this relationship may vary depending on the significance of other drivers of spatial variation in water balance (for instance soil hydraulic properties) and vegetation distribution (for instance, energy or nutrient availability, or disturbance regimes) within a particular catchment (Boisvenue and Running, 2006). Therefore, caution must be employed before interpreting vegetation patterns in purely hydrological terms because vegetation responds to other environmental gradients (e.g., in disturbance, nutrient availability or elevation) and co-variation across these gradients often exists (Valencia *et al.*, 2004).

3.2.4 Assessment based on dedicated measurements

The measurement of runoff is of course the most direct way of gaining insight into the hydrological behaviour of catchments for the purpose of PUB. Spot measurement can be very helpful if time and resources – as well as access – permit such an activity (Figure 3.6). Multiple studies have shown that even limited runoff observations can result in a significant reduction in predictive uncertainty in rainfall–runoff modelling (McIntyre and Wheater, 2004; Rojas-Serna *et al.*, 2006; Perrin *et al.*, 2007; Juston *et al.*, 2009; Seibert and Beven, 2009). Such measurements could be used to further refine the model parameters that have been either locally estimated or transferred. Care needs to be taken to account for the particular conditions under which the measurements are taken (e.g., low flow period during summer) to not unduly bias the parameter estimates. Krasovskaia (1988) proposed a procedure in which catchment characteristics are used for identifying representative locations for runoff spot gauging. She also gave an indication of the errors involved in using spot-gauged data as compared to other methods of measuring and estimating runoff. The value of such a short-term measurement campaign for the direct estimation of signatures will depend on the signature under study.

The data mentioned above can be interpreted creatively depending on available information to guide PUB model selection and constrained to maximise PUB. No two PUB exercises will be the same in terms of the data available and the particular characteristics of the system under study. Hydrological intuition built through years of experience can be invaluable for PUB. Unfortunately there is no single or simple recipe that can be passed on. PUB skill will be largely situation and practitioner specific, but can be enhanced with creative interrogation and synthesis of available observations (Jackisch *et al.*, 2011). How data at these different levels can be used for the prediction of specific signatures is discussed in the following chapters and only illustrative examples are given here. The approach to interrogating the landscape depends on the type of runoff signature one is interested in. For example, if one is interested in the flood runoff of a recently occurring flood, the IPEC (Intensive Post Event Campaign) concepts give guidelines on how to interpret high water marks and river morphology (Borga *et al.*, 2008; also see Chapter 9). Multiple authors have reported on the value of post-event field surveys for understanding flood water levels (Brauer *et al.*, 2011). If one is interested in low flows, one typically takes spot measurements of runoff during a low flow period and relates them to the runoff in neighbouring catchments. If one is interested in continuous runoff predictions using a rainfall–runoff model, then multiple runoff measurements during well-chosen time periods might be most helpful.

3.3 Runoff data

3.3.1 What runoff data are needed for PUB?

Observed runoff is an integrative indicator of the predominant hydrological processes in a catchment. Therefore runoff data are the most valuable source of information, and cannot be adequately replaced by other data sources. All PUB methods – and it does not matter how appropriate or innovative – are only the second best option after the use of observed runoff data. However, if the best option is not available we have to think about alternative strategies to gain insight into catchment runoff characteristics. To use stream gauge time series data from neighbouring gauges is a good strategy, because the data structure and sensitivity are similar. Depending on the aim of the PUB study, information about catchment runoff at different temporal scales is useful for predictions in the field of various hydrological aspects, such as low flow, flood forecasting and design value estimation. The data needed can best be discussed separately for statistical and process-based methods.

Statistical methods for predicting runoff signatures usually require runoff data in neighbouring catchments. This is for identifying pooling groups as well as for the statistical predictive methods. For example regression equations between catchment characteristics and runoff in neighbouring catchments are used to estimate runoff at the target location based on the catchment characteristics in that catchment.

Process-based methods for predicting runoff often need runoff data in neighbouring catchments for estimating model parameters through calibration that are then transferred in space, or to transfer runoff characteristics to act as constraints. Most importantly, runoff data may be available at upstream or downstream locations. If these are close, the more elaborate methods in Chapters 5 to 10 may not be needed and simply scaling of the observed runoff to the target area by the ratio of the catchment areas may be more straightforward and more reliable. Also, opportunistic gauging or short-term measurements at the basin of interest can provide very valuable insight and aid as predictive constraint. Generally, stream gauge rich environments or regions might lend themselves best to statistical approaches to PUB since interpolation distances are mostly short. On the other hand, stream gauge poor environments might require more process-based approaches to PUB. Ideally, both tracks can be taken to constrain likely predictions.

3.3.2 What runoff data are there?

Although not fully globally available, an extensive database is available (GRDB, Global Runoff Data Base) at the Global Runoff Data Center (GRDC) containing runoff records from about 7300 gauging stations from 156 countries, with an average record length of 38 years. GRDC operates under the auspices of the World Meteorological Organization (WMO) and also offers other data products, such as freshwater fluxes into oceans along coastlines, and river basin outlines. A second database, also available through the GRDC, is the European Water Archive (EWA) of EUROFRIEND, the European group of the FRIEND (Flow Regimes from International Experimental and Network Data) initiative. EWA also contains information about smaller, relatively undisturbed catchments. Data are stored from about 3700 gauging stations in 29 countries. However, most of the gauging stations are concentrated in Western Europe. A more regional database than EWA, also hosted by GRDC, is the ARDB (Arctic Runoff Data Base), which is actually a subset of GRDB. The database currently holds river runoff time series data from a total of 2405 gauging stations in the arctic region with the earliest records from 1877 and an average time series length of 33 years, with a range from 1 to 123 years. There are 1024 stations featuring daily data, while 2193 stations only contain monthly data. At the GRDC website, there are various other data sets and subsets that might be suitable for specific purposes and data availability will vary widely depending upon the country and region of interest.

An emerging technology to gauge water levels remotely is laser altimetry by satellites, for which spatial and temporal densities are rapidly increasing through the launch of more and more satellites (such as TOPEX/Poseidon, Jason-1, ICESat etc.) (Lettenmaier and Famiglietti, 2006; Alsdorf *et al*., 2007). Not only can laser altimetry potentially be used to record lake and river levels (Höfle *et al*., 2009), it can also be used to measure cross-sections (by measuring the width at different levels) or to derive rating curves (on the basis of slopes and cross-sectional information). In the future it could also be used for real-time flood forecasting or flood inundation modelling.

The availability of continuous and long-term data sets on runoff varies dramatically throughout the world (Kundzewicz, 2007). The lack of runoff data everywhere and the decline of existing gauging stations are of course the reasons for PUB in the first place (Stockstad, 1999), despite the fact that the practical value of runoff data is often much larger than the cost of their monitoring (Cordery and Cloke, 1992). The decline of networks also suggests that in many cases there will be inactive gauges that nonetheless will provide some indication of the dynamics of the system during previous time periods and conditions (e.g., Winsemius *et al*., 2009). Also, availability of data may sometimes be an issue due to administrative barriers (Viglione *et al*., 2010a).

Regardless of how the runoff observations are obtained, measurement uncertainty will always be present and can be considerable. Assessment of data quality and estimation of data uncertainty are therefore important steps in any modelling exercise. Stream gauges typically take continuous measurements of river stage, which are translated into runoff values using a rating curve. The stage–discharge relationship in the rating curve has been derived from spot measurements at a location with a (reasonably) fixed cross-sectional geometry at different flow conditions or has been pre-calibrated for a particular flow control structure. Many studies have estimated the magnitude and impact of rating curve uncertainty on runoff data and hydrological modelling (Clarke *et al.*, 2000; Peterson-Øverleir, 2004; Di Baldassarre and Montanari, 2009; Liu *et al.*, 2009; McMillan *et al.*, 2010). Major sources of uncertainty include data scarcity at high or low flow conditions, flow outside the control structure during high flow conditions or changes to the channel geomorphology. In some cases the rating curve and the data points it was calibrated to might be available and uncertainty can reasonably be estimated. Uncertainty will likely be larger when ephemeral streams are considered, due to the difficulty of measuring runoff in such streams (Blasch *et al.*, 2002; Adams *et al.*, 2006). The consideration of uncertainty in the runoff estimates (historical or spot gauging) can be useful to account appropriately for the value of data available and avoid over-conditioning.

3.3.3 How valuable are runoff data for PUB?

Transferring hydrological information (e.g., model parameters, hydrological indices, runoff values) from neighbouring gauged to ungauged catchments has been widely investigated in recent decades as a method for runoff prediction in ungauged basins (Merz and Blöschl, 2004; Oudin *et al.*, 2008). These works showed that use of data from the nearby donors generally, though not always, improves the quality of the runoff predictions. As runoff propagation through branching networks provides a fundamental constraint to the distance metric, upstream and downstream catchments would have to be treated differently from neighbouring catchments that do not share a subcatchment. Also, climate plays a role in the predictive power of data transfer. Patil and Stieglitz (2011) showed that high runoff similarity among nearby catchments (and, therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evaporation-dominated regions.

3.4 Meteorological data and water balance components

3.4.1 What meteorological data and water balance components are needed for PUB?

Appropriate meteorological inputs (precipitation, air temperature, evaporation, snow cover) are needed to estimate the required runoff response in ungauged basins either based on rainfall–runoff models or transferred information from gauged catchments. Depending on the objectives of the PUB study, meteorological data at different temporal and spatial scales are useful for predictions of various runoff signatures (low flow, flood forecasting, design value).

Statistical methods for runoff predictions often require catchment precipitation data. Analogously to the use of runoff data, this is for identifying pooling groups as well as for statistical predictive methods. For example, catchment precipitation estimates (for instance, the mean annual precipitation) are sometimes used as an auxiliary variable in regionalisation methods (Chapters 8 and 9).

Process-based methods for predicting runoff are always driven by meteorological data as model forcing. Actual soil moisture conditions directly affect runoff generation processes and therefore are also important for flood and low flow prediction. Soil moisture is usually simulated as an internal model state in hydrological models, while the main emphasis lies in runoff simulation. Soil moisture data provide useful information to simulate the temporal and spatial soil moisture dynamics in a more realistic way.

3.4.2 Precipitation

Information about precipitation at different temporal and spatial scales is essential for many PUB applications. It is used as an auxiliary variable in statistical analysis (runoff regression) or as input for hydrological rainfall–runoff models. Precipitation data are available at the global scale as a modelled and remotely sensed product down to the point scale at rain gauges. The temporal scale varies from minutes (at rain gauges) to monthly mean values for the global products.

Global precipitation data: Many precipitation databases are available globally. Global precipitation data are usually a combined product from rain gauges, weather radar, numerical weather prediction models and estimates from remote sensing (Cheema and Bastiaanssen, 2012). Examples are the Climate Research Unit database, CMAP (CPC Merged Analysis of Precipitation) and WORLDCLIM (Hijmans *et al.*, 2005). The last has a very high spatial resolution (1 km or 30 arc-seconds), but contains only monthly climatologies. Reanalysis data are the output of numerical weather prediction models, which are conditioned on available actual observations using data assimilation routines. The NCEP/NCAR reanalysis data are available from 1948 at a spatial resolution of approximately 210 km (Kistler *et al.*, 2001; Kanamitsu *et al.*, 2002) and at a 32 km resolution for North America from 1979 (Mesinger *et al.*, 2006). ECMWF offers three major reanalysis products: ERA15 (1978–94, *c*. 120 km spatial resolution), ERA40 (1957–2001, 100 km), ERA-Interim (1989–present, 80 km) (Simmons *et al.*, 2007). Since 1997, the Tropical Rainfall Measuring Mission (TRMM)

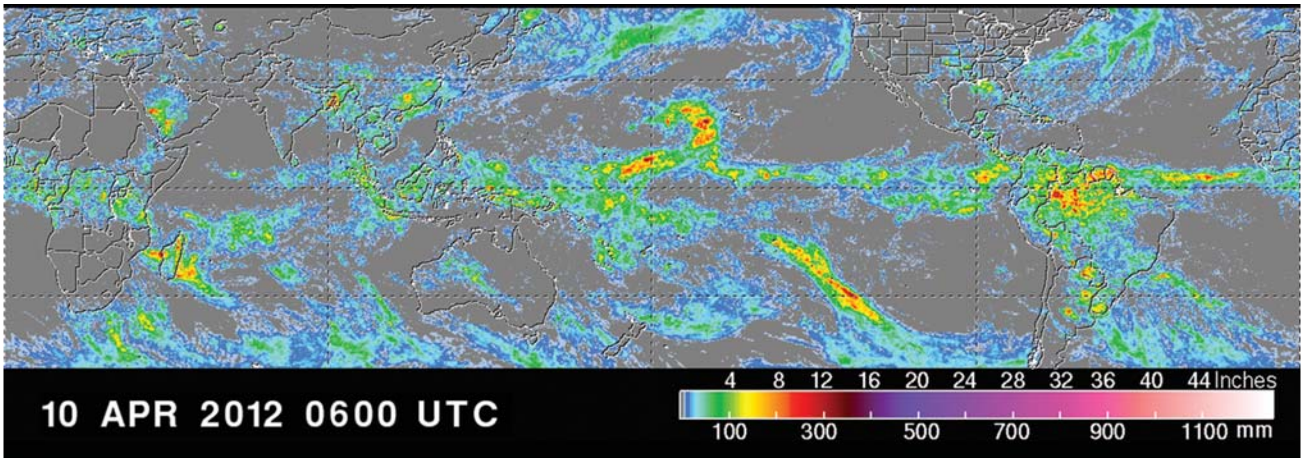

Figure 3.7. Weekly global rainfall accumulation compiled from Tropical Rainfall Measuring Mission (TRMM) data. From http://trmm.gsfc.nasa.gov.

observes tropical rainfall intensities. The final precipitation product, which is available from the TRMM website, is composed from various sensors (TRMM and other satellites) and has a spatial resolution of up to 0.25 degrees, but is limited to 50° S to 50° N. There are products with different temporal resolutions ranging from 3 hours to monthly values (Cheema and Bastiaanssen, 2012). Figure 3.7 shows the weekly global rainfall accumulation for April 2012 derived from TRMM. The Global Precipitation Climatology Project (GPCP), which will be the successor to the TRMM, is a composite database from various sources including rain gauge data. Daily values are available at 1 × 1 degree resolution from 1996 to present (Huffman *et al*., 2001). The launch of the Global Precipitation Measurement (GPM) mission (Uijlenhoet, 2008) is planned for 2013. GPM will make similar observations as TRMM, but will cover a larger domain (80% of the globe) with a higher temporal resolution of 3 hours.

Regional precipitation data: Weather radar networks play a central role in precipitation monitoring at the meso-scale, i.e., at regional scale, due to their ability to obtain spatio-temporal information about precipitation structure at a much higher resolution than conventional rain gauge networks (Figure 3.8). A weather radar measures reflectivity, which is directly proportional to the amount of electromagnetic energy scattered back to the radar by cloud and precipitation particles (e.g., raindrops, snowflakes, hail). Quantitative precipitation estimates (QPE) from radars are typically based on power-law relationships between rain rate and radar reflectivity. Precipitation estimates obtained by weather radars may be affected by multiple sources of error (see below); hence, merging with precipitation data from rain gauge networks is often seen as a way to combine the large-scale observation capability of the radar with the point-scale accuracy of the gauges (Velasco-Forero *et al*., 2009).

An example of a weather radar monitoring network is provided by the Next Generation Weather Radar system (NEXRAD) in the USA, which comprises 159 Weather Surveillance Radar-1988 Doppler (WSR-88D) sites throughout the USA and at selected overseas locations. In Europe, the OPERA project aims to provide a European platform wherein expertise on operationally oriented weather radar issues is exchanged and data management procedures (including data exchange) are optimised.

Few studies have been devoted to the statistics of extreme areal rainfall depths obtained from weather radar (Morin *et al*., 2005). The increased quality of quantitative precipitation estimates from radar and the long time series that have become available have led to a renewed interest in this kind of research in recent years (Overeem *et al*., 2010).

Local precipitation data: At local scale, rain gauges provide essential data for hydrological analyses, climatological and statistical investigations, and reference values to adjust radar-based and satellite-based products. Precipitation is observed at a large number of rain gauges (about 200 000 worldwide) in national meteorological or hydrological networks. Most of the data are used mainly in a national framework. Data from a subset of the stations (nominally from 8000 SYNOP stations) is exchanged globally among the national meteorological services using the World Weather Watch Global Telecommunication System (GTS). Monthly accumulated observations are also globally exchanged as CLIMAT via GTS from nominally 2200 stations. The CLIMAT and SYNOP collections are partly overlapping. Users can obtain the global, regional or national synoptic or climate data from the national meteorological services on request.

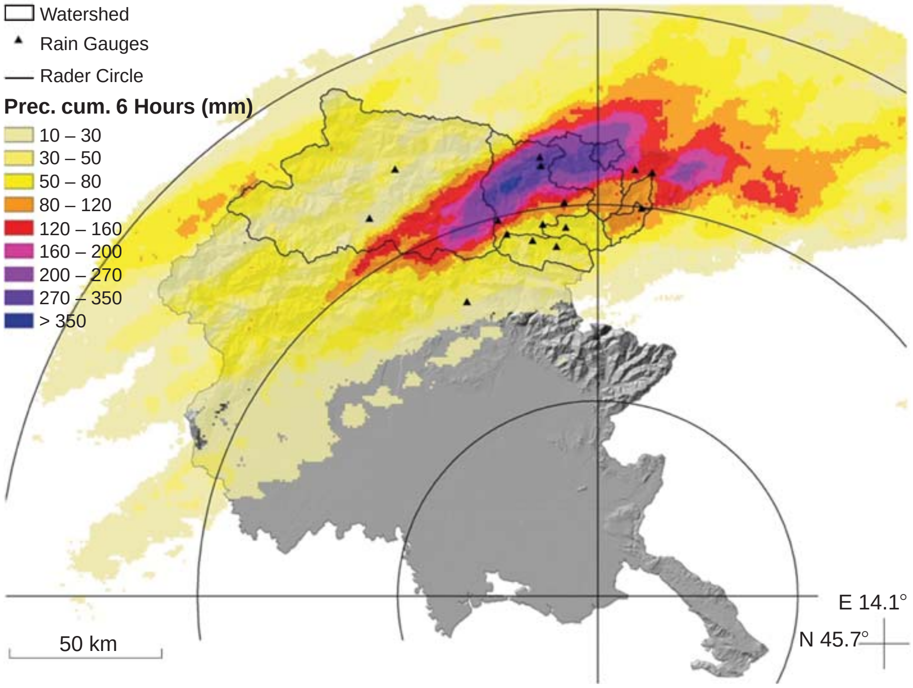

Figure 3.8. Radar-derived rainfall accumulations for a flash flood in north-eastern Italy in 2003.

The Global Precipitation Climatology Centre (GPCC) provides monthly precipitation data sets and products from 1951 to the present, calculated from global station data (Rudolf *et al*., 2003). The GPCC is operated by Deutscher Wetterdienst (DWD, National Meteorological Service of Germany) as a German contribution to the World Climate Research Programme (WCRP).

Precipitation data from rain gauges provides an essential reference to adjust satellite- and radar-based products. Validation of remotely sensed precipitation products using *in-situ* rain gauge data requires separation of the effects of natural variability from the measurement/estimation uncertainty (Ciach and Krajewski, 1999). This, in turn, implies the need for estimation and characterisation of the variability in space and time across spatial and temporal scales, which for rainfall requires specialised networks (e.g., Moore *et al*., 2000; Ciach and Krajewski, 2006).

How good are precipitation data? The effective use of satellite precipitation estimates in hydrology (e.g., Hossain and Anagnostou, 2004; Sorooshian *et al*., 2009) is very much dependent upon the type of application and the accuracy, spatial resolution, temporal resolution and latency of the estimates: different applications have different data requirements. For small temporal and spatial scales, satellite-based estimates are subject to quite large errors. For applications that imply larger spatial/temporal scale, satellite-derived precipitation products can be of great benefit (Yilmaz *et al*., 2005). For instance, hydrological model simulations based on TRMM precipitation input over the La Plata basins (with areas ranging up to 1 100 000 km^2) showed a good ability to capture daily flood events and to represent low flows, although peak flows tend to be biased upward (Su *et al*., 2008). This kind of analysis demonstrates the potential of TRMM products for hydrological forecasting in data-sparse regions at appropriate spatial scales.

The use of ground-based radar rainfall estimation for hydrological applications, such as runoff modelling, has gained momentum in the past two decades with the development of correction procedures, which are capable of considering the highly non-linear physics of radar detection of precipitation. Three broad areas of errors may be identified: (i) the electronic stability of the radar system, (ii) the determination of the detection space and (iii) the fluctuation of the atmospheric conditions. See Villarini and Krajewski (2010) for a more general discussion of error sources. When heavy precipitation in complex terrain is considered, major sources of atmospheric variability include the vertical variability of the echo interacting with the visibility of the radar beam (shielding by mountains and earth curvature) and signal attenuation by rain (an important error source for X- and C- band weather radar). The vertical profile of reflectivity induces large differences in radar measurements taken at different altitudes. In both cases, valuable results can be obtained by applying inverse procedures (Germann *et al*., 2006).

Even though measured precipitation amounts from rain gauges are generally more accurate than remotely sensed precipitation data, rain gauges have their own error sources

(Lanza and Vuerich, 2009). In the case of tipping-bucket rain gauge data, Ciach (2003) conducted experimental studies to develop mathematical models of rain gauge rainfall accumulation random errors. The standard errors decrease with increasing rain amount and time integration scale. Another conclusion from these studies is that tipping-bucket rain gauges, when well maintained and deployed as a pair (Steiner *et al*., 1999), provide accurate observations of rainfall accumulations at temporal scales of 10 min and larger. Systematic errors in rain gauge measurements can be attributed to wind effects, which have been extensively studied experimentally (e.g., Sevruk and Hamon, 1984; Yang *et al*., 1998) and numerically (Constantinescu *et al*., 2007).

3.4.3 Snow cover data

In the past several decades, the growing importance of the climatic change issue has prompted new needs for PUB studies requiring snow cover information over a wide range of spatial and temporal scales (Blöschl, 1999). At very large scales, global climate models have new requirements for information on the global distribution of snow cover and snow-water equivalent at monthly and climatologically averaged time scales for validating snow cover simulations as an input to runoff models. At regional scales, hydrological models require information on the spatial distribution of snow cover properties to validate approaches to account for subgrid-scale variations in snow with terrain and vegetation cover. At local scales, validation of multilayer physical snowpack models requires detailed information on snowpack structure, surface albedo, temperature profiles, snowmelt and surface energy fluxes (Blöschl and Kirnbauer, 1991; Blöschl *et al*., 1991a, b).

Space-borne passive microwave radiometers, such as SMMR (Scanning Multichannel Microwave Radiometer), SSM/I (Special Sensor Microwave/Imager) and AMSR-E (Advanced Microwave Scanning Radiometer-Earth Observing System), can penetrate clouds to detect microwave energy emitted by snow and ice and provide information on snow-water equivalent or snow depth. Space-borne passive microwave data are well suited for snow cover monitoring because of characteristics such as all-weather imaging, a wide swath width with frequent overpass times, and a long available time series. But the coarse spatial resolution (25 km of AMSR-E is the best available now) hinders their application in operational hydrological modelling and snow-caused disasters monitoring.

Optical sensors such as AVHRR (Advanced Very High Resolution Radiometer), MODIS (Moderate Resolution Imaging Spectroradiometer), SPOT and Landsat have been well developed to produce snow cover maps with high spatial resolution. Among these products, MODIS is among the most attractive to assist in estimating runoff in ungauged basins because of its spatial resolution of 500 m and daily availability from the year 2000 in various product variants (Parajka and Blöschl, 2012). The accuracy has been found to be excellent for hydrological purposes (Parajka and Blöschl, 2006). The main limitation is cloud cover, but a number of cloud removal methods have been developed (Parajka and Blöschl, 2008; Parajka *et al*., 2010b).

Ground-based measurements of snow properties are still needed both to improve understanding of surface–atmosphere exchange processes and to ground truth new remote sensing algorithms. A review of methods for measuring snowpack water equivalent, depth and density is provided by Lundberg *et al.* (2010).

3.4.4 Potential evaporation

Many runoff prediction methods need to estimate evaporation as well, and many of them estimate evaporation on the basis of a *potential evaporation*, E_p, which is defined as the evaporation that would occur if there were no moisture constraint or if the system evaporated at full capacity. It is therefore an important source of data, crucial for PUB.

However, potential evaporation is never measured directly. It is either inferred from other meteorological data (i.e., pan evaporation data), or estimated on the basis of a suite of other basic meteorological measurements. Pan evaporation, despite its acknowledged flaws, remains one of the most widely distributed meteorological measurements required for runoff predictions. Its advantage is that it offers ready measurement of the integrated effects of radiation, wind, temperature and humidity on the loss of water from a saturated water surface. Pan evaporation is generally not a proxy for potential evaporation or actual evaporation due to the differences in the energy balance of pans compared to the natural environment. These can include differences in the pan albedo, the potential for significant heat storage within the pan, different turbulence, temperature and humidity conditions above the pan compared to other sites of interest, and the potential for lateral heat transfer through the pan walls. Therefore, the measurements are applied with a correction, called the pan coefficient.

Alternatively to evaporation pans, a suite of empirical and energy-balance based approaches are available for estimating E_p on the basis of other meteorological data, with the complexity (and often performance) of these methods increasing as the breadth of data at weather stations is increased. For example, the Hargreaves equation computes E_p purely on the basis of data on radiation and temperature. Although simple in formulation, its use of the daily temperature range accounts for effects of cloudiness and is generally correlated with vapour pressure deficits and wind speed. It is widely used in data-short situations and has been evaluated against measured data in multiple studies.

The Penman equation estimates E_p on the basis of data on net radiation, air temperature, atmospheric humidity and wind speed. The Priestley and Taylor equation is a simplified form of the Penman equation: it also needs data on net radiation and air temperature but not wind speed. The Penman–Monteith equation is an adaptation of the Penman equation that accounts for the effects of evaporation taking place from vegetated surfaces, resulting in a correction to the E_p estimates based on the resistance of the plant canopy (stomatal resistance) to diffusion of water fluxes. In this way, the Penman–Monteith equation can be used as a model for evaporation directly, or alternatively, if the stomatal resistance is taken at its minimum value, it can be used to estimate E_p as well.

Note that, throughout the book, the term evaporation (E) is used to describe evaporation from free water surfaces, soils and plant surfaces as well as transpiration from vegetation.

3.4.5 Remotely sensed data for calculating actual evaporation

At the global scale remote sensing data is an important tool to derive estimates of evaporation patterns, E. There are three broad approaches to remote sensing of E: direct empirical methods (Glenn *et al*., 2007), residual methods (Kalma *et al*., 2008) and methods based on vegetation indices (Glenn *et al*., 2010).

Direct methods are based on semi-empirical relationships between E and surface features that can be observed with remote sensing approaches. A widely used example is the relationship between E and the temperature difference between vegetated and non-vegetated areas. These temperature differences are observable using thermal infrared imaging.

Residual methods are based upon computing the energy budget for the land surface using a combination of empirical relationships and modelled assumptions. Widely used operational models such as SEBAL, S-SEBI and ALEXI are examples of this approach. The Surface Energy Balance Algorithm for Land (SEBAL) of Bastiaanssen *et al.* (1998) requires spatially distributed, visible, near-infrared and thermal-infrared data, which can be taken from Landsat Thematic Mapper. Although approaches differ methodologically, several of these methods have been validated by comparison with moisture flux tower stations in a variety of landscapes and are considered operational (e.g., Bastiaanssen and Chandrapala, 2003; Kustas and Anderson, 2009). Residual methods generally have an error or uncertainty factor of 10–30%, which is within the range of error or uncertainty of the ground evaporation measurement methods by which they are validated (Courault *et al*., 2005).

Vegetation index methods combine vegetation indices (VI) from satellites with ground measurements of actual evaporation (E) and meteorological data to project evaporation over a wide range of biome types and scales of measurement, from local to global estimates. The majority of these indices use time series imagery from MODIS on the Terra satellite to project E over seasons and years. Vegetation indices are usually estimated from combinations of the signals in visible and near infrared bands. However, VI methods cannot estimate bare soil evaporation or differences in stomatal conductance among species and as affected by environmental factors, and these must be approximated from ground data or additional remote sensing data. Coefficients of determination between modelled E and measured E are in the range of 0.45–0.95, and root mean square errors are in the range of 10–30% of mean E values across biomes, similar to methods that use thermal infrared bands to estimate E and within the range of accuracy of the ground measurements by which they are calibrated or validated (Glenn *et al*., 2010).

3.4.6 Remote sensing of soil moisture and basin storage

In general, two types of soil moisture data are available (Grayson *et al*., 2002). At the point scale, *in-situ* measurements based on sensors at different soil depths are available. The representative area of the sensors is very small (in the range of centimetres or metres). At the global and regional scales remotely sensed patterns of soil moisture are available. Global estimates of soil moisture are currently made from space by several sensors on-board satellites. Soil moisture retrieval has been the subject of many studies and measurement campaigns. Various sensors are currently operational that can provide estimates of soil moisture. Most of these sensors operate in the microwave domain, and can be active (radar) or passive (radiometers). Advantages of the microwave domain are its independence of solar illumination (day and night capability), and its lack of cloud cover sensitivity. Lower frequencies (longer wavelengths) have the additional advantages of a relatively high sensitivity to soil water content, a deeper soil penetration, and less disturbance by vegetation and atmosphere (Hurkmans *et al*., 2004). However, in spite of these advantages there are still many challenges in reliably obtaining soil moisture estimates, especially in densely vegetated or inhabited areas (radio-frequency interference). In addition, only the soil moisture content of the top few centimetres of the soil profile is typically estimated by this technology (this has to be converted to root zone moisture) and, especially in the case of passive sensors, the spatial resolution is very low (of the order of 50 km).

One widely used sensor for soil moisture is the Advanced Microwave Scanning Radiometer (AMSR-E) on NASA's Earth Observing System (EOS; hence the E in AMSR-E). One of the most recently introduced passive sensors is the Soil Moisture and Ocean Salinity (SMOS) satellite launched in November 2009 (Kerr *et al*., 2001, 2010). Another mission planned to start in 2014/15 is the Soil Moisture Active Passive (SMAP) mission initiated by NASA (Wagner *et al*., 2007). One of the first active soil moisture data sets was derived from the ERS scatterometer data for the period 1992–2000 (Wagner *et al*., 2003). Its successor is the Advanced Scatterometer (ASCAT), which uses a very similar measurement concept while improving significantly on the spatial (25 km) and temporal (1–2 days) resolution. ASCAT has thus very comparable sampling characteristics to SMOS and the SMAP radiometer (Wagner *et al*., 2007). Soil moisture estimates at a higher spatial resolution are derived by the Synthetic Aperture Radar (SAR) instruments on-board ESA's ENVISAT, or ESA's European Remote Sensing (ERS) satellites (Wagner *et al*., 2008; Doubková *et al*., 2012). While the spatial resolution of these instruments is typically higher, applications of SAR soil moisture retrievals are typically limited to small areas or specific catchments (e.g., Pauwels *et al*., 2001; van Oevelen, 2000).

3.5 Catchment characterisation

Basin and catchment characterisation is typically focused on assessment and quantification of those aspects of physical and ecological structure that influence the storage, movement and release of water to evaporation and runoff. As such, topography, soil characteristics, geology, stream network geometry, land cover and land use are of primary interest for PUB. These variables are reflections of long-term hydrological and geomorphic processes and act to mediate contemporary hydrological processes such as runoff generation and evaporation, and catchment storage. Catchment characterisation can be accomplished via remotely sensed data (e.g., topography and land cover classification) and field assessment. As indicated in the case studies at the end of this chapter, catchment characteristics can inform relative and absolute, as well as qualitative and quantitative, assessment of likely catchment response to climate forcing. For example, geological information can provide insight into deeper groundwater contributions to runoff, while distributions of vegetation cover can inform runoff production mechanisms. Surface flow path lengths, structure and accumulation can provide additional insights into the patterns of water redistribution and hydrological connectivity of uplands to streams (Chirico *et al*., 2005; Jencso *et al*., 2010; Jencso and McGlynn, 2011).

3.5.1 Topography

Some topographic data is available for most regions of the world. The US Geological Survey (USGS) has built a 30 arc-second digital elevation model (DEM) of the world called GTOPO30. Hydrologically relevant derivatives, such as catchment boundaries, river networks, slope, flow direction, aspect, topographic wetness index and flow accumulation have been extracted from GTOPO30 and are available in the USGS HYDRO-1K geographic database at a resolution of 1 km. Recently, the Shuttle Radar Topography Mission (SRTM) updated the global 30-arc second DEM (Farr *et al*., 2007). SRTM topographic data are available (Figure 3.9), although the accuracy is much lower in mountainous terrain than in flat terrain (Ludwig and Schneider, 2006). At the national scale, many countries have elevation information at a very fine spatial resolution that is in the range of a few metres, however, it is not always freely available. An example of a freely available DEM is the National Elevation Dataset (NED) at 10 m resolution for the conterminous USA, Alaska, Hawaii and territorial islands.

Increasingly, airborne LIDAR data are becoming available. Most data are currently being obtained through dedicated research projects for regions with small spatial extent, but large-scale observation missions are becoming feasible. A number of countries around the world are currently creating a state-wide DEM based on airborne LIDAR data with a resolution in the order of 1 m. This form of high-resolution topography and vegetation height and density data will become increasingly available in the future. It will prove to be very valuable for inundation modelling and thus offers new opportunities for connecting processes and form at an ever-increasing range of scales, e.g., explicit extraction of channel heads (Tarolli and Dalla Fontana, 2009). The full value of this very high resolution topographic information still has to be exploited (Mallet and Bretar, 2009).

3.5.2 Land cover and land use

Several global land cover data sets have been compiled from remote sensing imagery. One of the older ones, often applied in large-scale modelling studies (e.g., Troy *et al*., 2008; Nijssen *et al*., 2001) is a global land cover classification system that was compiled by the University of Maryland's Department of Geography. Fourteen land cover classes are distinguished, based on AVHRR imagery from the period 1989–94. Data are available at

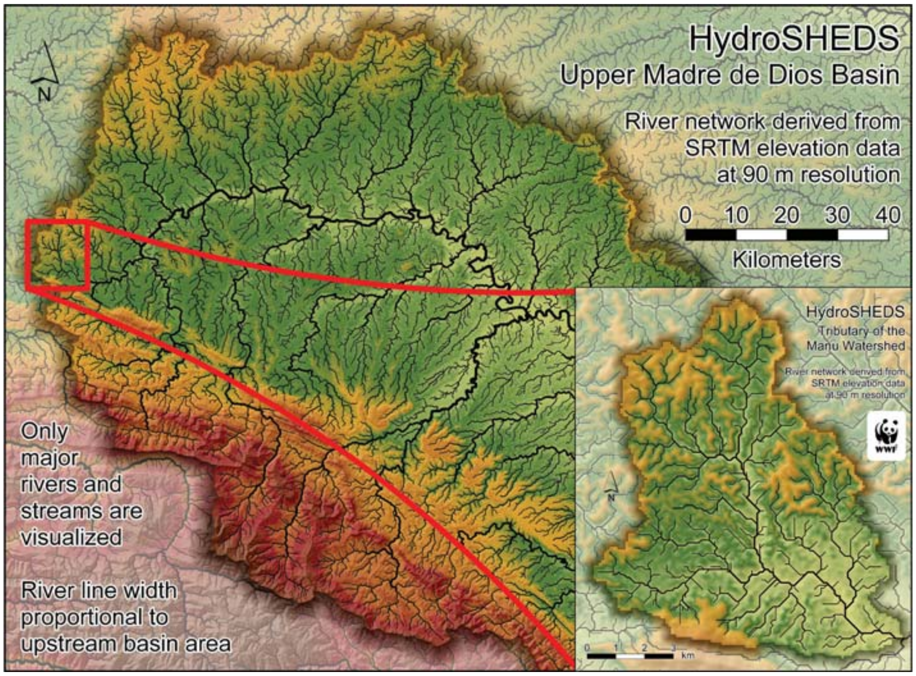

Figure 3.9. Example of a global data set that will be needed for a hyper-resolution hydrological model. The data set consists of elevation, stream networks, catchment boundaries, drainage directions, and ancillary data layers such as flow accumulations, distances, and river topology at various resolutions from approximately 90 m to 10 km and is based on data from NASA's Shuttle Radar Topography Mission. From Wood *et al*. (2011).

three resolutions (1 km, 8 km, and 1 degree). For modelling purposes, hydrologically relevant parameters (evaporation resistance, leaf area index etc.) need to be associated with the assigned land use classes. The Global Land Cover Characterization (GLCC) has been more recently developed through a joint effort of the USGS, the University of Nebraska-Lincoln (UNL), and the European Joint Research Center (JRC). This data set was also compiled from AVHRR data at a resolution of 1 km (or 30 arc-seconds), but more land cover classes have been identified (Figure 3.10). Another very recent global land cover data set, released in September 2008, is the GlobCover project of the ESA. This data set, compiled from ENVISAT MERIS (MEdium Resolution Imaging Spectrometer) images between January 2005 and June 2006, has a spatial resolution of 300 metres. Assessing the accuracy of satellite-derived land cover data is a challenge as a range of different assessment methods are used in the scientific community (Foody, 2002) and the data sets are not always consistent (Giri *et al*., 2005; Mayaux *et al*., 2006).

Besides global data sets, continental-scale land cover maps have been developed, especially for the USA and Europe. Two examples of maps for Europe are the CORINE (Coordination of Information on the Environment) and PELCOM (Pan-European Land Cover Monitoring and Mapping project; Mücher *et al*., 2000) databases. Regional, basin-wide, and local land cover and land use maps have also been developed, but their availability varies widely across countries and the globe.

3.5.3 Soils and geology

Whereas land cover data can be estimated relatively easily from remote sensing, this is much more difficult for soil properties. The FAO-UNESCO digital soil map of the world, compiled between 1971 and 1981, has been used in many global analyses (e.g., Nijssen *et al*., 2001; Hurkmans *et al*., 2008). It has a spatial resolution of 5 arc-minutes, and is compiled from over 600 national soil maps and over 11 000 other maps that were provided by national soil organisations (Reynolds *et al*., 2000). This map has been extended to the FAO Soil Database system (SDB), where for each mapping unit in the soil map, parameters have been assigned to the topsoil (0–30 cm) and the subsoil (30–100 cm). Parameters include soil texture classes (percentages of sand, clay and silt), porosity, bulk density and organic carbon fragments (Reynolds *et al*., 2000). A very recent expansion of the FAO soil map of the world is the Harmonized World Soil Database (HWSD; Nachtergaele *et al*., 2009). This data set is a joint effort of FAO, IIASA (International Institute for Applied Systems Analysis), ISRIC World Soil Information, Institute of Soil Sciences, Chinese Academy of Sciences and the Joint Research Center. It is basically a high-resolution (30 arc-second) soil map of the world, with each pixel containing data including organic carbon, pH, soil depth, water storage capacity, sand, silt and clay contents, USDA texture, exchangeable nutrients, sodicity, salinity, lime and gypsum fractions, and other properties. This data is available for two layers: 0–30 cm and 30–100 cm. Additional information about HWSD is provided by Nachtergaele *et al*.

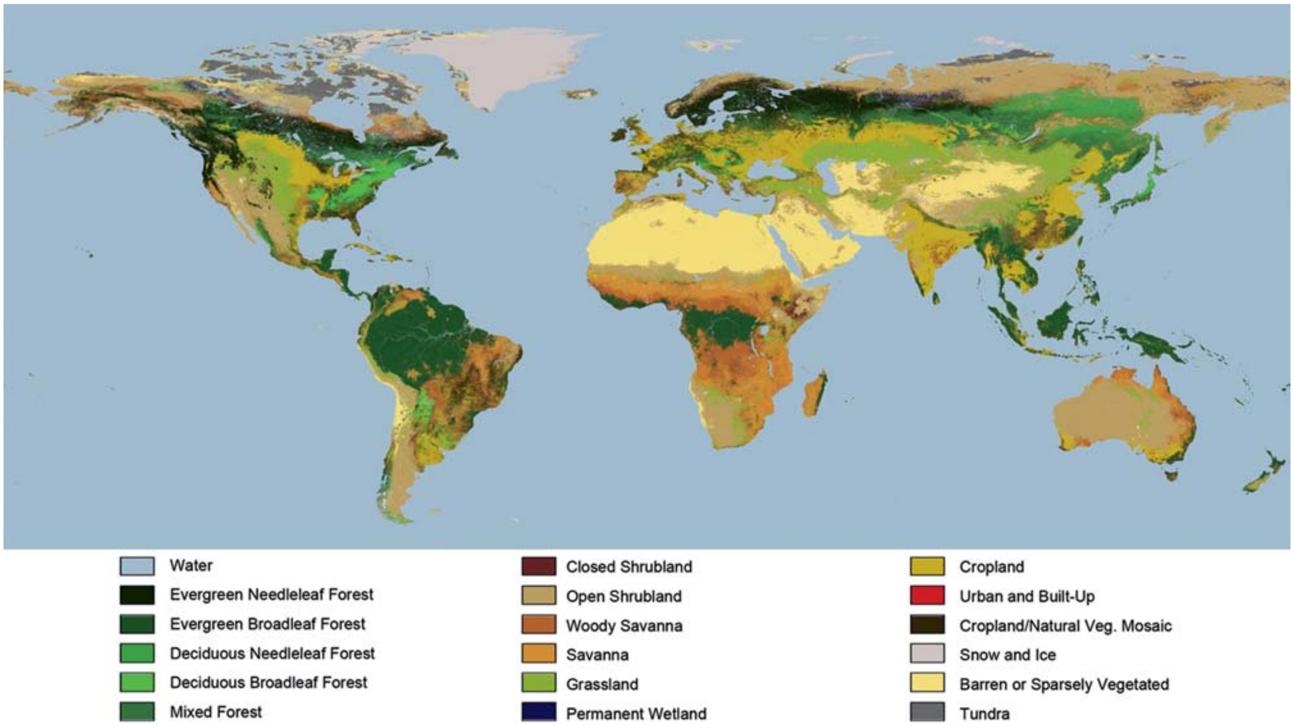

Figure 3.10. Land cover information from satellite data. http://www.nasa.gov/images/content/121557main_landCover.jpg.

(2009). For many cases, not only information on the topsoil (say the upper metre) may be relevant, as is provided by FAO and HWSD, but also data of deeper aquifers and groundwater systems. The Worldwide Hydrogeological Mapping and Assessment Project (WHYMAP), provides such maps by combining various national, regional and global sources.

In a very few cases, extra effort has been made to create a hydrologically focused soil classification. UK soils have been delineated according to their hydrological properties to produce the 29-class Hydrology Of Soil Types (HOST) classification (Figure 3.11). The HOST classification is based on a number of conceptual models that describe dominant pathways of water movement through the soil and, where appropriate, substrate. The HOST data set is available at a 1 km grid that records, for each grid square, the percentage of the 1 km × 1 km area given to each HOST class present (Boorman *et al*., 1995). Efforts have been made to expand such hydrologically relevant catchment characteristics across Europe (Schneider *et al*., 2007).

3.6 Data on anthropogenic effects

Human activities have a significant impact on the terrestrial water cycle (Braden *et al*., 2009), but quantifying their impact is often difficult (Wagener *et al*., 2010). Major activities include land cover changes such as urbanisation and deforestation, abstractions for irrigation and energy production, and consumptive water use. Related to these activities are increasing emissions of greenhouse gases that alter our climate, as well as water resources infrastructure that changes flow paths and storage behaviour of river basins. For example, during the last century, irrigable land increased from 40 million hectares (Mha) to 215 Mha (Freydank and Siebert, 2008). About 40% of the current irrigable land is supplied with surface water that is impounded by large artificial reservoirs and dams built on rivers (Lempérière, 2006). Figure 3.12 provides illustrative examples of anthropogenic effects on runoff due to hydropower generation and irrigation abstractions. At larger spatial scales, land use changes can be observed using remotely sensed information as discussed above. However, the historical extent of this information is rather short, and other, much more time consuming approaches, are needed to create a historical timeline.

Dams are constructed for different purposes: diversion, irrigation, flood protection, hydropower, water supply, recreation, navigation etc. The world has approximately 845 000 dams (Jacquot, 2009), although an exact number is not known. About 50 000 of these are classified as ‘large’ (i.e., over 15 m high) by the International Commission on Large Dams (ICOLD, 2009). The water impounded in these large dams amounts to about 10% of the annual river runoff and covers one-third that of the

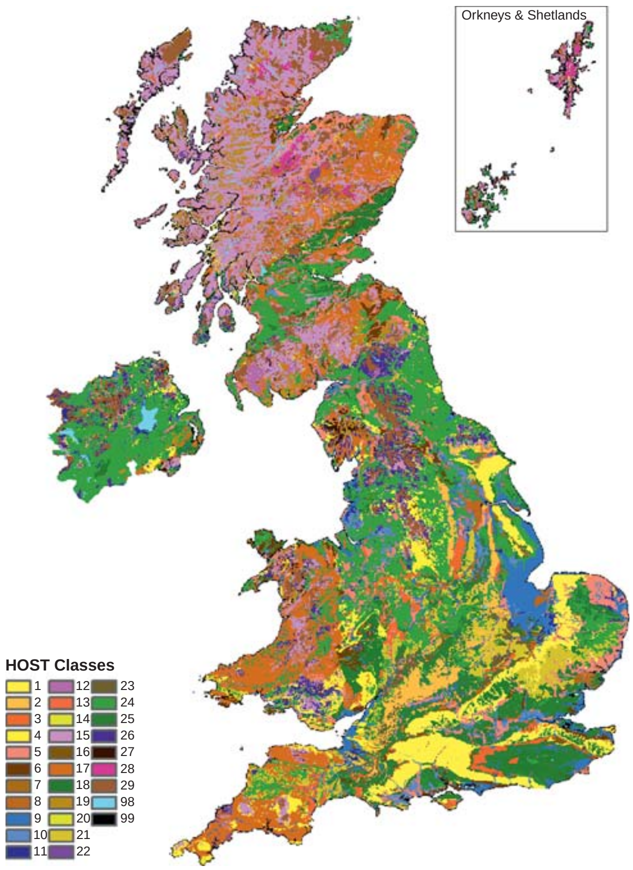

Figure 3.11. Hydrology of Soil Types (HOST) classification system for the UK at 1 km resolution. © NERC–CEH, © Cranfield University and © The James Hutton Institute.

Earth's natural lakes in terms of area (Jacquot, 2009). Despite established recognition of the many critical environmental and social trade-offs associated with dams and reservoirs, global data sets describing dam characteristics and their geographical distribution are largely incomplete. Figure 3.13 shows the distribution reported in the Global Reservoir and Dam (GRanD) database of large dams around the world along with their main purpose (Lehner *et al.*, 2011; Lehner and Döll, 2004). According to the GRanD database, about 34% of these large dams are engaged in irrigation. GRanD data include (in most cases) the dam and reservoir names, spatial coordinates, construction year, surface area, storage capacity, dam height, main purpose and elevation.

3.7 Illustrative examples of hierarchical data acquisition

We end this chapter with a presentation of three different examples involving PUB, each offering unique challenges to predictions, and requiring different strategies for hierarchical data acquisition. The first, the Tenderfoot Creek study, involves a well-established and self-organised catchment, which requires standard hierarchical measurements that exploit the natural organisation of the catchment. The second, Chicken Creek artificial catchment in Germany, offers unique challenges due to the fact it is an artificial catchment rehabilitated after decades of mining activities, and it will take some time to fully understand the dominant processes in a fast changing landscape; it therefore offers unique challenges to the modeller. The third, in the Selška Sora catchment in Slovenia, is a forensic study aimed at understanding the mechanisms that led to flooding, and highlights the challenges in deciphering the mechanisms that led to recorded floods on the basis of the markers left behind. Each example represents the diversity of problems faced under PUB, and the creativity that can be brought to bear on addressing the learning and prediction challenges of PUB.

3.7.1 Understanding process controls on runoff (Tenderfoot Creek, Montana, USA)

The case study describes a sequence of steps and inferences that could be drawn about the Tenderfoot Creek Experimental Forest (TCEF) headwater catchment located in the Little Belt Mountains of Central Montana, USA, utilising hierarchical data acquisition in the PUB context. Each level of the hierarchy narrows the likely catchment runoff behaviour to enhance PUB. The first step includes inferences drawn from general hydrological understanding of runoff behaviour in the context of the climate, biogeography and physiography of the area. Second, inferences about likely runoff behaviour can be drawn from nationally or globally available data. Third, field visits further constrain possible behaviour with inference from simple field observations.

Catchments in the Little Belt Mountains and similar environments are characterised by shallow throughflow runoff processes and variable source area hydrology and are therefore likely to dominate TCEF hydrology because of their physiographic setting, climate and likely weather patterns. Shallow, permeable soils overlying less permeable or nearly impermeable bedrock lead to perched, transient water tables in the soil and weathered bedrock zone. If deeper groundwater rise into the weathered bedrock/soil zone is a significant mechanism, shallow throughflow can still be a dominant runoff process because of the dramatic increase in hydraulic conductivity above the bedrock zone. Steep slopes and complex topography further promote rapid throughflow above the soil–bedrock interface. Convergence and divergence in the topography result in more diffuse or more focused flow accumulation and influence landscape scale runoff patterns, drainage rates and resulting soil moisture distributions.

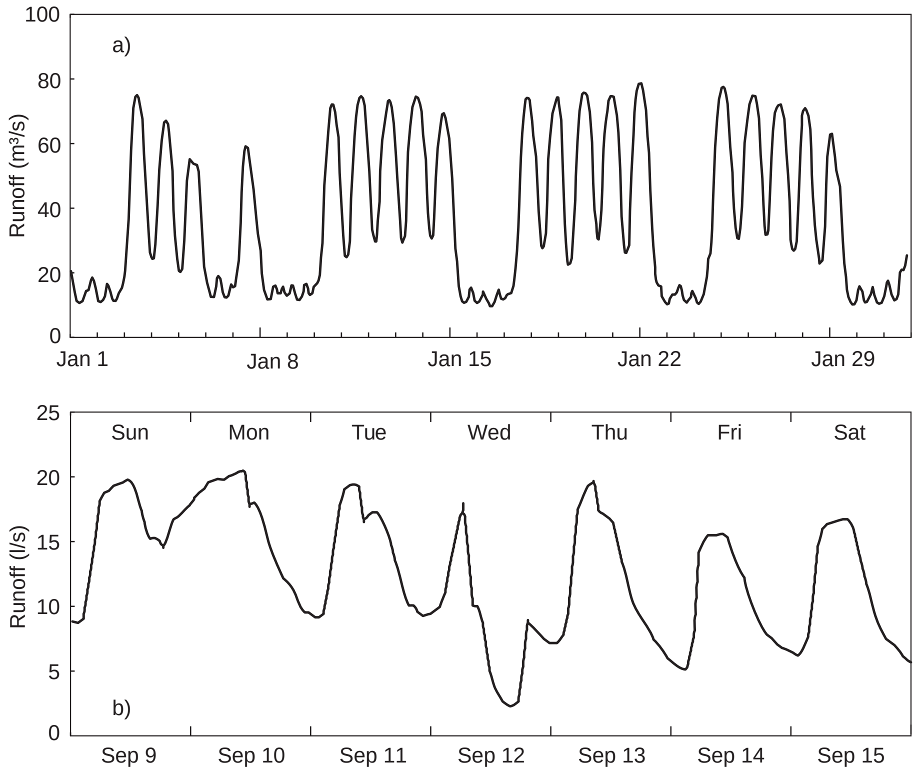

Figure 3.12. Examples of anthropogenic effects on runoff. (a) Runoff of the Inn at Kajetansbrücke, Austria, illustrating hydropower regulation effects on runoff. Note the pattern of the weekdays/weekend and 6 January as a holiday (Epiphany). (b) Daily runoff pattern at Vudee weir, Tanzania, dominated by farmers managing water diversions. During the day farmers divert water according to agreements with downstream users. On Sunday they release water for downstream use. On Wednesday a nearby group of farmers are allowed to irrigate. From Mul *et al*. (2011).

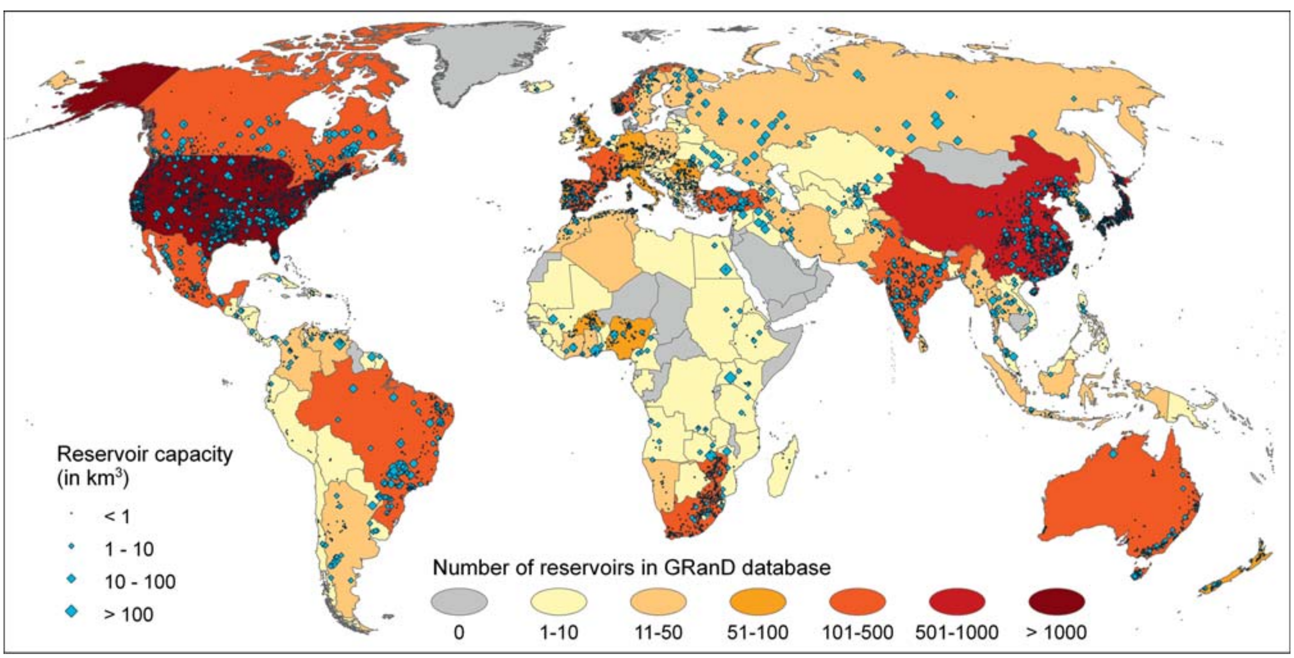

Figure 3.13. Global distribution (by country) of large reservoirs. From Lehner *et al*. (2011).

Snowmelt-dominated water inputs and warm, sunny, dry summers in the region lead to strong seasonality of hydrological behaviour, starting with a long winter period of frozen ground and snow accumulation that can last from November until June. During this period, runoff is minimal and the catchment stores water in the snowpack for more intense melt delivery with spring snowmelt. The duration and intensity of annual snowmelt is climate dependent and

Figure 3.14. Tenderfoot Creek Experimental Forest catchment. Note the gentle mountain topography and forested landscape that includes areas of disturbance (forest harvest). Photo: F. Nippgen.

its peak varies by up to a month or more. This forms the dominant runoff event of the year. The timing and intensity of snowmelt delivery to the catchment soil strongly impact the magnitude of dynamics of the runoff hydrograph. Additionally, the temporal intersection with available energy and vegetation productivity lead to differential evaporation from year to year in this water-limited environment. Following snowmelt, the seasonal recession declines rapidly due to the shallow soils and steep slopes that promote rapid soil water drainage. Additionally, strong evaporation further reduces catchment storage and thus water available for runoff. Summer rainstorms produce only modest increases in runoff due to unrequited catchment storage. Decreased potential evaporation and vegetation productivity in the autumn lead to small increases in runoff into the winter snow accumulation period.

Seasonal low flow occurs in late August and early September, with peak snowmelt runoff occurring in April through June. Annual runoff ratios (ratio of runoff to precipitation) fall by between 0.2 and 0.4 in these high-elevation snowmelt-dominated semi-arid environments.

Nationally available topography data indicate that TCEF's catchment area is 22 km^2, elevation ranges from 1900 to 2400 m, and it contains first- through third-order streams that form distant headwaters of the Mississippi River system, which drains to the Gulf of Mexico. National vegetation products indicate that the forested catchment is predominantly lodgepole pine (*Pinus contorta*). The location of the catchment at high elevation in the northern Rocky Mountains, USA, corroborates that it is a snowmelt-dominated hydrological system with 40–90% of annual precipitation in the form of snow and a short snow-free growing season of 3–5 months.

Precipitation inputs can vary by up to 50% from year to year in this region and the timing of snowmelt can vary by months. Annual and seasonal evaporation vary significantly as a function of snowmelt timing and summer rains since it is a strongly water-limited, as opposed to energy-limited, system.

Trees in TCEF are mostly lodgepole pine, a highly adaptable tree that can grow in a wide range of environments, from water-logged bogs to dry sandy soils. The presence of sagebrush in the area, however, suggests a semi-arid environment. Analysis of widely available topographic and surficial geology data indicate that TCEF ranges from north-facing to south-facing; the main drainage runs east to west with north- and south-facing subcatchments; the slopes are moderate for mountainous terrain; the hillslopes are relatively planar; and the riparian valley bottoms are limited to 2–4% of the landscape. The catchments show little evidence of glaciation and therefore soils were likely formed on local shale, sandstone and granite from low to high elevation, suggesting differential permeability and bedrock weathering that could exhibit a broad range of conditions from intact to highly weathered and fractured bedrock. The landscape form suggests some disequilibrium with current climate conditions.

Tenderfoot Creek is a tributary of the Smith River, which has a downstream real-time stream gauge maintained and served on the Internet by the USGS. Historical and real-time runoff conditions that include contributions from TCEF and other nearby mountain catchments corroborate inferences drawn from hard and soft information described above.

The value of field visits to TCEF is largely a function of the time of year (hydrological season) and the spatial extent of the observations. Regardless of season, initial observations confirm that the landscape is of moderate relief and complexity with relatively gentle convex slopes and moderately planar uplands (Figure 3.14). Open lodgepole pine forest and wet riparian meadows are readily apparent, and simple depth to bedrock probing confirms that the soils are shallow (~1 m). Little evidence of overland flow is present, suggesting subsurface flow dominated hydrology. Stream morphology and streambed material size indicate moderate peak runoff magnitudes. Taken together, these observations suggest that the hydrological dynamics are moderate and likely lack a flashy response to snowmelt and precipitation. Evidence of recent forest disturbance from logging suggests that the response of some tributaries will be more rapid during spring snowmelt and sustain higher levels of summer baseflow due to altered snow energy balances and decreased evaporation. Summer dry season observations indicate low runoff and therefore a steep recession from spring snowmelt (Figure 3.15). Dry uplands and wet riparian soils imply riparian and perhaps

Figure 3.15. Early winter snow cover and frozen streams lead to low baseflow and increasing amounts of water stored in the snowpack for spring melt. High flow conditions driven by enhanced landscape hydrological connectivity and variable source area dynamics. Decreasing baseflow through summer growing season and transition to autumn. Photos: F. Nippgen and C. Kelleher.

Figure 3.16. Photo of the artificial Chicken Creek catchment near Cottbus, Germany. Photo: BTU Cottbus FZLB, 2007.

deeper groundwater sources of runoff with little active upland hydrology except for zero-order basins and areas of greater upslope accumulation as evidenced by exfiltration and the hillslope–riparian topographic transition. Field reconnaissance during more hydrologically active times (e.g., spring snowmelt or rainstorms) reveals subsurface stormflow (throughflow) dominated hydrology with variable source area saturated overland flow. Variable landscape contributions to runoff generation are evident in saturation extending from riparian zones into convergent hillslopes of greater area accumulation. Little to no infiltration excess overland flow is observable save in areas of exposed bedrock and forest roads.

Despite this, the strength of inference that can be drawn from the data hierarchy, quantification of the specific magnitude and timing of catchment runoff dynamics, and the relative magnitudes and spatial distributions of runoff process will remain uncertain without additional data collection and interpretation. Attributing specific runoff dynamics to catchment form and runoff processes can require multiple years of intensive field observations, but can yield insight into those aspects of catchments that can be used to constrain PUB elsewhere.

3.7.2 Runoff predictions using rainfall–runoff models (Chicken Creek, Germany)

A PUB comparison study using 12 hydrological models was performed at the artificial Chicken Creek catchment in Germany in the context of the Transregio-SFB 38 research project (Holländer *et al.*, 2009; Bormann *et al.*, 2011a, 2011b). The modellers were tasked with modelling the catchment with varying degrees of information available to them. The catchment has a size of 6 ha (450 m × 130 m) and was created in 2005 (Gerwin *et al.*, 2009; Figures 3.16 and 3.17). It is bounded at the bottom through a 2 m clay layer, which is covered by 2–3 m of (mainly) sand. A lake has formed in a depression that was implemented close to the catchment outlet. Regional annual average temperature is 9.3 °C (1971–2000) and annual precipitation varies between 335 mm/yr and 865 mm/yr. No vegetation was artificially added to the catchment.

'Artificial catchments are per se the opposite of ungauged catchments because they are supposed to provide a well-documented case (e.g. a clear definition of catchment geometry and boundary conditions)'(Holländer *et al.*, 2009). However, in this study it was assumed to be ungauged in the sense that most of the available information on catchment characteristics was withheld by the organisers of the model inter-comparison study. Time series of hydrological fluxes (e.g., runoff) and state

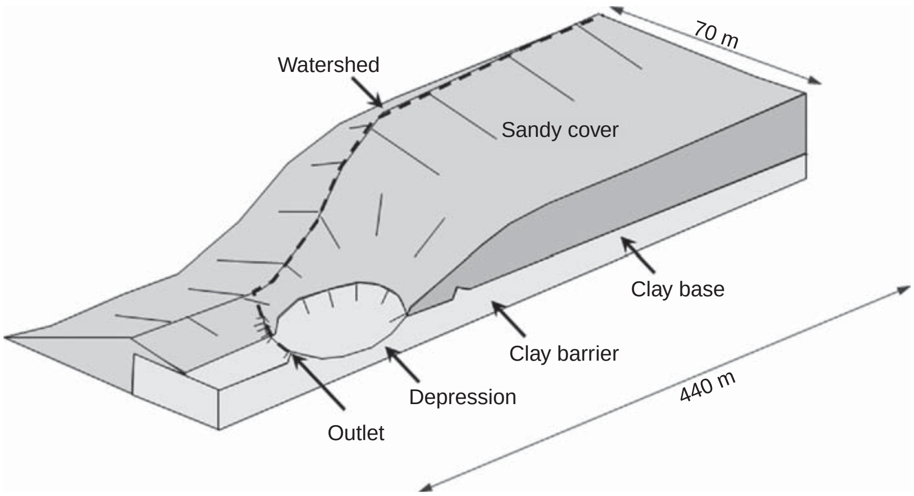

Figure 3.17. Cross-section of the Chicken Creek catchment. From Bormann *et al*. (2011b).

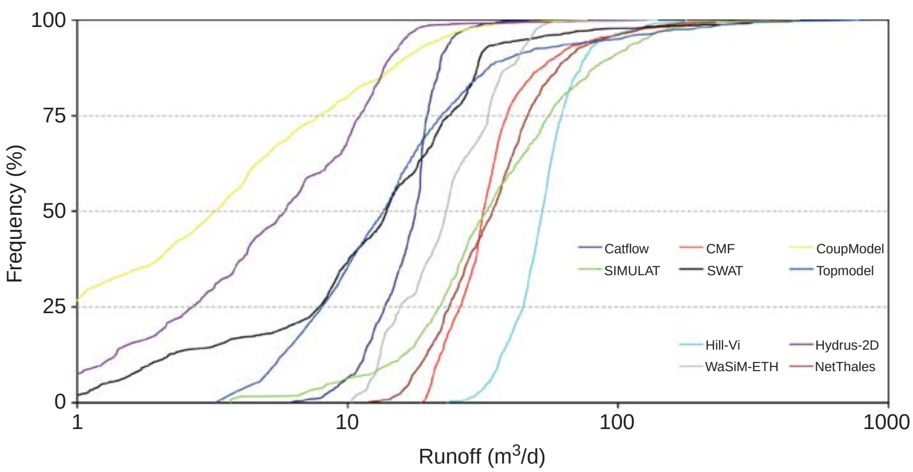

Figure 3.18. Differences in frequency distributions of the different models during *a-priori* simulation, the first prediction for the Chicken Creek. From Holländer *et al*. (2009).

variables (e.g., soil moisture, groundwater tables) were withheld as well in the first modelling steps. Therefore, model predictions were done *a priori*, without guidance from gauged data, although the catchment is intensely monitored with respect to water and matter dynamics as well as system characteristics (Gerwin *et al*., 2009).

The comparison study is broken up into four different modelling stages, reflecting the hierarchy of data acquisition discussed in the rest of this chapter: (i) *A-priori* modelling based only on data about soil texture, soil thickness, clay layer, topography, vegetation cover, hourly climate data, air photography and initial groundwater levels. Modellers were not allowed to visit the catchment. (ii) A walk through the catchment, after which the modellers discussed and compared their *a-priori* model simulations as a group. (iii) Additional observations including soil hydraulics, soil physical data, soil water content and infiltration capacity. (iv) Runoff observations (for calibration) from a subcatchment (1.8 ha). Three of these modelling steps have so far been executed and are summarised briefly below. The models applied encompass different modelling philosophies, ranging from one-dimensional to three-dimensional models regarding their spatial representation. Most of the models describe the hydrological processes in a physical way, whereas only a few models are based on a lumped, conceptual concept. Eight of the twelve models describe the unsaturated soil water flow by the Richards equation, and ten models use the Penman–Monteith approach to calculate potential evaporation.

The results of the study showed a very large spread of model results (runoff at the outlet) across the models after stage one (Figure 3.18). Models simulated from 10% to 330% of observed mean annual runoff. According to Holländer *et al*. (2009), those differences could mainly be attributed to differences in model parameterisation and conceptualisation. Unknown initial conditions in terms of soil moisture content were another important issue to be tackled by the modellers. ‘Runoff was mainly predicted as

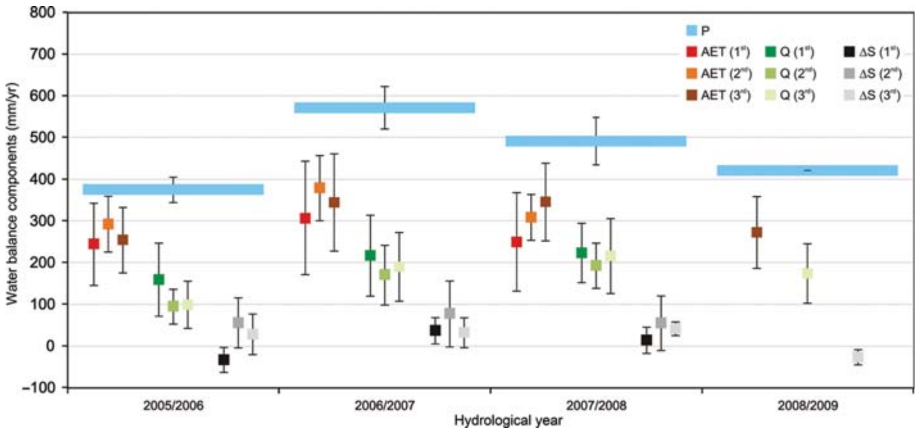

Figure 3.19. Change in annual water balance components (mean and standard deviation) during the three modelling stages for the Chicken Creek. The variability in precipitation is caused by precipitation correction by a few models. From Bormann *et al.* (2011b).

subsurface flow with little direct runoff. In reality, surface runoff was a major flow component despite the fairly coarse soil texture. The actual evaporation (AE) and the ratio between actual and potential E was systematically overestimated by nine of the ten models. None of the model simulations came even close to the observed water balance for the entire 3-year study period' (Holländer *et al.*, 2009).

The spread of the model simulations narrowed during stage two, after modellers had discussed their results and had visited the catchment. As a consequence of the discussions and the field visit, modellers tended to change the model setup in the same direction (resulting from a common process understanding). All modellers tended to reduce the total runoff generation while increasing surface runoff generation, since a biological soil crust had been identified (Fischer *et al.*, 2010). Some modellers also adapted the representation of subsurface storage behaviour and changed initial conditions because it had emerged from discussions that the catchment was dry after construction.

In the third modelling stage, modellers were asked to select the required data from an available data pool considering hypothetical costs they would be willing to pay for the data. Most modellers asked for soil hydraulic and soil physical data as well as for soil moisture and infiltration rates, while only a few modellers used the extended vegetation data set, the new digital elevation model and the new aerial photo. Most of the modellers used the data for reassessing model parameters and adjusting initial conditions. However, the spread of the models after these adjustments remained similar to that of the second modelling step. The additional observations available during the third step led to smaller changes in the model simulations than those due to initial data, joint discussion and actual visits to the catchment (e.g., water balance terms; Figure 3.19).

Overall, the study participants concluded: 'the comparison indicates that, in addition to model philosophy, the personal judgment of the modellers was a major source of the differences in the model results. The model parameterization and choice of initial conditions depended on the modeller's judgment and were therefore a result of the modeller's experience in terms of model types and case studies' (Bormann *et al.*, 2011b). The study therefore confirms the findings of previous studies (e.g., Diekkrüger *et al.*, 1995) on the importance of the modeller's subjective decisions, particularly in the case of *a-priori* prediction. 'The most important parameters to be presumed were the soil parameters and the initial soil water content while plant parameterization had, in this particular case of sparse vegetation, only a minor influence on the results' (Holländer *et al.*, 2009).

The study further showed that the use of soft as well as hard data is valuable in the case of sparsely gauged catchments. Soft data, e.g., obtained from field visits or even aerial photos, can inform the modeller about dominant or at least important hydrological processes in a catchment that will help improve hydrological process understanding. The modeller can then decide how to use such information in the modelling process. In this study, additional data predominantly only confirmed the modeller's assumptions that were based on field visits and discussion. They did, however, assist in improving the adequate choice of initial and boundary conditions. After carrying out the fourth modelling stage, consisting of model calibration against observed event runoff from a subcatchment, further analysis of the predictive uncertainty of the *a-priori* modelling steps will be feasible.

3.7.3 Forensic analysis of magnitude and causes of a flood (Selška Sora, Slovenia)

Observations of traces left by water and sediments during flood events provide an opportunity for developing spatially detailed estimates of peak runoff along the stream network (Figure 3.20). This information is helpful for better understanding the role of rainfall accumulation rates and of soil and land use properties in runoff generation in the context of

Figure 3.20. (a) Example of a flood mark. The vegetation removed from the rocky bank and the moss drenched with silt on the downstream side of the tree show the highest level reached by floodwater (red line). (b) The arrow shows the tree with the flood mark and a phase of the topographic survey of the river section. (c) Surveying the stream bed. Photos: M. Borga.

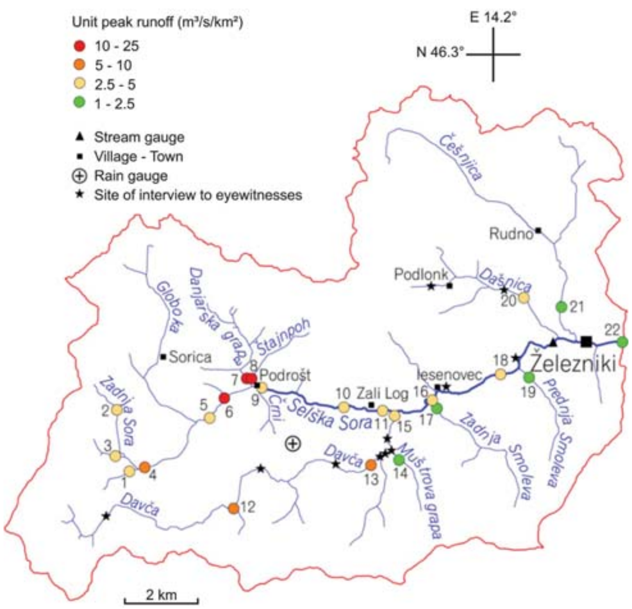

Figure 3.21. Map of the Selška Sora catchment in Slovenia with location of runoff estimates, interviews with eyewitnesses and central values of unit peak runoff. From Zanon *et al.* (2010).

PUB and for flood events characterised by sharp gradients in runoff response properties (such as flash floods). Indirect methods for flood peak estimation include the slope–area, contracted opening, flow-over-dam or flow-through-culvert approaches. However, any survey has to capture not only the maxima of peak runoff; less intense responses within the flood-impacted region are important as well. These lesser events can be contrasted with the corresponding generating rainfall intensities and depths obtained by weather radar reanalysis, thus permitting identification of the catchment properties controlling the rate-limiting processes (Zanon *et al.*, 2010). Clearly, not all sections of a river may be suitable for indirect peak runoff estimation. However, Borga *et al.* (2008) have shown that, provided that a careful logistical planning and properly staffed infrastructure is ensured, post-event surveys may deliver a spatially consistent analysis of the historical flood response. Surveying the geomorphic response, through mapping of landslide/debris flow initiation and deposition areas, is important as well. This may help to properly identify the flow processes that occurred in the basin and hence to avoid questionable peak runoff estimates due to incorrect identification and documentation of debris flows.

An example of a map of unit peak runoff values obtained during a post-flood survey is shown in Figure 3.21 for an extreme flash flood that occurred in September 2007 in Slovenia (Zanon *et al.*, 2010). Examination of the flood response shows that the extent and the position of the karst terrain provide major geological controls on the runoff response in the region during storms. Differences in geology, combined with the orographic and climatic influences, led to pronounced contrasts in flood response between nearby basins, with the major flooding occurring in an area outside the region that received the largest rainfall intensities and accumulations.

Eyewitness accounts and observations represent an integral part of the flash flood response survey. It should be noted that these 'observations' might be collected as digital imagery from movies and pictures. Such observations represent an extremely important information source to refine the assessment of flow type/depth, the estimates of flow velocity and runoff, and for the evaluation of flooding extent. Interviews with eyewitnesses provide information and anecdotal evidence on the time sequence and dynamics of the flood, and as such they add a time dimension to the spatial patterns of a flash flood response. It should be recognised that accuracy of the witnesses' accounts is limited (up to ±15 min, according to Borga *et al.*, 2008). Consequently, when these observations are used to estimate the timing of the flood peaks, their information content should be related to the catchment response time, and therefore to the catchment scale.

The utility of the individual observations gathered by means of the flash flood survey may be extended using hydrological models driven by the space–time estimates of rainfall obtained from radar reanalysis (when available). Ruiz-Villanueva *et al*. (2011) integrated the surveying and modelling phases through a three-step procedure (applied to a medium-size catchment in south-west Germany), which reflects the hierarchy of data use considered in this chapter: (i) *A-priori* modelling of peak runoff at multiple locations based only on land use/land cover data, soil properties, soil thickness and radar rainfall data. (ii) Calibration of the model using runoff data from a (distant) downstream stream gauge, which include the whole area impacted by the flood. (iii) Comparison with the runoff observations collected from the post-flood survey and identification of the critical areas/processes responsible for outlying responses. The methodology based on post-flood survey affords examination of key hypotheses concerning the hydrology and hydraulics of catchment response under flash-flood conditions. Examples include (i) role of antecedent soil moisture conditions in flood magnitude; (ii) role of land use and catchment properties in runoff generation; and (iii) dependence of flood properties on basin scale by means of space–time scaling properties of precipitation.

Surveys of flash-flood response may provide valuable insights; however, generalising the findings beyond the areas of interest can prove to be difficult. Each storm episode seems to have particularities that cannot be specified in full detail. Advancing the understanding in the context of flash-flood studies, which are by necessity opportunistic and event-based, requires the development of a parsimonious avenue to synthesis. This may be based on classification and similarity concepts, which can be profitably used when the processes are not fully understood (Blöschl, 2006). Contrasting different case studies and learning from the similarities and dissimilarities should play a central role in PUB studies.

3.8 Summary of key points

- Predictions in ungauged basins (PUB) in one way or another involves extrapolation from gauged to ungauged catchments, which needs data of all kinds. Three kinds of data will be discussed in this book: runoff data, climate data and catchment data.
- The need for data can be summarised under three categories: (i) data needed to read and understand the landscape in a hydrological context; (ii) data needed to develop regression relationships that will be used in statistical models; and (iii) data needed for process-based models, such as climatic forcing and parameter values, data to assist with model development (to make inferences from rainfall–runoff data), and to calibrate or validate models developed elsewhere.
- However, data are more than just inputs to a model. Data have hydrological context and contain hydrological content. Data will be the ultimate source of the understanding that is embedded in all models, because when understood properly they reflect the co-evolution that is common to all catchments. Therefore, there is value and much to be learned from the combination of runoff, climate and catchment data, a learning process that we have called '*reading the landscape*'.
- The information content of data products required for accurate PUB, from global data sets to local observations, is highly scale dependent and increases with decreasing temporal and spatial scale of prediction. This is because system heterogeneity is increasingly subsumed at larger spatial and temporal scales, leading to simpler catchment response to climate forcing. On the other hand, at small time and space scales, the heterogeneities and process complexities are much stronger, and are not attenuated, and thus need considerably more data to resolve them.
- The scale dependency of data requirements therefore necessitates a hierarchical strategy of data acquisition. Given the constraints provided by available resources and time, different data acquisition strategies may be adopted at various levels. Global and low resolution data sets, generally based on remote sensing, provide generalised information at low cost. Regional data sources of varying availability and accuracy provide detailed information at higher cost over smaller scales. Finally, with increasing time and financial resources, organisation and collection of short-term measurements may provide a better understanding of the catchment response at local scale.
- Large or regional data sets, even of low resolution, are an important basis for performing comparative hydrology, to generate *a-priori* expectations of dominant processes, while very detailed data on the local scale help to confirm and improve process understanding. Extrapolation from gauged to ungauged basins requires that one finds connections between what happens locally and elsewhere: this requires a framework to connect.
- In general two kinds of data can be distinguished: hard data measured in the field and soft/proxy data that provide additional information on hydrological systems. For PUB the combination of available soft and hard data relating to runoff, climate and catchment, through the reading of the landscape, plays an important role in order to exploit the available information and describe runoff processes in the best possible way.
- Field reconnaissance and expert judgement play critical roles in the assessment of local system characteristics

and play important roles in the data acquisition strategy. The relative strength of different hydrological processes and dominant runoff generation mechanism are not easily inferred from topography, remote sensing and conventional hydro-meteorological data alone. Field visits allow for comparison of similar gauged catchments or heavily researched and more completely understood catchments, thereby allowing transfer of the relevant information.

- As modelling and methodological power has increased there has been a reduction in 'data power', particularly in hydrological data collection. While the hydrological community has access to large data sets of unprecedented quality over large scales, e.g., remotely sensed data from satellites, the collection of more conventional data at small scales has suffered. There is a need to increase the awareness of the value of such data, especially the gauging of dynamic hydrological variables in strategic locations and in a transferable manner, and demonstrate the value of targeted gauging of currently inadequate or non-existent data sources by quantifying the links between increased 'data power' and improved model predictions.

4 Process realism: flow paths and storage

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4.1 Predictions: right for the right reasons

Runoff estimates in ungauged basins will always be based on the application of some type of model that represents the processes operating in the catchment. The level of detail at which these processes are represented varies with the model type, ranging from statistical models that represent the processes in a basic way to detailed process-based models that attempt to capture the key aspects of the bio-physical catchment structure and their dynamic controls on storage, flow paths and flow processes. One of the key characteristics one would like a model to have is process realism, i.e., the model should be a close representation of the real-world hydrological processes (see Section 2.6). The main reason for the need for process realism is that the PUB problem is essentially an extrapolation problem, and extrapolations tend to be more reliable if the processes are represented in a faithful way. The extrapolation can be either in space, focused on estimating key runoff signatures from similar neighbouring catchments, or an extrapolation with the use of basic climate and catchment data but without the ability to calibrate the model against runoff data. Calibration against runoff data is not an option in ungauged basins.

The model can still fit the data well, however, even if it is not realistic in the sense described above. For example, a regression model of low flows on the basis of catchment characteristics may fit the data in the region well, but if the coefficients do not truly represent the main process controls on low flows in the region (e.g., geology, precipitation), chances are that the model will not perform well in an ungauged catchment. In other words, if the model lacks realism and is simply a statistical best fit to the data, the biases and uncertainties may turn out to be large. A realistic model, in contrast, can be extrapolated more reliably to ungauged basins. As Klemeš (1986a, p.178S) put it: 'For a good mathematical model it is not enough to work well. It must work well for the right reasons. It must reflect, even if only in a simplified form, the essential features of the physical prototype.'

A crucial aspect one expects of a realistic model is to represent the subsurface well (Beven, 2000). The subsurface structure of the catchment determines the time-invariant controls on the gradients of hydraulic potential that drive subsurface water flows, their dependence on internal states and the patterns of flow resistance. Gradients and resistances together determine the spectrum of subsurface flow velocities and flow paths. Catchments have evolved through the interaction of several landscape processes, climate and vegetation, and the non-linearity of the processes and process interactions involved has invariably produced an intricate pattern of surface and subsurface flow paths – tortuous and inter-connected flow paths operating at a multitude of scales. While there are a number of geophysical measurement methods available to characterise the subsurface structure that governs these flow paths, they tend to be time consuming to perform and the level of detail with which these can be resolved at the catchment scale remains limited. Understanding flow paths and storage at the catchment scale is thus a major challenge. This chapter therefore focuses on the realism of flow paths and storage representations at the catchment scale for the purpose of estimating runoff in ungauged catchments.

As rain falls on the ground, part of the water is intercepted by vegetation (and the soil, including leaf litter) and evaporates directly, part of the water infiltrates into the soil, and the remaining part of the water runs off on the surface. This partitioning occurs at multiple scales and can be conceptualised in terms of several hillslope runoff mechanisms that together link up to the catchment scale. These include infiltration excess overland flow when the rainfall intensity is larger than the ability of the soil to infiltrate; saturation excess overland flow when the soil is saturated due to prior rainfall and/or upwelling groundwater; and subsurface flow through interconnected networks of vertical and lateral preferential flow paths. These preferential flow paths reduce flow resistance along

* Coordinating contributor

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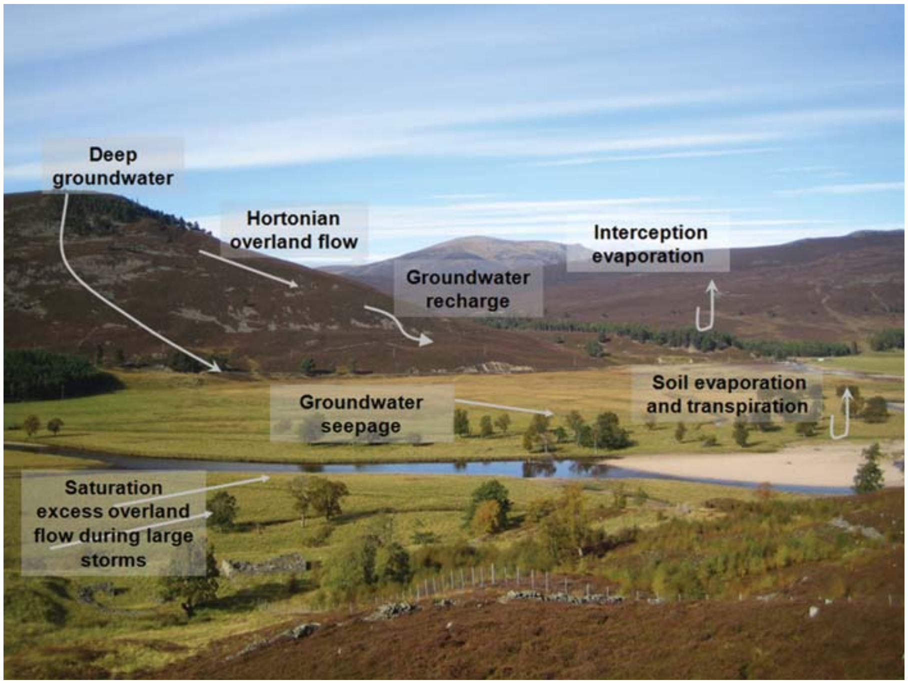

Figure 4.1. Different parts of the landscape may be amenable to different flow pathways. Example from Alltachlair, the River Dee and Beinn a Bhuird, with typical flow paths to be expected in this type of landscape. Photo: N. Corby.

their main direction, and thus accelerate the flows for a given gradient; they organise the flows as they create strong anisotropy in flow resistances and reflect the co-evolution of the (sub-)surface, hydrological processes and eco-system in the past towards a spatial organisation. In general, subsurface flow can be shallow (close to the surface in the soil) or deeper and occurs in the pore spaces of porous media, such as soil or regolith, and in cracks or fissures of the underlying bedrock. Which part of the given set of morphologically connected flow paths is activated depends on the supply of water as well as the presence of stored water. Furthermore, it is important to note that each flow path is active on a different time scale. Functional connectivity of flow paths and thus hydrological connectivity is thus dynamic, and changes with time. Figure 4.1 shows examples of surface and subsurface flow paths that can be active at a given location. Eventually, the water in these flow paths emerges at a stream at the foot of a hillslope or further downstream. It is these flow paths and the storage capacities of the various landscape units present that should ideally be identified in order to design a realistic model of a given ungauged catchment. In other words, it is crucial to identify the location, the time scales and the threshold dynamics of the flow paths present in the catchment (Zehe *et al.*, 2007).

If the dominant flow paths together with their threshold patterns, time scales and storage capacities are well characterised a model has the potential to reproduce the catchment response dynamics well under varying wetness conditions. This has important implications for the estimation of the runoff signatures. For example, while baseflows are mostly sustained by groundwater and its seasonal fluctuations, peak flows are frequently controlled by additional flow paths, which become gradually connected to the stream with increased catchment wetness and which are characterised by much shorter time scales and lower storage capacities.

If information about flow paths and storage in a catchment is known, it can be used in a number of ways to inform the estimation of runoff signatures in ungauged basins.

- Information on flow paths and storage can be directly used in *ungauged* catchments to inform the choice of model structure, constrain *a-priori* model parameters, and thus to estimate runoff signatures.
- Information on flow paths and storage can be used to assist in transposing runoff signatures from gauged to ungauged basins, e.g., by grouping catchments and landscape units according to similar flow paths and storage characteristics.
- Finally, information on flow paths and storage can provide guidance on the choice of model structure and model parameters in *gauged* catchments. More realistic model parameters and a more realistic model structure in gauged catchments would then be expected to translate into more reliable estimates of runoff signatures in ungauged catchments.

Information about flow paths and storage can be obtained either through a top-down approach or a bottom-up approach. The top-down approach examines the collective system response observed in the catchment and tries to interpret it in terms of the controls that may have caused that response (Sivapalan *et al*., 2003b). The collective system response may be the runoff from the catchment or it could also be environmental tracers that give additional information on the sources, flow paths, travel times and storage. The main strength of the top-down approach is that it captures the functional behaviour of the catchment in an integral way. Because of the wealth of information that tracers can provide they are particularly appealing for understanding the activation of flow paths and storage. There are artificial tracers (i.e., applied externally into the system) and environmental tracers where the naturally occurring chemical and isotopic signatures of the waters are exploited (Leibundgut *et al*., 2009). In ungauged basins, very often tracer data are unavailable. However, there is potential for transposing relationships between flow path or storage indices (such as proportion of event/pre-event water and mean transit times) and bio-geo-physical catchment characteristics that have been developed in gauged catchments. These relationships can subsequently be used to estimate the respective flow path/storage indices in ungauged basins.

The bottom-up approach utilises knowledge of component processes that operate within the catchment. These are controlled by the bio-geo-physical catchment structure – soils, geology and topography – and climate, among other controls. Much effort has been spent on understanding how structural features of catchments control these component processes in research catchments (e.g., Zehe *et al*., 2001). The main strength of the bottom-up approach is that the component processes can be connected to the characteristics of the flow paths (e.g., location of the flow paths, residence times), i.e., to the perceptual model of the catchment. For estimating runoff signatures in ungauged basins, the bottom-up approach can be assisted by terrain analyses or reconnaissance field trips where, say, erosion marks are used to judge the presence of surface flow paths.

This chapter specifically focuses on flow paths and storage. We review top-down and bottom-up approaches of understanding flow paths and relate integral flow path/storage characteristics to the process controls, so as to provide a link between the top-down and bottom-up approaches. Finally, we provide some guidance as to how predictions of runoff signatures in ungauged basins can be informed by an understanding of flow paths and storage.

4.2 Process controls on flow paths and storage

Climate and landforms control flow paths in a number of ways. First, the most direct way is through the water and energy input. For example, in regions with humid climates, relatively gentle slopes and predominantly convex landforms, runoff is usually generated in a narrow area close to the streams where there is good subsurface connectivity (Kirkby, 2005). The distance water travels in the subsurface therefore tends to be shorter than in arid climates, where the most significant flows can occur at depths of hundreds of metres (Möller *et al*., 2007). In a similar way, flow paths can vary significantly between seasons. For example, in Mediterranean and monsoonal climates flow paths tend to be shorter during the wet part of the year than during the dry part. During the dry part of the year slow shallow subsurface movement of water through hillslopes maintains low flows. However, the steep topography of the north-west USA and western Canada means that preferential flow paths dominate runoff generation, despite the Mediterranean climate. Second, climate controls flow paths indirectly through soil moisture. High soil moisture states tend to produce faster and shallower flow paths (e.g., Grayson *et al*., 1997; Western *et al*., 2004) than lower soil moisture states. However, in hydrophobic soils, the opposite can be the case when infiltration increases with increasing soil moisture (Zehe *et al*., 2007). Snowmelt typically causes surface saturation and therefore surface or shallow flow paths, and similar effects can occur with frozen ground (Carey and Woo, 1998). Third, climate controls flow paths through the co-evolution of landscapes, vegetation and soils where flow paths reflect the dynamic equilibrium between drainage and storage functions of a catchment (Savenije, 2010; Zehe *et al*., 2010).

In arid environments with limited vegetation cover but high rainfall intensities, infiltration excess overland flow tends to occur (Smith and Goodrich, 2005). In humid environments with well-developed vegetation cover and frequent occurrence of frontal rainfall systems, saturation excess runoff generation is a more likely mechanism. Also, in humid catchments efficient subsurface drainage features may have developed that are conducive to fast subsurface response (McGlynn *et al*., 2002). In arid regions the interplay of landscape, geology and rainfall tends to result in highly non-linear runoff generation processes. In the coastal mountains of Oman (Figure 4.2b), for example, most of the surface runoff is generated during high intensity storms on bare rock. Some of it may re-infiltrate into debris fans resulting in the recharge of local aquifers (right valley side of Figure 4.2b). The date plantations in the photograph are an indication of the existence of a shallow aquifer. The surface runoff during the flash floods is then routed out to the coastal plain (Figure 4.2a), where much of the water may infiltrate into the groundwater below the Wadi, or discharge into the sea (Al-Rawas and Valeo, 2009, 2010).

Topography and landscape characteristics control flow paths at different time scales. Surface and bedrock

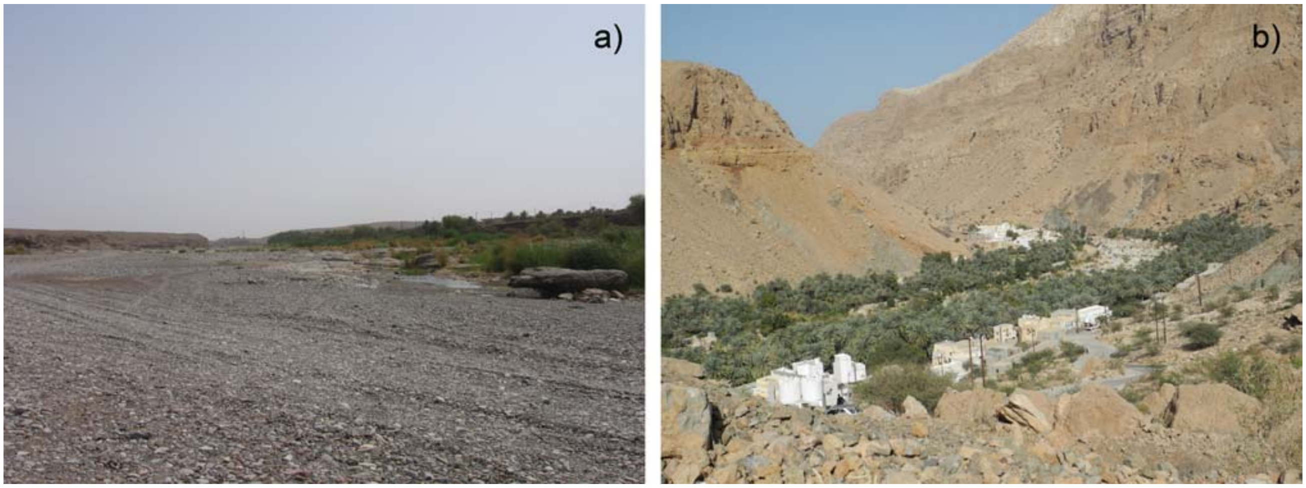

Figure 4.2. (a) Wadi Al-Khoudh in the coastal plains of Oman. Photo G. Al-Rawas. (b) Wadi Tiwi in the coastal mountains of Oman. Photo R. Kirnbauer.

topography exert time invariant controls on gradients that drive lateral flows (because each represents an inclined material interface across which flow resistance changes significantly). At the event scale, topography controls both the directions of surface and subsurface flows and the strength of the forces that drive these flows. This controls flow redistribution at seasonal time scales, which in turn may control soil moisture patterns (Western *et al*., 1998a, b, 2002), which affect flow resistances in the soil matrix, activation of apparent preferential flow paths and separation of surface and subsurface flows. At longer time scales of soil formation and landscape evolution, topography indirectly controls water flow through co-evolutionary soil (pedological) and vegetation (ecological) processes. The connectivity of surface flow paths is essential for the actual stream runoff, as not all of the runoff generated locally may reach a stream channel, but may re-infiltrate along the way (Kirkby, 2005; Western *et al*., 2001b). Similarly, the connectivity of subsurface flow paths is often highly important.

The soil characteristics play a key role in the partitioning of rain water into surface and subsurface flow paths. At the local scale, the partitioning can be seen as essentially a soil physical problem. Soil physical characteristics may be inferred from widely available data such as soil texture (e.g., Wösten *et al*., 1999; Nyberg, 1995; Hernandez *et al*., 2000). However, macropores and other preferential flow paths often dominate the infiltration behaviour even more than the characteristics of the soil matrix (Bouma *et al*., 2011). Also, as one moves up in scale to hillslopes and the catchment, the layering of the soil and its spatial arrangement, in particular along hillslopes, become increasingly relevant. Because of the co-evolution of soils with vegetation and water movement within the catchment, soils tends to be spatially organised, a notion represented in the catena concept (Milne, 1935; Jenny, 1941).

In pristine areas the evolution of vegetation and soils is strongly interlinked (Markart *et al*., 2004). Typically, soil profiles evolve along the hillslopes driving mass, nutrient and heat flows with feedbacks on the potential gradients and vertical flow resistances within the profiles, as both are controlled by soil texture and the pore size distribution. These may lead to long-term feedbacks involving the regimes of water, heat and nutrient flows and hence the habitat for soil organisms and vegetation, which in turn alter the macropore and root networks. Land management in urban, forest and agricultural areas will impact on this organised architecture and will likely transform the runoff pathways (see Chapter 2). Surface sealing and soil compaction tend to increase the importance of surface flow paths relative to subsurface flow, contributing to a flashier runoff response (Moglen, 2009). Agricultural activities may lead to compaction and soil disturbance, and consequently disturbance of soil organisms with feedbacks on preferential pathways, depending on the nature of tillage practices (e.g., Ndiaye *et al*., 2005). Similarly, forestry practices, including forest roads, may affect flow paths significantly (e.g., Luce, 2002; Buttle, 2011). These may exhibit scale effects where land use change effects tend to taper off with increasing catchment size (Blöschl *et al*., 2007). In general, the above-mentioned land use changes, from urbanisation to agriculture and to forest harvesting, tend to increase peak runoff and reduce water storage in individual catchments, but the relationships tend to be more complex and not easily decipherable, as illustrated by numerous paired catchment experiments and modelling studies on floods (Bronstert *et al*., 2002; Robinson *et al*., 2003) and water yield (Andréassian, 2004; Brown *et al*., 2005).

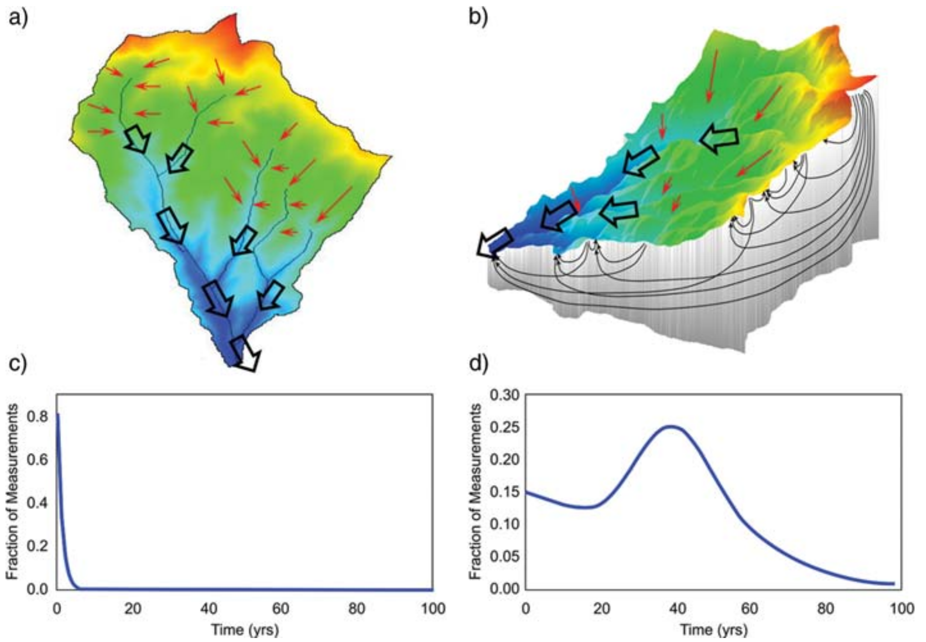

Figure 4.3. Travel time distributions at the catchment outlet when considering only short flow paths on the hillslope and in the stream network (a, c) and longer flow paths through deeper groundwater (b, d). From Frisbee *et al*. (2011).

While soils and soil structure (connected vertical and lateral preferential pathways) strongly control the dynamics of relatively fast responding local flow paths with time scales ranging between days and years, geology controls deeper flow paths that are commonly active on the regional scale and at time scales from years to decades (Gleeson and Manning, 2008; Möller *et al*., 2007). The active flow paths and residence times depend strongly on the aquifer structure (Kupfersberger and Blöschl, 1995). For example, Schaller and Fan (2009) and Fan *et al*. (2007) showed that geological discontinuities such as fault lines are a first-order control of the direction of flow in deep flow paths. Flow paths are highly sensitive to the strata dip angle, and travel times can thus differ by a factor of up to two at opposite stream banks due to strata dip angles. Karst flow systems tend to be highly dynamic and the connection with surface water may be a function of the groundwater levels (e.g., Bonacci *et al*., 2008; Filipponi *et al*., 2009). The response characteristics then depend on the relative contributions from the matrix, fracture and conduit system – the preferential flow network in the Karst – leading to vastly contrasting time scales of catchment response (Florea and Vacher, 2007). Karst aquifers can also lead to significant subsurface water transfers between catchments (e.g., Quinn *et al*., 2006). The importance of considering both shallow and deep flow paths has been illustrated by Frisbee *et al*. (2011). In a simulation study they analysed the contribution of different types of flow paths to the travel time distribution at the catchment outlet (Figure 4.3). Clearly, including longer flow paths through the deeper groundwater system increases the estimated travel times significantly, which will be the more complete representation of the subsurface flow system. Flow paths can be grouped into 'similarity zones' where geology, climate, vegetation and water table conditions are distinct (Duffy, 2004): shallow water tables in steep upland hillslopes over bedrock, deep water tables and shallow water tables in the alluvium. Even shallower bedrock can convey substantial water fluxes, as illustrated by Anderson *et al*. (1997) for a steep catchment in the Oregon Coast Range.

4.3 Inference of flow paths and storage from response characteristics

4.3.1 Inference from runoff

Learning from temporal patterns of runoff in one catchment

Analysis of the observed runoff dynamics can be used to infer catchment storage and subsurface characteristics by a top-down approach (Tallaksen, 1995). The classic method is runoff recession analysis. The main advantages of recession analyses are that rainfall can be assumed to be zero, or at least small (so difficulties with any errors in catchment rainfall estimation are avoided), and that the hydrograph represents an aggregate measure of catchment behaviour (Sivapalan *et al*., 2003b). There are two classes of methods for interpreting the runoff recession. The first class is based on empirical storage–runoff relationships and/or on conceptualising the catchment as a set of linear or non-linear reservoirs. In the most basic method, the integral under an exponential curve fitted to the runoff recession curve represents an estimate of total catchment storage. The traditional runoff component analysis (Schwarze *et al.*, 1989) assumes that the rainfall–runoff transformation can be represented by a combination of linear reservoirs and identifies a number of runoff components with different response times. The usual assumption is that the fast response component relates to shallow flow paths and slow response to deep flow paths, but this has led to much debate and controversy (Kirchner, 2003; Merz *et al.*, 2006). More elaborate methods have been presented based on non-linear relationships between groundwater discharge and storage (e.g., Wittenberg and Sivapalan, 1999). Typically, the temporal change of runoff is plotted versus runoff itself (e.g., Kirchner, 2009; Sayama *et al.*, 2011). Linearity of this relationship suggests that the catchment operates like a linear reservoir; any deviations give an indication of the non-linearity. In both cases, response times and storage can be inferred under some assumptions (e.g., runoff is a monotonically increasing function of catchment wetness, which applies only in humid climates).

In the second class of methods the runoff recession is interpreted from a process perspective through the application of Darcy's law to typical hillslopes, with a number of simplifying assumptions (e.g., linearisation of the equation). Brutsaert and Nieber (1977), for example, estimated the catchment-scale saturated hydraulic conductivity and the mean aquifer depth from analysis of recession curves. Rupp and Selker (2006) extended their analysis to settings where slope is an important driver of flow, or where hydraulic parameters vary with depth. As noted by Troch *et al.* (1993), when estimating the catchment-scale hydraulic conductivity by the Brutsaert–Nieber technique, the resulting values are generally one to two magnitudes larger than their laboratory-derived counterparts. This is because the catchment-scale estimates implicitly incorporate the effects of preferential flow, i.e., flow along connected pathways of high hydraulic conductivity/low flow resistance that extend in the main direction of the driving gradients. Clearly this is a result one would not be able to obtain by the bottom-up approach of simulating runoff using mechanistic, distributed models, because the effects of the natural co-evolution of catchment characteristics are not yet quantified.

Learning from spatial patterns of runoff in many catchments

To take advantage of recession analysis for estimating runoff in ungauged catchments it is useful to identify the storage/flow path characteristics in gauged catchments and relate them to catchment characteristics that are available everywhere, so the relationship can be used for ungauged catchments. These can be either statistical relationships (e.g., regressions) or process-based hydrological models.

Figure 4.4. Different pathways in the Löhnersbach, Austria. Tributary from left hillslope (N, Neuhausen) has shallow pathways causing subsurface flow paths to disconnect during dry periods, resulting in small low flows. Tributary from right hillslope (K, Klammbach) has deeper flow paths that stay connected with the main stream and sustain higher low flows (see Figure 4.5). Photo: P. Haas. From Kirnbauer *et al.* (2005).

This means that the recession analysis is combined with the Darwinian approach of learning from many catchments to obtain information that can be generalised to ungauged catchments (see Chapter 2). It is therefore necessary to understand how the storage–runoff relationship or, more generally, the runoff response, is related to catchment characteristics and to learn from the differences between catchments. This is the basis of the comparative hydrology approach (Section 2.2). As Sivapalan (2009, p. 1395) suggested,

> Instead of attempting to reproduce the response of individual catchments, research should advance comparative hydrology, aiming to characterize and learn from the similarities as well as the differences between catchments in different places, and interpret these in terms of underlying climate–landscape–human controls.

The comparative hydrology approach is illustrated here by a comparative analysis of runoff from the Löhnersbach in Austria (Figure 4.4). Figure 4.5 shows the contributions of two subcatchments to runoff at the outlet of the entire 16 km² catchment. The Neuhausengraben (Figure 4.4, left in the photo, partly cleared) constitutes about 8% of the catchment area, which is equivalent to its runoff contribution during high flows. As the catchment dries out the runoff contributions drop dramatically and the tributary eventually falls dry. This can be explained by small transmissivities and storage capacities producing shallow flow paths, so runoff cannot be sustained over longer time periods. In contrast, the Klammbach (Figure 4.4, right in the photo, forested) constitutes about 15% of the Löhnersbach catchment area. As the catchment dries out its relative contributions to runoff actually increase because of the

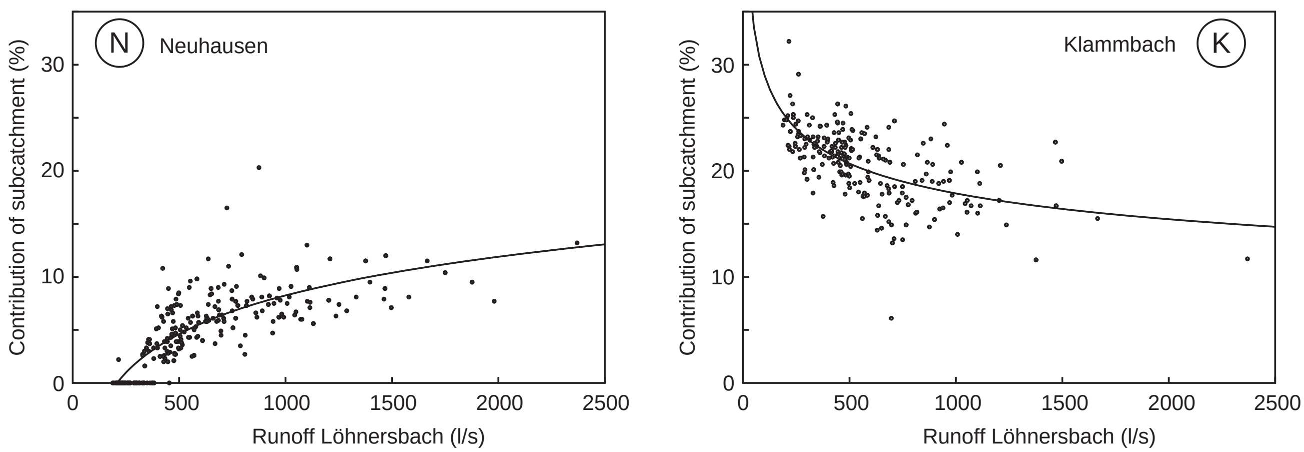

Figure 4.5. Percentage runoff contribution to the Löhnersbach from the left tributary (N, Neuhausen) and the right tributary (K, Klammbach) plotted against runoff at the total catchment outlet. Simultaneous runoff measurements during 1993–7. From Kirnbauer *et al*. (2005).

large storage capacity and deep flow paths of this subcatchment. The much larger storage and the longer pathways are related to the higher degree of weathering and the dip angle of the bedrock fractures, being normal to the topographic slope. It is clear, therefore, that even within small catchments, the relative contributions of surface/near surface flow paths versus deeper flow paths can vary significantly and detailed spatial spot gauging can assist in understanding these differences (comparative hydrology at a small scale).

A number of studies have reported on regression analyses performed between runoff response characteristics and catchment characteristics to identify the main controls. For example, Sayama *et al*. (2011) found the maximum volume of storage change to be positively correlated with catchment slope, which they explained by lower subsurface connectivity in steeper catchments. At a larger scale, Gaál *et al*. (2012) performed a regional analysis of flood event time scales based on the concept of comparative hydrology. In one of their regions, the catchment form had adapted to flashy floods (due to convective storms) and produced an efficient drainage network. This enhanced understanding of surface flow paths and the flashiness of the flood response. In another region, a tortuous drainage network had evolved, which led to deeper flow paths and more dampened flood response. Both systems were a manifestation of the co-evolution of landform and hydrological processes within the constraints of the geology in the regions. In a similar study in the USA, albeit focusing on longer time scales, Schaller and Fan (2009) related the subsurface losses and gains of catchments estimated from the water balance (using runoff data, rainfall data and evaporation estimates) to climate and geological factors. Figure 4.6, taken from Schaller and Fan, shows the subsurface losses and gains over the Colorado River and the coastal basins in Texas. It shows that most of the upstream catchments in the north-west lose water into the subsurface while some of the coastal catchments gain water from the subsurface. This is because of the regional topographic gradients. However, there is a cluster of catchments situated over the Balcones fault zone (see Figure 4.6) where the highly permeable carbonate rocks force groundwater upward to the land surface. Numerous springs exist along the Balcones fault zone, often where faulting has placed highly permeable units adjacent to impermeable units. In this case, the elevation gradient from the west to the east is punctuated by a geological singularity, which significantly alters groundwater flow paths.

4.3.2 Inference from tracers

Learning from temporal patterns of tracers in one catchment

Tracer data can yield integral fingerprints of activated flow paths and storage at different spatial and temporal scales (Leibundgut *et al*., 2009). It is important to recognise that tracers give information on the movement of particles (related to the hydraulic conductivity of the soil medium) while runoff tends to give information on the propagation of pressure (related to the compressibility of the medium). The concentration of tracers therefore scales differently from pressure in the advection dispersion equation that is often used to interpret the results. It is therefore important not to confuse the two. One option is artificial tracers, which are markers added to the system to trace the movement of water, and these can include chloride, bromide, and various dyes including fluorescent ones. Alternatively, the occurrence and variability of tracers naturally occurring in the environment can be exploited, such as the chemical and isotopic composition of water. Tracers exploit

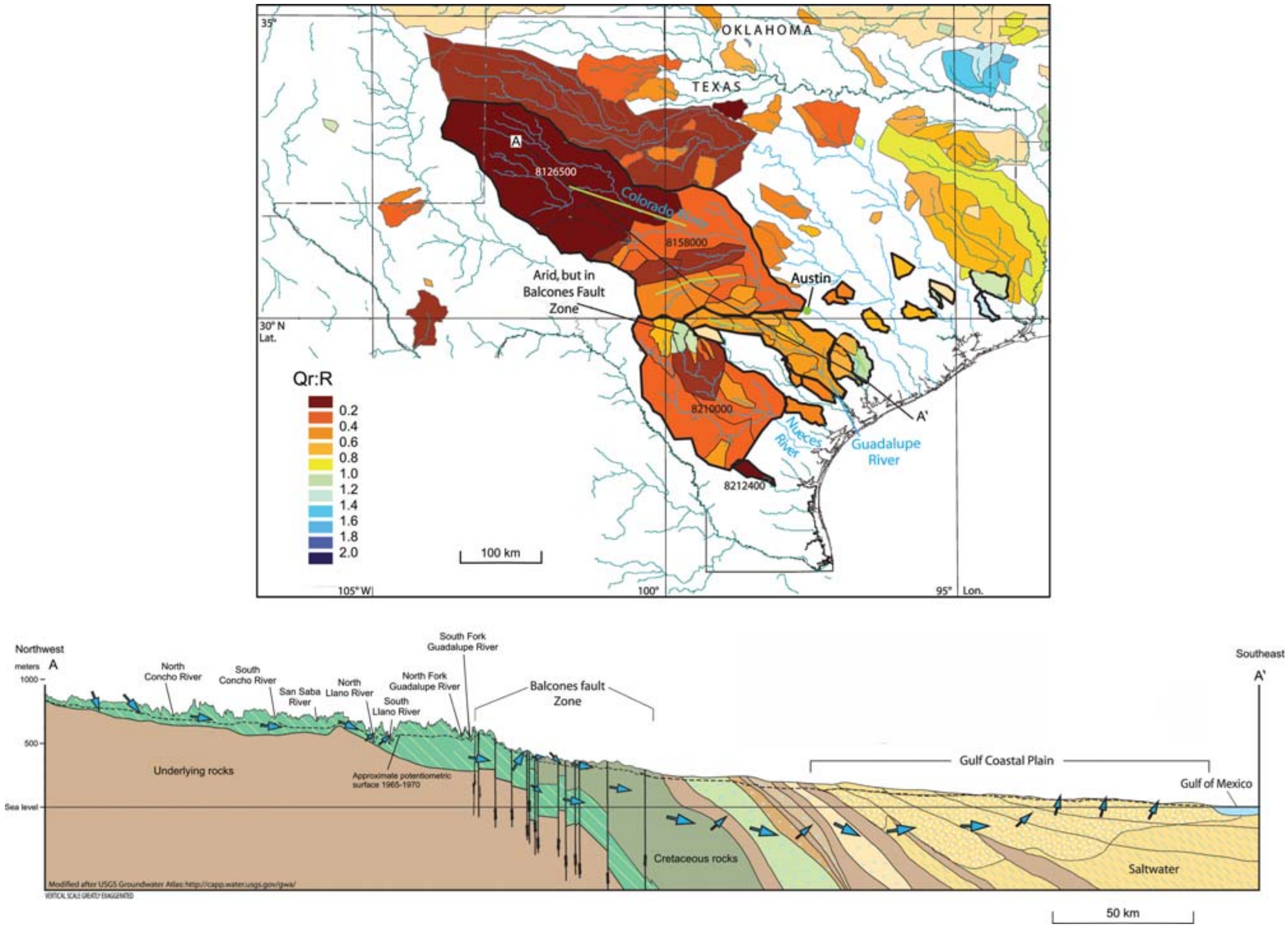

Figure 4.6. (Top) Ratio of runoff to precipitation minus evaporation (Qr:R) over Colorado River and lowland and coastal basins in Texas. Catchments that are groundwater exporters (Qr:$R < 1$) brown, groundwater importers (Qr:$R > 1$) blue. (Bottom) Geological cross-section. From Schaller and Fan (2009).

different physical concepts related to the movement of water and associated substances through a catchment. These include: (i) mixing, (ii) advection and dispersion, and (iii) decay. Each of the concepts can be used to infer different pieces of information from the tracers.

Mixing: sources and pathways of water in the catchment: The idea of end member mixing analysis (EMMA) is that runoff consists of two or more sources that can be distinguished in terms of their isotopic and/or chemical characteristics, e.g., subsurface water and surface runoff. The isotopic contents of groundwater and surface runoff need to be sufficiently different for the method to give meaningful results. Also, the isotopic contents should vary only to a limited extent with time, which is not always the case (Hooper and Shoemaker, 1986). Finally, the method assumes perfect mixing of the sources, which is not consistent with the occurrence of preferential flow. The mass balance equations for water and the tracer(s) then give the relative contribution of the sources, e.g., the proportion of event runoff that comes from rain through rapid flow paths (surface and preferential flow paths) and the contribution of pre-event water in the subsurface that is mobilised by pressure transfer. The fraction of pre-event water is usually larger than the fraction of event water and changes dynamically with time (e.g., Harris *et al*., 1995; Buttle and Peters, 1997; Laudon, 2002). Figure 4.7 illustrates the EMMA for the San Pedro River, Arizona (Baillie *et al*., 2007). Basin groundwater (far away from the stream) is isotopically light, and primarily comprises winter precipitation that has recharged in the mountains. In contrast, riparian groundwater is isotopically heavier, due to groundwater recharge by isotopically heavy summer (monsoon) precipitation during floods. The baseflow sources of the San Pedro River vary along the river reach (triangles in Figure 4.7). In the losing reaches of the river, stream recharge from the riparian aquifer (recharged by monsoon floods) dominates, while in the gaining reaches of the river, basin groundwater plays a significant role in baseflow. For the

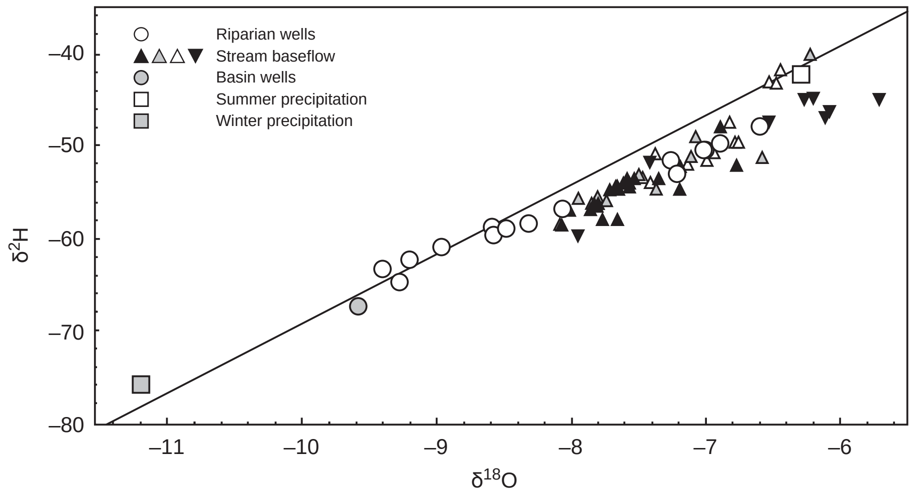

Figure 4.7. Stable isotopes collected in the San Pedro River study area, Arizona. End members are winter and summer precipitation shown as squares. Groundwater and baseflow isotopic characteristics vary between these two end members, depending on the source of water. Basin groundwater recharged from winter precipitation, riparian groundwater recharged by summer precipitation. From Baillie *et al.* (2007).

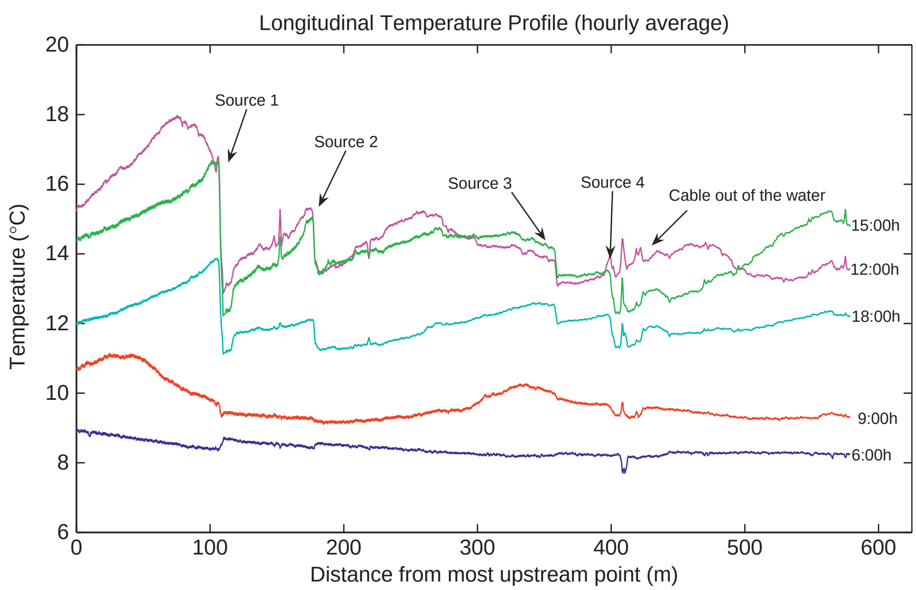

Figure 4.8. Observed longitudinal temperature profile of the Maisbich stream in Luxembourg at different times on 26 April 2006. Clear temperature jumps can be seen at the location of the groundwater inflows (sources). From Westhoff *et al.* (2007).

San Pedro River as a whole, this result means that roughly 50% of the water observed in the river is from groundwater locally recharged during the summer monsoon.

Water temperatures are also excellent natural tracers to identify stream/aquifer interactions (Becker *et al.*, 2004; Conant, 2004; Constantz *et al.*, 2003; Selker *et al.*, 2006). An example is shown in Figure 4.8, where the longitudinal distribution of stream temperatures has been observed by distributed temperature sensing (TDS) with fibre optic cables (Westhoff *et al.*, 2007). During the day time (e.g., 12:00 noon) the stream water is warmer than groundwater, so the subsurface inflow sources into the stream are indicated by sudden decreases of the stream temperature along the stream course. Conversely, during the night or early in the morning (e.g., 6:00 AM) the stream water is colder than groundwater, so there are sudden increases in the temperature. Based on these observations and a number of assumptions on the thermal characteristics of the system, the exchange fluxes can be estimated (e.g., Westhoff *et al.*, 2011).

Advection and dispersion: transit times of the water in the catchment: The transit time distribution (TTD) characterises the time the water molecules need to travel from the surface where they fall (as rainfall) to the catchment outlet (or any other point in the catchment) (Maloszewski and Zuber, 1982; Jury and Roth, 1990; McGuire and McDonnell, 2006). The mean and the variance of TTD are related to advection and dispersion, respectively, which in turn are related to the mean and variance of hydraulic resistances along the flow paths as well as the lengths of the active flow paths. If the average distance to the stream and the

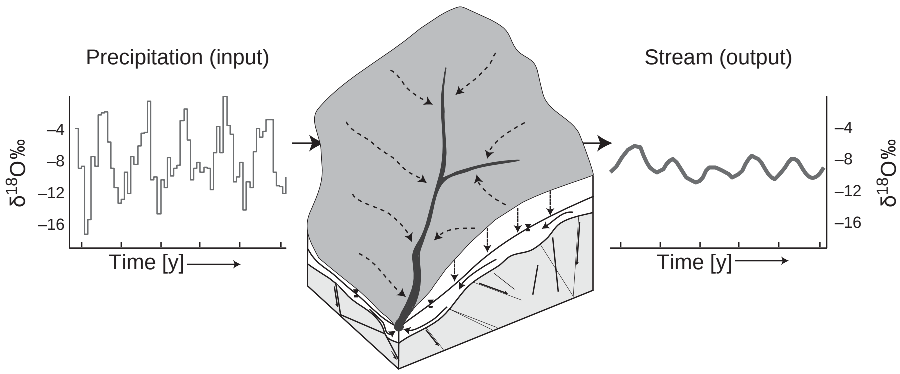

Figure 4.9. By comparing isotopic concentrations, $\delta^{18}O$, of inputs and outputs, information on flow paths and storage can be inferred. From McGuire and McDonnell (2006).

gradients of the hydraulic potentials can be estimated from bedrock topography (or surface topography as a surrogate), mean transit times (MTT) can be related to average transmissivities along the flow paths. The fast component of the TTD usually stems from vertical and lateral preferential flow in the unsaturated zone, so contains proxy information about the vertical extent of the unsaturated soil store. The slower component of the TTD usually reflects time scales for deep percolation into the saturated zone and travel times through the groundwater system, so contains information about the vertical extent of the aquifer system, tortuosity of flow paths and the pattern of transmissivity along the flow paths. Both environmental tracers (isotopic and/or chemical characteristics of the waters, e.g., Tetzlaff *et al*., 2009a, b) and artificial tracers (Sánchez-Vila and Carrera, 2004; Blöschl and Zehe, 2005) can be used to infer the TTD of the activated flow paths by deconvolution of the tracer signals of the input (e.g., rainfall) and the output (Figure 4.9). Transit time analysis can also be combined with mixing analysis (e.g., Katsuyama *et al*., 2009). Transit time distributions are often assumed to be constant during the year, but there may be strong seasonal variations due to variations in precipitation, evaporation, and in catchment water storage and the associated activation of dominant flow paths (Hrachowitz *et al*., 2010; Heidbüchel *et al*., 2012).

Learning from decay of tracers: age of the water in the catchment: Some chemicals and isotopes in the atmosphere show long-term trends and these can be exploited to identify the age of the input waters (i.e., precipitation) to catchments. The traditional tracer used to determine the age of precipitation is the radioactive hydrogen isotope tritium (^3H). The high levels of atmospheric nuclear weapons testing that took place prior to the enactment of the Partial Test Ban Treaty in 1963 resulted in high atmospheric tritium concentrations. The subsequent decay of tritium then allowed the determination of the age of precipitation. However, due to radioactive decay, the atmospheric tritium concentrations in many parts of the world have approached their detection limit. Because of this, other tracers, such as chlorofluorocarbons (CFC), are being increasingly used (see Kalbus *et al*. (2006) for a review).

Learning from spatial patterns of tracers in many catchments

In most instances of catchments without runoff data, there are no tracer data available. It is then necessary to relate information from tracer data that are more widely available to climate and catchment characteristics. This can be done either through hydrological models or through regression analyses. A number of studies have identified the dominant controls of transit times (and therefore the most useful climate/catchment characteristics for prediction in ungauged catchments), which differ between different hydroclimatic regions.

In the peat-dominated catchments and the wet climate of Scotland, soil properties rather than catchment structure and organisation are the first-order controls on MTT (e.g., Tetzlaff *et al*., 2009a). Specifically, the proportion of fast-responding soils taken from the Hydrology of Soil Types (HOST) classification (Boorman *et al*., 1995) explains most of the spatial variability in MTT (Table 4.1). If additional variables are taken into account (precipitation intensity, drainage density and topographic wetness index) the explanatory power can be further improved ($R^2 = 0.88$, Hrachowitz *et al*., 2009). In contrast, soil types are of less importance than catchment structure in regions such as the Pacific North-West of the USA, and topographic indices, such as the ratio of median flow path length over median flow path gradient, can explain MTT ($R^2 = 0.91$) (McGuire *et al*., 2005). In the Maimai catchment in New Zealand, a similarly significant relationship between MTT and flow path distance was found (Stewart and McDonnell, 1991). The low importance of soil types in explaining MTT suggests that, in these wet forested areas, a well-organised network of preferential pathways integrates the drainage process, and most drainage water bypasses the soil water store. In some semi-arid, snowmelt-dominated

Table 4.1. *Correlations between mean transit time (MTT) and various catchment characteristics. Most important control in a region highlighted in bold italics*

Catchment characteristics	R^2	Location	Study
Topographic aspect	0.28	Arizona	Broxton *et al.* (2009)
Flow paths length/gradient	0.30	Europe, USA	Tetzlaff *et al.* (2009b)
Flow path gradient	0.08	Europe, USA	Tetzlaff *et al.* (2009b)
Bedrock infiltration	0.85	Japan	Katsuyama *et al.* (2010)
Flow paths length	0.98	New Zealand	Dunn *et al.* (2007)
Distance from divide	0.50	New Zealand	Vaché and McDonnell (2006)
Topographic wetness index	0.92	Oregon	Tetzlaff *et al.* (2009b)
Flow paths length/gradient	0.91	Oregon	McGuire *et al.* (2005)
Upslope area	0.88	Oregon	Tetzlaff *et al.* (2009b)
Flow paths length	0.72	Oregon	McGuire *et al.* (2005)
Flow path gradient	0.65	Oregon	McGuire *et al.* (2005)
Distance from stream	0.62	Oregon	Tetzlaff *et al.* (2009b)
Proportion responsive soil cover	0.94	Scotland	Soulsby *et al.* (2006)
Downslope index gradient	0.83	Scotland	Tetzlaff *et al.* (2009b)
Proportion responsive soil cover	0.80	Scotland	Hrachowitz *et al.* (2009)
Proportion responsive soil cover	0.76	Scotland	Tetzlaff *et al.* (2009a)
Flow paths length/gradient	0.74	Scotland	Tetzlaff *et al.* (2009b)
Flow path gradient	0.67	Scotland	Soulsby and Tetzlaff (2008)
Proportion responsive soil cover	0.60	Scotland	Soulsby and Tetzlaff (2008)
Drainage density	0.59	Scotland	Hrachowitz *et al.* (2009)
Flow path gradient	0.42	Scotland	Tetzlaff *et al.* (2009a)
Precipitation	0.25	Scotland	Hrachowitz *et al.* (2009)
Proportion of wetlands	0.59	Sweden	Lyon *et al.* (2010)
Flow path gradient	0.52	Sweden	Lyon *et al.* (2010)
Flow paths length/gradient	0.43	Sweden	Lyon *et al.* (2010)
Peclet number	0.40	Sweden	Lyon *et al.* (2010)
Flow paths length/gradient	0.32	Sweden	Tetzlaff *et al.* (2009b)

areas of Arizona, Broxton *et al.* (2009) pointed out that the south-facing slopes consistently accommodated faster responding flow paths due to the more rapid snowmelt as compared to the north-facing slopes. It is possible that this effect is also related to higher biomass production on the south-facing slopes as a result of the co-evolution of soil structure and vegetation. In the northern hemisphere, south-facing slopes offer more direct radiation input, which favours biomass production, root growth and litter-fall-feeding small organisms, which altogether is conducive for the development of preferential pathways.

In a comparison of catchments from Europe and North America, Tetzlaff *et al.* (2009b) found that transit times tended to be lower in the steepest catchments. In flatter areas topographic control weakened, in particular where less permeable soils gave rise to overland flow and lower transit times. Katsuyama *et al.* (2010), studying the Kiryu catchment in Japan, which is underlain by saprolite, argued that bedrock permeability and groundwater dynamics are first-order controls on the dominant flow pathways. In northern Sweden, where mire wetlands are an important part of the landscape, Lyon *et al.* (2010) found that transit times decrease with the proportion of wetlands. Table 4.1 summarises a number of comparative studies on transit times organised by region. The table highlights the role of topography in Oregon and New Zealand and the role of responsive soils in Scotland. An example of MTTs plotted against catchment characteristics is shown in Figure 4.10.

Few studies have related MTT to climate and/or wetness conditions. This, however, is crucial for realistically representing processes that are active at multiple time scales, depending on catchment wetness (e.g., Hrachowitz *et al.*, 2010). For example, Heidbüchel *et al.* (2012) found MTTs of 360 days in a semi-arid catchment in Arizona contrasting the 144 days found in a humid catchment in Switzerland. The longer transit times in the semi-arid catchment are due to the very long dry periods in spring and autumn when runoff is mainly derived from groundwater storage, while the humid catchment receives rainfall throughout the year, reflecting catchment water storage that is more often closer to full capacity, leading to shorter transit times.

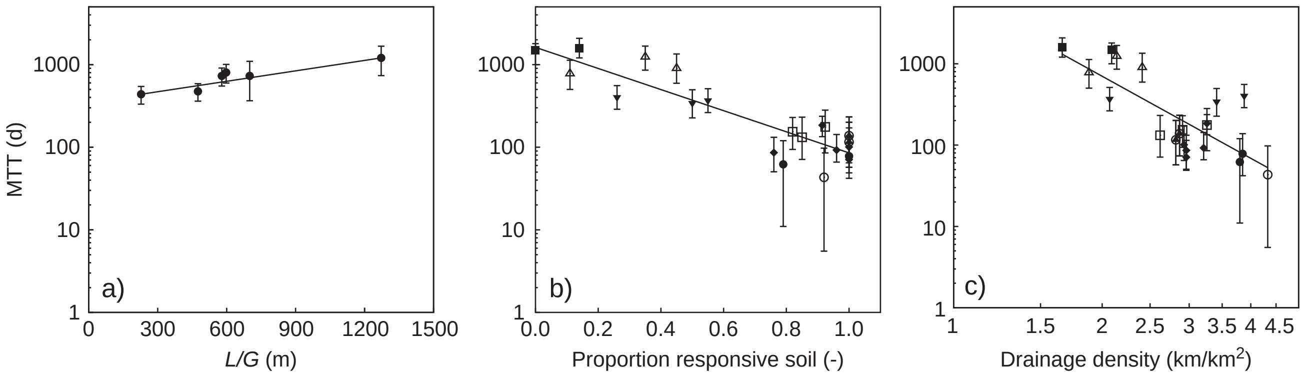

Figure 4.10. Mean transit times (MTT) from stable isotope analysis plotted against (a) ratio of flow paths length and gradient (*L/G*) for catchments in Oregon. After McGuire *et al.* (2005). (b, c) Proportion of responsive soils and drainage density for catchments in Scotland. After Hrachowitz *et al.* (2009).

4.4 Estimating flow paths and storage in ungauged basins

4.4.1 Distributed process-based models

Mathematical modelling provides a powerful method for estimating flow paths in catchments based on a bottom-up approach. The modelling can take many forms, including lumped models and spatially explicit (distributed) models of catchment surface and subsurface response (Grayson and Blöschl, 2001). The general idea behind distributed models is usually Newtonian mechanics, i.e., start from the laboratory-scale constitutive relations such as Darcy's law and combine them with balance equations (e.g., mass balance, momentum balance etc.) and additional assumptions about hydrological processes and their spatial variability. The fundamental belief behind this approach is that these small-scale governing equations can be combined on the basis of an *a-priori* concept of how catchments work. The approach usually adopts a mechanistic concept that a catchment is composed of many hillslopes (or smaller elements, in some cases), each of which consists of soil profiles, and the hillslopes (or other smaller building blocks) are connected by stream paths (Zehe *et al.*, 2007). For groundwater flow and transport problems such distributed models are the obvious choice, since spatial groundwater level data are often available (Figure 4.11). For runoff simulations, however, several challenges have been recognised in early work (Freeze and Harlan, 1969); they are mostly related to scale issues, and the lack of unifying governing equations representing the various flow paths at the catchment scale (Beven, 2001). The debate of the 1980s and early 1990s about the relative merits of models of different levels of complexity has now largely subsided, as it has been realised that the value of such distributed models really hinges on the degree to which they can be validated in a spatially distributed way (Grayson *et al.*, 2002).

For ungauged catchments, distributed models can still be very useful provided the uncertainty associated with the predictions of flow paths, storage and ultimately runoff is analysed and documented. The models can be used as a quantification of the perceptual model the analyst has developed on the basis of the subsurface catchment structure, the flow paths and the permeability of soils, and how these relate to the dynamic catchment response. The modelling may include combined groundwater–surface water models to infer stream–aquifer interactions, as illustrated by Massuel *et al.* (2011) for a catchment in south-west Niger. Some of the variables needed for the hydrological modelling (depth to bedrock, average hydraulic resistances and retention properties of the soils) can be estimated from proxy data within some (admittedly wide) limits of uncertainty. Even in the absence of runoff data, such a model can be tested by ad hoc field surveys (e.g., seismic surveys, spot sampling of streamflow and soil moisture) and more qualitative methods of reading the landscape (see Chapter 3). Because of these issues, and for computational convenience, several index methods have been developed as alternatives to estimate flow paths and storage in ungauged catchments.

4.4.2 Index methods

Simplified representations of hydrological processes within a catchment where topography is the most important control can be achieved by topographic indices (Moore *et al.*, 1991). Such indices provide the water storage available in different parts of the catchment, as well as the partitioning of surface and subsurface flow paths, and can therefore be used as the basis for estimating runoff in ungauged basins. There are two alternative paradigms currently in operation for representing topographic controls on hydrological processes. The first is Newtonian, and the classic example is the topographic wetness index of

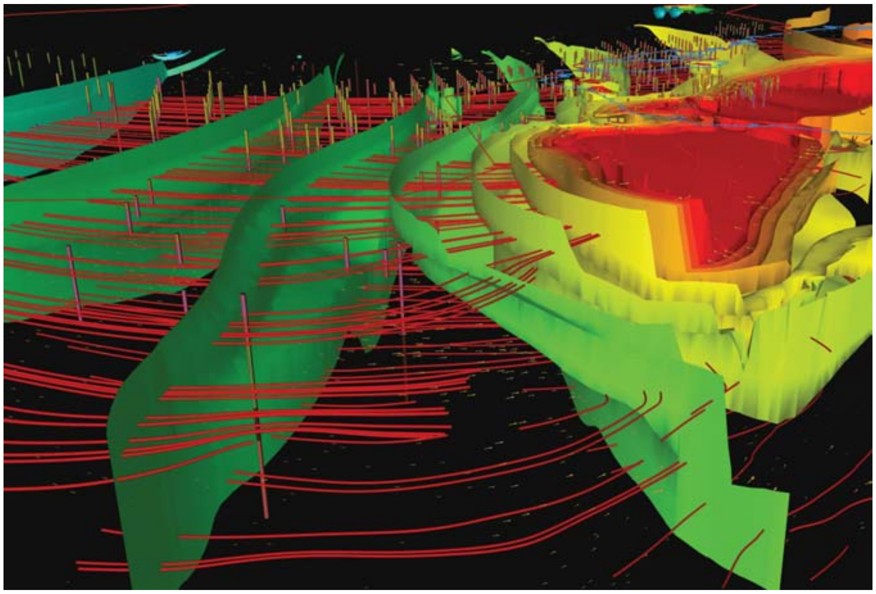

Figure 4.11. Flow paths (red lines) and potential surfaces simulated by a three-dimensional groundwater model for the aquifer on the Arabian peninsula. Vertical lines are the bore holes for which groundwater level data are available. From Rink *et al*. (2012).

Beven and Kirkby (1979) to predict zones of saturation. The wetness index is based on four assumptions (Blöschl and Sivapalan, 1995): (i) the lateral subsurface flow rate is proportional to the local slope, $\tan\beta$ of the terrain. This implies kinematic flow, small slopes and that the water-table is parallel to the topography; (ii) hydraulic conductivity decreases exponentially with depth and storage deficit is assumed to be distributed linearly with depth; (iii) recharge is assumed to be spatially uniform and (iv) steady-state conditions apply, so the lateral subsurface flow rate is proportional to the recharge and the area drained per unit contour length at a point. From these assumptions the wetness index can be derived as the logarithm of the ratio of contributing area and local slope. Other indices (Barling *et al*., 1994; Borga *et al*., 2002; Richardson *et al*., 2009) differ in terms of their assumptions but in essence they are similar in that they are effectively simplified distributed hydrological models based on mass balance, application of Darcy's law and several additional assumptions. These indices have been tested by a number of authors (e.g., Rodhe and Seibert, 1999; Western *et al*., 2001b), showing in many cases that they can predict the spatial soil moisture patterns well, provided the main assumptions are satisfied. This suggests that it is indeed possible to reduce the complexity of distributed models to representation of simple topographic indices if one focuses on the dominant processes that are actually operative in a particular landscape. However, for them to work, these need to be already known in ungauged catchments.

The second paradigm does not start from the local equations but examines flow paths at the landscape scale. The underlying idea is that landscapes have evolved in a co-evolutionary way with diverse feedbacks between hydrology, climate, geomorphology and ecology, and so topographic indices may have a certain level of predictive power that goes beyond the mere application of Darcy's law. In this more holistic approach, different units in a catchment (e.g., 'nose', 'slope' and 'hollow'; Hack and Goodlett, 1960; England and Holtan, 1969; Krasovskaia, 1982) may have different functions and are typically formed by different processes (Blöschl and Sivapalan, 1995). An example of this approach is the landscape classification idea of Winter (2001), who subdivided the continental USA into hydrological landscape units (upland, valley side and lowland), exploiting the combination of topographic, geological and climatic conditions. Based on similar concepts, Rennó *et al*. (2008) proposed the 'Height Above the Nearest Drainage' (HAND) model, in which topography is normalised according to the local relative heights found along the drainage network. Field data are needed to calibrate the modelled predictions, e.g., by expert knowledge, reconnaissance field trips, or short-term measurements to assess the groundwater table (Figure 4.12). The soil water maps from this type of terrain index can assist in parameterising distributed models or can be directly used to discern surface and subsurface flow paths in the landscape. Savenije (2010) and Gharari *et al*. (2011) noted that this type of approach may capture feedback processes between water flow and geomorphic and vegetation processes.

4.4.3 Methods based on proxy data

Another class of methods starts from field-scale irrigation experiments, reconnaissance field trips and other hydrological measurements to infer the runoff mechanisms at

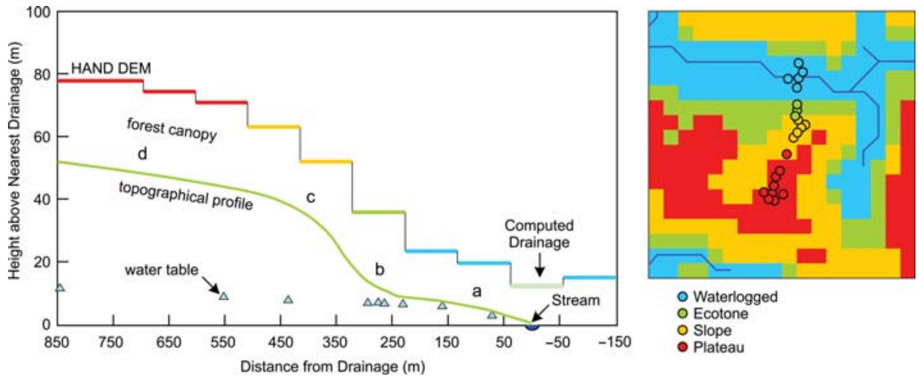

Figure 4.12. (Left) Local topography with estimated classes of HAND model for site C1 in the Asu catchment, central Amazonia. Triangles show average water table. Classes are (a) waterlogged, (b) ecotone, (c) slope and (d) plateau. After Nobre *et al.* (2011). (Right) Comparison of the HAND model classes (pixels) with field assessment (circles).

the field scale. Peschke *et al.* (1999) mapped the type of runoff generation mechanism for different catchment states in a small German catchment based on many years of field experience. They then developed an expert system, known as FLAB, that estimates the dominant runoff mechanism, such as Hortonian (infiltration excess) overland flow and saturation excess overland flow, interflow (shallow subsurface flow), recharge and storage for a given point in the landscape and a given event size. The expert system is based on macro-scale rules, rather than on laboratory-scale equations and therefore implicitly accounts for the natural co-evolution of soils, landscape and vegetation in a catchment. Scherrer and Naef (2003) developed a similar prediction scheme for dominant runoff processes and storage based on irrigation experiments, where the focus was on the vertical soil structure and topography. The scheme was tested in a number of studies (e.g., Naef *et al*., 2002; Scherrer *et al*., 2007; Hellebrand *et al*., 2011). As the scheme requires detailed information about the soil profile, a simplified scheme was proposed by Schmocker-Fackel *et al*. (2007) that uses regionally available data rather than data collected during reconnaissance field trips. The field-based information on runoff mechanisms, however, tends to be more informative than the regional information. Much information can be obtained during field trips by *reading the landscape* (see Chapter 3).

Markart *et al*. (2004) went a step further and explicitly exploited the co-evolution of soils and vegetation in Alpine catchments. The idea behind this approach is that, depending on the soil characteristics and soil moisture dynamics, different plant communities will be encountered, which in turn will affect soil structure and the soil moisture state. Markart *et al*. therefore exploited both vegetation type and soil characteristics for inferring the relative contributions of surface and subsurface runoff. The indicators used include vegetation species, land use, soil texture, drainage density and slope, which can be assessed during reconnaissance field trips. The maps so obtained could then be used to assist in parameterising distributed models in ungauged catchments (e.g., Rogger *et al*., 2012b). Both Scherrer and Naef (2003) and Markart *et al*. (2004) focused on shallow subsurface flows. For deeper subsurface flows an assessment of the hydrogeology is needed. Rogger *et al*. (2012a) proposed a framework to identify dominant hydrogeological processes within a catchment based on orthophotos, geological maps, hydrogeological maps, digital terrain models, maps of unconsolidated sediments, runoff spot gauging and the use of hydrogeological expert judgement during field trips. The method of Rogger *et al*. distinguished five hydrogeological runoff process classes: deep groundwater flow, shallow groundwater flow, interflow, surface runoff on rocks, glaciers or saturated areas and karstic areas (Figure 4.13). Such hydrogeological classification can provide qualitative information for rainfall–runoff modelling about the storage capacities and the depth of subsurface flows in ungauged catchments. Additional information on the subsurface can be provided by tracer data, in particular if they can be related to climate and catchment characteristics (see Section 4.3.2) they can be used in ungauged catchments.

4.5 Informing predictions of runoff in ungauged basins

In the previous sections we have discussed the process realism of runoff predictions with respect to flow paths and storage and the kinds of information that can contribute to achieve this realism in ungauged basins. The most important item is an understanding of the *flow system* of the catchments of interest, in particular how deep the flow paths are in different parts of the catchment, how well they are connected, and how long the water stays in the catchment. Key to this understanding is a hydrogeological concept, based on the geological history and architecture of the catchment.

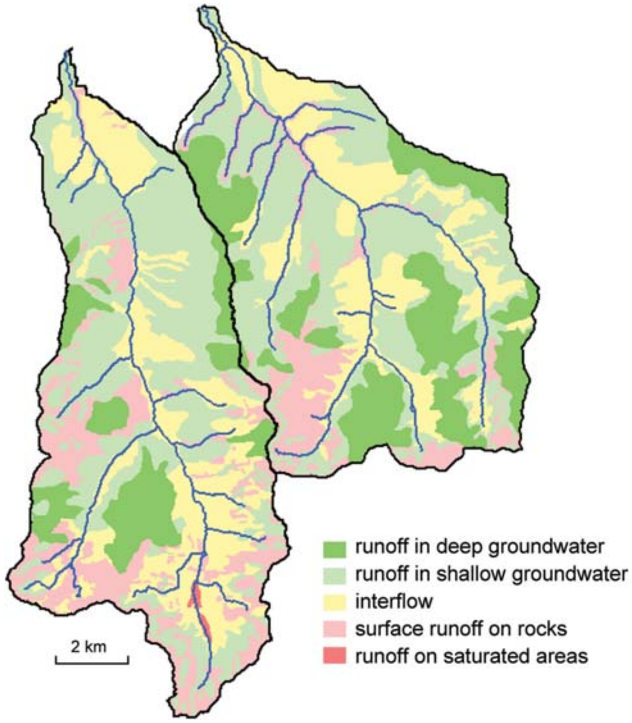

Figure 4.13. Hydrogeological response units in the Wattenbach (left) and Weerbach (right) catchments, Austria. From Rogger *et al.* (2012a).

Process realism, however, is not an absolute quantity. It depends on the runoff signatures being predicted. Depending on the signatures, information about flow paths and storage can be used in a number of ways to inform runoff predictions in ungauged basins.

4.5.1 Process-based (rainfall–runoff) methods

Runoff signatures can be predicted by process-based methods from rainfall through some kind of rainfall–runoff model, as discussed in Sections 5.4, 6.4 etc. In conceptual rainfall–runoff models, where the flow paths are represented in a simplified way, understanding of the flow system may assist in the selection of the model structure. The catchment may consist of highly permeable fractured rocks with aquifers that have a lot of storage, deep flow paths and long residence time. Alternatively the permeability may be low with shallow soils inducing shallow flow paths, or porous aquifers. The stream may be connected to or disconnected from the subsurface system. Depending on the flow system, the model structure may look different in each of these cases. The parameters related to storage and response times may also be different. In physics-based runoff models, information on flow paths and storage is beneficial during the parameter-setting stage, e.g., depth to the aquitard, bedrock topography, and the presence of fractures that may conduct large volumes of water. Setting model structure and parameters in a realistic way, based on information on flow paths, can be either quantitative (e.g., by using data on depth to the bedrock) or qualitative (e.g., by obtaining a conceptual model of the flow system, see e.g., Blöschl *et al.*, 2008; Clark *et al.*, 2011). In both instances, setting model structure and parameters in a realistic way has implications for predicting all the runoff signatures (annual and seasonal runoff, flow duration curve, low flows, floods, hydrographs), although the importance of the flow path information varies between signatures. For runoff hydrographs, the flashiness of the catchment depends on the magnitude of storage and the responsiveness of flow paths, as represented by the structure and parameters of the model. For low flows, information on the depth at which flow processes occur (whether they occur on the surface, shallow subsurface or deep subsurface), the magnitude of deep storage (either in the fractured rocks or in porous aquifers feeding a stream during low flow periods) and aquifer characteristics may all assist in choosing model structure and parameters. Similar things apply to floods, although the focus is usually on shallower flow paths. For seasonal runoff predictions, the magnitude of subsurface storage is mainly of interest, which may also indirectly affect the annual runoff (see Chapter 5). For annual runoff it may also be very important whether a catchment loses or gains water through subsurface flow paths, i.e., whether there are any interbasin transfers.

4.5.2 Statistical methods

The alternative group of methods for predicting runoff in ungauged basins is statistical methods (see Sections 5.3, 6.3 etc.). In most of these methods, relationships between catchment characteristics and runoff signature are established from regional data and then used for the predictions. Although these relationships are usually considered black-box models, much can be gained by interpreting the relationships in a process-based, if simplified and aggregated, way, in order for them to be realistic, and provide the right predictions for the right reasons. An understanding of the flow paths and storage can be beneficial for statistical methods for a number of reasons: (i) Flow path and storage understanding can assist in the selection of catchment characteristics. These should be selected not only on the basis of the goodness of fit of the relationship between regional runoff signatures and catchment characteristics but also on the basis of what they represent hydrologically. They are simple hydrological models themselves, i.e., they represent the processes at an aggregate level. For example, one may have the choice to use catchment characteristics related to either soils or geology. This choice should really depend on where the flow paths are in the catchment of interest – through the soils or deeper in the geology. Soil characteristics as predictors may be misleading and lead to spurious correlations if the flow paths are actually much deeper. (ii) Similarly, it is useful to interpret the *coefficients* in the relationships between runoff signatures and catchment characteristics (e.g., regression coefficients in terms of the sign of the coefficients depending on simplified concepts of the flow paths). For example, one would expect floods to be negatively correlated with soil depth if the saturation excess mechanism is the dominant flood-producing mechanism, and positively correlated with the percentage of clay if infiltration excess is the dominant mechanism. One would expect low flows to be positively correlated with the permeability of the bedrock as this suggests higher storage, although this may depend on the particular flow system. Similar considerations apply to other runoff signatures, in particular flow duration curves and hydrographs.

4.5.3 Role of field visits, reading the landscape, photos and other proxy data

Some of the information on flow paths and storage to be used in ungauged basins may be available from existing databases, be they global, regional or local (see Chapter 3). This may include existing reports on the hydrological processes in the catchment of interest derived from previous studies. Other information needs to be collected during the study. It is particularly important to perform field trips that allow extra information to be collected relevant to the signature of interest. For example, an important question on whether surface runoff occurs (and at which event magnitudes) can be addressed through collection of proxy data during field trips, e.g., by erosion marks (see Section 3.7). Additional information can be obtained by 'reading the landscape', to get an understanding of how the process of co-evolution of climate, landform, vegetation, soils and geology has shaped the landscape. The dynamics of flow paths and storage are often reflected in visible geomorphic features in the landscape. Examples are the existence of highly permeable debris fans and deposits from landslides that, once known, can be represented in the model. For example, reading the geomorphic features of the landscape assisted Rogger *et al*. (2012a) to set the storage parameters for a runoff model for predicting floods. It is always a good idea to create photo-documentation of the catchment to record landscape features in order to better understand how the catchment works hydrologically. The proxy data obtained can be used by many of the different methods for predicting runoff in ungauged basins (see Sections 5.4.3, 6.4.3 etc.). Additionally, and importantly, it is always beneficial to take extra measurements if possible, particularly measurements of runoff. Spot gauging, or perhaps even installing a stream gauge to obtain a short runoff record in the catchment of interest may provide very valuable information on the runoff signature of interest. Short runoff records may be exploited by many methods for predicting runoff in ungauged basins (see Sections 5.3.4, 6.3.4 etc.)

4.5.4 Regional interpretation and similarity

Spatial interpretation of all this information may always be helpful. This means that rather than directly inputting the information on flow paths and storage into a process-based or statistical model, the information is first plotted on a map with real landscape features. This allows the information to be related to the landscape processes. It may assist in understanding how the landscape is organised from a hydrological perspective and enable patterns to be detected, and highlight how the catchment of interest fits into the regional pattern. In the second step, the information can be entered into a quantitative model, either process-based or statistical. Regional visualisation of indices of flow paths and storage may involve maps of recession parameters and baseflow indices estimated from runoff. This may perhaps be assisted by residence times estimated from tracers and other regional proxy data such as the presence of springs (see e.g., Chapter 8), against the backdrop of the regional hydrogeology and the climate. The type of maps one chooses to draw may, again, depend on the runoff signature of interest. For example, maps may consist of flood response times against the backdrop of soils, geology and mean annual precipitation in the case of floods; and recession parameters and mean transit times from tracers (if available) against the backdrop of geology in the case of low flows. The purpose of such a regional interpretation for comparing catchments across the landscape is to assist in the regionalisation step based on the hydrological similarity between catchments (see Sections 5.2.2, 6.2.2 etc.). In this comparative approach, qualitative information on similarity can be made useful for quantitative estimates. For example, the ungauged catchment of interest may contain massive debris deposits near the stream that are not present in the neighbouring (gauged) catchment. From this comparison one can infer that the ungauged catchment may respond more slowly during floods because some of the rainfall will percolate deeper in the ground and have deeper flow paths than in the neighbouring catchment, resulting in smaller flood peaks (Merz and Blöschl, 2008a, b). Sections 5.2.3, 6.2.3 etc. provide quantitative methods of how this similarity or dissimilarity can be exploited for estimating runoff signatures in ungauged basins. If runoff model parameters are transferred from similar gauged catchments (Chapter 10) one would of course also hope that the flow paths in those gauged catchments are represented in realistic ways, i.e., that the runoff model is not obtained through hydrograph fitting but is right for the right reasons. The information on flow paths and storage can therefore also be useful for setting model structure and model parameters in neighbouring catchments that are gauged. Again, methods are available where flow path information, e.g., from tracers, can be used to choose more realistic model structures over less realistic structures (Vaché and McDonnell, 2006; Son and Sivapalan 2007; Birkel *et al.*, 2010).

4.6 Summary of key points

- Flow paths and storage are catchment dynamic characteristics that may not be visible on the surface, but have a key role in the nature of hydrological processes occurring in catchments, and are strongly reflected in their runoff signatures. The intricate patterns of interconnected surface and subsurface flow paths occurring at a multitude of scales are a result of the co-evolution of climate, vegetation and other landscape features through the interaction of several earth system processes, including flow processes.
- In order that a model can be reliably extrapolated to ungauged basins, it has to predict accurately for the right reasons, i.e., it must reflect essential hydrological processes within the catchment, and must correctly represent the flow paths in the subsurface.
- Flow path estimation in ungauged basins can be achieved by both top-down and bottom-up approaches. The top-down approach examines the collective system response observed in the catchment, such as runoff or tracers, and attempts to infer the functional behaviour in an integrated way. Tracers are particularly appealing for understanding the activation of flow paths and storage. In ungauged basins, very often, no tracer data are available, but relationships between flow path/storage indices and bio-geo-physical catchment characteristics could be obtained from studies in gauged catchments and then used to extrapolate to ungauged catchments on the basis of similarity.
- The bottom-up approach reasons on the basis of component processes within catchments, which are controlled by the bio-geo-physical catchment structure. Findings in research catchments can help to understand how structural features of catchments control these flow paths. For estimating runoff signatures in ungauged basins, the bottom-up approach can be assisted by index-based terrain analyses that help generate the distribution of available storage across the catchment, as well as partitioning surface and subsurface flow paths. Other indices are based on the concept of co-evolution, and account for diverse feedback processes between hydrology, climate, geomorphology and ecology. The idea here is that different landscape units within a catchment may have different functions and are typically formed by different processes, and can therefore be easily distinguished.
- Information on flow paths and storage is beneficial for predicting runoff signatures in ungauged basins as it underpins the perceptual model of the flow system. In process-based models, understanding of the flow system helps define the model structure and/or parameter values. In statistical models, such as regressions, it provides guidance on the selection of catchment characteristics and interpretation of the coefficients.
- Reading the landscape in terms of geomorphic features, vegetation, soils, rock outcrops and land use will assist in choosing model structure and setting model parameters. Reconnaissance field trips documented by photographs are an essential way to achieve this. It is always beneficial to take extra measurements, particularly measurements of runoff through spot gauging or installing a stream gauge.

5 Prediction of annual runoff in ungauged basins

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5.1 How much water do we have?

Human civilisation depends upon a reliable water supply. One critical role of practical hydrology in delivering this supply is estimating the reliability of water resources available for meeting human and environmental needs. Two key elements of water resources planning are the long-term mean rate at which river runoff is generated, and its variability from year to year. For example, water supply reservoirs are designed to smooth out fluctuations in inflows and provide a reliable yield of water to sustain human needs. Successful reservoir design must therefore account for the mean and inter-annual variability of river inflows. Inter-annual variability also provides a way to quantify its sensitivity to variations in driving factors such as climate. Fundamental understanding of the nature and causes of variability of annual runoff is critical to assessing how the reliability of water supplies will change when the drivers of variability might change in the future, e.g., climate change, land use and land cover changes. Such understanding is needed globally to improve water availability and livelihoods for large human populations worldwide, as well as protecting the natural environment. Equally important, achieving an understanding of the average water flows and their variability on a continental scale is an exciting aspect of earth system sciences per se, as the water flows are intimately connected to many processes in the oceans, in the atmosphere, on the land surface and in the shallow subsurface.

This chapter focuses on prediction of annual runoff in ungauged catchments. We define annual runoff as the total volume of water discharging past a point of interest in a river or stream in one year divided by the contributing catchment area. Using this definition, the units of runoff are usually mm/yr. If the total volume of water discharging past a point is the variable of interest, volume units of m^3 $year^{-1}$ or millions of m^3 $year^{-1}$ and terms such as annual runoff volume are adopted.

* Coordinating contributor

Mean annual runoff is the average of annual runoff values estimated over many years. Its inter-annual variability is usually quantified in terms of the standard deviation (or coefficient of variation) of annual runoff. It can also be expressed in terms of the *growth-curve* (i.e., cumulative frequency distribution scaled by the long-term mean, see Chapter 9 for examples in the context of floods) of the annual runoff. Although commonly treated as constants (i.e., stationary in the statistical sense) both the mean and inter-annual variability of runoff may change over time as a result of long-term (natural) changes in climate, catchment characteristics or anthropogenic factors. For example, Kuczera (1987) and Vertessy *et al*. (2001) describe inter-decadal to century-scale changes in runoff due to non-stationary water use of Mountain Ash (*E. regnans*) forest during regrowth following disturbance by fire.

Annual runoff is used in the preliminary design of water supply systems (McMahon and Adeloye, 2005) involved in allocating water for the environment, irrigation, industry, human consumption, hydropower, navigation, recreation and catchment management. Techniques for preliminary analysis associated with the sizing of water supply systems or estimating the annual yield from an existing system are available and were reviewed by McMahon *et al*. (2007a) using a global database of annual (and monthly) runoff. Estimates of mean annual runoff, its variability and auto-correlation are needed for many of these techniques. Annual runoff is also used to assess climate change impacts on water resources (Arnell, 1999; Milly *et al*., 2005) and land use change impacts on catchment yield (Bren *et al*., 2006; Komatsu *et al*., 2011). Other uses of annual runoff include analyses with respect to the global water crisis, water and sustainability, global food production, and understanding of the global water cycle (e.g., Vörösmarty *et al*., 2010).

Annual runoff and its inter-annual variability are important diagnostics of the surface water balance of a landscape, especially at large spatial scales. Annual runoff variability is one of several signatures of runoff variability (Sivapalan, 2005, Wagener *et al*., 2007), the others being the regime curve (see Chapter 6), the flow duration curve

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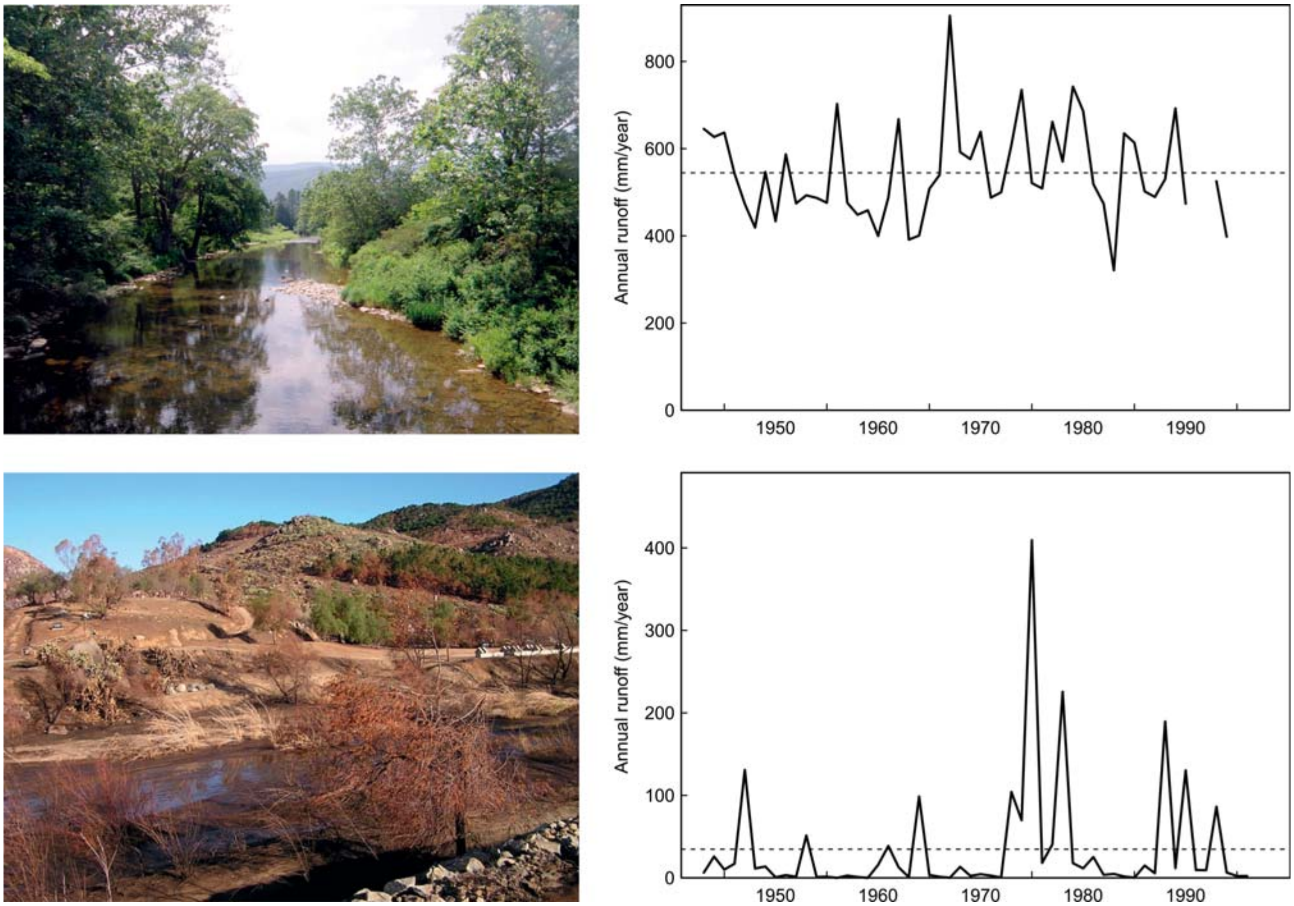

Figure 5.1. Annual runoff in two US catchments: (top) Williams River in West Virginia (332 km^2) and (bottom) Santa Ysabel Creek in California (290 km^2). Photos: C. Clark, M. B Stowe.

(see Chapter 7) and the flood frequency curve (see Chapter 9). Understanding the drivers and causes of annual runoff variability can improve our ability to predict runoff variability at all time scales, including the complete runoff hydrograph (see Chapter 10). These signatures can assist in the development and parameterisation of rainfall–runoff models (Farmer *et al.*, 2003; Bárdossy, 2007). Mean annual runoff is also often used as an index to normalise other signatures as part of regionalisation studies. For example, it is common to estimate normalised flow duration curves for ungauged catchments, where the normalisation is with respect to the mean runoff (McMahon and Adeloye, 2005) or the median runoff (Best *et al.*, 2003).

5.2 Annual runoff: processes and similarity

Figure 5.1 presents examples of mean annual runoff and annual runoff variability from two catchments of similar size located in the USA, but in two contrasting climates: the relatively wet West Virginia and the dry Southern California. The pictures are representative of the landscape and vegetation for the two catchments. The catchment in West Virginia (Figure 5.1, top row) has much higher mean annual runoff (close to 1000 mm/yr) with moderate inter-annual variability (range of about ±300 mm). The catchment in California (Figure 5.1, bottom row) has instead a very low mean annual runoff (below 50 mm/yr) but high variability between years (close to zero and/or exceeding three times the mean). It is interesting to explore why there is much less runoff but with greater variability in the Californian river compared to that in West Virginia. Predicting annual runoff in ungauged basins is the starting point for predicting all other runoff signatures in this book. Therefore, insight into the causal processes leading to the long-term mean and variability, and how similarity and dissimilarity between catchments can be defined is essential.

This chapter begins by discussing the process controls on the nature and extent of annual runoff variability, and how these are governed by the combined effects of climate, soils and vegetation (including land cover change). Understanding of these catchment physiographic and process controls is used to formulate a list of similarity indices that

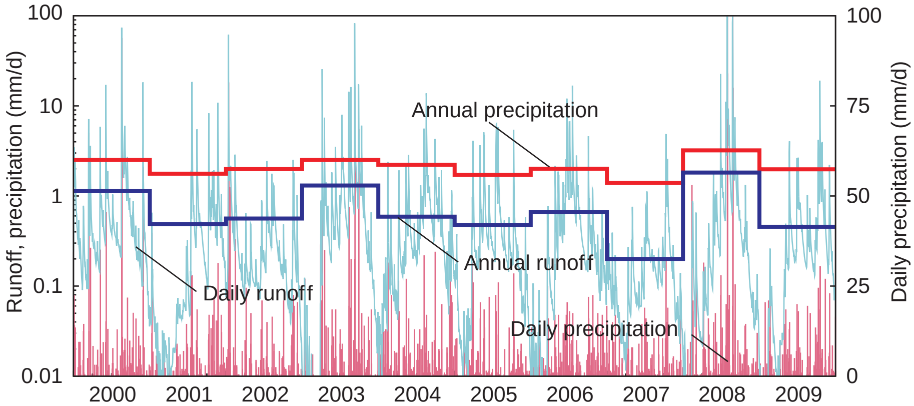

Figure 5.2. Daily precipitation and runoff time series, with the annual series superimposed as thick lines. Here, the seasonal cycle is driven mainly by potential evaporation. Data are from the Stanton River at Cheddar Valley, a 43 km^2 catchment in north Canterbury, New Zealand.

can be used to group similar catchments. Relationships that can be used to extrapolate from ungauged to gauged catchments in hydrologically similar (i.e., homogeneous) regions are developed, and their performance in making predictions for ungauged basins is reviewed.

5.2.1 Processes

Figure 5.2 illustrates runoff variability for a catchment in New Zealand across a range of time scales, from less than hourly up to inter-annual variation. Runoff variability at the annual scale (red line) is an aggregate measure that is damped compared to the high-frequency variation, but can be affected to some extent by the presence of event-scale or seasonal fluctuations. Potentially, the inter-annual fluctuations in runoff could be disaggregated into a component that directly reflects annual fluctuations in precipitation and potential evaporation, and a component that reflects the *timing of precipitation*, especially in relation to potential evaporation (Montanari *et al*., 2006), and is sensitive to higher-frequency variations in rainfall–runoff processes (Jothityangkoon and Sivapalan, 2009). The term evaporation (E) is used throughout this book to describe evaporation from free water surfaces, soils and plant surfaces, as well as transpiration from vegetation. Another potential contribution could be the carry-over of soil moisture (and groundwater) storage between years. For example, Xu *et al*. (2012) showed that this carry-over could affect annual runoff for catchments dominated by woody vegetation in Australia. The factors that contribute to these and their manifestation at the annual scale are discussed next.

A catchment partitions the sequence of incoming precipitation events into runoff, evaporation, surface storage (lakes, snowpack, glaciers etc.) and subsurface storage (soil moisture, groundwater etc.). This partitioning can be expressed formally through a water balance equation. Water balance partitioning can be examined from the event (storm and inter-storm) scale up to the seasonal (wet and dry season) scale. Two distinct phases can be seen in a catchment's response to individual precipitation and melting events: one associated with the wetting phase, dominated by runoff processes, and another with the drying phase, when evaporation becomes a dominant process. Some processes, such as deep percolation of surface storages and subsurface drainage, operate continuously during both phases.

The catchment's response during the wetting phase depends upon precipitation characteristics (water inputs), catchment properties, and antecedent wetness, the accumulated net effect of many previous storms. The catchment's response during the drying phase depends on (i) the water release characteristics of catchment storage, determined by topography, geology at long time scales and by soils at short time scales; and (ii) the evaporation of water between precipitation events, which depends on the nature, extent and physiological dynamics of vegetation within the catchment. The history of these interactions over seasonal and annual periods is embedded in the water balance, but is also ultimately reflected in the type (e.g., physiology) and dynamic behaviour (e.g., phenology) of the vegetation cover, the soil characteristics and the landscape shape, which co-evolve on time scales from years to millennia. The next sections describe the processes underpinning annual runoff variability, including climate forcing, catchment (physical) processes, catchment (biological) processes and global change.

Climate forcing

Annual water balance and annual runoff variability are governed, to first order, by the relative availability of water (precipitation) and energy (evaporation potential), while subsurface and biological processes modulate these effects. This suggests that climate is the biggest driver of annual variability. Differences in the availability of water and energy can explain much of the annual runoff variability

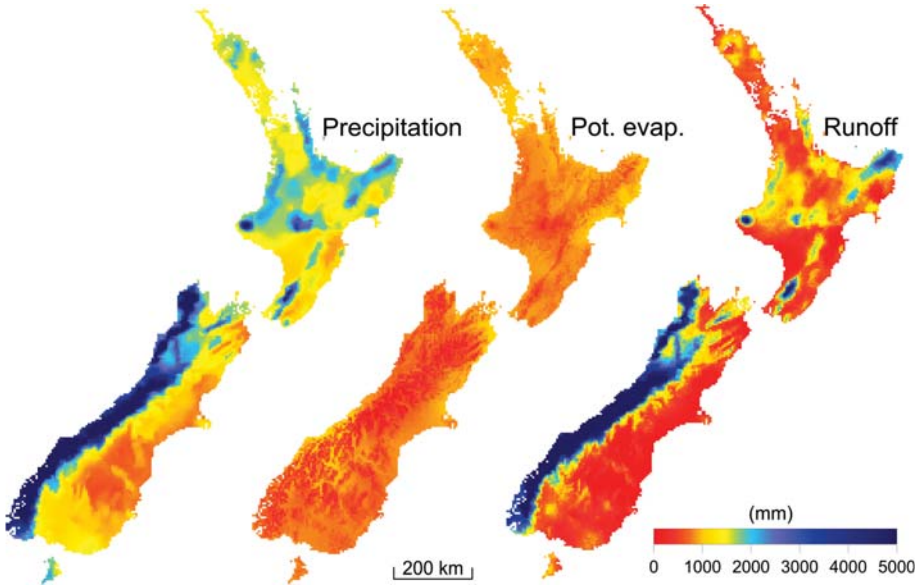

Figure 5.3. Long-term mean precipitation, potential evaporation and local runoff (mm/yr) in New Zealand. From Woods *et al*. (2006).

observed in nature, as in the case of the catchments shown in Figure 5.1. The climate in West Virginia is humid, which means that on an annual time scale more water arrives in the catchment than energy can remove it through evaporation. Therefore the magnitude of annual runoff in the West Virginian Williams River is always high. In contrast, Southern California has an arid climate. More energy is available to evaporate water than precipitation provides to the catchment. Hence evaporation is high and mean annual runoff in the Santa Ysabel Creek is low. More interestingly, the aridity of the climate also determines the high between-year runoff variability, because of the non-linearity of the rainfall–runoff relationship. This is due to threshold effects (e.g., the fact that, depending on the year, precipitation can be higher or lower than the potential evaporation) that mean that small differences in precipitation can translate into much higher differences in runoff, even at the annual scale. In the Santa Ysabel Creek, there are many years with zero runoff. In a humid climate, such as for the Williams River, precipitation always exceeds potential evaporation at the annual scale, so that the rainfall–runoff relationship is more linear and the between-year variability of runoff is moderate (reflecting the between-year variability of precipitation).

Differences in annual runoff variability between catchments, to first order, are caused by differences in the relative availability of water and energy. However, additional factors are differences in seasonality and storminess of precipitation events, as demonstrated by Jothityangkoon and Sivapalan (2009) in several Australian and New Zealand catchments. Figure 5.3 presents a further illustration of how available water (mean annual precipitation) and available energy (expressed through mean annual evaporation potential, E_p) in New Zealand, presented on a rectangular grid nationally, governs spatial variations of mean annual runoff, dividing New Zealand into relatively wet and dry regions.

The relative availability of water and energy can be formalised in the form of the aridity index, denoted by E_p/P, and defined as the ratio of mean annual potential evaporation to mean annual precipitation. The aridity index forms the basis of several empirical relationships between mean annual evaporation (and hence mean annual runoff) (Budyko, 1974; Turc, 1954). The most famous and widely used one is that by Budyko (1974), which is therefore called the Budyko curve (Fu, 1981; Choudhury, 1999; Zhang *et al*., 2001; Yang *et al*., 2008). It plots E/P (ratio of mean annual actual evaporation to mean annual precipitation) as a function of E_p/P (see Figure 5.4 for over 331 catchments in Australia; Donohue *et al*., 2007). The Budyko curve is an empirical relationship, and yet it brings out a number of principles that are crucial to the organisation of this book. First of all, it introduces a key similarity index, E_p/P, unique to hydrology, to express the relative availability of water and energy, and thus helps to classify hydrological landscapes into various degrees of aridity. Second, while clearly recognising a certain amount of scatter, the fact that most catchments of the world (on average) follow the Budyko curve confirms the significance of water–energy availability as a first-order control on catchment properties. Other climatic and catchment factors either (i) contribute to the scatter, or (ii) are themselves governed by climate. The relative effects of most of these factors are included in theoretical frameworks (e.g., Milly, 1994a, b; Woods, 2003).

One climatic factor that does contribute to annual runoff variability is the relative seasonality of annual precipitation

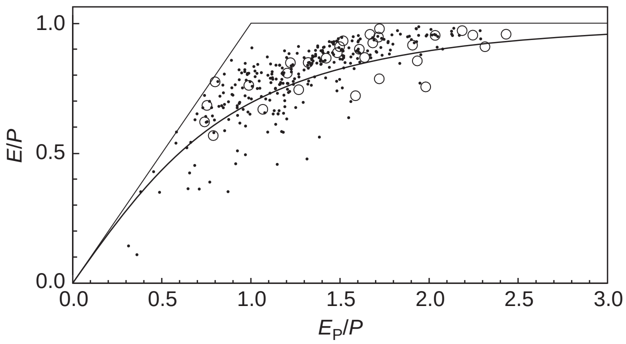

Figure 5.4. Budyko curve and points representing 331 catchments in Australia. Large, hollow circles denote the 30 moderate-sized catchments (≥1000 km^2) and small circles denote the remaining 301 smaller catchments (<1000 km^2). From Donohue *et al*. (2007). Data are from Peel *et al*. (2000) and Raupach *et al*. (2001).

and annual potential evaporation (used as a surrogate for energy available, see Milly *et al*., 1994a, b and Potter *et al*., 2005). These may be either *in phase* – where maxima in potential evaporation (E_p) coincide with annual maxima in precipitation (P) – or *out of phase* – where annual maxima in E_p coincide with annual minima in P (Figure 5.5a). Many regions of the world exhibit strong seasonality in climate forcing, ranging from completely in phase to completely out of phase. The relative seasonality of precipitation and potential evaporation has significant impacts on mean annual runoff and inter-annual variability. In catchments where rainfall and potential evaporation are out of phase, runoff production is enhanced, and evaporation reduced, and vice versa. If P and E_p are out of phase (solid lines in Figure 5.5a), there is an excess of water compared to energy during the wet season. When this water accumulates beyond the ability of the catchment to store it, runoff is generated. In contrast, when P and E_p are in phase (dashed lines in Figure 5.5a) or there is no seasonality at all, evaporation reduces the accumulation of water, and thus reduces runoff generation. This phenomenon explains why runoff is observed in otherwise arid regions: although annually the Mediterranean climates of the south-west of Western Australia and Southern California have a deficit of precipitation compared to energy, during cool wet winters there is a localised water excess that generates runoff. (Note that in other arid places seasonal phasing is less important, because infiltration excess is the dominant runoff mechanism and storage of water in the catchment matters less). The effects of in-phase and out-of-phase seasonality are highlighted in Figure 5.5b, which presents annual water balance data from the USA within a Budyko style framework, with the catchments stratified by whether precipitation and E_p are in phase or out of phase. The observations show that evaporation is reduced (and runoff enhanced) in catchments where precipitation and E_p are out of phase.

Of course, within-year climatic variability on all time scales can impact annual runoff variability. For example, the statistics of rainfall inter-arrival, modified by runoff generation processes and vegetation uptake, have been shown to predict the mean and variance of annual runoff (Porporato *et al*., 2004; Zanardo *et al*., 2012). A detailed example of the effects of precipitation timing was presented by Montanari *et al*. (2006), who showed that annual runoff in the monsoonal area of Northern Australia could vary by a factor of 100% between two years with equivalent annual precipitation, solely due to precipitation in the wet year arriving slightly later in the wet season when evaporation potential was smaller.

Analyses of the effects of within-year climate variability on annual runoff have to be put in the context of co-evolution of climate, soils and vegetation, because over time the landscape and vegetation adapt to the climate forcing and develop functional features unique to a particular region. This was illustrated by a comparative study by Jothityangkoon and Sivapalan (2009) in Australia, which showed that the dominant climate regimes (e.g., seasonality dominated in Western Australia, storminess dominated in Queensland) governed the inter-annual variability of annual runoff.

Catchment (physical) processes

If the Budyko curve is taken as representing the first-order effects of water and energy availability on annual runoff variability, then the scatter around the curves shown in Figures 5.4 and 5.5 is evidence of the second-order effects of catchment storage on annual runoff. Based on detailed analysis of hundreds of catchments across the continental USA, Wolock and McCabe (1999) concluded that, to improve predictions of mean annual runoff beyond the Budyko relationship, soil moisture storage capacity, seasonality in water supply and seasonality in water demand had to be accounted for.

Catchment storage includes temporary storage in the snowpack and/or soil moisture and longer-term storage in lakes, glaciers and groundwater. Climate fluctuations that lead to an excess of water, relative to the capability of the catchment to infiltrate and store water, will favour the generation of runoff at the expense of evaporation. On the other hand, climate fluctuations that promote the infiltration and storage of water for extended periods favour evaporation, since they provide the opportunity for water to be evaporated. The storage effect can be pronounced on seasonal time scales where soil water storage can provide water for evaporation during extended precipitation-free periods, sustaining vegetation that otherwise would not

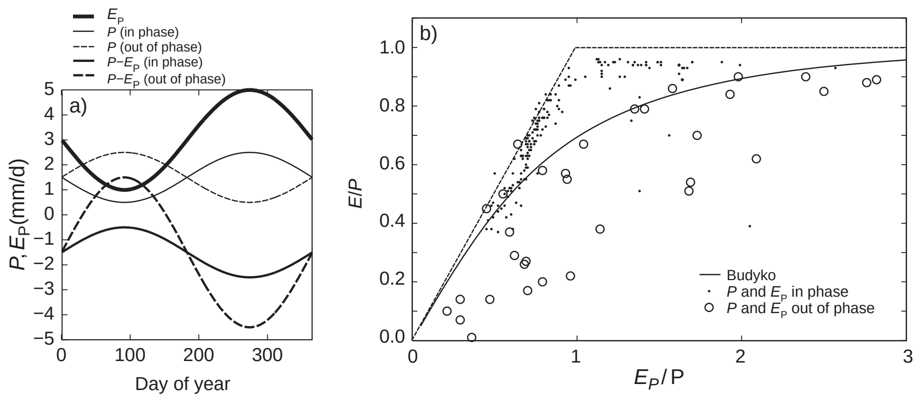

Figure 5.5. (a) Conceptual sketch of the effect of precipitation (P) and potential evaporation (E_P) being in or out of phase. (b) Observed relation of the aridity index (potential evaporation/precipitation) to the ratio of actual evaporation/precipitation for climate divisions according to whether precipitation and potential evaporation are in phase or out of phase in the continental USA. From Wolock and McCabe (1999).

survive such long droughts. Alternatively, the catchment may store water in locations that do not favour evaporation, such as deep, slow flowing groundwater.

The effects of soil type on average annual runoff have been identified by, for example, Wang *et al.* (2009), who showed that soil textural differences may strongly modify the impact of climate on regional water balance. Specifically they found evidence in Nebraska, USA, that soil texture (via influences on recharge and groundwater storage) can exert a significant control on mean annual water balance and inter-annual variability of water balance at catchment scales. In Australia, Potter *et al.* (2005) concluded that infiltration excess is a likely cause of significant deviations between predicted and actual values of average annual runoff, for summer-rainfall dominated catchments.

Topographic variation is another catchment characteristic that can change the annual water balance. On sloping sites, the water balance can be viewed as a competition between subsurface drainage and vegetation uptake, mediated by soil moisture. Conditions that favour drainage (e.g., steep slopes, permeable soils) then lead to higher annual runoff via subsurface flow and lower storage, whereas poor drainability (e.g., flat land, less permeable soils) lead to higher storage and less subsurface flow. This accumulation of water storage can, however, lead to higher surface runoff. Topographic effects are greatest when climatic inputs are strongly seasonal (Yokoo *et al.*, 2008).

An excellent example of where the combined effects of soil type (texture) and topographic slope have an impact on the spatial distribution of annual runoff (as a ratio of annual precipitation) is the Illinois River basin in Oklahoma (Figure 5.6). In this case, a modelling study by Li *et al.* (2012) showed that the soils tend to become more permeable as one moves from east to west towards the outlet, while the topographic slope also increases in the same direction, giving rise to considerable spatial variability in annual runoff ratio. Quite often, while the aridity index provides a good first-order estimate of total annual runoff,

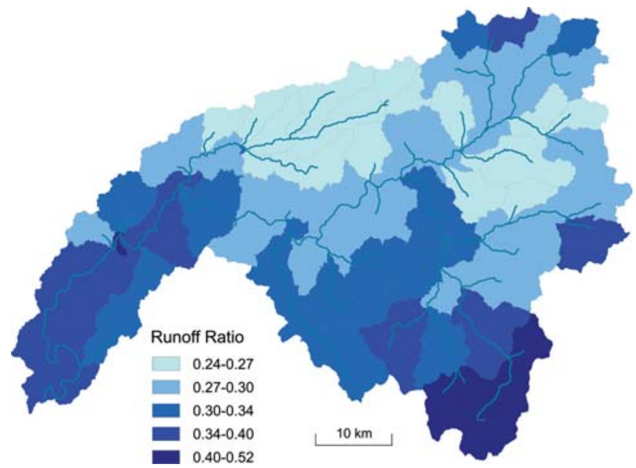

Figure 5.6. Annual runoff ratio (mean annual runoff to mean annual precipitation) estimated for several subcatchments within the Illinois River basin, with outlet near Tahlequah, Oklahoma, USA. From Li *et al.* (2012).

catchment processes tend to determine the relative contributions of surface and subsurface runoff (Reggiani *et al.*, 2000; Sivapalan *et al.*, 2011b). This was also the case in the Illinois River basin, with saturation excess the dominant runoff mechanism in the eastern part of the catchment, whereas subsurface flow was the dominant runoff process in the west near the catchment outlet (Li *et al.*, 2012; see also Chapter 10).

Other catchment processes that impact on annual runoff variability include channel transmission losses in arid regions, storage of water by lakes and wetlands, contributions of regional groundwater aquifers, and snow storage and melt processes in cold, humid regions. To provide a detailed representation of these various catchment effects and their impacts on annual runoff, especially in large heterogeneous catchments, one may need continuous simulation models, which are discussed in Chapter 10.

Catchment (biological) processes
Vegetation cover affects both the wetting and the drying phases of the catchment's response to precipitation. Vegetation adjusts, acclimatises and adapts its physiology to conditions of different water availability on time scales ranging from individual storm events (of the order of minutes to hours) to evolutionary change (of the order of decades to millennia). Vegetation links water availability to geomorphic and pedological change, so that on long time scales the physical and biological components of catchments co-evolve.

In the wetting phase, the dominant effect of vegetation cover is to reduce water availability for catchment wetting through interception by plant leaves and by leaf litter (Gerrits *et al*., 2007, 2010). The proportion of precipitation lost due to interception is of the order of 10–30%, and may be the component of the catchment water balance that is most sensitive to vegetation change (Brown *et al*., 2005). Interception losses tend to be inversely proportional to precipitation intensity and directly proportional to density of the vegetation (Muzylo *et al*., 2009). In catchments with low precipitation intensity and dense vegetation cover, interception losses are higher, e.g., if savanna ecosystems in Botswana receive less than 400 mm of annual precipitation, interception loss is close to 100% of the annual water balance (Savenije, 2004).

During the drying phase, vegetation imposes significant changes on the dynamics of evaporation, first through a trade-off between bare soil evaporation (dominant where vegetation cover is sparse) and transpiration (dominant when canopies close and vegetation cover is extensive) (Laurenroth and Bradford, 2006) (Figure 5.7). Vegetation shades soil surfaces, increases near-surface humidity, and increases the aerodynamic roughness of the land surface, suppressing evaporation beneath vegetation canopies (Kelliher *et al*., 1993). The presence of vegetation modifies catchment drying in two important ways. First, plant root systems extend throughout the subsurface and allow reserves of water that would otherwise be isolated from significant evaporative demand to be connected to the atmosphere. Phreatophytic plants, for instance, directly tap groundwater reserves. Second, transpiration of water is regulated by stomata. Stomata allow plants to regulate transpiration in two ways. During periods when conditions are unfavourable for photosynthesis, plants shut stomata. Thus, transpiration tends to be very low during low-light conditions or overnight, for example. More significantly, even when conditions are suitable for photosynthesis, plants may shut stomata to prevent unfavourably low water potentials occurring in their canopy. Thus, even when atmospheric conditions become favourable for drying, vegetation stomatal responses may inhibit transpiration, slowing the rate of catchment drying.

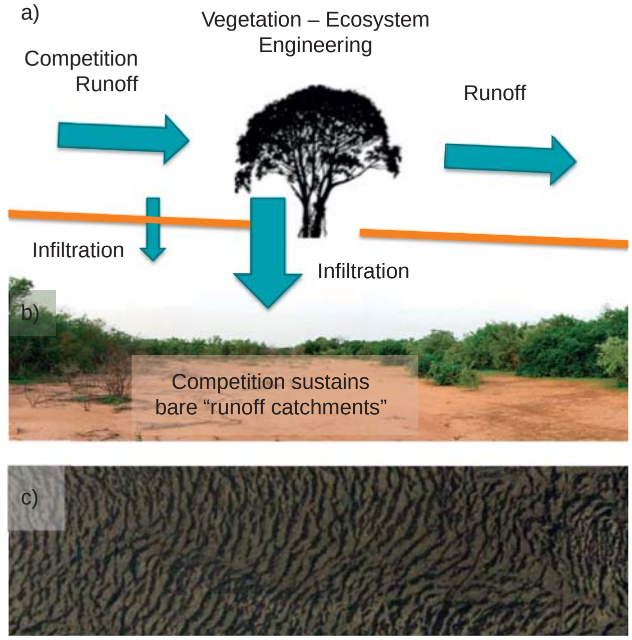

Figure 5.7. Vegetation 'engineers' its environment, often creating conditions that sustain further vegetation growth. The bare areas generate Hortonian runoff, which runs downslope and infiltrates in vegetated sites (a and b). Competition for water between individual plants leads to vegetation growing in organised patterns (c), allowing higher biomass and transpiration than could occur in the absence of the feedback between vegetation presence and soil properties.

Vegetation also displays adaptive features on seasonal and inter-annual time scales. For instance, many plants grow fewer leaves or actively shed leaves during periods of water stress, creating a relationship between leaf area and water availability, and reducing the transpiring surface area. These relationships may allow water balance partitioning to be inferred from observation of metrics of catchment 'greenness' such as the normalised difference vegetation index (NDVI). For instance, the Horton index – a ratio of evaporation to plant-available water on annual time scales (Troch *et al*., 2009) – appears to be significantly and negatively related to catchment-scale annual NDVI in most water-limited basins (Brooks *et al*., 2011), and to mean annual NDVI across 320 test basins in the USA (Voepel *et al*., 2011). Ultimately, vegetation strategies modulate transpiration to prevent negative extremes in plant water potentials, and in doing so reduce variability in catchment water balance. When water balance is measured in terms of the Horton index, for instance, inter-annual variability is markedly damped, primarily being expressed in terms of the partitioning of water to rapid runoff generation (Troch *et al*., 2009), and with the greatest sensitivity in water balance arising in the fast flow components that are effectively sequestered from vegetation water uptake (Harman *et al*., 2011a, b). In Australia, woody vegetation was shown to buffer annual transpiration more effectively than non-woody vegetation, presumably due to differences in root zone depth (Xu *et al*., 2012).

Vegetation cover is therefore both a response to the partitioning of the water balance and a driver of the annual water balance dynamics. Vegetation is also a significant driver of weathering, of soil biogeochemistry, and a determinant of soil hydraulic properties (Thompson *et al*., 2010; Lucas, 2001). The role of vegetation in modifying its local hydraulic environment can result in striking organisation of the landscape. For instance, modification of soil hydraulic properties by vegetation can result in the formation of spatial patterns in vegetation distribution, in which bands of vegetation are interspersed with regions of bare soil (Borgogno *et al*., 2009; Thompson *et al*., 2011a). In northern hemisphere rugged landscapes, the difference in energy balance between north- and south-facing slopes regularly leads to drought-adapted vegetation communities on the south-facing slopes, and mesic vegetation on the north-facing slopes. These vegetation differences are also reflected in differences in soil depth, and carbon and nutrient content (lower on the south-facing slopes) (Burnett *et al*., 2008; Klemmedson and Weinhold, 1992; Franzmeier *et al*., 1969). These differences alter the storage capacity and habitat quality of the slopes, providing a positive feedback that exacerbates the differences between slopes with different aspects, and ultimately driving both water balance and catchment evolution (with vegetation, for instance, suppressing erosion and runoff on north-facing slopes, e.g., Cerdà, 1998; Istanbulluoglu *et al*., 2008).

Effects of global change

Given that the primary control of annual runoff variability is climate, through the relative availability of water and energy, changes in the magnitude or timing of precipitation and temperature (or potential evaporation) could contribute to major changes in annual runoff. A first-order indication of the expected change can be approximated via the Budyko curve. Changes in mean temperature (and hence mean annual evaporation) and in mean annual precipitation can be expressed as changes in the aridity index, E_p/P. Depending on the magnitude of this change, one could 'move along the Budyko curve' and determine the new value of E/P. For example, if the potential evaporation remains constant and annual precipitation decreases, E_p/P will then increase (i.e., become more arid), and annual runoff would be expected to decrease. A dramatic illustration of exactly this effect arises in south-west Western Australia, as illustrated in Figure 5.8. Observation records in Jarrahdale (near Perth) over the past 100 years indicate that annual precipitation went through a 16% step-change reduction in 1975, and another small reduction in 1997. The consequent increases in aridity in this strongly seasonal Mediterranean climate led to more dramatic reductions in river flows to Perth's dams. For example, the 16% reduction in precipitation led to a 55% reduction in runoff.

Predicting runoff response to climatic changes is not usually this straightforward (Montanari *et al*., 2010). For example, reductions in precipitation could lead to increased water stress on the vegetation, leading to possible forest thinning, changes in vegetation composition, disease infestation and die-off, all of which can modify annual runoff. The Budyko curve cannot capture the transient changes in annual runoff associated with these modifications, and may not be sensitive to vegetation or soil changes even once the catchment reaches a new equilibrium.

Increases in average temperature promote not only vegetation change, but also changes in snowfall, snow storage and snowmelt regimes. These changes are likely to alter seasonal runoff, and result in new patterns of annual runoff as well. Several regions of the world have already seen major dramatic changes as a result of increases in temperature, e.g., the Himalayas in India and Nepal, and California in the western USA.

Since seasonality of climate, distribution of precipitation throughout the year, and temporal patterns of precipitation can be key determinants of inter-annual runoff variability (Montanari *et al*., 2006), any changes in the seasonality of these controls can also impact annual runoff. There are historical examples where changes to the monsoon dynamics and timing have led to huge changes in annual runoff variability and collapse of entire civilisations, as in the cases of the Indus Valley (Giosan *et al*., 2012) and the Maya (Medina-Elizalde and Rohling, 2012).

Human-induced land use, water use and land cover changes are the remaining catchment-scale factors altering annual runoff. Examples include forest planting and harvesting, forest conversion to agricultural crops and urban settlements, regulation of runoff by upstream storage, and withdrawals for consumptive use (irrigation, municipal and industrial use) (Peel *et al*., 2010; Vogel, 2011). Vegetation change can be caused by human intervention, or may occur because of adaptation to climate change. For example, replacing a forest with crops or pasture typically reduces evaporation, increasing annual runoff. This change can manifest differently in different environments, depending on the runoff generation processes. The effect of land use and land cover change on runoff has been the subject of many paired catchment studies around the world (e.g., Peck and Williamson, 1987; Brown *et al*., 2005; Bari and Smettem, 2006), revealing, for instance, that transient responses to land use change persist for longer during afforestation than deforestation experiments, that land use changes disproportionately affect low flows, and that there

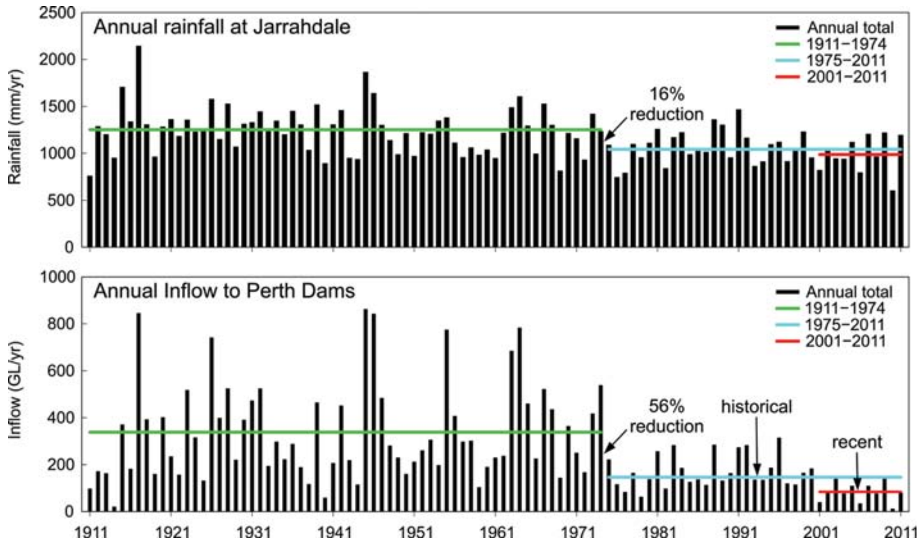

Figure 5.8. Reduction in runoff in the south-west of Western Australia, and its relation to annual rainfall. Data from the WA Water Corporation.

is considerable variability in the timing and sometimes directionality of water balance responses to change (Andréassian, 2004; Brown *et al*., 2005).

5.2.2 Similarity measures

The process controls on annual runoff variability described above point naturally to indices or *similarity measures* that can be used to organise regions into groups with similar hydrological characteristics. Similarity measures can be defined to describe runoff patterns, climate and catchment morphology.

Runoff similarity: Based on runoff data, the similarity between catchments can be expressed in terms of mean annual runoff (flow volume rescaled by catchment area), or in terms of a runoff ratio (or coefficient): the ratio of mean annual runoff to mean annual precipitation. Inter-annual variability can be expressed in terms of the coefficient of variation (CV) of annual runoff, or in terms of a growth curve (cumulative distribution rescaled by the mean). Catchment responses to dynamic changes in climate or land use can be captured in terms of runoff elasticity, i.e., proportional change in runoff divided by proportional change in the climate or land use feature. For example, the precipitation elasticity could be defined as the proportional change in annual runoff over the proportional change in annual precipitation.

Climate similarity indices: Given the primary control of water and energy availability on annual runoff variability, the aridity index, E_p/P, is an obvious climate similarity measure with a proven predictive capacity. Figure 5.9a shows a global map of the aridity index. Locations with high aridity index usually have low runoff ratios, i.e., mean annual runoff is a small fraction of mean annual precipitation.

Within-year variability and in particular the relative seasonality of (or phase difference between) precipitation and potential evaporation also impact runoff variability. This seasonality can be computed with a seasonality index, $|\delta_P - E_p\ \delta_E/P|$, where δ_P and δ_E are the amplitudes of the precipitation and potential evaporation curves. Figure 5.9b presents the global distribution of the phase differences between precipitation and potential evaporation. A combination of the aridity index and the relative seasonality are needed to predict annual runoff in some regions. For example, in Mediterranean climates (e.g., south-west Western Australia, Southern California, southern Spain etc.) observed runoff amounts are inconsistent with predictions made from the annual aridity index: the prevailing out-of-phase seasonality (Figure 5.9b) elevates seasonal runoff production. Figure 5.9c shows the inter-annual variability of annual precipitation, expressed as the coefficient of variation; it is typically largest in arid locations (Figure 5.9a).

Catchment similarity indices: Within a region with homogeneous climate (e.g., similar aridity values, similar seasonality of precipitation and potential evaporation), differences in annual runoff relate to catchment processes, e.g., storage and vegetation uptake. Similarity indices to describe these processes should reflect soil water holding capacity, soil texture (or saturated hydraulic conductivity), topographic slope and vegetation cover.

A dimensionless similarity framework for quantifying the relative roles of multiple factors in annual water balance was developed by Woods (2003) based on the pioneering work by Milly (1993, 1994a, b), and by Yokoo *et al*. (2008) based on the physically based model of annual water balance by Reggiani *et al*. (2000). A similar framework was developed by Jothityangkoon and Sivapalan

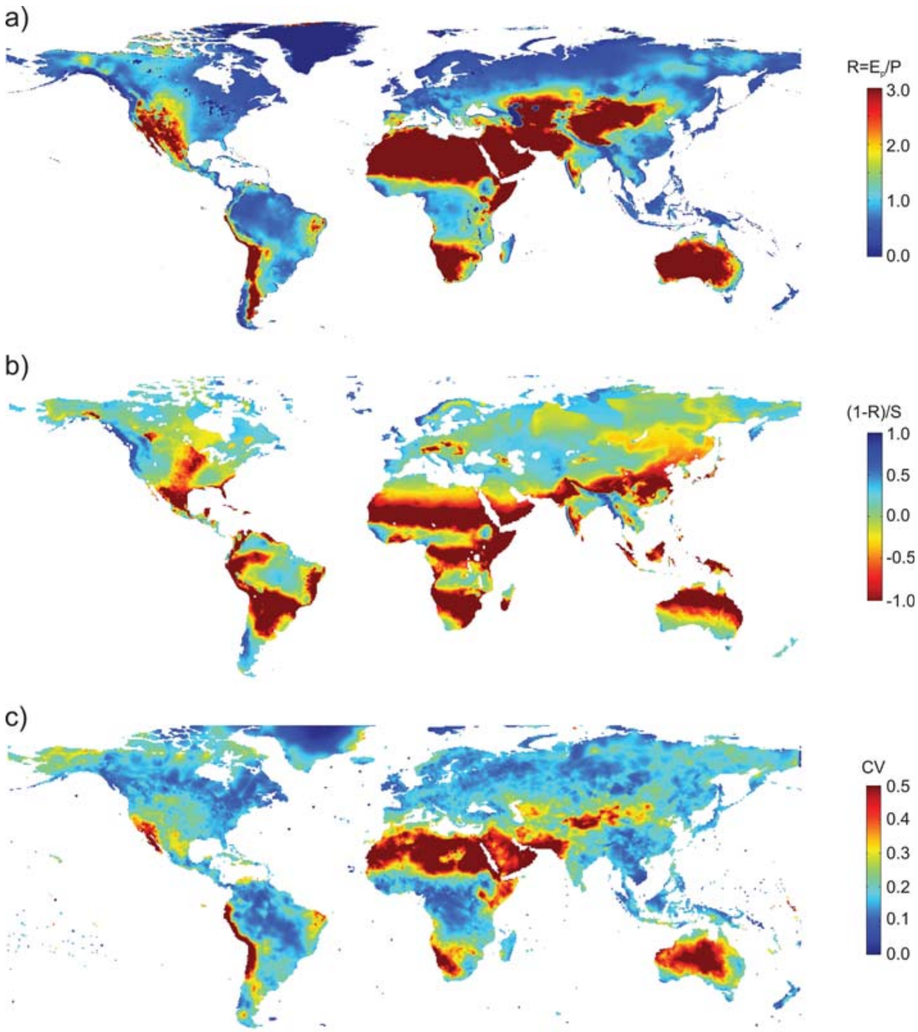

Figure 5.9. (a) Global distribution of the aridity index, using precipitation estimates of New *et al*. (2002) and potential evaporation estimates of Ahn and Tateishi (1994). (b) Global distribution of the dimensionless seasonal amplitude of precipitation surplus, obtained by differencing sinusoidal functions fitted to the mean monthly precipitation and potential evaporation used in (a) above. (c) Global distribution of the inter-annual variability of precipitation, calculated as the coefficient of variation of the 1961–90 annual precipitation estimates of Mitchell and Jones (2005).

(2009) with similarity indices expressed as a ratio of climate and catchment time scales. Table 5.1 presents an example of catchment similarity indices, combining soil, vegetation and precipitation properties, and explanations of their physical meaning and context, taken from Wagener *et al*. (2007). These indices measure ratios of fluxes, storage volumes or time scales.

5.2.3 Catchment grouping

Catchment grouping is at the core of PUB. The prediction of runoff in ungauged catchments is based on what is observed in, and what can be understood from, other similar catchments. Similarity metrics provide a way of describing the behaviour of individual catchments in terms of annual runoff. The next section of this chapter discusses how to transfer this information from measurements in a set of catchments to make predictions in another. This transfer requires approaches to group similar catchments together, and then to use this information for prediction. These procedures – *regionalisation* or grouping, *statistical prediction* and *process-based prediction* – are to some extent generic and applicable to all runoff signatures (Chapter 5 to 10). We have attempted to make this section of the chapter generic and comprehensive in order to provide detailed background to the relevant techniques.

Regionalisation methods are based on the assumption that the area under study, or the group of catchments considered, is *homogeneous* (Blöschl, 2011). Homogeneity in this context means that the processes leading to a signature of interest (e.g., annual runoff, seasonal runoff, flow duration curve etc.) are not changing in space or between sites. Homogeneity permits the simplifying assumption that there is a unique relationship between predictors and the signature for a given group of catchments. The literature on flood frequency analysis, for example, proposes a number of

Table 5.1. *Dimensionless numbers for pore-water dominated hydrology at long time scales*

Dimensionless groups		Dimensionless number	Interpretation	Application
Climate	E_p/P	Aridity index, R	Ratio of average demand for moisture to average supply of moisture	Approximate water balance (e.g., using Budyko curve)
	$\lvert\delta_p - R\,\delta_E\rvert$	Seasonality index, S	Amplitude of the seasonal cycle of precipitation minus potential evaporation	Seasonal pattern of atmospheric moisture surplus/deficit
Canopy and soil	$w_{cm}/(P/N)$	Canopy storage index, W_c	Ratio of canopy storage to characteristic rainfall event depth	Throughfall
	$k\tau_e/(P/N)$	Relative infiltration, K	Ratio of characteristic infiltration rate to characteristic rainfall event rate	Infiltration excess
	$w_{rm}/P\tau$	Rootzone storage index, W_r	Ratio of soil water storage capacity to annual rainfall	Seasonal filling of soil moisture deficit
Saturated flow	$DL/(T_o \tan\beta\tau)$	Advection response index, t_o	Ratio of travel time for advective signal to duration of seasonal forcing	Responsiveness of lateral subsurface flow
	$T_o \tan\beta/LP$	Relative transmissivity, T	Ratio of maximum lateral outflow to characteristic water input rate	Depth to water table
	—	Slope of topographic index distribution, ω	Rate at which saturated area expands	Saturation excess runoff

Climate variables: mean annual precipitation, P; mean annual potential evaporation, E_p; dimensionless amplitudes of precipitation and potential evaporation, δ_P, δ_E; number of rain events per unit time, N; duration of annual cycle, τ; characteristic duration of rainfall event, τ_e.
Canopy and soil variables: average interception storage, w_{cm}; mean saturated hydraulic conductivity at surface, k; rootzone water holding capacity, w_{rm}.
Saturated flow variables: depth to bedrock (or aquifer thickness), D; length of hillslope (or other relevant flowpath), L; transmissivity, T_o; slope of topography (or head gradient), $\tan\beta$.
After Woods (2003) and Wagener *et al.* (2007).

homogeneity tests for the index flood method. Dalrymple (1960) proposed a test, described in several classic textbooks (e.g., Chow, 1964), to assess flood homogeneity by analysing the variability of the maximum annual flood peak CV and/or skewness (CS) across multiple sites (see also, among others, Lettenmaier *et al.*, 1987; Stedinger and Lu, 1995; Hosking and Wallis, 1997). Viglione *et al.* (2007b) compared the power of several homogeneity tests and Castellarin *et al.* (2008) showed how the cross-correlation among sites can affect the performance of the tests.

In this book, the term homogeneity is used in a still more comprehensive way, to mean that a single model structure can be used to describe variability across a group. For example, a group of catchments could be considered homogeneous if a single regression model, parameterised with different catchment characteristics, can capture the variability of a hydrological signature of interest for the group. If geostatistical methods are being applied, then the assumption that a given spatial correlation structure is valid for a given study area effectively enforces homogeneity within that study area (a single model of the correlation structure can describe the spatial variability). Where process-based methods are used, a group of catchments are hydrologically homogeneous (similar) if the same dominant processes drive the behaviour of all the catchments (Wagener *et al.*, 2007). For instance, the assumptions of the derived distribution approach might hold across a homogeneous group, or a given model structure of a rainfall–runoff model might apply to all the catchments under consideration. Chapter 10 will deal with regionalisation of *model parameters* – for this approach to be valid the model structure must be fixed for the whole region: that is, the region must be hydrologically homogeneous in terms of model structure. Although this comprehensive idea of hydrological homogeneity (similarity) is not rigorously statistically defined, it is very useful in practice and will appear throughout this book.

When grouping catchments, there is a trade-off between hydrological homogeneity and the size of the group. Larger pooling groups improve the reliability of estimates made for a target catchment, to the extent that the pooling

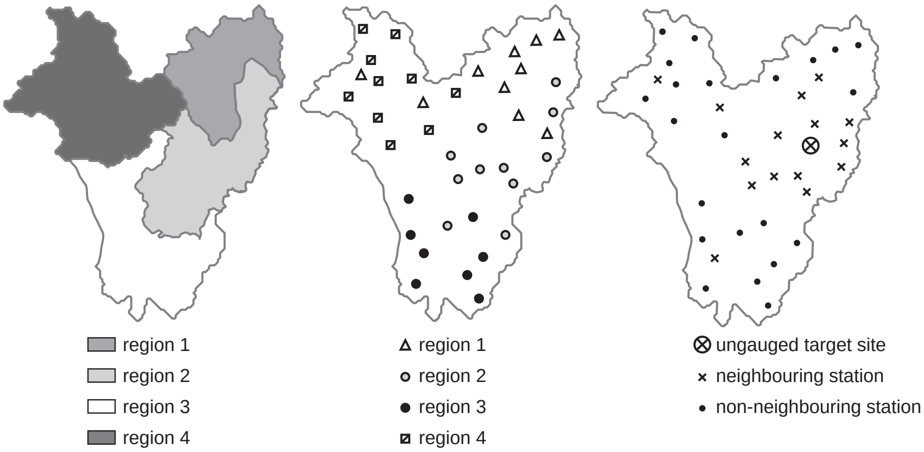

Figure 5.10. Different types of catchment grouping to determine hydrologically homogeneous regions: geographically contiguous regions (left); non-contiguous regions (middle); pooling group targeted to the site of interest (right). After Ouarda *et al*. (2001).

group is homogeneous. Pooling groups, however, are never truly homogeneous; and as the size of a group increases, it tends to become less homogeneous. Methods are therefore needed to optimise the group composition and size (e.g., see Reed *et al*., 1999; Laaha and Blöschl, 2006a).

Groups can be defined in terms of two features: (i) their construction (fixed or targeted to the ungauged catchment of interest), and (ii) spatial contiguity of groups (contiguous or non-contiguous). Fixed groups are constructed once during an analysis. They are intended to be globally valid for any site in the study area. They are typically used in index methods (e.g., groups used in the index flood method of Dalrymple, 1960), regression models and geostatistical models of heterogeneous study areas. For regression methods, the set of individual models for each group of catchments within the study area is called a regional regression model. Examples of fixed groups are in the first two study areas in Figure 5.10. Targeted groups are constructed for each site individually when a prediction is performed for that site. They are typically used in regional frequency analysis (e.g., flow index method or region-of-influence approach, see e.g., Merz and Blöschl, 2005). Based on the idea of developing different groups for each target site, Burn (1990a, b) developed the so-called region of influence (ROI) approach, which was further refined with the addition of a hierarchical feature by Zrinji and Burn (1994). One example is the third study area at the right in Figure 5.10.

Both fixed and targeted grouping methods may lead to classifications that are contiguous in space (regions) or non-contiguous (groups). The study area at the left of Figure 5.10 is subdivided into contiguous regions, while the one in the centre is subdivided into non-contiguous regions. Methods that yield contiguous groups implicitly exploit spatial proximity in addition to other similarity measures. This is advantageous in homogeneous landscapes with smoothly varying catchment characteristics. A possible advantage of non-contiguous groups is their greater flexibility to include catchments that are scatted in space, but are hydrologically similar.

In order to make predictions in ungauged sites, the site of interest needs to be *allocated* to the homogeneous groups, adding further predictive uncertainty to the analysis. For contiguous regions this step is usually straightforward, i.e., ungauged catchments are allocated according to their geographic location. For non-contiguous groups, an allocation rule needs to be defined based on available catchment characteristics for the ungauged site. Statistical methods such as discriminant analysis or classification trees (Laaha and Blöschl, 2006a) or Andrew's curves (Nathan and McMahon, 1990) can be used to derive decision criteria on the basis of available catchment characteristics from the data set of gauged catchments. The criteria are then applied to allocate ungauged catchments to groups.

A number of methods, called pooling methods, are used for subdividing regions into sub-regions or catchment groups. They differ in terms of how the groups are delineated (i.e., which subjective reasoning or algorithm is used) and what information is used (e.g., catchment characteristics, catchment and runoff characteristics, seasonality, etc.) Most of the methods can be used for both fixed and targeted grouping (see Laaha and Blöschl (2006a, b) for a discussion of the state-of-the-art of grouping methods for low flows).

One example of a pooling method that involves subjective reasoning is the *residual pattern approach*. This approach assumes that a single model for runoff prediction applies to the entire study area, but that regional heterogeneity that is not captured in the model results in localised deviations from the predictions, called residuals. These residuals are then mapped and, if patterns in sign and magnitude are recognised, they are used to delineate contiguous regions that are assumed to be homogeneous. In general,

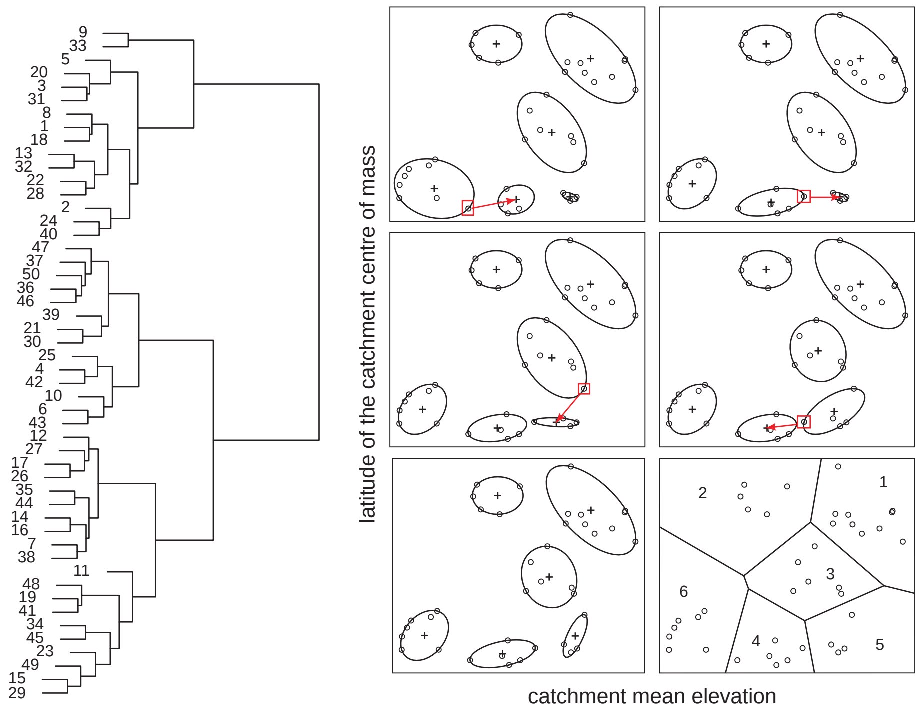

Figure 5.11. Cluster analysis in Piemonte, Italy: Ward hierarchical agglomerative algorithm and reallocation rule. The similarity metrics used for the classification are catchment mean elevation and longitude of the catchment centre of mass. From Viglione (2007).

this pattern recognition is done subjectively and the homogeneous regions are delineated manually on maps, choosing their boundaries on the basis of geographic/hydrological interpretation (see Tasker, 1972; Choquette, 1988; Jingyi and Hall, 2004). A drawback of this approach lies in the quality of the initial model, i.e., residuals may be artefacts of an unsuitable model rather than a reflection of localised catchment characteristics.

Methods that, in principle, do not need subjective reasoning are, for example, the *cluster analysis* methods (see Kaufman and Rousseeuw, 1990; Parajka *et al.*, 2010; Kingston *et al.*, 2011). In cluster analysis, catchment/climate characteristics are used to automatically classify catchments into similar groups by means of a clustering algorithm. In reality, cluster analysis involves a number of subjective choices (as evaluated by Bower *et al.*, 2004). For example, the selection of catchment/climate characteristics to be used and their relative weighting are crucial (Nathan and McMahon, 1990). In addition, one has to provide a way to set the final number of clusters, which has to account for the trade-off between hydrological homogeneity and the size of the group.

An example of cluster analysis is illustrated for a case study in Italy in Figure 5.11. The Ward hierarchical algorithm (Ward, 1963) is used to classify catchments based on two characteristics: the catchment mean elevation and latitude of its centre of mass. The algorithm starts by assuming that each site is contained within its own unique cluster. The clusters are then progressively merged in a way that minimises the information loss (see Figure 5.11, left), where information is measured as the sum of squared deviations of each site from the centroid of its cluster. The Ward algorithm generates compact clusters with evenly distributed elements. However, it does not allow element reallocation, so the final configuration is not guaranteed to be optimal. Reallocation procedures can be applied concurrently while clustering the sites. For example, Viglione *et al.* (2007a) used a reallocation technique with the Ward algorithm in a regional analysis of annual runoff in north-western Italy (Figure 5.11, right). This reallocation guaranteed that every site lay closer to the centre of mass of its cluster than to the centres of mass of any other group. The final regions are contiguous based on catchment characteristics (as shown in Figure 5.11, bottom right), but are generally non-contiguous geographically (see Figure 5.16 for example).

The classification applied by Viglione (2007) (Figure 5.11) is based on two characteristics: the catchment mean elevation and latitude of its centre of mass. These were selected because of their correlation with the CV of annual runoff (see Section 5.3.2) estimated through a statistical method. One alternative to statistical methods for the selection of catchment/climate characteristics for grouping is based on process understanding (as discussed in Section 5.2.1 for annual runoff). The classification shown previously in Figure 5.5b, for example, grouped catchments on the basis of seasonality in the relative phase of precipitation and potential evaporation (Wolock and McCabe, 1999). Seasonality has also been used for classification to identify low flows and floods (see e.g., Young *et al.*, 2003; Laaha and Blöschl, 2006b), based on the assumption that differences in the occurrence of low flows or floods within a year are a reflection of differences in hydrological processes and can thus be used to define homogeneous regions. Homogeneous groups can be delineated manually on a map, or by means of statistical grouping techniques.

5.3 Statistical methods of predicting annual runoff in ungauged basins

To predict runoff signatures in ungauged catchments, transfer mechanisms are needed to link information from other catchments to the catchment of interest. Regional statistical techniques have been a topic of intensive exploration in this area. These techniques treat the prediction of a target variable as the problem of estimating a random variable, while explaining the maximum amount of the spatial variance. Similar statistical assumptions and structures are used for many different predicted runoff signatures. In Chapters 5 to 10 these methods are reviewed, under the topics of:

- *regression methods*, where specific runoff signatures are transferred based on their relationship with catchment and climatic attributes via some analytical expression;
- *index methods*, which assume that a known, quantitative runoff, catchment or climatic signature is constant within a defined homogeneous region, except for a locally varying scaling index;
- *geostatistical and proximity methods*, which exploit spatial smoothness of the runoff signature. Here 'spatial' may refer to either geographic space or a parameter space defined by catchment attributes;
- *runoff estimation from short-records*, which exploits the relationship between moments of short runoff records and runoff in neighbouring catchments.

5.3.1 Regression methods

Mean annual runoff

Regressions are one of the simplest statistical methods used to estimate mean annual runoff. The relationships often exploit independent variables that are prime drivers in runoff generation, for example, mean annual precipitation, or that are clearly related to runoff volume, such as catchment area. An early application of regional modelling of annual runoff was by Langbein (1949), who developed graphical relationships between mean annual runoff, precipitation and temperature in the USA.

More complex multivariate analyses include additional independent variables, e.g., hydroclimate, area, elevation and land cover. Hawley and McCuen (1982) discuss numerous advantages of multivariate regional regression analysis to estimate mean annual runoff. Water yield estimates from regression methods are objectively reproducible, their bias is minimised by the method, and uncertainty associated with them can be quantified under explicit assumptions. A less evident advantage is that regression methods may capture relationships that are evident in the data, but for which no theoretical explanation is available, for example due to the co-evolution of vegetation, landscape and hydrological response. In regression models, mean annual runoff is related typically to geomorphic and climate characteristics. Examples for the USA include Lull and Sopper (1966) and Johnson (1970) for New England, Thomas and Benson (1970) for regions in the western, central and southern USA, Majtenyi (1972) for areas of South Dakota, Hawley and McCuen (1982) for the western USA, and Vogel *et al.* (1997) for the north-eastern USA. Vogel *et al.* (1999) developed regional multivariate models to estimate mean and variances of annual runoff across 18 regions in the USA. The results of Vogel *et al*. (1999) are discussed further in Section 5.5.1. Figure 5.12 presents one case study in north-western Italy (Viglione *et al*., 2007a). The mean annual runoff was obtained by a non-linear regression with the mean annual precipitation and the catchment average elevation. Elevation provides a surrogate for temperature (and therefore energy, vegetation type, snow processes and their seasonal variation). Cross-validation results are shown, along with the 90% prediction intervals for the regression in Figure 5.12b.

Duan *et al*. (2010) used principal component analysis to relate 51 years of annual runoff data for 11 stream gauging stations in north-west China to annual precipitation, evaporation and catchment characteristics. The regional regression model accounted for 87% of the variance in the runoff estimates. The eight variables included in the model are annual precipitation, annual surface water evaporation, sub-basin centroid coordinates, sub-basin centroid elevation, sub-basin area, sub-basin wetland area and sub-basin shape factor.

Inter-annual variability

Kalinin (1971) was probably the first researcher to develop an empirical relationship to estimate the coefficient of variation of annual runoff (CV). The CV was related to the catchment area through a two-parameter, decreasing, non-linear relationship. The decrease of the CV of annual runoff with area is to be expected, as a result of space–time averaging. McMahon *et al*. (1992) related the CV to the mean annual runoff with a power-law relationship, which

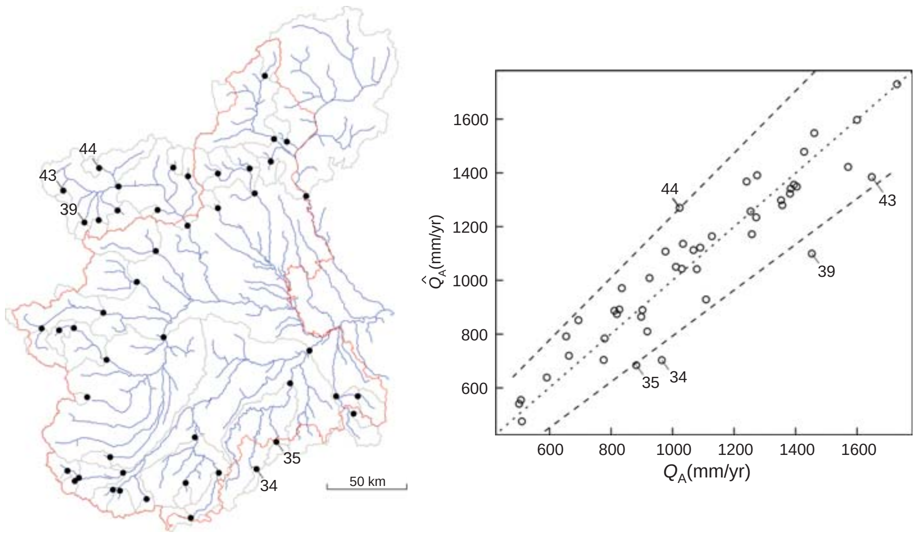

Figure 5.12. Mean annual runoff estimated from regressions vs. observations. The dashed lines correspond to the 90% prediction intervals. The map shows the outlets of 47 catchments in north-western Italy. Adapted from Viglione *et al.* (2007a).

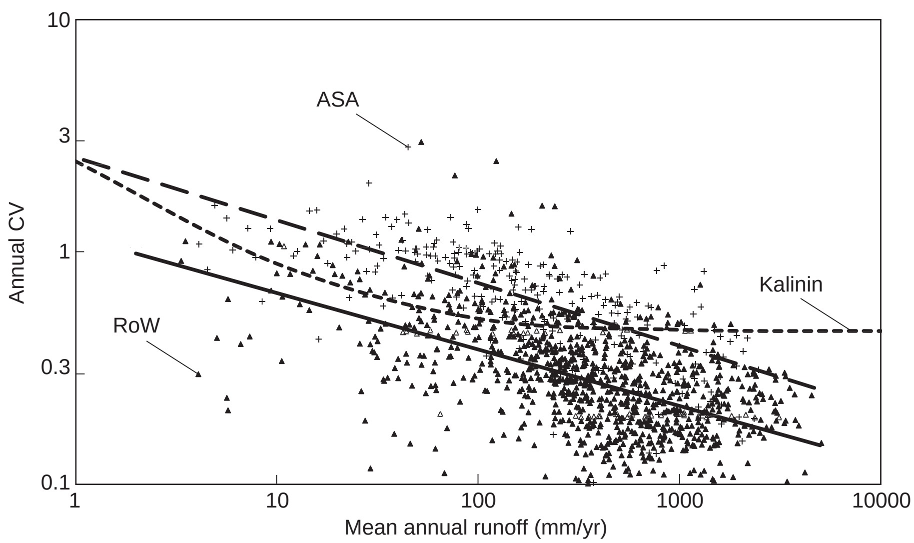

Figure 5.13. Coefficient of variation of annual runoff versus mean annual runoff. Dashed line relates to Australia and Southern Africa (ASA), solid line relates to the rest of world (RoW). From McMahon *et al.* (2007b), Koster and Suarez (1999).

indicated that arid (less rainy) catchments are characterised by more variability. Figure 5.13 shows the results of applying this approach to a global data set, stratified into Australia and Southern Africa and the Rest of the World (McMahon *et al.*, 2007b). The CV of annual runoff in Australia and Southern Africa is significantly higher than the rest of the world, for a given mean annual runoff.

5.3.2 Index methods

Index methods assume that the locally scaled signature of interest, or some functional form of it, is the same for all catchments in the group, which is called homogeneous if it fulfils this assumption. In the following, index methods for mean and variability of the annual runoff are discussed.

Mean annual runoff

Budyko-type models Budyko-type models offer the potential to estimate mean annual actual evaporation from the aridity index and precipitation without calibration. Mean annual runoff is then estimated as the residual of precipitation and evaporation. Budkyo-type models include: Schreiber (Schreiber, 1904), Ol'dekop (Ol'dekop, 1911), Turc–Pike (Turc, 1954; Pike, 1964; Milly and Dunne, 2002), Budyko (Budyko, 1974), Fu (Fu, 1981; Zhang *et al.*, 2004; Yang *et al.*, 2007); Choudhury–Yang (Choudhury, 1999; Yang *et al.*, 2008), Zhang two-parameter model (Zhang *et al.*, 2001), and a linear model by Potter and Zhang (2009). These models are driven by the aridity index, and they do not use explicit conceptualisations of catchment processes. They typically include one parameter, treated as fixed and not necessarily related to

Table 5.2. *Functional (Budyko-type) relationships* F(φ) *plotted in Figure 5.14*

Model	Model details	References
Schreiber	$F(\varphi) = [1 - \exp(-\varphi)]$	Schreiber (1904)
Ol'dekop	$F(\varphi) = \varphi \cdot \tanh(\varphi^{-1})$	Ol'dekop (1911)
Generalised Turc–Pike	$F(\varphi) = [1 + \varphi^{-v}]^{-1/v}$ For the Turc–Pike model, $v = 2$	Milly and Dunne (2002), Turc (1954), Pike (1964)
Budyko	$F(\varphi) = \{\varphi[1 - \exp(-\varphi)]\tanh(\varphi^{-1})\}^{0.5}$	Budyko (1974)
Fu–Zhang	$F(\varphi) = 1 + \varphi - [1 + (\varphi)^{\gamma}]^{\gamma^{-1}}$	Fu (1981), Zhang *et al.* (2004)
Zhang two-parameter model	$F(\varphi) = (1 + w \cdot \varphi)(1 + w \cdot \varphi + \varphi^{-1})^{-1}$	Zhang *et al.* (2001)
Linear model	$F(\varphi) = b \cdot \varphi$	Potter and Zhang (2009)

φ is the aridity index, w, v, γ, and b are parameters

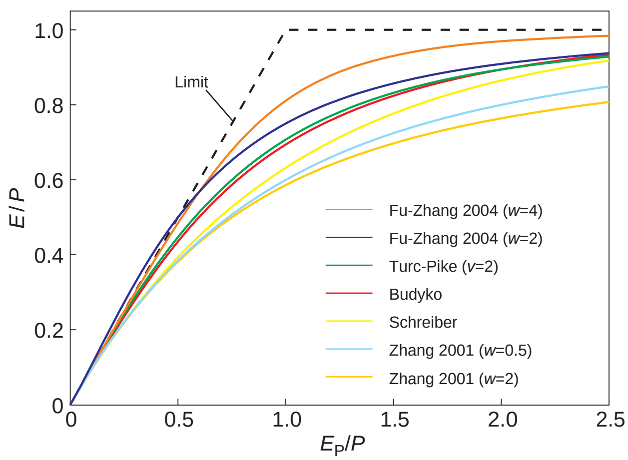

Figure 5.14. $F(\varphi)$ for a collection of Budyko-type methods listed in Table 5.2.

catchment or climate characteristics. Although the functional forms and parameter values in Budyko-type models are (usually) selected empirically, they do capture hydrological reasoning in the form of the physical constraints of water – and energy – limitation on evaporation. They are classified here as an index-type statistical model, with more hydrological reasoning than a simple regression model, but less than a truly process-based model. 'Improved-Budyko' models, which include additional representations of seasonal or event-scale variability and catchment characteristics to improve model performance, are discussed with other process-based methods in Section 5.4.

The general form of the Budyko relationship is $E_A/P_A = F(\varphi)$, where E_A is the mean annual actual catchment evaporation, P_A is the mean annual catchment precipitation and φ is the aridity index defined as E_{pA}/P_A, where E_{pA} is mean annual catchment potential evaporation. Budyko-type models can be treated as an index method because the functional form $F(\varphi)$ can be treated as the climatic homogeneity signature, and the aridity index φ as the locally varying scaling index. Table 5.2 presents a list of Budyko-type functional relationships found in the literature. They reproduce the control of annual climate on runoff to differing extents. Their limitations include the omission of seasonal and event-scale variability, and their very limited capacity to represent catchment characteristics.

More recent applications of the models in Table 5.2 relate to estimating mean annual actual catchment evaporation (Zhang *et al.*, 2004; Yang *et al.*, 2008; Potter and Zhang, 2009). With assumptions of a long-term steady-state storage and neglecting groundwater recharge, however, $E_A = P_A - Q_A$, where Q_A is the mean annual runoff. In Figure 5.15 Yang *et al.* (2007) plotted the Fu–Zhang curves with the fitted parameters for each region (the Tibetan Plateau, Loess Plateau, Haihe River basin and inland river basins) against data from 108 catchments. In their work, they use the Fu–Zhang equation for predicting the annual water balance in ungauged basins. The annual water balance of a catchment can be represented as (McMahon e*t al.*, 2011):

$$Q_A = P_A\left(1 - F(\varphi) - \frac{\operatorname{cov}\left(P_t, F(\varphi)_t\right)}{P_A}\right) \tag{5.1}$$

where $F(\varphi)_t$ is the annual value of the functional relationship between annual actual evaporation and annual precipitation for year t, and $\operatorname{cov}(P_t, F(\varphi)_t)$ is the temporal covariance of precipitation P_t and $F(\varphi)_t$, both considered for year t. McMahon *et al.* (2011) found that the simple Schreiber (1904) relationship performed satisfactorily on 699 worldwide catchments when used in Equation (5.1).

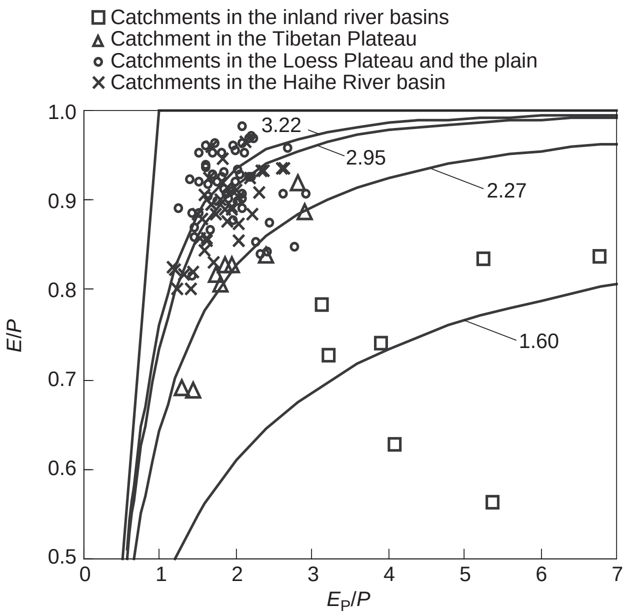

Figure 5.15. Fu–Zhang-type Budyko curves, with parameter γ fitted to data for each region (ranging from 1.60 to 3.22), and points representing over 108 catchments in China. From Yang *et al*. (2007).

Also, McMahon *et al*. (2011) show that setting the covariance term in Equation (5.1) to zero has minimal impact on the mean annual runoff estimates. With this simplification, the following simple equation suitable for a PUB application holds:

$$Q_A = P_A \exp(-\varphi) \tag{5.2}$$

Thus, to estimate the mean annual runoff for a catchment, estimates of mean annual precipitation and mean annual potential evaporation are required. If the vegetation typology of the target catchment can be defined (as either forested or grassland), the Fu–Zhang model can be applied and combined with Equation (5.1). Assuming again that there is no correlation between annual precipitation and actual evaporation, this gives the simple relationship:

$$Q_A = P_A\left((1+\varphi^{\gamma})^{\gamma^{-1}} - \varphi\right) \tag{5.3}$$

where γ is 2.84 for forested catchments and 2.55 for grassed catchments (Zhang *et al*., 2004).

In New Zealand, Woods *et al*. (2006) found that the Fu–Zhang model with $\gamma = 4.35$ provided a useful approximation to long-term point estimates of soil water balance at a climatically diverse set of locations. On this basis a national model of mean annual runoff was developed and validated. In a number of studies, several relationships between the long-term mean annual runoff, long-term total mean annual precipitation and long-term mean annual air temperatures from gridded maps were derived using the Budyko–Turc framework (Hlavčová *et al*., 2006; Parajka and Szolgay, 1998).

Inter-annual variability

Budyko-type models Comparatively little research has addressed the inter-annual variability of runoff, relative to the mean annual runoff. Assuming negligible inter-annual variability in potential evaporation and negligible covariance between precipitation and potential evaporation, Koster and Suarez (1999) derived the following relationship for the ratio between the standard deviation of annual runoff and the standard deviation of annual precipitation:

$$\frac{\sigma_Q}{\sigma_P} = 1 - F(\varphi) + F'(\varphi) \tag{5.4}$$

where $F'(\varphi)$ is the derivative of $F(\varphi)$ with respect to φ. Using the same assumptions, McMahon *et al*. (2011) derived a similar relationship that simplifies to:

$$\sigma_Q = (1+\varphi)\exp(-\varphi)\sigma_P \tag{5.5}$$

if the Schreiber (1904) formula in Table 5.2 is used. However, McMahon *et al*. (2011) also found that, for the 699 worldwide catchments considered in their study, the assumption that precipitation and potential evaporation were uncorrelated underestimated the standard deviation of the annual runoff by ~21%. Using an analysis of annual data for 42 catchments worldwide, Milly and Dunne (2002) explored the relationship between the anomaly of annual runoff volumes and the anomaly of precipitation (depth), and the previous year's runoff volume. Milly and Dunne (2002) concluded that for humid catchments 80–90% of the variance in annual runoff was explained by annual precipitation. For arid catchments the explained variance fell to about 60% (range 40%–80%). Starting from the work of Koster and Suarez (1999), Sankarasubramanian and Vogel (2002) proposed a relationship that depends on both aridity index φ and a soil moisture storage index (details are in Section 5.4.1, since a derived distribution method is used). All these methods neglected the within-year variability of precipitation, evaporation and storage, which have been shown to affect the inter-annual variability in Q_A (Milly 1994b, and see Section 5.4.1).

Probability distribution of annual runoff Regional frequency analysis is a broadly extended statistical procedure to transfer information from gauged to ungauged basins. It

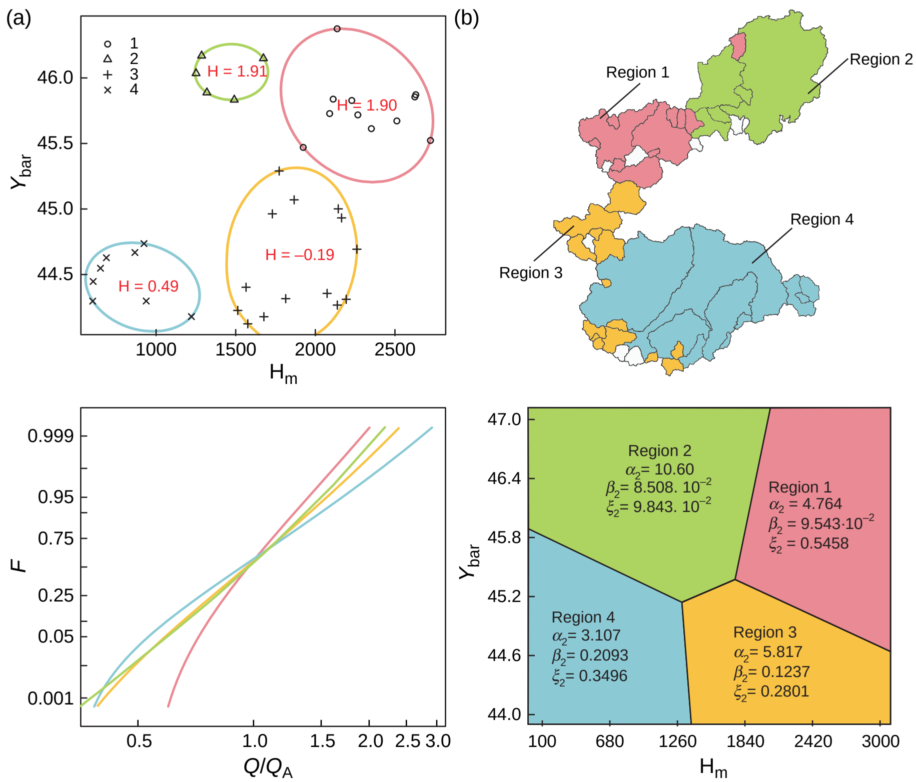

Figure 5.16. Homogeneous regions and estimated growth curves for annual runoff in north-western Italy. (a) Result of cluster analysis in the space of catchment characteristics (H_m: average catchment elevation (m a.s.l.); Y_{bar}: longitude of the centre of mass of the basin (deg)), where H is the homogeneity measure of Hosking and Wallis (1997); (b) catchment groups in the geographic space; (c) Pearson type III growth curves associated to the four regions (F: non-exceedance probability); and (d) allocation rule for ungauged catchments in the space of catchment characteristics (α, β and ξ are the parameters of the Pearson type III distribution). Adapted from Viglione (2007a).

is based on the hypothesis that while the mean annual runoff may vary between different sites within a statistically homogeneous distribution, the remainder of the probability distribution is identical. The regionalisation of the mean annual runoff is usually performed with one of the statistical methods addressed in Section 5.3.1, while pooling of data in homogeneous regions is used to estimate the regional growth curves (i.e., probability distributions rescaled by the mean). Vogel and Wilson (1996) present some applications related to the USA, while in Italy some previous works can be traced back to Ferraresi *et al*. (1988) and Claps and Mancino (2002).

A case study of regional frequency analysis is provided by the study of Viglione (2007a), who performed an index flow regional frequency analysis in north-western Italy. The mean annual runoff was obtained through regression (see Figure 5.12), and the between-year variability of the annual runoff divided by the mean was considered fixed in homogeneous regions obtained through cluster analysis. Figure 5.16a shows the results of the cluster analysis (Ward algorithm and reallocation) in the space of the similarity indices, in this case the mean catchment elevation and the latitude of the centre of mass of the catchment. These two attributes have the following hydrological interpretation: mean elevation is a surrogate for temperature and seasonality of snow processes; while latitude in the study area correlates to the climatic gradient from the drier south to the rainiest part of the region in the north. These two catchment attributes are related to slope and shape of the growth curve (Ganora *et al*., 2009). The number of clusters was selected using a homogeneity test (Hosking and Wallis, 1997), and the homogeneous regions are shown graphically in Figure 5.16b. Figure 5.16c shows the estimated growth curves for the four regions. The Pearson type III distribution was used to model the growth curves. Figure 5.16d shows how ungauged catchments in the region were allocated to the groups. The parameters of the Pearson type III distribution to be used as growth curves of the ungauged catchment were chosen by selecting the appropriate region based on its mean elevation and latitude. Regions 1 and 4 present the largest difference in the shape of the growth curves and are at the extremes in the attributes space. Region 1, corresponding to the Valle d'Aosta region in the north-west, is characterised by very high elevation and a cold-alpine climate. The between-year variability of annual runoff was less pronounced than in other parts of the study area, and in particular than in Region 4, located in the south and characterised by low elevation and a temperate climate. This higher runoff variability is attributed to higher mean annual evaporation and a more non-linear relationship between precipitation and runoff.

5.3.3 Geostatistics and proximity methods

Traditional runoff maps present isolines or isopleths of Q_A at the outlet or centroid of a catchment to illustrate the runoff depth through space. Such maps were initially drawn from manual interpolation of measured runoff data (Gannett, 1912 referred to by Yan *et al*., 2011). Mean annual runoff depth maps for the USA were produced by Busby (1963) and Gebert *et al*. (1987) and by Bishop and Church (1992), who used automated regional mapping for the north-eastern USA. A range of techniques are now available that objectively consider nearby values to determine the isolines and to estimate accuracy across the map (e.g., Hutchinson, 1995). Based on a comparison of eight automated procedures with a manual method to map runoff in the eastern USA, Bishop and Church (1995) concluded that automated methods provided runoff estimates equal to or better than the manual method. These mapping methods are statistical interpolation procedures (Blöschl and Grayson, 2000). They use spatial proximity as a similarity measure to estimate the value of a variable of interest (in this case Q_A) at ungauged locations.

Geostatistical methods also use spatial (or hydrological) proximity as a similarity measure (Merz and Blöschl, 2005), but they are distinct from interpolation methods because (i) they deal with random variables, (ii) they account for the spatial correlation structure and (iii) they de-cluster redundant information (e.g., when two gauging stations are close in space and their observations are correlated in time, this information is considered once and not twice). While standard geostatistics applies to problems that are continuous in space (such as meteorological fields or estimation in mineral exploration), the problem in hydrology is to estimate runoff on a stream network. The difference is the topological structure and therefore the way spatial distance is formulated. Gottschalk (1993a, b) pioneered a new method for the interpolation of runoff. It takes full account of the fact that runoff is to be integrated to streamflow, thus considering the hierarchical structure of the basin drainage system. To achieve this, distance is measured along the river network and the covariogram for points is replaced by a covariogram for the drainage basins, i.e., a covariogram model for the whole river system needs is developed. Building on the work of Gottschalk (1993a, b) and Gottschalk and Krasovskaia (1998), Sauquet *et al*. (2000a, b) developed a hierarchical disaggregation method (also see Sauquet, 2004, 2006). In their approach, the drainage basin is divided into sub-basins in a hierarchy of scales. The first level in a larger drainage basin is usually already well defined by existing observation stations in the main rivers constituting the first level of sub-basins. These basins are in their turn divided into a second level of sub-basins (or grid cells), and observation stations with appropriate basin scales are chosen as the background for the interpolation. The interpolation procedure guarantees that the water balance equation is satisfied so that the sum of runoff from this second level of basins is equal to that of the first-order basin accommodating them. The procedure can be repeated to a third level and so on. Auxiliary runoff values to supplement or replace observed runoff values can be calculated for points in space in a regular or irregular pattern by means of empirical relationships and water balance models. In this way information from precipitation stations and on topography and other catchment characteristics can be included to resolve small-scale variability not covered by regular runoff observation networks. From a hydrological perspective, the key point of the method is that it incorporates water balance constraints, i.e., at confluences the water balance is fully satisfied. The method is also consistent with runoff measurements within prescribed uncertainties. The method was tested in a number of regions including the Rhône River in France. Yan *et al*. (2011, 2012) applied their method to the Huaihe River basin in China (121 000 km^2 catchment area). The resulting runoff map (Figure 5.17) has a 10 km × 10 km resolution and the runoff map along the river has a 1 km basic length unit. There is a strong north–south precipitation gradient in the region, which translates into a similar gradient in annual runoff (Figure 5.17).

5.3.4 Estimation from short records

When only a short river runoff record is available at the point of interest, the mean and inter-annual variability of the short data series are likely to provide a biased estimate of the runoff statistics. This issue is of particular concern if climate fluctuates on time scales longer than the length of the measured runoff record. It is unclear, in general, on what time scales climate could be reliably treated as stationary, and therefore on what time scales it is meaningful to speak of long-term mean and variability metrics. Regardless, it is still important to account for known sources of climate variability when estimating the statistics of annual runoff.

Correlation with longer runoff record

A common method for improving the reliability of runoff statistics estimates is to establish a correlation between a short record and a longer record at a hydrologically similar catchment. For example, Figure 5.18 shows a short runoff record with 7 years' data, and a Q_A of 1190 mm/yr, along with a long runoff record of 19 years, whose mean value is 1930 mm/yr over the 7 years of common record, and 2300 mm/yr over the 19 years. The fitted regression line is used to transform the 2300 mm/yr at the site with the long record into an estimated mean of

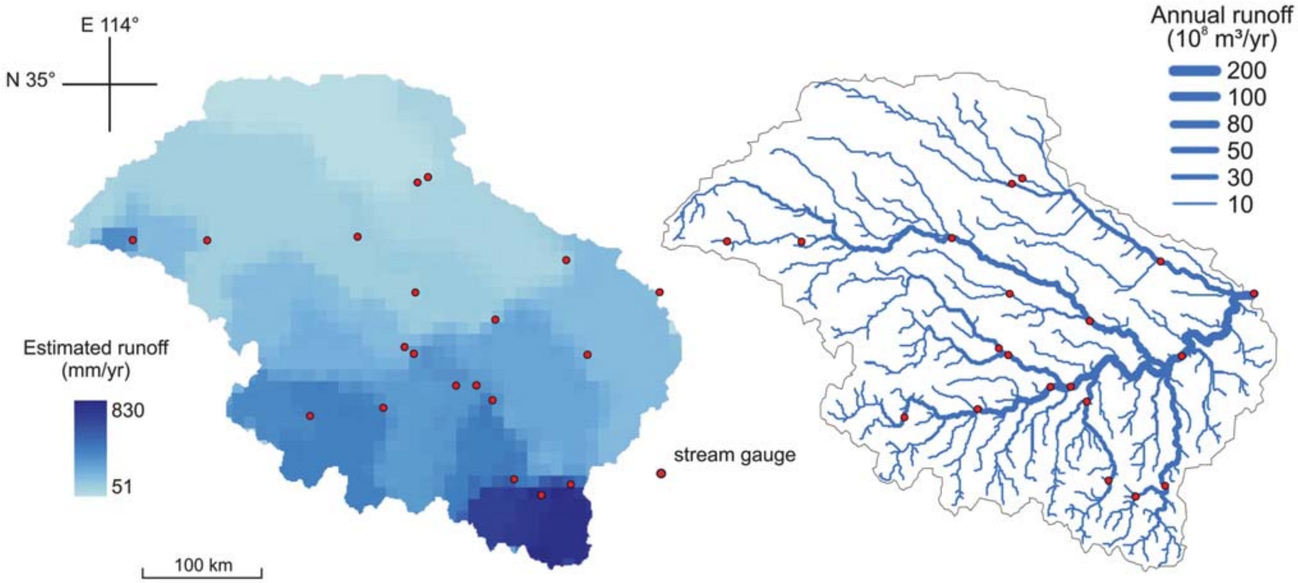

Figure 5.17. (Left) Estimated mean annual runoff for the Huaihe River basin, China; (right) runoff mapped along the Huaihe River network, China. From Yan *et al.* (2011).

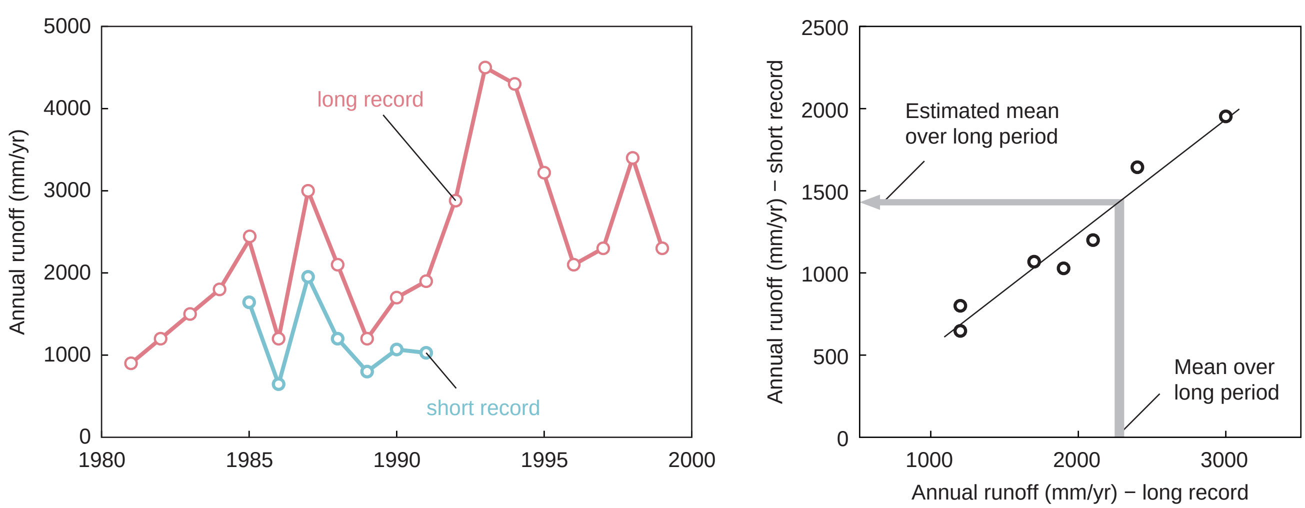

Figure 5.18. Illustration of using linear regression to estimate the mean runoff when a short runoff record is available, by using a longer record of a hydrologically similar catchment.

1450 mm/yr, which is significantly different from the original estimate of 1190 mm/yr.

Rainfall–runoff modelling

A second, more complicated method, requiring a long precipitation record for the catchment of interest, involves the calibration of a rainfall–runoff model to the short record, and then running the model for the full period of the precipitation record, to produce a longer runoff record whose mean and inter-annual variability can then be calculated. Clearly, this belongs to the process-based category of approaches, and is only presented here in the context of the use of short records. More details on process-based methods are presented next in this chapter, and also in Chapter 10.

5.4 Process-based methods of predicting annual runoff in ungauged basins

5.4.1 Derived distribution methods

Where an acceptable model of a hydrological process is available, and the probability distribution of the model inputs is known, it is possible to integrate the model

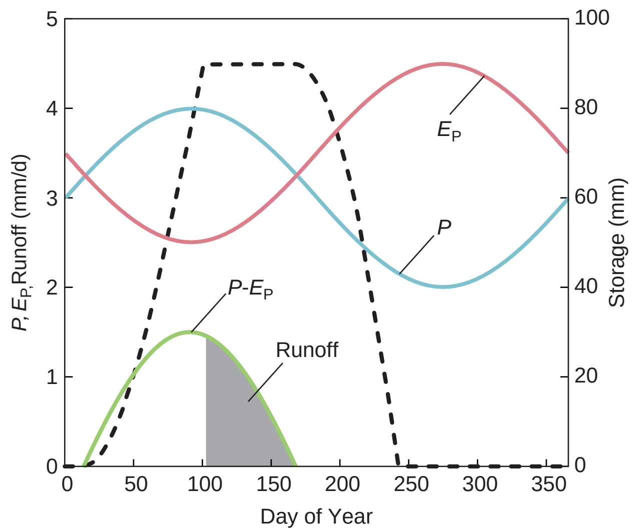

Figure 5.19. Simple model of the interaction between mean climate, seasonality and soil water storage.

equations over the distribution of inputs, to obtain the probability distribution of the model output. This technique is known as the derived distribution approach. There are many examples of applications of this approach in hydrology (e.g., Eagleson, 1972; Hebson and Wood, 1982; Ramirez and Senarath, 2000; Sivapalan *et al.*, 2005). To estimate annual (or shorter time-step) runoff, Budyko-type models require modification to account for the catchment water storage (Zhang *et al.*, 2008a; Tekleab *et al.*, 2011). Models that incorporate monthly or seasonal storage processes include the 'abcd' model (Thomas, 1981; Sankarasubramanian and Vogel, 2002), Milly's seasonal water storage model (Milly, 1994b), and the combined seasonal/event model of Woods (2003).

Figure 5.19 shows a simplified example of this type of model. Precipitation and potential evaporation are assumed to be sine curves (blue and brown traces), and their difference (green trace) is the excess water available. A soil water store (black dashed trace) fills during the first part of the wet season (when $P > E_p$), and once storage reaches its capacity (90 mm in this case), any further excess water generates runoff (solid black region). The area of the black region is the annual runoff. Water is assumed to evaporate at the potential rate during the wet season and whenever stored water is present. Once the dry season begins (when $P < E_p$), storage starts to empty, with water evaporating at the potential rate until storage is exhausted.

Models such as that shown in Figure 5.19 can be implemented for ungauged catchments if climate and soil water holding capacity data are available. Global data sets exist for precipitation (New *et al.*, 2002), potential evaporation (Ahn and Tateishi, 1994) and soil water holding capacity (Global Soil Data Task Group, 2000); in some countries a higher resolution national data set is available. Milly (1994b) showed that a model of this simplicity was unable to reliably predict annual runoff throughout central and eastern USA, mainly because temporal fluctuations in water availability at the event scale were not represented. Models that include event-scale storage processes include Milly's stochastic soil water model (Milly, 1993; Potter and Zhang, 2009), Woods (2003) and the stochastic-dynamic soil water storage model of Rodriguez-Iturbe (Rodriguez-Iturbe *et al.*, 1999; Laio *et al.*, 2001; Porporato *et al.*, 2004). See Milly (2001) for a comparison of some of these approaches.

Based on a theoretical analysis of an idealised water balance, Milly (1994b) developed analytical solutions to estimate annual runoff, representing both event-scale and seasonal variations in climate. He tested this method without model calibration, for data from catchments located east of the Rocky Mountains in the USA. He concluded that the seasonal fluctuation of the forcings was always relevant, especially in arid catchments, while the effect of local spatial variability of soil water holding capacity on annual runoff was negligibly small. By extending Milly's approach to include variable phase shifts in the representation of seasonal climate, Potter *et al.* (2005) made estimates of the water balance of 262 Australian catchments; results are presented in Figure 5.20. Potter *et al.* (2005) found satisfactory results except for catchments with summer-dominated rainfall, where they hypothesised that infiltration excess was a dominant runoff generation mechanism, not represented in their model.

In their analytical approach, Sankarasubramanian and Vogel (2002) adopted the 'abcd' model (Alley, 1984) as an alternative to Budyko-type models in order to be able to account for effects of the dynamics of soil moisture. They derived relationships capable of predicting actual evaporation and the inter-annual variability of runoff, which depended on both the aridity index and a soil moisture storage index, related to one of the model parameters. To apply the method to ungauged catchments, the soil moisture storage index was estimated using monthly time series of precipitation, potential evaporation and an estimate of maximum soil moisture holding capacity. This is available globally at a 0.5 degree resolution (Dunne and Wilmott, 1996).

5.4.2 Continuous models

Annual runoff and inter-annual variability

Hydrologists now have access to a plethora of conceptual precipitation–runoff models. These range from simple single storage models with annual time steps, through to complex theoretically based models with time steps of less

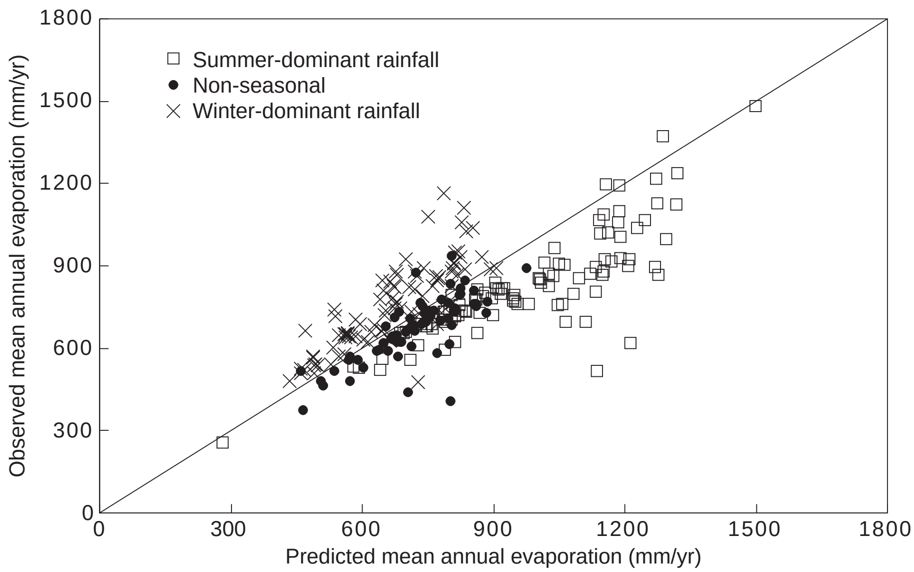

Figure 5.20. Observed mean annual evaporation plotted versus modelled predictions, for 262 catchments in Australia. Catchments are labelled by seasonality of rainfall. The 1:1 line is plotted for reference. From Potter *et al*. (2005).

than an hour. To compute a time series of annual runoff in a PUB setting requires a time series of precipitation and relevant forcing variables for the target catchment, along with appropriate model parameters. Assuming that a reasonable predicted time series of runoff output can be obtained from the model, the mean, inter-annual variability and auto-correlation of annual runoff can be computed from the statistics of this time series. Other annual series-based analyses include trend analysis (Chiew and McMahon, 1993; Salas, 1993; Milly *et al*., 2008), runs analysis (Yevjevich, 1967; Saldarriaga and Yevjevich, 1970; Sen, 1976; Hisdal *et al*., 2001; Peel *et al*., 2004a, 2005), establishing the probability distribution function of the annual runoff (Vogel and Wilson, 1996; McMahon *et al*., 2007b), and analysing the time series structure of the data that will allow more sophisticated analysis such as stochastic data generation to be carried out (Matalas, 1967; Stedinger and Taylor, 1982a, b; Hipel and McLeod, 1994; Thyer *et al*., 2002).

The difficulty in applying continuous models is two-fold: (i) identifying an appropriate model structure and (ii) obtaining the necessary parameter set(s) that allow the model to produce plausible runoff values. *Parameter regionalisation* to ungauged catchments is often confounded by poor parameter identification at gauged catchments. There are numerous sources of parameter uncertainty, including errors in input data, errors in model structure and errors of the calibration data. Even the choice of the objective function and optimisation technique for calibration contribute to uncertainty (see Peel and Blöschl, 2011, and references therein). These issues are discussed in more detail within the PUB framework in Chapter 10 and are not addressed here. There are few practical methods and only limited guidance for objectively assessing model structure for ungauged catchments (e.g., when using lumped conceptual models, more arid catchments generally require more complex models). Once a model structure is chosen, there are many methods for parameter estimation (see Section 10.4). Thus, the benefits of making high resolution temporal predictions trade off to some extent against the challenges imposed by managing uncertainty in these predictions.

5.4.3 Proxy data on annual runoff processes

Tree ring chronology and paleoclimatology

Proxy data allow analysts to extend time series of annual runoff to periods prior to runoff observations. A statistical relationship, usually regression, is established between observed runoff and one or more proxy data series, which is then used to synthesise a time series of annual runoff driven by the long proxy records. An abundance of literature exists where tree ring chronology or other paleoclimate proxy records are used to develop satisfactory relationships with observed annual runoff data. The NOAA Satellite and Information Service (NOAA Paleoclimatology, 2011) lists runoff reconstructions for several US rivers, the Selenge River in Mongolia, and the Burdekin River and other Queensland rivers in Australia. Examples of recent runoff reconstructions outside the USA include three Canadian prairie rivers (Case and Macdonald, 2003), the Churchill River in northern Saskatchewan, Canada (1840–2002) (Beriault and Sauchyn, 2006), four rivers in coastal Queensland, Australia (Lough, 2007), the Murray River in Australia (1783–1988) (Gallant and Gergis, 2011), the Yellow River in western China (Gou *et al*., 2007), the Manasi River in north-west China (Yuan *et al.*, 2007) and the Maule River in Chile (1590–2000) (Urrutia *et al.*, 2011).

All the above techniques are based on correlating annual runoff to a proxy time series record. Saito *et al.* (2008) and Gray and McCabe (2010) extended this approach by incorporating a simple water balance model with annual time series of tree ring data modified to represent annual precipitation as input. Gray and McCabe (2010) incorporated temperature as well. The procedure requires further research but the results are encouraging.

Beyond tree ring analysis Xu *et al.* (2012) recently showed that vegetation cover may be useful as a proxy for annual runoff. Their study used elasticity analysis to quantify the effects of climate variability on hydrological partitioning (including total, surface and subsurface runoff) and vegetation cover (including total, woody and non-woody vegetation cover). They concluded that annual runoff, evaporation and runoff coefficient increase with vegetation cover for catchments in which woody vegetation is dominant and annual precipitation is relatively high. These results suggest that vegetation cover may be used as a runoff proxy, but further research is needed.

Remote sensing

Despite tremendous promise, remote sensing data do not yet offer reliable means to estimate time series of annual runoff at ungauged sites. Research to estimate annual runoff via remote sensing follows two lines of enquiry. In the first approach, remote sensing is used to estimate the components of the water balance independently. For example, evaporation can be estimated using thermal methods that relate evaporation to the temperature difference between soil and vegetation canopies; or through residual energy balance techniques in which thermal observations of air and surface temperature are used to estimate net radiation and soil heat flux, and a variety of competing schemes then employed to parameterise sensible heat fluxes. These techniques are employed by the land surface schemes SEBAL, SEBS and ALEXI/DIS-ALEXI (Couralt *et al.*, 2005; Bastiaanssen *et al.*, 1998; Anderson and Kustas, 2008). Precipitation can be estimated using satellite radar data (e.g., TRMM), microwave products are available to estimate shallow soil moisture and, at large scales, the GRACE mission can constrain estimates of storage change. Runoff is then computed as the residual of the water balance. Gao *et al.* (2010), however, found that closure of the water balance is not currently possible using remote sensing in large catchments. Combining modelling and observations through data assimilation, however, offers an opportunity to reduce modelling errors. In the second approach, remote sensing is used to estimate hydraulic aspects of surface water, such as river top width, and then compute runoff through the use of a rating curve. Alsdorf *et al.* (2007) reviews progress in this area of research.

Figure 5.21 presents the results from an application of remote sensing to obtain distributed estimates of annual runoff across Sri Lanka, taken from Bastiaanssen and Chandrapala (2003). In this case, the SEBAL technique of Bastiaanssen *et al.* (1998) was used to first estimate annual actual evaporation, and then, through combining these estimates with measured and interpolated rainfall, a rainfall surplus (gross rainfall minus actual evaporation) was obtained, which was then partitioned into several large basins. Figure 5.21b shows comparisons of monthly runoff for two selected river basins, and Figure 5.21c presents comparisons between measured and estimated (based on remote sensing) annual runoff volumes for the majority of river basins across the country, indicating that there is considerable potential for this method to estimate annual runoff over large river basins.

5.5 Comparative assessment

The aim of the comparative assessment of annual runoff predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1 in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. In Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation (or just goodness of fitted regressions where the cross-validation results were not available). In the leave-one-out cross-validation each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

5.5.1 Level 1 assessment

Table A5.1 lists the 34 studies evaluating mean annual runoff and Table A5.2 lists the 9 studies evaluating inter-annual runoff variability used in the Level 1 assessment.

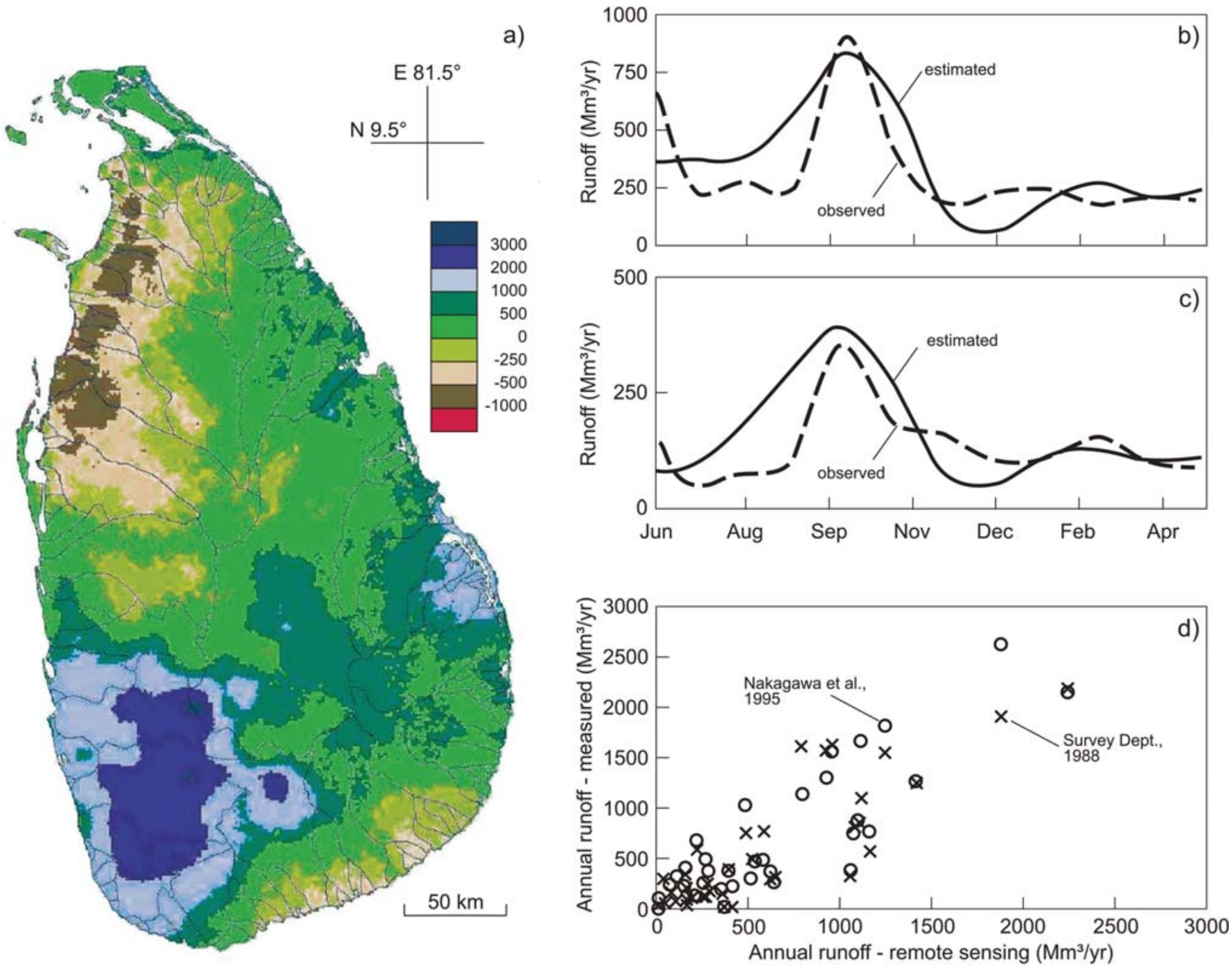

Figure 5.21. (a) Rainfall surplus (gross rainfall minus actual evaporation) between June 1999 and April 2000 across Sri Lanka, with the river basin boundaries superimposed; (b) observed and remote sensing predicted runoff for Kelani Ganga and Gin Ganga, two major rivers in Sri Lanka between June 1999 and April 2000; (c) comparison of measured and predicted runoff volumes for a majority of river basins in Sri Lanka. From Bastiaanssen and Chandrapala (2003).

Many of these studies are based on large data sets providing a broad range of results from catchments in different climates. The number of catchments the studies evaluate ranges from 1 in local studies to more than 1000 in global studies. There are several studies that compare different regionalisation approaches, which results in a total of 41 and 19 results for predictive performance of annual runoff and inter-annual variability, respectively. The regionalisation methods used are regression, index methods, spatial proximity, process-based methods and methods using proxy data. The performance measure used in the assessment is the squared correlation coefficient, r^2, between predicted and observed mean annual runoff and between predicted and observed standard deviation of annual runoff. It is important to note that performance values presented in Tables A5.1 and A5.2 differ greatly depending on whether they are reported as specific mean annual runoff (in mm) or as volumetric runoff (in m^3). Performance values tend to be much higher when annual runoff is expressed in volumetric units (i.e., in m^3) since they include the effect of catchment area, which is always a strong predictor of runoff volume. In the figures that follow, this distinction is highlighted by displaying the performance values based on volumetric units as *crosses* and those based on specific runoff as *circles*. For comparison with the other runoff signatures in Chapter 12, the r^2 of annual runoff were calculated for all methods in all studies with the exception of tree rings. The 25% and 75% quantiles of these r^2 are 0.65 and 0.91, respectively.

Figure 5.22 and Tables A5.1 and A5.2 indicate that overall a good global coverage was achieved. For annual runoff, the assessments in humid and cold climates dominate, while the inter-annual variability is mostly assessed globally over several climate zones.

The analyses from the literature were stratified using the climate classes based on the updated Köppen–Geiger climate classification of Peel *et al*. (2007). The following classification criteria were applied. All locations with mean annual precipitation lower than a threshold value are classified as belonging to the B climate in Peel *et al*. (2007) and as 'arid' in this assessment. If 70% of the mean annual precipitation occurs in winter, the threshold (in mm) is 20 times the mean annual temperature (in degrees Celsius). If 70% of the mean annual precipitation occurs in summer, the threshold is 20 times the mean annual temperature + 28. Otherwise the threshold is 20 times the mean annual temperature + 14. For areas where mean annual precipitation exceeds the threshold, other climate types are possible. In this assessment, the locations where the temperature of the coldest month is not lower than 18 °C are called 'tropical' (A climate in Peel *et al*., 2007). The locations where the temperature of the hottest month is above 10 °C and the temperature of the coldest month is between 0 and 18 °C are defined as 'humid' (C climate in Peel *et al*., 2007). In this assessment, the locations with a Mediterranean climate (Csa and Csb) have been considered 'arid', even though they would belong to the C climate in Peel *et al*. (2007). Finally, locations where the temperature of the coldest month does not exceed 0 °C are defined as 'cold' (D and E climates in Peel *et al*., 2007). In studies where catchments from different climate classes were analysed together, the dominant climate class was used in the assessment. In the cases where catchments from all around the world were analysed in the same study, the climate class has been defined as 'global'.

Figure 5.22. Map indicating the countries included in the Level 1 assessment.

How good are the predictions in different climates?
Figure 5.23 shows that the highest performances are obtained for the cold and humid catchments, while they tend to be lower in arid regions. This indicates that the prediction of annual runoff in regions with a 'surplus of water over energy' is easier than in drier climates. The main reason behind this is that in arid regions a higher variability of dominant processes and the possibility of feedbacks with physiographic characteristics (i.e., evaporation, geology and vegetation) complicate the estimation of annual runoff.

Which method performs best?
Figure 5.24 compares the performance of different methods for estimating annual runoff and inter-annual runoff variability. The regionalisation methods used here are regression, index methods, spatial proximity and process-based methods for the performance of spatial predictions and methods using proxy data (i.e., tree rings) for the temporal accuracy of runoff estimation. The analysis includes ten results for annual runoff and ten results for inter-annual runoff variability that used different regression approaches to estimate annual runoff characteristics. The index method group includes eight results for annual runoff and nine results for inter-annual runoff variability that applied different Budyko-type models. The spatial proximity group consists of ten results for annual runoff.

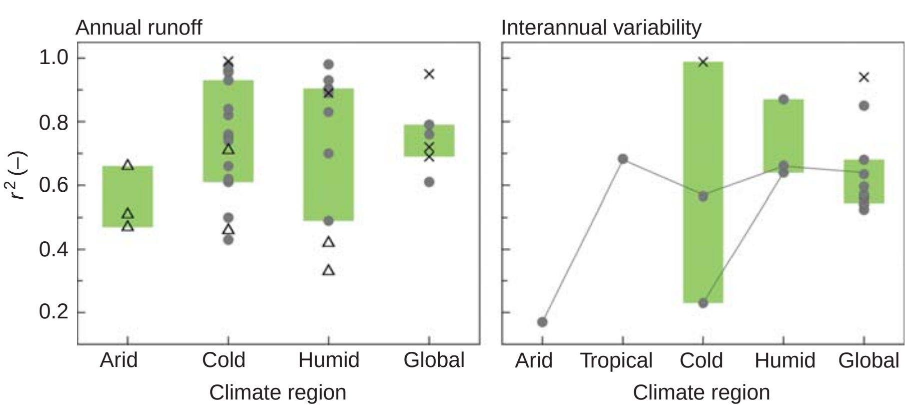

Figure 5.23. Squared correlation coefficient (r^2) of predicting annual runoff (left) and inter-annual runoff (right) in ungauged basins stratified by climate. Each symbol refers to a result from the studies shown in Table A5.1 (annual runoff) and Table A5.2 (inter-annual runoff). Triangles indicate the temporal variability assessment based on tree rings. Lines indicate studies where the same method was applied across different climate regions. Boxes show 25%–75% quantiles.

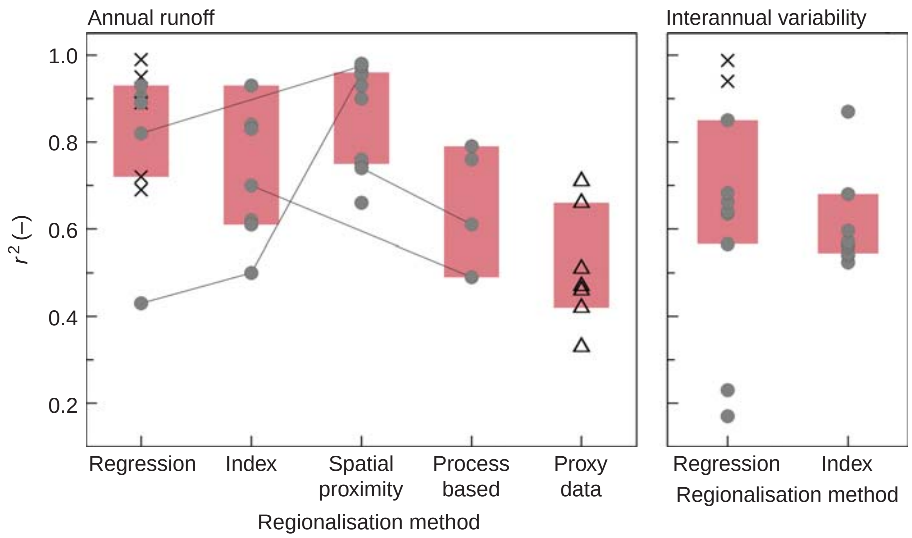

Figure 5.24. Squared correlation coefficient (r^2) of predicting annual runoff (left) and inter-annual runoff (right) in ungauged basins stratified by regionalisation method. Each symbol refers to a result from the studies shown in Table A5.1 (annual runoff) and Table A5.2 (inter-annual runoff). Lines indicate studies that compared different methods for the same set of catchments. Boxes show 25%–75% quantiles.

These are all interpolation methods including geostatistical approaches. Process-based models are only rarely applied and are represented here by four results that used different rainfall–runoff models. Finally, eight results that estimate annual runoff based on proxy data are available.

For annual runoff, spatial proximity methods show the best performance with median r^2 values close to 0.89. These results are mainly from north-eastern USA and France where a considerable number of stream gauges exist. The performance of regression methods tends to be slightly lower. The studies come from a mix of continents. Two studies in Europe compared spatial proximity with regression and found significantly better performance of spatial proximity. In regions where annual runoff varies rather smoothly in space and where a reasonable number of stream gauges exist, it is not surprising that spatial proximity methods would perform well. It should also be noted that some of the results for the regression methods are based on volumetric runoff values (crosses in Figure 5.24) so, if only specific runoff is considered, the median performance is actually lower.

Index methods (such as Budyko) also perform quite well, in fact as well as or better than regression, considering that some of the regression results are for volumetric runoff. The performance of process-based methods (mainly runoff models) tends to be lower, with a median r^2 of around 0.7. Clearly, the performance strongly depends on the way the models are calibrated to existing runoff data. For completeness, methods that use tree ring (proxy) data were included but, not surprisingly, suggest that the main focus of tree ring chronology is to reconstruct past runoff variability rather than to predict runoff in the present climate.

For the prediction of inter-annual runoff variability the regression and index methods perform similarly, with a median r^2 of 0.65 and 0.57 respectively. The results of the regression method have a much larger scatter. In general, the performance is somewhat lower than the performance obtained for mean annual runoff since, clearly, inter-annual variability is harder to predict.

How does data availability impact performance?
Figure 5.25 shows the predictive performance as a function of the number of catchments analysed in each study. Most of the studies used relatively large data sets, although this probably reflects the fact that most studies evaluate the accuracy of predictions in space. An exception is the prediction of temporal variability by proxy methods (i.e., tree rings), which is usually tested only on single catchments.

The results indicate that the performance does not seem to depend on the size of the data set. Apparently, only data from a small number of gauged catchments are needed in order to predict mean annual runoff within the study area in ungauged basins. There may be two effects related to scale. The first is that the total heterogeneity tends to increase as the size of a region increases, which would be expected to lower the performance if the same method is used in the entire region. The second is that, with increasing sample size, the methods may be adjusted more reliably to the existing runoff data. These two effects may counterbalance each other as the size of the data set increases. The prediction of inter-annual runoff variability, on the other hand, is more specific and improves with the availability of larger data sets.

More detailed insight into the dependency of performance on both method and number of catchments per study is shown in Figure 5.26. Index-based methods have been evaluated mostly for data sets with more than 200 catchments, while spatial proximity and regression methods

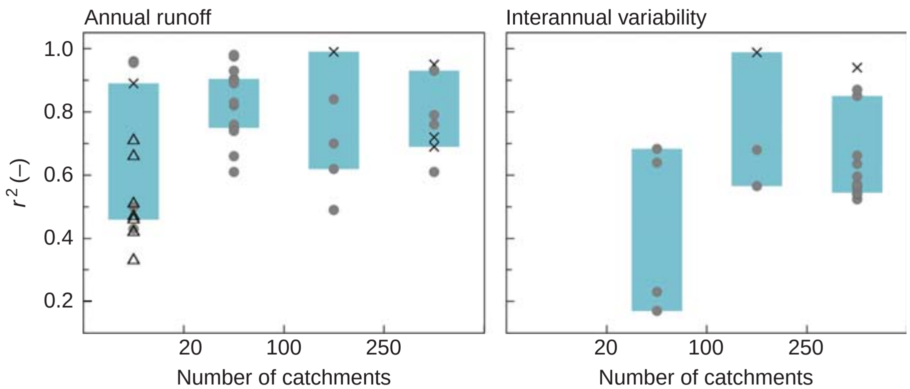

Figure 5.25. Squared correlation coefficient (r^2) of predicting annual runoff (left) and inter-annual runoff (right) in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies shown in Table A5.1 (annual runoff) and Table A5.2 (inter-annual runoff). Triangles indicate the temporal variability assessment based on tree rings. Boxes show 25%–75% quantiles.

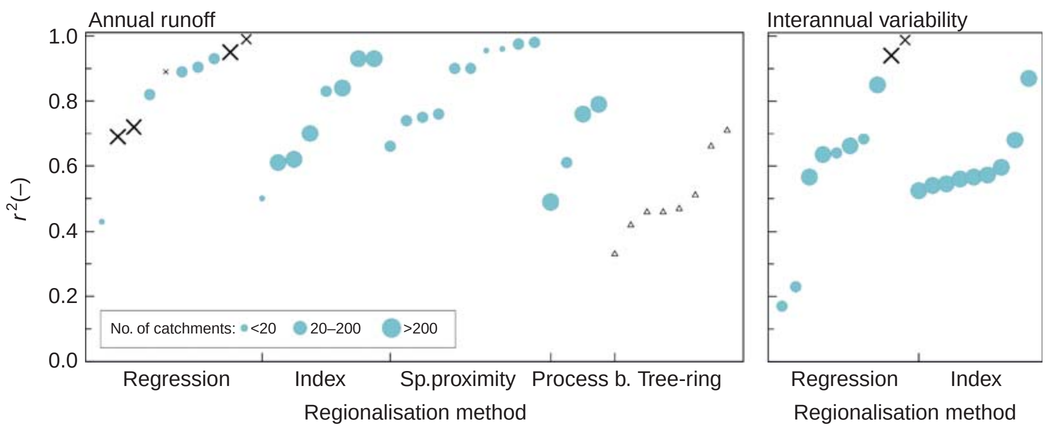

Figure 5.26. Squared correlation coefficient (r^2) of predicting annual runoff (left) and inter-annual runoff (right) in ungauged basins stratified by the regionalisation method and ranked by performance. Each symbol refers to a result from the studies shown in Table A5.1 (annual runoff) and Table A5.2 (inter-annual runoff). Circles refer to the performance indicators based on specific runoff, crosses to the ones based on volumetric units. Circle size indicates number of catchments per study.

have been mainly tested for data sets with less than 200 catchments. The type of method seems to more strongly control the performance than the number of catchments per study.

The comparison between regression and index methods for inter-annual runoff variability indicates that the methods have been tested on very similar data set sizes with similar performance.

Main findings of Level 1 assessment

- In cold and humid regions the performance of predicting the mean and variability of annual runoff in ungauged basins tends to be better than in other climates.
- Methods based on spatial proximity perform best, followed by index methods and regressions, which perform similarly.
- At the scale of the analysis (regional and global) the performance of the processed methods available for the analysis is lower. Calibration seems to be essential.
- Predictions of mean annual runoff do not depend on the number of catchments in the study, while predictions of annual runoff variability improve with the number of catchments.

5.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A5.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and inter-study comparison of results. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. The Level 2 assessment is based on the global data set of Peel *et al.* (2010) that provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment. This data set combines data from

861 catchments located in 82 countries around the world. No data for the inter-annual runoff variability were available, so the Level 2 assessment presents only results for mean annual runoff. In order to identify differences in global and local scale analysis an additional assessment for 220 catchments in Austria was also performed (Viglione *et al.*, 2013b). Based on the data availability and global coverage, three approaches were applied: two statistical approaches, global and regional regression, and a Budyko index model. The normalised error (NE) and the absolute normalised error (ANE) were used as performance indicators (Table 2.2). The NE highlights biases in the methods, while the ANE is a measure of the overall performance. For comparison with the other runoff signatures in Chapter 12, the r^2 of annual runoff were calculated for all methods of both the global and the Austrian data. The 25% and 75% quantiles of these r^2 are 0.52 and 0.81, respectively.

Performance measures are presented in the following figures as a function of the aridity index, mean annual air temperature, mean elevation and catchment area. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e., higher up in the plot is better.

To what extent does runoff prediction performance depend on climate and catchment characteristics?

Before analysing the NE and ANE of the three chosen approaches, a regression analysis of mean annual runoff with area, mean annual precipitation and mean annual temperature (T_A) was performed in order to understand which predictors are important for mean annual runoff under different climatic conditions. The r^2-value, calculated based on specific runoff, did not exceed 0.5 for any of the regressions. This indicates that the size of catchments and global climate variability control only part of mean annual runoff patterns. While all three predictors were significant for estimating mean annual runoff in humid, cold and arid conditions, the analysis showed that for tropical climates T_A does not play any role.

The ANE error measure of mean annual runoff with respect to the four climate and catchment characteristics is presented in Figure 5.27. The results clearly indicate that the performance of all models decreases with increasing aridity (top panel). For global regression and regional regression the median ANE is around 0.2 for humid catchments and 1 or larger for arid catchments. For the Budyko approach, the errors in the arid catchments are smaller than for the other methods. Apparently the structure of the Budyko is more suited to predicting mean annual runoff in arid catchments than regressions. The regression models tend to overestimate mean annual runoff in arid catchments (Figure 5.28), while Budyko generally tends to underestimate mean annual runoff. It should be noted that the Budyko relationship was not calibrated but the regression coefficients were. The dependence of ANE on air temperature shows a similar, but less pronounced pattern. This means the difficult climates to predict are the arid catchments and not necessarily the catchments with a warm climate.

A clear relationship does not seem to exist between ANE and catchment area. For regression models, the variability of ANE performance between catchments of the same size is larger than for the Budyko model. This variability is the largest for catchments larger than 1000 km^2. The Budyko model seems to be a robust method. Even though there is a tendency for underestimating runoff, the results are more consistent for a given catchment size.

Which method performs best?

Figure 5.29 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments, and catchments with an aridity index below and above 1, respectively. Overall the Budyko model performs better than the two regression approaches. Regional regressions perform better than global regression. While the performance in humid catchments is quite similar for all three approaches, in arid regions the performance of the Budyko approach is much better than that of regressions. The built-in principle of water versus energy competition included in the Budyko model appears to provide an inherent advantage for mean annual runoff prediction compared to purely statistical approaches, particularly in arid regions. It should also be noted that in arid regions the regional regressions perform significantly better than global regressions, while this is not the case in humid regions.

Global scale results vs. local scale results

The results of the Level 2 assessments compared the performance of statistical and index methods on a global scale. The performance of methods for mean annual runoff prediction in a particular region depends on the hydrological variability, as well as data availability. As an example, Figure 5.30 compares different approaches for mean annual runoff prediction in 220 catchments in Austria (Viglione *et al.*, 2013b), which is generally humid with the aridity index ranging from 0.2 to 1.4. The following methods were used: the global regression model fitted to the global data set of Peel *et al.* (2010) using catchment area, mean annual precipitation and air temperature as catchment characteristics; the Budyko approach; a regional regression model fitted to the Austrian data (using the same catchment characteristics as

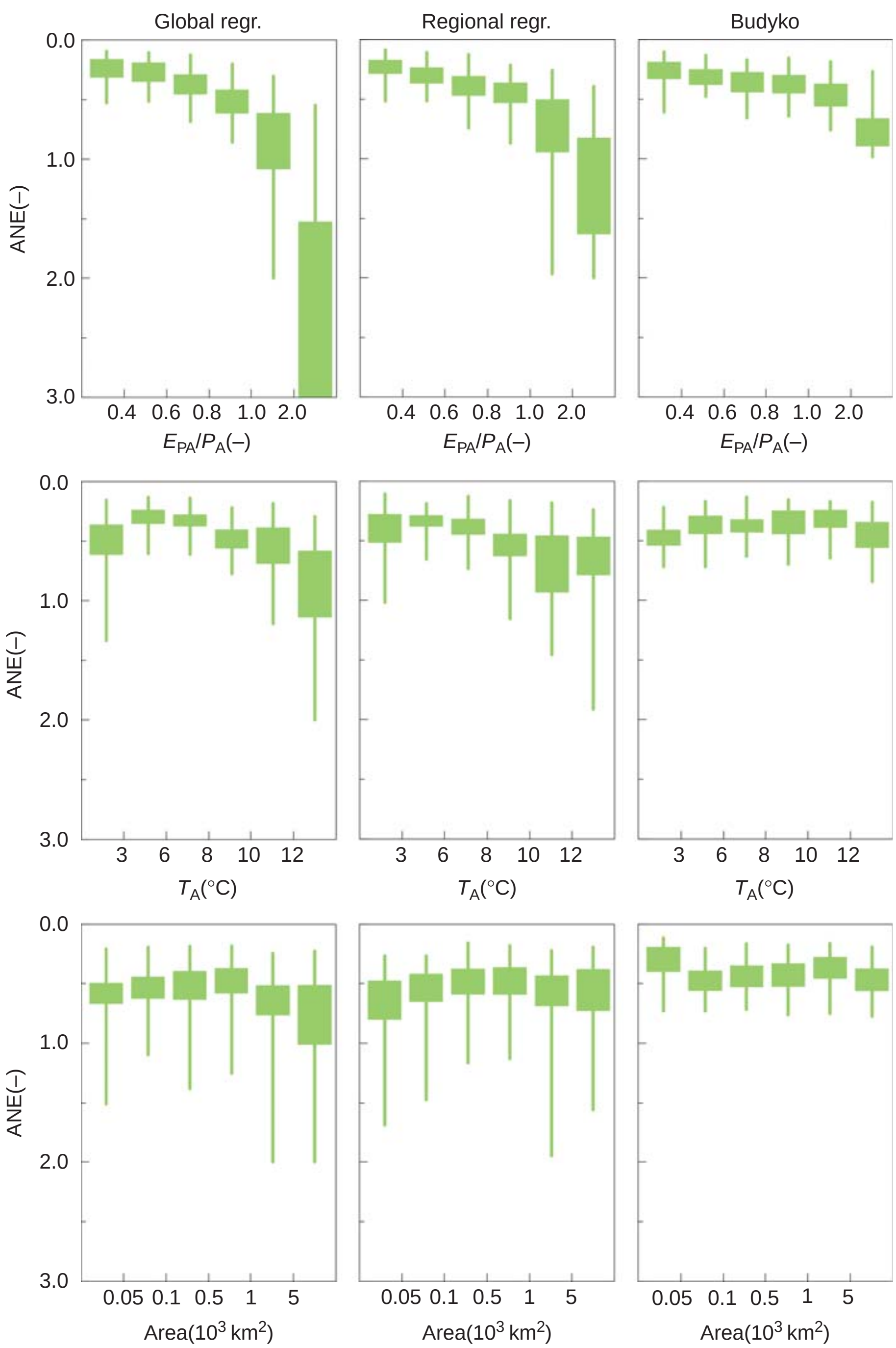

Figure 5.27. Absolute normalised error (ANE) of predicting annual runoff in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A) and catchment area for different methods. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

for the global regression: catchment area, mean annual precipitation and air temperature); a process-based (conceptual soil moisture accounting model at the daily time scale); and a geostatistical method (top-kriging). Overall the performance is much better than that of the global predictions as one would expect given the higher data availability. The global regression model gives ANE of around 0.3 as opposed to 0.4 for all humid catchments of the Level 2 assessment (Figure 5.29) indicating that the Austrian data set is in a range where the regression model works well. The Budyko model and the regional regressions perform better than the global regressions. Note, again, that Budyko was not calibrated to the Austrian data, while the regional regressions were. The

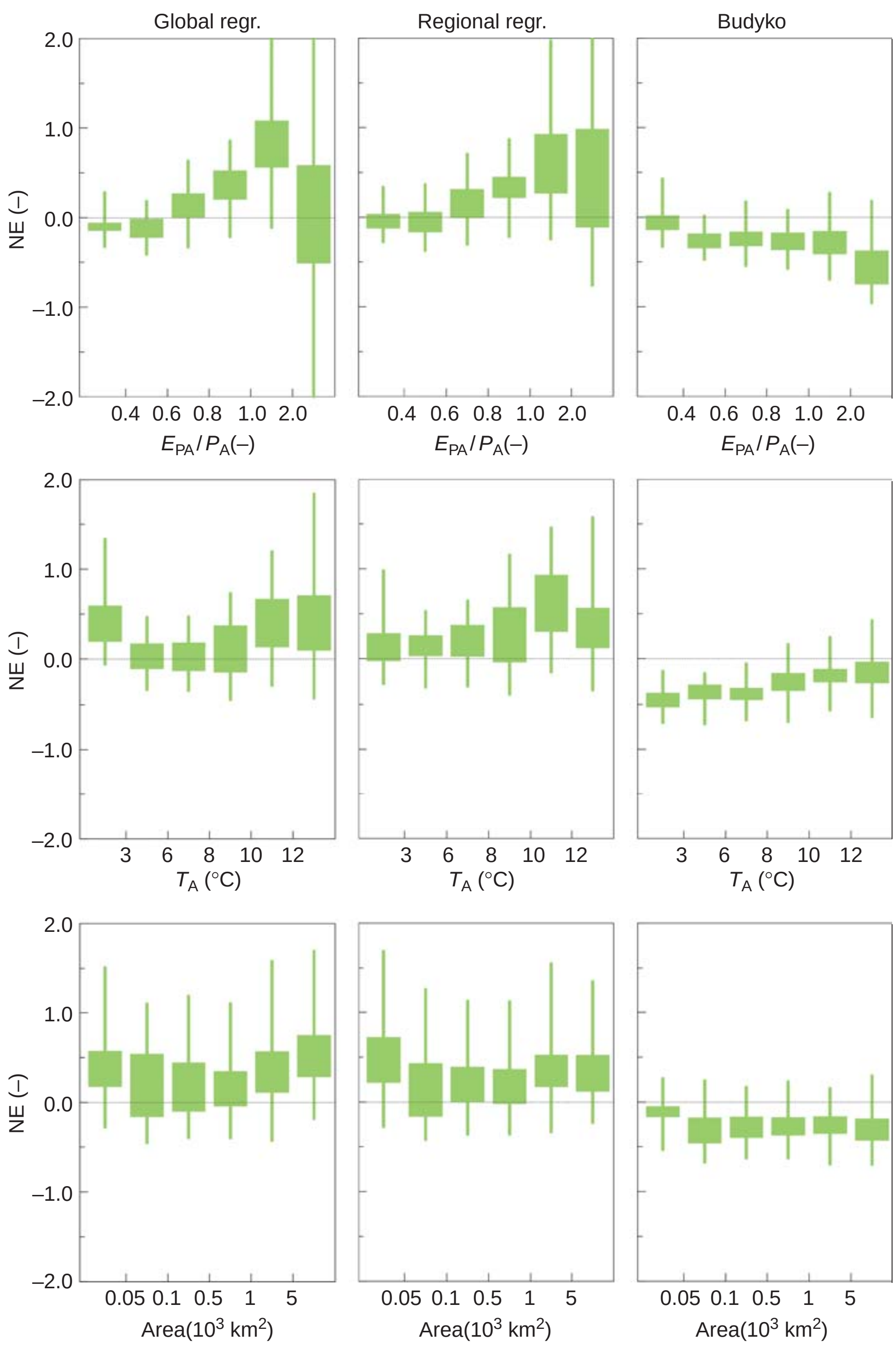

Figure 5.28. Normalised error (NE) of predicting annual runoff in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A) and catchment area for different methods. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

process-based approach and geostatistics perform best in predicting mean annual runoff in ungauged basins. This indicates that the use of regional data can improve the predictions significantly beyond global methods. The results also point towards the strength of the Budyko model, which is very good even though it was not calibrated.

Main findings of Level 2 assessment

- The performance of all methods of predicting mean annual runoff in ungauged basins decreases with increasing aridity.
- There is a tendency for the performance of the regression methods to decrease with air temperature but no apparent dependence on catchment size.

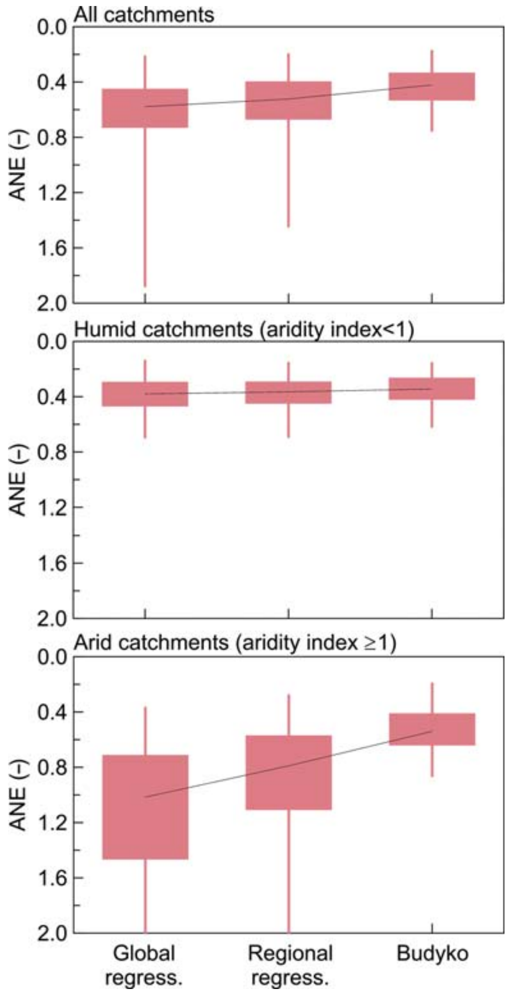

Figure 5.29. Absolute normalised error (ANE) of predicting mean annual runoff in ungauged basins for different regionalisation methods, stratified by aridity. (Top) All catchments; (centre) humid catchments (aridity index < 1); (bottom) arid catchments (aridity index ≥ 1). Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

- The Budyko approach tends to underestimate mean annual runoff. The regression models tend to overestimate runoff in arid catchments.
- In humid catchments, the Budyko approach and regression methods perform similarly.
- In arid catchments, the Budyko approach performs much better than the regression methods. Regional regressions perform better than global regression.
- In a regional case study, the performance of predicting mean annual runoff in ungauged basins for different methods increases in the following order: global regression, Budyko model, regional regression, process-based method and geostatistical approach.

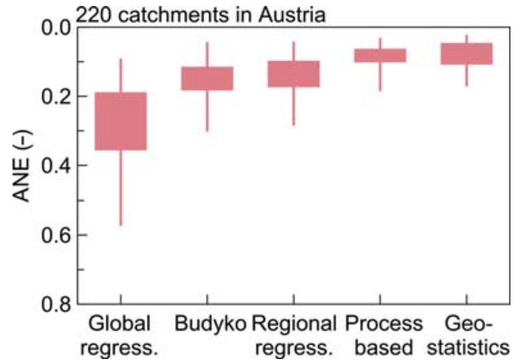

Figure 5.30. Absolute normalised error (ANE) of mean annual runoff estimated by global regression, Budyko model, regional regression (fitted to Austrian data), process-based (conceptual hydrological model) and geostatistical (top-kriging) approach in 209 humid catchments in Austria.

5.6 Summary of key points

- Annual runoff variability reflects, and is governed by, the relative availability of water (annual precipitation) and energy (expressed in terms of the annual potential evaporation). Consequently, the aridity index (the ratio of potential evaporation to precipitation) is the most widely used similarity measure for annual runoff.
- Increasingly, traditional interpolated spatial maps of mean annual runoff are being replaced with predictions based on regressions with climate and catchment attributes (as predictors and as surrogates for runoff processes), geostatistical interpolations in data-rich regions, and the application of index-based methods that exploit the competition between water and energy (e.g., Budyko curve and related methods).
- Budyko-type methods have the advantage that they reflect the co-variation of climate, catchment properties (including vegetation) and runoff, and exploit their interrelationships in a holistic way. Another advantage of Budyko-type methods is that they exemplify the benefits of a comparative hydrology approach, learning from similarities and differences between different places.
- Under humid, arid and cold climate conditions, catchment area, mean annual temperature and mean annual precipitation are important predictors for mean annual runoff in the regression approach (with the exception of tropical climates where mean annual temperature does not have much predictive power). This reflects the capacity of these predictors to capture the combined effects of several process controls on annual runoff. Co-evolutionary indices that are reflective of annual runoff variability are drainage density and vegetation patterns (fraction of vegetation cover, as well as relative fractions of deep-rooted trees and shrubs).

- Process-based methods, especially those that belong to the derived distribution category, can assist in interpreting the process basis of the index-based relationships (e.g., Budyko), help understand their applicability to different situations, and can explain the reasons for the scatter (and hence uncertainty) around the mean Budyko curve.
- Comparative assessment of all methods used for prediction of annual runoff in ungauged basins indicated that predictive performance decreases with increasing aridity (shown in both Level 1 and 2 assessments). Budyko-type index methods perform better in arid regions (Level 2 assessment) compared to regression approaches, as they are built around the principle of water versus energy competition. Spatial proximity methods (e.g., geostatistics) outperform other techniques (Level 1 and 2 assessments). They require stream gauges in the region of interest.
- Annual runoff variability represents the foundation (i.e., low frequency variation) on which all other runoff variability is built. Understanding annual runoff variability is the key to understanding the remainder of the variability found in the runoff hydrograph. Annual runoff variability is also the signature that best reflects the co-evolution of climate, soils, vegetation and topography. Therefore, there is much to be gained from understanding the nature of annual runoff variability and how it connects to vegetation, drainage density and other patterns, which are all a result of the same co-evolutionary processes. Comparative hydrology represents a clear way forward for the joint investigation of these co-evolutionary patterns across different parts of the world.

6 Prediction of seasonal runoff in ungauged basins

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6.1 When do we have water?

Many regions of the world experience strong seasonality in climate (i.e., precipitation and temperature), and strong seasonal runoff variability. Predictable patterns in seasonal water availability are of significant benefit to society because they allow reliable planning and infrastructure development to supply water for agriculture (food production), municipal use (drinking water) and energy (hydropower production); and to efficiently allocate water between competing end users, including ecosystems. In Norway, the reliability of seasonal runoff has enabled that country to depend almost exclusively on hydropower for its energy needs. Human settlements in the vast Gangetic plain in northern India have historically depended on reliable seasonal runoff, including snowmelt, generated in the Himalayas. Figure 6.1 presents the hyetograph of estimated areal average precipitation over the Upper Ganges basin (87 000 km^2) and the runoff hydrograph measured near Kanpur (Bharati *et al*., 2011). There is a regular pattern in the seasonal runoff that mirrors seasonality in precipitation, which is also influenced by a strong orographic effect in this part of the world.

While reliability in seasonal runoff (where it exists) confers much benefit to society, unpredictability in the magnitude and timing of precipitation and runoff events can lead to frequent unplanned water shortages and human suffering. In the Indian example, however, the construction of dams and water infrastructure all along the river, a changing monsoon regime and rising temperatures are all starting to alter the magnitude and timing of runoff in the Upper Ganges, with concerns that these changes and the resulting lack of reliability have the potential to adversely impact millions of people further downstream (Bharati *et al*., 2011). Indeed, several nations in South Asia already regularly suffer from the lack of predictability and reliability of monsoonal precipitation, so this has become a recurring problem.

Information about seasonal runoff variations in ungauged basins is essential not only for the management of water resources (e.g., Hannah *et al*., 2011), but also for water quality and hydro-ecological management (Sauquet *et al*., 2008). Flow and temperature are primary determinants of the productivity of stream and floodplain ecosystems (Harris *et al*., 2000), and numerous ecological processes in rivers are sensitive to their seasonal variations (e.g., Biggs and Close, 1989; Richter *et al*., 1996; Poff

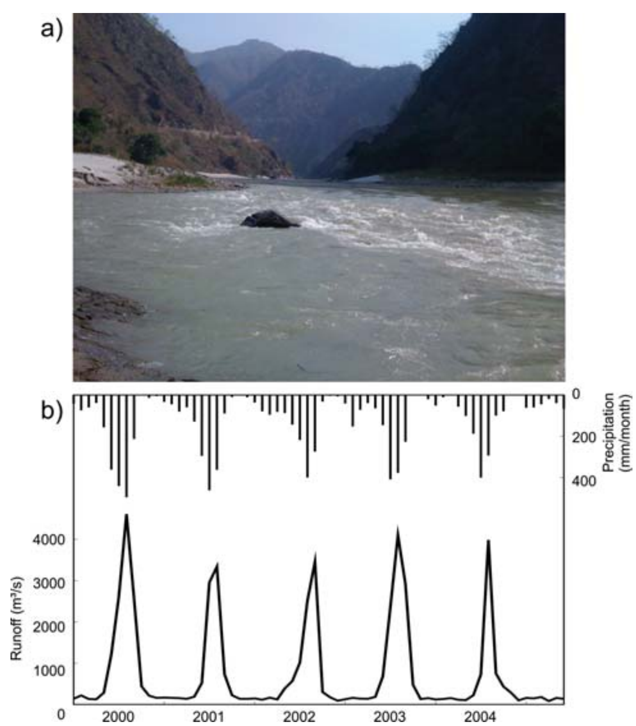

Figure 6.1. (a) View of Upper Ganges at Rishikesh in northern India; (b) monthly precipitation and runoff measured at the outlet at Kanpur Barrage. From Bharati *et al*. (2011). Photo: V. Smakhtin.

* Coordinating contributor

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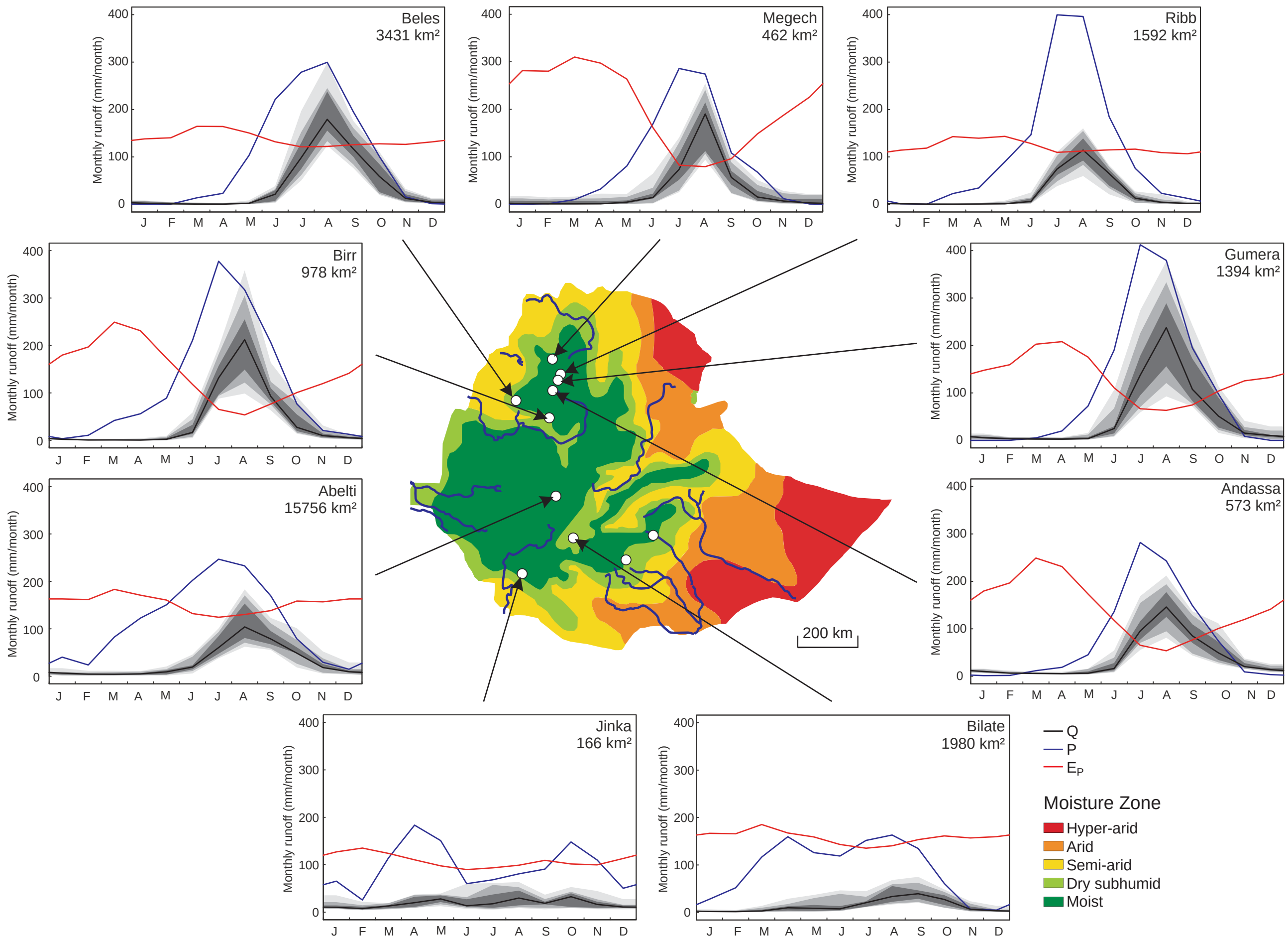

Figure 6.2. Regional differences in seasonality of precipitation (P), potential evaporation(E_P) and runoff (Q) across Ethiopia. Colours on the map refer to aridity classes. Courtesy: Belete Berhanu.

et al., 1997; Cattanéo, 2005; Beechie *et al.*, 2006; Monk *et al.*, 2006, 2007, 2008; Olden *et al.*, 2006). The European Water Framework Directive has formalised the need for predictions of seasonal runoff variations within their river water quality and ecosystem health assessment framework. Seasonal runoff predictions in ungauged basins are also needed to support decision making about water supply and hydropower production (Niadas and Mentezelopoulos, 2008; Weingartner *et al.*, 2012). Estimating natural flow regimes in catchments where runoff is already modified by human impacts is essential for planning restoration activities (e.g., Petts, 2007). The questions of when water is available, how much water is available, and how reliably these questions can be answered, are therefore key issues for hydrologists concerned with environmental protection, infrastructure development and water resources management.

The focus of this chapter is on the mean seasonal pattern of runoff variability over the annual cycle (hydrological year), which is termed the 'seasonal flow regime', or 'flow regime' for short (e.g., Harris *et al.*, 2000; Bower *et al.*, 2004). However, the chapter will discuss the variability of seasonal runoff between years as well, since it has a significant bearing on the reliability of water resources for various human and environmental uses. The seasonal flow regime is a valuable indicator that can be employed in comparative studies (Falkenmark and Chapman, 1989) that classify and compare hydrological signatures across regions, nations and continents. Figure 6.2, for example, shows runoff, precipitation and potential evaporation (E_p) regimes for several catchments in Ethiopia. The regimes indicate clear regional heterogeneity. In the north of the country the flow regime has a single peak, immediately following a single peak in precipitation. In the south, there is little seasonality in runoff, and precipitation is bimodal. Even without detailed knowledge of the hydrology of Ethiopia, the flow regimes presented in Figure 6.2 provide a basis for hypothesising the likely locations and severity of events such as floods, droughts and low flow conditions. Inferences drawn from the flow regime curves are particularly valuable if these curves are highly reproducible from year to year, especially where there is a strong seasonality in the runoff. These characteristics generally indicate locations with simple hydrological responses that have a clear connection to dominant climatic drivers.

There are several ways of characterising the flow regime (both quantitative and qualitative), as a way to assist in the regionalisation of seasonal runoff in ungauged basins. Quantitatively, it is common to express the flow regime in a non-dimensional way as the monthly sequence of the Pardé coefficients (Pardé, 1933):

$$PK_i = \frac{Q_i}{Q_A} \tag{6.1}$$

where PK_i is the Pardé coefficient of month i (–), Q_i is the mean monthly runoff (ensemble averaged over a number of years) in month i (m^3/s), and Q_A is the mean annual runoff (averaged over the same years) (m^3/s). The Pardé coefficient allows for a quantitative inter-comparison of catchments with different absolute magnitudes of runoff. A more qualitative way to characterise seasonal flow regime, however, is through the use of 'regime type', which is usually based on a description of the long-term seasonality of runoff. Regime types may be defined on the basis of the seasons of the year in which runoff maxima or minima occur, the climatic and catchment characteristics, or the causal processes driving the seasonal runoff. For example, the regime typology identified in the *Hydrological Atlas of Switzerland* (Weingartner and Aschwanden, 1992) describes three main regime types: glacial (ice-fed), nival (snow-fed) and pluvial (rain-fed) regimes. Both the quantitative (e.g., Pardé coefficients) and qualitative (e.g., regime type) approaches are widely used in the regionalisation of seasonal runoff behaviour and will be reviewed later on in this chapter.

The seasonal flow regime builds a bridge between rapid variations in runoff, for example, captured by the flow duration curve (Chapter 7), while also directly impacting variability on long time scales, e.g., the annual and inter-annual (Chapter 5). Seasonality and variation in storage impact the occurrence of low flows (Chapter 8) and determine antecedent conditions, thus impacting the flood frequency curve (Chapter 9). The flow regime therefore informs runoff predictions over the full range of time scales addressed in this book (Chapters 5–10). The aim of this chapter is to review the processes that control seasonal runoff variability, to develop the foundation for its regionalisation through similarity indices, and to provide an overview and comparative performance assessment of different methods used to predict it in ungauged basins.

6.2 Seasonal runoff: processes and similarity

Examples of seasonal runoff and the flow regime for two very different catchments in Austria are shown in Figure 6.3. The photographs show the contrasting landforms and vegetation of the catchments. The catchment in the top row of Figure 6.3, the Lafnitz River, is a mid-elevation catchment in the eastern part of Austria, characterised by moderate annual precipitation and subject to human regulation. The flow regime of the Lafnitz exhibits little seasonality, and high relative variability (from year to year). The catchment in the bottom row of Figure 6.3, the Lech River, is a small, pristine Alpine catchment located at a higher elevation and receiving higher mean annual precipitation including significant snow. The seasonality in the flow regime is in this case very pronounced and, in comparison to the Lafnitz River, there is relatively less variability from year to year. It is of interest to understand why the seasonality is so strong in one river but not in the other and to explore why runoff in the catchment that has high seasonality is more consistent between years than in the catchment that shows little seasonality. Understanding the causes of these differences is essential if one wants to select methods for predicting flow regimes in ungauged basins and interpret the results of these methods.

This section reviews the dominant processes responsible for the shapes of flow regimes, and identifies similarity indices that can be used to relate known flow regimes to those of ungauged catchments. As in the case of annual runoff (Chapter 5), regionalisation and extrapolation of seasonal flow regimes relies heavily on grouping methods. Specific grouping techniques relevant to the flow regime curve are also reviewed.

6.2.1 Processes

The seasonal flow regime is also a basic hydrological fingerprint of a catchment reflecting the interplay of climate, geology, land use, vegetation cover and human modification. As in the case of annual runoff (Chapter 5), seasonal runoff variations are driven by the relative seasonality in precipitation and potential evaporation. At seasonal time scales, however, catchment storage processes often play a relatively more important role in driving runoff fluctuations than they do at annual time scales. Total continental water storage consists of water on vegetation surfaces, in the biomass in the unsaturated

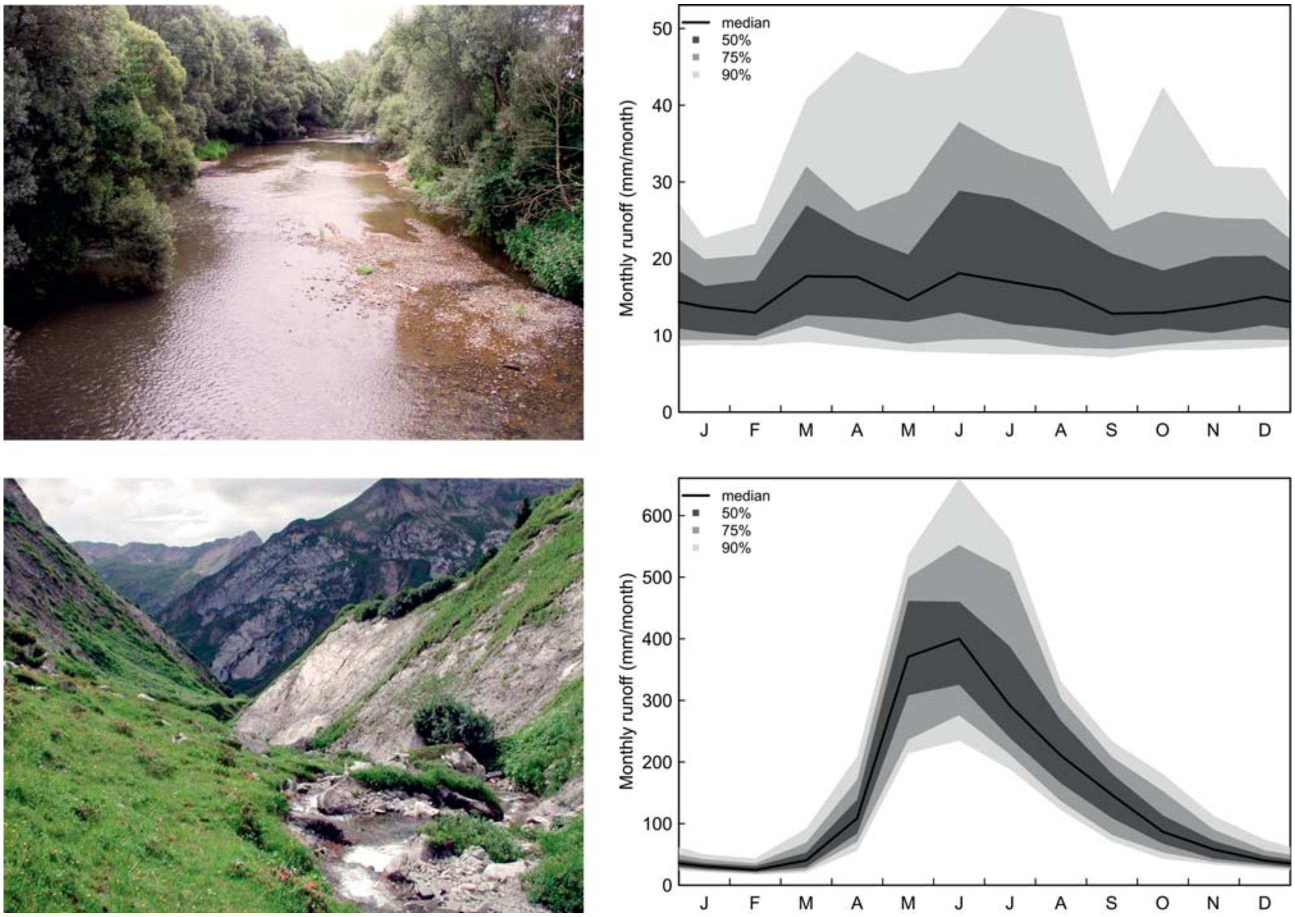

Figure 6.3. (Top) Lafnitz River at Dobersdorf, Austria (area 925 km^2, elevations range from 198 to 1725 m a.s.l., mean precipitation 806 mm/yr, porous aquifer in quaternary sediments). (Bottom) Lech River at Lech, Austria (area 84.3 km^2, elevation 519–2378 m a.s.l., mean precipitation 1513 mm/yr, permeable hard-rock aquifer, chalk-shale). Photos: HD Burgenland, C. Reszler.

soil or rock zone, in groundwater, snow and ice, and water in rivers, wetlands, natural lakes and man-made reservoirs. Here the role of storage in snow and ice, which has an intrinsically seasonal component, is separated from the role of storage in geological and soil formations, which are influenced primarily by climatic seasonality. Other factors, including the seasonality of vegetation activity (phenology) and transpiration losses, are also discussed.

Climate forcing

The first-order control on seasonality of runoff generation is climate (Bower *et al*., 2004). Many regions of the world exhibit strong seasonality in climate forcing, ranging from completely in-phase to completely out-of-phase (Section 5.2.1). Figure 6.2, for example, presented a regional picture of seasonal variation of precipitation, potential evaporation and runoff in Ethiopia. The relative strength of seasonality in water and energy availability, e.g., a strong uni-modal pattern of precipitation in the north of the country, combined with a pronounced seasonality in E_p, and a strongly bimodal pattern of precipitation in the south of Ethiopia, where E_p varies only a little throughout the year, are closely associated with the regional variations in runoff seasonality.

As alluded to earlier in the example of Asian monsoonal climates, in many areas the major source of uncertainty in predicting seasonal runoff variability is prediction of seasonal precipitation variability. Such hydrometeorological variations require investigation and understanding of climate at the global and regional level. For example, large-scale atmospheric circulation patterns such as the North Atlantic Oscillation influence regional climate (e.g., precipitation, humidity and air temperature), with direct consequences for river runoff (Laizé and Hannah, 2010). Improved understanding of climate seasonality, in the context of regional climate features, and their relationship to the flow regime is needed to improve predictions of

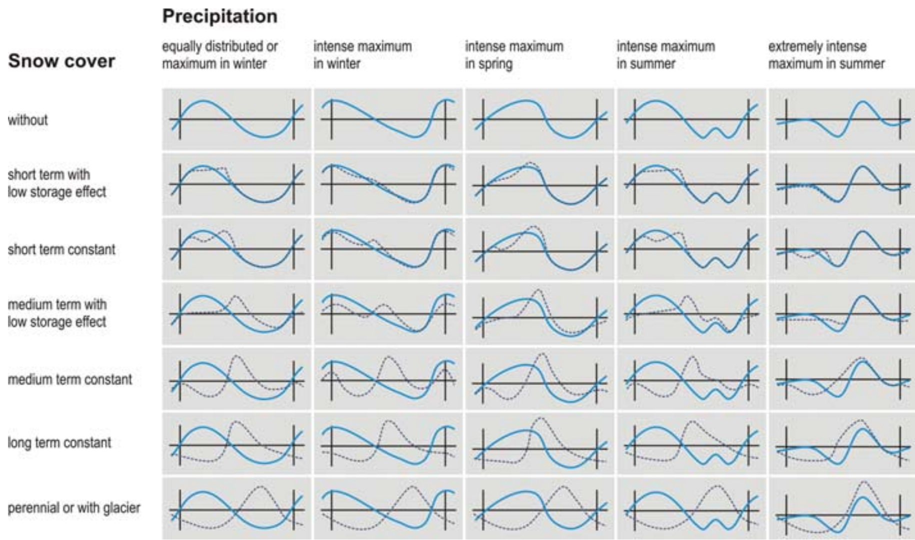

Figure 6.4. Schematic of the influence of precipitation and snow cover on the shape of the runoff regime. Blue lines represent the seasonal runoff regime without the effect of snow; grey lines represent the seasonal runoff regime with the effect of snow storage and melting. After Grimm (1968).

runoff seasonality in different places and at different times (Cloke and Hannah, 2011). Better quantification of the inter-connections between climate, atmosphere, land and surface hydrology is particularly important (Kingston *et al*., 2009). This research lies in the realm of hydrometeorology and climate science, and is not treated extensively here.

Catchment processes: storage in snow, ice and glaciers
As mentioned above, the role of storage has a significant impact on seasonality in runoff, strongly modulating the seasonality in climate. In this section we separate the effects of storage in snow and ice (dominant in cold regions), and storage in soils and aquifers (common to all regions), as they have different manifestations in seasonal flow regimes.

In cold regions, storage processes related to the accumulation and melting of the snowpack, ice and glaciers drive the strong seasonal runoff patterns. These effects are clearly illustrated in the comparison of the regimes of the Lafnitz and Lech Rivers in Austria presented earlier (Figure 6.3). The lowland Lafnitz River has low storage of frozen precipitation in its catchment, and therefore a generally flat flow regime. The Lech River, however, experiences pronounced seasonal snow accumulation and a well-defined snowmelt period, generating a highly seasonal flow regime. The relatively low between-year runoff variability in the Lech River reflects the low between-year variability in energy input (the regular seasonality that drives snow accumulation and melt). For the lowland Lafnitz River, the randomness of precipitation plays the dominant role in determining the between-year runoff variability. If one considers a larger region, such as Austria and Slovakia, one sees that in the snow-dominated mountainous parts of the region the seasonality is very stable even at the decadal scale, while the variability is higher in the hilly regions or the lowlands, where many mechanisms (e.g., convective vs. synoptic precipitation) may be equally important (Parajka *et al*., 2008, 2009a). In general, frozen water storage affects the flow regimes of rivers that drain mountainous regions (e.g., Alps, Himalayas, Rockies, Andes), polar regions (particularly in the northern hemisphere), and regions with a continental climate (e.g., the interiors of Russia and North America).

A generalised example of the interaction between seasonality in precipitation and the role of snow cover, as revealed in the seasonal flow regimes of European rivers, is presented in Figure 6.4 (Grimm, 1968). The flow regime in the first row on the left depicts a catchment from the temperate climate zone with equal seasonal rainfall distribution, no snowfall and high evaporation rates during the summer. The varied flow regimes along the horizontal axis result from different patterns of seasonal distribution of precipitation, while variation along the vertical axis arises due to the influence of snow. While the input of precipitation and energy (net radiation) determine the basic pattern of seasonal runoff, storage and snowmelt at the local level strongly modify the flow regimes.

Glaciers have a major influence on river flow regimes (e.g., Hannah *et al*., 1999, 2000, 2005). As little as 10% ice cover in a catchment can significantly affect river runoff (Fountain and Tangborn, 1985) (see also Figure 6.16). Glacier-driven catchments have a characteristic seasonal runoff pattern of peak glacier-melt in mid–late

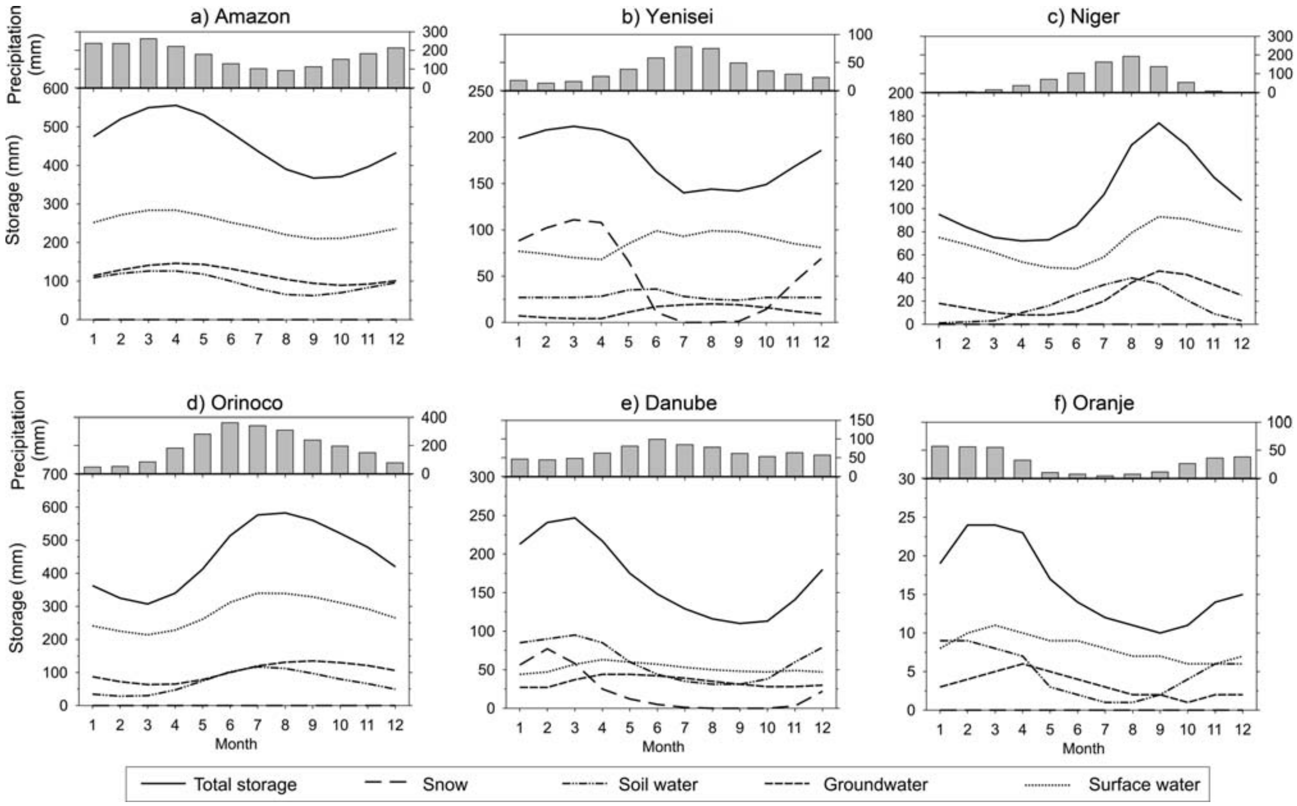

Figure 6.5. Annual cycle of precipitation and water storage components for large river basins; mean monthly values for the period 1961–95. Dominance of snow storage in cold regions and soil and groundwater storage in temperate and tropical regions is shown. From Güntner *et al*. (2007).

summer, generally following energy availability closely (Röthlisberger and Lang, 1987). This contrasts with purely snowmelt-driven catchments, where the loss of seasonal snowpack trades off against energy availability, often leading to peak runoff in late spring or early summer.

Catchment processes: storage in soil and groundwater

In contrast to snow and glacial processes, storage of water within the catchment's soils and aquifers does not have a directly seasonal component, but tends to reflect a response to the seasonality of water input via precipitation and evaporative losses via transpiration. Baseflow is usually proportional to storage, so the seasonality of storage helps to shape the flow regime. Water storage in soils and aquifers is important due to its role in supplying the evaporative demand of plants, and providing a reservoir, often used to supply human extractive uses. Seasonal variations represent the dominant time variable signal of water storage change (Güntner *et al*., 2007). Figure 6.5 shows the annual cycle of variability of precipitation and various components of water storage for six large river basins around the world. The annual fluctuations in total storage range from around 35% in the Amazon to around 60% in the Oranje and Niger Rivers. The contribution of individual storage compartments to total storage variability differs between the climate zones. Snow storage dominates in cold and polar regions (e.g., the Yenisei River), and soil water and groundwater dominate in the temperate and tropical zone. Groundwater storage changes tend to be expressed at inter-annual rather than seasonal levels due to the longer residence times in groundwater. Seasonal groundwater recharge, however, is often important in sustaining low flow phases (see e.g., Wood *et al*., 2001).

To support a process-based explanation of the link between the seasonal pattern of storage mechanisms within soil water and groundwater stores and the seasonal pattern of runoff generation, we use the classic example from the Havel River first presented by Wundt (1953) (Figure 6.6). During winter, precipitation exceeds evaporation, allowing an accumulation of soil and groundwater storage, and (eventually) increased runoff generation. The stored water sustains runoff during spring and summer when evaporation exceeds precipitation, but is depleted during this period. The net result is a mild seasonality in runoff, which

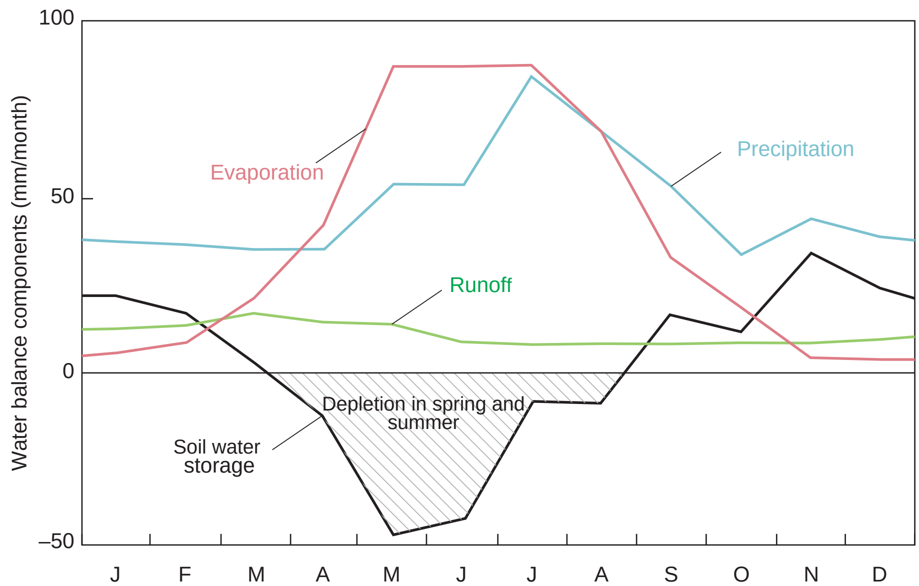

Figure 6.6. Seasonal water balance component of the Havel River (northern Germany). Adapted from Wundt (1953).

peaks during spring but is sustained through summer by loss of water from the soil storage, and consequently exhibits much less relative variation than the climatic drivers (evaporation and precipitation).

The many examples presented above (see Figures 6.4, 6.5 and 6.6) show that the effects of storage in snow versus storage in soils and groundwater can produce very different results in terms of the seasonality of runoff. In essence, the effect of storage on seasonality of runoff is largely a product of the dynamics of storage. When storage dynamics are out-of-phase with the precipitation–evaporation (P-E) seasonality (as in the Havel River), storage will tend to buffer the seasonal variation imposed by the relative availability of water and energy. Conversely, if storage dynamics are in phase with P-E dynamics, as in the case of snow accumulation and melt, storage acts to exaggerate the underlying seasonality.

Land surface processes and vegetation phenology

Vegetation dynamics provide a throttle on transpiration losses from catchments. When vegetation is actively transpiring, catchment storage tends to be depleted, runoff declines, and larger precipitation events are needed to generate runoff. Vegetation can thus play a major role in regional runoff seasonality, especially when vegetation activity is itself seasonal or variable. An example of such rapid vegetation change, in terms of both leaf area index (LAI) and photosynthetic capacity, is shown by work on the deciduous forests in north-eastern USA (Thompson *et al.*, 2011a). Studies of eddy-covariance records demonstrate that a spring increase in potential evaporation (primarily driven by energy availability) preceded the observed increase in transpiration by approximately one month. The difference appears to be primarily associated with vegetation activity. In deciduous sites, such as the Morgan Monroe State Forest shown in Figure 6.7, increases in evaporation (*E*) lagged behind increases in leaf area, suggesting that full canopy activity was not achieved during the early part of the growing season, despite increasing leaf area. Temperature limitations were correlated with the lag, suggesting that reduced stomatal functioning due to low temperatures may have been responsible. Applying a correction for soil temperature (Jolly *et al.*, 2005) allowed estimation of the correct seasonality in evaporation (Thompson *et al.*, 2011a).

The consequences of variability in vegetation activity, beyond measurements of LAI alone, appear to be relevant in attempts to model the properties of the seasonal flow regime curve. Seasonality in the flow regime may occur even when seasonality in precipitation is weak (e.g., in south-eastern USA). Temperature corrections that mimic phenological variation are needed in order to reproduce the seasonality in the flow regime curves in Appalachia and the eastern USA (Ye *et al.*, 2012), suggesting that accounting for vegetation function while estimating evaporation is an outstanding challenge for seasonal runoff prediction.

The role of vegetation activity in changing runoff behaviour can be identified by a direct analysis of runoff dynamics during the spring period as vegetation activity increases. Czikowsky and Fitzjarrald (2004) explored whether

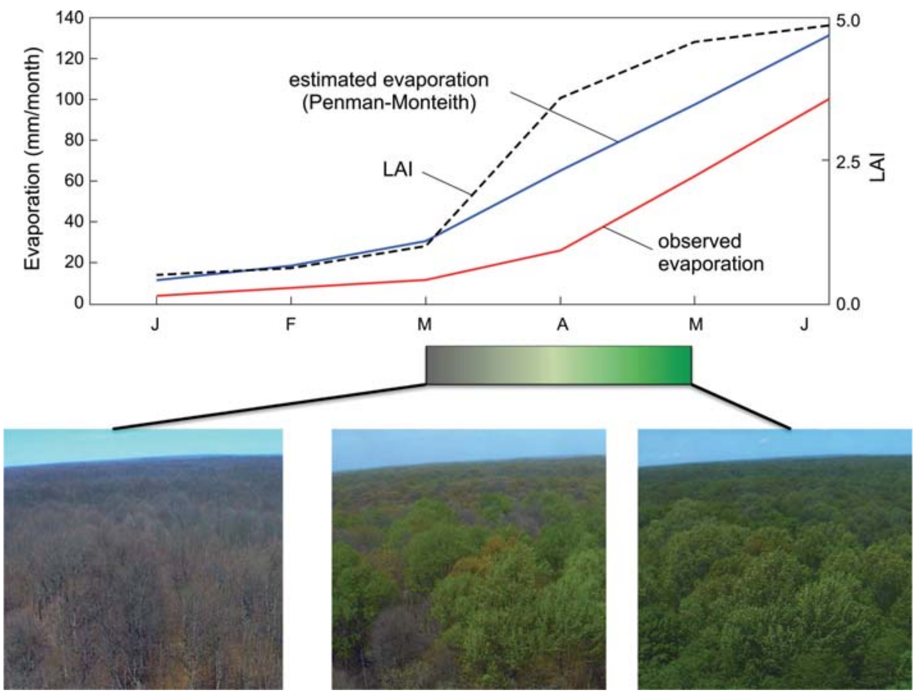

Figure 6.7. Lag in evaporation (E) relative to leaf area index (LAI) increase and potential evaporation (E_p) increase at the deciduous Morgan Monroe State Forest, Indiana, USA, during the first 6 months of the year. Results are averages of E_p computations (using the Penman–Monteith equation) and measurements over a 6-year period. Photos: D. Dragoni.

changes in seasonal flow regime could be used to track vegetation phenology and the onset of spring in eastern USA. Three *runoff metrics* were examined: (i) the difference between precipitation and runoff volume ($P-R$), calculated with a 30-day moving average; (ii) a measure of the mean recession constant, estimated as the time period required for a flood hydrograph to decay to $1/e$ of its peak; and (iii) the amplitude of diurnal runoff oscillations; all of which are impacted by increased transpiration activity. These runoff metrics were computed for 73 locations where comparison could be made between hydrological 'spring onset' and independent estimates of spring increase. The results are schematised in Figure 6.8 and demonstrate coherent relationships between the phenological signature identified in the runoff record (i.e., panels a, b and c, relating to the above runoff metrics) and that inferred from terrestrial measurements. The delay of 20–25 days in the hydrological spring compared to the atmospheric conditions mirrors the delay between potential and actual evaporation observed at the Morgan Monroe site (Figure 6.7), and likely reflects the time scale needed for increased evaporation to change catchment storage at the end of winter, and may be influenced by the proportion of deciduous species in the catchment. The runoff-based estimates of spring date can also be used to track the onset of spring conditions across eastern USA (Czikowsky and Fitzjarrald, 2004).

The most important message from Figure 6.8 is that the signature of phenology in runoff data is thus strong enough to allow seasonal changes and bud-burst dynamics to be inferred directly from runoff observations. The implication of these observations for seasonal runoff predictions is that the spring increase in evaporation associated with trees leafing out significantly impacts runoff volumes and dynamics, and cannot be ignored under these circumstances. On the other hand, phenology does not appear to have a strong effect in areas with uniformly high potential evaporation and leaf area, such as the Amazon rainforest (Czikowsky *et al.*, unpublished data). In areas with significant deciduous forests (including dry or drought deciduous forests in the tropics and deciduous Mediterranean environments), however, the rapid increase or decrease in transpiration associated with leaf dynamics can impose significant changes on seasonal runoff (Cayan *et al.*, 2001).

Inter-annual variability in the flow regime

There are often significant variations in the seasonal patterns of runoff between years (see the grey bands in Figure 6.3). Inter-annual variability of seasonal runoff can be quantified by calculating the stability (or regularity) of the seasonal flow regimes (Krasovskaia, 1995; Pfaundler *et al.*, 2006). Changes in the timing of the seasonal flow regime can be related to the seasonal distribution and quantity of precipitation, while changes in the magnitude of the flow regime curve have been linked to large-scale atmospheric circulation, strength and timing of monsoonal systems, and the effectiveness of catchment storage in

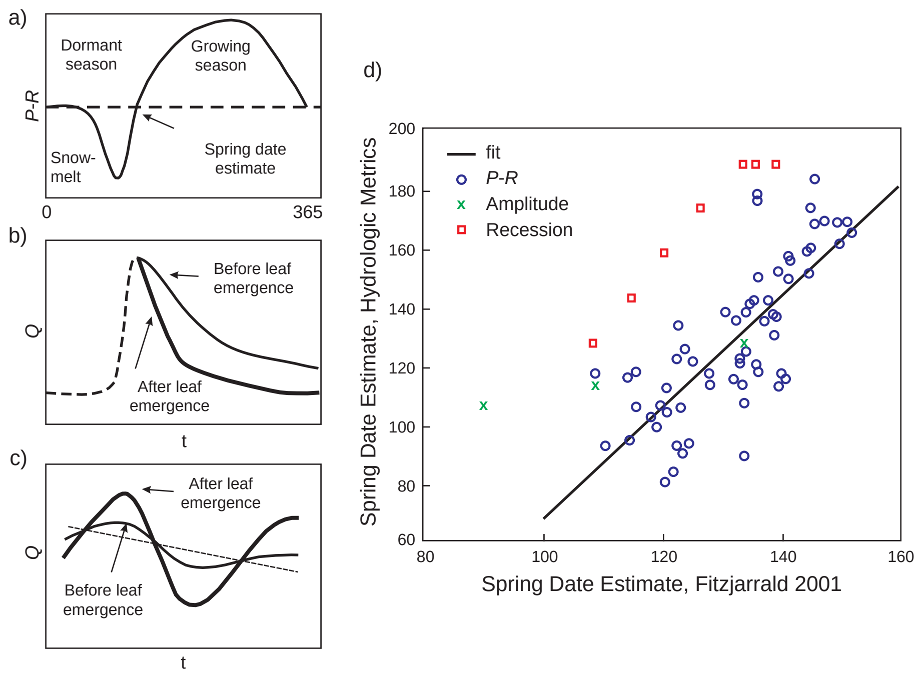

Figure 6.8. Runoff metrics used by Czikowsky and Fitzjarrald (2004) to differentiate runoff behaviour before and after vegetation activity increases in spring. (a) The 30-day moving average difference between precipitation and runoff, $P - R$; (b) more rapid recession dynamics due to increased evaporation; (c) increases in the amplitude of diurnal runoff oscillations; (d) hydrological predictions of spring date (based on each of the three runoff metrics) compared to standard meteorological (Bowen ratio) estimates of spring date from Fitzjarrald *et al.* (2001) show a delay of 20–25 days that can be attributed to the role of vegetation phenology.

snow, ice or soils in buffering these variations (Bower and Hannah, 2002; Bower *et al.*, 2004; Hannah *et al.*, 2005). The temporal stability of flow regimes has not been as widely studied as the variation in flow regime between catchments (but see Krasovskaia, 1997; Krasovskaia *et al.*, 2003; Bower *et al.*, 2004; Hannah *et al.*, 2005; Monk *et al.*, 2006, 2008). The stability of flow regimes relates directly to the reliability of seasonal patterns of runoff. There is potential to directly include year-to-year variability within classification schemes for regionalisation.

Figure 6.9 shows the inter-annual variability of the seasonal runoff in four rivers in Switzerland from 1993 to 2006. In the Alpine catchment of the Rhône (left panel), the change in the seasonal pattern from one year to the next is minimal (highly stable) due to the dominant influence of accumulation and melting of snow and ice. The Pardé coefficients (Equation 6.1) derived from the whole time series are representative for almost all individual years. Seasonal runoff estimates for catchments outside the Alpine zone are much less stable, as the regular pattern of water availability imposed by snow and ice diminishes, and the influence of rain and evaporation variability increase.

Change (human impacts)

There are very few river systems worldwide that have not experienced some change in the flow regime due to human modification: for example, one study found that globally 172 out of 292 rivers investigated were regulated by dams (Nilsson *et al.*, 2005). While regime modification is usually associated with dams, dam construction and operation may be intended for hydroelectric power production, water supply, flood mitigation, irrigation, navigation (increase of low flows) or recreation (Chapter 3). Hydropower production is particularly important in mountainous areas and may significantly affect the flow regime (Zolezzi *et al.*, 2011). Figure 6.10 gives an example of the development of reservoir capacity in the Rhône basin in Switzerland. During the 1960s, numerous reservoirs were constructed. This led to a significant reduction in the number of days with high flows (>400 m^3/s) and low flows (<50 m^3/s), reducing the amplitude and variability of the flow regime. Weingartner (1999) and Holko *et al.* (2011) give further examples of runoff modification through reservoir operation.

Modifications to the flow regime may also occur due to hydropower production, transfers of water from one catchment to another and irrigation (Maheshwari *et al.*, 1995; Shao *et al.*, 2003; Sauquet *et al.*, 2008). Withdrawals for irrigation frequently modify the natural flow regime in the drier regions of the world. Global food production involves a consumptive water use of 6800 km^3/yr, of which approximately 1800 km^3/yr (57 000 m^3/s) is supplied from rivers and groundwater (Falkenmark and Rockström, 2005). Land use change and urbanisation also influence the process of runoff generation, recharge of groundwater, evaporation rates and the runoff pattern. Land use change effects, typically, are most important in small catchments because of their local nature (Blöschl *et al.*, 2007).

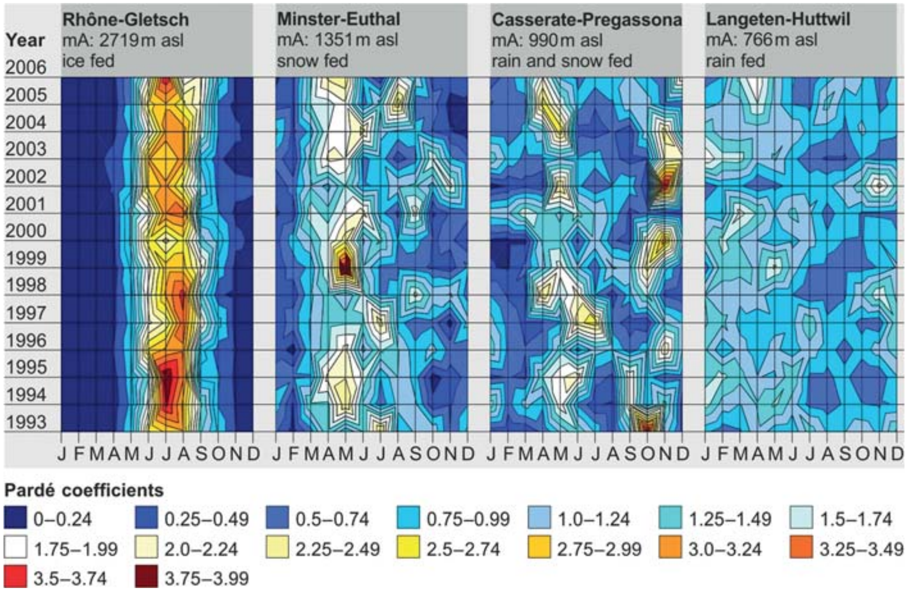

Figure 6.9. Inter-annual variability of seasonal runoff in four selected Swiss catchments; mA: mean altitude. From Pfaundler *et al*. (2006).

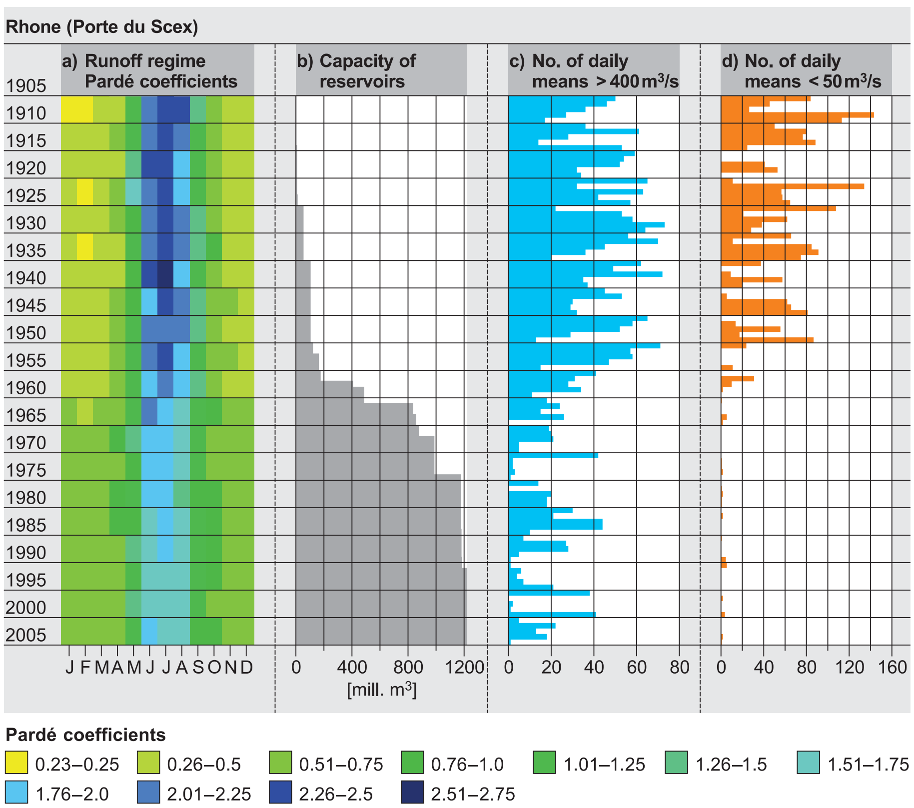

Figure 6.10. Development of reservoir capacity within the Rhône basin, Switzerland, at the inflow to Lake Geneva and its impact on runoff pattern (Pardé coefficient, see Equation 6.1). From Wehren *et al*. (2010).

6.2.2 Similarity measures

Catchments where the dominant drivers of seasonality and storage are similar (Section 6.2.1) could be hypothesised to have similar flow regimes. Although this hypothesis must be tested, it suggests that similarity indices for flow regimes should be derived based on both runoff data (*hydrological* similarity), and on climate and catchment characteristics (*climatic* and *catchment* similarity), see Figure 2.8 of Chapter 2 for definitions. If these indices can be related to the dominant processes described in Section 6.2.1, and to each

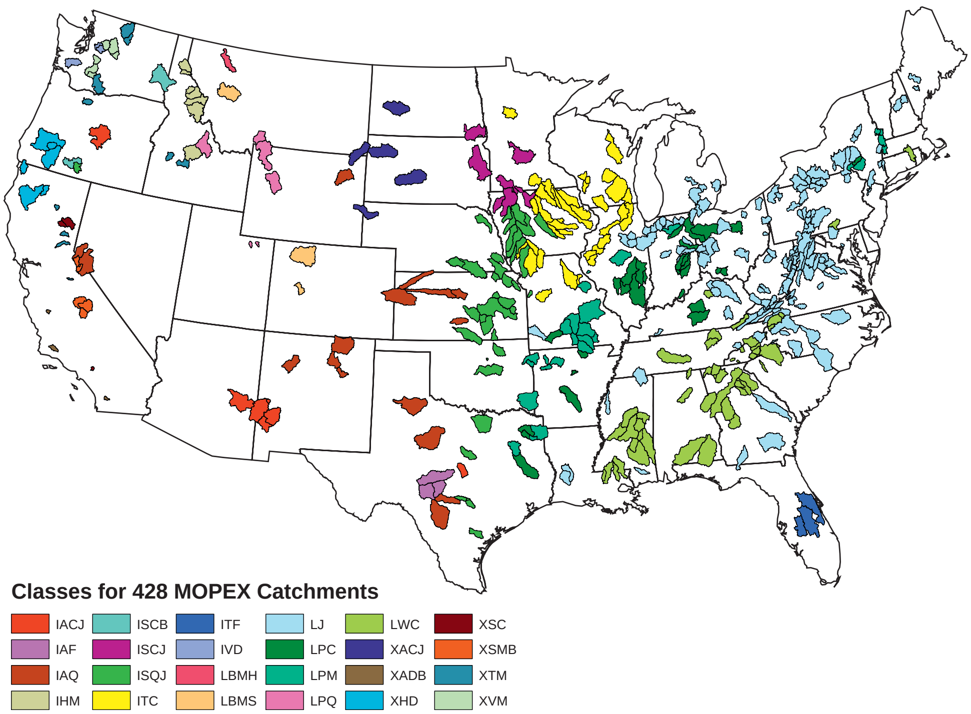

Figure 6.11. Classification of 428 catchments in the USA on the basis of similarity of seasonal flow regimes. From Coopersmith *et al.* (2012).

other, then climate and catchment characteristics can plausibly be used to group catchments with similar flow regimes (Section 6.2.3) and to estimate flow regimes for ungauged basins (Sections 6.3 and 6.4).

Runoff similarity indices

Similarity in runoff seasonality between catchments may be accounted for by considering the shape and magnitude of the flow regime curves independently or jointly (Hannah *et al.*, 2000, 2005). Qualitative approaches involve an interpretation of spatial patterns of the flow regime curves when superimposed on maps. The resulting classifications are usually discriminated between different sources of runoff (rain, glaciers, snowmelt, groundwater) and quantitative measures of the regime pattern (Krasovskaia, 1997). There have been many attempts to relate indices describing the regime type (e.g., the timing of runoff maxima and minima, the number of peaks or the amplitude of the flow regime curve) to the dominant processes (precipitation, evaporation, storage etc.). These efforts are often most successful in heterogeneous regions where water sources and dynamics vary markedly through space. Other similarity metrics include the ranking of monthly mean runoff, which has been used to distinguish glacial regimes (which have highest monthly mean runoff occurring in July followed by August and June) from snow regimes (where the ranking is June–May–July) in the Swiss Alps (Aschwanden and Weingartner, 1985); the development of composite indices, including timing and intensity of peak mean runoff and annual runoff (Grimm, 1968); and spectral analyses, where the monthly runoff is decomposed into harmonic components (Fourier series). The relative magnitude of the components of different wavelengths can then be used to classify and regionalise flow regimes by mapping and/or interpolation (Herrmann, 1970; Herrmann and Egger, 1980a, 1980b; Aschwanden and Weingartner, 1985; Shun and Duffy, 1999). Wavelet analysis, which allows for time variation in the harmonics, is gaining attention in flow regime studies (e.g., Smith *et al.*, 1998; Massei *et al.*, 2009; Rossi *et al.*, 2009).

Climate similarity indices

The seasonal flow regime is controlled by the relative timing of precipitation and potential evaporation, and the ability of the landscape to store water. Climate similarity indices that capture such variation include the Köppen–Geiger classification (Köppen and Geiger, 1936; Peel *et al.*, 2007), and the aridity index (Budyko, 1974) (see Section 5.2.1). Climate similarity indices have been effectively related to the seasonal flow regime, using a combination of the aridity index, seasonality indices for precipitation including its variability and timing, and timing of peak runoff (Coopersmith *et al.*, 2012). As shown in Figure 6.11, Coopersmith *et al.* (2012) found that 331 out

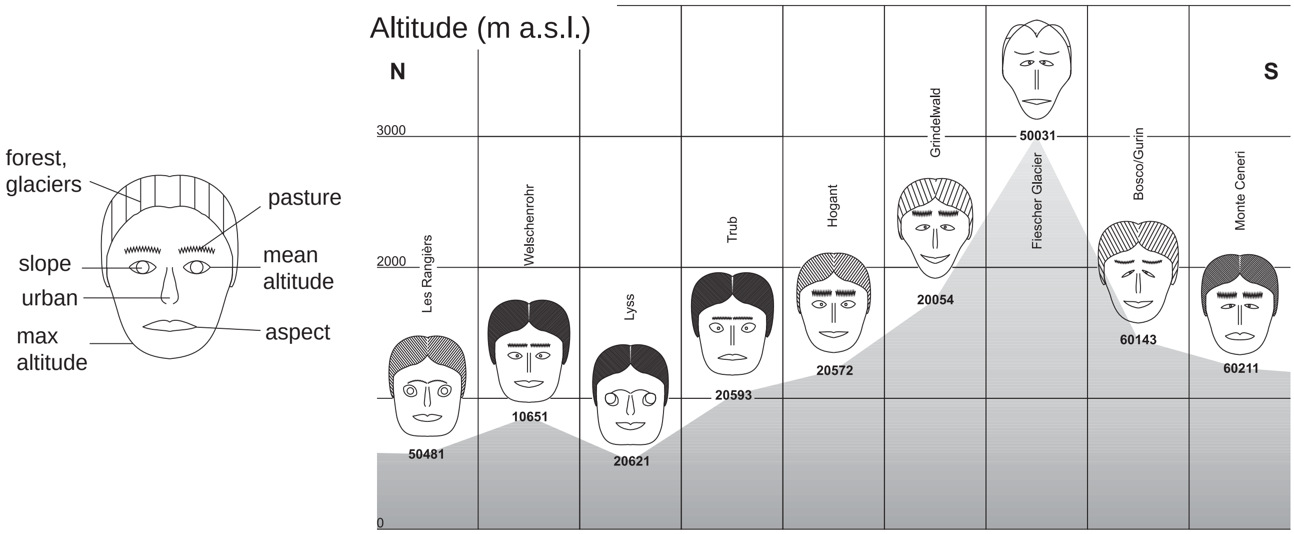

Figure 6.12. North–south transect across Switzerland in terms of basin characteristics visualised by Chernoff faces. From Weingartner (1999).

of 428 catchments studied as part of the international Model Parameter Estimation Experiment (MOPEX) in the USA fall into just six dominant groups when analysed according to hybrid climate and runoff regime similarity indices. Most of the classes turned out to be contiguous. For example, the LJ class in the north-east (light blue) is characterised by low seasonality of precipitation and late precipitation peak and covers a large geographical region.

Catchment similarity indices

The basin characteristics most relevant to regime classification include indices describing the surface and subsurface structure (e.g., catchment area, average elevation and slope, drainage density, properties of soils and rocks); land use (e.g., area of forests, area of glaciers); and hydroclimatology (e.g., antecedent conditions). Numerous indices can be developed that relate to these catchment structural features, including elevation, ice (glacial) coverage, drainage density, forested area and surface permeability (bare rock coverage) (Breinlinger, 1995; Laizé and Hannah, 2010). The role of structural features on seasonal runoff can be highly variable: for instance, a given basin property might influence runoff in one season, but not in others and, when compared to climate inputs, many properties have limited influence (Laizé and Hannah, 2010).

Hybrids of climate and catchment similarity have accounted for interception capacity, root zone storage, subsurface flow response and capacity and geomorphology in addition to aridity (Woods, 2003). Process-based models have also been used to derive other similarity indices, for example the aridity index, a storage capacity index and a drainability index (Yokoo *et al.*, 2008), although evaluation of the effectiveness of these similarity indices for the classification of seasonal flow regimes is ongoing. Clearly there is a plurality of indices or classifications being considered or used to characterise similarity of seasonal flow regime, both process-based and more holistic.

Visualisation of multidimensional indices

It is not easy to visualise many indices at the same time. A variety of symbolic representations, including trees, castles and humans, exist that can be used to represent catchment characteristics (Hartigan, 1975; Kleiner and Hartigan, 1981; Chernoff, 1973). For example, each element of a face can be assigned to a catchment characteristic. The value of the respective characteristics defines the shape of the element (e.g., the thickness of hair). These 'Chernoff faces' are a useful qualitative tool for identifying differences and similarities because most people can recognise the differences between faces. Figure 6.12 shows an example of using Chernoff faces to distinguish catchments along one north–south transect across Switzerland (Weingartner, 1999). The shape, size, placement and orientation of facial features – e.g., eyes, ears, mouth and nose – represent particular features of the catchments. Similarity in the appearance of faces should correlate to their similarity in parameter space. This example used an existing hydrological classification for Swiss catchments based on basin characteristics (Breinlinger, 1995). Faces of ungauged catchments were allocated to the classification by comparing the facial features of ungauged catchments to the classified examples. The results suggested that the Chernoff faces approach was appropriate for a first-order classification, largely due to the subjective nature of classifying catchments based on facial recognition (Weingartner, 1999).

As illustrated by the Chernoff faces example, techniques to visualise multivariate data may be an easy way to detect similarities, but are generally qualitative in nature. Because of subjective interpretation of images, it is also challenging to rank the importance of different parameters in this way. The advantage of subjective multivariate data, on the other hand, lies in the innate tendency of the human brain to identify patterns and undertake classifications, which is not always readily reproducible via algorithmic methods. A quantitative alternative for multidimensional visualisation, which is more algorithmic, is the Andrews curve (Andrews, 1972). An Andrews curve represents the characteristics of one catchment by the sum of a number of harmonics, each of them weighted with the magnitude of a catchment characteristic. Similar catchments have similar Andrews curves, allowing ungauged sites to be directly compared with other catchments that might represent a similar flow regime. An example of the application of Andrews curves for catchments in the southern part of Switzerland, in the context of PUB, is presented in Weingartner (1999).

6.2.3 Catchment grouping

As highlighted in Chapter 5, techniques of grouping and classification underpin most attempts to relate the hydrological behaviour of ungauged catchments to measured properties of gauged systems. This section focuses particularly on techniques for grouping that are *specific* to seasonal variations in runoff and the flow regime.

Grouping based on runoff-regime types

A classification of catchments according to a particular flow regime type offers an immediate approach for grouping, and has been used for over 100 years to classify global catchments (Woeikof, 1885; Arnell *et al*., 1993). Highly influential regime classification approaches include those of Pardé (1933), and L'vovich (1938). In 1933 Pardé published his classic regime classification, which inspired generations of hydrologists. Pardé's classification is qualitatively based on the driving processes, timing of the maxima and minima of runoff and inter-annual variability. The three basic regime types of Pardé (1933) are:

- Simple regimes with only two hydrological seasons (high and low water) and one primary driving process. The respective regime curve has only one peak.
- Complex I regimes with several hydrological phases induced by the contributions of different processes to runoff at different points across the hydrological year, e.g. rainfall, snowmelt. The respective regime curve exhibits several peaks.
- Complex II regimes can be found in large rivers, which have tributaries with different types of flow regimes, whereas simple regimes and Complex I regimes are more likely to characterise medium and small catchments. Complex II regimes cannot be directly related to specific hydrological processes. They result from the stacking or overlapping of various processes from the constituent sub-basins.

L'vovich's (1938) classification scheme is a development of Woeikof's work. Whilst elaborated independently, it is quite similar to the classification of Pardé (1933). L'vovich's classification is based on the seasonal timing and intensity of the largest mean monthly runoff (e.g., spring maximum with more than 50% of total annual runoff). Furthermore, the main generation processes of runoff are included (e.g., snow-fed). L'vovich's classification scheme was developed using data from small catchments where there is a more direct link between dominant processes and regime type. L'vovich's study was the basis for a global regime classification presented in the *Mira-Atlas*, published in 1964. In the same year, the UNESCO asked the International Geographical Union (IGU) to found a commission to contribute to the first International Hydrological Decade (1965–74). One of the main tasks of this new IGU commission was to analyse and map the flow regimes of the world. There has since been an explosion of studies focused on regime type and classification. Examples of studies include Kresser (1961), Gottschalk *et al*. (1979), Aschwanden and Weingartner (1985), Haines *et al*. (1988), Gustard *et al*. (1989) and Krasovskaia and Gottschalk (1992).

Grouping based on runoff: statistical approaches

Using similarity indices to define the flow regime (Section 6.2.2), objective methods to obtain groups with similar flow regime can be derived. As in the case of mean annual runoff variability (Chapter 5), cluster analysis (CA) is a common tool (e.g., Gottschalk, 1985; Haines *et al*., 1988; Guetter and Georgakakos, 1993; Dettinger and Diaz, 2000; Harris *et al*., 2000; Bower *et al*., 2004; Hannah *et al*., 2005; Monk *et al*., 2008; Laizé and Hannah, 2010; Kingston *et al*., 2011). As discussed in Chapter 5, CA depends upon the definition of distance metrics that can be applied between groups: for analysis of seasonal runoff variability these distances are usually defined in terms of Pardé coefficients or Fourier coefficients.

The application of CA to regional basins rarely results in spatially coherent groupings of catchments when applied to either annual runoff or to the seasonal flow regime. An example of the results of CA (Ward's method, see Chapter 5) applied to long-term river flow regimes based on their shape (dimensionless form) and magnitude (size) is shown for 28 Nepalese Himalayan basins in Figure 6.13 (Hannah *et al*., 2005). The groupings are

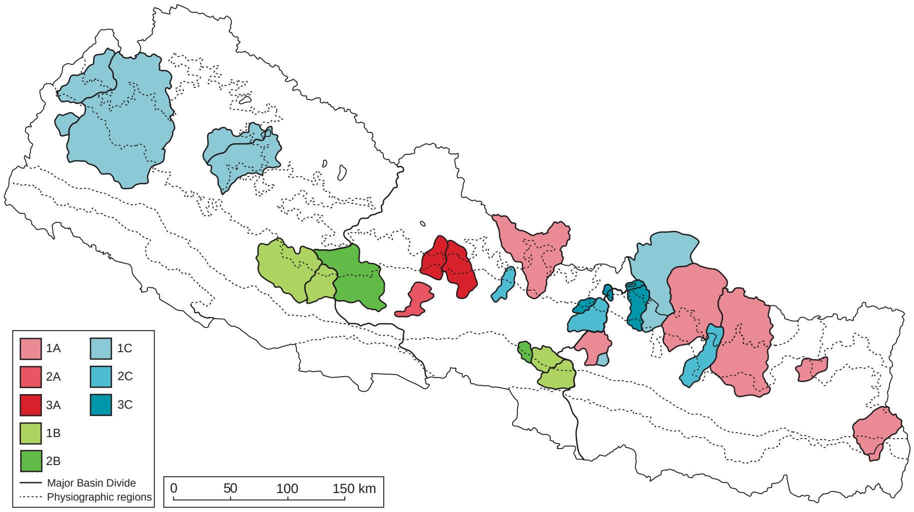

Figure 6.13. Flow regime classes across Nepal (1–3: increasing regime magnitude; A: July–August peak, B: August–September peak, C: marked August peak). From Hannah *et al.* (2005).

clearly discontinuous in space, but identify basin-by-basin physical and climatic controls on the flow regime, including basin latitude and longitude (which determine properties of the monsoonal rainfall); basin area above the snowline (i.e., melt-water contributions); basin geology (i.e., groundwater contributions); altitude and regional-local topography (i.e.. rain-shadowing and redirection of moist air masses).

A frequently employed clustering technique used within CA is the k-means clustering algorithm, which minimises the sum of squares of distances between catchments and their cluster centroids. Figure 6.14 shows an example of a k-means cluster analysis of seasonal runoff (Dettinger and Diaz, 2000) applied to 1137 stations around the world. The cluster analysis allowed a regionalisation of the 'shapes' of the seasonal flow regime according to membership in a cluster of rivers with similar shapes. Figure 6.14a presents the shapes of several representative clusters, while Figure 6.14b presents their spatial distribution as categorised by the month of peak runoff. Taking an example, Dettinger and Diaz explain that the cluster associated with September peaks has (on average) little runoff in other months (light solid magenta curve in Figure 6.14a), and members of this cluster are located mostly in subtropical regions (magenta areas in Figure 6.14b) where monsoon precipitation induces large runoff in the boreal autumn with low flows during much of the rest of the year.

Grouping based on catchment characteristics and climate: contiguous region

The simplest hypothesis for estimating homogeneous regions is that areas that are located within a given spatial proximity to each other should be hydrologically similar, in respect of the flow regime. The simplicity of this approach has an obvious attraction, but it is challenging to identify the number of independent groups and their boundaries from a purely map-based approach (Gustard, 1992). There are examples where the regime curve or more often the regime type is assigned to a region, which has been identified *a priori* based on political, administrative, climatic and hydrological (river basins) boundaries (Grimm, 1968; Keller, 1968; Arnell *et al.*, 1990; Smith *et al.*, 1998). Regions based on political/administrative boundaries may have limited physical significance (Lins, 1997). Nevertheless, they are often used due to the administrative organisation of hydrological databases and the difficulties of data exchange in and among countries (e.g., Viglione *et al.*, 2010c). Also hydrological boundaries (river basins) can be inappropriate if one considers that, for example, several major rivers cut across multiple countries and climatic zones. Additionally, there may be challenges related to the definition of the regime classification (which type of regime is present) and the regionalisation of the regime (where the regime type actually occurs) is often unclear. Hydrologists commonly find that models for estimating seasonal runoff in ungauged basins are applicable only within a limited region (Gottschalk, 1985), and that 'the hydro-climatic region in which a catchment is located should play an important role in any classification system' (Wagener *et al.*, 2007, p. 16). One way to codify this experience is to find ways to classify regions, and to ensure that data sets are available to characterise the hydrology of basins within each region. For example, Toebes and Palmer (1969) divided New Zealand into 90 regions based on geology and climate, and proposed that precipitation and runoff monitoring should be undertaken in a representative basin for each region (Duncan and Woods, 2004). Geographic grouping can be used to define the extent of applicability of calibrated and validated hydrological models for prediction in ungauged sites (Gustard, 1992):

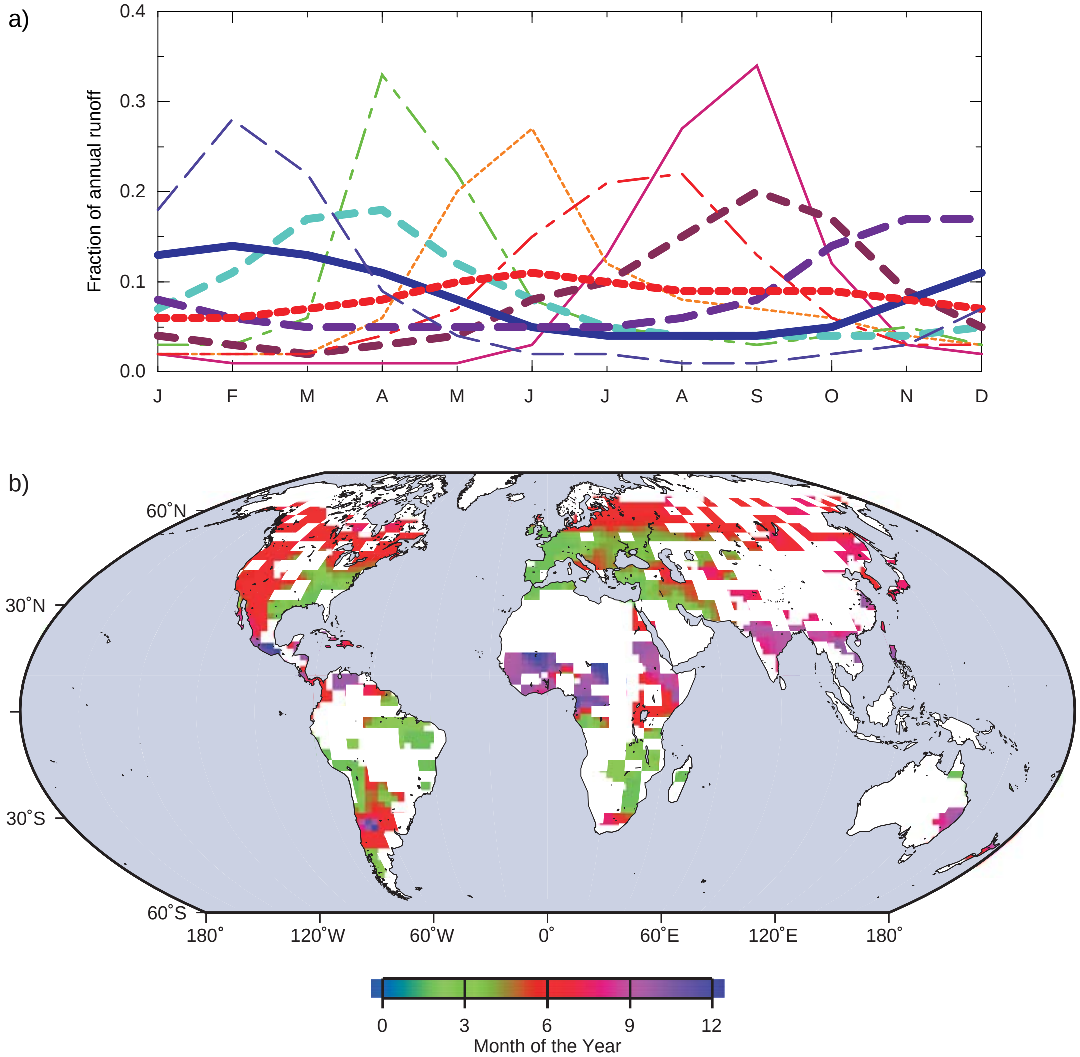

Figure 6.14. Clusters of mean monthly runoff: (a) Pardé coefficients of the clusters; (b) distribution of sites in the clusters, with cluster indicated by the peak month in (a). From Dettinger and Diaz (2000).

the 'regional regression approach' of Laaha and Blöschl (2006a) is based on this idea. In the most basic case, both a model structure and model parameters are applicable across a geographic region; however, contiguous regions may still be considered homogeneous if parameters are location specific, but a single model structure can be held in common (Gottschalk, 1985).

An alternative to defining coherent regions based on proximity is to rely on global climatological classifications to identify areas with similar flow regimes. Existing classifications, e.g., Köppen (1936) and Budyko (1974), have indeed been identified as determinants of runoff seasonality in some studies (Beckinsale, 1969). The relationship between climatic regions and seasonal runoff variability is often less direct than the relationship between climatic region and annual runoff, due to the nested/aggregated nature of river basins and the importance of geology, catchment morphology and land use for driving runoff generation at intra-annual time scales (Section 6.2.1). These complications have led some authors to suggest that climatic regions should *not* be used as a basis for the extrapolation of flow regimes between basins (Haines *et al*., 1988).

Clustering techniques can be applied to the delineation of geographical areas. In an example of 139 catchments in Sweden (Gottschalk, 1985), the results of the cluster analysis were graphically summarised in a dendrogram. Groups from the dendrogram were mapped and used to identify hydrological regions with similar monthly runoff patterns,

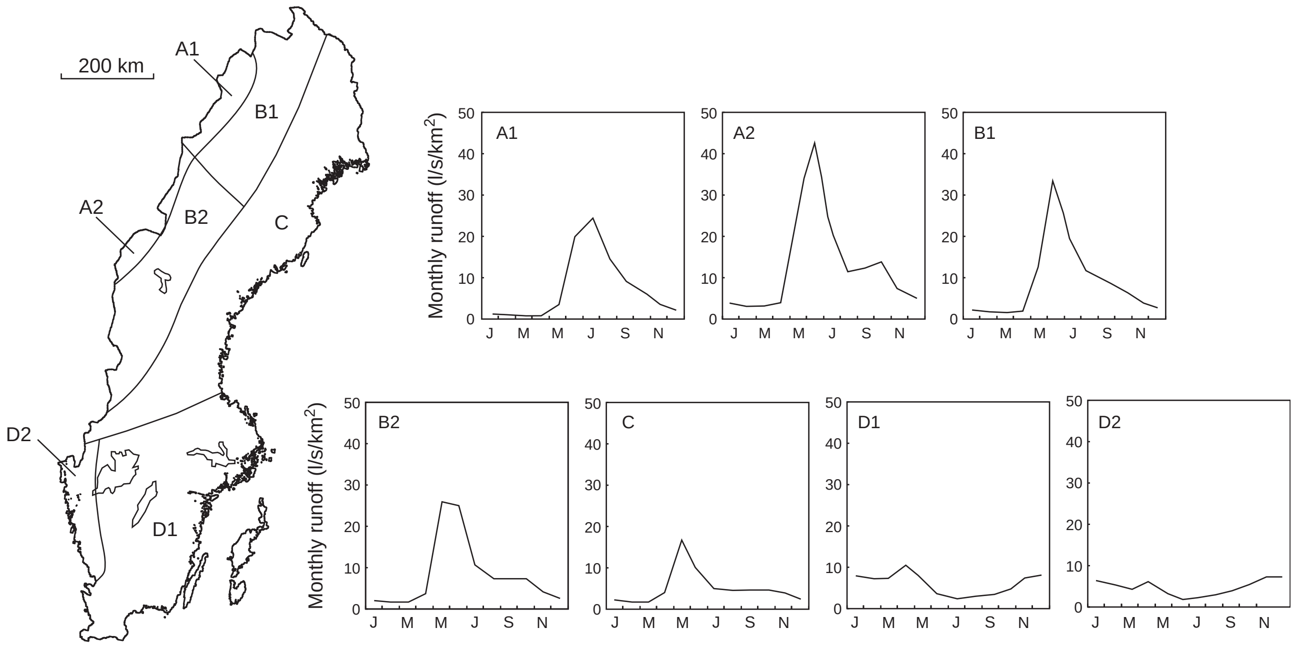

Figure 6.15. Hydrological regions of Sweden (left) and first empirical orthogonal function for each region (right). From Gottschalk (1985).

resulting in the geographically contiguous groups shown in Figure 6.15.

Grouping based on catchment characteristics and climate: non-contiguous regions

When formal statistical grouping techniques are applied to either runoff data or to catchment characteristics, the resulting groups are typically non-contiguous in geographic space. Although this leads to a spatially complex prediction task, geographical independence of the clusters ensures that they are not constrained to particular spatial scales, but defined instead from physical and climatic parameters (Snelder *et al*., 2009). The same range of statistical techniques that are used to group catchments on the basis of runoff characteristics can be applied, instead, to physical and climatic data: distance measures are now defined within a multivariate parameter space composed of the physically relevant catchment descriptors.

These approaches can be used when the physical and climatic factors used for analysis correspond well to the variations in flow regime. Environmental regionalisation principles (Bailey, 1995), extended to account for network conditions, climate, sources of runoff (including 'mountain', 'hill','low elevation' and 'lakes') and ecological characteristics, were used to map the rivers of New Zealand (Snelder and Biggs, 2002). The resulting groups could be classified as, for example, glacial mountain sources of runoff with glaciers constituting more than 2% of the catchment area (Duncan and Woods, 2004). Each region had a characteristic flow regime. The combination of climate and source of runoff was then used to predict Pardé coefficients for all rivers in New Zealand.

In contrast to statistical classification of the runoff regime alone, the multiple kinds of physical and climate data that can be used to characterise basins allow techniques such as classification trees to be employed. A classification tree tries to reproduce a flow regime classification, based on runoff data, in an attribute space defined by measured catchment characteristics. Threshold values are used to direct the classification approach: for example, all Swiss catchments with a mean altitude above 1500 m a.s.l. would be classified into one group (alpine river regimes), all catchments at lower altitude would be classified into another group. One goal of using classification trees is to find simple ways to reproduce the results of cluster analysis through a series of simple 'yes/no' decisions. However, identifying such algorithms has proven challenging in practice (Haines *et al*., 1988). Classification trees can be extended to include regressions (see Section 6.3.1).

One of the challenges associated with using physical and climate characteristics for grouping lies with their explanatory power. For example, hierarchical cluster analysis (Ward's method) of approximately 1000 small Swiss catchments generated groups that, when visualised through the Andrews curve, were found to have large internal heterogeneity. That is, the resulting groups had limited potential to describe similarities and differences between catchments (Breinlinger, 1995).

6.3 Statistical methods of predicting seasonal runoff in ungauged basins

6.3.1 Regression methods

Through regression methods, quantiles of monthly runoff or parameters of the flow regime curve are transferred to the ungauged site based on their relationship with catchment characteristics. Multiple regression approaches – linear, log-linear, power-law or non-linear Fourier coefficients – can be adopted (Gan *et al*., 1991). Different regression relationships may apply for different times of year: for example, in a study of 26 US Geological Survey gauging stations on unregulated, rural rivers in Maine with at least a 10-year record, the monthly runoff during winter was found to be inversely proportional to the distance between the coast and the drainage basin centroid (Dudley, 2004). This relationship, however, reversed in May when higher runoff occurred in basins further from the coast (which stored greater winter snowpack and released it in the spring) (Kingston *et al*., 2007). Monthly runoff during summer was positively related to the areal fraction of the drainage basin underlain by sand and gravel aquifers, which sustained streams during low flow conditions in the summer and early fall. Generalised least squares regression techniques were used to derive the final coefficients and measures of uncertainty for the regression equations. Stratification of catchments may be necessary before applying regression models: for example, improved results were obtained for multivariate regressions when catchments were classified into 'snowmelt', 'rain', 'rain and snow' and 'variable' water sources. Thus, regionalisation and data pooling may be highly beneficial for making predictions at ungauged sites (Sanborn and Bledsoe, 2006). Formal methods exist for joint pooling and regression optimisation, such as the classification and regression tree or 'CART' model (Breiman *et al*., 1984). The random forest model (Ho, 1995) extends the regression tree approach. Random forests consist of many decision trees, and the output for the random forest is given by the modal response of all the individual decision trees. Application of a random forest model to French flow regimes classified 157 hydrological indices, which were collapsed to nine PCA axes, which were then assigned to individual river sections using the random forest model (Snelder *et al*., 2009). The predictive performance of the model was highest when the study area was subdivided into only a few individual regions.

Aschwanden *et al*. (1986b) proposed a method that is based on Fourier analysis of seasonal runoff data. They estimated Fourier coefficients using runoff data at several gauged locations in the Swiss plateau to describe the seasonal pattern and then developed regional regressions between the Fourier coefficients and spatial positions of the station. On the basis of this they were able to estimate all Fourier coefficients, through interpolation, on to a 10 km × 10 km grid, and in this way constructed the seasonal flow regime across the entire region, and also characterised their regime types.

6.3.2 Index methods

Index methods associate a non-dimensional regime (i.e., Pardé coefficients PK_i) to an ungauged catchment by (visual) mapping, interpolation or assignment to homogeneous regions. Monthly average runoff Q_i^{loc} for month i at an ungauged location *loc* are computed by multiplying the regionalised Pardé coefficients PK_i^{reg} by the mean annual runoff Q_A^{loc} (regionalised as discussed in Chapter 5):

$$Q_i^{loc} = PK_i^{reg} \cdot Q_A^{loc} \tag{6.2}$$

Several approaches to their use have been developed and are outlined below.

The Pardé coefficients or other characteristics of the seasonal runoff pattern are transferred from a representative station or group of stations to the ungauged catchment. To perform this transfer, allocation methods are developed. The final allocation must be critically reviewed based on the rainfall–runoff processes operating in the study catchment. A straightforward example of an index approach is based on the assumption that the Pardé coefficients are uniform within a region. If the mean annual runoff in the ungauged catchment is known (Chapter 5), then the monthly average runoff can be computed by multiplying the Pardé coefficients by the mean annual runoff.

Hydrological similarity can be defined either in geographical space or in attribute space, where similarity is defined based on catchment characteristics. Similarity in attribute space may perform better than spatial proximity (see Mosley, 1981; Weingartner, 1999). Features of topography, geology and vegetation can assist in discriminating regional seasonal runoff patterns (Gottschalk *et al*., 1979). For example, by combining observations of flow regime type and catchment characteristics, a 0.5° grid of

Scandinavia was interpolated around classified stations, allowing a map of flow regimes to be developed (Krasovskaia and Gottschalk, 1992). The same approach failed for Western Europe, apparently because catchment characteristics were not detailed enough to support this mapping (Krasovskaia *et al*., 1994).

Allocation rules can be developed on the basis of catchment and climate characteristics for a region. For example, predictions of mean monthly runoff in Switzerland (Spreafico, 1986) classified alpine regions based on the mean altitude of a catchment and proportion of the catchment area covered by ice (Aschwanden and Weingartner, 1985). The first characteristic is a strong indicator of the significance of snow for the seasonal runoff patterns, particularly the duration of the snow cover in winter and the timing and intensity of the snowmelt in spring, whereas the second characteristic indicates the importance of ice melt for the runoff during summer time. The threshold values for each flow regime class were determined graphically (Figure 6.16a). On the basis of catchment altitude and ice, regime types can then be assigned to the ungauged sites (Figure 6.16b). Several representative stream gauges are usually available, again allowing a transfer of monthly Pardé coefficients to the ungauged site on the basis of the regime types. There is no strict rule for selecting the representative stream gauges, which means there is an inherent subjective component. Similarities in the attribute space are a first criterion for selection, while a nearest-neighbourhood approach is an improvement allowing more objective selection.

6.3.3 Geostatistical and proximity methods

Spatial proximity has often been considered the most important factor in transferring information from gauged to ungauged catchments. The simplest regionalisation methods assume that the closer a location of interest is to a gauging station the more similar the flow regime or the regime type is (Korzun, 1978; Arnell *et al*., 1993). Maps describing monthly runoff variability can be used to predict in ungauged regions. Electronic maps allow a broader range of scales to be addressed through these techniques (e.g., Lienert *et al*., 2009) and a large number of stations can be mapped. Mapping procedures are not true regionalisations but they support the extrapolation of gauged information to ungauged sites.

Andrews curves (Andrews, 1972; see Section 6.2.2 for more details of the method) allow nearest-neighbour approaches to be used to identify gauged locations that are most similar to ungauged sites of interest (Weingartner, 1999). Once the nearest neighbours are determined, Pardé coefficients can be transferred from the most similar representative catchment. Alternatively, a weighted mean of the Pardé coefficients of several similar catchments could be used. Andrews (1972) showed that the area between two Andrews curves is proportional to the Euclidian distance between points in a *k*-dimensional attribute space: the weight can thus be calculated as being inversely proportional to the area between the Andrews curves for the gauged and ungauged sites.

Simple interpolation methods such as nearest-neighbour methods and splines assume that geographical proximity is the key factor in determining a hydrological parameter. They have been used by Acreman and Wiltshire (1989) and by Arnell *et al*. (1993) for the regionalisation of monthly runoff. They have also been used for the regionalisation of the Fourier harmonics of the regime curve (Hermann and Egger, 1980a, b; Aschwanden and Weingartner, 1985). These methods should, however, be applied with caution since river runoff is generally related to accumulated area and temporal variation, rather than a simple 2D spatial variation (Gottschalk *et al*., 2006). Isolines of runoff are therefore rarely as reliable as plots formed for hydrometeorological variables that vary smoothly in space.

Geostatistical methods assume that runoff at the target site can be estimated as a weighted mean of runoff at the gauges. The main difference between interpolation methods and geostatistics is that, in the latter, the runoff at the target site is considered a random variable. Geostatistical methods account for spatial correlation structure and de-cluster redundant information from gauging stations close in space. Kriging (Kitanidis, 1997) is the most commonly used geostatistical method. However, standard kriging techniques cannot be applied straightforwardly to estimate runoff characteristics since they are not adapted to handle variables organised within a network and related to specific areas rather than to points. Several developments have been suggested to address these theoretical issues (see Section 8.3.3 for a discussion). A direct (geo-) statistical method to estimate the 12 monthly means of the flow regime is to evaluate them independently, month by month, in which case a spatio-temporal interpolator has to be developed. On the other hand, the space-time covariance structure could be incorporated, as for the spatio-temporal interpolation procedure developed for daily runoff by Skøien and Blöschl (2007). Further developments should incorporate non-stationarity in the space-time covariance structure.

An instructive example of how to estimate the mean monthly runoff at ungauged sites is given by Sauquet *et al*. (2008). The method combines an application of empirical orthogonal functions (see below) and an adapted geostatistical interpolation scheme to match the runoff data. The procedure is applied in two steps. First, the

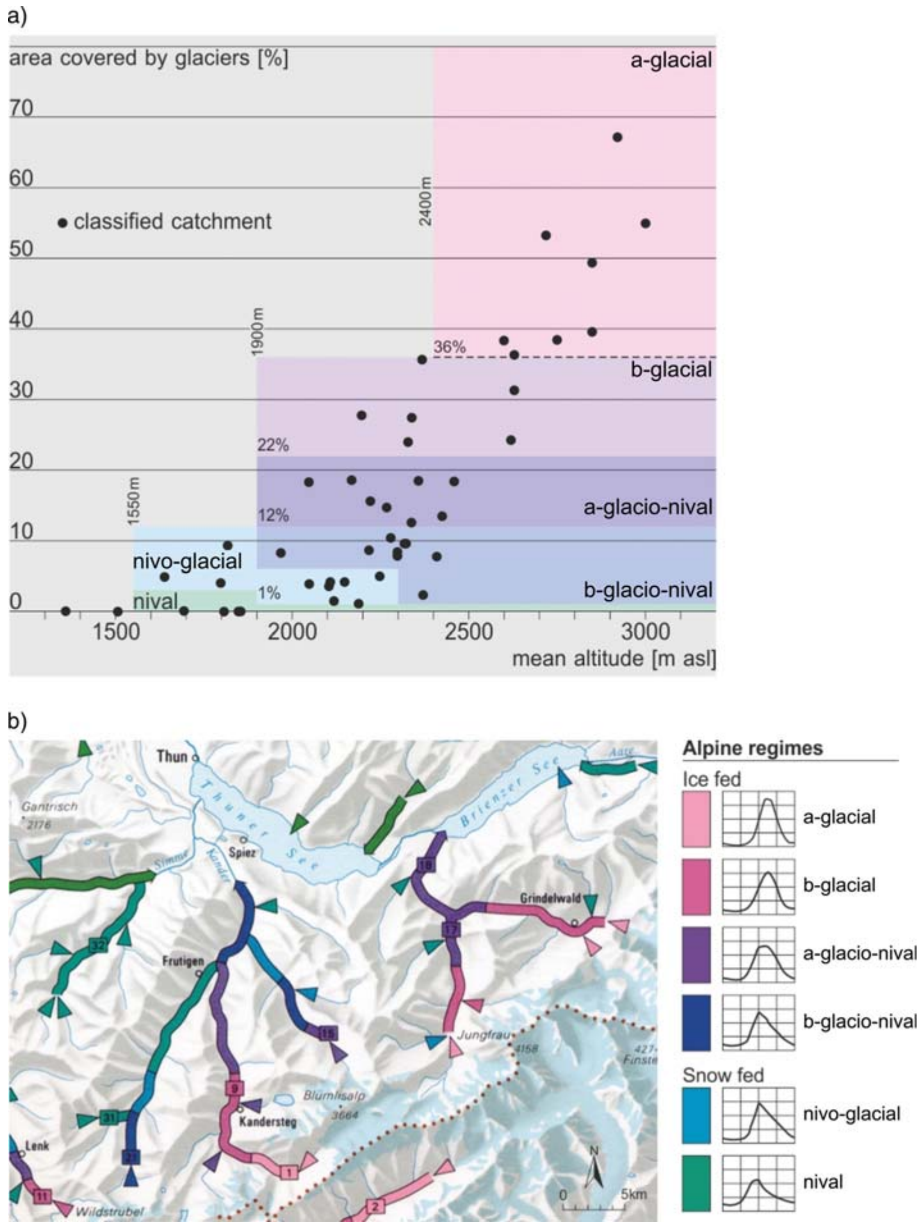

Figure 6.16. (a) Graphical classification of the Swiss Alpine flow regime types in the attribute space of average elevation and proportion of areas with glaciers. (b) Flow regime in part of Switzerland. The colours indicate the regime type. The arrows represent catchments smaller than 10 km^2. From the regime map in the *Hydrological Atlas of Switzerland* (Weingartner and Aschwanden, 1992).

fraction of runoff without pronounced karstic influences and free from human regulation is obtained using objective methods for each element of a partition of the study area. Estimates are obtained by temporal redistribution of annual values, q_a. The 12 mean monthly runoff values divided by q_a are first computed at each gauged location. Empirical orthogonal function (EOF) expansion allows interpretation of each normalised runoff pattern as a linear combination of functions defined at the regional scale with the weights that need to be estimated. The interpolation procedure applied is based on geostatistical techniques adapted to account for the related drainage basin supporting areas. This step results in 12 maps of monthly runoff for the whole of France, but omitting influences of karst aquifers and man-made regulations (Figure 6.17). Second, corrections to estimates are made to model local deviations in runoff along the river network. The discontinuities are mainly due to human activities and karstic aquifers, and are not well suited for interpolation since they are not spatially organised. The procedure considers these abrupt changes as corrections. These corrections are deduced from downstream-gauged basins under the constraint of water balance and assigned to the location of the hydraulic structures or to elementary cells controlled by karst aquifers. The categorisation of the estimated monthly pattern at each point of the map into 12 river regime groups with Euclidean distance as similarity

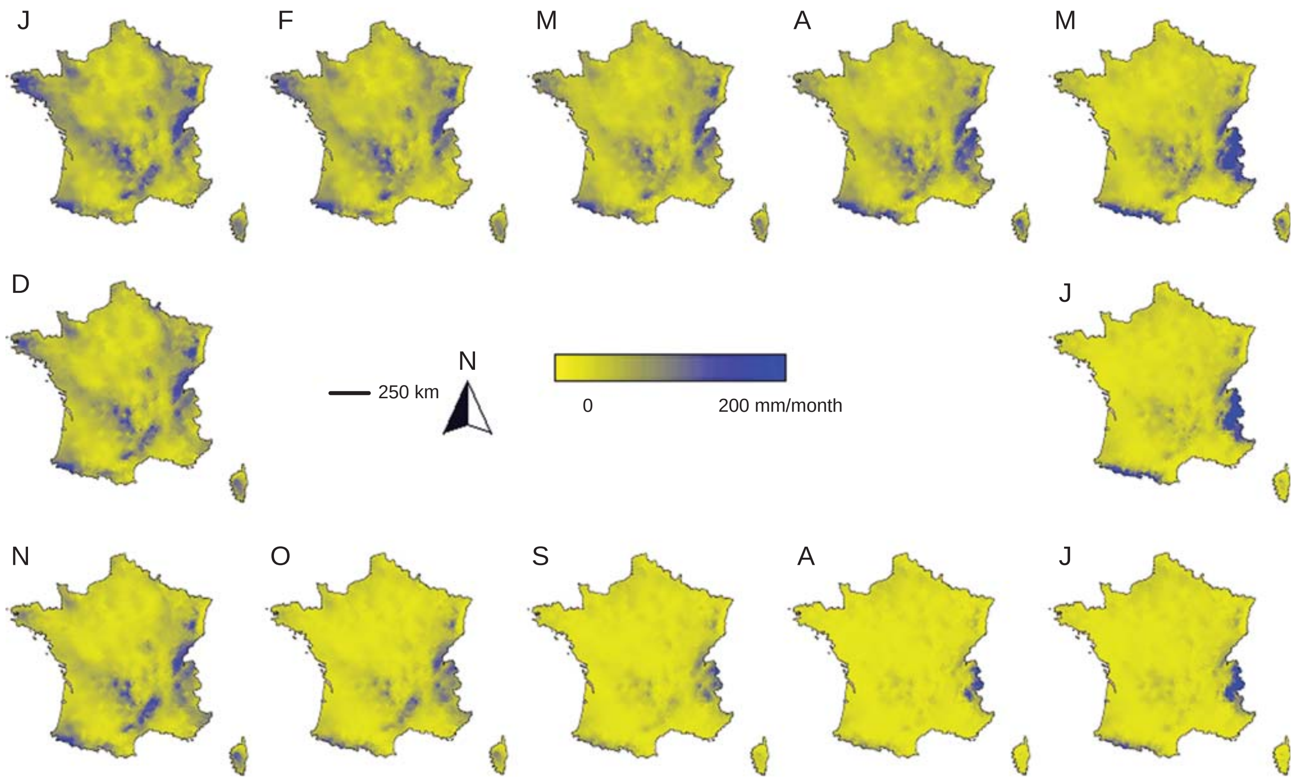

Figure 6.17. Mean monthly runoff in France estimated from 872 gauging stations for the period 1981–2000. From Sauquet *et al*. (2008).

criteria allowed the construction of a flow-regime map of France, as illustrated in Figure 6.18. The predictive accuracy of geostatistical interpolation is presented in the comparative assessment in Section 6.5.

6.3.4 Runoff estimation from short records

Short-term measurements can provide meaningful information on seasonal runoff characteristics at a site. This is true in regions with stable regime patterns. The stability of a regime (see Section 6.2.1) is directly linked to the time of observation required to estimate the long-term monthly mean runoff (Rosenberg, 1979; Pfaundler *et al*., 2006). The more stable a regime is, the shorter the observation period needed to achieve a given accuracy. In regions with a high degree of inter-annual variability, i.e., low stability, the long-term mean flow regime does not describe the conditions in individual years well. In this case, the mean curve may be an artefact of averaging rather than a representation of the hydrological dynamics (Figure 6.9).

To extend a short runoff record, a relationship between the short record and a longer (available) record must be established. These relationships can be based on the correlation between monthly runoff (Brown, 1961; Wright, 1976) determined through simple or multiple regression methods on linear or logarithmically transformed data (e.g., Alley and Burns, 1983). The data can be stratified by month, season, precipitation volume, or other climatic discriminators. For example, Dey and Goswami (1984) found that runoff from Himalayan rivers was linearly correlated during the snowmelt period.

Runoff records may also be reconstructed based on drainage area ratios, regression-based estimates of monthly means and standard deviations using basin characteristics, and linear and logarithmic correlation of concurrent runoff records (Hirsch, 1979, 1982). Vogel and Stedinger (1985) developed improved estimators of the mean and variance for short-record gauges and applied them for peak annual floods and monthly runoff. Longer concurrent monthly records greatly enhanced the attractiveness of record augmentation procedures for estimating the statistics of runoff occurring in each month because the parameters of the model relating the runoff at the two sites can be estimated more precisely than for floods. However, the relationship between the concurrent runoff at the two sites will, in general, exhibit some variation from month to month so that this increased precision is achieved by introducing some bias into the analysis, which is relevant for time series reconstruction but not for regime runoff transfer.

Solow and Gorelick (1986) applied co-kriging to estimation of missing monthly runoff values in three records

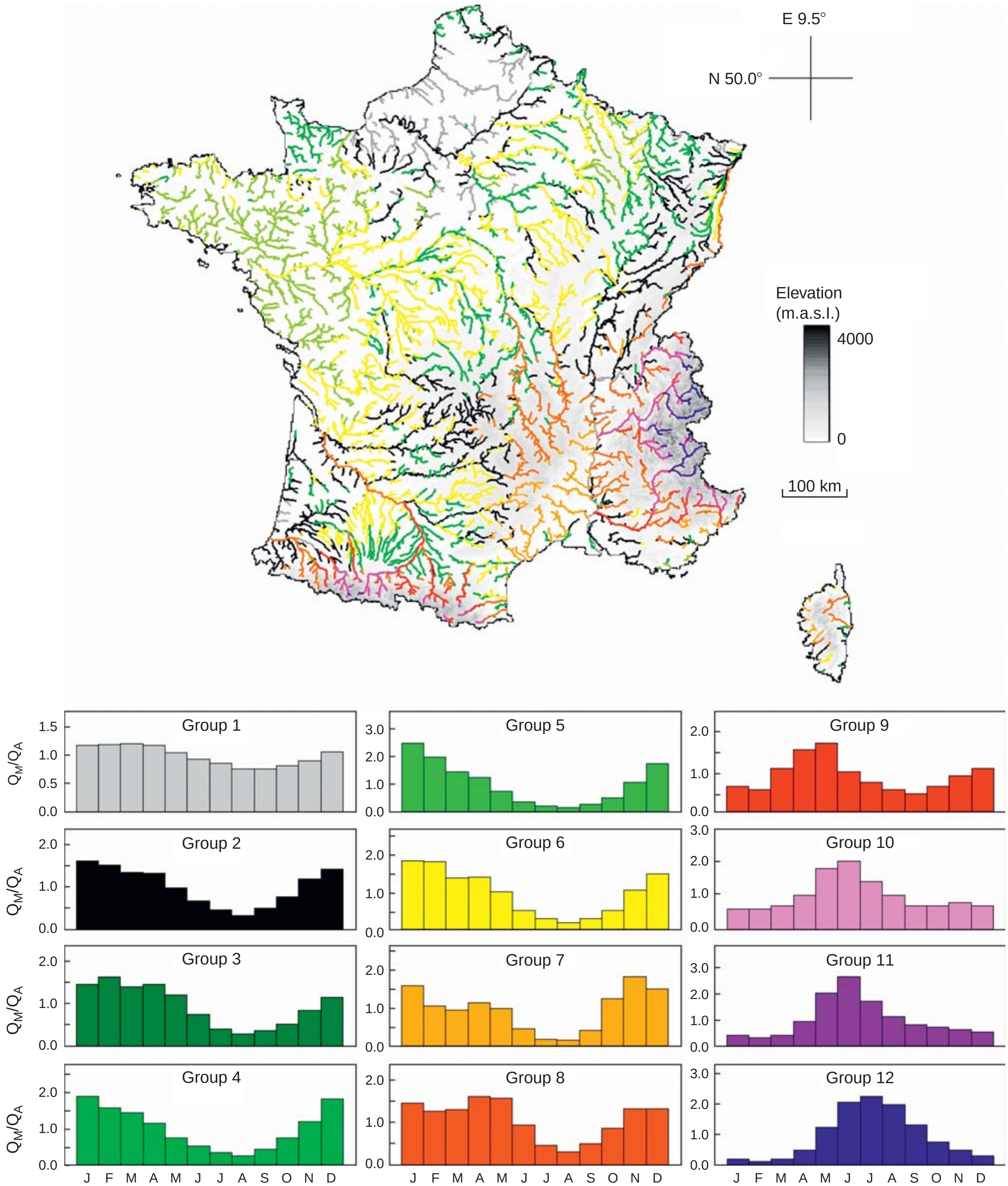

Figure 6.18. River flow regime (top) based on the 12 reference hydrographs for France (bottom). From Sauquet *et al*. (2008).

from gauging stations in west central Virginia. Missing values were estimated from the pattern of auto- and cross-correlation among standardised residual log-flow records. Investigation of the sensitivity of estimation to data configuration showed that, when observations were available within two months of a missing value, the estimation was improved by accounting for correlation. Bakke *et al*. (1999) adjusted short-term estimates at poorly gauged basins based on regional relationships between the long-term mean monthly runoff and the mean monthly runoff computed for the short period of records established for each month on a data set of nearby stations.

6.4 Process-based methods of predicting seasonal runoff in ungauged basins

The statistical approaches to regionalising runoff regimes described in the previous sections depend on the existence of runoff data that capture adequately the diversity of regimes at multiple spatial scales, from headwater catchments to major river basins. Since many regions are sparsely gauged, even in developed countries, an alternative approach involves the use of process-based methods to regionalise seasonal flow regimes. Process-based methods may be the most promising to determine the seasonal runoff variation at ungauged sites. This is especially so when there is considerable inter-annual variability, which is the case in semi-arid regions, or those parts of the world impacted by monsoons. Process-based models also offer more flexibility in the evaluation of the seasonal variation, e.g., aspects such as inter-annual variability can be incorporated directly. A further benefit of process-based models is that they are better adapted to accounting for changes in climate and land use than statistical methods.

6.4.1 Derived distribution methods

To apply a derived distribution approach requires parsimonious models of both the climate and the processes that transform climate inputs into seasonal runoff. Milly and Wetherald (2002) conceptualised the effects of land processes on variability of monthly river runoff, taking a spectral approach. The power spectrum of monthly runoff can be interpreted as the product of the power spectrum of monthly catchment total precipitation (which is typically white or slightly red) and several filters that have physical significance. The filters are associated with (i) the conversion of total precipitation (sum of rainfall and snowfall) to effective rainfall (liquid flux to the ground surface from above), (ii) the conversion of effective rainfall to soil water excess, and (iii) the conversion of soil water excess to runoff.

Milly and Wetherald (2002) made inferences about the roles of each filter through analysis of observations and output from a global model of the ocean–atmosphere–land system. They found that the first filter causes a snowmelt-related amplification of high-frequency variability in those basins that receive substantial snowfall. The second filter causes a relatively constant reduction in variability across all frequencies and could be predicted well using the Budyko curve. The third filter, associated with groundwater and surface water storage in the river basin, causes a strong reduction in high-frequency variability of many basins. The strength of this reduction can be quantified by an average residence time of water in storage, which is typically on the order of 20–50 days. The residence time is demonstrably influenced by freezing conditions in the basin, fractional cover of the basin by lakes, and runoff ratio (ratio of mean runoff to mean precipitation). The purpose of this modelling framework was to synthesise the observed and modelled data; it has not been used for prediction in ungauged basins.

Derived distribution methods can be used to apply process descriptions such as those suggested by Milly and Wetherald (2002) to convert the monthly variation in climate into monthly variation in runoff. As noted above, although several methods have been suggested for using this approach to prediction of seasonal flow regimes, only incomplete results are available at present. For example, using an analytical model of climate, snow accumulation and melt, Woods (2009) presented predictions of snowmelt timing and magnitude, as a component of ungauged predictions of seasonal snowpack evolution. The method produced reliable ungauged predictions of snowpack in six different geographic regions of the western USA (see Figure 6.19), and so could potentially be used as a basis for ungauged prediction of seasonal runoff from catchments in snow-dominated regions.

Similarly, analytical soil water balance models with a seasonal component have been developed; see, for example, Milly (1994a, b), Laio *et al*. (2002) and Woods (2003), though none of them have been used for estimating seasonal runoff regimes in ungauged basins. Only the latter explicitly predicts the time variation of runoff within a year. These models all use an idealised representation of the climate forcing, with storm events modelled as a Poisson process, and seasonal variation in rainfall and potential evaporation modelled as sinusoidal curves. Snow processes are not included, and nor are lakes; McDonnell and Woods (2004) suggested that these both need to be included in a general treatment of the water balance. Interception by plants is modelled using either a fixed loss from each storm or a simple stochastic storage model. Soil water storage is modelled using variations on the 'bucket' model (for a comparison, see Milly, 2001). The conversion of soil

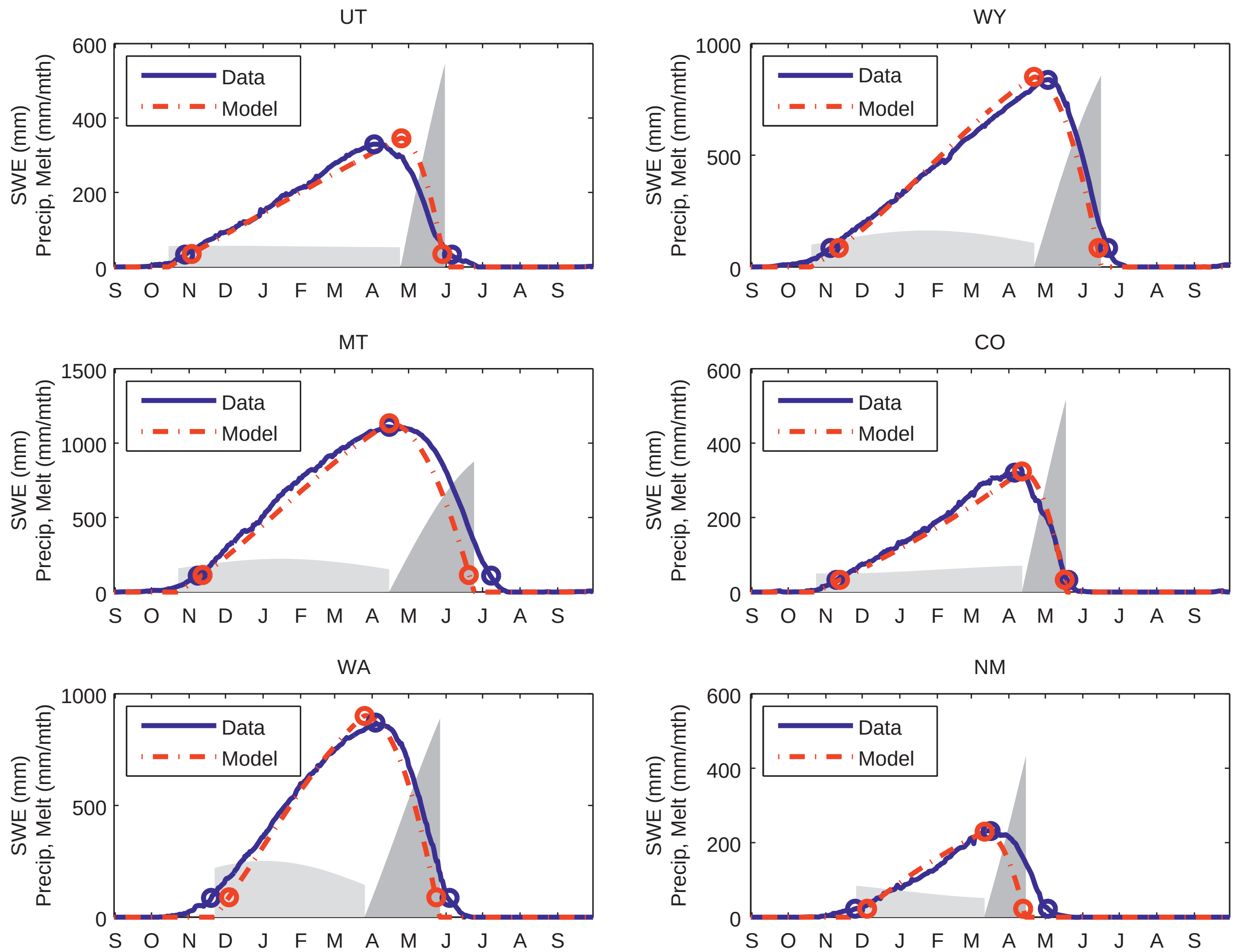

Figure 6.19. Comparison of measured (solid lines) and modelled (broken lines) time series of average snowpack storage for each day of the year, in Utah, Wyoming, Montana, Colorado, Washington and New Mexico. Circles on measured and modelled traces indicate the peak snow-water equivalent (SWE) and the dates near the start and end of the snow season when storage is 10% of peak SWE. Light shaded area at left indicates modelled snowfall rate, and darker area at right indicates melt rate. Total melt equals total snowfall. After Woods (2009).

water excess to runoff is modelled in one case using a lumped reservoir model (Woods, 2003), for which at least one parameter must be estimated.

6.4.2 Continuous models

While continuous runoff models are often applied at the daily time scale (see Chapter 10) there are a number of studies that directly estimate monthly runoff and the flow regime in ungauged basins. Specifically, a number of comparative studies have examined the suitability of different parameter regionalisation methods. Cutore *et al.* (2007) compared two methods. The first involves a regional calibration of a model to all the gauged basins in the region to produce a common set of parameters. The second procedure is a regression approach where the model is first calibrated *separately* on each of the gauged catchments and then the calibrated parameters are related to the catchment characteristics by regressions (see Section 10.4.4). Both regionalisation procedures have provided satisfactory results in Sicily in terms of mean error, root mean square error and efficiency. The results also indicated that models based on regional calibration appear to be robust for estimating runoff in ungauged basins. In a somewhat similar study in north-western Italy, Bartolini *et al.* (2011) compared parameter regionalisation by a common regional parameter set with separate calibration of the model to each of the catchments, using a water balance model with two calibration parameters. The results are consistent with those of Cutore *et al.* (2007) in that the common parameter set was found to be more robust than the separate calibration to each catchment. Their results (Figure 6.20)

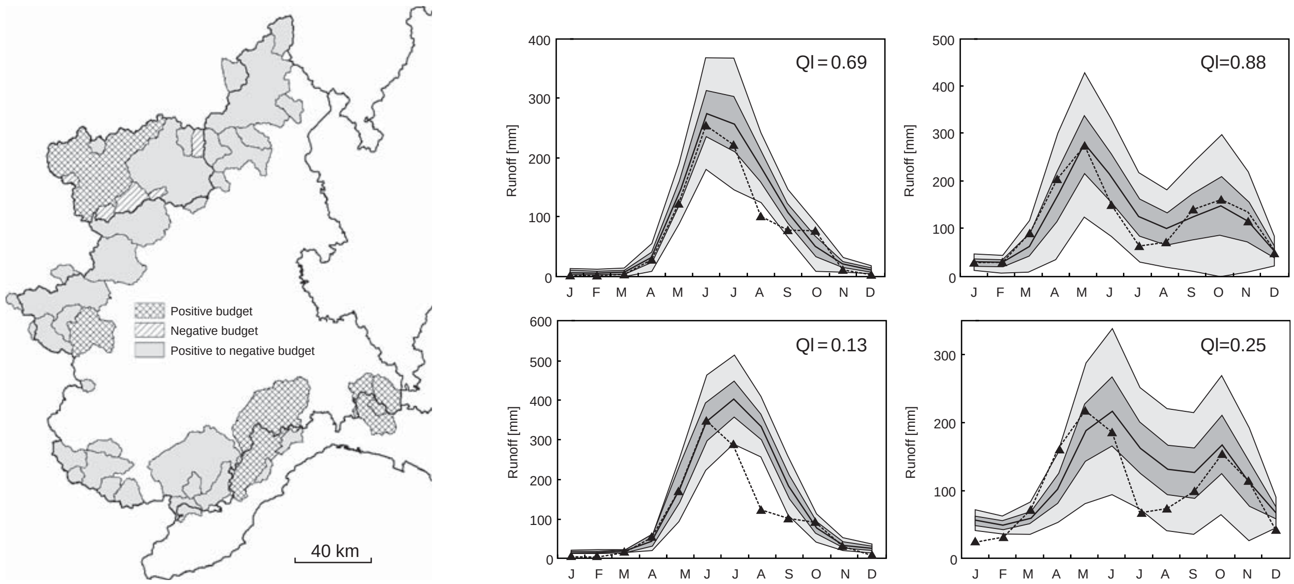

Figure 6.20. Modelled vs. observed monthly runoff curves in north-western Italy. (a) Study domain and the catchments used for the model application; (b) observed (solid line) and simulated (dashed line) flow regime curves, along with confidence bands of observed runoff at 40% (80%) for four representative catchments: Savara at Eau Rousse, Sesia at Ponte Aranco, Rutor at Promise, and Toce at Candoglia. In the upper right corner of each panel a measure of model performance, the quality index, QI, is reported. From Bartolini *et al.* (2011).

highlight the strong seasonality of the high mountain catchments of the region due to snow processes.

A downscaling method was proposed by Schreider *et al.* (2002). They first calibrated a rainfall–runoff model to data at the outlet of a catchment, and then predicted mean monthly runoff at each grid cell within this catchment applying a downscaling technique based on a topographic index similar to the wetness index (Beven *et al.*, 1995). They tested the model for two catchments in northern Thailand and obtained an accuracy of 13–17% of the relative error at the monthly time step. Yet another parameter regionalisation method based on kriging was proposed by Vandewiele and Elias (1995) and tested on catchments in Belgium. Moore *et al.* (2012) assessed the accuracy of a simple grid-based monthly water balance model in British Columbia in western Canada. Monthly mean runoff was estimated at all grid cells, which were then aggregated to estimate the corresponding runoff values for a number of gauged catchments in the region. The model was implemented without calibration, using *a-priori* parameter values that are based on either previous studies or the authors' past experience. The results are presented in Figure 6.21, in which the left-hand column presents some of the more successful results, while the right-hand column presents some of the less successfully reproduced hydrographs. The water balance model was demonstrated to be robust at predicting the relative magnitudes of monthly runoff in terms of rank, but is not consistently effective at predicting the Pardé coefficients. Also, annual runoff is predicted with modest accuracy: the mean absolute error was 25.4% of the gauged value, and 52% of the streams had errors less than 20%. The authors suggested that the main causes for the prediction errors were the gridded climate data, especially precipitation for areas with sparse gauges. In any case, the model was clearly able to distinguish various regime types, i.e., between pluvial, hybrid and melt-dominated.

A typical example of a rainfall runoff model where the simulations are performed at a daily time step and runoff is then aggregated to a monthly time step has been presented by Zappa (2002) and Viviroli and Weingartner (2012). They simulated runoff for all of Switzerland (41 000 km^2) using the PREVAH model (Viviroli *et al.*, 2009a), using daily meteorological data at a resolution of 500 × 500 m^2 as an input. They first used *a-priori* model parameters (termed 'initial model' in Figure 6.22). In a second step they adjusted the model parameter based on water balance data from about 200 gauged catchments (Schädler and Weingartner, 2002). The resulting simulations are from the optimised model. Model verifications by Pfaundler and Zappa (2009) included comparisons against measured monthly runoff (Figure 6.22). Figure 6.23 shows local mean monthly runoff in August simulated by this model in a perspective view. It highlights the large gradient from the pre-alpine zone near Lake Thun to the high mountains where the catchments are ice fed. From a hydrological point of view, this visualisation is misleading since it suggests a spatially

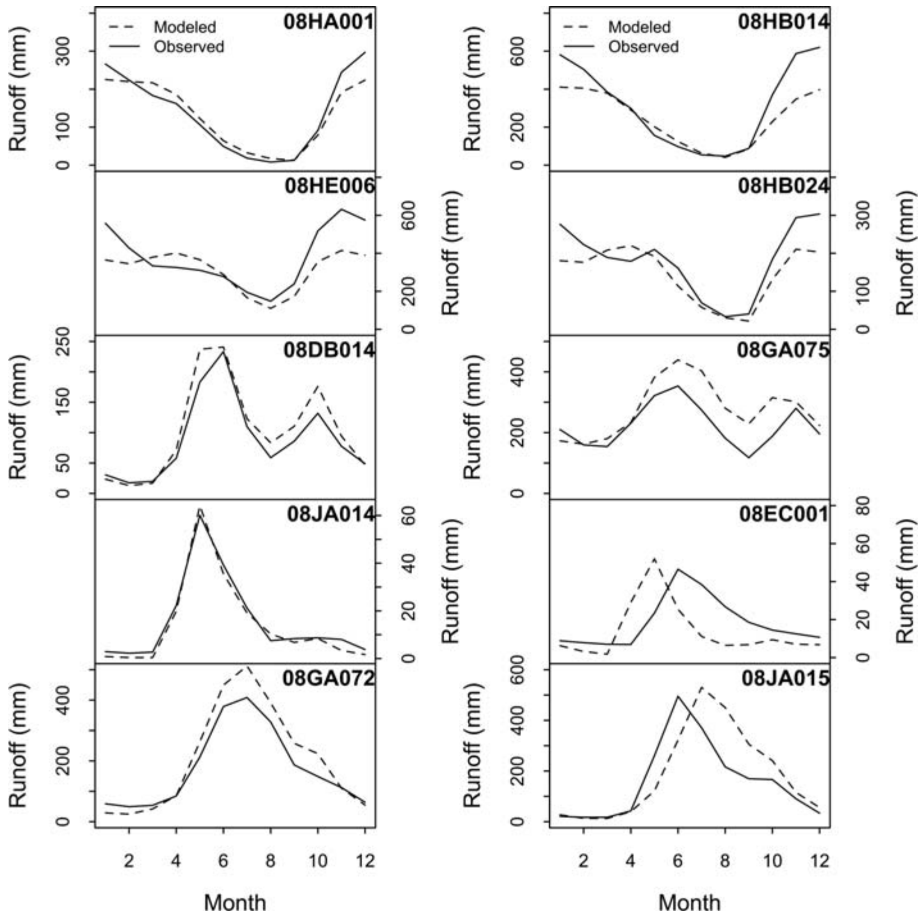

Figure 6.21. Seasonal hydrograph results for a variety of catchments in British Columbia. First to fifth rows are examples of the following runoff regimes: pluvial, hybrid regime with rainfall dominant, hybrid regime with snowmelt dominant, and glacier fed. The left column presents well-modelled regime curves, the right column poorly modelled ones. From Moore *et al*. (2011).

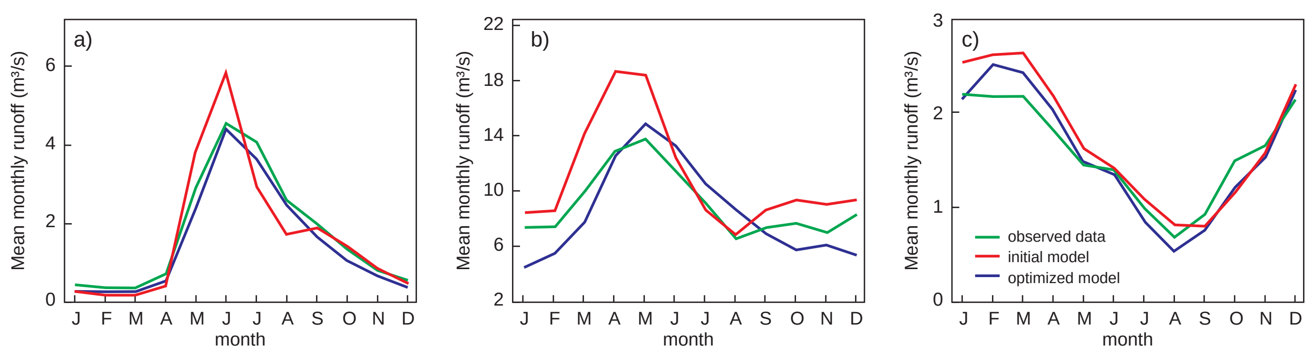

Figure 6.22. Mean monthly runoff for three catchments in Switzerland: (a) Dischmabach at Davos, (b) Sense at Thörishaus and (c) Mentue at Yvonand. From Pfaundler and Zappa (2009).

continuous variation in Euclidean space, which is not the case in reality due to the organisation of the landscape around the river network. However, spatially distributed estimates are important, particularly in snow-controlled environments (Kirnbauer *et al*., 1994; Nester *et al*., 2012).

Predicting runoff in ungauged basins by daily rainfall–runoff models is discussed in more detail in Chapter 10.

6.5 Comparative assessment

The aim of the comparative assessment of seasonal runoff predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of

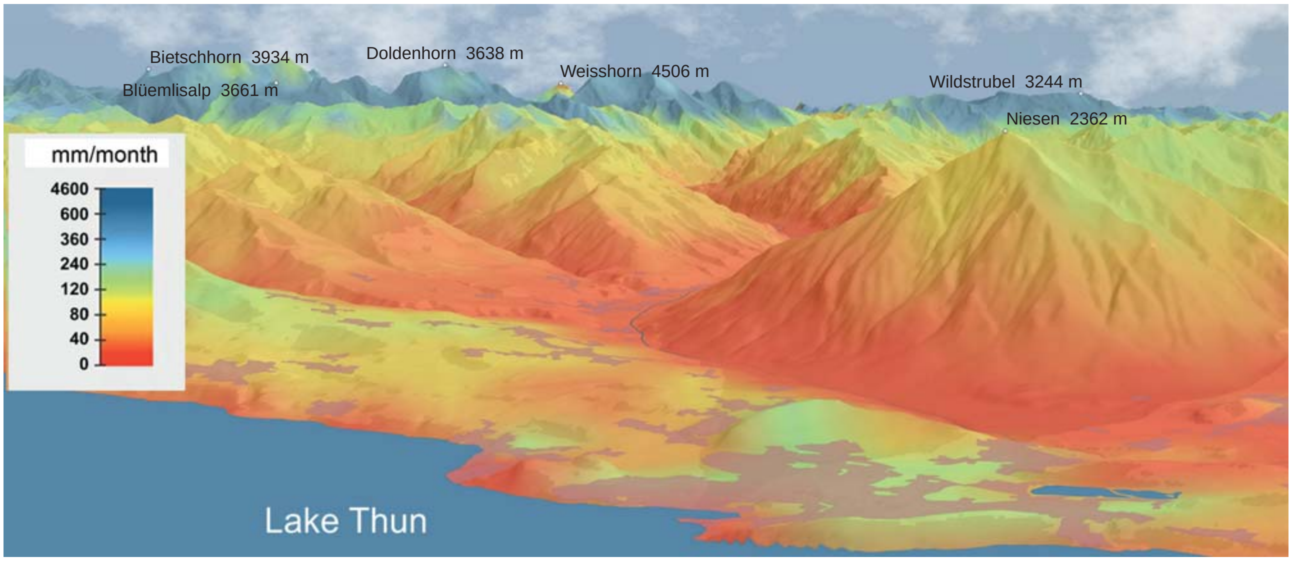

Figure 6.23. Mean monthly runoff in August in the Bernese Oberland, Switzerland. From *Atlas of Switzerland* (2010).

catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1 in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. In both Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

6.5.1 Level 1 assessment

Table A6.1 (Appendix) lists the 26 individual studies reporting the performance of prediction of seasonal runoff in ungauged basins. Some of the studies reported performance measures that were not compatible with the other studies and/or performed goodness of fit analysis instead of cross-validation. The remaining seven studies performed leave-one-out cross-validation and the performance measures were broadly similar. These were used in the Level 1 assessment (indicated in Table A6.1). The number of catchments evaluated in each study ranged from 8 to 226, with a median of 38. There are several studies that compared different hydrological models and/or regionalisation approaches, giving a total of 13 results for predictive performance. The regionalisation methods used are regression, geostatistics and process-based approaches. The studies are quite heterogeneous in terms of performance measures and the way they were applied. The performance measures used are the median Nash–Sutcliffe efficiency (NSE) of the 12 long-term mean monthly runoff values, with the exception of two studies that used monthly runoff time series. One study reported the median of the r^2 calculated from comparing predicted specific runoff for each month independently. Another study reported the Spearman correlation coefficient of the long-term mean monthly runoff. Even though these performance measures are not strictly speaking comparable, values close to 1 imply good performances, and smaller values imply a lower performance. Different performance measures are indicated by different symbols in the plots. For comparison with the other runoff signatures in Chapter 12, the median NSE of monthly runoff were calculated for all methods in all studies. The 25% and 75% quantiles of these NSE are 0.66 and 0.89, respectively.

Figure 6.24 and Table A6.1 indicate that the studies were performed in North America, Europe, South Africa and Australia. Three main science questions are addressed below.

How good are the predictions in different climates?
Figure 6.25 shows that the performance in cold and humid regions is significantly better than in arid regions. The median NSE increases from around 0.7 for arid to more than 0.9 for humid areas. One study (Sanborn and Bledsoe,

Figure 6.24. Map indicating the countries included in the Level 1 assessment.

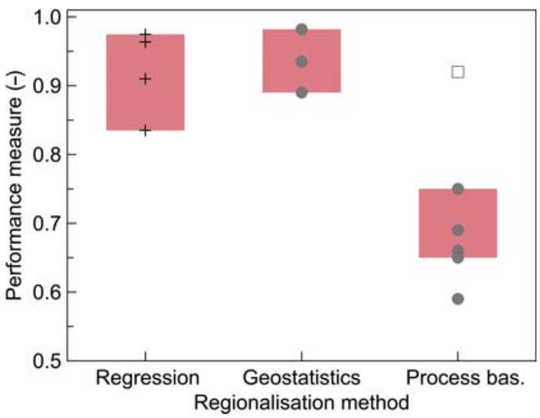

Figure 6.26. Median Nash–Sutcliffe efficiency (NSE) (circles), median spatial per-month adjusted r^2 (pluses) and median Spearman correlation coefficient (squares) of predicting seasonal runoff in ungauged basins stratified by regionalisation method. Each symbol refers to a result from the studies shown in Table A6.1. Boxes show 25%–75% quantiles.

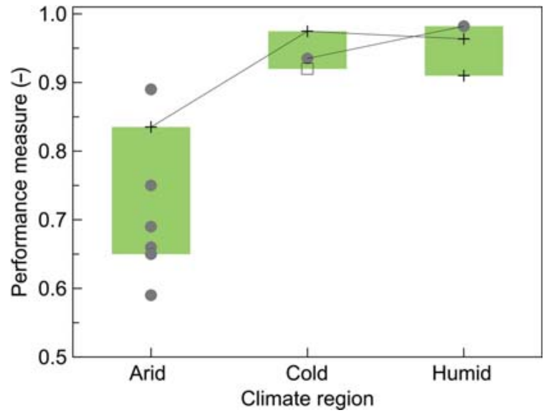

Figure 6.25. Median Nash–Sutcliffe efficiency (NSE) (circles), median spatial per-month adjusted r^2 (pluses) and median Spearman correlation coefficient (squares) of predicting seasonal runoff in ungauged basins stratified by climate. Each symbol refers to a result from the studies shown in Table A6.1. Lines indicate studies where the same method was applied across different climate regions. Boxes show 25%–75% quantiles.

2006), indicated by the grey line in Figure 6.25, compared arid, cold and humid regions, obtaining r^2 values from 0.83 in the arid region to more than 0.9 in cold and humid regions. Interestingly, more performance assessments are available for arid regions (Colorado, southern France, Southern Africa, Sicily, New South Wales) and in some of them more than one method was assessed. A number of factors may contribute to the better performance in cold and humid regions. These include the presence of snow processes that tend to make the runoff regime more predictable, generally less spatial hydrological variability than may be present in arid regions, and perhaps a higher stream gauge density.

Which method performs best?

The regionalisation methods represented in the assessment included two studies with four different regression models used to transfer model parameters, two studies that applied geostatistics for a total of three regions in France, and process-based methods including six studies that used different rainfall–runoff models. Figure 6.26 shows that, overall, geostatistics works best. The NSE (full circles) obtained with geostatistics is around 0.9, while it is around 0.7 for process-based methods. In this latter case, the efficiency is calculated on the entire simulated monthly time series and not on 12 values only, which may partly explain the lower performance. All geostatistical methods included in Figure 6.26 are from France. They include catchments from the more arid south (Sauquet *et al.*, 2000a), humid Brittany and Normandy, and the cold mountainous part of the Rhône-Alps (Sauquet *et al.*, 2008). The fact that the application of geostatistics in a relatively arid area outperforms other methods in arid regions shows that spatial proximity is a good similarity measure for runoff regime, which is controlled mainly by a precipitation regime that is smooth in space, provided stream gauge density is not too low. It is important to note that the geostatistical methods take the stream network structure into account, which seems to be one of the keys to good predictive performance.

How does data availability impact performance?

Figure 6.27 shows the performance as a function of the number of catchments analysed in each study. There is a clear trend for the performance to increase with the number of catchments (and therefore stream gauges) available in the study. For a runoff signature such as runoff seasonality, which varies rather smoothly in space,

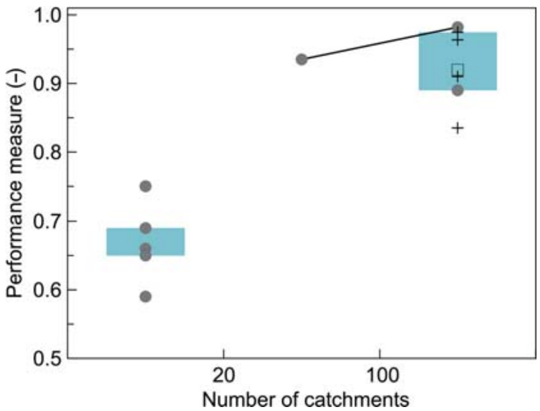

Figure 6.27. Median Nash–Sutcliffe efficiency (NSE) (circles), median spatial per-month adjusted r^2 (pluses) and median Spearman correlation coefficient (squares) of predicting seasonal runoff in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies shown in Table A6.1. Lines indicate a study that compared the same methods in different regions. Boxes show 25%–75% quantiles.

apparently, much can be gained by the availability of runoff stations to identify the dominant processes at the ungauged sites.

Main findings of Level 1 assessment

- In humid and cold regions the performance of predictions of seasonal runoff in ungauged basins is significantly better than in arid climates.
- Geostatistical methods perform better than process-based methods in regions with medium to high stream gauge density if the stream network structure is taken into account.
- The performance clearly increases with the number of stream gauges in the region.

6.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A6.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and inter-study comparison of results. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. Two study authors from the Level 1 assessment studies, plus two other authors provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment (Table A6.2). This data set combines data from 1641 catchments, four groups of regionalisation methods and four catchment characteristics. The regionalisation methods are regression, spatial proximity, geostatistics and process-based approaches. The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area.

To make the Level 2 assessment comparable with both the Level 1 assessment of seasonal runoff and the assessment in the other chapters of this book, two performance measures were used. In both instances, the performance is estimated from the predicted Pardé coefficients rather than on the monthly runoff, since annual runoff is dealt with in Chapter 5. The first performance measure is the NSE calculated on the 12 Pardé coefficients for each site. The second performance measure is the normalised error (NE) of the range of the Pardé coefficients (max-min) as well as the absolute value of the latter (ANE). The NE and ANE identify how well the strength of the seasonality is predicted. The NE highlights biases in the methods while the ANE is a measure of the overall performance. The predictive performance of the timing of the maximum was also analysed but is not presented here because it was always very good. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e., higher up in the plot is better. For comparison with the other runoff signatures in Chapter 12, the median NSE of monthly Pardé coefficients were calculated for all methods in each study separately. The 25% and 75% quantiles of these NSE are 0.84 and 0.91, respectively.

To what extent does runoff prediction performance depend on climate and catchment characteristics?

The assessment of the predictive performance of the models with respect to the four climate and catchment characteristics is presented in Figures 6.28–6.30. The top panels of Figures 6.28 and 6.29 show a clear decrease of NSE performance and increase of ANE error of the regression and spatial proximity approaches with aridity for aridity indices greater than 1. For the most arid catchments, predicting the range of the runoff regime is difficult as they may depend on the local soil moisture status and local precipitation effects. These are catchments from the US data set. For geostatistics and process-based methods, no clear dependence on the aridity is apparent. All methods are unbiased with regards to aridity (Figure 6.30) except spatial proximity, which shows a slight underestimation for humid places.

Figures 6.28 and 6.29 indicate that the dependence of the performance on air temperature and elevation depends on the region. In Austria the NSE performance of the regression method increases with elevation and decreases with temperature, due to the fact that the seasonality of

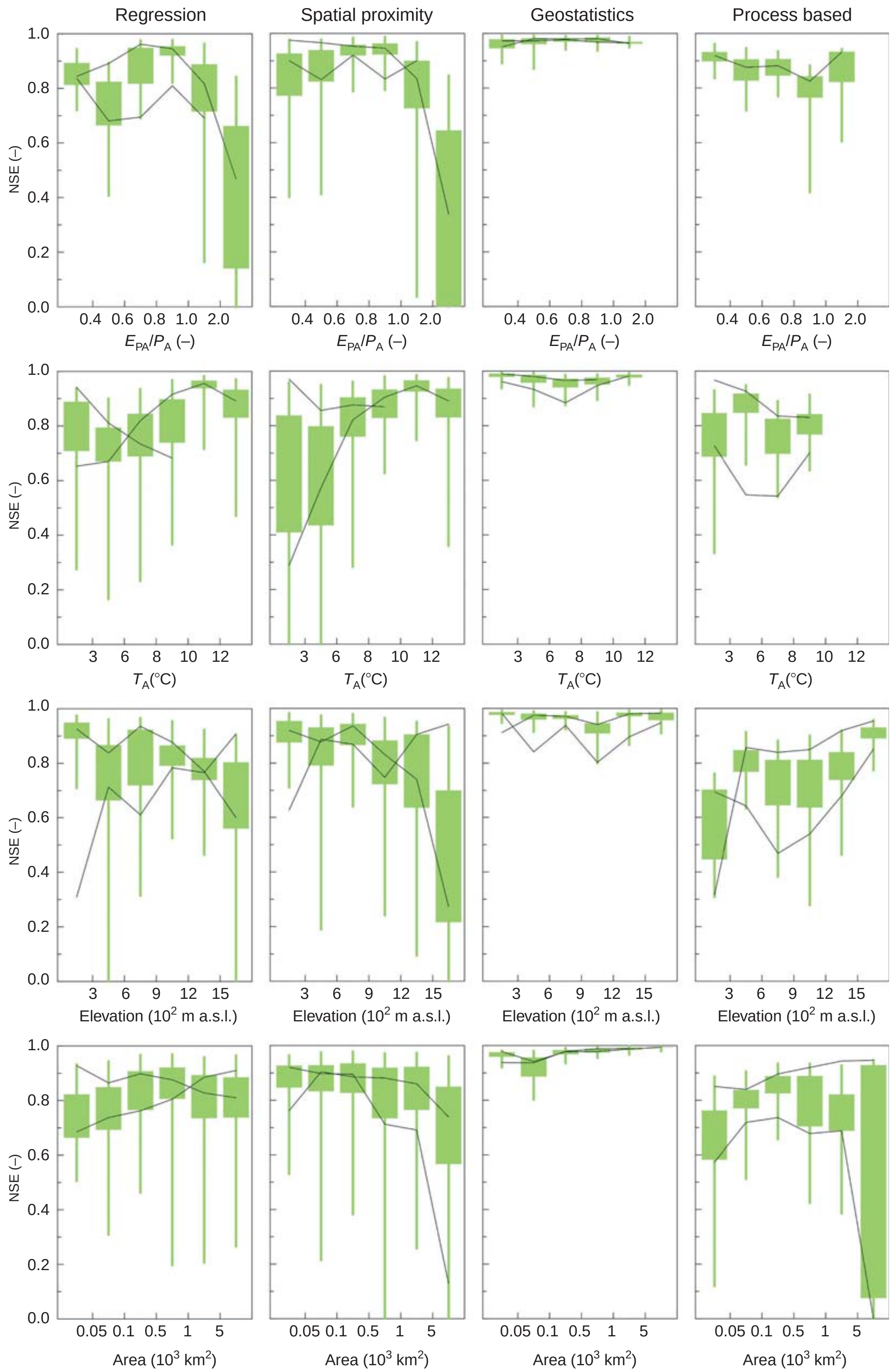

Figure 6.28. Nash–Sutcliffe efficiency (NSE) of predicting the Pardé coefficients of seasonal runoff in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different methods. Lines connect median efficiencies for the same studies. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

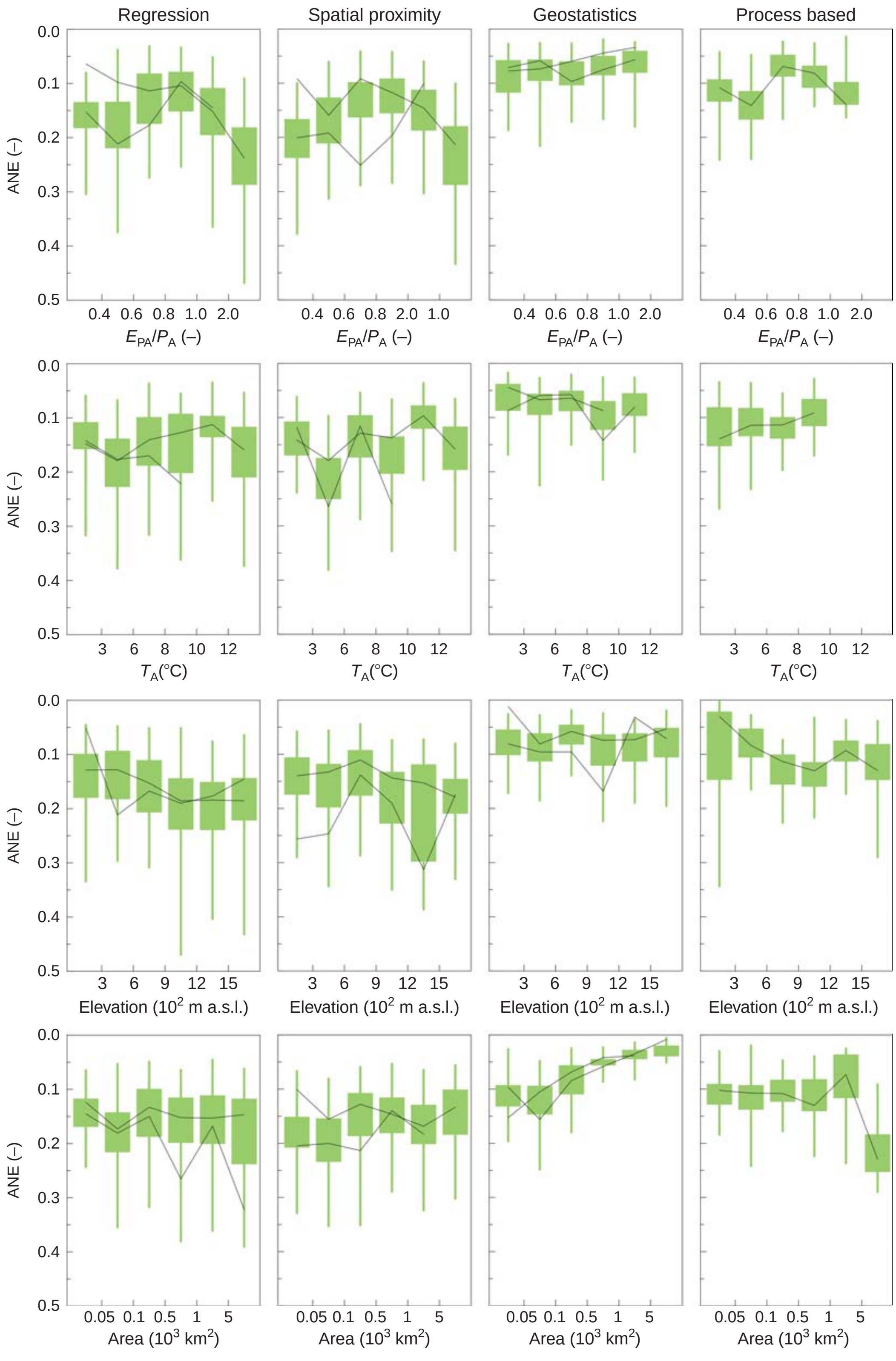

Figure 6.29. Absolute normalised error (ANE) of predicting seasonal runoff in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different methods. Lines connect median efficiencies for the same studies. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

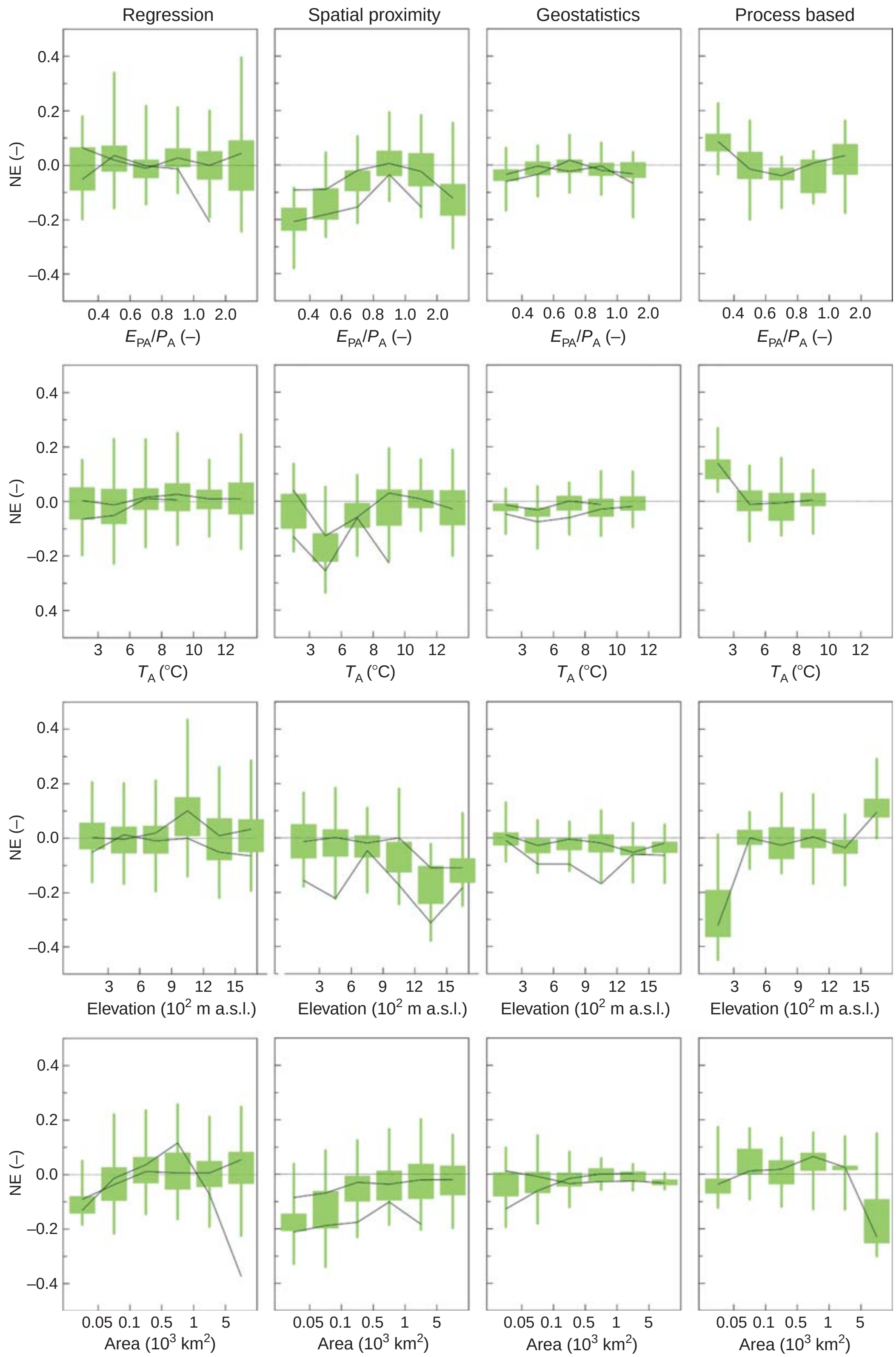

Figure 6.30. Normalised error (NE) of predicting seasonal runoff in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different methods. Lines connect median efficiencies for the same studies. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

runoff in snow-dominated catchments is easy to predict. In contrast, in the USA, high elevations correspond to arid places in the western part of the country, for which the prediction is harder. A similar pattern occurs for the spatial proximity method. The performance of geostatistics does not show a dependence on elevation or temperature as it is always very good. There is a slight increase in NSE predictive performance with elevation for the process-based approach. The predictions at the lowest elevations are slightly biased (Figure 6.30), which may be due to the weaker seasonality.

The performance of the geostatistical methods increases with catchment area. As the catchment area increases, the overlapping areas between gauged and ungauged catchments tend to be bigger, so the correlations along the stream network are likely to increase, which will improve the performance of the geostatistical methods. In the case of regression, the NSE performance increases with catchment area in Austria and slightly decreases in the USA (Figure 6.28). These differences may be related to the co-location of catchments with climate regions. In Austria aridity tends to increase with catchment area while in the USA it tends to decrease. Overall, the performances in the USA tend to be higher. In Austria a single (global) regression was used, while in the USA regional regressions were used that may be better suited for accounting for differences in the hydrological processes. The NSE performance of the spatial proximity method tends to decrease with catchment area, which is related to the selection of donor catchment on the basis of geographical distance between the catchment outlets of the gauged and ungauged catchments, so may not be a good assumption for large catchments.

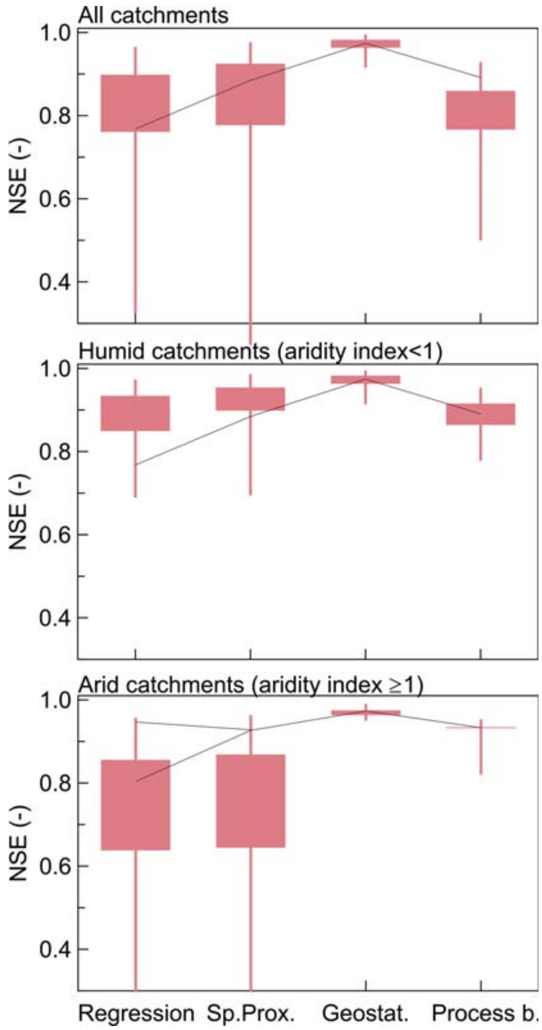

Figure 6.31. Nash–Sutcliffe efficiency (NSE) of predicting the Pardé coefficients of seasonal runoff in ungauged basins for different regionalisation methods, stratified by aridity. (Top) All catchments; (centre) humid catchments (aridity index < 1); (bottom) arid catchments (aridity index ≥ 1). Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

Which method performs best?

Figure 6.31 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments in Table A6.2, and catchments with an aridity index below and above 1, respectively. In all cases geostatistical methods perform much better than any other method. This is because the processes driving seasonal runoff (seasonality in precipitation, storage) are smooth in space, so seasonal runoff is also smooth. This is exactly the assumption geostatistics is based on. It is interesting that geostatistics performs much better than the spatial proximity method for the same data set (black line). Both methods use spatial distance as a similarity measure but spatial distance is defined differently. In the case of the spatial proximity method distance is defined as geographical distance between the catchment outlets of the gauged and ungauged catchments. In the geostatistical methods used here, distance is defined in a way that takes into account the nested organisation of the landscape into catchments and the stream network. Clearly, the stream network structure is a spatial landscape feature that should be explicitly represented when estimating seasonal runoff in ungauged basins.

In humid catchments spatial proximity is the second best approach, while for arid catchments spatial proximity does not perform better than regression methods. This is because arid regions tend to be more heterogeneous than humid ones. Process-based methods show good results in arid catchments, but only a few catchments were available to assess the performance.

Main findings of Level 2 assessment

- The performance of the regression and spatial proximity methods for predicting seasonal runoff in ungauged basins decreases with increasing aridity for aridity indices larger than 1.
- The dependence of performance on air temperature and catchment elevation differs between regions and is related to the role of aridity and snow at different elevations.
- The performance of geostatistical methods increases with catchment area because the overlapping areas between gauged and ungauged catchments tend to be bigger.
- Spatial proximity methods perform better than regression because the processes driving seasonal runoff (seasonality in precipitation, storage) are smooth in space, but this requires stream gauge data in the region.
- Geostatistical methods perform even better because they are based on the assumption of smoothness of the driving processes and take the stream network structure into account.

6.6 Summary of key points

- Seasonal flow regime is the signature that represents the mean within-year variability of runoff. In relation to annual runoff, the seasonal flow regime reflects the processes of storage that operate on seasonal time scales. Storage in soils and groundwater has the effect of attenuating the relative differences in water (precipitation) and energy (potential evaporation) availability (both magnitude and timing), whereas storage in snow and ice (glaciers) accentuates these differences. These differences give rise to differences in regime types across the world. Monsoons also introduce significant seasonality, but tend to exhibit considerable inter-annual variability.
- Therefore, temperature variations in cold regions (where snowfall is significant), and the relative amplitude and timing of precipitation and temperature are the key controls and similarity indices for the seasonal flow regime. Other similarity indices include storage capacity in the subsurface, and elevation and other topographic features that govern snow storage. Co-evolutionary indices that reflect and also impact seasonal flow regime include vegetation cover and phenology.
- A widely used method for predicting seasonal flow regime is through delineation into 'regime types'. This belongs to the category of index methods, and embraces the natural organisation and co-evolution of catchments in the environment, including features such as topographic elevation as a control on environmental variability, distance from the ocean, position of the landscape in regional weather patterns, and the organisation of vegetation patterns in the context of water and energy variability. It is at the seasonal time scale that all of these features have a collective impact on seasonal runoff variability, through their impact on storage processes, and in this sense the regime types are analogous to the Budyko relationship that underpins annual runoff.
- Just as in the case of annual runoff, process-based methods of the derived distribution kind can be valuable to help interpret index-type relationships of seasonal flow regimes (i.e., regime types, regime behaviour) in particular regions in the context of the relative variability of water and energy availability and the attenuating and/or accentuating effects of storage mechanisms. The understanding gained can be used to interpret and explain the differences between the regime types that one finds in different regions.
- The 'regime type' and process-based approaches to the study and prediction of seasonal flow regime represent two schools of thought, coming from geography and engineering. They represent, respectively, a holistic, co-evolutionary view of catchment systems and a reductionist or mechanistic view. This chapter, and for that matter the book itself, represents an attempt to achieve a synthesis of these two schools of thought for improved predictions and advancement of the science of hydrology.
- Comparative assessment of all methods being used for predictions of seasonal runoff in ungauged basins indicated that predictive performance becomes worse with increasing aridity (both Level 1 and Level 2 assessments). Geostatistical methods that take the stream network structure into account were shown to work best at both Levels 1 and 2; this is because seasonal runoff variability tends to be smooth in space, and so is easy to capture by spatial correlations based on observations. Geostatistical methods require stream gauges in the region of interest.
- The seasonal flow regime can be seen as the 'connective tissue' or the backbone that connects runoff variability at all other time scales and the associated signatures. Seasonality affects annual runoff variability, it is a major control of the flow duration curve, it helps set up the antecedent soil moisture for flood estimation, and it is a key control on low flows. Seasonal flow regime is the most important diagnostic in the estimation of the complete hydrograph. It is the key to predicting the other runoff signatures.
- There needs to be a concerted and increased effort to look at regime types from around the world in a comparative manner, and to understand and classify them in terms of the underlying climate and landscape controls, through a synthesis of the process-based (reductionist) and geographic (holistic) world views. This will help advance the cause of predictions everywhere.

7 Prediction of flow duration curves in ungauged basins

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7.1 For how long do we have water?

A wide variety of approaches have been adopted to quantify runoff variability, with differing degrees of emphasis on high flows (floods), low flows, seasonal variation of flows, and annual flows, and many of these are discussed in other chapters of this book. An additional feature of runoff variability that has considerable practical relevance is the period of time runoff remains higher than a specified magnitude, otherwise known as 'flow duration'. The flow duration curve (FDC), which is the subject of this chapter, is a graphical representation of the frequency, or the fraction of time (hence the word duration) during which a specified magnitude of runoff is equalled or exceeded. Representation of the entire runoff hydrograph time series (typically daily runoff, but it can also be hourly, or even monthly) in the form of the FDC makes the latter a compact signature of runoff variability, and a valuable tool to diagnose rainfall–runoff responses in gauged catchments at a holistic level, and to regionalise them to ungauged catchments. However, by representing runoff variability in the frequency domain as the FDC, information on the timing of the runoff response is lost. The latter is better reflected in the basin's runoff seasonal flow regime (Chapter 6) and, of course, in the complete runoff hydrograph (see Chapter 10).

The FDCs (for daily runoff) can be constructed empirically for gauged sites by (i) ranking observed runoff in ascending order and (ii) plotting each ordered observation versus its corresponding duration (e.g., in days), or its fractional duration (which is dimensionless). Comparisons of FDCs between catchments of different sizes or in different climatic regions can be assisted by expressing the FDC in terms of normalised runoff (normalised by drainage area or by mean annual runoff). If a stronger emphasis is needed to be given to either the low flow or the flood portion of the FDC, then it can be plotted semi-logarithmically, expressing the logarithm of runoff as a function of (fractional) duration.

The FDC can be constructed for the entire runoff record giving a long-term representation of the runoff regime, or as an ensemble of annual FDCs (AFDCs) estimated for each year of record (Vogel and Fennessey, 1994, 1995). Together, these offer a perspective of the between-year, or inter-annual, variability of the FDCs, which can be considerable in some locations, and enable the estimation of the mean or median of the AFDCs as well as the variances or confidence intervals of the runoff quantiles. The mean or median AFDC is a hypothetical AFDC, which describes the annual runoff regime for a typical hydrological year. Normally the median AFDC is preferred to the mean AFDC because it is less sensitive to the presence of abnormally wet or dry years in the observed runoff time series (Vogel and Fennessey, 1994). Figure 7.1 presents an example of the construction of the long-term FDC, and the ensemble of AFDCs based on the daily runoff record of the Kamp River taken at Zwettl in Austria.

Because of its ability to condense a wealth of information about runoff variability into a single graphic image, and because of the relevance of runoff variability to both human water use and the maintenance of environmental health, the FDC is used in a wide range of applications (Vogel and Fennessey, 1995). The FDC can help quantify the ability and reliability of a river to meet demand for water by humans (for municipal and industrial uses, irrigated agriculture), and has been the basis for the design of small reservoirs or schemes for water uptake from rivers (Dingman, 1981; McMahon, 1993). FDCs are heavily used in the design and operation of hydropower schemes, for maximising hydropower production. Increasingly, as humans interfere with the runoff of the river for hydropower production or through extractions for domestic and industrial consumption, the downstream environment tends to suffer. FDCs are increasingly used to determine and set environmental flow standards to protect the aquatic habitat and maintain and restore ecosystem health (Poff *et al*., 1997; Olden and Poff, 2003). For example, the US Fish and Wildlife Service (Milhous *et al*., 1990) use FDCs for determining the suitability of river corridors as

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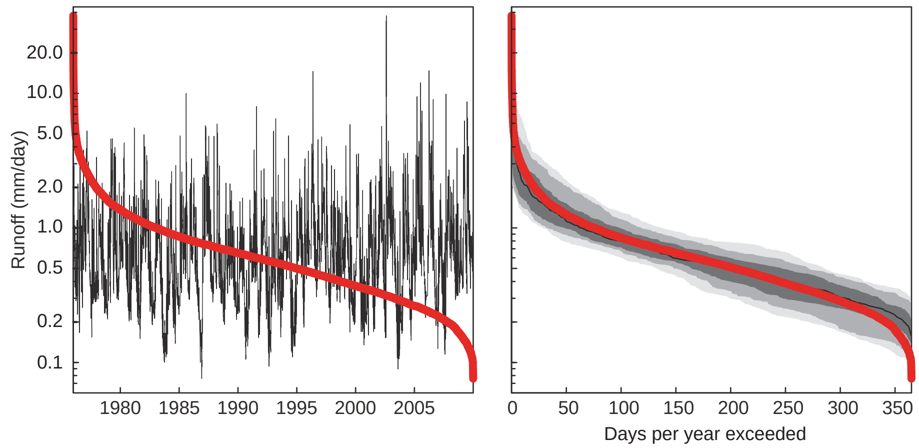

Figure 7.1. Definition of flow duration curves (FDC). (Left) Daily hydrograph based on measured daily runoff of the Kamp River at Zwettl in Austria, juxtaposed against the long-term (period-of-record) FDC (red line). (Right) Quantiles of the annual FDCs, with long-term FDC (red line).

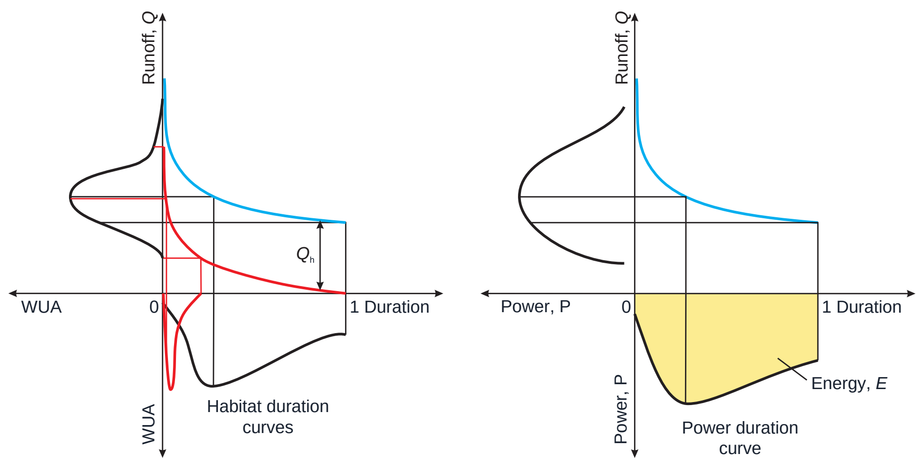

Figure 7.2. Two illustrations of the utilisation of FDCs: (Left) Construction of two habitat duration curves from FDCs and a rating curve for weighted useable area (WUA), an indicator of habitat suitability for specified wildlife species: the higher the value the higher the suitability. The two habitat (WUA) duration curves are for the natural scenario (blue line) and for an altered scenario characterised by upstream human abstraction, Q_h (red line). (Right) Construction of the power–duration curve based on a typical power–runoff relationship (area under the power–duration curve is a measure of the hydroelectric power that may be produced over the period of interest).

ecological habitats. FDCs are also used to determine the optimum allocation of water for different human uses, and for the environment (Alaouze, 1991), and for the purpose of evaluating the impact of alterations in flow regimes. In this respect, Vogel *et al.* (2007b) introduced the concepts of eco-deficit and eco-surplus, both indicators estimated based on the FDC.

Figure 7.2 presents two different applications of the FDC, the first one for setting design standards for environmental flows (left) and the second for hydropower production (right). Both involve the construction of appropriate water resource indices, relating to habitat conditions or hydropower potential respectively, through the combination of the FDC with a rating curve for the index of interest (Vogel and Fennessey, 1995; Bonta and Cleland, 2003). Figure 7.2 (left) illustrates the construction of two habitat duration curves, one for the natural scenario (blue) and the other for a control scenario that accounts for water extractions upstream (red). The water resource index in this case is the total habitat area (weighted useable area, WUA). The rating curve that connects WUA to runoff, which can be derived via simulation based on ecological considerations is shown (Milhous *et al.*, 1990). The construction of a power–duration curve is also shown (Figure 7.2, right), highlighting the within-year variability of the amount of hydroelectric power that can be produced. Once again, a key component in this construction is the relationship between hydropower and runoff, which are the design characteristics of a particular type of hydropower scheme.

Finally, since the FDCs are a key signature of runoff variability, they can also be used for evaluating rainfall–

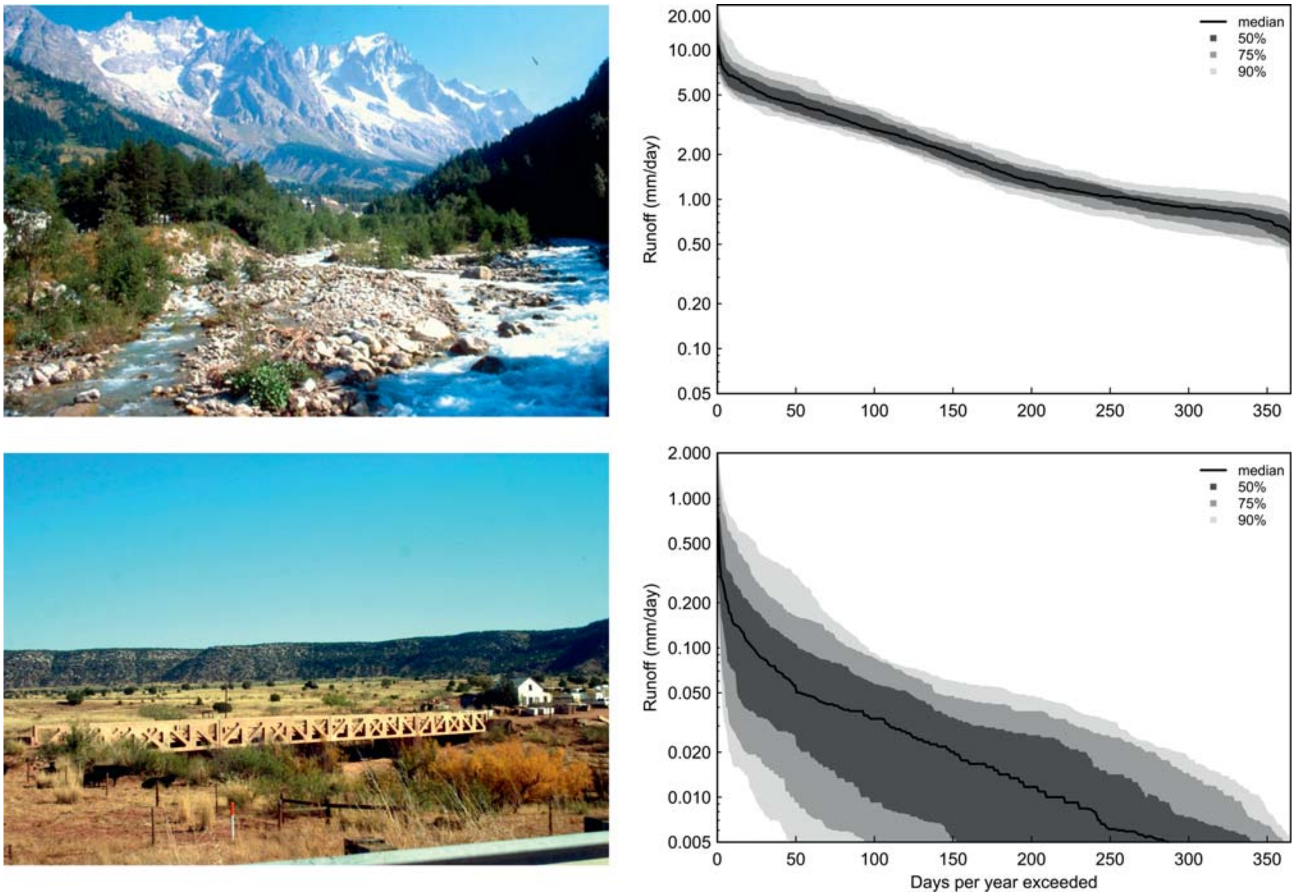

Figure 7.3. Median and between-year variability of FDCs. (Top) Dora Baltea at Tavagnasco, Italy (area 3311 km^2, mean annual precipitation 949 mm); (bottom) Mora near Shoemaker, New Mexico, USA (area 2859 km^2, mean annual precipitation 483 mm). Photos: A. Maiorana, K. Ahler.

runoff model output and for calibrating such models (e.g., Fennessey, 1994; Westerberg *et al*., 2011), for filling gaps and extending daily runoff time series and, when a regional FDC model is available, for generating runoff series in ungauged river basins (Chapter 10). FDCs can also be used to define low flows and perform low flow frequency analyses (Chapter 8).

7.2 Flow duration curves: processes and similarity

Figure 7.3 presents illustrative examples of two FDCs for comparative analysis. The FDCs have been plotted for two catchments of similar size, but located in contrasting hydrological regions, one in northern Italy and the other in New Mexico, USA. The FDCs indicate that the catchment in New Mexico is not only ephemeral, but also has significant inter-annual (between-year) variability, a normal characteristic for ephemeral catchments. On the other hand, the catchment in northern Italy is perennial, but with very little inter-annual variability. It is clear that the FDCs for each catchment are very different, and this section aims to address why they are so different. For predictions in ungauged basins it is essential to understand what factors cause FDCs to vary between catchments. The notion of hydrological similarity in the context of FDCs helps us to group similar catchments together. Understanding of the climatic and landscape (catchment) controls on the FDCs can enable the extrapolation of empirical FDCs derived from gauged catchments to ungauged catchments within a similar or homogeneous region. Likewise, understanding of the process controls of the observed FDCs helps not only to delineate homogeneous regions but also to use appropriate process models to extrapolate/reconstruct FDCs in ungauged basins.

This section first discusses the process controls responsible for the shapes of FDCs, and how these are governed by the combination of climate and catchment characteristics. This understanding is then used to formulate a list of similarity indices that can be used to group similar catchments, and to develop relationships to extrapolate FDCs from ungauged to gauged catchments in hydrologically similar (i.e., homogeneous) regions.

7.2.1 Processes

The FDC represents a distillation of the within-year, or intra-annual, variability of runoff, presented in the frequency domain. The FDC arises from the interplay of climate regime, catchment size and morphology, vegetation cover, and the properties of the subsurface domain, which together control the various runoff components. The shape of the FDC is therefore governed by both precipitation variability and how water moves through the catchment. Deciphering the controls of both climate processes (e.g., precipitation, temperature, radiation or potential evaporation) and catchment characteristics (i.e., soil, topography, vegetation type and functioning, catchment size, human impacts) on the shape of FDCs is the key to their prediction in ungauged basins.

As the major climate control on the FDC of a river basin is precipitation, one can expect signatures of precipitation variability to be reflected, to varying degrees, in the runoff variability of a catchment. For example, the FDC at the high flow end may closely resemble the statistics of precipitation due to the dominance of fast flow processes, whereas for intermediate flows the dominant control may be represented by soil water storage and its partitioning into evaporation and slow flows. On the other hand, low flows could be governed, in the absence of precipitation, by the competition between deep groundwater flows and riparian evaporation (see Chapter 4).

Figure 7.4 presents two illustrative examples, both based on numerical simulations, which demonstrate that different parts of the FDC can be governed by different process controls. Figure 7.4 (top) presents model-predicted partitioning of total hillslope runoff according to whether it relates to slow matrix flow (slow and uniform water movement through the subsurface) or both rapid and slow preferential flow (water movement through wormholes, cracks etc.) (Beckers and Alila, 2004), and their representation in the corresponding FDCs. Yokoo and Sivapalan (2011) carried out independent work on the basis of which they postulated that the FDC can be partitioned into three distinct parts, each of which is governed by different mechanisms or process controls (Figure 7.4 bottom): (i) the upper part, which represents high flows, is governed by flood processes for which the dominant control is the interaction of extreme rainfall and fast runoff processes; (ii) the middle part relates to the mean runoff and its seasonality, for which the dominant control is the competition and seasonal interaction between available water, energy and storage (see Section 5.2.1); and (iii) the lower part is governed by baseflow recession behaviour over dry periods for which the dominant control is the competition between geologically controlled deep drainage and riparian zone evaporation.

The changing process controls can be recognised in the FDCs presented in Figure 7.3. For example, the headwaters of the Alpine catchment in northern Italy (top) are characterised by the presence of glaciers. Glacial melting leads to maximum flows in summer, which due to the type of geology contributes to significant groundwater recharge in summer and releases substantial amounts of water to the river in winter as well. The presence of glaciers, and of snow processes in general, is the reason for the low between-year variability in the annual FDCs because the seasonal energy input is very stable on an annual time scale. The high baseflow results because of the summer groundwater recharge, reflected in the flatness of the curve. In contrast, the catchment in New Mexico (bottom) has a semi-arid climate (with mean annual precipitation below 500 mm). The FDC mainly reflects precipitation variability (both within-year and between-year), the dominance of mostly surface and near-surface fast flow processes, and the absence of substantial subsurface storage, which would, if present, contribute delayed flows. These factors result in an ephemeral stream, with a FDC that is, on average, characterised by a steeper slope than the mountainous Italian catchment.

Climate forcing

Climate impacts the FDC in several ways. The annual mean of the FDC (or the annual runoff) is governed by the aridity of the climate, as measured by the ratio of annual potential evaporation to precipitation, E_p/P, which reflects the competition between water and energy availability (as shown in Chapter 5: Annual runoff). The slope of the FDC in the middle part of the curve, which is related to the variance of daily runoff, can be affected by the competition between the seasonality of precipitation and that of potential evaporation (including whether they are in-phase or out-of-phase), as mediated by subsurface drainage. Additional aspects of climate that can impact the FDC include the amount and timing of precipitation as snowfall, the eventual melting of accumulated snow, and also seasonal and spatial variations of vegetation cover and functioning (i.e., phenology), which affect the amount and timing of evaporation, and therefore the amount and timing of runoff (see Section 6.2). The seasonality of both snow processes and phenology can be attributed to the seasonal variations of air temperature (which is a climatic feature).

The net effect of these within-year interactions between climate seasonality and storage processes is clearly reflected in the seasonal flow regime (seasonal variability

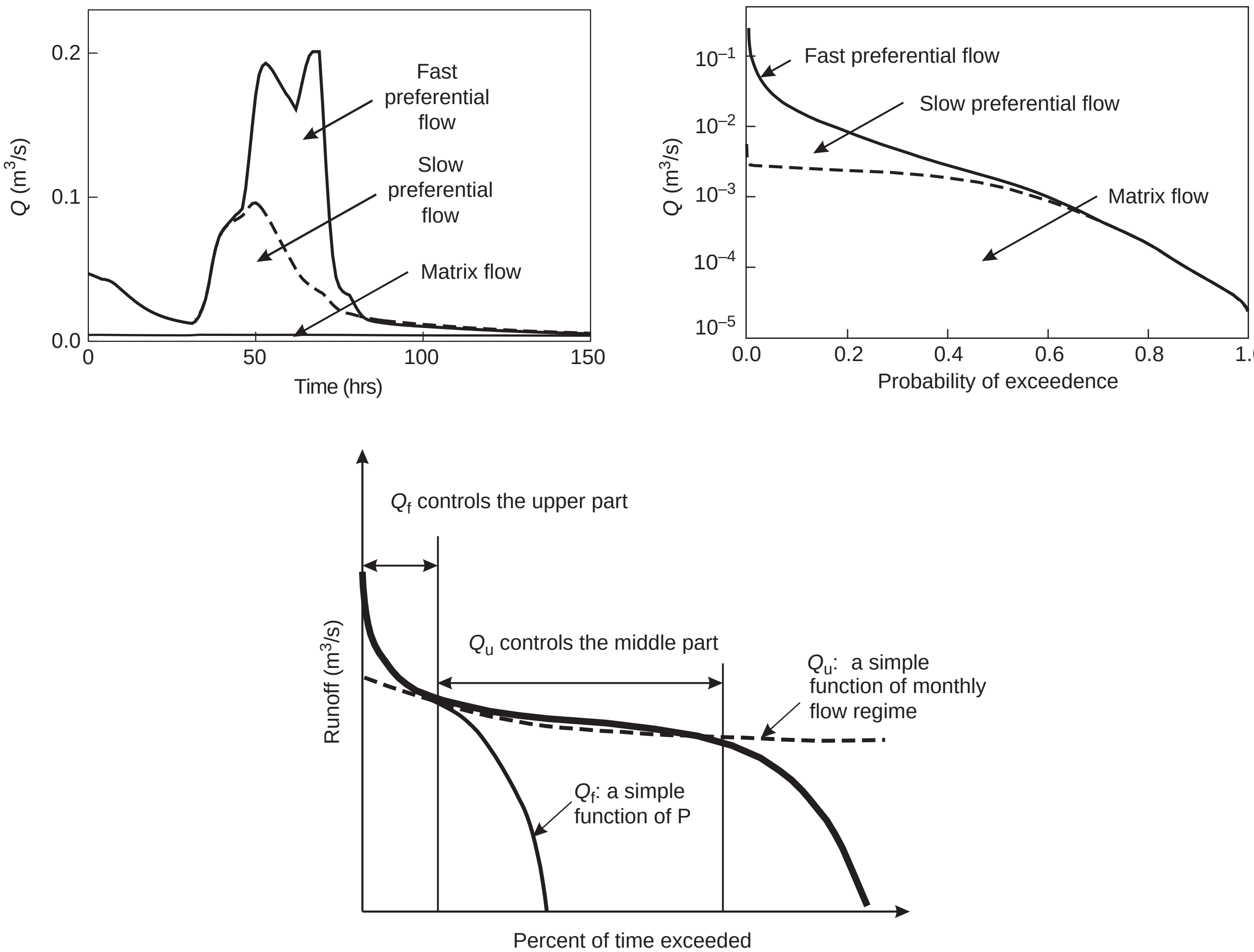

Figure 7.4. Illustration of process controls of different parts of the FDCs. (Top left) Model-predicted contributions of matrix flow and hillslope preferential flow, fast and slow, to runoff at hillslope scale for a single flood event. (Top right) Contributions of model-predicted matrix flow and preferential flows (fast and slow) to the FDC for a given water year (Beckers and Alila, 2004). (Bottom) Schematic diagram illustrating the understanding gained through model simulations regarding the shapes of the FDCs and controls on the different parts of the FDC based on the partitioning of total runoff into fast (Q_f) and slow (Q_u) flows (Yaeger *et al.*, 2012; Yokoo and Sivapalan, 2011).

of runoff), which is the subject of study in Chapter 6. They can also manifest in the shape of the FDC, as shown in Figure 7.5, which presents several examples of both regime curves and FDCs from several catchments located across the continental USA. The results presented in Figure 7.5 show that the removal of the time element leads to the possibility that two catchments with different regime curves may yet have similar shapes of the FDCs, especially in humid catchments. For the catchment in Montana (MT) (Figure 7.5, red line) the peak in runoff caused by snowmelt is quite prominent, but for the rest of the year, runoff is relatively constant. This is manifested in the flat slope of the FDC, with a slight uptick at the low-probability end that includes the annual snowmelt events. Contrast this with the ephemeral, semi-arid catchment in Northern California (Figure 7.5, black line), where the runoff varies a great deal throughout the year, manifested in a much steeper FDC overall, and tending to zero runoff at 90% exceedance probability. Catchments with very different runoff coefficients have different FDCs, whereas catchments with very similar runoff coefficients have similar FDCs, as illustrated by two forested catchments in Pennsylvania (PA) and Virginia (VA) (Figure 7.5, blue and yellow lines respectively). In both of these catchments the seasonal pattern of leaf-out in the spring and leaf-drop in the fall (i.e., indicators of phenology) are seen in the decrease in runoff from about May to October, even though the precipitation is fairly constant all year. The effect of phenology is less clear in the FDC, however, where the two catchments are nearly indistinguishable from one another and only slightly different from the Montana (MT) catchment. The results presented in Figure 7.5 highlight

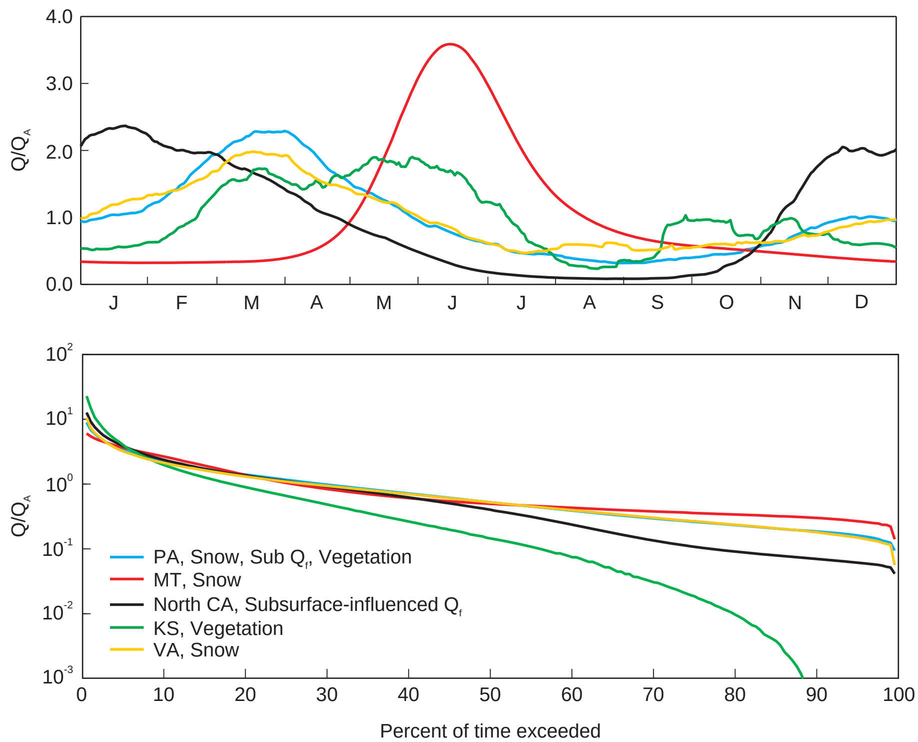

Figure 7.5. Smoothed seasonal flow regimes (using a 30-day moving window) (top), and long-term FDCs (bottom), based on 50-year record of observed daily runoff, normalised by mean annual daily runoff, from USA catchments located in Pennsylvania (PA), Montana (MT), Northern California (North CA), Kansas (KS) and Virginia (VA). From Yaeger *et al*. (2012).

two key messages: (i) the seasonal flow regime (discussed in detail in Chapter 6) serves as the connective tissue between the high and low flow ends of the FDC, and (ii) due to the elimination of the timing of processes, catchments with different regime curves may yet give rise to similar shapes of the FDCs.

Catchment characteristics

The within-year variability of runoff that is reflected in the FDC arises through the interaction of within-year variability of climate forcing (precipitation, radiation and temperature, including seasonal vegetation dynamics) with the landscape, including the subsurface, and the resulting filtering of the variability. The nature and extent of such filtering determines the shape of the FDCs. For example, catchments that are dominated by rapidly responding near-surface runoff processes will have steeper FDCs (with the possibility of high frequency of zero runoff), whereas catchments where slow processes dominate runoff generation may have less steep FDCs (see Figure 7.4). Key catchment characteristics that impact on the shape of the FDC include surface soil and vegetation characteristics that determine the partitioning of incoming precipitation into interception, infiltration and overland (fast) runoff. Water that infiltrates into the soil is then partitioned into subsurface storage, subsurface (slow) drainage and evaporation through plant uptake and transpiration. These are all governed by geology through its impact on soil depth and soil permeability, vegetation cover and dynamics (with attendant impacts on root zone depth), and human-induced land use and land cover changes.

Work over the past few decades has contributed to the accumulation of considerable empirical knowledge on the effects of these catchment characteristics upon the shape of FDCs. Musiake *et al*. (1975) investigated the effects of geology and climate type on the shape of FDCs in mountainous catchments in Japan. Ward and Robinson (1990) provided a summary of the effects of dominant soil types on FDCs in UK catchments. Fennessey and Vogel (1990) documented the important influence of catchment relief on the shape of FDCs. Burt and Swank (1992) investigated the effects of vegetation type on the FDCs. Figure 7.6 presents an illustration of the effect of geology on the shape of the FDCs for two catchments in the UK. The Eden at Penshurst is a rural catchment with scattered settlements developed on sands and clays, while the Test at Broadlands is underlain by permeable formations, 90% of which consist of chalk but with some tertiary deposits. The FDCs of the two catchments are very different. That of the Test is much flatter, which is related to storage in the chalk aquifer and the close stream–aquifer interactions.

Environmental change

When extrapolating FDCs to ungauged basins it is important to recognise that the FDCs may be modified by environmental change, i.e., land use changes, water

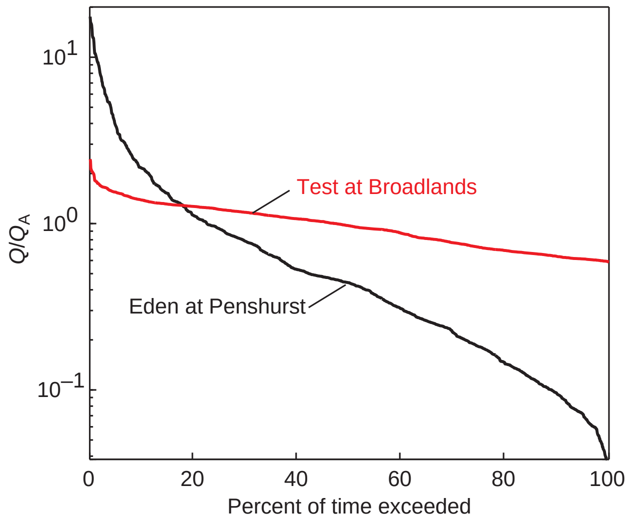

Figure 7.6. Flow duration curves normalised by the mean runoff for the Eden at Penshurst, UK (area 224 km², mean annual precipitation 825 mm, clay-dominated in the lower parts), and the River Test at Broadlands, UK (area 1040 km², mean annual precipitation 815 mm, chalk-dominated catchment). Redrawn from Yadav *et al*. (2007).

abstractions, return flows, impoundments or climate change. In recent times, several experimental and empirical studies have been carried out to explore the effects of human-induced changes to the landscape, especially vegetation cover, on the FDCs. Brown *et al*. (2005) presented a review of Australian and New Zealand case studies on the impacts of changing vegetation cover. Figure 7.7a depicts the FDC response to conversion of deep-rooted native forest to shallow-rooted pasture in the Wights catchment in south-western Western Australia, a relatively dry region where the annual actual evaporation of forests approaches annual precipitation. In this case, the replacement of native forest by pastures has led to a rapid rise of the groundwater table, and associated groundwater runoff (Schofield, 1996), resulting in large increases in low flows. On the other hand, Figure 7.7b shows that reforestation has the opposite effect on the FDC. It presents the FDCs for the Red Hill catchment in Tumut, New South Wales, Australia, under one-year and eight-year-old pines, indicating a 50% reduction in high flows and a 100% reduction in low flows with increasing age of the pines, with runoff in the low flow range ceasing once the pine plantation becomes well established (Vertessy, 2000).

Other kinds of anthropogenic impacts on the landscape can also exert a strong influence on the FDCs, such as water abstractions and construction of reservoirs (Brown *et al*., 2005; Smakhtin, 1999). Mu *et al*. (2007) analysed the effects of soil conservation measures (i.e., afforestation, creation of stable pastures, construction of terraces and sediment-trapping dams) on the FDCs for four different catchments located in the middle reaches of the Yellow River in China, characterised by semi-arid continental monsoon climate. They showed significant changes in normalised FDCs between the baseline (1957–77) and treatment (1978–2003) periods, with three of the four study catchments showing significant reductions in runoff, especially in the range of low flows. All these studies represent a fundamental wealth of knowledge that can assist in the identification of the dominant catchment processes that control the shape of the FDC under environmental change.

7.2.2 Similarity measures

Extrapolation and/or transfer of FDCs from gauged to ungauged catchments is critically dependent upon the notion of hydrological similarity, i.e., what are the relevant physical (climatic and landscape) parameters that make two catchments similar. Understanding hydrological similarity requires knowledge and understanding of the relationships between characteristics of the FDC (magnitude, shape etc.) and appropriate climatic and landscape characteristics.

Runoff similarity

Natural indices for assessing similarity among FDCs on the basis of runoff alone are the *slope* of the FDC or the *parameters* of probability distributions fitted to them. Examples of these similarity indices for a large number of catchments in the USA are presented in Figures 7.8 and 7.9. Figure 7.8a presents a map of the ensemble average slope (over 50 years) of the middle limb of the FDC for catchments in the eastern USA based on the work of Sawicz *et al*. (2011). The slopes were estimated on the basis of the difference between 33% and 66% quantiles of runoff for each year. The slope of the FDC in the middle part of the curve, which is related to the variance of daily runoff, is the result of the competition between the seasonality of precipitation and that of potential evaporation, and is mediated by subsurface drainage, thus providing a suitable synthetic similarity measure for the whole FDC.

On the other hand, Figure 7.8b presents a linear interpolation of the catchment average slopes of the FDC based on the distances between the corresponding stream gauging stations. Clearly, this distance or proximity-based measure of similarity is the default case, which can be substantially improved if the physical controls of the FDC are well understood. Understanding of such connections between the slopes of the FDCs and climate and/or catchment characteristics could provide a more advanced and hydrologically sound regionalisation of the FDCs; this is illustrated in the next example.

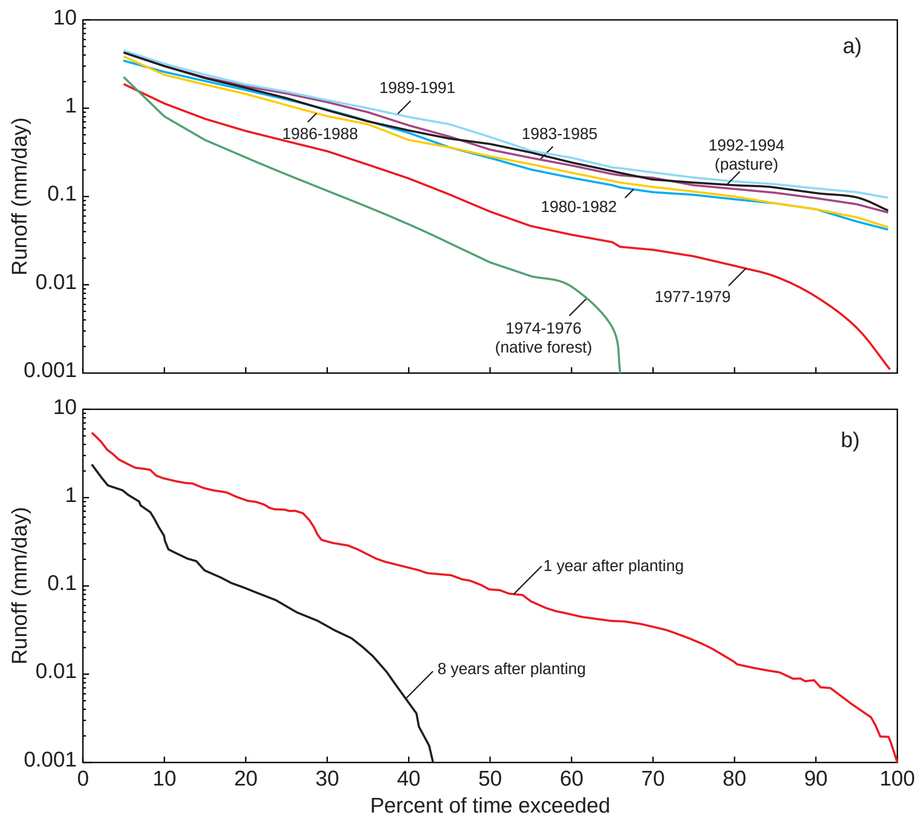

Figure 7.7. (a) Response of FDCs to conversion of native forest to pasture in the Wights catchment in south-west Western Australia. (b) Flow duration curves for the Red Hill catchment, near Tumut, New South Wales, Australia, showing considerable difference between one-year-old pines and eight-year-old pines. After Vertessy (2000) and Brown *et al*. (2005).

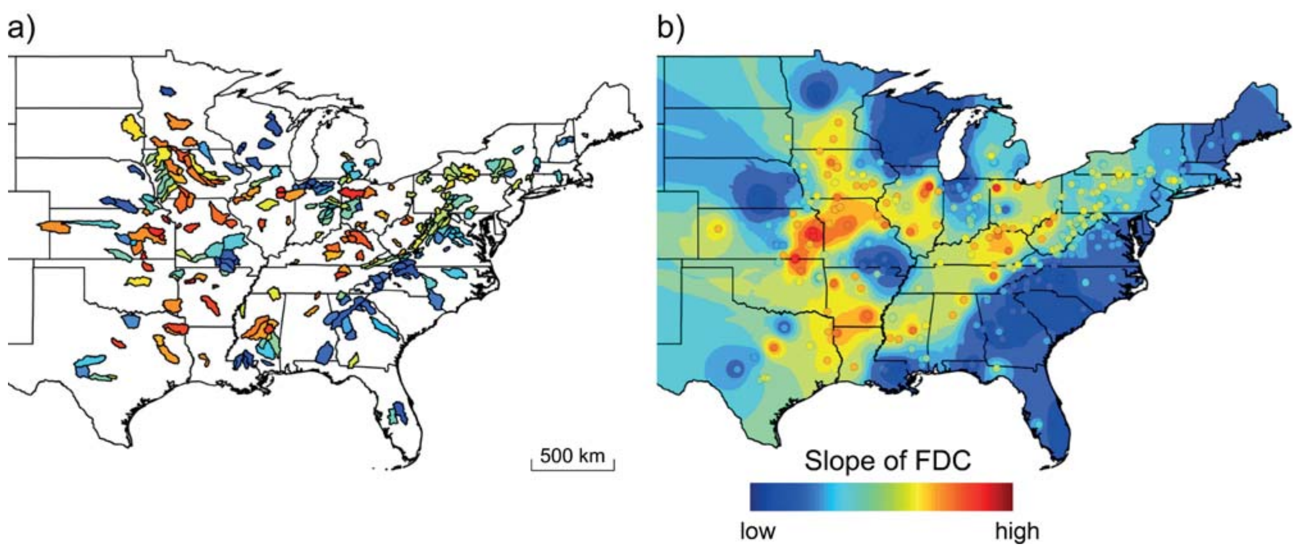

Figure 7.8. Slope of the FDC for the eastern USA using the data of Sawicz *et al*. (2011): (a) catchment average values; (b) linear interpolation between USGS gauging stations. In both cases, the colour is representative of the magnitude of the slope of the FDC.

Cheng *et al*. (2012) carried out a comparative analysis of the FDCs for 197 catchments across the USA following the approach presented in Yokoo and Sivapalan (2011). They constructed FDCs for precipitation, fast (surface) runoff, slow (subsurface) runoff and total runoff, which they termed in this order PDC, FFDC, SFDC and TFDC and fitted a *three-parameter* truncated gamma distribution to each of these duration curves. For example, they fitted a three-

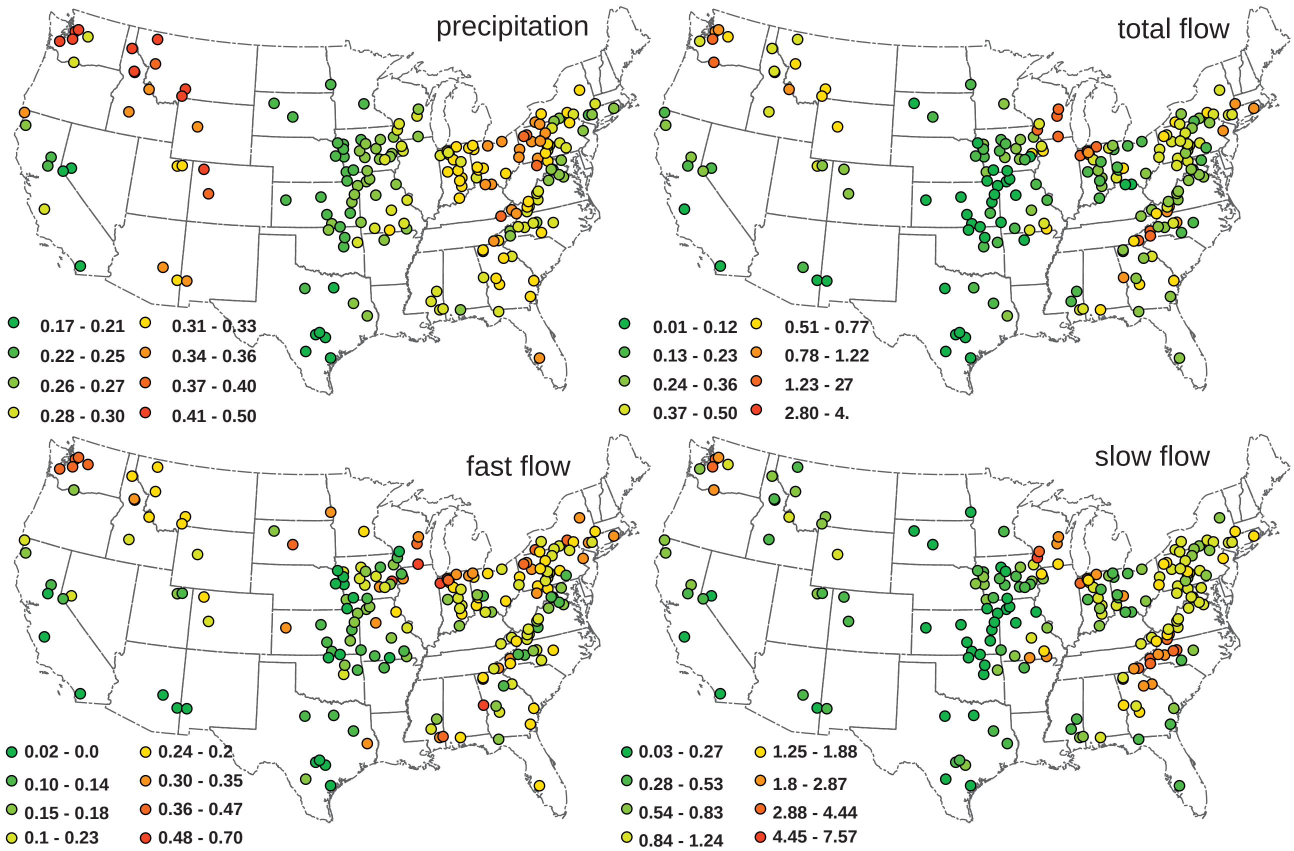

Figure 7.9. Regional distribution of the shape parameter κ of the FDCs for 197 catchments across the continental USA. From Cheng *et al*. (2012).

parameter mixed gamma distribution to scaled daily total runoff (scaled by mean daily runoff), which is given by:

$$f(q,\kappa,\theta,\alpha) = \begin{cases} \alpha, & q = 0 \\ (1-\alpha)\cdot g(q,\kappa,\theta), & q > 0 \end{cases} \qquad (7.1)$$

where α is the probability of zero runoff, i.e., the number of zero runoff days divided by the total length of runoff records; $g(\,)$ represents the probability distribution function of the gamma distribution; and κ and θ are parameters of the gamma distribution, satisfying the condition that $\kappa \cdot \theta = 1/(1-\alpha)$. This means that two of the three parameters α, κ and θ and the mean daily runoff will be sufficient to characterise the duration curves. Cheng *et al*. (2012) found that the statistical model parameters showed interesting regional patterns. For example, Figure 7.9 presents the regional patterns of the shape parameter κ across the continental USA. In each case these patterns also reveal how the shapes of the duration curves change from precipitation to fast flow, slow flow and total runoff, raising questions about the role of climate, catchment properties and the resulting process interactions.

Sauquet and Catalogne (2011) assessed hydrological similarity through two simple indicators: the concavity index (IC) and the seasonality ratio (SR). The concavity index is calculated as IC $= (Q_{10} - Q_{99})/(Q_1 - Q_{99})$ and measures the contrast between low flow and high flow regimes, representing the shape of the dimensionless FDC. Figure 7.10 represents the spatial distribution of the IC in France: values close to 1 are observed where large aquifers (e.g., in northern France) and storage in snowpacks (e.g., in mountainous areas) moderate the variability of daily runoff. Values close to 0 are found in catchments exposed to contrasting climate (e.g., small catchments in the Mediterranean area experiencing hot and dry summers and intense short rainy events in autumn) and also to catchments with no storage capacity (e.g., founded on impermeable substrata) resulting in severe low flow and quick runoff response to precipitation events. The seasonality ratio is the ratio of summer and winter median runoff. SR $\approx$ 1 applies to catchments with nearly uniform runoff throughout the year, often when significant groundwater contributions filter out seasonal climatic variability. Catchments influenced by

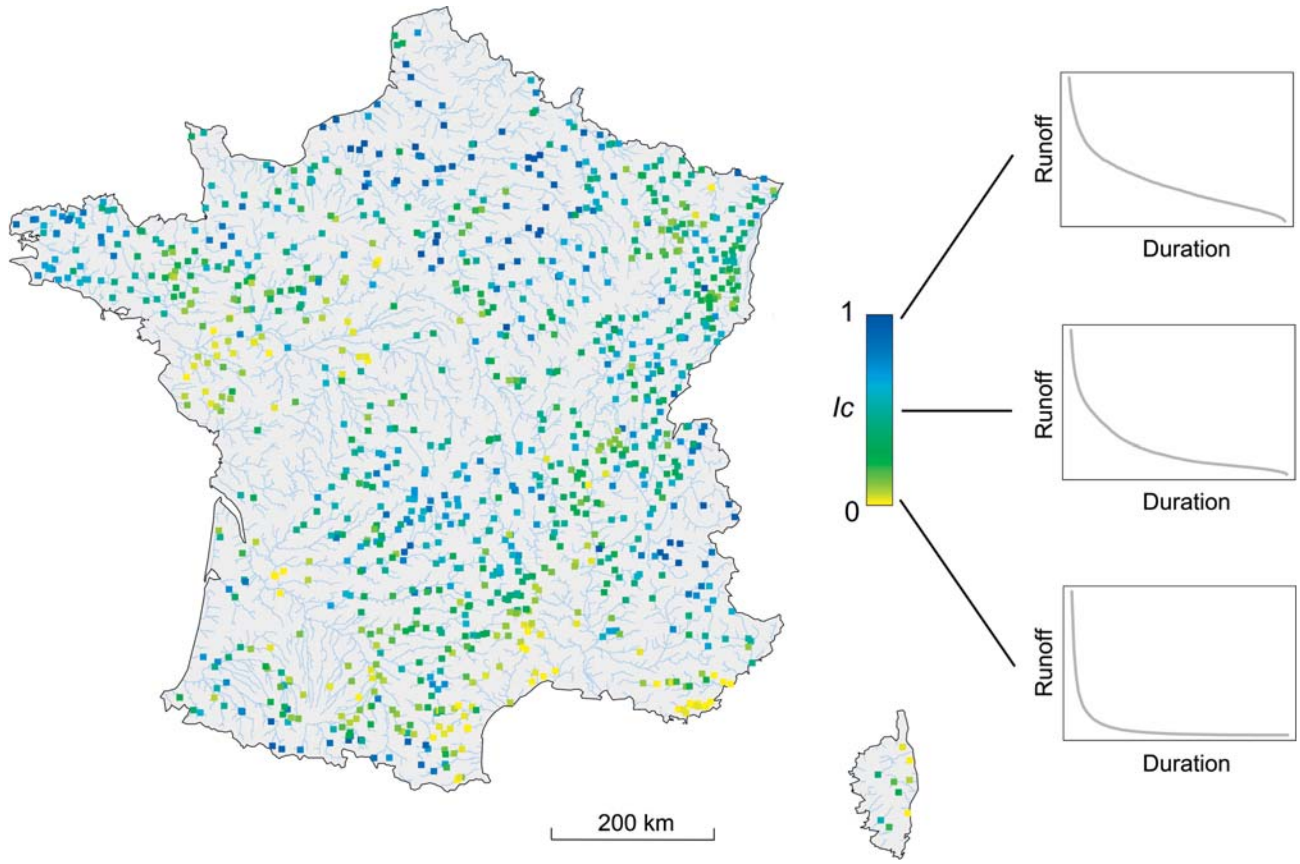

Figure 7.10. Concavity index (IC) observed at gauged catchments in France plotted on the location of their centre of gravity. From Sauquet and Catalogne (2011).

snowmelt-fed processes display SR < 1, whereas this variable is above 1 for typical rainfall-fed catchments with low flow in summer and high flow in winter. The variation in SR is governed by geology and air temperature, and is consequently subject to topographic influences in France. Sauquet and Catalogne (2011) use IC and SR together to identify homogeneous regions in terms of the shape of FDC in France through different classification methods (see Section 7.2.3).

In contrast to these studies, Ganora *et al*. (2009) defined a metric to quantify the differences as distances between FDCs and relate these distances to differences among catchments in terms of catchment and climatic characteristics. The main advantage of using distances between curves, rather than specific characteristics such as the slopes or model parameters, is that the entire curve is considered and not just their statistics/parameters. The method also allows one to compare the difference between FDCs with the differences between curves relating to climatic and catchment characteristics (e.g., information on the hypsometric curve can be used instead of the mean catchment elevation of the elevation range).

Climate similarity

Regionalisation of FDCs works best if the daily runoff is normalised by the mean daily runoff. The mean daily runoff can be predicted, to first order, by the catchment's aridity index, which then becomes the primary indicator of catchment similarity. For example, Cheng *et al*. (2012) found a strong relationship between mean daily runoff and the aridity index, consistent with results presented in Chapter 5. Castellarin *et al*. (2007a) show that the parameter representing the position of the FDC, which is linked to the mean annual runoff, is related to the mean annual net precipitation, along with the catchment area. Similar findings have been found by other studies (e.g., Viola *et al*., 2011; Li *et al*., 2010). Once the runoff is scaled by the mean daily runoff, the resulting annual FDCs are governed by several climatic and landscape characteristics that impact the transformation of the within-year variability of precipitation into the corresponding variability of runoff. The scale parameter used by Castellarin *et al*. (2007a), which represents the within-year variability of runoff, is correlated to the variability of the annual net precipitation. As per the framework provided by Yokoo and Sivapalan

(2011), the first-order control on the normalised FDC is the duration curve of precipitation (i.e., PDC, see Figures 7.4 and 7.9). This is especially true in the case of the FDC estimated for the fast flows (FFDC, see Figure 7.9). Cheng *et al.* (2012) derived a climatic index, $P_{\max}\alpha_{\mathrm{p}}$, based on the precipitation time series, and found that it had considerable explanatory power for FFDC, where $P_{\max}$ is the maximum daily precipitation and α_{p} is the probability of zero precipitation (i.e., fraction of non-rainy days within the year). As in the case of annual runoff (Sivapalan *et al.*, 2011b) the results of Cheng *et al.* (2012) also showed that there is a certain level of space-time symmetry, the variability of the FDCs between catchments being matched by their variability between years.

Other climatic controls on the shape of the FDC could be seasonality of precipitation and regional potential evaporation, including their relative magnitudes and phase difference. For example, Cheng *et al.* (2012) considered the value of the seasonality index, which represents a measure of within-year variability of precipitation, as a potential climatic index for the regional patterns of the FDC for slow flows (i.e., SFDC), although the relationship was not very strong.

Catchment similarity

The majority of the studies reported in the literature on the regionalisation of FDCs have followed statistical approaches, in which case they attempt to relate quantitative measures of the FDCs (slope of the FDC, parameters of statistical distributions) to appropriate catchment characteristics. Catchment characteristics usually considered as potential indicators of the magnitude and shape of the FDCs are catchment size, vegetation cover (Ouarda *et al.*, 2000) and surficial geology (e.g., Holmes *et al.*, 2002; Castellarin *et al.*, 2004a). Castellarin *et al.* (2007a) found that the parameter representing the shape of the FDC depended on the overall catchment soil permeability. Sauquet and Catalogne (2011) found that the catchment yield and the percentage of impermeable substratum, both representing the effect of geology, controlled the slope of the FDC curve. They also found that the slope of the FDC decreased with increasing catchment size, and suggested that this may be due to increasing storage capacities, and the combinations of different river runoff patterns originating from upstream tributaries. Catchment area, percentage of permeable area, and areal average of the Soil Conservation Service Curve Number (SCS-CN), along with mean annual precipitation, were found to be correlated with the shape of the FDC by Viola *et al.* (2011). Soil and geological factors were statistically related to the shape of the FDC by several authors: Croker *et al.* (2003; soil classes and baseflow index), Mohamoud (2008; available water capacity, soil depth, soil texture classes and baseflow index), Holmes *et al.* (2002; HOST soil classes, see Chapter 4), Claps and Fiorentino (1997; baseflow index) and Rianna *et al.* (2011; percentage of volcanic/carbonatic substrata). Li *et al.* (2010) found the leaf area index (LAI) to be related, together with the elevation difference, to the standard deviation of runoff, thus being inversely proportional to the slope of the FDC: this may be due to their differential impacts on evaporation between summer and winter.

Despite this valuable work, the literature on process-based approaches is still sparse. From a process perspective, the shape of the FDC (especially the middle part of the FDC, quantified by the slope of the FDC) can be influenced by the catchment's storage capacity (both surface and groundwater stores) and associated residence times (Lane and Lei, 1950), and how they interact with the seasonality of precipitation and potential evaporation. Without substantial storage from which to derive subsequent baseflow, catchments will be characterised by steep FDCs and probably also experience a high frequency of zero runoff. Catchments with adequate storage to support baseflow, on the other hand, will have FDCs with flatter slopes. This is usually also reflected in the magnitude of the baseflow index, the ratio of total volume of subsurface flow to precipitation on an annual time scale. This is confirmed by the work of Cheng *et al.* (2012), who found a significant relationship between the shape parameter of the FDC, κ, and the catchments' baseflow index (BI), as shown in Figure 7.11. Whereas Figure 7.11a focuses on the variability between catchments, the results in Figure 7.11b show the nature of the variability between years for a subset of eight selected catchments, demonstrating considerable space-time symmetry in these relationships.

The existence of significant relationships between quantitative indices characterising the shape of the FDC (e.g., slope of the FDC, parameters of statistical distributions) and climatic and catchment characteristics, such as the aridity index, baseflow index and the precipitation index, can enable hydrologically sound regionalisations, including grouping of similar catchments with the use of more readily available climatic characteristics and catchment characteristics, instead of only using distance, as shown in Figure 7.8b.

7.2.3 Catchment grouping

The grouping of catchments helps towards the estimation of FDCs in two ways: (i) the classification of catchments underpinning the grouping contributes towards increased understanding of catchment behaviour, and (ii) the pooling of similar catchments increases the sample size, and thus improves the accuracy and robustness of the estimation of FDCs in ungauged basins. Nevertheless, the scientific

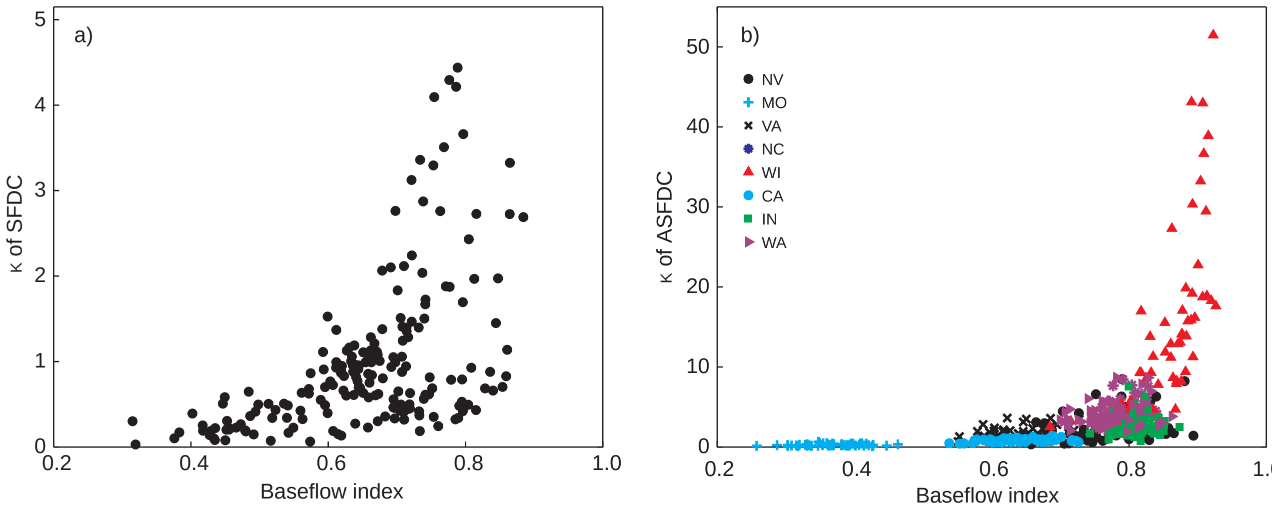

Figure 7.11. Relationship between the shape parameter κ (of the gamma distribution) of the SFDC (FDC for slow flows) and the baseflow index for 197 catchments across continental USA: (a) variability between catchments using multi-year rainfall–runoff data; (b) variability between years for eight selected catchments. From Cheng *et al.* (2012).

literature has not yet reached consensus on the best grouping method or on how to select the most suitable pooling approach, which remains therefore an open problem in the regionalisation of FDCs.

The process of grouping catchments involves two steps: (i) the choice of some kind of quantitative similarity index that will serve as the basis for choosing similar catchments; and (ii) a grouping method that uses estimates of the similarity index and organises the catchments into distinct groups (Blöschl, 2005a). Section 7.2.2 presented a survey of the indices that can be used to group hydrologically similar catchments. These indices can be based on measured runoff and reflect the signature that is being predicted. Alternatively, the grouping can be done using non-parametric approaches; for example, Ganora *et al.* (2009) defined a metric to quantify the differences – measured as a distance – between the FDCs and then related these distances to differences among catchments in terms of catchment and climatic characteristics.

If a robust relationship can be found between the slope of the FDC (or any other FDC similarity index) with catchment and/or climate characteristics, then the catchment characteristics or climate classes can be used to delineate the catchments into hydrologically similar groups. One can also use non-parametric approaches to delineating catchment groups on the basis of climate, using several indicators together to group catchments (as was done for the seasonal flow regime by Coopersmith *et al.*, 2012, see Chapter 6) or on the basis of surrogates for climate and catchment characteristics, including combinations of these, as the basis for grouping catchments. An example is the baseflow index (e.g., Claps and Fiorentino, 1997; Croker *et al.*, 2003; Cheng *et al.*, 2012), which although derived from runoff reflects the interaction of climate and geology.

One way of grouping catchments is by delineating fixed and contiguous (i.e., geographically identifiable) regions (e.g., Castellarin *et al.*, 2004a; Mohamoud, 2008; Viola *et al.*, 2011). One can expect that contiguous areas will be characterised by similar climate, topography and geology (and all other characteristics that derive from them such as soils and vegetation) giving rise to similar catchment hydrological response, and therefore similar FDCs. Of course, this is not the only possibility. One catchment can be similar in terms of the processes leading to the FDC to another catchment that is not necessarily contiguous. Cluster analysis seems to be the prevailing approach concerning the regionalisation of FDCs with which catchments can be grouped based on the similarity indices discussed above (see e.g., Castellarin *et al.*, 2004a, in central Italy; Sauquet and Catalogne, 2011, in France; Tsakiris *et al.*, 2011, in Massachusetts, USA; Ley *et al.*, 2011, in Germany).

Several methods have been proposed in the literature for grouping catchments. There are algorithms that work directly on basin characteristics through the definition of a measure of distance (e.g., Ganora *et al.*, 2009; Sauquet and Catalogne, 2011). Other clustering algorithms are based on the utilisation of non-linear approaches such as regression tree clustering (Sauquet and Catalogne, 2011) or unsupervised neural networks (self-organising maps; see e.g., Ley *et al.*, 2011). Whether or not the climate or catchment characteristics or a combination of both should be used in the cluster analysis depends on the dominant processes. However, clustering procedures exist to assist in the

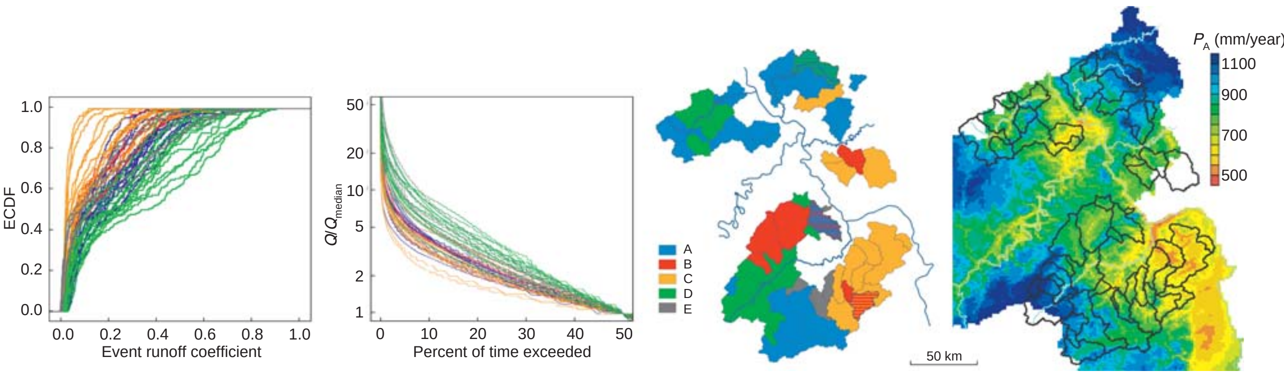

Figure 7.12. Clusters by catchment response behaviour: empirical distribution function of event runoff coefficients (ECDF), FDC (Q/Q_{median}), clusters and mean annual precipitation in Rhineland-Palatinate, Germany. From Ley *et al*. (2011).

selection of the most statistically relevant characteristics. For instance, some clustering algorithms work on a derived variable obtained by applying, for instance, principal component analysis or canonical correlation analysis to catchment characteristics (see e.g., Sanborn and Bledsoe, 2006; Sauquet and Catalogne, 2011).

Whichever clustering method is used it is important to give a hydrological interpretation of the groups. For example, Ley *et al*. (2011) grouped catchments by training self-organising maps and implementing hierarchical clustering. They assumed catchments to be similar if the distribution of event runoff coefficients (Merz *et al*., 2006) and the FDCs were similar. The results of their grouping for the Rhineland-Palatinate, Germany, are given in Figure 7.12. The spatial arrangement of the clusters is consistent with the distribution of mean annual precipitation. Clusters A and D lie in the high precipitation areas (mean annual precipitation of around 1000 mm), Cluster C in the low precipitation areas (600 mm), and Cluster B lies in between these groups. They note that there is a strong positive correlation between mean annual precipitation and the mean event runoff coefficients. With increasing mean annual precipitation, it is more likely that initial conditions are wet, which increases runoff. Climate has the largest influence on runoff, both because of the direct input to runoff at the event scale and through the co-evolutionary processes affecting the drainage characteristics, landform, soils and vegetation (Sivapalan, 2005; Norbiato *et al*., 2009).

In many cases fixed regions are obtained through clustering. However, from a practical point of view, focused pooling could be an advantage, i.e., clusters identified on the basis of the hydrological affinity with the target site, such as the region of influence (RoI) approach (see e.g., Holmes *et al*., 2002). Studies adopting focused-pooling approaches (Holmes *et al*., 2002) predate recent applications of studies based on the identification of fixed and contiguous regions (see, for example, the studies performed by Mohamoud, 2008, for a Mid-Atlantic Region of the USA, by Viola *et al*., 2011 for Sicily, or by Niadas, 2005, for a western north-western region in Greece) or application of clustering algorithms (e.g. Sanborn and Bledsoe, 2006, Colorado, USA, clustering on the basis of principal component analysis, or Lin and Wang, 2006, Southern Taiwan, clustering algorithm with self-organising maps).

The grouping techniques discussed above should always be followed by interpretation and hydrological reasoning (Merz and Blöschl, 2008). For example, Rianna *et al*. (2011) applied a cluster analysis using catchment area, altitude and geographical coordinates as explanatory variables, these being the most correlated ones with specific quantiles of runoff. They delineated three regions in this way, which coincide with the Apenninic, coastal and Tiber River zones in central Italy. Since the last region turned out to be heterogeneous according to a homogeneity test, and because geology was suspected to be the cause, the percentage of substrate (volcanic or carbonatic) was added to the other variables in the cluster analysis and different configurations of the regions were hypothesised. In the end, the Tiber River subcatchments were divided into two regions at the left and right banks of the river, which are characterised by different substrata. After the further subdivision, all four regions turned out to be statistically homogeneous in terms of shape of the FDCs.

7.3 Statistical methods of predicting flow duration curves in ungauged basins

The grouping methods discussed above can assist in predicting FDCs in ungauged basins. The focus of this section is on their prediction with statistical methods on the basis of FDCs in neighbouring catchments and catchment/

climate characteristics. Methods for estimating FDCs in ungauged basins can be classified in many different ways. This chapter reviews the methods by four broad categories: regression methods, index methods, geostatistics and methods that use short runoff records.

7.3.1 Regression methods

The regression methods considered in this section are methods that estimate each flow quantile separately from climate/catchment characteristics. The method consists of two main steps. First, a number of empirical runoff quantiles or percentiles (i.e., empirical runoff values associated with a given duration) are regionalised through a series of multiple regression models. Second, the regional estimates of runoff quantiles are analytically or graphically interpolated across the quantiles (see e.g., Franchini and Suppo, 1996; Smakhtin, 2001; Shu and Ouarda, 2012). An early example of regionalisation of FDCs reported in the literature is the work of Lane and Lei (1950); their model utilises a variability index, which is a measure of runoff variability specifically related to FDC and calculated as the standard deviation of the logarithms of the 5th, 15th, 25th, …, 85th and 95th runoff quantiles. Nathan and McMahon (1991, 1992) used the assumption of linearity of FDC in lognormal space and defined a full curve for ungauged sites by estimating only two runoff quantiles, one from the area of low probability of exceedance (10th percentile) and one from high probability of exceedance (90th percentile, or percentage of time with zero runoff for intermittent rivers). Shu and Ouarda (2012) proposed an improved regression-based logarithmic interpolation (RBLI) method for FDC estimation at ungauged sites. The RBLI approach integrates regional regression for percentile runoff estimation and logarithmic interpolation to obtain runoff between fixed exceedance percentage points. The proposed procedure uses multiple source sites for information transfer and introduces three different weighting schemes (geographical distance weighted, drainage area weighted and catchment characteristics weighted) in an effort to maximise the use of regional information.

Quantile regression generally makes no assumptions concerning the distribution or shape of the FDC (but there are exceptions, see e.g., Franchini and Suppo, 1996) and avoids the normalisation by an index runoff and the use of a regional dimensionless FDC. Quantile regression focuses on the regionalisation of runoff percentiles, which have a clear physical meaning and are generally straightforward to model through regional regression relationships, particularly for low and medium durations. On the one hand, when a sufficient number of quantiles are regionalised, the method may produce smooth and continuous FDC predictions and provide runoff estimation for the full range of exceedance probability values. However, regressing a large number of runoff quantiles means a large number of multiple regression models to be identified; also, the practical application of regression models to ungauged basins may result in inconsistent estimates of the runoff quantiles, that is, the estimate of $Q(D_1)$ may be smaller than the estimate of $Q(D_2)$, with durations $D_1 < D_2$. Archfield (2009) and Archfield *et al*. (2010) employ a recursive regression approach to ensure that such inconsistent results do not occur.

7.3.2 Index flow methods

The index flow methods considered in this section include two types of methods. The first are parametric methods where the parameters of a distribution function representing the FDC are regionalised. The second method assumes that the FDCs scaled with an index flow of all catchments in a region are assumed to be the same. The two methods are grouped under index flow methods here because in both instances some rescaling of the FDC is involved. For both methods an index flow needs to be estimated for the ungauged basins. The index flow is, typically, the mean annual runoff (see e.g., Smakhtin *et al*., 1997; Ganora *et al*., 2009) or the median daily runoff (see e.g., Ley *et al*., 2011).

Parametric methods

A general parametric approach may use models for representing the normalised FDCs, parameterising the model and regionalising its parameters through regression (see e.g., LeBoutillier and Waylen, 1993a, b; Castellarin *et al*., 2004a, 2007a). The approach is generally implemented as follows: a suitable frequency distribution is chosen as the parent distribution for a particular region; the distribution parameters are estimated on a local basis for the gauged river basins located in the pooling group of sites using the runoff observations; regional regression models are then identified for predicting the distribution parameters on the basis of the geomorphological and climatic characteristics of the basins. The frequency regime of daily runoff may not be accurately described by theoretical distributions with less than four parameters (see e.g., LeBoutillier and Waylen, 1993a; Castellarin *et al*., 2004a, 2007a; Archfield, 2009). This statement, true in principle, conflicts with the practical need to limit the number of parameters. A small number of parameters increases the chance of assigning clear meaning to each one (e.g., position, scale, shape) and a small number of multiple regression models need to be identified during the regionalisation phase.

Castellarin *et al*. (2004a) proposed a model of FDCs that analytically relates annual FDCs to long-term FDCs

(Vogel and Fennessey, 1994). The model is able to capture the inter-annual variability of AFDCs without representing the serial correlation and seasonality of daily runoff. This is accomplished by standardising the daily runoff by dividing by the annual runoff for the year in which the runoff occurred. This simple step avoids the need for more complex theoretical analyses requiring assumptions regarding the stochastic structure of daily runoff series, such as persistence and seasonality (Castellarin *et al*., 2004b). The model assumes that daily runoff is the product of two independent random variables, an index flow (assumed equal to the annual runoff) and dimensionless daily runoff. The index flow represents the variability between dry and wet years and it is mainly controlled by annual precipitation. The dimensionless daily runoff represents the within-year variability, which is mainly controlled by climate, size and permeability of the basin.

Castellarin *et al*. (2007a) represent the distribution of the index flow by a two-parameter logistic distribution, and the distribution of the dimensionless daily runoff by a three-parameter kappa distribution (i.e., a four-parameter kappa distribution with unit mean). They estimated the position parameter of the logistic distribution (which represents mean annual runoff) by regressions from area and mean annual net precipitation, and the scale parameter (which represents the between-year variability of annual runoff) from the variability of annual net precipitation. The position parameter of the kappa distribution (which represents the within-year variability) was estimated from catchment permeability and elevation range. Castellarin *et al*. (2007a) showed by cross-validation that the model outperforms traditional parameter regression models that focus solely on the long-term FDC, without describing inter-annual variability explicitly. In interpreting the catchment characteristics they found that when predicting FDCs in ungauged basins it is important to consider the full range of runoff processes controlling the FDC. On the one hand, these are processes that operate at the event and seasonal time scales and are represented by the precipitation inputs, elevation gradients and subsurface permeability. On the other hand, processes at longer time scales may be involved through the co-evolution of catchments. For example, higher precipitation rates in a catchment may lead to different land forms and soil types than in a low precipitation catchment. Long-term precipitation is then no longer an index of precipitation input alone but also an index of the landform and soil processes that control the FDC.

In the central Italian context of the work of Rianna *et al*. (2011), basin area and mean annual precipitation appear to control the high flow limb of the FDC while the geological heterogeneity controls the low flows. Rianna *et al*. (2011) applied an adaptation of the model to intermittent streams and illustrated a regional application of the model in cross-validation. Shao *et al*. (2009) also reported a parametric model for interpreting and predicting the no flow fraction as a function of basin characteristics. Li *et al*. (2010) regionalised the parameters of lognormal distributions representing the FDC across Australia. Figure 7.13, taken from Li *et al*. (2010), shows that the performance of their index method (within catchment Nash–Sutcliffe efficiency (NSE) calculated on several quantiles of the FDC) outperforms other standard methods such as linear regression, nearest catchment and a method based on hydrological similarity. One advantage of the model proposed by Li *et al*. (2010), which is central to the scope of this book, is the fact that results can be interpreted hydrologically, since the relative importance of the model parameter of interest is quantified by the magnitude of the coefficients. For instance, they found that the position of the FDC (which is related to the mean annual runoff) is positively correlated with the mean annual precipitation and negatively correlated with mean annual potential evaporation. This is in line with the general understanding of the Budyko curve, which indicates that the aridity index is the dominant control on mean annual runoff (see Chapter 5). The FDC parameter related to the standard deviation of runoff is strongly related to both the standard deviation and mean annual precipitation. The standard deviation of runoff increases with decreased mean annual precipitation, indicating higher runoff variability in drier catchments. The standard deviation of runoff is also affected by the presence of vegetation in the catchment, as represented by LAI. It can be seen that the variability of runoff decreases with the LAI, suggesting lower runoff variability from more heavily vegetated catchments. The model of FDC used by Li *et al*. (2010) also includes a non-cease-to-flow parameter (i.e., observed non-zero flow proportion), which is mainly affected by the aridity index, as would be expected, but also by elevation difference, since catchments with steeper slopes are more likely to experience cease-flow conditions. Woody vegetation increases the possibility of having cease-flow days as it is capable of extracting soil moisture, leading to decreased baseflow. Interestingly, catchment area and geographic location do not appear sufficiently explanatory for the shape of the FDC: first, because specific runoff data are used, and second, most of the influence of geographical locations has been explained by other covariates.

Rescaled flow duration curve

These methods are based on rescaling the FDC by an index flow and assume that the scaled FDC does not vary within a homogeneous region. Two steps are needed: (i) identification of pooling groups of gauged sites that can be assumed homogeneous in terms of the scaled FDC,

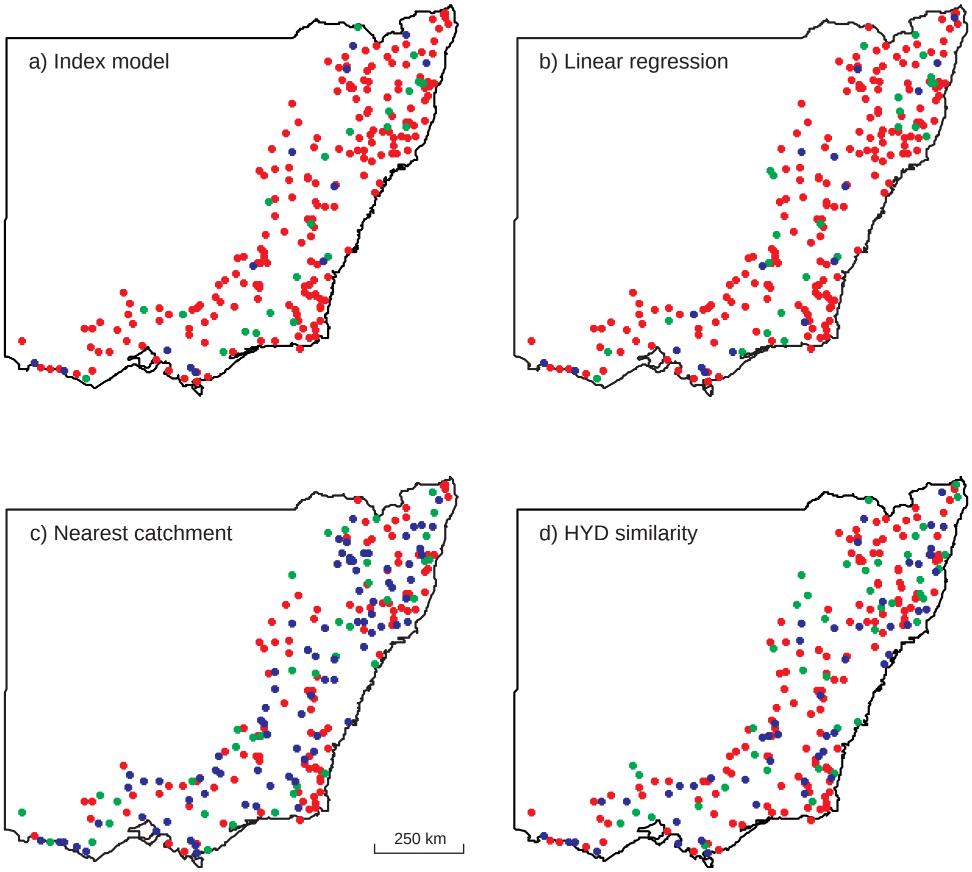

Figure 7.13. Nash–Sutcliffe efficiency (NSE) of quantiles of the FDC obtained from four regional models in south-east Australia. Three colours denote three categories based on the range of within-catchment NSE (red: above 0.75; green: between 0.5 and 0.75; blue: below 0.5). From Li *et al.* (2010).

and (ii) the definition of an allocation rule to assign ungauged sites to a group. In the European FRIEND (1989) study, dimensionless daily FDCs were averaged within pooling groups of catchments. A similar approach was used by Hughes and Smakhtin (1996) and Smakhtin *et al.* (1997) to construct seasonal FDCs for one of the primary drainage regions of South Africa, and by Castellarin *et al.* (2004a) to construct six dimensionless daily FDCs for six hydrologically similar pooling groups of sites (see also Chapter 11, Case studies). Ganora *et al.* (2009) presented the construction of regional dimensionless FDC, in which the pooling group of gauged sites is identified through cluster analysis using a distance metric that quantifies the dissimilarity between pairs of curves, and the FDC of each cluster is identified as the mean normalised duration curve. Minimum catchment elevation and, less importantly, mean hillslope length were found to be the best explanatory variables for the grouping of catchments in north-western Italy and Switzerland that were part of the study by Ganora *et al.* (2009) and were used to subdivide the study area into two homogeneous regions (Figure 7.14). The minimum catchment elevation could be interpreted as a surrogate for the seasonality of flow regimes in the region, which is controlled by snow, glaciers and precipitation regime in Alpine catchments as opposed to lowland mixed regimes and the Apennine–Mediterranean bimodal regime in the south-east of the region (with lower elevations). Similarly, in Nepal, Arora *et al.* (2005) used elevation in their relationship for non-dimensional flow, since more variability happens at higher elevations. Regime is controlled by snow, glaciers and precipitation (of which elevation and area are surrogates), and the regime curve controls the FDC, as discussed in Section 7.2.

Croker *et al.* (2003) proposed a theoretical framework to address the construction of FDCs in arid regions of the world with ungauged ephemeral or intermittent streams. They presented a regional model to estimate the probability of zero/non-zero flows for Portuguese ungauged river basins. The model estimates the probability of zero flows as a function of the mean annual precipitation, as a surrogate of both geographical location and climatic conditions, allowing the derivation of FDCs for ungauged river basins, either ephemeral or perennial.

Parametric methods and rescaled FDC methods are complementary. Parametric methods enable one to model the entire curve, resulting in runoff estimates associated with any duration of the FDC, but often more than three

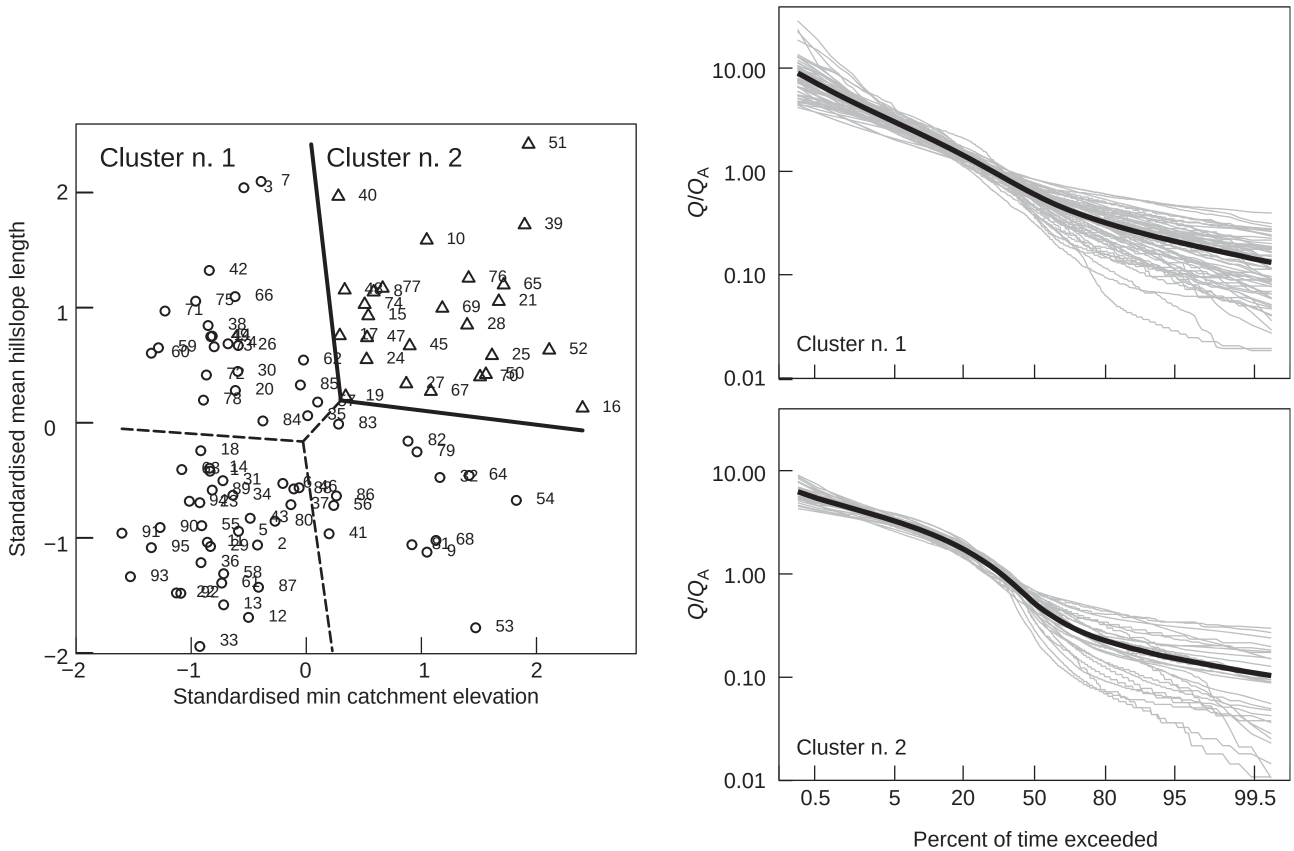

Figure 7.14. (Left) Non-contiguous regions in the space of catchment characteristics (standardised to have zero mean and unit variance). The dashed lines represent the boundaries between the four clusters obtained before merging the clusters whose FDCs cannot be considered significantly different. The final two disjoint regions are separated by the solid line. (Right) FDCs grouped by cluster (grey) and corresponding regional curves (black). From Ganora *et al*. (2009).

parameters are needed to fit the observed distribution well and it may be difficult to regionalise three or more parameters (Castellarin *et al*., 2007a). The main advantage of rescaled FDC methods is that there is no need to fit a distribution function, but identifying a homogeneous group may be more important. Also, the index flow (usually the annual runoff) needs to be estimated in the ungauged basin. Methods for predicting annual runoff are discussed in Chapter 5.

7.3.3 Geostatistical methods

Recent studies have proposed several regionalisation approaches that depend only partially on, if not dispense with, the delineation of a homogeneous pooling group of sites, which is a critical phase and a common prerequisite for the application of FDC regionalisation approaches (Grimaldi *et al*., 2011). These approaches apply geostatistics criteria to the challenge of regionalising hydrological information. The first is called physiographic space-based interpolation (PSBI), or canonical kriging, and performs the spatial interpolation of the desired characteristics of the FDC in terms of geomorphoclimatic characteristics (Chokmani and Ouarda, 2004; Castiglioni *et al*., 2009). The second technique, named topological kriging or top-kriging, is analogous to a spatial interpolation method for runoff-related variables, which interpolates the runoff value of interest (i.e., low flow indices, annual runoff etc.) along the stream network by taking the area and the nested nature of catchments into account (Skøien *et al*., 2006; Skøien and Blöschl, 2007; Castiglioni *et al*., 2009).

These approaches are particularly appealing for predictions in ungauged basins as they provide a continuous representation of the quantity of interest along the stream network (top-kriging), or in the physiographic space (PSBI). Potential applications of these approaches include the estimation of FDC in a region (see e.g., Skøien and Blöschl, 2007; Castiglioni *et al*., 2009). Some preliminary studies show application of PSBI to the problem of FDCs, where the analyses apply a three-dimensional kriging

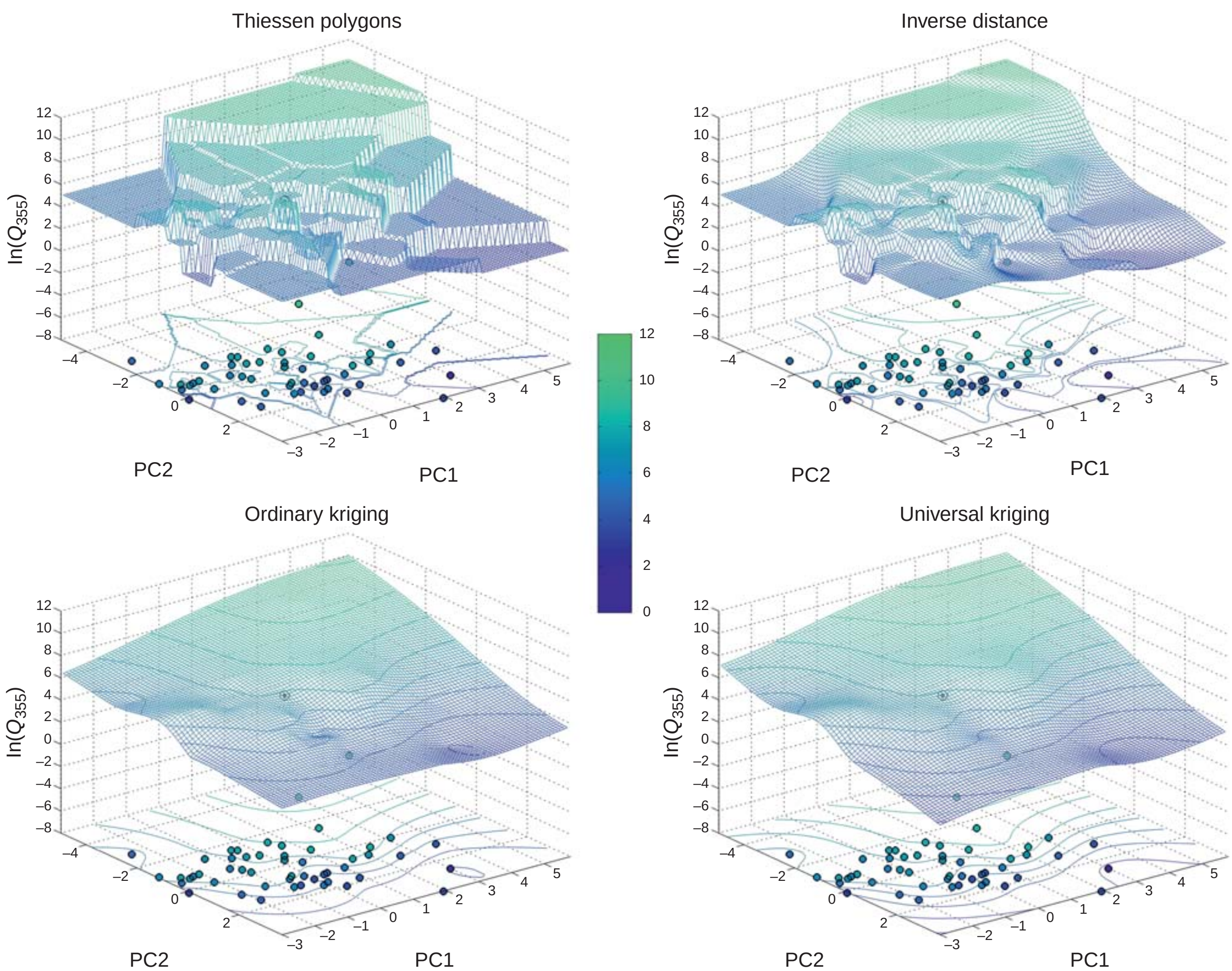

Figure 7.15. Spatial interpolation in the principal component space for the estimation of a quantile of the FDC (Q_{97} low flow). Representation of the surfaces generated in the space of catchment characteristics by four different techniques for the River Aterno at L'Aquila, Italy. From Castiglioni *et al*. (2009).

technique for interpolating long-term dimensionless FDCs in the physiographical space. The horizontal coordinates are the first and second canonical variables of the set of available catchment characteristics (i.e., two-dimensional physiographic space), whereas the vertical coordinate is the runoff duration (see Figure 7.15).

7.3.4 Estimation from short records

Castellarin *et al*. (2004a) presented a series of resampling experiments to assess the sensitivity of empirical FDCs to the sample length (see Chapter 11, Case studies, for more details). The analysis considers a number of river basins with long series of daily runoff, and compares the cross-validated FDCs predicted with three different regional approaches (i.e., quantile regression, parametric and non-parametric) with empirical estimates of long-term FDCs based upon a few years of observation (one, two and five years). This resampling experiment shows that predictions of long-term FDCs based upon five years of observed runoff largely outperform the best performing regional model, while one or two years of daily runoff are generally sufficient to obtain predictions of FDCs that are as accurate as the ones retrieved through regionalisation. This result highlights the value associated with observed runoff, even for short series. As a general remark, the regional estimation of the FDC for ungauged basins should be performed, where possible, by applying different approaches and selecting the estimated FDC only after a scrupulous analysis of the suitability of each regional model to the particular sub-region where the ungauged site is located (Castellarin *et al*., 2004a). Also, it is generally not advisable to rely completely on any regional model, which should be used to provide a first-order approximation of FDCs. The practical utilisation of the estimated FDC for design purposes should be supported through additional, perhaps ad-hoc, measurement campaigns.

7.4 Process-based methods of predicting flow duration curves in ungauged basins

Deciphering the separate controls of both climate processes (e.g., precipitation, temperature, radiation or potential evaporation) and catchment characteristics (e.g., soil, topography, vegetation type and functioning, catchment size, human impacts) on the shape of FDCs represents a key issue for hydrologists. This issue can be best addressed by using process-based approaches that link the drivers (input fluxes of water and energy), the state of the system (storage terms) and its response (output fluxes). To be most effective, process-based methods need to include, as a basic ingredient, the time variability of precipitation inputs to a catchment at all time scales extracted from available observations. They need to describe how this variability is propagated through the catchment system and is finally manifest in the catchment's FDC. In this way, process-based methods provide an excellent basis to interpret (or reinterpret) and evaluate the results from application of well-established statistical methods, as well as evaluate possible changes in the FDC induced by observed or predicted changes to the climatic drivers (e.g., precipitation) or landscape characteristics (e.g., land uses).

Work on predictions of FDCs, especially in ungauged basins, has been mostly statistical and empirical, which has gained strength in the last two decades. However, application of process-based approaches has lagged behind, no doubt due to the difficulties of merging the statistical and dynamical aspects of runoff variability, especially over a wide range of time scales, as is required in the case of the FDCs. Indeed, in this respect, the comparison with derived distribution methods in flood frequency (see Chapter 9) is quite stark. If the FDCs are brought up at all in the context of process-based modelling, they appear to be just one outcome or by-product of continuous rainfall–runoff models. For example, FDCs are used as one of the signatures of runoff variability (Farmer *et al*., 2003), or are used in the calibration or performance assessment of rainfall–runoff models (Westerberg *et al*., 2011). Only in rare instances is the estimation or prediction of the FDCs the actual goal of the modelling (Mostert *et al*., 1993; Tshimanga *et al*., 2011), and even then these applications are in gauged catchments and applications in ungauged catchments are conspicuously absent.

In recent times there have been several efforts that have begun to approach FDCs from a process perspective. The focus so far has been on developing understanding of the climatic and catchment controls on the FDCs, very similar to the steps that were made in the early days of the derived flood frequency work (e.g., Eagleson, 1972; Sivapalan *et al*., 1990). These methods have not yet matured to the point that they can be used to predict FDCs in ungauged basins, but they show considerable promise. Therefore, in the sections below a brief summary is given of these approaches, to highlight their main strengths and weakness (so far) with a view to recognising the importance of such work for predictions of FDCs in ungauged basins, and to complement the significant advances made through statistical methods. As in all other chapters, this review is organised into two parts: (i) derived distribution approaches that aim to capture the process controls on the FDCs in an analytical or quasi-analytical way so as to provide process insights into the regional patterns that arise from statistical methods, and thus improve regionalisation efforts, and (ii) continuous rainfall–runoff simulation methods that generate continuous runoff time series, from which FDCs can be constructed, but nevertheless enable sensitivity studies that will again provide insights to observed patterns.

7.4.1 Derived distribution methods

Flow duration curves may be derived from precipitation analytically in a way similar to the derived flood frequency method of Eagleson (1972) with a number of simplifications. Botter *et al*. (2007a) adopted a stochastic-analytical model that consists of (i) a simple lumped (deterministic) model subsurface drainage (slow flow), governed by a field capacity threshold and a characteristic residence time; and (ii) stationary sequences of random precipitation events, whose arrival times are Poisson distributed, and precipitation depths are gamma distributed. The rainfall–runoff model enabled them to estimate slow flow volumes analytically which, when combined with the statistical characterisation of the precipitation, enabled them to derive the probability density function of slow flow volumes, which represents a form of the slow flow component of the FDC. The analytical formulation also enabled them to relate the runoff variability to the underlying catchment properties and key precipitation event characteristics.

Subsequently, the earlier model of Botter *et al*. (2007a, b) has been extended by Muneepeerakul *et al*. (2010) to include a *fast flow component* as well, and by Botter *et al*. (2009) to include non-linearities in the subsurface storage–runoff relationship. The ability of the stochastic dynamic model to reproduce observed FDCs has been tested in several catchments in the USA and Europe (Botter *et al.*, 2010). Although the stochastic dynamic framework (e.g., Botter *et al.*, 2007a, b, 2009, 2010) is capable of providing insights into the climatic and catchment controls of the FDCs, its potential for application to ungauged basins is constrained by the assumptions made in the work done to date (e.g., Poisson precipitation arrivals). In circumstances where there is strong seasonality in the climate inputs, constant (but different) parameter values have been adopted for each season. The routing of runoff in the river, the associated time delays and, in particular, the carryover of soil moisture storage between seasons has been neglected, so that the method works best in places where seasonality is low. This highlights the need for a more general framework, one for the entire year that captures within-year variations in climate and soil moisture storage, especially in the light of the strong role that seasonality plays in controlling the middle part of the FDC, the role played by hydrogeology and long flow pathways that control low flows, and the role played by high precipitation events that govern high flows.

Yokoo and Sivapalan (2011) proposed a conceptual framework to reconstruct FDCs by disaggregating the FDCs of total runoff into two components, i.e., *fast flow* duration curves and *slow flow* duration curves, similar to the earlier work of Botter *et al*. (2007a, b) and Muneepeerakul *et al*. (2010). The approach of Yokoo and Sivapalan (2011) was formulated on the basis of numerical simulations of the water balance of hypothetical catchments with the use of a physically based rainfall–runoff model, and driven by artificial precipitation inputs generated by a stochastic rainfall model. These simulations by Yokoo and Sivapalan (2011) revealed a clear relationship between the fast flow FDC and the duration curve of precipitation (PDC) and between the slow flow FDC and the catchment's runoff regime curve (mean seasonal runoff). In doing so Yokoo and Sivapalan (2011) proposed a new conceptual framework for the estimation of FDCs in ungauged basins, through building bridges between the fast and slow flow parts of total runoff as precipitation variability cascades through the catchment system, and through recourse to understanding the respective process controls. Yokoo and Sivapalan (2011) carried out preliminary analyses on a few selected catchments within the USA to demonstrate the feasibility of their approach. However, their approach has not been applied and tested in ungauged catchments. Nevertheless, there is promise that, through a combination of the stochastic dynamic approach of Botter *et al*. (2007a, b) and Muneepeerakul *et al*. (2010), and the numerical simulation approach of Yokoo and Sivapalan (2011), one can make considerable advances in the area of process-based approaches to the predictions of FDCs in ungauged basins.

7.4.2 Continuous models

Long-term numerical simulations of the soil water balance equation coupled to some routing scheme to reproduce the movement of water in soils and streams are greatly beneficial to explore the dependence of the features of the FDC on the underlying hydrological and climatic processes, as all the driving processes (precipitation, soil moisture dynamics, transport in channels and hillslopes) may be described in much more detail than may be possible with analytical models. An example of continuous model simulations to describe FDC is described in the following; it refers to the approach developed by several authors using the Pitman (1973) monthly rainfall–runoff model, which has been used extensively in Southern Africa, particularly in ungauged catchments. The most recent description of the model is provided in Hughes (2006). This conceptual model includes the primary processes that are responsible for the magnitude and shape of the FDC: surface runoff (based on a triangular distribution of catchment absorption rates and monthly precipitation total) and a non-linear drainage function dependent on the soil moisture storage level partitioned into rapid (interflow) and slow (groundwater) components, the latter accounting for groundwater recharge and runoff components. The balance between the contributions of the three components (surface runoff, interflow and groundwater discharge) determines the shape of the FDC, and this balance is clearly a reflection of the climate and catchment characteristics (as represented by the model parameters). The model can also simulate the effects of anthropogenic impacts (abstractions, reservoir storage, impacts of different vegetation cover, etc.) on FDCs (Hughes and Mantel, 2010).

One way of assessing the model performance is to compare simulated FDCs to either FDCs derived from gauged data or regionalised estimates of the FDCs for ungauged situations. Figure 7.16 shows results for two dry catchments in Botswana and Zimbabwe. For the ephemeral river in Botswana, while most of the FDC can be simulated, the frequency of zero flow is much more difficult to capture even after calibration. This may be related to poor precipitation definition in semi-arid areas, but may also be related to some processes not being adequately represented by the model (e.g., dynamic vegetation changes, see Mostert *et al*., 1993). For the perennial (but relatively dry) river in Zimbabwe (Figure 7.16b), the results indicate poor agreement in the case of low flows; part of the reason for this can be attributed to upstream development impacts (small farm dams, etc.) on the observed runoff data.

While all of the results given above, and also those extracted from a related report (Hughes, 1997a, b), include model calibrations, and are therefore not applications in ungauged basins, one of the conclusions was that

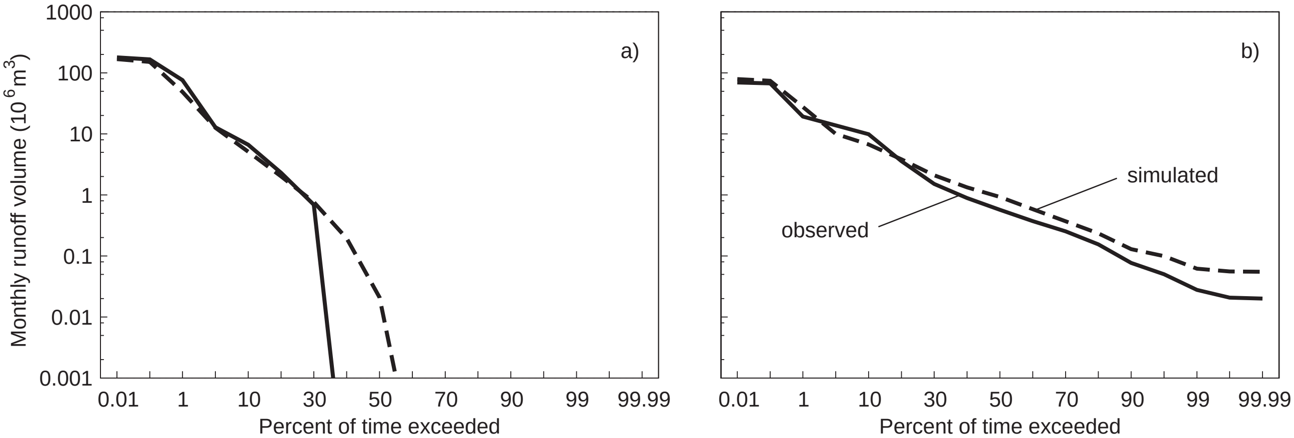

Figure 7.16. Simulated monthly FDCs in (a) a dry region (Tati catchment, Botswana, 570 km^2) and (b) a somewhat wetter region (Mwarazi catchment, Zimbabwe, 202 km^2).

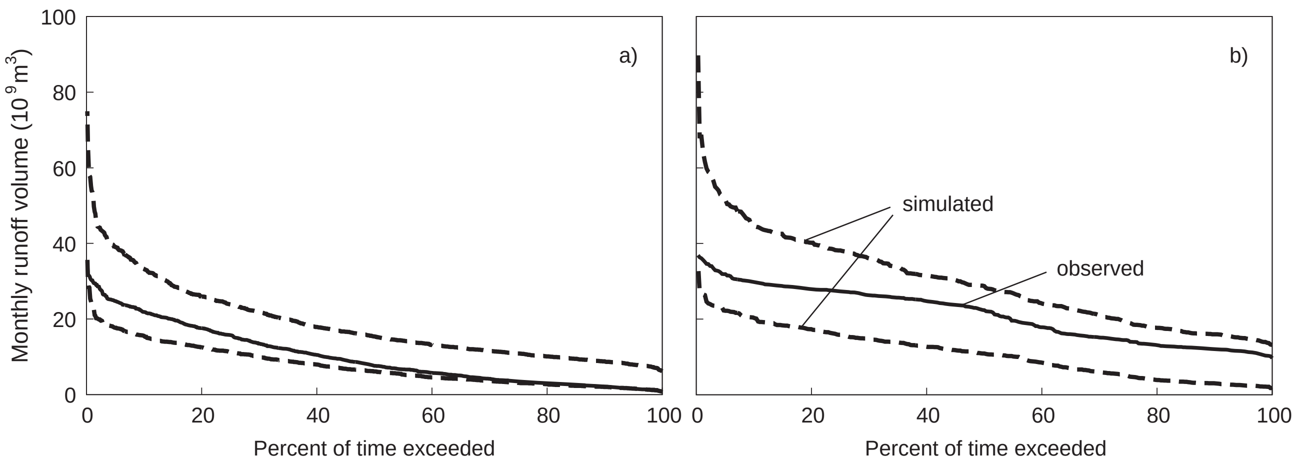

Figure 7.17. Uncertainty simulation results for two of the gauged upper catchments in the Congo River basin: (a) sub-basin 82, (b) sub-basin 85. Dashed lines show 90% uncertainty bounds. From Tshimanga *et al*. (2011).

variations in parameter values were generally a reflection of what might be expected given the conceptual interpretation of the model structure and the limited knowledge available about the physical catchment characteristics of the sites used. These observations, plus additional experience over many years of applying the Pitman model, contributed to the development and application of parameter estimation approaches for the Pitman model, as reported in Kapangaziwiri and Hughes (2008). The approach adopted for parameter selection in Kapangaziwiri and Hughes (2008) is based on *a-priori* estimation of most of the parameters of the Pitman model using estimates of physical basin properties. The results for selected basins show that the revised parameters are at least as good as regionalised sets (using techniques discussed in Chapter 10) or give satisfactory results in areas where no regionalised parameters exist. However, in order to make the approach applicable to ungauged catchments, the remaining parameters, mostly associated with interception and evaporation processes, should also be estimated *a priori* (without calibration).

Hughes and Mantel (2010) used the Pitman model for Monte Carlo sampling from parameter probability distributions to generate ensemble outputs of time series and therefore also estimates of uncertainty of FDCs. This may be useful for ungauged basins where it is difficult to evaluate the applicability of a single regionalised parameter set. An example of this application is presented in Chapter 11 (Case studies). Some of these principles have been applied to setting up the model for the large Congo River basin (Tshimanga *et al.*, 2011). Figure 7.17 shows two examples of initial uncertainty estimates based on FDCs for the upper parts of the Congo River basin. The uncertainty is quite large, and in some cases (e.g., low flows for sub-basin 82) is biased relative to observed low flows. There also appears to be a problem with over-prediction of runoff peaks, which may be related to inadequate storage, infrequent excessive surface runoff generation, or inadequate attention to attenuation of flood peaks due to floodplain storage. The use of FDCs has allowed these model deficiencies to be identified, and has prompted further study towards model improvement.

Even though the use of continuous models allows for a more detailed description of the driving processes, it has the consequence of significantly increasing model complexity, possibly increased accuracy, but also lengthening simulation times and increasing the number of parameters. As a result, there is a danger that the individual role of each climatic factor and hydrological process contributing to the shape of the FDC cannot be isolated easily, leading to limited transferability to other catchments/climates. A range of approaches are therefore needed for introducing process understanding into predictive models, ranging from simple, targeted models to complex, distributed models. In future, process-based methods should be designed in such a way to benefit from and complement the experiences arising from well-established statistical methods, and in this way to help improve the performance of statistical regionalisations as well (see e.g., Di Prinzio *et al*., 2011).

7.5 Comparative assessment

The aim of the comparative assessment of FDC predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1, in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. In both Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

7.5.1 Level 1 assessment

Table A7.1 lists 13 studies that deal with the estimation of FDCs in ungauged basins. Some of the studies reported performance measures that were not compatible with the other studies and/or performed goodness of fit analysis instead of cross-validation. The remaining 10 studies performed leave-one-out cross-validation and the performance measures were broadly similar. These were used in the Level 1 assessment (indicated in Table A7.1). The number of catchments evaluated in each study ranges from 8 to 1080, with a median of 49. There are several studies that compare different hydrological models and/or regionalisation approaches, which give a total of 27 results for predictive performance. The regionalisation methods used are index methods, regression approaches and estimation from short records. The studies are quite heterogeneous in terms of performance measures and the way they are applied. Typically applied performance measures are the absolute normalised error in the centre of the FDC; the proportion of sites with Nash–Sutcliffe (NSE) calculated over quantiles lower than 0.75; the proportion of sites with absolute normalised error (ANE) lower than 1; and the mean relative root mean square error. Even though these performance measures are not strictly speaking comparable, values close to 0 imply good performances, and large values imply a lower performance. Note that these all represent errors (rather than skill), so they have been plotted downwards on the vertical axis to make them consistent with the performance measures in the other chapters, i.e., higher up in the plot is better. Different performance measures were indicated by different symbols in the plots. For comparison with the other runoff signatures in Chapter 12, the NSE of the quantiles of the FDC were back-calculated from the percentage of sites with the NSE lower than 0.75 by applying an empirical relationship from Level 2. The 25% and 75% quantiles of these NSE are 0.60 and 0.90, respectively.

Figure 7.18 and Table A7.1 indicate that the studies were performed in Europe, Asia, Australia and North America. Most available studies were for humid and tropical climates. Three main science questions are addressed below.

How good are the predictions in different climates?

In Figure 7.19 it is important to compare similar performance measures. The absolute normalised errors (full circles) in humid regions are smaller than those in the arid regions. The proportion of sites with NSE lower than 0.75 (pluses) in humid regions show some scatter and the majority of them are larger than that for the cold regions. This means that from this limited comparison there is a tendency for the regionalisation methods in humid regions

Figure 7.18. Map indicating the countries included in the Level 1 assessment.

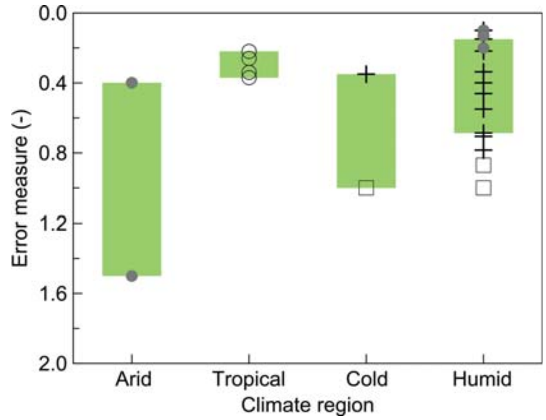

Figure 7.19. Absolute normalised error in the centre of the FDC (full circles), the proportion of sites with Nash–Sutcliffe efficiency calculated over quantiles lower than 0.75 (pluses), the proportion of sites with absolute normalised error lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by climate. Each symbol refers to a result from the studies indicated in Table A7.1. Boxes show 25%–75% quantiles.

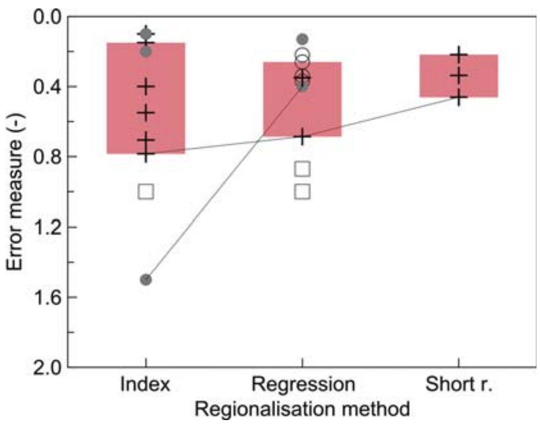

Figure 7.20. Absolute normalised error in the centre of the FDC (full circles), the proportion of sites with Nash–Sutcliffe efficiency calculated over quantiles lower than 0.75 (pluses), the proportion of sites with absolute normalised error lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by regionalisation method. Each symbol refers to a result from the studies listed in Table A7.1. Lines indicate studies that compared different methods for the same set of catchments. Boxes show 25%–75% quantiles.

to perform slightly better than in tropical regions and slightly lower than in cold regions.

Which method performs best?

The regionalisation methods represented in the assessment included 13 results for index methods, 11 results for regression approaches and 3 results for estimated FDC from short records of 1, 2 and 5 years. The assessments in each group are not based on exactly the same regionalisation approach, but the methodology is similar. Figure 7.20 indicates that methods using short records seem to have the best performance, even though there are few studies. The study that compared all three methods for the same catchments using the same performance measure (shown in Figure 7.20 as grey lines) shows that predictions of long-term FDCs based upon 1, 2 and 5 years of observed runoff all outperform any of the other methods. More detailed comparisons (Castellarin *et al.*, 2004a) with other error measures suggest that 5 years of observed runoff give better estimates of FDC in all respects but with just 1 and 2 years the estimate depends on the error measure examined. The study that compared the index method with two quantile regression methods found that the two regression methods resulted in the same performance, which was better than that of the quantile regression. However, this comparison was only over two catchments. In both comparative studies, the regressions methods perform better than the index method, but when one considers all studies the index method performs best.

How does data availability impact performance?

Figure 7.21 shows that performance increases with the number of catchments used in the analysis. The trend is particularly clear for the comparison for the intermediate classes (shown as pluses) of catchment number (from 20 to 250 catchments per study). Also, the comparison between the smallest and largest classes (full circles) is clear. Statistical regularity would suggest that the smaller sample sizes would account for some of this decrease in performance. This is consistent with other studies that have evaluated the effect of sample size on regionalisation (Spence *et al.*, 2007). This trend is due to the higher stream gauge density in the larger studies. These results suggest that even if one is interested in

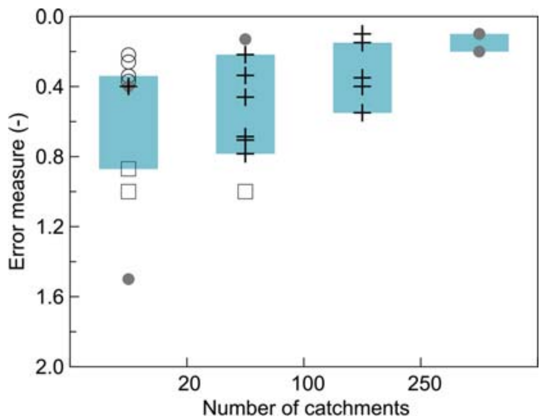

Figure 7.21. Absolute normalised error in the middle of the FDC (full circles), the proportion of sites with Nash–Sutcliffe efficiency calculated over quantiles lower than 0.75 (pluses), the proportion of sites with absolute normalised error lower than 1 (empty squares), and the mean relative root mean square error (empty circles) of predicting FDCs in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies indicated in Table A7.1. Boxes show 25%–75% quantiles.

estimating a FDC for a single catchment it may be worth basing the regionalisation on a large number of catchments.

Main findings of Level 1 assessment

– The prediction performance of flow duration curves in ungauged basins tends to be better in humid climates than in arid climates.
– Methods that use short runoff records at the site of interest perform better than any regionalisation method provided at least 1 year of daily runoff data are available, and significantly better if 2–5 years of data are available.
– The performance increases clearly with number of stream gauges in the region.

7.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A7.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and comparison of results between studies. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. Four study authors from the Level 1 assessment, plus three other authors, provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment (Table A7.2). This data set combines data from 1419 catchments, four groups of regionalisation methods and four catchment characteristics. The regionalisation methods are regression approaches, index methods, geostatistics and process-based methods. The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area.

The performance assessment was based on the slope of the middle part of the FDC defined as the difference between the 30% and 70% normalised runoff quantiles divided by 40. This slope quantifies the relative change of runoff for 1% difference in exceedance probability. It was chosen for this analysis because it is a specific feature of the FDC, while the upper and lower parts of the FDC are related to floods and low flows treated in Chapters 8 and 9. Furthermore, it is related to the variance of daily runoff and to climate and catchment processes as discussed in Section 7.2. The performance was then calculated as the normalised error (NE) and absolute normalised (ANE) (Table 2.2) of the slope. The NE highlights biases in the methods while the ANE is a measure of the overall performance. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e. higher up in the plot is better. For comparison with the other runoff signatures in Chapter 12, R^2 of the slope of the FDC were calculated for all methods in each study separately, which gave a median of 0.26. Also, the NSE of the quantiles of the scaled FDC were calculated, which gave a median of 0.98. Other evaluation measures may lie in between. As an indicative range of typical performances, a range of 0.40 to 0.95 is shown in Chapter 12.

To what extent does runoff prediction performance depend on climate and catchment characteristics?

The assessment of the predictive performance of the different methods with respect to the four climate and catchment characteristics is presented in Figures 7.22 and 7.23. The top panels of both figures show the dependence of performance on aridity. For the regression method performance clearly decreases with aridity. For the most arid catchments (aridity indices between 1 and 2), the regression approach tends to overestimate the slope of the FDC (Figure 7.23). For all the other methods, the decrease in performance with aridity is less clear, perhaps with the exception of the process-based methods. It should be noted that the methods were applied to different regions: regression to France and the USA, and the other methods to Austria and northern Italy where the catchments are never very arid. While generally one would expect a decrease of performance with increasing aridity, since arid regions tend to be more heterogeneous than humid ones, there may also be differences in the results for the different

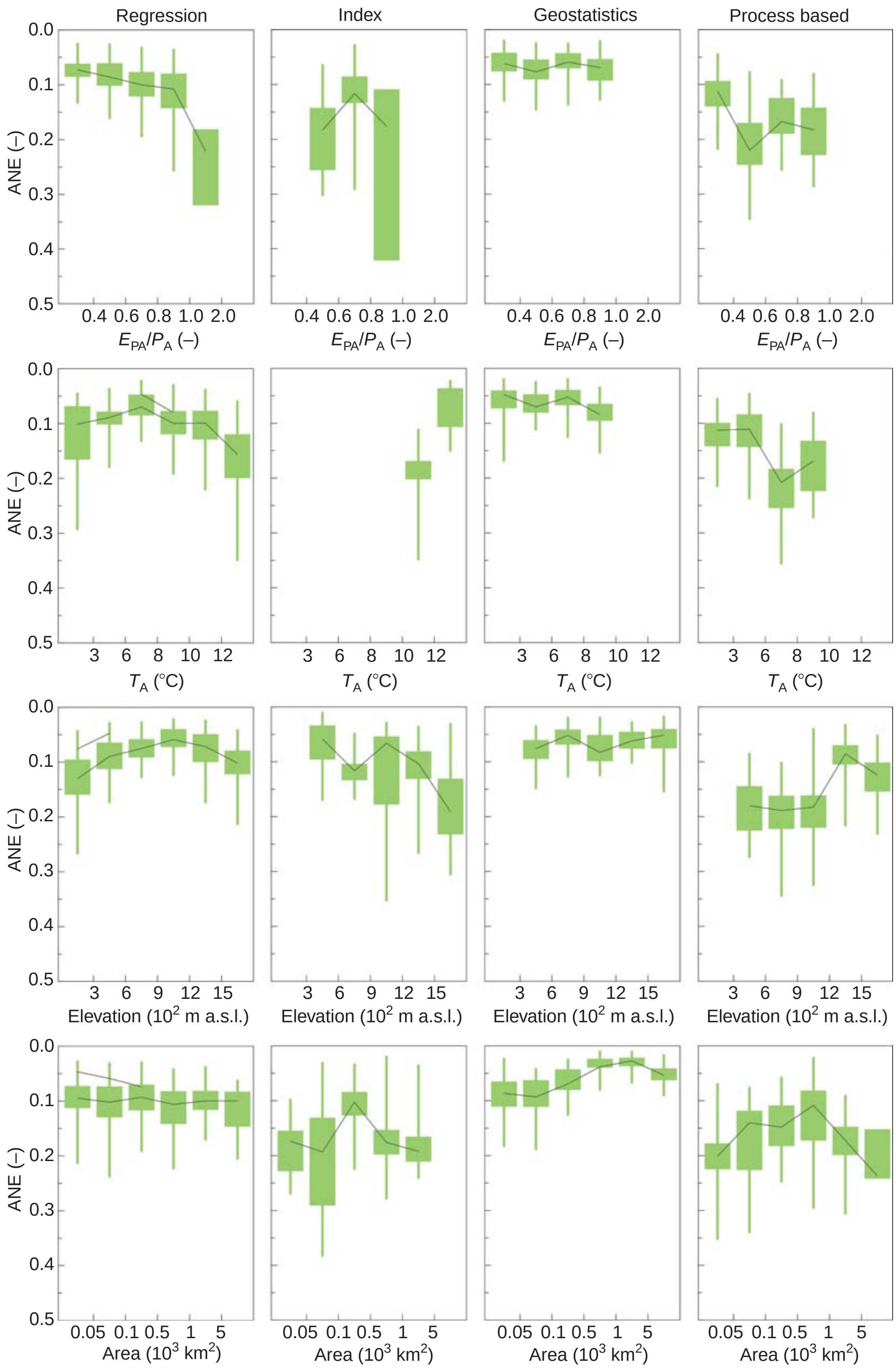

Figure 7.22. Absolute normalised error (ANE) of predicting the slopes of the FDCs in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature T_A, mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

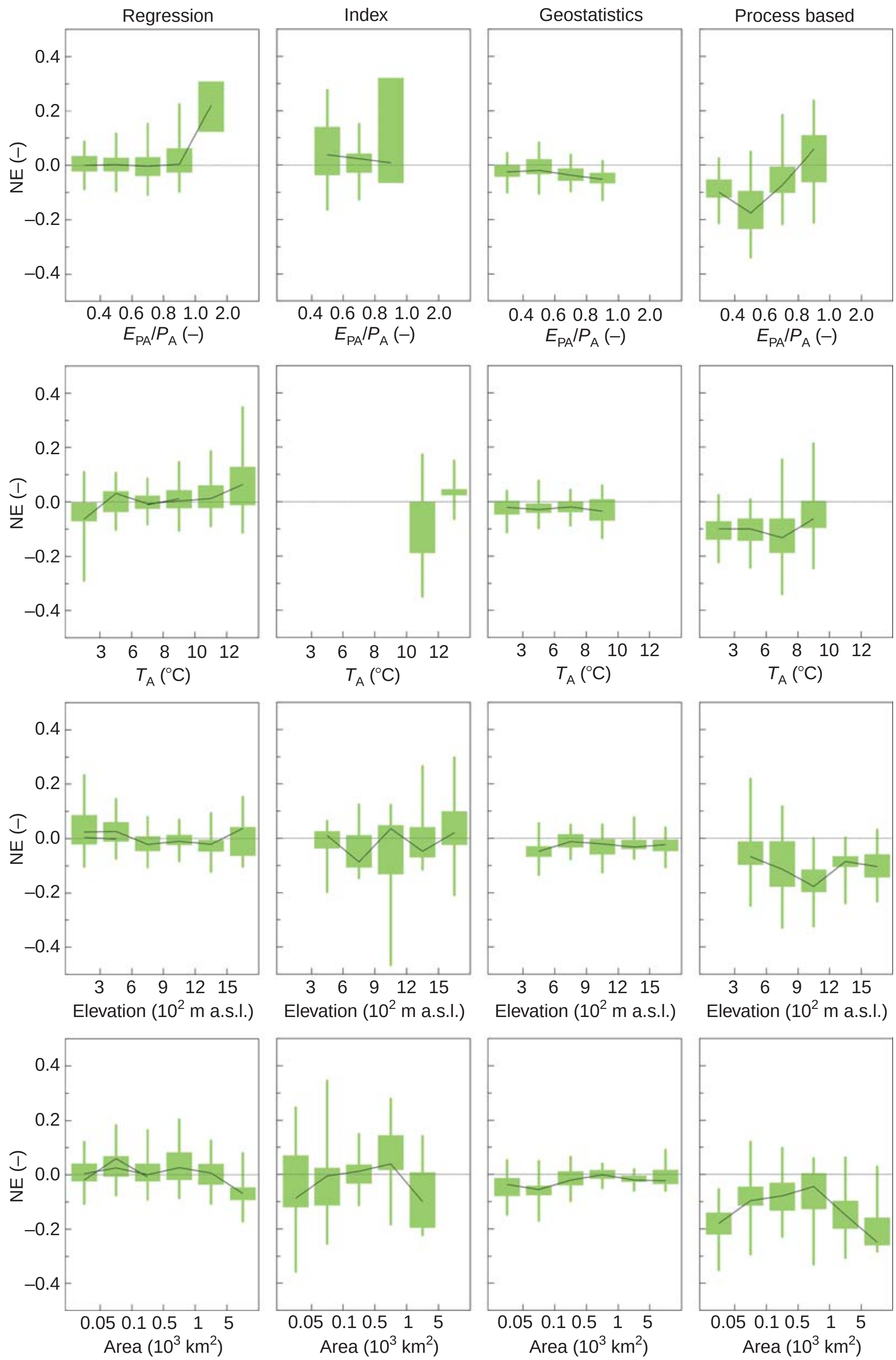

Figure 7.23. Normalised error (NE) of predicting the slopes of the FDCs in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature T_A, mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

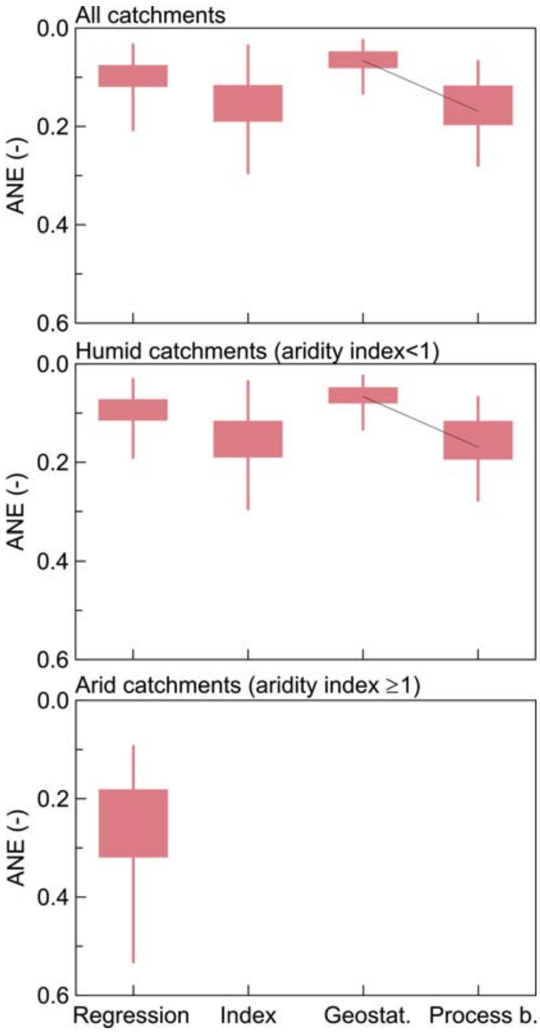

Figure 7.24. Absolute normalised error (ANE) of predicting the slopes of the FDCs in ungauged basins for different regionalisation methods, stratified by aridity. (Top) All catchments; (centre) humid catchments (aridity index < 1); (bottom) arid catchments (aridity index ≥ 1). Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles.

methods that are related to differences in the regions. A similar but less pronounced pattern can be observed for the relationship between performance and mean annual temperature T_A (second row, Figures 7.22 and 7.23).

The performances of the methods as a function of catchment elevation show a complex pattern. For the regressions, the performance seems to increase with elevation, peak around 1000 m a.s.l. and then decrease. This dependence may be related to a slight decrease of aridity with elevation for the lower catchments in France and a slight increase for the higher catchments (Figure 10.39), while in the other regions examined aridity generally decreases with elevation. The differences in the performances are therefore, again, at least partly a reflection of the differences in the hydrological characteristics in the regions in which they were applied. Geostatistical methods have been applied mainly to Austria (with a small number of catchments from the USA) and the slight increase in performance with elevation may be a reflection of the increasing importance of snow processes, where the FDCs may be easier to predict than in precipitation-dominated runoff regimes.

The performance of the geostatistical methods strongly increases with catchment area, while index and process-based methods work better for intermediate catchment sizes. Clearly, as the catchment area increases, the overlapping areas between gauged and ungauged catchments tend to be larger, so the correlations along the stream network are likely to increase, which will improve the performance of the geostatistical methods. For the other methods the controls are less clear. For the smallest and largest catchments both the index and the process-based methods tend to underestimate the slope of the FDC. For the process-based methods (continuous runoff models) this is related to the calibration that has been done on the basis of minimising NSE of observed and simulated daily runoff. For that case study, the slope of the FDC was not captured well even in the calibration. This points towards the importance of carefully choosing objective functions in the calibration of runoff models in the context of the application of interest.

Which method performs best?

Figure 7.24 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments of Table A7.2, and catchments with an aridity index below and above 1, respectively. The results indicate that, overall, geostatistical methods perform best, followed by the regression methods. The data sets used for the two methods were from Austria and France, respectively, which both have a relatively dense stream gauge network. The lower performance of the index method in Italy may be related to the lower stream gauge density. This is consistent with the dependence of the performance on the number of catchments in the Level 1 assessment (Figure 7.21). There were insufficient studies for a complete comparison of the methods between arid and humid catchments.

Main findings of Level 2 assessment

– The performance of all methods for predicting the slope of the FDC in ungauged basins decreases with increasing aridity, although the strength of decrease differs between regions.

- There is a slight tendency for the performance to decrease with increasing air temperature. The pattern of elevation dependence is more complex and may relate to the regional patterns of aridity and snow processes.
- The performances increase with catchment size for the case of geostatistics. Scale dependencies are less clear for the other methods. The process-based methods underestimate the slope of the FDC for the smallest and largest catchments.
- Geostatistics and regression methods perform better than the other methods. This may be partly related to the higher stream gauge density of the data sets used for these methods.

7.6 Summary of key points

- The flow duration curve (FDC) is a statistical (i.e., frequency domain) representation of runoff variability at all time scales (from inter-annual variability all the way to event-scale variability), and therefore it embeds within it aspects of all the other signatures studied in this book. The mean of the FDC is mean annual runoff. The seasonal flow regime smoothens out variability at both short (i.e., floods) and long (i.e., low flows) time scales; consequently the middle part of the FDC reflects runoff variability that is reflected in the seasonal flow regime.
- Similarity indices for FDC therefore include the aridity index (for annual runoff variability), geology (for low flows), storage capacity, mountain elevation and temperature (for seasonal runoff variability), and event characteristics (for floods).
- The FDC also reflects the multiplicity of pathways within the catchment that water follows and the associated time scales, and hence it connects to all of the co-evolutionary processes impacting, and impacted by, water flow processes, such as ecological, geomorphological and pedological processes.
- Current predictions of FDCs are heavily dominated by statistical methods. Geology or geology/soil related indices and topographic elevation (in mountainous regions) are the most frequently used predictors of the slope/shape of FDCs, in addition to the aridity index, which governs the mean of the FDC.
- Process-based methods are not widely used for predicting FDCs in ungauged basins; however, there is great potential for an increased use of process-based methods, especially as we gain improved understanding of the underlying process controls.
- Comparative assessment of several prediction methods indicated that, at least for some of the methods (e.g., regressions), predictive performance decreases with increasing aridity (Level 1 and 2 assessments). Predictions based on availability or collection of short records outperform regionalisation methods in humid regions, where inter-annual variability is small (Level 1 assessment), whereas this may not be the case in arid regions due to the fact that inter-annual variability is much larger, and short records are insufficient to fully capture this variability. Performance of geostatistical methods is good (Level 2 assessment). These methods require stream gauges in the region of interest.
- Much more insight into the FDC can be gained if the contributions of both annual runoff variability and also seasonal flow regime can be separated from the FDC, with the distribution of the residuals explored through the use of process-based models, especially of the derived distribution type. Approached in this way, there is considerable scope to approach the FDCs in a comparative manner, through bringing out the differences of the FDCs between different places (e.g., climates and landscapes), and seeking explanations for their differences using understanding of the underlying process controls.
- Considerable potential exists for a joint investigation of spatial patterns (within regions, along a river network, and between regions) of not only FDCs, but also associated co-evolutionary features such as hydraulic geometry, sediment stratigraphy, riparian vegetation and patterns of biodiversity of aquatic biota.

8 Prediction of low flows in ungauged basins

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8.1 How dry will it be?

Rivers often undergo periods of low flows that sometimes last for a long time. In some places, and river reaches, the river may even cease to flow entirely. While both ecosystems and humans have adapted to low flow conditions in various ways, the actual amount of water in the stream is critically important for a number of life-sustaining functions. River water is often used for drinking and household use, irrigation and energy production as well as industrial uses. These demands for water often remain constant throughout low flow periods. Rivers and streams also have important ecosystem functions. The health of a range of aquatic and riverine ecosystems is closely linked to the runoff variability in the stream, of which low flow periods are an integral part (Gustard and Demuth, 2009; Smakhtin, 2001). With increasing human population and improving lifestyles, the demand for water has increased dramatically, putting more pressure on available water resources. This is especially true in places where water abstractions, water transfers, damming of rivers and pumping of groundwater have exacerbated the low flow problem. Managing water resources efficiently and effectively during low flow periods has therefore become an important part of integrated water resources management.

To assist in all these management tasks, accurate predictions of low flows are needed. Additionally, understanding low flows in the context of the natural hydrological regime and the underlying climate, landscape and human controls is an interesting science question in itself.

Depending on the application and the science question, different low flow characteristics may be of interest (see Smakhtin, 2001; Hisdal *et al.*, 2004; Gustard and Demuth, 2009): (i) characteristics that represent low flow runoff with a certain probability; (ii) characteristics that represent durations or deficit volumes of low flows; and (iii) characteristics that represent how quickly the low flow runoff decreases with time. Indices that relate to the first group (i.e., representing runoff) include the following:

- Flow quantiles (Q_x): runoff values exceeded x% of the time corresponding to points on the flow duration curve (Chapter 7). For perennial streams, 90th or 95th quantiles (i.e., Q_{90} and Q_{95}) are often used, while for intermittent or ephemeral streams, quantiles based on runoff within a typical runoff season, or quantiles with a lower exceedance probability (e.g., 60%) may be more appropriate (Smakhtin, 2001). Flow quantiles are relatively robust to measurement errors and anthropogenic effects (Laaha, 2000), which has made them widely used around the world (Smakhtin, 2001).
- Mean annual minimum flows over d consecutive days (MAM_d): long-term average of runoff during the driest period of each year. A moving average time window of 7 or 10 days is often used to remove fluctuations of the hydrograph due to measurement errors or anthropogenic effects (Laaha, 2000). The choice of the moving window size may also depend on the problem at hand. The magnitudes of mean annual minimum flows over 7 or 10 consecutive days are often similar to Q_{95} (e.g., Smakhtin, 2001; Laaha *et al.*, 2005).
- Instead of the mean, annual low flows $Q_{d,T}$ of a given return period T can be used, where $Q_{d,T}$ (d-day, T-year runoff) relates to the annual minimum d-day low flow that is expected to occur, on average, once every T years. They are estimated by extreme value statistics from a d-day moving average of the daily hydrograph. The 7-day runoff with a return period of 10 years ($Q_{7,10}$) is often used in the USA and Canada (e.g., Kroll *et al.*, 2004).

The second group, runoff deficit indices, measure the runoff volume below a runoff demand function, which may be related to irrigation water requirements, cooling water for industrial plants, drinking water supply, minimum water depth for navigation, or environmental flows to support stream ecology (Yevjevich, 1967; Nathan and McMahon, 1990; Hisdal *et al.*, 2004). Duration indices measure the maximum or average duration of dry spells

* Coordinating contributor

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below a runoff threshold. The duration or frequency of dry spells (or no flow) may be a particularly useful index in arid regions.

The third group of characteristics represents how fast the low flow runoff decreases with time and includes the baseflow index, which represents the proportion of runoff that originates from deep storage in the catchment (Institute of Hydrology: IH, 1980). Another characteristic is the recession parameter, which measures the rate of decay of the runoff hydrograph during dry periods and is related to the outflow of stored water from within the catchment (Tallaksen, 1995; Eng and Milly, 2007; Gustard and Demuth, 2009).

Low flow characteristics are best estimated from long runoff records at the site of interest, and a minimum record length of about 20–30 years is usually recommended (e.g., DVWK, 1983; Hisdal *et al*., 2004). In ungauged basins where such data are unavailable, low flow characteristics need to be estimated from regional information and from auxiliary, local data. This chapter deals with the prediction of low flows in ungauged basins with a main focus on low flow indices (i.e., Q_x, MAM$_d$, $Q_{d,T}$) as they are the most important runoff signatures for low flows from a practical perspective. Also, these low flow indices are a subset of the full spectrum of variability embedded in the complete runoff hydrograph and are therefore a key signature of natural runoff variability, which is interesting to understand per se from a process perspective.

Low flows are runoff extremes and therefore share some common features with floods (Chapter 9), although they are at the other end of the spectrum of variability. Both may be more variable than other runoff signatures as they are extremes, and both may be difficult to estimate from short records. However, floods can tend to be very localised, in particular flash floods caused by convective precipitation (Borga *et al*., 2010), while low flows caused by droughts may extend over much larger spatial and temporal scales.

8.2 Low flows: processes and similarity

Low flows are the result of a complex combination of processes related to the climate and the catchment. They are a manifestation of the interactions between climate inputs during particular critical periods of the year and complex flow pathways that result from the heterogeneous patterns of geology, soils and vegetation cover in the landscape. Understanding the subsurface flow paths (Chapter 4), in addition to the climatic conditions, is therefore particularly important for predicting low flows in ungauged basins. In order to predict low flows in ungauged basins one needs to understand these processes in some detail and to understand what makes two catchments similar in terms of the driving processes and the low flow variability. Figure 8.1 presents runoff hydrographs of two catchments in the UK along with the photographs of the streams. The low flow behaviours of the two catchments are completely different. The South Tyne at Featherstone (Figure 8.1 top) is a quickly responding (flashy) stream, which can be inferred also by the evident bank erosion in the picture, while the Kennet at Theale (Figure 8.1 bottom) has more damped dynamics, reflected in the gentler landscape. As a consequence, the South Tyne experiences more frequent low flow periods than the Kennet, and low flow runoff, relative to the mean runoff, is also much lower. From a hydrological point of view it is of interest to understand why the low flow behaviour of these two streams is different (i.e., why is the South Tyne so much flashier than the Kennet), to identify the causal processes, and explore how similarity and dissimilarity between catchments can be defined in terms of low flow processes.

8.2.1 Processes

What are the processes causing low flows? Precipitation that falls on a catchment undergoes several transformations: it is partitioned at the surface into overland flow and infiltration, and the infiltrated water is stored in the soil and the aquifer below and eventually released or drained as streamflow. River flow falls because release or drainage stops or becomes low for prolonged periods of time. There are therefore two main component processes driving low flows, those related to precipitation and other climate variables, and those related to catchment processes in the soil and aquifers.

Climate

Climate controls the water fluxes at the land surface of catchments through the variation of precipitation and evaporation over the year, which in turn determine the fluxes of water into the streams. With respect to generating processes and seasonal occurrence, two types of low flows can be distinguished (Figure 8.2). The first type occurs as a consequence of persistent dry and warm weather periods, when evaporation exceeds precipitation. This leads to depletion of subsurface storages and causes runoff recession. This is the case in most arid places, or even in humid places under summer, dry conditions, when there is very little precipitation and the evaporation rates are very high. These are often called summer low flows (Figure 8.2a). The second type of low flows occurs in cold regions, where low flows are caused by the freezing of water. This causes precipitation to be temporarily stored in the snow or ice cover, again causing runoff recession. Subsurface pathways may also be frozen, thereby preventing water

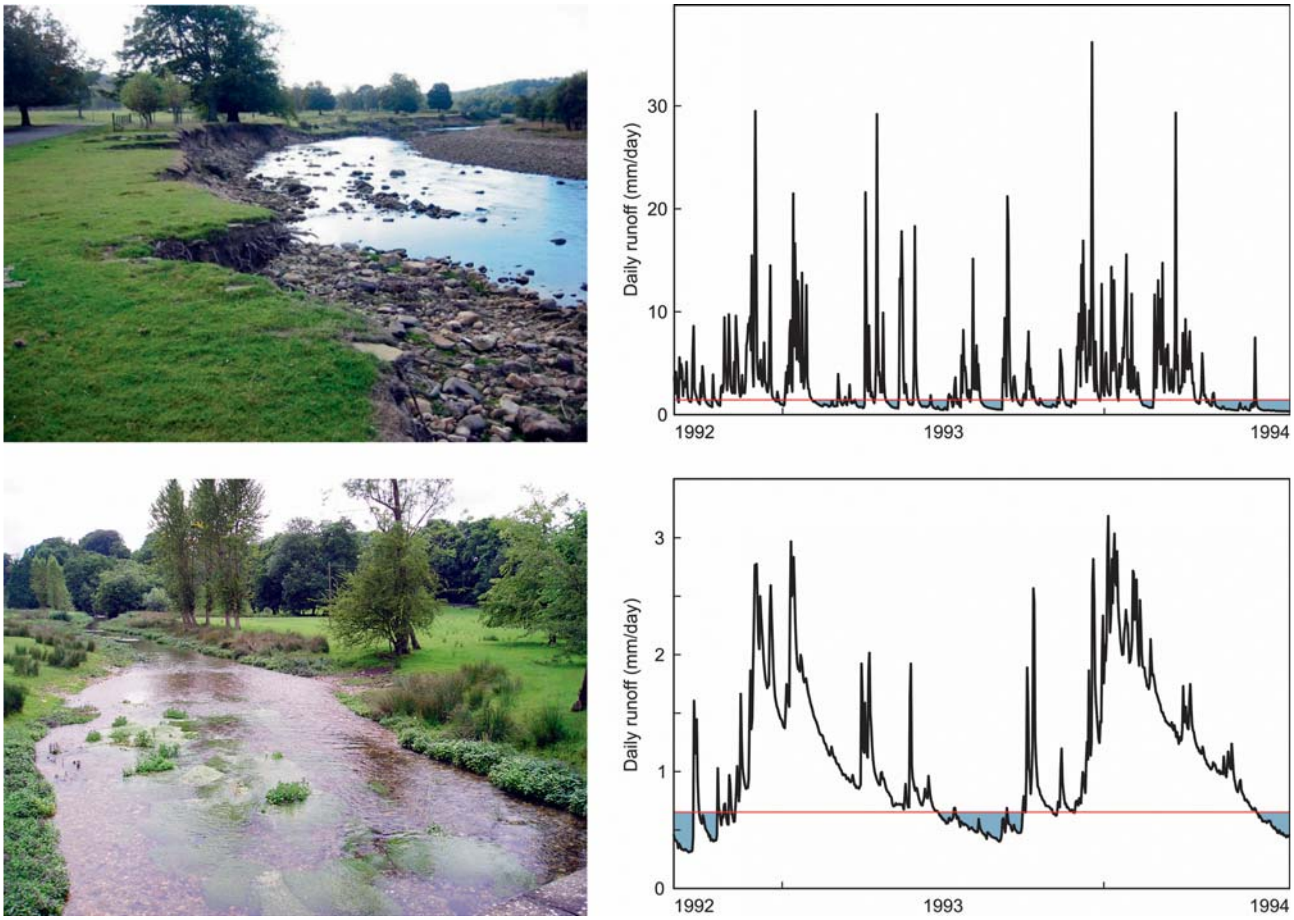

Figure 8.1. Comparative photos and hydrographs of the South Tyne at Featherstone, UK (top), and the Kennet at Theale, UK (bottom). Red line indicates Q_{50}, shaded areas are deficit volumes below Q_{50}. Photos: (top) Environment Agency, (bottom) N. McIntyre.

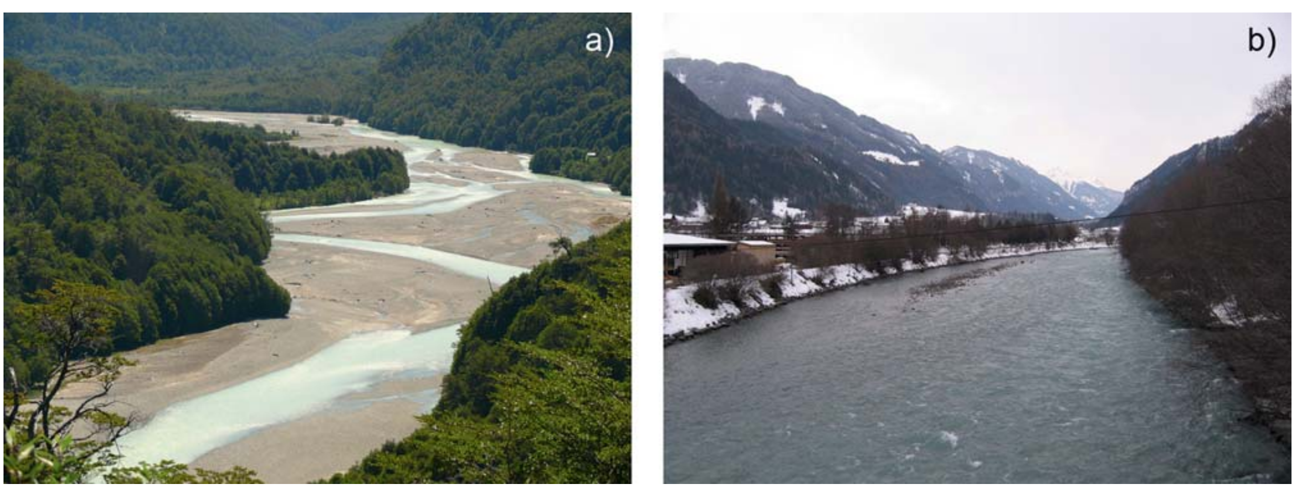

Figure 8.2. Summer and winter low flows. (a) Baker River, Chile; (b) Inn River, Austria. Photos: (a) A. Tranmer; (b) Creative Commons License.

movement and resulting in low flow. These are often called winter low flows (Figure 8.2b). As air temperatures rise with the onset of spring, ice and snowmelt and the subsurface pathways become reactivated. The melt water is added to the system, restoring flows that may persist into the summer, even if there is low summer precipitation.

In mid- and high-latitude climates, there is often one particular season of low flow occurrence: either summer or winter. In low-latitude climates, there may be more than one dry season and consequently more than one distinct low flow period. In arid and semi-arid climates, the combination of low precipitation and high evaporation results in sparse river networks and ephemeral flows. These regime types reflect the major impact of climate on low flows and climate maps provide a valuable source of information for assessing the climatic drivers and the expected seasonality of low flows. Seasonality of low flows, in turn, is an indicator of the regime type and may help identify characteristic processes as a basis for regionalisation (Laaha and Blöschl, 2006a; WMO, 2008; van Loon and van Lanen, 2011). The seasonal variability may be compounded by strong inter-annual variability, as experienced in countries such as Ethiopia, South Africa, Australia and India (Chapter 6).

Catchment processes

Catchment processes, especially those factors that control storage within a catchment, are very important for low flow conditions, as they affect the rate of depletion of runoff (WMO, 2008; van Lanen *et al.*, 2004b). Topographic slope, soil depth and texture, geology and land cover (e.g., lakes, bogs) all determine the storage and drainage properties (i.e., whether they are fast-responding or slow-responding catchments) and geology is usually the most important factor of these catchment processes. Fast-responding catchments may respond to precipitation events with a larger number of short-lived low flow events. On the other hand, in slow-responding catchments the number of low flow events may be smaller, but they may last longer.

Surface processes (interception, surface and snowpack storage) determine how much of the incoming precipitation infiltrates into the soil. The permeability of the topsoil, in combination with catchment topography, determines the rate at which water infiltrates and how fast soil moisture is replenished. Soil water is depleted by evaporation and transpiration, governed by the climate, vegetation and soil properties. Water-saturated soils (e.g., swamps and bogs) are subject to the highest evaporation losses, generally considered equivalent to evaporation from open water surfaces. The drainage capacity of the soil determines how quickly the infiltrated water may recharge the groundwater system.

The groundwater potential gradients along with the storage characteristics and hydraulic conductivity of the aquifer all govern the overall storage and release properties of the aquifer and, in consequence, groundwater discharge into the stream. During dry periods, groundwater discharge will continue as storage is slowly depleted. In hilly or mountainous regions, discharge from shallow aquifers of weathered hard rock often provides the most important source during dry periods. In lowland areas (for example, deltas, coastal plains), deep aquifers typically exist beneath shallow aquifers, and aquifer layers are often connected. In lowland areas or large valleys, aquifers thus act as large storage systems and are able to feed rivers during prolonged dry periods.

Depending on the storage characteristics of the aquifers, the low flow characteristics may vary immensely, and this is the reason for the different low flow behaviours seen in the two catchments in Figure 8.1. The less flashy Kennet overlies a highly fractured chalk aquifer that allows rapid infiltration of precipitation (Maurice, 2009). It closely interacts with the highly pervious chalk aquifer system leading to sustained low flows. In contrast, the more flashy South Tyne catchment is underlain by carboniferous limestone that does not allow such rapid infiltration, leading to more overland runoff.

Storage can also occur in lakes that maintain low flows during dry periods, in particular in humid climates. In arid climates, however, lake evaporation may in fact decrease low flows downstream of the lake.

Low flows are a runoff signature that may be very strongly affected by anthropogenic activities, including abstractions from and discharges into rivers and reservoir storage. Groundwater abstractions close to a river can also have a major impact on the low flow regime (e.g., Clausen *et al.*, 1994; van Lanen and van de Weerd, 1994; van Lanen *et al.*, 2004b). Discharges from treatment plants can also have a great effect on the low flow regime and in some instances the artificial discharges may be larger than the natural runoff (Gustard and Demuth, 2009). Reservoirs may have a major effect on low flows, governed primarily by the mode of their operation. In the case of reservoirs used for hydropower, peak power production will result in a redistribution of runoff over time and cause fluctuations that are particularly apparent during low flow periods. This is illustrated in Figure 8.3 which shows monthly runoff (left) and the daily average fluctuations in the hourly average (right) (see Holko *et al.*, 2011, for method). Before 1990 the fluctuations are small during the winter months (October to March), which can be attributed to the river's winter low flow regime, meaning that runoff is consistently low throughout the winter. In April 1990, however, the situation changes and the winter fluctuations increase dramatically. This is because the Wald power plant was put into operation and the stream gauge was then moved below the power plant in April 1990.

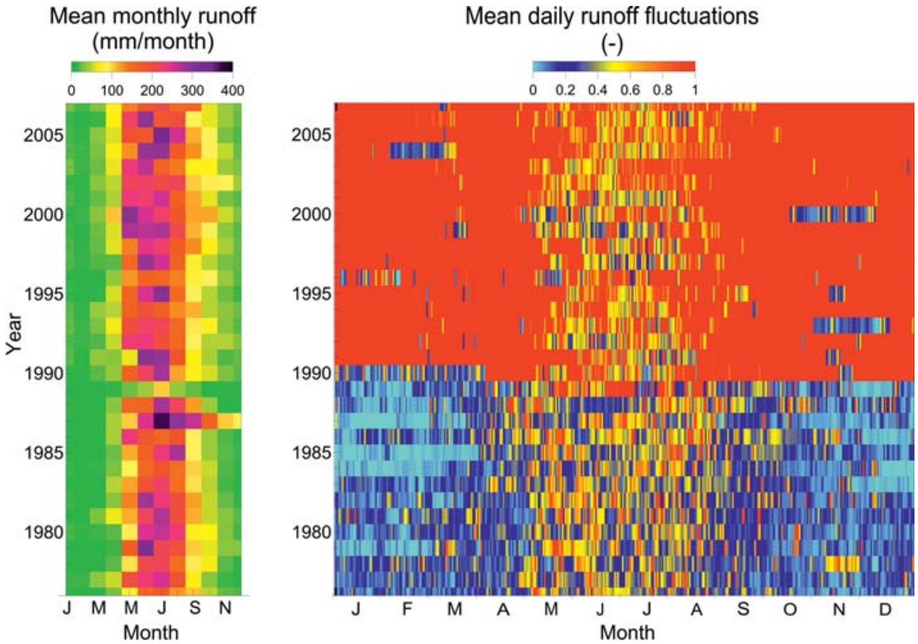

Figure 8.3. Impact of reservoir operation, apparent from April 1990 onwards, on the amplitude of runoff fluctuations (0: low fluctuation, 1: high fluctuation) for the Salzach River at Wald, Austria. (Left) Monthly runoff, (right) daily average fluctuations of hourly runoff. Fluctuations are calculated as the mean absolute differences of hourly runoff scaled by the mean runoff for each day.

Other anthropogenic effects on the low flow regime include land use changes, such as deforestation, afforestation or urbanisation. Van Lanen *et al*. (2004b) reviewed the relationship between hydrological processes and low flows and the impact of human influences on droughts. Land use effects have been studied by temporal analyses of runoff before and after the human interferences and comparative analyses such as paired catchment studies (e.g., Brown *et al*., 2005; Holko and Kostka, 2008; Schumann *et al*., 2009). Land use/land cover change, typically, is a local phenomenon, so its impact is likely to strongly decrease with catchment size. The position in the landscape will modulate the scale effects. In contrast, climate impacts may occur at larger scales so one would expect them to be apparent in both small and large catchments and be consistent in a region (Blöschl *et al*., 2007).

The combined effect of the various catchment and climate related processes discussed above can thus be seen to control the observed patterns of low flows over space and time. Understanding their relative roles is useful for interpreting differences and similarities of low flow regimes between places, to assist in estimating low flows in ungauged basins.

8.2.2 Similarity measures

This section discusses measures of hydrological similarity relevant to low flows. Catchments that are similar in terms of their shape, topography, climate, hydrogeology and land cover can be expected to be similar in terms of their low flow regime as well, if these characteristics relate to the low flow processes discussed above. Measures of similarity may relate to low flow runoff itself, to climate characteristics and to catchment characteristics.

Runoff similarity

One group of similarity measures extracts properties of the hydrograph that reflect the effects of climate forcing and catchment controls on the low flow regime in a collective way. Most importantly, they describe the timing of low flows (seasonality and the delay in the response to precipitation). In circumstances where these runoff properties can be related to climate or catchment characteristics, or to geographic location, these properties can be profitably used to identify catchments exhibiting a similar low flow regime. In particular, similarity measures that reflect seasonality, the response time or flashiness, baseflows and the recession behaviour may be useful in regionalisation studies.

Seasonality of low flows is an indicator of the regime type and may help identify characteristic processes as a basis for regionalisation (Laaha and Blöschl, 2006b). This is most important in regions where both summer and winter low flows occur, as these two types are governed by different processes and need to be treated separately. Seasonality is mainly related to climate. In a region with uniform climate, differences in seasonality may arise from the different timing of runoff recessions, governed by geology and other catchment characteristics. A number of similarity measures for characterising low flow seasonality have been proposed that differ in terms of complexity and information content. The most common measure is the low

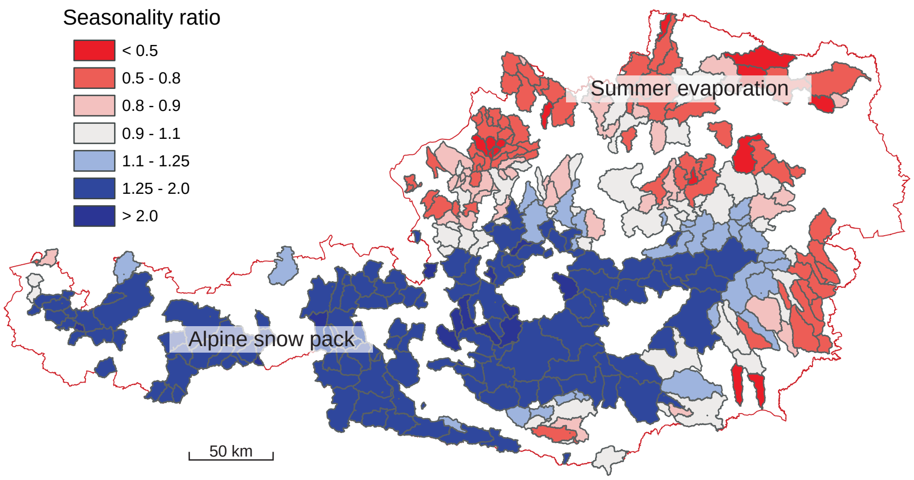

Figure 8.4. Seasonality ratio, i.e., the ratio of summer and winter Q_{95} low flow runoff in Austria. Blue shades indicate a winter low flow regime, red shades indicate a summer low flow regime. White: no data. From Laaha and Blöschl (2006b).

flow *seasonality index* (Young *et al*., 2000c; Laaha and Blöschl, 2006b). This index is similar to the seasonality index used by Burn (1997) to analyse floods, but estimates the mean day of occurrence from a partial series of the Julian date when the flow decreases below some threshold. The mean day of occurrence and the strength of seasonality are derived from circular statistics (Mardia, 1972). Another measure is the *seasonal histogram* (Laaha and Blöschl, 2006b), which is obtained by plotting the frequency of low flow days within each calendar month against months. The seasonal histogram contains more detailed information on the low flow regime than the seasonality index. A simple and informative measure is the *seasonality ratio* (Laaha and Blöschl, 2006b), which is the ratio of summer and winter low flows, based on some low flow index calculated separately for the summer and winter seasons. Seasonality ratios greater than one indicate higher runoff in summer than in winter and indicate a winter low flow regime. Seasonality ratios less than one indicate a summer low flow regime. The magnitude of the number represents the strength of the seasonality. Figure 8.4 shows an example of the seasonality ratio, which highlights the prevalence of winter low flows (blue) in the west and summer low flows (red) in the east of the region. Together with the other seasonality measures discussed above, the map is useful for identifying dominant low flow processes as a basis for regionalisation (Laaha and Blöschl, 2006a). The seasonality of low flows is an important link to another runoff signature, the seasonal runoff (Chapter 6), and is therefore an important variable to characterise the hydrological behaviour of catchments.

A stream may receive water from different flow paths: overland flow, interflow, and shallow and deep groundwater discharge (Chapter 4). Overland flow and interflow respond quickly to rainfall or melting snow, whereas groundwater discharge responds slowly with a time lag of several days, months or years. Catchments dominated by overland flow, interflow and/or shallow saturated subsurface flow are usually quickly responding or ‘flashy’ catchments (e.g., van Lanen *et al*., 2004a; van Lanen *et al*., 2012). Typical examples are clay catchments with shallow water tables and a dense drainage network, and catchments with steep relief and shallow impermeable bedrock. Catchments fed primarily by groundwater discharge are usually slowly responding catchments. They are typically lowland catchments with a substantial aquifer. The flashiness of a catchment may be quantified by the recession behaviour: a flashy catchment with a fast response to precipitation tends to exhibit steeper recession behaviour. Recession parameters can be calculated from the runoff hydrograph during periods without rain and can then be combined into master recession curves to characterise the overall catchment behaviour during recessions (see Chapter 4). Flashiness can also be quantified by the baseflow contribution. Baseflow is usually estimated by baseflow separation techniques that divide the total runoff into a quick (usually shallow flow) component and a slow (storage-delayed) component (see e.g., IH, 1980; Hisdal and Tallaksen, 2004). This can be achieved either by several variants of digital filters (Lyne and Hollick, 1979; Arnold *et al*., 1995) or with the support of tracer techniques (see Chapter 4). The long-term ratio of the slow runoff component and total runoff is the baseflow index. Figure 8.5 shows typical hydrographs of a flashy and a slowly responding catchment. For the Thompson catchment the baseflow index is 0.31, while for the Elkhart it is 0.9 (Sawicz *et al*., 2011). The Elkhart catchment contains large wetlands and lakes, and the thick glacial sediments and complex topography detain water, releasing it slowly over long periods of time, thus providing for more sustained flow rates long after the initiating precipitation events (USACE, 2010). In the Thompson the storage is much smaller.

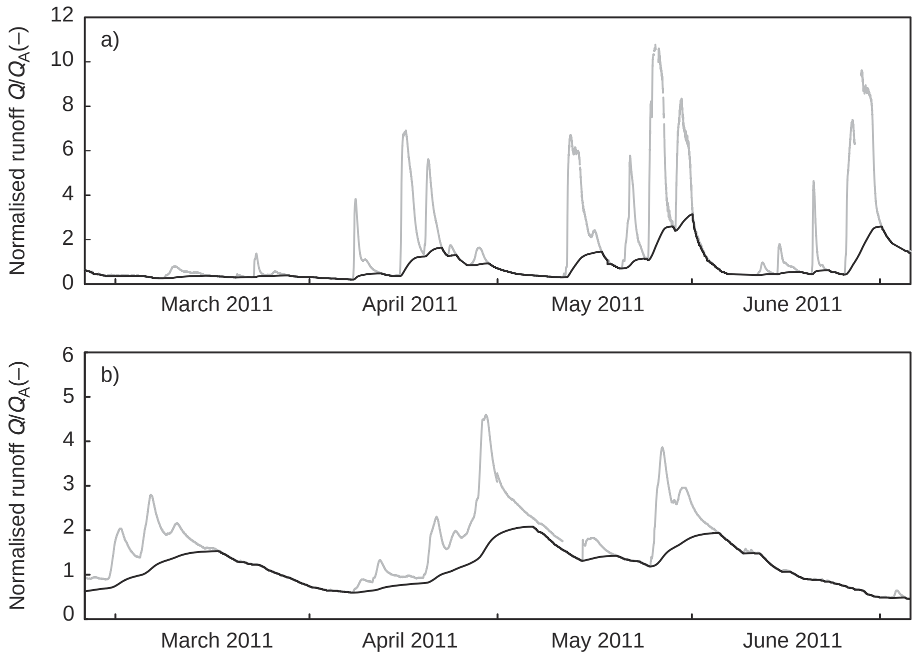

Figure 8.5. Hydrographs of daily runoff and baseflow for (a) Thompson River at Davis, Iowa (1816 km²), and (b) Elkhart River at Goshen, Indiana (1538 km²). Baseflow shown as thick black line calculated by digital filter.

Climate similarity

If no runoff data are available in a particular catchment, similarity measures may be based either on climate or on catchment characteristics. Important climatic characteristics include long-term mean annual values of precipitation, air temperature and the aridity index. Indices may also include the seasonal distribution of these climate variables, e.g., represented by monthly or seasonal mean values of precipitation (see Chapter 6). The choice of the similarity measures needs to be guided by knowledge of the low flow processes. In arid climates, for example, many rivers regularly dry out, and the low flow runoff of such rivers will be zero. In monsoon areas practically all precipitation occurs during a rainy phase of the year and low flow occurs at the end of the post-monsoon recession period. Timing of climate characteristics is therefore an important similarity parameter. If snow processes are involved, parameters related to the deposition or melting of snow may become very important. In alpine climates, low flow generation processes may change with catchment altitude because of freezing and melting, so altitude may be a relevant similarity index.

Catchment similarity

Hydrogeological and pedological information may be characterised by properties of the aquifers and soils such as porosity, permeability, storage coefficient, transmissivity and hydraulic conductivity. In hard rock aquifers, the locales of faults and interfaces between different geological units can be extremely important for low flows. These parameters are usually difficult to obtain at the landscape scale. Hydrogeological and soil classes from thematic maps are usually used instead. Also, a number of surrogate measures are used. Vegetation may be an indicator of soil processes through co-evolution of vegetation, soils and geology. Vegetation may be obtained from land cover classifications such as the CORINE (Coordination of Information on the Environment) data set programme of the European Commission. Topographic elevation may be a surrogate for a number of processes including snow, geology, soils and length of the subsurface flow paths. Which of the catchment characteristics are most important for low flow regionalisation depends on regional factors such as climatic and geographic conditions, as well as on the particular low flow index to be estimated (Demuth and Young, 2004). Demuth and Young (2004) reviewed catchment descriptors used in regional low flow estimation models. In a case study across Europe, Demuth (1993) showed that geology and topography were key parameters for estimating low flow characteristics. In fact, geology and topography are often interrelated as a result of the co-evolution of climate, landscape, vegetation and soils. Climate and catchment characteristics are used in almost all low flow regionalisation methods.

Spatial proximity is a simple similarity measure used sometimes, based on the rationale that catchments that are close to each other may have similar runoff processes, and thus a similar low flow regime, although this may not always be the case because of small-scale geological heterogeneities. Proximity is used in low flow regionalisation in three ways: (i) in geostatistical models where more weight is given to nearby gauges than to distant gauges

(Section 8.3.3); (ii) in record augmentation methods where closeby gauges are typically used as donor sites (Section 8.3.4); and (iii) in the index methods and the region of influence approach where proximity is directly used to identify similar sites in a given region (Section 8.3.2). Proximity may be measured based on distance in Euclidean space in the landscape or, preferably, along the stream network in order to account for stream network topology (Sections 8.3.3 and 8.3.4).

8.2.3 Catchment grouping

Methods for estimating low flows in ungauged basins usually require that the region is homogeneous with respect to low flow processes. This is because they assume that there is a unique relationship between low flow characteristics and catchment/climate characteristics in a region. Heterogeneous regions therefore need to be divided into sub-regions that can be considered homogeneous. A number of methods for subdividing regions into sub-regions or catchment groups are typically used for low flow regionalisation.

Cluster analysis based on catchment/climate characteristics

In this method similarity is defined in terms of the similarity of the catchment/climate characteristics. Hence the selection and weighting of these characteristics is crucial for obtaining classifications that are relevant for low flow regionalisation (Nathan and McMahon, 1990). In a regionalisation study for Q_{95} in north-western Italy, Vezza *et al.* (2010) selected mean annual precipitation, mean catchment elevation, slope of the longest drainage path and proportion of crops and grasslands, and obtained the grouping shown in Figure 8.6a. Andrews curves (see Chapter 6) were used to examine the homogeneity of each group visually. The regions were not contiguous in space, even though they show a similar spatial organisation.

Residual pattern approach based on runoff and catchment/climate characteristics

This method (e.g., Hayes, 1992) first fits a regression model between the low flow index and catchment/climate characteristics for the entire domain, and then maps the differences between the regression estimates and the low flow data, to be analysed for typical patterns in the sign and magnitude of the differences. The approach assumes that residual patterns arise from regional heterogeneity not captured by a global regression model, and a manual subdivision of the study area will improve the performance of the model. An example is presented in Figure 8.6b, taken from Vezza *et al.* (2010), who fitted a regression model to all data (an additive regression of Q_{95} with mean annual precipitation, mean catchment elevation, slope of the longest drainage path and proportion of crop and grasslands). They then manually delineated four regions, as shown in Figure 8.6b, based on the spatial pattern of the residuals. Due to the manual generalisation, the regions can be made contiguous, but the method is subjective and may be inappropriate if the initial model is far from perfect.

Regression trees

Regression trees (Breiman *et al.*, 1984; Laaha and Blöschl, 2006a) aim to divide a heterogeneous domain into a number of homogeneous groups by maximising the homogeneity of low flows and catchment characteristics within each group simultaneously. The homogeneity of groups is commonly assessed by the spatial variance of low flows. For the regression tree model, the optimum number of groups can be determined by a cross-validation approach. Regression trees yield groups that are often non-contiguous in space. Vezza *et al.* (2010) use the regression tree to divide the study domain into three regions, as represented in Figure 8.6c. The method shows that the percentage cover with forest or bare rock were relevant parameters with which to differentiate groups. Forested areas (Group 1) are located in the Apennine hilly zones and piedmont areas. These catchments are characterised by a low flow regime with a strong drought period occurring during summer. Group 2 (Alpine region) has low flows occurring during winter and is affected by snow cover and freezing soils. Group 3 is composed of highlands and rock areas. These catchments are located in the upper part of the Alps and have a winter low flow regime. Once the regression tree is fitted to the data, it can be used to allocate ungauged catchments to the groups obtained by the regression tree, and to estimate the low flow characteristic at the site of interest (Laaha and Blöschl, 2006a). Regression trees are able to account for non-linearity otherwise not easily accommodated in linear regressions. Also, catchment classification allows one to implicitly take into account factors affecting low flows that cannot be easily included in the regression models, such as unknown controls that do not change within the region but across the regions, and differences in the sign of the regression coefficients within a region. For example, catchment elevation may be negatively correlated to winter low flows but positively correlated to summer low flows.

Seasonality approach

An alternative to the above methods is to explicitly take the seasonality of low flows into account (Young *et al.*, 2000c; Laaha and Blöschl, 2006b). The approach builds on the notion that differences in the occurrence of low flows within a year are a reflection of differences in the hydrological processes and are therefore likely to be useful for

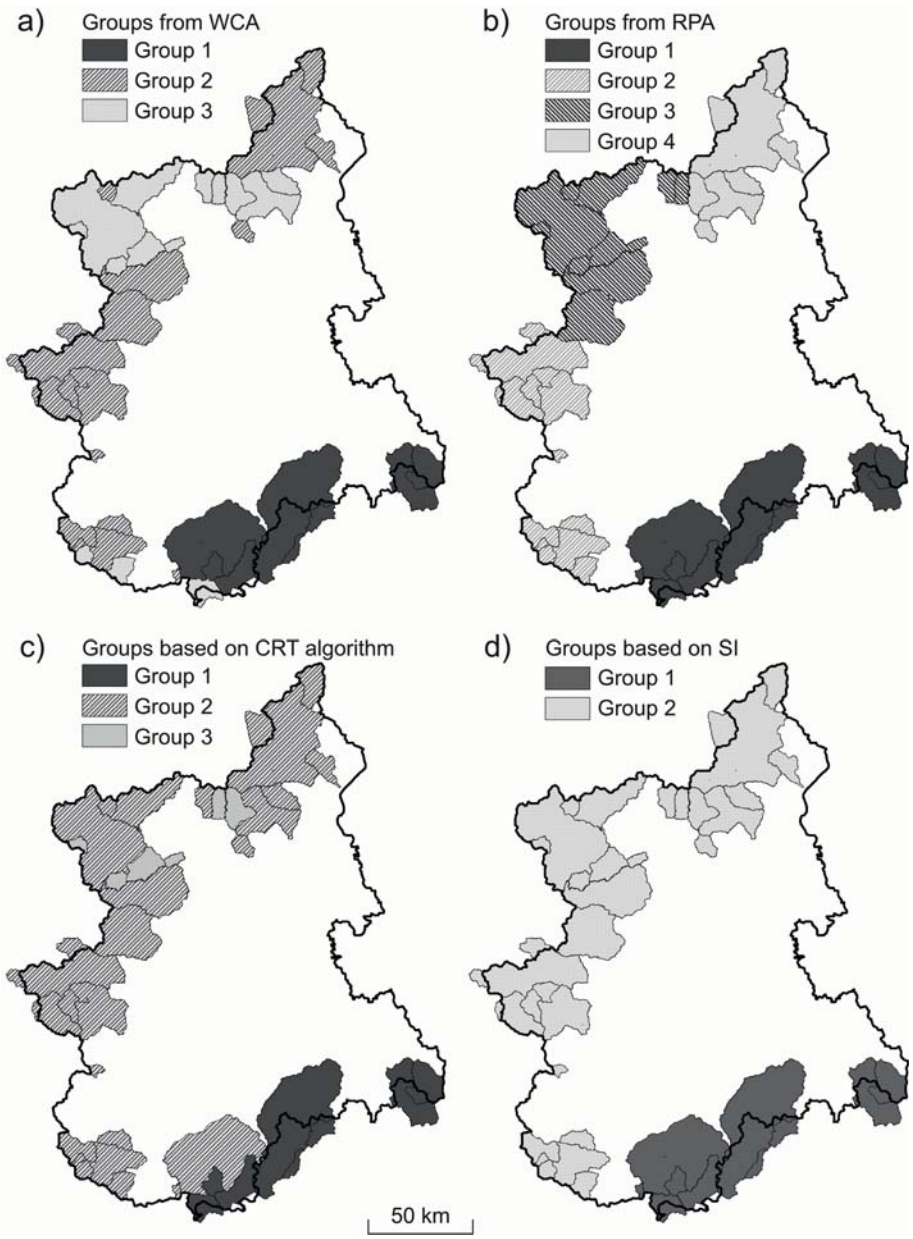

Figure 8.6. Catchment groupings in north-west Italy, based on four grouping methods for low flows: (a) weighted cluster analysis (WCA); (b) residual pattern approach (RPA); (c) classification and regression trees (CRT); (d) seasonality indices method (SI). From Vezza *et al.* (2010).

finding homogeneous regions. Laaha and Blöschl (2006b) considered three seasonality indices, the variability and mean day of occurrence of Q_{95}, the seasonality ratio between summer and winter low flows, and the seasonality histogram. They found this method to work very well for Austrian conditions, which is likely related to the strong contrast in seasonality of low flows in their area. Vezza *et al.* (2010) examined similar seasonality indices and classified their domain into two main units (Figure 8.6d). Group 1 is the Apennine–Mediterranean area where low flows normally occur during summer and Group 2 is the Alpine region, characterised by winter low flows. In fact, all classification methods used by Vezza *et al.* (2010) separate the south-eastern Apennine–Mediterranean area from the rest of the study domain (the Alps mountain range), even though they used different attributes to carry out this division (e.g., the percentage of forest, seasonality of low flows, combination of several parameters) (Figure 8.6). This suggests that the obtained classification is robust.

A number of studies compared the relative strengths of the grouping methods (Nathan and McMahon, 1992, in Australia; Laaha and Blöschl, 2007, in Austria; Vezza *et al.*, 2010, in north-west Italy; Engeland and Hisdal, 2009, in Norway; and Aschwanden and Kan, 1999, in Switzerland). Their findings regarding the best grouping methods to be used for regional regressions differ. This is partly because of the different techniques that have been evaluated, but also because of the different settings of the studies. The Australian study, for instance, found that a weighted cluster analysis based on catchment characteristics that were weighted according to the coefficients of a global regression model was better suited than ordinary cluster analysis and a global regression model. This was also found in the Austrian study, though alternative catchment classifications based on seasonality analysis and the regression tree performed better. Regression trees were found to be more suitable than cluster analysis in the Austrian and north-west Italian study. For highly seasonal regimes, seasonality measures contain essential information about dominant processes, which can be profitably used in catchment classification as indicated in the Austrian, Norwegian and north-west Italian studies.

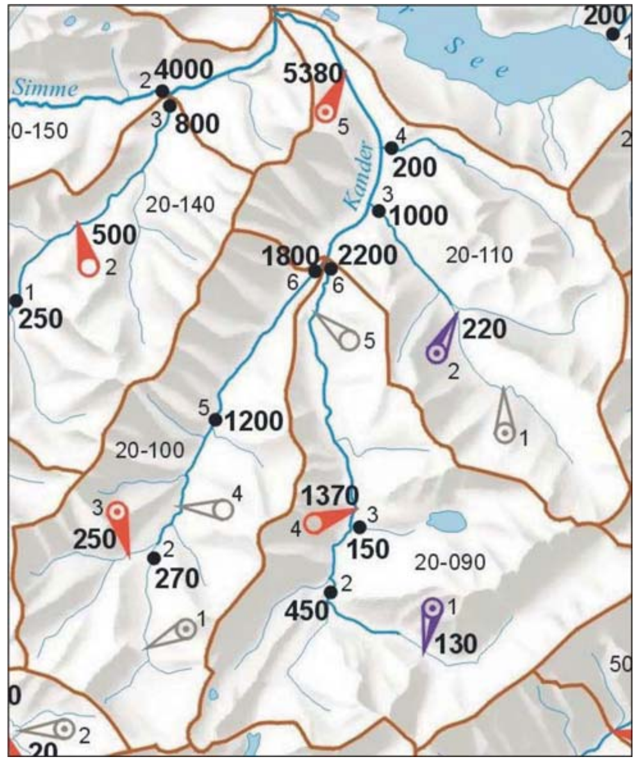

Figure 8.7. Low flows in the Kander catchment, Switzerland. Big bold numbers are Q_{95} low flows (l/s), Small numbers are catchment indices. Triangles indicate stream gauges from which low flows have been estimated (red: period 1984–93; purple: other period; grey: not used for regionalisation). Points indicate cross-sections where low flows have been estimated by regression. Map is 25 km across. From Aschwanden and Kan (1999).

8.3 Statistical methods of predicting low flows in ungauged basins

On the basis of the grouping methods discussed above, low flows in ungauged basins can be estimated by transferring information from one or more nearby gauged basins. The simplest methods are specific runoff techniques, where runoff per unit area is assumed to be spatially uniform (Dyck, 1976). However, this is not always appropriate, so more sophisticated statistical methods have been developed, which exploit either correlations between low flows and catchment/climate characteristics or correlations between low flows across space. Both kinds of approaches involve hydrological similarity measures, in the latter case, on the basis of spatial proximity.

8.3.1 Regression methods

Multiple regression is a frequently used method to develop a relationship between the low runoff statistic of interest, such as Q_{95}, and catchment/climate characteristics (see also synthesis in Section 8.5). Additive and multiplicative regression models are commonly used, and the choice between the two forms is generally guided by an analysis of the residual structure (e.g., Draper and Smith, 1998). Vogel and Kroll (1992) showed the multiplicative form to be consistent with a theoretically based low flow model derived from hillslope runoff models, and suggested that it may be a natural choice, while Laaha and Blöschl (2006a) found their data to be better represented by the additive form.

Low flow regression models have been developed for many regions throughout the world, including Europe (Gustard *et al.*, 1989; 1992; Demuth, 1993; Laaha and Blöschl, 2007; Engeland and Hisdal, 2009), Australia (Nathan and McMahon, 1992) and the USA (Thomas and Benson, 1970; Kroll *et al.*, 2004). If the study domain is large or very heterogeneous in terms of the low flow processes it is useful to split the region into groups by methods such as those discussed above. For each of the regions a regression model is then fitted independently. This is termed the regional regression approach, as opposed to the global regression approach where only one regression model is used for the entire domain. A typical example of a regional regression is shown in Figure 8.7. Aschwanden and Kan (1999) grouped Switzerland into six regions based on the residual patterns of a global regression model. For each of the regions they fitted a regression model independently between specific low flows and catchment characteristics and cross-validated it. In the final presentation (Figure 8.7) they combined the estimates from a 10-year standard period with estimates from shorter records, as available, to best exploit the information in the runoff data they had. An important part of

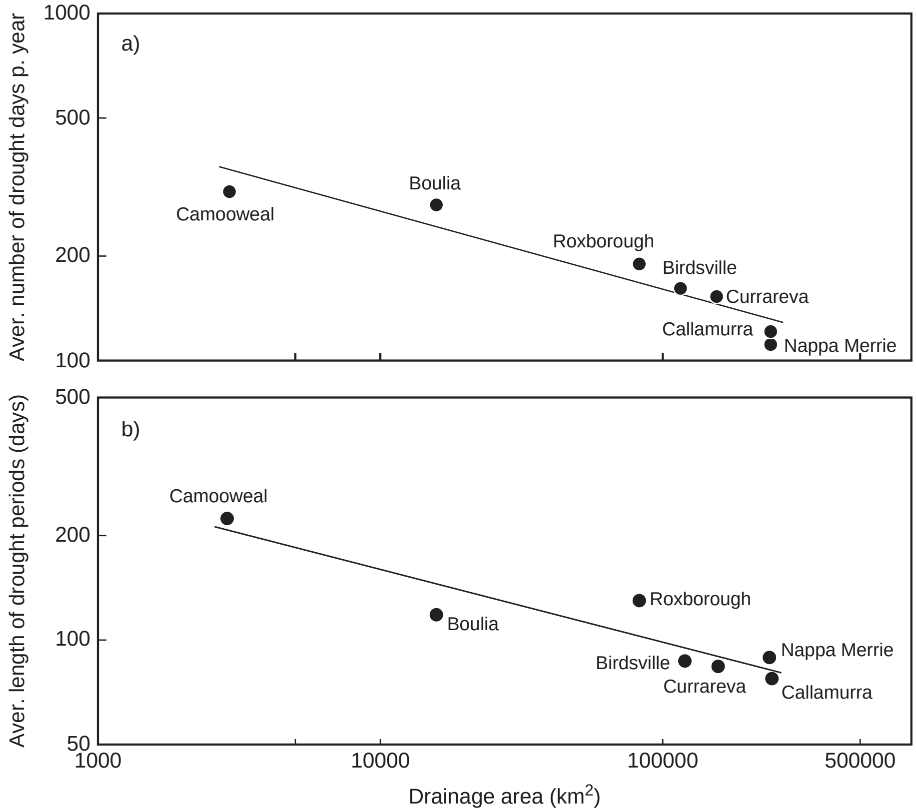

Figure 8.8. Average number of days per year without runoff (a) and average length of the no-flow period (b) plotted versus catchment area for streams in the Lake Eyre basin, Australia. The trend is mainly due to catchment storage on the surface. For photos of two catchments see Figure 8.9. From Knighton and Nanson (2001).

their approach was that they interpreted the estimates for each ungauged basin hydrologically in the regional context of the gauged basins.

In arid places, Q_{95} or $Q_{7,10}$ may no longer be a meaningful low flow index if river flow ceases for an extended period of time during the year. Alternative indices are the duration and the frequency of dry spells (or no flow). An example of this is shown in Figure 8.8 from the Lake Eyre basin, Australia where the average number of days per year without runoff (top) and average length of the no-flow period (bottom) are plotted versus catchment area. As the catchment area increases, the days without runoff become less frequent, and the periods of no-flow become shorter. The Lake Eyre basin is arid, so the channel transmission losses can be substantial and runoff volumes tend to decrease downstream. There is also a rainfall gradient with annual rainfall varying from 600 mm/yr in the upstream areas to 200 mm/yr in the downstream areas. However, the inverse relationship between catchment area and the no-flow period mostly reflects the combination of increasing area of the contributing catchment (i.e., surface storage) and flow attenuation over the very long flow paths in the Lake Eyre Basin catchments. Much of the flow is generated in the upper to middle reaches of the Lake Eyre Basin. Large rivers and the flows become increasingly attenuated as they flow downstream over very long and low gradients. So the lower number of no-flow periods in the downstream (large catchment areas) reaches are a reflection of channel–floodplain storage and very low gradients. After the last tributary junction there is typically little inflow from the arid surrounding catchment and the rivers experience large transmission losses (McMahon *et al*., 2008). The photos in Figure 8.9 illustrate the low gradient landscape. Figure 2.1 in Chapter 2 shows a satellite image of part of the catchment highlighting the complex nature of the flow paths.

There are a number of concerns with the application of regional regression models. If data are far from the regression line (i.e., outliers) regression coefficients can be inappropriate for the remainder of the catchments. Leverage statistics have been developed to identify data points that have an inordinate influence on the model (Rousseeuw and van Zomeren, 1990). It is important to check whether outliers are due to data problems or due to real unusual behaviour of catchments. Geology can be highly heterogeneous over short distances and this can be reflected in particularly high or low numbers for low flow values. Typically, the analyst examines the unusual catchments in more detail by exploring the hydrological processes, e.g., through examination of hydrogeological data and maps and, ideally, visiting the catchment. Another possible

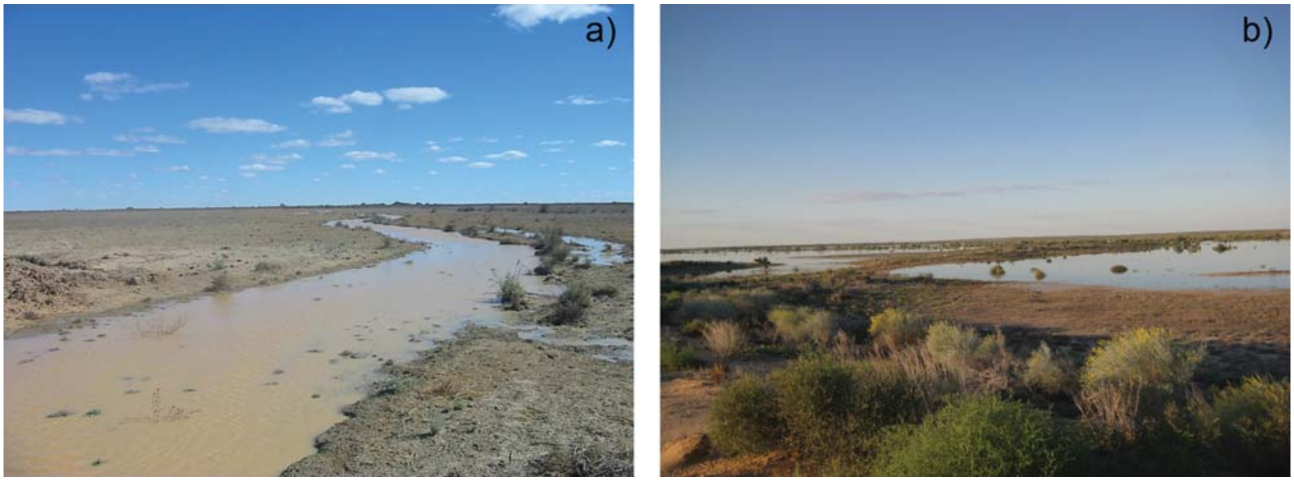

Figure 8.9. (a) Diamantina near Birdsville, at the forefront of a flow event that is beginning to spread out over a vast, poorly channelised floodplain. (b) Lower Cooper near Callamurra showing low gradient floodplains with little channelisation. Photos: J. Costelloe.

concern with the regression approach is that the catchment characteristics may be correlated, causing a redundancy in information and leading to multi-collinearity. Multi-collinearity can cause the variance of parameter estimators to be inflated, which may lead to apparently good model fits but poor performance when applied to a validation data set. Multi-collinearity can be checked by variance inflation factors (Kroll *et al*., 2004), and dealt with either by principal component analysis (Demuth, 1993) or by a stepwise regression approach where only those catchment characteristics that provide statistically significant information and are independent from the other catchment characteristics already used are included in the regression (Demuth, 1993; Tallaksen and van Lanen, 2004; Laaha and Blöschl, 2006a). The stepwise approach is particularly useful if the number of catchment characteristics is large (Kroll *et al*., 2004).

The choice of the catchment/climate characteristics should always be guided by the understanding of the hydology in the area (WMO, 2008; DWA, 2009). It is therefore important to interpret the catchment/climate characteristics that are found to be significant during a regression analysis from a hydrological perspective, i.e., to link the statistical analysis to the hydrological processes operating at the catchment scale. Vogel and Kroll (1992) found that, in central western Massachusetts, low flow statistics were highly correlated with the product of catchment area, average basin slope and baseflow recession constant, with the baseflow recession constant acting as a surrogate for both basin hydraulic conductivity and drainable soil porosity. In fact, hydrogeological indices, such as the baseflow index and the baseflow recession parameter often have high explanatory power (Demuth, 1993; Tallaksen, 1995; Kroll *et al*., 2004), but for ungauged basins they need to be regionalised as well. Laaha and Blöschl (2006a) found that precipitation, topography (slope and elevation characteristics) and hydrogeological classes were the most significant catchment characteristics. Annual precipitation was particularly relevant through its role of replenishing the water reservoirs. Vezza *et al*. (2010) interpreted the regression coefficients between low flows and catchment/climate characteristics in the following way (Figure 8.6a): in the south-eastern Apennine–Mediterranean part of the area (Group 1), the elevation of the catchments is the relevant characteristic because high elevation is related to low evaporation, more precipitation due to orographic effects and late spring snowmelt. Elevation is the main control also in the small elevated highlands catchment in the north-west (Group 3), where low flows are relatively low and occur in winter, because of freezing processes that are more or less effective for different elevations. In the remaining Alpine range (Group 2), low flows are higher (climate is wetter than in the Apennine area and warmer than in the highlands), they occur in winter and vary according to precipitation, elevation (because of evaporation), catchment size (because of interactions with aquifers) and land cover (which controls evaporation, infiltration capacity and recharge of groundwater systems). The interpretation of these controls suggests that, in order to obtain plausible regression models that can be used for extrapolation to ungauged basins, it is essential to examine the sign and relative magnitude of the coefficients hydrologically (Section 8.2). Similarly, it is useful to check the results of the regression model by leave-one-out cross-validation, plot the errors on a geographic map and interpret them

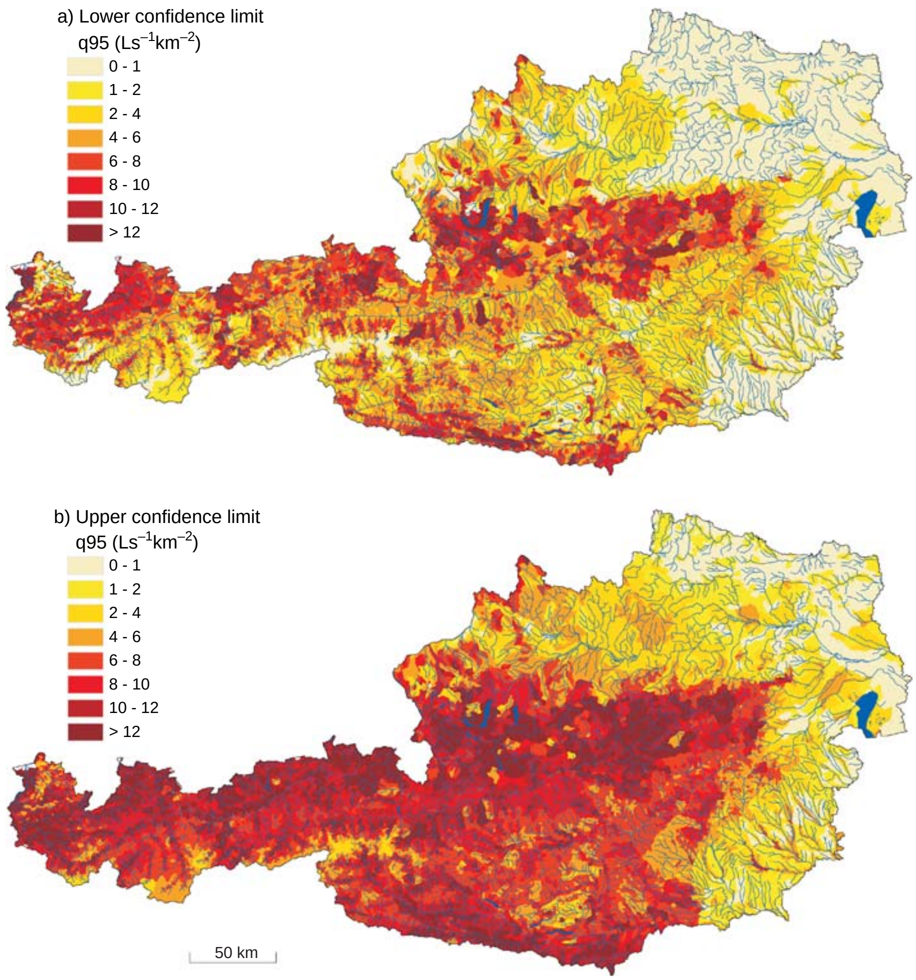

Figure 8.10. Uncertainty of Q_{95} low flow estimates in ungauged basins in Austria expressed as confidence bounds (expected low flow plus or minus the error standard deviation). From Laaha and Blöschl (2007).

hydrologically. The uncertainties of the predictors may significantly vary in space. Laaha and Blöschl (2007) proposed an error model that accounts for both low flow measurement errors and the prediction errors of multiple regressions. An example of the uncertainty is given in Figure 8.10 in terms of the confidence bounds, defined as the expected low flow plus and minus the error standard deviation. They note that these uncertainties provide regional information. In an application case, this should be complemented by local information from site visits (in particular about any anthropogenic effects) and hydrological reasoning should be exercised based on this additional local information.

8.3.2 Index low flow methods

Low flow runoff of a given return period, such as T-year annual d-day minima ($Q_{d,T}$), is estimated by statistical frequency analysis. Regional frequency methods have been developed to obtain estimates at sites with no observations or improve at-site estimates with few observations. The most common regional frequency method is the index method, first introduced for floods (Dalrymple, 1960), and later extended to low flow studies (Clausen and Pearson, 1995; Madsen and Rosbjerg, 1998). The method assumes that the low flow distribution, scaled by an index low flow, is uniform within a region. If the index low flow is known at an ungauged site, the low flow associated with a given return period can be estimated as the product of the index low flow and the scaled distribution. The index low flow is usually taken as the mean or median of the annual minimum runoff. Clausen and Pearson (1995) tested the method to estimate both the maximum duration and maximum volumetric deficit of runoff in New Zealand. Catchments from three regions with different climate and physical properties were used in their study. For both low flow indices the index low flow (i.e., the mean of the annual minima) was found to vary with catchment and climatic characteristics except for one region subject to very high annual precipitation, where the index low flow was almost constant. The lognormal distribution was identified as the most suitable three-parameter distribution for both low flow indices, according to best fit. The hydrological differences between the regions were reflected by clear differences in the distribution parameters.

The index method assumes that the stream gauge data are independent, i.e., that at different gauges different events are observed. Because of the large spatial extension of most low flow events this may not always be the case, so there is a need to account for their spatial correlations (Hosking and Wallis, 1997) in order to ensure that the uncertainty of the low estimates is not underestimated. In order to estimate the return periods of a given low flow runoff, distribution functions are usually fitted to the extreme value series. Tallaksen *et al.* (2004) reviewed methods for estimating the parameters of the distribution functions and recommended that the choice of the distribution function should be guided by statistical judgement in combination with the hydrological interpretation of low flow processes in the study area. For minimum flows, the distribution function should be skewed and have a finite lower limit greater than or equal to zero, such as the generalised extreme value (GEV) distribution for annual minimum series (e.g., Zaidman *et al.*, 2003; Demuth and Külls, 1997) and the generalised Pareto (GP) distribution for partial duration series (e.g., Tallaksen and Hisdal, 1997; Madsen and Rosbjerg, 1998; Meigh *et al.*, 2002). Apart from GEV and GP distributions, different forms of Weibull, Gumbel, Pearson Type III, lognormal, Gamma and other distributions have been used (Vogel and Kroll, 1989; Pearson, 1995; Vogel and Wilson, 1996; Chen *et al.*, 2006; Modarres, 2008). Some of them are special cases of the two limiting distributions. Gottschalk and Perzyna (1989) suggested that the Weibull distribution for annual minimum series is consistent with linear low flow recessions which, along with its flexibility, have made it a common choice in low flow studies around the world (Tallaksen, 2000).

To infer the index parameter for ungauged sites, regression analyses with catchment and climatic characteristics are often used. Tallaksen *et al.* (2004) used the generalised least squares regression method in three regions in Germany to estimate the index values for low flow durations and deficit volumes. Land use, morphometry and soil characteristics as well as the mean annual precipitation were found to be important characteristics. In cases where at-site runoff data were available, they recommended combining these data with the regional estimates by a weighted mean, with weights chosen according to the relative uncertainties (Madsen and Rosbjerg, 1997). The resulting model was shown to perform well in estimating the T-year low flow duration and deficit volume in the region.

While the above methods focused on extreme value distributions based on the index low flow method, it is also possible to scale the low flow quantiles of the flow duration curve by an index flow. Young *et al.* (2003) used a region of influence approach where, for each ungauged basin, they selected a number of donor catchments that were similar to the ungauged basins in terms of catchment and climate characteristics. They then assumed that the low flow variable (such as Q_{95}) scaled by the mean annual runoff in the ungauged basin is the same as the weighted mean of the corresponding values from the donor catchments. They chose the weight on the basis of inverse distances, which gives more weight to catchments that are close to the ungauged basin. They obtained a performance similar to regression models for the UK catchments, if similarity was defined on the basis of the hydrology of soil types (HOST) classification (Boorman *et al.*, 1995).

8.3.3 Geostatistical methods

Geostatistical approaches exploit the spatial correlations of low flows based on the rationale that catchments that are geographically close to each other may exhibit similar processes. The low flows in the basins are estimated as the weighted mean of the observations and the weights are estimated from the spatial correlations as a function of spatial distance. Traditional geostatistics have been developed in resource exploration and meteorology (Matheron, 1965; Gandin, 1963) where spatial distance is clearly defined. However, river networks exhibit a tree-like structure, which needs to be accommodated in the estimation methods. Gottschalk (1993a) was probably the first to develop a method for calculating covariance along a stream network based on river distance, which he used to estimate runoff based on water balance constraints in river junctions (Gottschalk, 1993b). Similar methods were proposed by Ver Hoef *et al.* (2006) and Cressie *et al.* (2006). An alternative is to consider catchments as two-dimensional objects superimposed on the steam network where runoff generation is conceptualised as a spatially continuous process, which is defined for any point in the landscape (Viglione *et al.*, 2010a, b), and runoff is the integral of local runoff over the catchment. Sauquet *et al.* (2000a), Sauquet (2006) and Gottschalk *et al.* (2006) proposed a method where the spatial dependence of runoff of catchments of different sizes is modelled by a regularised covariogram. The problem of nested catchments is addressed by disaggregating observed runoff into runoff contributions from subcatchments or grid cells. Similar to Gottschalk (1993b), they included water balance constraints into the kriging system. A similar method, known as top-kriging, was developed by Skøien *et al.* (2006), which does not use water balance constraints but addresses

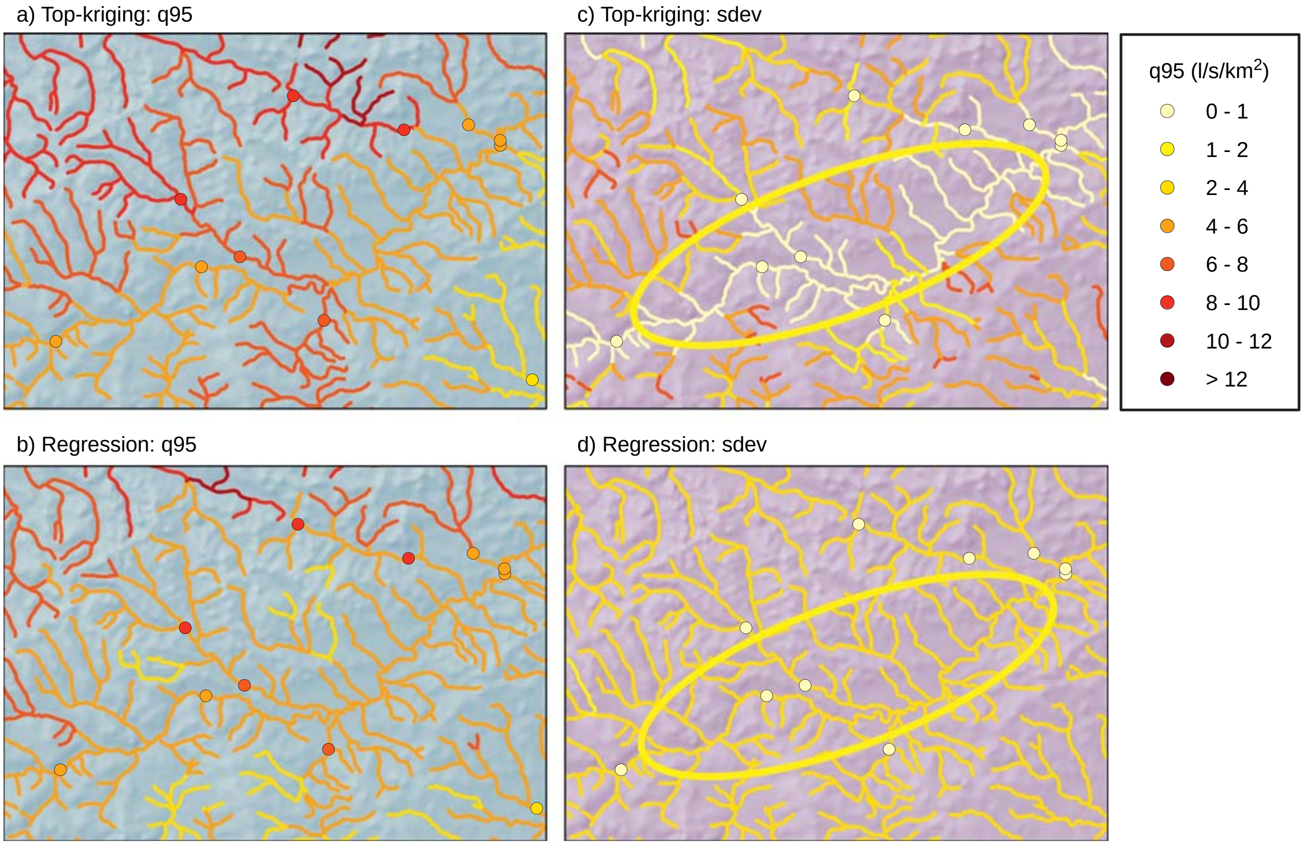

Figure 8.11. Q_{95} low flow predictions in ungauged basins by top-kriging (top left) and regression (bottom left) for the Mur River, Austria. Right panels indicate uncertainty standard deviations. For the main river (ellipses) the estimated uncertainty is lower in the case of top-kriging but for the headwaters it is higher. The area shown is 100 km across. From Laaha *et al.* (2012).

the problem of nested catchments by integrating the point variogram over the drainage area and maps the runoff estimates back to the stream network.

In order to apply geostatistical methods to low flow indices (i.e., Q_{95}), a variogram model is needed. For geostatistics on stream networks, the variogram cannot be directly estimated from sample data because of the different catchment sizes and the nested nature of catchments. A number of methods exist to estimate the variogram where the variograms valid for different catchment sizes are estimated from the point variogram by integration and the parameters are found by optimisation against the runoff data (e.g., Skøien *et al.*, 2003; Laaha *et al.*, 2013). An example of the geostatistical method is presented in Figure 8.11. Along with the estimates of the Q_{95} low flows, the figure presents estimates of the uncertainty of the predictions, expressed as error standard deviations. It is interesting that the geostatistical method estimates uncertainties that not only depend on the location of the ungauged basins with respect to stream gauges but also strongly depend on the catchment size. For the main stream marked yellow, for example, the estimates of the uncertainty are much smaller than those of a regression model for the same reach. For smaller catchment areas, however, the estimates of the uncertainties are much larger. It is clear that the performance of the geostatistical approach will depend on two main factors: the stream gauge density and the degree of spatial heterogeneity of the low flow processes. The approach seems to be best suited for areas with medium or high stream gauge densities and in areas that are geologically rather homogeneous. In the case studies summarised in Section 8.5, the geostatistical approach tends to outperform global regressions for low flow predictions.

To account for spatially heterogeneous regions, the geostatistical method has been extended to combine it with multiple regression methods, in which the residuals of the regressions are used for the spatial geostatistical estimation. Predictive accuracy of this method is described in detail in Section 8.5, and the results suggest that the combined method performed better ($R^2 = 0.73$) than geostatistics alone ($R^2 = 0.61$), but did not yield an improvement over regional regression ($R^2 = 0.74$). In Austria, a spatially adjusted regression ($R^2 = 0.75$) performed better than regional regression ($R^2 = 0.70$) but gave no improvement over the top-kriging model ($R^2 = 0.75$). An alternative combination is physiographic space-based interpolation (PSBI) (Castiglioni *et al*., 2011), which was originally proposed for floods (Chokmani and Ouarda, 2004). The main idea of PBSI is to perform kriging in a transformed space of catchment characteristics by multivariate analysis. Standard point-kriging methods are then applied for spatial estimation. The method has some similarities with the region of influence approach, where regional averaging is performed by a weighted mean of similar stations. In PSBI the weights are estimated from variograms. The correlations along the stream network are accounted for indirectly through the catchment characteristics.

8.3.4 Estimation from short records

In some instances there may be short runoff records available for a catchment that is otherwise ungauged. These runoff records may not be representative of the longer time period that is normally used for the estimation of low flows. Methods are therefore needed that relate the low flow estimates from the short runoff records to the longer hydrological history of the basin on the basis of regional information. A number of methods are currently in use.

In *record augmentation* a relationship is established between the runoff at the subject site and runoff at a nearby donor site where a long runoff record is available. Donor sites are usually selected on the basis of spatial distance, similarity of catchment characteristics or correlation of runoff between the sites (Vogel and Stedinger, 1985; Laaha and Blöschl, 2005). Laaha and Blöschl (2005) suggested that choosing an immediate downstream neighbour may be a better choice than other methods. Early studies on record augmentation suggested use of regression estimators of the mean and variance of runoff and transformation of runoff to obtain approximately normally distributed data (Fiering, 1963; Matalas and Jacobs, 1964). An augmented estimator of the low flow statistic at the subject site is then achieved by linear combination of the statistics estimated from the short record at the subject site with a regression estimate from additional record years at a donor site. The regression relationship used for transferring the low flow statistics of the donor site to the subject site is established from the overlapping records of the subject and donor sites. Vogel and Stedinger (1985) introduced improved record augmentation procedures by using a weighting factor to account for the strength of correlation between the subject and donor sites. Vogel and Kroll (1991) tested the improved record augmentation procedure to minimum annual low flows and found a substantial decrease in estimation variance, especially for longer (10–15 years) gauging periods. The serial correlation associated with low flow sequences, however, reduces those gains considerably. Alternatively, a *multiplicative scaling approach* has been proposed (Robson and Reed, 1999; Laaha and Blöschl, 2005). The approach assumes (i) that low flow characteristics calculated from a short observation period will differ from that of the entire observation period by a scaling factor, and (ii) that the scaling factor of the subject site can be inferred from an appropriate donor site. The scaling factor can be weighted to account for the strength of correlation between the subject and donor sites and the length of the overlap period between the subject and donor site. A number of studies compared the performance of record augmentation with regionalisation methods that do not use local runoff data. In a study in Austria, Laaha and Blöschl (2005) found that *record augmentation* with one year of local runoff data gave more accurate low flow estimates than any other regionalisation method. In a study in France, Chopart and Sauquet (2008) found that spot gauging may also give more accurate low flow estimates than various regionalisation methods, provided nearby stations with longer runoff records are available.

Another related technique is *record extension*, which simulates an extended runoff record rather than estimating specific runoff statistics. Hirsch (1982) compared four record extension techniques using both Monte Carlo and jack-knife simulations, and found that linear maintenance of variance techniques, i.e., those that preserve the mean and variance of the short record, yielded more accurate estimates of historic low flow characteristics than regression techniques. This method was recently applied by Eng *et al*. (2011) for the entire USA. Vogel and Stedinger (1985) proposed a similar estimator, which Ahearn (2008) used to improve the estimation of low runoff statistics in Connecticut, USA.

In the *baseflow correlation* (or *regression*) *method* a regression relationship between single runoff measurements at a short-record subject site and synchronous flows at a long-record donor gauge is used to estimate low flow characteristics at the subject site (Figure 8.12). Unlike record augmentation where a substantial record is required, baseflow correlation can be performed with only a limited number of runoff measurements at the subject site (about 5–15 measurements). The key to this method is that the runoff at subject and donor sites is under baseflow conditions when a measurement is taken, meaning that all contributions to runoff are from groundwater discharge or release from other large stores, e.g., lakes and glaciers (Reilly and Kroll, 2003). The baseflow correlation method assumes a linear relationship between the logarithm of the annual minimum runoff series at the subject and donor sites (Stedinger and Thomas, 1985). Since annual minimum runoff is not available at the short record site, it is assumed

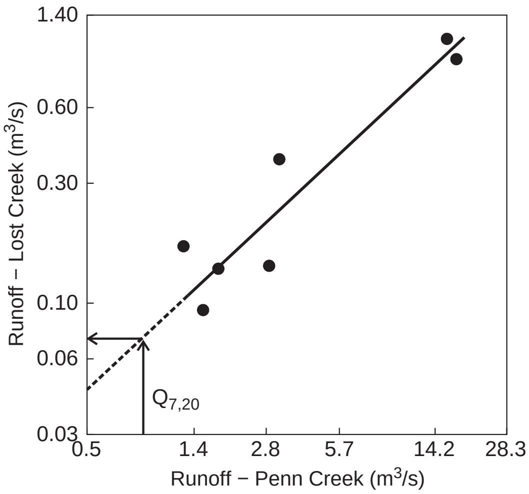

Figure 8.12. Estimation of low flow index $Q_{7,20}$ at Lost Creek, USA, using the baseflow correlation method. Runoff records from Lost Creek (subject site) are plotted versus the long record data for Penn Creek (donor gauge), and a regression line is used to transfer the low flow with a return period of 20 years from the donor site to the subject site. From Riggs (1985).

that the relationship between annual minimum flows is similar to the relationship between instantaneous baseflows. Zhang and Kroll (2007a) found the assumptions generally to be reasonable for the USA. Stedinger and Thomas (1985) examined the performance of baseflow correlation with 20 pairs of runoff sites, and Reilly and Kroll (2003) expanded this analysis to over 1300 runoff sites in the USA. They found this method to perform well when baseflow measurements of independent low flow events and donor sites located within 200 km were used. The method is improved as the number of baseflow measurements is increased, although some levelling off of performance was observed with more than 15 baseflow measurements. When only five baseflow measurements are available, the use of multiple donor sites can significantly improve the performance of this method (Zhang and Kroll, 2007a, b).

Augmented regression refers to the inclusion of runoff-derived indices in regional regression models. With this technique, a small number of runoff measurements are applied to estimate catchment indices that are difficult to obtain by other means. For low runoff statistics, these indices often relate to the hydrogeology of the catchment. Vogel and Kroll (1992) employed estimators of the baseflow recession constant in a physically derived regression model to improve low runoff statistics in Massachusetts. Kroll *et al.* (2004) examined the use of baseflow recession constants and the baseflow index in regional regressions throughout the USA. They found that the inclusion of these hydrogeological indices improved the low flow predictions in every region. Eng and Milly (2007) found a baseflow recession time constant to improve the regional regression model in the eastern USA. The trade-offs between data length and the performance of these techniques have not yet been fully explored.

8.4 Process-based methods of predicting low flows in ungauged basins

While statistical methods exploit only static information, process-based methods additionally exploit dynamic information of the hydrograph and explicitly represent the dynamics of low flow processes. For low flow prediction, these methods focus on the recession parts of the hydrograph. The methods can be formulated either in the probability space (derived distribution methods) or as simulation models of the whole runoff hydrograph (Chapter 10). This section discusses some specific aspects of process-based models with regard to low flow prediction in ungauged basins. One advantage of process-based models is that they can explicitly account for any changes in the precipitation regime and the catchment response characteristics. Also, they may be able to represent local peculiarities of catchments such as abstractions in more detail than statistical methods.

8.4.1 Derived distribution methods

In the derived distribution approach, the low flow indices are obtained by combining the statistical characteristics of precipitation with those of the catchment response. Gottschalk and Perzyna (1989) incorporated runoff processes in a distribution function of low flow in terms of baseflow recession. The derived distribution function contains four parameters of which two are determined from a traditional recession analysis of low flow periods. The other two are derived from a statistical analysis of the maximum length of ‘dry weather’ periods when precipitation is less than an assumed threshold value. The distribution function with the same parameters can be applied to calculate mean low flow for different durations. They tested the method for summer low flows in gauged catchments in southern and western Norway. Gottschalk *et al.* (1997) extended this body of work to deduce expressions for a family of low flow distributions related to linear and non-linear recession models. The distributions included the Weibull distribution. The approach was shown to be promising in regions where it is difficult to fit a regional distribution to the sample data and to estimate low flow distributions in ungauged basins (Pacheco *et al.*, 2006). Specifically, Pacheco *et al.* (2006) extended the previous work of Gottschalk *et al.* (1997) to

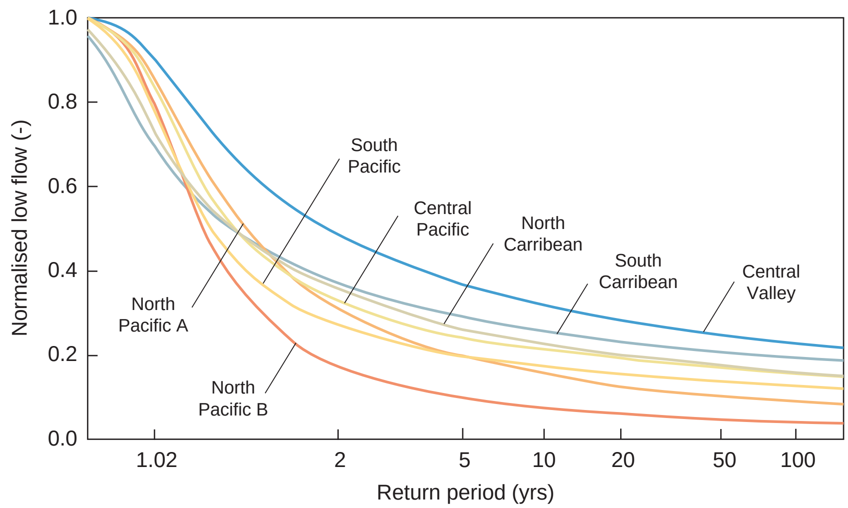

Figure 8.13. Regional low flow distributions in Costa Rica estimated by the derived distribution approach. The low flow distributions relate to annual minima scaled by a reference low flow. After Pacheco *et al.* (2006).

apply to low flow data from humid tropical conditions. They assumed dry spells to be exponentially distributed and assumed non-linear low flow recession behaviour. Their model allowed them to estimate physically interpretable parameters from the low flow distributions. These include the average length of dry spells and the intensity of events. They then grouped the gauged catchments for all of Costa Rica according to these parameters and obtained derived low flow distributions for each of these groups from representative parameters. The derived distributions are shown in Figure 8.13. The distributions suggest that, in Costa Rica, the Northern Pacific region is the driest region and that the rivers on the Caribbean slopes have relatively high low flows, even during the dry period.

8.4.2 Continuous models

Runoff time series simulated by continuous rainfall–runoff models in ungauged basins can also be used to estimate low flow characteristics. Rainfall–runoff models are dealt with in Chapter 10, so this section focuses on the specifics of low flows. Since low flow characteristics very much depend on the subsurface characteristics of the catchment related to long flow paths (Chapter 4) rainfall–runoff models for low flow estimation need to represent these well. For conceptual models that are calibrated against runoff data this is usually ensured by using the logarithm of runoff instead of runoff itself in the calibration (e.g., Seibert, 2005). The model parameters are then transferred from gauged to ungauged basins as discussed in Chapter 10. Examples are multiple regressions used for lumped models to relate model parameters to catchment characteristics (e.g., Abdulla and Lettenmaier, 1997; Xu, 1999) and regional calibration procedures that relate model parameters to the characteristics of each modelling unit (e.g., grid cells; Engeland *et al.*, 2001). Some studies that simultaneously address the estimation of regional parameters and modelling uncertainties for distributed models apply multi-objective and Bayesian methods (Engeland *et al.*, 2006). A case study in south-western Norway (Engeland and Hisdal, 2009) suggested that a regional regression may give better estimators of low flow characteristics in ungauged catchments than a distributed hydrological model.

Coupled groundwater–surface water models that simulate water flow driven by potential gradients have been tested by van Lanen *et al.* (1997) for the purpose of predicting low flows in ungauged basins. They emphasised the strength of the simpler conceptual models over the more complex coupled models and suggested that very detailed information on the subsurface is needed for low flow characteristics to be represented well without calibration. Coupled groundwater–surface water models are usually calibrated with groundwater level data in addition to runoff. The strength of such coupled models lies in their ability to incorporate management scenarios into low flow predictions, such as the impact of human influences on low flows (e.g., abstractions, land use change, climate change) (Querner *et al.*, 1997), the impacts of drought mitigation measures (Querner and van Lanen, 2001) and the value of indicators for assessing the regional groundwater resources that will impact the low flow regime (Henriksen *et al.*, 2008).

8.4.3 Proxy data on low flow processes

Explorative field surveys can provide useful, qualitative information about low flows and their temporal variability. Climate data (e.g., from high-resolution global databases with long time series of climate data, see Chapter 3)

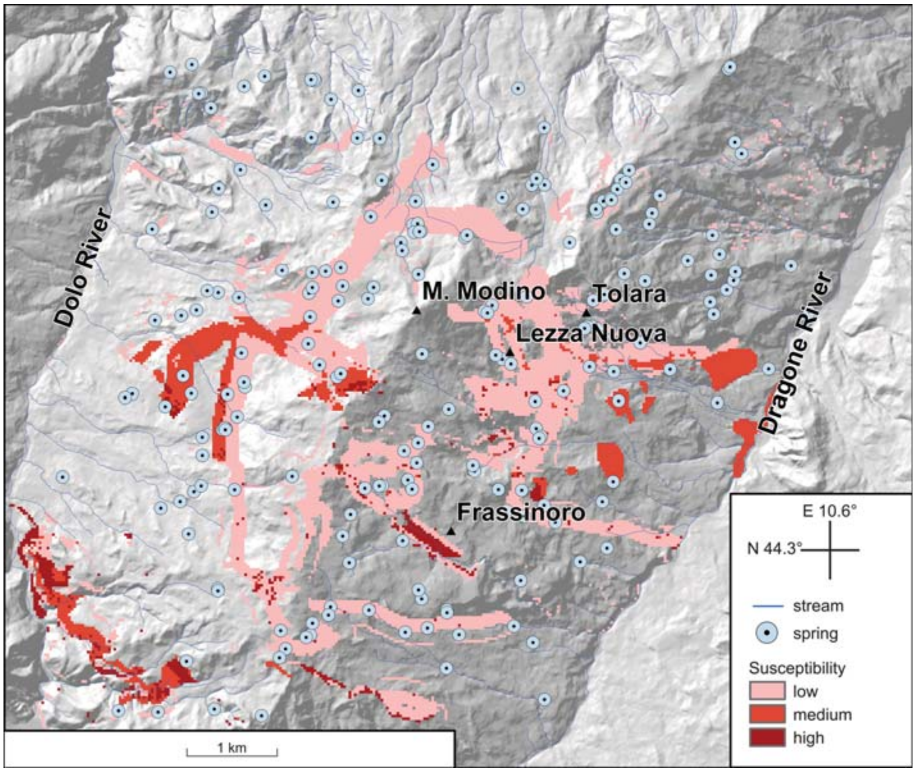

Figure 8.14. Susceptibility of rocks to springs estimated by hydrogeological factors in a mountain region in Emilia Romagna, Italy. The susceptibility can be used for estimating low flows in ungauged basins. After Cervi *et al*. (2007).

provide the hydroclimatic context. Field surveys help to identify the physical catchment structure that controls the spatio-temporal patterns of low flows. Synoptic runoff measurements (i.e., spot measurements at several locations along the stream network in a short time interval) can be very valuable for determining the main sources of flow during low flow periods. Among other things, these methods can be used for testing distributed hydrological models (e.g., Engeland *et al*., 2002). In dry climates, vegetation on the valley bottom can be a valuable proxy for low flow characteristics. Lowering the water table and/or reducing overbank flooding may result in changes in the density, productivity and species composition of wetland and riparian vegetation (Smakhtin, 2001). Johnson (1998) showed, for instance, that changes of up to 25% can result from adding or removing forestry. An overview of the effect of changes in the vegetation on low flows in humid regions is given in Price (2011).

Another type of proxy information for predicting low flows is the spatial distribution of springs, which is closely linked to the catchment's geology. There is often a direct correlation between the spatial arrangement of geological units in a basin and low flow runoff (Rogers and Armbruster, 1990; Gustard *et al*., 1987; Musiake *et al*., 1984). Cervi *et al*. (2007) and Cervi (2009) proposed using the spatial distribution of perennial springs to assist in the estimation of low flows in ungauged mountain basins. They developed a method of identifying zones of susceptibility to springs based on a number of geological factors, including hydrogeological facies, surface deposits and distance from faults. They identified different classes for each of these factors by analysing existing geological maps, aerial photographs, field surveys and additional permeability measurements. They then related these factors to the location of springs by a Bayesian method, which allowed them to map the susceptibility zones (Figure 8.14). The zones of highest susceptibility are located mostly where the permeable flysch overlies clay formations. The position of the springs is determined by the tectonics that has caused the overlay of hydrogeological structures with different permeabilities. The superficial deposits, however, are less important, but springs occur where lithotypes of contrasting characteristics are in contact.

8.5 Comparative assessment

The aim of the comparative assessment of low flow predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on the methods to choose in particular environments. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1 in terms of how the performance depends on climate and catchment characteristics as well as on the method chosen. More details are reported in the comparative study of Salinas *et al*. (2013). In both Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

8.5.1 Level 1 assessment

Table A8.1 summarises the 19 studies that were used for the Level 1 assessment. The number of catchments in each study ranges from 40 to 1003, with a median of 150. Several studies compare different approaches which results in a total of 27 results for predictive performance. The selection of studies was guided by the overall aim of supporting geographical coverage, but preference was given to studies that optimally served the benchmarking aim by providing a comparative assessment of two or more methods on a larger data set, by using performance measures obtained by cross-validation, and by focusing on standardised low flow indices (specific runoff, or standardised low flows) to factor out the dominance of catchment area on the low flow estimates. The regionalisation methods used are process-based methods, geostatistics, global regression, regional regression and estimation from short record methods (record augmentation methods). Three performance measures were used in the assessment: the coefficient of determination (R^2) of estimated and observed low flow indices, the root mean square error (RMSE), and the relative root mean square error (RRMSE), i.e., RMSE divided by the average low flow index over the study area (Table 2.2). In cases where not all performance measures were available, they were back-calculated from the available data where possible (indicated in Table A8.1). For the comparisons, only those studies were used where R^2 was available or could be back-calculated. Even if the studies listed in Table A8.1 are not completely compatible, e.g., due to different low flow characteristics or evaluation methods, the collection of studies does provide an indication of the performance range to be expected for different methods of predicting low flows in ungauged basins around the world. For comparison with the other runoff signatures in Chapter 12, the R^2 of predicting low flow indices were calculated for all methods in all studies with the exception of tree rings. The 25% and 75% quantiles of these R^2 are 0.57 and 0.78, respectively.

Figure 8.15. Map indicating the countries included in the Level 1 assessment. After Salinas *et al*. (2013).

Figure 8.15 shows the global coverage of the studies listed in Table A8.1. Most of the cross-validation assessments were performed in Europe and North America and only a few studies cover Australia and Asia (Table A8.1). Most available studies were for humid and cold climates, and fewer studies in monsoon, semi-arid, arid and tropical climates.

How good are the predictions in different climates?

Figure 8.16 shows that the highest performance is obtained for humid catchments, but there are also studies in humid climates that report a significantly lower performance. In arid climates, the performance is never very high, but more studies are needed to clearly show this behaviour. The most likely reason for this finding is that arid regions tend to be very heterogeneous with a high variability of low flow producing processes, and low flows generally tend to be lower and more variable, and therefore harder to predict. Cold environments exhibit the largest performance range. This could be because this class contains sub-polar and mountainous environments that may be hydrologically very complex, with many different storage types that complicate low flow behaviour (ice/groundwater).

Which method performs best?

The regionalisation methods represented in the assessment included: one result from the process-based methods group (continuous runoff models); four results from the geostatistics group of methods where runoff at the target site was estimated as a weighted mean of runoff at the surrounding gauges; ten global regression and seven regional regression results from the regression methods group; and five results from the short records group that used various methods. The assessments in each group are not based on exactly the

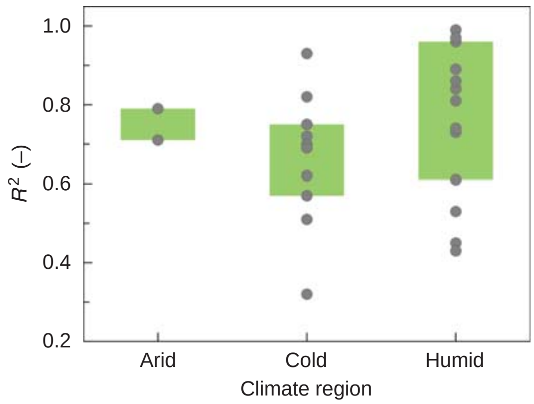

Figure 8.16. Coefficient of determination (R^2) of predicting low flows in ungauged basins stratified by climate. Each circle refers to a result from the studies in Table A8.1. Boxes show 25%–75% quantiles. After Salinas *et al*. (2013).

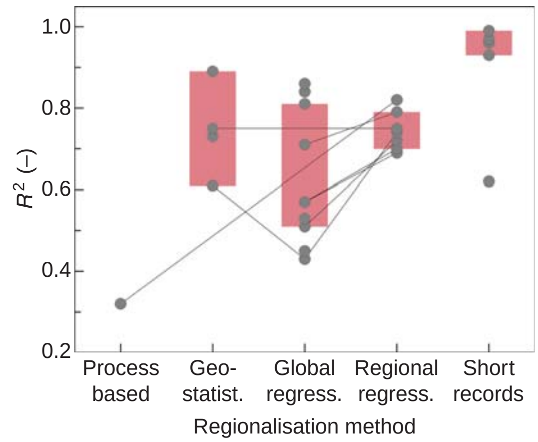

Figure 8.17. Coefficient of determination (R^2) of predicting low flows in ungauged basins stratified by regionalisation method. Each circle refers to a result from the studies in Table A8.1. Lines indicate studies that compared different methods for the same set of catchments. Boxes show 25%–75% quantiles. After Salinas *et al*. (2013).

same regionalisation approach, but the methodology is similar. There are also differences in the low flow indices used. They include Q_{95}, $Q_{7,10}$, $Q_{\text{mon},5}$, all standardised by catchment area or mean flow, and the dimensionless baseflow index (BFI). In particular Q_{95} low flows are usually closely correlated to $Q_{7,10}$ so that a comparison across the various indices should provide consistent results at the level of detail used for the comparisons. Figure 8.17 shows a large performance range across the regionalisation methods. Overall, it is clear that low flow predictions from short records ($R^2 = 0.62$ to 0.99) perform best. The method performs significantly better than all other methods, provided continuous runoff measurements from at least 3–5 years of observations at the site of interest are used. A lower performance (0.62) is obtained when using a single flow measurement during the low flow period. The performance of global regression ranges from 0.43 to 0.86. Studies from high-mountain environments have a lower performance (Austria: 0.57, Switzerland: 0.51, Nepal: 0.53, India: 0.45), perhaps because the heterogeneity of the low flow process in the landscape (including snow) poses difficulties for applying one single regionalisation model for the entire domain, so division into sub-regions may be necessary. Global regression is better suited to smaller regions (e.g., German region Baden-Württemberg) and studies in less seasonal climates (e.g., New South Wales and Victoria in Australia). The four results from geostatistical models give performances between 0.61 and 0.89. A continuous runoff model, tested in only one study used in the meta-analysis, gave lower performance than the statistical methods.

The studies examined differ in terms of the hydrological characteristics and data availability, so a comparison of methods for different regions will involve some uncertainty. It is therefore useful to apply each different method to the same catchment. A number of studies available in the literature have performed such a comparison and the results are indicated as grey lines in Figure 8.17. Most of the studies compare global and regional regressions. The comparisons clearly show that the regional regressions always perform better than the global regressions. The studies that conduct this comparison show that the average performance of global regressions is around 0.5 and this increases to 0.7 for regional regressions. It should be noted that the performance reported is cross-validation performance for ungauged basins, so better performance is related to better predictions rather than improved goodness of fit of the regressions. There are also a few studies that compared geostatistical methods with regional regression methods. In one study from France (Plasse and Sauquet, 2010), the geostatistical method was based on distance between the catchment centres of gravity. The performance was better than for global regression and worse than that of regional regression. If the stream network structure is taken into account, the performance of geostatistical methods can in fact be higher than that of regional regression as illustrated in the Austrian case studies (Laaha *et al*., 2007, 2013). Finally, one study (Engeland and Hisdal, 2009) compared process-based methods with regional regressions and found that the regressions gave better results. Clearly, application of process-based methods does not per se include the performance of low flow estimation but their value depends on the amount of information available for careful parameterisation of the model. However, process-based methods have more

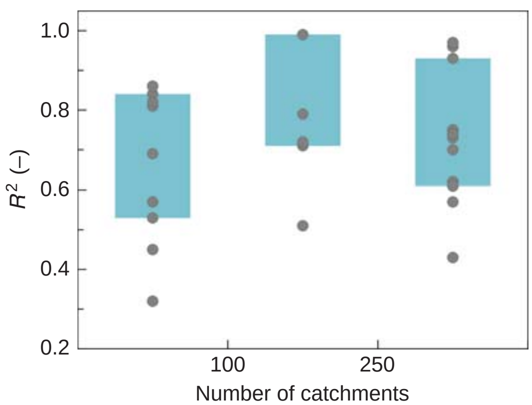

Figure 8.18. Coefficient of determination (R^2) of predicting low flows in ungauged basins stratified by the number of catchments within each study. Each circle refers to a result from the studies in Table A8.1. Boxes show 25%–75% quantiles. After Salinas *et al.* (2013).

potential to explore the impact of environmental change than statistical methods.

How does data availability impact performance?
Figure 8.18 shows the predictive performance (R^2) as a function of the number of catchments analysed in each study. It is clear that the studies with less than 100 catchments have, on average, the lowest performance and performance increases with the number of catchments used in analysis. This is because of the higher stream gauge density in the larger studies. The performance decreases for very large data sets (>250 catchments). This decrease is related to the higher heterogeneity of larger study areas and to the fact that a number of the studies used global regression methods that did not perform very well in these regions.

Main findings of Level 1 assessment

- In humid regions the performance of predicting low flows in ungauged basins tends to be better than in other climates.
- Methods that use short runoff records at the site of interest perform significantly better than any regionalisation method provided 3–5 years of data are available.
- Regional regressions that divide a domain into sub-regions and apply regression models separately always perform much better than global regressions.
- Geostatistical methods can perform better than regional regressions in regions with medium to high stream gauge density if the stream network structure is taken into account.
- The performance tends to increase with number of stations in a region but may decrease if global regressions are used in the large regions.

8.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A8.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and comparison of results between studies. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. Six study authors from the Level 1 assessment provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment (Table A8.2). This data set combines data from 2455 catchments, four groups of regionalisation methods and four catchment characteristics. The regionalisation methods are geostatistics, global regression, regional regression and estimation from short records (see Salinas *et al.*, 2013). The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area. As performance indicators the normalised error (NE) and the absolute normalised error (ANE) were used (Table 2.2). The NE highlights biases in the methods while the ANE is a measure of the overall performance. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e., higher up in the plot is better. For comparison with the other runoff signatures in Chapter 12, the R^2 of predicting low flow indices were calculated for all methods in each study separately. The 25% and 75% quantiles of these R^2 are 0.57 and 0.73, respectively.

To what extent does runoff prediction performance depend on climate and catchment characteristics?
The assessment of the predictive performance of the models with respect to the four climate and catchment characteristics is presented in Figures 8.19 and 8.20. Overall, the errors, ANE and NE, clearly increase with increasing aridity and mean annual temperature T_A. This means that the performance is consistently lower in warmer, drier and more arid environments. These are regions that tend to be particularly heterogeneous and low flows may be small, which makes them particularly hard to predict.

Figures 8.19 and 8.20 indicate that there is a tendency for performance to increase with catchment elevation. The average of all methods shows that errors decrease from 0.37 for low land catchments (mean elevation < 200 m a.s.l.) to 0.16 for high mountain catchments. This may be partially due to the higher specific discharges of mountainous catchments compared to lowland catchments, which may increase predictability. Also, in the high mountains, low flows may be of a winter low flow type, so low flows may depend on frost strength, which is closely related to

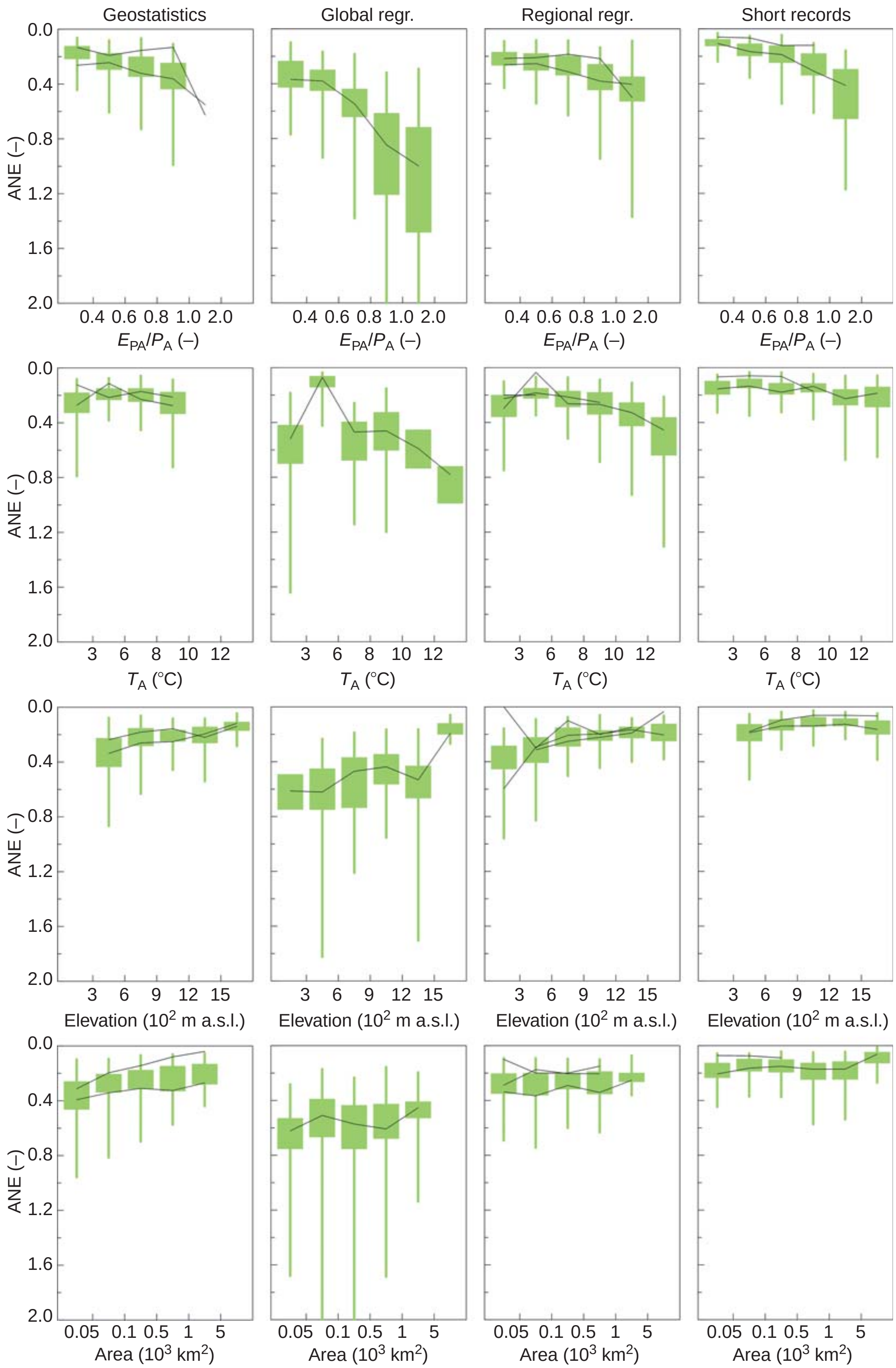

Figure 8.19. Absolute normalised error (ANE) of predicting low flows in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al*. (2013).

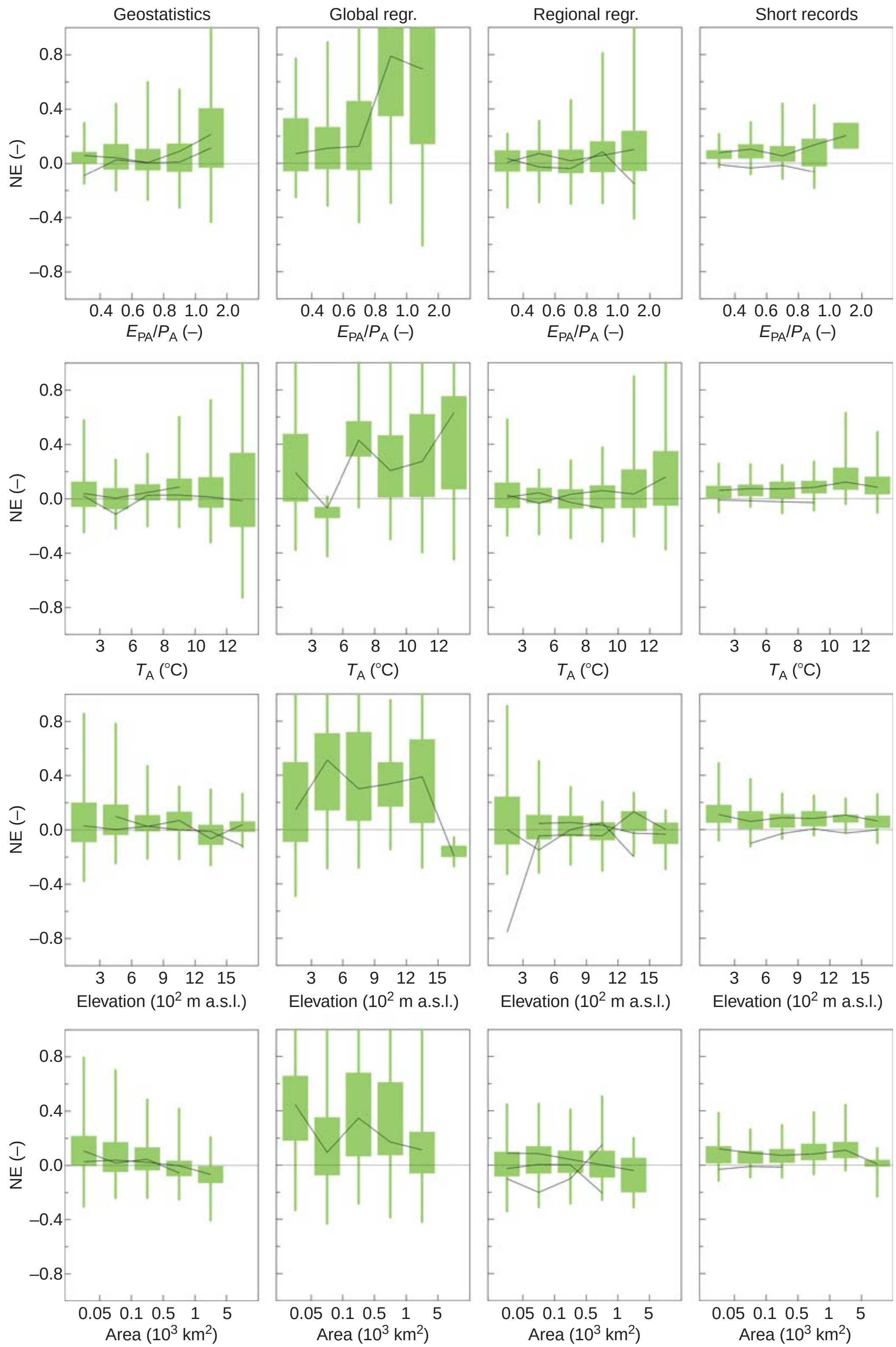

Figure 8.20. Normalised error (NE) of predicting low flows in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al*. (2013).

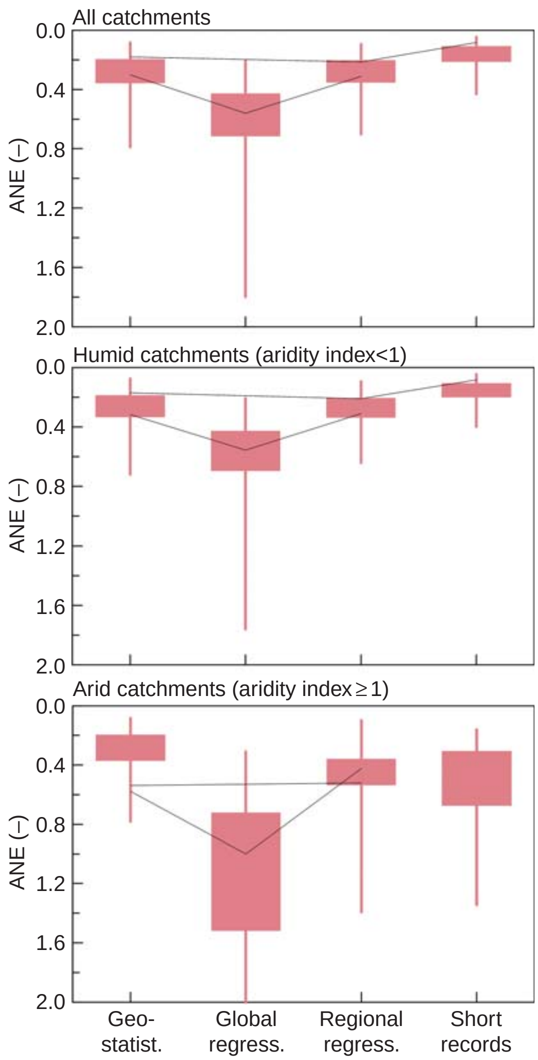

Figure 8.21. Absolute normalised error (ANE) of predicting low flows in ungauged basins for different regionalisation methods, stratified by aridity. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al*. (2013).

catchment elevation. The bottom panels in the figures show the performance as a function of catchment scale. For all methods the performance increases with catchment scale. This may be related to both data availability and space-time aggregation of runoff processes in the catchments, which will increase the predictability. The exceptions are methods that use short runoff records at the site of interest. In these cases, the performance dependence on catchment size is less pronounced than for the other methods. These types of methods may be more dependent on the representativeness of the short runoff record to the temporal variability of low flows, so the dependence on the spatial variability and therefore catchment size may be lower.

Which method performs best?

Figure 8.21 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments in Table A8.2, and catchments with an aridity index below and above 1, respectively. Overall, for all catchments the performance of the global regression is much lower than that of any other method. This is consistent with the Level 1 assessment. In the arid catchments the performance of the global regression is particularly low and the absolute normalised errors are, on average, around 1.1. The poor performance of the global regression methods is partly related to the biases of the methods but the random errors are also large (Figure 8.20). In the humid regions the short records perform better than any other method. This is, again, consistent with the Level 1 assessment. However, this is no longer the case for the arid catchments. For the arid catchments, the performance of the short records is in fact lower than those of the geostatistical methods and regional regression. It appears that in arid regions the variability of the low flows between years may be larger than in other climates, which makes the record augmentation and other methods based on short runoff records at the site of interest perform less well. Another possible explication of the lower performance of short records in arid regions is that gauging networks are typically sparser in arid regions, so that donor gauges are further away, less similar, and in final consequence less appropriate for record augmentation. Methods may be needed in arid regions that specifically acount for the runoff generation processes in the region, and preferably are based on proxy data that account for these processes.

Main findings of Level 2 assessment

- The performance of all methods for predicting low flows in ungauged basins worsens with increasing aridity and air temperature.
- There is a tendency for the performance to improve with catchment elevation.
- Performance improves with catchment size, with the exception of methods that use short runoff records at the site of interest, which may be more dependent on the temporal variability of low flows than on the spatial variability.
- The global regression methods always exhibit lower performance than other methods, particularly in arid catchments.
- In humid conditions, methods that use short runoff records at the site of interest perform much better than any other methods. However, this is no longer the case in arid regions when regional regressions may perform better.

8.6 Summary of key points

- This chapter dealt with low flows, the part of the spectrum of runoff variability when there is very little flow in the river. Low flows can be defined in several ways, the most common being the annual runoff minima, or the magnitude of runoff that is exceeded 95% of the time. Sometimes, runoff variability during the period of time in the year over which flows remain low or are close to the minimum is used to characterise the low flow regime.
- The low flow distribution represents a composite signature that reflects the interplay of several features: climate during the dry period of the year, storage in subsurface (including deep aquifers) and associated long flow paths, evaporation (especially from the riparian zone vegetation) and, in cold climates, the effects of snow storage.
- Winter low flows (in cold, snow-affected regions) are controlled by temperature and antecedent precipitation. Summer low flows (as a result of prolonged dry spells) are controlled by aridity of the catchment, the sequence of rain events during the normal dry part of the year, by storage properties of the underground, and by vegetation.
- Characteristic similarity measures include the time of the year that low flows occur (e.g., winter or summer), local geology (which determines the long flow pathways that bring water to the river from deep water stores) and large-scale climate patterns (which determine larger scale patterns of low flows). Co-evolutionary indices that determine similarity include patterns of riparian vegetation (e.g., an oasis present in the middle of a desert is an extreme example), connectivity and distribution of lakes and wetlands in riparian landscapes (e.g., billabongs in Australia).
- Most of the methods used for low flow predictions are statistical, partly because there is not enough information on hydrogeology (which is an important control) and this information, when available, is hard to quantify. There is considerable potential to use more dynamic predictors that include time (e.g., sequencing of rainfall events, spring runoff, runoff recession curves), link these to regression coefficients obtained during the application of statistical methods, and to interpret them from hydrological process perspectives.
- Comparative assessment of several prediction methods for low flows indicates that predictive performance gets worse with increasing aridity (both Level 1 and Level 2 assessments). The performance improves with increasing catchment area (Level 2 assessment), ostensibly because of the presence of longer water flow pathways that accompany increasing catchment size. The availability of short records is particularly useful to improve performance of low flow predictions (both Levels 1 and 2), especially in humid regions, and is perhaps not as useful in arid regions because of strong inter-annual variability (Level 2). Of the various methods, regional regressions have been shown to be better than global regressions (from Level 1 and Level 2 assessment).
- There is considerable scope to use process information on the hydrogeological catchment architecture and climate drivers (summer/winter low flows) to identify low flow regimes at regional and global scales and interpret the differences and similarities through comparative hydrology.

9 Prediction of floods in ungauged basins

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9.1 How high will the flood be?

Floods are one of the most burning societal issues catchment hydrology has to face. Flood-related economic losses have increased dramatically over the past decades in most parts of the world, and the number of flood fatalities has increased in some continents (Di Baldassarre *et al.*, 2010). Floods are shaping the patterns of human behaviour in many ways. Flood risk is a major factor controlling settlement patterns near rivers. Much of the infrastructure near streams is susceptible to flood damage in some form or another and floods may disrupt mobility and livelihood. While floods are often only viewed from a perspective of damage and destruction they may play an essential role in ecosystems. In river wetlands, for example, regular flooding sustains the dynamics of soil moisture and groundwater necessary for ecosystem functioning.

Predictions of floods are therefore needed for a wide variety of societal purposes. Integrated flood risk management (e.g., EU, 2007) aims at coordinating the various management goals related to floods. Part of the management plan is the prudent design of the infrastructure involving design of dam spillways, bridges, road culverts and levees. Residential area zoning, floodplain management and urban design are other important aspects of integrated flood management. For all of these purposes one needs to know the level of flood water or flood runoff that may occur with a given probability.

This chapter focuses on the prediction of floods in ungauged catchments. In the context of this book flood prediction is defined as the estimation of flood runoff and the associated exceedance probability at an unknown future point in time, as opposed to real-time flood forecasting where forecasts are made for the immediate future. The focus is on river floods induced by heavy rain, sometimes in association with snowmelt, but dam breach floods, ice jam floods, and floods due to other processes are not dealt with in this chapter.

One of the ways that humanity has learned to live with floods is to understand the severity of flooding in terms of the frequency or probability of flooding. Hydrology then needs to understand the risk of rare or extreme events, and factor that risk in cost-benefit analyses of engineering decisions. Therefore, the quantity of interest in flood estimation is the magnitude of the flood (normally flood runoff at a particular point at a river, or the corresponding stage or water level) for a specified return period (also called average recurrence interval). An example is the so-called 100-year flood, the magnitude of the annual maximum flood that will be exceeded, on average, once in 100 years; put another way, there is a 1% chance in any year that the largest flood of the year will exceed the 100-year magnitude. The choice of return period in specific circumstances depends on the risk society is prepared to accept, and is usually decided on the basis of consensus or cost-benefit analysis. For example, a lower return period might be accepted for design of a stormwater drain than for design of a dam spillway, since the potential damage is lower in the case of the former. This chapter is particularly concerned with the flood frequency curve.

From the perspective of runoff variability, the flood frequency curve is an extreme value distribution that lies at the long tail of the distribution of all flood peaks that may occur in the catchment. It is constructed by plotting the frequency of a flood (in terms of the return period) against its runoff. Floods are a subset of the full spectrum of runoff variability experienced in the catchment, as reflected in the complete hydrograph. In spite of this unique feature of representing extremes, the flood frequency curve reflects the net result of the interactions between rainfall variability, vegetation, soils and geology, which in turn are related to climatic and landscape hydrological processes. Floods are therefore closely related to

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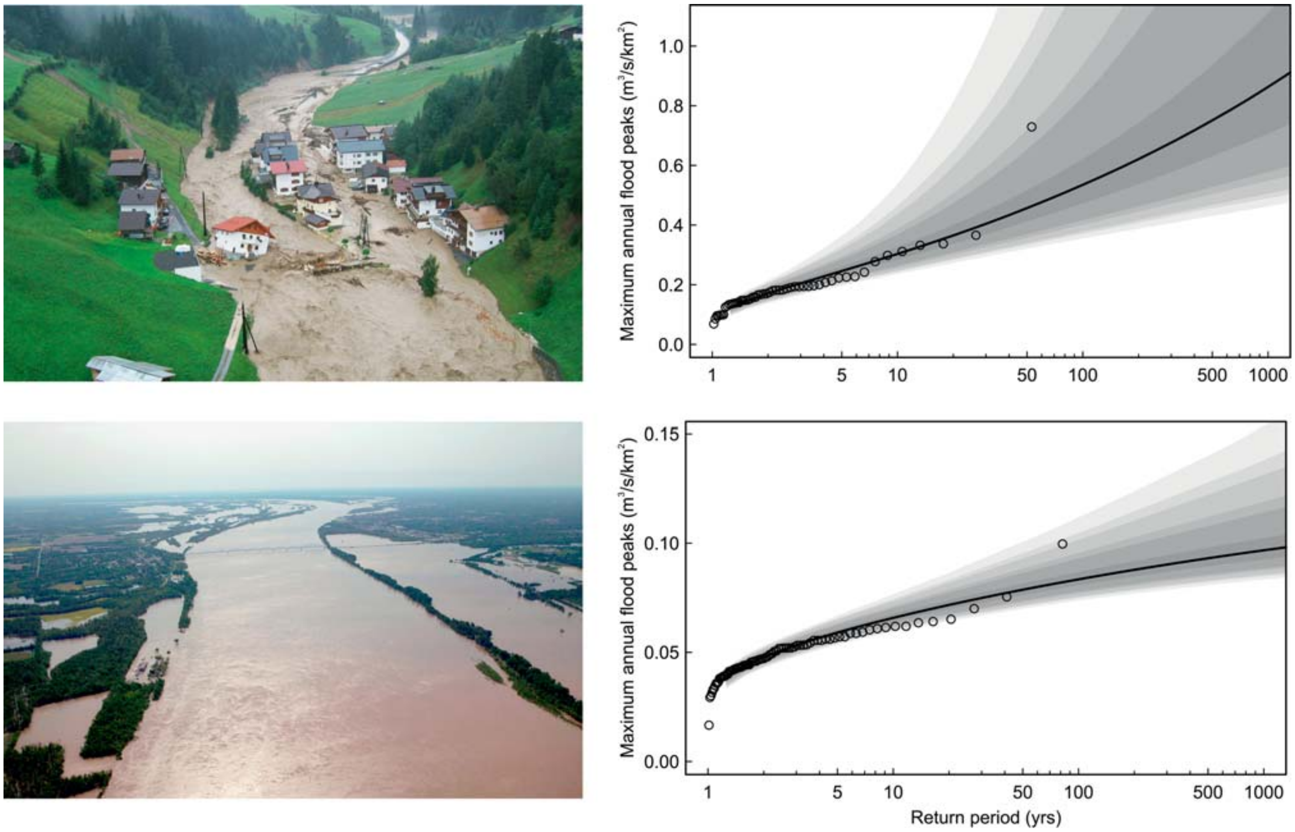

Figure 9.1. Comparative photos and flood frequency curves. (Top) 2005 flood of the Trisanna at Kappl Nederle, Austria (area 385 km^2, median elevation 2300 m a.s.l.); (bottom) 2011 flood of the Ohio at Metropolis, USA (area 526 000 km^2, median elevation 84 m a.s.l.). Generalised extreme value distribution fitted to the maximum annual floods by a Bayesian method. Grey shading represents the confidence intervals from 50% to 99.9%. Photos: (top) ASI / Land Tirol / B. H. Landeck; (bottom) B. Dodson.

the other runoff signatures discussed in this book, in particular annual runoff (Chapter 5), which reflects the average behaviour of the catchment system, and seasonal runoff (Chapter 6), which reflects the within-year variability of precipitation, snow and soil moisture. Floods are apparent in the flow duration curve (Chapter 7) and in the entire hydrograph (Chapter 10), and they share some similarities with low flows as they are both runoff extremes (Chapter 8). These connections can help improve flood predictions, and help advance predictions in general through the improved understanding that is generated.

9.2 Floods: processes and similarity

What makes two catchments similar in terms of flood frequencies? Figure 9.1 shows floods in two catchments in different parts of the world along with their flood frequency curves. In the Trisanna River in Tirol, Austria (Figure 9.1 top), the annual maximum runoff peaks, represented as open circles in the graph, have values between 0.1 and 0.4 (m^3/s)/km^2 with the exception of one event. The August 2005 event was the highest flood on record (shown in the picture) and had a specific discharge of 0.73 (m^3/s)/km^2. In the Ohio River (Figure 9.1 bottom) the observed specific discharges are always lower than 0.1 (m^3/s)/km^2. Even the April 2011 event (shown in picture), which was one of the most damaging floods in the USA in the last century, only had a specific discharge of 0.068 (m^3/s)/km^2. From a hydrological point of view, it is of interest to understand why the specific runoff peaks in the Austrian catchment are so much higher than those in the USA catchment. In addition, the variability of the observed peak runoff events in the Trisanna is higher than that in the USA (coefficient of variation 0.5 and 0.2 respectively). This translates into a steeper flood frequency curve for the Trisanna, and a flatter flood frequency curve for the Ohio River. It is interesting to explore these differences in terms of the causal processes shaping the flood frequency curves.

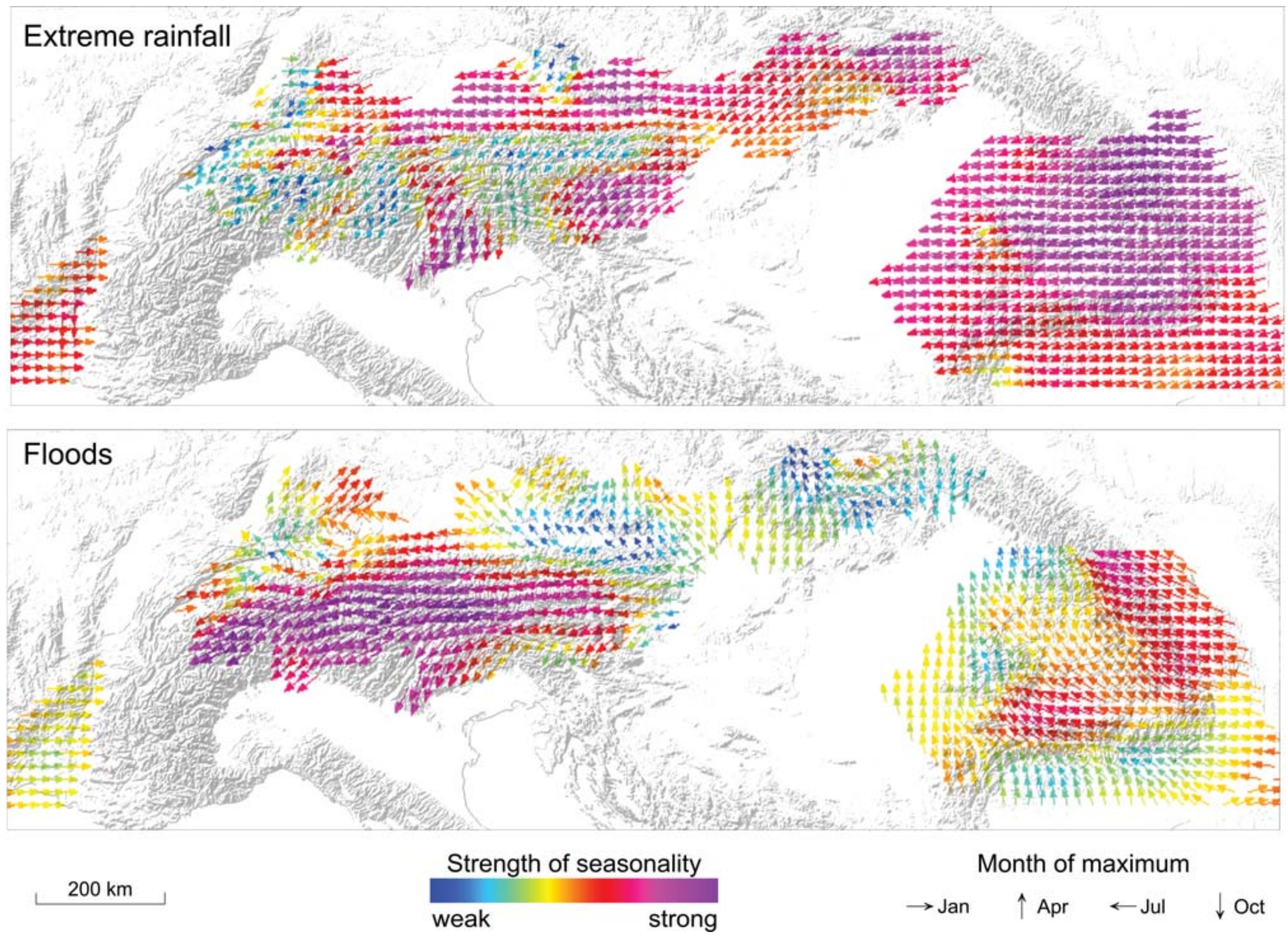

Figure 9.2. Seasonality of annual maximum daily precipitation (top) and maximum annual flood (bottom) in Central Europe in the period 1961–2000, showing the strength of seasonality (colours) and the season of maxima (directions). The seasonality strength is weak if the events occur uniformly throughout the year; it is strong if all maxima occur in the same period of the year. From Parajka *et al.* (2010a).

9.2.1 Processes

Climate forcing

Floods can be generated by a range of processes related to extreme rainfall. Depending on the meteorological conditions, extreme rainfall can be produced by convective storms where a strong updraft of warm moist air due to buoyancy effects in the atmosphere is often produced by strong radiation. These storms often cover small spatial scales of a few kilometres, last for a few hours or less, and can reach very high intensities. Rainfall can also be produced by large-scale atmospheric mechanisms due to dynamic lifting or orographic effects (synoptic events). This rainfall usually covers larger space scales and has a longer duration though the intensities may be lower. Advection of moist air from the sea is extremely important in various settings, e.g., France (Gaume *et al.*, 2002), and in particular in tropical or sub-tropical regions where cyclones occur (e.g., Hirschboeck, 1987; House and Hirschboeck, 1997). Floods can also be produced by snowmelt in cold regions and rain on snow events (Waylen and Woo, 1982; Stedinger *et al.*, 1993; Sui and Koehler, 2011; Merz and Blöschl, 2003).

The flood frequency curve is the combined effect of rainfall variability at many time scales and the interactions with landscape dynamics, in particular the soil moisture and snow processes (e.g., Robinson and Sivapalan, 1997b; Sivapalan *et al.*, 2005). Flood processes are often seasonal, i.e., the floods do not occur in all months with the same probability. In several parts of the world seasonality of climate is strong, and there are significant differences between different regions on account of the differences in seasonality. The interplay between atmospheric processes and the catchment state (soil moisture and snow) is illustrated in Figure 9.2 for the Alps and Carpathians in Europe. In the northern part of the Alps the annual precipitation maxima typically occur in July and August (arrows in Figure 9.2 top, pointing left) and closer to the Mediterranean extreme rainfall occurs later in the season. The timing of the floods (Figure 9.2 bottom), however, may differ from that of the extreme rainfall. In the mountain ranges this is due to snow processes. For example, even if there are October rainfall maxima, the flood maxima may cluster around June and July due to snowmelt. In the lowlands this is due to the interplay of soil moisture with extreme rainfall. For example, even if there are July rainfall maxima, the flood maxima may occur in December and January when the soil moisture is largest in the catchments due to low evaporation.

Not only is there often considerable intra-annual variability of rainfall and floods but also inter-annual (e.g., El Niño and La Niña variability), and even inter-decadal variability (e.g., Inter-decadal Pacific Oscillation (IPO), Pacific Decadal Oscillation etc.) of precipitation, all of which can impact the shape of the flood frequency curve. Figure 9.3a presents the flood frequency curves in Eastern Australia under El Niño and La Niña conditions along with the associated 90% confidence limits (Kiem *et al.*, 2003). Much higher flood risk is associated with La Niña events as opposed to El Niño. In Figure 9.3b the flood frequency curves are shown for IPO negative (<−0.5) against non-negative IPO phases. It can be seen that IPO negative phases correspond to a much increased flood risk when compared to the non-negative phases of IPO. It is therefore clear that monitoring of the multi-decadal IPO phase may provide valuable insight into flood risk on multi-decadal scales, whilst the joint occurrence of inter-annual La Niña events within the IPO negative phase represents further elevated flood risk in Eastern Australia. Depending on the region there are a number of processes related to climate that modulate the inter-annual precipitation variability (Kundzewicz, 2012) including soil moisture, and snow storage and melt (Parajka *et al.*, 2010; Blöschl *et al.*, 2012).

Runoff generation

Rainfall and snowmelt run off the land surface or infiltrate into the soil through a variety of mechanisms including infiltration excess, saturation excess and subsurface stormflow (see Chapters 4 and 10). Mechanisms that involve surface flow paths such as infiltration excess and saturation excess produce a quick response, whereas mechanisms that involve subsurface flow paths in general produce a relatively slower response, and yet can make a significant impact on the shape of the flood frequency curve (Samuel and Sivapalan, 2008). The mechanism that operates in a specific catchment, or during a specific event depends on the rainfall intensity and depth, soils, vegetation and topography and especially on the antecedent wetness of the catchment, which reflects a carry-over or memory of previous events. The effect of antecedent wetness on the flood frequency curve can be significant (Wood, 1976; Komma *et al.*, 2007). In arid regions where infiltration excess runoff often dominates, antecedent soil moisture tends to be

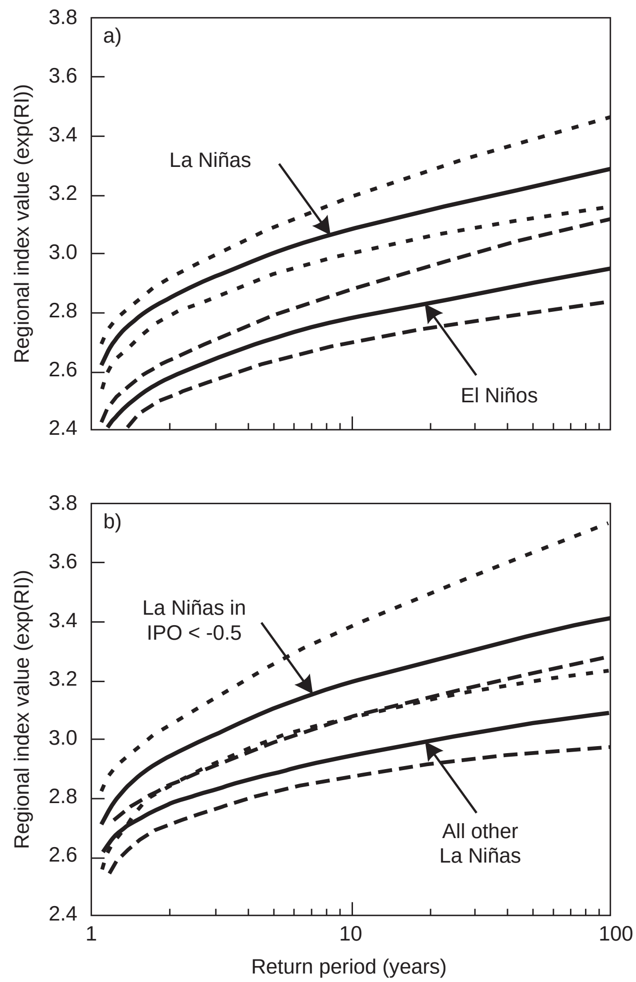

Figure 9.3. Regional flood frequency curves in New South Wales, Australia, with 90% confidence bounds (dashed). RI is, for each year, the regional average of the flood runoff normalised by its long-term mean. (a) Floods under El Niño and La Niña conditions; (b) floods during negative (∼1946–76) and non-negative Inter-decadal Pacific Oscillation phases (∼1924–43, 1979–97). From Kiem *et al.* (2003).

mainly random. On the other hand, in many catchments around the world that exhibit strong seasonality in climate forcing, e.g., humid or temperate climates in Europe or North America, and in Mediterranean catchments in southern Europe, Western Australia, and western USA, antecedent soil moisture exhibits a strong (systematic) seasonal component, and has been shown to have a significant impact on the flood frequency curve (e.g., Sivapalan *et al.*, 2005). In parts of Western Australia, floods with a return period less than 10 years are typically winter floods, whereas floods with a return period longer than 30 years tend to be summer floods, despite generally drier soils in summer (Sivandran, 2002). This arises due to different mechanisms of rain-producing events (frontal events in

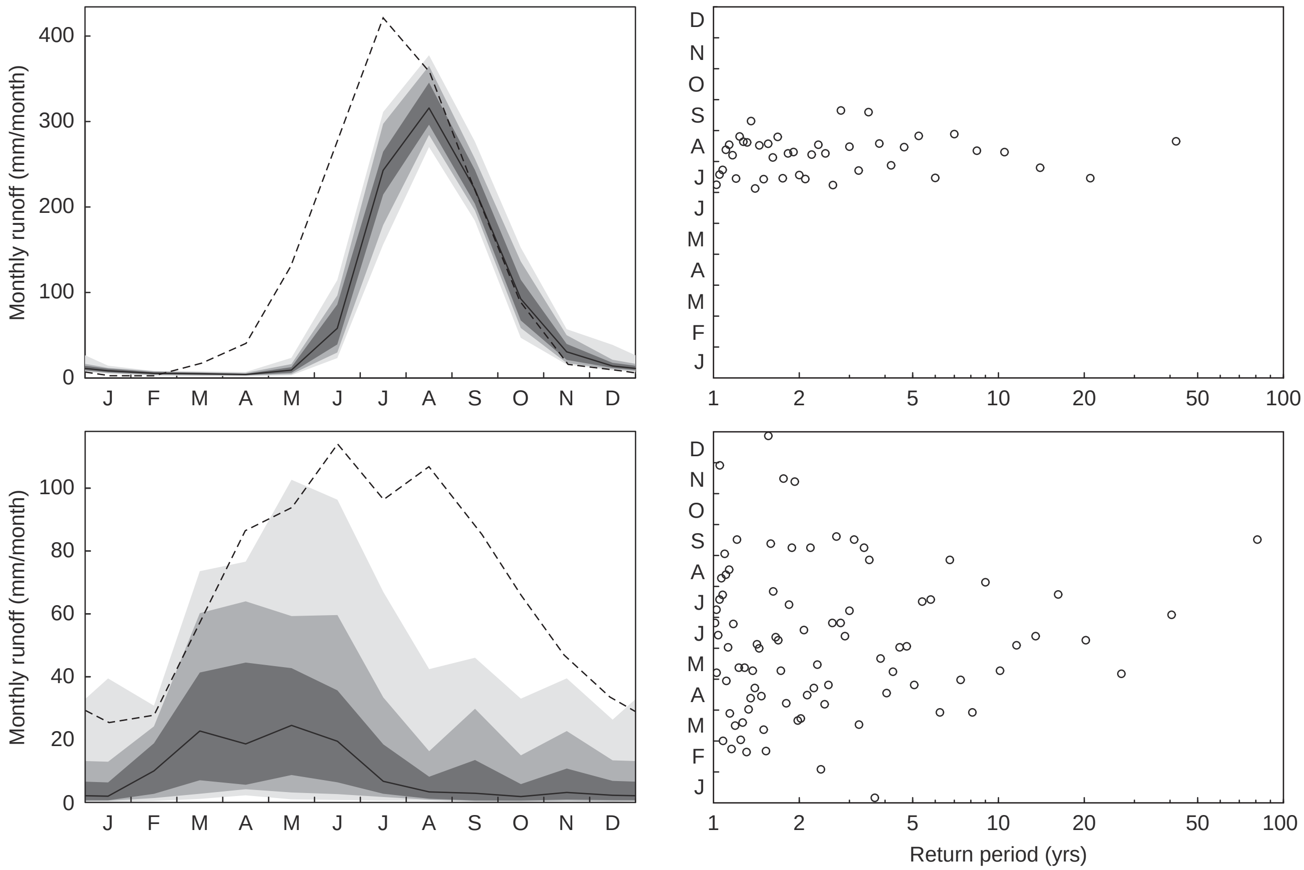

Figure 9.4. Seasonality of monthly runoff (shaded areas), precipitation (dashed lines) and flood frequency (points). (Top) Gilgel Abbay River, Blue Nile near Merawi, Ethiopia (1664 km²); (bottom) Thompson River at Davis City, Iowa, USA (1816 km²).

winter, thunderstorms and tropical cyclones in summer), and their interaction with different flooding processes dominating in different times of the year. Figure 9.4 shows the net effect of soil moisture on the timing of the flood frequency curve. In the Gilgel Abbay River, a tributary of the Blue Nile in Ethiopia, rainfall maxima occur in July. Runoff lags a little behind rainfall due to storage effects and the largest floods occur in August. For the Thompson River in Iowa, USA, rainfall maxima occur between June and August and monthly runoff peaks occur between March and June, i.e., earlier because of the higher soil moisture in spring due to snowmelt. This interplay of rainfall and soil moisture produces a pattern of floods mostly in May, but the largest floods may occur later in the season, e.g., September. This is because antecedent soil moisture will be less important if the rainfall depths are very large. Rainfall characteristics become increasingly important as the magnitude of an event increases, and the largest rainstorms occur in September.

The precipitation intensity and depth have a very strong effect on what mechanisms operate during a specific event. Low or moderate intensity rainfalls with a longer duration generally tend to produce subsurface stormflow and saturation excess overland flow, while high intensity events tend to favour infiltration excess runoff. Two or more mechanisms may operate in different parts of the same catchment during the same event. Alternatively, different mechanisms may dominate during different events. With increasing intensity or event depth that goes beyond a threshold, there could be a switch from saturation excess to infiltration excess runoff, or from subsurface stormflow to saturation (storage) excess, and both of these may be reflected in a sudden increase in runoff in the flood frequency curve (Sivapalan *et al.*, 1990; Samuel and Sivapalan, 2008; Gioia *et al.*, 2008). Historically, such steep increases have often been treated as outliers, but an interpretation in terms of the flood generation processes may be more insightful. This is illustrated in Figure 9.5 for an Alpine catchment in Austria. The figure shows different areas contributing to fast surface runoff for events of different magnitudes. During smaller events (events 1 and 2) only very few areas contribute to direct surface runoff, such as sealed areas and rocks. As the event magnitude

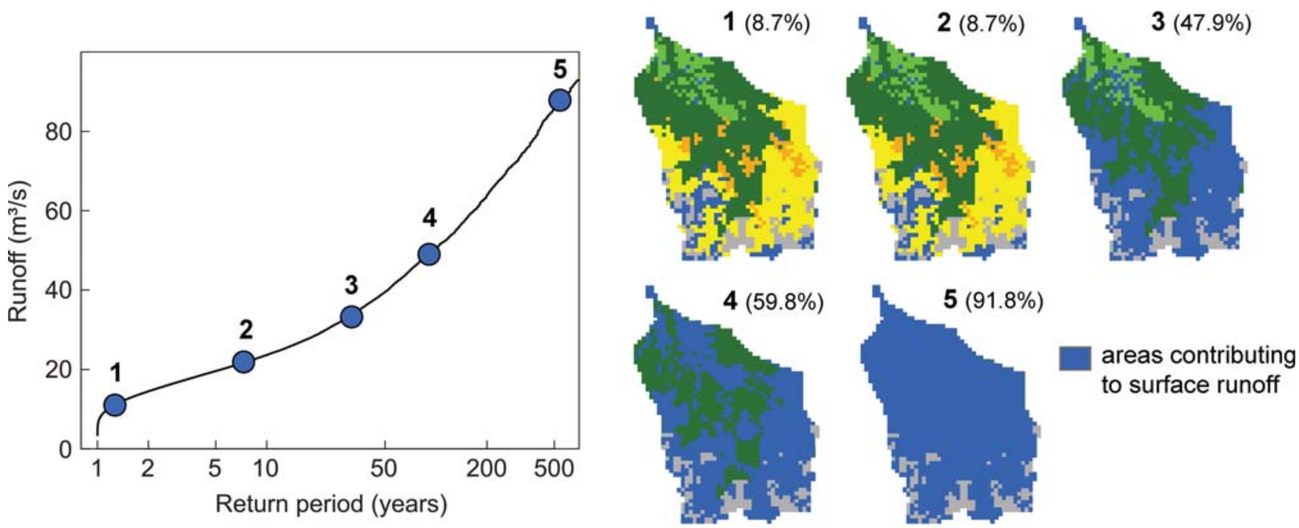

Figure 9.5. Runoff generation in the Weerbach catchment, Alpine Austria. (Right) Areas contributing to fast surface runoff for events of different magnitudes (1, low magnitude to 5, high magnitude). The percentage contributing area is given in parentheses. Blue indicates areas contributing to surface runoff; colours relate to different hydrological response units. (Left) The simulated flood frequency curve with these events indicated shows non-linearity due to a change of processes. From Rogger *et al*. (2012a).

increases the contributing areas expand, causing the marked non-linearity in the flood frequency curve. At event magnitudes larger than those shown, the flood frequency curves flatten off. In this example, there is a threshold that controls the shape in the flood frequency curve related to the storage capacity of the catchment. In other hydrological settings, different threshold processes may occur (e.g., Zehe and Sivapalan, 2009; Struthers and Sivapalan, 2007) that may produce similar non-linearities or step changes in the flood frequency curve, particularly if the catchments are small.

Runoff routing

Runoff that is generated locally flows off the surface or through the subsurface of the hillslopes to the streams. These runoff routing processes reflect the temporary storage of storm runoff in its passage to any specified point in the river network (including the catchment outlet), and the competition between the rate of runoff generation and the rate of runoff release from the catchment. They determine the shape of the flood hydrograph and therefore the flood peak. Runoff routing is affected by two main factors: (i) the size and shape of the catchment and the topology of the river network. These determine the distribution of distances that the water has to travel to reach the outlet; (ii) roughness and slope of land surface, the soil hydraulic properties, hydrogeology and properties of the river channel cross-section (i.e. hydraulic geometry) across the river network. These together determine the flow velocities in the various pathways water takes to reach the outlet. A key factor determining the magnitude of the flood peak is the relative time scale of the storm duration and, at the same time, the mean response time of the catchment. This interplay can give rise to resonance (Robinson and Sivapalan, 1997a,b; Blöschl and Sivapalan, 1997). The largest floods are often produced by storms with durations similar to the response time of the catchment (Viglione and Blöschl, 2009c), which is the basis of many methods of design flood estimation, such as the rational method (see Section 9.4). This leads to a scale effect: in catchments where the response times are short, the largest floods are produced by short duration storms. Conversely, in catchments with long response times the largest floods are produced by long duration storms. Even though this is generally the case, other factors can modulate this behaviour, such as multiple storms and the seasonality of soil wetness, which can produce quite different flow paths and therefore response times in different parts of the year (Sivapalan, 2005).

Change: human impacts

There are few streams around the world that do not have some sort of human-induced modification. Land use modifications (e.g., deforestation, construction of roads, buildings and other infrastructure) affect runoff generation and routing throughout the catchment. Commonly cited consequences of urban development include reduced catchment response times combined with increased runoff volumes, resulting from introduction of impervious surfaces and

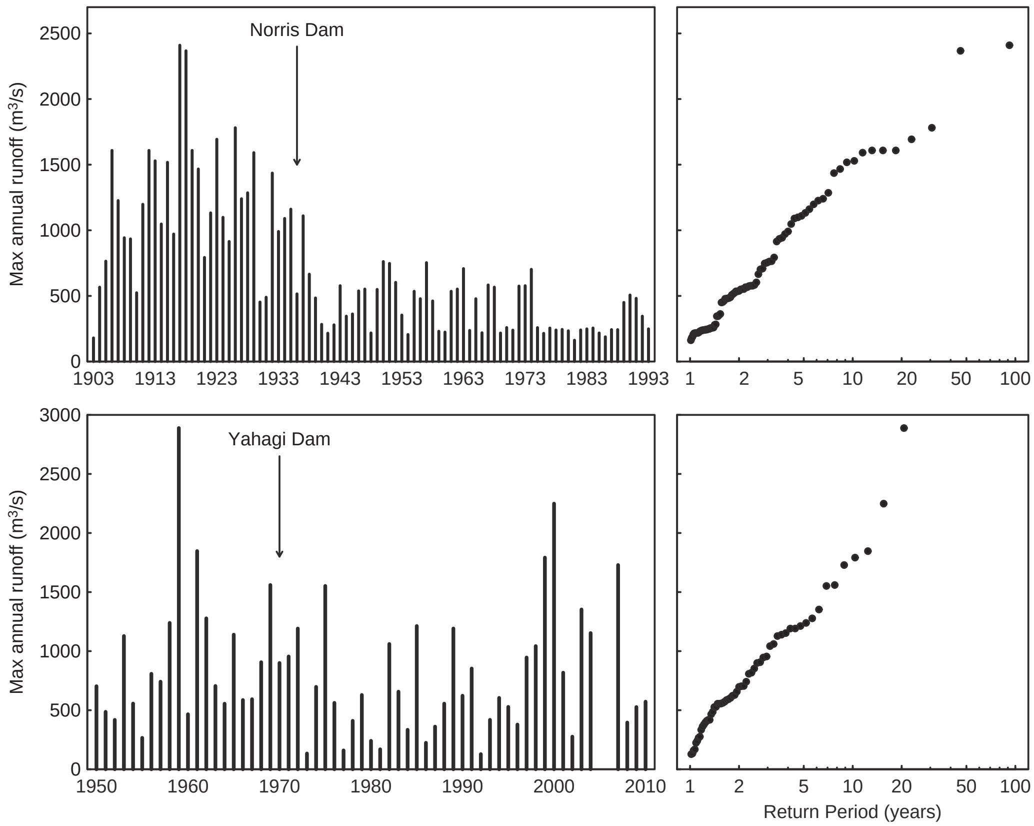

Figure 9.6. Maximum annual daily runoff and flood frequencies. (Top) Clinch River below the Norris Dam, Tennesee, USA (catchment area, 7545 km^2). The Norris Dam was installed in 1936 with 3.1 km^3 storage capacity. The annual runoff of the river is 3.4 km^3. (Bottom) Yahagi River at Iwazu, Japan (catchment area, 1356 km^2). The Yahagi Dam is located 50 km upstream of the gauge and was installed in 1970 with 0.075 km^3 storage capacity. The annual runoff of the river is 1.4 km^3 at the stream gauge. Data: Japan River Association, River Discharge Year Book, 1950–2010, courtesy of ICHARM. Construction of flood frequency curves from non-stationary flood time series may not be meaningful.

more effective drainage systems. The net effect of these changes on storm runoff is an increase in peak runoff. In particular, this is often observed for smaller floods, whereas larger floods are relatively less affected (Hollis, 1975; Hundecha and Bárdossy, 2004). The construction of flood mitigation structures such as retention basins and polders in association with urban developments will usually result in a reduction in downstream flood risk (Apel *et al.*, 2004, 2006). Because of their local nature, land use change effects are more important in small catchments (Blöschl *et al.*, 2007).

Another human-induced modification is storage of water in dams for irrigation, hydroelectric power production and other water uses. The flood regime of a very large number of rivers around the world is affected by dams (Graf, 1999; Nilsson *et al.*, 2005). As an example, Figure 9.6 (top) shows the Clinch River in Tennessee, USA. The Norris Dam was constructed in 1936 with a storage capacity of 3.1 km^3. This is similar to the magnitude of the river's total annual runoff of 3.4 km^3. Construction of the Norris Dam resulted in a very significant reduction in the flood peaks, as shown in Figure 9.6. This change is clearly visible in the time series of the floods, but it is not visible in the flood frequency curve. Figure 9.6 (bottom) shows the Yahagi River at Iwazu, Japan. The Yahagi Dam, located 50 km upstream of the gauge, was installed in 1970. Its storage capacity is 0.075 km^3 and the total annual runoff of the river is 1.4 km^3 at the stream gauge. The flood time series indicate that the smaller floods seem to have decreased but there is no apparent effect on the larger floods. In this case the anthropogenic impacts are less apparent in the flood records. These examples illustrate three points. First, it may not be meaningful to construct flood frequency curves from non-stationary flood data because, as shown for the Clinch River, it is not clear as to what the parent distribution of floods would refer. Second, it is important to not only check the flood time series for any non-stationarities but to also examine the presence of hydraulic structures and other water resources activities relevant to floods in the catchment area. Third, the flood peak reduction mainly depends on the free volume of the reservoir relative to the flood volume (Fitzhugh and Vogel, 2010), so during extreme floods the free reservoir capacity may be exhausted, leading to very little peak reduction and unexpectedly large floods downstream of the reservoir (Blöschl, 2008; Salazar *et al.*, 2012).

9.2.2 Similarity measures

Regionalisation of flood frequency behaviour from gauged to ungauged catchments critically depends on the notion of similarity. With respect to flood frequency, two catchments can be deemed to be similar if their flood frequency curves are similar in some respect arising from the similarity in the flood generating processes. The most basic approach to similarity is spatial proximity, i.e., assuming that catchments that are close to each other behave in a hydrologically similar way (Merz and Blöschl, 2005). The rationale for this concept is that the controls on the rainfall–runoff relationship are likely to vary smoothly in space, or are uniform in predefined regions. Merz and Blöschl (2005) showed, in a comparative study in Austria, that spatial proximity is a significantly better predictor of regional flood frequencies than any other catchment characteristic. Bates *et al.* (1998), in an Australian study, showed that super-groups, consisting of sites within aggregated homogeneous regions that have reasonably similar flood responses, show some degree of spatial coherence. In the UK, Kjeldsen and Jones (2009, 2010) found geographical proximity of catchments to be a useful surrogate to compensate for the inability of lumped catchment characteristics to explain between-basin differences in the observed index flood. There are elaborate similarity measures that are adopted in practice that account in a more detailed way for the flood generating processes and the characteristics of flood runoff.

Runoff similarity

Due to different catchment sizes, two catchments can be hydrologically similar and still have different flood frequency curves. The flood frequency curves may perhaps be similar in terms of their shape but not in terms of their magnitudes. One way of measuring similarity in regional flood frequency analysis that accounts for these differences is to scale the flood frequency curve by an index flood, which is usually taken as the mean or median of the annual maximum flood peaks. If the scaled flood frequency curves (also called the growth curves) are similar, then the catchments are deemed to be similar.

Instead of the growth curve (non-parametrically), one can also assess similarity by comparing the moments or parameters of the flood frequency distribution (Merz and Böschl, 2009b). The coefficient of variation (CV) of the flood peaks reflects the steepness of the growth curve. The CV has been the most commonly used similarity measure in regional flood frequency analysis. For example, the index flood method (see Section 9.3.2) works on the assumption of constant CV within a homogeneous region. The coefficient of skewness is the third-order moment and reflects the curvature of the flood frequency curve. It can be used to define higher order measures of similarity, which become important to capture more complex flood frequency distributions. A number of studies have shown evidence that the CV is actually scale dependent and relate it to a number of factors, depending on the particular hydrological context of the region analysed. For example, Smith (1992) presented the scale dependence of CV in the Appalachian region of north-eastern USA, which showed an apparent increase of CV up to about 100 km^2, and a decrease subsequently. Smith proposed alternative explanations: errors in stream gauging vs. spatial organisation of extreme precipitation and the downstream changes in the channel/floodplain system. Gupta and Dawdy (1995) suggested an alternative explanation; in small catchments CV may be governed by catchment response and at large scales by the spatial scaling of precipitation. Robinson and Sivapalan (1997b) attributed the scaling of CV to the combined effects of the interactions between precipitation duration and catchment response time (which dominates at small scales), and to the scaling of precipitation with catchment size (which dominates at large scales). Blöschl and Sivapalan (1997), using extensive flood frequency data in Austria, showed that the scale dependence confirmed the role of the time-scale interactions, but showed that scale dependence is a combined result of several factors.

An important similarity measure that has received significant attention in recent years is the seasonality of the floods (Merz *et al.*, 1999; Jain and Lall, 2000; Petrow *et al.*, 2007). The average period within the year that floods occur and how variable that period is can be quantified by circular statistics (Mardia, 1972; Burn, 1997). These are the parameters shown in Figure 9.2. This seasonality index has been used to identify flood similarity at the regional scale and to group catchments into regions with similar flood processes (Piock-Ellena *et al.*, 1999; Castellarin *et al.*, 2001; Sivapalan *et al.*, 2005; Parajka *et al.*, 2010a). Seasonality is also used as a diagnostic in the UK Flood estimation handbook (IH, 1999). It is also interesting to see whether the flood seasonality changes with the magnitudes of the events (Figure 9.4) and with time. Both dependencies may shed light on the flood driving processes and assist in regionalisation. For example, Parajka *et al.* (2009a) found a trend towards an increase in winter floods due to a warmer climate in parts of Central Europe. This

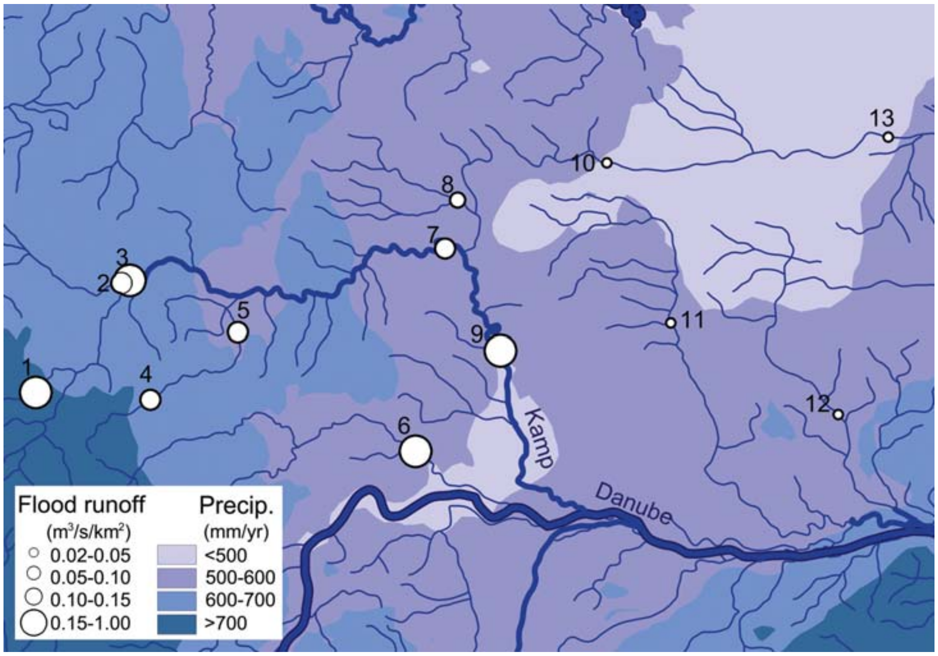

Figure 9.7. Map of mean annual flood runoff normalised to a standard catchment area of 100 km² and mean annual precipitation for the Kamp and Pulkau regions in northern Austria. From Merz and Blöschl (2008b).

change was more pronounced in the lowland and hilly regions than in the mountains.

Climate similarity

Climate similarity in the context of floods can be quantified by the similarity of extreme rainfall. Intensity–duration–frequency (IDF) curves represent the cumulative distribution of extreme rainfall for a given aggregation interval. The flood frequency curve is a non-linear transformation of the IDF curve to capture the effects of runoff generation (e.g., by choosing a runoff coefficient that corresponds to the return period of interest) and routing (e.g., by choosing a storm duration that resonates with catchment mean response time). Climate similarity can also be quantified by the seasonality of extreme rainfall and by atmospheric circulation patterns (Petrow *et al*., 2007, 2009; Parajka *et al*., 2010a).

Many studies have shown that mean annual precipitation is an excellent similarity measure for flood frequency (see e.g., Madsen *et al*., 1997; Reed *et al*., 1999; Merz *et al*., Merz and Blöschl, 2008a, b, 2009b and references therein). An example is shown in Figure 9.7, where both the mean annual flood and mean annual precipitation have a tendency to decrease from west to east. The eastern part of the region differs from the west not only in terms of precipitation but also in terms of soils and the efficiency of the drainage network. For example, the average event runoff coefficients in the west are around 0.25 while they are less than 0.1 in the east. There are therefore a number of reasons why mean annual precipitation is a useful similarity measure for the flood frequency curve. First, mean annual precipitation is usually highly correlated with event precipitation as it is an aggregated measure of the actual events occurring in the catchment. Second, mean annual precipitation is an important control of soil moisture at the seasonal scale, and soil moisture itself is an important control of floods, in particular if saturation excess runoff generation dominates, but is also important for other mechanisms (e.g., Zehe and Blöschl, 2004). Third, because of the co-evolution of climate, vegetation, soils and landforms, there is often a close linkage between the rainfall regime and the soils and landform, which themselves are important controls of floods at the event scale (see Chapter 2 for a discussion of co-evolution). Mean annual precipitation is therefore a similarity index that may capture the results of catchment co-evolution relevant to floods.

Catchment similarity

Catchment area is one of the most important similarity measures for a number of reasons. At the basic level, flood peaks will be larger for larger catchments, simply due to the fact that the total rainfall volume is larger. Of course, this will be moderated by the heterogeneity of rainfall and runoff processes within the catchment. Increasing catchment area leads to a reduction in the average amount of precipitation the catchment receives. This is because rainstorms are likely to affect only a portion of the large catchments, while they may affect the complete area of a small catchment. Due to the relationship between catchment area and response time, increasing catchment area also leads to a higher attenuation of the flood peaks. Rates of runoff generation could also change with increasing catchment area, due to changes in the dominant runoff processes. For example, specific mean annual floods (i.e., flood peaks scaled by the catchment area) tend to decrease with increasing catchment area (Eaton *et al*., 2002) as it is less likely that large areas will be fully covered by rainstorms and also fully saturated (Viglione *et al*., 2010a, b). For all these reasons, catchment size is the main reason why the specific runoff peaks of the large Ohio River catchment (526 000 km^2) (Figure 9.1) are so much lower than those of the small Trisanna catchment (385 km^2).

The slopes of the two flood frequency curves in Figure 9.1 are very different. The small Trisanna catchment has a steeper flood frequency curve than the Ohio. As discussed above, many authors have investigated the nature of the scaling of the coefficient of variation of floods with area (Smith, 1992; Gupta and Dawdy, 1995; Blöschl and Sivapalan, 1997; Robinson and Sivapalan, 1997a; Iacobellis *et al*., 2002) and have come out with different interpretations. Catchment size is again the main reason for the steeper slope of the Trisanna's flood frequency curve compared to that of the Ohio River. This is because, in any particular year, the probability of an extreme rainfall event hitting the small Trisanna catchment is lower, resulting in high variability and a steep flood frequency curve. In contrast, it is more likely that during any particular year a part of the large Ohio catchment is affected by an intense rainfall event.

Other catchment characteristics that contribute to similarity and differences in flood frequency curves include soil characteristics and land use. An important catchment-related similarity measure is the fraction of the catchment area that is urbanised. This is an indicator of surface flow processes, which will increase the flood peaks. Geomorphological characteristics include drainage density and topographic elevation. Figure 9.8 shows photographs and flood hydrographs from the Gurk and Buwe regions in Austria. The Gurk catchment has a dampened flood response while the Buwe catchment is very flashy. The catchment sizes do not differ much (432 and 184 km^2) and annual precipitation and elevation are also similar. However, they are different in their landforms. The landscape of the Gurk is mountainous with flat valley bottoms and well-rounded hills, while the landscape of the Buwe region shows deeply incised channels. They are also different in the flood-producing storm types and the geology. The storm events in the Gurk are mainly synoptic, there is large subsurface storage (highly permeable rock) and the surface flow paths are tortuous (Figure 9.8), thus resulting in dampened floods. Because of this, there is little erosion and increased potential for soil development, which in turn tends to dampen flood response. On the other hand, in the Buwe region floods are produced by convective storms with partial coverage of catchments and the soils are shallow, thus resulting in flash floods. Because of this, there is high erosion, which reduces soil depth and increases the efficiency of the drainage network, which in turn tends to increase the flashiness of flood response. Figure 2.3 (Chapter 2) illustrates the processes involved. This example of comparative hydrology illustrates that the patterns apparent in the landscape are largely the result of the co-evolution of climate, vegetation, soils and landform, and may give predictive power to similarity indices such as drainage density that goes beyond hydraulic relationships.

Event similarity

While the similarity measures discussed above relate to hydrological characteristics of the catchment system as a whole, in order to understand why two catchments are similar in terms of their flood frequencies it may often be very useful to break down the similarity into individual events. These can then be used for regionalisation in ungauged basins. One way of framing event similarity in terms of the component process is by the derived flood frequency framework, proposed by Eagleson (1972), later generalised by Wood (1976), continued by Fiorentino and Iacobellis (2001), and extended by Sivapalan *et al*. (2005). Each independent flood peak in the complete data series is caused by an independent precipitation event. The relationship between precipitation (characterised by intensity and duration) and the resulting flood peak involves two kinds of transformations, i.e., runoff generation and runoff routing, and these are impacted by antecedent soil wetness. Probability enters the picture by the fact that event characteristics of precipitation (e.g., rainfall intensity and duration) are random, and so is antecedent soil wetness. Derived distribution analysis can enable us to obtain analytically (in simple cases), or otherwise numerically, the cumulative distribution function (cdf) of the population of flood peaks that occur in a catchment. Extreme value theory, on the basis of the number of flood events within one year (or in the general case, the uneven distribution of events within the year if they are seasonally dependent) allows us to derive or estimate the extreme value distribution and thus the (annual) flood frequency curve (see Sivapalan *et al*., 2005). The power of the derived flood frequency approach is that, in a mechanistic way, it helps to isolate the various contributions to the flood frequency curve, and hence has considerable explanatory power to analyse similarity of flood frequency behaviour between catchments. There have been several efforts at developing such a similarity framework, focusing separately on each of the component processes: climate, catchment runoff and

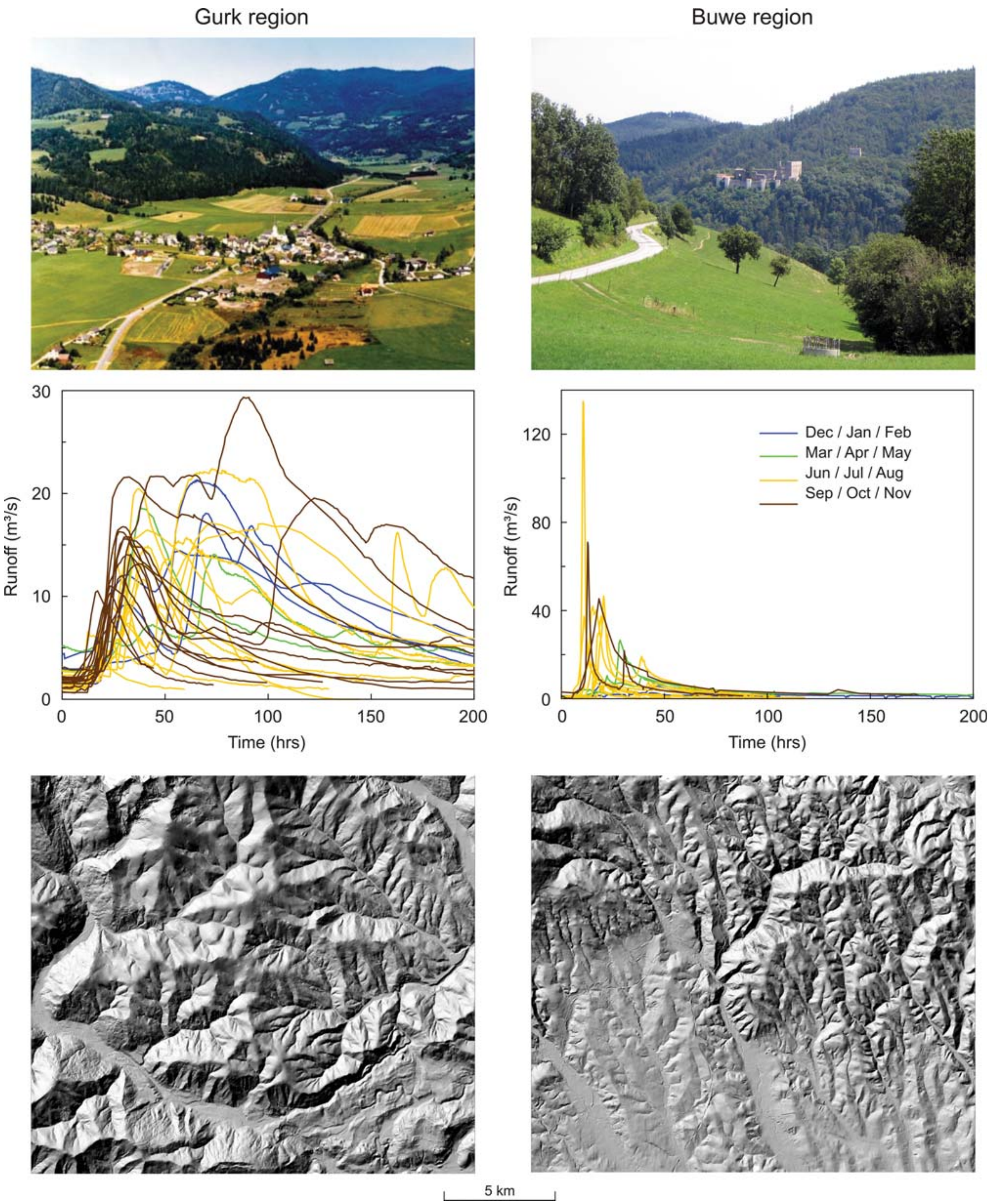

Figure 9.8. Photos, hydrographs and topography for the Gurk (left) and the Buwe (right) regions in Austria. Note the tortuous drainage network of the Gurk and the efficient drainage network in the Buwe. The different drainage networks have evolved as a result of interplay between catchment and climate processes at the landscape evolution time scale, modulated by geology. The hydrograph shown for the Gurk region is for the Glan at Zollfeld with an area of 432 km², mean elevation of 734 m, mean annual precipitation of 859 mm. The corresponding values for the Buwe region (Raab at Mitterdorf) are 184 km², 749 m, 878 mm. From Gaál *et al*. (2012). Photos: (left) R. Graimann; (right) Stadtgemeinde Kirchschlag i.d.B.W.

antecedent conditions. Sivapalan *et al*. (1987) developed a similarity theory for runoff generation, based on an event runoff generation model that incorporated both infiltration excess and saturation excess overland flow. They identified five non-dimensional similarity parameters that represented the interrelationships of topography, soil and rainfall, which lead to similar catchment responses. Larsen *et al*. (1994) confirmed the value of this similarity theory in actual catchments in Western Australia, and Robinson and Sivapalan (1995) extended the theory to develop a lumped conceptual model of runoff generation at the catchment scale, within the similarity framework. Likewise Hebson and Wood (1982) developed a similarity framework for runoff routing, based on the geomorphological instantaneous unit hydrograph (GIUH) approach, and developed dimensionless similarity indices to characterise similarity and differences between catchments, using aspects of the geomorphological structure of the river network. Robinson and Sivapalan (1997a) came up with a similarity (regime) theory for flood frequency on the basis of the ratio of mean storm duration to mean catchment response time, and also accounted for the effects of antecedent soil wetness, which allowed them to attribute the similarities in the CV of the flood frequency curve. Sivapalan *et al*. (2002, 2005) extended this similarity framework to separate the catchment response into a hillslope response time and a network response time, and also introduced the effects of antecedent soil wetness. By using a similar approach Allamano *et al*. (2009) identified the effect of temperature on the flood frequency distribution in mountainous basins.

While the derived flood frequency approach is useful to obtain event-scale similarity measures by combining the component processes into the flood frequency curve, the opposite approach classifies observed flood events into event types, thereby establishing similarity between flood events on an observational basis. Hirschboeck (1987) performed a detailed analysis on causal mechanisms of floods in a number of catchments in Arizona based on surface and upper weather maps (Hirschboeck, 1988) which she used to classify floods into types. This scheme was updated by House and Hirschboeck (1997) and simplified into three event types (tropical, convective and frontal events). The body of work on causal mechanisms allowed Hirschboeck (1987) and Alila and Mtiraoui (2002) to examine the flood statistics for each group of events and to derive more complex hydroclimatically defined probability distributions to characterise the flood frequency curves than those before. Merz and Blöschl (2003) developed a classification scheme for floods based on process indicators, including the timing of the floods, storm duration, rainfall depth, snowmelt, catchment state, runoff response dynamics and the spatial coherence of floods. They found significantly different flood frequency statistics for long-rain floods, short-rain floods, flash floods, rain-on-snow floods and snowmelt floods in Austria. The coefficient of variation (CV) of the flood samples stratified by process type decreased with catchment area for most process types, with the exception of flash floods for which CV increased with catchment area. Figure 9.9 shows two examples in which flood types are distinguished in the flood frequency plots based on the typology of Merz and Blöschl (2003). In the Krumbach catchment in south-eastern Austria, which is a rather warm region with rolling hills, convective events occur frequently and floods mainly occur in summer when the soils are dry. The largest floods are associated with short-rain floods and flash floods. As a result of these processes, the flood frequency curve tends to arch upwards, indicating large skewness. In the Kleine Mühl in the North of Austria, close to the Czech border, the climate is cooler. Floods tend to occur in winter and early spring when the soil moisture status is high, often associated with rain on snow. As a result of these processes, the flood frequency curve tends to arch downwards, indicating low skewness. The flood process types thus provide insight into whether two catchments are similar at the event scale and the effects of that similarity on the shape of the flood frequency curve. They can be used in regionalisation studies to assist in interpreting homogeneous regions of similar flood-producing processes.

9.2.3 Catchment grouping

The principle underpinning catchment grouping in flood frequency analysis is that extreme events that have not been observed in a particular location could already have been observed somewhere else. Therefore, data from many sites are pooled in order to obtain a representative sample of what could happen in a particular location. On the basis of the similarity measures discussed above, catchments can be grouped into homogeneous regions that can be used for flood predictions in ungauged basins and for enhancing flood predictions if only short flood records are available. Even 50 years of data must be considered a short record when flood peaks with return periods in excess of 100 years need to be estimated (the ungauged case can be considered as a particularly unfortunate case where zero years of data are available). There are a number of options for how the grouping can be performed.

Fixed groups

The classic approach consists of subdividing the study domain into a number of fixed, contiguous regions that are used to regionalise floods for all catchments in the area. This grouping is used in the index flood method (Dalrymple, 1960) and the UK *Flood Studies Report* (FSR) (NERC, 1975). The assumption of this method is that areas

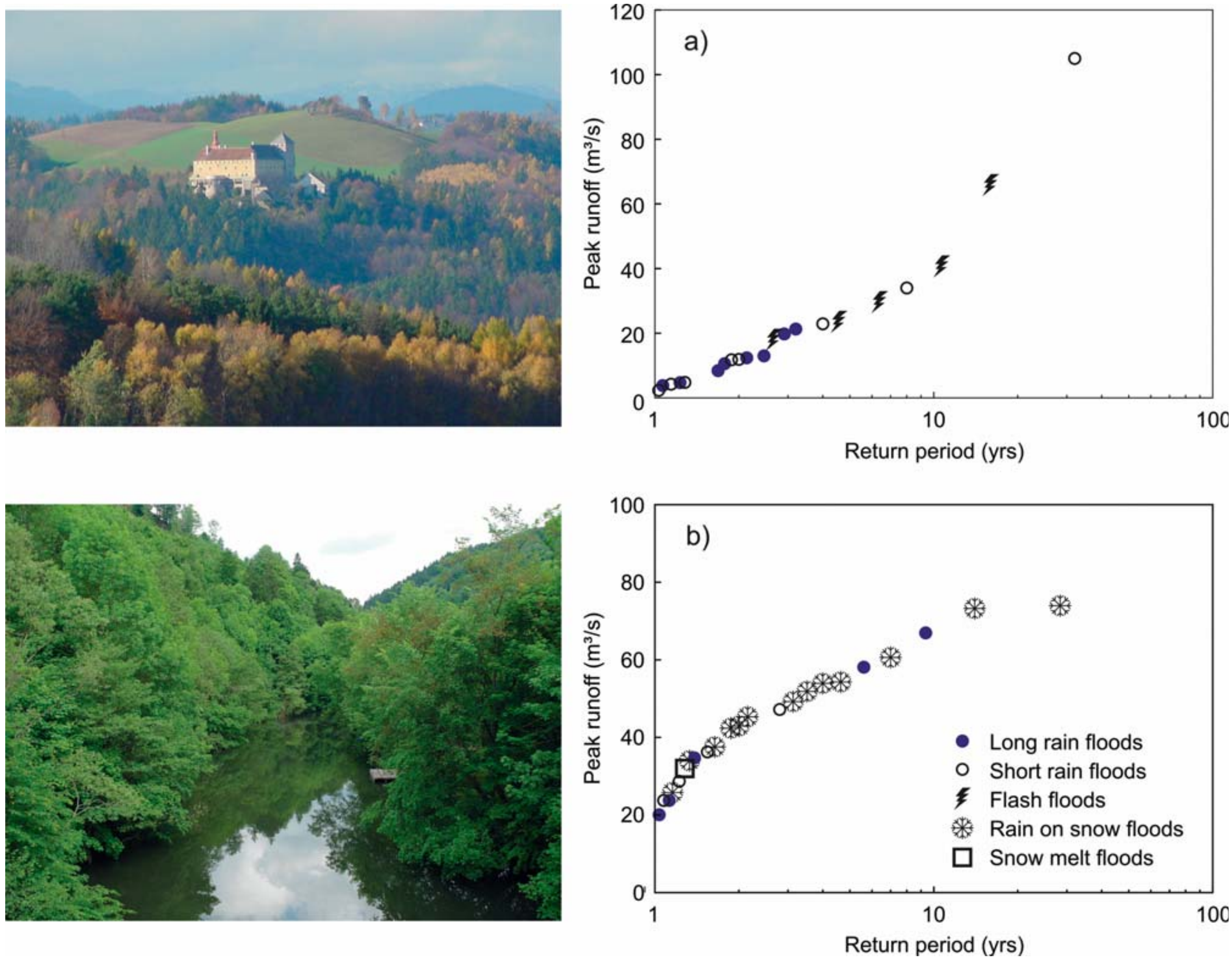

Figure 9.9. Flood frequency plots with the process types indicated for two streams in Austria: (a) Krumbach at Krumbach (43 km² catchment area); (b) Kleine Mühl at Obermühl (200 km²). From Merz and Blöschl (2008b). Photos: (a) Steindy (b) D. Stancin.

close to each other are characterised by similar climate, topography, geology, soils and landuse, which gives rise to similar catchment hydrological response and therefore to similar floods. The grouping is usually found by combining maps of the catchment characteristics or by geographical boundaries (Beable and McKerchar, 1982), sometimes supported by the mapping of the residuals from a regression model (Wandle, 1977; Tasker, 1982; Choquette, 1988; Jingyi and Hall, 2004; see Section 8.2.3).

The assumption of contiguous regions can be relaxed to allow the catchment groups to be non-contiguous. The group of catchments is then selected on the basis of climate and catchment characteristics alone, without using spatial proximity as a similarity measure. Multivariate statistical methods, and in particular cluster analysis, are common methods to perform the grouping (see e.g., Acreman and Sinclair, 1986; Burn and Goel, 2000). The grouping can also involve flood characteristics and climate characteristics, in particular the seasonality of the floods (Castellarin *et al*., 2001; Piock-Ellena *et al*., 1999). Since the groups are non-contiguous, an allocation rule is needed to associate ungauged basins to a particular group.

Different group for each target catchment

An alternative is the region of influence (ROI) approach (Burn, 1990a), which assigns a different pooling group to each catchment of interest. This pooling group is the region of influence, i.e., a set of gauged basins that are similar to the ungauged basin of interest. Similarity between catchments is usually measured by the root mean square difference of all the catchment and climate characteristics in a pair of catchments. The characteristics are usually standardised by their standard deviation or transformed in another way to make them comparable. The ROI approach is used in the UK *Flood Estimation Handbook* (IH, 1999). It is possible to assign weights to the catchment characteristics to give preference to some of them on the basis of a prior understanding of what should be the important hydrological controls (Kjeldsen and Jones, 2007, 2009). Typical characteristics used for the grouping are mean annual rainfall, catchment area, and a baseflow index derived from HOST soil data (hydrology of soil type classification in UK).

In a case study in Arkansas, USA, Tasker *et al*. (1996) found that the grouping by the ROI method produced lower root mean square errors of the 50-year flood in ungauged basins than other grouping methods. However, Merz and Blöschl (2005) suggested that the ROI method may not perform as well as other grouping methods (e.g., spatial proximity) if the catchment characteristics do not reflect the underlying flood generation processes well. Clearly, the choice of donor catchments and the availability and choice of suitable catchment characteristics are essential (see also Section 10.3.2). An example of the selection of a pooling group for the UK is shown in Figure 9.10. The target catchment is the River Dee at Polhollick and the catchment characteristics used are catchment area, mean annual precipitation, index of flood attenuation from lakes and reservoir and the proportion of catchment covered by the 100-year flood maps of the Environment Agency.

Sometimes the catchment/climate characteristics are correlated, in which case it may be useful to transform the characteristics by canonical correlation analysis (CCA). This method has been applied to finding ROI pooling groups by Cavadias (1990) and Ouarda *et al*. (2008), and also for identifying non-overlapping groups of similar basins (as in Di Prinzio *et al*., 2011). Regression trees (Breiman *et al*., 1984; Laaha and Blöschl, 2006a) are another grouping method that divides a heterogeneous domain into a number of homogeneous groups by maximising the homogeneity of floods and catchment characteristics within each group simultaneously. Burn (1997) used a genetic algorithm and Shu and Burn (2004a) applied the method of fuzzy expert systems and genetic algorithms for the delineation of homogeneous pooling groups. Numerous studies have used classification methods based on artificial neural networks (e.g., Jingyi and Hall, 2004; Lin and Chen, 2006; Srinivas *et al*., 2008; Di Prinzio *et al*., 2011; Ley *et al*., 2011).

Whatever the classification method is, the pooling groups will never be fully homogeneous in terms of hydrological response. A number of methods have been proposed to test for the homogeneity of the groups, i.e., to examine if the groups obtained from climate/catchment characteristics are statistically similar in terms of runoff (e.g., whether they have the same CV or the same growth curve). A widely used homogeneity test is that of Hosking and Wallis (1993). Viglione *et al*. (2007b) compared the power of several statistical homogeneity tests and Castellarin *et al*. (2008) showed how the cross-correlation among sites can affect the performance of these tests. As these tests use flood peak data, they can only be performed for gauged basins, so their value for ungauged basins is limited.

Figure 9.10. The pooling group for estimating floods for the River Dee at Polhollick (indicated with a cross) consists of data from 20 gauged catchments (dots) considered to be hydrologically similar to the subject site. The FSR regions (NERC, 1975) are shown in colour.

There is a trade-off between group size and regional homogeneity. To avoid a biased estimate, the selected stations should ideally belong to a reasonably homogeneous group in terms of hydrological processes, which includes the ungauged sites where flood estimates are required. However, there is also a need for a sufficiently large sample of gauged sites to properly define the parameters in the model. In a Monte Carlo study with prescribed type and level of heterogeneity, Hosking and Wallis (1988) discuss this trade-off (also see IH, 1999).

The grouping methods discussed above are sometimes used as black box or optimisation procedures to get the best statistical performance of the regionalisation methods in a region. However, the hydrological interpretation of the location of the groups in the landscape is a necessary step for building confidence in the groups, to ensure that the groups reflect real hydrological processes and are not an artefact of the data and the methods used (Merz and Blöschl, 2008a, b). It is important to justify by hydrological reasoning why catchments are grouped together, beyond stating that a similarity measure was minimised. The hydrological interpretation needs to give an account of the flood-producing processes and to explain why the hydrologist thinks they are similar in the group. The hydrological interpretation can be guided by process indicators at the regional scale, such as the seasonality of the floods and the rainfall regime (e.g., Castellarin *et al*., 2001; Parajka *et al*., 2010a), the flood types in a region (House and Hirschboeck, 1997; Merz and Blöschl, 2003), and the runoff generation processes as simulated by regional runoff models (e.g., Samaniego *et al*., 2010b). While such an interpretation involves more effort than an optimisation method, it will enhance the credibility of flood predictions in ungauged basins with both statistical and process-based methods.

9.3 Statistical methods of predicting floods in ungauged basins

Once a group of catchments has been identified that are hydrologically similar to the ungauged basin of interest, the flood peak data in those catchments can be analysed to transfer them, in some way, to the ungauged basin. There are various methods for doing this that differ in several ways: (i) in the way they formulate the model between flood peak data and catchment/climate characteristics; (ii) in the way they estimate the parameters of that model; (iii) in the way they apply the grouping; and (iv) in the way they account for the correlations among the variables (e.g., Cunnane, 1988).

9.3.1 Regression methods

The regression approach assumes that there is a relationship between a flood peak runoff of a given return period (i.e., quantile Q_{T}) and catchment/climate characteristic, or there is a relationship between the parameters of the distribution function of flood peaks and catchment/climate characteristics (Thomas and Benson, 1970). In general, this relationship is non-linear, but often the relationship is approximated by a linear model with transformed variables, e.g., by a logarithmic transform (see e.g., Thomas and Benson, 1970; Pandey and Nguyen, 1999; Griffis and Stedinger, 2007). For example, in regional estimation of flood quantiles, this corresponds to a power law relationship such as

$$Q_T = k(T)A^{\alpha(T)}P^{\beta(T)}S^{\gamma(T)}\ldots \tag{9.1}$$

where k, α, β and γ are the parameters of the regression model and A, P and S are catchment/climate characteristics. Analogous relationships can be developed for parameters of the flood frequency curves as well. The parameters represent the flood generation processes in a simplified way. These processes may vary within a region. Instead of applying a global regression within the study area, the area is sometimes subdivided into regions. These are not necessarily homogeneous regions with respect to the flood frequency curve (Figure 2.10a) but are homogeneous with respect to the parameters of the regression model (Figure 2.10b). For example, Thomas and Benson (1970) used multiple least squares regression to predict flood quantiles for four different regions in the USA. Subsequently, Tasker *et al*. (1996) found that subdivision into smaller geographically based sub-regions led to more accurate results. Haddad *et al*. (2011b) used a variable group of catchments specific to the ungauged basins of interest, whose membership was selected to minimise the regression model error instead of the heterogeneity in the catchment characteristics. This approach therefore formally minimised the unaccounted-for heterogeneity in the regression model. In all instances, the parameters of the regression model need to be estimated in some way. There are a number of options by which this can be conducted, which are discussed below.

Ordinary least squares, weighted least squares The simplest method is ordinary least squares (OLS). While it produces unbiased estimates, it lumps sampling and model errors into a single error term, assuming it has zero mean and constant variance, and the errors are uncorrelated. This leads to an overestimate of predictive error and inefficiency when sampling errors vary from site to site (i.e., larger sampling errors where short flood peak records are available). The weighted least squares (WLS) procedure (Tasker, 1980) accounts for the sampling error introduced by unequal record lengths.

Generalised least squares Sampling errors are often *correlated* in neighbouring catchments, being impacted typically by the same storms, unless small-scale convective storms are dominant. Generalised least squares (GLS) regression is an extension of WLS that also accounts for cross-correlation of flood peaks between sites (Stedinger and Tasker, 1985). Rosbjerg (2007) demonstrates the

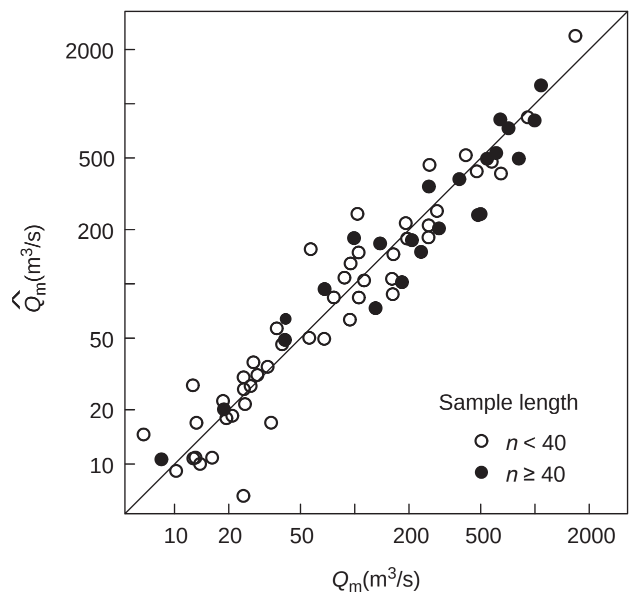

Figure 9.11. Observed versus estimated mean annual floods obtained with the GLS method for the Piemonte region, Italy. From Laio *et al*. (2011).

importance of including the cross-correlation of flood peaks for properly quantifying the uncertainty of flood quantile estimates. An example of using the GLS method for estimation of the moments of maximum annual peak series is provided in Figure 9.11. The regressions (Laio *et al*., 2011) capture the variability of the mean annual flood peak well. The selected best model is a power law relationship (Equation 9.1) and includes four characteristics: mean annual flood peaks are positively related to catchment area, to mean annual precipitation, to the mean maximum annual precipitation intensity for one hour interval, and to a permeability index of the soil. The exponent related to catchment area is 0.8, meaning that the specific mean annual flood (in $(m^3/s)/km^2$) actually decreases with catchment area, consistent with the literature.

A careful regression analysis uses diagnostics to validate assumptions about the error model. Tasker and Stedinger (1989) improved the representation of the overall regression error for the GLS method of Stedinger and Tasker (1985) by treating the total regression error as a sum of the sampling error for the estimates of the flood statistics and a modelling error in modelling the true index floods across catchments using regression. One drawback of the regression approach is that there is a tendency for residuals to cluster (NERC, 1975). This can also be interpreted as the existence of local flood controlling factors not currently captured by the available lumped catchment characteristics. IH (1999) and Kjeldsen and Jones (2009, 2010) accounted for the clustering tendency in the regression model framework. They noted that in these cases the correlation coefficient between regression model errors may be non-zero and included this tendency for clustering and related it to geographical distance between catchment centroids. This concept therefore uses spatial proximity as one of the similarity measures.

Other methods of parameter estimation Alternatives to using generalised least square techniques for estimating the regression model parameters are available. For example, Kjeldsen and Jones (2009) used a maximum-likelihood method, while Reis *et al*. (2005) and Micevski and Kuczera (2009) used Bayesian approaches. Pandey and Nguyen (1999) found that using estimation methods directly in non-linear regressions produced better results than log-linear models for quantile estimation. Gupta *et al*. (1994) proposed a simple non-linear method to estimate the parameters of relationships between flood peak CV and quantiles with catchment area within their multi-scaling theory (see Section 9.2.1). Yet another alternative is to use artificial neural networks (ANNs) (Shu and Burn, 2004b; Dawson *et al*., 2006; Shu and Ouarda, 2008) that are able to account for non-linear relationships between catchment characteristics and the flood peaks, and the catchment characteristics among themselves. In a study in Quebec, Canada, Shu and Ouarda (2007) used basin area, mean basin slope and the fraction of the basin area covered with lakes, which were negatively correlated with the specific flood quantiles, and mean annual precipitation and mean annual days over 0 °C, which were positively correlated (see Figure 9.12). The joint ANN–CCA method identified that mean annual precipitation and the fraction of the basin area covered with lakes are the most important variables, followed by the mean basin slope. In a region such as Quebec it is not surprising that the percentage of lakes has to be taken into account in regional analyses of most signatures, and of floods in particular.

Non-parametric regression is an alternative method that does not make any assumptions on the form of the regression function. Gingras and Adamowski (1995) found parametric and non-parametric regression relationships to provide equally good estimates, suggesting noise in the data is dominating the signal.

Hydrological interpretation
In the previous sections we have argued that a relationship can be established between flood characteristics (e.g., quantile peaks, CV of the maximum annual peak flows, parameters of the flood frequency curve, etc.) and catchment and climatic characteristics. The regression approach finds correlations between flood and catchment characteristics, but this does not ensure a causal relationship,

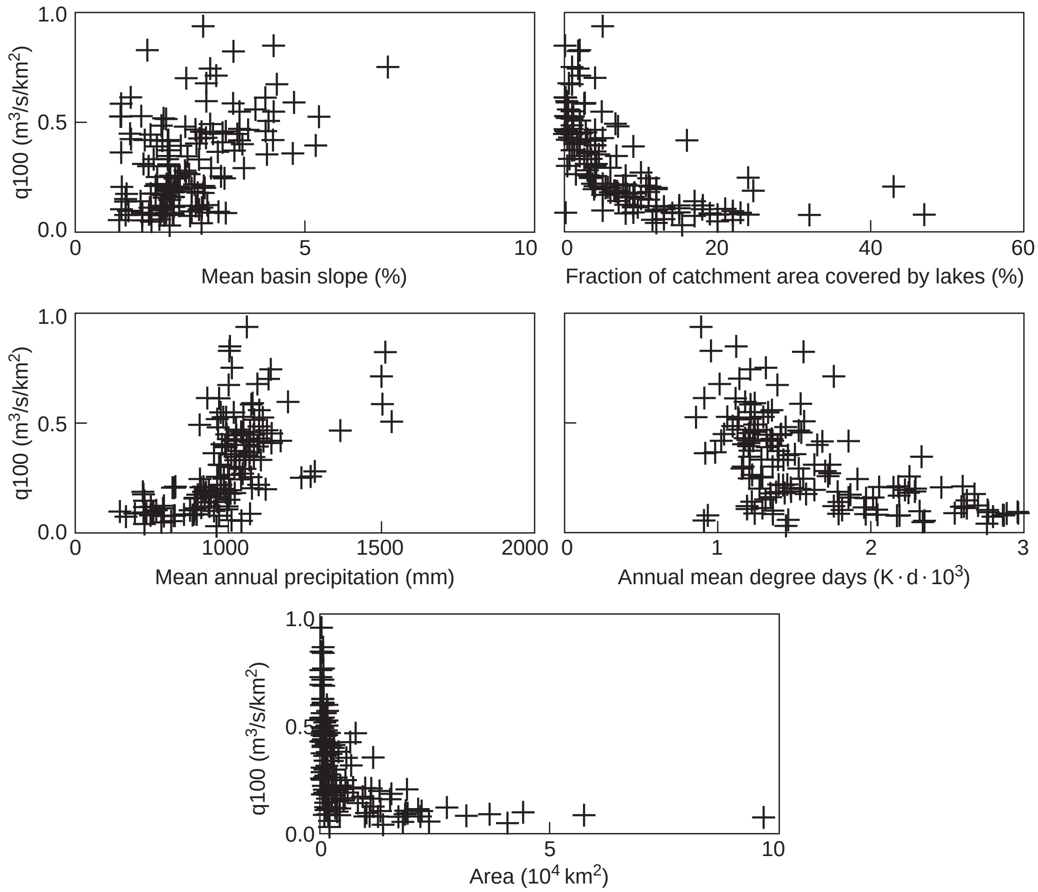

Figure 9.12. Specific 100-year floods plotted against catchment characteristics for 151 catchments in Quebec, Canada. From Shu and Ouarda (2007).

particularly when there is considerable scatter in the relationship. It is therefore essential to interpret the relationships found in regressions from a hydrological perspective. This will assist in understanding the limits of predictability of this relationship and the associated uncertainties. The interpretation can take advantage of the similarity measures discussed in Section 9.2.2. As an example, Figure 9.13 shows a power law relationship between the parameters of the generalised extreme value (GEV) distribution and annual maximum peak, indicating a strong log-log linear relationship between the location and scale parameters of the GEV distribution with respect to catchment area. The interesting thing is now to interpret, say, the slope of the relationship of the location parameter (top panel) with respect to the slopes found by other authors around the world in a comparative analysis. For example, Merz and Blöschl (2008a, b) found for a region in Austria that the slope strongly depended on the regional rainfall regime. In a region such as Buwe (Figure 9.8), where convective precipitation is the main flood generation mechanism, the relationship between specific floods and area was steep, while in a region with synoptic rainfall, such as Gurk (Figure 9.8), the relationship was much flatter. The different scaling of the floods is a reflection of the scaling of the driving processes and space-time interconnections of the rainfall–runoff process (Skøien and Blöschl, 2006). Alternatively, the characteristics of such relationships can be interpreted by process reasoning, making use of the derived flood frequency approach as dicussed above (e.g., Robinson and Sivapalan, 1997a). These two methods, comparative and process-based, are complementary. Both shed light on the driving processes, but from different angles.

9.3.2 Index flood methods

Growth curves

In the previous sections we have seen how the selection of stations to be used in a regression analysis is a key issue. The idea of pooling together data from similar catchments

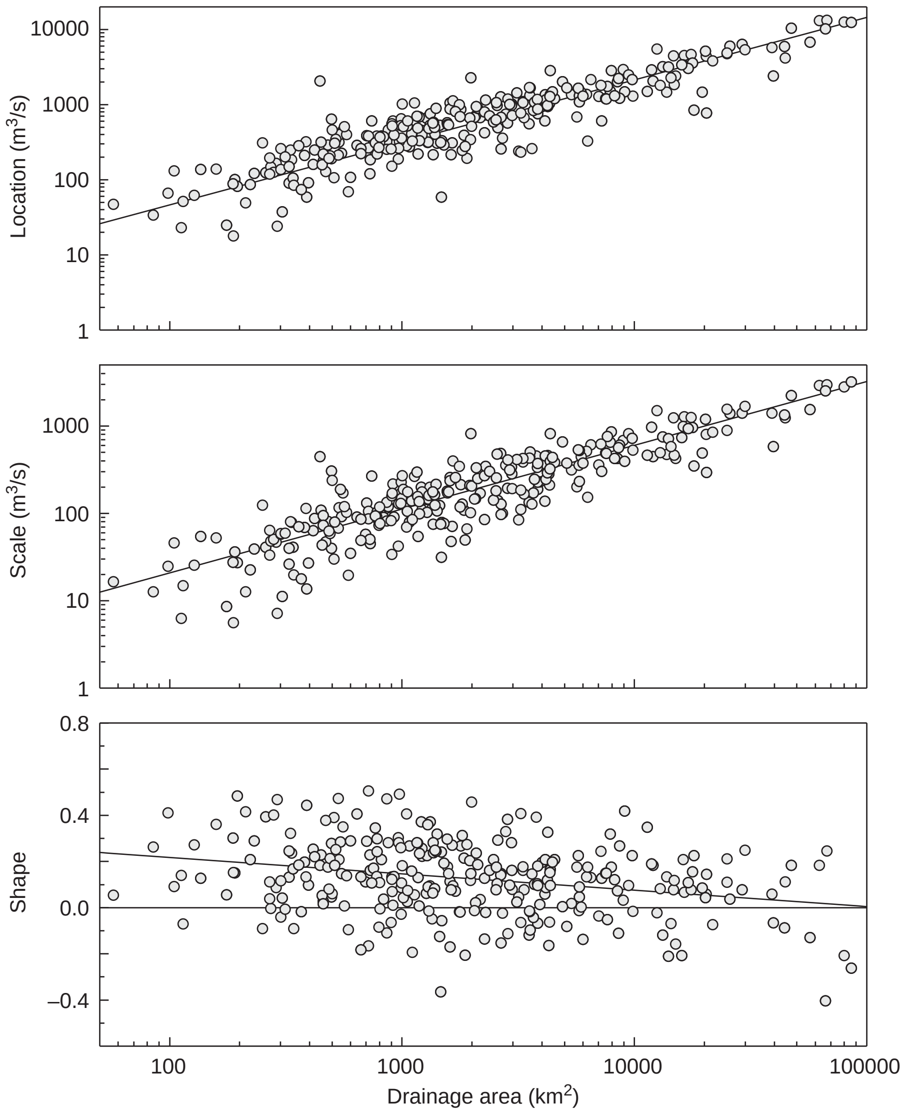

Figure 9.13. Parameters of the GEV distribution as a function of drainage area fitted to annual maximum peak runoff in the eastern USA. From Villarini and Smith (2010).

together is also behind the index flood method (Dalrymple, 1960; Hosking and Wallis, 1997). The method involves the formation of a collection of catchments, not necessarily geographically contiguous, that can be considered to be similar in terms of hydrological response, as discussed in Section 9.2.3. The index flood method estimates the T-year flood as the product of a scale factor, which is called the index flood (often defined as the mean or median annual maximum flood), and a growth factor, which describes the relationship between the dimensionless flood and the return period, T (the so-called growth curve). In general

$$q_T = g(T) f(A, P, S, \ldots) \tag{9.2}$$

where $g(T)$ is called the growth curve and the index flood is expressed as a function of climatic and catchment characteristics such as area, mean annual precipitation etc. In the simplest case, a regression can be used to approximate f (see Section 9.3.1), but more complex methods exist such as geostatistics or process-based methods (see e.g., Bocchiola *et al.*, 2003 and the following sections). Hereafter the focus is on the estimation of the growth curve $g(T)$.

Farquharson *et al.* (1992) observed that climate seems to be the principal factor in determining the shape of regional flood frequency curves (i.e., of the growth curves). Figure 9.14 shows flood growth curves estimated using annual maximum flood series from catchments in different semi-arid and arid regions from 12 countries in five continents. As discussed in Section 9.2, climate is one of the controls on the shape of the flood frequency curve, which is very evident in Figure 9.14 where the growth curves in arid catchments have much higher slope (i.e., variability) and skewness (i.e., 'propensity to outliers') than in humid

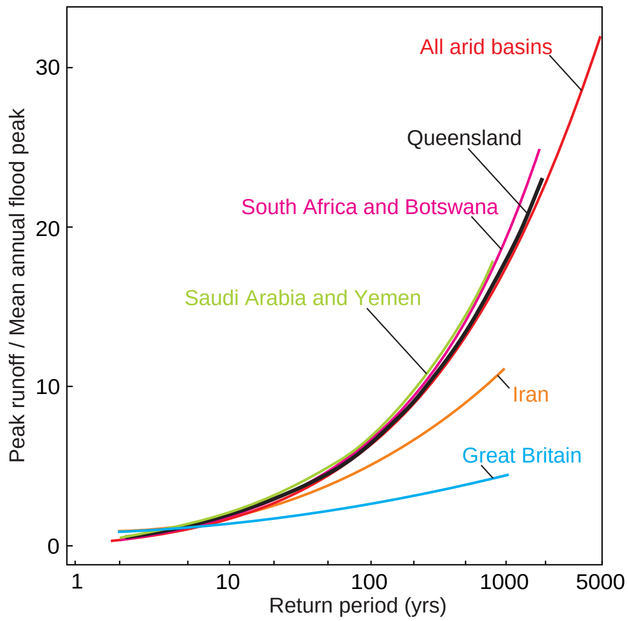

Figure 9.14. Flood growth curves in different regions around the world. From Farquharson *et al*. (1992).

catchments. More importantly, however, the results presented in Figure 9.14 illustrate that one can organise the global distribution of flood frequency curves (i.e., growth curves) into distinct classes or regimes based on climate (aridity). In a sense, these results parallel the organisation of annual water balance using the Budyko framework (Chapter 5). There is already considerable evidence that shows that both of these runoff signatures mirror landscape signatures such as a scaled drainage density (Wang and Wu, 2012) and fraction of deep-rooted vegetation (Xu *et al*., 2012), which are also strongly correlated to climate aridity. This is further evidence of co-evolution of several catchment characteristics and climate, resulting in emergent patterns and associated runoff signatures, which provide alternative predictors of a co-evolutionary kind, such as aridity, drainage density, vegetation cover and catchment area.

Comparison of index method with regressions

In Equation (9.2) the index flood is site dependent, while the growth curve is assumed to be the same for the entire homogeneous pooling group. The index flood method thus assumes that the distribution of flood peaks at different sites within a pooling group is the same except for a scale parameter, which is the index flood for a site. The procedure has been developed to improve the estimation of the growth curve due to the exploitation of information from the entire homogeneous group as opposed to one-site samples. The main difference with regression methods is that the relationship of flood quantiles or model parameters with catchment characteristics in Equation (9.1) depends on the return period, while in Equation (9.2) the function *f*( ), which defines the index flood in terms of catchment characteristics, does not (see e.g., Gupta *et al*., 1994). Also, regional regressions assume continuous variability of flood frequency curve characteristics across space and/or climate/catchment characteristics, while the index flood method identifies groups of catchments, which share the same growth curve (see Laio *et al*., 2011). As a rule, the GLS regression diagnostics do not support this assumption (Micevski and Kuczera, 2009). Cross-correlation between flows at stations in a pooling group can also increase the uncertainty of estimates of extreme flow quantiles (Rosbjerg, 2007). This can affect the evaluation of the homogeneity of the pooling group (Castellarin *et al*., 2008). From a practical perspective, while the underlying assumption of an invariant growth curve is usually rejected by the evidence, the fact that sampling error dominates model error ensures the index flood method is a reasonable approximation. In a comparative study, Rosbjerg (2007) found that the index flood method led to quantile estimates with slightly less uncertainty than quantile regression. It should be noted that the index flood method typically uses a regression approach to estimate the scale factor (the index flood). Therefore, its efficacy is contingent on the sound application of the regression approach.

Relaxing the assumptions

There is research in the direction of weakening the main assumption underlying the index flood method, i.e., the requirement for a homogeneous region. For example, Kjeldsen and Jones (2009) proposed a version of the index flood method that relaxes the requirement for a homogeneous region by incorporating the difference between basins (heterogeneity) into the weighting assigned to each member of a pooling group. Thus, information from gauged sites was weighted according to the degree of similarity to the target site as well as the record length. More generally, in the empirical Bayes method introduced by Kuczera (1982), parameters for an ungauged site are inferred from the prior distribution obtained either from regional data in terms of observations or from physical characteristics at the other sites in the region. The method requires that a common model for the occurrence of extreme events in the region is formulated. Similar to the method of Kjeldsen and Jones (2009), the empirical Bayes method does not prescribe strict homogeneity as is done by the index flood method, which assumes that all properties are identical after scaling. Thus, the index flood method can be considered a special case of an empirical Bayes model in which the prior distribution concentrates the probability mass at a single point. Inferring the prior information from generalised least squares (GLS) regression ensures that inter-site correlation is properly accounted for and, accordingly, the estimation uncertainty is realistically assessed. Madsen and Rosbjerg (1997) applied the method in a regional study of 48 New Zealand catchments using regional data as prior information.

An adjustment procedure was introduced in the *Flood Estimation Handbook* (IH, 1999), where a regression-based estimate of the index flood at an ungauged location is adjusted by scaling it with the ratio of predicted to observed floods at a nearby gauged site. The *Flood Estimation Handbook* (IH, 1999) suggests that the gauged catchment should ideally be located just upstream or downstream of the subject site. If no such data are available, alternative data might be sought within the same catchment, or from a nearby or hydrologically similar catchment, where hydrological similarity is defined as a combination of catchment area, mean annual precipitation and soil type. A modified version of the adjustment procedure was presented by Kjeldsen and Jones (2007), who found that discounting the adjustment according to geographical distance improved the performance of the method.

Hydrological interpretation
Index flood studies have been interpreted in a broader context by Meigh *et al*. (1997) for numerous countries around the world. Figure 9.15 shows mean annual flood peaks and the 500-year flood scaled by the mean annual flood from their study plotted against the median annual precipitation. The scaled 500-year flood is an indication of the steepness of the growth curve. For humid, high rainfall regions the average flood is relatively large, but the flood frequency curve is not very steep; rare floods (occurring once in every 100 to 1000 years) are not very much larger than the average flood. Conversely, in arid regions, the average flood is small, but rare floods can be extremely large multiples of the average. Clearly, this is related to differences in the flood generating processes. The rainfall regime may be more variable in arid than in humid regions, with a small number of extraordinary events (Wheater *et al*., 2007). Also, the runoff generation process will be different where the abstraction in arid regions tends to be large, making the rainfall–runoff process more non-linear than in humid regions (Chapter 4). The combined effect of the differences in the rainfall regime and runoff generation then leads to enormous differences in the growth curves. Similar comparative interpretations are possible for smaller regions where the differences in the flood frequency curves are more subtle.

9.3.3 Geostatistical methods

Top-kriging
While the regression approach with generalised least squares accounts for inter-site correlations of the flood events, it does so without accounting for the location of the stream gauges on the stream network. Geostatistical methods developed for hydrological applications explicitly account for the spatial correlations along the stream network. The top-kriging, or topological kriging, method of Skøien *et al*. (2006) is based on integrating a point variogram of runoff generation over nested catchments, which maps on the correlations along the stream network. Figure 9.16 (top left) presents an example of their approach for estimating the 100-year flood on the stream network, on the basis of regionalising the flood moments. To highlight the spatial patterns, the 100-year flood was scaled by catchment area $A^{0.33}$ (where A is catchment area), which, for the region they studied, minimises the scale dependence. For comparison, Figure 9.16 (bottom left) shows the estimates from ordinary kriging (Merz and Blöschl, 2005). The measurements are shown as circles in both figures with the same colour-coding. For both methods, the estimates next to the stream gauges are almost equal to the measurements of the stream gauge itself. Along the streams, on the other hand, the ordinary kriging estimates differ substantially from the top-kriging estimates, the main difference being that ordinary kriging uses Euclidean distance in space. For top-kriging the specific floods are around 0.65 $(m^3/s)/km^2$ for the main stream in the centre of the region shown, lower to the north of it and larger to the south of it, as suggested by the stream gauges. In contrast, ordinary kriging does not account for the stream network structure, so the flood data on the main stream and the tributaries are dealt with in the same way. The panels on the left of Figure 9.16 show the uncertainties expressed as the coefficient of variation of the estimates. Both methods estimate the lowest uncertainties close to the measurements. Top-kriging gives relatively small uncertainties on the main river while the uncertainties of some of the tributaries are considerably larger: the uncertainties are small for those tributaries where measurements are available, but rather large for tributaries without any measurements. It is interesting that the uncertainty increases substantially with decreasing catchment area. The uncertainties estimated by ordinary kriging (Figure 9.16 bottom right) do not reflect this expected pattern.

Geostatistics combined with catchment characteristics
Geostatistical methods can be extended in a number of ways to account for differences in the catchment and climate characteristics in the landscape. Chokmani and Ouarda (2004) used kriging in physiographic space to estimate quantiles for ungauged catchments. They used both canonical correlation analysis (CCA) and principal component analysis to define the multivariate space in which kriging was applied. A similar approach was used by Ouarda *et al*. (2008) in a comparison of regionalisation techniques in Mexico. CCA has also been used in

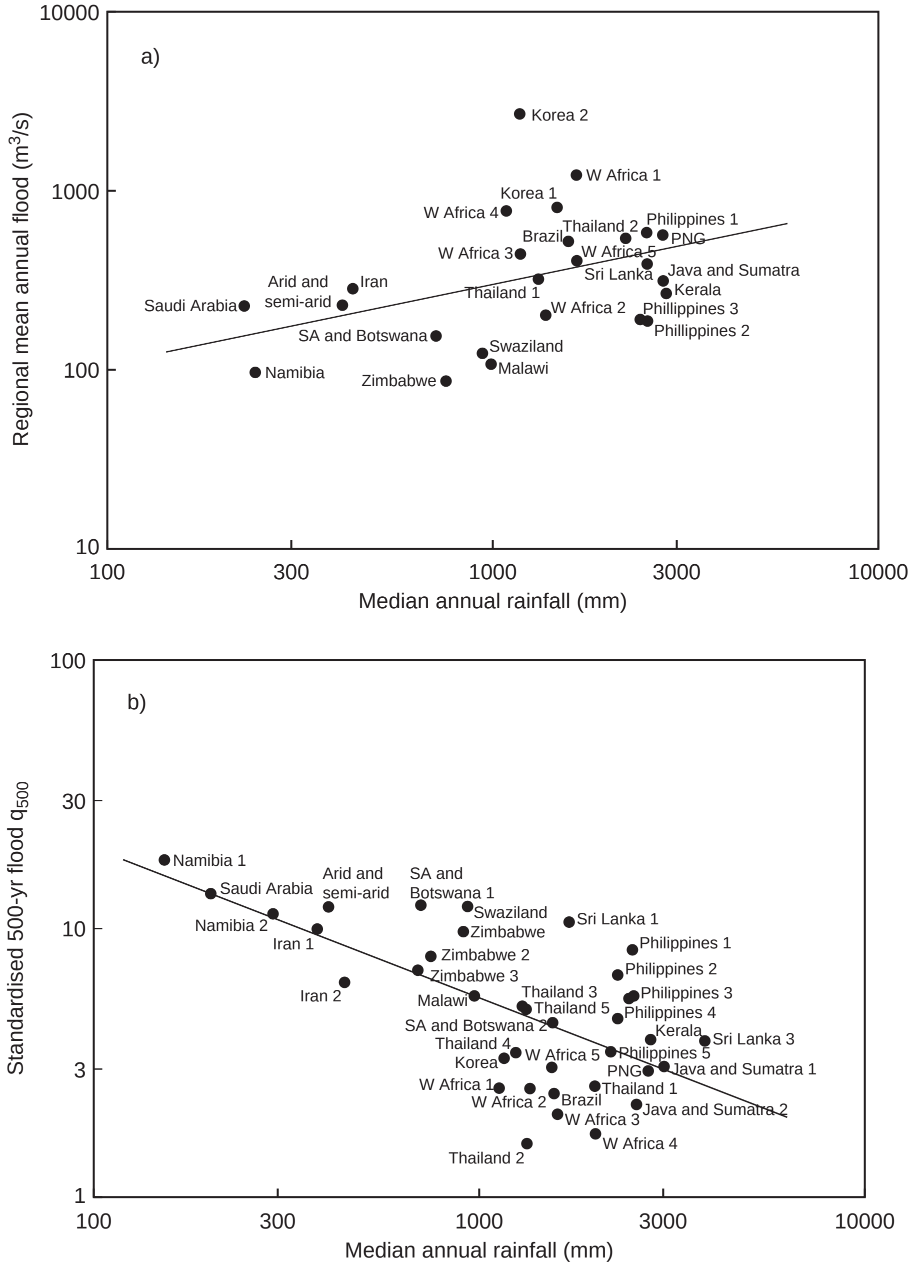

Figure 9.15. Regional mean annual flood (a) and 500-year flood (b) scaled by mean annual flood as a function of median annual precipitation for regions around the world. From Meigh *et al*. (1997).

conjunction with ANNs to define a hydrological neighbourhood and to define the relationship between catchment/climate and flood quantiles (Cavadias, 1990; Ribeiro-Corréa *et al*., 1995; Ouarda *et al*., 2008; Shu and Ouarda, 2007). As an alternative, geostatistical methods can be combined with regression methods as proposed by Skøien *et al*. (2006). They correlated the flood moments with catchment/climate characteristics such as mean annual precipitation and the FARL (flood attenuation by reservoirs and lakes) index and regionalised the residuals to the top-kriging methods. The method allowed them to both account for local catchment effects and exploit the spatial similarity of floods along the stream network. Example applications include Saxonia (Walther *et al*., 2011), Tirol (Rogger *et al*., 2011) and Austria as a whole (Merz *et al*., 2008). Their approach is illustrated in the case study of Section 11.10 in the context of implementing the European Flood Framework directive.

9.3.4 Estimation from short records

The index flood method can be used not only for estimating floods in ungauged basins but also in basins with short records (Dalrymple, 1960). The approach is the same as for

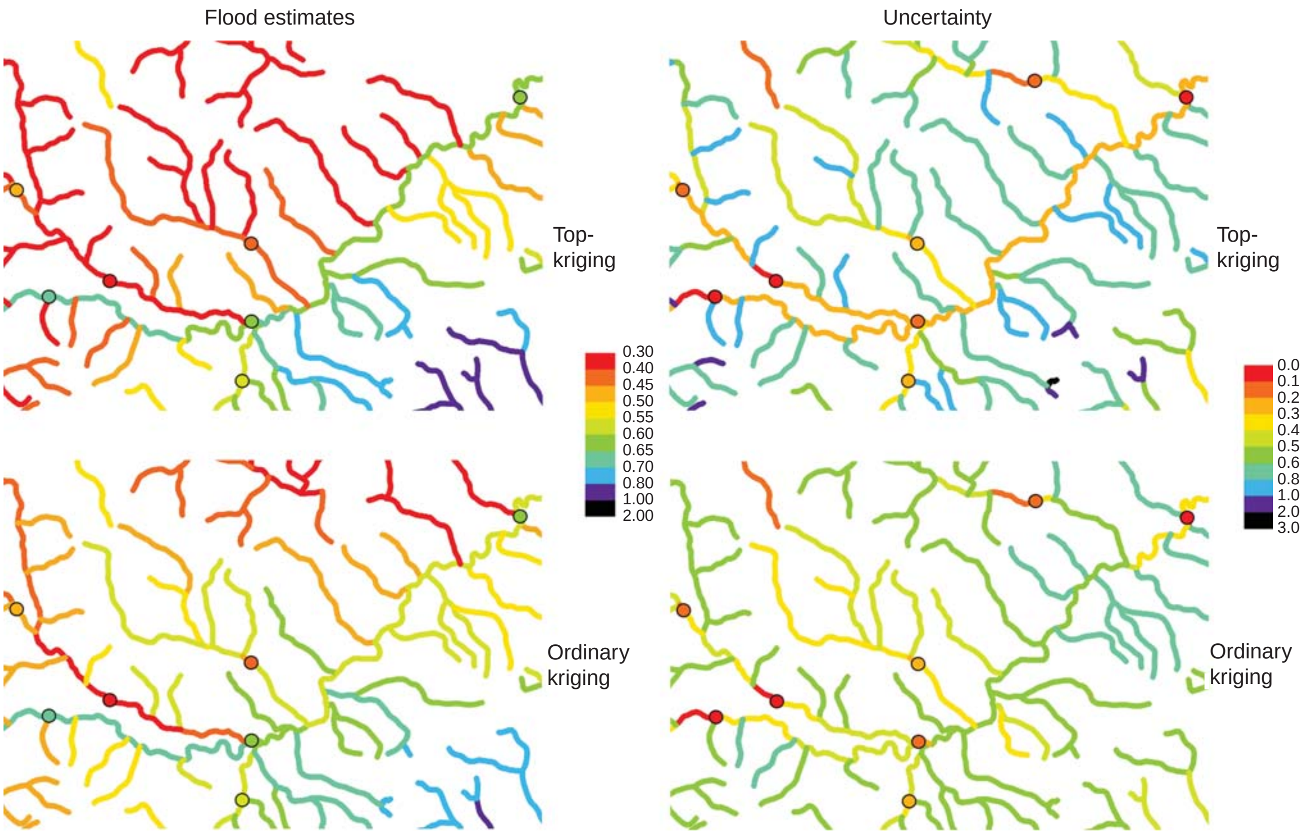

Figure 9.16. Normalised specific 100-year flood ($(m^3/s)/km^2$) and uncertainties expressed as coefficient of variation estimated by top-kriging (top) and ordinary kriging (bottom) colour-coded on the stream network of the Mur region, Austria. The main stream flows from bottom left to top right. The measurements and their uncertainties are shown as circles at the location of the stream gauges. From Skøien *et al*. (2006).

ungauged catchments in that data from many sites in a region are pooled to estimate the growth curve, which is assumed constant in the homogeneous region. Local data are used to estimate the index flood (mean or median annual flood peak) (e.g., NERC, 1975; Hebson and Cunnane, 1987). Similarly, most other regional estimation methods discussed previously can be combined with local runoff data from short records. Madsen and Rosbjerg (1997) tested the performance of the regional method for regional heterogeneity and intersite dependence. For small to moderate sample sizes, the regional estimator was found to be superior to the at-site estimator even in extremely heterogeneous regions, as the relative performance of the regional estimator was better in regions with a negative shape parameter. When the record length increases, the relative performance of the regional estimator decreases, but it is still preferable to at-site estimation in moderately heterogeneous and homogeneous regions for large sample sizes (Hosking and Wallis, 1988).

Envelope curves are based on the same idea of homogeneous regions and exploit short records. An envelope curve is a curve drawn to envelop maximum observed flood peaks experienced in a region as a function of drainage area. They are often used in practice as a first guess against which to compare flood frequency estimates, in particular for large return periods. Figure 9.17 presents envelope curves for major flash floods in Europe (Gaume *et al*., 2009; Marchi *et al*., 2010; Borga *et al*., 2011). The envelope curve shown in the figure was obtained from another data set by Gaume *et al*. (2009) and was found to be consistent. The highest unit peak runoff values correspond to events from the Mediterranean region. For small basin areas, the flash floods observed under a continental climate, namely in Slovakia, also attain high values of unit runoff, even though the peaks of these unit runoff values seem to decrease upstream at a faster rate than for events in the Mediterranean region. This behaviour highlights the different spatial and temporal scales of the runoff-generating storm events.

On the basis of simplifying assumptions, recent papers have introduced a probabilistic interpretation of regional envelope curves and formulated an empirical estimator of their associated return period (see Castellarin *et al*., 2005, 2009; Vogel *et al*., 2007a; Viglione *et al*., 2012).

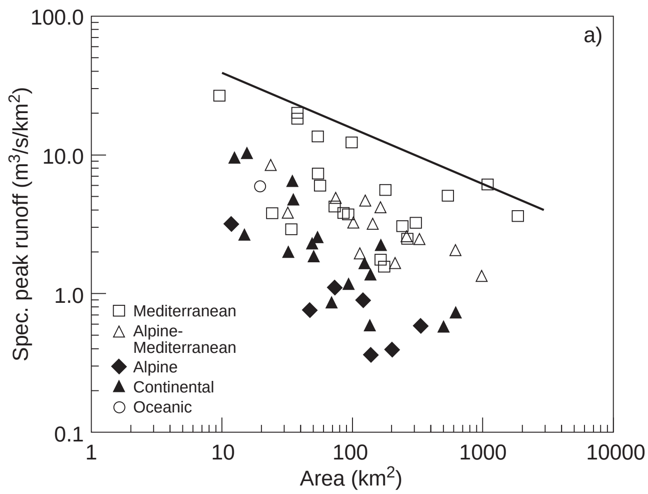

Figure 9.17. Specific maximum observed floods versus catchment area in central and southern Europe. Line shows the envelope curve of Gaume *et al*. (2009). Floods stratified by (a) climatic regions and (b) measurement methods (for post-event analysis see Section 3.7.3). From Marchi *et al*. (2010).

Probabilistic regional envelope curves have been tested in Italy (see e.g., Castellarin *et al*., 2007b) and Germany (Guse *et al*., 2010).

9.4 Process-based methods of predicting floods in ungauged basins

An alternative to the statistical methods of regional flood frequency that rely entirely on regional runoff or flood data is to start with local or regional information on rainfall and convert it to a flood using a rainfall–runoff model. Because this approach uses rainfall, it can be deemed a process-based method, and the transformation from rainfall to flood peak may involve models ranging from very simple to very complex.

There are advantages and disadvantages to process-based methods over regional flood frequency methods. First, in most countries, rainfall observation networks are much denser and have been maintained for much longer than stream gauging networks. Therefore, the extremes of rainfall frequency distributions are likely to be more accurately estimated than flood frequency extremes. Process-based approaches exploit this advantage. Second, process-based methods are designed to mimic the most important rainfall–runoff–flood processes, including local effects from, say, hydraulic structures. In contrast, regional flood frequency analysis is only able to transfer statistical information about annual maximum flood peaks from similar catchments. This advantage from process-based approaches becomes relevant if large return periods are of interest, as the more extreme floods may be the result of altogether different processes than are accounted for in the limited flood data. In other words, process-based approaches are potentially more reliable for describing more extreme floods. On the other hand, process-based methods suffer from the fact that the parameters of the rainfall–runoff model (or even the model structure itself) need to be specified in ungauged catchments. Usually, these parameters are estimated through some kind of calibration in gauged catchments, and then transferred or regionalised to the ungauged catchment in question. Uncertainties are involved, especially if the models are complex, with several parameters that need to be specified (see Chapter 10). This problem is made worse by the fact that the calibration must account for extreme floods, not just ordinary floods, i.e., there must be confidence that a flood of a specified return period predicted by the model is consistent with what will be expected in the ungauged catchment.

The classic example of process-based methods is the so-called rational method (dating back to the 1850s, see Bedient and Huber, 1988), which is widely used all around the world. It belongs to the category of derived distribution (event-based) approaches, and can be used to illustrate the general principles and problems of process-based methods. The input to the model is the so-called design storm, which is derived from intensity–duration–frequency (IDF) curves for the catchment or region of interest. The IDF curves provide the annual maximum rainfall intensity of a specified return period, and averaged over a specified duration. The rational method then estimates the design flood by a deceptively simple formula (although in reality it is nowhere near as simple as it appears), called the rational formula:

$$Q_T = C_T \cdot I_{T,tc} \cdot A \tag{9.3}$$

where A is the area of the catchment, and $I_{T,tc}$ is the annual maximum rainfall intensity with a return period T averaged over duration t_r (t_r is chosen to be equal to the mean response time t_c of the catchment), and C_T is an apparent runoff coefficient. In reality C_T is really a conversion factor that transforms the average rainfall intensity $I_{T,tc}$ to the flood peak Q_T of return period T. So, in a sense the rational formula stands for the entirety of the rainfall–runoff–flood peak model used here (combining the runoff generation part and the runoff routing part). The choice of $t_r = t_c$ reflects the nature of the simplest possible runoff routing model used, which assumes that the highest flood peak is produced under resonance conditions. The rational method has survived numerous criticisms regarding its over-simplification of the rainfall–runoff transformation, and it is still one of the most widely used approaches by practitioners around the world to estimate design floods, particularly in small ungauged basins (Australian Rainfall and Runoff, 1987; Brath *et al.*, 2001; Jiapeng *et al.*, 2003; Pegram and Parak, 2004).

The manner in which the rational method is made applicable for predictions in ungauged catchments is quite instructive. The IDF curves that go into the method are estimated for the region of interest from available rainfall data, and therefore are regionally applicable. Flood predictions at a range of return periods produced by the rational method are conditioned (e.g., calibrated) on flood frequency data at a number of gauged catchments in the region. In other words, the runoff coefficients C_T are estimated for all gauged catchments in the region as a function of return period T. Once this is done, regional averages of these C_T values can be estimated, which can then be adopted for any ungauged basin in the region. Alternatively, if considerable flood data exist in the region, then regional relationships of the runoff coefficients can be generated in terms of measurable climatic and catchment characteristics, which can be used to interpolate between the gauged catchments. In this way, the method ensures that the predictions are grounded in observed data, and over time there is accumulation of knowledge that continuously improves the accuracy of predictions by the rational method in ungauged basins in the region. The output from such a regional data-based approach is illustrated by Figure 9.18, which shows a map of the 10-year runoff coefficient for eastern New South Wales, Australia. The runoff coefficients were obtained from a regional analysis using gauged data and catchment characteristics. It is worth noting that Rahman *et al.* (2011b) compared this approach against a fixed-region quantile regression approach and showed the regression approach was preferred.

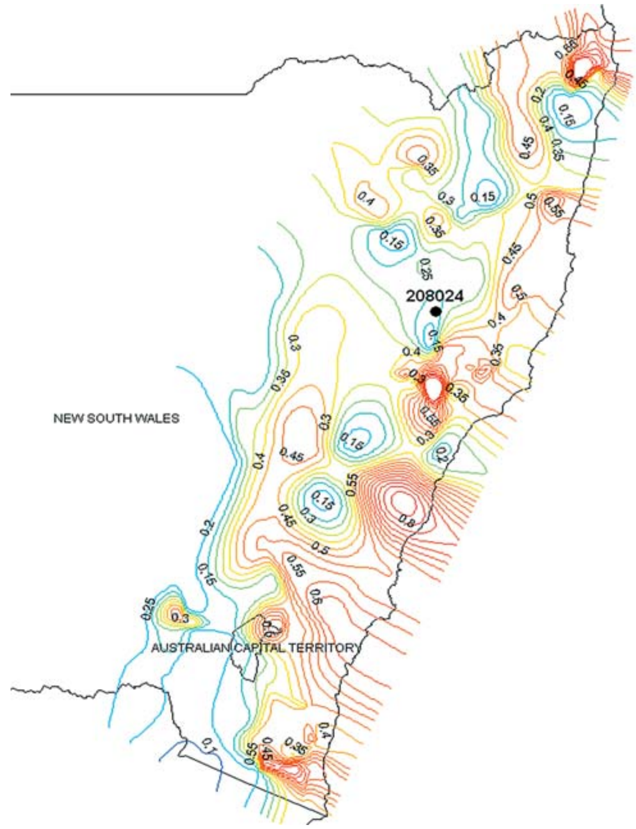

Figure 9.18. Map of regionalised runoff coefficients of the rational formula C_{10} values (see Equation 9.3) for eastern New South Wales, Australia. From Rahman *et al.* (2011b).

Process-based methods that will be surveyed in the forthcoming sub-sections are considerably more advanced in terms of the physical realism of the rainfall–runoff model used. Nevertheless, the key factor in all methods is how the principles illustrated above with respect to the rational method are followed. The link to regional flood frequency data and the use of appropriate parameter values that are conditioned on such data will be the weakest link in these more advanced process-based methods.

9.4.1 Derived distribution methods

Two kinds of derived distribution methods are distinguished here. The first class of methods is the design storm methods, commonly used in engineering practice, which are similar to the rational method discussed above, even though they take into account processes in a more explicit way. In the design storm method the flood peak arising from a single storm is estimated. The second class of methods estimates the entire population of flood events. These methods have been developed by the scientific community, and are at the base of the derived flood frequency framework discussed in Section 9.2.1 and of the similarity theory of flood frequency discussed in Section 9.2.2. Both design storm methods and 'scientific' methods that estimate the entire population of flood events are essentially event-based methods with a major distinction: in the first case the events are not actual observed ones, but are designed in such a way that the mapping between storm and flood return periods is known; in the second case the method involves real (or close to real) events and the mapping to the flood frequency curve is derived, either analytically or numerically (in the frequency domain).

Design storm methods

Design storm methods simulate floods for a discrete 'design' storm and have a long tradition in engineering hydrology (Pilgrim and Cordery, 1993; Viglione *et al.*, 2009b). They usually consist of three parts: (i) a design storm that is usually expressed in the form of a joint probability of rainfall intensity and duration; (ii) a deterministic rainfall–runoff model that transforms the rainfall input (i.e., design storm) into the flood peak – this model usually contains a runoff generation sub-model or a component to estimate effective rainfall, and a flow routing component to convert the volume of runoff generated (or rainfall excess) to the peak runoff or flood peak; and (iii) a methodology or framework in which the two above components are combined within a probabilistic framework, and conditioned on regional flood data, to enable prediction of the flood of a specified return period for an ungauged basin. Each of these components is discussed in turn.

Rainfall inputs to drive the runoff model can usually be obtained from two types of sources: (i) a design rainfall and (ii) a stochastic rainfall model. Design rainfall values are published for many regions in the world, e.g., Australia (Australian Rainfall and Runoff, 1987), Germany (DWA, 2012), USA (Chow *et al.*, 1988; Bonnin *et al.*, 2004), UK (Houghton-Carr, 1999; Kjeldsen, 2007). They are usually presented in the form of IDF curves (Svensson and Jones, 2010). Within the chosen storm duration, the rainfall intensity can be assumed to be uniform in time, or to follow a predefined (design) within-storm intensity pattern. Alternatively to assuming standard within-storm patterns, one could generate a population of equally likely within-storm patterns using stochastic rainfall models while maintaining the storm duration and mean rainfall intensity (e.g., Acreman, 1990; Robinson and Sivapalan, 1997b; Onof *et al.*, 2000; Haberlandt *et al.*, 2008). This way, instead of producing a single design flood, one could generate an ensemble of design storms, and hence flood peaks, using the rainfall–runoff models. In space, the rainfall intensity is usually assumed to be uniform across the catchment, although for larger catchments the design rainfall intensity estimated from the IDF curve may be reduced using a so-called areal reduction factor or ARF (e.g., Australian Rainfall and Runoff, 1987). Stochastic rainfall models are now available to generate realistic spatial patterns that can mimic the scaling of average rainfall intensity with increasing catchment area (Menabde and Sivapalan, 2001; Burton *et al.*, 2008). However, to fully benefit from these, the rainfall–runoff models must be spatially distributed as well (see Chapter 10).

Model structure The structure of the event-based rainfall–runoff model is often kept simple, particularly in ungauged basins. The runoff generation in rainfall–runoff models used for flood estimation in ungauged catchments is often based on the concept of effective rainfall represented by empirical methods such as Phi-index and W-index methods and SCS curve numbers (Australian Rainfall and Runoff, 1987; SCS, 1985). The most common approach adopted for runoff routing involves the use of the unit hydrograph (Dooge, 1959). Although the unit hydrograph is based on strong assumptions, which are only rough approximations of the flood runoff processes, the use of unit hydrographs has proved to be a very useful approximation, especially when large flood events are used for calibration (Lamb, 2005). Other runoff routing methods used in practice include storage routing models, based on a set of linear or non-linear reservoirs or the kinematic wave approach (Pilgrim and Cordery, 1993). Again, these models often perform well when their parameters can be calibrated against observed data.

Estimating model parameters in ungauged basins Regardless of the combination of rainfall–runoff models used, the biggest challenge and concern for their application to ungauged catchments is the choice of appropriate parameters: a parameter related to the runoff generation, and a parameter related to runoff routing. There are numerous recommendations regarding how to obtain model parameters in ungauged catchments, but they all fall into one of two categories: (i) transpositions from similar, gauged catchments; and (ii) the use of empirical formulas based on some form of regional analysis (e.g., Snyder, 1938; Mockus, 1957; SCS, 1985; Akan, 1993; Pilgrim and Cordery, 1993; USACE, 1994; ASCE, 1996; Houghton-Carr, 1999; Merz *et al.*, 2006). Australian Rainfall and Runoff (1987) presents design values for infiltration capacity and initial loss for several regions of the country as a function of return period. One of the most widely used methods around the world to estimate runoff generation in ungauged catchments is the US SCS curve number method (SCS, 1985; USACE, 1994). The method calculates effective rainfall as a function of rainfall depth, catchment characteristics and antecedent soil moisture and was developed from experimental catchment data in the USA (SCS, 1956). The degree to which the method can be generalised beyond its original domain of applicability has been examined by a number of studies. For example, Merz and Blöschl (2009a) compared the SCS curve number derived from soil type, land use and antecedent rainfall according to the SCS curve number method with the curve number back-calculated from event runoff coefficients for events in numerous Austrian catchments. The results showed that the back-calculated SCS curve numbers were not correlated with the predicted SCS curve numbers. In areas with large rainfall, runoff coefficients tended to be high, but these were also the forested areas where the SCS method predicts the smallest runoff coefficients. A similar result was found by Hoesein *et al*. (1989), who tested the SCS curve number method with a procedure analogous to the probabilistic rational method in eastern Australia. These comparisons illustrate that care must be taken when extrapolating empirical relationships such as the SCS curve number method beyond the regime of runoff processes for which they were developed. More recent methods estimate event-based model parameters on the basis of irrigation experiments. Examples include the methods of Markart *et al*. (2004) and Scherrer and Naef (2003), who related runoff coefficients and surface roughness to indicators such as vegetation species, land use, soil texture, drainage density and slope, which can be assessed during reconnaissance field trips. They then developed a rule-based method that allowed them to estimate the model parameters for ungauged basins. The spatial distributions obtained could then be used to assist in parameterising distributed models in ungauged catchments (e.g., Rogger *et al*., 2012a b; see Chapter 4).

Antecedent soil moisture and mapping of rainfall to flood return periods The second major challenge to the application of event-based methods for flood predictions in ungauged catchments is how the model parameters change with the event magnitude and how these changes are related to the return periods of the rainfall and the floods. In other words, parameter dependence on return period must be known *a priori* for its application in ungauged basins. From a process point of view, the relationship between the return periods of the rainfall inputs and flood peak must account for the storm duration, storm intensity, temporal and spatial storm patterns and the dynamics of runoff generation, which are controlled by antecedent wetness conditions, soils and topography, evaporation and other processes (Lamb, 2005). Viglione and Blöschl (2009) and Viglione *et al*. (2009a) analysed the role of the storm duration and the antecedent wetness conditions, expressed in the form of the runoff coefficient, in the mapping of rainfall and flood return periods using the derived distribution approach.

They found that, unless adjustments are made to the parameters of the rainfall–runoff model, the return period of the flood peak could be much higher than the return period of the design storm (Figure 9.19a). The ratio of the return period of rainfall and runoff depends mainly on the average wetness of the catchment. In arid climates the return period of the flood peak could be of the order of hundreds of times that of the rainfall return period, while in humid climates the maximum flood return period is never more than a few times that of the corresponding storm. Figure 9.19b shows the non-exceedance probability of the runoff coefficient providing the match of the design storm and flood return periods obtained in a hypothetical simulation study for varying climate and return periods. There is no unique non-exceedance probability of the runoff coefficients that give a 1:1 correspondence of T_P and T_Q. For the driest system, it significantly depends on the return period (ranging from 0.5 to 0.8), while it is almost constant and close to 0.8 for the wettest system. In all cases, however, it is evident that the runoff coefficient that gives the 1:1 matching of design storm and flood return periods is greater than the median value that has been suggested for use in a common application of the design storm method (e.g., Pilgrim and Cordery, 1993).

For this reason, applications of event-based methods are usually preceded by analysis of rainfall–runoff–flood data from several catchments in the region to enable estimation of these relationships. Such relationships are either embodied in regional guidelines (e.g., Australian Rainfall and Runoff, 1987) or performed on a case-by-case basis for the ungauged basin of interest. The model parameters that transform a T-year storm into a T-year flood peak, i.e. are return-period neutral, are mapped regionally and are then used in routine predictions. Although this procedure may be affected by considerable error due to uncertainties in the return period (see e.g., Rahman *et al*., 2011b), there is the potential for local processes such as floodplain inundations and obstruction by hydraulic structures to be included. For whichever model is used, a general recommendation is to analyse runoff data from similar gauged catchments in the region whenever possible to estimate the model parameters in ungauged catchments (IH, 1999; Blöschl, 2005).

Estimating the entire population of flood events
One approach that overcomes the problem of assigning return periods to individual events does so by transforming the probability distributions of rainfall into probability distributions of floods using a rainfall–runoff model (e.g., Eagleson, 1972; Wood, 1976; Gottschalk and Weingartner,

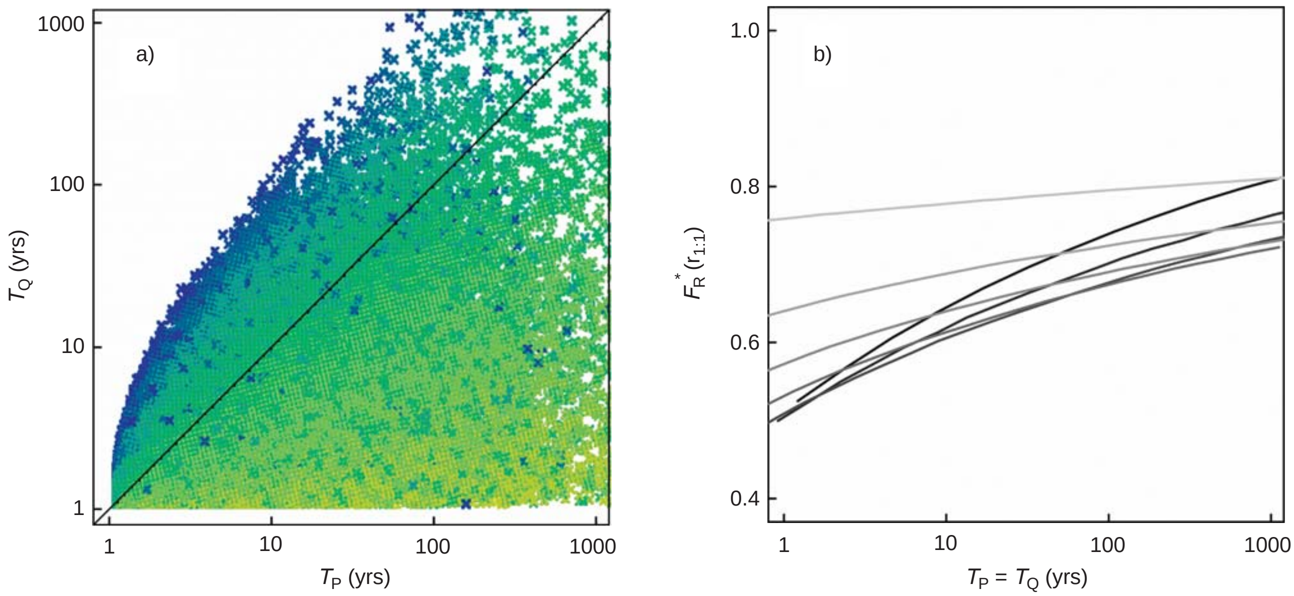

Figure 9.19. Mapping of design storm to flood peak return periods. (a) Return periods of design storms (T_P) vs. return period of associated flood peaks (T_Q) with varying runoff coefficients (yellow: low, blue: high); (b) non-exceedance probability of the runoff coefficient producing the maximum annual events providing the match of the design storm and flood return periods for varying climate (light: wet, dark: dry). From Viglione *et al*. (2009a).

1998; Sivapalan *et al*., 2005). Iacobellis *et al*. (2011) exploited a two-component derived distribution, based on the concept of variable source area applied to two different runoff thresholds related to infiltration excess and saturation excess mechanisms. Their regional analysis showed that based on the *a-priori* information provided by several catchment characteristics related to basin climate, geology, geomorphology and landcover it was possible to explain more than 70% of the spatial variability of the distribution parameters in southern Italy.

So far, despite the considerable interest in this approach in the scientific literature, the impact of these derived flood frequency methods on practical flood estimation, even in gauged catchments, has been modest. The main problem is the difficulty in quantifying the joint probabilities of the various controls on the flood frequency curve, such as rainfall duration, temporal patterns, multiple events, soil moisture and routing characteristics. In ungauged catchments, this problem is exacerbated by the fact that no runoff data can be used to infer type and parameters of these joint distributions. Potentially, however, regionalisation of parameter procedures could be used (described in detail in Chapter 10) and the derived distribution method could then be applied to ungauged catchments.

Simpler, but statistically less rigorous methods have enjoyed some popularity where the derived distribution approach is combined with flood regionalisation. This avoids some of the joint probability problems. An example is the Gradex method (Guillot, 1972; Duband *et al*., 1994; Naghettini *et al*., 1996), which assumes that beyond a threshold return period any additional rainfall produces a corresponding increase in runoff without losses. The method lends itself to predicting floods in ungauged basins, where floods of a small return period are regionalised by statistical methods and extrapolated to large return periods on the basis of regionalised precipitation (e.g., Merz *et al*., 1999).

Within this estimation framework, important information can be exploited by remote sensing products, such as digital elevation models, land cover and vegetation indices, which can contribute to providing reliable predictions in ungauged basins. Going further, one could apply the continuous models directly and use them to simulate continuous runoff and from this extract annual maximum flood peaks with which to construct the flood frequency curve. This is discussed in the next section.

9.4.2 Continuous models

Continuous runoff models simulate runoff processes in a time explicit manner. Runoff models are discussed in more detail in Chapter 10, and therefore this chapter will only focus on specific issues that will be encountered in more targeted applications of continuous models for flood estimation.

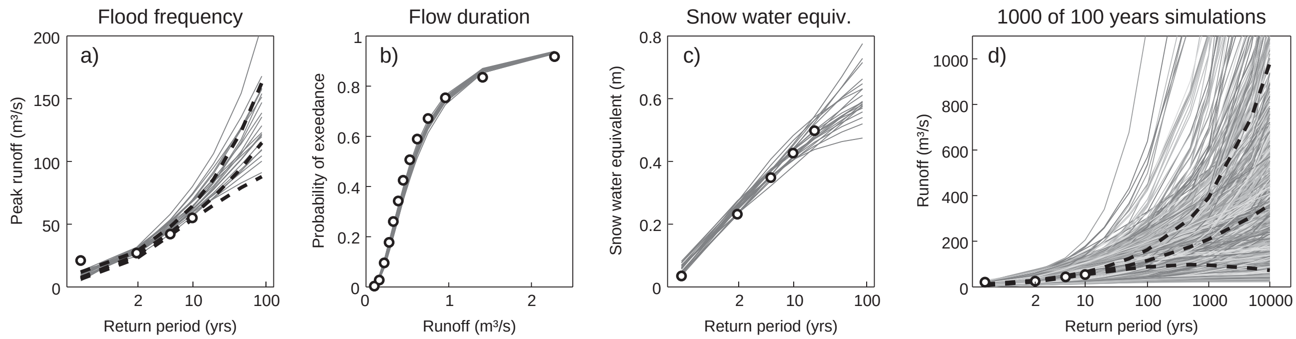

Figure 9.20. Comparison of ungauged process-based estimation and gauged statistical estimation of the flood frequency curve for the Joseful Dul catchment in the Czech Republic. Circles refer to data or reference values, dashed lines to statistical procedures and shaded lines to ensembles of modelled behaviours. From Blazkova and Beven (2002).

Continuous models for estimating a flood of a given return period are usually driven by rainfall generated by a stochastic rainfall model (Robinson and Sivapalan, 1997b; Menabde and Sivapalan, 2001; Viglione *et al.*, 2012) and the simulated runoff hydrograph is evaluated in terms of flood peaks in the same way as an observed hydrograph. There is therefore no issue with the mapping of the return periods. However, other issues remain. Since the concern is accurate reproduction of annual maximum floods with increasing return period, there needs to be explicit recognition that the model faithfully reproduces the runoff processes that realistically could occur under extreme conditions. Specifically, the issue is whether the model accurately reproduces the processes associated with changing runoff generation mechanisms and dynamics of flood movement and inundation that could be faced under extreme conditions. This is hard to achieve and verify, since it is quite likely that the conditions experienced are different from those during normal flows, and therefore cannot be accomplished by simply calibrating against a continuous runoff hydrograph. Information from field visits (Chapters 3 and 4) and other information about the flow paths and local runoff processes may assist in capturing the transition from normal to extreme events.

Similarly to event-based models, the model parameters need to be estimated for the ungauged basin. Different methods have been proposed in the literature for parameter transfer to ungauged conditions (see Chapter 10). The options are: *a-priori* estimation of model parameters; constraining model parameters by dynamic proxy data and runoff; and transferring calibrated model parameters from gauged catchments. The last is the most common approach for continuous runoff models and can be obtained by spatial proximity methods, regional calibration and downscaling methods, and regressions between model parameters and catchment characteristics. The conventional approaches employ a two-step procedure to establish transfer functions: gauged catchments are identified for which calibration of model parameters is separately carried out; then a transfer function relationship is identified, which associates a parameter value to hydrological characteristics through a regression procedure.

The calibration of continuous models to be used in flood frequency analysis is focused on flood peaks. For example, in Lamb and Kay (2004) the parameters are calibrated for gauged catchments in order to minimise the difference between the ranked simulated and observed flood peaks and are then regionalised through multiple regressions with catchment characteristics. They found their results for catchments in Great Britain to be similar to those obtained by a conventional statistical method. Other examples of continuous modelling to estimate flood probability in ungauged catchments include Sweden (Harlin and Kung, 1992), UK (Calver *et al.*, 1999, 2004; Lamb, 2005), Czech Republic (Blazkova and Beven, 2002, 2004) and Austria (Rogger *et al.*, 2012a, b). Blazkova and Beven (2002) calibrated model parameters for a Czech catchment treated as ungauged with the generalised likelihood uncertainty estimation (GLUE) methodology of Beven and Binley (1992), conditioned to the statistical regional estimation of flood quantiles for low return periods (e.g., up to 10 years), flow duration characteristics and maximum annual snow-water equivalent. The model was then used to estimate high return period floods with a Monte Carlo procedure. An example of the simulations is shown in Figure 9.20. The figure illustrates the enormous spread of simulations that may be encountered in Monte Carlo simulations even though the simulations are constrained by regional information.

So far the relative performances of the continuous simulation method and regional statistical methods have not been fully evaluated. Lamb and Kay (2004) show results similar to the statistical procedure and Rahman *et al.* (2011b) show worse performance. It is clear that the performance of the simulation methods very much depends on the

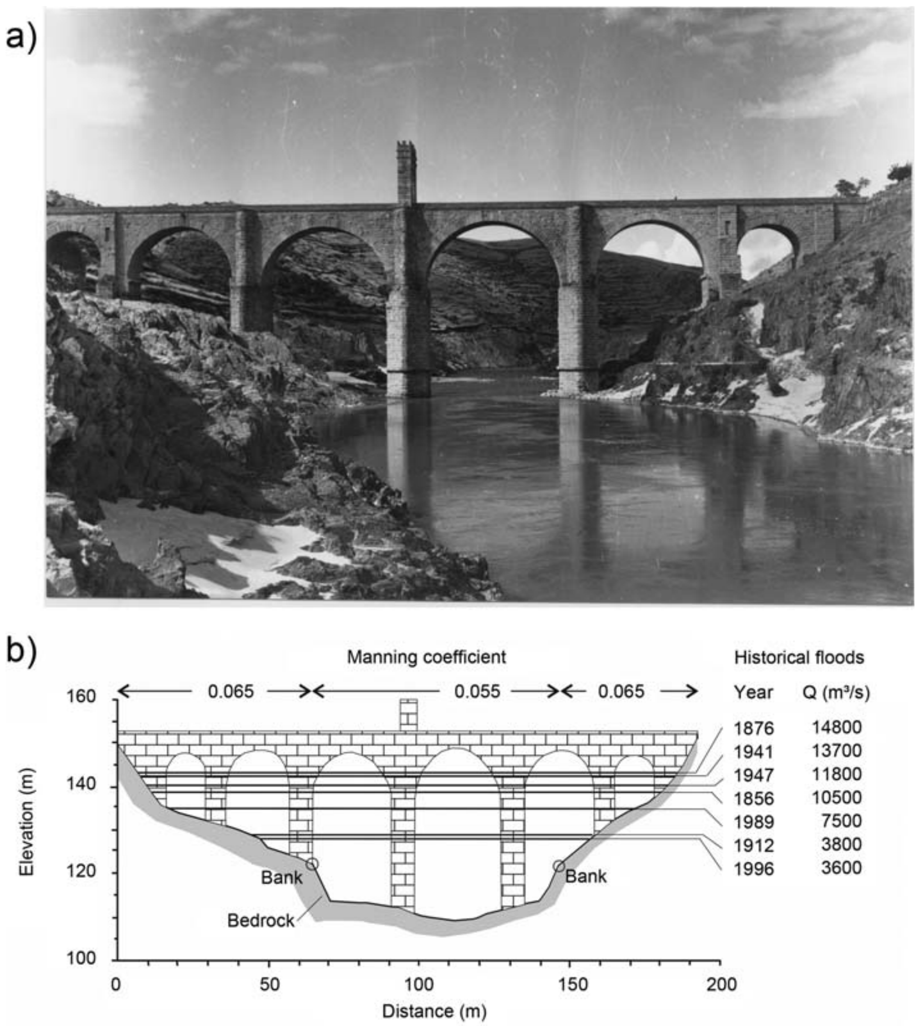

Figure 9.21. Cross-section of the Alcantara bridge (Tagus River, Spain) showing different peak water stages during historic floods, which have been related to the rating curve (right) obtained from one-dimensional hydraulic modelling of a 1 km long reach. In the centre, the date and estimated runoff from the rating curve are indicated for the reported historical floods. From Benito (2003).

amount of information on the catchment processes that is used for the selection of the parameters and the model structure. It is likely that the relative performance depends more on the available information and the skill of the modeller than on generalisable characteristics of the model or the approach (see Section 3.7.2). Other information on the behaviour of the catchment during floods would therefore be extremely useful in order to assist in flood frequency estimation in ungauged basins. One such piece of information is proxy data.

9.4.3 Proxy data on flood processes

Historical flood information

In ungauged basins, a continuous runoff record will be unavailable, but there may be observations of a few extraordinary floods. Indeed, non-systematic historical flood data (i.e., human records of flood peaks; Stedinger and Baker, 1987) can be very useful in predicting floods. Historical flood data are usually derived by the analysis of chronicles and documents that do not usually give many details on the particular flood, but do provide information on its impacts (proxy data; e.g., Benito *et al.*, 2004). In particular, historical archives may provide the date of occurrence of past floods, information on the meteorological situation and some indication about the peak water levels (e.g., flood marks on buildings, bridges, trees etc.; see Figure 9.21).

Historical water levels can be converted into runoff by means of hydraulic modelling (e.g., Calenda *et al.*, 2005). In this context, interesting examples of historical flood data are the Nile flood stages, from AD 640 to 1921 (Hassan, 1981), and the reconstruction of Tiber flood peaks performed by Calenda *et al.* (2005). The *Hydrological Sciences Journal* recently published a Special Issue on this topic (Brázdil and Kundzewicz, 2006). Hydraulic procedures unavoidably introduce additional sources of uncertainty as several assumptions (e.g., slope, roughness and cross-section geometry) need to be made to complete the

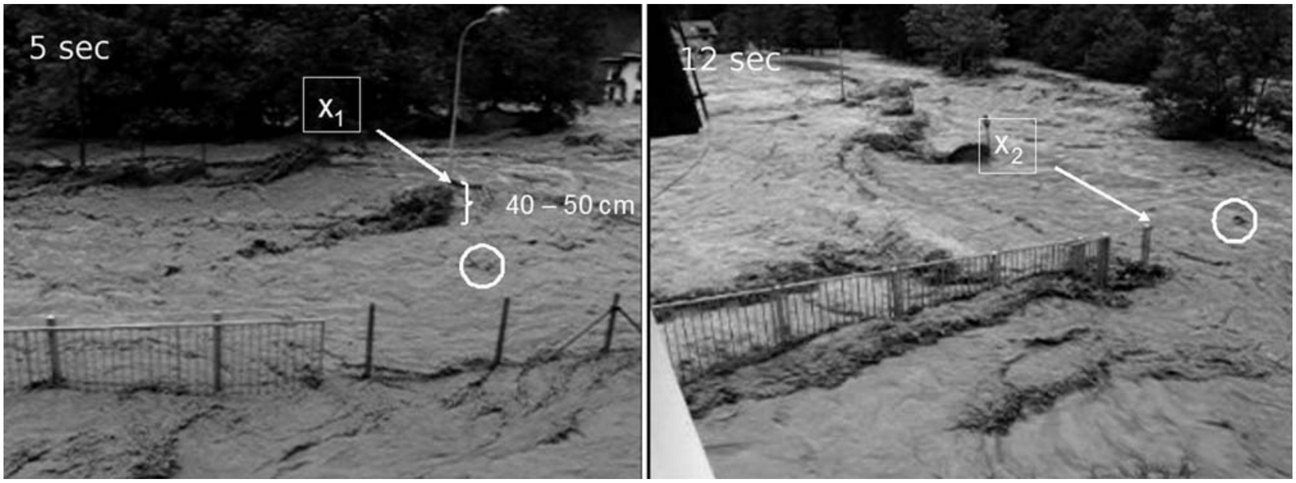

Figure 9.22. Pictures extracted from a movie taken during the 18 September 2007 flood in the Selka Sora catchment (western Slovenia) at the entrance to Zelezniki. Distance between the sections marked as X_1 and X_2 is 21 m, giving a velocity of 3 m/s in the reach. From Marchi *et al*. (2009).

estimation. Nevertheless, Cong and Xu (1987) showed that, even if historical data on large floods are affected by such inevitable errors, this additional information is often valuable for the purposes of flood frequency analysis. Besides, it should be noted that even in the case of systematic data recorded in gauging stations, river flow data associated with high magnitude floods suffer from considerable uncertainty caused by errors introduced during extrapolation of the stage-discharge rating curve (e.g., Di Baldassarre and Montanari, 2009). An additional technique to obtain useful information on past floods is the analysis of paleo-flood data (Stedinger and Baker, 1987).

When estimating floods in ungauged basins from historical flood data or paleo-flood data, techniques are needed that are able to cope with coarse and irregular information (Leese, 1973; Stedinger and Cohn, 1986; Reis and Stedinger, 2005). Hence, for this type of data the common approach is to statistically analyse the river runoff in terms of exceedances (or non-exceedances) of runoff threshold values. When working with historic and paleo-flood data, the hypothesis of stationarity cannot usually be used because of the effects of human-induced catchment modifications (e.g., dams and channelisation) and natural climatic variability. Hence, the statistical analysis of paleo-flood data has to explicitly cope with non-stationarity (e.g., Benito *et al*., 2004). Micevski and Kuczera (2009) developed a Bayesian approach that can combine at-site information, such as gauged flows and historic information, with information from the regional regression model. This augmentation with short at-site records is particularly valuable as uncertainty in regional estimates of the index flood is particularly severe.

Recent post-event information

Another approach to obtain proxy information on flood events is by means of post-flood event campaigns. These field surveys are performed in catchments shortly after major flood events have occurred (see Section 3.7.3) in order to identify traces left by the water and sediments. Flood marks and damage at bridges and other infrastructure are indicators of the height of the river water level during the flood event, while patterns of landsliding or debris flow initiation and deposition provide information on the geomorphic response of the catchment. During these campaigns eyewitness interviews are also carried out, which can provide useful information on the timing and magnitude of the flood peak (Marchi *et al*., 2009).

Additional documentation on flood characteristics can be gathered from photographs and movies recorded during the flood. Floodwater velocity can be obtained and compared with computations of flow velocity from hydraulic models. In Figure 9.22 the velocity of a floating object is approximately estimated by timing the passage of the object, which was visible on the movie, between landmarks a known distance apart. Borga *et al*. (2008) have shown how this information can be used to carefully reconstruct peak runoff. Figure 9.17 illustrated the importance of collecting information on major events in ungauged catchments. Figure 9.17b shows that in more than half of the cases, 80% of the data for basins less than 100 km^2 were collected by means of post-flood surveys, following the methodology described in Borga *et al*. (2008). These proportions identify the observational problem that characterises flash floods, which is

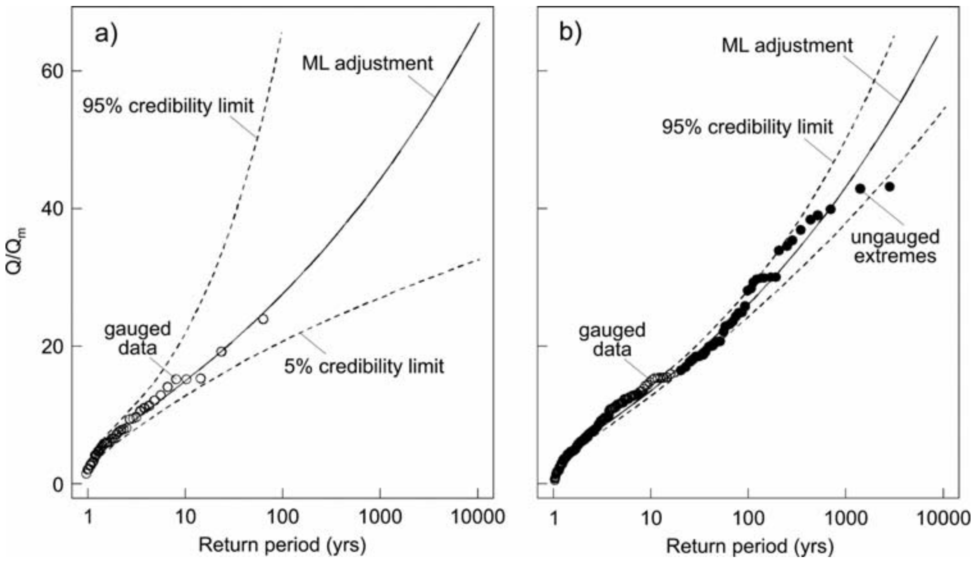

Figure 9.23. Fitted GEV distributions and 90% credible intervals in the Ardèche region, France: (a) data from the St Martin gauging station on the Ardèche River; (b) including the regional gauged data set and the set of ungauged extremes from post-event surveys. ML adjustment refers to the Maximum Likelihood estimate. From Gaume *et al*. (2010).

especially severe for events characterised by a small spatial extent. Overall, these observations point out the unique role of post-flood surveys in flash flood analysis. As well as for historic and paleo-floods, the reconstructed information on flood post-event surveys can be incorporated in statistical regional flood frequency analyses. Gaume *et al*. (2010) proposed a method for reducing the uncertainties in estimating regional flood quantiles using post-event survey data of major flash floods in ungauged catchments. They applied the method in Slovakia and the south of France and showed that the additional information was able to increase the confidence in regional estimation of the growth curve, provided that the set of ungauged extremes is the result of comprehensive sampling over the selected region (see Figure 9.23).

The use of proxy data and knowledge has been extended by the flood frequency hydrology framework developed by Merz and Blöschl (2008a, b) and Viglione *et al.* (2013a). They provide a number of examples of local hydrological effects that cannot be easily captured through the usual lumped catchment characteristics. To account for them, additional hydrological interpretation is required in a 'forensic' analysis. They analysed regional runoff information not usually used in frequency analysis, such as the hydrograph shapes, regional flood timing, runoff coefficients for events of different magnitudes, flood types, historical photos, inundation maps, precipitation information, topographic configuration, landforms, vegetation and hydrological activity derived from field trips to place the flood frequency in a regional context. In all instances the aim was not to conduct detailed rainfall–runoff modelling, but to develop a more detailed interpretation of the regional flood frequency behaviour. These pieces of information allowed them to infer whether the floods in the target catchments were expected to be smaller or larger than the regional trend, and gave them indications about the shape of the flood frequency curve. They then provided a number of suggestions on how these diverse pieces of information can be combined to come up with flood prediction that exploits the maximum amount of information about the flood generating processes in the catchment and region of interest.

9.5 Comparative assessment

The aim of the comparative assessment of flood predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in runoff prediction performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies of Level 1 in terms of how the performance

Figure 9.24. Map indicating the countries included in the Level 1 assessment. After Salinas *et al*. (2013).

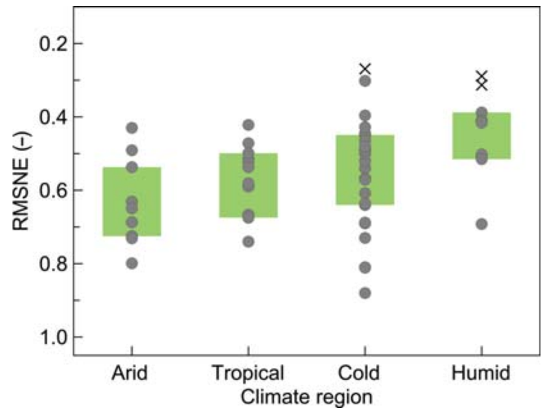

Figure 9.25. Root mean square normalised error (RMSNE) of predicting the 100-year floods in ungauged basins stratified by climate. Each symbol refers to a result from the studies in Table A9.1. Circles indicate cross-validation performance on specific values, crosses indicate cross-validation performance on volumes. Boxes show 25%–75% quantiles. After Salinas *et al*. (2013).

depends on climate and catchment characteristics as well as on the method chosen. More details on the comparative study are reported in Salinas *et al*. (2013). In both Level 1 and Level 2 assessments, the runoff prediction performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The runoff prediction performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

9.5.1 Level 1 assessment

Table A9.1 (Appendix) summarises the 31 individual studies used in the Level 1 assessment. Many of these studies are based on large data sets providing a broad range of results from catchments in different climates. The number of catchments evaluated in the studies ranges from 8 to 600, with a median of 29. Several studies compare different regionalisation approaches or use different sub-regions for the assessment. Removal of these leads to a total of 49 results for evaluating runoff prediction performance. The regionalisation methods used are regression approaches, index methods and geostatistics. In the majority of the studies performance is specified as root mean square normalised error (RMSNE, Table 2.2) on the 100-year flood quantile or the 100-year specific flood quantile. Note that RMSNE represents errors (rather than skill), so it has been plotted downwards on the vertical axis to make it consistent with the performance measures in the other chapters, i.e. higher up in the plot indicates better performance. For comparison with the other runoff signatures in Chapter 12, the R^2 of the 100-year flood quantile for all methods in all studies were back-calculated from the RMSNE by applying an empirical relationship from Level 2. The 25% and 75% quantiles of these R^2 are 0.41 and 0.70, respectively.

Figure 9.24 and Table A9.1 show that most of the studies came from Europe and North America, but a few studies from South America, Africa and Asia were also available. With respect to climate, it is apparent that evaluations in cold regions dominate. There were only a few studies in mountain regions, which were combined with the cold and humid regions in the analyses. Three main science questions are addressed below.

How good are the predictions in different climates?
Figure 9.25 shows that runoff predictions in the humid regions exhibit smaller errors than runoff prediction in arid regions. This means that the predictive performance clearly decreases with increasing aridity. There are a number of factors that may contribute to this dependence. The inter-annual variability (e.g., in terms of CV of the annual peak runoff time series) of floods in arid regions is usually bigger than in other climates, due to the associated stronger non-linearities and threshold effects in drier regions. This means that the floods are more difficult to estimate from short records. The stronger non-linearity also implies that the spatial hydrological variability in the flood-producing processes will impact more strongly on the flood frequency curve, so even catchments that are close to each other may exhibit quite different flood frequency curves, which reflects poorly on the regionalised predictions. In contrast, humid catchments tend to be more linear, so the predictability is better.

The biggest range of performances is found in cold climates. This may be partly related to the larger number of studies available for these regions. Also, in cold regions a wide variety of flood-producing processes may exist, including snow and rain-on-snow, which may lead to different performance, depending on the prevailing processes.

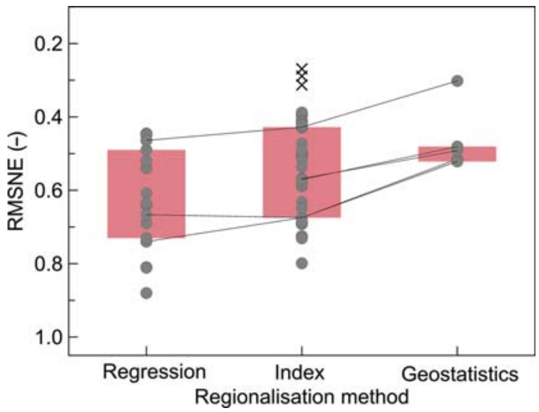

Figure 9.26. Root mean square normalised error (RMSNE) of predicting the 100-year floods in ungauged basins stratified by regionalisation method. Each symbol refers to a result from the studies shown in Table A9.1. Circles indicate cross-validation performance on specific values, crosses indicate cross-validation performance on volumes. Boxes show 25%–75% quantiles. After Salinas *et al*. (2013).

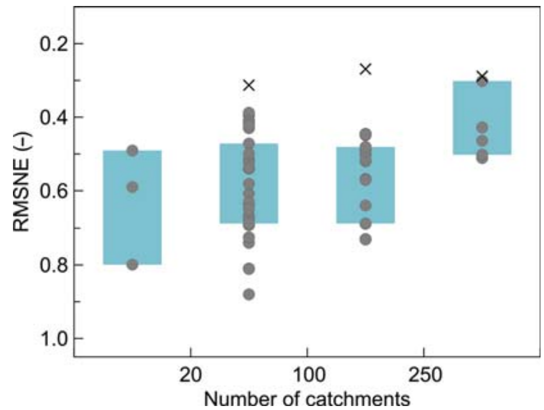

Figure 9.27. Root mean square normalised error (RMSNE) of predicting the 100-year floods in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies shown in Table A9.1. Circles indicate cross-validation performance on specific values, crosses indicate cross-validation performance on volumes. Boxes show 25%–75% quantiles. After Salinas *et al*. (2013).

For example, snowmelt floods tend to be more predictable than rain-on-snow floods (e.g., Sui and Koehler, 2001).

Which method performs best?

The regionalisation methods represented in the assessment included: (i) regression methods, i.e., 18 results from different regression models where the flood quantiles or the distribution parameters had been transferred to ungauged basins; (ii) index methods, i.e., 34 results where a regional growth curve had been defined for homogeneous regions; (iii) geostatistics methods, i.e., 5 results where runoff at the target site was estimated as a weighted mean of runoff at the surrounding gauges. While the assessments made by each group are not based on exactly the same regionalisation approach, the methodology is similar.

Figure 9.26 shows that the geostatistical methods perform best (RMSNE of 0.30–0.52) across the studies analysed, although the number of studies is small compared to the other groups. The regression methods have the lowest performance, i.e., the largest predictive errors (median RMSNE of 0.62), and the index methods fall in between. These results are confirmed by studies that compared different approaches in the same region (grey lines in Figure 9.26). It appears that it may be difficult to find catchment characteristics that are representative of the flood generating processes. For example, subsurface characteristics are an important control for flood generation and these are difficult to capture unless detailed field surveys are available. Index methods and geostatistics are less dependent on the catchment characteristics as they usually take advantage of both spatial proximity (either through spatial correlations or homogeneous regions) and correlations to catchment characteristics. It is also the case that the geostatistical studies of Table A9.1 have been performed in data-rich environments, which may partly explain their better performance.

It is interesting to note that the number of studies applying regression and index methods is much larger than those applying geostatistics, which is because they have a longer tradition in hydrology.

How does data availability impact performance?

Figure 9.27 shows the RMSNE as a function of the number of catchments analysed in each study. The errors clearly decrease and the performance increases with the number of catchments included in the analysis. This is because of the higher stream gauge density in the larger studies, which makes the transfer of floods across the landscape more accurate, in particular if there is a stream gauge upstream or downstream of the target site. Also, the regionalisation methods may be robust if the total number of stations is larger.

Main findings of Level 1 assessment

- In humid regions predictive performance of floods in ungauged basins tends to be better than in other climates. In arid regions the performance is lowest.
- Geostatistical methods tend to perform better than the other methods, regressions tend to have the lowest performance, and index methods lie between geostatistic and regression methods. This suggests that it

may be difficult to find catchment characteristics that are suitable for regression methods.

– Runoff prediction performance increases clearly with number of stations in a region, highlighting the need for a dense stream gauge network for predicting floods in ungauged basins.

9.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A9.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and inter-study comparison of results. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. Five authors from studies included in the Level 1 assessment provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment (Table A9.2). This data set combines data from 1640 catchments, three groups of regionalisation methods and four catchment characteristics. The regionalisation methods are regression, index methods and geostatistics. The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area. The performance was assessed based on the 100-year floods. The normalised error (NE) and the absolute normalised error (ANE) were used as runoff prediction performance indicators (Table 2.2). The NE highlights biases in the methods, while the ANE is a measure of the overall performance. Note that the ANE is an error measure, so it has been plotted downwards on the vertical axis to make it comparable with the performance measures, i.e., higher up in the plot indicates better performance. For comparison with the other runoff signatures in Chapter 12, the R^2 of the 100-year flood quantile were calculated for all methods in each study separately, considering only those sites with at least 40 years of data. The 25% and 75% quantiles of these R^2 are 0.53 and 0.70, respectively.

To what extent does runoff prediction performance depend on climate and catchment characteristics?

The assessment of the ANE and NE error measures with respect to the four climate and catchment characteristics is presented in Figures 9.28 and 9.29, respectively. The lines indicate the median runoff prediction performance of catchments belonging to the same study. The top panel shows that the errors, ANE and NE, clearly increase with increasing aridity, i.e., there is a decrease in performance with aridity for all three methods. This is also supported by the lines representing comparative studies. This clear trend is in line with the Level 1 assessment. Arid regions tend to be more heterogeneous than humid regions and runoff processes are more non-linear. There is also a decrease in performance with the air temperature (T_A). In the catchments analysed, the warmer catchments tend to be those with the larger aridity index, so this is consistent with the dependence on aridity. There is a slight increase in performance with elevation but, in contrast to aridity and air temperature, the biases do not change much with elevation. In the studies examined here, the highest elevation catchments are influenced by snowmelt, so there is a tendency for the flood predictions to improve if snowmelt is involved in the flood generation processes.

The results stratified by catchment area (fourth panel, Figures 9.28 and 9.29) indicate a clear increase in performance (decrease of ANE) with increasing catchment area for all methods. The increasing performance with catchment size is likely related to two factors. The first is related to the data availability. As the catchment size increases the likelihood that gauged subcatchments are available as donor stations increases. This will lead to more reliable transfer of the flood characteristics. Additionally, for larger catchments, there are aggregation effects on the flood generating processes, so floods tend to be less flashy and therefore easier to predict. None of the methods is biased in relation to catchment area (fourth panel, Figure 9.29).

Which method performs best?

Figure 9.30 summarises the runoff prediction performance of different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments in Table A9.2, and catchments with an aridity index below and above 1, respectively. Analysis of the overall performance of the three methods shows that performance is similar for geostatistics and index methods, which have a slightly better performance than the regression methods. For humid catchments, again, the performance of geostatistics is slightly better than index methods, and the performance of the regression methods is slightly lower. For dry catchments, however, the index methods perform significantly worse than the other two methods. The low performance of the index flood methods in arid regions may be related to the underlying assumption of using the same non-dimensional flood frequency curve (i.e., growth curve) in the entire region. Arid regions may be spatially more heterogeneous, leading to lower performance. More importantly, most arid catchments are strongly biased in that the predictions overestimate the 100-year floods (Figure 9.29, top centre). The median normalised error is

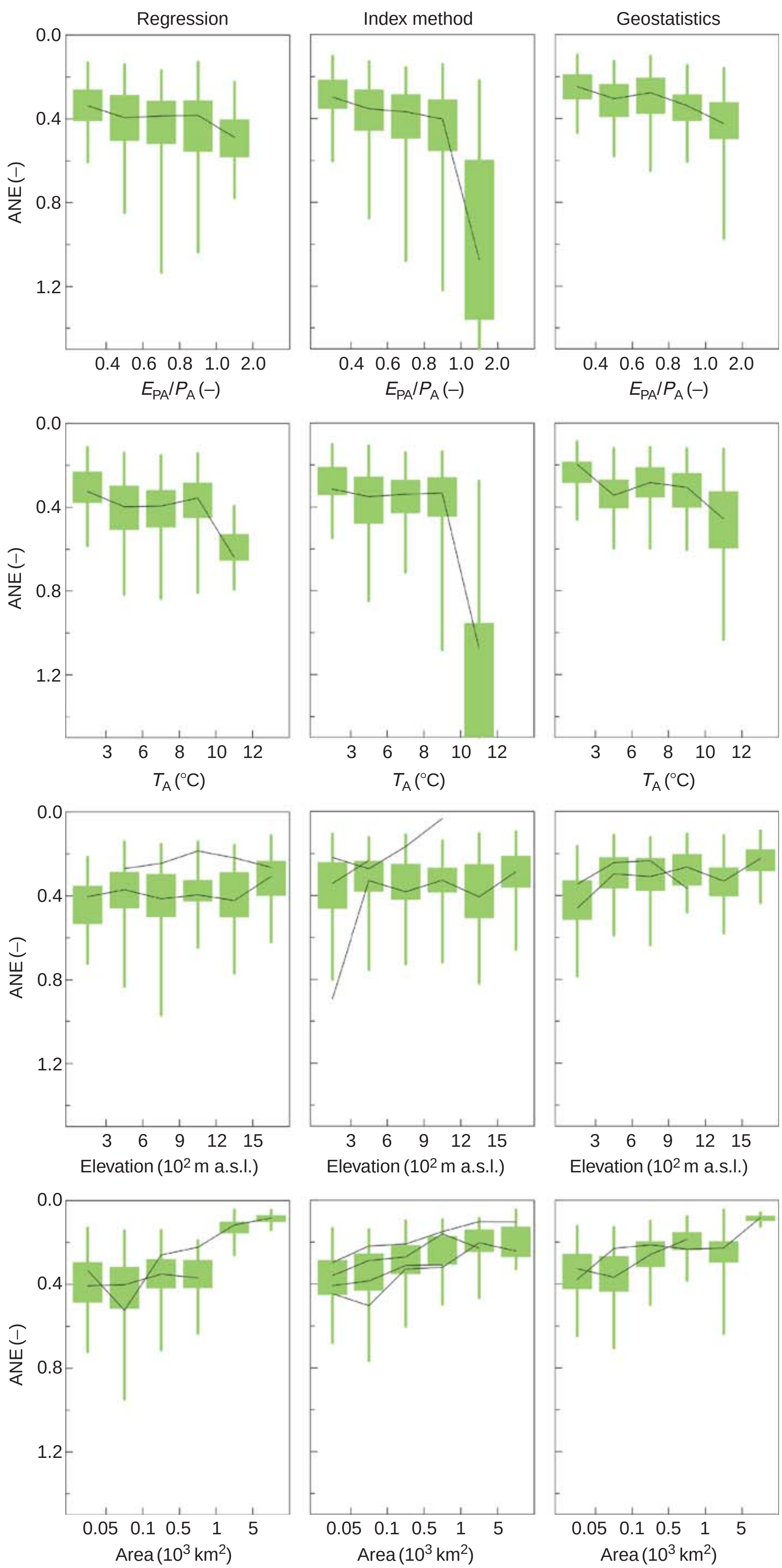

Figure 9.28. Absolute normalised error (ANE) of predicting the 100-year flood in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different parameter regionalisation methods. Lines connect median errors for the same studies. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al.* (2013).

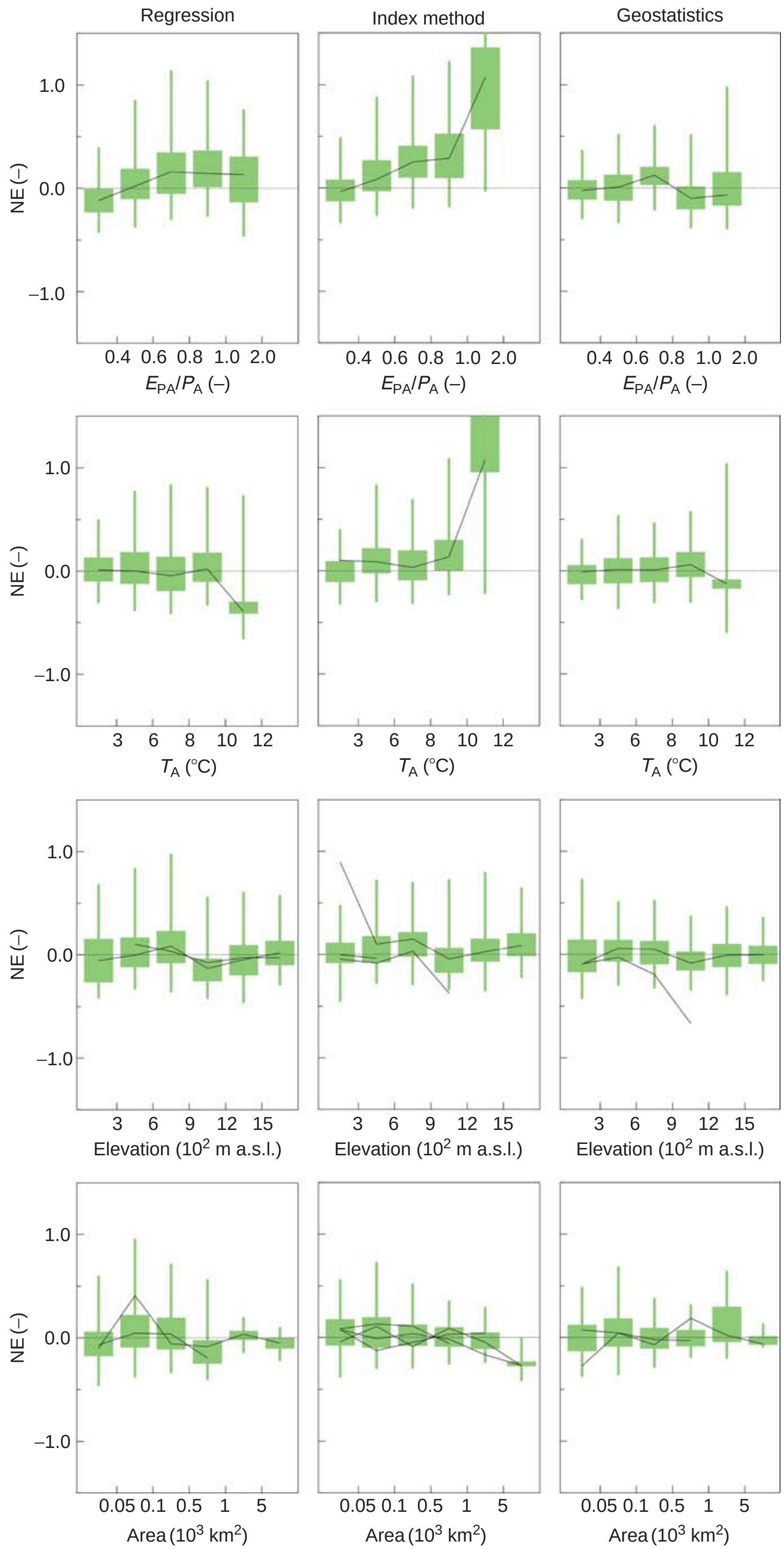

Figure 9.29. Normalised error (NE) of predicting the 100-year flood in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different parameter regionalisation methods. Lines connect median errors for the same studies. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al*. (2013).

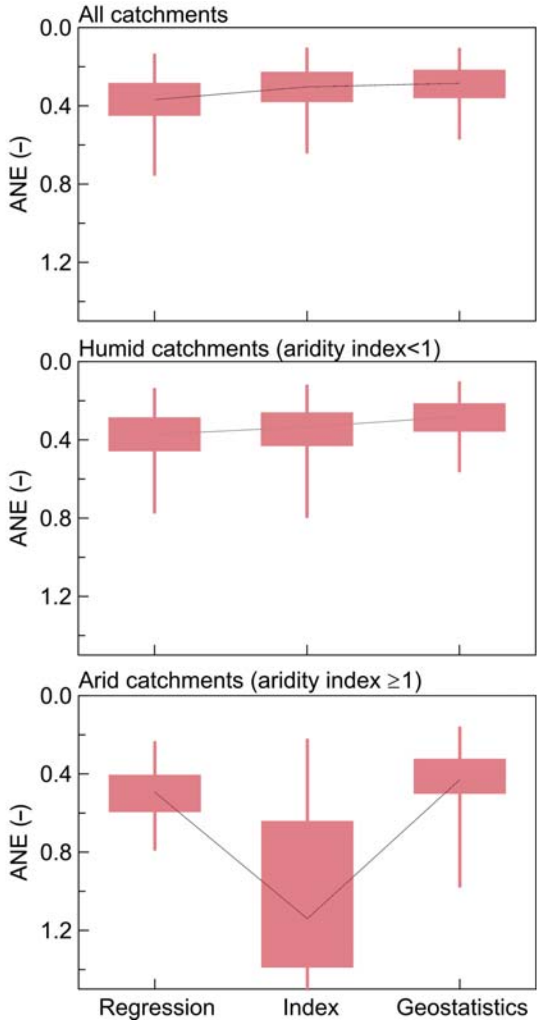

Figure 9.30. Absolute normalised error (ANE) of predicting the 100-year flood in ungauged basins for different regionalisation methods, stratified by aridity. Lines connect median absolute normalised errors for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Salinas *et al.* (2013).

1.0, indicating that typically the methods predict twice the floods actually observed. If a homogeneous region contains both arid catchments with relatively lower floods and wetter catchments with higher floods, the homogeneity assumption will tend to lead to an overestimation in those catchments with the lower floods. The other two methods, however, remain unbiased for the most arid catchments.

Main findings of Level 2 assessment

– The flood prediction performance of all methods for ungauged basins decreases with increasing aridity and air temperature.
– There is a tendency for the performance to increase with catchment elevation.
– There is a clear increase in the performance of all methods with catchment size. In larger catchments runoff data from subcatchments or close downstream neighbours are often available and aggregation effects may make floods more predictable than in smaller catchments.
– In humid conditions index methods and geostatistical methods perform slightly better than regression methods. However, in arid conditions the index methods are significantly biased and significantly overestimate the 100-year floods in the catchments analysed.

9.6 Summary of key points

- The flood frequency curve is a particular signature of runoff variability that describes the (inter-annual) distribution of the annual maximum runoff. The flood frequency curve arises through the interaction of event rainfall variability with several catchment processes (e.g., runoff generation, runoff routing, evaporation as controlled by antecedent soil moisture).
- The flood frequency curve reflects the distribution of rainfall in time (duration, intensity, frequency) and space (patchiness, orographic effects, storm movement), the distribution of water flow paths (surface, subsurface, channel), the seasonality of climate and the resulting soil moisture variations, and the interplay of all of these. These are then the process elements that impact the flood frequency curve.
- However, floods shape landscapes through soil erosion and deposition, the generation and maintenance of river networks, and associated soil and vegetation patterns. Just as in the case of geomorphology (Haff, 1996), all of these can be deemed emergent patterns, and can therefore serve as predictors of flood frequency. Examples of co-evolutionary or emergent variables as predictors include mean annual precipitation and drainage density (because they explain, over long time scales, both the event characteristics, antecedent soil moisture and drainage patterns), and the hypsometric curve, which characterises the distribution of elevation within a catchment.
- Over the past decades there has been an expansion in the use of more temporal, spatial and causal information in flood frequency estimation. With the passing of time it is now possible to identify long-term trends in the data. The expansion of the spatial scope of flood frequency estimation enables one to identify spatial trends. Increased availability of data and improved process understanding help to better interpret and learn from these spatial and temporal trends. Also, there is an increasing tendency, in data-rich regions, to utilise the

stream network structure to generate improved flood predictions in ungauged basins. Overall, progress in all of these areas is helping to advance the field of flood frequency hydrology generally.

- Deciphering these regional patterns, and juxtaposing them against regional climate patterns, patterns of landscape organisation, and patterns of inundation obtained from satellites during major floods, are examples of strategies that can be adopted globally, including in developing countries.
- Comparative performance assessment of several flood frequency estimation methods has indicated, as in all previous signatures, that predictive performance worsens with increasing aridity (both Level 1 and Level 2 assessments). Also, as expected, predictive performance increases with increasing catchment area (Level 2 assessment). Both Level 1 and Level 2 assessments indicated that the geostatistics method has the best performance (especially when data availability is high), index methods work next best, and regression methods relatively the worst. The Level 2 assessment also indicated that index methods do not work well in arid regions.
- Flood frequency hydrology deals with the extreme end of the natural runoff variability, yet in a way that combines process hydrology, comparative hydrology and paleohydrology (including learning from the recent past history of floods). Connecting these to patterns of other co-evolutionary indices in the landscape can be exciting, and has the potential to reveal much about all aspects of catchment hydrology, eventually leading to improved predictions.

10 Prediction of runoff hydrographs in ungauged basins

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10.1 What are the dynamics of runoff?

The runoff hydrograph, i.e., the time series of river runoff, is the result of numerous interacting processes within the catchment. Precipitation, runoff generation at the land surface, infiltration into the subsurface, the uptake from vegetation and consequent transpiration, and evaporation from the soil determine how much water will reach the river (i.e., the volume of the hydrograph). Water movement through various flow paths on the land surface (including the river network), in the unsaturated zone and in the groundwater (Chapter 4) determines the dynamics of the runoff (i.e., the hydrograph shape). The hydrograph is the aggregated result of many such processes. It is the most complete runoff signature, but at the same time the most complex to understand. Indeed, all other signatures discussed in the book are technically extracted from the runoff hydrograph by averaging, estimating probabilities or taking extremes of the runoff time series. The mean annual runoff (Chapter 5) gives the hydrograph volume and is controlled by the competition between water and energy. Seasonality (Chapter 6) provides the principal periodic fluctuation of the hydrograph within the year, which can be related to climate seasonality and catchment storages. The flow duration curve (Chapter 7) aggregates all runoff fluctuations in one single signature, which is the probability distribution of runoff. Low flows and floods (Chapters 8 and 9) are the extremes of the hydrograph. All the signatures allow us to extract information on different aspects of the catchment runoff dynamics that would be difficult to see by looking at the hydrograph alone. However, while the signatures capture the full range of runoff temporal variability, they miss one critical piece of information in the runoff hydrograph: the sequence of runoff in time. The example given in Figure 10.1 illustrates this point for a seven-month period in Austria and Bavaria. In the uppermost mountain parts in Tirol (south-west of basin, Figure 10.1) the runoff hydrograph of Galtür is controlled by individual rainstorms with very little baseflow. As one proceeds downstream, Brixlegg has a large baseflow contribution due to snowmelt and there are weekly fluctuations due to hydropower. Further downstream, Schärding shows the combined effect of Brixlegg and the flashy response from some tributaries. In the north-east of the basin, Hofkirchen, the response is dampened due to the sandy aquifers with high storage capacities in this sub-basin, and all of these patterns combine to produce the runoff response seen at the most downstream gauge, Kienstock. There are interesting patterns depicting time evolution as water passes through the stream network, modulated by the hydrological characteristics of the tributaries.

This chapter deals with predicting the entire runoff hydrograph in ungauged basins. Runoff hydrographs form the basis for a wide range of hydrological investigations and water resources management tasks. From a scientific perspective one may be interested in predicting hydrographs in ungauged basins in order to understand how the individual processes combine to produce catchment response. From a practical perspective one may be interested in obtaining design characteristics for spillways, culverts and embankments. One may also be interested in water resources management applications such as water allocation for irrigation, industry and human use, hydropower operation and environmental flow estimation. Predictions of hydrographs in ungauged basins are also essential for risk management such as in flood and drought forecasting. Finally, there is considerable interest in assessing the effects of environmental changes (e.g., land use, hydraulic structures, climate) on the runoff hydrograph and in predicting water quality characteristics, for which accurate runoff predictions are essential (Sachs and McArthur, 2005; Blöschl and Montanari, 2010; Kovacs *et al.*, 2012).

While in the past lumped runoff predictions at one point of the stream network were the norm, there is an increasing

* Coordinating contributor

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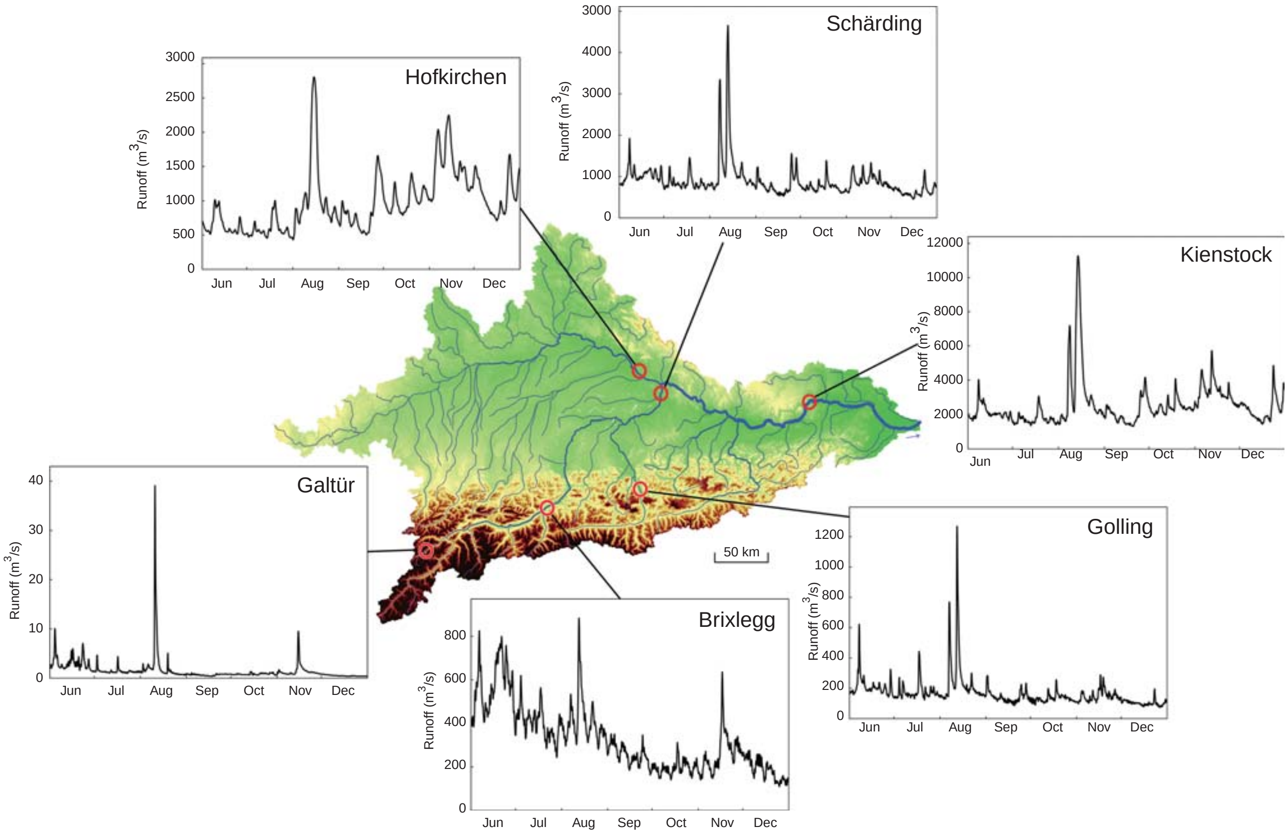


Figure 10.1. Runoff hydrographs observed at different points of the river network in Austria and Bavaria as used for the Danube runoff forecasting system. From bottom-left clockwise: Galtür (98 km²), Hofkirchen (47 600 km²), Schärding (25 660 km²), Kienstock (95 970 km²), Golling (3556 km²) and Brixlegg (8504 km²). Period shown is from June to December 2002. After Nester *et al*. (2011).

need for distributed predictions at every point of the river network, which Beven (2007) dubbed as 'predictions everywhere'. The runoff predictions performed for the Danube (Figure 10.1) are an example of this, i.e., the prediction of runoff at all points of the river network and at all points in time.

This chapter is an extension of the material presented in Chapters 5 to 9, in that the signatures covered in those chapters are subsets of the full range of temporal variability embedded in complete hydrographs. The understanding of these signatures is essential for understanding the complete runoff hydrograph (and vice versa, e.g., Claps and Laio, 2003) and can influence the choice of methods for its prediction. Indeed, the link between the various signatures of variability and hydrograph predictions works in both directions. On the one hand, the quality of hydrograph predictions can be assessed by the ability to reproduce each of the signatures, in order to ensure that the predictions are right for the right reasons (Klemeš, 1986a; Jothityangkoon *et al*., 2001). On the other hand, complete hydrograph predictions remain one of the ways to predict any of the signatures individually.

10.2 Runoff dynamics: processes and similarity

Figure 10.2 shows the hydrographs for two catchments of very different size located in the USA and Austria. The Vermilion catchment in Illinois (top row of Figure 10.2) is a very flat prairie catchment of 3341 km^2 almost completely exploited for agriculture (see the top-left picture). The Gurk catchment, however, is a mountainous catchment of 230 km^2 located in southern Austria. The hydrograph of the Vermilion river is very flashy, i.e., the catchment responds almost immediately to rain with apparently no storage, while the Gurk river has a much more dampened response to precipitation. At first this can seem counterintuitive, since the more-than-ten-times larger catchment is much flashier than the small one, while one would expect higher response times for larger catchments. From a hydrological point of view it is therefore of interest to understand why the Vermilion is flashier than the Gurk, even though it is much larger. Understanding the causal processes responsible for the hydrograph shape is essential to define similarity and dissimilarity between catchments.

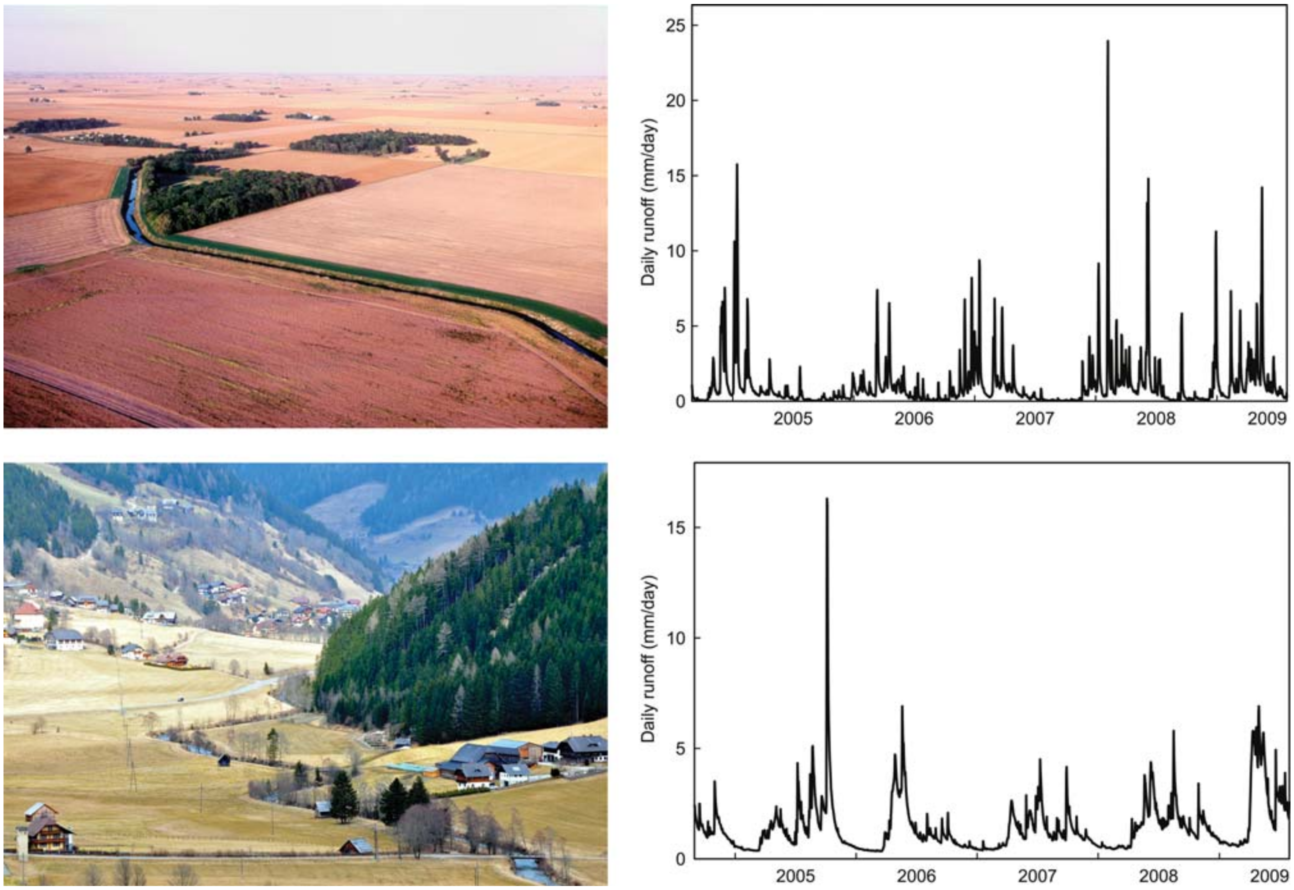


Figure 10.2. Comparison of the Vermilion catchment in Illinois (3341 km²) dominated by short flow paths due to tile drainage (top) and the Gurk catchment in Austria (230 km²) dominated by long flow paths in deeply weathered bedrock (bottom). Photos: B. Rhoads, Creative Commons License.

10.2.1 Processes

Runoff variability across the landscape arises from interactions between the spatio-temporal variability of precipitation and the spatial heterogeneity of soils, topography, vegetation and the stream network morphology. As discussed in detail in Chapter 4, the processes affecting runoff variability are physical (e.g., open channel flow), chemical (e.g., soil cracking and associated changes in infiltration) and biological (e.g., transpiration by plants and soil disruption by animals such as earth worms).

Runoff is generated by rainfall or melting snow. Runoff generation varies temporally and spatially due to the interplay of wetting and drying phases. During the wetting phase, runoff at the hillslopes may be generated by various mechanisms (Figure 10.3): infiltration excess runoff (or Hortonian overland flow) occurs when the rate of rainfall on a surface exceeds the rate at which water can infiltrate the ground. In Figure 10.3a the surface ponding is due to soil compaction; saturation excess runoff occurs in areas with shallow water tables when the soil is saturated and the depression storage filled, and rain continues to fall. In Figure 10.3b the water table is close to the surface due to the vicinity of a stream; and subsurface storm flow occurs when water infiltrated on an up-slope portion of the catchment exfiltrates closer to the channel as is the case in Figure 10.3c. There is a diversity of more complex phenomena such as runon infiltration where surface runoff generated on an up-slope portion of the catchment infiltrates closer to the channel (Figure 10.3d). All of these processes at the hillslope scale depend on the soil physical characteristics (e.g., hydraulic conductivity), the characteristics of macropores, the layering of the subsurface (e.g., soil depth) and the evolution of the soil characteristics along the hillslope (catena). Equally important, the soil moisture state controls all of these phenomena in a number of ways, e.g., through the occurrence of shallow water tables and the activation of fast flow paths.

During the drying phase, the amount of runoff may be reduced in a number of possible ways. Part of the water may evaporate from the soil surface or transpire from the

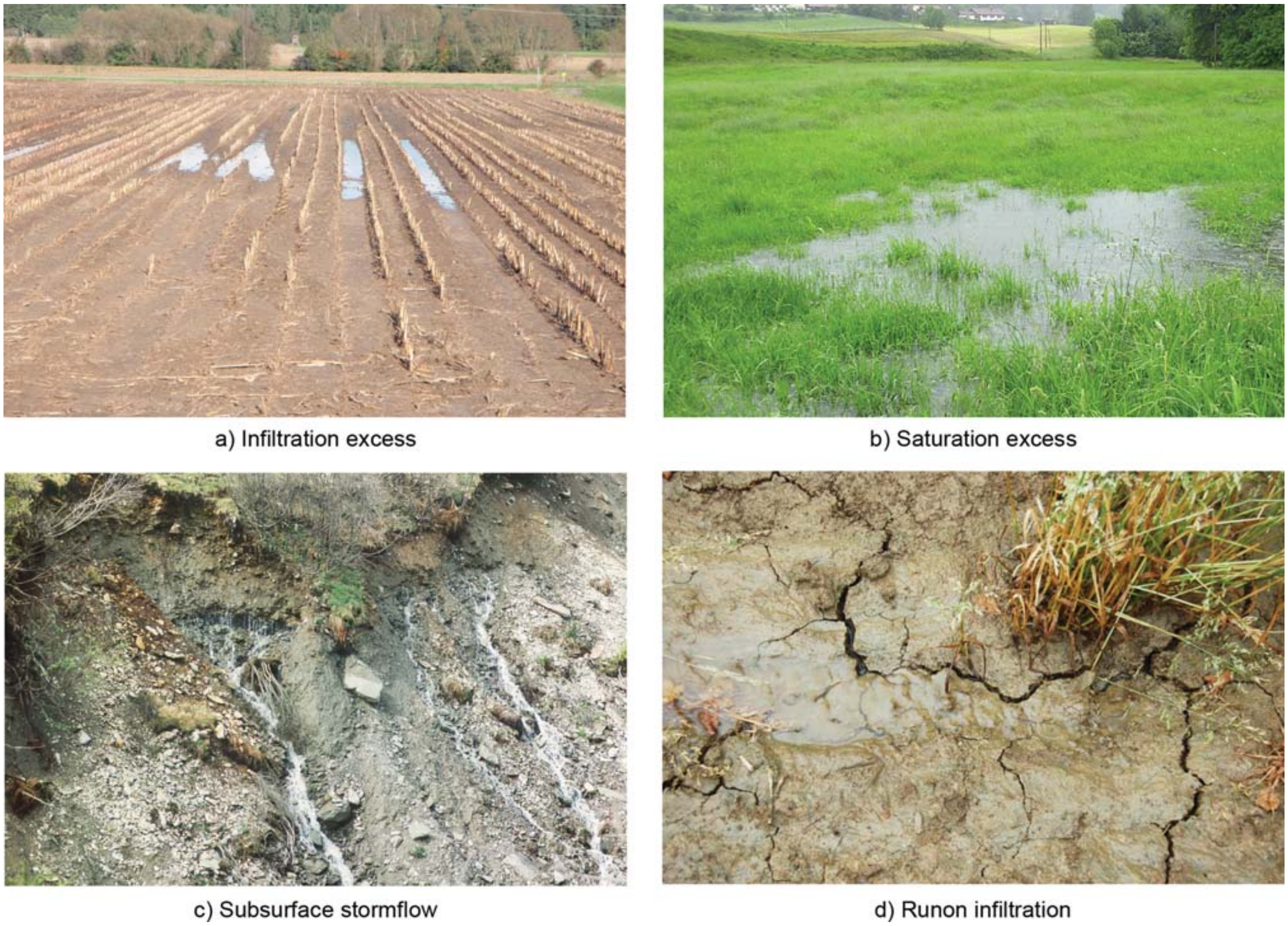


Figure 10.3. Runoff generation mechanisms at the hillslope scale. (a) Infiltration excess near the Hydrological Open Air Laboratory (HOAL), Austria (Photo: E. Murer); (b) saturation excess runoff in the Ebniter catchment, Austria (Photo: E. Zehe); (c) subsurface stormflow in the Löhnersbach catchment, Austria (Photo: R. Kirnbauer); (d) runon infiltration in the HOAL (Photo: A. Eder).

vegetation. The former is controlled by the meteorological conditions, the latter both by the meteorological conditions (water vapour deficit) and by the stomatal resistance of the plants. Water may become temporarily stored in microtopographic depressions or the canopy from which it will evaporate, again controlled by the meteorological conditions. Finally, part of the water may run off on the surface or in the subsurface. These processes have a number of characteristic time scales: the diurnal cycle of evaporation in response to solar radiation fluctuations; a time scale associated with the wetting/drying phase of days or weeks; and the annual cycle of evaporation, again in response to the seasonality of solar radiation. Over long time periods the effects of the drying processes are embedded in the seasonal variations of runoff (e.g., seasonal flow regime, Chapter 6) and the long-term water balance (e.g., annual runoff, Chapter 5). The entire spectrum of this variability is reflected in the catchment's flow duration curve (Chapter 7).

Surface runoff generated locally moves down the hillslopes towards the nearest river channel. The main controls are the topographic slope, roughness and the microtopographic characteristics (e.g., tortuosity of the rills). In the subsurface, water moves along the gradients of the hydraulic potential, where macropore flow usually constitutes the main part of the flow in the soil, while the matrix contributes less. Due to the heterogeneity of the land surface and that of the underlying subsurface soil medium, the water movement over and through the hillslopes takes place via a multiplicity of pathways, such as surface runoff, subsurface stormflow and deep groundwater flow in either porous media or fractured rocks (Chapter 4). Depending on the length, resistance and connectivity of the flow paths, the runoff dynamics may differ vastly (Kollet and Maxwell, 2006). This is illustrated in Figure 10.2. The Vermilion catchment in Illinois has shallow depths to the aquifers and is tile drained. This is because, historically,

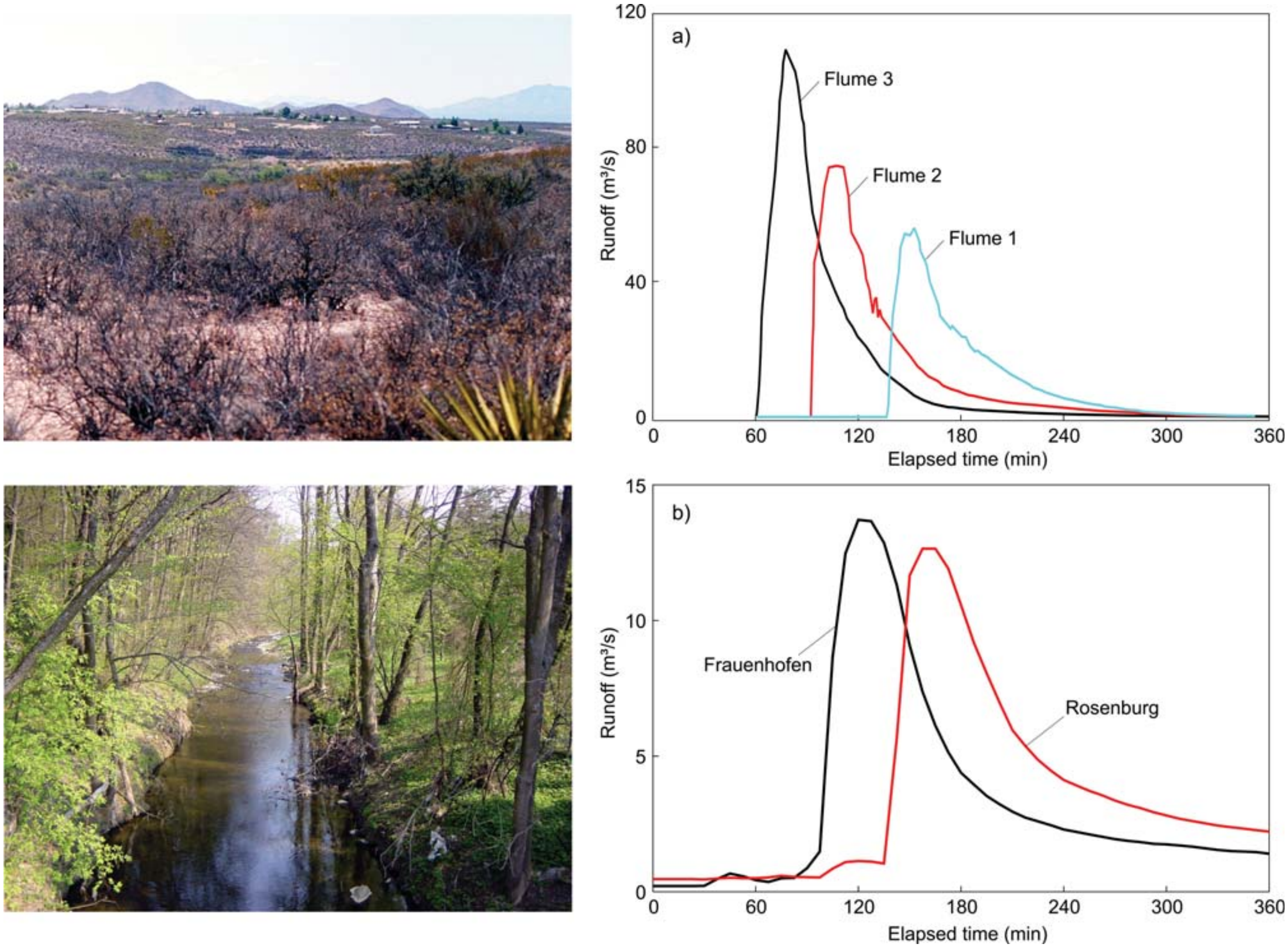


Figure 10.4. Comparison of the catchment of a losing stream in an arid climate (Walnut Gulch, Arizona, top) and a slightly gaining stream in a humid climate (Taffa, Austria, bottom). Photos: D. Goodrich, C. Reszler.

the prairies have been swampy and most of the area has been tile drained for agricultural purposes (Herget, 1978; Hay and Stall, 1974). The flow paths tend to be very short: macropore flow from the surface into the tile drains, which are connected efficiently to the drainage channels. The runoff response is therefore very flashy. In contrast, the Gurk catchment has event response times of a few days, even though the catchment area is much smaller than that of the Vermilion. This is due to large subsurface contributions to stormflow as a result of the highly permeable rock (weathered phyllites) (see Gaál *et al*., 2012, and Section 9.2.2).

When water reaches the channels, channel routing takes place. The movement of the water in the channel is controlled by the stream geometry, the roughness and the water level itself. Often there is a complex interaction between the stream water and the aquifer (e.g., Derx *et al*., 2010). Depending on the relative water levels of the stream and the aquifer, the stream may lose or gain water from the aquifer and this may vary with time. Typically, arid climates often have losing streams, while in humid climates gaining streams prevail, but almost always this varies very much along the reach over short distances (Section 2.2.2). An example of streams in arid and humid climates is given in Figure 10.4.

So far, the processes involved in producing the runoff hydrographs have been discussed from a Newtonian perspective, in the spirit of Freeze and Harlan's (1969) blueprint for a physically based, digitally simulated hydrological response model. As discussed in Section 2.1.1, catchments are complex systems resulting from the co-evolution of climate, geology, soils, topography and vegetation, so there may be interdependencies among the characteristics across a wide range of time scales that go beyond the description above. For example, the slow response of the Gurk catchment in Figure 10.2 is a result of the co-evolution of landform and hydrological processes where the large subsurface contributions lead

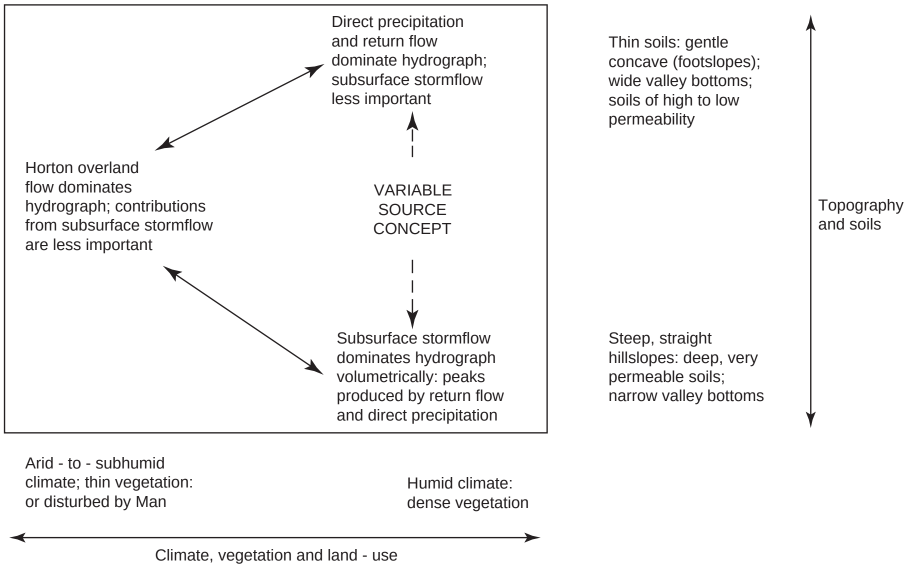


Figure 10.5. Dominant processes of runoff generation mechanisms at the hillslope scale. From Dunne (1978).

to relatively little erosion and a less efficient drainage system in the landscape than in other areas (Gaál *et al.*, 2012). Because of this, a comparative approach across different climates and landscape regions may reveal interesting patterns of catchment behaviour (Falkenmark and Chapman, 1989). The schematic in Figure 10.5 suggests that catchments in arid climates will more likely experience higher precipitation intensities and sparser vegetation cover leading to the runoff hydrograph being dominated by Horton overland flow. Infiltrated water in arid places has less opportunity to pass through the root zone and recharge groundwater due to the high atmospheric demand and hence high evaporation rates. On the other hand, the dominance of horizontal fluxes increases with increasing humidity and steepness of catchments. Catchments in humid regions tend to have hydrographs dominated by subsurface stormflow, particularly where soils are deep and permeable. If soils are thinner, subsurface storm flow may be less important and saturation excess runoff may be more important. Figure 10.5, in fact, can be interpreted as depicting schematically the co-evolution of catchments and the resulting runoff mechanisms. Catchments located at higher altitudes typically have significant snow cover and therefore a strong seasonal storage component. The seasonality of water inputs tends to be out of phase with that of the energy inputs in these catchments and snow accumulation and snowmelt often dominate the runoff hydrograph.

With increasing catchment size, runoff variability is increasingly dominated by stream channel flow processes, including delay and attenuation associated with the hydraulics of the flow, along with channel losses and uptake by riparian vegetation (in arid regions), floodplain inundation, and changing morphology and hydraulic geometry of river networks. Large catchments are also affected by increased spatial heterogeneity, including substantial changes in the nature of climate inputs and dominant processes (e.g., dominance of snow processes in headwater regions and the influence of porous aquifers in downstream areas). The runoff hydrograph observed at any point in the stream network therefore embeds within it all the hydrological variability associated with the co-evolution of the catchment.

The runoff dynamics of catchments can change with time, in particular if human modifications have occurred. The most common modification is through the construction of dams and other hydraulic structures, which, through the effects of associated impoundments and controls, tend to reduce the variability of runoff. Extraction of river water for irrigated agriculture has the effect of increasing evaporation and reducing river runoff, whereas withdrawals of water for municipal water supply and other human uses are eventually returned after human consumption, which may reduce the runoff variability and increase low flows (Wang and Cai, 2009). In many agricultural landscapes tile drainage is a major factor that may modify the dynamics of the runoff hydrographs (see Figure 10.2). Changes in the vegetation cover may alter the runoff dynamics significantly. Typically, the removal of forest leads to reductions of evaporation, increases in antecedent wetness, and thus increases in the fraction of precipitation that is converted to runoff (Bosch and Hewlett, 1982).

Figure 10.6 illustrates the effect of forest removal on the runoff dynamics, the result of a paired catchment study in the forested south-west of Western Australia, experiencing a Mediterranean climate. Salmon (0.82 km^2) and Wights (0.94 km^2) are neighbouring catchments. Salmon has remained fully forested, whereas Wights was fully cleared

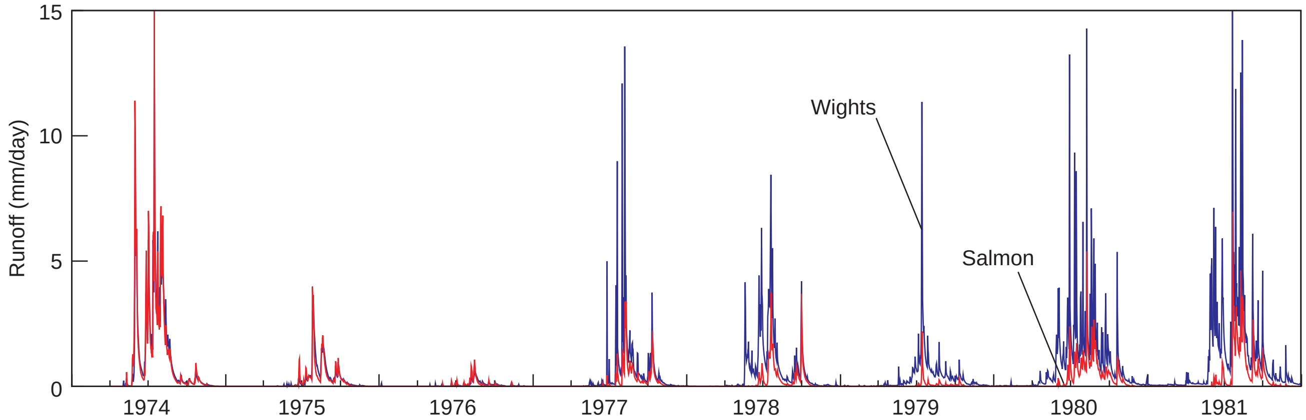


Figure 10.6. Runoff hydrographs observed in Salmon and Wights catchments in the south-west of Western Australia demonstrating change in the runoff dynamics due to land use change. Joint monitoring started in 1974, forest clearing on Wights occurred in 1976, whereas Salmon remained forested. Adapted from Sivapalan *et al.* (1996).

forest in 1976 (2 years after monitoring started, which continued until recent times), and replaced by shallow-rooted pasture. The removal of the deep-rooted Eucalyptus forest meant sharp reduction of evaporation, increased recharge, gradual water table rise (over a 6-year period), and overall increase in the wetness, and the net result is increased runoff. This can be clearly seen in Figure 10.6, most notably after 1977, resulting even in summer flows in a previously ephemeral catchment.

Urbanisation may shortcut the flow paths and therefore may result in flashier runoff hydrographs, which will cause lower baseflow, and higher flood peaks (e.g., Konrad and Booth, 2005). Urban runoff is controlled by the distribution and connectivity of sealed areas, by the topography as well as the characteristics of any sewer systems.

10.2.2 Similarity measures

In order to transfer information on the runoff hydrograph across the landscape, e.g., from gauged to ungauged catchments, one needs to identify what hydrological similarity is. A very simple measure of hydrological similarity is spatial proximity, based on the rationale that the controls on the runoff hydrograph may vary smoothly in space, so the runoff hydrographs in catchments that are close to each other will be similar. However, hydrological processes are often more complex than this as the runoff generation processes may vary tremendously over short distances. An alternative therefore is to define hydrological similarity in terms of runoff signatures (runoff similarity) and in terms of climate and catchment characteristics (climate and catchment similarities, see Figure 2.8) that are related to the dominant processes of Section 10.2.1.

Runoff similarity

What makes two catchments similar in terms of the complete runoff hydrographs? There are many facets to a runoff hydrograph, so this will depend on which facets we are interested. Clearly, one or a combination of the signatures of runoff variability discussed in Chapters 5 to 9 (i.e., annual, seasonal, flow duration curve etc.) are obvious candidates to be used in similarity measures, especially if used in a hierarchical manner, considering that they capture different parts of the full spectrum of variability embedded in runoff hydrographs.

Figure 10.7 shows how the individual runoff signatures are related to the complete hydrograph for two catchments in Australia: Harvey River catchment (148 km^2), 120 km south of Perth, Western Australia, and Seventeen Mile Creek catchment (619 km^2) located in the Katherine region, near Darwin in northern Australia. According to the Köppen climate classification, Perth is located in a temperate climate region, with a distinctly dry summer period, with high precipitation during the cold winter period (May–October) and almost no precipitation during the November–April summer period (annual precipitation is 928 mm). Darwin is located in the tropical region of Australia, with the majority of precipitation during the wet season (November–April), and very little precipitation in the dry season (May–October) (annual precipitation is 979 mm, only slightly higher than Perth). The annual potential evaporation in Perth is 1757 mm, and in Darwin it is 2220 (30% higher).

Both catchments exhibit strong seasonality of runoff (Perth due to its Mediterranean climate and Darwin due to its monsoon climate, although the timing is different), yet with considerable inter-annual variability in the annual, monthly and daily flows (i.e., flow duration curves),

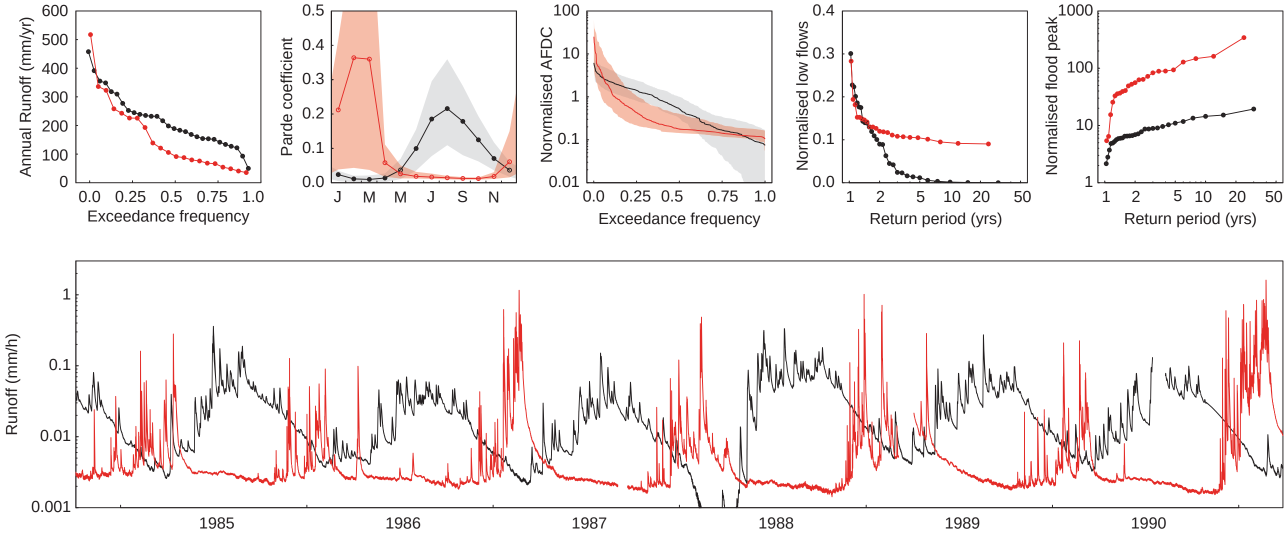


Figure 10.7. Signatures of runoff variability for two catchments: Harvey River catchment (148 km²), near Perth (black lines); and Seventeen Mile Creek catchment (619 km²), near Darwin (red lines). (Top, from left to right) Distribution of annual runoff, seasonal runoff regime, flow duration curve, distribution of annual q_{95} low flows, and distribution of annual floods. (Bottom) Hydrographs of the two catchments. Courtesy Jos Samuel.

especially Darwin. On the other hand, the hydrographs indicate that Darwin experiences more episodic runoff responses with higher runoff peaks, due to the high rainfall intensities experienced. This is also reflected in the flow duration curves, and in the much higher flood peaks in the flood frequency curves. On the other hand, low flows in Darwin are much higher than in Perth, and fairly invariant between years (note much lower inter-annual variability of flow duration curves at the low flow end). This is due to the presence of a shallow regional groundwater aquifer, which maintains low flows at a relatively high rate in all years.

However, these signatures do not fully capture every aspect of variability represented in a runoff hydrograph. In arid basins, for example, the sequencing of runoff events (e.g., average period between events) and the non-linear relationship between event runoff and precipitation (e.g., expressed by runoff coefficient functions) can be more powerful indicators of hydrological similarity. Similarly, in terms of process realism, total runoff can be decomposed into its various components (e.g., infiltration excess, saturation excess, subsurface stormflow), and runoff similarity can be extended to cover the relative dominance of these processes, and patterns of their temporal and spatial variations. These can be ascertained in gauged basins on the basis of baseflow separation procedures, assisted by environmental tracers (see Chapter 4), and through the use of physics-based models, conditioned on measured runoff hydrographs.

Climate similarity

Climate similarity, in the context of runoff hydrographs, can be expressed at many scales, as discussed in several previous chapters. At the annual scale, similarity is governed by the competition between water available (e.g., annual precipitation, P) and energy available for evaporation, normally expressed in terms of annual potential evaporation, E_p (Budyko, 1974; L'vovich, 1979). In this case, climate similarity can then be expressed in terms of the aridity index, E_p/P. In the case of seasonal flow, the relative timing of P and E_p is a key similarity measure (i.e., in phase or out of phase). In cold regions, the seasonal energy or temperature variation, in relation to precipitation variability, is an additional similarity measure, since it determines the occurrence and timing of precipitation as snow and snowmelt. The climatic regime, including radiation energy (or E_p) and temperature as well as precipitation, also controls the nature of vegetation cover dynamics, e.g., phenology (Czikowsky and Fitzjarrald, 2009), aspects of which cannot be simply expressed in terms of quantitative measures, and are typically presented through ecosystem classifications at regional scales.

Additional features of the climate inputs relevant to runoff hydrographs include the sequencing of precipitation events (which may be expressed in terms of precipitation duration curves, see Chapter 7), characteristic spatial distribution patterns (e.g., orographic effects, patchiness) and storm movement. Patchy and episodic precipitation in arid regions give rise to episodic, localised runoff events and

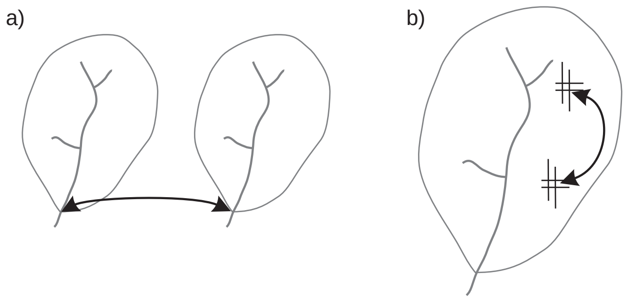


Figure 10.8. Two types of catchment similarity: (a) similarity between two different catchments considered as holistic functional units; and (b) similarity between two different functional units within the same large catchment.

likely flash flooding, whereas more uniform, widespread precipitation produces runoff fields that cause more widespread and persistent flooding (Viglione *et al*., 2010ba, b; Zoccatelli *et al*., 2011). These differences in precipitation regimes can have different impacts not only on runoff fields but also on vegetation patterns that develop in response to precipitation, and on soil erosion and channel morphology. Thus, in the long term, through such co-evolution processes, they may lead to differences in catchment characteristics that are attributable to the climate as well, and give rise to fundamental differences in runoff behaviour. For example, the dominant control on runoff variability in northern Queensland, Australia, is storminess, whereas in south-west Australia the dominant feature is the seasonality of precipitation (Jothityangkoon and Sivapalan, 2009; Samuel and Sivapalan, 2008). These characteristics have implications for the type of models that are needed in different regions.

Catchment similarity

Catchment similarity can be defined in two different ways (Figure 10.8). The first is the similarity of two catchments as a whole, based on catchment-scale indicators (Figure 10.8a). This type of similarity measure can be used to transfer model structures or calibrated model parameters from gauged to ungauged catchments. The most important control on the way catchments transform climate inputs into runoff variability, and therefore the most important similarity index for catchments as a whole, is catchment area, because of its aggregation effects and the fact that bigger storage is commonly associated with catchment size (Nester *et al*., 2011). With respect to runoff generation and partitioning, the factors that govern similarity are those relating to the soils and geology. The saturated hydraulic conductivity of surface soils is the key to determining if infiltration excess runoff is dominant, especially in relation to typical precipitation intensities, and quite often soil texture can provide a first indication of infiltration capacity. Soil depth is another determinant of runoff generation, including its distribution in space, especially in relation to annual precipitation, or typical event rainfall depth. Therefore the depth to bedrock or to an impermeable stratum would be indicative of the likelihood of saturation excess and/or subsurface stormflow within the catchment. Vegetation type and cover play important roles in the water balance and catchment co-evolution. For these reasons geology, soil texture and vegetation cover are potential similarity indicators at the catchment scale. The hypsometric curve expresses how the area of the catchment is distributed according to elevation, and thus governs the distribution of topographic gradients that drive the flow, and is therefore another catchment-scale similarity indicator.

The second type of similarity is between different landscape units as represented by computational pixels, hillslopes or subcatchments *within* a catchment (Figure 10.8b). Measures of this type of similarity can be used in spatially distributed modelling to reduce the dimensionality of the parameter estimation problem (Blöschl *et al*., 1995; Grayson and Blöschl, 2000). The similarity measures are similar to those for the whole catchments; however, they relate to smaller landscape units. Often, index methods are used for this purpose (Section 4.4.2). Topographic indices such as that of Beven and Kirkby (1979) can be used to delineate similar regions within a catchment. Figure 10.9 presents an example of the delineation of a catchment into functional landscape units. These are wetlands, hillslopes and plateaus, corresponding to three dominant runoff generation mechanisms: saturation excess overland flow, storage excess subsurface flow, and deep percolation. In the hydrological response unit (HRU) concept (Leavesley, 1973; Flügel, 1995) the catchment is partitioned on the basis of slope aspect, vegetation type and soil type. Each resulting subunit is considered homogeneous with respect to its hydrological response. The characteristic of the vertical soil profile is often essential and therefore a useful similarity parameter. An example is the HOST classification, where the interaction between soils, geology and topography has been used to identify seven classes, each of which is considered homogeneous with respect to local soil response. More generally, measures of similarity could include surface infiltration capacity (permeable vs. impermeable soils), soil depth (deep vs. shallow soils), topographic slope and lateral saturated hydraulic conductivity (indicating well drained vs. poorly drained soils). Of course, many of these features could exhibit organised heterogeneity within a catchment, such as soil and vegetation catenas, and these can be additional indicators of catchment similarity.

Similarity measures (such as aridity index, topographic wetness index, runoff coefficient, bifurcation ratio and

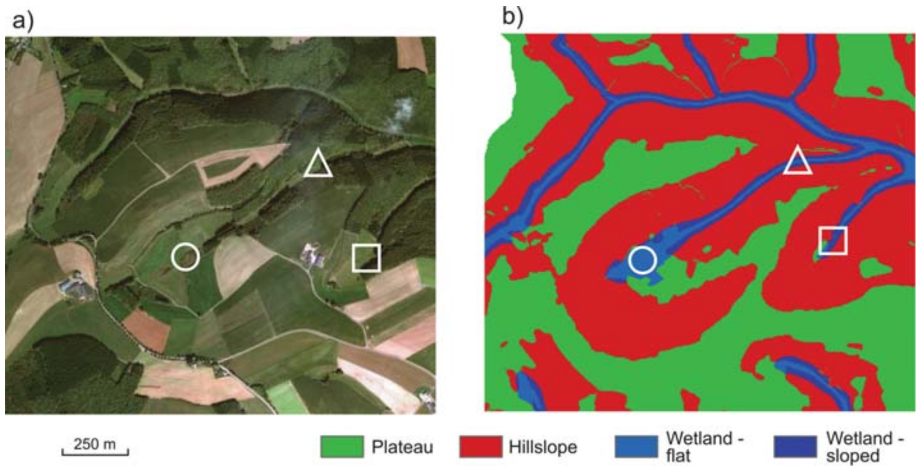


Figure 10.9. (a) Aerial photo of the headwater of the Wark catchment, Luxembourg; (b) categorised landscape units based on topographic analysis. Symbols indicate identical positions on the two maps. From Gharari *et al.* (2011).

other usually dimensionless quantities) differ in terms of the processes they aim to represent (Blöschl, 2005). A suitable choice of the similarity measures depends on the dominant runoff generation mechanism one expects in the catchments. In other words, similarity relates to the prevailing feature of runoff generation and routing, rather than similarity of hydrological systems as a whole (Kuchment and Gelfan, 2009). An example is the similarity parameters based on the relative dominance of the infiltration excess and saturation excess mechanisms of Robinson and Sivapalan (1995; see Section 9.2). For the arid steppe region where the infiltration excess mechanism of runoff generation dominates, Kuchment and Gelfan (2009) found that dimensionless indices derived from the Richards equation work well as similarity measures to transfer calibrated parameters from gauged to ungauged basins. Also, there are cases where the similarity defined on the available catchment/climate characteristics does not fully map to the hydrological similarity (Oudin *et al.*, 2010). Clearly, it is important to define what processes are to be captured by the similarity measures and choose them accordingly, within the limits of data availability, and any additional data that may be collected, e.g. through field visits.

10.2.3 Catchment grouping

On the basis of the similarity measures, catchments can be grouped into regions that are considered homogeneous in terms of runoff processes. For the purpose of estimating runoff hydrographs in ungauged basins, catchment grouping is needed for a number of purposes. Most importantly, if a group can be considered homogeneous in terms of runoff processes, the same relationships between catchment characteristics (e.g., soil depth) and model parameters can be used in the entire region (see Figure 2.10). The group of catchments can also be used to transfer the model structure from gauged to ungauged catchments. Finally, the grouping can provide insight into what are the main runoff processes at the regional scale. The techniques used for catchment classification are discussed in detail in Section 5.2. Here we discuss aspects that are specific to runoff hydrographs.

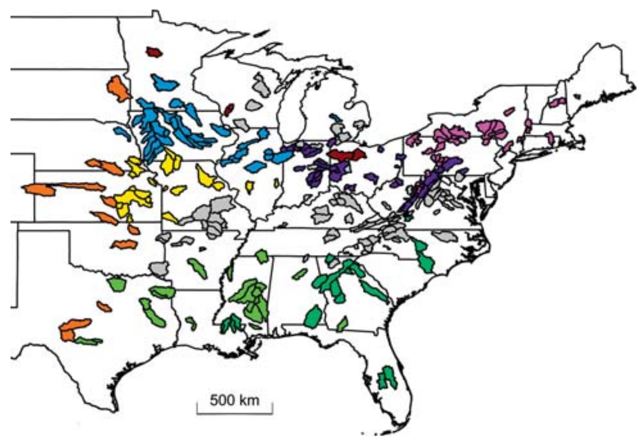


Figure 10.10. Clusters of catchments according to their runoff signatures in the eastern half of the USA. From Sawicz *et al.* (2011).

Grouping based on runoff similarity

Grouping of catchments can be done on the basis of one or more of the runoff signatures discussed in Chapters 5 to 9, i.e., using the signatures as a measure of runoff similarity. Figure 10.10 presents an example of catchment grouping in the eastern half of the USA based on runoff similarity. In this case, the signatures used were mean annual runoff ratio, slope of the flow duration curve, runoff elasticity

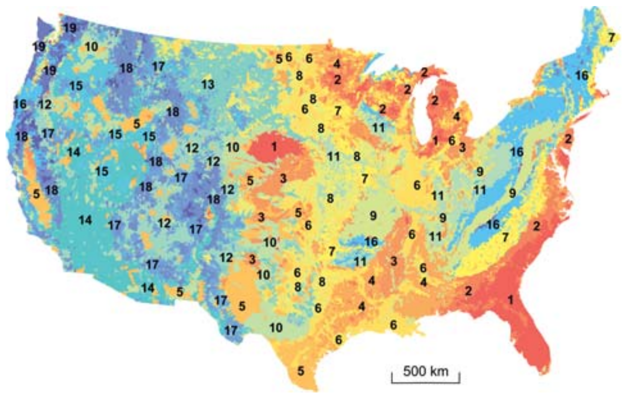


Figure 10.11. Hydrological landscape regions in the USA ranging from flat land (group 1, red) to mountainous (group 20, blue). From Wolock *et al*. (2004).

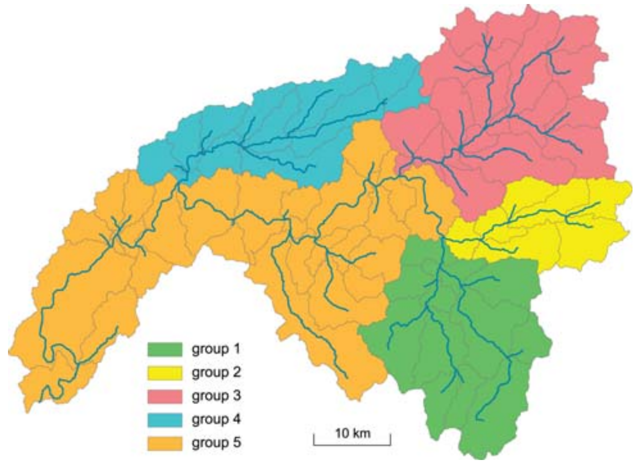


Figure 10.12. Subcatchments within the Illinois River basin grouped on the basis of clay ratio, topographic slope, regional geology and dominant runoff generation mechanisms. Increasing group numbers are accompanied by decreasing clay content of soils (hence increasing saturated hydraulic conductivity) and increasing topographic slope. This leads to decreasing saturation excess runoff and increasing subsurface stormflow, as a fraction of total runoff. From Li *et al*. (2012).

(the sensitivity of runoff to the variability of precipitation), baseflow index, and the number of snow days. Cluster analysis was then used to identify nine classes: Catchments in the north-eastern USA (pink cluster) are characterised by high runoff coefficients and large amounts of snow; catchments slightly further to the south (in Pennsylvania and Virginia, purple cluster) by lower runoff ratios and less dominant snow storage, long storm durations and relatively poorly drained soils; further to the south (grey cluster) by less snow, less seasonal precipitation, a higher percentage of sandy soils and low relief. The number of snow days decreases even further in the blue-green cluster and catchment storage is high resulting in higher baseflow. In the west of this cluster group, in the southern Mississippi River basin (green cluster) there is somewhat lower baseflow. The catchments located furthest west (orange cluster) are more arid, experience the lowest precipitation and lowest runoff ratios. Catchments south of Iowa (yellow cluster) have the lowest baseflows, which is related to very poorly drained soils. Numerous other examples of catchment grouping based on runoff classification are reviewed in Olden *et al*. (2012) and Kennard *et al*. (2010).

Grouping based on climate and catchment characteristics
Catchments can also be grouped on the basis of climate and catchment characteristics. Wolock *et al*. (2004) used the hydrological landscapes concept of Winter (2001) to group catchments into hydrological landscape regions according to their similarity of landform (e.g., relief, percentage of flatland), geological texture (permeability of soil estimated from percentage of sand; bedrock permeability from lithological groups) and climate characteristics (mean annual precipitation minus potential evaporation). They combined principal component analysis and cluster analysis to obtain 20 groups. The groups range from flatlands (red in Figure 10.11) to mountainous (blue in Figure 10.11). Group 1, for example has very flat terrain and very permeable soils and bedrock and a surplus of precipitation over potential evaporation, so both shallow and deep groundwater are likely to occur. Group 6 has impermeable soils and bedrock and a sub-humid climate, so overland flow is likely to occur. Group 20, in contrast, is mountainous, has permeable soils, impermeable bedrock and a humid climate, so shallow groundwater flow is likely to occur. There are differences between this grouping and the runoff grouping in Figure 10.10. In Figure 10.11, geology and topography seem to be strongly reflected in the grouping, while in Figure 10.10 climate may be more important.

Landscape units can also be grouped into HRUs on the basis of slope aspect, vegetation type and soil type. These can then be used as a basis for inferring model parameters from landscape characteristics for distributed hydrological models. The way the layers of information are combined can have various degrees of process representation. Flügel (1995) combined the layers by reasoning for a unit to represent, for example, ‘rangeland on gley soil at the valley floor with shallow groundwater over impervious bedrock’. Figure 10.12 presents an example of catchment grouping in a large catchment in Oklahoma, USA, on the basis of clay ratio of soils, regional geology and topographic slope, and their combined effect on dominant runoff generation mechanisms. Increasing group numbers indicate decreasing clay content of soils (thus increasing saturated hydraulic conductivity), accompanied also by increasing topographic slope. The net effect of this is that increasing group numbers mean that the fraction of runoff by saturation excess decreases (from about 80% of total runoff to less than 20%), while the fraction of subsurface stormflow increases from about 20% to more than 80%). The catchment groups are also nested subcatchments within the large catchment, and the grouping is used to explore the effects of changing dominant processes on the runoff routing behaviour within the river network.

10.3 Statistical methods of predicting runoff hydrographs in ungauged basins

Statistical methods use available runoff time series data from neighbouring catchments (donor catchments) to estimate runoff hydrographs at ungauged locations based on one or more of the similarity measures and/or grouping methods discussed above. In this book, statistical methods of predicting runoff hydrographs in ungauged basins refer to methods that do not use precipitation or do so in a statistical way. Methods that use precipitation based on balance equations are dealt with in Section 10.4.

The main advantage of statistically based runoff simulation methods is that they avoid the use of uncertain input variables such as precipitation and potential evaporation. For several of the methods that will be described here catchment characteristics are also unnecessary. The disadvantage is that most of these methods are data intensive, i.e., can only be applied in medium to densely gauged regions, and they are not applicable when one is interested in the causal relationship between precipitation and runoff, as in the case of runoff forecasting. Even when considerable data exist, there are several challenges to the application of statistical methods for predictions of runoff time series in ungauged locations. This has to do with the nature of the spatially random field that is runoff. There are several challenges to the application of statistical methods for predictions of runoff time series in ungauged locations. As described in Section 10.2, the runoff field has the imprint of the river network, and therefore, even though it is a spatially correlated random field, its correlation structure is very different from that of the rainfall point process that produced it (Skøien and Blöschl, 2006b, 2006c). Therefore the spatial dependency and correlation structure have to be expressed not in terms of Euclidean distance but distance measured along the river network in a hierarchical manner (Skøien *et al.*, 2006), and must include the scale effects due to the relative catchment sizes on the runoff variability, including along a river network in the case of nested catchments. While a possible approach for continuous runoff prediction is to predict the runoff as a weighted average of surrounding observations, the weights must take into account not only the spatial distance between the target catchment and the neighbours, and associated correlation coefficient, but, in the case of nested catchments, also the particular topology of streams and rivers that possibly link them.

10.3.1 Regression methods

The use of regression to directly transfer the full hydrograph to ungauged locations is rather unusual. There are some historical examples though that focused on infilling missing runoff time series by transferring information from other gauged locations using regression. For example, Kritski and Menkel (1950) developed a method for hydrograph estimation of natural runoff for a catchment affected by construction of a reservoir using regression-based transformation of hydrographs measured in an unchanged analogue catchment. Martin (1964) related monthly runoff of one basin to those of a nearby basin with different regressions and showed that including information on the monthly time series of precipitation generally improved the results. A very similar method was proposed by Raman *et al.* (1995) for extending short records. The fact that precipitation inputs are used makes these procedures look like extremely simplified models, such as those discussed in Section 10.4, but without physical or conceptual interpretation of the obtained relationships. The most common approaches for hydrograph transfer are variants of the index method, which is discussed in the next section.

10.3.2 Index methods

Index methods work on the principle of similarity, i.e., the assumption that the nature of (temporal) variability in the ungauged catchment is in some sense similar to that of the donor catchment(s). This section discusses three different index methods to estimate continuous runoff at an ungauged location, assuming varying degrees of similarity. In all cases, estimated continuous runoff time series at the ungauged or recipient catchment spans the whole period of observed record at the donor catchment(s) and require regionalised estimates or direct measurements of key statistics of runoff at both the ungauged and donor catchments.

The simplest form of similarity is to assume that the time series of runoff, once normalised by the mean flow, is identical between the donor catchment and the ungauged catchment. This, when combined with a regionalised relationship between mean flow and catchment size, enables one to regionalise observed runoff. For example, the drainage area ratio method (Stedinger *et al.*, 1993) assumes that the runoff at the donor and recipient ungauged catchments only differ because the sizes of the drainage areas at the respective catchments are different. For a given time, the drainage area ratio method assumes that the runoff per unit area at the donor and recipient catchments are equal and estimated runoff is determined by the equation (in this case assuming a linear relationship of mean flow with catchment area).

An extension of the drainage area method is the maintenance-of-variance (MOVE) method (Hirsch, 1979). In this case the method assumes that the runoff values differ only by the mean and standard deviation, and that the time series normalised by both the mean and standard deviation, i.e., (runoff − mean) divided by the standard deviation, is preserved between the donor and recipient catchments. In this case, the method works by regionalising both the mean and standard deviation between the donor and recipient catchments. Note that both the drainage area ratio and MOVE methods use the runoff at the analogue catchment to estimate both the magnitude and timing of the runoff at the ungauged catchment.

One can go one step further: instead of regionalising just the mean and the variance, one can regionalise the entire within-year variability or probability distribution of runoff, e.g., as expressed in the flow duration curve. Several authors have used a two-part method to first estimate the flow duration curve at the ungauged catchment through an appropriate regionalisation procedure, and used the timing of the observed runoff at the donor catchment to determine the time series of runoff at the recipient ungauged catchment (Fennessey, 1994; Hughes and Smakhtin, 1996; Smakhtin *et al.*, 1997; Smakhtin and Masse, 2000; Mohamoud, 2008; Archfield *et al.*, 2010; Shu and Ourda, 2012). For a given point in time the exceedance probability of the runoff of the donor is then used to estimate the runoff at the ungauged site using the regionalised flow duration curve. The flow duration curve can be estimated by any number of methods as described in Chapter 7.

Selecting the donor catchment

The transfer methods presented all transfer the timing of the runoff from the donor catchment to the ungauged catchment. Whereas previous application of these methods selected the donor catchment located closest to the ungauged location or a stream gauge located upstream or downstream of the ungauged location, if some runoff information were known at the ungauged location, one would use the correlation between the time series to select the donor catchment, as is done in the MOVE methods (Hirsch, 1982; Vogel and Stedinger, 1985) for record augmentation and patching. For this reason, Archfield and Vogel (2010) developed a geostatistical approach to select the donor catchment for runoff transfer methods that move the runoff time series at a donor catchment to an ungauged location where no measurements exist to estimate the correlation in runoff between the two locations. The method, termed the

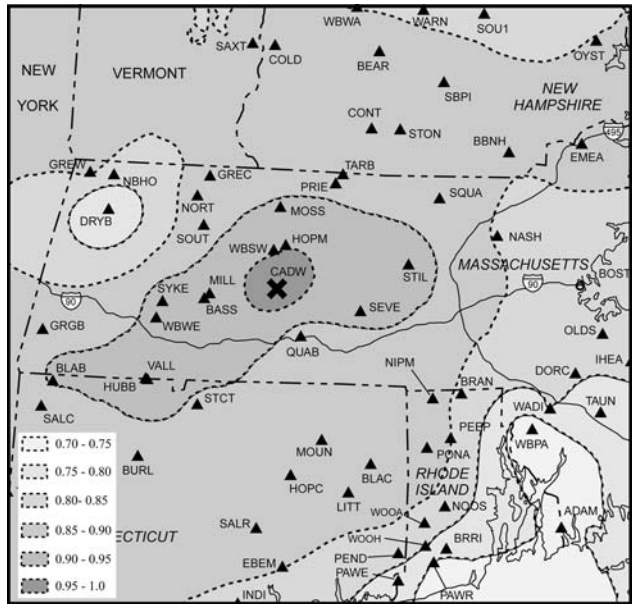


Figure 10.13. Estimated correlations between runoff at Cadwell Creek near Belchertown, Massachusetts (CADW, indicated by the cross) and any other location in the study region. Size of the area is 220 km across. From Archfield and Vogel (2010).

map correlation method, calculates the cross-correlation coefficients of runoff with all the other stream gauges and then interpolates these correlation coefficients in space using kriging. The procedure is repeated for each of the stream gauges. This means there will be a total of n maps of correlations for n stream gauges in the region. For a given ungauged catchment, the map out of the n maps is selected for which the catchment outlet location corresponds to the highest interpolated correlation coefficient. The stream gauge from which that map was produced is then used as the donor for the ungauged catchment. Figure 10.13 presents one of the n correlation maps produced by Archfield and Vogel (2010). Although their method did not take the stream network structure into account, they showed that their method gave better runoff estimates than when choosing the nearest stream gauge as the donor.

Harvey *et al.* (2012) compared various methods for estimating runoff from short records for catchments in the UK, and suggested that index methods based on transforming exceedance probabilities and multiple regression approaches performed best. They also showed that choice of the donor station has a strong influence on the performance.

10.3.3 Geostatistical methods

Geostatistical methods (Gandin, 1963; Matheron, 1963) exploit the spatial correlation of the variable of interest and provide an estimate of that variable as the weighted

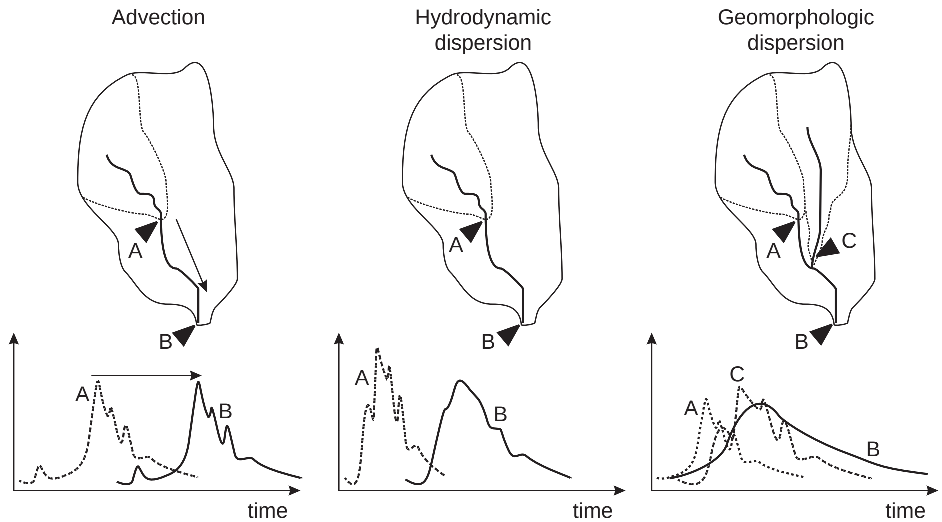


Figure 10.14. Schematic of runoff routing processes represented by top-kriging. Hydrographs for locations A, B and C are shown. From Skøien and Blöschl (2007).

average of the measurements in the neighbourhood. The weights can be found from the expected correlations of the variable at the observation and prediction locations. Geostatistical methods provide estimates of the uncertainty and allow for measurement errors (De Marsily, 1986, p. 300; Merz and Blöschl, 2005). While traditional geostatistical methods such as ordinary kriging are not suitable for stream networks, the top-kriging approach of Skøien *et al*. (2006) does account for the stream network structure. Based on their concepts, Skøien and Blöschl (2007) proposed a new method, termed spatio-temporal top-kriging, which estimates runoff time series at all locations of a river network. The main idea of the approach is to conceptualise catchments as space-time filters and to exploit the space-time correlations of runoff along the stream network topology. The spatio-temporal top-kriging method represents two main groups of processes that control runoff. The first group consists of variables that are continuous in space and includes precipitation, evaporation and soil characteristics. In top-kriging their variability is represented by the point variogram that is based on Euclidian distances. The second group of processes is related to routing on the hillslope and in the stream network. Their effect cannot be represented by Euclidian distances. Top-kriging represents these processes in three ways. (i) The channel network structure and the similarity between upstream and downstream neighbours are represented by the catchment area that drains to a particular location on the stream network. The catchment areas are defined by their boundaries in space. (ii) Advective runoff routing (Figure 10.14 left) is represented by a simple routing model that takes into account the travel time between upstream and downstream neighbours. (iii) Dispersive routing is represented by the space-time filter (Skøien and Blöschl, 2006a). Dispersive effects include hillslope routing as well as hydrodynamic and geomorphological dispersion (Figure 10.14 centre and right). Hydrodynamic dispersion is caused by different travel times in the stream within individual reaches, while geomorphological dispersion is related to the different lengths and junctions of the stream network and results in a superposition of runoff from the tributaries.

Using this method, Skøien and Blöschl (2007) estimated runoff time series with hourly resolution at many locations of the stream network in Austria. An example for daily runoff is shown in Figure 10.15 for two points in time. Note that top-kriging captures the routing of high runoff depths (>15 mm/d) in small catchments on 26 March down the stream network on 27 March. Cross-validation tests showed that for their catchments the median Nash–Sutcliffe efficiency (NSE) was 0.87, as compared to 0.67 for estimates of a deterministic runoff model that used regionalised model parameters. The much better performance of top-kriging is because it avoids precipitation data errors and avoids the parameter identifiability issues of traditional runoff models. The analyses indicate that the kriging variance can be used as an estimate of the predictive uncertainty for identifying catchments with potentially poor estimates.

10.4 Process-based methods of predicting runoff hydrographs in ungauged basins

Process-based methods are rainfall–runoff models that estimate the runoff hydrograph from precipitation and other climate variables. The main challenge in ungauged catchments is the lack of local runoff data that could be used for model selection and calibration. There is a wide

Table 10.1. *Information that can be used to assist in model structure selection in view of process fidelity*

	A-priori perception of processes	Field data, reading the landscape	Model structure from similar gauged catchments
Physics-based models	x	x	
Index-based models	x	(x)	
Conceptual models	x	(x)	x

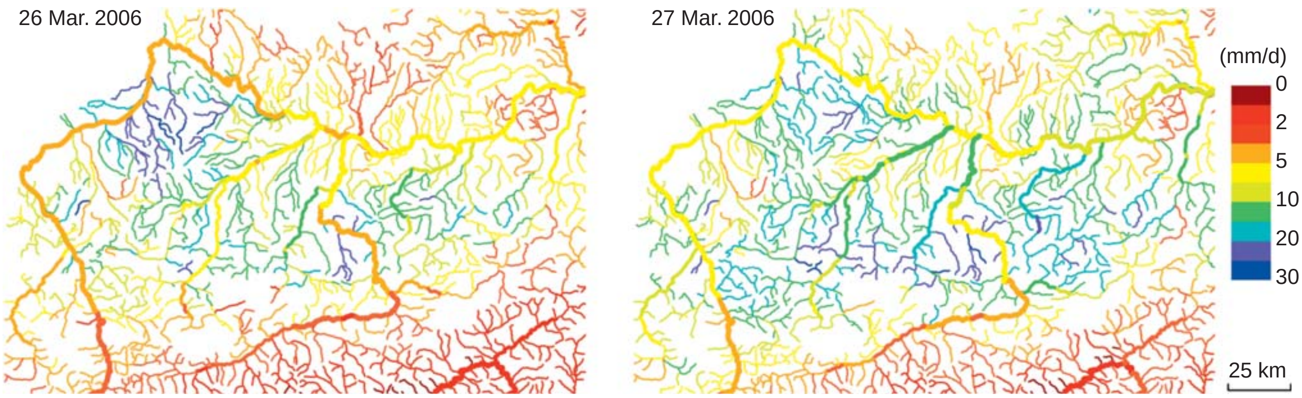


Figure 10.15. Runoff predicted by top-kriging in northern Austria for all locations on the stream network. Note that top-kriging captures the routing of high runoff depths (>15 mm/day) in small catchments on 26 March down the stream network on 27 March 2006.

variety of models, ranging from physics-based models based on laboratory-scale equations to index-based models and lumped conceptual models, and everything in between (Singh and Frevert, 2005). Although there is a continuous spectrum of model complexity, in this section we classify the models into three groups for clarity: (i) physics-based models, (ii) index-based models and (iii) conceptual models. For these model types, the similarity concepts discussed above are used in different ways to select the model structure and parameters in ungauged basins (Blöschl, 2005).

10.4.1 Structure of rainfall–runoff models for ungauged basins

The starting point for predicting the runoff hydrograph in ungauged basins using rainfall–runoff models is the choice of a suitable model structure. The model structure represents a formalised perception of how the catchment system is organised and how the various parts are interconnected. Selection of the type of model for predictions in ungauged basins usually depends on a number of factors. Most importantly, one usually strives to represent the runoff processes in a realistic way, so that the model can be safely used in a predictive mode, i.e. one aims at model structures that reflect the catchment characteristics such as topography, soils, geology, vegetation and the physics of water flow processes in a realistic way. The level of detail with which this is done, however, varies widely. Three groups of information can be used to guide model selection in view of process fidelity (Table 10.1).

- *A-priori perception of processes*: Very often, modellers have at least some basic prior knowledge of the flow processes in the catchment for a given hydroclimate and landscape setting. These may provide an idea about what the dominant processes could be, to guide what should be the essential model components and what simplifications may be possible. For example, in regions where stream–aquifer interactions are important for runoff (e.g., Denmark), an obvious model choice based on this prior perception is coupled groundwater–surface water models.
- *Field data, reading the landscape*: The model choice can be assisted through field data collected in the catchment and a process of rapid assessment, including field visits, data analysis and even preliminary modelling. Such a rapid assessment might inform what model structures are feasible (with respect to money and time) at the scale of interest, as a trade-off between

in-depth representation of local structures and patterns and the adequacy of adopting simpler modelling approaches given the dominant processes and their physical controls. Examples of such a rapid assessment at different scales are presented in Blume *et al.* (2008a, b).

- *Model structure from similar gauged catchments*: An alternative approach is to use the same model structure as in similar, gauged catchments where the structure is identified from runoff data. To select suitable donor catchments, similarity measures such as those in Section 10.2.2 may be used.

Additional considerations in selecting a model structure are the modelling purpose (e.g., operational vs. investigative models), data availability (more complex models require larger data availability), resource constraints (simpler models with lower budgets), and the modeller's experience (choosing models one has experience with, see Section 3.7.2). The following sections discuss model structure selection for physics-based models, index-based models and conceptual models, expanding on the information in Table 10.1.

Physics-based models

Physics-based models are physically consistent and explicitly account for the potential gradients and resistances that determine water flows along the multiple flow paths, based on balance equations (e.g., Richards equation, St Venant equations). The main information one uses to guide model structure are (i) *a-priori* perception of processes in the catchment and (ii) field data from the catchment and reading the landscape (Table 10.1). Runoff data are not usually used to determine the model structure, so model selection in ungauged basins is no different from model selection in gauged basins.

The model structure choices one has are the dimensionality of the flow system (one, two or three dimensions), and which processes to include (e.g., macropores). In both instances the decisions may be guided by the modellers' experience in other, similar catchments. Process similarity in terms of the perceptual model of the flow system is applied here.

The dimensionality of the flow system Fully physics-based models, such as Hydrogeosphere or Hydrus-3D, solve the governing equations at the highest resolution (three-dimensional subsurface, two-dimensional surface) and require two- or three-dimensional information on the time-invariant controls on gradients and flow resistances. They have the advantage that they can accommodate the highest amount of information and thus explore in greater detail how structural properties of the catchment system control runoff. For example, groundwater level data can be directly used in these types of models to check the internal state variables.

However, they have the disadvantage that they do need the highest amount of information, and are computationally demanding. The next class of physics-based models, such as CATFLOW (Zehe and Blöschl, 2004), hillslope-storage Boussinesq (hsB) model (Troch *et al.*, 2003) and THALES (Grayson *et al.*, 1995), reduce the dimensionality of the modelling problem by neglecting flows that are perpendicular to the main downslope flow paths, and concentrate on downslope flows on hillslopes. Thus they have the advantage of being less computationally demanding, and need much less information for model setup, and can therefore be more easily applied at large scales. However, clearly they have the disadvantage that they work most effectively where their assumptions hold best and cannot, for example, explore three-dimensional effects such as deep groundwater flows. They are therefore most applicable in headwater catchments. In the marsh of the Palo Alto Baylands, California, where the flow system is controlled by the interactions of the surface water in the tidal channels and the groundwater, Moffett *et al.* (2012) selected a three-dimensional representation of the coupled system (Figure 10.16) with spatially variable hydraulic conductivity and evaporation estimated from field data. Because the soils are clay, the saturation values are very high. The spatial patterns of soil moisture represent the interplay of surface and groundwater flow for a given topography, forced by the tidal signal and evaporation (Western *et al.*, 1999).

Processes to include Based on available information from hydrogeological maps and pedo-geomorphological reasoning, one may construct the likely subsurface architecture and decide on the relevant processes to include. Examples are the presence of macropore flow, runon infiltration and stream–aquifer interactions. These choices can be assisted by taking distributed observations within the catchment, for instance using soil and geophysical surveys, drilling exercises, installation of soil moisture sensors, groundwater level recorders etc. Similarly, the land surface can be mapped to document the nature of soil cover as it impacts on infiltration characteristics of soils and roughness properties that govern overland flow. Kollet and Maxwell (2008) were particularly interested in the linkage between groundwater dynamics and the mass and energy balance at the land surface. They therefore explicitly represented this linkage via shallow soil moisture in a model that simulates three-dimensional variably saturated subsurface flow as well as overland flow (Figure 10.17).

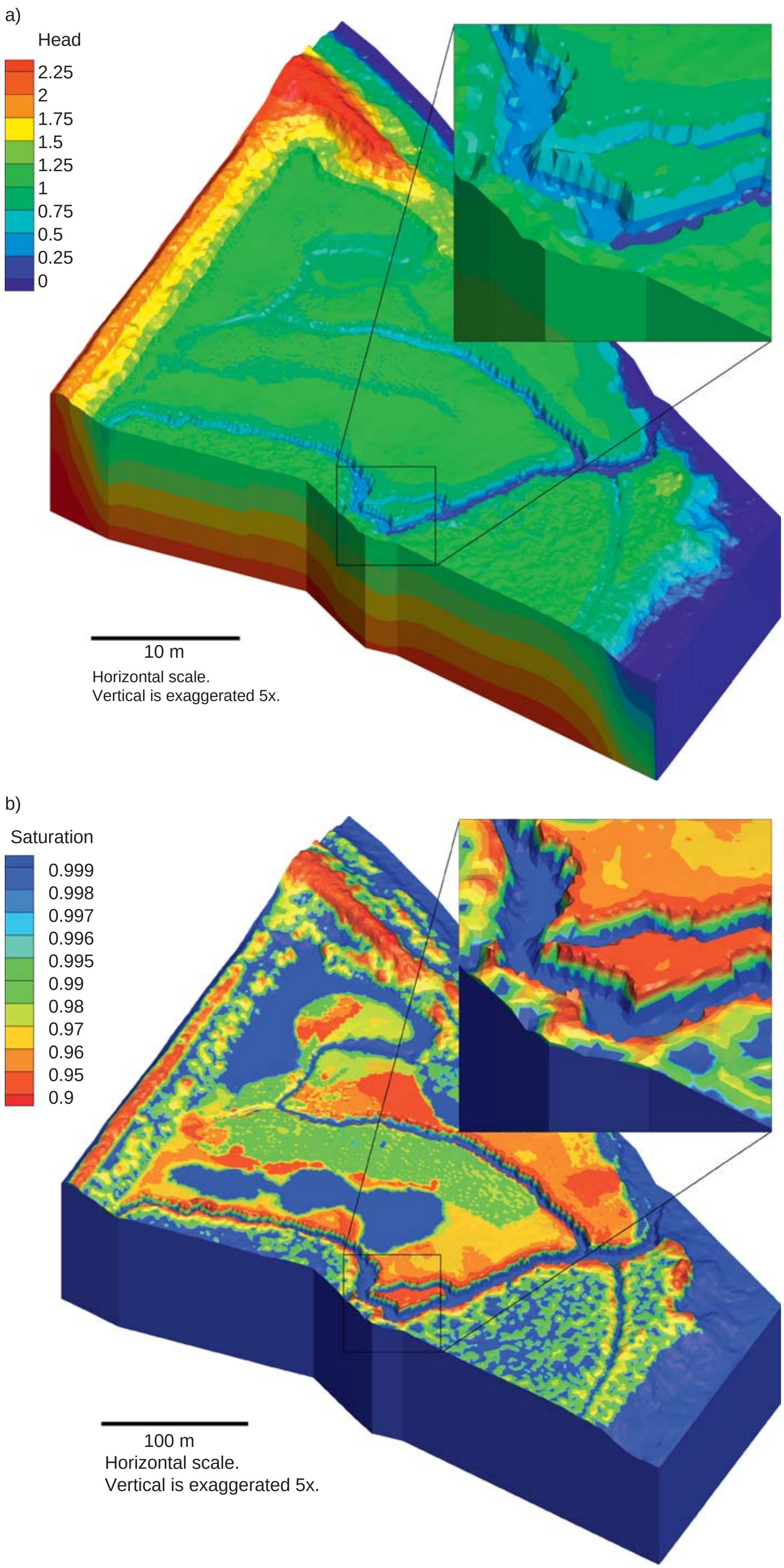


Figure 10.16. Salt marsh ecohydrological zonation due to heterogeneous vegetation–groundwater–surface water interactions. The marsh has an area of about 0.9 ha. (a) Hydraulic head; (b) saturation. From Moffett *et al*. (2012).

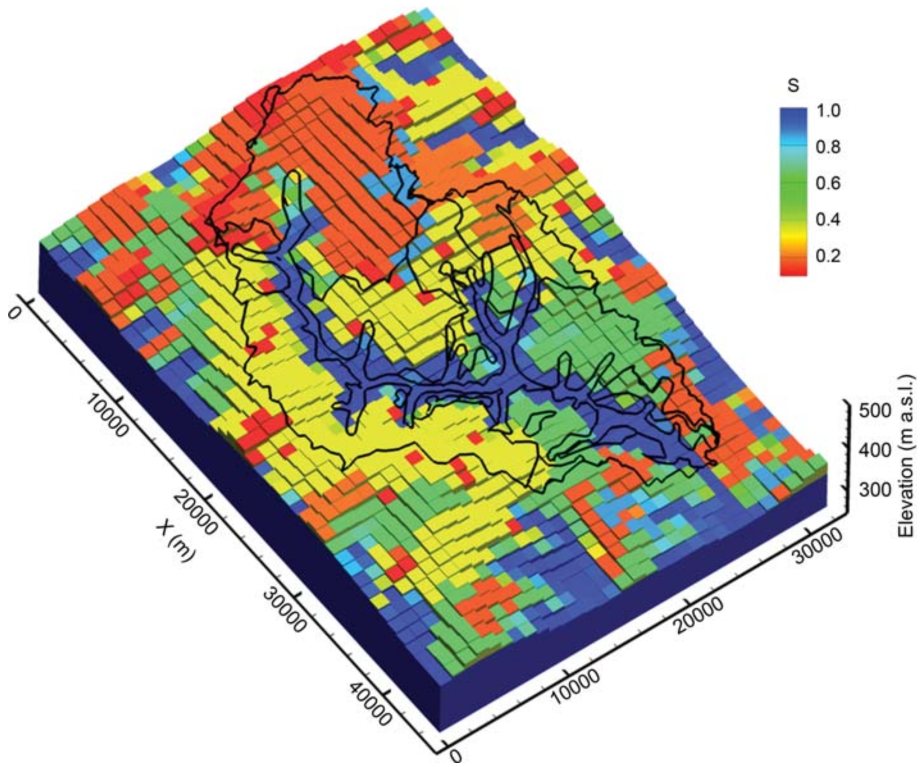


Figure 10.17. Relative soil saturation (*S*) simulated for the Little Washita catchment, Oklahoma, for mid June 1999; 600 km² catchment area. From Kollet and Maxwell (2008).

Index-based models

Index-based rainfall–runoff models are based on simplified representations of hydrological processes within a catchment, often with the topography as the most important control (Section 4.4.2). The models make explicit assumptions about the catchment architecture and the dominant processes, and then focus on an explicit treatment of this identified dominant process along an assumed dominant flow path. An example of this type of model is TOPMODEL (Beven and Kirkby, 1979) based on the topographic wetness index, which assumes that all parts of the landscape with the same ratio of recharge and drainage behave hydrologically similarly. TOPMODEL was originally developed in the UK, as a way to capture the topographic controls on the generation of saturation excess runoff, and in this sense is applicable to catchments where saturation excess runoff is dominant. There are two similarity concepts invoked. The first is the assumption that all locations within a catchment behave hydrologically similarly if the wetness index is the same. The second is the similarity of the dominant runoff processes, in this case saturation excess runoff, which is usually decided upon by *a-priori* perception of processes, in some instances by field data and reading the landscape. The same model structure can be applied to all those catchments where the underlying assumption of saturation excess runoff being the dominant mechanism is fulfilled. In other words, due to the approximations made *a priori*, they explore a selected set of dynamics that assists in model structure choice, but prevents them from being applied universally. Other examples include the VIC model (Liang *et al*., 1994), which assumes that the local soil storage capacity is distributed in space across the catchment according to the Xinanjiang distribution, the ECOMAG model (Motovilov *et al*., 1999a, b) and the YHyM model (Takeuchi *et al*., 1999, 2008; Bastola *et al*., 2008; see Section 11.19).

Conceptual models

Conceptual models make some assumptions about the main flow processes at the catchment scale. Typically they consist of a number of storage elements that are connected by fluxes. Both lumped and spatially distributed models are in use. Because the conceptual models are not based on governing equations for mass, momentum and energy balances (apart from mass balance), different model structures have been adopted in different parts of the world (e.g., Kokkonen *et al*., 2003; Littlewood *et al*., 2003; Littlewood and Croke, 2008; Post, 2009). The advantage of these models is that they are easy to construct, quick to implement with the minimum of information, and are computationally very efficient. However, care must be taken to represent the runoff processes in a realistic manner. To assist in choosing a suitable structure for a conceptual model in an ungauged basin, two kinds of similarities can

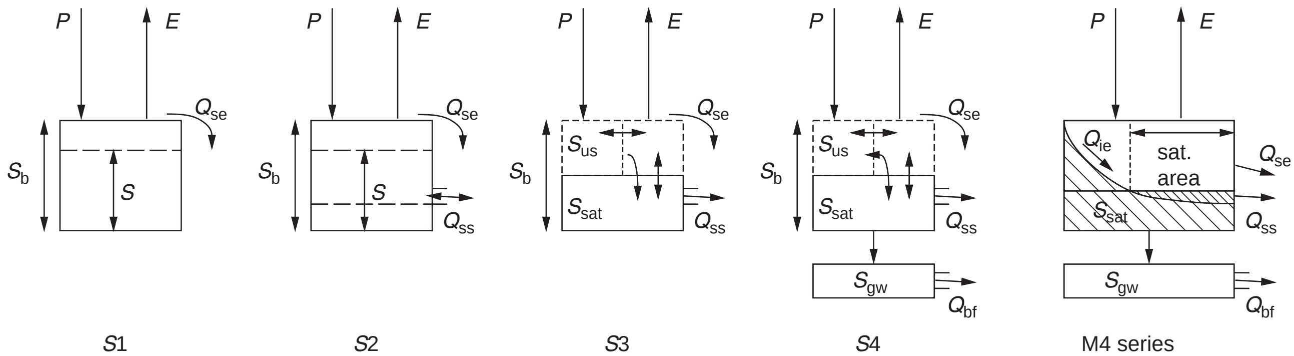


Figure 10.18. Schematic describing the increasing complexity of the models used (S1–S4). M4 provides an example of how a single-bucket configuration (S4 in this case) is represented in the multiple-bucket form. From Farmer *et al.* (2003).

be invoked: similarity between ungauged and gauged catchments in order to transpose the model structure in space, and similarity between landscape units in order to assist in defining the model structure within the catchment of interest (Figure 10.8).

Similarity between ungauged and gauged catchments The idea of this possibility is to select a gauged catchment that is hydrologically similar to the ungauged catchment of interest. This similarity can be established by the methods discussed in Section 10.2, e.g., by the clustering methods of Figure 10.10 and assuming that the cluster applies to a contiguous region. For the gauged catchment a suitable structure of the conceptual model can then be identified on the basis of runoff, and other hydrological data that may be available in that catchment through a diagnostic framework. Numerous studies have demonstrated the usefulness of multiple data sources for model structure selection in gauged basins (e.g., Wagener *et al.*, 2001; Blöschl *et al.*, 2008; Clark *et al.*, 2011) and in particular tracer data (Son and Sivapalan, 2007; Fenicia *et al.*, 2008a, b; Hellebrand *et al.*, 2011; Birkel *et al.*, 2011; also see Chapter 4). In each case, one aims to account for the dominant processes unique to each locality. For example, it is likely that in some arid environments subsurface drainage may not be well developed, especially in places where there is not a perennial ecosystem that facilitates the creation of subsurface drainage. In such environments, rapid subsurface flow may be small or absent and the dominant mechanisms are likely to be infiltration excess overland flow and deep percolation. Evaporation will make up for a large fraction of the water balance and precipitation is often highly variable. Distributed models may be necessary to capture the spatially heterogeneous runoff generation and routing processes (Reszler *et al.*, 2008). In wet environments, on the other hand, high levels of saturation may make it difficult to separate between different runoff components, and simple bucket models may perform very well (e.g., Atkinson *et al.*, 2002; Fenicia *et al.*, 2008a). These examples suggest that model structures needed to capture essential processes can differ along a climate gradient and one model may not work equally well everywhere. A suite of such lumped conceptual models, ranging in complexity from simple, single bucket models to configurations involving multiple buckets, is presented in Figure 10.18. The model structure found suitable in the gauged catchment is then applied in the similar ungauged catchment. This is the most common approach of selecting conceptual model structures that goes beyond an *a-priori* perception of processes.

Similarity between landscape units Model structure conceptualisation may also be guided by the topographic organisation and other spatial characteristics of the landscape reflective of the functioning of the catchment, as they can reveal the nature of dominant hydrological processes operating in the landscape. For the case of typical Western European catchments in a temperate climate, Savenije (2010) proposed a model structure on the basis of three landscape units: wetland, hillslope and plateau. In contrast to most conceptual models, the runoff processes of these landscape units act in parallel, whereby it is assumed that they have direct pathways to the drainage system: the plateau through the groundwater system, the hillslope through rapid subsurface flow (and to a smaller extent the groundwater) and the wetlands (or riparian zones) through saturation overland flow. To identify and quantify these landscape units, the method uses an independent landscape classification based on topographical information: the height above the nearest drain (HAND, Rennó *et al.*, 2008) and the slope of the terrain. The advantage of this method is that landscape information is used to select relatively simple model structures, targeted to specific runoff mechanisms. In the wetland zone, slopes are modest and the groundwater level is close to the surface. The model structure represents the saturation excess overland flow (SOF) process as a function of soil moisture. On the

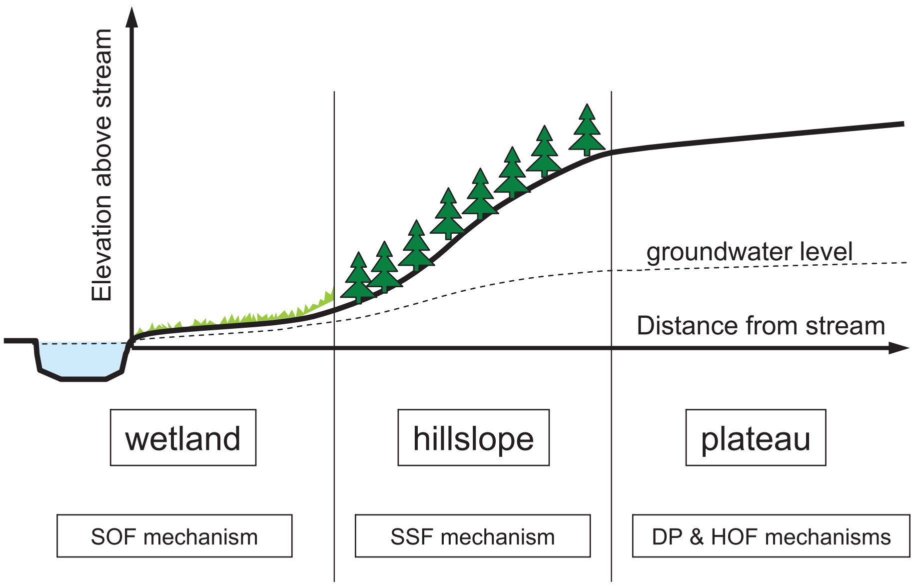


Figure 10.19. Conceptualisation of dominant hydrological processes based on a landscape classification into wetlands, hillslopes and plateaus. From Savenije (2010).

hillslopes, subsurface drainage through preferential pathways and storage excess subsurface flow (SSF) are dominant. After subtraction of interception, the rainfall is partitioned by a beta function into fast subsurface runoff and soil moisture storage. Part of the fast runoff may be directed to the groundwater reservoir through preferential recharge or percolation. This groundwater reservoir is connected to the plateau, where it receives recharge by deep percolation (DP), which is the balance between precipitation and evaporation. On the plateaus, the unsaturated reservoir that constrains evaporation is key to determining the percolation. During extreme rainfall events, the plateaus may also trigger infiltration excess or Hortonian overland flow (HOF) towards the drainage system, represented by a threshold in the model structure.

In essence, this type of model reflects the natural organisation and co-evolution of the landscape. The same can be said about the role of geology, and models tailored to particular geological formations could also be developed; for example in the UK, catchments vary between chalk and clay dominated ones, each requiring very different model structures (Lee *et al.*, 2005). The hydrological landscape units in Figure 10.19 are another example of how the similarity between landscape units could be used for deciding on the structure of a conceptual rainfall–runoff model. This approach of selecting conceptual model structures is emerging and new research on this is expected in the near future.

10.4.2 Parameters of rainfall–runoff models in ungauged basins: overview

Once a suitable model structure has been chosen for the catchment in question, the important next step is to estimate a set of model parameters. In gauged catchments, some or all of the model parameters are usually calibrated to observed runoff in order to reduce bias in the runoff hydrograph predictions. Calibration can correct for biases in the inputs such as precipitation. Calibration can also correct for errors due to empirical elements in the model equations and processes that are not accounted for such as macropore flow in a particular hydrological setting. Finally, calibration can correct for the effects of heterogeneity of the media properties (both soil and vegetation), which are never known very well. In ungauged catchments, however, calibration to observed runoff is not an option. Alternatives are needed.

Methods for obtaining suitable model parameters in ungauged basins depend on the nature of the parameter and on the information that is available in a particular case. The nature and meaning of parameters differs depending on the type of model used. The more process-based a model is, the more the parameters reflect measurable landscape characteristics relating to the catchment. In contrast, the more conceptual the model is, the more the parameters reflect the functional aspect of the entire catchment, and the less they are related to measurable landscape characteristics. Since the models used for estimating runoff hydrographs in ungauged basins span the entire range from physics-based to conceptual, a variety of methods for estimating model parameters in ungauged basins have been proposed. The methods can be grouped into four main categories (Figure 10.20): (a) *a-priori* estimation of model parameters from catchment characteristics; (b) transfer of calibrated model parameters from gauged catchments; (c) constraining model parameters by regionalised runoff characteristics; (d) constraining model parameters by dynamic proxy data.

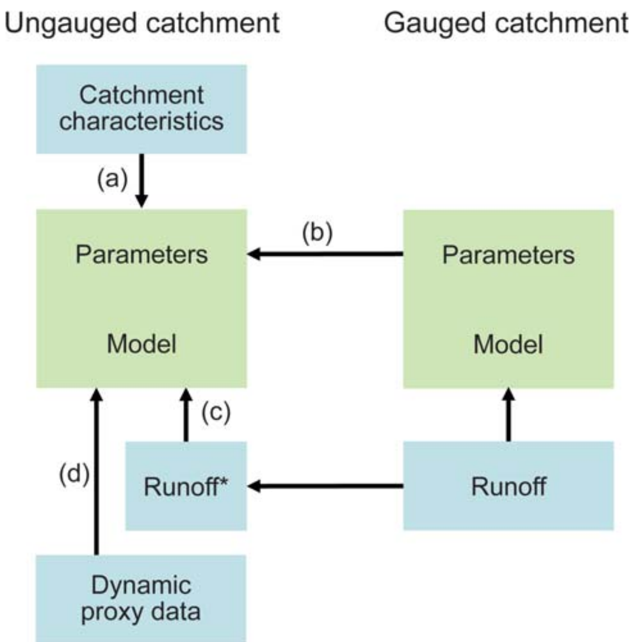


Figure 10.20. Schematic representation of parameter estimation approaches for predictions in ungauged basins. (a) *A-priori* estimation of model parameters from catchment characteristics; (b) transfer of calibrated model parameters from gauged catchments; (c) constraining model parameters by regionalised runoff characteristics*; (d) constraining model parameters by dynamic proxy data.

10.4.3 *A-priori* estimation of model parameters

Parameters of physics-based models are those that can be observed in the field or estimated directly from measurements of catchment or channel characteristics without the use of runoff data. They possess a physical meaning beyond the particular model used. Examples include roughness parameters such as Manning's *n*, hydraulic conductivity, soil depth and surface albedo. Process-based model parameters can be inferred from field measurements or from remote sensing data. The former are usually local-scale measurements and therefore best suited for small catchments, while the latter are more appropriate for large catchments. Often, parameters are inferred from qualitative information or surrogates. Below, a brief summary is given of three main categories of model parameters as used in physics-based rainfall–runoff models and how they can be related to surrogates more widely available than the model parameters themselves, based on Blöschl (2005a). For the case of conceptual and index models, the parameters cannot be directly measured, but there are empirical relationships that have been found useful. A practical discussion of some of the parameter estimation methods is given in Duan *et al.* (2001) and Vieux (2001).

Soil hydraulic characteristics

Soil hydraulic characteristics, such as the saturated conductivity, porosity and soil water release, are usually estimated from infiltration experiments at the plot scale in the field or, alternatively, from laboratory core tests. Important characteristics estimated for the soil matrix (as opposed to macropores) are the unsaturated hydraulic conductivity as a function of saturation and the relationship between suction and saturation. In addition, measurements on the dependence of the hydraulic parameters on freezing processes may be necessary (Zhao *et al.*, 1997; Gelfan, 2006). These characteristics can be directly used in the physics-based models that are based on the Richards equation.

If only a few or no measurements are available, soil hydraulic characteristics are usually estimated from relationships to soil texture (often defined by percentage sand, silt, clay, organic matter, and perhaps bulk density). These relationships are termed pedo-transfer functions (Wösten *et al.*, 2001). The appeal of pedo-transfer functions is that soil texture data are now widely available in databases such as the State Soil Geographic (STATSGO) and the Soil Survey Geographic (SSURGO) databases in North America (USDA, 1991; USDA NRCS, 1995) and the European soil database (Jamagne *et al.*, 2002). The justification of using pedo-transfer functions is that the grain size distribution (defined by the soil texture) should also be relevant to the pore size distribution (which in turn is related to soil hydraulic properties). Unfortunately, this is not often the case because peds and cracks, rather than the grain size distribution, tend to dominate the hydraulic properties. It is therefore not uncommon for soil properties to vary as much between soil types as within a soil type (e.g., Warrick *et al.*, 1990) and for other influences such as terrain to be important to soil hydraulic properties (Gessler *et al.*, 1995). This makes Wösten *et al.* (2001) conclude that pedo-transfer functions are sufficiently accurate for interpolation purposes between soil hydraulic measurements in the catchment of interest, whereas they are not recommended to be used in catchments where no measurements are available. If no measurements are available, it would seem that a minimum requirement for the use of pedo-transfer functions would be that the catchment of interest is hydrologically similar to those catchments in which they were derived (see Section 10.2). Figure 10.21 shows an example of the application of pedo-transfer functions based on clay content to estimate saturated hydraulic conductivity values, taken from the STATSGO data set. The soil texture in the downstream parts of the catchment indicates lower clay content than the upstream parts, which is reflected in higher hydraulic conductivities estimated by the pedo-transfer function.

While the soil physical parameters are, strictly speaking, only applicable to physically based models based on the

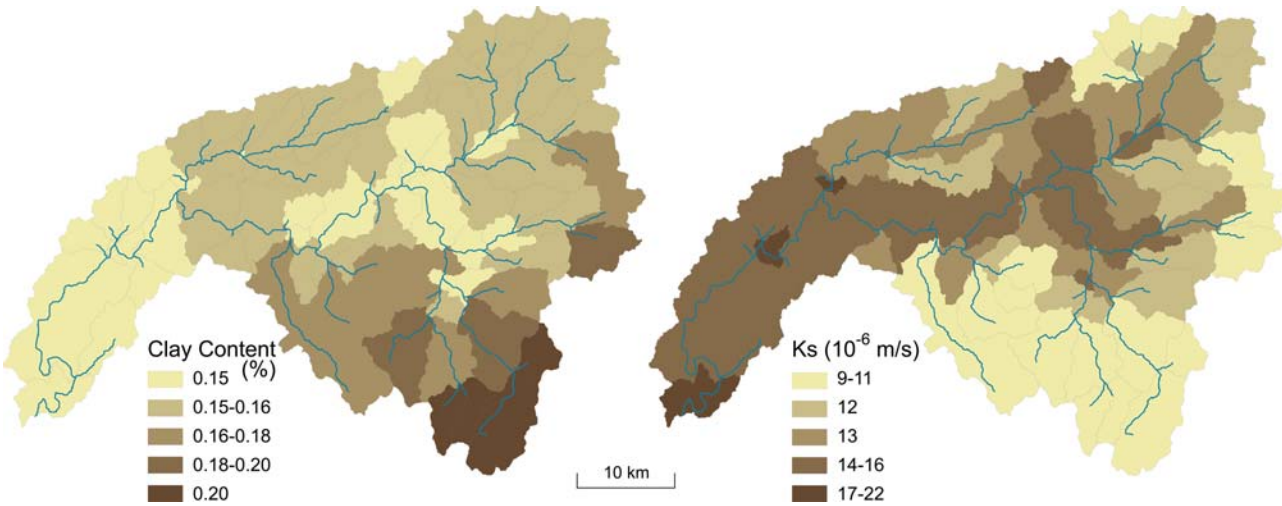


Figure 10.21. (Left) Clay content averaged over the top 40 cm of the soil across the Illinois River basin in Oklahoma, USA, obtained from STATSGO. (Right) Corresponding saturated hydraulic conductivity, derived from pedo-transfer functions. From Li *et al*. (2012).

Richards equation (or similar equations), soil data are also widely used to set *a-priori* parameters of conceptual hydrological models where the model parameters are defined at the catchment or element scale rather than at the local scale. Koren *et al*. (2000) and Anderson *et al*. (2006) developed a framework in which the model parameters of a conceptual model were related to observable soil properties. They assumed that plant-extractable and gravitational soil moisture can be derived from soil properties such as saturated moisture content, field capacity and wilting point, which in turn can be estimated from dominant soil texture available in spatial grids for different soil layers. Mapping from soil texture to physical property is performed via a look-up table constructed from empirical relationships documented in Clapp and Hornberger (1978) and Cosby *et al*. (1984). The results of Anderson *et al*. (2006), Mednick (2010) and Zhang *et al*. (2011) indicate that the model predictions can be further improved when based on a finer-scale soil database and combined with high-resolution land cover data. As suggested by Tesfa *et al*. (2009), detailed experimental soil observations at the catchment of interest may considerably improve estimates above those derived from the SSURGO data set and also allow the creation of spatial patterns of soil characteristics on a small catchment scale.

Vegetation characteristics

The leaf area index, the fraction of green vegetation, and the fraction of absorbed photosynthetic active radiation are vegetation characteristics that can be used in rainfall–runoff models to estimate evaporation. These vegetation characteristics can be related to land cover classes although the relationships are not always unique (e.g., Kite and Droogers, 2000). Land cover classes, in turn, can be estimated from a range of satellite data based on indices such as the normalised difference vegetation index (NDVI). There exist numerous satellite (e.g., AVHRR and Landsat) based land cover maps such as the European CORINE land cover data set (Büttner *et al*., 2002), data sets for North America (see e.g., Gallo *et al*., 2001) as well as global data sets (e.g., Hansen *et al*., 2000; Tucker *et al*., 2004, see Chapter 3). Recent developments use LiDAR (light detecting and ranging) data to identify the vegetation structure. LiDAR measures the signal travel time of laser pulses between the terrain and the airborne platform, which is directly proportional to the distance from which the structure of the microtopography and vegetation can be inferred. LiDAR methods have been developed for mapping of vegetation in forests, shrublands and other landscapes (Farid *et al*., 2008; Mitchell *et al*., 2011; Eysn *et al*., 2012). Also, LiDAR has been combined with other remotely sensed data for vegetation classification to give more detailed information on the canopy characteristics (e.g., Puttonen *et al*., 2011). The main strength of LiDAR data for hydrological modelling is the high spatial resolution (e.g., Cobby *et al*., 2003).

Surface roughness and hydraulic geometry

Surface roughness parameters such as Manning's n are usually determined by *in-situ* experiments on irrigation plots (e.g., Hessel *et al*., 2003). If measurements are unavailable, tabulated values in the literature are often used that are a function of land cover and sometimes topographic slope (Engman, 1986). Ideally, the locality to which the roughness values are applied should be similar to those where they have been measured. Land cover type can be obtained either from field surveys or from analyses of satellite data. LiDAR is an attractive alternative that has recently received a lot of attention. There are a number of methods to obtain roughness estimates from a large number of data points at a higher spatial resolution than the resolution that is used for digital elevation models. Hollaus *et al*. (2011) estimated roughness as the standard deviation of subgrid data points. Casas *et al*. (2010) estimated roughnesses using an equation based on mixing layer theory resulting in a co-varied relationship between roughness height and topographic content. LiDAR can be combined with other remote sensing data such as multispectral images (Forzieri *et al*., 2011, 2012). Typically the roughness estimates are then used in hydrodynamic modelling of ungauged basins (Smith *et al*., 2004).

The hydraulic geometry of streams can be obtained from field surveys, possibly assisted by LiDAR. The photos in Figure 10.22 show cross-sectional profiles surveyed in the field. They were included in a distributed hydrological model of the catchment (Rogger *et al*., 2012a). The photos illustrate that, even without quantitative measurements, creating a photo documentation of the catchment can be extremely important. This, in fact, applies to all the *a-priori* parameters. Field visits can provide extremely useful information that supports understanding of the dominant hydrological processes. Information from field visits has been used to determine estimates of when the stream exceeds bankfull discharge and retention in the floodplain starts (Figure 10.22). In addition, understanding flow processes on the hillslopes can be greatly assisted by such field visits, e.g., by judging where overland flow may occur as assessed by erosion marks. There is much information that cannot easily be quantified numerically that can be very useful for the modelling of runoff in ungauged basins. Sections 3.7.2 and 3.7.3 provide examples where the understanding of flow processes in the catchment is improved during field visits, which is complementary to remotely sensed data or large-scale spatial databases. Sections 11.13 and 11.14 provide further examples of the value of field visits for estimating runoff in ungauged basins.

There have been a number of inter-comparison studies that have examined how well runoff can be predicted in ungauged basins on the basis of *a-priori* model parameters, i.e., without calibrating the parameters to the catchment of interest or neighbouring catchments. One such inter-comparison project was the MOPEX (Model Parameter Estimation Experiment; Schaake *et al*., 2006; Duan *et al*., 2006), which was performed in 12 selected catchments in south-eastern USA. The hydrologists participating in the inter-comparison used different methods to obtain these *a-priori* parameters, such as those proposed by Koren *et al*. (2000) and Anderson *et al*. (2006). They were asked to simulate daily runoff at a number of locations without having access to local runoff data, and their predictions were later compared with the runoff measurements. They were also compared to a different set of simulations with the same models where calibration to local runoff data was allowed. Over the catchments studied, the median NSE of daily runoff using *a-priori* parameters was 0.2–0.6, depending on the model (Figure 10.23). When calibrated to local runoff, the median NSE increased to 0.4–0.75. The performance of monthly runoff is somewhat higher, particularly for the calibration period (Figure 10.23). These comparisons suggest that there is a clear role for calibration in order to improve model performance over the use of *a-priori* values. The project outcomes also suggest that even with a reasonable specification of soil characteristics, the look-up tables relating soil texture classes to soil hydraulic properties (e.g., Koren *et al*., 2000) may not be applicable at large spatial scales because those tables were created under laboratory conditions and are applicable to point or plot scales. To study the transferability of model parameters to other catchment conditions, data from a wide range of climatic conditions should be used. Such comparisons are important, perhaps globally, in the context of comparative hydrology to get a better understanding of what parameter ranges are applicable in different environments.

As mentioned above, the meaning of the parameters differs depending on the type of model. However, even for process-based models there are a number of difficulties with using measured parameters in rainfall–runoff models that are related to scale, as suggested in the MOPEX study above and elsewhere (Blöschl and Sivapalan, 1995). The measurement volume is usually much smaller than the model element size, and in most cases there are only a few measurement locations within a catchment and the spacing between the measurements is therefore large. This means that the measured parameter is not defined in exactly the same way as in the model even if it shares the same name (Beven, 1989). In principle, both scale disparities can be addressed by upscaling procedures (Blöschl, 2005c). In practice, one often neglects the incompatibility related to the support and addresses the incompatibility related to the spacing by some sort of interpolation procedure. Also, model parameters that are usually considered static, such as the saturated hydraulic conductivity, may in fact be dynamic and depend on a range of processes occurring in the catchment that are not captured by physics-based models. This is illustrated by data from sprinkling experiments in Figure 10.24. Simulated rainfall of a constant intensity was applied onto plots until equilibrium was achieved and surface runoff occurred. The ratio of surface runoff (at equilibrium) and rainfall intensity is the runoff coefficient, which is not dependent on initial soil moisture. The experiments were performed twice at the

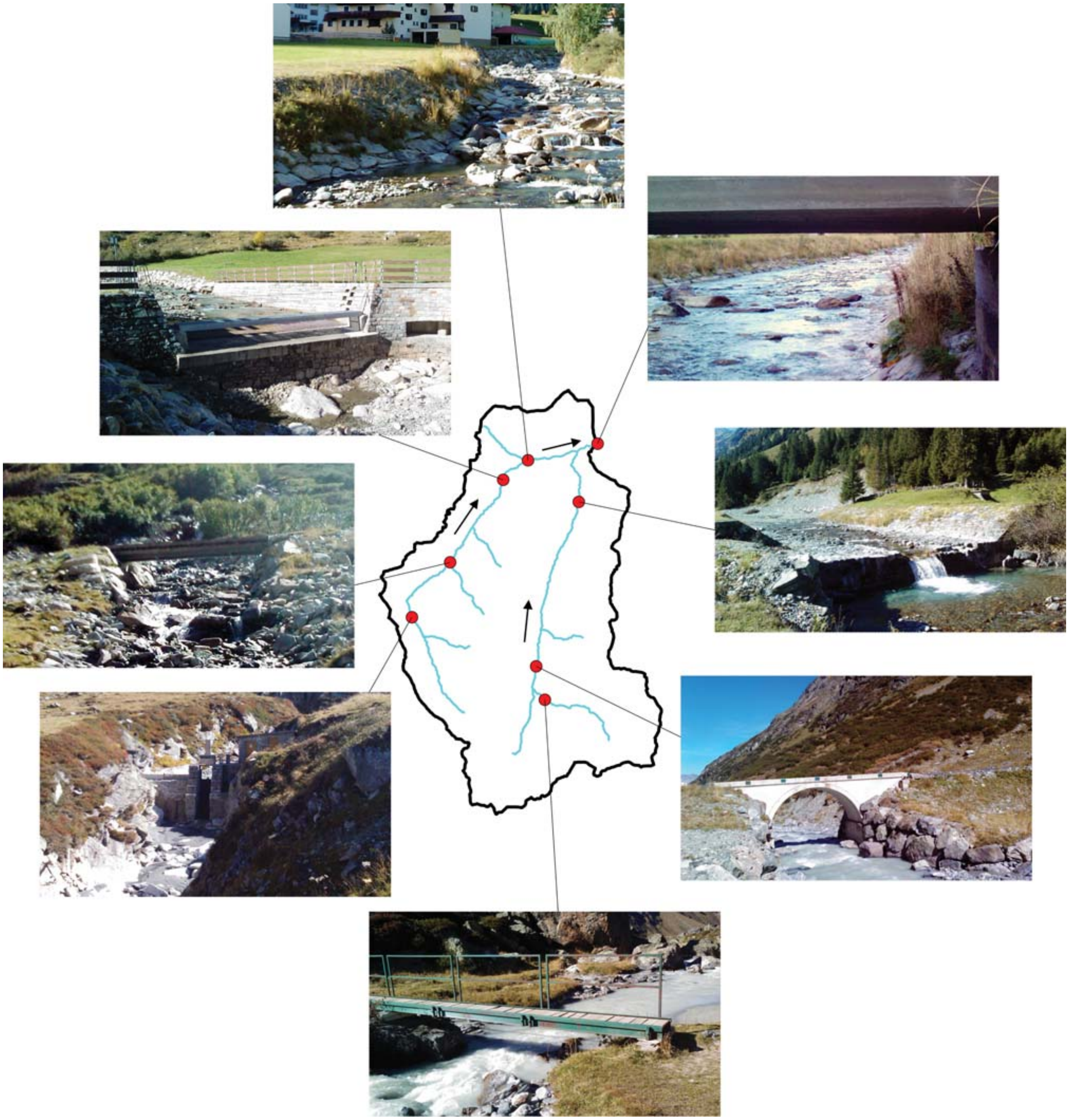


Figure 10.22. Hydraulic geometry from field surveys in the Trisanna catchment, Tirol, Austria; area 98 km². From Kohl (2011).

same sites, the first time in spring and the second time in late summer or autumn. For most of the sites the summer and autumn runoff coefficients were found to be much larger than the spring ones, in some instances by a factor of 10. The sites were located on pastures where grazing by cattle during summer leads to soil compaction and increased runoff. During winter, earthworms and other animal activities increase the soil permeability, thereby lowering the spring runoff coefficient, before another cycle of compaction follows. A detailed process model would have to model the cattle activity (with data on the number of head per unit area) and earthworm activity. Clearly, one cannot hope to reduce all uncertainty by including more detail into the models.

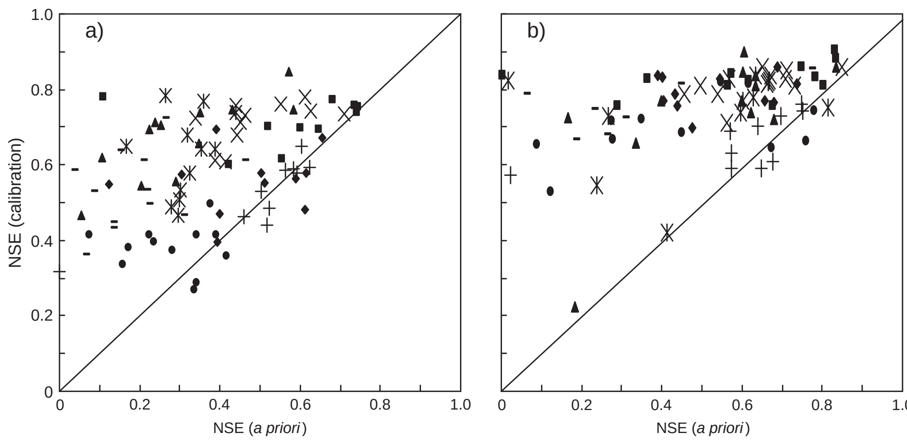


Figure 10.23. Nash–Sutcliffe performance for *a-priori* parameters and calibrated parameters in the MOPEX model inter-comparison project performed in 12 catchments in south-east USA. (a) Daily runoff performance; (b) monthly runoff performance. Different symbols denote different models. From Duan *et al.* (2006).

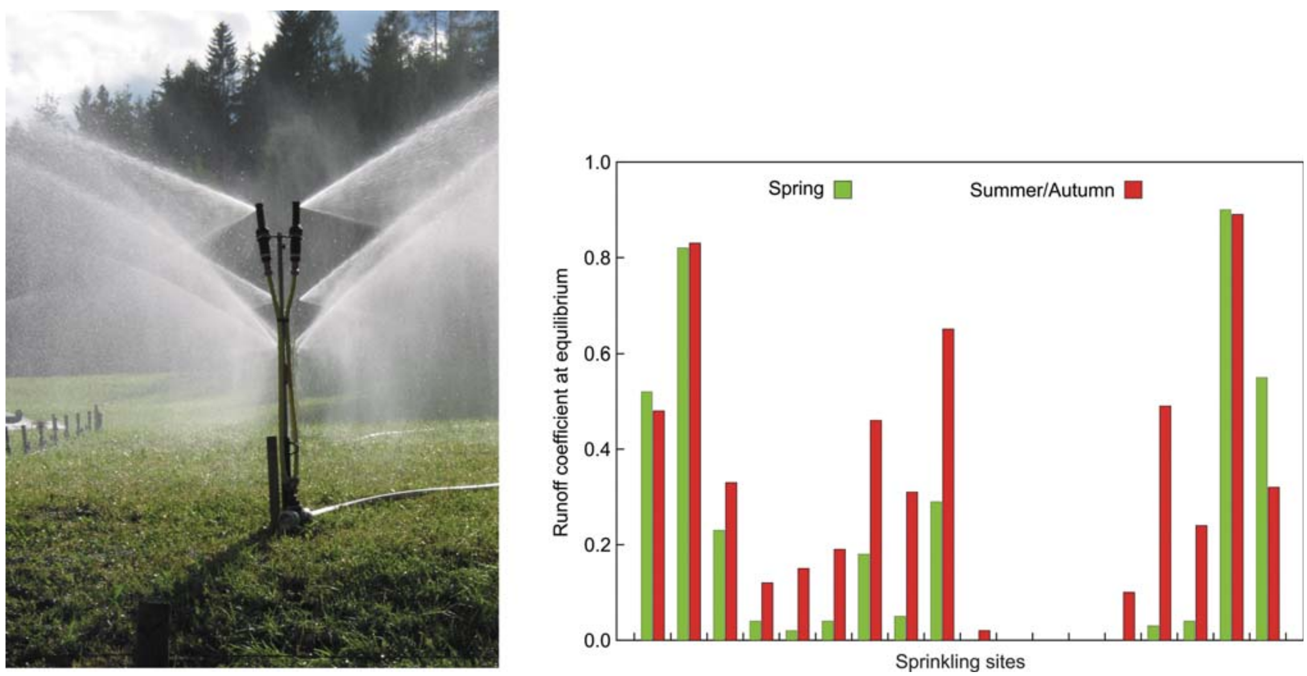


Figure 10.24. Results of sprinkling experiments in the Austrian Alps. The larger runoff coefficients in summer and autumn are due to soil compaction by cattle. Redrawn from Kohl and Markart (2002). Photo: G. Markart.

Because of these difficulties, parameters of physics-based models applied in gauged catchments are often allowed some degree of calibration within a physically justifiable range to adjust some of the measurement or estimation biases. For ungauged catchments, it may therefore be of value to transfer these parameters from similar catchments in the region by one of the methods outlined in the sections below, in addition to measuring the parameters in the field (or estimating them from remotely sensed data). In fact, estimating the parameters from two or more different sources will likely increase their reliability. The distinction between the calibration parameters of conceptual models and physics-based parameters is therefore not a sharp one, there is a gradual transition from what one would call a calibration parameter and a process-based parameter, depending on the type and extent of information available in any particular case.

10.4.4 Transfer of calibrated model parameters from gauged catchments

Most of the parameters in conceptual models cannot be measured or inferred from measurements but need to be transposed from gauged catchments in the region. The transposition typically involves the following steps (Blöschl, 2005):

(a) Delineation of homogeneous regions and/or identification of one or more gauged catchments, termed donor catchments, based on any of the similarity measures discussed in Section 10.2.
(b) Estimation of model parameters for the donor catchments by manual or automatic calibration on observed runoff data.
(c) Selection of catchment characteristics that are deemed to affect catchment response to rainfall. This is either based on an *a-priori* understanding of what catchment characteristics may be relevant to a particular model parameter or on some goodness-of-fit measure.
(d) Setting up models relating each rainfall–runoff model parameter to a set of catchment characteristics. In this step, commonly, multiple linear regressions are used and some or all of the catchment characteristics are (e.g., logarithmically) transformed.
(e) Testing the strength of the relationship of (d), e.g., by some goodness-of-fit measure such as a correlation coefficient.
(f) Estimating each parameter of the rainfall–runoff model for the ungauged catchment from the (regression) model.
(g) Simulating runoff for the ungauged catchment of interest by applying the same model as in (b), using the regionally transposed model parameters.
(h) Testing the transposition by cross-validation. A gauged catchment is assumed to be ungauged, runoff is simulated as in (g) and then compared with the locally observed runoff.

Some of these steps can be skipped depending on data availability and the regionalisation method chosen.

Spatial proximity, similarity and model averaging

The most straightforward approach for transferring calibrated model parameters to ungauged basins is to identify one or more similar gauged catchments in the region (termed donor or analogue catchments), and assume that the *entire* parameter set is also valid in the ungauged basins. The justification for the approach is that if two catchments are similar in their catchment characteristics one would hope that their hydrological response should be similar too, so the model parameter values should be similar. There are three main ways the entire parameter set is transferred from the donor catchment(s) to the catchment of interest:

- *Spatial proximity*: If one assumes that climate and catchment characteristics vary only smoothly in space then spatial proximity between the catchments may be a suitable similarity measure to select the donor catchment. Proximity is usually defined on the basis of distances to the catchment outlets or catchment centroids (Zvolensky *et al*., 2008; Li *et al*., 2009). It is also possible to use the geostatistical distances (or Ghosh distances) that account for the nestedness of the catchments (e.g., Skøien and Blöschl, 2007; Gottschalk *et al*., 2011).
- *Similarity*: An alternative is to choose the donor on the basis of the similarity of the climate and catchment characteristic in the two catchments. Similarity is usually measured by the root mean square difference of all the characteristics in a pair of catchments. The characteristics are usually standardised by their standard deviation or transformed in another way to make them comparable. Studies that chose a donor on the basis of this method use a wide range of climate and catchment characteristics. Kokkonen *et al*. (2003) transferred the complete parameter set from the catchment with the most similar elevation of the catchment outlet. McIntyre *et al*. (2004) defined the most similar catchment in terms of the catchment area, standardised annual average precipitation and baseflow index. Other studies used a larger number of characteristics, such as Parajka *et al*. (2005), who defined the similarity by mean catchment elevation, stream network density, lake index, areal proportion of porous aquifers, land use, soils and geology, and Zhang and Chiew (2009), who identified the most similar catchments in terms of area, mean elevation, slope, stream length, aridity, woody vegetation fraction and plant available water holding capacity.
- *Model averaging*: Sometimes a weighted combination of the parameter sets from more than one donor catchment is used, where the catchments are selected based on either proximity, catchment characteristics or both (Goswami *et al*., 2007; Kim and Kaluarachchi, 2008; Seibert and Beven, 2009). One can either assume a fixed subdivision of the region into groups of catchments or, alternatively, allow each catchment to have its own group of donor catchments (Burn and Boorman, 1993; Young, 2000).

In all three methods it is important that the catchments selected as donors are indeed hydrologically similar, i.e., have similar flow systems. It is possible that some of the donors are disinformative even though their climate/catchment characteristics are similar to the ungauged basins. Transferring parameters from such catchments decreases the model performance in the ungauged basin compared to using, say, the mean parameter set of all the catchments in the region. Boldetti *et al*. (2010) addressed this issue and proposed an approach to detect potentially undesirable donor catchments by an iterative approach.

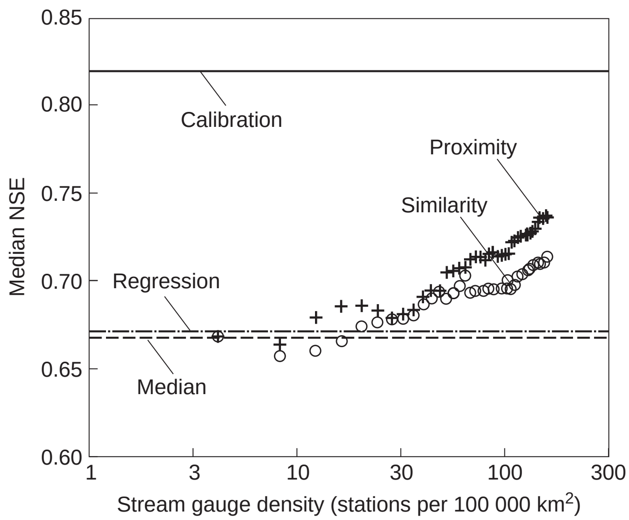


Figure 10.25. Effect of stream gauge density of possible donor catchments on the Nash–Sutcliffe performance of predicting runoff in ungauged basins by a conceptual runoff model based on spatial proximity and similarity approaches in France. From Oudin *et al.* (2008).

One would expect that the performance of the spatial proximity-based method depends on the density of stream gauging stations since it builds on the spatial smoothness of the controls. Oudin *et al.* (2008) assessed the effect of the stream gauge density by progressively decreasing the density of possible donor catchments used for each ungauged catchment. The analysis was performed for a total of 913 catchments in France. Figure 10.25 presents their results in terms of the median model efficiencies in their region as a function of stream gauge density. This shows that with 5 to 20 gauges per 100 000 km², the performance of both proximity and similarity methods is around 0.67 and increases for higher stream gauge densities. The regression approach (see below) gives a performance of 0.67 irrespective of the number of gauges. This means that even with a moderate number of stream gauges, the proximity and similarity methods outperform the regression. The two stream gauge network examples in Chapter 3 (Figure 3.4) represent stream gauge densities of about 50 gauges (Ethiopia) and 500 gauges (Austria) per 100 000 km², assuming that half the stream gauges can actually be used for transferring parameters to ungauged basins (while the other half may either be regionally non-representative or have data problems). Applying the proximity curve in Figure 10.25 to these two cases gives performances of 0.70 and 0.75 for Ethiopia and Austria, respectively. Of course, the actual performances in these two countries will be different as the hydrological variability and the data quality will be different.

Regression between calibrated model parameters and catchment characteristics

An alternative approach is to relate the calibrated model parameters individually to catchment characteristics in the gauged catchments through empirical relationships, and use these to estimate the model parameters in the ungauged basin. Regression models have been tested in different studies. For example, Kokkonen *et al.* (2003) found the drying parameter of the IHACRES model to be negatively related to mean overland flow distance ($r = -0.76$) and the time constant governing the rate of recession in the slow store to be related to topographic slope ($r = 0.66$) in the Coweeta catchment, North Carolina. Merz and Blöschl (2004) found the very fast storage coefficient to be negatively correlated with elevation and slope, implying that direct surface runoff may be particularly flashy in the high altitude catchments in Austria. The R^2 of the relationship, however, never exceeded 0.37. Seibert (1999) related the model parameters of the HBV model (Bergström, 1976) to attributes of 11 Swedish catchments within the NOPEX area. The relationships between forest percentage and snow parameters could be interpreted on hydrological grounds but other relationships could not. The rank correlation coefficient between a non-linearity parameter of runoff generation and catchment area was $r^2 = 0.87$, but most other parameters exhibited few significant correlations with catchment attributes. Young (2006) suggested that regressions may be useful for runoff models with a small number of parameters (less than five). For a study in the UK they were able to relate the mean storage capacity and the quick flow routing time constant from a runoff model to the fractional extents of HOST soil classes.

Another example of the regression approach is presented in Figure 10.26, taken from the work of Carrillo *et al.* (2011), who applied the semi-distributed hsB model developed by Troch *et al.* (2003) to 12 catchments across a climate gradient east of the Rocky Mountains, USA. They performed regressions on all readily available catchment characteristics to different model parameters, in an attempt to reveal useful regionalisation patterns. Only a small number of significant relationships were obtained in this way, as shown in Figure 10.26. Although most parameters were not related to catchment characteristics, some relationships were found for six non-snow dominated catchments. The few significant regressions that were obtained all have some association with vegetation cover, indicating the role of vegetation in the co-evolution of catchment characteristics with climate, perhaps through biotic manipulation of soils.

Ideally, the relationship between model parameters and catchment characteristics should be hydrologically justifiable to give confidence for extrapolation to ungauged basins. However, as suggested in some of the studies

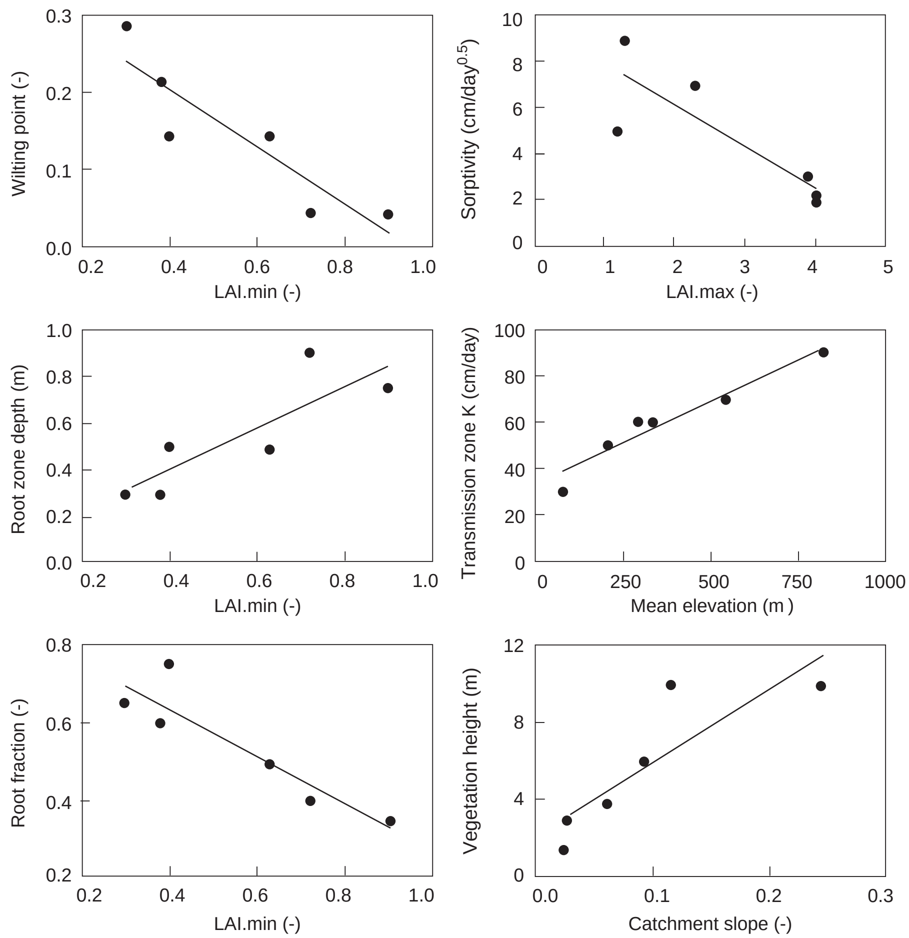


Figure 10.26. Relationships between catchment characteristics (minimum and maximum LAI (leaf area index), mean elevation and mean catchment slope) and different model parameters for six non-snow dominated catchments in the Rocky Mountains, USA. From Carrillo *et al.* (2011).

discussed above and in the literature (e.g., Sefton and Howarth, 1998; Peel *et al.*, 2000; Fernandez *et al.*, 2000), often no significant relationships between calibrated model parameters and catchment characteristics can be found. There are two main issues involved (Blöschl, 2005).

First, catchment characteristics may not represent the hydrological processes of interest very well. This applies in particular to subsurface characteristics such as soil and geological properties. This also applies to characteristics such as percentage land use or percentage soil unit that may be easily calculated from existing maps, but the hydrological interpretation may not always be clear. Also, soil texture may not always be a meaningful characteristic, depending on the runoff mechanisms operative in a catchment. Catchment characteristics may be needed that better reflect the hydrological processes expected in a particular catchment rather than a one size fits all solution. The HOST soil classification is an example where soils are indeed quantified from a hydrological perspective. The interpretation of catchment and climate characteristics may involve co-evolution processes of the catchment system at long time scales.

Second, runoff model parameters generally cannot be identified from observed runoff very well. Parameter identification is an ill-posed problem related to parameter inter-dependencies (Beven and Freer, 2001), i.e., different sets of parameter values give similar runoff situation performance (Kokkonen *et al.*, 2003; Wagener *et al.*, 2004). There are a number of ways to address the second issue and improve parameter estimation, either by reducing the number of free model parameters by fixing some of them, changing the model structure, calibrating the model at a number of stream gauges simultaneously, or by using additional information on the hydrological processes such as *a-priori* information and proxy data. In the following, the last two options are explored in more detail as they are most relevant to ungauged basins.

Regional calibration and downscaling of parameters

An alternative to the approaches above is to establish relationships between parameters and catchment characteristics and to calibrate the *coefficients* of these relationships instead of the parameters themselves. Usually, a number of stream gauges in a region are used for calibration. This means, instead of the two-step procedure above of first estimating model parameters at each site and then relating them to catchment characteristics, these two steps are implemented concurrently. The main motivation for doing this is to find more reliable parameters than is possible by calibrating the model parameters themselves and to make use of the spatial information contained in the catchment characteristics. There are two variants of this approach (see Figure 10.8). (i) In regional calibration, typically, a lumped rainfall–runoff model is applied to a number of gauged catchments in a region and the coefficients of the relationships between (lumped) model parameters and (average) catchment characteristics are calibrated (e.g., Fernandez *et al*., 2000). (ii) In the downscaling approach, a distributed rainfall–runoff model is applied to one or more gauged catchments in a region and the coefficients of the relationships between model parameters and catchment characteristics at the grid (or subcatchment) scale are calibrated (e.g., Bandaragoda *et al*., 2004). While the model discretisation and the number of stream gauges differs between the two methods, the overall idea of relating model parameters to catchment characteristics as part of the calibration remains the same.

Regional calibration Fernandez *et al*. (2000) calibrated a monthly water balance model concurrently with regressions between model parameters and catchment characteristics in 33 catchments by optimising a compound objective function involving runoff simulation efficiency and goodness-of-fit of the regressions. Hlavčová *et al.* (2000) and Szolgay *et al.* (2003) identified groups of catchments by cluster analysis based on catchment characteristics and then assumed uniform model parameters in each group. In a similar study, Drogue *et al.* (2002) assumed two parameters of an hourly conceptual catchment model to be uniform in a region and stratified two other parameters by lithological groups. Lamb *et al.* (2000), Kay *et al.* (2006) and Wagener and Wheater (2006) first estimated those parameters that could be identified with the least uncertainty from local calibration in a region and related them to catchment characteristics, estimated the parameter from the regression for each catchment and fixed this parameter value for the remainder of the analysis. In a second step they re-calibrated the model to all catchments (without changing the values of the previously identified parameter) and identified the next parameter that could be estimated with least uncertainty. They then proceeded to obtain regressions with catchment characteristics for all parameters. Engeland *et al.* (2006), on the other hand, used a multi-objective method to calibrate simultaneously regional parameter sets for the regional Ecomag rainfall–runoff model to streamflow data from seven catchments, as in the Saone catchment in France. They accounted for parameter uncertainty in the procedure and, based on validation, they concluded that this uncertainty cannot explain all the simulation errors, i.e., structural errors in the model are more important than parameter uncertainties (see also Engeland and Gottschalk, 2002). In a much larger area, Parajka *et al.* (2007a, b) calibrated all model parameters simultaneously in 320 catchments and used local (proxy) information on the runoff processes, such as snow cover data, to improve the parameter estimates over those that are only based on runoff.

When using lumped models the regional calibration increases the number of calibration coefficients as compared to individual calibration of parameters themselves, e.g., from four parameters to eight regression coefficients in a study by Fernandez *et al*. (2000). However, there is also an increase in the amount of runoff information that is available for calibration as multiple stream gauges are used. The important issue is, of course, whether regional calibration actually improves runoff predictions in ungauged basins as compared to other approaches (e.g., regression, *a-priori* parameters). Studies by Fernandez *et al*. (2000) and Szolgay *et al.* (2003) indicate that regional calibration improved the relationships between model parameters and catchment characteristics but did not improve the runoff simulations at ungauged sites. Cross-validation analyses by Parajka *et al*. (2007a) showed a slight improvement in runoff predictions in ungauged catchments over other regionalisation approaches. This suggests that the main value in the approach lies in obtaining more realistic parameter values, which may be very useful when extrapolating the models to conditions of environmental change.

Downscaling method One starting point for the downscaling method is *a-priori* model parameters (see Section 10.4.3). Bandaragoda *et al.* (2004) applied a distributed model to each sub-basin of the Illinois River. They estimated Green and Ampt soil parameters *a priori* from STATSGO soil texture using the Clapp and Hornberger (1978) relationship, and estimated the vegetation parameters from satellite data. They calibrated one (spatially constant) multiplier for each parameter to adjust the *a-priori* parameters while retaining the relative spatial pattern obtained from the soils and vegetation data. In a similar study Pokhrel *et al*. (2008) used a relationship with three coefficients to relate calibrated model parameters to the *a-priori* parameters. Alternatively, the concept of HRUs (see Section 10.2.2; Arheimer, 2006; Arheimer *et al*., 2011) lends itself particularly well to the downscaling of parameters of distributed hydrological models from landscape characteristics. A typical case study is presented in Section 11.20 for 198 stream gauges (and numerous subcatchments) in Sweden. They defined hydrological response units on the basis of land use and soil type. In a stepwise procedure they calibrated 15 parameters for each land use and soil type, and another 10 global parameters. They calibrated parameters related to soil parameters first, after which another group of parameters (e.g., river routing) was calibrated. The calibration proceeded from upstream to downstream catchments. Internal model variables (such as flow components) were checked for plausibility. A similar stepwise approach was proposed by Blöschl (2008) and Blöschl *et al*. (2008), who first identified the parameters related to the seasonal scale (e.g., related to evaporation and groundwater) and then the parameters related to the event scale by stratifying events by type (e.g., synoptic, convective and snowmelt events). Their parameter identification approach was supported by groundwater level and flood inundation data. Hundecha *et al*. (2008) proposed regional estimation of parameters based on kriging in the space of the catchment characteristics.

In these studies, the HRUs are usually defined at the element scale, but there is a lot of variability within each model element. To account for this subgrid variability, Samaniego *et al*. (2010a, b) proposed a multiscale parameter regionalisation method where parameters at a large grid scale are related to parameters at a finer scale by upscaling operators such as the harmonic mean. The fine-scale parameters are then related to fine-scale catchment characteristics in a similar way as in other studies (e.g., Hundecha and Bárdossy, 2004; Götzinger and Bárdossy, 2007; Hartmann and Bárdossy, 2005). An application of this method to the Upper Neckar basin in Figure 10.27 shows the porosities of the top soil layer at various scales (from 1 to 8 km) estimated by both their new (multiscale) method and the traditional (standard) method. For comparison, porosity at a scale of 100 m is shown. Figure 10.27 indicates that the multiscale method preserves the fine-scale spatial pattern significantly better than the standard methods as the grid size increases. The non-linear aggregation effects are more realistically represented than in the standard method, which makes the method less dependent on model element size.

When using distributed models in the downscaling procedure, the total number of calibration parameters decreases as compared to the product of model elements and model parameters per element. For example, Samaniego *et al*. (2011) use 28 parameters per element, which gives a total of 28 000 parameters for 1000 cells. With the downscaling procedure, only 62 coefficients need to be calibrated. The smaller number of parameters allows their identification more robustly from runoff and other data, which usually improves the internal (ungauged) runoff predictive performance over the use of *a-priori* data (e.g., Bandaragoda *et al*., 2004; Pokhrel *et al*., 2008).

In the Distributed Model Intercomparison Project (DMIP; Reed *et al*., 2004) 12 distributed models were compared in three basins in the Oklahoma region, to assess (among other things) how well the distributed models perform at internal (ungauged) nodes. They found that, on average, the performance was poorer in the ungauged internal catchments than at the catchment outlet and that some element of calibration improved the performance over the use of *a-priori* parameters. In a follow-up project (Smith *et al*., 2012), 16 models were compared. Figure 10.28 shows some of the results of that inter-comparison. The median correlation coefficients for the calibration period (solid line in Figure 10.28) at the gauged locations are around 0.7. As one moves to ungauged internal nodes, the performance drops to about 0.5, although there is a lot of variation between catchments and between models. Similarly, the validation performance (dashed line) drops from about 0.6 to about 0.4. There is in fact a trend from large to small basins, indicating that the predictive uncertainty increases from large gauged basins to small ungauged basins. It is interesting that all models gave relatively poor performance at basin eight (Blue River at Connerville), which is due to the complex hydrogeology of the basin (Halihan *et al*., 2009) that none of the models were able to capture. This points to a need for understanding the hydrological processes in a catchment prior to runoff modelling, based on any available information (in this case, in particular, hydrogeology) beyond the runoff hydrographs, to ensure that the model is right for the right reasons.

10.4.5 Constraining model parameters by dynamic proxy data and runoff

Model parameters in ungauged basins can be obtained from catchment characteristics *a priori* (Section 10.4.3), they can be transferred from calibrated parameters in neighbouring catchments (Section 10.4.4), or they can be estimated from dynamic data in the ungauged catchments of interest, such as soil moisture or regionalised runoff. The latter is covered in this section. These three paths to estimating model parameters are not mutually exclusive. All combinations are possible, depending on data availability, and have been analysed in the literature on ungauged basins. In fact, the usual approach is to use the dynamic data to constrain the parameters beyond what is estimated from alternative sources (*a priori* or transferred from gauged catchments). For spatially distributed models,

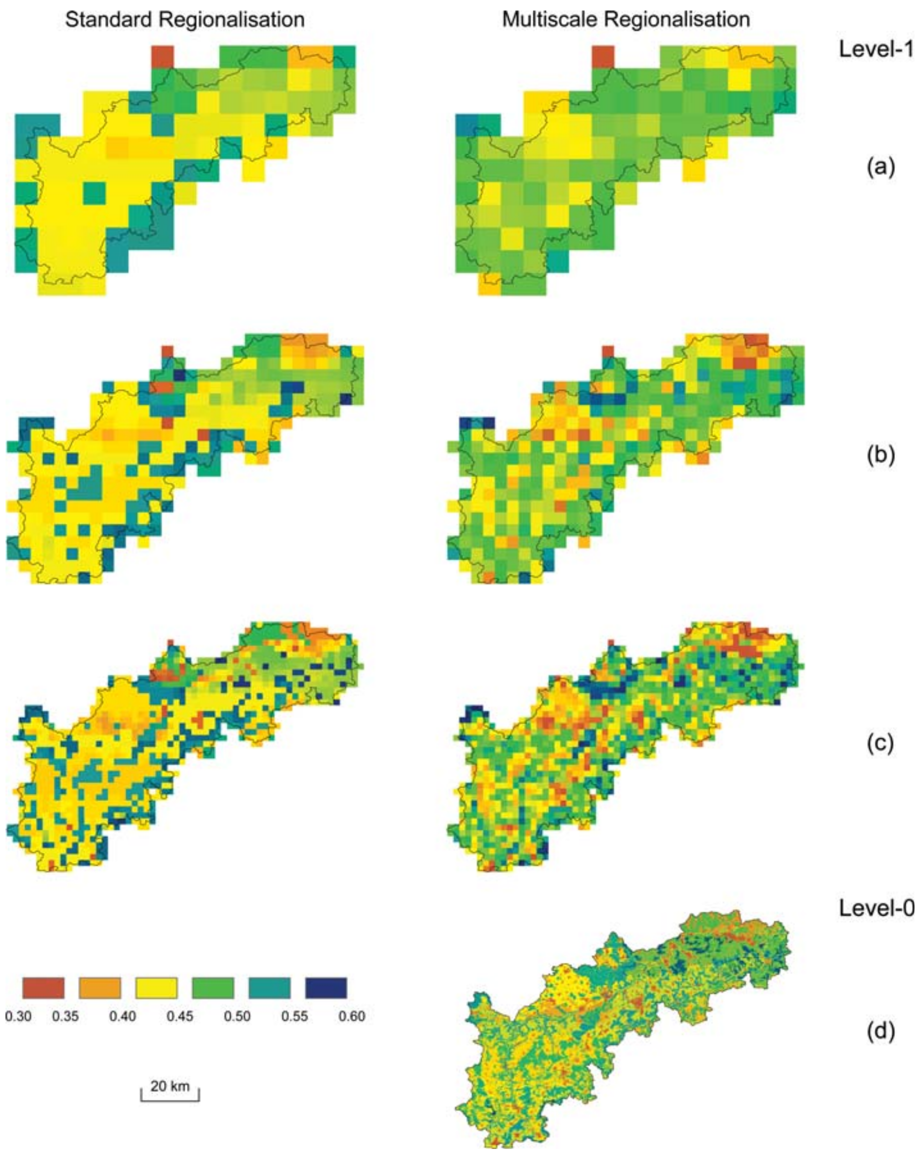


Figure 10.27. Spatial variability of the porosity (mm/mm) of the topsoil layer estimated from runoff by two methods: standard regionalisation (left) and multiscale regionalisation (right). For the Neckar catchment. Level-0 refers to the porosity at the 100 m scale and is provided as a reference. From Samaniego *et al.* (2011).

spatial patterns of dynamic data are of particular interest (Grayson and Blöschl, 2001).

Regionalised runoff

Chapters 5–10 of this book have reviewed methods for estimating runoff signatures in ungauged basins. An obvious choice for dynamic data constraining model parameters in an ungauged basin is therefore prediction of one or more of the signatures discussed in this book. The basic steps of the approach are: select and extract runoff signatures from gauged catchments in the region; estimate the runoff signatures with any of the statistical methods discussed in Chapters 5–10; implement a rainfall–runoff model at the ungauged locations and estimate, if possible, the model parameters from catchment characteristics or regional information. Use the regionalised runoff signatures to condition or constrain the model parameters obtained from the other sources of information. For example, this information on signatures in the ungauged catchment can be used to reject all those model parameters that do not produce simulations that are consistent with the regionalised runoff signatures.

The signatures that are suitable for this purpose depend on the dominant hydrological processes and on which aspect of the hydrograph one is interested in representing particularly well. If one is interested in the distribution of runoff within the year (e.g., for irrigation management), an obvious choice is the seasonal runoff regime curve (Chapter 6). If one is interested in low flow behaviour (e.g., for a drought forecasting model), an obvious choice

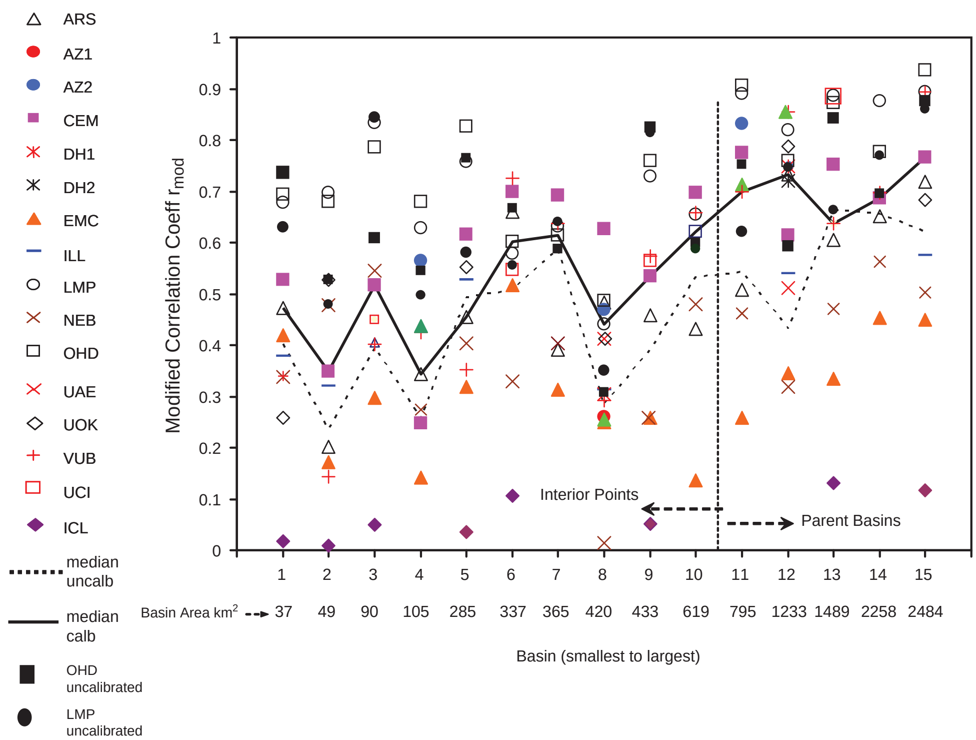


Figure 10.28. Overall performance (correlation coefficient, r_{mod}, see McCuen and Snyder, 1975) for the DMIP2 model inter-comparison project for hourly runoff simulations in the Oklahoma region. Symbols relate to different models. The solid line is the median of the calibrated models, while the dashed line is the median for the uncalibrated models. Catchments are organised in order of increasing drainage area. From Smith *et al.* (2012).

is a low flow characteristic (Chapter 8). If one is interested in the runoff behaviour during high flows (e.g., for flood design), an obvious choice is a flood characteristic (Chapter 9). Other runoff characteristics not discussed as a separate chapter in this book can also be profitably used, such as the runoff ratio (i.e., how water is released from the catchment), baseflow index (i.e., how water travels through the catchment) and the recession curve (i.e., how quickly the catchment relaxes after a rainfall event). In many instances it is prudent to use a combination of a number of runoff signatures to reflect a spectrum of processes well, including the runoff hydrographs estimated by the statistical methods in Section 10.3.

A number of studies have used this method. Bárdossy (2007) considered parameter sets as transferable if the corresponding model performance (defined as the Nash–Sutcliffe efficiency) on the donor catchment was good and the regional runoff statistics (means and variances of annual runoff estimated from catchment characteristics and annual climate statistics) of the recipient catchment were well reproduced by the model. Results for a number of catchments in Germany showed that the parameters transferred according to the above criteria performed well on the target catchments. Boughton and Chiew (2007) constrained the model parameters by mean annual runoff estimated from a regression against catchment and climate characteristics. Yadav *et al.* (2007) and Zhang *et al.* (2008c) used various regionalised runoff signatures (including the uncertainty in their regionalisation) to constrain a simple lumped runoff model for catchments in England and Wales in a Monte Carlo framework. They assessed the predictions with respect to their consistency regarding the regionalised ranges of three signatures. The resulting prediction uncertainty was estimated to be reduced in the order of 50%. An example of simulations run by Zhang *et al.* (2008a) is shown in Figure 10.29. The estimated uncertainty bounds that use regionalised runoff signatures (white ranges) are clearly narrower than those that do not use regionalised runoff signatures (grey ranges). The authors noted that performance decreased with increasing baseflow index, which suggests that it is the suitability of the model that controls how easily one can find suitable parameter sets, since the chosen runoff model was likely to be less suitable for high baseflow catchments. In a similar study, Bulygina *et al.* (2009) conditioned a runoff model on a regionalised baseflow index in a Bayesian framework, achieving NSE between 0.7 and 0.8 at different internal gauges. Kapangaziwiri *et al.* (2009) tested the signature regionalisation strategy in South Africa.

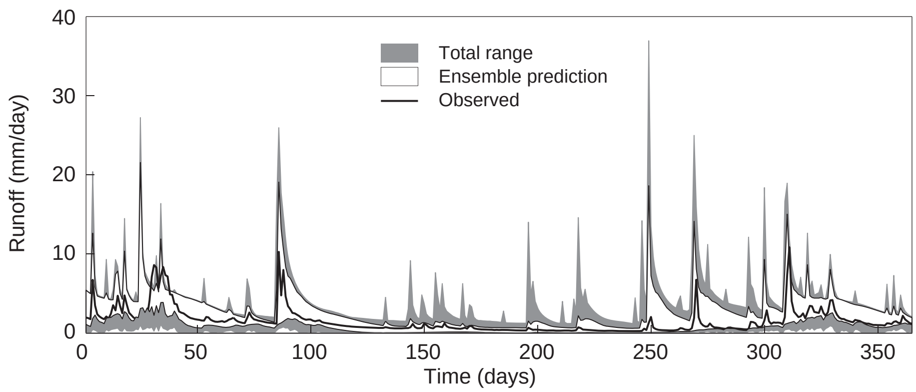


Figure 10.29. Runoff simulations constrained by regionalised runoff signatures for the Kirkbymills catchment in the UK. Shown are observed (black thick line) and predicted runoff (grey range is unconstrained and white range is constrained). From Zhang *et al.* (2008a).

Advantages of the approach are its independence of a hydrological model and that it is complementary to an *a-priori* estimation of model parameters, similar to all other methods that constrain the model parameters on dynamic response data of the catchment (see below). However, the performance of the method strongly depends on how well the runoff signatures have been regionalised.

Short runoff records in the catchment of interest

In his review on the subject in the *Encyclopaedia of Hydrological Sciences*, Blöschl (2005a) noted: 'It may seem strange to end a review of rainfall–runoff modelling in ungauged catchments with a note on the value of runoff data, but that, in my opinion is the state of the science.' Since then, the use of short runoff records for estimating model parameters in otherwise ungauged basins has received renewed interest (e.g., Seibert and Beven, 2009; Tada and Beven, 2012). Methods to constrain the model parameters include calibration of hydrological models in the spectral domain (Montanari and Toth, 2007; Winsemius *et al*., 2009), which has the advantage that precipitation and runoff data do not have to be available for the same period.

A particularly interesting question is how many runoff measurements are needed to obtain model parameters that are not very different from those obtained from a longer runoff record and give similar runoff predictions. Perrin *et al*. (2007) found that 100–350 measurements were needed, Seibert and Beven (2009) found this to be 32 measurements, while Kuchment and Gelfan (2009) and Merz *et al*. (2009) found that three and five years of daily runoff data were needed, respectively (Figure 10.30). It appears that the number of measurements required depends on how the measurements are distributed in time. Perrin *et al*. (2007) and Seibert and Beven (2009) used random sampling, while Merz *et al*. (2009) used consecutive days, which explains the difference. Clearly, it is important that the sampling covers both high and low

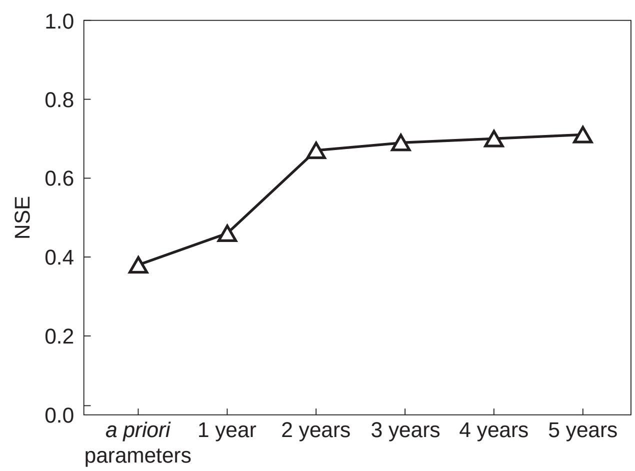


Figure 10.30. Effect of runoff record length used for model calibration on the Nash–Sutcliffe runoff model performance for the Seim catchment in central European Russia (catchment area 7460 km²). From Kuchment and Gelfan (2009).

flows. Accounting for long-term climate fluctuations is more difficult (Peel and Blöschl, 2011) as the runoff performance will not only depend on the number of observations but on the time lag between the short runoff record that is available and the period one is interested in. Specifically, Merz *et al.* (2011) found for their study region in Austria that the runoff simulation errors using calibration parameters from short runoff records significantly increased with the time lag. For median flows the relative errors increased from 1 to 16% as the time lag moved from 0 to 25 years, and for high flows the change was from 9 to 25%. Clearly, long-term fluctuations in runoff need to be carefully accounted for when estimating runoff model parameters. Chapters 5, 8 and 9 of this book review methods of how this can be done for the case of annual runoff, low flows and floods, and these methods may provide some guidance also for the case of estimating runoff hydrographs from short records.

Snow cover patterns

In cold regions snow is an important part of the water balance, so getting snow deposition and snowmelt parameters right is essential for predicting runoff in ungauged basins. In gauged basins, model parameters related to snow processes are usually (partly) estimated from runoff data and often they can be improved by using snow information within the basin (e.g., Parajka and Blöschl, 2006, 2008b). In ungauged basins, information on snow within the basin can improve the parameter estimates above *a-priori* estimates and estimates from neighbouring catchments in a similar way. The basic steps of the approach are: obtain snow data (either ground-based or, more often, satellite data) in the catchment of interest; implement a rainfall–runoff model at the ungauged location and estimate, if possible, the parameters from catchment characteristics or regional information; use the snow information to condition or constrain the model parameters obtained from the other sources of information. Obviously, the snow information is particularly relevant to model parameters related to snow processes, so these are the ones that can be improved by the snow data. The snow data may also help to update the simulated snow states themselves, which may improve the runoff predictions.

Snow information that has received much attention recently is snow cover images from the Moderate Resolution Imaging Spectroradiometer (MODIS), which measures visible and infrared radiation. MODIS provides twice-daily coverage at a spatial resolution of about 500 m pixel size. Cloud obscuration has been found to be the major obstacle to applying MODIS data, but there are numerous techniques that can effectively reduce cloud cover, either by combination with other satellite data and geo-data such as elevation or by spatio-temporal filters (Parajka *et al*., 2008a, 2010b). Numerous studies have assimilated snow cover data into rainfall–runoff models and found that the parameter estimates, the snow simulations and/or the runoff predictions were indeed significantly improved (see Parajka and Blöschl, 2012 for a review). Rodell and Houser (2004) and Andreadis and Lettenmaier (2006) assimilated MODIS snow cover into a hydrological model and found more accurate snow cover simulations. Udnaes *et al*. (2007) and Şorman *et al*. (2009) examined the potential of MODIS data for estimating the parameters of a conceptual hydrological model. They found improved snow model performance and small (but distinct) improvements of the runoff model efficiency. Parajka and Blöschl (2008b) showed that, in a verification mode, the median NSE of runoff over 148 catchments increased from 0.67 to 0.70 if MODIS data were used for calibration as compared to the case where no MODIS data were used. As an example, Figure 10.31 shows a comparison of MODIS snow patterns with simulations. In one variant (centre panel) the model was calibrated to runoff alone, while in the other variant (lower panel), MODIS snow cover was used to constrain the model parameters. Particularly in the eastern part of the region, the improvements of the snow simulations are apparent when MODIS data are used for constraining the model parameters. Note that each pixel in the image is ungauged. Clark *et al*. (2006) assimilated MODIS snow covered area (SCA) into a hydrological model by an ensemble Kalman filter. They suggested that the efficiency in improving runoff predictions depends on the speed of the transition from full snow cover to no snow coverage.

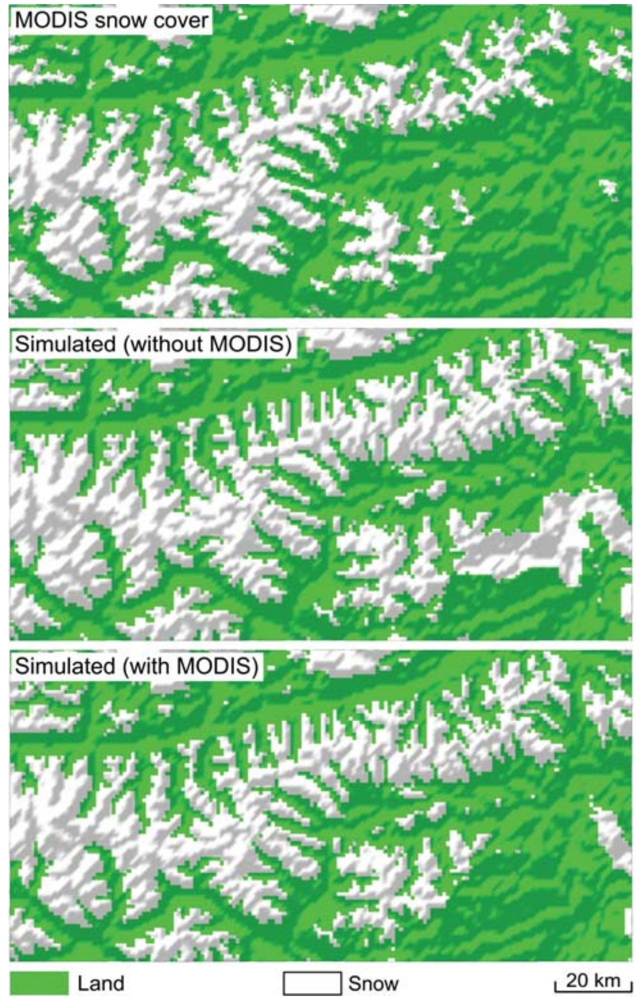


Figure 10.31. Comparison of MODIS snow cover data (top panel) with snow simulations with (bottom panel) and without (centre panel) using MODIS for constraining model parameters. The region shown is part of the Eastern Alps on 2 May 2001. From Parajka and Blöschl (2012).

Soil moisture and groundwater storage

Observed soil moisture data are another kind of dynamic data that may help improve model parameters over *a-priori* estimates in ungauged basins. Obtaining representative soil moisture data within an ungauged basin is difficult mainly because of scale issues (Western and Blöschl, 1999; Western *et al*., 2001b, 2003). Ground measurements may be representative of the entire root zone but are usually limited to a few spots in a catchment (Grayson *et al*., 1997). Spaceborne estimates of soil moisture can be retrieved for large areas (e.g., Wagner *et al*., 2003) but may be limited by shallow penetration depths, which are much smaller than the root depth represented in many hydrological models. Numerous methods have been developed for dealing with this incompatibility, including downscaling schemes and multilayer soil hydrological models (Houser e*t al*., 2000; Walker *et al*., 2001; Schuurmans and Troch, 2003) but challenges remain. There is a multitude of soil moisture products that can be used to constrain the model parameters in ungauged basins, such as ERS scatterometer data (Wagner *et al*., 2007). The soil moisture data may also help to update the simulated soil moisture states themselves, which may improve the runoff predictions.

Soil moisture can be assimilated into the hydrological models by a range of techniques such as variants of the ensemble Kalman filter (e.g., Moradkhani *et al*., 2005; Komma *et al*., 2008; Crow and Ryu, 2009). A number of synthetic experiments demonstrated the usefulness of soil moisture data (e.g., Crow and Ryu, 2009). Meier *et al*. (2011) assimilated ERS scatterometer data into a model for three subcatchments of the Zambezi River basin and found significant improvements of the runoff predictions over cases where no soil moisture data were used. Parajka *et al*. (2006, 2009b) constrained regionalised *a-priori* information about the model parameters with soil moisture from the ERS scatterometer data for 320 Austrian catchments treated as ungauged. These data improved the runoff predictions in lowland agricultural catchments characterised by low vegetation and small topographical variability, but this was not the case in Alpine catchments. The value of using satellite soil moisture data for constraining model parameters apparently depends on the surface characteristics. A review of the potential of remotely sensed soil moisture for runoff predictions is given in Bronstert *et al*. (2012).

Important dynamic data on the subsurface are groundwater levels. In physics-based models that use Darcy's law, the use of groundwater level data is of course a standard procedure (e.g., Refsgaard, 1997, 2001; see Figure 4.11). For conceptual models, Kuczera and Mroczkowski (1998), for example, suggested that, in their study, groundwater level data did not constrain the parameters of a runoff model much. The usefulness of groundwater level data for runoff simulations may depend on how spatially representative they are, i.e., how heterogeneous the aquifer is. Although at a larger scale, satellite data from GRACE (Gravity Recovery and Climate Experiment) may also have potential to constrain the parameters of runoff models as they capture the total water storage in a catchment (Güntner, 2008; Klees *et al*., 2008).

Evaporation

A major source of uncertainty in predicting runoff in ungauged basins is the evaporation. Constraining model parameters by estimates of evaporation is therefore attractive. Winsemius *et al*. (2008) constrained land surface related parameter distributions of a conceptual semi-distributed hydrological model by time series of satellite-based evaporation. They estimated evaporation by the surface energy balance algorithm for land (SEBAL) (Allen *et al*., 2007) and applied the approach to the ungauged Luangwa River basin in Zambia. Remote sensing not only provided the satellite data information on the largest outgoing water balance term, evaporation, but also on the depletion of soil moisture during the dry season. They distributed the model parameters to which evaporation is sensitive on the basis of dominant land cover characteristics within the catchment, and conditioned them on satellite evaporation estimates by Monte Carlo sampling. The parameters so constrained were spatially clustered and consistent with hydrological landscape units: wetland dominated areas, forested areas and highlands, which allowed a useful hydrological interpretation. The method clearly improved the parameter estimates beyond only using *a-priori* information. In a somewhat similar study, Li *et al*. (2009) calculated actual evaporation directly using the Penman–Monteith equation, with the surface conductance in the Penman–Monteith equation estimated from remotely sensed (MODIS) LAI. These data assisted in estimating the parameters of a daily runoff model in ungauged basins. Their results indicated that the use of LAI data improved both the runoff model efficiency during the calibration period as well as the daily runoff prediction in ungauged catchments. The study concluded that further improvements in model structure may help to improve the efficiency of the remotely sensed data integration.

Water level and inundation patterns

Water level data are another valuable piece of information for estimating model parameters in ungauged basins. Sun *et al*. (2011) used satellite radar altimetric observations of river water levels at the basin outlet to calibrate a hydrological model, as a surrogate of runoff data. They coupled the hydrological model with a hydraulic model describing the relationship between runoff and water stage. The methodology was illustrated by a case study in the Upper Mississippi basin using TOPEX/ Poseidon (T/P) satellite data. Even without any runoff data, the runoff predictions of the hydrological model were fairly reasonable. The authors also demonstrated for their case that model parameter uncertainty was the main source of uncertainty, while the contribution of remote sensing data uncertainty was much smaller. Remotely sensed inundation patterns can also be used profitably to improve model parameter estimation (e.g., Grayson *et al*., 2002; Bauer, 2004).

Tracers (possibly regionalised)
When tracer data are available, they can be used to improve the conceptual understanding and therefore the model structure for the catchment of interest (e.g., Fenicia *et al*., 2008a b; Son and Sivapalan, 2007). Tracer data may also have potential to reduce the uncertainty of the model parameters and improve the runoff predictions in ungauged basins. Using tracer information with an integrated multi-criteria calibration for a gauged catchment, Bergström *et al*. (2002) found that, while the runoff performance slightly decreased, the simulated tracer dynamics increased significantly. Vaché and McDonnell (2006) rejected unsuitable model parameters with the help of tracer data, thereby increasing confidence in the flow paths conceptualisation of a catchment. By adjusting the model structure and parameterisation, Birkel *et al*. (2011) improved the runoff model performance from a NSE of 0.71 to 0.74. McGuire *et al*. (2007) used tracers to constrain the feasible model parameter space. In ungauged catchments there are usually no tracer data available, but regionalisation methods discussed in Section 4.5 may have potential to assist in parameter estimation. As discussed in Chapter 4, it is important to recognise that tracers give information on the movement of particles (related to the hydraulic conductivity), while runoff gives information on the propagation of pressure (related to the compressibility of the medium). These differences need to be taken into account when using tracer data for constraining model parameters.

Soft data and expert judgement
All the data sources discussed above can be combined as available in order to constrain model parameters. Additionally, ‘soft data’ or qualitative information from field surveys have been suggested in the literature to improve model parameters beyond *a-priori* values (e.g., Blöschl, 2005). ‘Soft’ information is widely used in practical applications of catchment models where parameters are selected based on all sources of information available to the analyst and more formal methods for incorporating soft information have been proposed. Seibert and McDonnell (2002) used a fuzzy membership function to constrain model parameters for the Maimai catchment in New Zealand. They achieved very good fits to runoff when calibrating the parameters to runoff but other criteria, such as the simulated new water contributions to peak runoff, were not realistic. Constraining the model parameters by such soft data criteria resulted in lower runoff model performance but represented the runoff mechanisms better as interpreted by the field hydrologists. Winsemius *et al*. (2009) integrated hard and soft hydrological information to constrain model parameters of a conceptual runoff model based on the generalised likelihood uncertainty estimation (GLUE) method. The information they used was the shape of the recession curve of the hydrograph (hard hydrological information), spectral properties of daily runoff from a period that was different from the precipitation data period (hard statistical information), and monthly water balance estimates based on old monthly averaged records of precipitation and runoff (soft hydrological information). They tested the method for the Luangwa catchment in Zambia and found consistent parameter distributions and a considerable reduction in the uncertainty of the parameters as compared to using *a-priori* parameters. Various types of field-based soft data are also potentially useful for assisting in constraining parameters. Soft data include saturation areas as mapped in the early work of Dunne and Black (1970) and Dunne *et al*. (1975). There is renewed interest in saturation patterns as illustrated by a number of mapping projects (e.g., Kirnbauer *et al*., 2005) and their application in constraining parameter estimation in rainfall–runoff modelling (e.g., Franks *et al*., 1998). Soft information from reading the landscape (Chapter 3) is another option to be included in the parameter estimation process. Overall, this general approach of including soft information appears to have considerable potential for constraining parameters in ungauged catchments and exploiting any information one may have on the runoff process in the catchment.

10.5 Comparative assessment

The aim of the comparative assessment of runoff hydrograph predictions in ungauged basins is to learn from the similarities and differences between catchments in different places, and to interpret the differences in performance in terms of the underlying climate–landscape controls. Understanding these controls sheds light on the nature of catchments as complex systems and provides guidance on what methods to choose in a particular environment. The assessment is performed at two levels (see Section 2.4.3). The Level 1 assessment is a meta-analysis of studies reported in the literature. The Level 2 assessment involves a more focused and detailed analysis of individual basins from selected studies from Level 1 in terms of how the

Figure 10.32. Map indicating the countries included in the Level 1 assessment. After Parajka *et al.* (2013).

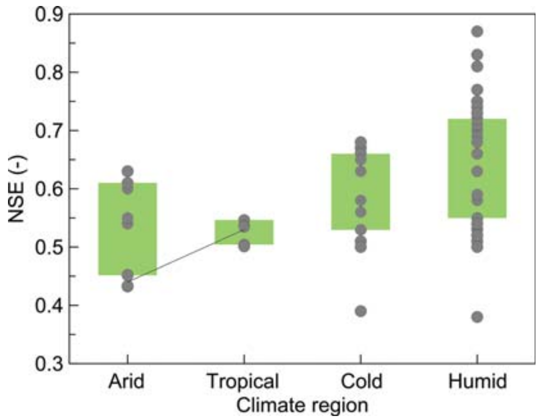


Figure 10.33. Median Nash–Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins stratified by climate. Each symbol refers to a result from the studies in Table A10.1. Lines indicate studies where the same method was applied across different climatic regions. Boxes show 25%–75% quantiles. After Parajka *et al.* (2013).

performance depends on climate and catchment characteristics as well as on the method chosen. More details are reported in the comparative study of Parajka *et al.* (2013). In both Level 1 and Level 2 assessments, the performance was evaluated by leave-one-out cross-validation, where each catchment was treated as ungauged and the runoff predictions were then compared to the observed runoff. The performances obtained by the comparative assessment are estimates of the total uncertainty of runoff predictions in these ungauged basins.

10.5.1 Level 1 assessment

Table A10.1 (Appendix) lists the 33 individual studies used in the Level 1 assessment. Many of these studies are based on large data sets providing a broad range of results from catchments in different climates. The number of catchments in each study ranges from 3 to 913, with a median of 36. Several studies compare different hydrological models and/or regionalisation approaches, which results in a total of 75 results for predictive performance. The studies differ in terms of the time periods used and data availability. However, almost all the studies used lumped conceptual runoff models, a few studies used semi-distributed (Parajka *et al.*, 2005), HRU-based (Viviroli *et al.*, 2009a, b) or distributed models (Allasia *et al.*, 2006; Samaniego *et al.*, 2010a, b). The regionalisation methods used are spatial proximity, similarity, model averaging, parameter regression and regional calibration (see Section 10.4.4). Most of the studies evaluate performance by the NSE of daily runoff using leave-one-out cross-validation. For comparison with the other runoff signatures in Chapter 12, the median NSE of daily runoff were calculated for all methods in all studies. The 25% and 75% quantiles of these NSE are 0.53 and 0.68, respectively.

Figure 10.32 and Table A10.1 indicate that most of the studies were performed in Europe and Australia, and more studies were performed in humid than in tropical and arid climates. There were only a few studies including catchments from high mountain regions. Regionalisation performance in these catchments was not evaluated separately and the results for this climate class were presented combined with cold and humid catchments. Three main science questions are addressed below.

How good are the predictions in different climates?
Figure 10.33 shows that the performance of runoff predictions tends to be lower in arid than in cold and humid regions. The median NSE is 0.54, 0.64 and 0.66 in arid, cold and humid regions, respectively. There is only one study that compares the performance of the same method for different climatic conditions: the study of Petheram *et al.* (2012) indicated by the grey line in Figure 10.33. Their results show that, in Australia, the NSE runoff efficiency is higher in tropical than in arid catchments. The main reason that the methods perform less well in arid regions appears to be that arid regions tend to be spatially more heterogeneous and the hydrological processes more non-linear.

Which method performs best?
As mentioned above, the parameter regionalisation methods used in the studies were spatial proximity, similarity, model averaging, parameter regression and regional calibration. The assessments in each group are not based on exactly the same regionalisation approach, but the methodology is similar. The spatial proximity group consists of 33 results that include the nearest-neighbour, kriging and inverse distance weighting interpolation methods. The similarity group uses parameters from the most similar catchment in terms of catchment and/or climate characteristics. The parameter regression

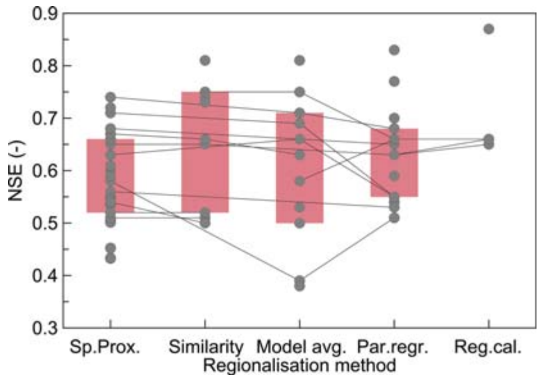


Figure 10.34. Median Nash–Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins stratified by regionalisation method (see Section 10.4.4). Each symbol refers to a result from the studies in Table A10.1. Lines indicate studies that compared different methods for the same set of catchments. Boxes show 25%–75% quantiles. After Parajka *et al*. (2013).

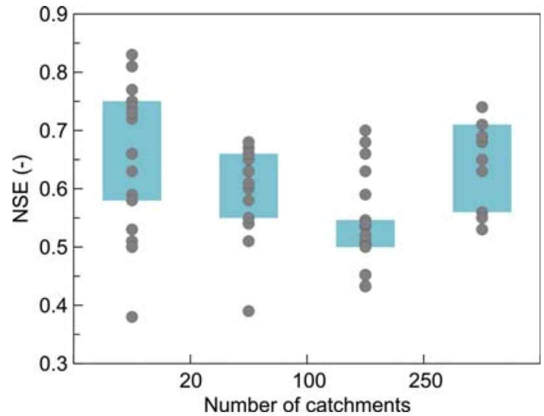


Figure 10.35. Median Nash–Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins stratified by the number of catchments within each study. Each symbol refers to a result from the studies in Table A10.1. Boxes show 25%–75% quantiles. After Parajka *et al*. (2013).

group includes 17 results with different regression models used for transfer of model parameters and one study (Boughton and Chiew, 2007) in which a hydrological model is calibrated to a runoff signature (mean annual runoff) estimated by a regression model. The model averaging group includes 11 results from either a regional pooling (averaging) of model parameters or ensemble runoff simulations for ungauged catchments. Finally, the regional calibration group includes four results from parameter estimation and model calibration simultaneously in a number of gauged catchments in a region.

The comparison of the methods (Figure 10.34) indicates that the difference between the studies within each group is larger than between the groups. The NSE performance within each group is, for most of the assessments, within the range 0.5 to 0.75, while the median NSE for each group varies between 0.58 (spatial proximity) and 0.66 (similarity). The results of studies that compare different approaches (shown as grey lines in the figure) indicate that the predictive performance of parameter regression is poorer than the other methods, with the exception of one study (Samuel *et al*., 2011a), where the simple average of model parameters performed the worst. In this case, however, the predictive performance is generally lower than in other published studies. The reasons why one approach to regionalisation may work better than others are discussed within several inter-comparison studies and other reviews (Merz and Blöschl, 2004; Oudin *et al*., 2008; Parajka *et al*., 2005; Vogel, 2005). Oudin *et al*. (2008), for example, reported that spatial proximity slightly outperformed physical similarity methods in regions with dense networks of runoff observations. They reported that predictive performance of these two approaches becomes similar when the density of stations decreases to less than 60 stations per 100 000 km^2. Parajka *et al*. (2005) reported that a significant similarity in catchment characteristics over relatively short distances in Austria was probably one of the reasons why the spatial proximity and similarity regionalisation methods performed the best.

How does data availability impact performance?
Figure 10.35 shows the median Nash–Sutcliffe performance as a function of the number of catchments analysed in each study. As would be expected, the studies with less than 20 catchments have the largest scatter in the performance because of the smallest sample size. As the number of catchments increases there is a tendency for the performance to decrease. It is possible that in some of the studies with few catchments these catchments were hand-picked in terms of suitability for regionalisation and this happens less frequently in the studies with more catchments. For studies with more than 250 catchments the performance, however, tends to increase. Again, some selection of catchments based on automated methods may have been performed at that scale.

More detailed insight on the dependency of performance on both method and number of catchments per study is shown in Figure 10.36. The maximum performance exceeds 0.8 for similarity, regression and model averaging methods, but this performance is documented only on smaller data sets. Interestingly, the performance for similarity-based regionalisation is clearly lower for assessments with large data sets. There are only a few studies that compare daily runoff prediction obtained by different groups of methods over larger data sets (e.g., three or more groups of methods and validation in more than 25 catchments). These studies suggest that for regions with dense networks of gauging stations (e.g., France or Austria) the spatial proximity

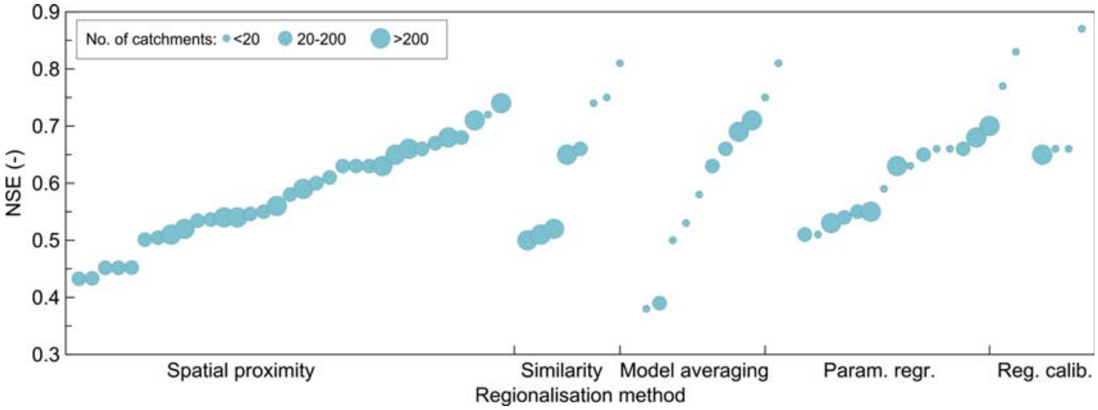


Figure 10.36. Median Nash–Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins stratified by the regionalisation method and ranked by performance. Each symbol refers to a result from the studies in Table A10.1. Circle size indicates number of catchments per study. After Parajka *et al*. (2013).

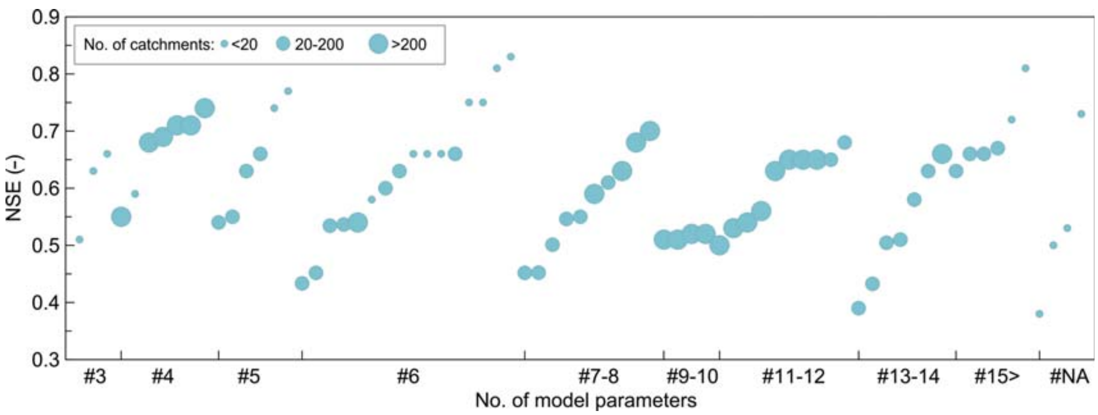


Figure 10.37. Median Nash-Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins stratified by model complexity (number of transferred model parameters) and ranked by performance. Each symbol refers to a result from the studies in Table A10.1. Circle size indicates number of catchments per study. After Parajka *et al*. (2013).

approach performed best. Oudin *et al*. (2008) concluded that, for France, spatial proximity provided the best regionalisation method while the regression approach was the least satisfactory. The results of Parajka *et al*. (2005) indicate that, for Austria, kriging and the similarity-based approach performed equally well and significantly better than regression or global or local parameter mean. The results of Samuel *et al*. (2011a) showed that also for less dense networks of gauges in Ontario (Canada), spatial proximity methods can perform more favourably than methods that use catchment characteristics, and coupling of spatial proximity and similarity methods provided better performance than regression and model averaging approaches.

How does model complexity impact performance?
To assess the effect of model complexity the studies were grouped in terms of the number of model parameters that were regionalised (Figure 10.37). The results indicate that overall the models with different complexity tend to have similar performances. The median of the performance for each group of models is around 0.65, with the exception of the group of 9–10 model parameters, which is lower. The largest variability (between 0.5 and 0.88) is found for regionalisation of models with 11–12 parameters. Studies that explored regionalisation performance of models with different complexity (Viney *et al*., 2009; Chiew *et al*., 2010; Petheram *et al*., 2012) suggest that whilst an increasing number of free parameters leads to increased calibration performance, the difference in runoff prediction performance was small or negligible (Viney *et al*., 2009; Petheram *et al*., 2012). The results of Oudin *et al*. (2008) showed that simpler models might also slightly outperform more complex models.

It is also interesting to compare what regionalisation methods have been used in different studies. The spatial proximity approach tends to be used for more complex models (more than nine transferred parameters). There is a tendency to apply simpler models in arid and mixed arid and humid catchments, while in humid and cold regions more complex models have been used.

Main findings of Level 1 assessment

- In humid and cold regions the performance of predicting daily runoff hydrographs in ungauged basins tends to be better than in arid regions.
- All regionalisation methods analysed (spatial proximity, similarity, model averaging, parameter regression and regional calibration) show a similar performance with considerable scatter within each method. There is a tendency towards a somewhat lower performance of regressions than other methods in those studies that apply different methods in the same region.
- Studies with few catchments and studies with a large number of catchments tend to exhibit better performance than studies with an intermediate number of catchments. For studies with a large number of catchments (dense stream gauge network) there is a tendency for spatial proximity and geostatistics to perform better than regression or regionalisation based on the simple averaging of model parameters.
- There is no clear dependence of the performance on the number of model parameters regionalised.

10.5.2 Level 2 assessment

The Level 1 synthesis of existing studies (Table A10.1) clearly showed that many studies only report summary statistics of regionalisation performance and/or catchment characteristics, which hampers detailed attribution of the performance and inter-study comparison of results. The objective of the Level 2 synthesis is to examine and explain the performance of the regionalisation methods in greater detail. Nine study authors out of the Level 1 assessment provided detailed information about climate and catchment characteristics in a consistent way and reported the regionalisation performance for each catchment (Table A10.2). This data set combines data from 1832 catchments, five groups of regionalisation methods and four catchment characteristics. The regionalisation methods are spatial proximity, similarity, model averaging, parameter regression and regional calibration. The catchment characteristics are aridity (potential evaporation by mean annual precipitation), mean annual air temperature, mean elevation and catchment area. For comparison with the other runoff signatures in Chapter 12, the median NSE of daily runoff were calculated for all methods in each study separately. The 25% and 75% quantiles of these NSE are 0.66 and 0.71, respectively.

To what extent does runoff prediction performance depend on climate and catchment characteristics?
The assessment of NSE predictive performance with respect to the four climate and catchment characteristics is presented in Figure 10.38. The top panel shows a very clear pattern of decreasing performance with aridity index for catchments with an aridity larger than 0.6. The performance in the humid catchments is generally above 0.6, while it decreases to 0.5 or less in more arid catchments. It appears that in humid catchments the rainfall–runoff processes are more linear, the hydrological states tend to be less variable and the controls on runoff are spatially less variable, so a better performance would be expected. For the regional calibration method there is little dependency of the performance on aridity, but these studies are from Germany and Austria, where the catchments are never very arid.

The relationships between performance and air temperature, and performance and elevation are more complex and depend on the region used for the assessment. There is a clear decrease of performance with increasing elevation in France (Oudin *et al*., 2008) and Australia (Zhang *et al*., 2008d) and a clear increase of performance with increasing elevation in Austria (Parajka *et al*., 2005). These differences are due to the different dependencies of aridity with elevation (Figure 10.39). While in Austria the aridity is less than 0.5 in catchments above 900 m a.s.l. and strongly decreases with increasing elevation, in France the aridity index exceeds 0.75 and actually increases with elevation. In Australia the aridity index is always larger than in the other regions. This pattern is consistent for all regionalisation approaches except regional calibration, which is for studies in Germany and Austria where the aridity range is smaller. The pattern for air temperature is similar, with a clear tendency of decreasing performance with increasing temperature in Austria and the opposite in France. Interestingly, the model averaging method has a low median and large scatter of performance in colder catchments, which may be due to snow processes. Similarly, as for other characteristics, the regional calibration is less sensitive to air temperature than the other methods.

The results show a very clear increase of the performance with catchment scale for all approaches and essentially all regions. The median performance is around 0.60 in small catchments (0–300 km^2), and increases to around 0.80 for larger catchments. Also, the variability in performance between the catchments decreases with catchment scale, i.e., the large catchments never give a very low performance. An exception is a slight increase of performance variability for the spatial proximity method in the largest catchments in Australia and France, but this is only for a small group of catchments. Overall, this very clear pattern of an increase of the performance with catchment

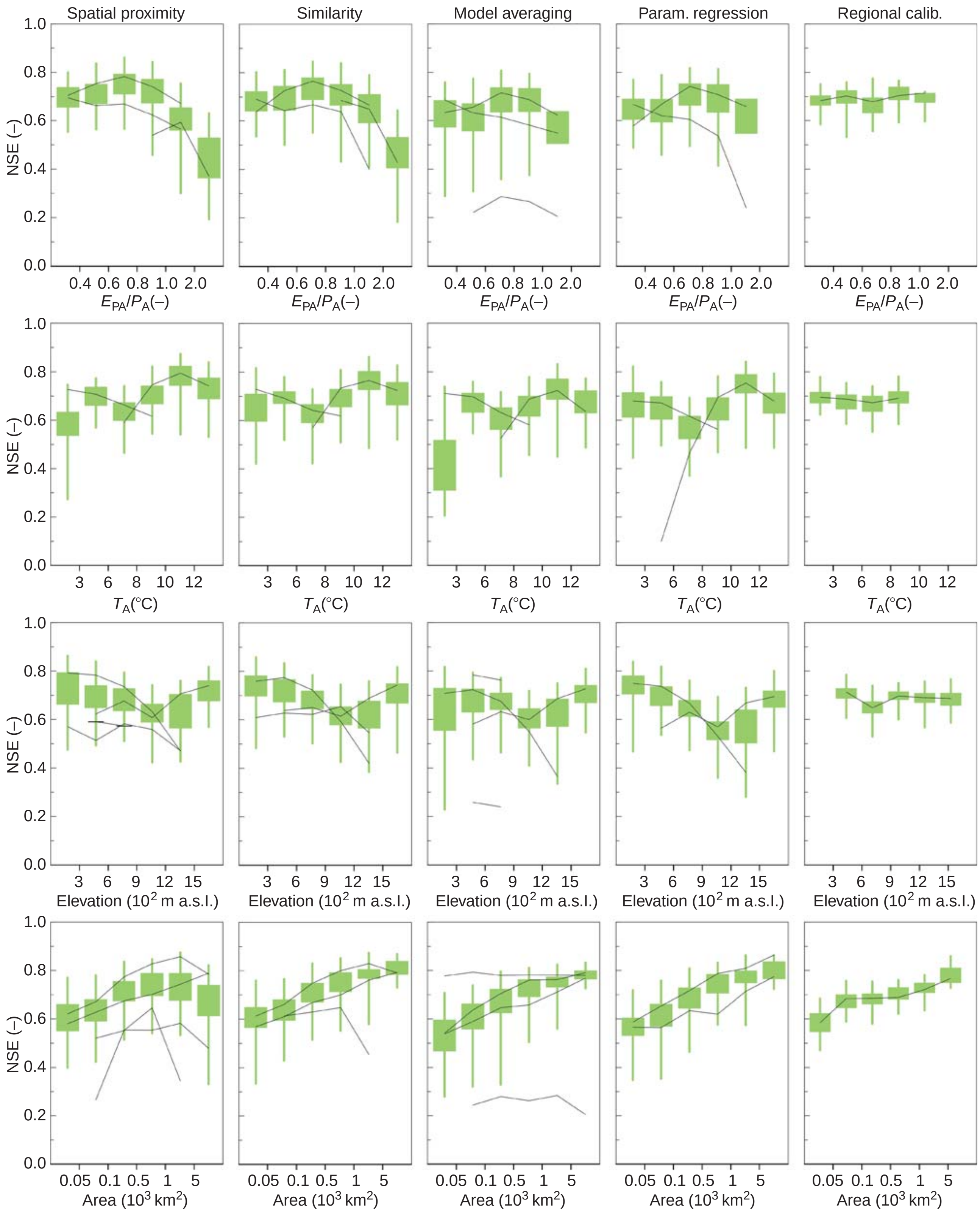


Figure 10.38. Nash–Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins as a function of aridity (E_{PA}/P_A), mean annual air temperature (T_A), mean elevation and catchment area for different parameter regionalisation methods. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. Modified after Parajka *et al.* (2013).

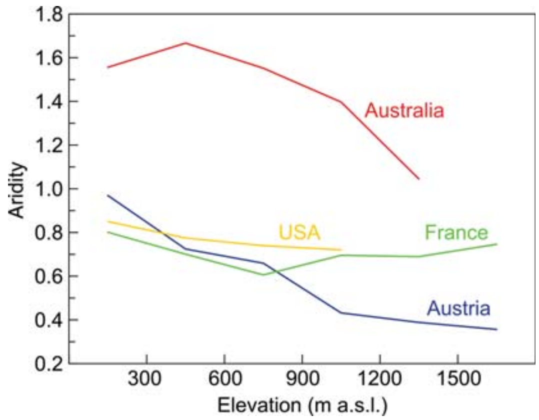


Figure 10.39. Aridity as a function of mean catchment elevation for the studies used in Level 2 (Table A10.2). The aridity represents the median over all catchments in a particular elevation class. After Parajka *et al*. (2013).

scale may be due to two reasons. The first is a trend for an increasing number of rain gauges within a catchment as the catchment size increases. The second may be related to the aggregation effect of runoff. As the catchment size increases some of the hydrological variability is averaged out due to an interplay of space-time scale processes that will improve hydrological simulation. Both effects are consistent with the scale effects of performance in gauged catchments (see e.g., Merz *et al*., 2009; Nester *et al*., 2011).

Which method performs best?

Figure 10.40 summarises the performance for different regionalisation approaches, stratified by the aridity index. The top, middle and bottom panels show the performance for all catchments in Table A10.2 and catchments with an aridity index below and above 1, respectively. Overall, in all catchments the spatial proximity and similarity methods perform slightly better than the parameter regression and model averaging approaches. In arid catchments, however, similarity and parameter regression tend to perform slightly better than spatial proximity and model averaging. These results suggest that climate characteristics more strongly impact on the runoff prediction performance in ungauged basins than the regionalisation method.

Main findings of Level 2 assessment

– The performance of all methods decreases with increasing aridity.
– The dependence of performance on elevation and air temperature differs by region and depends on how aridity varies with elevation and air temperature.

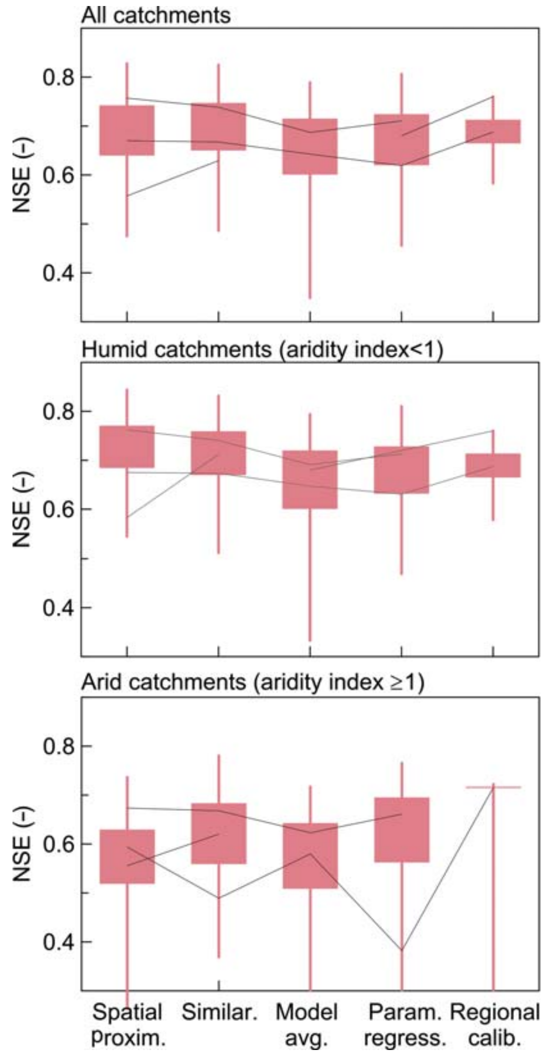


Figure 10.40. Nash-Sutcliffe efficiency (NSE) of predicting hydrographs in ungauged basins for different regionalisation methods, stratified by aridity. Lines connect median efficiencies for the same study. Boxes are 40%–60% quantiles, whiskers are 20%–80% quantiles. After Parajka *et al*. (2013).

– The performance of all methods increases with catchment area.
– In humid conditions spatial proximity and similarity methods perform best, while in arid catchments similarity and parameter regression perform slightly better than the other methods.

10.6 Summary of key points

- The runoff hydrograph represents the temporal pattern of runoff, in particular the full time sequencing of runoff over many years, and is therefore the composite of all the signatures of runoff variability discussed so far, and more. In particular, it retains the rise of runoff during and after events (wet phase) and the recession following events (dry phase), which are not included in any of the previous signatures. The runoff hydrograph is the net result of runoff generation processes during events, runoff routing (on both hillslopes and the river network), evaporation between events, including interactions amongst all of these processes, and reflects the net effect of the multiplicity of pathways and storages that water has passed through on its way to a point in the network.

- Measures that characterise the similarity of hydrographs include all of the similarity indices discussed in Chapters 5–9 in respect of the other signatures. However, to be effective they need to be organised hierarchically, starting with the aridity index, which determines annual runoff. Because the runoff hydrograph, as a signature, is itself an emergent pattern that reflects the co-evolution of the catchment structure along with climate, other co-evolutionary indices that might reflect the similarity of runoff behaviour include the way the landscape is organised in terms of landscape units (otherwise known as hydrological response units or HRUs), river network structure, the hypsometric curve etc.
- Both statistical and process-based methods have been used for predictions, although the trend is for increasing use of process-based methods. Nevertheless, in data-rich regions of the world, geostatistical methods that account for the network structure are seen to work much better in ungauged basins than process-based (rainfall–runoff) methods.
- When it comes to process-based methods, the choice of model structure is a key step, and it is always guided by prior knowledge of the hydrological system, the availability of data, and prior experience of the practitioner. This has led to a plurality of models being used. To avoid fragmentation and duplication, it might be valuable to group the world into classes of similar behaviour, based on some kind of classification scheme, and then to narrow down the number of models adopted. This would increase the experience with all such models, and through the sharing of this experience it could lead to improvement of the models themselves, and also improved predictive performance. This activity could take the form of a synthesis across processes, places and scales.
- Estimation of model parameters of process-based models can be accomplished in a number of ways, depending on data availability and model type: *a-priori* estimation, through transfer from gauged catchments, through regionalisation of runoff characteristics or signatures, through the use of dynamic proxy data, and their combinations. All of these are being used currently, and have their advantages and disadvantages. Given the co-evolutionary nature of catchment systems, however, there should be a renewed search for new kinds of predictors for rainfall–runoff relationships that reflect landscape organisation and/or regional climate patterns.
- It would be timely for catchment hydrology to transition away from traditional lumped models, and use the enormous amounts of spatial information becoming available as proxy data, such as snow, remotely sensed soil moisture and inundation patterns, as well as vegetation patterns, river network structure and soil catena etc., to build new and better models and constrain model predictions. The use of large-scale dynamic patterns should be supplemented with the use of field visits to assemble local data, through the fostering of a culture of *reading the landscape*. Equally, there should be a transition in modelling from just displaying and quantifying prediction uncertainty to understanding uncertainty hydrologically and to making efforts to reduce it.
- There is considerable scope to use the new generation of spatially distributed models to interrogate the differences between catchments in different hydroclimatic regions of the world, and in this way gain new insights into the types of model structure that will be needed in different climates, and lead towards a synthesis, a harmonisation of models and modelling approaches appropriate to different situations.
- In the book, the comparative assessments of runoff hydrograph predictions could only be done for lumped conceptual models. There have been too few distributed modelling studies available for the assessment, a situation that we hope will improve in the future, using the examples of DMIP (Smith *et al.*, 2004b) and DMIP2 (Smith *et al.*, 2012). The comparative assessment of these model predictions indicated that predictive performance gets worse with increasing aridity (both Level 1 and Level 2 assessments), and gets better with increasing catchment size (Level 2). The differences between parameter estimation methods did not impact markedly on model performance (Level 1). In humid catchments spatial proximity and similarity methods perform best, while in arid catchments similarity and parameter regression methods perform slightly better (Level 2 assessment).
- Runoff hydrograph predictions should increasingly focus on (i) distributed models, aimed at generating and interpreting space-time patterns, and (ii) comparative hydrology, aimed at understanding the differences between places. The generation of dynamic patterns and juxtaposing them against patterns of surrogate or proxy data (through field observations or remote sensing) should generate new questions to be answered through further research, instead of just becoming grist to optimisation schemes aimed at curve fitting, or to data assimilation techniques aimed at optimal predictions for operational use.

11 PUB in practice: case studies

H. H. G. Savenije and M. Sivapalan

11.1 Predictions in Ungauged Basins in a societal context

This book has so far presented the outcomes of a synthesis of thousands of studies from around the world connected to predictions in ungauged basins. It involved comparative assessment of several prediction methods, within a holistic framework, organised around processes, places and scales. This synthesis has helped to identify gaps in knowledge, understanding and predictive capability, and opportunities to make further improvements. To a large extent, the book has so far focused on the scientific process.

However, the practice of PUB is also a social process, as well as a scientific process. What is the role of PUB in a societal context? How is PUB being practiced now? How do the methods being used presently, and their performance, measure up against the ideals that emerge from this book? How will the outcomes of this synthesis advance hydrological predictions in the future?

Clearly, PUB is also a practical issue; it involves making day-to-day predictions and decisions in real places and affecting real people, undertaken by practitioners with a wide range of training and experience, and subject to their own strengths and limitations. Hydrologists are confronted with many challenges, which can be social and political, as well as scientific and technological. What are the difficulties faced by practitioners, on both the social and scientific fronts, and how can they be overcome?

The objective of this chapter is to let a representative cross-section of practitioners, drawn from several regions of the world, reflect on their experiences through short illustrations of the approaches they have adopted to address a PUB problem. The chosen case studies cover the full range of runoff predictions in ungauged basins, using a wide range of methods, in places spread across broad climatic and geographic gradients. We have undertaken a limited assessment of PUB practice seen in the case studies from two perspectives: (i) what lessons can be learned from the experiences of the case studies towards strengthening the outcomes of the synthesis, and (ii) how can the outcomes of the synthesis help advance the practice of PUB globally?

Scope of the comparative assessment

This chapter presents 19 real-world case studies, sufficient to represent the diversity of PUB applications around the world, but perhaps not numerous enough to be viewed as a truly scientific study.

The study authors were asked to reflect on how they addressed a PUB problem, independent of and uninfluenced by the work on this book, so as to provide a contrast between what is being practiced now and what could ideally be possible.

The case studies were chosen to be as representative of all geographic and climatic regions of the world as possible, including countries representing both the developed and the developing world (Table 11.1, Figure 11.1).

A diversity of prediction problems was aimed for, involving one or more of the signatures of runoff variability covered in this book (i.e., annual runoff, seasonal runoff, flow duration curve (FDC), low flows and floods).

Importantly, the case study authors were specifically asked to articulate the specific societal relevance and/or driver for the prediction problem that they tackled.

The case study descriptions are not meant to be comprehensive, and are only meant to provide an overview of the specific prediction problem, the methods used, the various limitations, and outcomes of the study, including impact on society. Readers interested in further details can find them in the references cited.

Summary of the case studies

The case studies revealed the great diversity of PUB problems being tackled in different parts of the world, ranging from local problems to regional and national problems. PUB issues are cross-cutting – there is much in common in terms of the problems faced and the prediction methods adopted between countries as different as China, Austria and Zimbabwe. A diversity of prediction methods are being used, both statistical and process-based.

The range of prediction problems being addressed covers the entire spectrum of runoff variability covered in

Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales, ed. Günter Blöschl, Murugesu Sivapalan, Thorsten Wagener, Alberto Viglione and Hubert Savenije. Published by Cambridge University Press.

Table 11.1. *Summary of the case studies*

Case study: section	Country	Climate	Nature of study	Method
11.2	India	Semi-arid	Annual runoff	Index
11.3	China	Semi-humid	Annual runoff	Spatial proximity
11.4	Russia	Continental/Cold	Annual runoff	Index
11.5	Canada	Continental/Cold	Inter-annual runoff	Process-based
11.6	South Africa and Lesotho	Semi-humid	Seasonal runoff	Process-based
11.7	North-east USA	Continental/Cold	Hydrographs	Regression/Geostatistics
11.8	Canada	Continental/Cold	Hydrographs	Process-based/Similarity
11.9	Italy	Semi-humid	FDC	Regression/Index
11.10	Austria	Continental/Cold	Floods	Geostatistics
11.11	Australia	Humid/Tropical/Arid	Floods	Regression
11.12	Chile	Humid	Flow path	Process-based/Regression
11.13	France	Semi-arid	Annual runoff	Short records
11.14	Zambia	Humid/Tropical	Hydrographs	Process-based
11.15	Ghana	Tropical/Semi-arid	Hydrographs	Process-based
11.16	South-west USA	Semi-arid	Hydrographs	Process-based
11.17	Zimbabwe	Sub-tropical	Annual runoff/Seasonal runoff/FDC/Low flows	Process-based/Regression
11.18	Australia	Humid/Tropical/Arid	Hydrographs	Process-based/Similarity
11.19	South-east Asia	Cold/Tropical	Hydrographs	Process-based
11.20	Sweden	Continental/Cold	Hydrographs	Process-based/Similarity

Figure 11.1. World map with the countries present in the case studies.

this book. These include mapping the patterns of annual runoff in major catchments in India (Biggs), China (Jia) and Russia (Korytny *et al.*), and dealing with parameter uncertainty in seasonal runoff predictions in South Africa using a monthly model (Hughes). Indeed, Biggs (India) overcame severe data limitations by invoking sound hydrological insights in the form of the Budyko curve. Pomeroy *et al.* (Canada) present the application of a distributed physically based cold regions hydrological model to predict inter-annual variability of annual runoff.

Archfield (USA) and Castellarin (Italy) present comprehensive studies involving estimation of key runoff indicators based on regionalisation of flow duration curves to ungauged sites. Similarly, Merz *et al.* (Austria) and Rahman *et al.* (Australia) present comprehensive national studies aimed at improving estimates of design floods in ungauged basins.

The study by Blume (Chile) focuses on understanding flow paths and storage characteristics in a steep, representative catchment in the Andes mountains, using both experimental work and detailed process modelling. Two studies in Africa by Winsemius and Savenije (Zambia) and Liebe *et al.* (Ghana) address critical issues related to model development and validation in data-poor situations, in each case coming up with truly innovative methods. The case study by Crabit *et al.* (France) presents a novel framework to define hydrological signatures of ephemeral streams on small poorly gauged agricultural catchments, on the basis of new soft monitoring techniques for rainfall and runoff measurements. The study by Kennedy *et al.* (USA) presents work on enhancements to a process model in the arid south-west of the USA to address issues related to urban development. Mazvimavi (Zimbabwe) presents a comprehensive study of runoff regionalisation using both statistical and process-based methods, reflecting the themes of the entire book.

The case studies by Viney (Australia), Samuel *et al.* (Canada), Takeuchi *et al.* (South-East Asia, Mekong Basin) and Arheimer and Lindström (Sweden) involve application of continuous rainfall–runoff models over large catchments or regions involving a large number of ungauged sites. Viney uses model averaging to obtain improved performance. Samuel *et al.* adopt strategies to improve model structures and to regionalise parameter estimates for improved performance. Takeuchi *et al*. apply a grid-based distributed process model across the entire Mekong River basin, involving six countries and 90 million inhabitants. Arheimer and Lindström apply a distributed process model for the entire country of Sweden and adopt several strategies to improve prediction performance.

Insights gained from the comparative assessment
Interestingly, in at least 7 of the 19 studies the authors report that their PUB work has been highly beneficial and has been well received in the community (Archfield, Samuel *et al*., Merz *et al*., Arheimer and Lindström, Castellarin, Winsemius and Savenije). This is a remarkable testament to the societal relevance of PUB.

Interestingly also, it appears that in developed countries (e.g., North America, Europe and Australia) the driver for the application of PUB is governmental or regulatory, or an industry. Examples include the EU Water Framework Directive (Arheimer and Lindström, Sweden) and the EU European Flood Directive (Merz *et al*., Austria), the focus on hydropower in Italy (Castellarin) and Canada (Samuel *et al*.), and the national push to update the Australian Rainfall and Runoff (Rahman *et al*.) and the Australian National Water Audit (Viney). The regularity of governmental push provides the motivation for much of the progress that is being made.

In contrast, the case studies reported from developing countries are being carried out either through individual efforts locally or by external players supported by foreign aid funds, in both cases on an ad hoc basis. There is no mention of an organised push for improved predictions at a regional or national scale. This has implications for PUB. Lack of organisation or direction also means that the studies can tend to be local, uncoordinated, unfunded and unappreciated. Consequently, there is much less scope for accumulation of knowledge and experience: if this situation is true as inferred and is widespread, as we think it could be, then it cannot be good for the practice of PUB.

Second, it appears that in developed countries, where there is much more data available, standard approaches (both statistical and process-based) are being used and the focus on PUB is helping to generate further improvements. Furthermore, in the humid countries amongst these, there is much more widespread use and trust in process-based methods as well. This is consistent with one of the outcomes of the synthesis that with increasing humidity or wetness performance of process methods tends to increase.

In contrast, in most developing countries data are very scarce, and many of the countries happen to be located in more arid parts of the world as well. Thus, there is not much scope for either statistical or process-based methods, unless significant investments are made to make advances on both fronts.

Yet it is refreshing to note that it is under these circumstances that we found the use of innovative and non-standard approaches (e.g., India, Zambia, Ghana), albeit in an ad hoc manner. This raises the question of how we can encourage and formalise these approaches, to empower local practitioners through targeted activities that generate understanding and develop home-grown solutions to local problems. These are the situations where one needs hydrologists to make genuine efforts to read the landscape, make inferences, aspire to come up with reasonable estimates, and then find independent information to validate them.

11.2 HYDROLOGICAL INSIGHTS FROM LONG-TERM RUNOFF PATTERNS ACROSS KRISHNA BASIN, INDIA

T. BIGGS

The issue from societal and hydrological perspectives
Peninsular India supports a large population whose livelihoods depend on water. Irrigated agriculture, in particular, is credited with increasing agricultural output and farmers' incomes. Irrigation depends on the availability of surface and groundwater, both of which vary in space, seasonally, and inter-annually. Despite the importance of water resources for the economy and society in India, conceptual and mathematical models on the climatic and land surface controls on runoff are not well developed. Inter-state conflict over scarce water resources has resulted in limited availability of stream discharge data, even among government agencies, so relatively little data on stream discharge is available. In response to the need for regional assessments of water and scenarios of change under different land cover and climate change, the International Water Management Institute, funded by various international organisations and in collaboration with universities in India, Australia, the USA and Europe, has performed integrated hydrological and economic analyses of the Krishna Basin, one of India's largest basins with acute surface water scarcity problems (Bouwer *et al*., 2006; Biggs *et al*., 2007; Immerzeel and Droogers, 2008; Immerzeel *et al*., 2008; Bouma *et al*., 2011). The hydrological models, which are calibrated to existing rainfall and runoff data, are useful for developing scenarios of water availability under land use and climate change for a particular catchment, but the understanding of the regional controls on runoff and how they respond to change is limited. Due to legal and political concerns of the three Indian states that share the basin, the models have only been applied to smaller

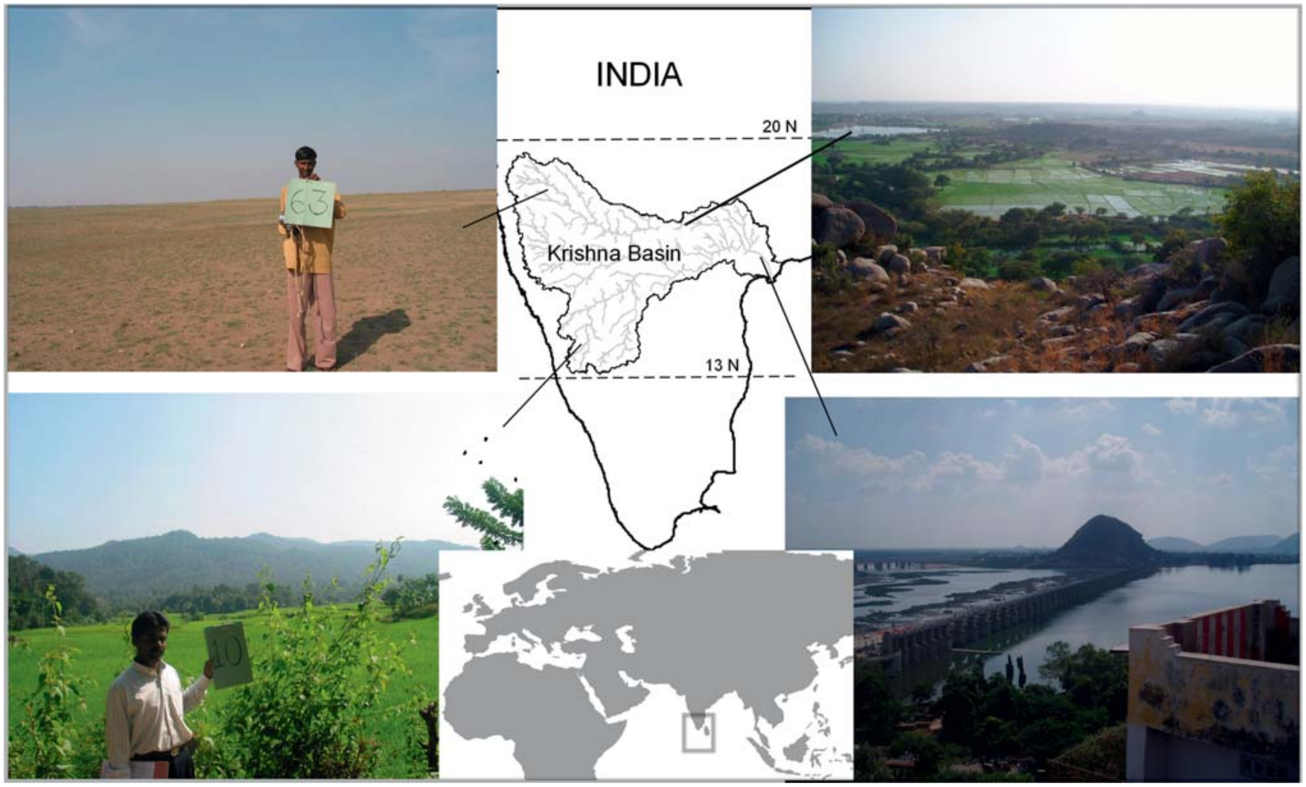


Figure 11.2. Location map of the Krishna Basin. Photos, clockwise from upper left: north-west basin, on the Deccan basalts in the rain shadow of the Western Ghats; central Deccan plateau on granitic outcrops and groundwater-irrigated rice paddy; the Krishna Barrage near the mouth of the Krishna River, showing low hills of the Eastern Ghats; and portion of the Western Ghats mountains. Photos on left courtesy of P. Thenkabail; photos on right: T. Biggs.

catchments within a single state, so regional comparisons have not been performed, further limiting the potential for prediction in ungauged basins. There is a critical need to understand the main processes governing annual runoff production in large river basins in India, and to quantify how runoff is affected by spatial and temporal climatic variability.

Southern India has some distinct geographic features that generate strong climatic and hydrological gradients. The hydrological consequences of this strong spatial gradient in precipitation are not well understood.

Therefore, the main research questions investigated were:

(1) Can a simple climatic index, calculated from satellite imagery and interpolated meteorological data, predict long-term runoff ratios over peninsular India?
(2) How much detail in the temporal and spatial distribution of climate is required to accurately predict regional patterns in long-term runoff?

Description of the study area

The Krishna River basin drains 258 948 km^2 of southern peninsular India (Biggs *et al.*, 2007) (Figure 11.2). It is the fourth largest river basin in India by area, and the fifth largest river by discharge. The river originates in the Western Ghats, flows across the Deccan Plateau, and discharges into the Bay of Bengal in the east.

The Krishna Basin, and peninsular India in general, is characterised by large spatial gradients in rainfall caused by the Western Ghats (Figures 11.2 and 11.3). The Western Ghats are relatively low-lying mountains, with elevations in the western part of the Krishna basin rarely exceeding 1400 m. Despite this relatively low elevation, rainfall in the Western Ghats exceeds 5000 mm/yr in some locations, compared with less than 400 mm/yr to the eastern, leeward side. This very large rainfall gradient is expected to have a large impact on the observed spatial distribution of runoff. The spatial gradient in precipitation is lower in the eastern part of the basin, where orographic effects are reduced over the much smaller and less extensive Eastern Ghats mountains, whose elevation rarely exceeds 500 m in the eastern part of the basin.

The soils of the basin are generally thin Inceptisols, Vertisols and Alfisols developed on the granites and basalts of the Deccan Plateau. Bedrock outcrops are common in some parts of the basin, with groundwater-irrigated areas and small reservoirs in the valley bottoms

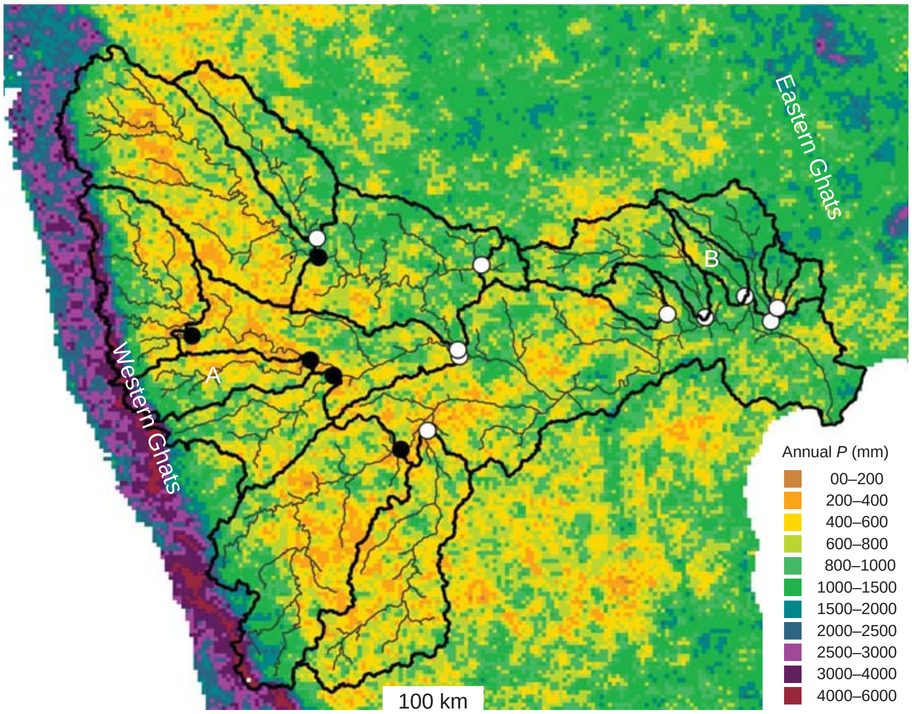


Figure 11.3. Annual precipitation in the Krishna Basin, with stream gauges and catchment boundaries used in the analysis. Black circles indicate catchments draining the Western Ghats, and open circles indicate catchments draining the Deccan Plateau. Precipitation is from TRMM 2B31 (Bookhagen and Burbank, 2010). Letters A and B indicate catchments chosen for the modelling.

(Figure 11.2). Groundwater is limited to fractured, hard-rock aquifers, which have limited storage and are quickly depleted if over-pumped (Dewandel *et al.*, 2006).

Irrigation expanded rapidly in the basin from 1960 to 1990. After 1990, the irrigated area stabilised as available surface water was consumed through crop evapotranspiration (Biggs *et al.*, 2008). In 2001, approximately 20% of the basin was irrigated, half by surface water and half by groundwater (Biggs *et al.*, 2006). The natural vegetation is dominated by low-lying grasses and scrub, with some deciduous forest in the Western Ghats (Figure 11.2).

Method

Budyko framework

A top-down approach was used to investigate the dominant controls on the long-term average, annual water balance. Top-down modelling, which is applicable where daily discharge data are not available, attempts to identify the key variables necessary for prediction in ungauged basins. In the Krishna Basin, daily runoff was available for only a few stations, and was unavailable for any stream draining the Western Ghats, which supply most of the basin's annual discharge. In addition, the available stream gauge data did not cover similar time periods, so comparison of the hydrology of a group of catchments required use of the long-term, decadal mean discharge.

The Budyko framework (Budyko, 1974; Monserud *et al.*, 1993; Zhang *et al.*, 2001) was used to estimate the long-term mean evaporation fraction, calculated as evaporation ($E = P - Q$) divided by precipitation (P), as a function of the aridity index, calculated as potential evaporation (E_p) divided by P (see Chapter 5, in particular Sections 5.3.2 and 5.4.1). The observed relationship between E_p/P and E/P was compared with Budyko-type models calibrated to other catchments (Zhang *et al.*, 2001), which include a single adjustable soil moisture storage parameter (w). In general, higher soil water storage values are associated with higher E/P and lower runoff coefficients.

Water budget model

Two catchments that had different E/P ratios but similar values of the aridity index were selected for further analysis of the impact of the monthly and spatial patterns of P and E_p on runoff (catchments A and B in Figures 11.3 and 11.4). The long-term E/P was calculated using two models:

(1) A lumped, monthly water balance model was constructed to test the hypothesis that the temporal distribution of P and E_p accounted for the observed differences in runoff for a given aridity index. For each month, precipitation in excess of E_p was assumed to be runoff. Given data limitations, the water balance does not reflect conditions in any particular year, but rather is the long-term, mean monthly water balance. The model does not account for soil moisture storage.

Table 11.2. *Inventory of discharge data used for the analysis*

River	Station	Catchment area (km^2)	Period of discharge record or precipitation (TRMM)	Mean annual P in Krishna Basin during period of discharge record (mm)	Percentage deviation of P from long-term mean
Ghataprabha (A)	Bagalkot	8 610	1976–95	844	0.8
Bhima	Takli	33 916	1970–96	839	0.2
Malaprabha	Huvanur	11 400	1975–97	855	2.1
Krishna	Kurundwad	15 190	1973–5, 1979–96	848	1.3
Tungabhadra	Oolenur	32 813	1988–95	872	4.2
Sina	Wadakal	12 092	1970–96	839	0.2
Krishna	Huvinhedgi	55 150	1976–93	846	1.0
Bhima	Gulbarga	69 863	1970–86	821	−1.9
Musi	Dameracherla	11 501	1968–80	835	−0.3
Palleru (B)	Palleru Bridge	2 928	1988–99	870	4.0
Munneru	Keesara	10 294	1988–95	872	4.2
Halia	Halia	3 243	1988–95	872	4.2
Kagna	Jeewangi	1 920	1988–95	872	4.2
Wyra	Madhira	1850	1988–99	870	4.0
Vedvathi	T Ramapuram	23 500	1971–75	804	−3.9
TRMM precipitation	—	—	1998–2009	833	−0.5
Long-term mean precipitation	—	—	1968–2009	837	0.0

Mean annual precipitation in the Krishna Basin is calculated from subdivision rainfall reported by the Indian Institute of Tropical Meteorology (IITM).
Top five catchments drain the Western Ghats (black circles in Figure 11.3), remaining catchments drain the Deccan Pleateau and Eastern Ghats.
(A) and (B) indicate the catchments selected for further analysis, which are indicated by A and B in Figure 11.3.

(2) A spatially distributed but temporally lumped model predicted E/P by dividing each catchment into different precipitation zones (500 mm increments). Annual E/P was then estimated for each zone from the annual E_p/P and the fitted Budyko curve for the Deccan Plateau. This model accounted for spatial variability in E_p/P and E/P, but not for temporal variability.

Data availability

Data on long-term mean discharge (Q) was available for 15 stream gauges in the basin, each covering a different range of years from 1968 to 1996 (Table 11.2). Basin sizes ranged from 1850 km^2 to 69 863 km^2. For nested basins, the discharge and drainage area of upstream gauges were subtracted from the observed discharge of downstream gauges, and P and E_p were calculated on the subcatchment. Estimates of naturalised runoff were available for some but not all of the catchments, so the observed long-term mean discharge was used.

High-resolution precipitation data were necessary to compute a climatic-mean precipitation in each catchment. Sufficient rain gauge data were not available for all catchments, particularly to capture the higher precipitation depths in the Western Ghats. For rain gauges with data, the data often did not overlap with the available discharge data. Therefore, long-term average P, Q and E_p were used to establish a Budyko curve. The average monthly and annual precipitation from 1998 to 2009 was calculated from high-resolution (4 km) TRMM 2B31 data. E was calculated as annual P minus the average annual discharge (Q). Potential evaporation (E_p) was calculated using the Penman–Monteith equation, using solar radiation from the surface radiation budget and interpolated climate parameters from 26 meteorological stations in the basin (see Biggs *et al.*, 2007 for details). The period of record of the TRMM precipitation did not overlap with the periods of record of most of the discharge stations (Table 11.2). It was assumed that both the rainfall and runoff records included enough years of data to represent the long-term climatic mean. In order to confirm that precipitation during each period of discharge record was representative of the long-term average, the precipitation in the Krishna Basin from the Indian Institute of Tropical Meteorology (IITM) was used to quantify precipitation over the period of each discharge record and of the period of TRMM precipitation data (Table 11.2). The percentage deviation of precipitation over each period of record from the long-term mean precipitation maximum gives an indication of how

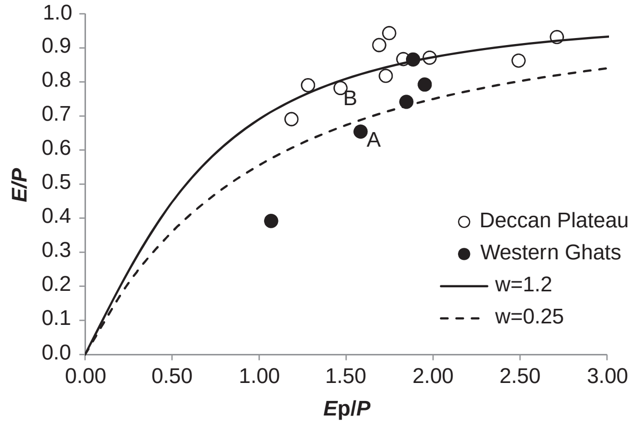


Figure 11.4. Budyko plot of catchments in the Krishna Basin. Black circles indicate catchments draining the Western Ghats, and open circles indicate catchments draining the Deccan Plateau. A and B indicate the catchments chosen for the modelling (see Figure 11.3 for their locations). The values of w are the catchment soil parameter from Zhang *et al*. (2001).

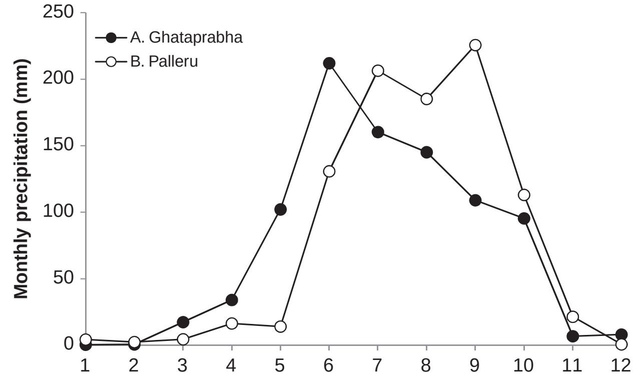


Figure 11.5. Monthly precipitation in the two catchments selected for modelling, one in the Western Ghats (A: Ghataprabha) and one in the Eastern Ghats (B: Palleru). The x-axis indicates the month, with January as month 1.

representative the period of discharge was of the long-term mean (1968–2009) in the basin. The percentage deviation was small, with a lower bound of −3.9% and an upper bound of +4.2%, suggesting that the discharge and TRMM time periods had mean precipitation that was similar to the long-term, climatic average.

Results

Question 1: Can a simple climatic index, calculated from satellite imagery and interpolated meteorological data, predict long-term runoff ratios over peninsular India?

The observed E/P ratios follow the pattern expected from the Budyko curve (Figure 11.4), but with two distinct runoff regimes. Basins draining the Deccan Plateau, which includes all catchments that do not drain the Western Ghats, have higher E/P and lower runoff ratios for a given climate compared with basins with some portion of their drainage area in the humid region of the Western Ghats. Catchments on the Deccan Plateau fit a Budyko curve with a soil capacity parameter of $w = 1.2$ (Zhang *et al*., 2001). The Western Ghats catchments showed a different Budyko relationship, which was approximately linear and had lower E/P values than catchments on the Deccan Plateau with the same climate. The catchments draining the Western Ghats did not follow any established Budyko curve.

Question 2: How much detail in the temporal and spatial distribution of climate is required to accurately predict regional patterns in long-term runoff?

Other top-down studies have emphasised the importance of both climatic variability, especially the timing of P and E_p, and land surface condition, including soil water holding capacity, on annual runoff (e.g., Farmer *et al*., 2003; see Chapter 5). Here we test for the importance of the monthly distribution of P and E_p using the monthly water balance on two catchments (Model 1). The impact of spatial distribution of P and E_p is tested using an annual, spatially distributed water budget (Model 2).

Precipitation is distributed differently in the two selected catchments, both temporally and spatially. Catchment A in the Western Ghats, the Ghataprabha catchment, has extreme spatial variability in rainfall: it receives more than 2000 mm/yr of rainfall in just 5% of its area, and 20% of its area receives less than 500 mm/yr. Catchment A also receives more of its rainfall in the early part of the monsoon, which is consistent with the earlier arrival of the south-west monsoon compared to the north-east monsoon. Catchment B in the Eastern Ghats, the Palleru catchment, has a much more spatially homogeneous precipitation field, and has no area where precipitation is more than 2000 mm/yr and only 1% less than 500 mm/yr. Catchment B receives more of its precipitation from the north-east monsoon in August through October (Figure 11.5).

The lumped, monthly model predicts the E/P of the catchment on the Deccan Plateau reasonably well (0.73 predicted versus 0.78 observed), but it incorrectly predicts that the catchment in the Western Ghats (A: Ghataprabha) has a higher E/P than the catchment in the Deccan Plateau (B: Palleru) (Table 11.3). The spatially distributed but temporally lumped model (2 in the methods) provided a more accurate prediction of E/P for the catchment on the Deccan Plateau than the lumped monthly water balance (0.80 versus 0.78 observed), but performed worse for the catchment draining the Western Ghats and did not accurately predict differences in the E/P ratios between the two catchments.

Table 11.3. *Observed and predicted long-term* E/P *for selected sub-basins. The sub-basin locations are indicated in Figure 11.3*

	Observed	Predicted, Model 1: temporally distributed, spatially lumped	Predicted, Model 2: temporally lumped, spatially distributed, $w = 1.2$
A: Ghataprabha	0.65	0.78	0.82
B: Palleru	0.78	0.73	0.80

Discussion

The Budyko analysis suggests that streams in southern India belong to one of two major hydrogeographic regimes. Catchments that have some fraction of their drainage area in the Western Ghats have significantly lower evaporation coefficients (*E*/*P*) and larger runoff coefficients compared to catchments draining the central Deccan Plateau and/or the Eastern Ghats, which is controlling for climate. The reason for the higher runoff generation in the Western Ghats is not demonstrated here, since neither the temporally distributed, spatially lumped model nor the temporally lumped, spatially distributed model was able to predict the high runoff coefficients in catchments draining the Western Ghats. The spatial heterogeneity in precipitation, in particular the extremely high precipitation in the Western Ghats, likely contributes to the high runoff coefficients, although other catchment properties, including soil type or land use, could contribute towards the regional differences. While both temporally and spatially lumped models yielded acceptable predictions of long-term *E*/*P* in areas with relatively homogeneously distributed precipitation on the Deccan Plateau, the lumped models did not yield accurate predictions in areas with highly heterogeneous precipitation. In the Western Ghats, this heterogeneity becomes particularly important, since the strong rain shadow creates a juxtaposition of high and low rainfall areas, which yields a low lumped precipitation value but high runoff.

The long-term average evaporation and runoff coefficients analysed here can serve as the starting point for understanding the geographic sources of water in southern India. Regionalisation of the kind presented here is necessary for determining the spatial and temporal distribution of water resources in ungauged basins, particularly given the scarcity of gauging stations. Due to inter-state conflicts over surface water allocation, this basic information on the spatial distribution of surface water is not available for many catchments in India. Quantitative estimates of runoff by climatic and geographic region is an important step forward in determining where water is generated in southern India and where it is used, and could be a starting point for encouraging further data-sharing among states. Inter-annual variability in water resources is as important as the long-term annual mean, so future efforts should focus on the roles of climate, soil and land cover impacts on inter-annual variations in the hydrology of the two different runoff regimes identified here.

11.3 PREDICTING MEAN ANNUAL RUNOFF ACROSS HUANGSHUI BASIN, CHINA

SHAOFENG JIA

The issue from societal and hydrological perspectives

The Huangshui Basin in China has great importance for Qinghai province. Half the population of Qinghai live in this river basin. Although the density of runoff gauges in the Huangshui Basin (0.8 station/1000 km^2) is less than what is common in more developed eastern China, it is still the most densely gauged area in Qinghai. In west Qinghai, the density of gauge stations is only 0.03 station/1000 km^2. Providing high-density spatial information of runoff depth based on readily available information from a DEM is of high societal value for water resources management in the Huangshui Basin. Moreover, the methodology developed in this case study to obtain runoff depth from a DEM, vegetation index and other easily obtainable information may be extended to other places in Qinghai province that are more sparsely gauged.

This study aimed to map the runoff depth across the mountainous region of the Huangshui catchment, making use of relationships between runoff depth and a range of geographic variables, including altitude, distance from water vapour source, and vegetation index. Using interpolation methods (see Section 5.3.3) and multiple linear regression techniques (see Section 5.3.1), we created a model to disaggregate the mean annual runoff measured at the gauging station to the entire basin area. It is thus a statistical interpolation and regionalisation method that makes use of readily available information to estimate annual runoff in ungauged areas.

Description of the study area

The Huangshui catchment is located in the east of Qinghai province. The Huangshui River is a first-order tributary of the Yellow River, flowing from north-west to south-east.

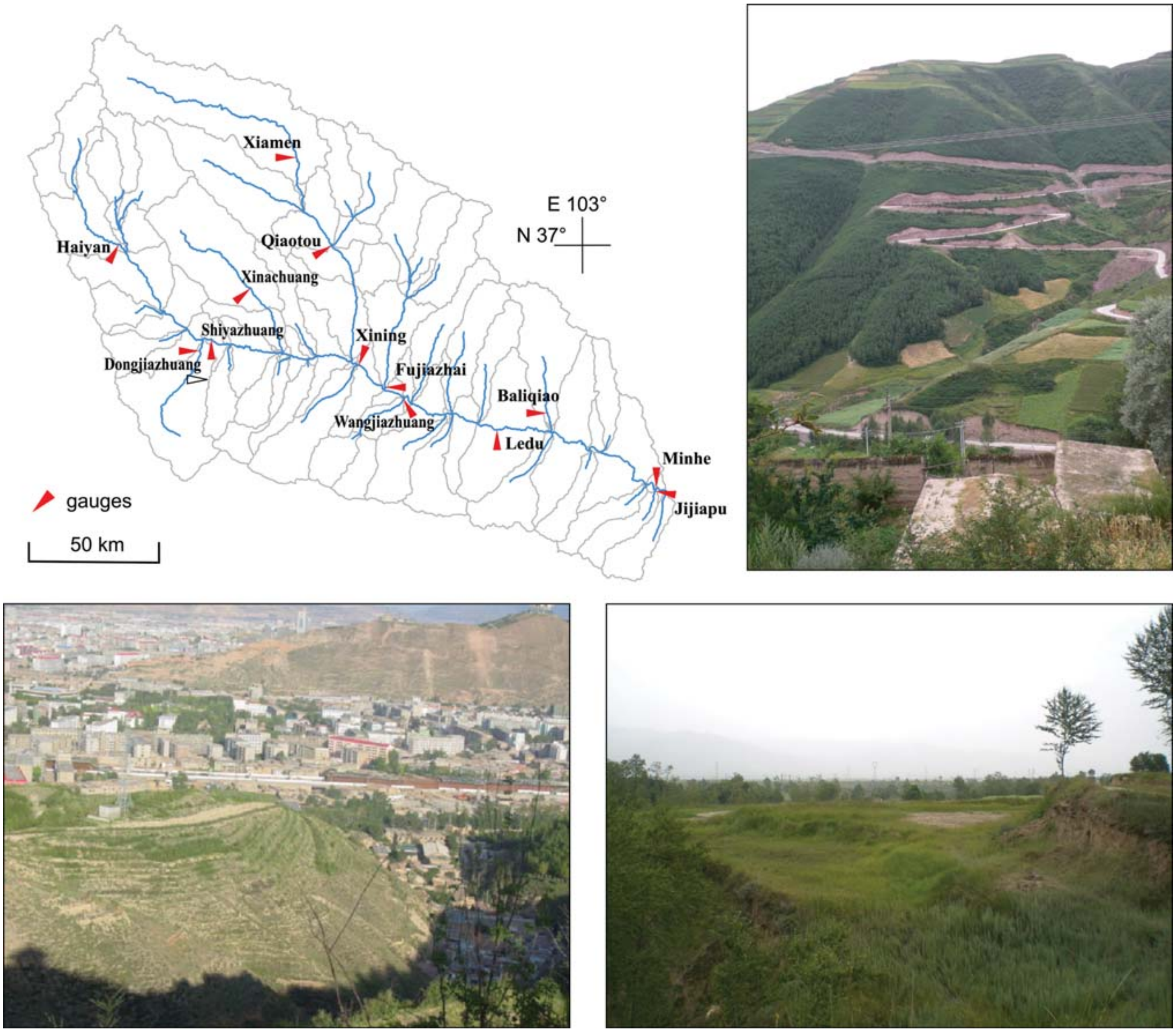


Figure 11.6. Location of the study area and positions of the 13 stream gauging stations. Pictures show (counter clockwise) Xining city, the capital of Qinghai province; arable land transferred back to grass and forest; arable land and roads in the mountainous area of the Huangshui Basin.

The Huangshui catchment covers an area of 16 120 km^2, has the shape of a leaf, and is located between 36°02′–37°28′ N and 100°42′–103°04′ E. There are 13 stream gauging stations in operation in the Huangshui catchment (Figure 11.6). The annual average runoff is 2.2×10^9 m^3/yr, the average flow rate is 66 m^3/s, and the average runoff depth is 138 mm/yr.

The Huangshui catchment is fed by water vapour from the Indian Ocean and Bay of Bengal. The climate is classified as semi-humid, with an average annual precipitation of 486 mm/yr. The annual precipitation distribution is very uneven, with a C_v ranging from 0.15 to 0.30. The upstream area receives much more precipitation than the downstream area. The annual precipitation in a valley area between Xining and Minhe varies from 250 mm/yr to 350 mm/yr, while more than 600 mm/yr precipitation is received in the mountain areas.

Huangshui catchment has a very inclining hypsography, with altitudes ranging from 4900 m to 1650 m, rising gradually from south-east to north-west. The minimum elevation is located in the valley near the Gansu–Qinghai border.

Along the river, we distinguish 13 non-overlapping drainage areas between existing gauges (see Figure 11.6).

Table 11.4. *Average annual runoff depth of drainage zones in Huangshui catchment*

Drainage zone	Drainage area (km^2)	Discharge (10^9 m^3/yr)	Runoff depth (mm/yr)
Xinachuan	809	1.633	201
Xiamen-Qiaotou	1466	2.696	184
Baliqiao	464	0.952	205
Xiamen	1308	3.617	277
Haiyan	715	0.473	66
Haiyan-Shiyazhuang	1732	1.786	103
Dongjiazhuang	636	0.840	132
Ledu-Minhe	1853	2.133	115
Fujiazhai	1112	2.056	185
Xining-Ledu	2521	2.506	99
Wangjiazhuang	370	0.437	118
Jijiabao	192	0.331	172
Shiyazhuang-Xining	2356	2.147	91

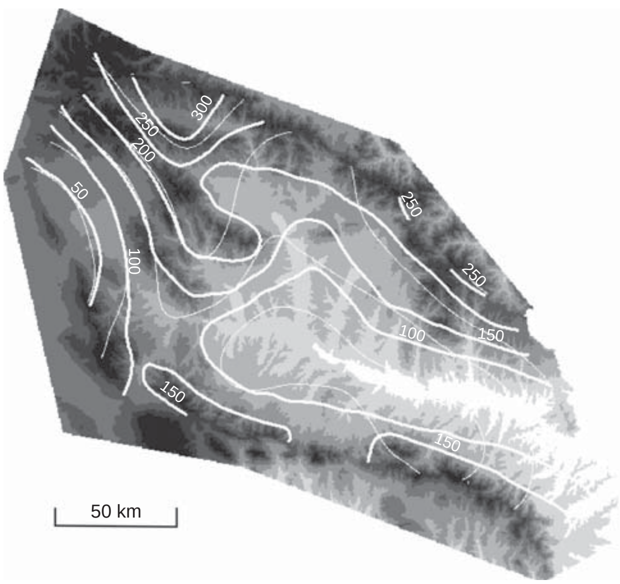


Figure 11.7. Revision based on DEM. White lines: after revision; white thin lines: before revision.

We used a period of 42 years, between 1958 and 2000, to calculate the average annual runoff depth of every drainage zone (Table 11.4). In addition, a digital elevation model (DEM, 50 m × 50 m) and a Landsat TM image (summer 2000) of Huangshui catchment were used in this study.

Method

First we assumed that the runoff depth of the centre point of the 13 drainage zones equals the average runoff depth of the drainage zone and mapped the runoff depth by using a normal interpolation method (spline). This resulted in the white lines in Figure 11.7.

Based on the spline contours, we revised the runoff depth contour by using DEM data. To revise the runoff depth contour we used the criterion that a runoff depth contour line should be nearly parallel to the elevation contour. This results in more detail in the interpolation.

Finally, we used vegetation depth as a proxy for annual runoff depth. Vegetation is a very important part of the environment. The vegetation can usually reflect the local landform, soil, geology, climate and elevation. Generally, vegetation cover is thick in places where precipitation is abundant, and is sparse in areas lacking precipitation. So we can assume that more precipitation is expected in an area where the vegetation cover is thick. And we can qualitatively determine that in an area where the vegetation cover is thick, more precipitation is received and runoff is also abundant, and vice versa. Based on the vegetation information on Landsat TM images, we revised the runoff depth contour further.

Results

After the contour lines had been revised using the DEM, the interpolation showed more detail (see Figure 11.7). Also the residuals became much smaller than those in the spline interpolation model. The standard deviation of relative residuals dropped from 13.4% to 12.1%, though the standard deviation of residuals increased a little (from 17.6 mm/yr to 18.0 mm/yr). The precision of the estimated values of the small runoff depths improved, apparently at the cost of a little less precision of the large runoff depths.

After the indicator for vegetation depth had been used, the contours became consistent with the vegetation coverage and we obtained revised runoff depth contours, as shown in Figure 11.8. The validation results showed that

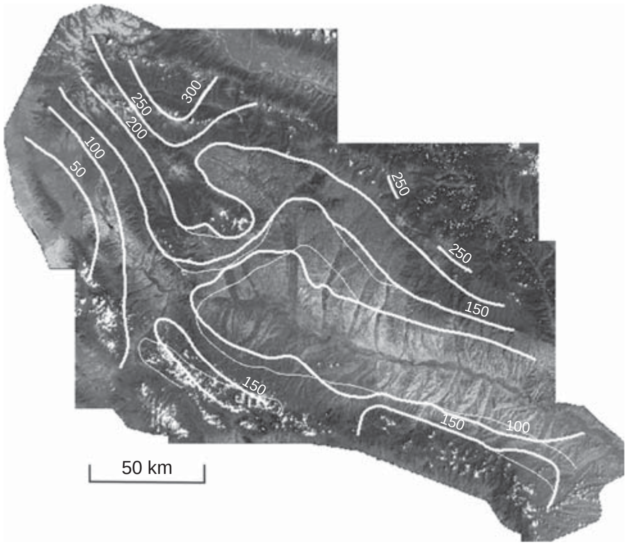


Figure 11.8. Revision based on vegetation depth.

the revised contours were improved. The standard deviation of the relative residuals dropped further to 11.7% and the absolute standard deviation dropped from 18.0 mm/yr to 16.5 mm/yr. Stepwise regression, however, indicated that the vegetation is strongly related to elevation and that it did not add much to what the elevation already provides. Moreover, in the valleys where crops are grown, the correlation between vegetation and runoff depth is not present.

Discussion

In this study, we succeeded in improving the precision of the mapping of annual runoff depth, using DEM and related geographic data. By comparing various models we reached the following conclusions:

(1) The mapping of annual runoff depth making use of spatially distributed data appears to be better than the empirical mapping still in use. This study shows that using GIS software to map runoff depth can not only improve the efficiency, but can also give a more reliable result.
(2) Geographical variables, such as elevation and vegetation cover, can be used to improve the precision of mapping of runoff depth.
(3) Using multiple linear regression techniques, we also created a regression model that relates runoff depth to altitude and distance to the source of water vapour. This regression model can achieve a similar precision to that obtained using spatial interpolation methods. But it fails to greatly improve the precision. The reason for this is that the relation between runoff depth and geographical characteristics is very complicated and it is not always possible to use one regression function to show these complex relations.
(4) The more detailed information obtained by this method on the spatial distribution of runoff is very useful for river basin management, such as the selection of reforestation areas, reservoir sites etc.
(5) One potential merit of the regression model is that it may be extended and used to predict runoff depth in ungauged basins with similar geographical conditions, whereas interpolation methods do not have this function. Because of the geographical difference between the north and the south in the study area, we used two different equations even in the same basin. This shows that it is very difficult to assess the geographical similarity between various areas, and it requires more effort and study to find a feasible method to decide whether an area's runoff depth can be estimated by the runoff depth equation of another area.

11.4 AN INDEX APPROACH TO MAPPING ANNUAL RUNOFF IN A SIBERIAN CATCHMENT, RUSSIA

L. M. KORYTNY, E. A. ILYICHYOVA AND B. GARTSMAN

The issue from societal and hydrological perspectives

By combining hydrology and geomorphology we can obtain a uniform principle to analyse structures of valleys and river networks. An innovation in the analysis of river systems is the introduction of entropy characteristics, which have high information content and are closely associated with hydrographic characteristics of river systems. (Gartsman *et al.*, 1976). The entropy characteristics take into account the number of elements in the structure and their distribution, and the interrelationships of these elements, which permit them to be used as informative parameters, closely associated with the functional characteristics of a river system. These parameters take account of the structural characteristics of river systems, such as hierarchy, ordering and co-subordination. This new approach is highly relevant for PUB, since it can derive mean annual discharge estimates on the basis of the physical characteristics of the basin structures. Such maps are of high societal value when planning water resources development in poorly gauged or ungauged basins.

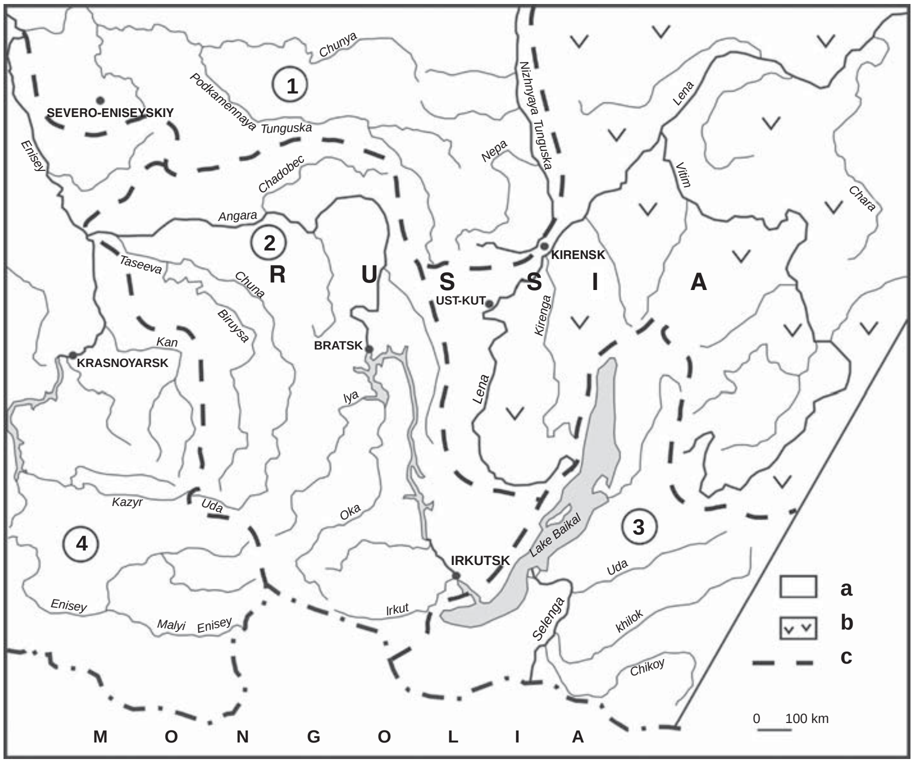


Figure 11.9. The hydrographic scheme of south-eastern Siberia: 'a' indicates the Yenisei River basin (sub-basins of (1) the Lower Tunguska and Podkamennaya Tunguska rivers, (2) the Angara River, (3) Lake Baikal and (4) the Yenisei itself); 'b' indicates the Lena River basin; and 'c' the water divides.

Figure 11.10. Mountain taiga and alpine tundra.

Description of the study area

The study deals with south-eastern Siberia, by which is meant the territory lying in the middle part of the Asian mainland (Figure 11.9). Hydrographically it includes basins of the upper and middle Yenisei and of the upper Lena.

Most of the catchments of the middle Yenisei and of the upper Lena are part of the Central Siberian Plateau. Tectonically, its core is represented by the Pre-Cambrian Siberian Platform. A distinguishing feature of the topographic relief is the monotonous flatness (with altitudes of 500 to 700 m) with incised valleys. The most severe incision is at the south-western margin of the plateau: the Yeniseisky Ridge, while the Pre-Sayan inter-montane trough lies on the south.

The territory is a typical taiga zone, with subzones of middle and southern taiga as well as sub-taiga with forest-steppe islands. The middle taiga occupying the northern part of the territory, and also the Yeniseisky Ridge, is dominated by larch: Siberian larch on the west, and Daurian larch on the east. The southern taiga is covered by pine and pine–larch forests. Further to the south, along the foothills, a zone of sub-taiga and forest-steppe landscapes extends like a strip, which is the home of pine and birch grass forests with inclusions of meadow steppes.

The basins of the upper Yenisei and Lake Baikal comprise the mountain formations of the Western and Eastern Sayan mountains, the Abakansky and the formations of the Pre-Baikalia and Transbaikalia. In between the mountain ranges there are depressions, such as Minusinskaya, Baikalskaya, Tunkinskaya, Barguzinskaya and others. Most of the formations have a middle-mountain relief (with altitudes of 800–2000 m) dominated by mountain ranges up to 3000 m or more high, with alpine relief. In the foothill areas, depressions and the lower parts of the slopes, there is a steppe and forest-steppe belt where grassy

Figure 11.11. Dark-coniferous forests in the Lena River valley.

Figure 11.12. Meadow steppes and valley forests in the Lena River basin.

meadow-steppe vegetation alternates with pine groves, and with larch and birch woodlands. The mountains of southern Siberia are characterised by the mountain-taiga belt occupying more than half of this territory dominated by coniferous forests consisting of fir, spruce and Siberian stone pine, with the inclusion of pine and larch. Higher elevations are occupied by the high-mountain belt, with characteristic mountain-tundra and mountain-meadow vegetation, snow patches and small glaciers.

This diversity of natural conditions in south-eastern Siberia is partly responsible for the differences in runoff formation.

Method

In a first step the stream network from a middle-scale topographic map was represented as a binary tree-graph. A binary tree-graph is a formal geometric structure where every reach of the stream without tributaries is represented as a link and every point of confluence is represented as a node, irrespective of the distances involved. Second, at every confluence the number of headwater catchments of each of the tributaries, S_1 and S_2, was determined. Then the Shannon entropy was calculated in every node

$$H = -P_1 \log P_1 - P_2 \log P_2$$

with

$$P_1 = \frac{S_1}{S_1 + S_2} \quad P_2 = \frac{S_2}{S_1 + S_2}$$

The total entropy for each node was calculated as the sum of all entropy values upstream of the node plus H at the node. For each stream gauge where mean annual runoff Q_m was available, the total entropy of the nearest upstream node was determined. The diagrams of Q_m versus the total entropy $\overline{M}(A)$ indicate a linear relationship within homogeneous regions. On the basis of this relationship, mean annual runoff can be calculated at any node of the network. $\overline{M}(A)$ increases with catchment area but is more informative than the catchment area itself as it has the stream network structure imbedded.

Mean runoff assessment and mapping of the rivers in the southern part of East Siberia

The input was provided by a stream network structure that was constructed without regard for the real geometry of the streams that constitute the river system. The network structure was constructed based on topographic maps at a scale of 1:300 000; water streams of all orders could be taken into account in detail at this scale.

The established relationships between structural measures (M, entropy) and average long-term discharge (Q_m, $\mathrm{m^3/s}$) for specific cross-sections based on hydrological information represent a family of lines $\alpha = Q/M$, represented by the numbers I–V (see Figure 11.13). Each of the obtained relationships (I, II, III etc.) corresponds to a certain area, or group of areas, characterised by a similar set of climatic, geological and hydrological conditions. On the basis of these, it is possible to determine the discharge of ungauged rivers according to observable conditions. To construct these relationships we used data from 250 stream gauge stations in river basins: 62 sites for the Lena, 46 for the Lake Baikal catchment, 69 for the Angara, and 73 points for the Yenisei and the Tunguskas.

For the river systems of the upper and middle parts of the Yenisei, the relationship between total structural measure $\overline{M}(A)$ and the mean discharge can be grouped into five

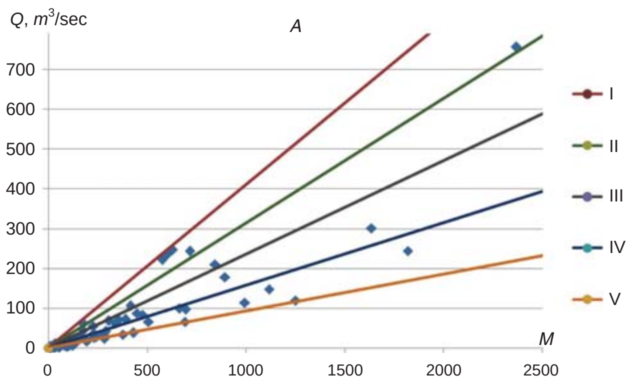


Figure 11.13. Relation between average annual runoff, Q_m, and the total entropy, $\overline{M}(A)$, for the Yenisei Basin.

classes (see Figure 11.13). The predominant platform regime of runoff and river network formation in the Angara River basin was responsible for three groups. In the Lena River basin, five groups were identified; each of the groups is characterised by the specific character of the hydrology and geological structure. The rivers of the Baikal catchment basin are organised into four groups.

Thus, the local dependencies of the average runoff on entropy combine rivers that are in similar or identical conditions of runoff formation, with the set of hydrological and structural parameters inherent in this group only. High values of α, the angle of inclination, are characteristic for well-developed and humid river systems lying, usually, in deeply incised high-mountain landscapes on rock with steep gradients, and with large amounts of atmospheric precipitation feeding the runoff. Extremely low values of the angle of inclination are typical for a river network of weakly differentiated uplands and valleys, usually, with a low density of channel network, low values of atmospheric precipitation, and with a small runoff that follows the overall gradient of the basin. In intermediate cases the dominant role can be played by any one of the factors of runoff and hydraulic network formation, namely, exposure of the mountain ranges relative to the moisture-carrying streams, age and composition of earth materials, the presence of karst etc. Thus, the local relationships $Q = f(M)$ can be used to determine the mean water discharge of river systems that have not been studied to date.

Results

Structural information, obtained for the entire topological space, makes it possible to carry out a detailed mapping of the water availability in the river systems. We present this in the form of an along-the-channel scale band (distribution diagram) (see Figure 11.14). This method is called 'localised diagrams'; it is a method of mapping phenomena having continuous or linear (strip) distributions. In this case the diagrams belong to a linear spatial element: a river channel. The diagrams are traced on both sides of a channel. The width of the diagrams is changed smoothly along the length of the river; at inflow points they fork, depending on the contributing discharge.

We distinguished three scales of water discharge: more than 500 m^3/s, 50–500 m^3/s and 5–50 m^3/s. Mapping begins where the average long-term discharge is more than 5 m^3/s, as a smaller discharge is difficult to map and would overload the map. At a more detailed scale, a more detailed elaboration of the rivers for smaller discharge is possible.

Discussion

With this method, it is possible to determine the discharge at any cross-section that allows optimisation of economic and security measures. It is possible to determine the water budgets of surface water resources in terms of landscape, natural-economic, ecological and administrative divisions. Using this method, we prepared the water content maps of the Lower Angara region and the Irkutsk region (Korytny and Ilyichyova, 2005).

11.5 PREDICTING SPATIAL PATTERNS OF INTER-ANNUAL RUNOFF VARIABILITY IN THE CANADIAN PRAIRIES

J. W. POMEROY, K. SHOOK, XING FANG AND T. BROWN

The issue from societal and hydrological perspectives

Western Canada contains a vast semi-arid to sub-humid agricultural region known as the Canadian Prairies. Large fractions of the Canadian Prairies are not normally hydrologically connected to any large-scale drainage system, and most of the large rivers in the region obtain the majority of their flow from the Rocky Mountains rather than locally (Pomeroy *et al.*, 2007a). Whilst the large rivers are gauged, the smaller streams in the Canadian Prairies are often ephemeral and ungauged. The streams are often part of poorly developed drainage basins that feed and are composed of numerous small post-glacial depressions. Though they do not normally contribute to river flow, these depressions can become important wetlands for migratory waterfowl that use them as habitat during the spring, summer and autumn (Smith *et al.*, 1964). On-farm water supplies are also provided by natural depressions and man-made 'dugouts', which are fed by local runoff and runoff due to the lack of suitable groundwater on many farms (Pomeroy

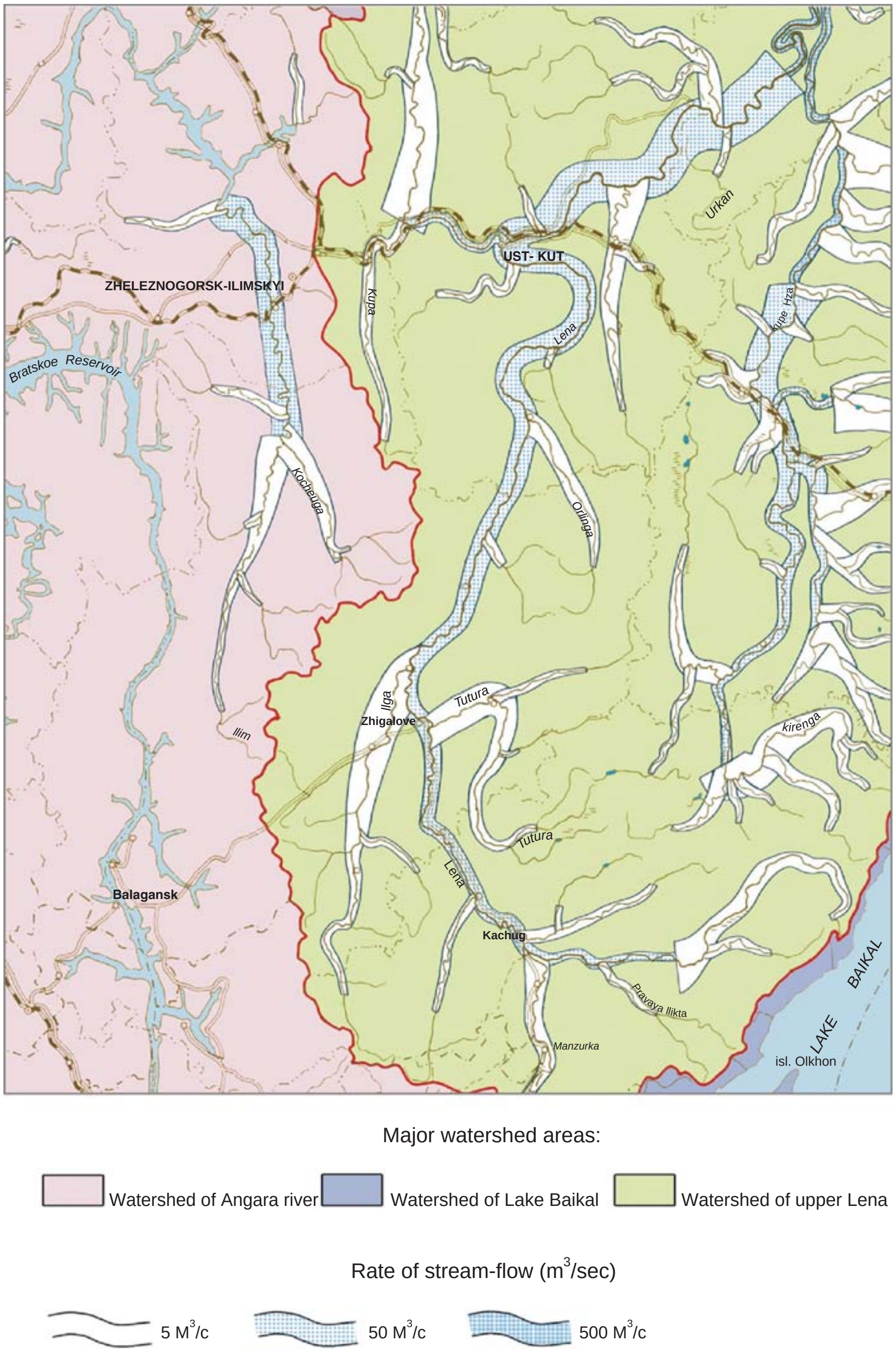


Figure 11.14. Map of mean annual runoff in part of the Yenisei Basin.

et al., 2007a). Both the regional waterfowl population and local on-farm surface water supplies are strongly influenced by the state of depressional storage, which itself is controlled by the flow of a multitude of small, ungauged ephemeral streams.

The water balance of these internally drained basins is controlled by local runoff generation, redistribution of snow, incident precipitation, evaporation, groundwater exchange and antecedent status of soil and depressional storage. Depending on the water balance, depressional storages vary from being shallow and seasonal to being deeper and relatively permanent. The region experiences great variability in inter-annual precipitation with important hydrological responses. In typical conditions the internally drained basins are considered non-contributing to larger river basin runoff (Godwin and Martin, 1975), however, during extremely wet

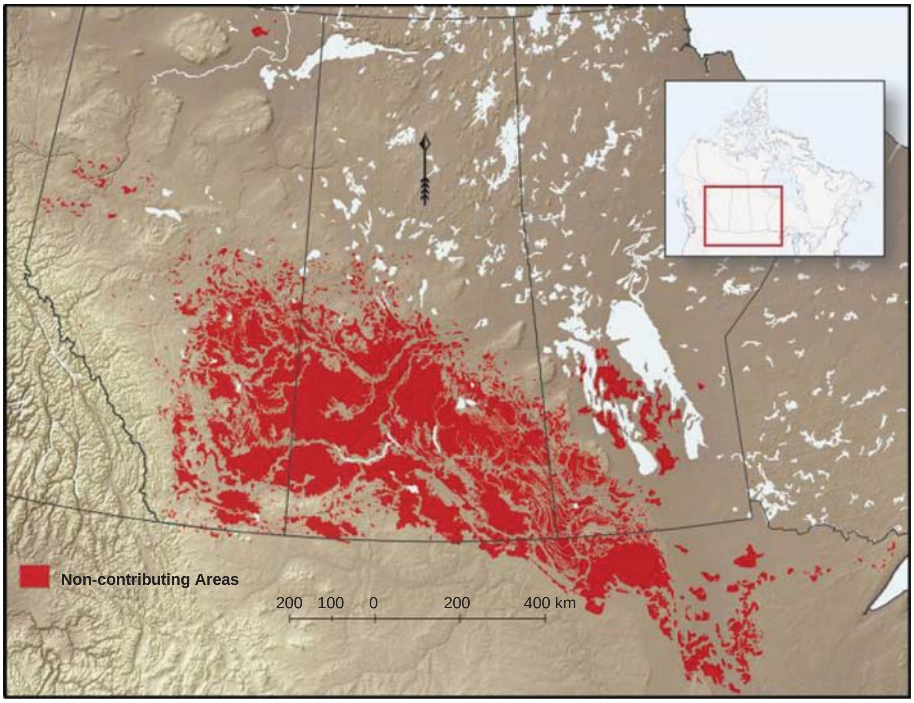


Figure 11.15. Non-contributing areas of drainage basins as delineated by Prairie Farm Rehabilitation Administration, Agriculture and Agrifood Canada and three Prairie Provinces.

conditions depressions connect to one another through the ‘fill and spill’ mechanism and can contribute to larger basin runoff and large-scale flooding. During droughts, many wetlands and dugouts dry out completely, causing waterfowl populations to crash due to lack of habitat and reductions in livestock due to lack of dugout water. While on-farm water supplies can be supplemented by water hauling, this is expensive and contributes to the failure of farms. For instance, the prairie drought of 1999–2005 was very severe and is regarded as the most expensive natural disaster in Canadian history, with the period 2000–1 being one of the worst on record (Bonsal and Regier, 2007). The gross domestic product dropped \$5.8 billion, agricultural production dropped \$3.6 billion and employment dropped by 41 000 due to the drought at its peak in 2001–2 (Stewart *et al.*, 2011). The number of prairie wetlands was the lowest on record. Methods used to index agricultural droughts and soil moisture are not suited for characterising hydrological drought as it affects depressional storage in this region because they cannot estimate runoff from the small ephemeral drainage systems that feed these wetlands and dugouts. Estimating the variability of runoff into these ungauged internally drained basins has posed a considerable scientific challenge of great societal interest in the region.

Description of the study area

The Canadian Prairies cover the southern part of the provinces of Alberta, Saskatchewan and Manitoba and are the northern limit of the North American Great Plains. Drainage networks in the region are poorly developed due to the post-glacial geomorphology, in which large areas are internally drained, and the dry climate (Figure 11.15). The northern fringe of the Prairies is covered by Parkland, which was a mixed deciduous forest, wetland and grassland complex that has been largely cultivated to cereal grains and oilseeds or converted to pasture since European settlement over 100 years ago. The region is characterised by relatively low precipitation, especially in the south-west part, due to the atmospheric flow barrier imposed by the Rocky Mountains, and experiences frequent water deficits and low soil moisture reserves. Annual precipitation in the prairie region of Saskatchewan ranges from 300 to 400 mm/yr, about one third of which occurs as snowfall. This is a cold region and it exhibits classic cold region hydrology with continuous snow cover and frozen soils over much of the region in the winter. Great variation in hydrology exists across the Prairies, with fairly well-drained, semi-arid basins in the south-west part and with many wetlands and lakes in the Parklands of the sub-humid north, central and eastern parts.

Much of the region is cultivated and devoted to the growing of cereal grains and oilseeds, with forage crops where soils are less suitable for cultivation. Most runoff occurs from spring snowmelt as a result of frozen soils and rapid release of water from snowpacks (Gray *et al.*, 1985) – the redistribution of snow in winter controls meltwater generation for runoff production. Summer runoff generation is usually negligible because of deep soils

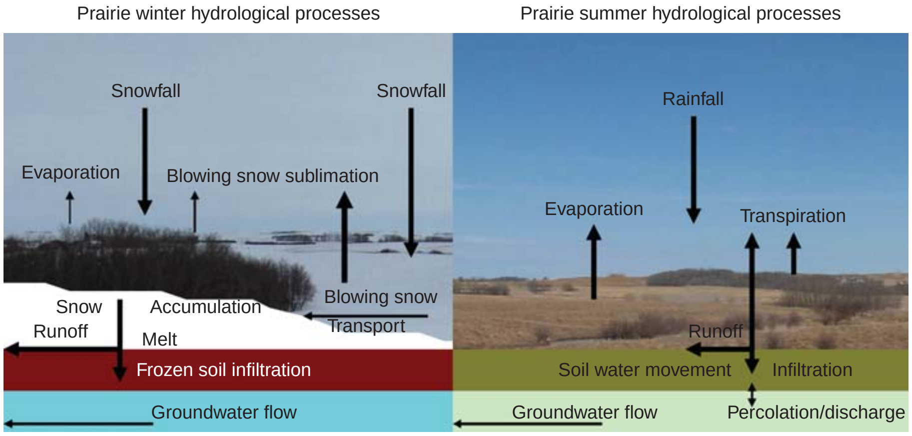


Figure 11.16. Prairie hydrological cycle: (left) winter processes, (right) summer processes.

characterised by good water-holding capacity, low to moderate levels of soil moisture and high unfrozen infiltration rates. Figure 11.16 shows the major hydrological processes in winter and summer in typical Canadian Prairie landscapes that contribute to hydrological cycling on small stream drainages.

Surface runoff generation is strongly affected by the climate variation over the Prairies. A synthetic drought analysis at a typical semi-arid prairie site suggested that spring stream discharge drops substantially under warmer and drier conditions and ceases completely when winter precipitation decreases by 50% or winter/spring air temperatures rise by 5 °C, as is common during drought. Water supply to wetlands is insufficient during drought due to lower discharge of surface runoff from local catchments. The hydrography of the Canadian Prairies is very repetitive, with many drainage basins consisting of assemblages of small ephemeral streams that feed into depressions, and their associated uplands. The vast majority of these small drainage basins are ungauged and the majority of larger basins in the region do not meet WMO standards for gauging density. Runoff in these small basins cannot be modelled using traditional techniques due to poorly developed drainage systems and mild topography.

Method

Cold Regions Hydrological Model platform

The Cold Regions Hydrological Model (CRHM) platform is a physically based hydrological model based on a modular, object-oriented structure in which component modules represent basin descriptions, observations or physically based algorithms for calculating hydrological processes. The component modules have been developed based on the results of over 45 years of research by the University of Saskatchewan and Environment Canada in cold regions environments. A full description of CRHM is provided by Pomeroy *et al*. (2007b). CRHM permits the assembly of a purpose-built model from a library of processes, and interfaces the model to the basin based on a user-selected spatial resolution. The hydrological processes are simulated on landscape units called hydrological response units (HRU, see Sections 10.2.2 and 10.2.3). HRUs are defined as spatial units of mass and energy balance calculation corresponding to hydrobiophysical landscape units, within which processes and states are represented by single sets of parameters, state variables and fluxes. HRUs can be finely scaled (hillslope segment), or coarsely scaled (sub-basin). HRUs in the prairies typically correspond to agricultural fields (stubble or fallow fields), natural cover (grassland or forest woodland) and bodies of water (lake or pond) (Fang and Pomeroy, 2008). CRHM has shown good simulations in a semi-arid, well-drained prairie basin (Fang and Pomeroy, 2007) and in a sub-humid, poorly and internally drained prairie basin (Fang and Pomeroy, 2008).

Virtual basin

Because the hydrography of the Canadian Prairies is repetitive, and because of the interaction amongst HRUs via blowing snow transport and runoff, a virtual basin can be defined based on a basin with well-known characteristics and can be considered a fundamental first-order runoff generation unit. The concept is very useful as an index for vast regions where, due to lack of gauging and subtle topography, not only is runoff unknown but drainage area and drainage network characteristics are poorly defined. A virtual basin was defined based on Creighton Tributary of the Bad Lake International Hydrological Decade (IHD) research basin in the south-western portion of the Canadian Prairies. Bad Lake is an internally drained wetland basin and Creighton is a small catchment (11.4 km^2) flowing into Bad Lake. Approximately 85% of the basin area was cultivated land (grain stubble and summer-fallow fields), and the rest of basin consisted of grassland for the periods

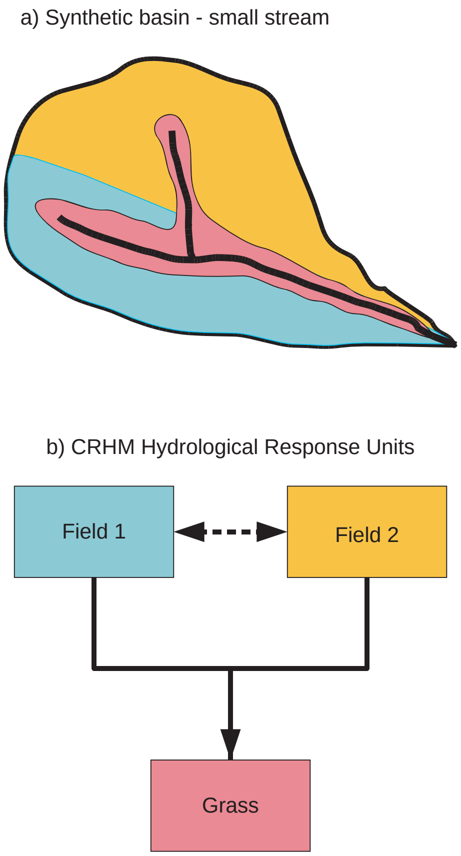


Figure 11.17. Schematic diagram of Creighton Tributary virtual basin (a) and CRHM hydrological response units (b). The dashed line indicates blowing snow redistribution.

of observation (Gray *et al.*, 1985). The basin is characterised by level open land with poor drainage and highland with rolling topography; it is drained by a grassland 'coulée' (sharp incised valley in the upland plain) from which flows Creighton Tributary. This stream flows intermittently, with most flow during and immediately after the snowmelt period. Runoff on Creighton Tributary was monitored from the 1960s to mid 1980s. Pomeroy *et al.* (2007b) showed that CRHM, with an appropriate model structure, could provide an excellent representation of runoff, snowpack and snowmelt timing in Creighton Tributary, without calibration of model parameters. A virtual Creighton Tributary model is applied to represent ungauged basin flow throughout the prairie region.

Virtual first-order basin regional simulation

To show how the hydrology of a basin modelled on Creighton Tributary varies with drought and wet cycles and with regional climatic variations, a virtual basin model was constructed based on that used by Pomeroy *et al.* (2007b) and Fang and Pomeroy (2007). The model, which is shown schematically in Figure 11.17, consists of three HRUs. Because of the practice of cereal crop rotation, HRUs 1 and 2 alternate between being fallow and cropped, with the third HRU representing a grassed stream channel. As the grass has a greater aerodynamic roughness height than the winter stubble remaining on the cropped HRU (and both are greater than that of the fallow), snow will be blown from the fallow to the cropped HRU, and from both to the grassed channel. The runoff from HRUs 1 and 2 will always drain to HRU 3, from which it exits the basin.

The virtual basin model was applied in continuous simulations across the Canadian Prairies over a multi-decadal period. Whilst topographic characteristics were held constant for the virtual basin, soil texture was permitted to vary with the location modelled – in general there are more clay soils in the eastern part of the region and more silty-loams in the west. This variation in texture has an important influence on runoff generation in the model. The model was applied with meteorological inputs from a few high-quality meteorological stations using observations of daily precipitation, and hourly air temperature, humidity, rainfall and wind speed. All data were obtained from the Data Access Integration (DAI) portal (http://loki.qc.ec.gc.ca/DAI/), which was created through the cooperation of a number of organisations. As many of the meteorological time series were discontinuous, owing to stations being moved, it was necessary to construct hybrid time series by combining data from several stations. In all cases the stations had been moved only short distances and were identified within the records as being at the same general location (i.e., town).

Because of the very poor density of measured solar radiation stations on the Canadian prairies, solar radiation was reconstructed using the techniques developed by Shook and Pomeroy (2011). The latitude was also permitted to vary with the location modelled to allow accurate calculation of the components of the radiation balance.

The stations and the prairie ecozone, as defined by Marshall *et al.* (1996), are shown in Figure 11.18. The model was spun-up by running it from 1 January 1960 to 1 January 1961. As there is typically no change in soil moisture over the frozen winter period and because the summer of 1959 was dry, the soil moisture at each location was initially set to be 50% of saturation – this is the only state variable that required spin-up to estimate.

All comparisons were made relative to values calculated from the climate normal period (1961–90) for each site modelled. The models were run from 1961 (allowing for one year of spin-up) through 1990, and the empirical cumulative distribution function (ECDF) was computed from the modelled annual discharges for each site. Having determined the normal period ECDF for each site, the exceedance probabilities were then determined for the

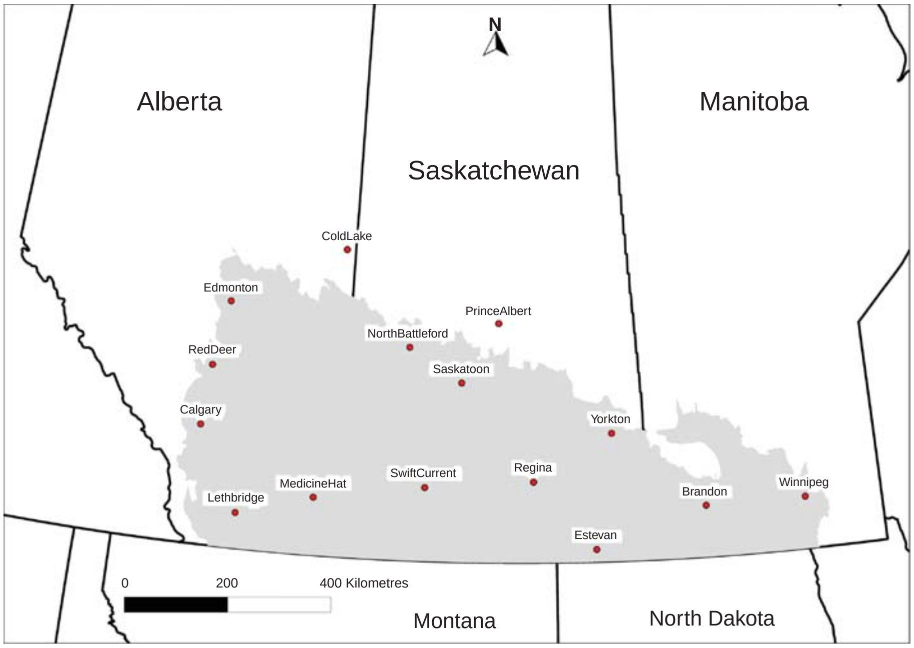


Figure 11.18. Stations used as model inputs in western Canada. The prairie ecozone is shaded. Projection is UTM 13.

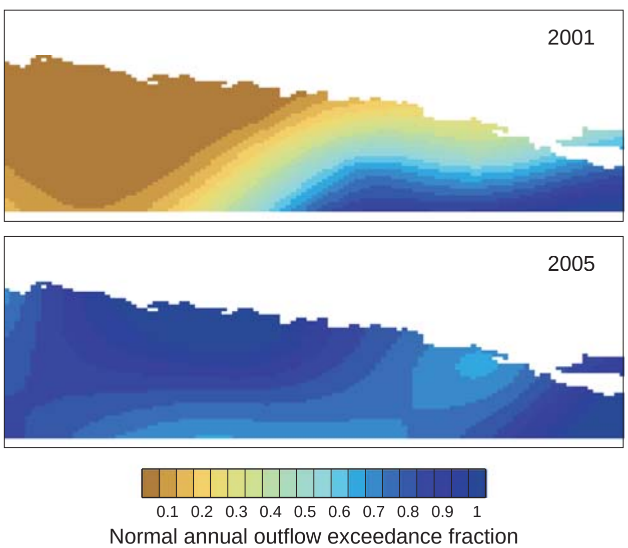


Figure 11.19. Annual runoff exceedance probability of the virtual basin over the 1999–2005 drought compared to the 30-year normal period (1961–90) with the maximum drought year (2001) and post-drought year (2005) selected. The Mercator projection was used for all maps.

annual discharges modelled for each of the years between 1999 and 2005, inclusive. All calculations were performed using the open source statistical language R (Ihaka and Gentleman, 1996).

The use of the normal ECDF permitted regional comparison of the virtual basin behaviour and provides an index to hydrological drought for ungauged basins. Because the distribution is computed for each location modelled, the frequencies are comparable from location to location. The exceedance probabilities were interpolated between stations using a continuous curvature spline (Smith and Wessel, 1990), gridded and plotted using the Generic Mapping Tools, which is a collection of command-line GIS tools for Linux and Unix available at gmt.soest.hawaii.edu.

Results

The gridded exceedance probabilities of the annual discharge from the virtual basin model are plotted in Figure 11.19 for a typical drought year (2001) and the post drought year (2005). Whilst 1999 was a moderate to wet year, in 2001 the hydrological drought was at its maximum and extended over large areas of the western and eastern Prairies; in 2002, it retreated from most of the region. In 2005 the annual discharge map shows a large volume of runoff, which was due to spring rainfall that was widely distributed across the region. This corresponded to record flooding in Alberta. The results show that hydrological drought included extremely wet regions, record dry regions and large spatial variability in surface water availability.

Discussion

Calculation of exceedance probabilities using physically based hydrological modelling for virtual basins is a new methodology for describing hydrological droughts in

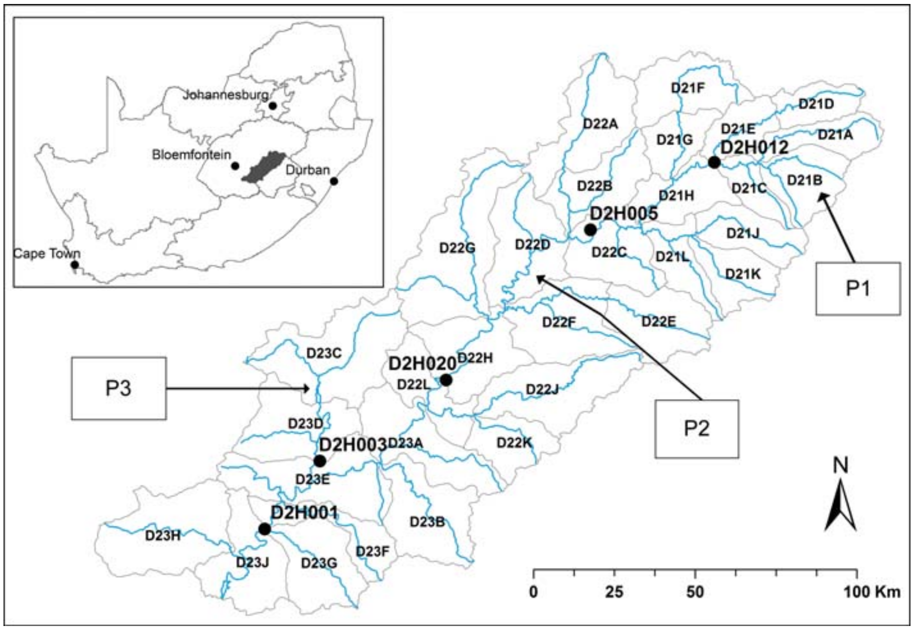


Figure 11.20. The Caledon River basin showing modelled sub-basins and runoff gauging stations (P1 to P3 refer to the Google Earth images in Figure 11.21).

ungauged regions such as the Canadian Prairies. Many streams in the region are ephemeral, and are not only ungauged, but lie in poorly defined internal drainage basins. Providing estimates of runoff variation in droughts and pluvials adds new information for land and water managers. The methodology was demonstrated by modelling the extent of hydrological droughts on the Canadian Prairies during the period 1999–2005 with reference to the normal period of 1961–90. Because suitable meteorological forcing data are only available at points separated by many hundreds of kilometres, only very large-scale spatial trends are discernible in runoff. Nevertheless, plots of interpolated exceedance probabilities were able to demonstrate the substantial spatial and temporal variation of the hydrological drought in regions where it would otherwise be unquantifiable.

11.6 SEASONAL FLOW PREDICTION WITH UNCERTAINTY IN SOUTH AFRICA AND LESOTHO

D. A. HUGHES

The issue from societal and hydrological perspectives

The water resources of the Caledon River basin are important locally to sustain water supplies for many small towns as well as the Lesotho capital city of Maseru, and for irrigated agriculture in the South African parts of the basin. They are also important regionally through an inter-basin transfer scheme abstracting water from Welbedacht dam for the city of Bloemfontein located in the Modder River basin to the north-west. As a consequence there exist many small farm dams as well as a number of much larger dams. Midgley *et al*. (1994) list a total of 53 impoundments with a combined storage capacity of approximately 202×10^6 m^3, compared with their estimate of the mean annual runoff of 1244×10^6 m^3. There are, however, many more small storage dams with unknown capacities that are not included in the list provided by Midgley *et al*. (1994). While there are six runoff gauging stations (Figure 11.20) within the study area, their data records are short and cover different periods, rarely measure the full range of high flows, and are impacted by poorly quantified upstream abstractions. The combined uncertainties in the observed data make the basin effectively an ungauged one. The observed data may be useful for constraining some aspects of simulated flow data, but are not useful for conventional model calibration.

Description of the study area

The Caledon River forms the north-western boundary between Lesotho and the Free State Province of South Africa (Figure 11.20) and is one of the major tributaries of the upper Orange River. The total area of the Caledon River basin at its junction with the Orange River is 21 884 km^2, while this study focuses on the area (15 270 km^2) upstream of Welbedacht dam (D23J). The headwater sub-basins rising within Lesotho are characterised by steep

Figure 11.21. Google Earth images of the upper parts of the basin in Lesotho (P1), the middle parts of the basin on the border between Lesotho and South Africa (P2), and a reservoir on one of the tributaries in the lower part of the basin (P3).

slopes (the north-western edge of the Drakensberg Mountains) with grassland vegetation. Land use consists of extensive rain-fed cultivation and cattle grazing (mostly subsistence agriculture) on the valley sides and bottoms. The topography in most of the South African parts of the basin is undulating, while land use is based on intensive cultivation with a mixture of rain-fed (mostly maize) and irrigated crops together with some cattle grazing. The majority of the basin is underlain by sandstones and shales, while the south-western parts of the basin are underlain by shales and mudstones. Soil characteristics are highly variable both in terms of depth and texture. Mean annual precipitation varies from over 1000 mm/yr in the Drakensberg Mountains to less than 600 mm/yr in the lower parts of the basin. Potential evaporation ranges from less than 1300 mm/yr in the headwaters to 1600 mm/yr downstream. The rainfall regime is highly seasonal, with approximately 70% of the rain falling between November and March.

Method

The hydrological model used in this study is the Pitman monthly model (see also Sections 6.4.2 and 7.4.2 for other examples) with revised surface–groundwater interaction routines (Hughes, 2004; Hughes *et al.*, 2006). The model has been widely used in the Southern Africa region for practical water resource assessments, traditionally based on parameter sets that were established through calibration at a limited number of gauging sites, followed by regionalisation using a relatively subjective approach based on perceived basin similarity. Midgley *et al.* (1994) provide parameter values for the 1946 sub-basins covering the whole of South Africa, Lesotho and Swaziland. Of these, 31 sub-basins form the Caledon River study area (see Figure 11.20). Kapangaziwiri and Hughes (2008) and Kapangaziwiri *et al.* (2009) report on an alternative approach to parameter estimation for the Pitman model that does not rely on calibration, includes uncertainty, and is based on the use of estimation equations using physical sub-basin properties (topography, soils, geology and vegetation) available from various sources (e.g., AGIS, 2007). The parameter uncertainty is estimated from the spatial variation in the physical sub-basin properties and expressed as means and standard deviations of normal distributions or maximum and minimum values of uniform distributions (Kapangaziwiri *et al.*, 2009). In this study a combined approach has been used. The Kapangaziwiri *et al.* (2009) approach has been applied to selected representative sub-basins (steep headwater areas of the north-east, less steep headwaters in the north-west and flatter downstream sub-basins) to establish the likely ranges of parameter values and their uncertainty distributions across the whole basin. The Midgley *et al.* (1994) parameter sets were used as a guide to extrapolating from the sample sub-basins to establish uncertain parameter sets for the whole basin.

The uncertainty version of the model (Hughes *et al.*, 2010) generates output ensembles (typically 10 000) based on Monte Carlo sampling of the parameter distributions independently for all 31 sub-basins. The original approach was based on unstructured (or unconstrained) sampling, but this resulted in highly reduced uncertainty in the downstream reaches compared to the upstream sub-basins. This reduced uncertainty is associated with the total possible parameter space being far greater than the number of ensembles and the fact that each of the downstream ensemble results is generated from a mix of upstream parameter effects. A revised approach involves structured sampling to ensure that more of the extreme parameter uncertainty effects are propagated downstream.

Results

Figure 11.22 presents the results as 1-month flow duration curves for the lower and upper bounds encompassing 90% of all the simulated ensembles. The only part of the model

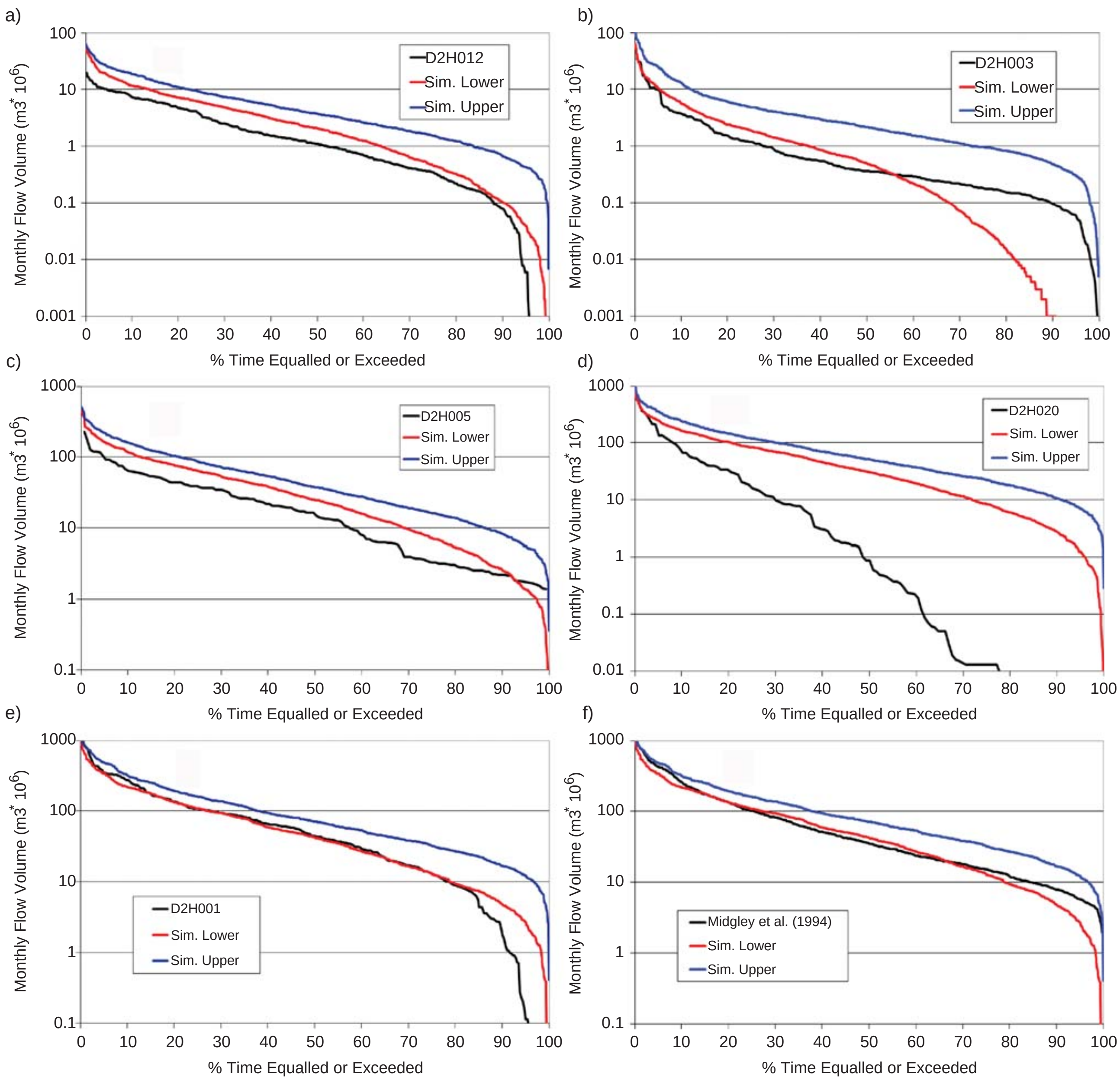


Figure 11.22. Results for the gauged sub-basins presented as 1-month flow duration curves for observed flows and the simulated upper and lower bounds of the uncertainty ensembles.

that has been subject to any form of calibration is the groundwater recharge parameters, and these have been established to match the range of mean annual recharge values given in DWAF (2005). The results are presented at the sites of the gauging stations to determine whether the local gauging data can be of any assistance in constraining the parameter uncertainty ranges, or identifying where the estimated parameter values are non-behavioural.

The records for D2H012 (1968 to 2010) are representative of present-day conditions in the northern headwaters. However, the peak daily flow observations are truncated and therefore the high flows are highly under-represented. While there are a relatively small number of farm dams in the upstream areas, it is assumed that the lowest flows will have been affected by some abstractions. The balance of the evidence suggests therefore that the simulations are behavioural (Figure 11.22a). The records at D2H003 (1935 to 1954) pre-date the construction of a major reservoir (14.2×10^6 m^3 storage), while a second reservoir (5.6×10^6 m^3 storage) has existed upstream since 1892. The

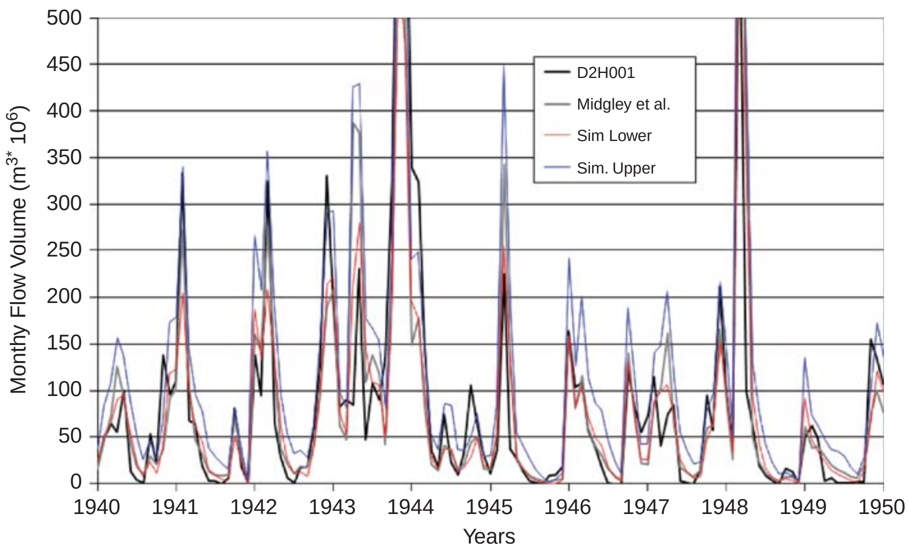


Figure 11.23. A 10-year sample of the time series of observed and simulated monthly flow volumes at D2H001 (sub-basin D23F).

pattern of observed daily flows through the dry season (more daily variations than would normally be expected) suggests that this reservoir was used for controlled releases down the tributary channel to the Caledon River (Figure 11.22b). Coupled with the very short period of record, these observations are not useful for assessing the simulation bounds.

The records at D2H005 (1942 to 1956) are similarly very short but are less affected by the limitations of the rating curve than at D2H012. The indications are that natural low flows are sustained to a greater extent than suggested by the model and this may be associated with an under-estimation of the interflow parameters of the model for the sub-basins draining the mountains of Lesotho (D21A, C, D, J, K and L – Figure 11.20). Without further information about maximum flood flows it is difficult to comment about the high flow simulations (Figure 11.22c). The gauge at D2H020 is currently operational and the records start in 1983, but there are missing data between 1991 and 2006. This gauge is located within the city area of Maseru but there is no documented explanation for the excessively long periods of zero flow compared to other sites on the main Caledon River (Figure 11.22d).

The final gauge before Welbedacht dam is located at D2H001 (13 421 km^2) and the records provide a relatively continuous data set from 1934 to 1961. While the main gauging station does not provide flood peak values, additional data for a rated flood section at the same site provide information that can be used to approximately fill the high flow data gaps, albeit with a high degree of uncertainty. The simulated ensemble band is compared with both the gauged records (infilled with estimated high flows – Figure 11.22e) as well as the simulations generated by Midgley *et al*. (1994) with an earlier version of the model and climate inputs that are identical to those used in this study (Figure 11.22f). Given that the observed high flows are quite uncertain and that some water abstractions were occurring even before the 1960s, the conclusions are that the ensembles generated by this study appear to be behavioural. Figure 11.22f indicates that this study has predicted a lower band of uncertainty for low flows than the Midgley *et al*. (1994) simulations, although this is not immediately evident in Figure 11.23, which represents a sample of the time series.

Discussion

The Caledon River basin is generally representative of the situation in many parts of South Africa, where the observed runoff data associated with gauging stations are of limited value for calibrating hydrological models to simulate natural conditions. However, as this study suggests, at least some of the observed data can be useful for assessing uncertainty ensemble outputs from models. Despite apparently behavioural uncertainty bounds at the basin outlet, there is an indication that the low flows for the steep topography (Lesotho) north-eastern parts of the basin have been under-simulated. These sub-basins are not covered by the AGIS (2007) soils database and their parameter distributions have been extrapolated from the headwater sub-basins that are within South Africa (upstream of D2H012). The results suggest that the estimated parameter values affecting the low flow response in these parts of the basin should be revisited. However, there is little available information upon which to base this revision. It is also noteworthy that the uncertainties in the climate input data (particularly precipitation estimates) will be greater in these remote parts of the basin than elsewhere.

This study concludes that an uncertainty approach to PUB can be a useful tool and that the methods suggested by Kapangaziwiri *et al*. (2009) are generally appropriate for quantifying parameter uncertainty in South Africa. However, it is not always straightforward to apply the parameter uncertainty estimation approach when the required physical basin property data are not readily available, as is the case in the Lesotho parts of the Caledon River basin.

11.7 SETTING ENVIRONMENTAL FLOW TARGETS IN NORTH-EAST USA

S. A. ARCHFIELD

The issue from societal and hydrological perspectives

This case study focuses on the north-eastern USA, where water managers are under increasing legal pressure to ensure that water for public supply is allocated with consideration for flows needed to support ecological services and not in excess of the total surface water available in a basin. Lack of runoff information at ungauged locations resulted in conflict between the state's largest stakeholder groups: the environmental advocacy groups and the water suppliers. With no information available to justify water allocation permits within ungauged catchments, environmental groups asserted that water managers were being too liberal in their allocations, resulting in lowered runoff that could not support environmental flows. Conversely, water suppliers claimed state water managers were being too conservative in their issuing of water allocation permits, thus limiting the water suppliers' abilities to meet customer demand. To provide a common framework for negotiation between these stakeholder groups and to inform the water-allocation decision-making process, water managers required a technically defensible decision-support tool to estimate the total surface water available in ungauged catchments across the region. The tool enables users to compare these runoff estimates to time-varying ecological flow targets and to compute water availability for ungauged basins in the north-eastern USA.

Description of the study area

The study area is located in the southern portion of the north-eastern USA (Figure 11.24) and covers an area of approximately 30 000 km^2. The region is characterised by a temperate climate with distinct seasons. Annual precipitation varies between 1000 and 1250 mm/yr and is evenly distributed throughout the year. Snowfall is common in the months of December, January and February, with more snow falling away from the coastal areas during these months. A record drought occurred over a several-year period during the mid to late 1960s. Understanding the sustainability of water allocation through a period of drought of such severity is of great interest to stakeholders in the study area. Therefore, it was important that estimated runoff included the period of record covering the 1960s drought.

The geology and hydrology of the study region were heavily affected by the growth and retreat of glaciers during the last ice age, which formed the present-day stream network and drainage patterns. The retreat of the glaciers filled the river valleys with outwash sands and gravel as well as fine- to coarse-grained lake deposits, and these sand and gravel deposits have been found to be important controls on the magnitude and timing of baseflows in the study region.

We selected those stream gauges for which the contributing catchment areas were considered to be least affected by regulation (Figure 11.24). Of the 66 stream gauges in the study region that fit this criterion, 48 stream gauges had at least 20 years of continuous daily runoff records that extended through the drought-of-record (black triangles in Figure 11.24). The distributions of selected catchment characteristics for the 66 stream gauges are shown in Figure 11.25. In general, the study stream gauges represent the likely values encountered at most ungauged basins in the region. For example, the range of mean annual precipitation observed at the study stream gauges (1100–1435 mm/yr) is representative of the range of mean annual precipitation values reported over the entire study region. More information on the stream gauges and catchment characteristics can be found in Archfield *et al*. (2010).

Method

Existing tools to estimate runoff at ungauged locations were determined to be inadequate for water allocation decisions. Low flow statistics were available at ungauged basins in Massachusetts through regional regression equations developed by Ries and Friesz (2000) that related flow statistics such as the median monthly August runoff to measureable physical and climatological characteristics of the basin. At the time these regional regression relations were developed, ecological flow targets were typically defined as a constant, minimum runoff that would remain in the river throughout a year to support ecological services and functions. However, in recent years, the work of Poff *et al*. (1997) challenged this convention. They declared that the ecological

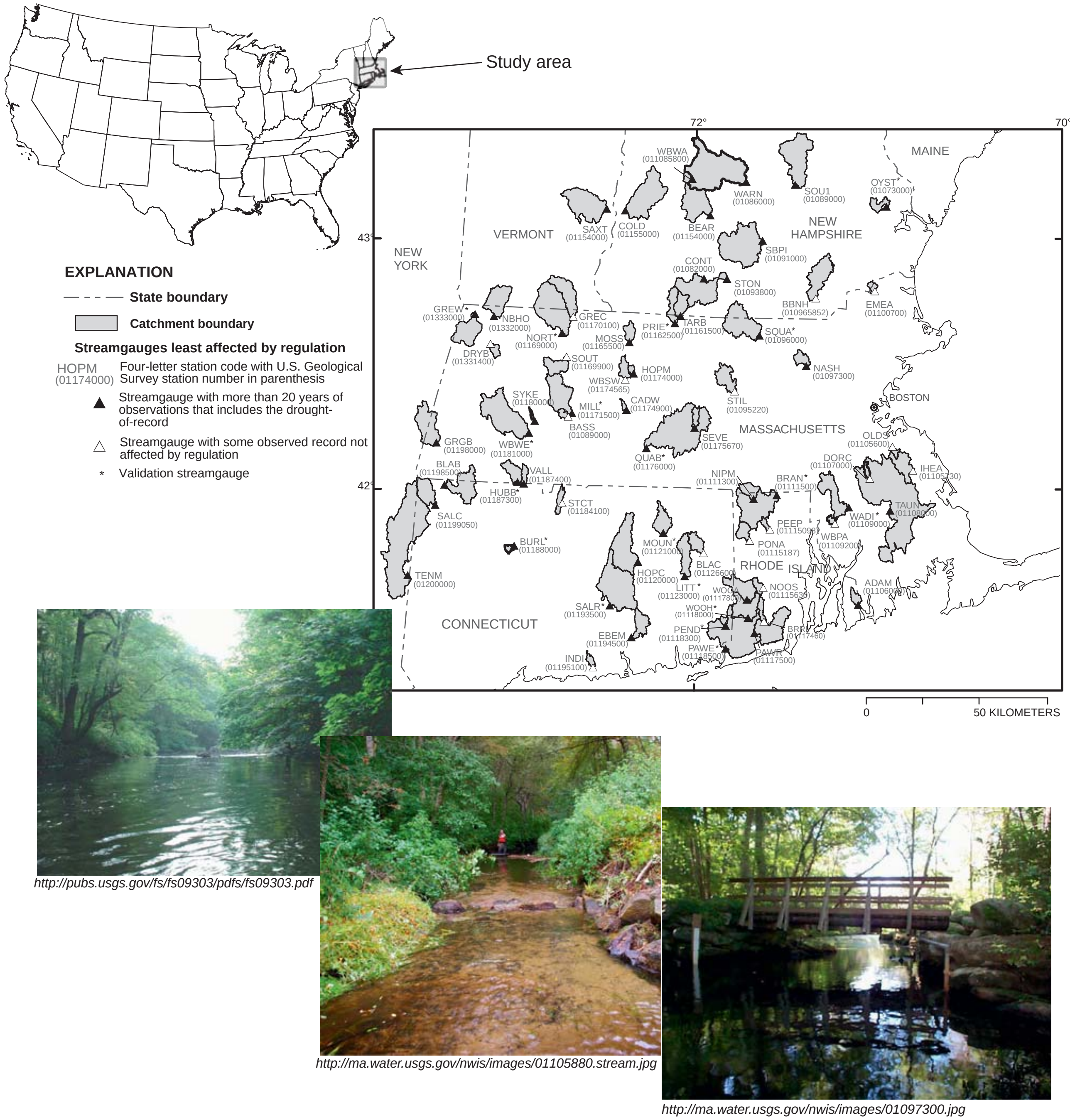


Figure 11.24. Examples of hydrological settings and stream gauges used to estimate daily runoff time series at ungauged locations in the north-eastern USA. Modified from Archfield *et al*. (2010).

flow needs of a basin should reproduce the ‘natural flow regime’, meaning that ecological flow needs should reflect the magnitude, frequency, duration, timing and rate of change that occurs naturally in runoff. Therefore, a constant runoff target would not be adequate to fully characterise and meet the ecological needs of a particular river and existing low flow regional regression equations could not be used for water allocation decisions. An additional consideration for the selection of the regionalisation method was the ability to incorporate the methods into an easy-to-use decision-support tool that required minimal training and resources. This consideration ruled out the use of regionally calibrated rainfall–runoff models to determine water availability at ungauged locations in the study area.

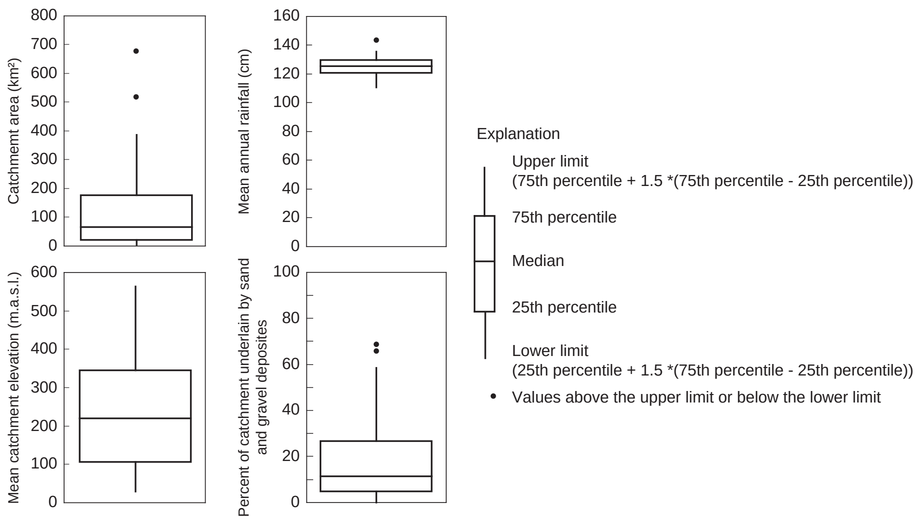


Figure 11.25. Range of catchment characteristics for the study stream gauges.

To estimate daily runoff at ungauged locations, this study utilised the methods described in Archfield and Vogel (2010) and Archfield *et al.* (2010), which are summarised here (for a contextual description see Section 10.3.2). First, a continuous daily flow duration curve was constructed by regional regression equations obtained by relating the physical and climate characteristics of 48 gauged basins (Figure 11.24, black triangles) to selected flow duration curve statistics (see Section 7.3.1). To ensure the estimated flow duration curves were representative of all flow conditions, only stream gauges with long records (greater than 20 years) that contained the drought-of-record were used to develop the regional flow duration curve regression equations. A continuous flow duration curve was then interpolated between the selected runoff statistics to obtain a continuous, daily flow duration curve. A reference stream gauge is then used to translate the flow duration curve into a hydrograph. Instead of using the nearest reference stream gauge, the study applied the map correlation method (see Archfield and Vogel, 2010). The map correlation method provides a geostatistical approach to select the reference stream gauge whose runoff time series is estimated to be most correlated with the ungauged location. Archfield and Vogel (2010) show that, for methods that transfer the timing of runoff from one basin to another, correlation between runoff can be an effective method to identify the reference stream gauge when compared to the selection of the nearest reference stream gauge. The full set of 66 study stream gauges (Figure 11.24) were used as possible reference stream gauges and included in the development of the map-correlation method.

Results

Stakeholders in the study area required estimated daily runoff that extended back to the drought-of-record and through to present-day (2004) runoff conditions. Therefore, daily runoff was estimated from 1 September 1960 through 30 August 2004 for an ungauged location. To validate the method, 18 stream gauges with observed runoff records for this period (Figure 11.24) were used in a leave-one-out cross-validation procedure. One-by-one, each stream gauge was removed and the location treated as ungauged.

Observed and estimated runoff were then compared at each of the removed stream gauges, and a NSE value and root mean square error (RMSE) values were computed for each of the 18 stream gauges using the natural-log values of the observed and estimated daily runoff. Unregulated daily runoff was able to be reliably estimated for ungauged locations across Massachusetts, with NSE values ranging from 0.98 to 0.69, with a median value of 0.86 (Figure 11.26); RMSE values ranged from 19% to 284%, of the mean with a median value of 55% (Figure 11.26). A comparison of observed and estimated hydrographs for stream gauges with the best (Hubbard River near West Harland, CT (HUBB)) and worst (Burlington Brook near Burlington, CT (BURL)) agreement over the period 1 October 1960, through 30 September 1962 – the period of time at the start of the worst drought of record – show good agreement in both real and log space (Figure 11.27; Archfield *et al.*, 2010).

Discussion

By providing technically defensible estimates of runoff time series in ungauged basins, stakeholders in the state of Massachusetts have now agreed upon the methods and decision-support tool as the framework for negotiation between environmental groups, water managers and water suppliers. The methods and goodness-of-fit results were disseminated to stakeholders in several formats. The map correlation method represented a new approach

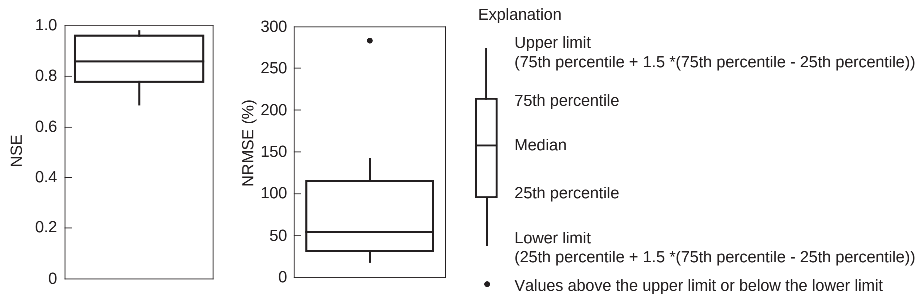


Figure 11.26. Distribution of goodness-of-fit statistics: (left) Nash–Sutcliffe efficiency values and (right) root mean square error, computed from observed and estimated mean, daily runoff values at the 18 validation stream gauges. From Archfield *et al*. (2010).

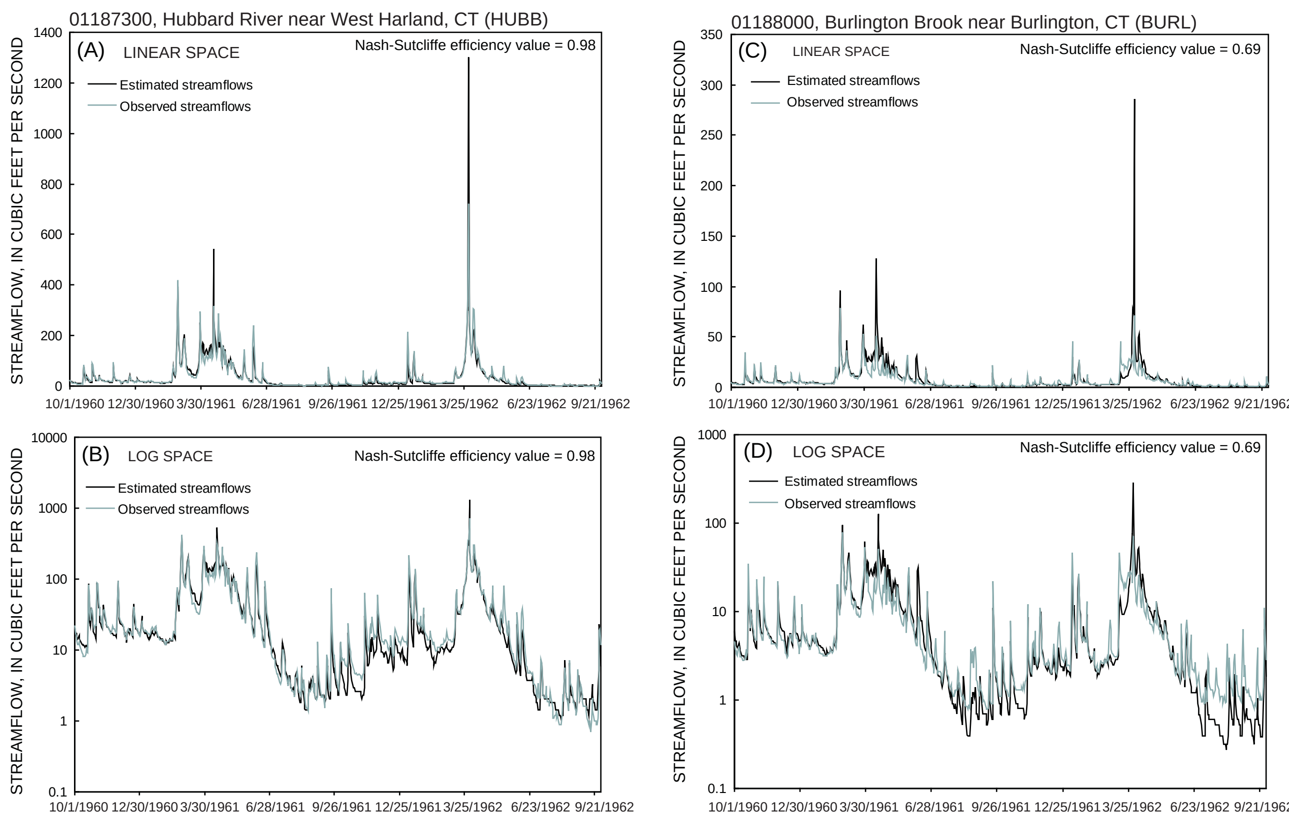


Figure 11.27. Observed and estimated runoff for US Geological Survey stream gauges (A and B) Hubbard River near West Harland, CT (HUBB), and (C and D) Burlington Brook near Burlington, CT (BURL), showing the best (A and B) and worst (C and D) agreement between unregulated observed and estimated mean daily runoff in linear space and log space; southern New England study area, 1960–2. From Archfield *et al*. (2010).

to select a reference stream gauge for information transfer to an ungauged location and was published as a journal article. The methods used to estimate daily runoff at ungauged locations in Massachusetts were published as a US Geological Survey report (Archfield *et al*., 2010) so this critical information could be made publicly available to the stakeholders and water managers who had the greatest need. Lastly, the methods developed for this study were coded into a publicly available decision-support tool for use by the water resources community, which is available to download from the US Geological Survey.

The decision-support tool is now being used to determine water allocation permits, assess the effects of various ecological flow targets on water availability, and identify sustainable water withdrawal scenarios for ungauged basins in Massachusetts. In addition to facilitating compromise between stakeholder groups and evaluating water allocation permits, the ability to estimate daily runoff at ungauged basins has led to additional studies that have mapped water availability at approximately 1400 ungauged basins across Massachusetts. This mapping provided a snapshot of water availability across Massachusetts for a range of hydrological statistics derived from the daily runoff estimates. Daily runoff was also able to be estimated at ungauged basins that coincide with fish-sampling locations to assess the relation between flow alteration and fish species and abundance. Such information is providing insight into the limits to which the ecology can tolerate changes in runoff and, ultimately, will help to determine ecological flow targets for rivers across the study area.

11.8 CONTINUOUS SIMULATION OF LOW FLOWS FOR HYDROPOWER DEVELOPMENT IN ONTARIO, CANADA

J. SAMUEL, P. COULIBALY AND R. A. METCALFE

The issue from societal and hydrological perspectives

Accurate baseflow estimation in ungauged basins is a difficult task in many Canadian catchments because of the large size of most basins, the high seasonal climatic variability, and the heterogeneity of physiographic conditions. The accuracy of baseflow estimates is particularly important for prescribing environmental flow and potential ecosystem and economic trade-offs in water development projects. Interest in hydropower development has significantly increased in Northern Ontario with the passing of the Ontario Green Energy Act (2009). Most basins in remote northern regions of Ontario are ungauged or poorly gauged. Estimating continuous flow series in these large ungauged basins remains a challenging task for assessing aquatic ecosystem effects of flow alteration as part of the approval process for hydropower projects. This case study presents some of the results of the optimal combined regionalisation and application of the rainfall–runoff model (MAC-HBV) identified for improved baseflow and runoff estimation in ungauged basins across Ontario. Hence, the method is particularly useful for estimating low flows (see Section 8.4.2 and Chapter 10). A detailed model description along with extended results is provided in Samuel *et al*. (2011b). The proposed modelling tool is now used by the Ontario Ministry of Natural Resources and waterpower developers for continuous runoff simulation in ungauged basins in Ontario.

Description of study area

A total of 111 basins distributed across the Province of Ontario with a total area of about 1 million km^2 and complete runoff records between 1976 and 1994 were selected for the study (Figure 11.28). Basin areas range between 100 and 100 000 km^2. The selected basins cover the range of observed basin attributes to meet model regionalisation, calibration and validation requirements and are representative of the diversity of basins across the Province of Ontario (Samuel *et al*., 2011a).

The climatology and landscape in the study area vary along the north–south gradient. The annual mean precipitation is ~800–1200 mm/yr in the south over an elevation range of 300–500 m, and ~400–600 mm/yr over an elevation range of 100–200 m in the northern region. In general, northern basins consist of predominantly coniferous forest, swamp, muskeg and small lakes, whereas basins in the southern region are dominated by mixed forests (*Atlas of Canada*, available at http://atlas.nrcan.gc.ca). The near-surface geology of basins in the south is dominated by gravel, sand and silt and less by rock compared to basins in the north.

A total of 146 precipitation stations and 110 temperature stations having less than 20% missing data for the 1960–97 period were selected as base stations for the study (Figure 11.28). Missing precipitation and air temperature data at the base stations were spatially patched and interpolated with data from all available climate stations using the inverse square distance weighted (IDW) method. Daily potential evaporation was estimated from daily temperature using a modified Thornthwaite equation (Samuel *et al*., 2011a).

Basin attributes used for the regionalisation include: (i) latitude; (ii) longitude; (iii) mean percentage slope; (iv) average elevation (m); (v) percentage of basin area covered by rooting depth deeper than 150 cm; (vi) percentage of basin area covered by coniferous, deciduous and mixed forest; and (vii) percentage of basin area covered by glaciofluvial till (see Samuel *et al*., 2011a). These attributes were considered best for determining physical similarity among basins and were selected using a cosine pattern similarity procedure (Samuel *et al*., 2011a).

Method

The combined modelling tool includes: (i) a physically based rainfall–runoff model (MAC-HBV); (ii) a dual regionalisation method (i.e., combined inverse distance weighted method (IDW) and physical similarity (PS) approach, referred to as IDW-PS); along with (iii) a Monte Carlo simulation approach (Samuel *et al*., 2011a).

The MAC-HBV model (Samuel *et al*., 2011a) is a variant of the original HBV model introduced by Bergström

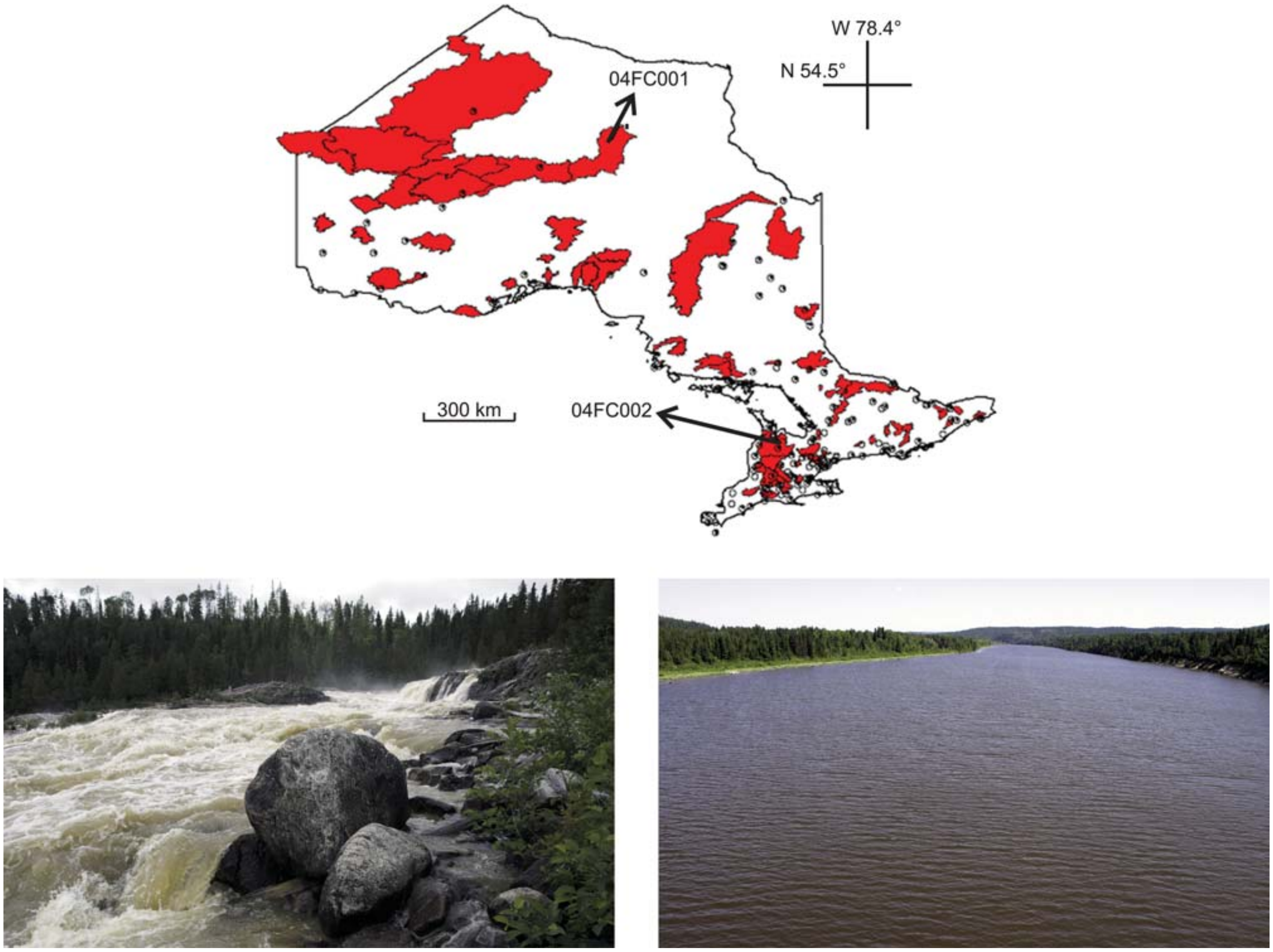


Figure 11.28. Locations of rainfall (white circles) and temperature (black dots) stations and gauged basins (red). Labels indicate the names of the basins selected for illustrating the model application results. (Left) location 04FC001, (right) location 04FC002. Adapted from Samuel *et al*. (2011b).

(1976). The MAC-HBV model structure takes advantage of some of the salient features of the model developed by Seibert (1999) and the one proposed by Merz and Blöschl (2004). The model uses Brent's parabolic interpolation (Press *et al*., 1992) to generate the optimised model parameter set.

To identify the optimal rainfall–runoff model structure that can improve both the estimation of baseflow and average daily runoff, five variants of the original MAC-HBV model (Model 0) have been investigated and tested in 111 basins. The variation in the MAC-HBV models includes: (i) extending possible ranges of maximum and minimum model parameters, especially related to deep soil and slow flow model parameters; (ii) modifying the model structure, e.g., by applying a non-linear storage discharge relationship, instead of a linear one, in the deep soil layers (in the hillslope routing components); or (iii) changing the objective function in the optimisation procedure by including additional criteria for model assessment on low flows. A summary of the changes implemented in each variant of the MAC-HBV model is presented in Table 11.5, while the details can be found in Samuel *et al*. (2011b).

The best MAC-HBV model variant identified was then combined with the dual regionalisation method (IDW-PS) for continuous flow estimation in ungauged basins. The dual or combined regionalisation approach (IDW-PS) takes advantage of both spatial proximity and physical similarity methods. In this approach, the basins are first grouped based on their physical similarity using a cosine-similarity method, and subsequently model parameters are transferred using the IDW approach for only the similarly grouped sites. In a comprehensive inter-comparison study, it was shown that the IDW-PS approach is the best

Table 11.5. *Summary of modifications made in each model variant as compared to the original MAC-HBV model (i.e., Model (0))*

Models	Change possible ranges of model parameters	Modify model structure	Modify objective function in the optimisation procedure
(0)	—	—	—
(1)	Yes	No	No
(2)	Yes	Yes	No
(3)	No	Yes	No
(4)	Yes	Yes	Yes
(5)	No	Yes	Yes

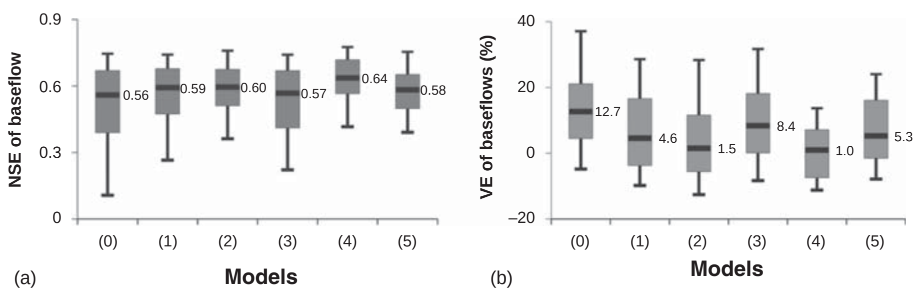


Figure 11.29. Model test results in gauged basins, including (a) Nash–Sutcliffe efficiency (NSE) and (b) volume error (VE) for baseflow. Boxes are delimited by the 25th and 75th percentiles, the median is marked with a thick line inside the boxes and the whiskers are delimited by the 10th and 90th percentiles. From Samuel *et al.* (2011b).

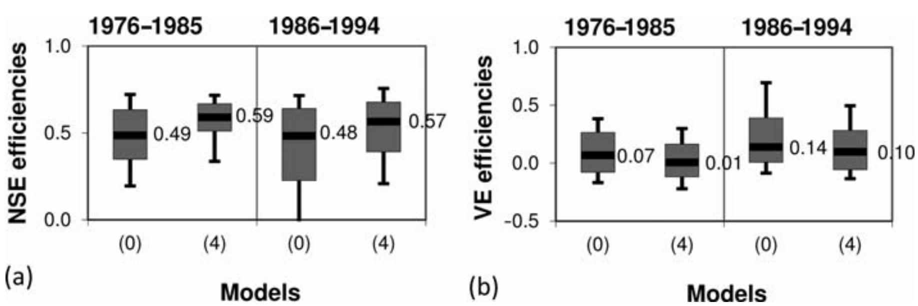


Figure 11.30. Baseflow estimation in ungauged basins: (a) NSE and (b) VE statistics. See Figure 11.29 for meanings of boxplots. From Samuel *et al.* (2011b).

regionalisation method for ungauged basins in Ontario (Samuel *et al.*, 2011a). To evaluate confidence intervals of estimated runoff and baseflow in ungauged basins, a modified Monte Carlo simulation approach was applied (see Samuel *et al.*, 2011a, b for details). Baseflow separation was done using a recursive digital filter (Nathan and McMahon, 1990). The algorithm separates baseflow from total runoff by passing the filter over the runoff record three consecutive times (forwards, backwards and forwards again). The performance of each MAC-HBV model variant was assessed using the Nash–Sutcliffe model efficiency (NSE) index, and volume error (VE).

Results

All the five variants of the model (i.e., Model (1) to Model (5)) show improvement in baseflow estimates, as compared to the original MAC-HBV model (Figure 11.29). The highest model improvement was found using Model (4), which included all the changes, i.e., changing the linear storage discharge relationship to a non-linear one; using a wider range of possible maximum and minimum values of model parameters, especially for the parameters related to subsurface/groundwater flows; and considering the average and low flows and VE in the objective function in the optimisation procedure. Model (4) has the highest NSE index (Figure 11.29a) and the lowest VE (Figure 11.29b) for baseflow.

Model (4) was then used with the combined regionalisation method to estimate flow in ungauged basins. Ninety basins that produced NSE index values higher than 0.5 were selected and the IDW-PS approach was applied to obtain model parameters for ungauged sites. Figure 11.30 shows Model (4) and Model (0) simulation results for the 111 ungauged basins. About 20% of improvement in NSE index has been achieved with Model (4) as compared to Model (0). In terms of VE, the improvement is up to 50%

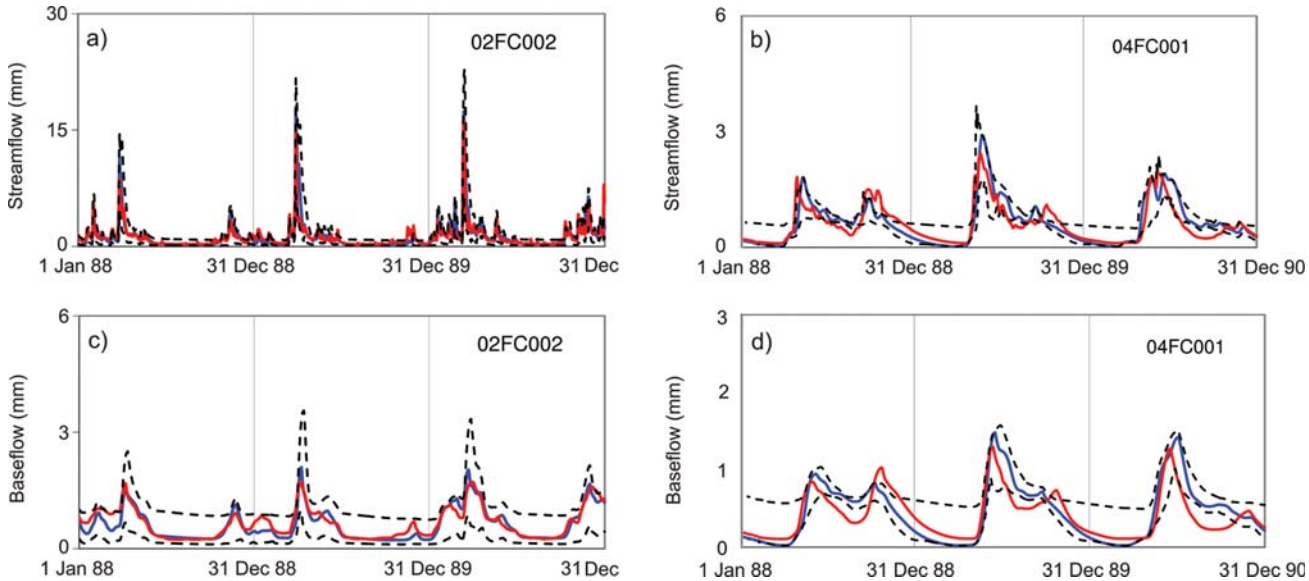


Figure 11.31. Hydrographs of simulated daily flow (red lines) and observed daily flow (blue lines). Model prediction confidence limits are shown in black dashed lines.

for Model (4) for both the 1976–85 and 1986–94 periods (Figures 11.29a and 11.29b, respectively).

Examples of simulated runoff and baseflows in ungauged basins in different regions using Model (4) are shown in Figure 11.31. The model captures quite well both daily runoff and baseflow variability. Basin 04FC001 shows slower recession limbs (Figures 11.31b and 11.31d), which is a characteristic of basins in northern regions due to flatter topography and the presence of small lakes. Basin 02FC002 with steeper recession limbs (Figures 11.31a and 11.31c) represents typical basins in southern regions where the topography is steeper and small lakes are generally absent.

Discussion

The proposed combined modelling tool has been applied and tested across the Province of Ontario for estimating continuous runoff at ungauged basins with great success. In addition to the results presented in this case study paper, more detailed results can be found in Samuel *et al*. (2011b).

It appears that the good performance of the optimal hydrological model identified for the Ontario basins can be attributed to the fact that site-specific hydrological attributes and hydrological processes have been captured by the model structure. The non-linear storage discharge relationship and the wide variability in model parameters control the delay and rate of outflow by allowing deeper soil to retain and release water through a non-linear function, especially during drier periods. Study results also show the importance of optimising both baseflow and runoff in the identification of an appropriate hydrological model for flow prediction in ungauged basins.

The optimal version of the MAC-HBV model combined with the dual regionalisation method (IDW-PS) is now used across Canada and in other countries for improved runoff and baseflow estimation in ungauged basins. The model performs well across heterogeneous landscapes, climatic conditions, and in basins varying significantly in size. Significant improvements (up to 50%) have been achieved for baseflow estimates, which is particularly important for reliable environmental flow prescriptions to mitigate the impact of flow regime alteration on river ecosystems, especially in the context of increasing hydropower development in Ontario.

11.9 ESTIMATING FLOW DURATION CURVES FOR HYDROPOWER DEVELOPMENT IN CENTRAL ITALY

A. CASTELLARIN

The issue from societal and hydrological perspectives

This case study reports on an extensive analysis performed over a wide and hydrologically complex area in central Italy (see also Castellarin *et al*., 2004a and 2007a). The analysis was promoted by the R&D division of Enel S.p.A. (l'Ente Nazionale per l'Energia Elettrica), an Italian energy provider, which at that time needed to develop a parsimonious yet as reliable as possible regional model for predicting long-term flow duration curves (FDCs) in ungauged sites located

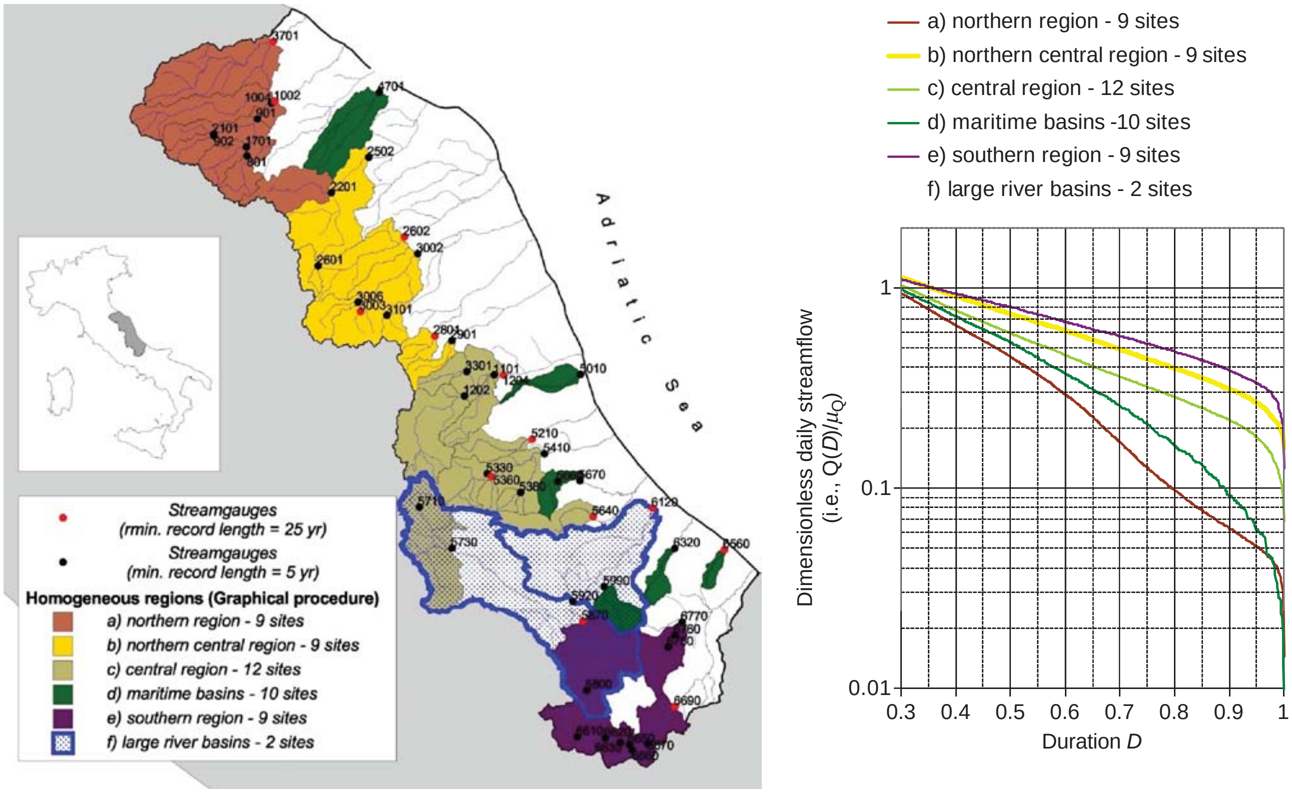


Figure 11.32. Study region and dimensionless flow duration curves (daily runoff divided by the long-term mean) for six homogeneous sub-regions. From Castellarin *et al*. (2004).

within a broad region of central Italy. The regional model would then have been used in the context of hydropower feasibility analyses to locate suitable sites (i.e., ungauged basins characterised by suitable surface water availability and runoff regimes). Also, the analysis was triggered by the fact that at that time the literature reported a large number of studies on FDC regionalisation, presenting several different approaches to this problem (see also Section 7.3); nevertheless, no study compared the reliability of the different regional approaches, and in fact the indications on the reliability of any of these regional models for the prediction of FDCs in ungauged sites were still very sparse.

Description of the study area

Figures 11.32 and 11.33 illustrate the study region, covering an area of 17 830 km^2 and 51 unregulated river basins, which are characterised by the absence of diversions, direct water abstractions, reservoirs etc. For these 51 river basins, daily runoff series observed within the time span 1921–2000 are available from the National Hydrographic Service of Italy (SIMN). The runoff regimes of the study area can be roughly classified into two large groups: (i) the maritime regime, with the maximum monthly runoff during winter and the minimum during summer, and (ii) the Apenninic regime, with two maxima, a lower maximum during spring and a higher one during autumn.

The record length at the gauges varies from a minimum of 5 years to a maximum of 67 years with a mean value of 24 years. Several geomorphological and climatic characteristics were determined for the 51 basins, such as the basin area A, an estimate of the permeable portion of the basin area A_P, maximum H_{max}, median H_{med}, and minimum H_{min}, elevations in metres above sea level $\Delta H = H_{med} - H_{min}$, and the main channel length L.

An extensive collection of hydrological information enabled the characterisation of the 51 river basins from a climatic and litho-pedological point of view. The climatic information was retrieved from an evenly spaced network of 88 thermometric sensors and 337 rain gauges. The monthly series of areal temperature and rainfall depth were evaluated for each river basin through the use of the Thiessen polygon method by referring to the thermo-pluviometric data collected in the same time span as the runoff observations. These measures were then utilised to derive 51 values of the mean annual temperature T_A, mean annual precipitation P_A, mean annual potential

Table 11.6. *Minimum, average standard deviation and maximum values of the geomorphological and climatic indices (or catchment descriptors) for 51 unregulated basins in the study region*

Index	A	A_P	H_{max}	H_{med}	H_{min}	L	T_A	P_A	E_{PA}	P_{NA}
units	km^2	%	m	m	m	km	°C	mm/yr	mm/yr	mm/yr
Minimum	31.6	0.1	279	178	3	10	8.3	824.2	581.7	13.9
Average	359.1	47.4	2078	938	351	37	11.6	1090.5	691.6	398.8
Std. Dev.	520.8	30.2	644	380	285	29	1.4	167.4	49.6	185.0
Maximum	3082.0	99.0	2914	1950	1103	160	15.3	1505.4	826.0	923.7

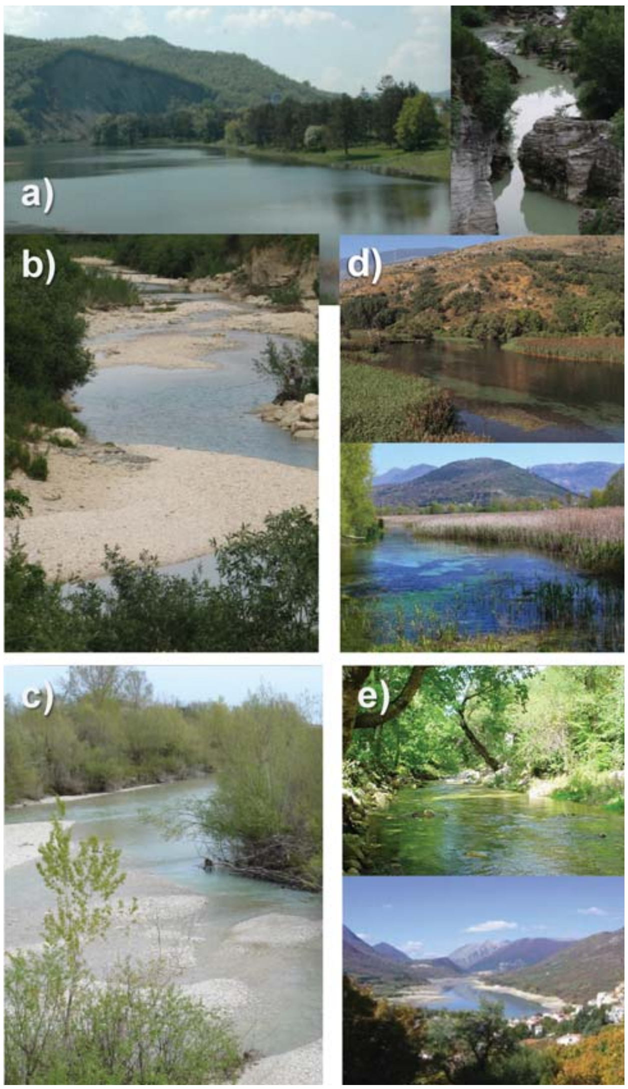


Figure 11.33. Characteristics of river basins in the study area (see also Figure 11.32): (a) northern region (courtesy of Fanoinforma.it © and Massimiliano Girolami, TDMitalia); (b) northern-central region (courtesy of Fabrizio Sulli ©, http://abruzzomolisenatura.forumfree.it/); (c) central region; (d) large river basins (courtesy of www.viaggioinabruzzo.it ©); (e) southern region (published by Pescasseroli Wonderland http://pescasseroli.p2pforum.it/ under CC Creative Commons license).

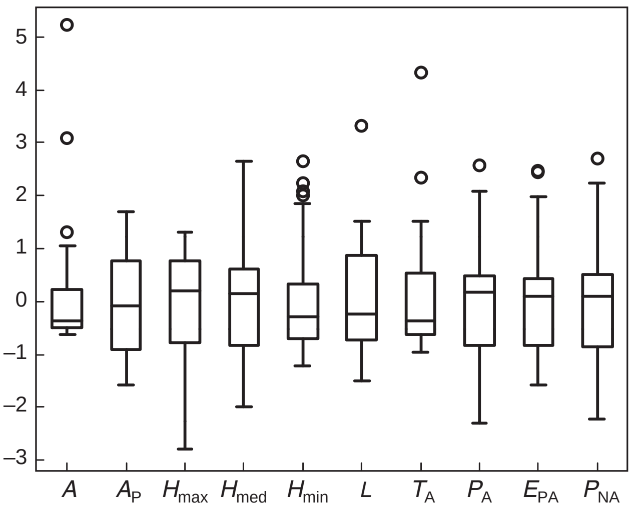


Figure 11.34. Variability of normalised catchment descriptors for the study region.

evaporation E_{pA}, and mean annual net precipitation $P_{NA} = P_A - E_{pA}$.

The significant variability of the geomorphological and climatic indices of interest for the 51 basins in the study area is well represented in Table 11.6 and Figure 11.34 and corresponds to a high hydrological complexity of the study region.

Method

Castellarin *et al.* (2004a) reviewed a number of regionalisation approaches proposed in the literature. The authors then performed a comparison of three different regionalisation approaches for the wide Italian region, as illustrated in Figure 11.32. The three regionalisation approaches were selected as prototypes of the various classes of methods proposed in the literature (see Section 7.3 for details) and, even though they are often characterised by different names, their practical implementation shows a similar degree of complexity.

Three methods were compared: a parameter regression method, named the 'statistical approach' (adapted from the

Table 11.7. *Indices of performance obtained by cross-validating the regional approaches (ungauged basins) and through a resampling experiment (scarcely gauged basins)*

	$\bar{\varepsilon}$	σ_{ε}	P_1 %	P_2 %	P_3 %
Cross-validation					
Statistical	–0.104	0.175	29.4	9.8	60.8
Parametric	0.109	0.314	31.4	9.8	58.8
Graphical	–0.134	0.141	21.6	21.6	56.9
Resampling experiment					
1 year	0.127	0.327	53.9	21.7	24.4
2 years	0.095	0.258	66.3	16.4	17.3
5 years	0.070	0.186	78.2	9.2	12.6

$\bar{\varepsilon}$ is the mean relative residual over all sites and durations of interest and σ_{ε} the standard deviation of the relative residuals; percentage of cases for which NSE > 0.75 (P_1, good to fair fit), $0.75 \geq$ NSE > 0.50 (P_2, fair to poor fit) and NSE ≤ 0.50 (P_3, poor fit), where NSE stands for Nash–Sutcliffe efficiency of predicted FDC over the durations of interest (i.e., $D \in [0.3, 1.0]$).

method presented by Fennessey and Vogel, 1990); a quantile regression method, named the ‘parametric approach’ (adapted from the method presented by Franchini and Suppo, 1996); and a non-parametric approach based upon the utilisation of dimensionless FDCs (see e.g., Figure 11.32), named the ‘graphical approach’ (adapted from Smakhtin *et al*., 1997). See Section 7.3 for a brief description of these methods.

The performance of each approach in predicting the long-term FDC for durations $D \in [0.3, 1.0]$ in ungauged sites was assessed through a comprehensive cross-validation procedure (i.e., leave-one-out, or jack-knife resampling procedure) and expressed through statistical indices and error–duration curves (see Table 11.7 and left panels in Figure 11.35).

A series of resampling experiments was carried out to assess the sensitivity of empirical FDCs to record length. The main aim of these experiments was to quantify for the same study area the reliability of estimates of the long-term FDC based upon short records (scarcely gauged catchments). The analysis considered 14 river basins with at least 25 years of daily runoff (see Figure 11.32), and consisted of the following steps: (i) from the n years of daily flows of the historical sample, the $m = n - l + 1$ consecutive sub-samples with record length equal to l years are extracted; (ii) the empirical FDCs of each sub-sample of record length l are constructed and compared with the empirical FDC of the entire period of record. The various comparisons of step (ii) are performed for durations $D \in [0.3, 1.0]$ and the results are summarised for the study area in terms of the same indices used for comparing the reliabilities of the three regional approaches (see Table 11.7 and right panels in Figure 11.35).

Results

The performance of the methods was tested in terms of cross-validation of the regional approaches, i.e., the assessment of the reliability of long-term FDCs predicted in ungauged basins through regional models, and through a resampling experiment, i.e., the reliability of long-term FDCs estimated on the basis of short records of 1, 2 or 5 years length (i.e., scarcely gauged basins). The results are presented in Table 11.7 and Figure 11.35.

The cross-validation shows that for ungauged sites the reliabilities of the three regional models are comparable to one another, even though they have different theoretical backgrounds and were implemented using different procedures. The error–duration curves of Figure 11.35 (left panels) are very similar, and also Table 11.7 (cross-validation) reports similar indices of reliability. In particular, it can be seen from index P_3 in Table 11.7 that the jack-knifed FDCs from all three models are poor fits to the corresponding empirical curves in roughly 60% of the cases.

When it comes to the prediction of long-term FDCs in scarcely gauged sites (estimation based on short records), the comparison of the error–duration curves reported in Figure 11.35 and the indices of Table 11.7 show that 5 years of observed runoff are generally sufficient to obtain better estimates of the long-term FDCs than those produced by the best performing regional model. This result highlights the remarkable value associated with observed runoff, even if they are exceptional.

Discussion

Concerning the cross-validation of the regional procedure, the three approaches show similar levels of overall reliability (slightly higher performance for statistical and

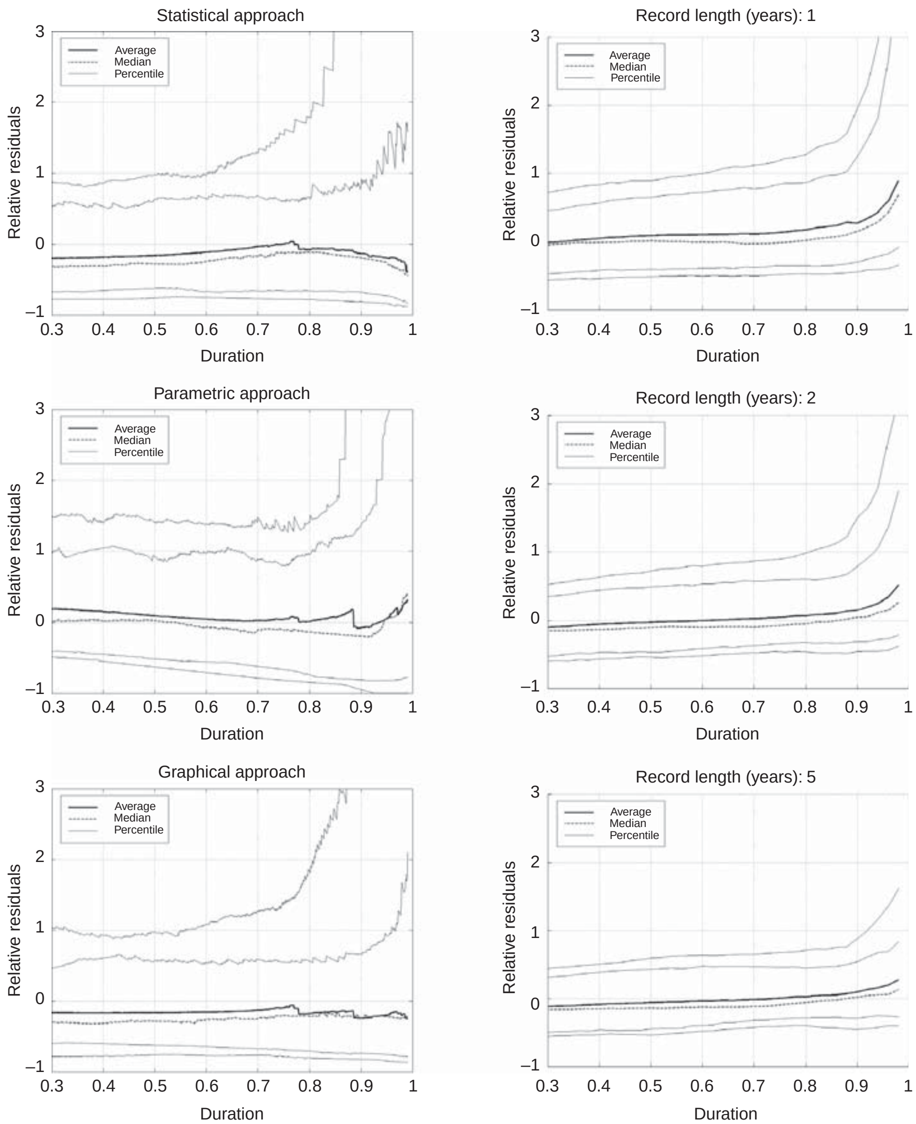


Figure 11.35. Error–duration curves obtained by cross-validating the regional approaches (ungauged basins, left panels) and through a resampling experiment (scarcely gauged basins, right panels); mean and median relative errors and bands containing 75% and 90% of the relative errors as a function of duration. From Castellarin *et al*. (2004).

graphical procedures), regardless of the differences between the methodologies. In fact, the overall reliability level does not seem to be associated with a particular theoretical approach (i.e., statistical or non-statistical) or computational procedure (e.g., utilisation of graphical devices), but rather with the descriptiveness of the hydrological information at hand (i.e., catchment descriptors available for the study area). Thus, the results suggest that one should select the most straightforward procedure, in this case graphical or statistical.

Concerning the resampling experiment, the construction of FDCs using a limited amount of runoff observations outperforms all regional procedures even when using short record lengths (i.e., 1 or 2 years): (i) regional procedures can be effectively adopted for a preliminary identification of candidate ungauged river basins with suitable water supply potentials, and (ii) FDCs estimated for ungauged sites with regional procedures should be validated on the basis of the runoff data collected during a short measurement campaign (i.e., 1 or 2 years), prior to a practical utilisation.

The case study demonstrates that this FDC regionalisation approach can be very useful in ungauged or poorly gauged basins to address societal questions, such as how much water is available for irrigation, hydropower or urban water supply. It also clearly demonstrates that even a very short series of observations (be they old data or very recently observed data) can greatly enhance the reliability of the method. This is particularly important for developing countries where no data, or only short and discontinuous data series, are available, and where through a short field campaign valuable information can be obtained.

Figure 11.36. Typical landscapes in Austria: (left) Alpine stream, (right) lowland stream. Photos: G. Blöschl, M. Zessner.

11.10 IMPLEMENTING THE EU FLOOD DIRECTIVE IN AUSTRIA

R. MERZ, G. HUMER AND G. BLÖSCHL

The issue from societal and hydrological perspectives

The European Flood Directive (2007/60/EC) was launched in November 2007 to achieve a more integrated management of the inland floods in the EU member states (EU, 2007). The Directive had been motivated by major flooding in Europe, such as the 2002 and 2005 floods, and a desire to manage floods in a more holistic way involving structural measures such as flood protection and non-structural measures such as flood warning and flood alertness of the public. The Flood Directive required all member states to carry out a preliminary assessment of potential flood risk areas by 2011. For these areas, flood risk maps need to be prepared by 2013 and associated flood risk management plans need to be prepared by 2015. Specifically, Article 6 of the Directive stipulates: 'Member States shall, at the level of the river basin district, or unit of management … prepare flood hazard maps and flood risk maps, at the most appropriate scale' and further: 'Flood hazard maps shall cover the geographical areas which could be flooded according to the following scenarios: (a) floods with a low probability, or extreme event scenarios; (b) floods with a medium probability (likely return period ≥ 100 years); (c) floods with a high probability, where appropriate.'

In Austria the Ministry of Agriculture, Forestry, Environment and Water Management started a national flood mapping project known as HORA (HOchwasserRisikoflächen Austria – Flood risk zones in Austria) to comply with the preliminary assessment requirements of the Flood Directive, and perform part of the flood hazard mapping. The project was also motivated by an interest of the Austrian Association of Insurance Companies (VVO) to obtain a tool for premium estimation, as floods have recently become insurable in Austria. The flood mapping project related to a total of 26 000 km of streams in Austria and consisted of three parts: estimation of flood discharges of a given return period; estimation of inundation areas by hydraulic models based on these discharges; and development of an internet application to offer public access to the flood hazard maps. This chapter is concerned with the first step. Specifically, the aim was to estimate the flood discharges associated with 30-, 100- and 200-year return periods for a total of about 10 586 basins, most of which are ungauged.

Description of the study area

With an area of 84 000 km², Austria is hydrologically quite diverse. The landscapes range from the lowlands in the east, with elevations from 114 m a.s.l., to the high Alps in the west, with the highest peak of almost 3800 m a.s.l. (Figure 11.36). Mean annual precipitation ranges from less than 400 mm/yr in the east to more than 3000 mm/yr in the west, where orographic effects tend to enhance precipitation. Land use is mainly agricultural in the lowlands, forested in the medium elevation ranges, while alpine vegetation and rocks prevail in the highest catchments. Because of the diversity of hydrological processes, flood generating mechanisms vary substantially across Austria (Merz and Blöschl, 2003; Parajka *et al.*, 2010a). In the Alps, runoff variability and floods are strongly affected by snow and glacier melt. In the lower Alpine region south of the Alps, snow is similarly important and snowmelt-dominated floods often occur in May. However, the largest

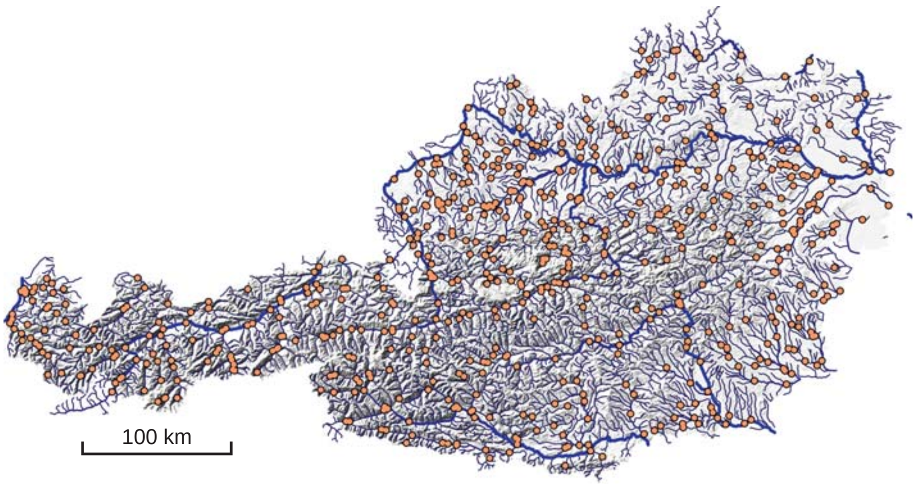


Figure 11.37. Topography, stream network and stream gauges in Austria used for the HORA project.

floods are caused by storm tracks from the Mediterranean and occur in autumn. In the lower Alpine region at the northern fringe of the Alps, rainfall is high because of the orographic barrier of the Alps to north-westerly airflows. In the northern lowlands, in contrast, rainfall is lower and floods may occur in both summer and winter. The winter floods are usually induced by rain-on-snow processes when antecedent snowmelt saturates the soils and relatively low rainfall intensities may then cause significant flooding. In the far east of Austria, annual rainfall is low and floods usually occur in summer as a result of frontal events, sometimes combined with local convective events. The south-east of Austria is hilly and conducive to convective events.

For estimating floods in ungauged basins in Austria, observed maximum annual flood peaks for 698 catchments were available with record lengths ranging from 5 to 182 years (Figure 11.37). All the data were quality controlled and corrected if necessary (Merz *et al*., 2008). Additionally, mean annual precipitation data, a 10 m digital elevation model, hydrogeology, land use, information on reservoirs and lakes and soil types were used. A digital river network with the associated catchment boundaries was also available for the 10 586 basins; 9888 of the basins were ungauged.

Method

Local flood data

As a starting point, the pre-processed flood peak samples of all the 698 stream gauges were used to estimate the first three statistical moments: mean annual flood (MAF), coefficient of variation (C_V) and coefficient of skewness (C_S). These local flood data were complemented by three types of information (Merz and Blöschl, 2008a, b): (i) *Temporal information expansion:* If the flood records were short (less than about 20 years), they were compared with longer records of neighbouring catchments in order to account for climate fluctuations. While formal climate adjustment methods exist (e.g., IH, 1999, Volume 3, p. 212; or Section 9.3.4 in this book), analysis of the data indicated that much of the information is qualitative, and therefore expert judgement was used for any adjustments of the flood moments. Similarly, the flood records were compared with historic flood information (such as historic photographs) where available in order to assess the relative magnitudes of the largest floods in a region (see Section 9.4.3). (ii) *Spatial information expansion:* Flood data from neighbouring catchments were also used to improve the at-site flood frequency estimation. For catchments up to a catchment area of about 10 000 km², maps with the 100-year flood regionalised by the top-kriging method discussed below were used to put the local flood estimates into context. For larger catchments the floods were plotted against stream length as longitudinal profiles to assess any inundation effects. (iii) *Causal information expansion:* Finally, the flood estimates for the stream gauges were compared with process information such as the rainfall records, runoff coefficients, hydrograph shapes and proxy data (see Section 9.4.3) and, if needed, any adjustments were performed.

Regionalisation method

The Vienna University of Technology had recently developed the top-kriging method (Skøien *et al*., 2006), which is the basis of the flood regionalisation to ungauged basins for implementing the EU Flood Directive in Austria. Top-kriging (see Section 9.3.3) is based on the spatial correlations of the flood moments and takes both catchment area and distance along the stream network into account. Also, the length of the flood record was taken into account by the KUD (kriging of uncertain data) approach (Merz and Blöschl, 2005) where the local kriging variance of the moments is estimated as a function of record length. Stations with short records can therefore be profitably used in the regionalisation. A number of additional controls were considered by adjusting the MAF:

$$\mathrm{MAF}^* = ln(\mathrm{MAF}{\cdot}A^{\beta}{\cdot}\alpha^{-\beta}{\cdot}\mathrm{FARL}^{-\gamma}{\cdot}F_{\mathrm{P}})$$

Specific flood discharges tend to decrease with catchment area and this effect was accounted for by scaling MAF by catchment area A, where α is the reference catchment area of 100 km^2 and β ranged between 0.25 and 0.40 depending on the flood process types (large for regions where flash floods prevail, small where frontal systems prevail). To account for the retention of reservoirs and lakes, the Flood Attenuation by Reservoirs and Lakes index, FARL (IH, 1999), was calculated for each catchment and again used to scale MAF. In Austria the floods are closely related to mean annual rainfall as an index of catchment soil moisture and river morphology (Merz and Blöschl, 2009b). To account for this effect, MAF within regions were correlated against mean annual catchment rainfall and the residual between the regression line and the local value was expressed as a factor F_{P}, which was used to scale MAF. The three flood moments (MAF*, C_{V}, C_{S}) were then regionalised to ungauged catchments by top-kriging. For each ungauged catchment, the equation above was inverted to estimate MAF from the top-kriging estimates of MAF*. The T-year floods were then estimated from the flood moments using the generalised extreme value (GEV) distribution for all nodes of the stream network. To account for local particularities of catchments, the estimates of the automatic regionalisation approach were used as a starting point for a manual adjustment similar to that for the local flood data. In this step, hydrogeology, soil type, land use, geomorphology and hydraulic structures such as retention basins were accounted for. The methods are discussed in more detail in Merz *et al.* (2008).

Results

The highest specific flood discharges occur at the northern fringe of the Alps. Topographic enhancement effects often result in high and persistent rainfalls. Due to the high pre-event soil moisture and high rainfall rates, large runoff rates occur regularly. In addition, the soils and the Flysch geology contribute to large discharges. At the southern fringe of the Alps, some of the largest floods in these catchments have resulted from high intensity precipitation associated with the advection of moist air from the Mediterranean. In the inner part of the high Alps, specific discharges are much lower, as catchments are much more orographically sheltered. The smallest specific flood discharges occur in the lowlands of eastern Austria. The small values are related both to much smaller rainfall inputs than in other parts of Austria and to relatively dry catchment conditions towards the Slovak and Hungarian border. As an example of the results, Figure 11.38 shows the normalised specific 100-year flood (MAF*) for the Danube region in Upper Austria. There is a high variability in the specific flood discharges of the tributaries. The tributaries from the North (e.g., Naarn, Klambach, Sarmingbach) show much lower specific discharges, while the tributaries from the south exhibit higher specific discharges than the Danube River. The top-kriging estimates on the Danube are similar to the measurements on the river and do not change much along the reach. In the top-kriging procedure the estimates on the main rivers are not much affected by the measurement of small tributaries, as top-kriging takes catchment area and the nested structure of the river network into account. However, estimates using other distance-based methods, such as ordinary kriging, differ substantially as they are too much influenced by the measurements at small tributaries along the main river.

To assess the performance of estimating the floods in ungauged basins, jack-knife estimates were calculated. For each stream gauge, the local flood data were withheld, the T-year floods were estimated from flood data of the neighbouring catchments only, and finally the flood estimates were compared with the local flood data. The results of the jack-knifing are given in Tables 11.8 and 11.9 as a function of catchment area and mean annual precipitation. The relative root mean square error (RRMSE) for the classes selected ranges between 20 and 65%. There is a clear trend for the RRMSE to decrease with catchment size and to decrease with mean annual precipitation. The smallest catchments show some bias, but for the other classes, the biases are relatively small.

Discussion

The HORA project was the first nation-wide estimation of flood frequencies in Austria. The scale of the project – 10 586 basins – required a strategy that had the capability of estimating the T-year flood for a large number of ungauged basins with an accuracy that was acceptable to the local water authorities. This goal was addressed by a combination of automatic methods and manual assessments by hydrologists. Experience from this study indicated that this strategy is indeed feasible. The combined approach in the project proved to be very efficient.

Traditionally, estimation of the T-year flood in a regional context has been based on flood peak samples only. The expanded (temporal, spatial and causal) information used in this study was extremely useful for

Table 11.8. *Cross-validation performance of estimating the 100-year flood in ungauged basins in Austria as a function of catchment area (only gauging stations with more than 40 years of flood records were used)*

Catchment area	Number of catchments	Rbias (%)	RRMSE (%)
<100 km²	65	18.7	43.4
100–1000 km²	180	8.38	40.5
>1000 km²	53	-4.56	19.6
All catchments	298	8.32	38.4

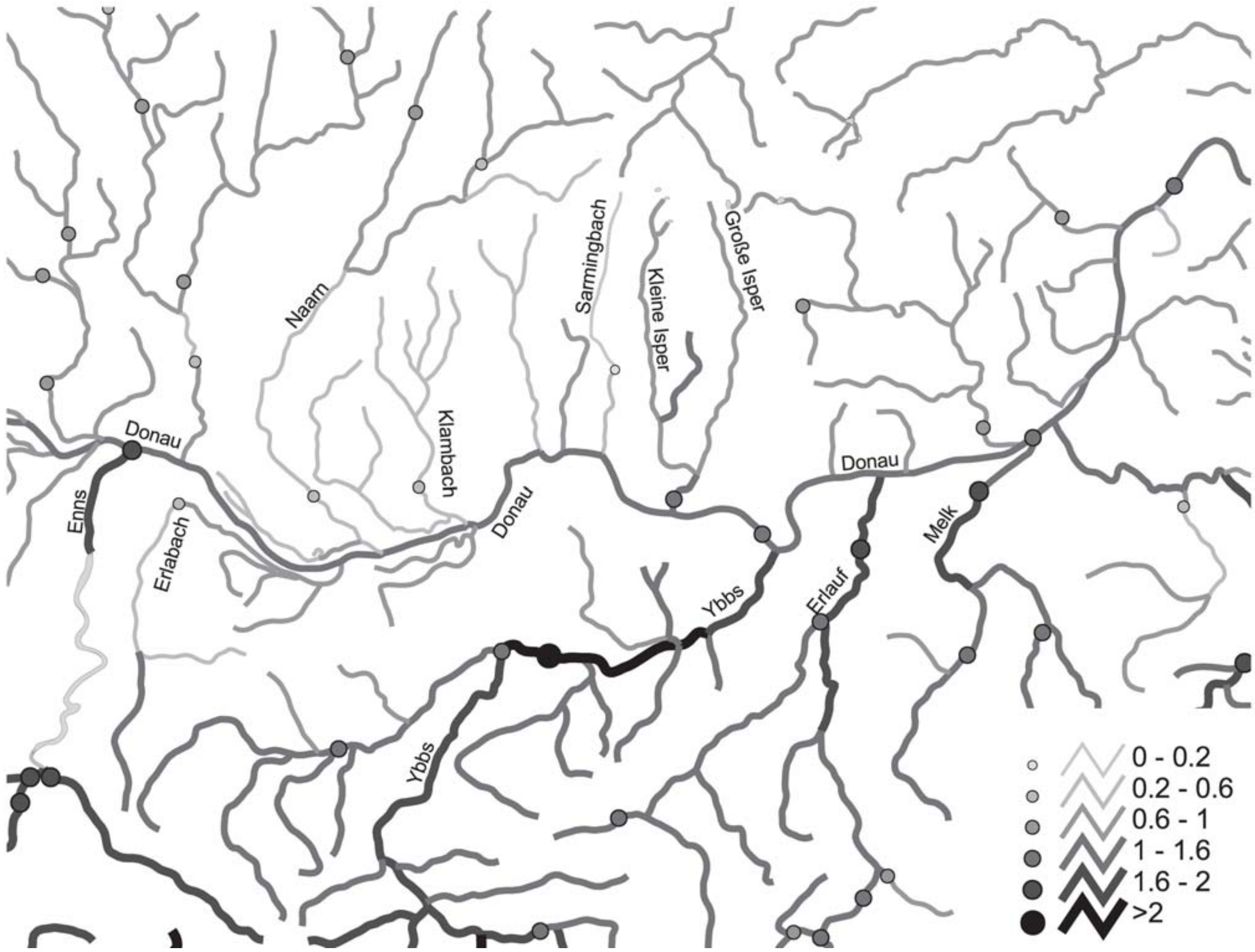


Figure 11.38. Estimates of the normalised specific 100-year flood from top-kriging (shown as width of the stream network) in the Danube region in Upper Austria. The estimates of the gauged catchments are shown as circles. Units are in $(m^3/s)/km^2$. From Merz *et al*. (2008).

enhancing the robustness and reliability of the estimates. Overall, the estimates of the *T*-year floods for the stream gauges of this study were deemed more reliable than statistical estimates from the flood samples alone, based on the judgement of the staff of the Hydrographic Services. The regionalisation approach – a combination of top-kriging based on spatial correlations with additional catchment attributes – was able to account for hydrological characteristics of the catchments including precipitation, catchment soil moisture (through mean annual precipitation) and flood retention by reservoirs and lakes. Leave-one-out cross-validation tests indicated that the accuracy of the estimates is very good across Austria. However, the accuracy differs in terms of catchment size (where floods in larger catchments are estimated more accurately than in smaller catchments) and mean annual precipitation (where

Table 11.9. *Cross-validation performance of estimating the 100-year flood in ungauged basins in Austria as a function of mean annual precipitation (MAP) (only gauging stations with more than 40 years of flood records were used)*

MAP (mm)	Number of catchments	Rbias (%)	RRMSE (%)
<800 mm	32	11.7	64.5
800–1500 mm	204	8.37	33.5
>1500 mm	62	6.40	34.9
All catchments	298	8.32	38.4

floods in wet catchments are estimated more accurately than in drier catchments). At the local scale, more detailed analyses involving rainfall–runoff modelling may be needed for specific projects to account for additional local effects.

An important step in estimating the flood discharges was the involvement of the Hydrographic Services. The interplay of formal regionalisation methods based on hard data with the understanding of local hydrologists based on proxy data turned out to be extremely helpful in estimating the flood discharges. The flood discharges estimated in this study were transformed to flood hazard zones by other project partners using hydraulic modelling, and were visualised on the Web (www.hochwasserrisiko.at) with public access. These zones are the main information for complying with the preliminary assessment requirements of the Flood Directive in Austria. The flood discharges from the HORA project are also used for producing the detailed flood hazard maps required by the Flood Directive. The results from the flood regionalisation are much appreciated by end-users of the water authorities and consultants in Austria, both in the context of implementing the Flood Directive and for other purposes of water resources management. In the meantime, the estimates of the HORA project have become a standard of flood estimates in Austria for a range of purposes.

11.11 REVISION OF AUSTRALIAN RAINFALL AND RUNOFF FOR IMPROVED FLOOD PREDICTIONS

A. RAHMAN, K. HADDAD, E. WEINMANN AND G. KUCZERA

The issue from societal and hydrological perspectives

Australia is the driest inhabited continent, with highly variable year to year water availability, leading to cycles of significant droughts and flooding. Episodes of serious flooding can affect large areas, such as experienced during the 2010–11 season in Queensland, when flooding impacted around 70% of the state and resulted in total damage to public infrastructure estimated to exceed Aus$5 billion (PWC, 2011). While the majority of this flood damage occurred in urban areas such as Brisbane, which are located in well-gauged river basins, a significant portion of it was experienced in ungauged basins distributed throughout the state. Limited design flood information for these areas may not only contribute to a larger flood damage bill, but also to greater trauma and personal loss suffered by people in these areas when a major flood event occurs.

Flood management involves various activities, e.g., flood risk assessment, flood forecasting, flood emergency management, flood plain development control, flood protection and insurance. For all of these studies, past information/data on flooding is a vital input. Due to the sheer size of Australia, recorded flood data have limited spatial coverage and hence ‘Prediction in Ungauged Basins’ is an important issue.

Australian Rainfall and Runoff (ARR), the national guide for flood estimation, has a dedicated chapter on ‘regional flood methods’. However, these methods were published in 1987. Recognising that the national flood database has been augmented with an additional 25 years of data and that there have been significant new developments in regional frequency analysis, the National Committee on Water Engineering of Engineers Australia initiated a review of the 1987 procedures.

Although regional flood frequency analysis (RFFA) methods are often intended for ‘quick flood estimation’ purposes, their application and importance is much broader in that they can serve as a benchmark for more advanced methods based on design storms and rainfall–runoff modelling. The current upgrade of regional flood estimation methods in Australia is intended to be released as an ‘easy to use’ web-based software to make design flood frequency information more accessible to the Australian community.

Description of the study area

Australia has an area of 7.7 million km^2, with a diverse landscape and climate. Up to about 75% of the country is classified as ‘semi-arid’ and ‘arid’. More than 80% of the continent receives annual rainfall less than 600 mm; only Antarctica receives less rainfall (on average) than

Figure 11.39. Wadbilliga River, New South Wales (95% forest cover). NSWTI (2012).

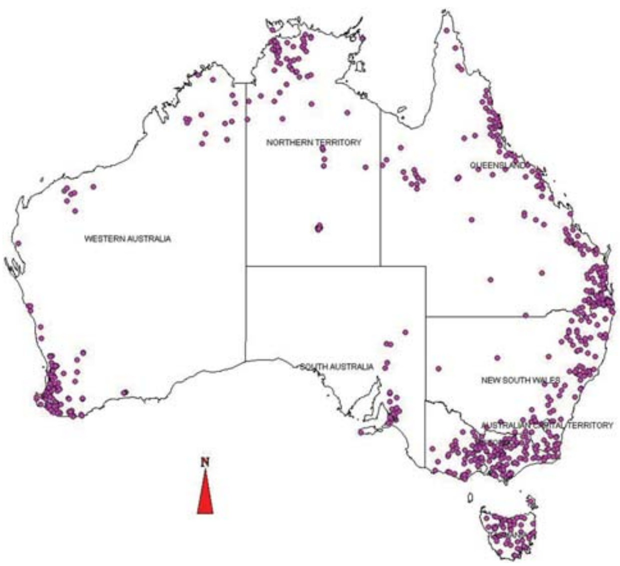


Figure 11.41. Geographical distributions of the selected 676 stations from all over Australia.

Australia. However, parts of the north-east coast receive over 4000 mm annually, with the Australian annual record being 12 461 mm at Mount Bellenden Ker in 2000. To deal with such climate diversity, development of RFFA methods would ideally need recorded flood data from many well-distributed stations with long records. However, this is not the case. As of 2006, there was 1 station per 180 000 km^2 in the semi-arid and arid regions and 1 per 2800 km^2 in the humid regions (with a threshold record length of 25 years and good quality data).

Australian basins vary significantly in topography, land cover and surface geology. In areas such as south-eastern Australia and Tasmania, many basins have extensive forest cover (see Figure 11.39 for example). In contrast, in the more arid regions, basins may have little vegetative cover, produce no runoff over most years, and yet infrequently experience severe flooding (see Figure 11.40 for example).

Figure 11.40. Arcoona Creek located in the semi-arid region of South Australia.

The development of regional flood estimates for the whole of Australia has to contend with a number of special issues: (i) the large size of the country and the substantial degree of variation in climate and flood-production characteristics between regions; (ii) a very broad range of basin sizes; (iii) low density of population in areas away from major cities and, associated with this, a relatively sparse stream gauging network; and (iv) difficulty in obtaining reliable flood gauging in remote areas.

A quality controlled national database consisting of 676 stations was prepared for the development of the ARR RFFA method (Figure 11.41). The selected basins are mainly rural with no major regulation by storages and no significant land use changes occurring over the period of runoff records. For the eastern states of Australia (New South Wales (NSW), Victoria and Queensland), the annual maximum flood record lengths of the selected stations range from 25 to 97 years, and basin areas range from 3 km^2 to 1010 km^2. Due to limited data availability, the minimum threshold record length and upper limit of basin size were relaxed for other parts of Australia to 19 years and 7500 km^2, respectively. In preparation of the runoff data, due care was exercised for in-filling minor gaps, detecting outliers and accounting for rating curve extrapolation error (details can be found in Haddad *et al*., 2010; Rahman *et al*., 2009, 2011a). The at-site flood frequency analysis was undertaken using a number of alternative distributions and parameter estimation methods, and it was found that the LP3 distribution with a Bayesian parameter estimation procedure (Kuczera, 1999) provided the best results.

Trend analysis showed that about 10% of Australian stations exhibited a downward trend in the annual maximum flood series data (Ishak *et al.*, 2010). Large parts of Australia were affected by severe drought starting in the 1990s, with the consequence that the post-1990 annual maximum flood series data for many stations were dominated by within-bank flows. It is not confirmed whether the detected decreasing trend in annual maximum flood series data for these stations is a part of long-term climate variability or due to climate change. Hence, it was decided to exclude those stations when developing the current RFFA methods. However, the impact of climate variability and change on regional floods is being further examined in order to develop some adjustment factors to be applied to the regional flood estimates obtained from the historic flood records.

Method

A number of RFFA models were developed and tested using the national database of 676 stations. These include the probabilistic rational method (PRM) (Australian Rainfall and Runoff, 1987) and various regression-based techniques (such as those discussed in Section 9.3.1): quantile regression technique (QRT) based on ordinary least squares (QRT-OLS) and on generalised least squares (QRT-GLS) (Tasker and Stedinger, 1989; Reis *et al.*, 2005; Gruber *et al.*, 2007) and parameter regression technique (PRT) based on GLS regression (PRT-GLS). In the PRT, prediction equations were developed for the first three moments of the LP3 distribution. Application of the Hosking and Wallis (1993) test (even after considering a number of possible alternative sub-regions) indicated that Australian annual maximum flood data exhibited a high degree of heterogeneity with an H statistic much larger than 1. Hence, the index flood method was not considered for general application in Australia.

Rahman *et al.* (2011a, b) compared QRT against the PRM, which is the mainstay of RFFA methods currently in use (Australian Rainfall and Runoff, 1987). They found that QRT outperformed PRM. The choice of regression estimation method was then evaluated, with Haddad *et al.* (2011a, b, c) and Haddad and Rahman (2011) concluding that the QRT-GLS method outperformed the QRT-OLS method.

The next phase of the assessment involved evaluating the QRT-GLS and PRT-GLS methods using the fixed region and region-of-influence (ROI) approaches (Burn, 1990a, b; Zrinji and Burn, 1994). A significant innovation over previous ROI applications was the use of GLS predictive error to guide the selection of the stations included in the ROI. The selected ROI contained the nearest N stations, where N was selected so as to minimise the predictive error, which accounts for both model and parameter uncertainty. This strategy seeks to minimise the heterogeneity unaccounted for by the regression predictors. It was found that the ROI approach clearly outperformed the fixed region approach (Hackelbusch *et al.*, 2009; Haddad and Rahman, 2012).

It was found that QRT and PRT methods performed very similarly for various Australian states. It is noted that the PRT method offers several practical advantages over the QRT: (i) PRT flood quantiles increase smoothly with increasing average recurrence intervals (ARIs), i.e., return periods; (ii) flood quantiles of any ARI (in the range of 2 to 100 years) can be estimated from the regional LP3 distribution; and (iii) it is straightforward to combine any at-site flood information with regional estimates using the approach described by Micevski and Kuczera (2009) to produce more accurate quantile estimates. For these reasons, the PRT has been recommended for general application in Australia. However, for the semi-arid and arid regions, due to data limitations, a simple index-flood method (similar to Farquharson *et al.*, 1992) has been adopted.

Results

Summary results of the application of the Bayesian-GLS regression for the fixed region and ROI approach for the state of New South Wales are presented below. The selection of the basin attributes took advantage of the ability of GLS regression to differentiate between sampling and model errors (for details, see Hackelbusch *et al.*, 2009 and Haddad and Rahman, 2012). The basin attributes reported below were the ones found to minimise model error. Examples of the prediction equations are:

QRT (Fixed region: NSW):

$$\ln(Q_2) = 4.06 + 1.26.\,z(area) + 2.42.\,z(I_{\mathrm{tc},2})$$

$$\ln(Q_5) = 5.11 + 1.19.\,z(area) + 2.08.\,z(I_{\mathrm{tc},5})$$

$$\ln(Q_{50}) = 6.55 + 1.01.\,z(area) + 1.73.\,z(I_{\mathrm{tc},50})$$

$$\ln(Q_{100}) = 6.47 + 0.97.\,z(area) + 1.50.\,z(I_{\mathrm{tc},100})$$

PRT (Fixed region: NSW):

$$\text{mean} = 4.09 + 0.67.\,z(area) + 2.31.\,z(I_{12,2})$$

$$\text{stdev} = 1.22–0.59.\,z(rain)–0.13.\,z(S1085)$$

$$\text{skew} = –0.42–0.10.\,z(area)–0.10.\,z(forest)$$

where the explanatory variables are transformed as

$$z(x_i) = ln(x_i) - \frac{1}{n}\sum_{i=1}^{n} ln(x_i),$$

area is basin area in km^2, $I_{12,2}$ is the design rainfall intensity for 12 hours duration and 2 years average recurrence

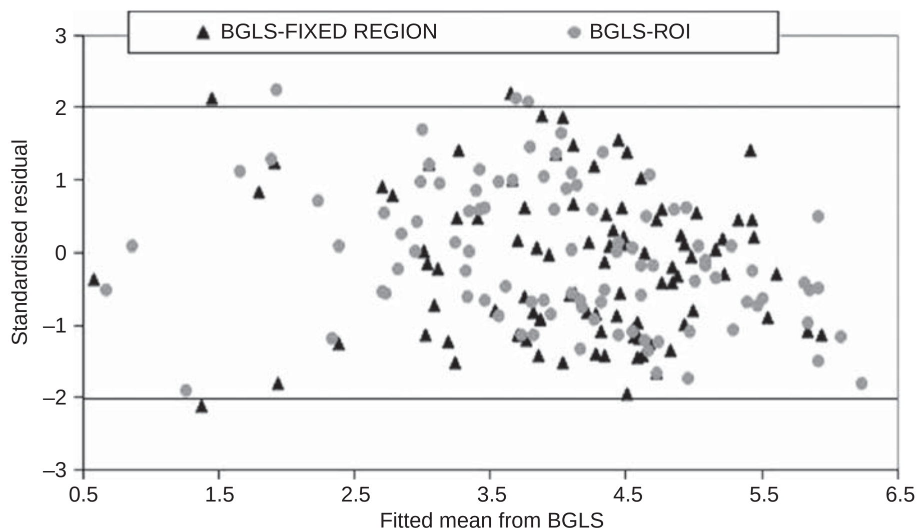


Figure 11.42. Plot of standardised residuals vs. predicted values for the mean flood model (PRT, fixed region and ROI, NSW).

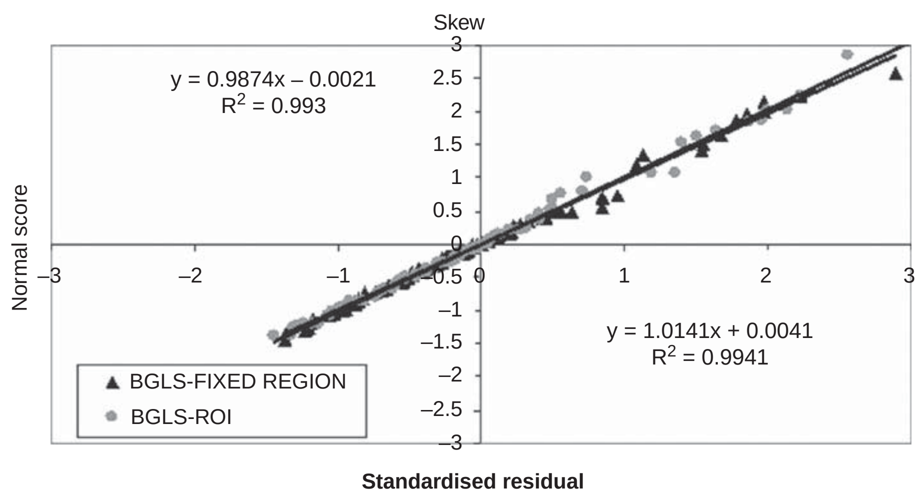


Figure 11.43. QQ-plot of the standardised residuals vs. *z* score for the skew model (PRT, fixed region, ROI, NSW).

interval (ARI), $I_{tc,Y}$ is the design rainfall intensity for duration equal to time of concentration (t_c) and *Y* year ARI, *rain* is mean annual rainfall (mm), *S1085* is the main stream slope of the central 75% of its length, and *forest* is the fraction of the basin area forested. Here t_c is obtained from $t_c = 0.76.\,area^{0.38}$, where t_c is in hours and *area* is in km^2. The parameters mean, stdev and skew correspond to the mean, standard deviation and skew of ln(Q) where Q is the annual maximum flood discharge.

The overall performance of the Bayesian GLS regression method was evaluated using leave-one-out cross-validation. The site of interest was left out in building the model, so it was in effect being treated as an ungauged site. This was repeated for all the sites considered in the study. The relative root mean square error (RRMSE) was used to assess model adequacy using a leave-one-out cross-validation approach.

To assess the underlying model assumptions (i.e., the normality and homoscedasticity of residuals), diagnostic plots of the standardised residuals vs. predicted values were examined. The predicted values were obtained from leave-one-out cross-validation. Figure 11.42 shows the plot for the fixed region and ROI models to predict the first parameter of the LP3 distribution, the mean flood. Under the assumption of normality one would expect about 95% of the standardised residual values to fall between ±2. For the LP3 mean flood this is largely the case. Moreover, the residuals appear to be homoscedastic with respect to the fitted LP3 mean flood. Similar results were obtained for the LP3 skew, LP3 standard deviation and flood quantile models.

Table 11.10. *RRMSE values from leave-one-out cross-validation for NSW*

Model	RRMSE(%)			
	PRT		QRT	
	Fixed region	ROI	Fixed region	ROI
Q_2	73	62	68	59
Q_5	65	54	70	59
Q_{10}	67	56	74	55
Q_{20}	72	57	83	53
Q_{50}	81	70	100	67
Q_{100}	90	75	100	72

The QQ-plots of the standardised residuals vs. normal score (z score) for the fixed region (based on leave-one-out cross-validation) and ROI were examined. Figure 11.43 presents results for the LP3 skew model, which show that all the points closely follow a straight line. Overall, it was found that the diagnostics did not reject the key GLS regression assumptions of normality and homoscedasticity of variance.

Table 11.10 presents the RRMSE values for the PRT and QRT models with both the fixed region and ROI. In terms of RRMSE, the ROI approach produces smaller values than the fixed region approach for all the ARIs. These statistics reveal that there are only modest differences between the performance of QRT and PRT. In view of the previously noted practical advantages of PRT over QRT, the PRT-ROI method has been selected for general application to Australia, except for the arid and semi-arid regions of interior Australia, where there is a very limited availability of gauged data.

Discussion

As part of the revision of the flood estimation guideline Australian Rainfall and Runoff, a major review of RFFA methods was undertaken. The first step involved an extensive data collation task with the assistance of state water authorities. This produced a high-quality database of 676 stations, which was used to evaluate a number of RFFA methods. In all the cases, leave-one-out cross-validation was conducted to estimate the relative accuracy of a RFFA model. It was found that Australia needs to be divided into six regions based on climate, topography and data availability. For the four regions with adequate station coverage, a GLS regression-based approach linked with a ROI approach that minimised predictive error performed best. For the remaining two regions that coincided with the data-poor arid regions, it was necessary to adopt the parsimonious index flood approach.

An important feature of the new RFFA methods is their ease of application. Web-based software will allow users to estimate flood quantiles at any location. It will also facilitate the management of future updates. In summary, the new RFFA methods represent a significant improvement in terms of data coverage, accuracy and ease of application over the current Australian methods.

11.12 UNDERSTANDING FLOW PATHS FOR HYDROGRAPH PREDICTION IN AN ANDEAN CATCHMENT, CHILE

T. BLUME

The issue from societal and hydrological perspectives

This study focuses on a small catchment in the Andes of southern Chile. For many decades, extensive land use changes have taken place in central and southern Chile, leading to conversion of vast areas of farmland and native forest to forest plantations of exotic species such as *Eucalyptus* and *Pinus radiata* (Monterey Pine). Governmental support through subsidies caused an increase in the area under plantation from 330 000 ha in 1974 to 1.5 million ha in 1992 and to 2.1 million ha in 2006. Land use changes of this spatial extent cannot remain without consequences and are likely to affect biodiversity, water and nutrient budgets as well as erosion and sediment transport. In recent years tourism and recreational land use (such as hiking and winter sports) have been gaining more importance and thus a new kind of pressure is exerted, especially in protected areas such as national parks. On the other hand, southern Chile offers the rare possibility to study hydrological and ecological systems that have not experienced anthropogenic intervention.

Understanding undisturbed systems therefore becomes increasingly important as many areas of the world are subject to fast changes, either in land use or in climate or even both. In contrast to systems with rapidly changing land use or climate, anthropogenically undisturbed systems of southern Chile are much more likely to be either close to or at steady state. Understanding the processes and process interactions in this steady state will help us to also improve our understanding of disturbed systems, the shift in processes that followed the disturbance, and maybe even the future process evolution towards a new steady state (Blume, 2008). However, the water authorities of most countries focus their efforts of data collection on larger and economically more relevant rivers; so when studying undisturbed systems one can rarely build on existing data sets and is thus faced with the challenge of working in an ungauged or data-scarce catchment.

Description of the study area

The research area is located on the southern slope of Volcán Lonquimay within the Reserva Forestal Malalcahuello (Figure 11.44). The catchment has a size of 6.26 km², ranges in elevation from 1120 to 1856 m, with mean slopes of 51% (Figure 11.45). Almost 80% of the catchment is covered with native forest of the types *Araucaria* and *Nothofagus* with a dense under-storey of bamboo (*Chusquea culeou*) (Figure 11.46a and b). The climate is temperate-humid with yearly rainfall ranging from 2000 mm/yr to over 3000 mm/yr. The soils are young little-developed volcanic ash soils with extremely high porosities (60–80%) and high hydraulic conductivities (10^{-5}–10^{-3} m/s). The study reported here was carried out from December 2003 to May 2006 and included several 1 to 2 month long field campaigns. Existing data prior to this study included data from two nearby climate stations where data were measured, (i) on a daily basis since 1989, and (ii) on an hourly basis since 1999. A stream gauging station (maintained by the Universidad Austral) at the main outlet of the catchment was under intermittent operation from 1998.

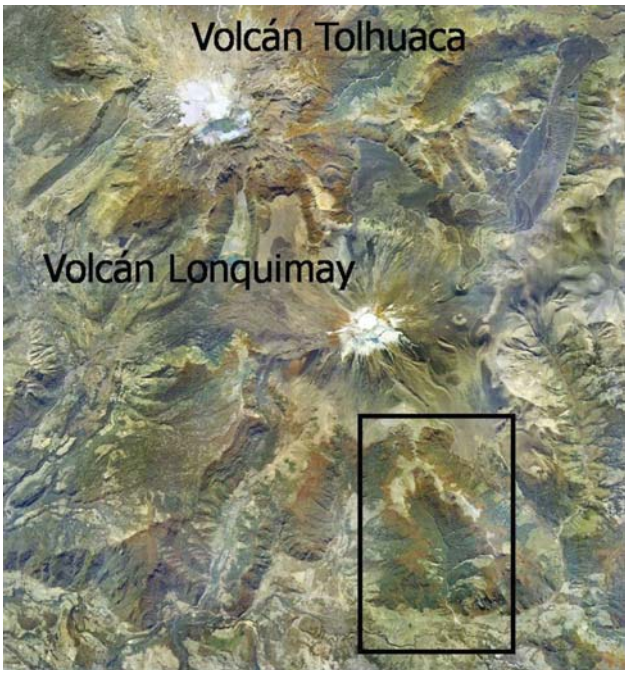


Figure 11.44. Aerial view of the region. Photo from www.sinia.cl, Sistema Nacional de Información Ambiental.

Methods

While remote sensing data can give us the 'big picture', i.e., large-scale information with usually coarse temporal resolution, this information is not of much use for process studies in small catchments, where the spatial extent is small and processes happen very fast. In this case we were also not able to transfer data and process knowledge from neighbouring larger catchments with longer time series of data as these catchments are more impacted by anthropogenic intervention, an effect we specifically wanted to exclude. Thus, a mixed approach of experimental work and modelling seemed to be the most promising (see Chapters 3 and 4).

Going into this study we were faced with many limitations: time, money, prior data and even accessibility of

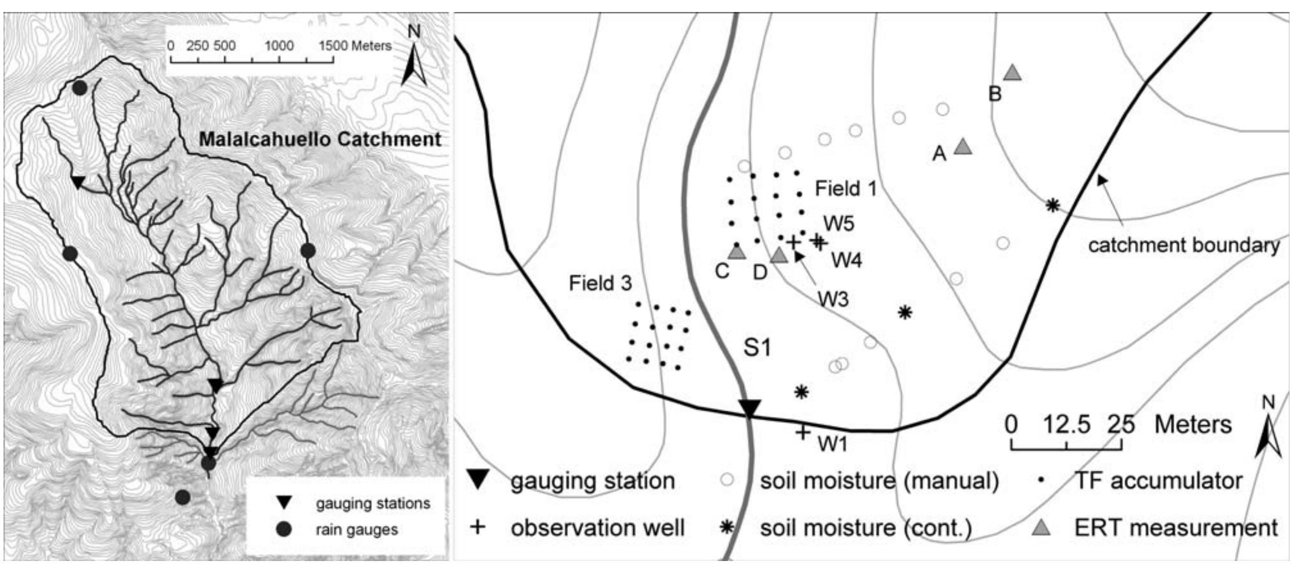


Figure 11.45. Catchment overview and focus area. From Blume *et al*. (2008a).

Figure 11.46. (a) Evergreen *Nothofagus* forest and (b) *Araucaria* forest (higher elevations). Photos: T. Blume.

the site. Working in data-scarce areas demands a combination of creativity with simple pragmatism, which in this case resulted in two choices: (i) to focus the experimental work on one typical hillslope, assuming that understanding the processes here would help in understanding the hydrological functioning of the entire catchment, and (ii) to use a multi-method approach, trying to amass data from a number of different measurements and experiments in order to piece together the hydrological puzzle within a relatively short time frame and with a relatively small budget (Blume, 2008; Blume *et al.*, 2008a, b).

As a counterpart to the experimental effort, both a top-down and a bottom-up modelling approach were used. The top-down approach used linear statistical models to predict catchment event response, i.e., event runoff coefficients (see Section 9.4), hoping that the parameters that proved to be significant for the prediction of runoff coefficients would also tell us something about the functioning of the catchment (Blume *et al.*, 2007). The bottom-up approach used the physically based model CATFLOW (Zehe *et al.*, 2001) to predict runoff generation (surface and subsurface) and was parameterised with parameters either measured directly in the field or taken from the literature (see Section 10.4.1). No calibration was carried out, but the model was used as a sounding board or as a platform for hypothesis testing. As only the assumed representative hillslope was simulated, specific flows from the hillslope were compared to specific discharge time series of the entire catchment. This approach seemed viable, as response times of runoff in this catchment are generally very short and often less than 30 minutes.

Results

During several field campaigns a wide variety of different data sets were collected: time series of groundwater, soil water, runoff and climate parameters were measured over the entire study, while some data were collected on an event basis (e.g., water chemistry and stable isotopes) or during experiments (dye tracers) (Blume *et al.*, 2008a). Furthermore, the structure of the subsurface was investigated by manual augering and one-dimensional electrical resistivity measurements and soil characteristics were determined *in situ* and from soil cores in the laboratory (Blume *et al.*, 2008b). An example of how these various data sources can be used to get an idea of the dominant hydrological processes is shown in Blume *et al.* (2009) (see Figure 11.47).

A linear statistical model for the prediction of event runoff coefficients was developed by investigating ten different predictors describing catchment state, hydrograph and event characteristics. The best linear statistical model for the Malalcahuello Catchment was surprisingly simple and included the predictors of pre-event discharge (a descriptor of catchment state) and total precipitation. This led to a prediction of event runoff coefficients with a NSE of 0.9 and using a jack-knifing validation procedure still produced an efficiency of 0.86 (Figure 11.48; Blume *et al.*, 2007; see Section 9.4).

The fact that preferential flow was found in all 12 dye-tracer experiments carried out under the forest (Blume *et al.*, 2008a, 2009) led to the hypothesis that preferential flow is essential for predicting runoff response in this catchment (see Chapter 4). Running different parameterisations of a physically based model allowed us to test this

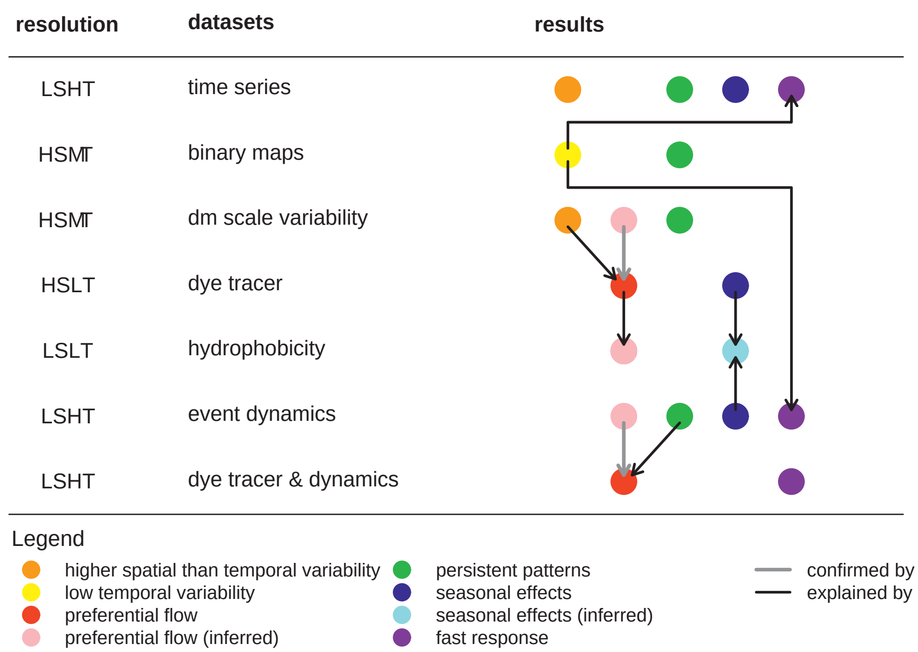


Figure 11.47. Example of the use of the multi-method approach: overview of data sets used in the soil moisture study, along with their temporal and spatial resolution, main results and synergetic effects. (L: low, M: medium, H: high, S: spatial, T: temporal; if not otherwise specified the data sets in column 2 refer to different aspects of the soil moisture data set). From Blume *et al.* (2009).

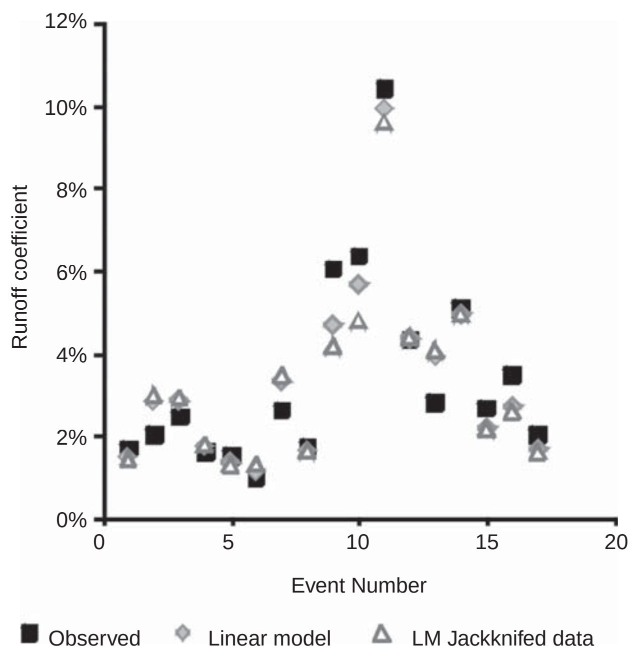


Figure 11.48. Data-based and predicted event runoff coefficients for 17 events. From Blume *et al.* (2007).

hypothesis. Preferential flow was parameterised in two different scenarios: (i) depth of preferential flow = 0.65m (Figure 11.49), (ii) depth of preferential flow = 1.3 m (Figure 11.50), which corresponds to the approximate rooting depth and is also in the same range as the observed length of flow paths of the dye-tracer experiments (1.15 m) (Blume *et al.*, 2008b).

The model implementing the longer preferential flow paths resulted in a hillslope response that mimicked catchment response quite well (Figure 11.49), on the other hand, reducing the depth of preferential flow paths to 0.65 m resulted in a dampened and unrealistic event response (Figure 11.50), thus confirming the importance of fast flow processes such as preferential subsurface flow (note: surface runoff is unlikely due to the very high porosities and permeabilities of the volcanic ash soils).

Discussion

The multi-method approach of gathering data under time – and financial – constraints and the general focus on one typical hillslope proved to be successful in the data-scarce Malalcahuello catchment, delivering much deeper insights than could be expected from rainfall and discharge time series alone.

Rainfall and runoff are generally the first parameters to be measured in previously ungauged catchments (see Chapter 3). In order to investigate the catchment's response to rainfall, event runoff coefficients are naturally one of the first parameters to be extracted from these short time series. The best predictors for these runoff coefficients can be determined with linear statistical models and can be used to infer runoff processes. The more additional data (e.g., on soil physics, hydrogeology or soft data such as observations of local residents) are gathered on targeted field campaigns, the better the results of the statistical model analysis that can be interpreted (Blume *et al.*, 2007).

The linear statistical model can also be used as an additional catchment descriptor. Event runoff coefficients

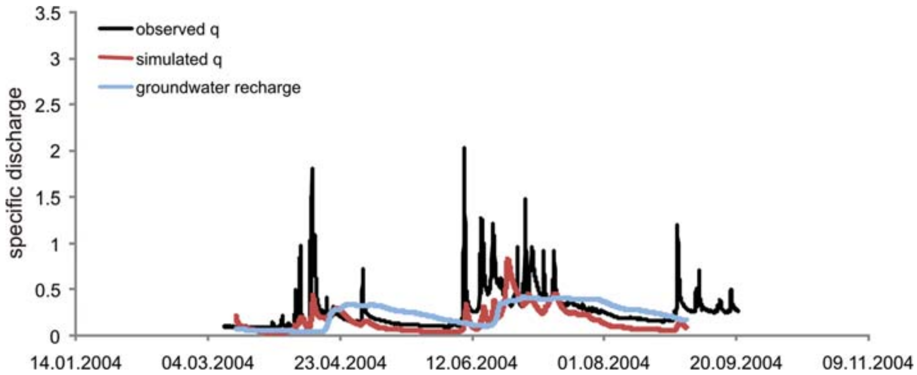


Figure 11.49. Simulated specific runoff for the modelled hillslope and measured specific runoff for the entire catchment for a macropore depth of 0.65 m.

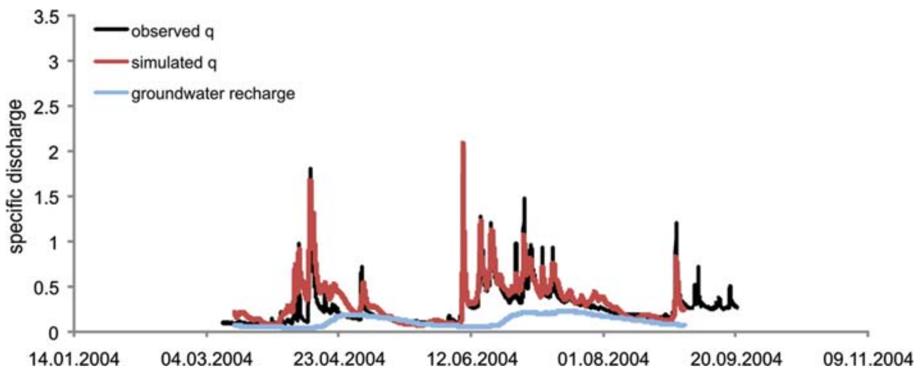


Figure 11.50. Simulated specific runoff for the modelled hillslope and measured specific runoff for the entire catchment for a macropore depth of 1.3 m.

and the resulting linear models might allow for classification of catchments with respect to runoff response. In the case of data-scarce catchments, correct classification and the resulting possibility of catchment inter-comparison (especially with data-rich catchments) will improve our understanding of runoff generation in the catchment at hand, as well as our understanding of hydrological similarity as a function of both the rainfall conditions and the bio-physiographic setting of the landscape, such as morphology, soils and vegetation cover (Blume *et al*., 2007). This is an important point within the PUB initiative, as catchment classification can help in the selection of appropriate models for predictions in ungauged catchments (Bonell *et al*., 2006).

The use of physically based models as a platform for hypothesis testing in combination with the multi-method data set described above proved to be an ideal approach for the generation and testing of process hypotheses and thus allowed for a more in-depth understanding of catchment functioning. Overall, the regionalisation approach of focusing experimental work on a single representative hillslope, and correspondingly using a representative hillslope for the simulation of catchment response worked well. However, it should be noted that the studied catchment is generally quite homogeneous in land cover and topography. In a more heterogeneous and larger catchment this approach will need to be extended to several hillslopes to account for different functional units.

Acknowledgements
Thanks to all the helpers in the field and A. Iroume and A. Huber (Universidad Austral de Chile) for logistic and technical assistance. This work was partially funded by the International Office of the BMBF (German Ministry for Education and Research) and CONICYT (Comisión Nacional de Investigación Científica y Tecnológica de Chile) and the Potsdam Graduate School of Earth Surface Processes, funded by the State of Brandenburg.

11.13 FREQUENCY OF RUNOFF OCCURRENCE IN EPHEMERAL CATCHMENTS IN FRANCE

A. CRABIT, F. COLIN AND R. MOUSSA

The issue from societal and hydrological perspectives
The population growth and associated human activities in Mediterranean and semi-arid regions increases hydrological risks. This induces more serious consequences of

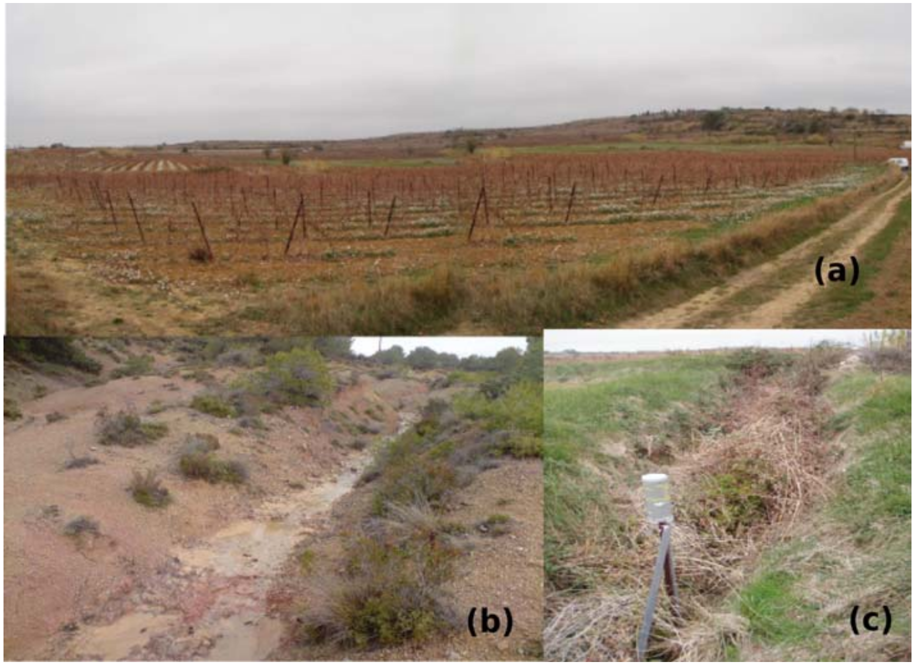


Figure 11.51. A Mediterranean vineyard landscape with (a) discontinuities (artificial channels and field mosaic of different land use), (b) low flows in an ephemeral stream and (c) non-aquatic vegetation in a dry stream.

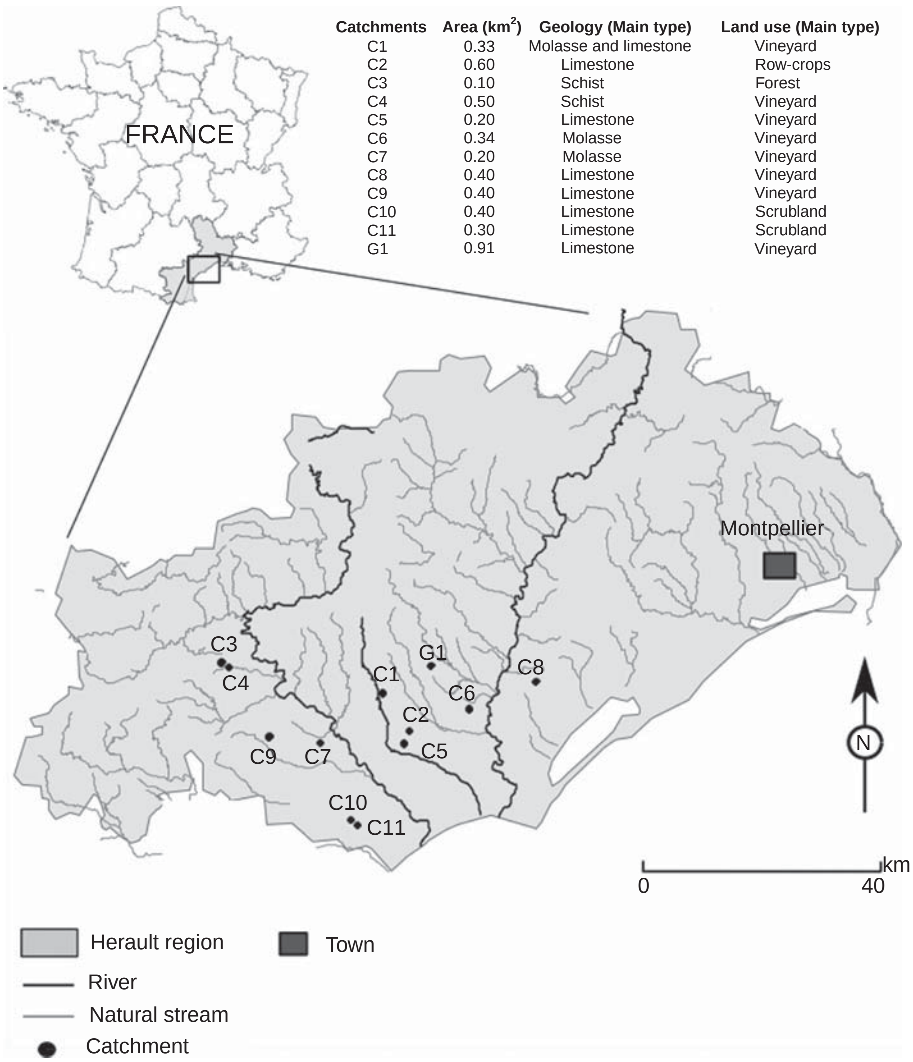
flooding events, newer and more significant causes of water pollution, and greater pressure on the scarce water resources.

In these regions most of the streams are ephemeral as they are dry throughout most of the year and generate flow only during brief periods after rainfall. The main reason for this is that rainfall events exhibit high intensities and short durations inducing Hortonian overland flows. Ephemeral streams provide a number of interesting problems for hydrologists anxious to answer questions relating to prediction in ungauged catchments and determination of catchment threshold behaviour (Zehe and Sivapalan, 2009), and thus give significant insight into catchment functioning and hydrological process understanding (Sivapalan *et al.*, 2003b). Owing to the lack of hydrological information on such catchments, estimating and predicting runoff is a significant challenge.

In agricultural landscapes, questions arise regarding the occurrence and magnitude of ephemeral streams, and the discontinuities caused by human activities. Such landscapes and associated ephemeral streams are shown in Figure 11.51. Temporal discontinuities may be induced by agricultural practices such as tillage, while spatial discontinuities are created by land use and roads patterns or infrastructure such as reservoirs and channels. These discontinuities may largely impact runoff coefficients (Moussa *et al.*, 2002) and the connectivity of water pathways (Dickinson and Whiteley, 1970).

The headwater catchment scale is a key scale for investigating these questions because hydrological processes and landscape management are jointly identifiable (Colin *et al.*, 2012). At the plot scale (100–10 000 m^2), agricultural organisation, landscape patterns and hydrological processes are incompletely represented, while at the catchment scale (>100 km^2) hydrological processes are smoothed and a detailed landscape description is difficult. Hence, the spatial variability of the geographic properties is easier to qualify exhaustively on small catchments (1 km^2) and therefore easier to relate to hydrological processes (Wood *et al.*, 1988). However, at this scale, all catchments could be considered as ungauged except for few experimental ones.

The use of hydrological signatures (such as runoff occurrence frequency, runoff coefficient magnitude, water balance) to compare and classify catchments (Wagener *et al.*, 2007; Sivapalan, 2005) appears as a first step in choosing appropriate models for poorly understood hydrological systems (McDonnell and Woods, 2004; Wagener *et al.*, 2005, 2007). The catchment behaviour signature, defined as a set of indicators related to the main hydrological processes, is a good way to appreciate similarity and/or dissimilarity between catchment hydrological functioning. These are the basis for hydrological behaviour diagnosis and allow the first propositions for corrective actions. Several approaches have been developed for estimating hydrological indicators and thus modelling catchment behaviour. One of them is based on the 'gauging the ungauged catchments' concept (Barthold



Catchments	Area (km^2)	Geology (Main type)	Land use (Main type)
C1	0.33	Molasse and limestone	Vineyard
C2	0.60	Limestone	Row-crops
C3	0.10	Schist	Forest
C4	0.50	Schist	Vineyard
C5	0.20	Limestone	Vineyard
C6	0.34	Molasse	Vineyard
C7	0.20	Molasse	Vineyard
C8	0.40	Limestone	Vineyard
C9	0.40	Limestone	Vineyard
C10	0.40	Limestone	Scrubland
C11	0.30	Limestone	Scrubland
G1	0.91	Limestone	Vineyard

Figure 11.52. Location and characteristics of the 11 poorly gauged catchments (noted C1 to C11) and of the Roujan (G1) experimental catchment.

et al., 2008; Seibert and Beven, 2009; Chapter 3 here), which is a major research challenge because of the current lack of tools to quickly diagnose the dominant processes of catchments for use in conceptual model development and prediction (Sivapalan, 2005). To establish these signatures, one promising method consists of developing innovative measurement strategies and associated framework analysis. This strategy may lead to development of a more complex modelling approach able to mitigate hydrological issues.

The aim of this study is to propose a framework to define hydrological signatures of ephemeral streams on small poorly gauged agricultural catchments. The methodology is based on the use of new soft monitoring techniques for rainfall and runoff measurements, and then the calculation of hydrological signatures for the comparison of the hydrological behaviour of catchments. Measurements were conducted on 11 small catchments located in the Hérault region of southern France.

Description of the study area

The 11 catchments were chosen based on their headwater position and diversity of geological and landscape characteristics (Figure 11.52). Mediterranean climate characterises the region: the average annual rainfall is 650 mm/yr, with a temporal bimodal distribution in two major rainy periods in spring and in autumn separated by a prolonged dry season. Most rainfall events show high intensities and short durations. The survey period was September 2008–September 2009. In addition to these catchments, the gauged Roujan catchment (G1) was examined. Research experiments have been conducted on this site since 1992 and have shown that the response to rainfall is dominated by Hortonian overland flows.

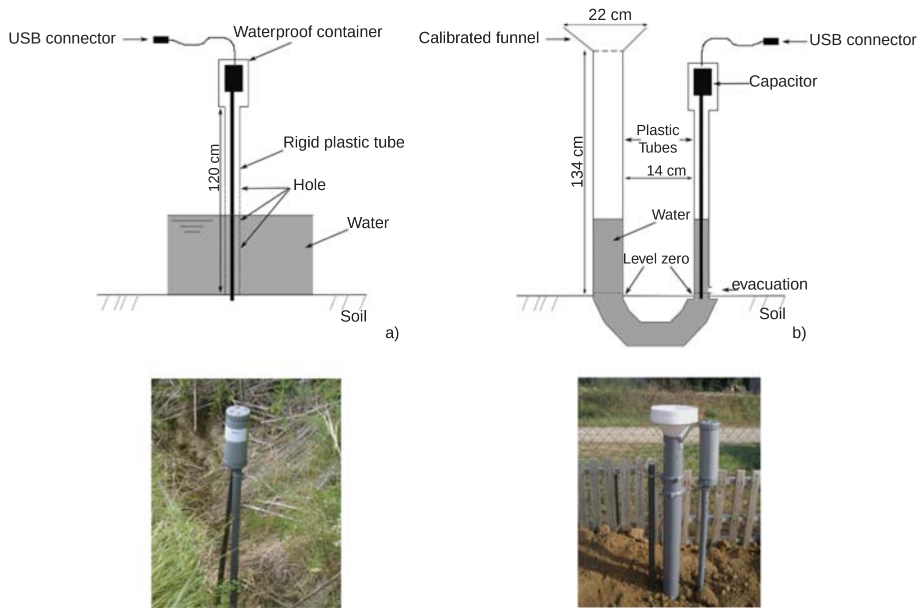


Figure 11.53. Illustration of the soft hydrological monitoring devices used as (a) a stage recorder and (b) a rain gauge. From Crabit *et al.* (2011a).

Method

Framework to define the hydrological signatures

We propose a three-step framework to define hydrological signatures at both the event and annual scales.

(1) *Soft hydrological monitoring*: The specifications for the measurement devices were that they are easy to install and easy to use, non-perturbing, robust and able to acquire high temporal frequency data with low energy consumption. Experimental settings were designed to acquire rainfall intensities and stage records at catchment outlets at 1-minute time steps (Figure 11.53). The chosen data logger consisted of a capacitor made up of two conductors (copper and water) and an insulator (Teflon). The measured capacitance depending on the surface of its conductors allows for the measurement of water depth. Laboratory tests show accurate results in dynamic conditions with a battery life of 3 weeks (Crabit *et al.*, 2011a).

(2) *Estimation of runoff*: Discharges at catchment outlets were estimated from the water depth measurements using rating curves. The rating curves were established for each outlet section, using the Manning equation and by taking into account specific roughness conditions. For each type of vegetation encountered in ephemeral streams (which is often non-aquatic vegetation), roughness coefficients were experimentally determined in controlled conditions (Crabit *et al.*, 2011b). Since the depth gauge was precisely measured, the discharge uncertainty came mainly from the values of the roughness coefficients. Hence, a range of values of roughness coefficients were considered, resulting in a range of estimated discharge values at each time step. Finally, the minimum and the maximum values of runoff were calculated for each flood event using the envelope of the rating curves.

(3) *Hydrological signatures*: Among the large number of possible indicators calculated from rainfall–runoff data, only those relevant for qualifying intermittent flows in ephemeral streams were retained (Crabit *et al.*, 2011b): the annual runoff coefficient A (denoted A_{min} and A_{max} when using respectively the minimum and maximum values of the estimated hydrograph), the total number of rainfall events N (with a total daily rainfall $>$ 5 mm), the total number of events when runoff occurs N_{r}, and the frequency of the catchment response $B = N_{\mathrm{r}}/N$.

Results

Hydrological signatures of the studied catchments

On the 12 studied catchments, the annual rainfall showed slight spatial variations ranging between 352 and 548 mm/yr (Figure 11.54) according to a north–south gradient. Even if the annual rainfalls were close for all the catchments, the annual runoff coefficients were highly variable: for example, A ranged between 0.01 and 0.02% for C7 and between 13.0 and 24.5% for C2. Detailed analysis highlighted that one single flood event runoff could represent 50% of the annual runoff. For example, in catchment C2, one rainfall event of 90.4 mm (representing 22% of the

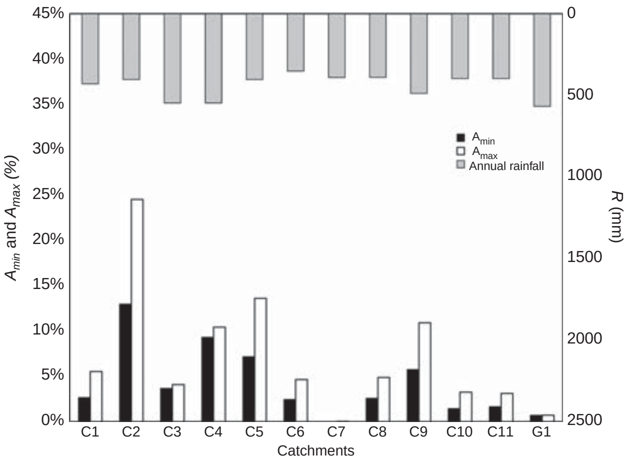


Figure 11.54. Annual rainfall (R) and runoff coefficients (ranging between A_{min} and A_{max}). From Crabit *et al.* (2011b).

annual rainfall amount) caused a runoff that accounted for 59% of the annual runoff. For ephemeral streams, these results show that a few events carry great weight in the annual water flows at the catchment outlet. When analysing the annual water budget, we observe that the actual evaporation (equal to the difference between the annual rainfall and the annual runoff) appears much lower than the mean inter-annual potential evaporation (around 1000 to 1500 mm/yr). These results confirm the water stress encountered in Mediterranean regions with differences from one catchment to another.

The annual runoff coefficient A and the frequency of occurrence of runoff event B are plotted as hydrological signatures in Figure 11.55. The hatched boxes represent the uncertainties (the uncertainty associated with B depends on the rainfall threshold chosen to define a rainfall event). In spite of these uncertainties, similarities and dissimilarities between catchment responses were observed: C1, C6 and C11 catchments appeared similar and different from C4 and C9. Figure 11.55 exhibits three extreme signatures: (i) C2 with a low value of B and high value of A; (ii) C7 with low values of both A and B; and (iii) C8 with a low value of A and a high value of B. A signature with high values of both A and B was not observed. This could be explained by a high density of impervious land (urban area, roads). The studied catchments covered by agricultural or natural land did not show this type of response.

Discussion

The proposed framework allowed the hydrological signatures of poorly gauged catchments to be compared. Such a network catchment survey gives opportunities in terms of catchment comparison under close climatic conditions for better understanding of processes in addition to classic

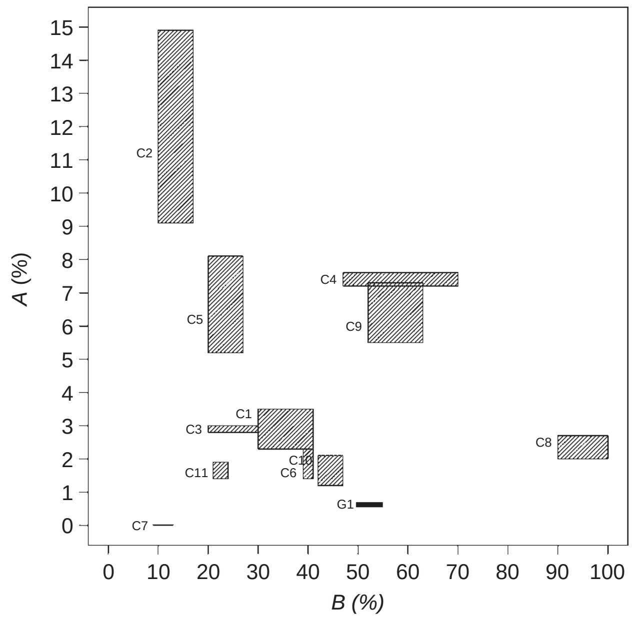


Figure 11.55. Annual runoff coefficients (A_{min} and A_{max}) plotted against the frequency of the catchment response B. From Crabit *et al.* (2011b).

long-term surveys on one (or few) catchment(s). Comparison would be helpful to assess the magnitude of processes in relation to anthropogenic forcing under various morphological and soil conditions. Comparison between a large number of catchments in many parts of the world opens a way to classifying catchments according to hydrological responses. This classification step would lead to a framework of 'Prediction in Ungauged Basins'. Lastly, the proposed new measurement techniques hold a lot of potential for validating hydrological models.

11.14 OVERCOMING DATA LIMITATIONS FOR HYDROGRAPH PREDICTION, LUANGWA BASIN, ZAMBIA

H. WINSEMIUS AND H. H. G. SAVENIJE

The issue from societal and hydrological perspectives

The Zambezi catchment in Southern Africa is shared by six countries (Angola, Zambia, Namibia, Botswana, Zimbabwe and Mozambique; see Figure 11.56). Besides being a major water resource in a semi-arid area, it is the provider of enormous amounts of actual and potential hydropower to an energy-scarce region. The real-time operation of the already existing hydropower dams (Kariba on the border between Zambia and Zimbabwe and Cahora Bassa in Mozambique) is complicated by

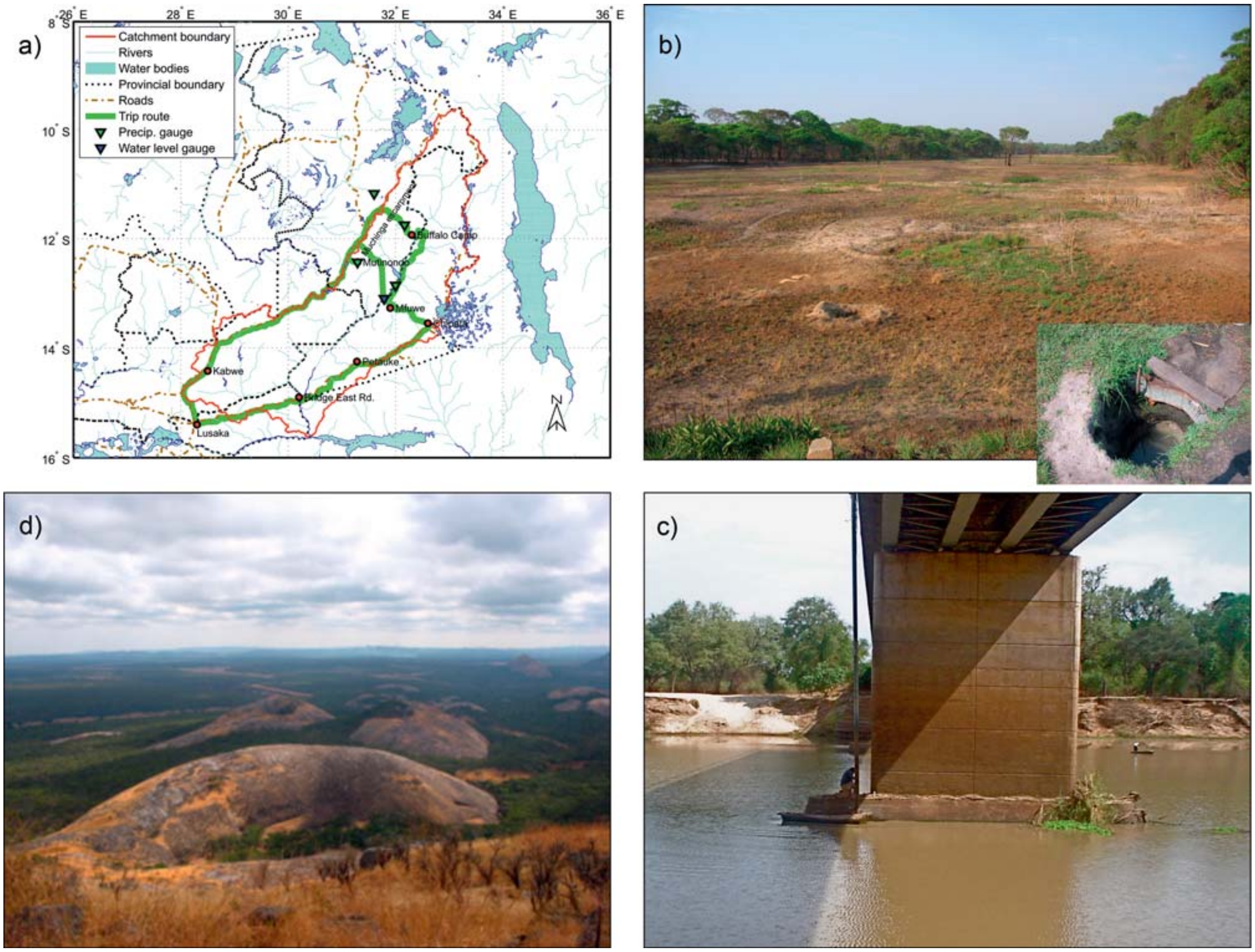


Figure 11.56. An impression of the Luangwa Basin within the Zambezi catchment. Clockwise we see (a) a map of the Zambezi catchment with Lake Kariba and Lake Cahora Bassa and the Luangwa Basin; (b) a typical ‘dambo’ wetland with an inset scoop hole; (c) the gauge that we installed at the Mfuwe bridge; and (d) the typical landscape of the Luangwa Basin.

the fact that large parts of the catchments are ungauged and that floods generated in these catchments can potentially damage these dams if discharges are not well anticipated. The Luangwa is a major Zambian tributary to the Zambezi, which joins the main river in between these two major dams. If floods are expected, then the Cahora Bassa dam needs to start spilling enough water to provide flood storage. If the operators spill too much, they may cause unnecessary harm downstream and lose valuable power generation potential; if they spill too little, they may damage the dam or even put the dam in danger of being destroyed. Operational flow prediction in the Luangwa is therefore very important. This makes the operators in Mozambique completely dependent on forecasts from Zambia, which has no gauging in place.

To develop an operational real-time flow prediction model in an ungauged basin, the opportunity is taken to make use of any hydrological information that may be available under such ungauged conditions (see Chapter 3). This can be done by effectively combining the information, both to constrain hydrological model parameters and to enhance model structure (Seibert and McDonnell, 2002; Winsemius *et al.*, 2006, 2008; Klees *et al.*, 2007; Yadav *et al.*, 2007; Fenicia *et al.*, 2008a). For information to be used during calibration, multi-objective calibration techniques have been proposed (Vrugt *et al.*, 2003), but in our case study (and many other potential case studies in the world) such calibration techniques are not applicable. In fact, a typical problem of many ungauged or scarcely gauged river basins in the world is that even when there are some ground data available, these may be sparse, inaccurate, intermittent, non-concomitant and collected at different time scales, hence it is not clear how one can integrate their non-conventional information content for use in predictions.

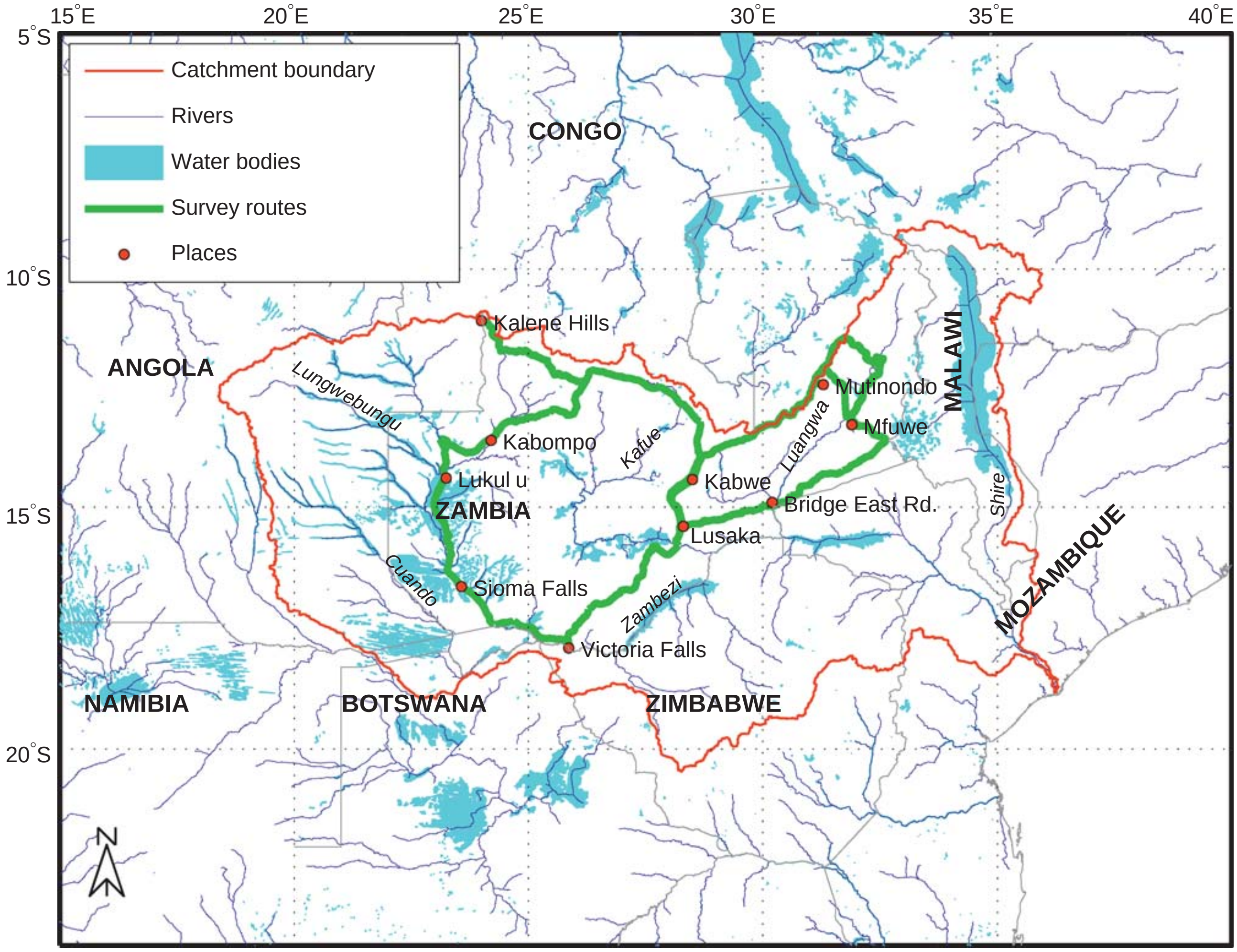


Figure 11.57. Luangwa Basin, located in Southern Africa. The study area is plotted in red. The large water bodies and larger wetlands (called 'dambos') are indicated in blue. The tarred road network is also plotted to emphasise the remoteness of the area. All smaller untarred roads inside the basin are only accessible in the dry season. At the bridge on Great East Road, only an old time series of daily discharge data is available.

This case study focuses on a real-world example of an ungauged basin. It demonstrates and applies a framework to integrate both hard and soft unconventional information in the form of signatures, delivered by available hydrological observations of poor quality, as mentioned above. The framework makes use of generalised likelihood uncertainty estimation, or GLUE (Beven and Binley, 1992), within the limits of acceptability approach (Beven, 2006) and has been presented earlier by Winsemius *et al*. (2009).

Description of the study area

The Luangwa River basin is a real-world PUB case (see Figure 11.57). The aim of the study was to calibrate a rainfall–runoff model that should be applicable for estimation of river flows at the daily time scale (see Chapter 10). This would be particularly useful for flood prediction and operation of the downstream reservoir, Lake Cahora Bassa, which is visible just below the Great East Road Bridge in Figure 11.57. The choice of a real-world example forced us to use unconventional methods to perform model inference.

The essence of this case study is that, rather than questioning whether the setup of such a model is possible and can be validated, we focus on whatever few data are available and extract the most out of these data. The crux is to identify small pieces of information from the few data available and combine these pieces of information into a scientifically sound model inference framework. The focus in this case study is on signatures from available discharge data and the decay of evaporation over time. The

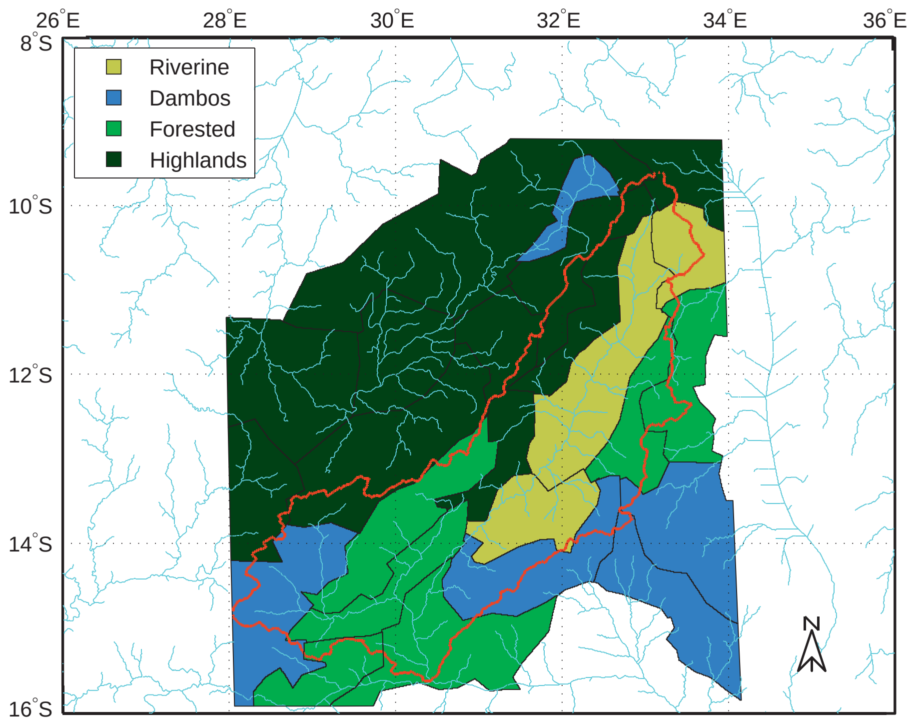


Figure 11.58. The disaggregated model units with their dominant land cover characteristics (hydrotopes).

evaporation estimates were derived using the SEBAL method (Bastiaanssen *et al.*, 1998). Satellite rainfall estimates (SRE) considered were product 3B42 of the Tropical Rainfall Measuring Mission (Huffman *et al.*, 2007) and the CPC/Famine Early Warning System (FEWS) daily estimates (Herman *et al.*, 1997). A 16-year data set of discharges was available at the outlet of the catchment, collected largely in the 1970s. Some of the challenges faced in this case study were:

- typical globally available satellite rainfall estimates (SRE) are non-concomitant with typically available calibration series (see Chapter 3);
- all information available is error prone: SRE are for instance typically biased, satellite evaporation is noisy and old discharge records may have gaps;
- validation material is not present.

A field visit was conducted to 'read the landscape' and to recover some of the main features of the basin (see Chapter 3). The Luangwa Basin is a relatively pristine and remote area of about 150 000 km^2, located in Zambia, Southern Africa. It consists partly of flash-flood generating mountainous areas and lower-lying floodplain and wetland areas with tropical savanna vegetation and some agriculture. The north-eastern boundary (the Muchinga escarpment) is densely forested and interspersed by pristine wetland areas and large basalt lava rocks. This area has a different hydroclimatology from the low-lying savannas. Temperatures on the escarpment are much lower and, given the presence of wetland vegetation in the 'dambos', these areas have a higher capability of retaining moisture during the dry season than the lower savanna regions. The average rainfall in the catchment is around 1000 mm/yr. Rainfall is concentrated in one wet season from November until April. Based on this impression and a time series of maps of normalised difference vegetation index (NDVI), a subdivision into hydrotopes was made and a simple hydrological model with a limited number of parameters was set up. Figure 11.58 shows the subdivision into hydrotopes.

The issue of validation material was also tackled during field visits. To ensure that (as far as possible) an unbiased and concomitant time series of rainfall and discharge was available, measurement equipment was installed at Mfuwe (location is indicated in Figure 11.57) to collect water levels over one wet season. These water levels were rated based on old rating data at the site. To bias correct SRE over the period for which validation data were collected, time series of local rainfall from lodges in the region were also collected (see Figure 11.57 for the locations).

Method

Framework to combine different sources of information into a calibrated model

Winsemius *et al.* (2009) developed a calibration framework to profit from any available data in a catchment, in this case signatures from the old discharge time series and the recession of evaporation during the dry season (see Section 10.4.5). The crux of the framework is that we take into account that the available observations and related catchment behaviour through the chosen signatures are uncertain and that the user does not have a conventional calibration data set at their disposal (i.e., a concomitant and long series of input and output data observed at the required time step).

The parameter inference of the framework is based on GLUE, using limits of acceptability (Beven, 2006) on the signatures to separate behavioural from non-behavioural models. A crucial issue tackled within the framework is how the limits of acceptability are derived in an objective way. Winsemius *et al*. (2009) showed that this can be done by estimating the uncertainty in the signatures. This is done by retrieving samples of the signature from available data on a year-by-year basis. The samples are then transformed to a Gaussian distribution using the normal quantile transform (Montanari and Brath, 2004) and the standard deviation used to construct a 95% confidence interval. Any sample that stays within the confidence interval of each signature is accepted as behavioural. We define a signature as 'hard' when this objective approach to defining the limits of acceptability can be followed and 'soft' if this objective approach cannot be followed. In this case, stronger assumptions on the nature of error are required or a subjective decision needs to be made on the limits.

The inference can be performed stepwise on each signature in turn. Analysis of the intermediate results provides the modeller with insights into which part of the parameter space and, consequently, which outputs are well constrained by means of the included information and what constraints are still lacking. The user may then decide what information has the potential to further condition the parameters and, if deemed feasible, to collect this information. After the collection of new information, the procedure may be repeated to update the parameter distributions with new targets. More information about the calibration framework is given by Winsemius *et al*. (2009).

Results

Chosen signatures and limits of acceptability

In order to apply the calibration framework proposed here, after analysing the available hydrological data, the following objectives have been identified along with the related target values to be used to drive the parameter estimation:

Slope of the recession limb of the hydrograph (see Section 10.4.5).

Hard hydrological information: spectral properties of non-concomitant daily river flows (Montanari and Toth, 2007; see Section 10.4.5).

Hard statistical information: It was assumed that the spectral density function of river flows can be constrained by the mean μ_Q, the standard deviation σ_Q and lag-1 autocorrelation $\rho_1(Q)$ of the river flow process. Therefore, μ_Q, σ_Q and $\rho_1(Q)$ allowed us to define a three-element target vector to resemble a spectral density objective function.

Monthly water balance estimates based on a monthly auxiliary rainfall runoff model, calibrated on the old monthly averaged records of rainfall and runoff (see Section 6.4.2): This is soft hydrological information because the limits could not be objectively defined following the framework outlined above. This auxiliary model has been calibrated using available monthly ground-station rainfall data from the Global Historical Climate Network (GHCN) in the period 1956–73. The model then allowed for a reconstruction of the monthly discharges at the basin outlet for the period 2002–6, the run time period of the daily modified HBV model. The daily time step model can then be constrained towards reproducing (in a statistical sense) the long-term discharges provided by the monthly auxiliary model. Further information on the derivation of the limits can be found in Winsemius *et al*. (2009).

Recession of evaporation in the dry season: This is soft information because only one dry season of evaporation estimates was available. Several targets were defined based on the evaporation being the total dry-season evaporation. Furthermore, the evaporation-sensitive parameters were constrained spatially distributed in an independent Monte Carlo experiment. This led to a number of preliminary constraints on parameters S_{max} and l_p, which are equivalent to the active soil moisture zone (i.e., where roots are actively transpiring) and the fraction of soil moisture, where transpiration becomes moisture limited. This experiment is fully described by Winsemius *et al.* (2008).

The derived limits of acceptability of each target value are given in Table 11.11. A large number of Monte Carlo runs were performed and analysed following the framework described above. In each run, all the above-shown targets were evaluated. Only models obeying all of these targets were accepted.

Validation

It should be clear by now that the calibration of the rainfall–runoff model, shown in the previous sections, is fully *indirect*, meaning that no concomitant time series of modelled and observed discharges could be generated to perform a classic direct calibration. The validation carried out here is therefore fully independent of any performed calibration and hence it is a validation in the true sense: not only have the collected records been left out in the

Table 11.11. *Limits of acceptability, based on the normal quantile transform*

Type of data used	Description	↓ lim	↑ lim
Discharge Great East Road Bridge	Recession slope (day^{-1})	0.0055	0.014
	$\rho_1(Q)$ (–)	0.968	0.994
	σ_Q (m^3/s)	269	1943
	Water balance:		
	Nov–Jan (mm/month)	−4.24	+10.69
	Feb–Apr (mm/month)	−20.7	+12.4
	May–Jun (mm/month)	−1.84	+3.3
	Jul–Oct (mm/month)	−0.91	+0.92
SEBAL evaporation maps	Evaporation per time step	$\mu \pm 0.3\mu$	
	Total dry-season evaporation	$\mu \pm 0.1\mu$	
	Parameter: $S_{\max}$ (mm)		
	Riverine	500	650
	Dambos	275	500
	Forested	1300	2000
	Highlands	1400	2000
	Parameter: l_p (-)		
	Riverine	0.75	1
	Dambos	1	1
	Forested	0.25	0.4
	Highlands	0.5	0.6

The water balance limits of acceptability are dependent on the output of the monthly HYMOD auxiliary model. Therefore, only the deviation (±) from the modelled output is given.

parameter inference process, they offer the ability to perform a direct comparison between modelled and observed discharges, given that we have knowledge of the rating curve and that the SRE rainfall corrected with the local gauges is accurate enough. One hundred accepted parameter sets were consequently used to force the hydrological model from the period September 2002 until August 2008. This ensured a generous spin-up time of 5 years for a proper initialisation of soil moisture storage. The result of the 100 discharge realisations at Mfuwe are plotted against the observed Mfuwe water levels in Figure 11.59.

As an independent validation, we can conclude that the simulated discharges, on average, indeed follow a straight line on the double-log plot, and that the slope of the line is within what may be expected of a rating curve. Apart from the hysteretic loops that are normal in the passing of a flood wave, we can conclude that the timing of the hydrograph is well captured. If we plot the observed hydrograph using this rating curve against the 100 realisations in Figure 11.60, then we can see that the timing of the start of the hydrograph (which is a threshold process) and the recession are well captured.

It is clearly evident that the validation has been generally successful. It provides independent credibility that the calibration framework, described in detail in the last two sections, is valid and useful for predictions in ungauged basins, where available data may be scarce, intermittent and non-concomitant, but where we are nonetheless forced to use them. More importantly, the randomly selected behavioural parameter sets produce an envelope of realisations that in most parts of the hydrograph encloses the observed flows. This means that the model is not over-conditioned, which is a soft proof that the framework indeed ensures a control on subjectivity.

Discussion

In this case study, a real world example of modelling an ungauged basin has been presented. Crucial components of our approach are outlined below:

(1) the modeller should get the look and feel of the dominant processes by 'reading the landscape' and linking it with catchment characteristics and information signatures;
(2) one should install water level recorders and rain gauges immediately during the first visit for validation purposes;
(3) rather than a classic hydrograph matching calibration, the modeller should focus on small pieces of

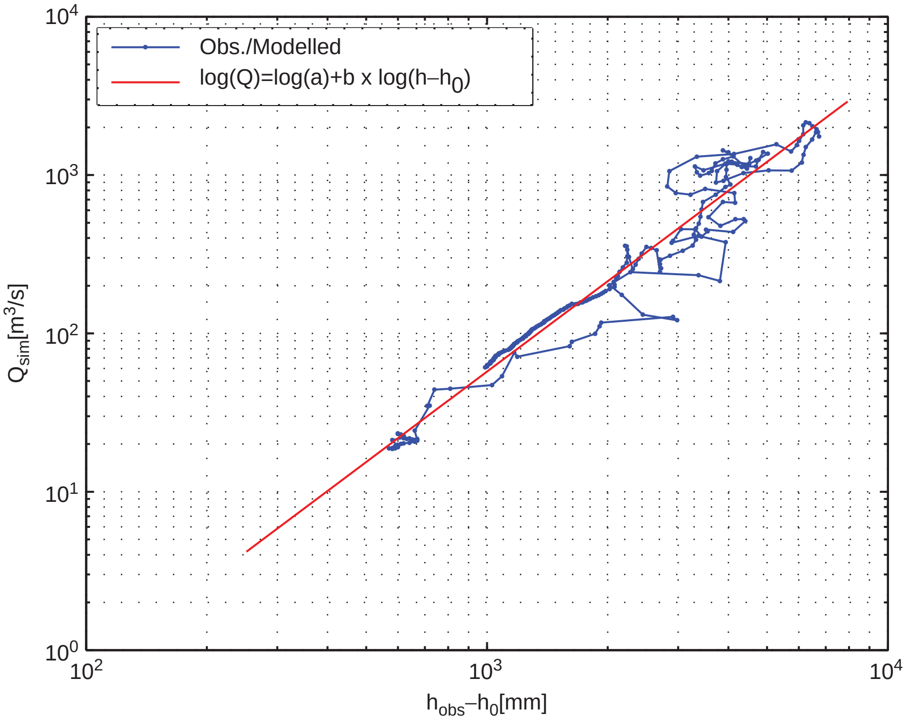


Figure 11.59. Rating relation between simulated discharge (i.e., the average of 100 realisations) and water levels with reference to h_0 at Mfuwe.

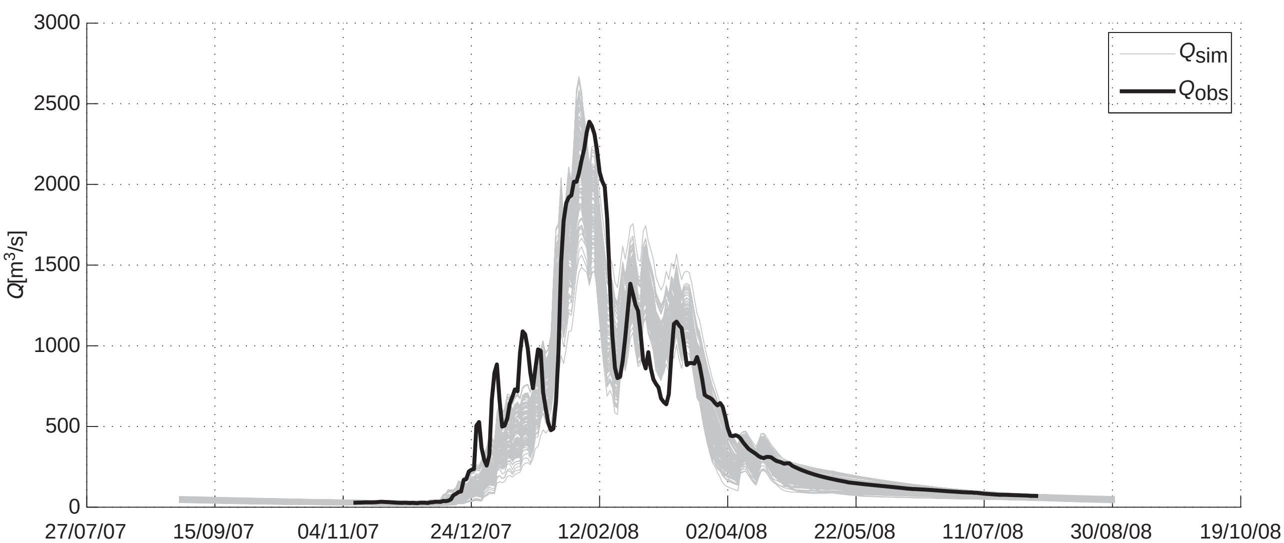


Figure 11.60. Validation of modelled discharge at Mfuwe. The gauged discharges are derived from *in-situ* measurements of water levels using the rating curve.

information (e.g., signatures) from any available data (even poor-quality, non-concomitant data), which in combination provide a strong constraint on model inference; and

(4) an objective framework should be applied, such as presented in this chapter, to combine the pieces of information for the purpose of model inference.

The model developed is currently working on-line, forced by real-time SRE rainfall and Meteosat meteorological information. It provides the water managers downstream with real-time information on the expected inflows of the Cahora Bassa reservoir and can be used to warn the population against imminent floods. This PUB study has thus made a valuable contribution to a societal problem.

11.15 REMOTELY SENSED LAKE LEVELS TO ASSIST RUNOFF MODELLING IN GHANA

J. LIEBE, N. VAN DE GIESEN, M. T. WALTER AND T. S. STEENHUIS

The issue from societal and hydrological perspectives

In semi-arid areas of the developing world, rural water supply is increasingly insufficient. Supplying the rural population in semi-arid developing countries with water requires spatially distributed sources of different qualities and quantities of water. Access to clean drinking water is being improved with borehole programmes, but the equally important large volume demand for non-drinking purposes is currently not addressed sufficiently. In many regions, small reservoirs act as multi-purpose water sources in support of irrigated agriculture and gardening, livestock watering and fishing, as well as personal hygiene, domestic uses and building. They are as important for rural development, health improvement and poverty reduction as for access to safe drinking water.

One of the key advantages of small reservoirs is their existence in large numbers, greatly improving the water availability at village level. They are often the only adequate and economically feasible source of large volume water supply for non-drinking purposes and important for economic development and the reduction of poverty. Their small size, existence in large numbers and widespread distribution leads to many desirable socio-economic effects. From a PUB perspective, they offer a unique possibility to monitor the occurrence and, to a lesser extent, quantity of runoff over large areas (see Chapter 3). In order to do this, a monitoring and modelling framework was developed based on radar (ASAR) imagery and a simple conceptual model. The case study concerns the Upper East Region of Ghana, a region with a relatively high density of small reservoirs. The method has previously been presented in Liebe *et al*. (2009a, b) and draws on several earlier publications regarding remote sensing of small reservoirs. The work is part of the Small Reservoirs Project (www.smallreservoirs.org).

Description of the study area

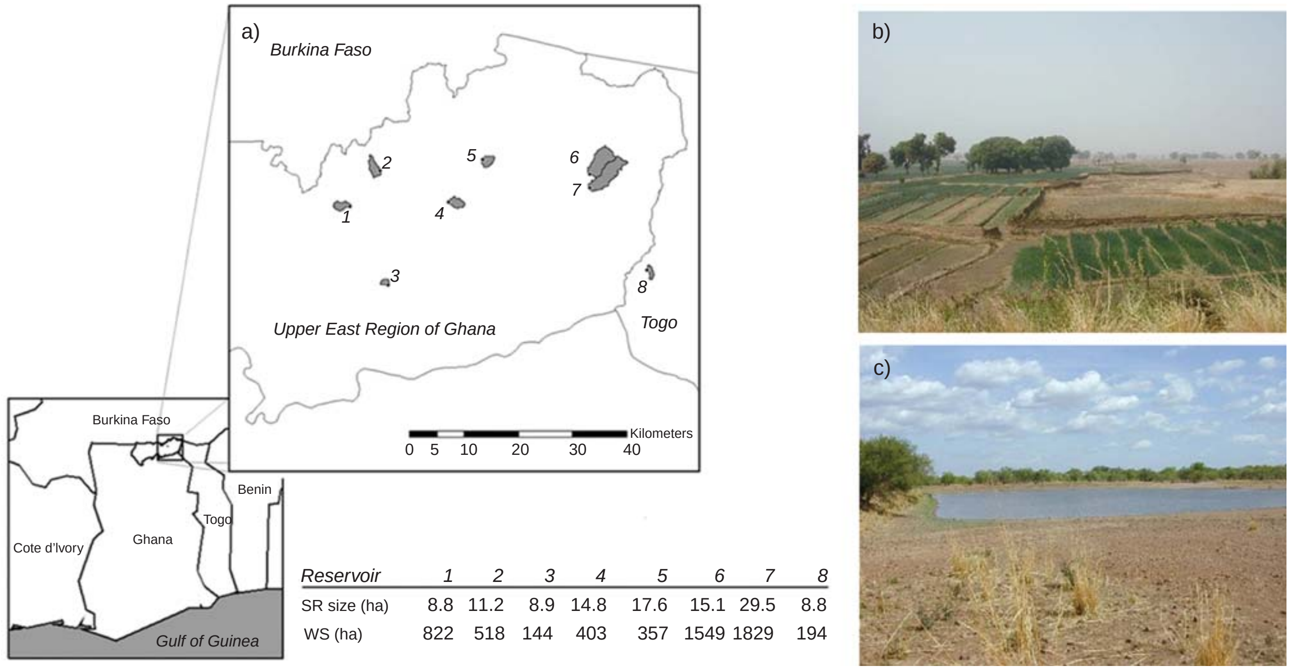
The Upper East Region of Ghana is situated in the centre of the Volta Basin. The Upper East is inhabited by approximately one million people and has a population density of about 100 inhabitants/km^2. With a poverty incidence of 88% in 1998/9, the Upper East has the largest proportion of poor people of Ghana's ten regions. The residents' incomes are generated from mostly rain-fed and some irrigated agriculture. Population growth places pressure on scarce land and water resources. The scarcity of usable water resources is mainly due to the climate, especially the mode of rainfall. The Upper East's semi-arid climate is characterised by a three-month, mono-modal rainy season. Ninety per cent of the region's total rainfall (986 mm/yr) occurs as thunderstorms, originating from squall lines. Rainfall intensities often exceed the soil's infiltration rates causing surface runoff, without significantly replenishing soil moisture and groundwater. Small reservoirs capture all runoff until they are filled, after which any incoming water flows over the spillway. In the Upper East Region, 154 reservoirs with a surface area between 1 ha and 100 ha were identified on the basis of remote sensing. In addition, two larger reservoirs (Tono, 1894 ha; Vea, 435 ha) are located in the area.

The landscape is slightly undulating with typical maximal height differences within the studied catchments of less than 100 m. Figure 11.61b shows a representative small irrigation scheme adjacent to a small reservoir and gives a general impression of the landscape during the dry season. The landscape can be described as a park landscape of fields with scattered individual trees. Figure 11.61c shows a very small reservoir at the end of the dry season, with the dam wall in the background.

Method

To calculate the catchment discharge, we combine time series of remotely sensed reservoir surface areas with known relationships between reservoir volume and surface area to calculate runoff volumes that are then used to parameterise the Thornthwaite–Mather (1955) water balance model. The reservoir surface areas were extracted with a spatial resolution of 30 m from 12 ENVISAT ASAR images as described in Liebe *et al*. (2009a). An example of one of the images and the reservoir outline is shown in Figure 11.62.

The reservoir's storage volumes were determined with a generalised area–volume equation developed by Liebe *et al*. (2005). Bimonthly inflow into the reservoir is estimated as the change in reservoir volume, adjusted for evaporation from and rain falling on its surface. Catchment runoff, on days with precipitation that fall within the bimonthly period, is interpolated. Stream network and the catchment area were extracted from SRTM V3 elevation data (Jarvis *et al*., 2008) after performing a pit-removal procedure and choosing the dam wall as a seed point. Daily rainfall data with a horizontal resolution of 10 km were provided by the Famine Early Warning Systems Network that is based on Meteosat infrared data, rain gauge reports and microwave satellite observations (Xie and Arkin, 1997).



Reservoir	1	2	3	4	5	6	7	8
SR size (ha)	8.8	11.2	8.9	14.8	17.6	15.1	29.5	8.8
WS (ha)	822	518	144	403	357	1549	1829	194

Figure 11.61. (a) Map showing location of study area and the eight catchments used in the case study. SR and WS relate to reservoir and catchment area, respectively. From Liebe *et al*. (2009b). (b) Typical small-scale irrigation (onions) and dry season landscape; and (c) very small reservoir (2 ha surface area) at the end of the dry season. Photos: J. Liebe.

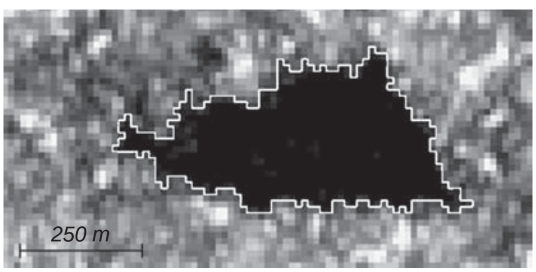


Figure 11.62. Small reservoir and outline (white) on Envisat ASAR.

A rainfall–runoff model was developed to predict the catchment outflow to the reservoir. It is based on the Thornthwaite–Mather procedure (Thornthwaite and Mather, 1955). In this procedure a water balance of the root zone is maintained. The actual evaporation is a linear function of the plant available water. At field capacity the evaporation is equal to the potential evaporation and at wilting point it is negligible. Any rainfall in excess of the maximum storage in the root zone, S_{max} (i.e., when the soil moisture exceeds field capacity), is released to the subsoil as percolation. The portion of the percolation (P_e) that recharges the reservoir as quickflow, Q_f, becomes generally greater the greater the rainfall amount. This relationship between contributing area and effective rainfall amounts is not known. In developing such a relationship it should have the properties that the contributing area is zero when rainfall just wets up the soil to field capacity and should be equal to 1 when rainfall approaches infinity. One such expression that satisfies these boundary conditions is

$$Q_f = P_e\Big(1 - \exp(-aP_e)\Big)$$

where a is a constant with dimension (T/L) expressed in (days/mm), which is an indicator of a catchment's sensitivity to runoff generation. Noting that P_e is equivalent to the effective rainfall as defined in Steenhuis *et al*. (1995), we can differentiate with P_e to obtain the contributing area, A_f:

$$A_f = 1 - (aP_e)\exp(-aP_e)$$

We can see this has the required property that A_f is 0 when the $P_e = 0$ and that it is equal to 1 when P_e goes to infinity.

Results

The catchments extracted from the SRTM DEM, including the reservoirs, range from 144 to 1829 ha (Figure 11.61). The results of the reservoir surface area classification obtained from the radar image analysis are listed in Table 11.12. On the basis of these remotely sensed

Table 11.12. *Reservoir surface areas (ha) classified from ENVISAT ASAR images*

	Reservoir size (ha)							
Date	1	2	3	4	5	6	7	8
21 May 2005	5.5	2.9	3.5	6.6	6.6	9.4	4.3	3.6
6 June 2005	5.8	3.7	3.1	7.8	3.3	10.2	25.0	4.1
24 June2005	6.1	4.7	3.7	10.0	12.6	12.9	26.3	4.8
11 July 2005	8.2	9.0	4.8	9.8	13.4	14.6	28.2	8.2
29 July 2005	8.8	10.9	7.2	10.2	17.0	14.1	29.5	8.6
15 August 2005	8.3	11.2	5.6	12.9	17.6	15.0	29.4	8.8
13 June2006	4.9	2.2	5.4	9.9	6.0	4.0	1.8	4.1
29 June 2006	5.1	2.3	5.3	9.9	6.6	3.9	2.4	4.3
11 July 2006	5.0	2.4	5.5	10.1	7.0	4.1	1.8	4.6
30 July 2006	8.0	5.9	7.2	13.7	10.9	12.6	21.3	7.6
3 August 2006	8.5	6.1	5.5	14.4	11.5	13.1	21.6	7.8
15 August 2006	8.7	7.4	8.9	14.8	14.1	15.1	27.0	8.6

The locations of the reservoirs are given in Figure 11.61**.**

surface areas, storage volumes over time were estimated. The resulting time series of reservoir storage volumes formed the basis for the calibration of the runoff model.

Rainfall

The method was applied for the time period extending from the dry season into the rainy season in 2005 and 2006. In 2005, the rainy season was segmented into three to five wet periods with distinct dry spells in between. In 2006, there were only three wet periods, which were separated by only short dry spells. The 'wet day' analysis was used as an indicator of the strength of the rainy season, where a day is considered wet when the rainfall in the 10 preceeding days exceeds 34 mm, and rainfall exceeds potential evaporation on that day. Although the rainfall in 2006 was, on average, only 3% below the rainfall in 2005, the rainfall patterns were distinctly different. Overall, the 2006 rainy season was shorter and occurred later than the rainy season in 2005. In 2006 there were 67 'wet days'. Fifty-nine per cent of rain fell on those days. In 2005, on average, 51% of the total precipitation fell on 63 wet days.

Calibration

The records for the eight reservoirs are divided into two years. The parameters S_{max} and a were calibrated using the 2005 data, and then used in 2006 for validation. In calibration, the S_{max} determines mainly the time of the first catchment contribution to the reservoir, while a is related to the total amount of effective rainfall that reaches the reservoir.

S_{max} was determined on the basis of the storage volume time series, specifically by taking into account the moment when reservoir levels rose for the first time. Initially, two S_{max} values were determined with the Thornthwaite–Mather procedure. The maximum S_{max} value was determined assuming that the first percolation occurred on the date that the first rise in the reservoir was observed at the time of the satellite image acquisition. The minimum S_{max} values were calculated assuming that the rise occurred at the preceeding satellite image acquisition date. In the Thornthwaite–Mather model the mean S_{max} value was used.

The shape factor value, a, was obtained by visually fitting predicted reservoir inflow to the observed inflow based on volume increases determined with satellite images. The method does not apply once the reservoir is full, because inflows are then routed through the reservoirs over their spillways and do not result in an increase in storage.

For each catchment, the calibrated minimum, maximum and mean values of S_{max} and the shape factor value, a, are reported in Table 11.13. The catchments' mean S_{max} values range from 25 to 45 mm, and the a values range from 0.01 to 0.08 day/mm. It is remarkable that, for these catchments that are spread over the northern part of Ghana and western part of Togo, similar S_{max} and a values can describe how and when the reservoirs fill up. Figure 11.63 gives an example of how information is extracted from the time series of storage volumes.

Validation

The 2006 season was used to validate model results. Figure 11.64 compares the observed reservoir volumes with the predicted cumulative quickflow (Qf) for the eight catchments. In both years, the reservoirs were spilling water in August and therefore images taken on 15 August 2005 and 15 August 2006 were omitted from the analysis, because

Table 11.13. *Measured catchment area and calibrated root zone storage,* S_{max}*, and catchment contributing factor,* a

Reservoir	1	2	3	4	5	6	7	8
Catchment area (ha)	822	518	144	403	357	1549	1829	194
S_{max} mean (mm)	45	42.5	45	42.5	32.5	25	45	37.5
S_{max} low/high (mm)	35/55	35/50	40/50	40/45	20/45	15/35	35/55	20/55
a (day/mm)	0.010	0.025	0.063	0.060	0.080	0.013	0.020	0.035

The location of the reservoirs is given in Figure 11.61.

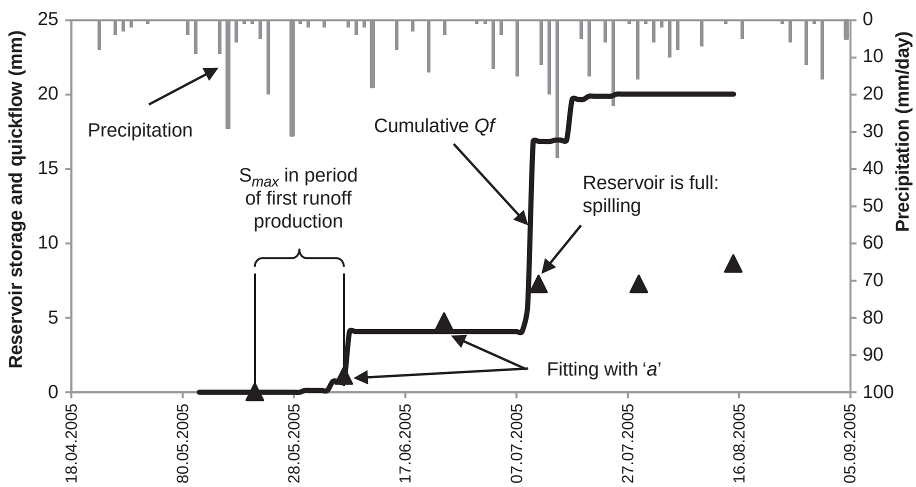


Figure 11.63. Example showing on the left axis, observed reservoir storage (triangles) and accumulated quickflow (mm) (bold line) and, on the right axis, the rainfall (mm/day), on the basis of which S_{max} and a have been estimated. The series covers the 2005 season for reservoir 6 in Figure 11.61.

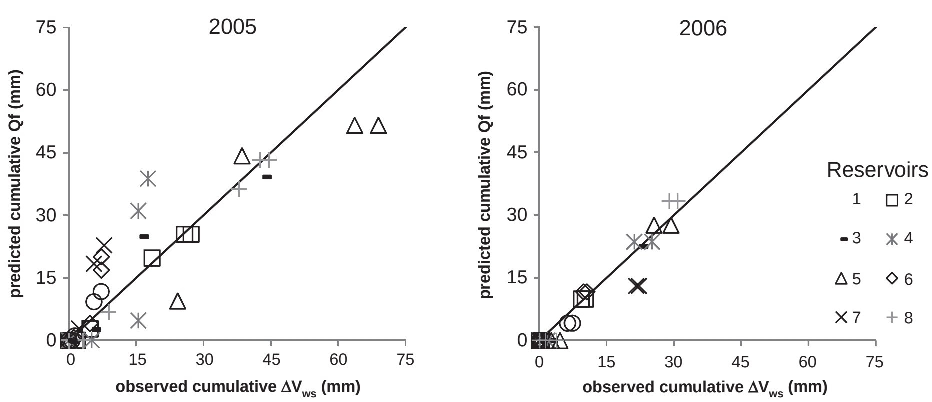


Figure 11.64. Observed and predicted cumulative runoff for all eight catchments, with (left) the calibration year 2005 and (right) the validation year 2006.

the reservoir areas became constant and could no longer be used as a runoff gauge. The data obtained from the satellite images and the volumes predicted by the model were well correlated with an overall coefficient of determination (r^2) of 0.83 in 2005, and of 0.92 in 2006.

Discussion

Despite the different rain patterns in 2005 and 2006, the Thornthwaite–Mather parameters AWC and a that were determined in the year 2005 are able to model the runoff in 2006. The filling process of small reservoirs comprises rainfall directly on their surface areas and a quickflow contribution from their catchments, made up of interflow and surface runoff.

Our results show that, in ungauged basins, time series of small reservoir surface areas can be used to parameterise and validate simple hydrological models. This is important since the array of new data products with good spatial and temporal resolution obtained from remote sensing can be used as input landscape parameters for hydrological models but do not provide detail on the temporal distribution of discharge from one or several rain storms. Thus, in data-scarce regions, reservoir areas in combination with regional reservoir area–volume relations and publicly available rain records can provide the catchment discharges to validate hydrological models such as the Thornthwaite–Mather model.

Especially in semi-arid Africa, irrigated agriculture from reservoirs is seen as one of the major ways of increasing food production. This will have a direct impact on stream discharge (Sachs and McArthur, 2005; UN Millennium Project). An indirect method, as presented here, can not only help to assess water resources and to monitor water stress, but also to understand the runoff generation in the study catchments, and allow impact assessment of small reservoirs on the available water resources.

11.16 MODEL ENHANCEMENTS FOR URBAN RUNOFF PREDICTIONS IN THE SOUTH-WEST USA

J. R. KENNEDY, D. C. GOODRICH AND C. L. UNKRICH

The issue from societal and hydrological perspectives

Population growth and urbanisation have occurred rapidly in the American south-west over the past several decades and they are projected to exceed those of other regions of the USA in the future. Urbanisation often leads to an increase in storm runoff. Urban rainfall–runoff models and regionalisation approaches typically consider storm runoff volume due to the increase in impervious surfaces, but less commonly consider the effect of changes in the infiltration rates of pervious surfaces in the built environment, or the effect of routing runoff from impermeable rooftops across permeable soils. Woltemade (2010) found a decrease in infiltrability in newer developments (post-2000), where the use of heavy machinery for site development was more common (as it is in the south-west USA). Also, in recent years, the increase in stormwater runoff associated with urbanisation has begun to be considered as a potentially renewable water resource. This runoff can be re-used directly, through rainwater harvesting efforts or recharge of aquifers through focused infiltration in detention basins or dry wells, or indirectly, by routing runoff to natural stream drainages where it can recharge. In arid environments, where upland surface recharge is minimal, increased runoff from urbanisation can lead to increased recharge, as rainfall that previously would have infiltrated and then evaporated or transpired is instead routed to an area where deep infiltration and recharge can occur. If PUB is to be successful in basins with significant and expanding urbanisation, accurate parameters and runoff characteristics for this type of built environment are needed.

Description of the study area

The study area is a 32-hectare mesquite grassland and a 13-hectare residential development (referred to as the grassland and urban catchments, respectively) in the city of Sierra Vista in south-eastern Arizona at 1300 m elevation (see Figure 11.65). Topographic relief is moderate, with a 31 m elevation difference between the highest point in the natural catchment and the outlet of the urbanised catchment. Construction within the urbanised catchment was conducted from 2001 to 2005 and is typical of most tract-style housing in the south-western USA. The site was completely graded and building pads for houses were compacted prior to construction. Houses 185 m^2 or larger are built on relatively uniform lots 1670 m^2 or larger and have similar building materials and landscaping (Figure 11.65). Streets are asphalt, 7.3 m wide, with rounded curbs. About 90% of roofs are sloped (25% to 35%) with corrugated cementitious tiles; the rest are low-slope (2% to 8%) with elastomeric coating. The tile roofs discharge runoff distributed along eaves, mostly without gutters, while flat roofs discharge through focused downspouts. A 1-metre wide pervious right of way exists between sidewalks and the street. Storm drainage is via surface streets except for a 1.3-hectare area that drains to the catchment outlet via a 61 cm corrugated metal pipe. Vegetation is immature, with only small areas of canopy cover. All pervious surfaces are covered with 2 to 4 cm diameter gravel mulch, about 10 cm deep, except for a few small irrigated turf areas. About 10% of yards have pervious weed barrier fabric underlying the gravel mulch. Stormwater runoff from the natural catchment is routed through the urbanised catchment. Runoff from both catchments is of short duration and baseflow is absent. Vegetation on the natural catchment consists of 3 to 6 m tall mesquite trees (*Prosopis velutina*), with relatively abundant inter-canopy grass up to 1 m tall. Vegetation transitions from mostly grass in the upper reaches to mostly mesquite in the lower reaches, and is seasonally dormant.

Stream stage was measured at 1-minute intervals by an automated bubble gauge upstream of a 90-degree v-notch weir at the channel connecting the two catchments and at the outlet of the combined catchments (Figure 11.65) from May 2005 until September 2008. Rainfall data were collected at 1-minute intervals at four weighing recording rain gauges in 2005 and 2006 (gauges 401, 402, 403 and 404), and at two additional rain gauges in 2007 and 2008 (gauges 420 and 424). From August 2006 onward, each

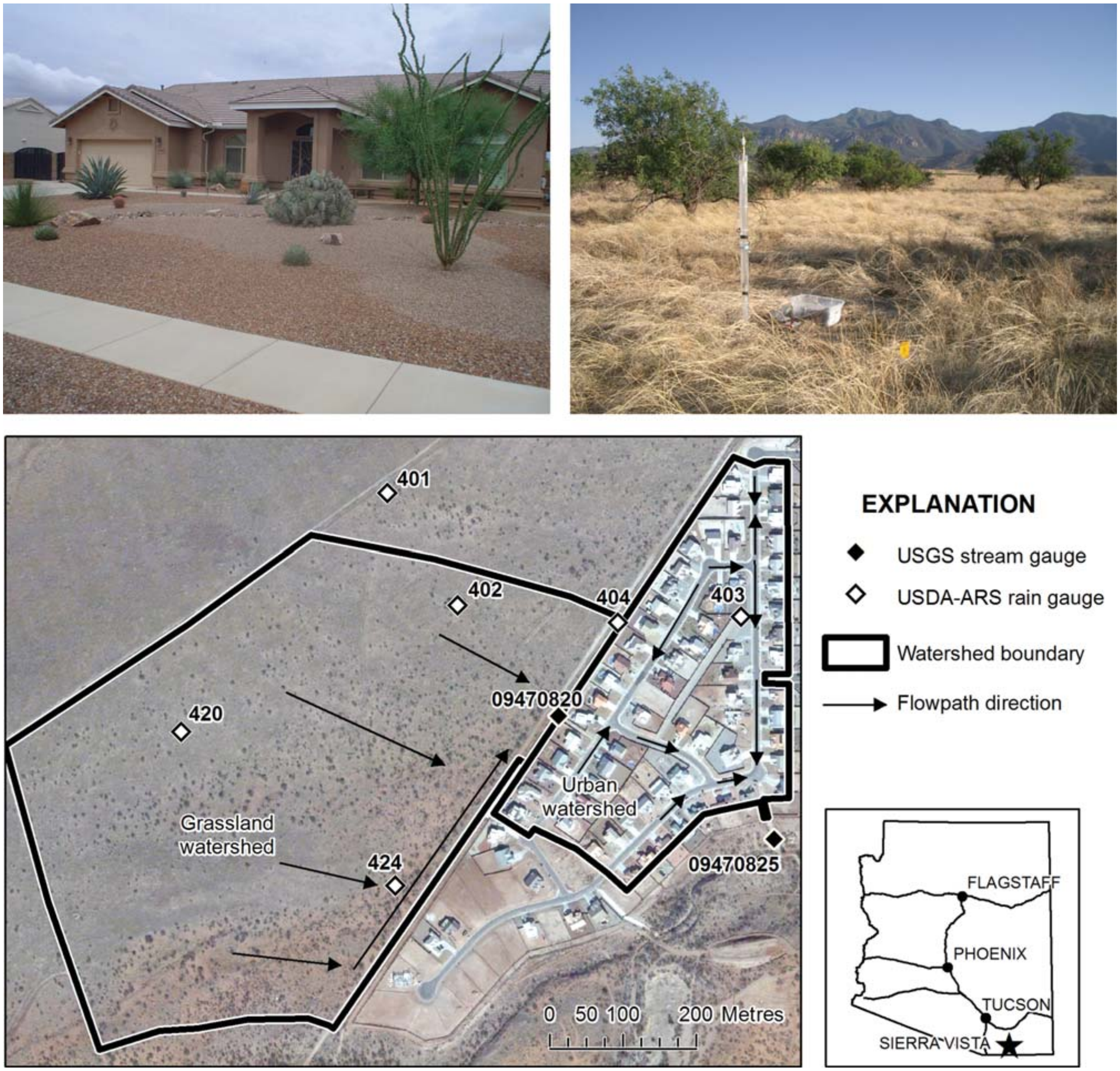


Figure 11.65. Study area photographs and map showing gauge locations, flow paths and catchment boundaries. The area in the upper right of the urban catchment drains directly to the catchment outlet through a buried culvert; runoff from the remaining area is routed along streets.

rain gauge was equipped with a Hydra-Probe[1] soil moisture sensor at 5 cm depth to provide initial soil moisture data for the rainfall–runoff model. To characterise land surface slope and catchment boundaries, a real-time kinematic GPS survey was conducted in both catchments. Survey data were used to construct a digital elevation model for comparison with the pre-construction elevations. Approximately 1.73×10^5 m^3 of cut material and 2.54×10^5 m^3 of fill material were moved during the grading process. Therefore, some additional amount of material beyond that created from the cut process was likely imported to the site. Tension infiltrometer measurements were made at 69 sites throughout both catchments to determine saturated hydraulic conductivity, on areas of both cut and fill in the urbanised catchment, and on both the upper, grass-dominated areas and the lower, mesquite-dominated areas in the natural catchment. Further details of

[1] Mention of this or other trade names does not imply endorsement by the U.S. Government.

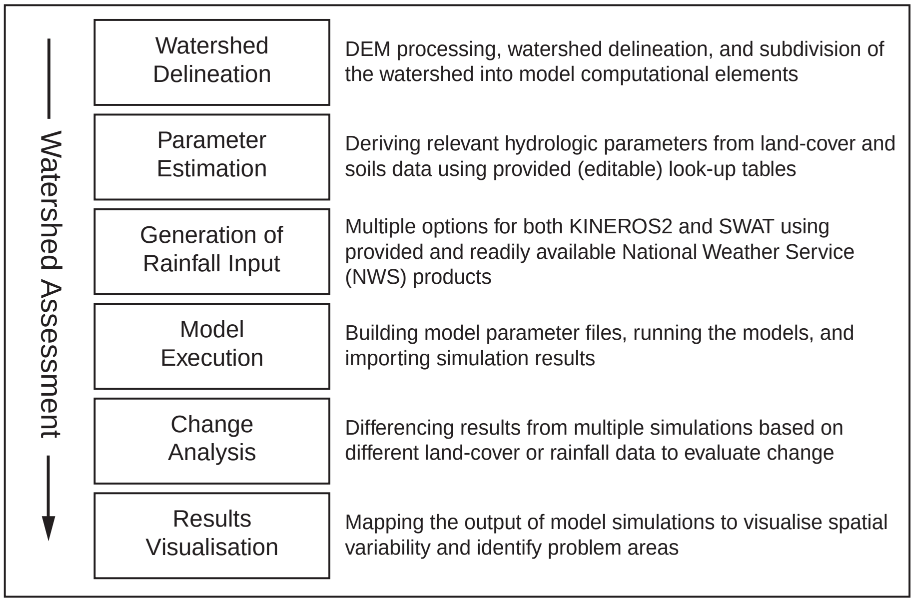


Figure 11.66. AGWA modules, and the sequence of steps for hydrological modelling and change detection.

the study area and the overall study are available in Kennedy (2007) and Kennedy *et al*. (2012).

Method

The KINEROS2 model (Smith *et al*., 1995; Semmens *et al*., 2008) was applied to these two catchments to test the transferability of model parameters to any catchment (see Chapter 10). The Automated Geospatial Catchment Assessment (AGWA) tool (Miller *et al*., 2007) can be used to set up KINEROS2, parameterise it with initial estimates, execute the model, and display results spatially in a GIS framework. In the parlance of PUB regionalisation, initial model parameters were estimated by relating readily available basin characteristics (soils, topography, land cover/land use) to values reported in field studies and literature through the use of look-up tables in AGWA. KINEROS2 is an event-based distributed rainfall–runoff–erosion model that represents a catchment as overland flow elements (planes or curvilinear surfaces) draining into channel model elements. The urban catchment was modelled with the KINEROS2 urban element (Semmens *et al*., 2008; Kennedy *et al*., 2012), a series of overland flow elements intended to represent a contiguous row of residential lots along one side of a street plus one-half of the street itself. The urban element simulates runoff from impervious areas directly connected to the street (e.g., roof to driveway to street), runoff from impervious areas that flows over a pervious area (e.g., roof to yard to street), and runoff from pervious areas directly and indirectly connected to the street. Both the geometric parameters (slope, area, flow length, width) and the hydraulic and infiltration parameters (roughness, porosity, saturated hydraulic conductivity) of the model elements are estimated within AGWA. AGWA employs globally available digital geographic coverages of soils, topography and land cover/land use.[2]

The sequence of AGWA operations and initial parameter estimation is depicted in Figure 11.66. After catchment delineation and discretisation to define model element polygons and their corresponding geometric parameters, the model element polygons are intersected with soils and land cover GIS layers to derive area-weighted averages of those properties for each model element. Pedo-transfer functions based on soil texture (Rawls *et al*., 1982) are used to define initial model element infiltration parameters. Assuming an average cover condition for each land cover/land use class, hydraulic roughness is estimated (Chow, 1959 among others). Trapezoidal channel morphology parameters are estimated using multivariate regressions based on variables derivable from the GIS coverages (Miller *et al*., 2003). If observed precipitation is not available, AGWA can access design storms from across the USA.

Results

It is instructive to examine the observed cumulative precipitation and runoff from the urban and grassland catchments to see the profound impact of urbanisation (Figure 11.67). Total runoff from the urban catchment is 26% of total precipitation; runoff from the grassland catchment is just 1%. If KINEROS2 can effectively model the urban

[2] For this study automatic parameterisation of the urban element by AGWA as a function of zoning/housing density had not yet been implemented and manual parameterisation was conducted.

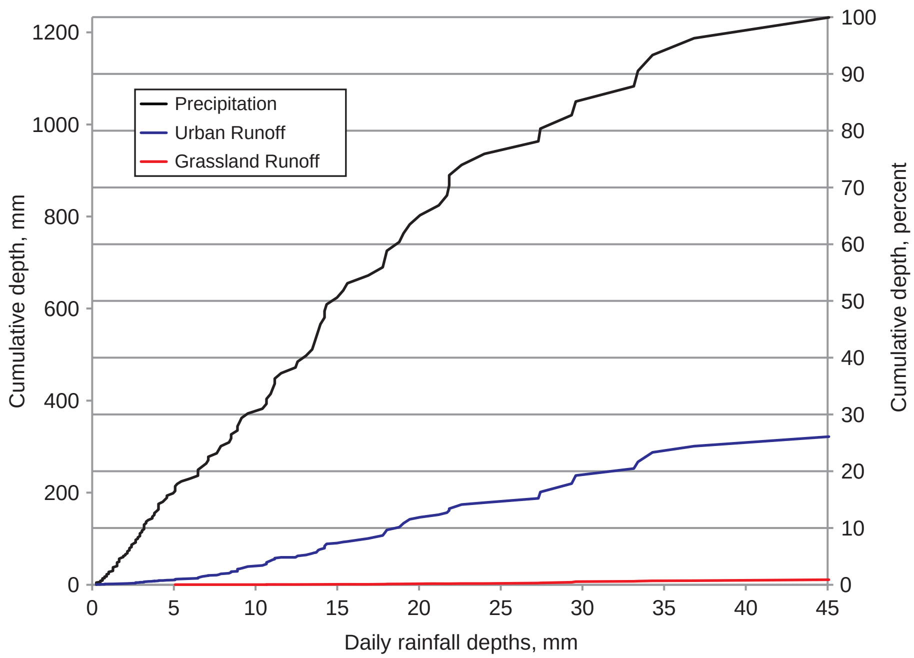


Figure 11.67. Cumulative distribution plots of daily rainfall depth, showing precipitation and runoff for the urban and grassland catchments from June 2005 through August 2008. All daily rainfall depths produced runoff from the urban catchment (runoff-producing rainfall occurred on 185 days total).

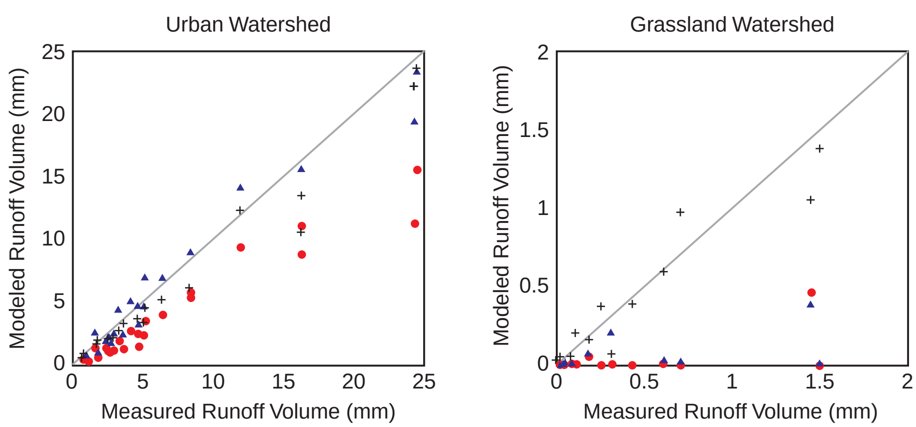


Figure 11.68. Modelled vs. measured runoff volume/unit area for the urban and grassland catchments using AGWA look-up table parameters for all events (red circles), a calibrated single set of parameters across all events (blue triangles), and an optimised parameter set for each individual event (black + symbol).

catchment response using the urban model element, it will be possible to estimate the contribution to increased runoff from the pervious and impervious areas independently. Expectations for physical or conceptual modelling of the response of the grassland catchment should be tempered by its low ratio of output signal (runoff) to input signal (rainfall). Even for large storms with the highest runoff coefficients, the volume of runoff per unit area is only 1 to 2 mm for the grassland catchment. When rainfall measurement error, up to 0.25 mm per 25 mm for the gauges in this study (Goodrich *et al*., 2008), is taken into consideration, the noise (rainfall uncertainty) to signal (runoff) ratio is large. This is a common challenge for modelling runoff in arid and semi-arid regions, as runoff ratios are small and runoff per unit area typically decreases with increasing catchment area (Goodrich *et al*., 1997).

KINEROS2 was used to simulate runoff response from both catchments with three parameter scenarios: (i) 'regional' look-up table parameters from AGWA with no adjustment; (ii) a single set of optimised parameters used for all runoff events: and (iii) optimised parameters for each event. For scenarios (ii) and (iii) the shuffled evolution complex Metropolis (SCEM – Vrugt *et al*., 2003) scheme was used to optimise four parameters over all catchment modelling elements. The parameters varied were saturated hydraulic conductivity (K_s), the coefficient of variation of K_s, the soil suction term (G), and hydraulic roughness. The results are illustrated in Figure 11.68. As expected, simulation results for the grassland catchment are poor. The regional AGWA parameters resulted in relatively good simulations for small to medium events. In all cases the optimised parameter sets improved simulation results.

Table 11.14. *Geometric mean and coefficient of variation for the catchment-scale (from SCEM optimisation) and point-scale (from tension infiltrometer measurement) estimates of* K_s

	Urban catchment		Grassland catchment	
	Mean K_s, mm/hr	Coeff. var.	Mean K_s, mm/hr	Coeff. var.
Catchment-scale	9.5	0.29	25	0.58
Point-scale	2.9	0.55	6.2	0.56
AGWA soil texture	26	—	26	—

The catchment-scale values are a sample of values optimised individually for 20 rainfall events. Point-scale values are a spatial sample.

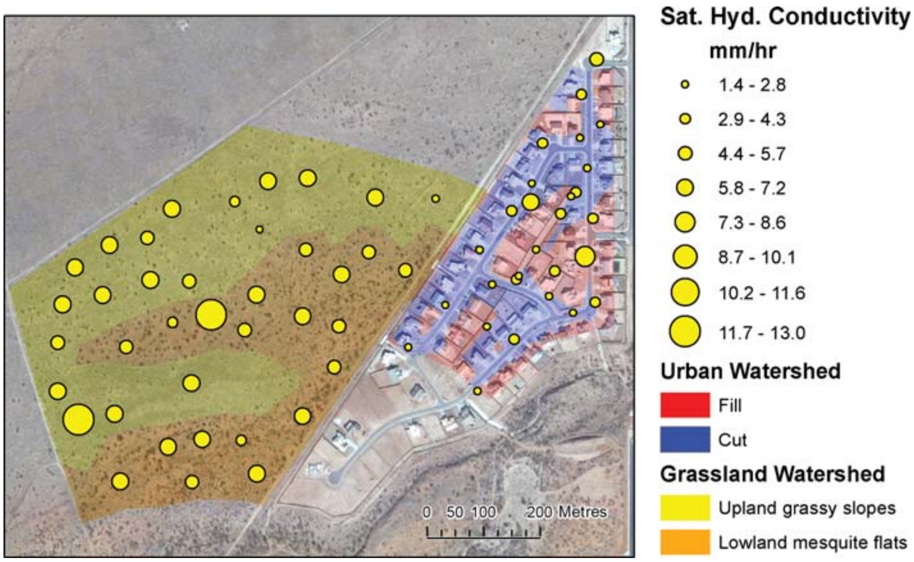


Figure 11.69. Tension infiltrometer measured saturated hydraulic conductivity values and their respective locations. In the urban catchment, pink regions denote areas of soil fill for site preparation and blue areas denote sites of soil cuts.

Closer examination of the infiltrometer measurements indicated that site preparation for the urban catchment did have a substantial impact on the measured K_s (Figure 11.69). Analysis of the optimised results resulted in three important findings. First, the effective saturated hydraulic conductivity determined using SCEM optimisation decreases from about 25 mm/hr in the grassland area to 9.5 mm/hr in the urban area, a change that is confirmed in direction, but not magnitude, by tension infiltrometer measurements, which average 6.2 and 2.9 mm/hr in the grassland and urban catchments, respectively. Second, assuming that prior to development the two catchments had identical infiltration properties, it is estimated that about 17% of the increase in runoff from the urban area comes from a change in pervious area properties (Kennedy *et al*., 2012). In other words, the expected volume of runoff would be 17% less than what was measured if rainfall infiltration occurred at the same rate as it did prior to development. Third, the values for the point-scale and optimised catchment-scale K_s estimates are similar for the urban catchment, but much less than would be expected from estimates based on soil texture (Table 11.14). The greater difference between the model-optimised and measured K_s estimates in the grassland catchment is attributed to compensating parameter adjustments by SCEM for model error, parameter error and (or) data error, exacerbated by the very small runoff coefficient.

Discussion

There are several important results of this study applicable to PUB. The first is that urbanisation impacts on catchment runoff response are not limited solely to the amount of impervious area that is constructed. In developments where heavy earth-moving and compaction equipment is used for site preparation, the developed infiltrating areas have a substantially lower rate of infiltration than adjacent undeveloped areas. In this study, that decrease in K_s resulted in an additional 17% increase in runoff volume beyond that created by impervious surfaces. Infiltration rates in these compacted soils may recover over time but additional measurements will be required. In addition, several strategic measurements with a tension infiltrometer in compacted soils would provide valuable infiltration model parameter estimates. Finally, this study forms the basis to modify AGWA look-up tables (transferrable 'regional' parameters) for developed infiltrating areas, which will extend the capability to apply KINEROS2 to this type of land use.

11.17 RUNOFF PREDICTIONS TO HELP MEET MILLENNIUM DEVELOPMENT GOALS IN ZIMBABWE

D. MAZVIMAVI

The issue from societal and hydrological perspectives

The sustainable planning and management of water resources requires knowledge on the availability of these resources and their spatial and temporal variability. This information is generally derived from gauging networks monitoring the various components of the water cycle. In some river basins, particularly those in Africa, these networks show many gaps, including those basins earmarked for the development of water resources. The reasons for the inadequate coverage are many. They include inadequate funding and personnel with relevant expertise; poor accessibility of some of the basins; and disfunctionality of institutions due to conflicts. Lack of adequate hydrological data contributes towards ill-designed infrastructure that does not provide the planned benefits. Without information about the spatial and temporal variability of the water resources, the potential and constraints in developing these resources are not well understood.

The international community, through the Millenium Development Goals, expressed a commitment to improving human wellbeing through creating and diversifying livelihood options, including increasing access to potable water. Some of the measures for improving human wellbeing include increasing food production. These efforts will inevitably increase water demand and the competition for water among various user groups. Sustainable water resources management requires balancing the water demand with the natural renewal rate of water. This requires information about the availability of water, which is impossible to estimate in ungauged river basins. Tools for improving predictions in river basins with inadequate data are therefore necessary to provide the information necessary for satisfying societal needs for water.

This study carried out in Zimbabwe had the aim of improving prediction of river flow statistics used routinely for water resources planning in ungauged basins (Mazvimavi, 2003). The objectives of the study were (i) to assess the potential of using river basin descriptors for predicting flow statistics; (ii) to examine the possibility of delineating basins into hydrologically homogeneous groups and to assess if such grouping improves prediction of flow statistics; and (iii) to examine if the parameters of selected rainfall–runoff models can be regionalised using basin descriptors.

Description of the study area

The study was conducted on 52 river basins in Zimbabwe (Figure 11.70), which is located in Southern Africa and covers a land area of 390 757 km^2. Altitude varies from 162 to 2592 m a.s.l. The elevation increases from both the south and north towards the central part of the country, which defines many of the catchments. The northern part of the country has the Gwayi, Manyame and Mazowe Rivers draining into the Zambezi River. Rivers on the southern part drain into the Limpopo River, which is shared with Botswana, South Africa and Mozambique. The Eastern Highlands, which have an elevation of 1800–2592 m, lie along the border with Mozambique. All the rivers in Zimbabwe eventually become part of trans-boundary rivers and introduce the special challenge of sharing hydrological data between the respective countries.

Zimbabwe has a tropical climate with one wet season and one dry season. However, areas of high elevation experience sub-tropical to temperate conditions. The wet season is from mid-November to mid-March, with the rest of the year being dry. Most of the rainfall occurs in the form of isolated thunderstorms with high intensity. This poses a problem for accurately measuring areal rainfall using a sparse network of rainfall stations. The spatial variation of rainfall is greatly influenced by altitude and distance from moistures sources such as the Indian Ocean on the east. Rainfall increases from west to east, and from the low-lying southern parts to areas at high elevation along the central part and the Eastern Highlands. The southern low-lying areas receive about 350 to 600 mm/yr of rainfall, while the central catchment receives 700–1200 mm/yr. The highest rainfall, 1200–2000 mm/yr, is received on the Eastern Highlands. Most parts of the country fall within the semi-arid zone. Areas receiving low rainfall, such as the southern and western parts, have high inter-annual variability of rainfall with a coefficient of variation of 30–40%; the coefficient is 20–30% in other parts of the country.

There are about 450 river gauging stations, mostly in the developed central part of the country (Figure 11.71). The earliest stations were developed during the 1920s. A considerable number of river flow measuring stations

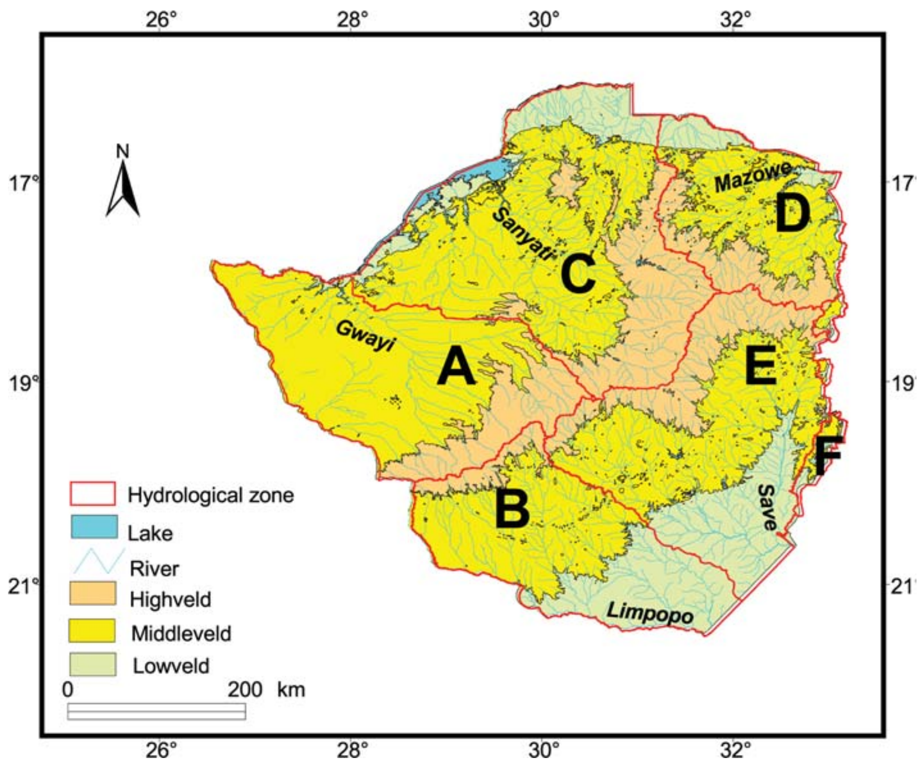


Figure 11.70. Main physical features of Zimbabwe. A: rivers draining into the Gwayi River and then into the Zambezi River; B: rivers draining into the Limpopo River; C: catchment of Manyame and Sanyati Rivers, which drain into the Zambezi River; D: basin of Mazowe River, which drains into the Zambezi River; E: area drained by Save and Runde Rivers; F: rivers draining from the Eastern Highlands towards the east into Mozambique.

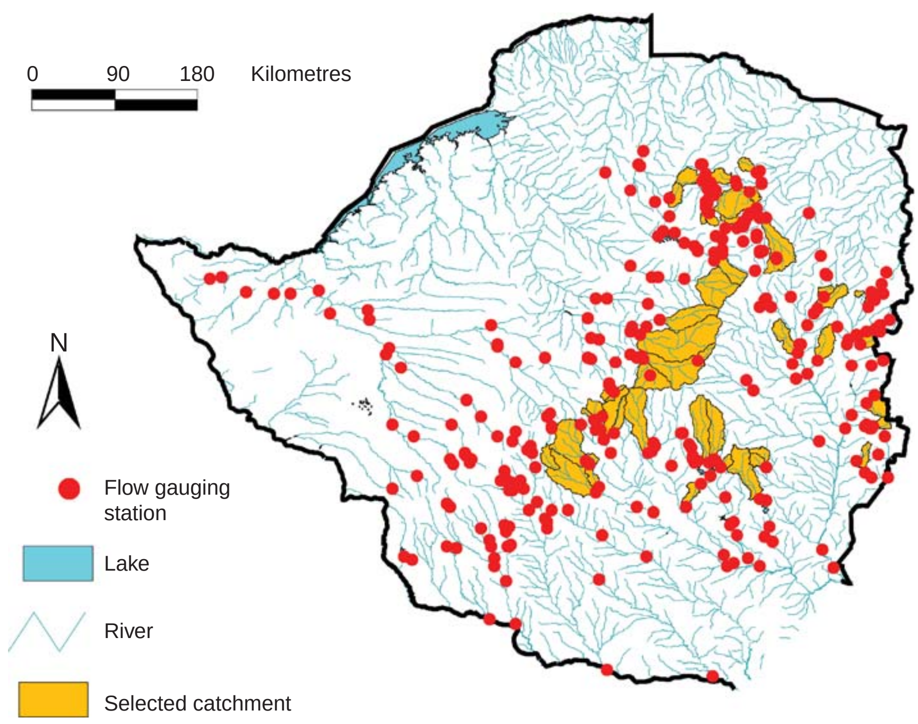


Figure 11.71. Locations of flow measuring stations in Zimbabwe, and selected catchments making up the study area.

were set up to monitor flow releases from dams and abstractions along rivers. Flow records of such stations do not fully reflect the natural hydrological responses, which adds further complexity to the ungauged basin problem.

Method

This study was aimed at using river basin descriptors for (i) predicting river flow statistics; (ii) identification of hydrological homogeneous regions for improving predictions; and (iii) for regionalising parameters of selected conceptual models. The flow statistics that are frequently used for planning and selected for this study are mean annual runoff, average flow for each month, the flow duration curve as represented by daily flows with specified exceedance probabilities (e.g., 25, 50, 75, 90% exceedance probability), and the baseflow index. This case study hence links to Chapter 5 (on annual flows), Chapter 6 (on seasonal flows), Chapter 7 (on flow duration curves) and Chapter 8 (on low flows). River basin descriptors considered to influence hydrological responses and selected for use in this study are average annual rainfall, average annual Class A pan evaporation rate, drainage density, basin slope indices, proportion of basin area covered by different lithologies, and proportion of the basin under various land cover types. The types and areas covered by the different lithologies were determined from the 1:500 000 Hydrogeological Map of Zimbabwe. Land cover types were obtained from a land cover map developed through classifying Landsat images (Kwesha, 2000). The drainage density was estimated from stream lengths determined by measuring the blue lines on 1:50 000 topographical maps. The 1997 USGS digital elevation model at 0.1 degree resolution was used to determine the slope for each of the pixels within the basins. A cumulative frequency distribution of slopes for all the pixels in each basin was then constructed, and slope values with selected cumulative frequencies (e.g. 10, 20, 50, 70, 90%) were estimated and used in this study.

Multiple regression and neural network methods were used to explore the relationships between basin descriptors and (i) river flow statistics, and (ii) calibrated parameter values of conceptual rainfall–runoff models. Hierarchical cluster analysis was used to identify basins belonging to hydrologically homogeneous groups. Classification was carried out using river basin descriptors that had been identified to explain the variability of all the flow statistics selected for this study. A multivariate analysis method, constrained ordination or redundancy analysis (Ter Braak and Prentice, 1988), which has the ability to identify independent variables or basin descriptors that explain the variability of multiple dependent variables or flow statistics, was used to determine basin descriptors to be used for classification. This approach was considered better than delineating hydrologically homogeneous groups of basins on the basis of geographical proximity, since geographical proximity is not always a sufficient condition for hydrological homogeneity.

Two monthly conceptual models were selected for regionalisation and these are (i) the four-parameter *ABCD* model (Thomas, 1981), and (ii) the twelve-parameter Pitman model (Pitman, 1973) (see Sections 6.4.2 and 7.4.2). Both models require monthly rainfall and potential evaporation data. The Pitman model is widely used in Southern Africa. The *ABCD* model considers a river basin to have a soil storage and groundwater storage. Actual rate of evaporation is assumed to be equal to the potential evaporation if the soil water content is at a maximum value, which depends on one of the parameter values, parameter B. Below the maximum soil water capacity the actual rate of evaporation is a linear or non-linear function of the ratio of the actual soil water to soil storage capacity. Two parameters, A and B, are used to estimate the rate of actual evaporation from the soil. Recharge to groundwater is estimated as a linear function of the excess soil water, and parameter C is used to estimate the recharge rate. Similarly, groundwater discharge to a river is assumed to be a linear function of the groundwater storage and is estimated using parameter D.

The version of the Pitman model used in this study has two storages, the interception storage and a subsurface storage. Details of this model are given in several references (Pitman, 1973; Mazvimavi, 2003) and are not repeated in this paper (other applications of the same model are discussed in Sections 6.4.2 and 7.4.2). For each basin, the interception capacity (I_{cap}), which depends on the type of vegetation, has to be provided, and the actual evaporation from interception is a function of the amount of precipitation received (see Section 5.2.1). The amount of surface runoff generated from pervious parts of the basin depends on the rainfall received, minimum (Z_{min}) and maximum (Z_{max}) absorption rate of water into the subsurface storage. Actual rate of evaporation from the subsurface storage depends on the amount of soil water stored relative to the maximum amount of subsurface storage of water (S_{cap}). The rate of subsurface runoff is estimated using the following parameters: S_l is subsurface moisture content below which no subsurface runoff occurs; FT is rate of subsurface runoff when the subsurface storage is equal to S_{cap}.

Model parameter values were calibrated manually and then fine tuned using automatic optimisation methods. This approach ensured that internal state variables were physically meaningful. The criteria used to ascertain whether simulated monthly flows were accurate were (i) the Nash–Sutcliffe coefficient of efficiency being greater than 0.70; (ii) the difference between means of the

Table 11.15. *Maximum, mean and minimum values of some of the basin descriptors and flow statistics for the 52 selected river basins*

Basin descriptor	Mean	Max	Min
Basin area (km^2)	505	2630	3.5
Average annual rainfall (mm/yr)	852	1797	554
Number of rainy days per year	71	126	45
Average annual US Class A pan evaporation (mm/yr)	1795	1946	1388
Median basin slope (%)	5.3	17.6	1.5
Drainage density (km km^{-2})	2.4	4.9	0.2
Average annual runoff (mm/yr)	140	778	39
Coefficient of variation of annual runoff (%)	95	133	52
Baseflow index	0.36	0.78	0.08
One-day recession constant	0.90	0.96	0.83
Runoff coefficient	0.15	0.43	0.06
*q*90	0.02	0.26	0.00
*q*70	0.08	0.47	0.00
*q*50	0.19	0.71	0.00
*q*20	0.85	1.47	0.19
*q*10	1.99	2.94	0.80

*q*90 is the daily flow with a 90% exceedance frequency normalised by the average daily flow.

observed and simulated monthly flows being within ±10%; (iii) the difference between the standard deviation of observed flows and that of simulated flows being within ±15%; and (iv) the visual assessment of the flow duration curve of the simulated monthly flows showed that it closely matched that of observed monthly flows.

The multiple regression method and neural network method were used to determine if the calibrated model parameters could be predicted using river basin descriptors.

Results

Table 11.15 presents a summary of the values of the basin descriptors and flow statistics for the 52 river basins selected for the study. The selected basins varied from very small to medium-sized basins. The selected basins were representative of low to high rainfall regions.

The flow duration curves were constructed using daily flows that had been divided by the average daily flow. Thus *q*90, *q*70, *q*50, *q*20 and *q*10 are dimensionless.

Prediction of flow statistics from basin descriptors

Mean annual runoff for the 52 river basins appeared to be linearly related to three parameters: the mean annual rainfall (Figure 11.72), proportion of the basin with gneissic granites, and slope ($r^2 = 0.81$). There was no significant improvement in the prediction of mean annual runoff using neural networks (see Section 7.2.3 for examples on neural network methods).

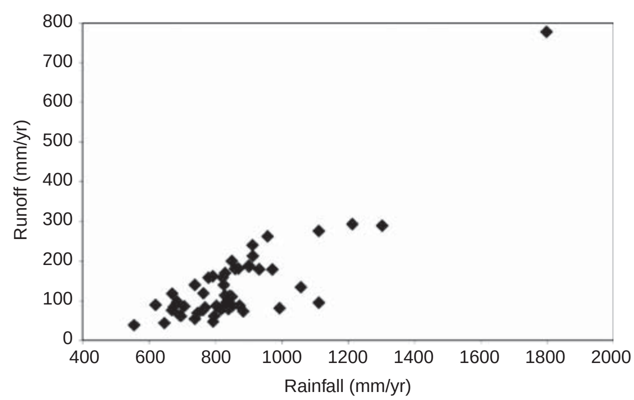


Figure 11.72. Mean annual runoff against mean annual rainfall.

The baseflow index could be predicted using: basin slope (Figure 11.73), the proportion of the basin area with grasslands, and the proportion of the basin having Kalahari sands ($r^2 = 0.69$) (see Chapter 8).

The shape of a flow duration curve depends on the relative contribution of baseflows to total flow. Perennial rivers have flow duration curves with gentle slopes while ephemeral (non-perennial) rivers characterised by frequent low to no flows and very few large flows have steep flow duration curves. For the 52 basins studied, the shape of the flow duration curve could be predicted by an exponential-type distribution which has two parameters that can be predicted from the baseflow index (Figure 11.74) (see Section 7.3.2).

Identification of hydrologically homogeneous groups

The results of constrained ordination or redundancy analysis showed that the variation among the 52 basins of selected multiple flow statistics or multiple responses (mean annual runoff, coefficient of variation of runoff, baseflow index, daily flows with 70% and 90% exceedance probability, number of days without flow) could be explained by average annual pan evaporation, average annual rainfall, median slope and land cover type. The basin descriptors explained 69% of the variability of the flow statistics (Table 11.16). Therefore, the identification of hydrologically homogeneous regions had to be based on these basin descriptors that explain the hydrological responses. Hierarchical cluster analysis aimed at identifying hydrologically homogeneous regions was therefore done using these basin descriptors.

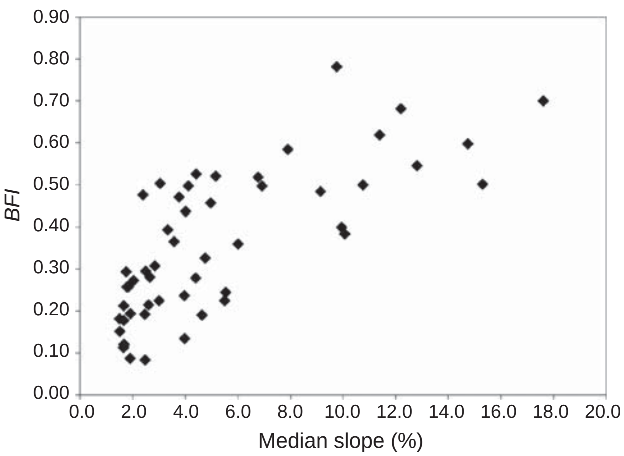


Figure 11.73. Influence of slope on baseflow index (BFI).

Table 11.16. *Proportion of variance of flow characteristics explained by basin descriptors*

Catchment characteristic	Percentage explained	Cumulative percentage
Average annual pan evaporation	51	51
Average annual rainfall	9	60
LC_{CG}	4	64
LC_{WD}	4	67
S_{50}	2	69

LC_{CG} is proportion of the basin with wooded grasslands and grasslands, LC_{WD} is proportion of the basin with woodlands. S_{50} is slope for which 50% of the pixels in the basin have values equal to or less than this value.

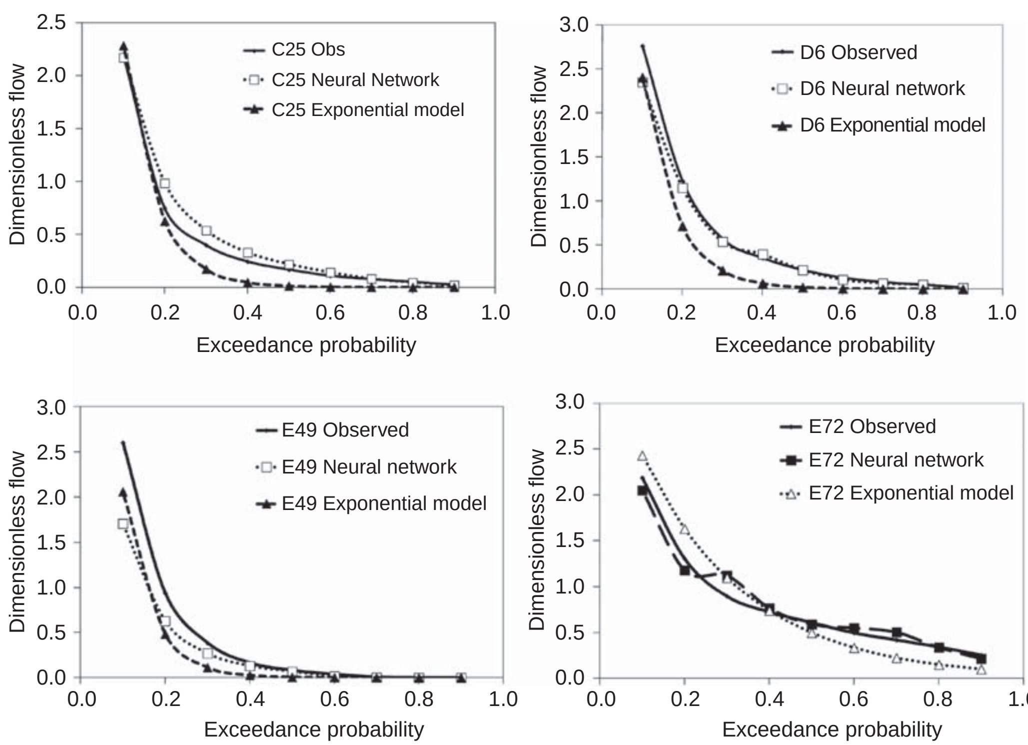


Figure 11.74. Comparison of flow duration curves based on observed daily flows and those predicted using an exponential model and a neural network for C25, D6, E49 and E72.

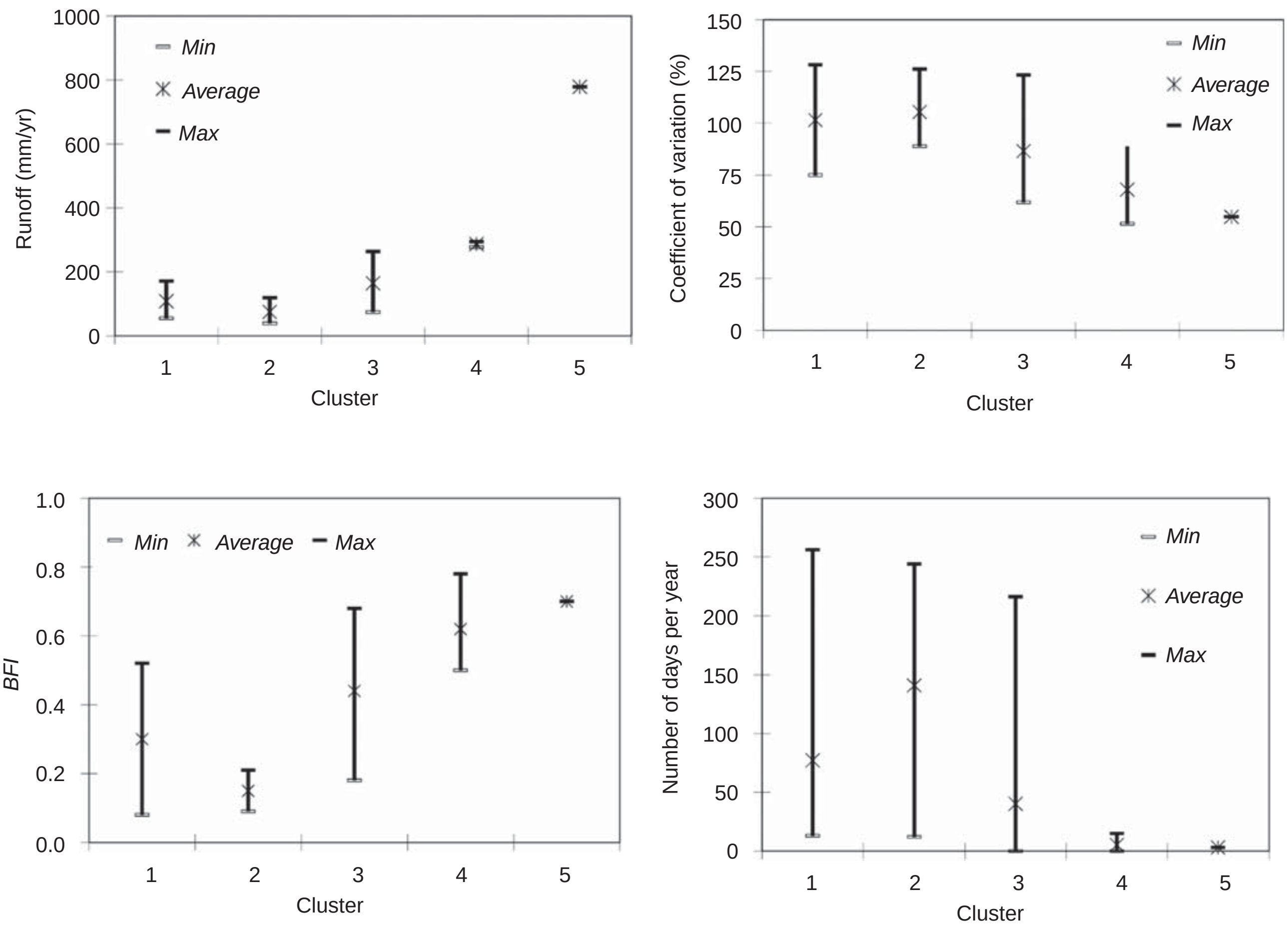


Figure 11.75. Variation of flow statistics among the five clusters derived using basin descriptors.

The number of hydrologically homogeneous groups of river basins identified using cluster analysis varied from two to eight. Cluster analysis was also carried out using flow statistics. A comparison was then made about the group membership between clusters based on basin descriptors and those derived using flow statistics. The high level of agreement between clusters based on basin descriptors and those from flow statistics was used to determine the number of clusters that represented hydrologically homogeneous regions. The Rg index (Everitt, 1993) was used to assess this level of agreement. Five groups of river basins gave the highest level of agreement, implying that these groups represented hydrologically homogeneous regions. The clusters varied from basins with low runoff in cluster 1 to high runoff in cluster 5 (see Figure 11.75).

The prediction of flow statistics from basin descriptors, however, did not improve with clustering, as is shown by the lack of a relationship between average annual runoff and average annual rainfall in Figure 11.76. The possible reason may be that the clustering resulted in delineation of basins into groups with narrow ranges in the variation of basin descriptors and possible flow statistics, which constrained the development of predictive equations.

Regionalisation of conceptual models

There were 30 basins that had adequate data for calibrating and validating the two conceptual models. A comparison of the observed and simulated monthly flows showed that the N-S coefficient of efficiency was greater than 0.70 on 70% of the 30 basins for both models. Monthly flows simulated using the *ABCD* model had both the mean and standard deviation falling within the acceptable range of 80% of the basins, while this was 90% for the Pitman model. Multi-decadal variability in rainfall resulted in the occurrence of several years with generally above average rainfall (e.g., the 1970s), and consequently an accumulation of groundwater, leading to high dry season flows during this period. This was followed by generally low rainfall during the 1980s and 1990s resulting in reduced accretion of groundwater and therefore low dry season

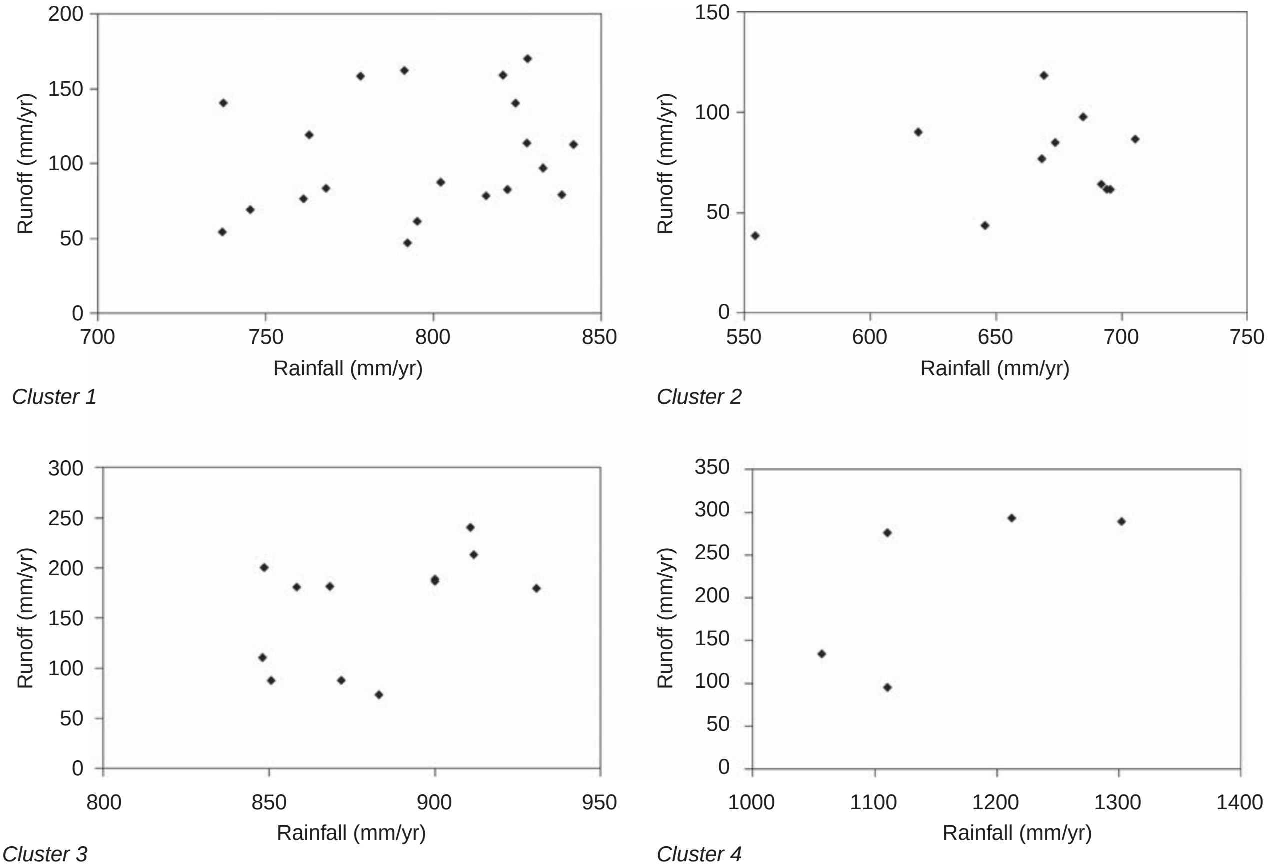


Figure 11.76. Relationship between mean annual runoff and mean annual rainfall for the four clusters derived using basin descriptors.

Table 11.17. *Illustration of equifinality of parameters of the ABCD model on basin E49 that has four different sets of parameters resulting in simulated monthly flows with similar statistics*

Parameter	Set 1	Set 2	Set 3	Set 4
A	0.9799	0.9852	0.9780	0.9766
B	504.5	571.4	558.3	618.1
C	0.2807	0.2807	0.1566	0.0000
D	0.8163	0.0000	1.0000	1.0000
Mean (10^6 m^3)	7.55	7.55	7.55	7.55
Std Dev (10^6 m^3)	14.20	12.66	13.82	13.32
Coef. eff.	0.89	0.87	0.89	0.89

Table 11.18. *Illustration of equifinality of Pitman model parameters on C25 with two sets of parameter values producing monthly flows with similar flow statistics*

	Set 1	Set 2
POW	2.1	2.7
S_{cap}	346.6	343.3
FT	21.4	35.0
Z_{min}	22.9	25.9
Z_{max}	1151.0	1205.6
% Difference in the mean	−3.3%	2.5%
% Difference in the standard deviation	−5.6%	−3.6%
Coefficient of efficiency	0.81	0.81

flows. The two rainfall–runoff models had problems simulating such decadal changes in dry season flows because groundwater storage and flow were not fully described by these models.

Equifinality of model parameters was encountered in both model applications (Tables 11.17 and 11.18). Equifinality of model parameters can be due to the structure of the model, which allowed for interactions between some parameters. Some of the Pitman model parameters were found to interact amongst themselves, which impacted on the flow simulations. The development of relationships between model parameters and basin descriptors becomes problematic due to parameters having no unique values for given physical conditions.

Table 11.19. *Correlation coefficients between Pitman model parameters and flow statistics and basin descriptors*

Flow statistic/basin descriptor	S_{cap}	*FT*
Average annual runoff	0.40	0.74
Baseflow index	0.60	0.77
One-day recession coefficient	0.40	0.76
q_{90}	0.61	0.73
q_{20}	0.54	0.71
Average annual rainfall	0.66	0.64
Average annual pan evaporation	–0.58	–0.40
S_{50}	0.39	0.58

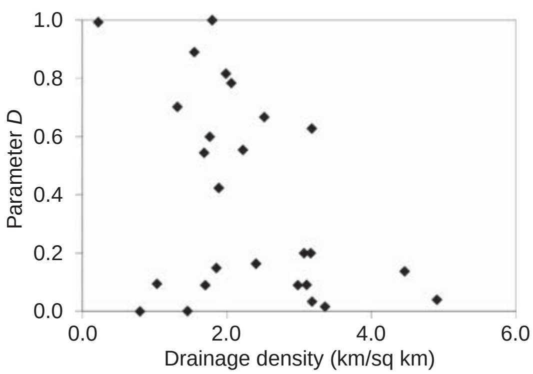


Figure 11.78. Relationship between parameter *D* of the *ABCD* model and drainage density.

For the *ABCD* model, parameters *B* and *D* had some relationships with basin descriptors. Parameter *B*, which is the maximum amount of precipitation and soil moisture available for evaporation, was found to be related to the average annual pan evaporation (Figure 11.77).

Parameter *D*, which determines the proportion of groundwater storage to be discharged into rivers, had a relationship with drainage density (Figure 11.78). The study area is underlain by the basement complex in which groundwater storage is mainly due to fracturing and weathering. Fracturing and weathering tend to facilitate formation of rivers causing an increase in drainage density. Figure 11.78 shows basin C6 to be an outlier in the relationship between parameter *D* and drainage density. This basin differs from all the others by being dominated by Upper Karoo sandstone, which does not commonly occur in the other basins. D27 and D28 have over the years been subjected to cultivation and abstraction of water for irrigation, which possibly explains their outlier behaviour.

Pitman model parameters did not show clearly defined relationships with basin descriptors. Some of the parameters had relationships with flow statistics (Table 11.19).

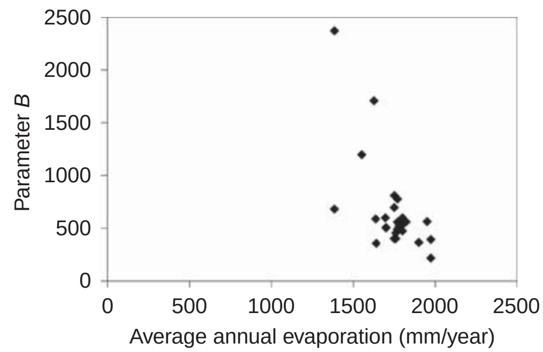


Figure 11.77. The relationship between parameter *B* of the *ABCD* model and average annual pan evaporation.

Hughes (1997b) inferred that it was possible to regionalise parameters of this model but without having done a quantitative analysis. This study raises doubts about the possibility of regionalising parameters of the version of the Pitman model used in this study.

Discussion

The most important flow statistics (average annual runoff, daily flows of specified exceedance frequency, and baseflow index) could be predicted using basin descriptors. The most important basin descriptors are average annual runoff, basin slope indices and average annual pan evaporation. Some of the basin descriptors have non-linear relationships with flow statistics, and neural networks provided predictions better than those made using multiple regression equations.

The delineation of river basins using basin descriptors into hydrologically homogeneous groups did not improve prediction of flow statistics. It is likely that the river basins considered already fall within a homogeneous group and further subdivision distorts relationships between basin descriptors and flow statistics.

Equifinality of model parameters was found to exist in both of the two conceptual models used. The cause of this is partly due to the structure of these models, which have parameters that interact with each other. A further cause of equifinality is the non-existence of a global optimum parameter value but several sub-optima. Two parameters of the simple *ABCD* model could be predicted from basin descriptors, specifically those influencing subsurface flow contributions. Regionalisation of the more complex Pitman model was, however, not successful. Subsequent studies by Kapangaziwiri and Hughes (2008) demonstrated the possibility of regionalising parameters of this model. Kapangaziwiri and Hughes (2008) did, however, use an improved version of this model with explicit routines for groundwater.

11.18 RUNOFF PREDICTIONS IN SUPPORT OF THE NATIONAL WATER AUDIT, AUSTRALIA

N. R. VINEY

The issue from societal and hydrological perspectives

Part of the Australian Bureau of Meteorology's mandate is to produce annual water audits and water resources assessments. These are to have a national scope and to use consistent estimation methods. Since only a small proportion of the continent is gauged for runoff, most of the runoff estimation relies on modelling. The aim of this study is to compare different methods for producing runoff estimates at a continental scale. The ultimate objective is to enable the production of continental-scale maps showing the spatial variability of runoff generation at a variety of time steps as well as provide best estimates by region for reporting in the National Water Account.

Study area and data

This study uses runoff data from 408 catchments across Australia (Figure 11.79). All catchments have areas greater than 50 km^2 and runoff that are not affected by flow regulation, irrigation withdrawals or urbanisation. All have at least 10 years of observed runoff data during 1975–2008. Daily

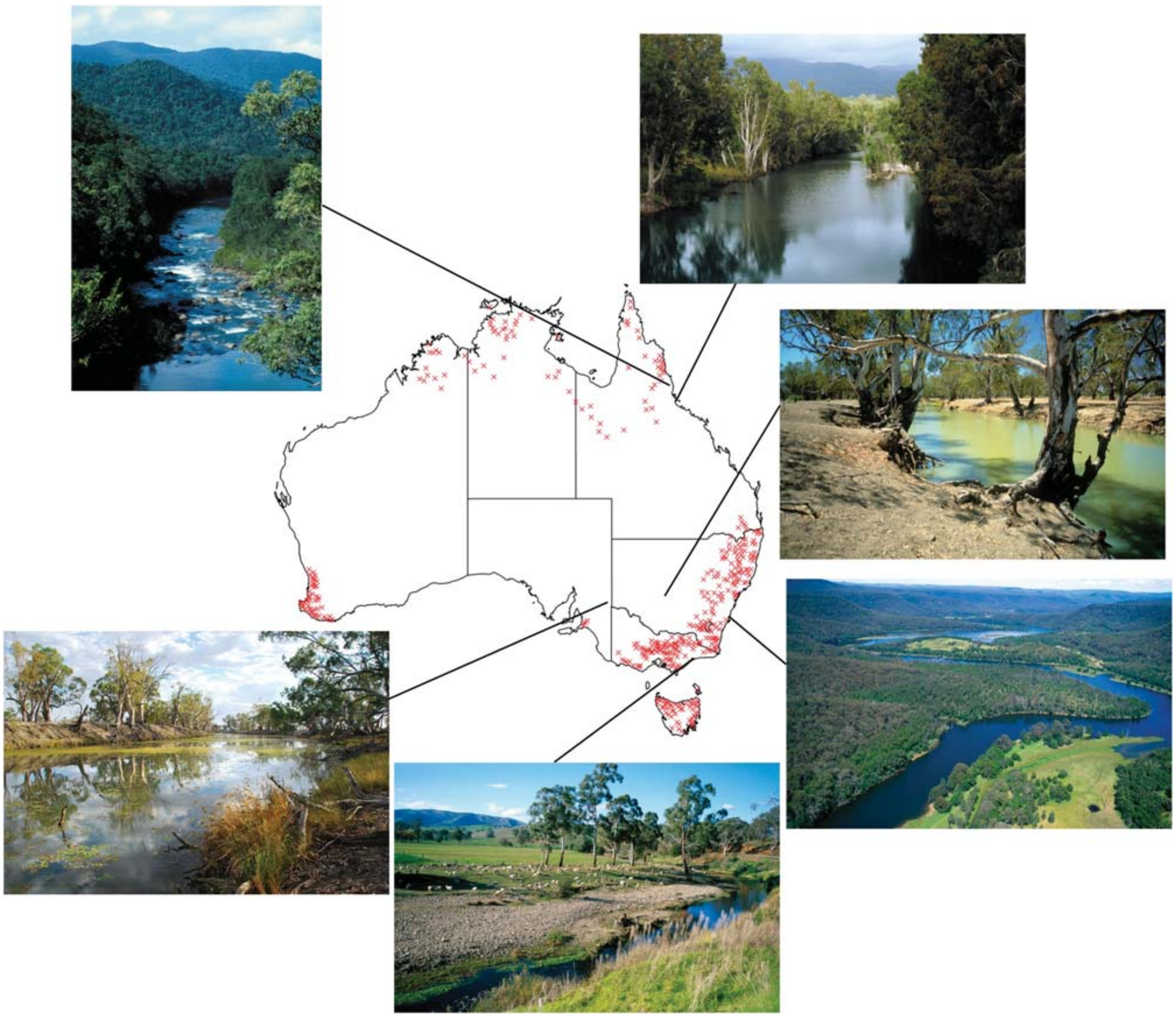


Figure 11.79. Locations of the 408 gauged catchments used in this study. Photos give an impression of the diversity of the landscape. Copyright CSIRO; photographers: Gregory Heath, Willem van Aken and Ian Overton.

rainfall input data are obtained from the Silo Data Drill (Jeffrey *et al*., 2001), a data set gridded at a 0.05° (~5 km) spacing. The Data Drill rainfall data are interpolated from point observations of daily rainfall. Areal potential evaporation data are also derived from the Data Drill.

Method

Models

Five lumped, conceptual, daily rainfall–runoff models are calibrated separately on each of the 408 catchments: AWBM (Boughton, 2004), IHACRES (Croke *et al*., 2006), Sacramento (Burnash *et al*., 1973), Simhyd (Chiew *et al*., 2002) and SMAR-G (Goswami *et al*., 2002). In this study six parameters are optimised for AWBM, seven for IHACRES, thirteen for Sacramento, six for Simhyd and eight for SMAR-G (see Section 10.4).

Each model is operated using the gridded rainfall and potential evaporation data in 0.05° × 0.05° grid cells across each catchment. For calibration, the observed runoff at the catchment outlet is compared with a spatial average of the modelled runoff in each grid cell within the catchment. The lumped models are thus spatialised to the extent that each grid cell within a catchment has different climate input. However, the same set of model parameters is used for all grid cells within a catchment.

In addition, three continental-scale models are also assessed. These are WaterDyn, which is implemented in AWAP (Raupach *et al*., 2009), AWRA-L version 0.5 (van Dijk, 2010) and CABLE (Kowalczyk *et al*., 2006). Typically, such models use a single set of parameters to describe the hydrological fluxes across the entire domain. These models are also usually uncalibrated or are calibrated using only a limited set of observations. They often have modelling objectives other than or in addition to runoff only.

Assessment in ungauged basins

One common regionalisation method is to transfer calibrated model parameters from a nearby gauged catchment (e.g., Oudin *et al*., 2008; Chiew *et al*., 2009). This is typically done using relatively parsimonious lumped catchment models. The key assumption implicit in this approach is that catchments in close proximity are likely to share similar soils, topography, land cover and climate and that they therefore have similar hydrological response characteristics. Model parameters calibrated for one catchment are therefore likely to predict runoff reasonably well for a nearby catchment. To generate a continent-wide representation of runoff generation, runoff in each part of the continent is modelled using parameters from the nearest gauged catchment (see Section 10.4.4).

Cross-verification of the spatialised models is achieved by modelling each catchment using its local climate data but with parameters taken from the nearest-neighbouring gauged catchment. The distance to the nearest neighbour (measured from centroid to centroid) ranges from 7 km to 278 km. This cross-verification procedure thus gives an indication of the likely quality of ungauged basin predictions that could be achieved if proximity was used as the sole regionalisation criterion.

An alternative option for prediction in ungauged basins is to use a model designed for continental-scale applications. In general, this requires a model whose design incorporates many of the processes that control spatial variability in runoff (e.g., land use, vegetation density). The use of a single set of parameters to describe the hydrological fluxes across the entire domain provides a consistent modelling strategy across the continent, but also makes greater demands on underlying data than conventional runoff models.

Although a combination of daily efficiency and bias is used for model calibration (for the lumped models), the criterion used to assess model performance is the monthly efficiency. This criterion is chosen because only monthly – but not daily – predictions are available (in this study) for AWAP and CABLE. Analysis of daily efficiency statistics for the six remaining models (not reported here) shows strong correlation between trends in daily and monthly efficiency. Prediction bias has also been assessed, and although the results are not presented here, they reinforce the conclusions that can be drawn from analysing monthly and daily efficiency.

Model averaging

A complementary modelling approach that has potential to reduce uncertainty in ungauged catchment predictions is the use of ensemble techniques, whereby predictions from different sources are pooled to produce a consensus prediction (e.g., Viney *et al*., 2009a). Ensembles may be constructed from different realisations of the same rainfall–runoff model (a single-model ensemble) or from several structurally different models (a multi-model ensemble). Several researchers have reported that the optimal number of members for both single-model and multi-model ensembles is about five.

Two ensemble or averaging schemes are also investigated. One is a multi-model average in which a daily runoff series is constructed by averaging the predicted flow of the constituent models. Two such averages are assessed: one using just the five spatialised models, and one using all eight models. In each case the model average is unweighted. The second ensemble scheme is a multi-donor averaging scheme (an example of the single-model approach). This is applicable only to the spatialised models and involves averaging

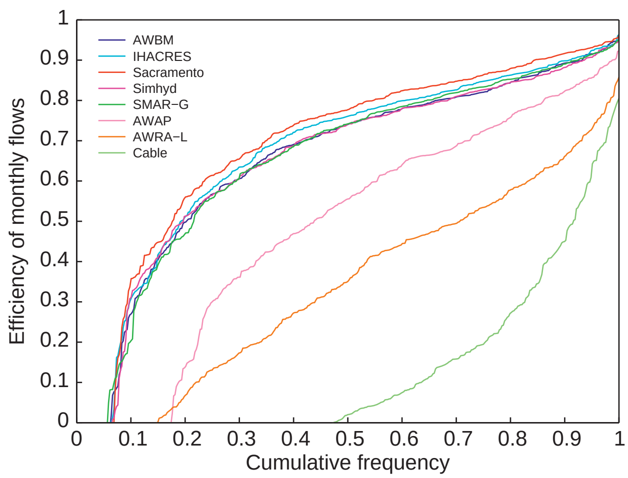


Figure 11.80. Cumulative distribution of monthly validation efficiencies for eight models.

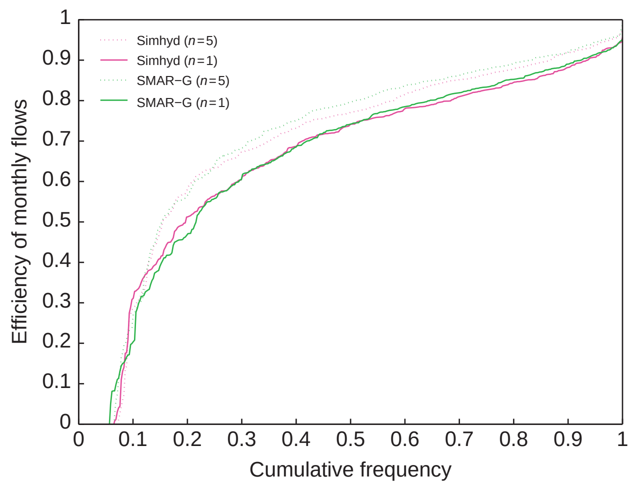


Figure 11.81. Cumulative distribution of monthly efficiency for two models using nearest-neighbour regionalisation and an average of regionalisation using parameters from the nearest five gauged catchments.

daily predictions derived from parameters calibrated on not just the nearest catchment (as in the case of the regionalisation described above), but from the nearest five catchments. Again the ensemble is unweighted.

Results

Model comparisons

There is little difference in performance of the five lumped models when regionalised using parameters from the nearest-neighbouring catchment (Figure 11.80). Despite this, it is evident that Sacramento gives slightly better monthly efficiencies than the other models. This is possibly due to it having more parameters available for optimisation. In contrast, the continental-scale models are considerably poorer, with AWAP typically being better than AWRA-L and AWRA-L better than CABLE. Similar conclusions on relative model performance can be drawn from analyses of daily efficiency and bias (not shown), although AWRA-L tends to have less prediction bias than AWAP, for which there is a strong tendency towards overprediction.

The evidence of Figure 11.80 strongly argues for continental-scale runoff predictions to be made using regionalised lumped models. Predictions from these models are likely to be significantly better than those of the three continental-scale models.

Multi-donor averaging Differences in performance between regionalisation using nearest-neighbour parameters only and that using an average of predictions using parameters from the nearest five catchments are shown in Figure 11.81 for two lumped models. In both cases there is significant improvement in performance when information from the five nearest catchments is used. Similar results occur for the other three lumped models. It is clear that introducing information from more than one nearby catchment improves model predictions. This improvement of multi-donor ensembles over nearest-neighbour regionalisation may be especially true in regions with high hydrological heterogeneity, where the nearest neighbour may not necessarily be the most appropriate donor, but the average of the five nearest donors provides a better representation of the target catchment.

Multi-model averaging A multi-model average constructed from the five lumped models tends to provide monthly predictions that are as good as or slightly better than those of the best individual model (Figure 11.82). This improvement tends to be even more pronounced for daily efficiencies (not shown) and is particularly noticeable in the lower half of the cumulative distributions, where it is apparent that predictions in the catchments that each of the spatialised models simulate poorly are significantly enhanced by model averaging.

The prediction efficiency of an eight-model average is also shown in Figure 11.82. This ensemble combines predictions from the five spatialised models – which are usually closely matched – with predictions from the three continental-scale models, which can be significantly poorer. Nonetheless, the monthly efficiencies for this ensemble are typically better than or equal to those of the five-member ensemble and the best of the spatialised models, especially in the lower half of the cumulative distributions.

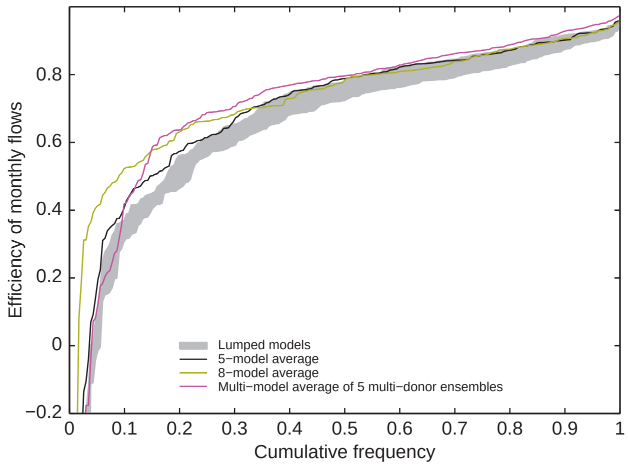


Figure 11.82. Cumulative distribution of monthly efficiency for two multi-model averages and a multi-model multi-donor average, with reference to the monthly efficiencies of the individual models. The range of efficiencies of the spatialised models is depicted by the shaded area.

Given the results depicted in Figures 11.80 and 11.81, an obvious extension is to analyse a multi-model average of the five multi-donor ensembles. Results from this are shown in Figure 11.82. The monthly efficiencies of this super-ensemble are typically greater than those of the five individual models and also of the five-model average using single donors. For much of the range of Figure 11.82, the super-ensemble is also better than the eight-model average.

Discussion

Two broad modelling approaches for producing continental estimates of runoff generation have been assessed. Spatialised lumped models using nearest-neighbour regionalisation are shown to provide better predictions than uncalibrated or minimally calibrated continental-scale models.

There are several caveats about this result. One is that this study has only assessed regionalisation performance using parameters from nearest-neighbour catchments, which, in the main, tend to be relatively close to the target catchment. In contrast, the distance over which spatialised model parameters will need to be transferred from gauged catchments in order to cover the entire continent is substantially larger in many areas. It is expected that prediction quality using nearest-neighbour regionalisation will decline as regionalisation distance increases and the parameters become less representative of the climate, soils, topography and vegetation of the target region or catchment.

Second, in applications where spatial patterns of runoff are required or where comparisons of runoff generation at several different locations are required, the nearest-neighbour approach suffers from using multiple parameter sets. These can lead to spatial discontinuities in runoff prediction and can yield a tessellated effect in maps of runoff generation.

The continental-scale models do not suffer from either of these drawbacks because they use a single set of parameters across the entire modelling domain. Furthermore, a recent study (Viney *et al*., 2011) using a calibrated version of AWRA-L (as opposed to the largely uncalibrated model using default parameter values described here) has shown that it is capable of producing runoff predictions in ungauged catchments that are of similar quality (in terms of efficiency and bias) as the spatialised models using nearest-neighbour regionalisation. This suggests that such models can indeed have the potential to provide credible continent-wide predictions of runoff.

Predictions of the spatialised models can be further improved by multi-donor averaging using model parameters calibrated on the nearest five gauged catchments. Multi-model averaging can also improve prediction performance. An eight-member model average, comprising unweighted contributions from the five spatialised models and the three continental-scale models, has been shown to produce better predictions than a five-member average that includes only the spatialised models.

This improvement occurs despite the fact that the eight-member ensemble includes the three continental-scale models whose predictions are typically significantly poorer. This tends to support the observations of Viney *et al*. (2009a) and others that even poorly performing models can bring important information to an ensemble that leads to improved ensemble performance. Furthermore, whereas the spatialised models have similar structures and are calibrated in a similar manner, thereby leading to relatively similar predictions, even in validation, the continental-scale models have structures and calibration methods that are quite dissimilar both to each other and to the spatialised models. The strong prediction performance of the eight-member ensemble may suggest that improvements in ensemble performance are greatest where there is a large degree of heterogeneity in the underlying structure of the constituent models.

In some applications it might not be possible to ascertain *a priori* which of several candidate models provides the best predictions in ungauged basins. The performance of the model averages here suggests that they are a desirable alternative to blindly choosing just a single model for regionalisation and will generally provide predictions that are better than a randomly selected model and at least as good as the best available model.

Acknowledgements

This work is supported by the WIRADA alliance between CSIRO and the Australian Bureau of Meteorology.

11.19 DISTRIBUTED RUNOFF PREDICTIONS IN THE MEKONG RIVER BASIN

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The issue from societal and hydrological perspectives

The Mekong River flows approximately 4200 km from the Tibetan Plateau to the South China Sea (Figure 11.83) and covers about 795 000 km^2, of which 620 000 km^2 lies in the lower Mekong basin (LMB) countries of Thailand, Laos, Cambodia and Vietnam, with the remainder in China and Myanmar. The population is growing rapidly in the Mekong River basin (MRB), projected to be 90 million by 2025 compared with 72 million in 2005, and this increases the competition for water while also contributing to decreases in water quality, particularly in the LMB (MRC, 2003). In addition to the increasing demand for water, floods are also a recurring event in the LMB, often resulting in loss of life and property, damage to agriculture and rural infrastructure, and major disruption to the social and economic activities of people living in the LMB

Figure 11.83. The Mekong River basin and sub-basins (block numbers indicated).

(MRC, 2003). The MRB also constitutes an extremely diverse and complex ecosystem, supporting some of the world's highest diversities of fish and snails, as well as a number of critically endangered species such as the Irrawaddy dolphin and the giant Mekong catfish (Yoshimura *et al*., 2009). Approximately 60 million inhabitants sustain their livelihood directly from the Mekong River, but the Mekong River also provides food staples, mainly rice, for about 300 million people (MRC, 2010).

Description of the study area

The Mekong River (Figure 11.83) is the world's twelfth longest river and tenth largest in terms of annual flow. The climate of MRB ranges from tropical in the LMB to cool temperate in the upper Mekong (China) where some of the peaks in the Tibetan Plateau are permanently snow-capped. Annual average precipitation in the basin is ~1405 mm and average evapotranspiration is ~825 mm. About 55% of the water in the lower basin arises from the mountainous regions along the eastern rim of the basin, with north-east Thailand contributing only 10% (MRC, 2003). Precipitation in the basin mainly occurs between May and October, associated with the south-west monsoon, and frequent flooding is observed in different parts of the MRB during this period. The north-east monsoon is from November to March and is associated with the cool and dry conditions of the MRB.

Compounding this high seasonal to inter-annual hydroclimatic variability, and the population increases already mentioned, are the potential impacts of anthropogenic climate change. In the Tropical Asia region where the MRB is located, the potential climate change impacts include strengthening of monsoon circulation, increases in surface temperature, increases in the magnitude and frequency of extreme rainfall events, and sea-level rise (Cruz *et al*., 2007). These projected changes could result in major impacts on the MRB's ecosystems and biodiversity; hydrology and water resources; agriculture, forestry, and fisheries; mountains and coastal lands; and human settlements and human health. In order to adapt to these projected changes it is necessary to understand historical and existing conditions (i.e., baseline) and also to robustly quantify the impacts of projected future climatic changes, particularly in relation to the current and projected hydrology, water resources and water environments (e.g., Kiem and Verdon-Kidd, 2011). This is problematic in large, mostly ungauged, basins like the MRB. This case study demonstrates how the Yamanashi Hydrological Model (YHyM) can be used as a tool to assess current and future water resource availability in large, poorly gauged basins like the MRB.

Method

The YHyM was developed at the University of Yamanashi (Japan), particularly for hydrological simulations of large river basins (Takeuchi *et al*., 1999, 2008; Ishidaira *et al*., 2000; Ao *et al*., 2003; Zhou *et al*., 2006; Hapuarachchi *et al*., 2008). It is a comprehensive grid-based distributed hydrological model (see Section 10.4.1) integrated with modules for estimating potential evapotranspiration, snow accumulation/melt, runoff generation, sediment transport, water quality and water use/control (e.g., dam/reservoir operations).

The core hydrological model of YHyM is an extension of the TOPMODEL concept (Beven and Kirkby, 1979) referred to as BTOPMC (blockwise TOPMODEL with Muskingum–Cunge method). This extension was made by redefining the topographical index by using an effective contributing area per unit grid cell area and introducing concepts of mean groundwater travel distance and groundwater dischargeability. This provides a link between hillslope hydrology and macro-hydrology (Takeuchi *et al*., 1999, 2008). The BTOPMC model has four parameters to be identified at each grid (maximum saturation deficit in root zone, groundwater dischargeability, river width and Manning's roughness coefficient) and one in each block (i.e., sub-basin), which is the groundwater discharge decay factor where the groundwater aquifer is assumed shared. Regardless of this extension and redefinition, the BTOPMC model uses all the original TOPMODEL equations in their basic form.

In this study we applied YHyM to the MRB to investigate current (1980–2000) and future (2080–99) hydrological conditions (refer to Hapuarachchi *et al*. (2008), Kiem *et al*. (2008) and Takeuchi *et al*. (2008) for a full description of the YHyM parameters and data inputs used in the MRB case study). Here we focus on the performance of YHyM in the ungauged, or poorly gauged, parts of the MRB and also on YHyM's ability to simulate variables other than runoff (e.g., soil moisture, actual evaporation), with particular emphasis on how parameters were estimated in the ungauged parts of the MRB.

Parameter estimation

The entire MRB was divided into nine blocks (Figure 11.83), taking into consideration the size, natural subbasins, and the Köppen climate classification. One of the main advantages of YHyM is that most of its parameters are physically based, thus the number of parameters that require tuning is parsimonious and the regionalisation of parameters is possible (e.g., Ao *et al*., 2006) (see Sections 10.4.3 and 10.4.4). Basic catchment characteristics such as elevation, slope, flow direction and river network were extracted from a digital elevation model. The channel width was assumed to be proportional to upstream catchment area

Table 11.20. *Module parameters*

Module	Parameter	Symbol	Extent	Range
BTOP (runoff generation)	Discharge decay factor	m	Block	0.01~0.1
	Groundwater discharge ability coefficients	D_{sand}, D_{silt}, D_{clay}	Basin	0.01~2.0
	Soil freezing threshold temperature (°C)	T_t	Basin	0.0~2.0
	Root zone soil moisture capacity (mm)	S_{rmax}	Grid cell	50–1500
	Block average Manning's coefficient	n_0	Block	0.01~0.8
Snow	Snow accumulation threshold temperature (°C)		Basin	–2.0~2.0
	Degree-day index		Basin	1.0~1.9
	Snowmelt threshold temperature (°C)		Basin	0.1~1.0
	Re-freezing coefficient		Basin	0.01~0.09

and calculated for a grid cell using an explicit relationship (Lu *et al*., 1989). The three-dimensional physiographic heterogeneity of the basin was considered mutually in terms of topography, soil types, vegetation cover and root depth. In this application we only use the runoff generation, snow and potential evapotranspiration modules, and the related module parameters are shown in Table 11.20.

Discharge decay factor (m) was assumed to be homogeneously distributed inside a block. Assuming that channel slope is proportional to the resistance of flow, BTOP uses the following equation to calculate the Manning's roughness coefficient (n) of a grid cell:

$$n = n_0\left(\frac{\tan\beta}{\tan\beta_0}\right)^{1/3}$$

where β is the local channel slope and β_0 is the block average slope. The groundwater discharge ability (D_0) of a grid cell was calculated following Hapuarachchi *et al*. (2004) as

$$D_0 = U_{clay}D_{clay} + U_{sand}D_{sand} + U_{silt}D_{silt}$$

where U_{clay}, U_{sand} and U_{silt} are the percentages of clay, sand and silt present in a particular grid cell, respectively. It is assumed that soil texture inside a grid cell is homogeneous; thus D_{clay}, D_{sand} and D_{silt} could represent additional soil textural properties (particle size, pore size, etc.). These parameters are defined for the whole basin and slight tuning is needed. The maximum storage capacity of the root zone ($S_{r\,max}$) for each grid cell was calculated as

$$S_{rmax} = RD(\theta_{fc} – \theta_{wp})$$

where RD is the depth of the root zone of a grid cell (obtained from literature based on the land use map); θ_{fc} is the field capacity (m/m); and θ_{wp} is the topsoil moisture content at wilting point (m/m). Literature values (Rawls *et al*., 1982) of θ_{fc} and θ_{wp} for each grid cell were defined based on the soil textural properties (from Food and Agriculture Organization soil map). The soil freezing threshold temperature of a block was also taken from the literature based on the major soil type present in the block. Typical values from the literature were also used for the snow module parameters (set for the whole basin) and hence slight tuning may be required. No evapotranspiration model parameters were tuned as they were all taken from the literature (Zhou *et al*., 2006).

Results

The overall validation (1977–2000) performance of YHyM at the outlet of each block is good (Nash–Sutcliffe scores of 0.7–0.84). The simulated and observed hydrographs at several locations within the MRB are shown in Figure 11.84, and it can be seen that low flows are simulated quite well. However, peak flows are sometimes overestimated, and it is thought that this is due to an insufficient number of rain gauge stations (only 65 for the whole MDB, and only one for Block 8 and none for Block 7) which reduces the ability to realistically replicate the spatial variability of rainfall over the MRB.

To demonstrate the applicability of YHyM to PUB, Figure 11.85 shows daily average catchment characteristics at all points in the MRB for an exemplar wet and dry month. Rainfall in areas with no rain gauge stations was approximated using data from nearby stations and applying the Thiessen polygon method. At times (e.g., high precipitation), this approximation was unrealistic and hindered the model performance to some extent. However, the model's performance at simulating some of the internal points with limited data (i.e., Thoeng, Ubon and Yasothon) was found to be satisfactory, suggesting YHyM is a useful tool in ungauged (or sparsely gauged) basins. Further research is required to investigate the details as to why, where and when YHyM performs well or poorly in the MRB (e.g., elevation effects, density of gauges, uncertainties associated with models inputs, uncertainty associated with observed runoff etc.).

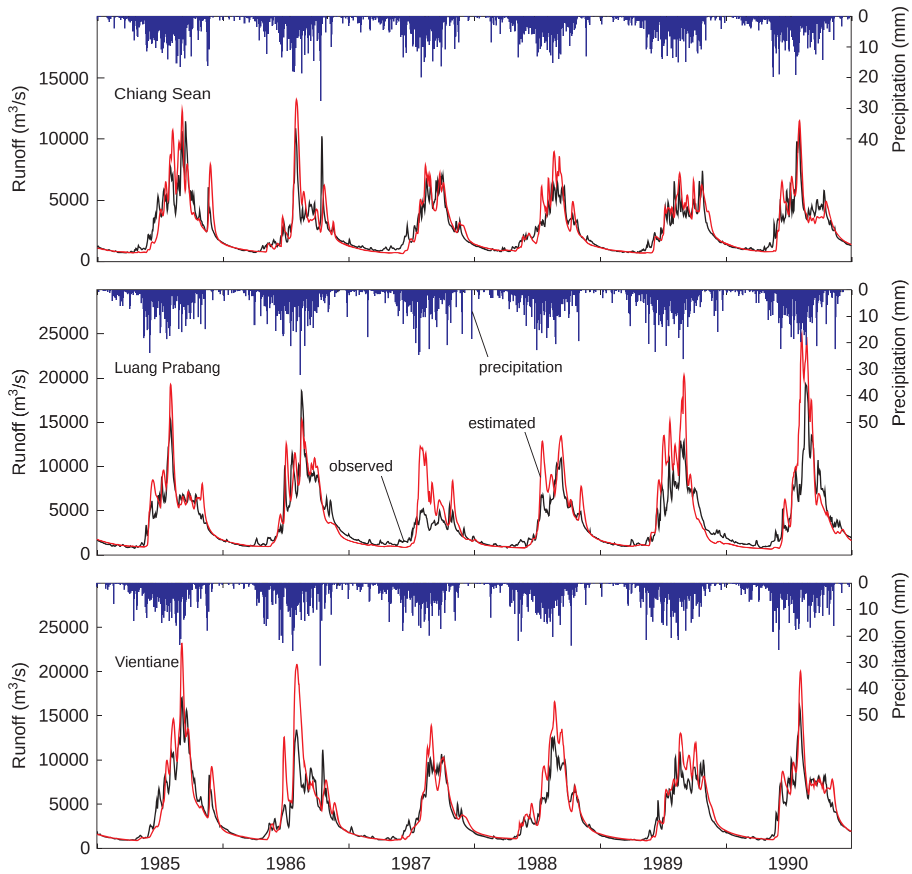

Figure 11.84. Hydrographs illustrating YHyM performance at various locations within the Mekong River basin.

Discussion

In this study we present a case study of hydrological modelling in the large, international, poorly gauged Mekong River basin. With the rapid increase of population in the basin, understanding the basin's hydrology is important for planning future water resources, protecting its extremely diverse and complex ecosystem, and flood mitigation. However, hydrological modelling in the MRB is challenging due to poor data observation networks that are at least partially a result of the MRB's trans-boundary nature. Thus, conceptual hydrological models are likely to fail in this situation, while distributed hydrological models combined with PUB principles may be more appropriate. Most of YHyM's parameters are derived using the physical catchment characteristics such as the elevation, soil properties and land cover properties. Thus, the number of parameters that require tuning is parsimonious and the regionalisation of parameters is possible.

Overall performance of the YHyM model applied to the MRB is good and the detailed analysis on the variation of soil moisture, evapotranspiration, interception evaporation and runoff estimations indicates that the YHyM replicates the natural hydrological responses of the basin well. In addition, the model accuracy (discharge and potential evaporation) at selected internal points of the basin is also reasonable, signifying that YHyM can achieve equal accuracy at each point in the basin, which is extremely important in water resources planning and management. This suggests that YHyM is a useful tool for addressing some of the issues identified by the PUB initiative.

The use and development of YHyM is now being extended jointly by the University of Yamanashi and other institutes, especially UNESCO-ICHARM. The main area of extension is the global application of the model to assess the impacts of climate change on floods and to enable real-time monitoring of flood occurrences throughout the world. YHyM is supported by a dense global coverage of stream networks and the combined use of observations, satellite information and modelled rainfall data. YHyM is becoming a hydrological simulation tool, useful for both research and teaching, that is applicable for flood forecasting and water resources planning and management in basins at any temporal and spatial scale located anywhere in the world – thus enabling monitoring of extremes and better understanding into potential trends or changes to hydrological conditions and water availability under different basin management, land use or climate change scenarios.

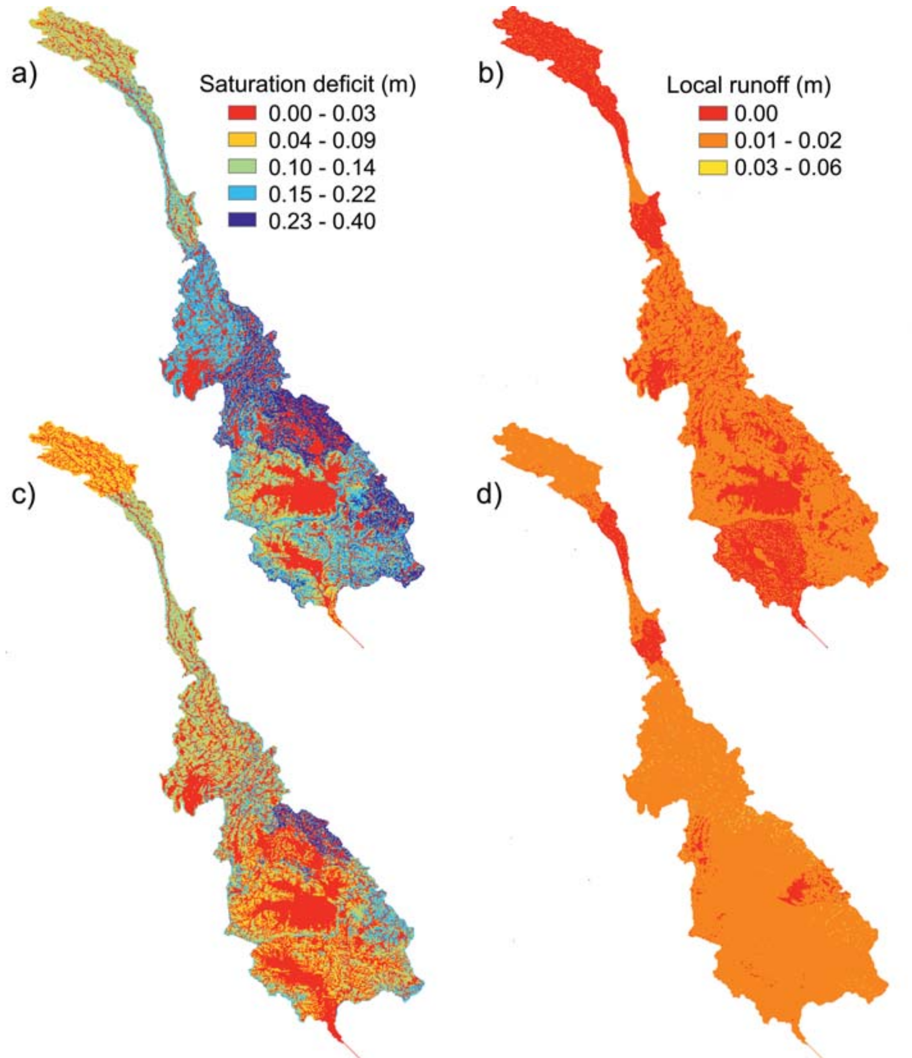

Figure 11.85. Daily average catchment characteristics for a dry month (March 1981, (a) and (b)) and a wet month (September 1981, (c) and (d)). (a) and (c) are saturation deficit, (b) and (d) are local runoff.

11.20 IMPLEMENTING THE EU WATER FRAMEWORK DIRECTIVE IN SWEDEN

B. ARHEIMER AND G. LINDSTRÖM

The issue from societal and hydrological perspectives

The European Water Framework Directive (WFD; European Parliament, Council, 2000) was launched in December 2000 to achieve a more integrated management of water-related environmental objectives in the EU member states (e.g., Chave, 2001). The directive takes a broad view of both water management to prevent any further deterioration of water bodies, and the protection and enhancement of the status of aquatic ecosystems and associated wetlands. The WFD prescribes that policy should focus on water as it flows through river basins to the sea, and it applies to inland surface water, groundwater, transitional (estuarine) and coastal waters. The ambition is to integrate both water quality and quantity issues, and surface and groundwater issues, and their management on the river basin scale. The overriding objective is to obtain a good status in *all* waters. In practice, the WFD demands reporting from all member states on the water status (i.e., hydro-morphological, physical, chemical and biological variables), measurement plans and achievements. The water management follows a defined six-year cycle, and is required to include local public participation. The implementation of the WFD was, and still is, a big challenge in many of the EU member states as it is ambitious and often required changes in both administration and legislation. To be able to report and manage water at the local waterbody level, it

Figure 11.86. Some different characters of Swedish rivers.

was also necessary to initiate extensive data collection, methodological development and technical solutions.

In Sweden, five new water districts with authority directly coming from the government were established and environmental quality objectives were considered in national legislation. In 2008 the Swedish Government demanded the Swedish Meteorological and Hydrological Institute (SMHI) to provide the relevant information at the resolution defined by the water authorities. Sweden is rich in surface water and the authorities requested data (e.g., river discharge) for 17 000 sites in 2009 and 38 000 sites in 2011. In comparison to these high numbers, only some 400 gauging stations for river runoff were available and, even though mobile stations were introduced to supplement these, methods for estimation and regionalisation had to be applied. Thus, a national hydrological model system with high resolution was implemented, using which most of the predictions were done for ungauged basins.

Description of study area

Sweden is a country in northern Europe of 450 000 km^2, which is rich in surface water, with more than 100 000 lakes larger in area than 0.01 km^2. The country is part of the Boreal forest belt and most of the country is covered by conifer forests. The north-western border towards Norway is a mountain range (the Scandes) of up to 2000 metres in height; the north-eastern border towards Finland is a river, while the longest border is the coastlines of the Baltic Sea and the North Sea. In total, 118 rivers discharge to the surrounding seas and with very few exceptions all of the river basins are on Swedish territory. Sweden has almost 10 million inhabitants who are mainly settled in the southern part and along the coastline. This is also where the agricultural regions are to be found. The study area thus shows a large variety in characteristic landscapes (Figure 11.86).

For the whole country, the water authorities have defined 7232 lakes and 15 563 river reaches for status reporting to the EU according to the WFD. However, the national monitoring programme is rather sparse, e.g., there are about 400 hydrological gauges and some 900 sites where grab samples of nutrient concentrations are taken every month. To estimate water and nutrient flows with the requested resolution the country was delineated into 17 000 (and later more than 35 000) catchments covering the country and associated basins in Norway and Finland (Figure 11.87). The delineation was received from the Swedish Water Archive at SMHI and has mainly been

Table 11.21. *The main characteristics of input data for hydrological modelling of Sweden*

Data type	Data	Resolution	Source
Meteorological data	Precipitation, air temperature. Daily sub-basin means from 1961 to present date	4 km grid based on precipitation and temperature station data	The PTHBV database (SMHI), Johansson (2002)
Geographical data	Sub-basin areas	Average = 28 or 10 km^2, median = 18 or 6 km^2	Swedish Water Archive (SMHI)
	Soil type	Grid, based on sampling with variable spatial resolution	Soils Database (Geological Survey of Sweden)
	Land use	250 m	Corine Land Cover 2000 (Swedish Land Survey)
	Elevation	50 m	GSD-Terrain Elevation Databank (Swedish Land Survey)
	Hydrographical network	Some 100 000 km of main stream length	Swedish Water Archive (SMHI)
Lake information	Depths, regulation rules, rating curves, 8 000–10 000 outlet lakes	Site specific	Swedish Water Archive (SMHI)

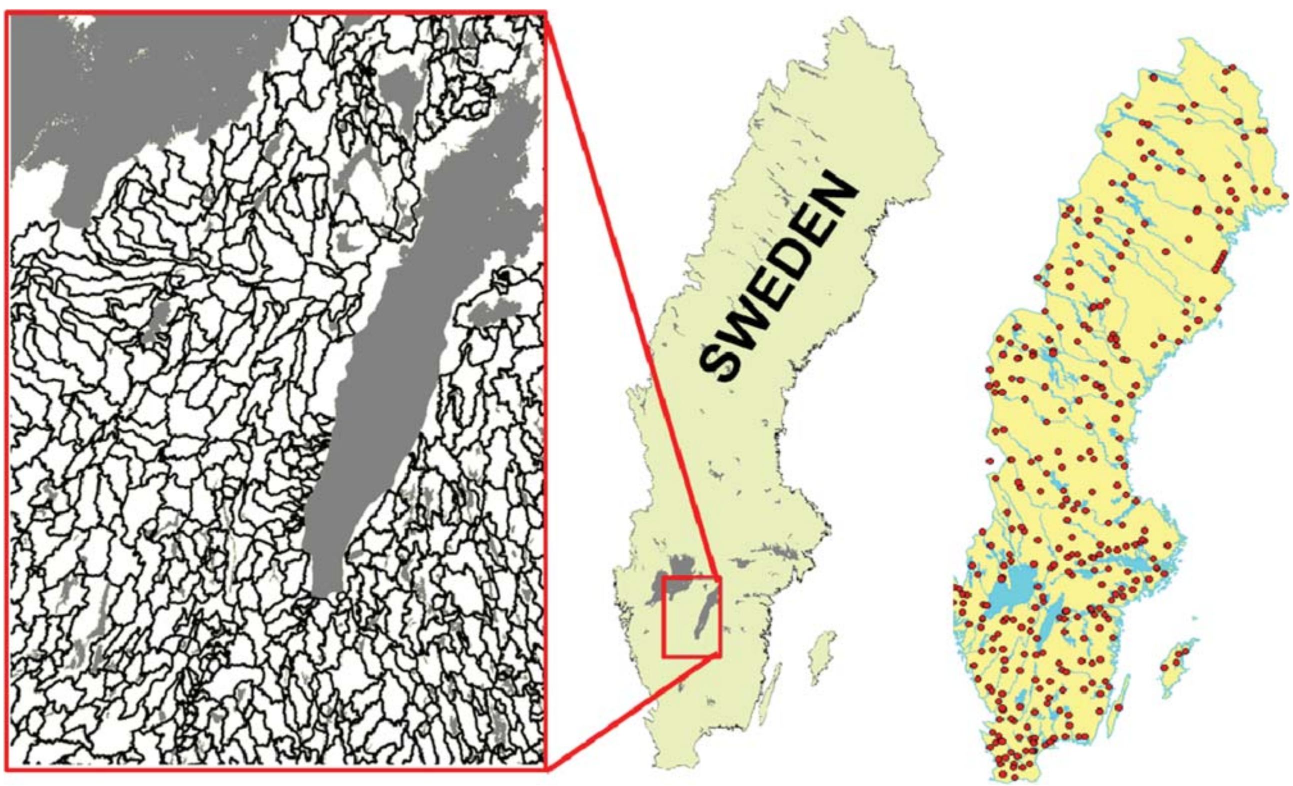

Figure 11.87. (Left) The spatial resolution of the Swedish modelling with the coarser resolution of 17 000 catchments (on average 28 km^2). (Right) Sites of available water gauges.

made manually by using topographic maps and field studies over several decades. Table 11.21 shows the information that was used for regionalisation to predict river flow in ungauged basins in Sweden.

Method

SMHI had recently developed the Hydrological Predictions for the Environment (HYPE) model (Lindström *et al.*, 2010) when the request came from the Swedish

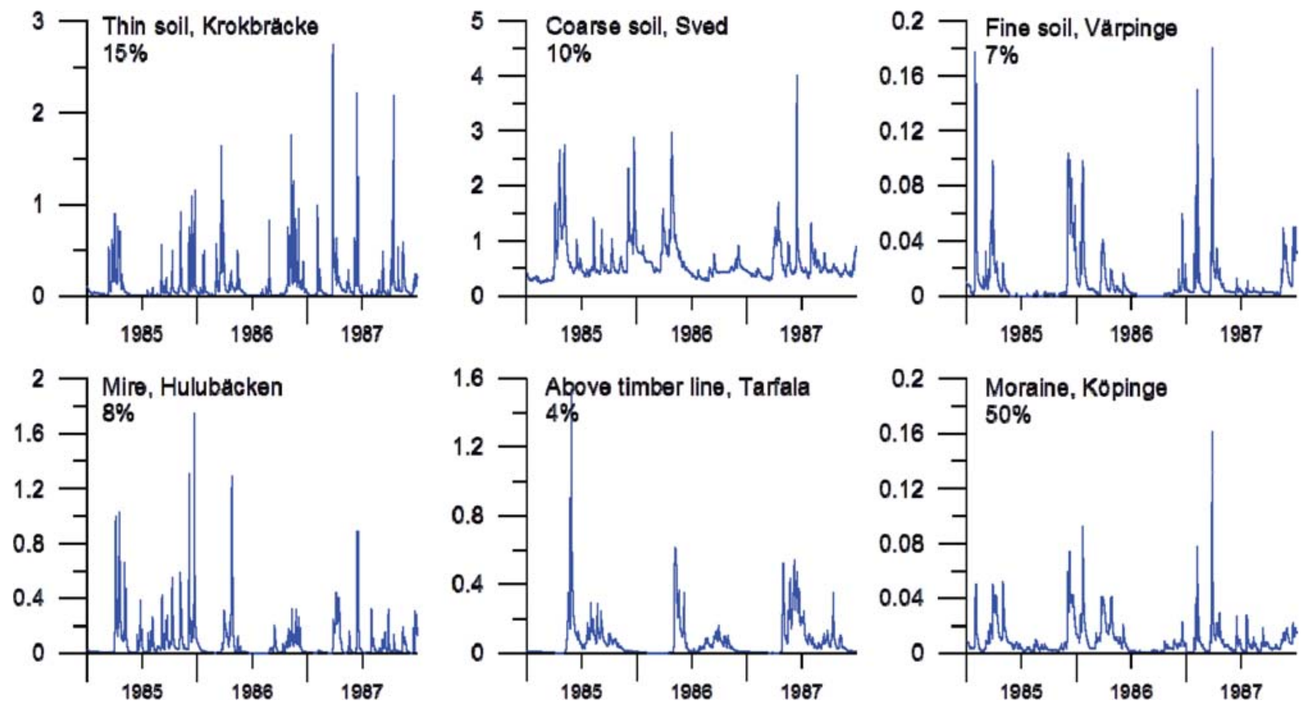

Figure 11.88. Observed hydrographs from some small Swedish catchments with different soil types. The percentages illustrate how large an area of the total Swedish surface each soil type represents.

government to deliver high-resolution model predictions of water and nutrients to water authorities, in order to support their WFD work. The HYPE model is a dynamic, semi-distributed and process-based model (see Section 10.4.1) based on well-known hydrological and nutrient transport concepts. In the model, the landscape is divided into classes according to soil type, vegetation and altitude. The soil representation is stratified, where the soil can be divided into three layers. In order to be able to cope with environmental issues, the flow paths include surface runoff, macropore flow, tile drainage and groundwater outflow from the individual soil layers (see Chapter 4). Rivers and lakes are described separately with routines for turnover and rating. Model coefficients are global, or are related to specific characteristics of hydrological response units (HRU), i.e., combinations of soil type and land use. The hydrographs from small catchments in Sweden may differ considerably due to differences in soil properties; for instance, thin soils are characterised by quick drainage and low baseflow, whereas coarse soils are characterised by sustained baseflow (Figure 11.88).

The HYPE model was applied nationally across the whole of Sweden (called S-HYPE) using a stepwise, multi-basin calibration technique (Donnelly *et al.*, 2009; Strömqvist *et al.*, 2012). In total, the HYPE model has many hundreds of rate coefficients, constants and parameters, which in theory could be adjusted. Most such values, however, were estimated from literature values and from previous modelling experiences (*a-priori* values, see Section 10.4.3). About 15 parameters for each land use and soil type and another 10 global parameters were regionally calibrated (see Section 10.4.4). The HYPE model is equipped with a Monte Carlo routine, which was applied during the model development to define the most sensitive parameters and parameter interactions. The model was applied for a 20-year period using a daily time step. The regionalisation method used for the Swedish model application can be summarised as follows.

Overall water balance (see Chapter 5)

In the first S-HYPE setup (Strömqvist *et al.*, 2012) the overall water balance was first evaluated against measured long-term discharge volumes at 198 SMHI runoff gauging stations (with a drainage basin area $\leq$ 2000 km^2), which provided a good geographic coverage of Sweden. The evaluation showed that the amount of precipitation in the mountainous area along the border with Norway was underestimated. Since precipitation was below the recorded discharge in some catchments, this was clearly not a model error, and instead indicates that the precipitation data set did not capture all precipitation at higher altitudes. This is a well-known problem in mountainous areas. The precipitation was therefore increased by 10% in sub-basins above 400 m a.s.l. Water balance evaluations also showed that discharge was overestimated by the model in the south-eastern part of Sweden, the driest region in the country. An evaporation correction factor was therefore introduced for this particular region as part of this initial water balance adjustment. The overall water balance was continuously checked and revised during the proceeding calibration steps.

Inclusion of in-situ *knowledge (see Chapter 3)*
Lakes and dams strongly affect all downstream basins in a river network. Simplified rating curves for 50 unregulated lakes were estimated for use in the HYPE model, based on observations from SMHI databases. Existing rating curves were applied wherever available. For regulated lakes and hydropower dams, regulation volumes and average outflow were taken from the SMHI Water Archive. These were used to construct a seasonal variation for each individual reservoir. For some 50 important reservoirs, a specific rating curve for the spillways was constructed based on observations of discharge and water levels. For the remaining reservoirs a generalised spillway module was constructed based on the specific curves.

Parameters linked to HRUs and simultaneous calibration for a large model domain, representing different characteristics
The first step was a definition of soil characteristics of HRU, e.g., soil layers, soil depths, combinations of soil type and land use. Then, calibration was performed on groups of similar representative gauged basins, trying to isolate key processes and characteristics. Calibration was made regionally (see Section 10.4.4) on a multi-basin level for the whole domain. It was assumed that differences in physiographical characteristics and forcing data were sufficient to account for spatial variability, while model coefficients were kept constant. Hence, a clay soil in southern Sweden has the same parameter setting as in the northern part of the country. The parameters so obtained were then applied everywhere, also for ungauged basins.

Stepwise, iterative calibration of parameter groups
Calibration of the model was carried out manually, following a stepwise approach taking one process at a time, to avoid equifinality and so that errors that were incurred in some model processes are not compensated by introducing errors in other parts of the model. Hence, groups of parameters responsible for certain flow paths or processes (e.g., soil water holding capacity) are calibrated first, after which another group of parameters (e.g., river routing) are calibrated. As the model concept follows the flow paths, the headwaters were calibrated first, then streams, lakes, rivers and finally the overall outlet to the sea was checked. The idea is to follow the water and nutrient fluxes through the landscape and to fix coefficients where data are available for a specific process or segment of processes (see Figure 11.89). Each step downstream in the model code included some reconsideration about the chosen parameter values as part of an iterative procedure. Water and nutrient concentrations were also calibrated iteratively, which further limited the degrees of freedom for parameter values. Yet, as described above, the same parameter set was used for the whole country and no river-basin specific calibration was made.

Expert judgements on dominant flow paths and response to events
During the procedure, internal model variables (such as flow separation in surface runoff, tile drainage, discharge from various soils) were checked visually in a test bench of catchments, to avoid unrealistic model behaviour due to parameter setting (see Chapter 10). For instance, surface runoff does not usually occur during summer in Sweden and should thus not be dominant in the model during this period. Moreover, in cold climates the snowmelt event is the dominant characteristic of the flow hydrograph and hence flow peaks were followed through river reaches in order to explore whether the transit times were realistic in the model setup.

Multi-variable validation
To judge model credibility, other observed (orthogonal) variables, i.e., other than river discharge (and concentrations), were used (see Section 10.4.5). For instance, these included observations of snowpack, groundwater fluctuations and water levels in lakes (Arheimer *et al.*, 2011). Finally, the overall model was validated against independent observations from gauges that had not been included during the model calibration, to examine model performance in ungauged basins.

Results
Assessment of the model performance was based on the statistical criteria of NSE (daily values) and relative error of water volume (RE). Absolute RE was on average less than 10% and the median NSE for the whole country was 0.67. The maximum NSE was 0.94 (period: 1999–2008).

The S-HYPE model setup is not dependent on site-specific calibration as previous models for Sweden were (e.g., Arheimer and Brandt, 1998; Arheimer, 2003). The purpose was to make the results in ungauged basins more reliable. The model was therefore also checked separately for the gauging sites that had been used in the regional calibration procedure, and other independent sites, which could then represent ungauged basins. This validation was

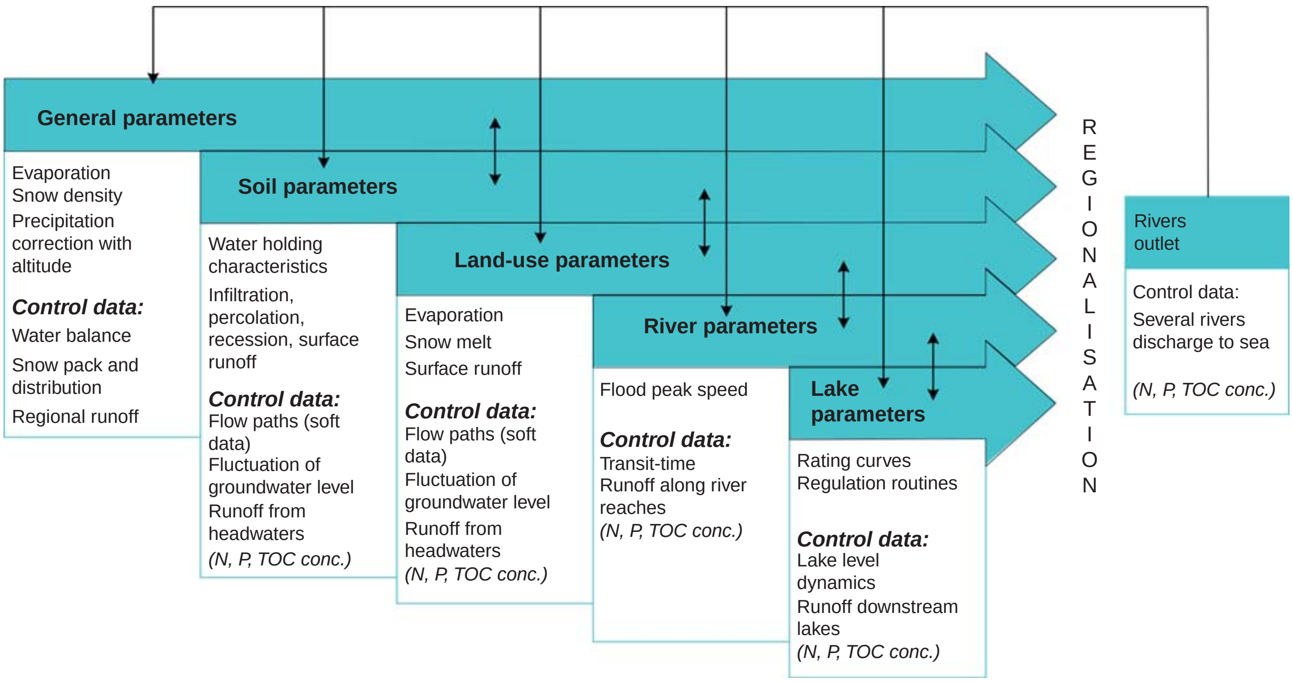

Figure 11.89. The scheme of the stepwise calibration procedure starting from the left with simultaneous multi-basin calibration. Parameters of specific processes or groups of processes are calibrated against control data (i.e., observations or soft data) and fixed before continuing with the next step along the model structure. Water and nutrient concentrations are calibrated iteratively and reconsideration of previous choices of parameter values is sometimes necessary.

Table 11.22. *Model performance of river runoff from catchments of various sizes and disturbance, and at all gauging stations*

	Catchment size			Disturbance		ALL
	<200	200–2000	>2000	Natural	Regulated	
Regional calibration						
No.	61	47	12	91	29	120
NSE	0.68	0.76	0.72	0.72	0.40	0.70
RE	–3	–6	–4	–3	–6	–4
Independent validation						
No.	41	124	121	114	172	286
NSE	0.66	0.69	0.49	0.78	0.45	0.62
RE	3	0	1	1	1	1

Some of the gauges were used for the regional calibration of the S-HYPE model or were given a specific rating curve. Others can be considered as ungauged (Validation sites).
Median values of Nash–Sutcliffe efficiency (NSE) and average relative volume error (RE) (%) are given.

made for catchments of various sizes, disturbances, soil types and land uses (Tables 11.22 and 11.23). It is difficult to compare these results as the number of catchments in each category differs, and due to differences in variance in discharge between basins. It should also be noted that the evaporation was adjusted by checking the overall water balance for the whole country and therefore the volume error is relatively small also for validation sites.

The median values of NSE were rather stable between gauged and ungauged basins. For natural rivers, the average NSE was higher for the large amount of independent validation sites (i.e. ungauged basins). This is mainly an effect of size since the calibration was performed on small headwaters. In total, average model performance was lower than the medians as a few stations were poorly simulated by the model. This could be caused by bad

Table 11.23. *Model performance of river runoff from catchments with various land use and soil types*

	Land Use (>50%)			Soil Type (>50%)			
	Forest	Arable	Mountain	Sand/Silt	Till	Clay	Peat
Regional calibration							
No.	69	21	1	18	48	2	1
NSE	0.71	0.69	0.73	0.65	0.71	0.71	0.40
RE	2	7	1	−1	−3	−7	−2
Independent validation							
No.	218	4	4	3	181	0	1
NSE	0.65	0.71	0.71	0.84	0.62	–	0.89
RE	2	7	1	−1	−1	–	3

Some of the gauges were used for the regional calibration of the S-HYPE model or were given a specific rating curve. Others can be considered as ungauged (validation sites).
Median values of Nash–Sutcliffe efficiency (NSE) and average relative volume error (RE) (%) are given.

quality of the gauging station, not representative model input data or missing process description in the model. The low performance in large rivers reflects the impact of regulations. Since the purpose of regulation is a redistribution of discharge between seasons, it only affects the timing (measured by NSE) and not the volume (measured by RE). No major difference in model performance could be referred to land use or soil types (Table 11.23).

At the outlets of the 27 largest, partly regulated, basins that drain to the sea the median NSE was 0.77. The corresponding number for the five unregulated river basins that drain to the sea was 0.89. In basins less than 200 km^2 in size, the NSE was still typically 0.67, but the errors were considerably larger in some small basins, which is a common phenomenon as both catchment area and the gridded meteorological data may be less representative at the small basin scale. Moreover, lake information is less precise in small basins and this has a major impact on the results.

Discussion

The regionalisation method used when applying the HYPE model for Sweden (S-HYPE) seems to provide useful results for water authorities also for catchments where no observed runoff data are available. It should be noted that model parameters for water discharge were chosen with additional consideration of nutrient concentrations, internal model variables and soft information. Only calibrating on water discharge would probably give higher values for gauged sites but thus may be for the wrong reasons. Among the performance measures mentioned in Chapter 2 the presented regionalisation method was chosen to achieve a high performance of 'realism'. It should also be noted that delineation of water divides and information about lake rating curves and dam regulations were absolutely crucial for the overall model performance, along with a reliable precipitation grid (cf. Chapter 3). These factors may actually be more important for model performance than the optimal tuning of parameters in hydrological models.

The calibration was made manually using the whole domain simultaneously (i.e. multi-basin approach), but for specific or groups of parameters represented by the gauging stations chosen for each part of the model (i.e. stepwise approach). Soft information and knowledge of the dominant hydrological features in the region were applied rather than numerical estimates of model performance. Visual inspection of interaction of multiple variables was used to judge overall model credibility. Such an approach requires an experienced hydrologist with good intuition, but is nevertheless very valuable to help exclude parameter combinations that are unrealistic physically although they provide good statistical fits of the integrated river discharge. It would be interesting to further evaluate to what extent the problem of equifinality is actually reduced when calibrating complex models in a stepwise manner, using smaller portions simultaneously for multiple-basins. The regionalisation method used for S-HYPE still included calibration of many soil and land use parameters in one single step, which suggests that this part of the model is probably still over-parameterised.

Finally, it should be mentioned that Swedish hydrology is largely dominated by lakes and snowmelt, whereas processes such as long-term groundwater storage and evaporation are less important to capture the overall hydrograph. It may be that the suggested regionalisation method (and hydrological model) of this case study is less successful in other climates and regions where other hydrological processes dominate, although the modular approach adopted may still be valuable. The S-HYPE model concept is revised continuously and several process algorithms are currently being reconsidered, both for flow paths in the soil and the surface water network.

The results from the S-HYPE model have been well received and appreciated by end-users in the Swedish water authorities and their consultancies for their WFD work on water status. Daily and monthly time series can be downloaded for free from http://vattenweb.smhi.se/ and so far this web address has had (in 2011) more than 5000 unique visitors. New model versions are being launched every second year. The model results are used for characterisation of water bodies and the sources of pollution. There is also a tool for impact assessment of remedies scenarios where the S-HYPE model is coupled to a coastal eutrophication model. Moreover, the S-HYPE model has been used in various national assessments, e.g. estimation of undisturbed conditions and climate change impacts on water and related environmental variables. Although the model system was originally developed for water quality analysis, the system is currently also being adapted for a national early warning service for floods and grass/forest fire, and for the daily snow map of Sweden. On-going interface development is mainly concerned with multi-variable visualisation techniques along with uncertainty estimates, and method transparency for end-users. The latter was found to be crucial for implementation of model results in practical water management.

11.21 Summary of key points

- The case study collection contains a great diversity of PUB problems that is being tackled around the world. It is clear PUB issues are cross-cutting – there is much in common in terms of the problems that are being faced and also prediction methods adopted (both statistical and process-based).
- The range of prediction problems addressed in the case studies covers the entire spectrum of runoff signatures in this book. There is much cross-fertilisation across these time scales of variability.
- From the case studies it became evident that PUB has clear societal relevance, with at least seven case studies where the authors reported that their runoff predictions in ungauged basins have been directly implemented in water resources management projects.
- Comparing the case studies from developed countries with those from developing countries, one can conclude that PUB activities in developed countries have a clear societal driver, be it government, regulatory framework, or industry. Apparently, this has provided the framework and motivation for much of the progress that is being made in PUB to benefit practice. However, there does not seem to be such an organised effort in developing countries, and PUB studies there tend to be localised, uncoordinated and often poorly funded and appreciated. Consequently, there is much less scope for accumulation of knowledge and experience.
- In many developed countries, where there is much more data available, standard approaches (both statistical and process-based) are being used and the focus on PUB is helping to generate further improvements. Furthermore, there is much more widespread use and trust in process-based methods as well. In contrast, in most developing countries data is very scarce, and many of them happen to be located in more arid parts of the world as well.
- This calls for more innovation and creativity, and the use of non-standard approaches, as already demonstrated by practitioners in several case studies reported here, which presented a creative and non-standard approach to predictions. Indeed, these may serve as models for future efforts in both developed and developing countries. The solution, it appears, is more hydrology and process insights, and not less, and hopefully this book can provide the framework and model for any such innovation.
- The PUB initiative seems well positioned to advance prediction practice in developed countries, rather than in developing countries for three reasons: (i) the prediction problems, especially in arid regions, are generally harder, (ii) data limitations are much more dire in poorer countries, and (iii) developing countries do not seem to be well organised to address local problems themselves, and to contribute to an accumulation of knowledge and experience. These issues need to be addressed head on in the future by the IAHS and other international organisations.

12 Outcomes of synthesis

Contributors: *H. V. Gupta,* G. Blöschl, J. J. McDonnell, H. H. G. Savenije, M. Sivapalan, A. Viglione and T. Wagener*

12.1 Learning from synthesis

This book has addressed the problem of *predictions of runoff in ungauged basins*, i.e., predictions of runoff at those locations where no runoff data are available, and is a contribution to the IAHS Predictions in Ungauged Basins (PUB) initiative (Sivapalan *et al*., 2003b). It has strived to bring together the outcomes of extant research on the problem of making predictions of runoff in ungauged basins that had previously remained disparate and fragmented, like scattered pieces of a jigsaw puzzle yet to reveal any coherent picture.

An original feature of the book is that it provides extensive and comparative assessments (in the form of blind tests) of the relative performance of runoff prediction methods in a large number of catchments from around the world. Rather than applying the prediction methods ourselves, we analysed the outcomes of many previous prediction efforts, and the collective experiences of their authors, who thus became partners in a unique community effort. The outcomes of this book therefore demonstrate the potential for new knowledge and insights to be gained through the practice of hydrology when a community of researchers organises around a pressing topic.

To respond to the fragmentation of knowledge implicit in multiple disparate studies, which became particularly obvious in the results of the comparative assessment, we have taken recourse to 'synthesis', which had the aim of unifying existing, diverse pieces of information to discover previously unrecognised connections, and to develop scientific understanding that is valid across multiple processes, places and scales (Blöschl, 2006; Sivapalan *et al*., 2011b).

Synthesis across *processes* is reflected in the independent exploration of runoff signatures at different temporal scales, ranging from annual runoff, to seasonal runoff, to the flow duration curve, to low flows, to floods and to the detailed runoff hydrograph. These signatures provide snapshots of the full spectrum of catchment processes that contribute to runoff variability at all scales, and have common origins in catchment hydrological processes (Jothityangkoon *et al*., 2001; Wagener *et al*., 2007). The dominant theme of hydrological similarity arises as a framework to perform synthesis across *places*. Hydrological similarity acts as a vehicle to advance understanding and predictions, and serves as the foundation for regionalisation, which remains at the heart of predictions in ungauged basins. Finally, a consistent treatment of statistical and process-based predictive techniques reflects the need to address a synthesis across *scales*. Statistical methods and process-based methods raise different challenges in terms of how to deal with scale issues, and require different approaches when used for predictions of runoff in ungauged basins. Intermediate approaches such as index methods are also adopted. By separating time scales of hydrological signatures, defining and relying upon hydrological similarity, and by suitably scaling the statistical and process-based predictive techniques used, the three core research issues or programmes outlined in the PUB Science Plan (SSG, 2003, p. 10) can be addressed:

> (1) Evaluating the performance of existing prediction methods that could be used in ungauged basins, through comparative analysis of a full range of methods and detailed investigations of the processes governing the quantity of interest …;
> (2) demonstrating the value of data, knowledge and process understanding for improved hydrological predictions …;
> (3) understanding the hydrological functioning, i.e., dominant processes, of basins at different time/space scales, and how these vary across scales in the different hydroclimatic regions of the world …
>
> Common amongst all three programmes will be the sharp focus on realistic estimation and eventual reduction of the level of predictive uncertainty. Robust measures of predictive uncertainty will be adopted as the criteria of success of PUB.

As outlined in the PUB Science Plan, predictive uncertainty, measured in this book by the cross-validation

* Coordinating contributor

Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales, ed. Günter Blöschl, Murugesu Sivapalan, Thorsten Wagener, Alberto Viglione and Hubert Savenije. Published by Cambridge University Press.

performance (blind testing) of the predictions of various runoff signatures, has formed the basis for comparison of predictive techniques in thousands of catchments from around the world.

Over the past decade, the IAHS PUB initiative has been the catalyst for a range of research activities organised around six PUB themes, and executed through a large number of national, regional and global PUB working groups. These themes, in abbreviated form, are: (i) catchment similarity and classification, (ii) conceptualisation of process heterogeneity, (iii) uncertainty analysis and model diagnostics, (iv) new data collection approaches, (v) new hydrological theory and (vi) new modelling approaches. These are also reflected in the frontispiece to this book, and also figure prominently in the guide to PUB best practice that appears in Chapter 13 (Recommendations). These research activities have contributed substantially to the literature, and have led to significant advances to the various elements of PUB.

This book firmly builds on the progress achieved during the PUB decade. Separate chapters have been devoted to (i) data collection approaches and learning from the data, and (ii) exploration of flow paths and storage as a way to understand the role of heterogeneity. Hydrological similarity is a recurring theme in every chapter, and is the basis for regionalisation approaches. The book has included a plurality of models and modelling approaches for predictions of the various runoff signatures, and has discussed their relative strengths and weaknesses. Uncertainty assessment through cross-validation in thousands of catchments from around the world has been another recurrent theme. Finally, the synthesis across processes, places and scales has given rise to a higher level synthesis of different theoretical frameworks of how to approach the PUB problem.

The specific outcomes of the comparative assessment reported in this book reflect the lessons learned from the diversity offered by nature's own experiments, covering about 25 000 catchments, and as expressed through thousands of observational, modelling and prediction studies surveyed. The outcomes of these studies are presented in hundreds of published articles that we reviewed; many of them were carried out within the last decade and were inspired by PUB. Most of the 130 contributors to this book are themselves members of the PUB community, and served as experts to summarise the state of the art of hydrological knowledge and predictions of the various runoff signatures. In these ways, the outcomes of the book represent the collective wisdom of the broad hydrology community, including the PUB community. The remainder of this chapter summarises the outcomes of the findings of the synthesis across processes, places and scales, highlighting successes, areas of persistent confusion, and opportunities for further research.

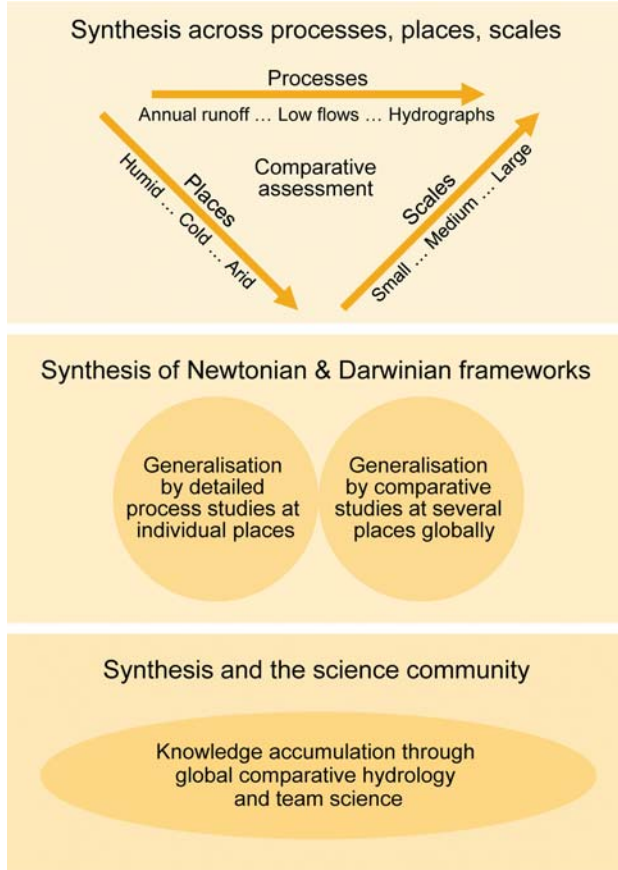

Figure 12.1. Organisation of the chapter: (top) synthesis through comparative assessment, (middle) approaches to generalisation through a higher level synthesis, and (bottom) knowledge accumulation through global comparative hydrology.

This chapter is organised into three parts (Figure 12.1). The first part presents the outcomes of the synthesis across processes, places and scales carried out in the form of comparative performance assessment of methods used for predicting the various runoff signatures, and the inferences that could be drawn from this assessment for advancing predictions. The second part of the chapter extends this discussion to include approaches needed to develop generalised understanding, through a higher level synthesis of Newtonian (detailed process studies in individual places) and Darwinian (comparative studies at several places globally) approaches. Finally, the third part of the chapter discusses the implications for the PUB community to facilitate knowledge accumulation through improved organisation and communication.

12.2 Synthesis across processes, places and scales

12.2.1 Synthesis across processes

Signatures are connected

Runoff signatures, collectively, reveal the nature of runoff variability in time and space. They are emergent properties of the hydrological functioning of catchments. Each signature reveals a different aspect of the catchment function. When juxtaposed with corresponding patterns of climate inputs and catchment characteristics, runoff signatures can help to explain the causes of hydrological variability and may thus assist with predictions. Since different aspects of climate and catchment characteristics control different signatures, a hierarchical exploration of these signatures helps to decipher these controls better than direct comparison or curve fitting of complex hydrology models against observed time series at one or more places.

The different chapters of the book: 5 (annual), 6 (seasonal), 7 (flow duration curve, daily), 8 (low flows), 9 (floods) and 10 (runoff hydrograph), focus on runoff variability on different temporal scales. The emergent controls or dominant drivers of this variability also change with the temporal scale of interest. In Chapter 5, annual runoff is clearly and predominantly governed by the relative availability of water and energy, as reflected in the Budyko curve. Other factors that alter mean annual runoff, such as the seasonality of precipitation and potential evaporation, and vegetation cover or soil type/depth, produce mostly secondary effects. When focusing on seasonal runoff, however, the dominant control becomes seasonality of precipitation and potential evaporation and storage in the soils, groundwater and as snow and ice. When it comes to the flow duration curve in Chapter 7, the controls become more complex: apart from temperature and seasonality, which control the middle part of the flow duration curve, low flows are predominantly governed by recharge and geology, and high flows are governed by storminess (event) characteristics of precipitation as well as antecedent conditions. These factors, and others, impact the complete hydrograph, as discussed in Chapter 10.

The discussion in Chapters 5 through 10 also brings out the interconnectedness of the runoff signatures. In spite of the fact that each reflects a distinct characteristic of runoff variability there are overlaps, to the extent that understanding or prediction of one signature can contribute to the same for other signatures. For example, relative seasonality of water and energy inputs contributes to both the mean and inter-annual variability of annual runoff. Seasonality of runoff largely structures the within-year variability captured in the flow duration curve, and governs the magnitude of its slope. Seasonality, through its impact on both precipitation inputs and the antecedent soil wetness, is a key factor in the magnitude and timing of annual maximum flood peaks. For these reasons, seasonality forms a strong basis for catchment classification in several regions of the world.

The connection across all signatures can be best illustrated by the example of Austria. Figure 12.2 presents snapshots of the spatial patterns of the mean values of the six runoff signatures: mean annual runoff (Chapter 5), timing of runoff maxima (Chapter 6), slope of the flow duration curve (Chapter 7), Q_{95} as a measure of low flow (Chapter 8), Q_5 as an indicator of high flow (Chapter 9), and an integral time scale, used as a measure of runoff temporal variability (Chapter 10). They represent different aspects of the full range of runoff variability across Austria, through spotlights that focus on particular aspects (or time scales) of that variability.

In Austria, the spatial patterns observed in different flow signatures can be traced back to a fairly small subset of key processes, particularly the role of snow, the absolute volume of precipitation, the seasonality of precipitation and evapotranspiration, and the typical runoff dynamics (slow versus flashy).

For example, snow dynamics are responsible for summer maxima in runoff in western Austria, for the steep flow duration curves associated with runoff events in these areas, for the emergence of winter minima in low flows, and finally for the long integral time scales of runoff peaks (Blöschl, 1996). The large volumes of runoff in western Austria, however, relate not to snow but to the effects of orographic lifting of north-westerly airflows at the rim of the Alps, leading to precipitation rates of more than 2000 mm/yr. Precipitation is lowest in the lowlands of the east, and the contrast with the Alps is exaggerated by higher evaporation in the east. The role of evaporation in the east is in-phase with precipitation maxima in summer, leading to runoff maxima in spring, and summer low flow conditions.

The spatial pattern of floods is also closely related to the spatial pattern of annual rainfall. This arises from three causes, direct rainfall input at the event scale, antecedent soil moisture, and landform–hydrology feedbacks, which produce more efficient drainage networks in high rainfall areas (Blöschl and Merz, 2008a, 2010). Otherwise, the role of the catchment morphology and geology in shaping hydrological signatures is most obvious in the flow duration curve and the runoff hydrograph. Aside from snow-dominated areas, flashy locations are associated with convective precipitation and rapidly draining soils, arising due to the co-evolution of climate, landscape and soils (Gaàl *et al*., 2012); in these regions the integral time scale of runoff is short, and the duration curves are flat. Slow dynamics in the hydrograph also arise in regions with highly pervious geology (as in the south of Austria), and are also reflected in large low flows and small floods.

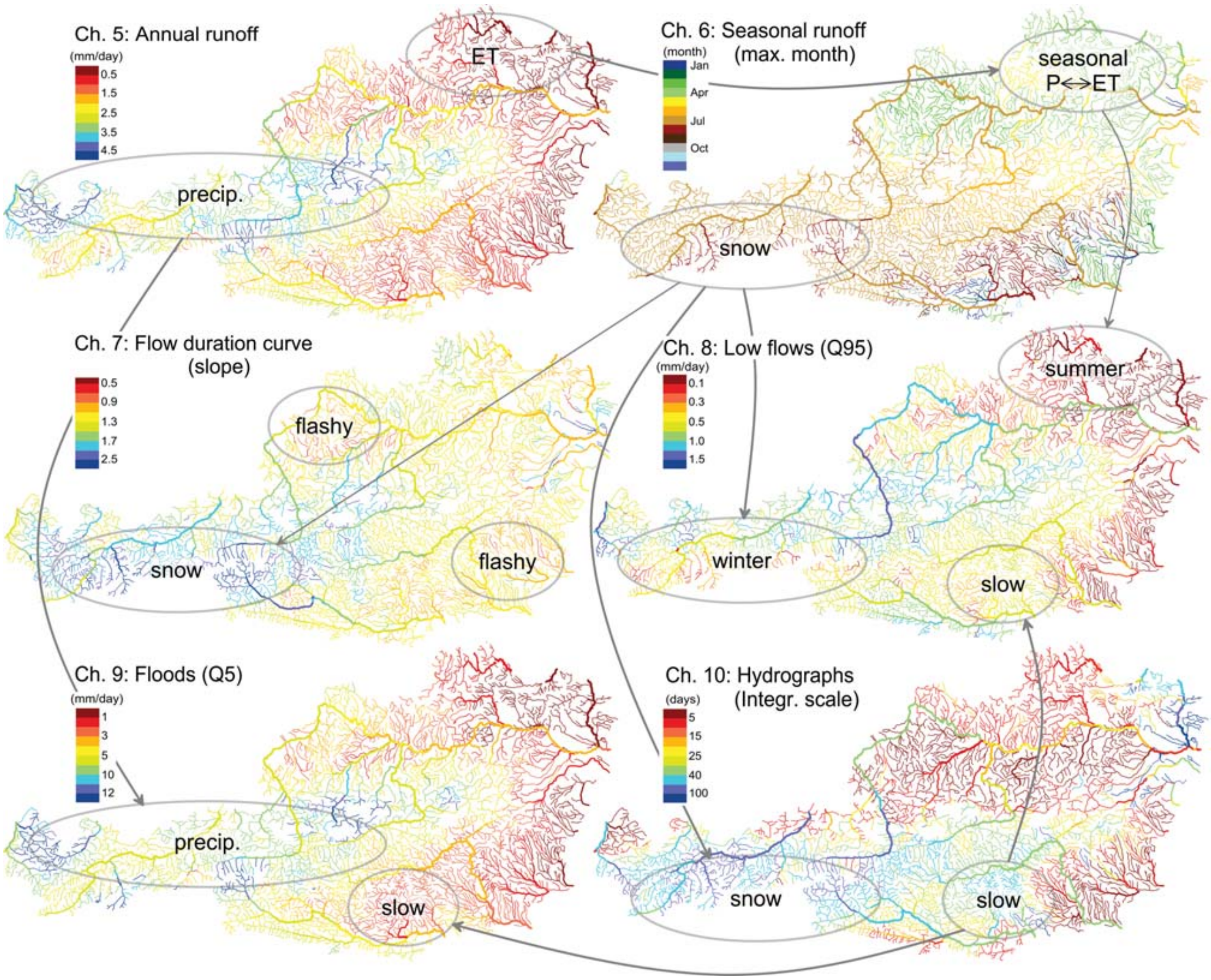

Figure 12.2. Connection of runoff signatures for ungauged basins (Chapters 5–10) illustrated for Austria. From Viglione *et al*. (2013b).

The fact that multiple runoff signatures in Austria respond to different individual process controls illustrates the complex connectivity between process and response. However, the connectivity of runoff signatures in other parts of the world is still richer. Whereas mountains and snowpacks control runoff variability in Austria, different factors dominate in other locations and climates. Runoff variability in the south-west of Western Australia, for example, is strongly governed by the seasonality of the Mediterranean climate, with cold wet winters and long dry and hot summers, and the presence of the Darling mountain range, whose combined effects are modulated by deep soils and deep-rooted Eucalyptus forests, giving rise to a rich regional runoff variability. Runoff variability across Sri Lanka, on the other hand, is governed by tropical monsoon climate, impacted by the north-east and south-west monsoons during different times of the year, which are modulated by orographic effects caused by the central highlands. There is thus a rich diversity of rainfall and runoff signatures around the island (see Figure 5.21, Chapter 5, for details).

How well can we predict the signatures, individually? Throughout the discussion of signatures in Chapters 5–10, an assessment of the performance of runoff prediction in ungauged basins was performed at two levels: Level 1 (L1) and Level 2 (L2). As mentioned in Chapter 2, the L1 assessments reported the average performance of distinct studies, without subdividing the studies on the basis of the size, extent, location etc. The L2 assessment assessed the performance of individual catchments. The sample size was larger in L1 than L2, with a wider range of climate and catchment characteristics, but the information provided for local catchments was more detailed in L2. In this section, we will classify and re-interpret the results of the

Table 12.1. *Method types used in the Level 1 and Level 2 assessments of Chapters 5–10*

		Ch. 5 Annual	Ch. 6 Seasonal	Ch. 7 FDC	Ch. 8 Low flows	Ch. 9 Floods	Ch. 10 Hydrographs
Level 1	number of studies	34 (40)	13 (26)	13 (25)	27 (29)	31 (49)	33 (75)
Level 2	number of studies	2	4	7	8	5	9
Level 1	number of catchments	12 141	643	1486	3200	3809	3554
Level 2	number of catchments	1081	1641	1419	2455	1740	1832
Level 1	methods used	statistical, process-based	statistical, process-based	statistical	statistical	statistical	process-based
Level 2	methods used	global regression	statistical, process-based	statistical, process-based	statistical	statistical	process-based

Level 1 refers to an assessment of the average performance of studies, Level 2 to an assessment of the performance for individual catchments. For Level 1/number of studies, the number of papers is given, and in brackets the number of results.

assessments to seek a deeper insight into the performances of predictive techniques.

About 25 000 catchments in 151 studies were analysed in the L1 assessment, and 10 000 catchments in the L2 assessment (Table 12.1). In most cases, statistical methods were used to predict runoff signatures in ungauged basins. Runoff hydrographs, however, were generally predicted with the use of process-based methods, such as conceptual rainfall–runoff models.

Figure 12.3 shows a summary of the cross-validation performance of runoff predictions in ungauged basins. For each of the signatures, assessment results from all studies and all methods were grouped together, and the 25% and 75% ranges from L1 and L2 assessment studies are shown separately. The results in the figure are all for blind tests, i.e., assuming no local runoff data were available. Overall, the L1 and L2 assessment results are consistent. However, there are some differences, which can be explained by differences in the selection of the catchments and/or performance measures used. For annual runoff the r^2 performance of the L2 assessment is lower than that of L1. This is because L2 is the aggregated result of a number of studies in different regions around the world, most of which were geared towards representing the particular characteristics of annual runoff in that region. L1, on the other hand, mainly consists of a global comparison where annual runoff was predicted globally with the same set of catchment characteristics, which yielded a lower performance than the dedicated studies. For seasonal runoff, the L1 results are from a mix of different performance measures, while in the L2 performance has been measured by the Nash–Sutcliffe efficiency (NSE) of the Pardé coefficients (i.e., mean monthly runoff scaled by mean annual runoff), which

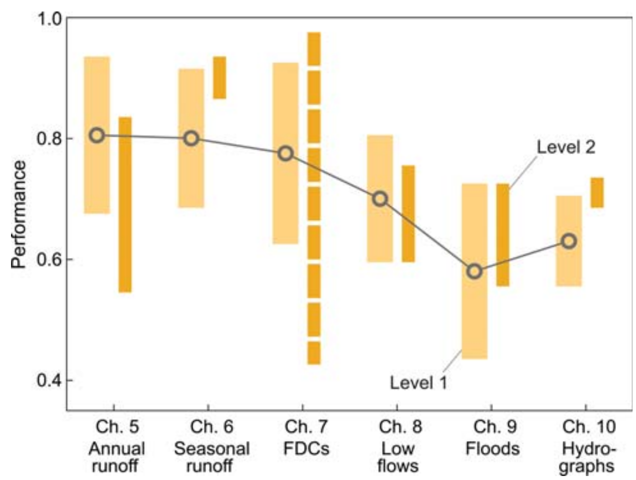

Figure 12.3. Comparison of cross-validation performance of prediction methods for different signatures. Ranges show approximate 25% and 75% ranges of results from Level 1 and Level 2 assesments. The figure is based on a total of about 25 000 catchments around the world. All are blind tests, i.e., assuming no local runoff data were available. Light orange bands: Level 1 (grey line is mid-point of the range for Level 1); dark orange bands: Level 2.

tends to be significantly higher than other performance measures. For flow duration curves, again, L1 is a mix of different performance measures, while in the L2 performance two measures were used: the NSE of the quantiles of the scaled flow duration curve which always gives results close to 1, and the R^2 of the slope of the flow duration curve which gave much lower values. The bar in Figure 12.3 is indicative that, in fact, the spread between the two measures found in L2 is even larger (see Section 7.5). For low flows, the results of L1 and L2 are fully consistent, as in both cases R^2 of specific Q_{95} low flows were used and the selection of the catchments was similar. Also, for floods, the results of L1 and L2 are consistent as in both cases R^2 of specific 100-year floods were used. However, in L2 there is a tendency to include studies with a larger number of catchments and longer runoff records, which explains why there are fewer studies with low performances. Finally, for the case of runoff hydrographs, there was a tendency to select studies with a large number of catchments with somewhat better NSE performance than in the case of L1. It should be noted that the ranges in Figure 12.3 do not represent the variability of performance between catchments but the variability of median performances of different studies. For hydrographs, the median performances of the L2 assessment are remarkably similar and vary little around 0.70.

How well can we predict signatures relative to each other? Figure 12.3 shows a decreasing trend in the quality of predictions as we move from annual runoff to seasonal to daily (FDC) time scales; low flows and the predictions of flood magnitudes were generally the poorest. The hydrograph predictions are somewhat better than those of the floods. The strength of the Level 1 and Level 2 assessments is that they cover a wide spectrum of processes, locations and methods, but this implies that the data set is quite heterogeneous as the climates, methods, data quality and observation periods differ between the signatures (Figure 12.3). Also, not all the performance measures are defined in exactly the same way. To help interpret Figure 12.3 and conduct a more consistent comparison across signatures, one consistent data set and one consistent method used in the chapters were selected to explore the relative performance of the predictions for each of the signatures. The method selected was top-kriging (a generalised version of kriging that accounts for river network structure) since it was assessed in most chapters. To enhance consistency the hydrographs were regionalised before the signatures were calculated, and the performance was assessed by cross-validation, in the same way it had been performed in all the chapters.

Figure 12.4 indicates that the performance is best for seasonal and annual runoff and runoff hydrographs, and is poorer for the prediction of low flows and floods. The higher predictability of mean annual runoff and seasonal runoff is due to the aggregation of runoff variation over a relatively long time period. They therefore vary more smoothly in space, which enhances their predictability. In contrast, low flows and floods are extremes. Extremes are generally harder to predict than averages, in part because they represent considerable process change, compared to the mean. Low flows are easier to predict than floods because droughts tend to persist over larger areas and

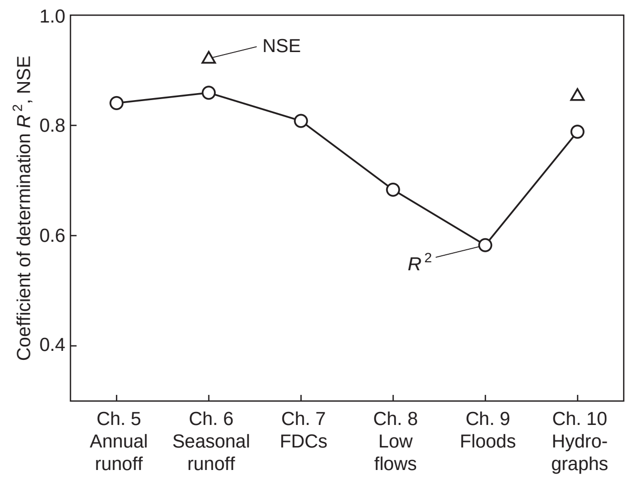

Figure 12.4. Same as Figure 12.3 but for Austria, to help interpret Figure 12.3, based on top-kriging of hydrographs as in Figure 12.1. Note: R^2 (open circles) for mean annual runoff, range of Pardé coefficient, slope of the flow duration curve, Q_{95} low flow, Q_5 high flow as a proxy for floods, runoff integral scale (i.e., measure of the average time lag over which runoff is correlated); median NSE (open triangles) for monthly runoff and daily runoff. From Viglione *et al.* (2013b).

longer time scales, making the estimation of low flows from other stream gauges in the area fairly robust. The Q_{95} low flow signature used in Chapter 9 is a less extreme runoff signature than the 100-year flood used in Chapter 9, and can be estimated more reliably from a runoff record of a given length, which may contribute to the better cross-validation performance. Although floods are not predicted well, runoff hydrographs can be predicted with some confidence. This is because most parts of the hydrographs are easy to predict. Although the extremes are harder to predict, the model efficiency metric treats all time steps with the same weight, reducing the impact of poorer predictive capacity for the flow extrema.

Due to their internal consistency, the model performances presented in Figure 12.4 can be used as a standard against which the assessment results of the book can be evaluated. Generally the pattern across signatures of the L1 and L2 assessments remains consistent with those presented in Figure 12.3. However, there are some subtle but important differences that shed light on the relative performance of the methods. The causes of the differences depend on the signatures:

- Annual runoff, seasonal runoff and flow duration curves: For these three runoff signatures the median performances of the L1 assessments (grey line in Figure 12.3) are somewhat lower than those of the Austrian data set (Figure 12.4). This is because L1 involves a number of studies with a lower stream gauge density than is available in

Austria. These differences highlight the importance of data for predicting runoff in ungauged basins.

- Runoff hydrographs: The L1 and L2 assessments give lower performances than those in assessment of the Austrian data (Figure 12.4). This is because the performance in Figure 12.4 has been obtained by a geostatistical regionalisation method that takes the stream network structure into account. The main difference between L2 and Figure 12.4 is in fact that the stream network structure is exploited by the geostatistical method, as the runoff model performance for the Austrian region is similar to those of the other studies in L2. This difference highlights the importance of including the stream network structure in predictive models of the runoff hydrographs.
- Low flows and floods: For these two signatures, the L1 and L2 performances are in fact higher than those in Figure 12.4, even though, again, there is a tendency for a lower stream gauge density in L1 and L2 than in Austria. This may be a surprising result but is in fact related to the method by which the low flows and floods have been predicted. In L1 and L2 targeted statistical methods were used to estimate floods and low flows. In the assessment of the Austrian data, however, the floods and low flows were computed as the extremes of a regionalised continuous runoff hydrograph. As discussed above, estimation of flow extrema from a hydrograph model that has been optimised for all values of the hydrograph tends to perform worse than using a different model that focuses on the extrema, and Figures 12.3 and 12.4 suggest that this is actually the case.

The distinction between the different methods of predicting flood and low flow behaviour highlights an important point: namely that improved hydrograph fitting should not necessarily be the ultimate or only goal of predictions in ungauged basins. Instead, methods must be optimised to predict specific signatures and their characteristics. In the Austrian example, a targeted method for floods gave significantly better performance (e.g. $R^2 = 0.76$, see Section 11.10) than those from the regionalised hydrographs ($R^2 = 0.58$) even though the hydrographs used to estimate these floods had a median regionalisation performance of NSE = 0.85, much better than most runoff models in L1 and L2. A detailed comparative approach focused on understanding individual signatures and how they are connected may provide more insights and eventually lead to better predictions than solely focusing on reproducing the full hydrograph.

12.2.2 Synthesis across places

Generic findings from chapters (non-assessment)

Because of the wide variety of runoff processes around the world, it is particularly challenging to overcome the fragmentation across places. To achieve synthesis across places, the notion of hydrological similarity has been used as a central theme throughout the book, to compare different catchments and landscape units, and to learn from the similarities and differences (just as medical practitioners pool information from many patients to examine differences and similarities). All regionalisation methods are based on the notion of hydrological similarity. This enables both model structures and model parameters to be extrapolated from gauged to ungauged catchments.

What makes two catchments similar, in terms of a particular runoff signature? In this book we have looked at the quantification of similarity in terms of runoff similarity, climate similarity and catchment similarity, each of which provides a particular view of hydrological similarity, and is therefore only an approximation to what we are looking for. One main underpinning of the concept of similarity is that the current state of any catchment is the result of the co-evolution of climate, soils, landscape and vegetation. Two catchments can be considered similar if they have followed similar trajectories of co-evolution, and are therefore functionally similar. The different parts of the system are configured similarly because they have undergone a similar history of co-evolution, and therefore their hydrological response is also likely to exhibit similar characteristics (e.g., runoff signatures). Almost all regionalisation methods use 'catchment similarity' to form catchment groupings, which then enables model parameters and model structures to be related to climate and/or catchment characteristics, leading to various ways to generalise the results (regionalise them) to ungauged catchments within the same homogeneous region.

There are two ways in which such similarity can be used. The first is in a lumped way, to use some overall index (e.g., aridity index), to determine if catchments are similar in some particular way (e.g., based on the process controls on the partitioning of precipitation). The signatures or model parameters can then be transferred across places. The second is in a distributed way, such that landscape units are considered similar if their *local* characteristics are similar, as is done in the topographic wetness index, or the topography-based classification of runoff mechanisms (Savenije, 2010), or in pedo-transfer functions (which are similarity relationships that relate texture to soil physical characteristics and are used to generalise from the measurement locations to the entire landscape). The L1 and L2 assessments were focused on catchment similarity in a lumped way only. Of course, it would be very useful to extend the assessment to include how the landscape similarity indices perform also, but this is left for future research.

Assessment of performance as a function of climate

A key element of this book has been a comparative hydrology approach to address the fragmentation of hydrological findings across individual case studies. Among other

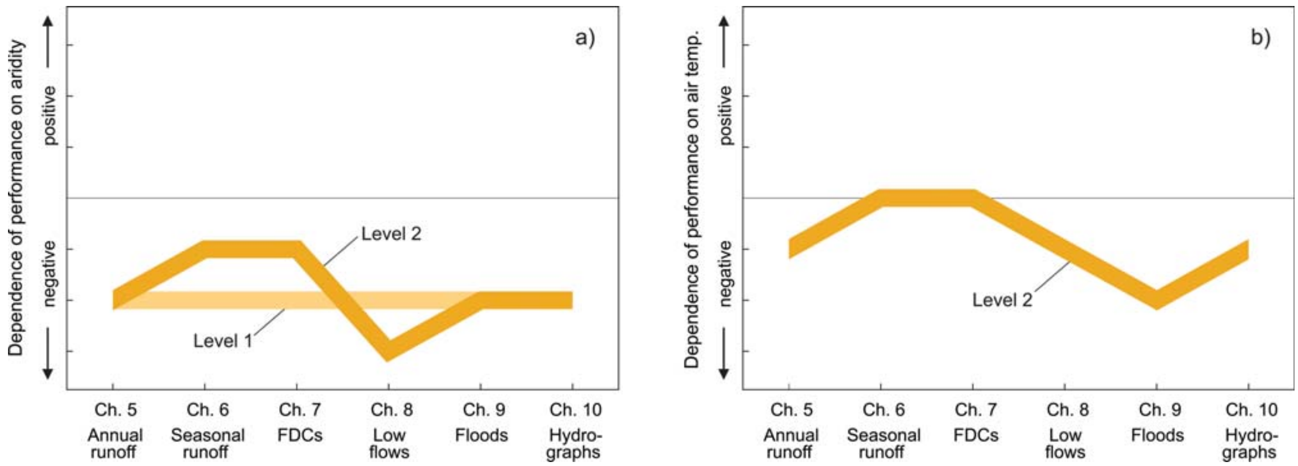

Figure 12.5. Dependence of cross-validation performance of runoff prediction methods in ungauged basins on (a) aridity index and (b) mean air temperature (Level 1 and Level 2 assessments from Chapters 5–10).

things, the comparative assessment aimed to understand whether general patterns exist beyond individual case studies and how well we can predict runoff in ungauged basins. Understanding the controls on performance will provide an opportunity to generalise the conclusions drawn from individual studies. Three climate-related controls – the aridity index, air temperature and topographic elevation – were examined. The figures in Chapters 5–10 were examined visually, and the dependence of runoff prediction performance on climate and catchment characteristics was classified as (either positive or negative) strong dependence, medium dependence, weak dependence or no dependence. Figure 12.5 summarises the dependencies for aridity and air temperature.

The aridity index (long-term ratio of potential evaporation and precipitation, averaged across the catchment) is an indicator of the relative availability of energy and water affecting the water balance (and therefore all runoff signatures). This dependence is clearly seen in Figure 12.5a. For all signatures, regionalisation performance decreases with increasing aridity index; this is true for both the L1 and L2 assessments. The dependence of performance on aridity is related to a number of factors. Most importantly, runoff processes tend to become more non-linear with increasing aridity (Atkinson *et al*., 2002; Farmer *et al*., 2003; Harman *et al*., 2011a). Consequently, runoff processes in arid climates tend to be more spatially heterogeneous than in humid or cold climates. Similarly, the temporal dynamics of runoff tend to be more episodic in arid climates. The relatively larger space-time variability of runoff then results in lower predictability in ungauged basins. Low flows have the strongest effect in the L2 assessment. This is because the low end of the runoff spectrum is very sensitive to climate, and low flows are particularly difficult to predict in arid regions. Overall, the consistency between the L1 and L2 assessments suggests that there exists a strong and consistent control of aridity on all runoff signatures, and that they can be generalised beyond the studies examined in this book.

Air temperature was expressed here as the long-term mean, spatially averaged across the catchment. In cold regions it is an indicator of the role of snow processes, which will, again, affect all runoff signatures. Of course, being strongly related to aridity, air temperature is not a fully independent variable. Figure 12.5 suggests performance can decrease with increasing temperature, but it depends on the signature examined. It is strongest for low flows, floods and runoff hydrographs. It appears that the existence of snow in a catchment leads to more regularity in runoff, thereby improving runoff predictions. This is particularly the case for hydrographs, as the model efficiency measure indicates how well temporal patterns of runoff are represented. This is also the case for floods. The flood statistics indicate that snowmelt-driven floods tend to be more predictable than other flood types. Similarly, for low flows in cold places, winter low flows related to snow storage are more predictable than summer low flows related to the interplay of precipitation and evaporation. For annual and seasonal runoff, the dependence is much less pronounced due to the averaging over longer time periods.

Topographic elevation, averaged over the catchment, is a composite indicator that reflects a range of processes related to elevation, such as long-term precipitation, soil moisture availability and air temperature. In some environments there will also be a relationship between elevation and aridity, and elevation and snow processes. The L2 assessments in Chapters 6–10 indicate that the effect of elevation on predictive performance is more complex than for aridity and air temperature. In many regions, predictive performance improves with increasing elevation because elevation is usually a surrogate for humidity (higher elevation corresponds to lower temperature and less energy and therefore higher humidity). In cold regions, the occurrence of snow is associated with high elevations. Both higher humidity and snow contribute to an improvement of prediction performance with elevation. However, there are other regions where the predictive performance in fact decreases with elevation, which may be related to an increase in aridity with higher elevation. Elevation therefore shows a complex pattern, which is more difficult to generalise because of varying co-dependencies among processes.

Generally, if the individual regions from the L2 assessments in Chapters 5–10 are examined, there is a tendency for better predictability when the runoff seasonality is strong and not so variable between years. This applies not only to predictions of seasonal runoff, but to other signatures as well, most notably the runoff hydrographs. In some parts of the world, seasonality is strong and predictable: this includes countries experiencing Mediterranean climate, or cold regions with a significant snowfall/snowmelt component. In both situations predictability tends to be higher across all signatures. On the other hand, in monsoon regions of the world (e.g., Asia, East Africa and northern Australia), where monsoons introduce strong seasonality, there is considerable inter-annual variability in the timing and magnitude of precipitation, which may actually reduce the predictability.

12.2.3 Synthesis across scales

Generic findings from chapters (non-assessment)

Hydrological processes occur at all scales, from microscopic water flow in soil pores to global-scale interactions of soil moisture and climate. The goal in this book is to predict catchment-scale runoff, which involves integration across spatial scales in some way. In the Newtonian context (see Chapter 2 for a detailed explanation), 'scale' stands for scaling from higher to lower spatial resolutions (upscaling) and vice versa (downscaling). Most of our understanding of processes is at relatively small scales (i.e., relative to the scales at which individual model elements are constructed), and yet predictions are needed at large (catchment) scales. The way we normally achieve such upscaling is to divide the landscape into different (subgrid) units, and use spatially distributed modelling methods (or other upscaling schemes that account for catena effects and other organised heterogeneity) to generate predictions at the larger scales. Scale also has an effect on the timing of runoff, since it determines the distance water has to travel. This is discussed in Chapter 4 in terms of transit time distributions.

Landscape characteristics, behaviour and dominant processes change with increasing catchment area. For example, headwater catchments tend to be steep (and so landslides are more common here), whereas flatland catchments are larger and tend to be dominated by groundwater aquifers, wide floodplains, frequent inundations etc. The two therefore exhibit very different behaviour patterns. With increasing catchment area new processes thus become dominant, in a manner that depends on climate. For example (see Chapter 2), in arid climates streams become 'losing' types (lose water to the underlying aquifer system, and/or to evaporation), while in humid climates streams tend to be 'gaining' types (are fed by water from adjacent aquifers). Such changes and transitions make catchment area a holistic similarity index (of the Darwinian kind) for runoff signatures. So, in the Darwinian context, scale or size can be viewed as a similarity parameter by itself, since it reflects the legacy of co-evolution of natural landscapes.

Another quality of scale is that data availability tends to increase with catchment size. Smaller catchments tend to be largely ungauged (see Chapter 3, Figure 3.1); as catchments get larger as one moves downstream, they are more likely to contain rainfall and runoff gauging stations, which contribute to improved model performance. Chapter 3 has proposed a hierarchical data collection approach that can exploit the trade-off between scale, data availability and costs. Global data sets provide more generalised information at lower costs to the individual user, whereas dedicated local measurements provide detailed information at high costs over small spatial scales. In this hierarchical data collection approach, one begins at the global scale and, depending on resources available, zooms in to different levels of detail at consecutively finer scales. When zooming in, a hierarchy of controls from climate to local catchment and anthropogenic effects become evident, and can therefore be deciphered.

On the other hand, distributed process-based models need large amounts of data, of the kind that generally tend to become less available with increasing scale. In fact, data such as soils and vegetation characteristics used for larger scale modelling tend to stem from regional databases compiled from both ground data and remote sensing data.

Performance as a function of catchment size

The comparative assessment of runoff prediction performance in ungauged basins in this book focused on the role of catchment scale as a similarity parameter. Again, the aim was to understand whether there are general patterns in

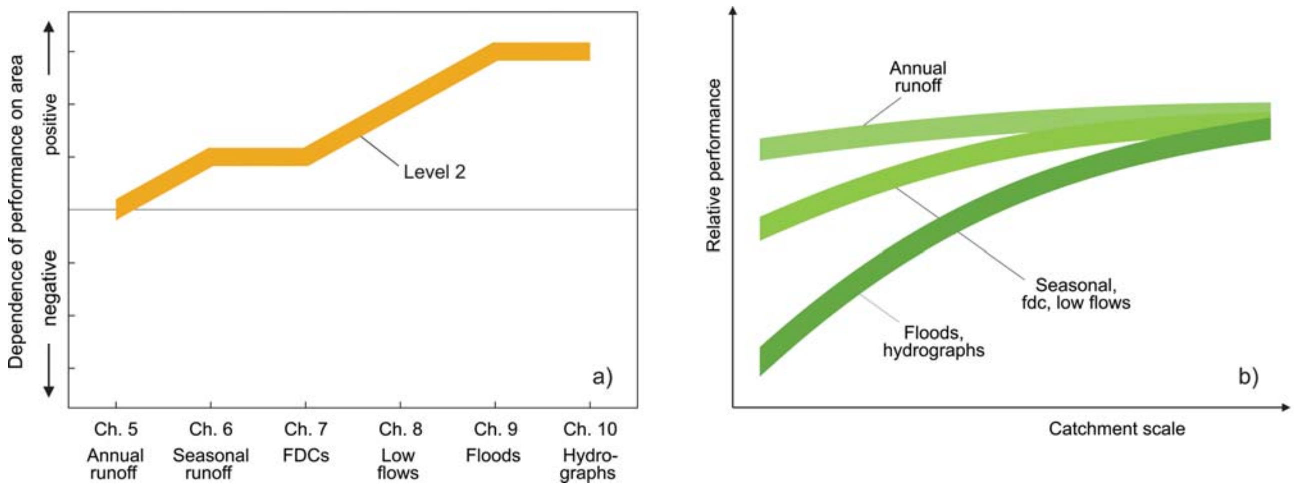

Figure 12.6. (a) Dependence of cross-validation performance of runoff prediction methods in ungauged basins on catchment area (Level 1 and Level 2 assessments from Chapters 5–10). (b) Schematic of how performance decreases with decreasing catchment scale (relative to large catchments).

how well we can predict runoff in ungauged basins that go beyond individual case studies.

Results from the assessment show that prediction performance increases with size of catchment for almost all signatures (Figure 12.6a). Two possible reasons can be attributed for this. First, larger catchments tend to produce smoother responses because, with increased area, the storage tends to be larger and causes an attenuation of small-scale variability, thereby increasing predictability. Second, larger catchments tend to have more observations that help to condition the predictions.

The degree to which performance depends on area differs between signatures. Floods, low flows and hydrographs show the strongest dependence. Area is important for floods because of the relatively short spatial scales of flood generating processes (depending on the event type), which affects the magnitude and timing of floods. The more extreme a flood, the stronger the attenuation with catchment scale because of the averaging of extremes (Sivapalan and Blöschl, 1998). The dependence is somewhat less for low flows because these tend to be large-scale processes of longer duration and have longer flow paths (Chapter 4). Because of the space–time connections of runoff processes, both spatial and temporal scales are reflected in the areal dependence. Area is less important for annual runoff, seasonal runoff and FDCs because they relate to larger time scales of aggregation. The areal dependence of runoff prediction performance is therefore strongly dependent on the runoff signature examined. The shorter the time scale of a signature, the smaller is the attenuating role of catchment storage and the stronger the dependence. This is illustrated schematically in Figure 12.6b.

Spacing of data and size of region with respect to natural variability

As mentioned above, the size of a catchment may impact predictive performance through the availability of data. In the context of regionalising runoff signatures, a key issue is how many stream gauges are available for estimating the runoff signatures in ungauged basins. The dependence of cross-validation performance on number of stream gauges per study from the L1 analyses is shown in Figure 12.7. For most signatures there is a positive dependence, i.e., performance increases with increasing number of stream gauges. This is not surprising, as more robust regionalisation estimates can be obtained with larger numbers of stations. An exception is the runoff hydrograph signature. Here, it should be noted that (in the assessment) hydrographs were estimated by process-based methods (using rain gauge data), while the other signatures were computed mainly using statistical methods. This may explain why the performance of runoff hydrograph estimates in ungauged basins is more dependent on number and quality of rain gauges (conditioned, of course, on the suitability of the model structure) than on the number of stream gauges in the region. Also, in the case of predicting hydrographs, the number of stream gauges was more closely related to the overall size of the study region than to the stream gauge density. One would expect that the performance of predicting hydrographs in ungauged basins will actually increase with increasing stream gauge density. This is illustrated in Figure 10.25 for a French case study. The relationship in Figure 12.7 encompasses all climates and catchment characteristics. The data of the assessment were not detailed enough to be stratified by climate/catchment

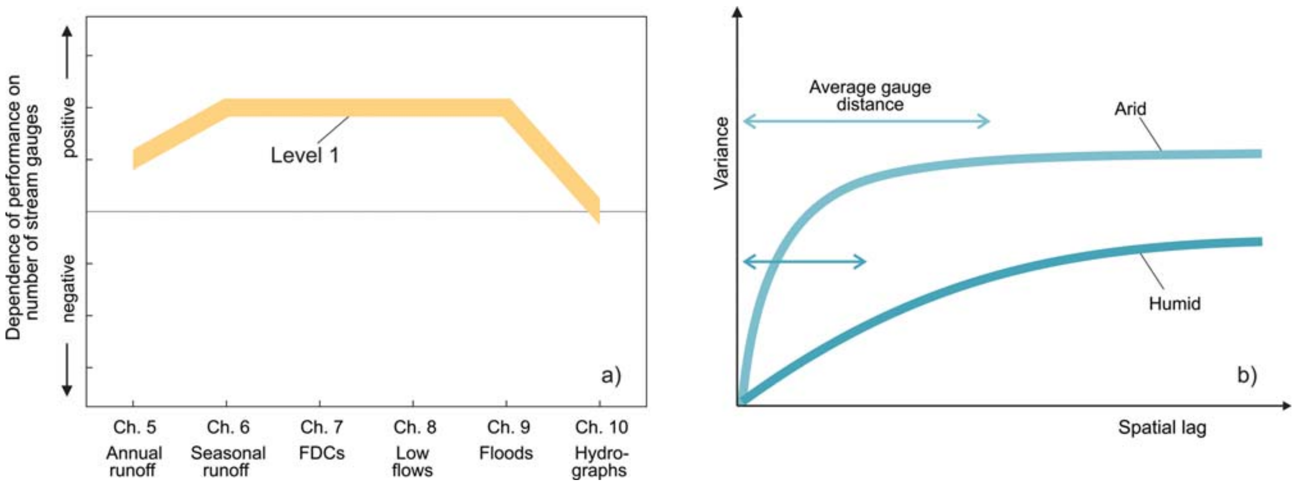

Figure 12.7. (a) Dependence of cross-validation performance of runoff prediction methods in ungauged basins on data availability (Level 1 and Level 2 assessments from Chapters 5–10). (b) Schematic of spatial hydrological variability (e.g., depth of runoff generation) versus distance between two points in a region. The schematic illustrates that arid regions tend to exhibit shorter spatial correlation and larger variability than humid regions, but the average distance of stream gauges tends to be larger.

characteristics. However, one would expect that the number of stream gauges (or stream gauge density) impacts differently on predictive performance in different climates.

In general, arid regions tend to have shorter correlation lengths and larger variability of runoff-related characteristics than humid regions, as illustrated in the variogram of Figure 12.7b. Arid regions would therefore need more gauges to capture the temporal and spatial variability, but achieving this is unrealistic in many arid parts of the world where (due to economic reasons) data density is typically lower than in humid regions. Methods that are able to exploit the specifics of the region would be needed here. Use of readily available landscape information, such as erosional patterns, based on the idea of reading the landscape (see Chapter 3), may assist in improving runoff predictions. Examples of the development of novel, low cost and creative approaches to deal with data scarcity are presented in the case study chapter (Chapter 11) for various climates and countries (India, Section 11.2; France, Section 11.13; Zambia, Section 11.14; Ghana, Section 11.15). As noted in Chapter 3, a balanced use of remote sensing data and local data, based on the local experience of hydrologists, can result in a useful strategy for predictions.

Overall, the comparisons indicate that runoff prediction performance is strongly related to runoff data availability and performance is lower in data-poor regions. Concerted efforts should therefore be made to increase the number and quality of stream gauges in data-poor regions. Installing a stream gauge is always the best option for determining runoff.

12.2.4 Inter-comparison of methods

Relative performance of different methods

The above analyses have examined general trends of prediction performance with respect to climate/catchment characteristics and data. This provides a general understanding of the controls on performance that goes beyond individual case studies. However, in the practical context of estimating runoff in ungauged basins the question is reversed. Here, one is interested in which method works best in a given setting. Do some methods naturally lead to better performance under specific circumstances? The assessments of Chapters 5–10 have addressed this question in the comparison of methods diagrams (red diagrams in Chapters 5–10). Table 12.2 provides a summary of these analyses indicating, for each signature, which two methods had the highest cross-validation performance for runoff predictions in ungauged basins. Table 12.3 shows the methods with lowest performance.

Comparing the best methods from the L1 assessment with the best methods from the L2 assessment, we find that (with a few exceptions) the results are almost identical. The same applies for the methods with lowest performance in Table 12.3. This important result indicates that the regions selected in the L2 assessment are indeed representative of the wider literature.

Overall, geostatistical methods that include consideration of river network structure seem to work quite well. These methods capture the way the landscape has evolved and how water moves through the landscape. However, geostatistical methods are data-based and work best when a dense network of stream gauges is available (they work less well when the network is sparse), which is not the case

Table 12.2. *The two methods with the highest cross-validation performance of runoff predictions in ungauged basins (Level 1 and Level 2 assessments from Chapters 5–10)*

Assessment	Catchments	Ch. 5 Annual	Ch. 6 Seasonal	Ch. 7 FDC	Ch. 8 Low flows	Ch. 9 Floods	Ch. 10 Hydrographs
Level 1	all	spatial proximity, regression	geostat, regression	short records, index	short records, geostat	geostat, index	∼
Level 2	all	index, regional regression	geostat, spatial proximity	geostat, regression	short records, process-based	geostat, index	similarity, spatial proximity
Level 2	humid	∼	geostat, spatial proximity	geostat, regression	short records, process-based	geostat, index	spatial proximity, similarity
Level 2	arid	index, regional regression	geostat, process-based		geostat, regional regression	geostat, regression	similarity, regression

Arid relates to catchments with an aridity index >1, humid to those with an aridity index <1.
∼ indicates more than two methods with similar performance.

Table 12.3. *The two methods with the lowest cross-validation performance of runoff predictions in ungauged basins (Level 1 and Level 2 assessments from Chapters 5–10)*

Assessment	Catchments	Ch. 5 Annual	Ch. 6 Seasonal	Ch. 7 FDC	Ch. 8 Low flows	Ch. 9 Floods	Ch. 10 Hydrographs
Level 1	all	process-based	process-based	regression	global regression	regression	∼
Level 2	all	global regression	process-based	process-based	global regression	regression	model average
Level 2	humid	∼	regression	process-based	global regression	regression	model average
Level 2	arid	global regression	regression, spatial proximity		global regression	index	model average

Arid relates to catchments with an aridity index >1, humid to those with an aridity index <1.
∼ indicates more than two methods with similar performance.

for ungauged (or poorly gauged) basins. Nevertheless, there is a message here for runoff prediction methods in ungauged basins. Many current statistical methods ignore the organisation of catchments by the stream network. They treat upstream and downstream catchments in the same way as neighbouring catchments that do not share the same catchment area. What are needed are methods that exploit the nested nature of catchments in a consistent way. A starting point for this may be the top-kriging approach to predictions in ungauged basins, as discussed in most of the chapters.

Regression methods generally perform less well than other methods in this assessment. In fact, regression is never found to be the best method. Why is this so? Regression methods hinge on the availability of predictors (climate and catchment characteristics) that are representative of the processes reflected by the runoff signatures. However, it has proved to be generally difficult to find useful predictors, in particular those that represent flow paths and storage characteristics of catchments. Very important parts of the hydrological activity take place underground (whereas available descriptors tend to be for the surface landscape), which may help explain why regression methods do not work as well as other methods. Clearly, a worthwhile research goal is to find ways to develop more informative predictors at the catchment scale.

In keeping with the above paragraph, global regression generally has much lower performance than regional regression. This is, arguably, because it imposes the same model structure everywhere, whereas regional regression allows for different predictors and coefficients in different parts of the region.

Overall, the reviews of Chapters 5–10 reveal a tendency for the selection of predictors by optimising the correlation coefficient between the runoff signature and the predictors. We suggest that this may not always be a good choice, and instead hydrological understanding of relevant controls should be used to guide selection of predictors (along with the statistical analysis) and, importantly, in interpretation of the coefficients found to fit the regression model well. This interpretation should involve consideration of co-evolutionary processes such as landscape evolution and the stream network characteristics.

The reviews also suggest that the index method has received more recent attention than the regression method. Each index method hinges on an underlying principle, e.g., the use of the aridity index in the Budyko method for predicting annual runoff. The assessment suggests that index methods work fairly well, a good example being the Budyko method for predicting annual runoff. Also, the index methods for flow duration curves and floods appear among the top-ranked methods. This suggests that the notion of hydrological similarity, based on universal principles such as the Budyko curve, may have value for predictions of runoff in ungauged basins. It seems that much can be learned by representing regional patterns in a way that leads to questions about the co-evolutionary principle(s) underlying them. The key is to represent information in a way that reveals possible universal relationships. This can then lead to better understanding of the signatures, including their best predictors and how they have arisen through co-evolution.

The need for greater synthesis

The assessment has not been very conclusive with regards to the comparison of process-based versus statistical methods. There is very little literature on consistent comparisons of this type. However, the literature reviews in Chapters 5–10 do suggest that for those signatures where traditionally the focus has been on the statistics much interest now resides in developing process-based methods and, conversely, for those signatures where process-based methods have been the norm new statistical methods of predictions in ungauged basins have been developed. In Chapter 5, there has been a major move towards index methods such as the Budyko method. The general conclusion in Chapter 6 is that we must move on from mapping approaches to invoke more process-based methods. The general conclusion in Chapter 7 and Chapter 8 is that prediction methods in the future must use process understanding in the regionalisation of flow duration curves and low flows. In particular, the conclusion is that more process-based methods that account for flow paths would lead to better predictions of low flows. The message in Chapter 9 is that process-based methods are useful but must be balanced by regional mapping and other Darwinian approaches.

In other words, there is now the recognition that a synthesis of process-based and statistical approaches is necessary to improve predictions. Chapter 9 highlights the benefit of learning from a synthesis of all relevant information in the landscape, a notion termed flood frequency hydrology. In Chapter 10, the new approaches are geostatistical methods that make explicit use of the stream network structure. Overall, the general trend is that predictions of some signatures where the best prediction methods are statistical could benefit from more process-based methods (this is the case for Chapters 5, 6, 7 and 8), while prediction of signatures where more process-based methods are being used could benefit from the use of statistical approaches. This suggestion about the value of a synthesis of statistical and process-based approaches to improve predictions is equivalent to a call for a synthesis of Newtonian and Darwinian approaches.

There are two different types of process-based approaches: (i) physics-based distributed models based on laboratory-scale equations, and (ii) conceptual, input–output models, with index-type models falling somewhere in between. In general, mechanistic models surveyed in the book are used mostly in groundwater, or mixed groundwater–surface water applications. Formal comparative assessments for mechanistic distributed models are rare, perhaps because these models are most data hungry, and setting them up for a particular catchment is labour intensive, involving numerous subjective decisions regarding model parameterisation; repeating this in many catchments at the same time poses enormous difficulties. On the other hand, most runoff models used for predictions in ungauged basins use conceptual (top-down) lumped models. Our comparative assessment has been for this latter case only. While a few inter-comparisons of distributed (mostly conceptual) models have been reported (notably the Distributed Model Inter-comparison Project, DMIP; Smith *et al*., 2004b; 2012), it appears that the biggest missing element in Chapter 10 is a performance assessment of distributed (mechanistic) process-based (Newtonian) models for ungauged basins. The purpose of such an inter-comparison would not be to ascertain which model or model group is preferable, but to learn from the differences in model behaviour in different catchments.

Dependence on climate

Since there exist important dependencies between predictive performance and climate, one would also expect that some methods work better in a given climate, while other methods may work better in another climate. From the L2 assessment, for most of the signatures, there are indeed clear differences between catchments in arid and humid climates (see Tables 12.2 and 12.3). Annual runoff in humid climates tends to be better predicted by the Budyko (index) method than by regression, while the converse is true of arid catchments. This may be because local soil characteristics and vegetation patterns may be more important in arid catchments than climate, and regression methods can better accommodate this. Similarly, seasonal runoff in humid climates tends to be better predicted by spatial proximity methods than by regressions, while the converse is true of arid catchments. Because humid catchments tend to be more spatially homogeneous than arid catchments, spatial proximity may be a better indicator of similarity. In humid climates, low flows tend to be better predicted in the presence of short records, while this is not the case in arid regions. This is because climate tends to be less variable in humid regions and short runoff records may be more representative of the runoff variability, while for arid regions this is not the case. In the case of floods, the index method does not work well in arid regions. Again, this may be related to the relatively much larger spatial heterogeneity, which makes the assumption of spatially uniform growth curves less suitable. In humid regions, hydrographs are predicted well by spatial proximity methods, but in arid regions the performance of the spatial proximity methods is much lower, again pointing towards the differences in spatial hydrological heterogeneity between humid and arid regions.

Overall, in humid regions, there is a tendency for proximity-based methods to work better than regression. In contrast, regression tends to work better than spatial proximity methods in arid regions. This is illustrated in Figure 12.8. This pattern should be expected, because arid regions tend to be spatially more heterogeneous, as illustrated in Figure 12.7b. It should be emphasised, however, that these are schematic trends, and for individual case studies one would expect a lot of variation about these trend lines.

Patterns from comparative hydrology
The comparative assessment has shown distinctive patterns of runoff prediction performance as a function of processes, places and scales. The comparison revealed consistent patterns of the relative performance of predictions of different runoff signatures across the Level 1 and Level 2 assessments. The comparison also showed that, for all runoff signatures, there are clear dependencies of the performance on aridity. The patterns were more complex for air temperature and catchment elevation but could be interpreted in the context of the hydrological processes. Furthermore, the comparison provided consistent results

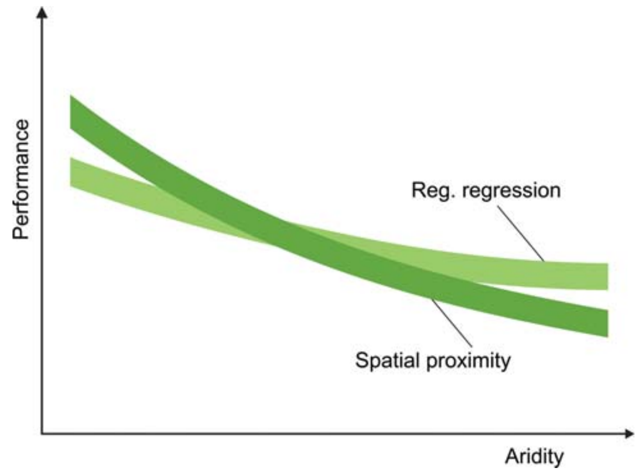

Figure 12.8. Schematic of how performance of predicting runoff signatures decreases with decreasing aridity for different regionalisation methods based on the assessment in this book.

of the effect of data availability on the predictive performance. The fact that consistent patterns were obtained by comparing a large number of catchments in different continents suggests that the comparative hydrology approach can be profitably used for generalising findings beyond individual case studies.

12.3 Synthesis of Newtonian and Darwinian frameworks

12.3.1 Evidence for co-evolution

Why is it that some methods work better in some places, and not in others? As anticipated in Chapter 2, this book advances the idea of catchments as 'organisms', and advocates that they be studied as 'complex systems'. The idea of catchments as organisms that have reached their current state through co-evolution naturally points towards the notion of emergent patterns, at the catchment scale, which reflect the history of co-evolution and provide insights into or reflect catchment scale responses, as manifested in the runoff signatures. The implications for predictions, in a geomorphological context, has been brilliantly expressed by Haff (1996), who noted:

> In large geomorphic systems, the construction of successful predictive models is likely to be based upon discovery of emergent variables and a corresponding dynamics, rather than upon scaling up the results of well-controlled laboratory-scale studies;

a notion also discussed by Harrison (2001) and others. Indeed, unlike in hydrology, there is in fact a long tradition of recognising co-evolution and applying comparative approaches in a number of earth sciences such as geomorphology and pedology, as also illustrated by the soil catena concept of Jenny (1980), for example. In hydrology,

Table 12.4. *Examples of Newtonian and Darwinian (co-evolutionary) similarity measures/predictors for the runoff signatures*

Similarity measures/ predictors	Ch. 5 Annual	Ch. 6 Seasonal	Ch. 7 FDC	Ch. 8 Low flows	Ch. 9 Floods	Ch. 10 Hydrographs
Newtonian	annual precipitation	air temperature, subsurface storage	air temperature, geology	precipitation, air temperature, geology	event characteristics, soil characteristics	soil characteristics, wetness index
Darwinian (co-evolutionary)	area, aridity, drainage density, vegetation	vegetation cover, phenology	aridity, hydraulic channel geometry	riparian vegetation, wetlands	mean annual precipitation, drainage density	aridity, hydrological landscape units

the Newtonian approach has remained the dominant paradigm since Freeze and Harlan's (1969) blueprint of a physically based model. Several pieces of evidence taken from this book show the value of the Darwinian approach in catchment hydrology and PUB. These are presented next.

Newtonian vs. Darwinian (co-evolutionary) similarity measures/predictors from the book

The most important evidence is probably the similarity measures discussed throughout the book. These similarity measures are also predictors of runoff in ungauged basins. They fall into two categories. The first type is based on the Newtonian paradigm of invoking direct causality; an example is the topographic wetness index of Beven and Kirkby (1979) that is based on the local competition of recharge and drainage mediated by Darcy's law (Table 12.4). The second type does not start from causality based on local- or small-scale equations, but arises from the treatment of the catchment as a complex system in which Darwinian (co-evolutionary) similarity measures are found or chosen that account for the diverse feedbacks between hydrology, climate, geomorphology, soils and vegetation (Table 12.4).

In the case of annual runoff (Chapter 5), the aridity index appears to be the clearest similarity measure, and therefore predictor, through the Budyko relationship. Aridity is thus a similarity measure of the Darwinian kind. As annual runoff is the foundation of all runoff signatures, aridity was also found to be useful in analysing all other signatures in terms of comparative performance. In discussing seasonal runoff (Chapter 6), the main similarity measures used (such as air temperature, or elevation as a proxy) are Newtonian, but vegetation cover and phenology may provide the basis for Darwinian type similarity measures. The use of Chernoff faces as a way to classify seasonal flow regimes (as seen in Chapter 6) is another indication that the holistic view of catchments as co-evolved objects is not rare in the literature. While Chapter 7 uses Newtonian similarity measures such as geology, an interesting Darwinian measure would be the hydraulic channel geometry, at-a-site and downstream, as it is indeed the result of the co-evolution of runoff along with the development of the stream network itself. Predictors of low flows (Chapter 8) depend on whether we are dealing with winter or summer low flows, so a first-order similarity measure is one that is able to discriminate between the two (such as air temperature, or elevation as a proxy). Storage, while hard to quantify, is a Newtonian index. Interestingly, the observation that low flow recession is often log-linear may, in fact, be a result of co-evolution, and can be used to predict low flows in the case of persistent droughts. Floods (Chapter 9) have particularly interesting Darwinian similarity measures because of the strong evolutionary interactions between floods, the landscape and soils. Mean annual precipitation is an excellent predictor of flood frequency, almost always much better than event-scale extreme precipitation. From a Newtonian perspective this is counterintuitive, but from a Darwinian perspective it is not. In many climatic regions (in particular humid regions) mean annual precipitation may be a good predictor because of a close correlation with extreme event-scale precipitation, antecedent (seasonal-scale) soil wetness, and (decadal-scale) evolutionary interactions with the landscape and soils. Other important Darwinian type similarity measures are catchment area and the stream network density. Out of all the runoff signatures, the case of floods provides the clearest sign that co-evolution is indeed operative and that the resulting emergent patterns can be used to make predictions. For runoff hydrographs (Chapter 10), Newtonian predictors such as soil characteristics estimated through pedo-transfer functions are used, but their areal representation in terms of hydrological response units is a Darwinian way of breaking up the landscapes into parts where similar hydrological processes operate as a result of co-evolution.

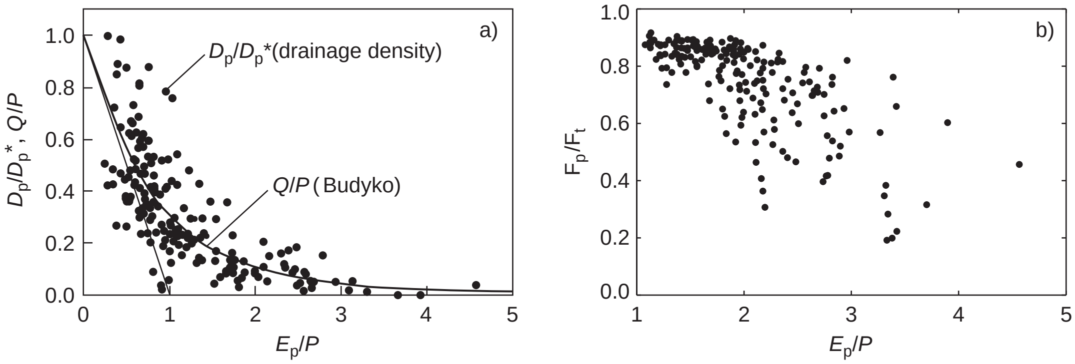

Figure 12.9. (a) Perennial stream density (D_p) normalised by its maximum D_p* versus aridity for 185 catchments in the USA (points) compared to mean runoff coefficients from the Budyko curve (line). From Wang and Wu (2012). (b) Ratio of deep-rooted vegetation to total vegetation versus aridity for 193 catchments in Australia. Adapted from Xu *et al*. (2012).

Studies from the literature in support of evidence for co-evolution

The idea of catchments as organisms that have reached their current state through co-evolution naturally points towards a comparative hydrology, with differences between different catchments and regions being seen as a manifestation of the different trajectories of co-evolution they may have followed. Therefore, there is much to be learned from the study of the similarity and differences of catchments, including the differences in the underlying controls, as these can ultimately help us to make improved predictions.

In the same way as the Budyko curve represents how the co-evolution of climate, soil, vegetation and topography explains annual runoff, the drainage patterns evident in the landscape can also be seen as a Darwinian pattern. On the one hand, drainage density determines the amount and timing of runoff generated by a catchment. On the other hand, it is the result of the processes whereby runoff is generated, and is hence governed by both the water balance at a range of scales and the vegetation patterns that develop. Wang and Wu (2012) pointed out the symmetry between water balance and drainage density patterns. They plotted a scaled drainage density in catchments across the USA (data taken from the National Hydrography Dataset) against the aridity index (Figure 12.9a) and found that density strongly decreases with aridity (for very arid places, the scaled drainage density is low). There are, apparently, feedbacks between climate, hydrology and landscape-forming processes that lead to the good explanatory power of aridity. The interesting point of their comparison is that their relationship between scaled drainage density and the aridity index is, in fact, very similar to the relationship between the annual runoff coefficient and aridity index (Figure 12.9). A similar study for the case of vegetation (Xu *et al*., 2012) found that the ratio of deep-rooted vegetation to total vegetation decreased with aridity (for very arid places, most vegetation is shallow rooted, see Figure 12.9b). Again, co-evolutionary feedback processes appear to be involved, causing different plant species to grow in response to climate patterns, which in turn affect the water balance of the catchments. These two examples illustrate that co-evolutionary feedback processes may be very relevant for hydrology at large. In general, there are three co-evolutionary features – runoff, drainage density and vegetation cover – and they all appear to be interconnected.

12.3.2 Comparative hydrology and the Newtonian–Darwinian synthesis

As indicated at the beginning of this book (Chapter 1), our goal here has been to carry out a synthesis based on studies of predictions in ungauged basins, by organising it along processes (runoff signatures), places (climate gradient) and scales (catchment area and data richness). Interesting patterns have emerged through this synthesis. In particular, the comparative analyses of prediction performances and their hydrological interpretation have indicated strong elements of both the Newtonian and Darwinian approaches to be applicable to predictions in ungauged basins (PUB).

When signatures are explored from a mechanistic or process perspective, exploring their process controls as a way to assist in their prediction, this represents the best aspects of the Newtonian approach. In this case, we follow the cascading of the variability in the climatic inputs through the catchment system, through interactions with the heterogeneity and structure of the catchment system, in this way contributing to process complexity and richness, and manifesting in the runoff variability that we see in the observed records. When this is repeated in several places, and assessed comparatively, this can contribute to a generalisation of our understanding of runoff variability. On the other hand, by performing comparative assessment of various prediction methods in a synoptic manner, across a population of catchments in a region or around the world, identifying the key predictors, and exploring their relative performances, we gain insights that help build generalised understanding into the behaviour of catchments, in a most Darwinian sense.

The power of the Newtonian approach derives ultimately from the fact that it is based on Newtonian mechanics, universal balance laws of mass, momentum and energy for simple systems with a clear causality. Specifically in hydrology, it benefits from the understanding gained of individual processes. While the Newtonian approach can be carried out both locally and spatially (e.g., by comparing predictions of distributed models with observed spatial patterns), for logistical reasons any new insights are gained from one or more local process studies. It will continue to gain predictive power through advances in observing and understanding processes, including through detailed observations at all scales, and improved theories to handle landscape heterogeneity and the complexity of flow pathways and residence times.

In contrast, the Darwinian approach recognises that catchments are complex systems that have co-evolved from the interplay of climate, landform, vegetation, soils and geology. It is much harder to learn about Darwinian systems from a single location; there is too much complexity. A viable approach to shedding light on complex systems is a comparative hydrology approach that contrasts different catchments in different regions around the world to learn about the processes of co-evolution. Thus, the Darwinian approach is synoptic, amenable to generating generalised understanding about the co-evolution of catchments, through comparative studies along climatic, geological and other gradients. Interestingly, Chapter 6 presented examples of two schools of thought in respect of seasonal runoff: the geographic, which focuses on classifying seasonal runoff into regime types and mapping them across the landscape, and the engineering, which focuses on quantitative estimation and is generally place-based. They are both valid approaches, and reflect competing paradigms, the Newtonian and Darwinian.

Of course, each paradigm has strengths and weaknesses. The Darwinian learns from contrasting different regions and interprets them in terms of the processes across many time and space scales. It allows for the results of feedback processes in the landscape, for co-dependencies and adaptive processes. However, because of the complexity, causality may not always be as clear as in the Newtonian approach. On the other hand, the power of the Newtonian approach is in explicitly including cause–effect relationships, but it quickly loses effectiveness in making general predictions by not being able to account for process interactions, feedbacks and parameter co-dependency that one invariably finds in natural co-evolved catchments. Therefore, a synthesis of both paradigms (see Figure 12.10) would help to advance hydrological prediction in a way that brings out the benefits of both, while overcoming their weaknesses (Harte, 2002). The synthesis may gain potency through a combination of simple causality and complex co-dependencies. For example, Gaál *et al.* (2012) illustrated how the comparison of catchments of contrasting characteristics can help to recognise the combined effect and interplay of flood processes on the landscape. They showed that, in one region, landform had adapted to the flashiness of floods, producing efficient drainage networks, which in turn enhanced the flashiness of the flood response. In other regions, tortuous drainage networks have evolved, which in turn retarded the flood response and impeded the evolution of an efficient drainage network. This is a result not likely to have been discovered by the Newtonian approach.

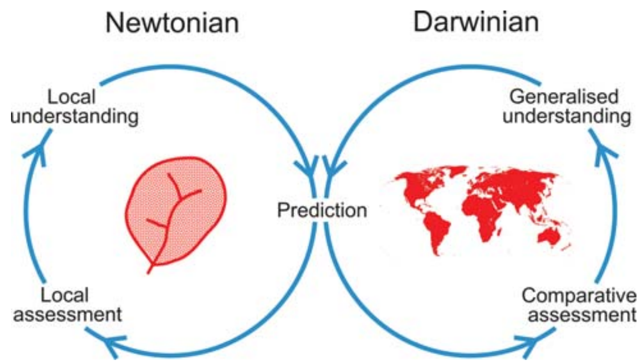

Figure 12.10. Synthesis of the Newtonian and Darwinian approaches through understanding, prediction and assessment.

The notion of a Newtonian–Darwinian synthesis has been a recurring theme right through the PUB decade (Sivapalan, 2003a, 2005; Sivapalan *et al.*, 2003; McDonnell *et al.*, 2007) as the possible framework to overcome the major challenges facing hydrological predictions and as the possible foundation for a new theory of hydrology at the catchment scale. This received a fillip through the Hydrological Synthesis Project of the US National Science Foundation (Sivapalan *et al.*, 2011b), and these ideas are further reinforced through the outcomes of the synthesis carried out for this book. Throughout the book, the analyses of prediction performances have indicated strong elements of both the Newtonian and Darwinian approaches to predictions in ungauged basins.

As we study differences in behaviour between catchments as legacies of co-evolution, the goal is to discover patterns and connections. The Budyko curve is the best example of an empirical co-evolutionary pattern, which remains to be deciphered at a fundamental level. When we combine it with related drainage density patterns (Wang and Wu, 2012), vegetation patterns (Xu *et al.*, 2012), and soil and vegetation catena effects (Hwang *et al.*, 2012), one is tempted to ask if there are deeper organising principles in action. Hydrologists have been

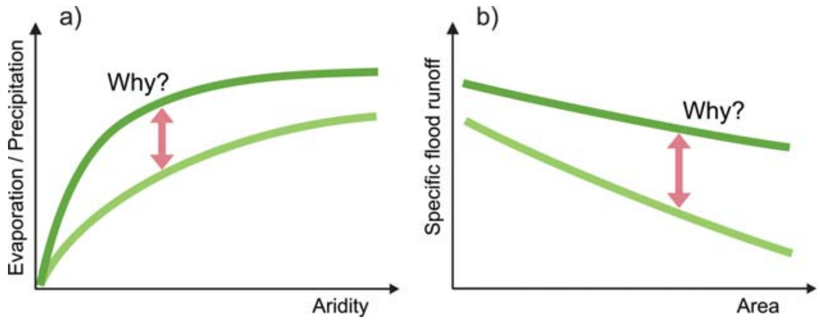

Figure 12.11. Comparative hydrology based on Darwinian concepts consists of exploiting the differences between regions to learn from them. (Left) Differences in the Budyko curve between regions. (Right) Differences of flood frequency scaling with area between regions.

interested in such questions for some time, and several candidate principles have been explored in different contexts, most of which take the form of optimality principles. Examples include minimum energy expenditure (Rodriguez-Iturbe *et al.*, 1992), ecological optimality (Eagleson, 1982), vegetation optimality (Schymanski *et al.*, 2009), maximum entropy production (Kleidon and Schymanski, 2008) and maximum energy dissipation (Zehe *et al.*, 2010). The search for the organising (Darwinian) principles is especially crucial to dealing with change, both climate change and human-induced land use and land cover changes (Schaefli *et al.*, 2011). Change predictions must account for not only simple (short-term) process changes but also more complex process interactions and feedbacks, such as metabolic processes. Simple Newtonian models will not be able to account for the likely trajectories of co-evolutionary change unless we constrain the degrees of freedom through some external principles. A search for organising principles must therefore underpin the Newtonian–Darwinian synthesis.

Moving from regionalisation to comparative hydrology

Regionalisation approaches to improve hydrological predictions using spatial data and concepts of similarity have been in use for decades, and are illustrated in this book through hundreds of examples. The Darwinian approach applied in this book also uses spatial data and similarity concepts, but the two approaches do this in a very different way. Regionalisation exploits the *similarity* of catchments within a region to improve predictions. In contrast, comparative hydrology exploits the *differences* between catchments in different regions to develop generalised understanding about the causes and controls that lead to these differences.

Regionalisation aims to combine local (at site) information and regional information to advance predictions. A typical example of the combination of local and regional information for the case of flood frequency analysis is the empirical Bayes approach (Kuczera, 1982). The method uses information from hydrologically similar basins to improve upon inference at a particular basin and is based on the concept of a super-population. It can lead to substantial improvements in performance over site-specific methods if the region is homogeneous in some sense. There has been significant progress during the PUB decade in regionalisation approaches that pool hydrologically meaningful information in the form of runoff signatures from neighbouring catchments to constrain parameter estimates and reduce predictive uncertainty (see e.g., Yadav *et al.*, 2007; Merz and Blöschl, 2008a, b; Bulygina *et al.*, 2009; Wagener and Montanari, 2011). Ultimately, the focus of such regionalisation efforts is improved prediction.

The synthesis of the Newtonian and Darwinian approaches based on comparative hydrology that we advocate here is different. Let us consider the Budyko curve (Figure 12.11a). A comparative hydrology approach would focus on *how* the Budyko curve comes about and *why* it differs between regions. By contrasting the Budyko curves between different regions their differences can be recognised (e.g., Wolock and McCabe, 1999, Chapter 5) and Newtonian approaches (such as process-based modelling of the atmosphere–vegetation–land interactions) may be brought to bear to help understand these differences in terms of co-evolutionary processes (e.g., drainage density, vegetation patterns etc.). Another example is the scaling of flood frequency with area (Figure 12.11b). A comparative hydrology approach would focus on *how* the flood frequency scaling comes about the way it does, and *why* it differs between regions (e.g., rain-fed and snowmelt-fed regimes). Again, by contrasting different regions the differences in the scaling can be detected and Newtonian approaches (such as derived flood frequency) may be invoked to help understand these differences in terms of co-evolutionary processes. Therefore, the goal is to develop generalised understanding.

Studies from the literature to illustrate synthesis of Newtonian and Darwinian approaches

While the synthesis of Newtonian and Darwinian approaches is a new paradigm, there are already a number of early examples that have led to improved understanding of co-evolutionary processes, and give us confidence that this is an

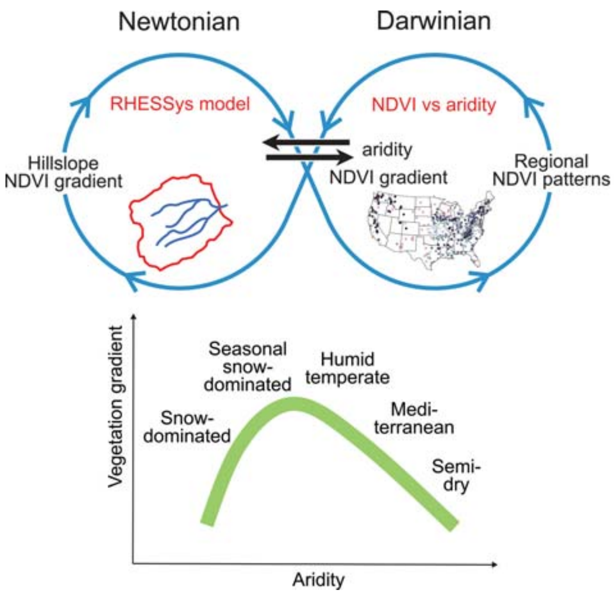

Figure 12.12. (Top) Synthesis of the Newtonian and Darwinian approaches, Coweeta, USA. (Bottom) A postulated relationship between vegetation gradient and aridity. Bottom graph redrawn from Hwang *et al*. (2012).

avenue well worth pursuing. In a comparative approach Hwang *et al*. (2012) focused on *why* long-term spatial development of forest ecosystems is different in different places. They sought guidance from regional work done by Troch *et al*. (2009), Brooks *et al*. (2011) and Voepel *et al*. (2011), with the use of over 400 catchments across continental USA. This work had shown a strong empirical, co-evolutionary (Darwinian) relationship between the Horton index (a form of aridity index focused on vegetation water uptake) and remotely sensed vegetation at the catchment scale (e.g., normalised difference vegetation index, NDVI). Within the Coweeta experimental catchment in North Carolina, Hwang *et al*. additionally found strong correlations between the Horton index and downslope gradient of the NDVI, and attributed this to a topographically driven, downslope groundwater subsidy. They then used extensive local hydrological observations, combined with simulations with a distributed ecohydrological model, RHESSYs (Band *et al*., 1993; Tague and Band, 2004), to characterise the patterns of seasonal flow regimes (Newtonian approach), interpret them in terms of ecohydrological processes and feedbacks occurring in forested headwater catchments, and to explore the role of downslope vegetation gradient in these interacting processes (Darwinian approach). On the basis of the understanding gained in this way, Hwang *et al*. had the foresight to postulate a new regional (and possibly global) relationship between the Horton index and downslope vegetation gradient that extends beyond the environmental conditions found in North Carolina (see Figure 12.12). Of course, this remains to be tested with additional work in the future. However, their work does illustrate the power to formulate globally generalisable relations through a combination of the Newtonian and Darwinian approaches.

12.3.3 A new unified uncertainty framework for PUB

Traditional uncertainty quantification

The traditional paradigm of uncertainty estimation in hydrology has been the method of ‘error propagation’ (e.g., Kuczera and Parent, 1998; Montanari and Brath, 2004; Liu and Gupta, 2007), and work on predictions in ungauged basins has not been an exception. In this approach, for any prediction method or model, one divides up the sources of uncertainty into (i) measurement uncertainty (measurement and interpolation errors of precipitation inputs and runoff measurements that are used in calibration), (ii) model parameter uncertainty, and (iii) model structure uncertainty. In a first step, one quantifies these uncertainties individually; e.g., measurement uncertainty on the basis of known instrument errors and the spatial statistical analyses, parameters uncertainty by assuming or inferring distribution functions of the parameters, and model structure uncertainty by assuming different model structures. In a second step, one then propagates them through the model to estimate resulting prediction uncertainty. If there is any additional information on the catchment systems (such as groundwater levels, remotely sensed snow cover data, information from reading the landscape in the field, or regionalised runoff signatures), this additional information can be assimilated to reduce the predictive uncertainty (Wagener and Montanari, 2011). The interest resides in one catchment, even though regional information may be used for reducing the uncertainty. There are an enormous number of techniques for this type of uncertainty estimation (see e.g., Liu and Gupta, 2007), and all have the element of error propagation. This fundamentally mirrors the Newtonian approach in its execution, and carries with it the same advantages and disadvantages – the ability to attribute individual error sources based on causal relationships, but the difficulty remains that effects of unknown feedbacks cannot be identified.

Uncertainty quantification based on comparative hydrology

The approach to uncertainty quantification in this book has been fundamentally different. Indeed, this book has focused on predictive uncertainty measured by cross-validation performance of the prediction of runoff signatures, in the form of blind testing. This comparative performance assessment is a Darwinian way of assessing predictions and estimating model uncertainty through an

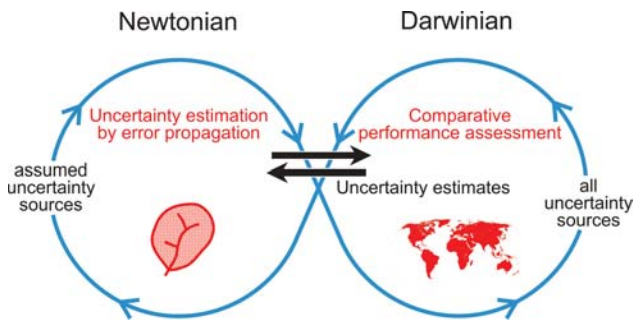

Figure 12.13. Synthesis of the Newtonian and Darwinian approaches for the case of uncertainty estimation.

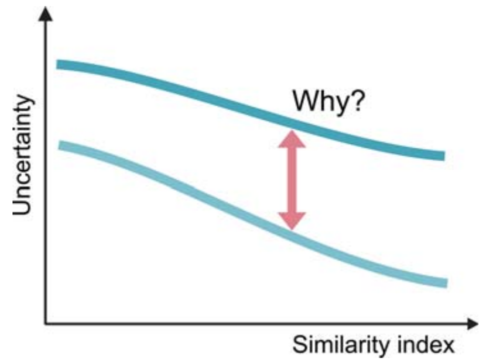

Figure 12.14. Comparative uncertainty estimation based on Darwinian concepts consists of exploiting the differences between regions to learn from them.

ensemble of predictions in different places. The difference between the traditional approach and the one adopted in this book is multifaceted. First, there is no error propagation involved in the analyses of this book; instead cross-validation performance is used as an estimator of total uncertainty. Second, uncertainty was analysed in a comparative way for a large number of catchments from around the world, so as to exploit the differences between regions to learn from them. An interesting question is why the uncertainties in these catchments are different, and what controls these differences. The focus, therefore, is not on Monte Carlo techniques or other error propagation methods, nor on reducing the uncertainty by optimisation schemes or data assimilation techniques. The comparative framework is about identifying the patterns so as to learn from them. Sections 12.2 and 12.3 of this chapter, as reviewed in detail, are about understanding the controls on model performances. We have investigated *why* performance decreases with increasing aridity index, i.e., why runoff predictions are more uncertain in arid catchments than they are in humid catchments, and interpreted these differences in terms of the underlying controlling factors.

Synthesis of the two uncertainty paradigms

Which of the two paradigms should be preferred for quantifying predictive uncertainty in ungauged basins? The truth is that both uncertainty paradigms have strengths and weaknesses, just as the Newtonian and Darwinian approaches do. Both are ways of understanding and quantifying the uncertainty, and are in fact complementary. The Newtonian uncertainty analysis approach is able to attribute individual error sources, and optimisation schemes and data assimilation techniques have an important role in optimal prediction for operational use. On the other hand, natural catchments around the world are complex objects, so Newtonian type sensitivity analyses may not explore the entire range of uncertainties, including any feedbacks across processes and scales, and dependencies in the error sources that may not be apparent in Newtonian models. The comparative uncertainty model, on the other hand, is more in tune with the notion of co-evolution. There are patterns of predictability due the complex nature of catchments that may not be easily foreseen, which has led to the notion of 'outliers' (Blöschl and Zehe, 2005). The presence of karst, for example, is hardly predictable in standard uncertainty models. What is therefore needed is a new uncertainty framework for PUB that accommodates the synthesis of the Newtonian and Darwinian approaches to predictions, to build on the strengths of both: a combination of error propagation methods with comparative performance and uncertainty assessment of the kind performed in this book, including all error sources, as well as model structure error (Figure 12.13).

This unified uncertainty framework for predictions in ungauged basins may start from comparative performance analyses just like those conducted in the assessment chapters in this book. The comparative uncertainty assessment focuses on *why* particular uncertainty patterns come about and why the uncertainty differs between regions (Figure 12.14). By contrasting different regions, the differences in the uncertainty can be detected and Newtonian approaches (such as process-based error propagation) may help in understanding these differences in terms of co-evolutionary processes. An interesting question is *why* the uncertainty is different in different regions of the world for a given model type, a given data availability and a given runoff signature that is to be predicted. This will contribute to enhanced understanding of the uncertainty associated with hydrological predictions in ungauged basins (more than can be extracted from individual case studies). Rather than heralding (in a paper) the 'success' of a modelling exercise because the uncertainty was small, or was reduced by a particular method, the aim should be to contribute to understanding. The combined comparative and error propagation uncertainty framework will contribute to a unification of what has been learned about prediction in ungauged basins around the world. Knowledge accumulates in this way.

12.4 Synthesis and the science community

12.4.1 Accumulation of knowledge in the hydrological sciences

What the new framework needs: models of various kinds, data of the right kind

While in the past the focus has been on individual studies, comparative hydrology is all about learning from patterns in data on a regional to global scale. Therefore, the advent of comparative hydrology introduces a brand new focus and emphasis on data, but on a global scale. Excellent examples already exist where comparative studies have contributed much to our understanding; substantial data sets have been an important basis in each case. The Model Parameter Estimation Experiment data set (MOPEX, Schaake *et al*., 2006; Duan *et al*., 2006) has been used by numerous researchers around the world for benchmarking studies (e.g., Hydrologic Synthesis special section in *Water Resources Research*, see Sivapalan *et al*., 2011b). Similarly, although spatially more limited, the data set used in the Distributed Model Inter-comparison Project (DMIP) has been very valuable for understanding the strengths and limitations of distributed rainfall–runoff models (Smith *et al*., 2004b, 2012). Global atmospheric data sets (van der Ent and Savenije, 2011) and regional flux tower data sets (Williams *et al*., 2012) have revealed interesting patterns of land–atmosphere interactions, and have led to improved understanding of the hydrological cycle at a range of scales.

The combined Darwinian–Newtonian framework proposed here requires not just traditional rainfall–runoff data (and other hydrological data, e.g., soil moisture, evaporation, snow, tracers), but also other kinds of data relating to all co-evolved entities (e.g., vegetation, topography, soil catena, drainage structure), not just in one catchment but in a large population of catchments around the world, along chosen natural (e.g., climatic) and anthropogenic (e.g., urban to rural to agricultural) gradients. This forces us to think more broadly about new data sources. High-resolution satellite data are one important data source relevant to hydrological studies aimed at exploring spatial connections, learning from landscape organisation, and exploiting the natural co-evolution and self-organisation of landscape features. At the other end of the spectrum, local data may be just as important for shedding light on catchment processes. This includes soft data and expert judgement of local hydrologists. Based on reading the landscape, geomorphological features of the landscape can provide useful insights into landscape co-evolution and self-organisation.

In the era of the Anthropocene (Crutzen, 2002; Sivapalan *et al*., 2012), we also need to collect data relating to human impacts, not just land cover changes, but also the volume of water abstractions for household use, irrigation and industrial use as well as return flows after water treatment. There is a lot of work needed to integrate these diverse data sources to generate patterns and meta-data sources, and new prediction methods that exploit these new data sources including the joint Newtonian–Darwinian uncertainty framework to assess the resulting uncertainties. This has to be formalised so that it becomes a valuable framework for the next phase of PUB (e.g., looking at catchments in colour, i.e., going away from lumped black-box models).

From data to information, knowledge and understanding

Gupta *et al*. (2008) pointed out that '*data*' are not the same thing as '*information*'. They noted that information is obtained by viewing data in context through perceptual and conceptual filtering. There may be multiple plausible contexts, and the most relevant context is generally given by an underlying theory. It is clear, therefore, that amassing large data sets, as needed for comparative hydrology, will not by itself render information. From the perspective of the science of hydrology as a whole it would be good to also go beyond representing only 'information for a particular catchment'. Ackoff (1989) and Bellinger *et al*. (2004) defined data, information, knowledge and understanding along the following lines (partly modified):

- Data represent a fact or statement of event without relation to other things, e.g., 'It is raining.'
- Information embodies the understanding of a relationship of some sort, possibly cause and effect, e.g., 'The temperature dropped 15 degrees and then it started raining.'
- Knowledge represents a pattern that connects and generally provides some predictability as to what will happen next, e.g., 'If the humidity is very high and the temperature drops substantially the atmosphere is often unlikely to be able to hold the moisture so it rains.'
- Understanding involves an element of extrapolation and is able to synthesise new knowledge from the previously held knowledge, e.g., 'The temperature–humidity relationship can be employed to predict or even speculate whether there will be more rain in a warmer climate.'

Clearly, we need techniques to exploit information from individual catchment studies, as well as the compilation of all studies from around the world. However, as a community collectively we need to go beyond that, and find systematic ways to (i) generate knowledge in terms of the patterns that connect across the multitude of studies and thereby provide a higher level of predictability as to what will happen next (Blöschl, 2006); and (ii) understanding that will enable extrapolation to new situations (Kumar, 2011). Hydrological synthesis is a vehicle for creating these connections and it is hoped that this book contributes to this kind of synthesis.

In the spirit of Bronowski (1956), synthesis must lead to the discovery (indeed, in a deep sense, creation) of order in what otherwise appears as disorder. In this sense the synthesis that we have carried out has indeed led to the discovery of order, as outlined above. By organising the synthesis along processes, places and scales we have managed to gain deep insights that otherwise would have remained hidden. Synthesis across scales has revealed the inter-connection between various signatures, including how seasonality is a connective tissue underlying all of the signatures. Synthesis across places has revealed the critical role that aridity and seasonality play in catchment responses. Synthesis across scales has revealed the strong dependence of the area–time scale dependence on various signatures, and on prediction performance. Most importantly, the study has revealed what methods work best in a particular climate. This is a particularly new and useful result that will advance hydrological prediction generally. It is hoped that this book contributes to converting data on predictions in ungauged basins into information and into knowledge that the community can use as a whole (see Figure 12.15).

Going further, the effort has led to a higher level of synthesis of two competing paradigms that the hydrology community has been grappling with: Newtonian and Darwinian. We have outlined the need for such a synthesis for improved predictions as well as for the advancement of the science, and have illustrated it with examples. This has also led to the call for a new uncertainty framework that is better suited to PUB, that combines the advantages of the

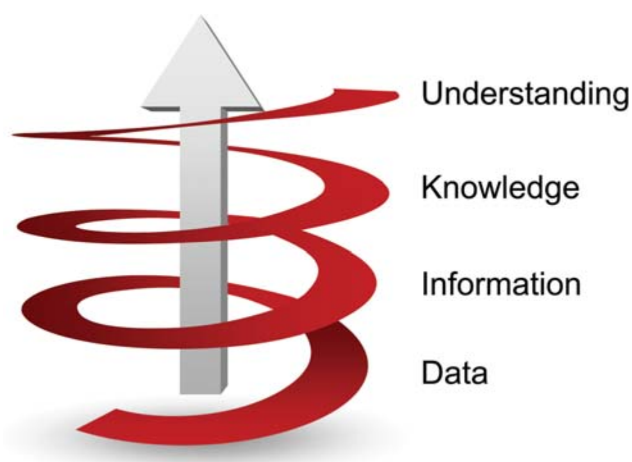

Figure 12.15. From data to information to knowledge to understanding in predictions in ungauged basins. presentationload.com.

Newtonian (error propagation) and Darwinian (comparative) approaches to uncertainty estimation.

The outcomes of the synthesis presented here represent an accumulation of knowledge, i.e., distilled knowledge. This accumulation of knowledge has only been possible through an organised community effort, a distillation achieved through synthesis organised across processes, places and scales (Figure 12.16). Given that both the PUB initiative in general and its synthesis in this book have, in each case, been the result of community efforts, what lessons have been learned from this effort? How can the community organise itself in the future to benefit from and build upon the progress made so far?

12.4.2 Role of the community

Accumulation of knowledge is an important and legitimate way to advance the state of a science, especially when it is an applied science such as hydrology. This book has clearly demonstrated the value of comparative assessment of previous experiences with prediction methods to contribute to an accumulation of knowledge. Accumulation of knowledge requires the community to organise, and there are important lessons that can be learned from the experience of putting together this book. From the results reported in several case studies (Chapter 11) we have noticed differences in the way hydrological communities within developed countries have organised and responded to the challenges of PUB, in contrast to the situation in developing countries. Lack of organisational and institutional drivers can prevent the accumulation of local knowledge, and can compound the disadvantages that hydrologists and practitioners in many developing countries already face, in terms of complexity of the hydrology and the lack of data and research funding.

In spite of the apparent success of the comparative assessment of model performances, it must be said that our assessment was hampered by the lack of critical and basic information that many published modelling studies failed to report; this is due to the absence of a reporting protocol and the lack of organisation across the modelling community. Indeed, as noted by Gupta *et al.* (2008):

> As a community, we have fallen into reliance on measures and procedures for model performance evaluation that say little more than how good or bad the model-to-data comparison is in some "average" sense.

In the past, reporting of most modelling studies was more heavily focused on demonstrating that the chosen models worked well and not so much on the underlying reasons, and reports especially failed to provide the hydrological insight needed to interpret the modelling results. For knowledge to accumulate it is essential that the

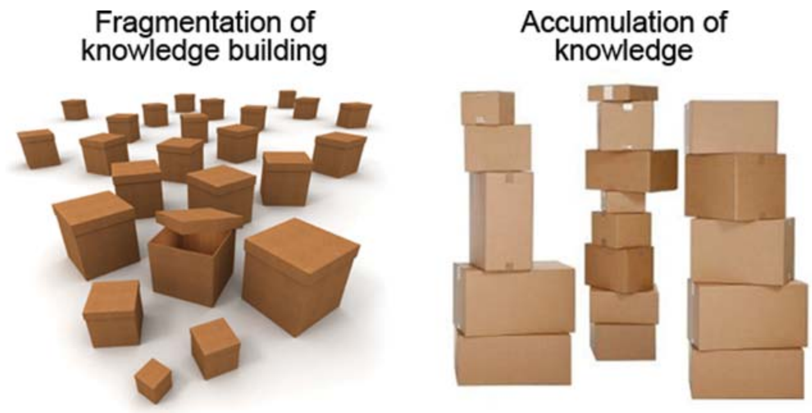

Figure 12.16. Accumulation of knowledge by concerted research effort and presentation of the findings in the literature others can build upon. clipartof.com.

publications are made useful to the reader by providing some degree of higher-level analysis of the results, both comparative (with other work) and synthetic (in terms of understanding).

So how can hydrological publications be made more useful to the reader? There are a number of possibilities/suggestions: As is good practice in most sciences, it would be useful if the publication mechanism made it possible for all of the relevant information to be accessible (both data and model codes), so that others can repeat the experiment(s) or to test other hypotheses using the same data. With increasingly larger data sets that cannot be printed within the size of a paper, reference to a data repository containing the data on which the analysis was based would also be very useful. Some journals have data appendices. For the comparative assessment reported in this book we approached the authors of the publications individually to send us their data. A data repository linked to the papers would have circumvented this step and thus would have been extremely useful. Also, for a comparative approach to succeed, the papers should provide not only aggregate information (e.g., average catchment size, average precipitation etc.) but also information on climate, geology and other characteristics that would enable a hydrological interpretation of their results and conclusions. The requirement for more specific information applies also to performance measures; what are required are not only hydrologically more useful measures (Gupta *et al.*, 2008; Schaefli and Gupta, 2007), but also that measures be constructed and reported at a more detailed and consistent level, e.g., using units of specific discharge rather than discharge.

Ultimately, this is a call for a new protocol, to be agreed upon by the hydrology community (including journal editors) that will provide standards and guidelines for presenting the outcomes of modelling studies. Basic reporting guidelines that recommend the presentation of critical information (including the outcomes of modelling studies) in a consistent way would substantially enhance the ability to perform comparative assessments, and thereby speed up the accumulation of knowledge. To be of use in comparative assessments across gradients of processes, places and scales, a minimum requirement is that basic information such as climate, geology, size of catchment and the dominant processes must be presented in a clear and obvious way.

The invoking of co-evolution and complex systems in this book confirms what is already well recognised: that hydrology is becoming a true earth system science. To accumulate knowledge and generate understanding must be the ultimate goals of our discipline. Enhanced communication between disciplines, and people in different places, is the only way that hydrology as an earth science and as an applied science can benefit from its practice globally. For this, hydrology must become one truly global science, and comparative hydrology and the synthesis of the Newtonian and Darwinian worldviews will be the vehicles that will help achieve this.

13 Recommendations

Contributors: *K. Takeuchi,* G. Blöschl, H. H. G. Savenije, J. C. Schaake, M. Sivapalan, A. Viglione, T. Wagener and G. Young*

This book is devoted to predicting runoff in ungauged basins (PUB), i.e. predicting runoff at those locations where no runoff data are available. It aimed at a synthesis of research on predictions of runoff in ungauged basins across processes, places and scales as a response to the dilemma of fragmentation in hydrology. It takes a comparative approach to learning from the differences and similarities between catchments around the world. The book also provides a comparative performance assessment (in the form of blind testing) of methods that are being used for predictions in ungauged basins, interpreted in a hydrologically meaningful way. It therefore throws light on the status of PUB at the present moment and can serve as a benchmark against which future progress on PUB can be judged. In so doing, the book has also come out with a new scientific framework that can guide the advances that are needed to underpin PUB and to advance the science of hydrology as a whole. The synthesis presented in the book is built on the collective experience of a large number of researchers around the world inspired by the PUB initiative of the International Association of Hydrological Sciences, which makes it truly a community effort. It has provided insights into the scientific, technical and societal factors that contribute to PUB.

Drawing from the lessons learned from the book, we are now in a position to make recommendations on the predictive, scientific and community aspects of PUB, and to offer best practice guidelines for runoff predictions in ungauged basins.

13.1 Advancing runoff predictions in ungauged basins

13.1.1 Understanding as the key to better predictions

Catchments must be treated as real objects in real places with real processes operating rather than as abstract concepts. Whatever methods are used for predictions, the focus needs to be on the hydrological interpretation of both the method and the results. The level of detail of the interpretation may vary with model complexity (from statistical to physics-based), yet the hydrological interpretation is still essential, informed by photographs of the dynamics taking place on the landscape. The interpretation may be in terms of physical causality or in terms of the co-evolution of catchments. For example, a physical interpretation may be gradient–flux relationships, whereas a co-evolutionary interpretation may be the Budyko curve.

13.1.2 Exploiting runoff signatures and linking them

Predicting runoff in ungauged basins requires a targeted approach where the focus is on a specific signature of interest. For example, if the interest is on the flood frequency curve the focus should be on processes that are relevant to floods, not on the hydrographs as a whole. The targeted approach benefits from connecting to other relevant signatures. For example, estimation of flood frequency can benefit from the study of the seasonal flow regime. The seasonality is a fingerprint of the catchment and therefore may assist in predicting all the runoff signatures (annual runoff, flow duration curve, low flows, floods), including the runoff hydrographs. The modelling of the signatures will benefit from following a hierarchical analysis from annual runoff down to seasonal runoff, the flow duration curve and the extremes (floods and low flows).

13.1.3 Addressing uncertainty from a process perspective

Estimating the uncertainty of runoff predictions in ungauged basins is essential. When doing this the focus should be on the hydrological interpretation of both the uncertainty method and the uncertainty results. Methods that draw on numerical experiments, such as Monte Carlo analyses, may be complemented by comparative

* Coordinating contributor

Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales, ed. Günter Blöschl, Murugesu Sivapalan, Thorsten Wagener, Alberto Viglione and Hubert Savenije. Published by Cambridge University Press.

assessment of the predictive uncertainty across many real catchments based on cross-validation. The Level 1 and Level 2 assessments in this book may provide guidance on the magnitude of uncertainty to be expected in different climates and catchment situations. Both kinds of uncertainty analyses may assist in the choice of prediction method.

13.1.4 Data availability and predictions

The predictive context varies vastly around the world due to differences in processes, data availability, modellers' experience and modelling purpose. There is therefore no single best method for all situations. In contrast, the particular circumstances one finds can be exploited to develop creative methods for runoff predictions using proxy data. A hierarchy of data collection approaches from global to regional to local may maximise the information gained from the available data sources. However, installing a stream gauge is always the best option. Runoff prediction performance is strongly related to runoff data availability and performance is lower in data-poor regions. Concerted efforts should therefore be made to increase the number and quality of stream gauges in data-poor regions.

13.2 Advancing hydrological science globally via PUB

13.2.1 Viewing catchments as complex systems

Catchments are complex adaptive systems that are the result of the co-evolution of climate, soils, topography and vegetation. They consist of many parts that are closely interconnected, the cause–effect relationships span many time and space scales, and processes and process interactions cannot be worked out easily. The process view of catchments should therefore be extended to include the interactions and feedbacks between water flow processes and geomorphological (erosion, sedimentation), pedological (pedogenesis), ecological and biogeochemical processes. Emergent patterns of interest in the landscape that are legacies of their co-evolution include runoff and water quality signatures, soil catenas, vegetation patterns, and the stream network structure.

13.2.2 Comparative hydrology to detect co-evolution patterns

Since complex systems are hard to analyse we suggest comparing landscapes across places in terms of their co-evolutionary patterns (river network structure, landforms, vegetation patterns, hydraulic geometry, soil and vegetation catena, and runoff signatures such as the Budyko curves. The aim is not to predict runoff by these comparative analyses but to learn from the differences between catchments to gain understanding of co-evolutionary processes. This is the Darwinian approach, which stands apart from regionalisation approaches in that the focus is on generalised understanding and not on predictions.

13.2.3 Newtonian–Darwinian synthesis

The Newtonian approach builds on local field observations and detailed process modelling to identify direct causality and causality chains. The synthesis of the Newtonian and Darwinian approaches will lead to a new understanding, benefiting from their complementary strengths: learning from process cascades and using such models to help interpret regional and global patterns; and learning from comparative studies that shed light on the co-evolution of real catchments. New model concepts can be built on the basis of the organising principles yet to be discovered through the Newtonian and Darwinian synthesis such as vegetation optimality, minimum energy expenditure and maximum entropy production.

13.2.4 The globe is our laboratory

The new approach requires assembling and processing patterns of all kinds, guided by the Newtonian–Darwinian synthesis, with a view to generating new understanding in hydrology. The synthesis involves a synthesis of concepts, models and data from various sources and disciplines. The efforts should be underpinned by a new uncertainty framework that combines aspects of error propagation (Newtonian) and cross-validation performance between regions (Darwinian), which accounts for the uncertainty arising from the different trajectories of co-evolution they may have followed. This data-based approach takes the view that the entire world is our laboratory, with catchments serving as nature's experiments.

13.3 Organising the hydrology community to advance science and predictions

13.3.1 Capacity building

New educational concepts are needed, including ways to treat catchments as complex systems and to promote the practice of comparative hydrology. In addition to teaching students basic knowledge about individual processes, we need to train them in the use of signatures, interpretation of the differences between different places, and viewing catchments as real objects rather than abstractions. Students need to understand runoff signatures and understand the interconnections between patterns of runoff, vegetation, drainage networks and geochemistry. Their education must, of necessity, be interdisciplinary and should include a range of techniques, from differential equations to understanding Newtonian dynamics to pattern-based approaches to assist with reading processes from the structure of the landscape.

13.3.2 Collaborative endeavour

To succeed in what was proposed above, collaboration is needed along three axes: Collaboration across processes involves linking different disciplines with different discourses that may be difficult but important to accommodate, such as social sciences versus natural sciences, engineering versus natural sciences. Collaboration across places involves linking researchers in different parts of the world to enable sharing experiences about different places. Collaboration across scales involves linking individuals to research groups of various sizes as a part of team science, which may need to overcome the challenges of communication, governance and funding, and to foster a culture of collaboration.

13.3.3 Knowledge accumulation

Team science requires a change in the mode of collaboration to succeed. We need a better communication culture that allows us to learn from each other, i.e., to communicate *information* rather than just *data*, to be able to benefit better from each other's work. Rather than reporting on modelling successes in the authors' catchments, the information needs to be generalisable to make it useful to the reader. Also, all experiments and analyses need to be repeatable by peers. This may need development and implementation of a universal protocol on reporting scientific results in the hydrological literature as well as establishment of freely accessible data repositories. Knowledge accumulation should be the overarching goal of hydrological research.

13.3.4 Hydrology, a global science

The world is our laboratory, and hydrology should become a truly global science. This transformation needs to be supported and nurtured. We need coordinating action to bring people from different regions of the world together on an equal footing. There may be mutual benefits by bringing people together to share experiences of using a diverse mix of high technology and creativity to come up with appropriate solutions to prediction problems within the socioeconomic context of the region of interest. This can be achieved through a coordinated web of efforts-such as WaterNet in Southern Africa, UNESCO-IHP RSC in Asia and the Pacific, MOPEX in America and FRIEND in Europe. The International Association of Hydrological Sciences can play a catalytic role in this process since their scope is global and their focus is on science. All of these activities will lead to the emergence of global comparative hydrology as a quantitative science able to face up to the prediction challenges of the future.

13.4 Best practice recommendations for predicting runoff in ungauged basins

Step 1 – Read the landscape: Go out to your catchment, look around, see what the landscape tells you, create a photo documentation, look at the hydrogeology, ask people about previous events, obtain global, regional and local data, map hydraulic structures and other modifications. If possible, install a stream gauge.

Step 2 – Runoff signatures and processes: Analyse all runoff signatures in nearby catchments to get an understanding of the hydrology of the catchment beyond the signature of interest. Runoff signatures include annual runoff, seasonal runoff, flow duration curve, low flows, floods and hydrographs.

Step 3 – Process similarity and grouping: On the basis of the first two steps and process similarity measures, find similar gauged catchments to assist in predicting runoff in the ungauged basin (grouping of landscape units and catchments). The similarity can be based on short-term and co-evolutionary processes.

Step 4 – Model: Build statistical and/or process-based model for the signature of interest; regionalise the parameters from similar catchments, taking advantage of *a-priori* information, dynamic proxy data and any other information on processes, including from the other signatures; account for correlations along the stream network. There is always more information than the hydrograph – use it.

Step 5 – Interpretation: Interpret the parameters of the model hydrologically and justify their values against what was learned during field trips and other data, to improve parameter choice and uncertainty estimation. Parameters are, e.g., regression coefficients and runoff model parameters.

Step 6 – Uncertainty: Assess uncertainty of predicted runoff by combining error propagation methods, regional cross-validation and hydrological interpretation against the backdrop of the uncertainty to be expected from comparative hydrology (Level 1 and 2 in this book). We now have a prediction of runoff signature including understanding of its credibility.

All steps: Communicate all of this in such a way that it contributes to the global and national body of knowledge in hydrology, especially process knowledge.

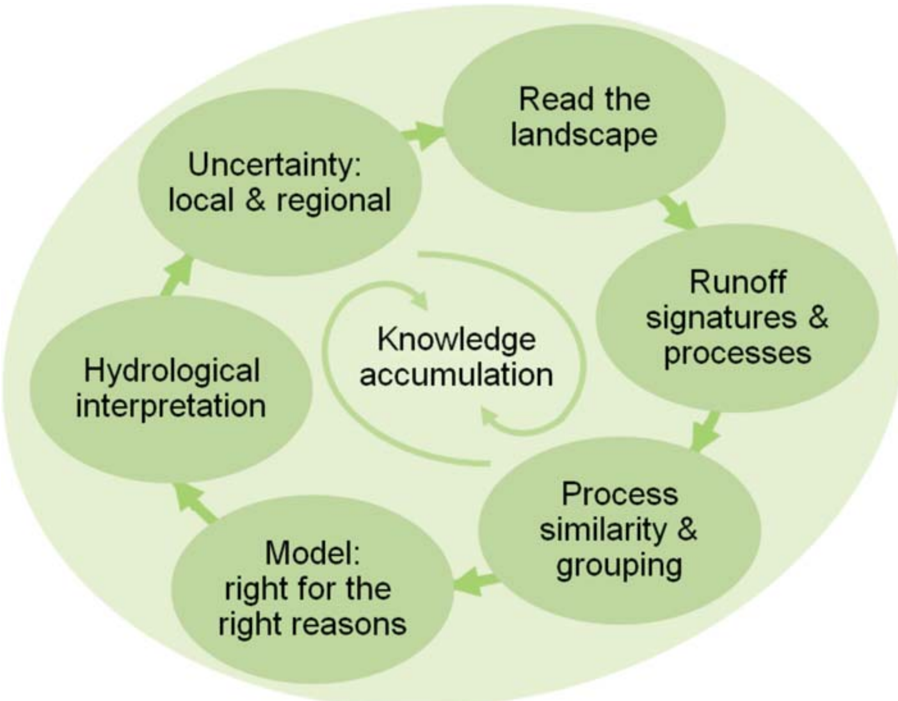

Figure 13.1. PUB best practice recommendations for predicting runoff in ungauged basins.

Appendix Summary of studies used in the comparative assessments

Table A5.1. *Summary of studies used in the comparative assessment of mean annual runoff estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	q_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Performance (r^2)	Error (RMSE in mm/yr)	Used in L1
Moore *et al.* (2012)	Canada (British Columbia)	Cold (Dfc)	0.8–6760				226	min 10 yrs	PB	q_A		−6.6 (bias in %)	
Yan *et al.* (2011)	China (Huaihe River)	Humid (Cfa, Cwa)		600–1000			20	1956–2008	SP	q_A	0.98		X
Urrutia *et al.* (2011)	Chile (Maule River)	Humid (Csb)	21 060	830–2300			1	1938–2000	PX	q_A	0.42 (R^2adj)		X
Tekleab *et al.* (2011)	Ethiopia (Upper Blue Nile)	Humid (Csa, Csb, Aw)	200–9672	1148–1757	489–4860	222–1400	20	1995–2004	IM	q_A	0.70–0.97 (R^2)	57–177	X
McMahon *et al.* (2011)	Global	Global	4–464·10^4	72–3566		3–3126	699	10 to 172 yrs	IM	q_A	0.58–0.62	180–225	X
Duan *et al.* (2010)	China (Hailar River)	Cold (Dwc)	3322–53 829	34–460	510–1622	10–145	11	1956–2006	R(P_A, E_{PA}, $A_{wetland}$, shape)	q_A	0.86–0.99		X
Donohue *et al.* (2010)	Australia	Humid (Cfa, Cfb, Csa, Csb, Bsk, Aw)	100–3000	300–2600		25–1800	221	1981–2006	IM (Budyko)	q_A	0.52–0.94 (R^2)	56–141	X
Watson *et al.* (2009)	USA (Wyoming)	Arid (Bsk)					3	1946–2000	PX	Q_A	0.38–0.61 (R^2adj)		X
Potter and Zhang (2009)	Australia	Humid (Cfa, Cfb, Csa, Csb, BSk, Aw)	50–2000				209	10 to 91 yrs	PB	q_A	0.49 (R^2)	73.4	X
Potter and Zhang (2009)	Australia	Humid (Cfa, Cfb, Csa, Csb, BSk, Aw)	50–2000				209	10 to 91 yrs	IM	q_A	−0.07–0.72 (R^2)	63–93	X
Potter and Zhang (2009)	Australia	Humid (Cfa, Cfb, Csa, Csb, BSk, Aw)	50–2000				209	10 to 91 yrs	R(E_{PA}/P_A)	q_A	−2.54 (R^2)	139	X
Zhang *et al.* (2008a)	Australia	Humid (Cfa, Cfb, Csa, Csb, BSk, Aw)	50–2000	282–2886			265		IM	q_A	0.93		X
Yuan *et al.* (2007)	China (Manasi River)	Arid (BWk)	5211		940–5289		1	1956–2000	PX	Q_A	0.51 (R^2)		X
Yang *et al.* (2007)	China	Cold (E, Dwc, Bsk)	272–94 800	150–750			108	1951–2000	IM	q_A	0.62	20.5	X
Viglione (2007)	North-western Italy	Humid (Cfa, Dfb)	20–8000	840–2100	480–2740	500–1730	47	1920–86	R(P_A, Elev, Budyko Index)	q_A	0.88–0.90 (R^2adj)	110–115	X
McMahon *et al.* (2007b)	Global	Global	115–65 200				1221	15 to 58 yrs	R(A)	Q_A	0.60–0.78		X

Table A5.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	q_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Performance (r^2)	Error (RMSE in mm/yr)	Used in L1
Gou *et al.* (2007)	China (Yellow River)	Humid (Cwa, Cfa)	680 000	300–500			1	1956–2001	PX	Q_A	0.25–0.41 (R^2)		X
Woodhouse and Lucas (2006)	USA (Upper Colorado River)	Cold (Dfb)					4	1906–95	PX	Q_A	0.64–0.81 (R^2)		X
Sauquet (2006)	France	Humid (Cfb, Dfc, Csa, Csb)	11–111 570	300–2500		70–1860	898/90	1981–2000	SP	q_A	0.6–0.97	35–178	X
Bren *et al.* (2006)	Southern Australia (Pine Creek)	Humid (Cfa, Cfb)	3.2	787			2	1988–2000	R(P_A, plant age)	q_A		95	
Beriault and Sauchyn (2006)	Canada (Churchill River)	Cold (Dfb, Dfc)	45 000–215 000				3	25 to 66 yrs	PX	Q_A	0.40–0.53 (R^2adj)		X
Carson and Munroe (2005)	USA (Utah)	Arid (Bsk)	262	675–925			1	1915–71	PX	Q_A	0.63–0.70 (R^2adj)		X
Case and MacDonald (2003)	Canada (Saskatchewan River)	Cold (Dfb, Dfc)					3	1912–98	PX	Q_A	0.34–0.59 (R^2adj)		X
Sankarasubramanian and Vogel (2002)	Continental USA	Global (Cfa, Dfa, Dfb, Bsk, Bsw, Csa, Csb, Dfc)					1337	min 10 yrs	PB	q_A	0.40–0.95		X
Parajka (2001)	Slovakia	Cold (Dfb, Dfc, E)	30–4800			140–1200	60/60	1951–80	IM	q_A	0.91–0.95	77–289	X
Parajka (2001)	Slovakia	Cold (Dfb, Dfc, E)	30–4800			140–1200	60/60	1951–80	SP	q_A	0.96–0.99	100–244	X
Parajka (2001)	Slovakia	Cold (Dfb, Dfc, E)	30–4800			140–1200	60/60	1951–80	R(P_A, T_A)	q_A	0.69–0.95	74–323	X
Vogel and Sankarasubramanian (2000)	Continental USA	Global (Cfa, Dfa, Dfb, Bsk, Bsw, Csa, Csb, Dfc)	3.5–3·10^7				1433	6 to 115 yrs	R(log A)	Q_A	0.28–0.99		X
Sauquet *et al.* (2000a)	France (Saône River)	Humid (Cfb)	54–11 700			313–1414	20	1960–97	SP	q_A	0.90	–23 (bias in mm)	X
Wolock and McCabe (1999)	Continental USA	Global (Cfa, Dfa, Dfb, Bsk, Bsw, Csa, Csb, Dfc)				23–2530	344 regions (not catchments)	1951–80	PB	q_A	0.64–0.93		X

Vogel *et al*. (1999)	Continental USA	Global (Cfa, Dfa, Dfb, Bsk, Bsw, Csa, Csb, Dfc)					1553	6 to 115 yrs	R(P_A, T_A, A)	Q_A	0.90–0.99		X
Bishop *et al*. (1998)	North-eastern USA	Cold (Dfb, Dfc)	1–4120				1230/31	1951–80	PB	q_A	0.54–0.69		X
Bishop *et al*. (1998)	North-eastern USA	Cold (Dfb, Dfc)	1–4120				1230/31	1951–80	SP	q_A	0.74–0.76		X
Vogel *et al*. (1997)	North-eastern USA	Cold (Dfb, Dfc)	5–18 000				166/166	1951–80	R(P_A, T_A, A, relief)	Q_A	0.99		X
Arnell (1995)	Western and northern Europe	Cold (Dfb, Dfc, Cfb)	29 000–160 000				3500/7	1951–80	IM	q_A	0.32–0.72	100–175	X
Arnell (1995)	Western and northern Europe	Cold (Dfb, Dfc, Cfb)	29 000–160 000				3500/7	1951–80	SP	q_A	0.94–0.97	63–145	X
Arnell (1995)	Western and northern Europe	Cold (Dfb, Dfc, Cfb)	29 000–160 000				3500/7	1951–80	R(P_A, E_{PA})	q_A	0.29–0.58	103–190	X
Bishop and Church (1995)	North-eastern USA	Cold (Dfb, Dfc)	1–4120				1230/93	1951–80	SP	q_A	0.69–0.80		X
Duell (1994)	USA (California and Nevada)	Arid (Csa, Csb, Dsb)	26–920	550–1780	1300–2400		19/19	1961–90	R(P_A, T_{july})	Q_A	0.82–0.96	13–24 (in %)	X
Bishop and Church (1992)	North-eastern USA	Cold (Dfb, Dfc)	2–17 230				441/50	1984	SP	q_A	0.60–0.72		X
Liebscher (1972)	Germany						74/74	1951–60	R(P_A, T_A)	q_A	0.89–0.90		X

R(*pred1*, *pred2*, …): regression method with predictors *pred1*, *pred2*, …
SP: spatial proximity method
PB: process-based method
IM: index method
PX: proxy data method
Q_A: mean annual runoff
q_A: specific mean annual runoff (Q_A/A)
No. of catchments (calibration/validation)
Period/No. of years (calibration/validation)

Table A5.2. *Summary of studies used in the comparative assessment of mean annual runoff inter-annual variability estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	PA (mm/yr)	Elevation (m a.s.l.)	q_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Performance (r^2)	Error (RMSE in mm/yr)	Used in L1
McMahon *et al.* (2011)	Global	Global	4–464·10^4	72–3566		3–3126	699	10 to 172 yrs	IM	CV_{qA}	0.52–0.57	65–1223	X
Komatsu *et al.* (2011)	Japan, New Zealand, USA	Humid (Cfa, Cfb)		712–2450			82		R(P_A)	CV_{qA}	0.23–0.64		X
Peel *et al.* (2010, 2004b)	Global	Global	4–464·10^4	72–3566		3–3126	699	10 to 172 yrs	R(CV_{PA}, E_{pA},φ)	CV_{qA}	0.17–0.68		X
Zhang *et al.* (2008a)	Australia	Humid (Cfa, Cfb, Csa, Csb, BSk, Aw)	50–2000	282–2886			265		IM	CV_{qA}	0.87		X
Yang *et al.* (2007)	China	Cold (E, Dwc, Bsk)	272–94 800	150–750			108	1951–2000	IM	CV_{qA}	0.68		X
McMahon *et al.* (2007b)	Global	Global	115–65 200				1221	15 to 58 yrs	R(A)	CV_{QA}	0.94		X
Bren *et al.* (2006)	Southern Australia, South Africa	Humid (Cfa, Cfb)	0.1–3.2	737–1400			8	8 to 35 yrs	R(P_A, plant age)	CV_{qA}		54–96	X
Sankarasubramanian and Vogel (2002)	Continental USA	Global (Cfa, Dfa, Dfb, Bsk, Bsw, Csa, Csb, Dfc)					458	min 10 yrs	R(φ, soils)	CV_{qA}/CV_{PA}	0.85		X
Vogel *et al.* (1997)	North-eastern USA	Cold (Dfb, Dfc)	5–18 130				166/166	1951–80	R(P_A, T_A, A, relief)	CV_{QA}	0.98		X

R(*pred1*, *pred2*, …): regression method with predictors *pred1*, *pred2*, …
IM: index method
No. of catchments (calibration/validation)
CV_{QA}: inter-annual variability of the mean annual runoff
CV_{qA}: inter-annual variability of the specific mean annual runoff
CV_{qA}/CV_{PA}: ratio between inter-annual variability of specific mean annual runoff and mean annual precipitation

Table A6.1. *Summary of studies used in the comparative assessment of seasonal runoff estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	q_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Performance (NSE, R^2)	Error	Error measure	Used in L1	Used in L2
Moore *et al.* (2012)	Canada (British Columbia)	Cold (Dfb, Dsb, Dfc, Cfb)	0.8–6760				226	min 10 yrs	PB	q_m	0.92			X	X
Bartolini *et al.* (2011)	North-west Italy	Cold (Dfb, Cfa)	40–3310		117–4727		40		PB	q_m					
Gitau and Chaubey (2010)	USA (Arkansas)	Humid (Cfa)	1400–6600				7/3		PB	q_d	0.53–0.83				
Gitau and Chaubey (2010)	USA (Arkansas)	Humid (Cfa)	1400–6600				7/3		PB	q_d	0.4–0.75				
Snelder *et al.* (2009)	France	Humid (Cfb, Csb, Dfc)	3–109 000	606–2060			763	1976–2006	R	q_m		0.37–0.64	PMR		
Sauquet *et al.* (2008)	France	Humid (Cfb, Csb, Dfc)	11.5–109 930			100–1500	154	1981–2000	G	q_m	0.98			X	X
Sauquet *et al.* (2008)	France	Humid (Cfb, Csb, Dfc)	11.5–109 930			100–1500	65	1981–2000	G	q_m	0.94			X	X
Kapangaziwiri and Hughes (2008)	South Africa, Zimbabwe and Mozambique	Arid (BWk, BSk, Aw, Cwa)	6.5–1100	575–1637			71		PB	q_m	0.60–0.85			X	
Cutore *et al.* (2007)	Italy (Sicily)	Arid (Csa)	19–1832		524–1479		9	15 to 38 yrs	PB	q_m	0.59			X	
Cutore *et al.* (2007)	Italy (Sicily)	Arid (Csa)	19–1832		524–1479		9	15 to 38 yrs	PB	q_m	0.66			X	
Cutore *et al.* (2007)	Italy (Sicily)	Arid (Csa)	19–1832		524–1479		9	15 to 38 yrs	PB	q_m	0.69			X	
Sanborn and Bledsoe (2006)	USA (Colorado, Washington, Oregon)	Cold (Dsc, Cfb)	4–19 632	335–4500	0–3180		62	min 20 yrs	R	q_m	0.963–0.985			X	
Sanborn and Bledsoe (2006)	USA (Colorado, Washington, Oregon)	Humid (Cfb)	4–19 632	335–4500	0–3180		37	min 20 yrs	R	q_m	0.91–0.98			X	
Sanborn and Bledsoe (2006)	USA (Colorado, Washington, Oregon)	Humid (Cfb, Dsc)	4–19 632	335–4500	0–3180		35	min 20 yrs	R	q_m	0.84–0.93			X	
Sanborn and Bledsoe (2006)	USA (Colorado, Washington, Oregon)	Arid (BSk, Dsc)	4–19 632	335–4500	0–3180		28	min 20 yrs	R	q_m	0.68–0.91			X	

Table A6.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	q_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Performance (NSE, R^2)	Error	Error measure	Used in L1	Used in L2
Markovic and Koch (2006)	Germany (Elbe River)	Humid (Cfb, Dfb)	5.68–103				8/2	1953–1960/ 1960–2000	G	$q_m^{(max)}$	0.98–0.99	6.4–12.7	RRMSE		
Dudley (2004)	USA (Maine)	Cold (Dfb)	25–3672	960–1217			26	min 10 yrs	R	q_m		11.1–30.2	RRMSE		
Hess (2002)	USA (Nevada)	Cold (Dfb, BSk)	0.93–137	429–640	2560–3109		6		R	q_m	0.21–0.87				
Baldwin *et al.* (2002)	USA (Utah)	Arid (BSk, Dfb, Dfa)					181		R	q_m		0.20–1.90	CV_{NE}		
Schreider *et al.* (2002)	Northern Thailand	Tropical (Am)					1/2		PB	q_m		0.13–0.18	NBIAS		
Hortness and Berenbrock (2001)	USA (Idaho)	Arid (BSk, Dsb)	7.77–34 705	208–1641	732–2896		200		IM	$q_{m,80}$, $q_{m,50}$, $q_{m,20}$		–15.3–18.1	NBIAS		
Sauquet *et al.* (2000)	South-east France	Arid (Csb, Csa)	50–96 500				201/11		G	q_m/q_A	0.70–0.98			X	
Peel *et al.* (2000)	Australia	Humid (Cwa, Cfa, Cfb, Csa)	51–1980	297–2445		3–2095	331		PB	q_m					
Abdulla and Lettenmaier (1997)	USA (Arkansas)	Humid (Cfa)	285–5278		53–2344		40/6		PB	q_d	0.05–0.80	0.37–0.82	RRMSE		
Raman *et al.* (1995)	India (Tamil Nadu)	Humid (Cwb, Cwa, Aw)	74.7	700			1	7/1	R	q_m		–0.24–0.32	NE		
Vandewiele and Elias (1995)	Belgium	Humid (Cfb)	19–1597				75	4 to 35 yrs	PB	q_m		3.43–4.76	RMSE (mm)		
Ibrahim and Cordery (1995)	Australia (New South Wales)	Arid (BSh, BWh, BSk)	190–1870	620–2400			18/8	15 to 50 yrs	PB	q_m	0.62–0.89			X	
Rankl *et al.* (1994)	USA (Wyoming)	Arid (BWk, BSk)					21		R	q_m	0.74–0.93	0.37–0.83	NE		
Rankl *et al.* (1994)	USA (Wyoming)	Arid (BWk, BSk)					21		R	q_m	0.65–0.95	0.34–1.00	NE		
Rankl *et al.* (1994)	USA (Wyoming)	Arid (BWk, BSk)					21		R	q_m		0.27–1.51	NE		
Gan *et al.* (1991)	Australia (south-east Victoria)	Humid (Cfb)	0.06–246	700–1400			59/12	5 to 25 yrs	R(A, P_A, P_{month})	q_m		–0.47–0.16	NBIAS		
Parrett and Johnson (1989)	USA (Montana)	Arid (BSk, Dfb)					17		R	q_m		0.35–1.57	NE		

Hirsch (1982)	USA (central West Virginia)	Cold (Dfb, Dfa, Cfa)	269–1194	512–762	7	50 yrs	R	$q_m^{(1)}$, $q_m^{(2)}$, $q_m^{(5)}$	–2.00–1.00	NE
Martin (1964)	Eastern USA	Humid (Cfa, Dfb)	722–11 629		6/6		R($q_{m,\ donor}$, P_A)	q_m	0.1–0.3	NE (*log* mm)

R(*pred1*, *pred2*, …): regression method with predictors *pred1*, *pred2*, …
G: geostatistical method
PB: process-based method
IM: index method
No. of catchments (calibration/validation)
Period/No. of years (calibration/validation)
q_m: mean monthly runoff (mm/month)
$q_{m,80}$, $q_{m,50}$, $q_{m,20}$: 80, 50 and 20 percentiles of daily runoff for every month
$q_m^{(1)}$, $q_m^{(2)}$, $q_m^{(5)}$: lowest, 2nd and 5th lowest daily runoff for every month
$q_m^{(max)}$: maximum daily runoff for every month
q_m/q_A: normalised mean monthly runoff
q_d: daily runoff
PMR: predictive misclassification rate (see Snelder *et al.*, 2009)
RRMSE: relative root mean square error
NE: normalised error
CV_{NE}: coefficient of variation of normalised error
NBIAS: normalised bias

Table A6.2. *Summary of information provided for the studies included in the Level 2 assessment, listing of studies with more detailed information about catchment characteristics and cross-validation performances*

Study	Region	No. of catchments	Method	Area (km^2)	P_A (mm)	E_{PA} (mm)	T_A (°C)	Elevation (m)	Aridity (−)
Viglione *et al*. (2013b)	Austria	209	R, SP, G, PB	13–7000	500–2300	280–800	0–10	180–2500	0.2–1.4
Farmer (2012)	USA	1027	SP, R	20–74 200	200–2600	700–1700	−1.4–22.5	7–3650	0.3–5.2
Moore *et al*. (2012)	Canada	226	PB	0.8–6800	400–5150	100–600	−3.4–9.5	50–2100	0.1–1.1
Sauquet *et al*. (2008)	France	179	G	11–22 180	650–2000	250–740	−2.1–11.5	50–2900	0.2–1.1

The catchment attributes and performance for a particular regionalisation method are available for each catchment and include area, mean catchment elevation, mean annual precipitation (P_A), mean annual potential evaporation (E_{PA}) and mean annual air temperature (T_A). Groups of regionalisation methods: regression methods (R), spatial proximity methods (SP), geostatistical methods (G) and process-based methods (PB).

Table A7.1. *Summary of studies used in the comparative assessment of flow duration curves estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Error	Error measure	Used in L1	Used in L2
Shu and Ouarda (2012)	Canada (Quebec)	Cold (Dfb)		646–1508	109		R	q_i	0.35	percNSlw75	X	
Sauquet and Catalogne (2011)	France	Humid (Cfb, Csb, Dfc)	1.4–110 000	600–2100	1080	1970–2008	IM	$q^{(1\ldots365)}$	0.20	meanANE	X	X
Sauquet and Catalogne (2011)	France	Humid (Cfb, Csb, Dfc)	1.4–110 000	600–2100	1080	1970–2008	IM	$q^{(1\ldots365)}$	0.10	meanANE	X	X
Sauquet and Catalogne (2011)	France	Humid (Cfb, Csb, Dfc)	1.4–110 000	600–2100	1080	1970–2008	IM	$q^{(1\ldots365)}$	0.10	meanANE	X	X
Sauquet and Catalogne (2011)	France	Humid (Cfb, Csb, Dfc)	1.4–110 000	600–2100	1080	1970–2008	IM	$q^{(1\ldots365)}$	0.20	meanANE	X	X
Rianna *et al*. (2011)	Northern Italy	Humid (Cfa)	50–1000	650–1350	8		IM	$q^{(1\ldots365)}$	0.40	percNSlw75	X	
Li *et al*. (2010)	South-east Australia	Humid (Cfb, Cfa)	50–2000	500–1500	227	10 to 90 yrs	IM	$q^{(1\ldots365)}$	0.10	percNSlw75	X	
Li *et al*. (2010)	South-east Australia	Humid (Cfb, Cfa)	50–2000	500–1500	227	10 to 90 yrs	IM	$q^{(1\ldots365)}$	0.15	percNSlw75	X	
Li *et al*. (2010)	South-east Australia	Humid (Cfb, Cfa)	50–2000	500–1500	227	10 to 90 yrs	IM	$q^{(1\ldots365)}$	0.40	percNSlw75	X	
Li *et al*. (2010)	South-east Australia	Humid (Cfb, Cfa)	50–2000	500–1500	227	10 to 90 yrs	IM	$q^{(1\ldots365)}$	0.55	percNSlw75	X	
Archfield *et al*. (2010)	USA (New England)	Cold (Dfb, Dfc)	10–762	1100–1450	66/47	1960–2004	R	q_i	0.54	median RRMSE	X	X
Ganora *et al*. (2009)	Italy and Switzerland	Cold (Dfb, Dfc, ET)	20–8000	840–1950	95		IM	$q^{(1\ldots365)}$	1.00	percANElw100	X	X
Rojanamon and Chaisomphob (2007)	Thailand	Tropical (Aw)	44–1380	800–1600	13/8	1965–2003	R	q_i	0.34	median RRMSE	X	
Rojanamon and Chaisomphob (2007)	Thailand	Tropical (Aw)	44–1380	800–1600	13/8	1965–2003	R	q_i	0.37	median RRMSE	X	
Rojanamon and Chaisomphob (2007)	Thailand	Tropical (Aw)	44–1380	800–1600	13/8	1965–2003	R	q_i	0.22	median RRMSE	X	
Rojanamon and Chaisomphob (2007)	Thailand	Tropical (Aw)	44–1380	800–1600	13/8	1965–2003	R	q_i	0.26	median RRMSE	X	
Castellarin *et al*. (2007a)	North-central Italy	Humid (Cfa)	60–1050	890–1300	18		IM	$q^{(1\ldots365)}$	1.00	percANElw100		X

Table A7.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	No. of catchments	Period/No. of years	Regionalisation method	Predicted variable	Error	Error measure	Used in L1	Used in L2
Arora *et al.* (2005)	India (western Himalaya)	Arid (BSh, Cwa, Cwb)	1566–22 400		9/2	14 to 23 yrs	IM	$q^{(1\ldots365)}$	1.50	meanANE	X	
Arora *et al.* (2005)	India (western Himalaya)	Arid (BSh, Cwa, Cwb)	1566–22 400		9/2	14 to 23 yrs	R	q_i	0.40	meanANE	X	
Arora *et al.* (2005)	India (western Himalaya)	Arid (BSh, Cwa, Cwb)	1566–22 400		9/2	14 to 23 yrs	R	q_i	0.40	meanANE	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	32–3082	824–1505	51		IM	q_i	0.71	percNSlw75	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	20–3070	824–1505	51		R	q_i	0.69	percNSlw75	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	20–3070	824–1505	51		IM	q_i	0.78	percNSlw75	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	20–3070	824–1505	51		SR	q_i	0.46	percNSlw75	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	20–3070	824–1505	51		SR	q_i	0.34	percNSlw75	X	
Castellarin *et al.* (2004a)	North-central Italy	Humid (Cfa)	20–3070	824–1505	51		SR	q_i	0.22	percNSlw75	X	
Yu *et al.* (2002)	Taiwan	Humid (Cfa)	42–683	1833–3376	15		R	q_i	1.00	percANElw100	X	
Yu *et al.* (2002)	Taiwan	Humid (Cfa)	42–683	1833–3376	15		R	q_i	0.87	percANElw100	X	
Holmes *et al.* (2002)	United Kingdon	Humid (Cfb)			523/130		R	q_{95}	0.64	median RRMSE		
Yu and Yang (1996)	Taiwan	Humid (Cfa)		2700	34		IM	Area under the FDC	0.30	NAE		

R: regression method
IM: index method
SR: short records method
percNSElw75: percentage of sites with NSE lower than 0.75
medianANE: mean absolute normalised error (in the middle of the FDC)
meanRRMSE: mean relative root mean square error
percANElw100: percentage of sites with median ANE lower than 100%
NAreaE: normalised area error
q_i: selection of runoff quantiles from the FDC
$q^{(1\ldots365)}$: all values from the FDC
No. of catchments (calibration/validation)

Table A7.2. *Summary of information provided for the studies included in the Level 2 assessment, listing studies with more detailed information about catchment characteristics and cross-validation performances*

Study	Region	No. of catchments	Method	Area (km^2)	P_A (mm)	E_{PA} (mm)	T_A (°C)	Elevation (m)	Aridity (–)
Viglione *et al*. (2013b)	Austria	209	G, PB	13–7000	500–2300	280–800	0–10	180–2500	0.2–1.4
Narda (2012)	Italy	23	IM	45–7000	600–1100			1670–2400	
Linhart *et al*. (2012)	USA	6	PB	720–4100	700–900	630–660	6.8–7.8		0.7–0.9
Sauquet and Catalogne (2011)	France	1080	R	1–110 000	600–2100	230–900	0.1–14.0	21–2980	0.2–1.3
Archfield *et al*. (2010)	USA	47	R	4–760	1100–1450	540–670	5.9–10.2	30–560	0.4–0.6
Ganora *et al*. (2009)	Italy	36	IM	20–8000	840–1950	450–950		480–2700	0.4–1.0
Castellarin *et al*. (2007)	Italy	18	IM	60–1050	890–1300	670–750	11.3–13.4	380–1300	0.5–0.8

The catchment attributes and performance for a particular regionalisation method are available for each catchment and include area, mean catchment elevation, mean annual precipitation (P_A), mean annual potential evaporation (E_{PA}) and mean annual air temperature (T_A). Groups of regionalisation methods: regression methods (R), index methods (IM), geostatistical methods (G) and process-based methods (PB).

Table A8.1. *Summary of studies used in the comparative assessment of low flows estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Regional method	Predicted variable	Performance (R^2)	Error (RRMSE)	Used in L1	Used in L2
Kroll (2012)	Western USA	Humid (Cfa, Dfb, Dfa)				150	GR	$q_{7,10}$		1.06		
Kroll (2012)	Western USA	Humid (Cfa, Dfb, Dfa)				150	SR	$q_{7,10}$		0.96		
Kroll (2012)	Western USA	Humid (Cfa, Dfb, Dfa)				150	SR	$q_{7,10}$		0.66		
Eng *et al*. (2011)	Eastern USA	Humid (Cfa, Dfb, Dfa)	3–2600	320–4600	5–3650	516	SR	$q_{7,10}$	0.96	0.31	X	X
Eng *et al*. (2011)	Eastern USA	Humid (Cfa, Dfb, Dfa)	3–2600	320–4600	5–3650	125	SR	$q_{7,10}$	0.99	0.21	X	X
Eng *et al*. (2011)	Eastern USA	Humid (Cfa, Dfb, Dfa)	3–2600	320–4600	5–3650	422	SR	$q_{7,10}$	0.97	0.22	X	X
Castiglioni *et al*. (2011)	Central Italy	Humid (Cfa)				51	G	q_{97}	0.89		X	
Plasse and Sauquet (2010)	France	Humid (Cfb, Dfb, Dfc, ET)	10–1940	660–2200	35–2250	1003	GR	$q_{mon,5}$	0.43	0.8	X	X
Plasse and Sauquet (2010)	France	Humid (Cfb, Dfb, Dfc, ET)	10–1940	660–2200	35–2250	1003	RR	$q_{mon,5}$	0.53–0.74	0.54–0.74	X	X
Plasse and Sauquet (2010)	France	Humid (Cfb, Dfb, Dfc, ET)	10–1940	660–2200	35–2250	1003	G	$q_{mon,5}$	0.61	0.75	X	X
Plasse and Sauquet (2010)	France	Humid (Cfb, Dfb, Dfc, ET)	10–1940	660–2200	35–2250	1003	G	$q_{mon,5}$	0.63–0.73	0.56–0.65	X	X
Vezza *et al*. (2010)	North-west Italy	Cold (Dfb, Cfa)				41	GR	q_{95}	0.57	0.38	X	
Vezza *et al*. (2010)	North-west Italy	Cold (Dfb, Cfa)				41	RR	q_{95}	0.53–0.69	0.33–0.40	X	
Engeland and Hisdal (2009)	South-west Norway	Cold (Dfc, ET, Dfb, Cfb)	6–1900	650–2700	180–1300	51	RR	q_{96}	0.82	0.32	X	X
Engeland and Hisdal (2009)	South-west Norway	Cold (Dfc, ET, Dfb, Cfb)	6–1900	650–2700	180–1300	51	PB	q_{96}	0.32	0.62	X	

Zhang *et al*. (2008c)	China (Dongjiang Basin)	Humid (Cwa, Cfa)					GR	$q_{7,10}$, $Q_{7,T}$				
Zhang *et al*. (2008c)	China (Dongjiang Basin)	Humid (Cwa, Cfa)					SR	$q_{7,10}$, $q_{7,T}$				
Laaha and Blöschl (2007)	Austria	Cold (Dfb, ET, ETH)	7–960	470–2100	200–2950	325	RR	q_{95}	0.75	0.31	X	
Laaha *et al*. (2007)	Austria	Cold (Dfb, ET, ETH)	2–1700	470–2030	200–2950	298	G	q_{95}	0.75	0.31	X	X
Chen *et al*. (2006)	China (Dongjiang Basin)	Humid (Cwa, Cfa)					IM	Q_d, T				
Laaha and Blöschl (2006a,b)	Austria	Cold (Dfb, ET, ETH)	7–960	470–2100	200–2950	325	GR	q_{95}	0.57	0.41	X	X
Laaha and Blöschl (2006a,b)	Austria	Cold (Dfb, ET, ETH)	7–960	470–2100	200–2950	325	RR	q_{95}	0.59–0.70	0.35–0.40	X	X
Pacheco *et al*. (2006)	Costa Rica	Tropical (Af, Aw)					IM	$\mathrm{MAM}_1/Q_\mathrm{A}$				
Laaha and Blöschl (2005)	Austria	Cold (Dfb, ET, ETH)	7–960	470–2100	200–2950	325	SR	q_{95}	0.62	0.39	X	X
Laaha and Blöschl (2005)	Austria	Cold (Dfb, ET, ETH)	7–960	470–2100	200–2950	325	SR	q_{95}	0.93	0.20	X	X
Rees *et al*. (2004)	Himalayas, Nepal and India	Humid (Cwb, Cwa)					SR	q_Jan				
Rees *et al*. (2004)	Himalayas, Nepal and India	Humid (Cwb, Cwa)					GR	q_Jan				
Rees *et al*. (2004)	Himalayas, Nepal and India	Humid (Cwb, Cwa)					RR	q_Jan				
Tallaksen *et al*. (2004)	Germany (Baden-Württemberg)	Humid (Cfb)					IM	max$D$, max$V$				

Table A8.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Regional method	Predicted variable	Performance (R^2)	Error (RRMSE)	Used in L1	Used in L2
Rees *et al.* (2002)	Himalayas, Nepal and India	Humid (Cwb, Cwa)				40	GR	q_{95}/q_A	0.45		X	
Rees *et al.* (2002)	Himalayas, Nepal and India	Humid (Cwb, Cwa)				40	GR	q_{95}/q_A	0.53		X	
Young *et al.* (2000a,b)	UK	Humid (Cfb)					IM	q_{95}/q_A		1.33 (f.s.e.)		
Young *et al.* (2000a,b)	UK	Humid (Cfb)					RR	q_{95}/q_A		1.71 (f.s.e.)		
Aschwanden and Kan (1999)	Switzerland	Cold (ET, Dfb, ETH, Dfc)				143	GR	q_{95}	0.51	0.48	X	
Aschwanden and Kan (1999)	Switzerland	Cold (ET, Dfb, ETH, Dfc)				143	RR	q_{95}	0.59–0.84	0.34	X	
Smakhtin (1997)	South Africa	Arid (BWk, BSk)					PB	q_x, MAM_d				
Demuth and Hagemann (1994)	Germany (Baden-Württemberg)	Humid (Cfb)				54	GR	BFI	0.86	0.21	X	
Demuth (1993)	Germany (Baden-Württemberg)	Humid (Cfb)				54	GR	BFI	0.81	0.25	X	
Demuth (1993)	Germany (Baden-Württemberg)	Humid (Cfb)				54	GR	BFI	0.84	0.23	X	
Gustard *et al.* (1992)	UK	Humid (Cfb)					GR	MAM_d/Q_A				
Gustard *et al.* (1992)	UK	Humid (Cfb)					RR	MAM_d/Q_A				
Nathan and McMahon (1990, 1992)	Australia (New South Wales, Victoria)	Arid (BSk, BWh BSh, Cfb, Cfa)				184	RR	BFI	0.75–0.83	0.08	X	

Nathan and McMahon (1990, 1992)	Australia (New South Wales, Victoria)	Arid (BSk, BWh BSh, Cfb, Cfa)	184	GR	BFI	0.71	0.19	X
Nathan and McMahon (1990, 1992)	Australia (New South Wales, Victoria)	Arid (BSk, BWh BSh, Cfb, Cfa)	184	RR	Sum$V$	0.75–0.93		
Nathan and McMahon (1990, 1992)	Australia (New South Wales, Victoria)	Arid (BSk, BWh BSh, Cfb, Cfa)	184	GR	Sum$V$	0.7		

GR: global regression method
RR: regional regression method
SR: short records method
G: geostatistical method
PB: process-based method
IM: index method
$q_{7,10}$: 7-days 10-yrs specific runoff
$q_{\mathrm{mon},5}$ (monthly 5-day minimum)
Sum$V$: volume sum below a runoff threshold
q_{95}, q_{96}, q_{97}: 95, 96 and 97% runoff quantiles
q_{95}/q_{A}: normalised q_{95} runoff quantile
BFI: Baseflow index

Table A8.2. *Summary of information provided for the studies included in the Level 2 assessment, listing of studies with more detailed information about catchment characteristics and cross-validation performances*

Study	Region	No. of catchments	Method	Area (km^2)	P_A (mm)	E_{PA} (mm)	T_A (°C)	Elevation (m)	Aridity (–)
Eng *et al.* (2011)	USA	1063	SR	3–2600	320–4600	390–1200	−2.0–22.5	5–3650	0.1–2.1
Plasse and Sauquet (2010)	France	607	GR, RR, G	10–1940	660–2200	480–1250	1.8–13.8	35–2250	0.3–1.7
Engeland and Hisdal (2009)	Norway	51	RR	6–1900	650–2700		−2.2–6.5	180–1300	
Laaha *et al.* (2013)	Austria	300	G	2–1700	470–2030	175–1000	−2.2–10.1	200–2950	0.1–1.2
Laaha and Blöschl (2006a)	Austria	325	RR	7–960	470–2100	170–650	−2.5–10.0	200–2950	0.2–1.3
Laaha and Blöschl (2005)	Austria	131	SR	7–960	470–2100	170–650	−2.5–10.0	200–2950	0.2–1.3

The catchment attributes and performance for a particular regionalisation method are available for each catchment and include: area, mean catchment elevation, mean annual precipitation (P_A), mean annual potential evaporation (E_{PA}) and mean annual air temperature (T_A). Groups of regionalisation methods: global regression methods (GR), regional regression methods (RR), short record methods (SR) and geostatistical methods (G).

Table A9.1. *Summary of studies used in the comparative assessment of floods estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Period/No. of years	Regional method	Predicted variable	Error (RMSNE)	Used in L1	Used in L2
Jimenez *et al.* (2012)	Spain	Arid (BSk, Csa, Csb, Cfb)	9.25–12 811	372–2348	190–2489	217	16 to 72 yrs	R	q_{100}	0.54	X	X
Grimaldi *et al.* (2012)	Central Italy	Humid (Cfa)						PB				
Sikorska *et al.* (2012)	Central Poland	Cold (Dfb)						PB				
Walther *et al.* (2011)	Germany (Saxony)	Cold (Dfb, Dfc)	1–6200	647–1339	140–940	170	20 to 93 yrs	G	q_{100}	0.46	X	X
Walther *et al.* (2011)	Germany (Saxony)	Cold (Dfb, Dfc)	1–6200	647–1339	140–940	170	20 to 93 yrs	IM	q_{100}	0.49	X	X
Kjeldsen and Jones (2010)	UK	Humid (Cfb)	1.6–4587.0	558–2848	26–680	602	4 to 117 yrs	IM	q_{100}	0.51	X	X
Kjeldsen and Jones (2010)	UK	Humid (Cfb)	1.6–4587.0	558–2848	26–680	602	4 to 117 yrs	IM	q_{100}	0.50	X	X
Guse *et al.* (2010)	Germany (Saxony)	Cold (Dfb, Dfc)	13–6170	647–1244	30–1215	90	20 to 150 yrs	R	q_{max}	0.81	X	
Guse *et al.* (2010)	Germany (Saxony)	Cold (Dfb, Dfc)	13–6170	647–1244	30–1215	90	20 to 150 yrs	R	q_{max}	0.88	X	
Koutsoyiannis *et al.* (2010)	Greece	Arid (Csa)						PB				
Saf (2009)	Turkey	Arid (Csa, Csb, BSk)				47	1960–2000	IM	Q_{100}/Q_m	0.43	X	
Chebana and Ouarda (2008)	Canada (southern Quebec)	Cold (Dfb, Dfc)	208–96 600	646–1534		151	min 15 yrs	R	q_{100}	0.44–0.45	X	
Chebana and Ouarda (2008)	Canada (southern Quebec)	Cold (Dfb, Dfc)	208–96 600	646–1534		151	min 15 yrs	R	q_{100}	0.49	X	
Chebana and Ouarda (2008)	Canada (southern Quebec)	Cold (Dfb, Dfc)	208–96 600	646–1534		151	min 15 yrs	R	q_{100}	0.64	X	
Srinivas *et al.* (2008)	USA (Indiana)	Cold (Dfa, Cfa)	0.28–28 813	864–1168	126–363	245		IM	q_{100}	0.69	X	X
Srinivas *et al.* (2008)	USA (Indiana)	Cold (Dfa, Cfa)	0.28–28 813	864–1168	126–363	245		IM	Q_{100}	0.27	X	X
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	R	q_{100}	0.74	X	
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	R	q_{100}	0.66	X	

Table A9.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Period/No. of years	Regional method	Predicted variable	Error (RMSNE)	Used in L1	Used in L2
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	IM	q_{100}	0.67	X	
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	IM	q_{100}	0.67	X	
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	G	q_{100}	0.51	X	
Ouarda *et al.* (2008)	Mexico	Tropical (Aw, Cwb)				29	1944–1999	G	q_{100}	0.52	X	
Patil (2008)	Germany (Baden-Wüttemberg)	Humid (Cfb)				41		PB				
Leclerc and Ouarda (2007)	Canada, USA	Cold (Dfb, Dfa)				29		R	q_{100}	0.61	X	
Cunderlik and Ouarda (2006)	Canada (southern Quebec)	Cold (Dfb, Dfc)	642–19 000			8		IM	Q_m	0.15		
Ouarda *et al.* (2006)	Canada (southern Quebec)	Cold (Dfb, Dfc)	355–23 600			63	10 to 75 yrs	IM	q_{100}	0.40	X	
Merz and Blöschl (2005)	Austria	Cold (Dfb, ET, ETH)	10–954	501–2312	165–2968	575	5 to 44 yrs	G	q_{100}	0.30	X	X
Merz and Blöschl (2005)	Austria	Cold (Dfb, ET, ETH)	10–954	501–2312	165–2968	575	5 to 44 yrs	R	q_{100}	0.46	X	X
Merz and Blöschl (2005)	Austria	Cold (Dfb, ET, ETH)	10–954	501–2312	165–2968	575	5 to 44 yrs	IM	q_{100}	0.43	X	X
Jingyi and Hall (2004)	China (Gan-Ming River)	Humid (Cfa)	685–4300	1674–1710	298–664	86	15 to 36 yrs	IM	Q_{20}, Q_{50}, Q_{100}, Q_{200}	0.31	X	
Chokmani and Ouarda (2004)	Canada (southern Quebec)	Cold (Dfb, Dfc)	208–96 600	646–1534		151	min 15 yrs	R	q_{100}	0.70	X	
Chokmani and Ouarda (2004)	Canada (southern Quebec)	Cold (Dfb, Dfc)	208–96 600	646–1534		151	min 15 yrs	R	q_{100}	0.51	X	
Kumar *et al.* (2003)	India (Middle Ganga Plains)	Humid (Cwa)	32.89–447.76			11	11 to 33 yrs	IM	Q_{100}/Q_m			

Cunderlik and Burn (2002)	UK	Humid (Cfb)	10–1000		424	15 to 49 yrs	IM	Q_{100}/Q_{m}	0.29	X
Javelle *et al.* (2002)	Canada (Quebec, Ontario)	Cold (Dfb, Dfc)	10–50 000		158	18 to 80 yrs	IM	q_{100}	0.50	X
Pandey and Nguyen (1999)	Canada (Quebec)	Cold (Dfb, Dfc)	3.9–86 900		71	20 to 62 yrs	R	q_{100}	0.64	X
Pandey and Nguyen (1999)	Canada (Quebec)	Cold (Dfb, Dfc)	3.9–86 900		71	20 to 62 yrs	R	q_{100}	0.81	X
Madsen *et al.* (1997)	New Zealand (South Island)	Humid (Cfb, Cfc)		680–7400	48	21 to 42 yrs	IM	q_{100}	0.41	X
Madsen *et al.* (1997)	New Zealand (South Island)	Humid (Cfb, Cfc)		680–7400	48	21 to 42 yrs	IM	q_{100}	0.39	X
Meigh *et al.* (1997)	Brazil (Rio Grande do Sul)	Humid (Cfa)			59		IM	q_{100}	0.42	X
Meigh *et al.* (1997)	Ivory Coast, Mali, Guinea, Ghana, Togo, Benin	Tropic (Aw, Am)			35		IM	q_{100}	0.47	X
Meigh *et al.* (1997)	Ivory Coast, Mali, Guinea, Ghana, Togo, Benin	Tropic (Aw, Am)			86		IM	q_{100}	0.50	X
Meigh *et al.* (1997)	Ivory Coast, Mali, Guinea, Ghana, Togo, Benin	Tropic (Aw, Am)			41		IM	q_{100}	0.53	X
Meigh *et al.* (1997)	Ivory Coast, Mali, Guinea, Ghana, Togo, Benin	Tropic (Aw, Am)			16		IM	q_{100}	0.59	X
Meigh *et al.* (1997)	Ivory Coast, Mali, Guinea, Ghana, Togo, Benin	Tropic (Aw, Am)			46		IM	q_{100}	0.42	X
Meigh *et al.* (1997)	Malawi	Humid (Cwa, Cwb)			28		IM	q_{100}	0.69	X
Meigh *et al.* (1997)	Namibia	Arid (BSh, BWh)			40		IM	q_{100}	0.63	X

Table A9.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Period/No. of years	Regional method	Predicted variable	Error (RMSNE)	Used in L1	Used in L2
Meigh *et al.* (1997)	Zimbabwe	Humid (Cwb, Cwa, BSh)				234		IM	q_{100}	0.515	X	
Meigh *et al.* (1997)	South Africa and Botswana	Arid (BSk, BWk)				109		IM	q_{100}	0.69	X	
Meigh *et al.* (1997)	Saudi Arabia	Arid (BWh)				28		IM	q_{100}	0.73	X	
Meigh *et al.* (1997)	Central Iran	Arid (BSk, BWh)				24		IM	q_{100}	0.65	X	
Meigh *et al.* (1997)	India (Kerala)	Tropical (Am)				75		IM	q_{100}	0.58	X	
Meigh *et al.* (1997)	Arid and semi-arid basins worldwide	Arid				162		IM	q_{100}	0.73	X	
GREHYS (1996)	Canada (Quebec, Ontario)	Cold (Dfb, Dfc)				33	min 35 yrs	IM	q_{100}	0.45	X	
Mignosa *et al.* (1995)	Central Italy	Humid (Cfa)						PB				
Zrinji and Burn (1994)	Canada (New Foundland)	Cold (Dfb, Dfc)				22	12 to 61 yrs	IM	Q_{20}, Q_{50}, Q_{100}, Q_{200}			
Farquharson *et al.* (1992)	Arid and semi-arid basins worldwide	Arid				162		IM	q_{100}	0.73	X	
McKerchar (1991)	New Zealand	H (Cfb, Cfc)				324		IM				
Burn (1990b)	Canada	C (Dfb, Dfc)	46–4200			45	20 to 42 yrs	IM				
Acreman and Wiltshire (1989)	UK	H (Cfb)				376		R				

R: regression method
IM: index method
G: geostatistical method
PB: process-based method
q_{100}: 100-year specific flood runoff
Q_{100}: 100-year flood runoff
Q_{100}/Q_m: 100-year flood runoff standarised by the mean annual flood

Table A9.2. *Summary of information provided for the studies included in the Level 2 assessment, listing studies with more detailed information about catchment characteristics and cross-validation performances*

Study	Region	No. of catchments	Method	Area (km^2)	P_A (mm)	E_{PA} (mm)	T_A (°C)	Elevation (m)	Aridity (–)
Jimenez *et al.* (2012)	Spain	217	R	9–12 800	370–2350	190–1070	2.6–16.0	350–2500	0.2–2.0
Walther *et al.* (2011)	Germany	170	IM, G	1–6200	647–1339			140–940	
Kjeldsen and Jones (2010)	UK	587	IM	1–4600	560–2850	290–550		26–680	0.1–0.9
Srinivas *et al.* (2008)	USA	245	IM	1–29 000	864–1168			120–360	
Merz and Blöschl (2005)	Austria	521	R, IM, G	10–955	500–2310	280–750	−2.8–10.4	50–3050	0.2–1.4

The catchment attributes and performance for a particular regionalisation method are available for each catchment and include: area, mean catchment elevation, mean annual precipitation (P_A), mean annual potential evaporation (E_{PA}) and mean annual air temperature (T_A). Groups of regionalisation methods are regression methods (R), index methods (IM) and geostatistical methods (G).

Table A10.1. *Summary of studies used in the comparative assessment of hydrographs estimation*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Period/No. of years	Hydrological model	No. of parameters	Regional method	Predicted variable	Nash–Sutcliffe efficiency	Used in L1	Used in L2
Petheram *et al.* (2012)	Northern Australia	Tropical (Aw, Bsh)		400–1800	50–600	105/105	1960–2007	AWBM	6	SP	Q_d	0.54	X	X
Petheram *et al.* (2012)	Northern Australia	Tropical (Aw, Bsh)		400–1800	50–600	105/105	1960–2007	SIMHYD	6	SP	Q_d	0.54	X	X
Petheram *et al.* (2012)	Northern Australia	Tropical (Aw, Bsh)		400–1800	50–600	105/105	1960–2007	IHACRES	7	SP	Q_d	0.55	X	X
Petheram *et al.* (2012)	Northern Australia	Tropical (Aw, Bsh)		400–1800	50–600	105/105	1960–2007	SMARG	8	SP	Q_d	0.53	X	X
Petheram *et al.* (2012)	Northern Australia	Tropical (Aw, Bsh)		400–1800	50–600	105/105	1960–2007	Sacramento	13	SP	Q_d	0.53	X	X
Samuel *et al.* (2011a)	Canada (Ontario)	Cold (Dfc, Dfb)	100–100 000	400–1200	100–500	94/94	1976–85/ 1986–94	MAC-HBV	14	SP	Q_d	0.57–0.59	X	
Samuel *et al.* (2011a)	Canada (Ontario)	Cold (Dfc, Dfb)	100–100 000	400–1200	100–500	94/94	1976–85/ 1986–94	MAC-HBV	14	MA	Q_d	0.31–0.46	X	
Samuel *et al.* (2011a)	Canada (Ontario)	Cold (Dfc, Dfb)	100–100 000	400–1200	100–500	94/94	1976–85/ 1986–94	MAC-HBV	14	R	Q_d	0.51–0.52	X	
Chiew (2010)	South-east Australia	Humid (Cfb, Cfa, Bsk, Bsh)				240/240	1975–2006	Sacramento	14	SM	Q_d	0.63	X	
Chiew (2010)	South-east Australia	Humid (Cfb, Cfa, Bsk, Bsh)				240/240	1975–2006	IHACRES	7	SM	Q_d	0.61	X	
Chiew (2010)	South-east Australia	Humid (Cfb, Cfa, Bsk, Bsh)				240/240	1975–2006	AWBM	7	SM	Q_d	0.60	X	
Chiew (2010)	South-east Australia	Humid (Cfb, Cfa, Bsk, Bsh)				240/240	1975–2006	SMARG	7	SM	Q_d	0.56	X	
Chiew (2010)	South-east Australia	Humid (Cfb, Cfa, Bsk, Bsh)				240/240	1975–2006	SIMHYD	6	SM	Q_d	0.55	X	
Samaniego *et al.* (2010b)	Germany	Humid (Cfb)	134–3969		240–1014	10/10	1979–2001	MHM	62	MA	Q_d	0.48–0.75	X	X
Samaniego *et al.* (2010b)	Germany	Humid (Cfb)	134–3969		240–1014	10/10	1979–2001	MHM	62	MA	Q_d	0.72–0.79	X	X
Samaniego *et al.* (2010a)	Germany	Humid (Cfb)	4–4002	714–1206	386–818	38/8	1980–8/ 1989–93	MHM	64	MA	Q_d	0.78–0.83	X	
Zhang and Chiew (2009)	South-east Australia	Humid (Cfa, Cfb)	51–2000		57–1445	210/210	1994–2000/ 2000–2006	SIMHYD	10	SP	Q_d	0.48–0.56	X	X
Zhang and Chiew (2009)	South-east Australia	Humid (Cfa, Cfb)	51–2000		57–1445	210/210	1994–2000/ 2000–6	SIMHYD	10	SM	Q_d	0.46–0.58	X	X
Zhang and Chiew (2009)	South-east Australia	Humid (Cfa, Cfb)	51–2000		57–1445	210/210	1994–2000/ 2000–6	Xinanjiang	12	SP	Q_d	0.51–0.56	X	X
Zhang and Chiew (2009)	South-east Australia	Humid (Cfa, Cfb)	51–2000		57–1445	210/210	1994–2000/ 2000–6	Xinanjiang	12	SM	Q_d	0.48–0.52	X	X
Viviroli *et al.* (2009a)	Switzerland	Cold (Dfb, Dfc, ET, ETH)	10–1000			140/49	1984–2003	PREVAH	12	SP	Q_h	0.67–0.70	X	X

Viviroli *et al.* (2009a)	Switzerland	Cold (Dfb, Dfc, ET, ETH)	10–1000			140/49	1984–2003	PREVAH	12	R	Q_h	0.65	X	X
Viney *et al.* (2009b)	South-east Australia	Arid (Bsk)	10–3500	550–3400		89/89	1975–2007	SMARG	8	SP	Q_d	0.60–0.62	X	
Viney *et al.* (2009b)	South-east Australia	Arid (Bsk)	10–3500	550–3400		89/89	1975–2007	Simhyd	6	SP	Q_d	0.63	X	
Viney *et al.* (2009b)	South-east Australia	Arid (Bsk)	10–3500	550–3400		89/89	1975–2007	Sacramento	13	SP	Q_d	0.60–0.67	X	
Viney *et al.* (2009b)	South-east Australia	Arid (Bsk)	10–3500	550–3400		89/89	1975–2007	IHACRES	7	SP	Q_d	0.50–0.59	X	
Viney *et al.* (2009b)	South-east Australia	Arid (Bsk)	10–3500	550–3400		89/89	1975–2007	AWBM	6	SP	Q_d	0.60–0.61	X	
Seibert and Beven (2009)	Sweden	Cold (Dfb, Dfc)	6–950			11/11	1981–90	HBV	12	MA	Q_d	0.5	X	
Reichl *et al.* (2009)	Australia	Humid (Cfa, Cfb)	53–2062	400–273	57–1326	184/89	1972–85	SimHyd	5	SP	Q_m	0.63	X	
Reichl *et al.* (2009)	Australia	Humid (Cfa, Cfb)	53–2062	400–273	57–1326	184/89	1972–85	SimHyd	5	R	Q_m	0.55	X	
Reichl *et al.* (2009)	Australia	Humid (Cfa, Cfb)	53–2062	400–273	57–1326	184/89	1972–85	SimHyd	5	MA	Q_m	0.66	X	
Post (2009)	Australia (Burdekin)	Arid (Bsh)	68–134146			24/24	1975–80/ 1980–85	IHACRES	5	R	Q_d	–0.64–0.74	X	
Li *et al.* (2009)	South-east Australia	Humid (Cfa, Cfb, Bsh, Bsk)	50–2000	406–1758		210/210	2000–2006	Xinanjiang	8–10	SP	Q_d	0.50–0.52	X	
Li *et al.* (2009)	South-east Australia	Humid (Cfa, Cfb, Bsh, Bsk)	50–2000	406–1758		210/210	2000–6	Xinanjiang	8–10	SM	Q_d	0.50–0.52	X	
Bulygina *et al.* (2009)	UK (Wales)	Humid (Cfb)	1.3–12.5	1670	170–438	6/6	Jan–Aug 2007	PDM	5	PX	Q_{15min}	0.65–0.84	X	
Zvolensky *et al.* (2008)	Slovakia	Cold (Dfb, Dfc, ET)	50–3800	700–1500	200–2000	23/23	1981–90/ 1991–2000	HBV	15	SM	Q_d	0.62–0.71	X	X
Zvolensky *et al.* (2008)	Slovakia	Cold (Dfb, Dfc, ET)	50–3800	700–1500	200–2000	23/23	1981–90/ 1991–2000	HBV	15	SP	Q_d	0.61–0.73	X	X
Zvolensky *et al.* (2008)	Slovakia	Cold (Dfb, Dfc, ET)	50–3800	700–1500	200–2000	23/23	1981–90/ 1991–2000	HBV	15	SP	Q_d	0.60–0.72	X	X
Zvolensky *et al.* (2008)	Slovakia	Cold (Dfb, Dfc, ET)	50–3800	700–1500	200–2000	23/23	1981–90/ 1991–2000	HBV	15	MA	Q_d	0.54–0.71	X	X
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–2005	TOPMO	6	MA	Q_d	0.69	X	X
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–5	TOPMO	6	SP	Q_d	0.71	X	X
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–5	TOPMO	6	R	Q_d	0.55	X	X
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–5	GR4J	4	MA	Q_d	0.71	X	X
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–5	GR4J	4	SP	Q_d	0.74	X	X

Table A10.1. *(cont.)*

Study	Region	Climate zone (Köppen classes)	Area (km^2)	P_A (mm/yr)	Elevation (m a.s.l.)	No. of catchments	Period/No. of years	Hydrological model	No. of parameters	Regional method	Predicted variable	Nash–Sutcliffe efficiency	Used in L1	Used in L2
Oudin *et al.* (2008)	France	Humid (Csb, Cfb, Dfb, Dfc)	10–9390	662–2182	24–2222	913/913	1996–2000/ 2001–5	GR4J	4	R	Q_d	0.68	X	X
Kim and Kaluarachchi (2008)	Ethiopia (Blue Nile)	Humid (Csa, Csb, Cwb, Aw)	111–10 139	1138–1892	1605–2644	18/18	5 yrs/2 yrs	Monthly water balance model (6p)		MA	Q_m	0.56–0.60	X	
Kim and Kaluarachchi (2008)	Ethiopia (Blue Nile)	Humid (Csa, Csb, Cwb, Aw)	111–10 139	1138–1892	1605–2644	18/18	5 yrs/2 yrs	Monthly water balance model	6	RC	Q_m	0.66	X	
Kim and Kaluarachchi (2008)	Ethiopia (Blue Nile)	Humid (Csa, Csb, Cwb, Aw)	111–10 139	1138–1892	1605–2644	18/18	5 yrs/2 yrs	Monthly water balance model	6	R	Q_m	0.66	X	
Hundecha *et al.* (2008)	Germany (River Rhine)	Humid (Cfb)	400–2100		10–1000	95	1983–88/ 1989–95	HBV	5	RC	Q_d	0.82–0.93	X	
Bastola *et al.* (2008)	Nepal, Japan, Australia, UK, France	Humid (Cfa, Cfb, Cwa, Aw)	25–8935	763–2366	79–1757	26/5	3 yrs	TOPMODEL	3	RC	Q_d	0.56–0.87	X	
Bastola *et al.* (2008)	Nepal, Japan, Australia, UK, France	Humid (Cfa, Cfb, Cwa, Aw)	25–8935	763–2366	79–1757	26/5	3 yrs	TOPMODEL	3	R	Q_d	0.41–0.86	X	
Parajka *et al.* (2007b)	Austria	Cold (Dfb, ET, ETH)	10–9770	400–2000	200–3000	320/320	1976–86/ 1987–97	HBV	11	RC	Q_d	0.63–0.67	X	X
Goswami *et al.* (2007)	France	Humid (Cfb, Csa)	32–371		79–863	13/13	7 yrs	7 models		SM	Q_d	0.33–0.73	X	
Goswami *et al.* (2007)	France	Humid (Cfb, Csa)	32–371		79–863	13/13	7 yrs	7 models		MA	Q_d	0.31–0.46	X	
Cutore *et al.* (2007)	Italy (eastern Sicily)	Humid (Csa)	19–1832		554–1479	9/9		Rainfall–runoff regression model	4	R	Q_m	0.48–0.81	X	
Boughton and Chiew (2007)	Australia and Tasmania	Humid (Cfa, Cfb, Csb, Bsk, Aw)	50–2000	390–2289		213/213	10 to 90 yrs	AWBM	8	R	Q_d	0–0.95	X	
Young (2006)	UK	Humid (Cfb)	3–1509		47–556	260/81	10 yrs/18 yrs	PDM	6	R	Q_d	0.66	X	
Wagener and Wheater (2006)	UK	Humid (Cfb)	28.5–1261	742–899		10/1	1989–96	PDM	5	R	Q_d	0.76–0.78	X	
Parajka et al. (2006)	Austria	Cold (Dfb, ET, ETH)	10–9770	400–2000	200–3000	320/320	1991–5/1996–2000	HBV	11	PX	Q_d	0.59–0.61	X	
Allasia *et al.* (2006)	South America (Uruguay River)	Humid (Cfa)	9870–52671			11/5	1985–1995	MGB-IPH		SM	Q_d	0.62–0.84	X	
Vogel (2005)	South-eastern USA	Humid (Cfa)	155–39847	1316–164	60–584	33/3	30 yrs	ABCD	4	RC	Q_m	0.69–0.93	X	

Parajka *et al*. (2005)	Austria	Cold (Dfb, ET, ETH)	10–9770	400–2000	200–3000	320/320	1976–86/ 1987–97	HBV	11	SM	Q_d	0.61–0.67	X	X
Parajka *et al*. (2005)	Austria	Cold (Dfb, ET, ETH)	10–9770	400–2000	200–3000	320/320	1976–86/ 1987–97	HBV	11	R	Q_d	0.60–0.65	X	X
Parajka *et al*. (2005)	Austria	Cold (Dfb, ET, ETH)	10–9770	400–2000	200–3000	320/320	1976–86/ 1987–97	HBV	11	SP	Q_d	0.62–0.67	X	X
McIntyre *et al*. (2005)	UK	Humid (Cfb)	1–1700	602–2860	37–557	127/127	1986–96	PDM	5	MA	Q_d	0.40–0.85	X	X
Merz and Blöschl (2004)	Austria	Cold (Dfb, ET, ETH)	3–5000	400–2000	200–3000	308/308	1976–86/ 1987–97	HBV	11	R	Q_d	0.49–0.56	X	
Merz and Blöschl (2004)	Austria	Cold (Dfb, ET, ETH)	3–5000	400–2000	200–3000	308/308	1976–86/ 1987–97	HBV	11	SP	Q_d	0.53–0.59	X	
McIntyre *et al*. (2004)	UK	Humid (Cfb)	132–578	640–1298		36/6	1989–94	PDM	6	MA	Q_d	0.75	X	
McIntyre *et al*. (2004)	UK	Humid (Cfb)	132–578	640–1298		36/6	1989–94	PDM	6	SM	Q_d	0.75	X	
McIntyre *et al*. (2004)	UK	Humid (Cfb)	132–578	640–1298		36/6	1989–94	PDM	6	R	Q_d	0.66	X	
Kokkonen *et al*. (2003)	USA (North Carolina)	Humid (Cfa)	0.09–1.44	1870–2500	696–1061	13/13	1937–9/1955–8	IHACRES	6	SM	Q_d	0.68–0.88	X	
Kokkonen *et al*. (2003)	USA (North Carolina)	Humid (Cfa)	0.09–1.44	1870–2500	696–1061	13/13	1937–9/1955–8	IHACRES	6	R	Q_d	0.6–0.88	X	

SP: spatial proximity method
SM: similarity method
MA: model averaging method
R: parameter regression method
RC: regional calibration
PX: proxy data method
No. of catchments (calibration/validation)
Period/No. of years (calibration/validation)
Q_{15min}: 15min runoff
Q_h: hourly runoff
Q_d: daily runoff
Q_m: monthly runoff

Table A10.2. *Summary of information provided for the studies included in the level 2 assessment, listing studies with more detailed information about catchment characteristics and cross-validation performances*

Study	Region	No. of catchments	Method	Area (km^2)	P_A (mm)	E_{PA} (mm)	T_A (°C)	Elevation (m)	Aridity (–)
Archfield *et al.* (2012)	USA	76	MA	20–35 300	830–1430	700–1200	7.1–22.5	26–1000	0.5–0.95
Petheram (2012)	Australia	105	SP	20–106 000	420–1750	1700–2020		26–740	1.0–4.4
Samaniego *et al.* (2010b)	Germany	10	RC	130–1130	900–1050	700–770	7.6–8.9	515–700	0.7–0.9
Zvolensky *et al.* (2008)	Slovakia	23	MA, SM, SP	20–3800	800–1350		3.8–6.9	580–1150	
Zhang and Chiew (2009)	Australia	210	SM, SP	50–2000	400–1750	100–1500		50–1450	0.1–3.1
Viviroli (2009a)	Switzerland	49	MA	15–1700				480–2450	
Oudin *et al.* (2008)	France	912	R, MA, SM, SP	10–9400	660–2200	480–1250	1.7–14.0	20–2200	0.3–1.7
Parajka *et al.* (2005, 2007b)	Austria	320	MA, R, SM, SP, RC	10–9800	470–2350	180–1000	−2–10	300–2600	0.2–1.4
McIntyre *et al.* (2005)	UK	127	MA	1–1700	600–2860	460–650		40–560	0.2–1.0

The catchment attributes and performance for a particular regionalisation method are available for each catchment and include: area, mean catchment elevation, mean annual precipitation (P_A), mean annual potential evaporation (E_{PA}) and mean annual air temperature (T_A). Groups of regionalisation methods are spatial proximity methods (SP), similarity methods (SM), parameter regression methods (R), model averaging methods (MA) and regional calibration methods (RC).

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