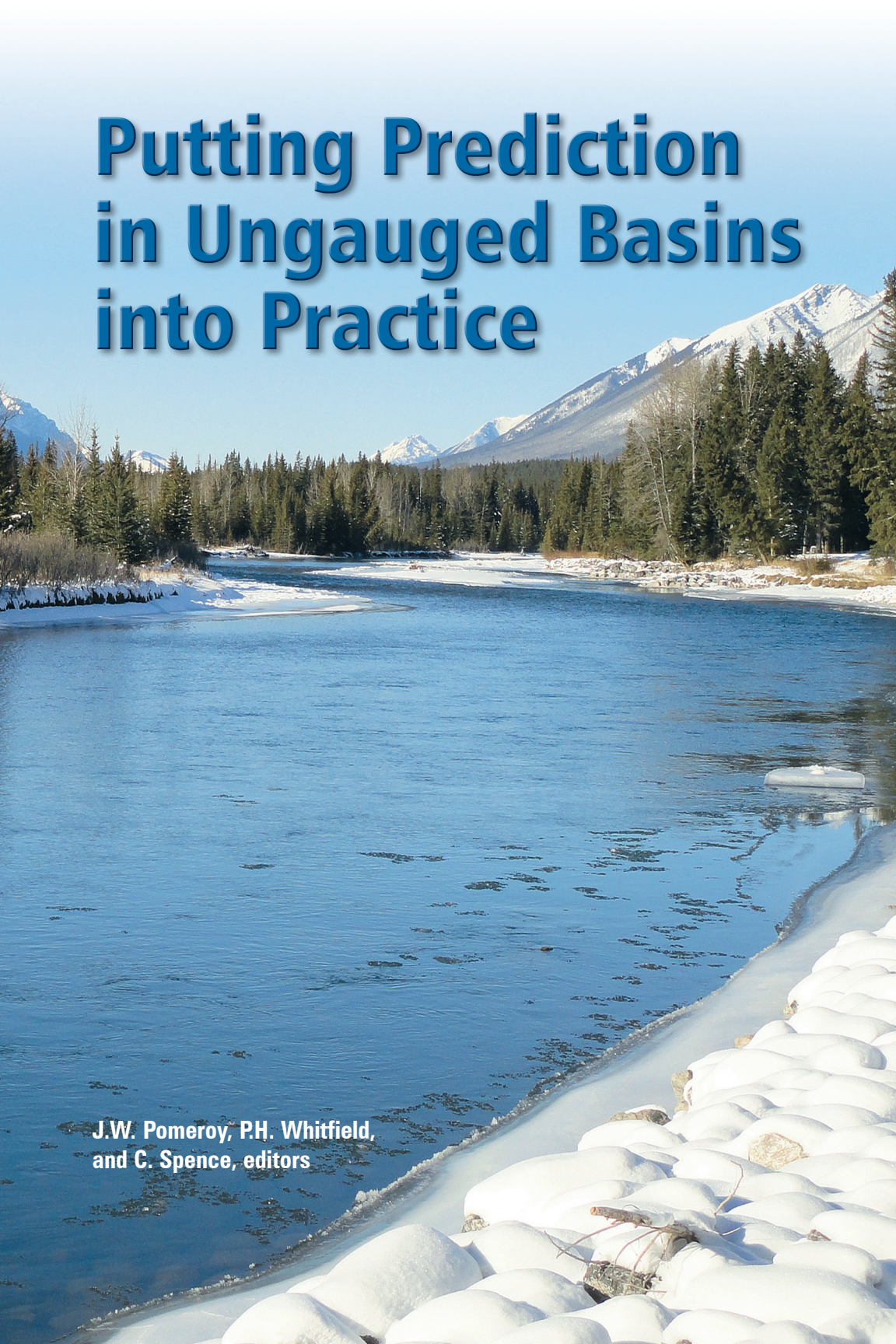
Putting Prediction in Ungauged Basins into Practice



J.W. Pomeroy, P.H. Whitfield,
and C. Spence, editors

Putting Prediction in Ungauged Basins into Practice

Edited by John W. Pomeroy, Paul H. Whitfield, and Christopher Spence.
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Canadian Water Resources Association
Association Canadienne des Ressources Hydriques

IAHS AISH
International Association of Hydrological Sciences
Association Internationale des Sciences hydrologiques

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PREFACE

As a part of the 4th Biennium of the International Association for Hydrological Sciences (IAHS) Decade for Prediction in Ungauged Basins (PUB), Canada hosted an international PUB Workshop entitled "Putting PUB into Practice" (P3) to discuss how the scientific results of the PUB initiative could be used to reduce uncertainty in practical water resource decision making. The goals of the 4th Biennium of PUB were to i) enhance communication with the scientific community and dialogue with the applications community, ii) include and analyze regional efforts and perspectives, iii) maximize the predictive value of available data, iv) incorporate process structure, variability and emergence into predictive approaches, v) improve realism in conceptual approaches, vi) utilize and assess new measurement and information technologies for basin inputs and characterization, and vii) develop improved models that reflect recently improved hydrological understanding. By addressing these goals it was hoped that the P3 Workshop could help to address several challenges that had become apparent during the PUB Decade, such as defining the appropriate use of sparse gauge observations, integrating physically based and conceptual methods in practice, and compensating for the limitations of regionalization approaches in vast ungauged regions that characterize much of the world. It was also anticipated that in addressing these goals PUB could develop approaches that would be relevant for the full range of hydroclimatic, ecological, and gauging situations in the world, for the implications of non-stationarity for changing how streamflow measurements are used for prediction, for prediction of multiple end points from the full hydrological cycle, for sharing approaches with global hydrological models and land surface schemes, and for estimating parameters and model structures using new types of information and basin classification schemes. With respect to the last point, it was hoped that better understanding of process behaviour, patterns, and scale emergence could be incorporated into innovative methods to parameterize physically based models for PUB.

Attendees of the Putting PUB into Practice Workshop in Canmore, Alberta, Canada, May 10-14, 2011

The P3 Workshop was held in the Canadian Rocky Mountain town of Canmore, Alberta on three exquisitely sunny days in May, 2011 and was attended by 75 energetic representatives who gathered from every inhabited continent and brought a range of disciplines stretching beyond traditional hydrology – from water resources engineering to atmospheric science – to the workshop. Practitioners, decision makers, computer programmers, writers, policy makers, students, and scientists attended the workshop to present, debate, and synthesize information, providing a wide perspective to discussion and transmission of information. The workshop was followed by a field trip guided by local author and naturalist Robert Sandford onto the grand Columbia Icefield – the frozen triple point headwater of three continental rivers: the Columbia, Athabasca, and Saskatchewan that flow into the Pacific Ocean, Arctic Ocean, and Hudson Bay respectively.

Those at the P3 Workshop examined a gradient from data-rich to data-poor regions and considered the needs of various hydroclimatic regions, seeking to share and consolidate between and across i) PUB themes and working groups, ii) a variety of regional efforts and perspectives, iii) approaches that maximized the predictive value of streamflow data and their use, iv) approaches that maximized the use of physically based theory – process structure, process variability, and their emergence into predictive approaches, and v) the inclusion of new measurement and information technologies for meteorological inputs, process verification, and catchment characterization. There was much exploration of improved models and tools that reflect improved hydrological understanding and their use in practice in a wide variety of situations. What was particularly impressive about the workshop were the open minded discussions towards addressing a difficult set of questions and the commonality of opinion that new physical concepts, basin conceptualizations, and technology were the key to moving forward with improved predictions. There was great enthusiasm for exchange of technical information between practitioners and scientists that bodes well for the future of both groups.

The P3 Workshop was supported by IAHS and the Canadian Society for Hydrological Sciences and organized by the Centre for Hydrology, University of Saskatchewan, Saskatoon and the Western Watershed Research Collaborative, Canmore. The workshop and its subsequent publication of this monograph by the Canadian Water Resources Association on behalf of IAHS were made possible by financial support from Alberta Innovates – Energy and

Environment Solutions, the Canada Excellence Research Chair in Water Security and Global Institute for Water Security of the University of Saskatchewan, the Improved Processes and Parameterization for Prediction in Cold Regions (IP3 Network), Alberta Environment, Hoskin Scientific, and Brewster Travel Canada. All are thanked for their generous support. Robert Sandford, Joni Onclin, Michael Allchin, Xing Fang, and Paul Whitfield are thanked for the special contribution to their workshop planning and logistics.

As many will know or learn, producing a monograph is not as simple as hosting a workshop, and the diligence and focus of Paul Whitfield and Chris Spence as co-editors kept this task moving forward to completion. Paul's editorial and organizational skills were particularly appreciated in this regard. Production of the volume involved the talented copy editing of Maureen Whitfield and designing of Philip Gregory, along with the support of the Canadian Water Resources Association for final publication in print and as a web host for electronic publication.

Finally, I would like to thank Dr. Gordon Young, President of the International Association of Hydrological Sciences at the time of this workshop, for his support of PUB, this workshop and monograph, and his deep understanding of the importance of better science and applications of science for the cold and developing regions of the world.

John Pomeroy

Chair of the 4th Biennium of the IAHS Decade for PUB (2009-2011)
Director, Centre for Hydrology, University of Saskatchewan,
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December 2013

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PUTTING PREDICTION IN UNGAUGED BASINS INTO PRACTICE

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1.1 ABSTRACT

The International Association for Hydrological Sciences (IAHS) Prediction in Ungauged Basins (PUB) initiative had the goal of decreasing the uncertainty in hydrological prediction. The 4th biennium of the PUB decade culminated in a 2011 workshop to summarize progress on sharing and consolidating efforts to maximize the use of new knowledge and techniques for prediction in ungauged basins in practice. The chapter summarizes the presentations and discussions that took place at the workshop. These followed four themes; maximizing the predictive value of available information, improving process realism in physically based predictive approaches, improving access to measurement and information technology for prediction, and reducing uncertainty in the face of environmental changes. It is hoped that this monograph provides a snapshot of the state of the art in prediction that can be used as a benchmark for further advances.

1.2 RÉSUMÉ

L'initiative Décennie de prévisions en bassins non jaugés (PBNJ) de l'AISH (Association internationale des sciences hydrologiques) avait pour but de diminuer l'incertitude entourant les prévisions hydrologiques. La 4e période biennale de la décennie de PBNJ a été couronnée par un atelier tenu en 2011, lequel visait à résumer les progrès entourant le partage et la consolidation des efforts en vue de maximiser l'utilisation des nouvelles connaissances et

techniques pour la prévision en bassins non jaugés dans la pratique. Le chapitre résume les présentations et les discussions qui ont eu lieu à l'atelier. Celles-ci ont porté sur quatre thèmes; maximiser la valeur prédictive des données, améliorer le réalisme du processus en ce qui concerne les approches prédictives fondées sur des critères physiques, améliorer l'accès aux mesures et aux technologies de l'information pour la prévision et réduire l'incertitude face aux modifications ou à la dégradation de l'environnement. Les intéressés espèrent que cette monographie présente un instantané de l'état actuel des réalisations en matière de prévisions pouvant servir de point de référence pour d'autres avancées.

1.3 INTRODUCTION

The overarching goal of the International Association for Hydrological Sciences (IAHS) Prediction in Ungauged (PUB) Initiative was to reduce uncertainty associated with prediction in ungauged basins. Prediction in ungauged basins remains difficult in many parts of the world because of an inadequate global gauging network for model calibration and regionalization using many current methods. This problem is most acute in developing countries and cold regions, which are among the most vulnerable regions to watershed stressors, but it is an issue everywhere. Poor gauging adds uncertainty to input data, model structure, and model parameterization. Non-stationarity in climate, land cover, and anthropogenic influences means even well gauged regions face uncertainty in prediction. The goals of the 4th biennium (2009-2011) of the PUB Initiative were to share and consolidate between and across PUB themes and working groups the variety of regional efforts, perspectives, and approaches that maximize the predictive value of streamflow data and their use. From May 10-14, 2011 in Canmore, Alberta, Canada, a workshop was convened to summarize and report on the progress made during the 4th biennium. The workshop consisted of invited theme papers, contributed case study papers, and work group discussions that all focused on how we presently predict within ungauged basins in areas where data availability ranges from very rich to very poor.

The core perspective of the workshop was evaluating how the availability of data affects how we make predictions, and seeking opportunities to transfer knowledge or skill or concepts amongst regions where data availability differs greatly. The invited papers and case studies follow four themes:

1. How to maximize the predictive value of available information.
2. How to improve process realism in physically based predictive approaches.
3. How to access measurement and information technology for prediction.
4. How to reduce uncertainty in the face of other environmental changes.

Within the workshops the participants considered how these would apply within data-rich, data-sparse, and data-poor watersheds and regions. This monograph is a summary and expansion of the presentations and discussions at the workshop; the expansion includes a sampling of PUB research and methodologies that could be of use to practitioners.

1.4 HOW TO MAXIMIZE THE PREDICTIVE VALUE OF AVAILABLE INFORMATION

The first suite of chapters provides different perspectives on how we are presently using available information and tools to make predictions in ungauged basins based on discussions at the workshop. Liu *et al*. (Chapter 2) describes how the predictive value of available data in ungauged basins is maximized in China. Based on the Chinese saying, "Even a clever housewife cannot cook a meal without rice", borrowing, substituting and generating are the three basic methods of obtaining information to model a basin of interest. That is specifically, extrapolating and/or interpolating amongst the data from adjacent catchments, or obtaining the information by simulation or experiments. These three approaches also apply to how knowledge and tools derived from hydrological prediction research can be applied to prediction in ungauged basins. Another approach to maximizing the use of existing information is provided by Clarke and Buarque (Chapter 3) in their description of a case study in the Amazon basin. In the Amazon, the estimation of precipitation is crucial for sound hydrological predictions in both ungauged and gauged basins. They present a parametric geostatistical model to estimate the Gumbel distribution of annual maximum one-day rainfall at sites without rain gauges in the Amazon and Tocantins basins of Brazil. Applying a model that is based upon all the available rain gauges produces better precipitation estimates than other methods.

Pomeroy *et al*. (Chapter 4) discussed how process hydrology study results from research basins could be used to generate physically based algorithms and appropriate model structures that could be used to predict in ungauged basins far away from the research basins. The application of deductive, inductive, and abductive approaches to derive models using physical rules, observed behavior, and borrowed hydrological relationships from similar ecosystems was demonstrated in Canadian basins. The value of intensive research basins as the source of information to be transferred to ungauged basins was emphasized.

Danny Marks reported at the workshop on how information from data-rich sites in mountain basins could be used to improve prediction at data-sparse sites in similar environments. In the mountains of western North America, nearly all the watersheds are ungauged. The hydrology of mountain basins is complicated and sensitive to weather and climate, and sufficiently non-linear that statistical rainfall/runoff or precipitation/runoff relationships are unreliable. While there are 50 years of research developing the techniques of hydrologic forecasting, Marks suggested that it is now time for hydrology and hydrological prediction to be addressed as a science and that prediction should be based on the understanding of meteorological, land surface, and hydrological processes and their interactions. He suggested that we re-evaluate our measurement strategy to better capture landscape gradients and the end-members and our understanding of the distributions of hydro-climatic parameters across complex landscapes. Marks also suggested that we continue to invest in basic hydrologic and hydroclimatic process research since the few existing outdoor laboratories provide high quality, long time series data records, allow us to characterize processes and distributions, and allow detailed uncertainty analysis. Only in a very few locations in the world is this possible, making these sites incredibly valuable.

1.5 HOW TO IMPROVE PROCESS REALISM IN PHYSICALLY BASED PREDICTIVE APPROACHES

The next suite of chapters addresses the importance of better understanding and representing geophysical processes in predictive tools. A study describing the use of physical principles to make predictions of floods in a Russian ungauged basin is presented in Gelfan (Chapter 5). The approach uses a data-rich small proxy-basin which is hydrologically similar to the poorly gauged study basin. First, a physically based model of flood

generation was developed in the proxy-basin, and then applied to the study basin. Using modelled daily meteorological forcing, the hydrological model generated a series of snowmelt flood hydrographs. The approach allows the derivation of frequency distribution of flood volume without utilizing any streamflow observations in the study basin. The proposed approach is targeted for hydrological engineering practice and considered as a suitable alternative to the traditional methods of flood risk assessment in ungauged or poorly gauged basins.

Jim McNamara reported to the workshop on the mutual reliance of improving process information and improving predictions in ungauged basins. For lumped models, statistical process representation is based upon coarse states, sparse data, and a small computational requirement. For fully distributed models, the physics based process representation relies on large data sets and fine resolution, requiring extensive computer resources. Semi-distributed and conceptual models fall in between lumped and distributed models. McNamara also addressed the issues of models which are right for the wrong reasons or wrong for the right reasons, reminding us that models need to get the right answers for the right reasons (Kirchner, 2006). McNamara discussed reductionism, an approach to understanding the nature of complex things by the interaction of their parts, and its contribution to PUB. He supported this reductionist approach in principle, suggesting that Newton was indeed correct; that model failures result from poor characterization of heterogeneous landscapes, and that hydrology is inherently a local science because of large regional variations in landscape variations; however, he also proposed that we could improve predictions by [1] retaining the computational efficiency and philosophy of lumped models, [2] observing how catchments create physically lumped properties, and replacing physical lumping in models with physically lumped properties. McNamara emphasized that storage is not commonly measured, is frequently estimated as the residual of the water balance, and is generally treated as a secondary model calibration target; yet improved characterization of storage will lead to improved predictions. He suggested that better understanding and description of the mechanisms responsible for storage and retention of water in the watershed are needed to improve predictions. Finally, he argued that true physically based models are a myth; that hydrological models can only address hydrologically relevant process and properties.

Jeff McDonnell reported to the workshop his belief that accurate prediction of headwater streamflow response implies adequate modelling of sources, flowpaths, and residence time of water and solutes (Hewlett and Troendle, 1975). McDonnell explained that quantifying the watershed residence time would improve model predictions. He demonstrated that for some basins there was no relationship between basin area and residence time, while in other basins there was a scaling of residence time and basin areas. McDonnell also argued that we need to be "getting the right answers for the right reasons" (Kirchner, 2006); developing models that are minimally parameterized and therefore stand some chance of failing the tests to which they are subjected. He demonstrated that defining residence time scaling could lead to significant improvements in process realism, and in some cases basin parameter transfer could be addressed within broad geological units.

1.6 HOW TO ACCESS MEASUREMENT AND INFORMATION TECHNOLOGY FOR PREDICTION

The third section discusses the essential first step in modelling and prediction of developing meteorological forcing data for input to hydrological models, whether for gauged or ungauged basins (Garen, Chapter 6). These forcing data may be from stations, and/or interpolations of real-time weather forecasting. Garen (Chapter 6) describes how preparation of forcing data can require significant database and software infrastructure, especially for real-time forecasting. In ungauged basins, without streamflow measurements to use as a check on simulation skill, it is especially critical to ensure that such model forcings are accurately prepared.

Hydrological ensemble forecasting is increasingly used in scientific and in operational modes (Renner and Werner, Chapter 7). Forecast ensembles are created either by forcing a hydrological model with meteorological ensemble forecast input or by running multiple hydrological models. While the resulting spaghetti plots provide some feeling of future variability, they are often difficult to interpret. Archived forecasts or hindcasts can be used as the basis for probabilistic forecasts that represent the predictive uncertainty of future flows and are thus useful for decision makers. The forecast horizon in combination with basin characteristics such as size and travel time, determine the contribution of different sources of uncertainty; knowledge that is crucial when aiming to improve forecast accuracy in either gauged or ungauged basins.

Vincent Fortin suggested to the workshop that there might soon be no such thing as a truly ungauged basin. Geostationary satellites today provide products such as rainfall estimates (PERSIANN), surface soil moisture (SMOS), water surface altimetry (SWOT), and water storage anomalies (GRACE). The availability of these types of data makes modelling the atmosphere over any basin easier and provides measurements of state variables (storage) and estimates of discharge of large rivers. Fortin described how re-analysis products and modern data-assimilation systems ingest massive amounts of data on the state of the atmosphere and provide physically based gridded datasets which can then be used for hydrological prediction. He also described products based upon the GEM atmospheric model that Environment Canada makes available; [1] CaPA: a near real-time precipitation analysis system, [2] MESH: a framework for surface and hydrology prediction. He demonstrated how these products have been applied to the prediction of water level changes in the Great Lakes basin. Today, the only (proven) method to forecast the weather for more than a few days is to forecast it everywhere by running a numerical weather prediction model (NWP) from initial conditions estimated from observations of the earth's atmosphere, oceans, and land. There are limits to what we can afford in terms of horizontal resolution, but GEM can zoom in on a region of interest using a limited-area model (LAM). Fortin also described ensemble forecasting where the aim is to represent uncertainty dynamically, based upon different initial conditions, different numerical models, or different weather forecasts. The differences between these model outputs should result in differences in forecasts that should reflect the uncertainty in estimates of initial conditions and in the limitations of our numerical models.

1.7 REDUCING UNCERTAINTY IN THE CONTEXT OF ENVIRONMENTAL CHANGES

Reducing uncertainty within prediction in ungauged basins is addressed in almost every PUB related publication and paper. In this workshop we asked some authors to consider other perspectives on uncertainty where the context of the prediction would contribute to the overall uncertainty. To start off this section of the monograph, Wheater *et al*. (Chapter 8) addressed how uncertainty could be reduced when land use change is creating non-stationarity. Prediction of the effects of changing land use and land management practices (i.e. catchment non-stationarity) for ungauged

catchments is an issue of considerable practical importance for catchment planning and management. The issues of land use non-stationarity raise difficult methodological and management challenges. Wheater *et al*. describe the development and application of a detailed physics based model with and without local data, to represent field-scale effects of land management practices. They suggest that addressing impacts of land management practice can be done through mapping of land management effects on soil structure and runoff processes, using regionalized indices of catchment response to constrain conceptual model parameterizations for ungauged application and upscaling the results to catchment scale using meta-models.

Regionalizing hydrological responses to ungauged catchments is a difficult problem (Post, Chapter 9); however, typical practical application of the PUB problem involves not just predicting the historical hydrological response of a catchment, but also requires a prediction of the hydrological response of a catchment into the future. Changes in catchment hydrological functioning can be brought about through changes in land use and land management, or through changes due to a changing climate. Post suggests that to solve this latter issue, we must first understand the hydrological functioning of a catchment under historical conditions; then we must improve the models used to represent this hydrological functioning; and finally modify the model structure to incorporate hydrological processes which are assumed will change under a changing climate. Water managers, however, require estimates of current and future water availability *now* in order to more effectively manage water resources. Solutions to the problem of non-stationarity need to be found, but assessments of water availability will continue using whatever methods and models are available.

Dornes (Chapter 10) addressed how we might combine both inductive and deductive approaches in prediction. Dornes demonstrates using a data driven modelling approach to represent landscape heterogeneity coupled with a physics based approach for detailed snowmelt process descriptions. Using a physically based hydrological land surface simulation, he demonstrated that using distributed initial conditions of snowcover and incoming solar radiation showed an appropriate representation of both the basin hydrographs and the snowcover ablation; however, aggregated simulations were unable to describe the dynamics of the basin streamflow when the runoff response was largely governed by solar radiation, but when temperature was a key factor in the onset of melt the differences were less. The modelling methodology

capitalized on the strength of both modelling approaches, and appears to be an effective method to reduce the size of the parameter sets and still retain physical reality. Therefore it can be a useful approach when applying physically based hydrological models in poorly or ungauged basins.

1.8 CASE STUDY PAPERS

The next section of the monograph includes short case study papers based upon some of the many posters that workshop participants presented on their personal experiences with prediction in ungauged basins. Several of these chapters address the issue of maximizing the predictive value of available information. Hughes (Chapter 11) reports on how predictions in ungauged basins are practiced at the national scale in South Africa. Minihane (Chapter 12) describes the procedures used for estimating the mean monthly discharges in the Lugenda River in northern Mozambique. Munro (Chapter 13) describes the methodology used to generate a runoff record for a recently ungauged glaciated watershed in the Canadian Rockies. Collectively these provide classic examples of the diversity of methodologies and scales of predicting in ungauged basins that exist.

Others addressed specific issues of process realism in making predictions. Keinzle (Chapter 14) reports on the procedure developed to estimate model parameters in a mountainous region in Canada. Littlewood (Chapter 15) describes how regionalization methods can be used to reduce the uncertainty of predicted flows in ungauged basins in the United Kingdom.

Several authors contributed case studies that deal with new technologies or newly available data types. Gutpta *et al*. (Chapter 16) consider the options available for near real time predictions of streamflow in the Canadian Prairies. Boyle *et al*. (Chapter 17) examined how SNODAS estimates of snow water equivalence can improve model predictions in snow dominated watersheds in the Rocky Mountains of the western United States. Kahl *et al*. (Chapter 18) describe how information from satellite imagery can be combined with an energy balance model to improve estimates of snow water equivalence in the Sierra Nevada in the western United States. Armstrong *et al*. (Chapter 19) show how prairie flooding, where runoff water fills glacial-legacy depressional storage to rapidly increase the basin contributing area, can be modelled using high resolution digital elevation models and a fill and spill runoff algorithm.

1.9 SUMMARIES

During the workshop, participants were tasked with synthesizing how the various approaches for prediction can be implemented in specific hydroclimatic regions given the typical availability of meteorological and catchment data and current understanding of hydrology. To ensure thorough evaluation of existing and new predictive methods, participants were tasked to examine a gradient of data-rich to data-poor contexts for that region. This permitted the sharing of ideas and consolidation of knowledge between and across the PUB Themes and Working Groups, and the variety of regional efforts and perspectives represented by research conducted during the PUB decade to date. Sessions summarized and synthesized the new approaches in hydrometeorological measurement, remote sensing, land surface modelling, process verification, catchment characterization and information management that have characterized development of innovative models during the PUB decade.

Whitfield *et al*. (Chapter 20) provide a summary and a synthesis of the discussion that occurred in the work groups. The work groups agreed that the lack of data with which to inform any type of predictive model, in combination with the wide diversity of hydrological landscapes, makes prediction in ungauged basins extraordinarily challenging. While the research of the past decade has great potential to advance the practice of hydrological prediction in ungauged basins, in particular thanks to the development of gridded hydrometeorological products and research activities in relatively data-rich research basins, the transfer to practice has been more limited. The work groups identified the need for continued detailed physical research, a watershed classification system and other tools designed to enhance the development of transferable data, indices, parameters, and indicators. A need was identified for standardized and generalized physiographic information to be collected using the same set of tools that are widely used by practicing hydrologists. Development and maintenance of these types of tools require ongoing communication and collaboration among all hydrologists. The work group summary includes recommendations that address the following needs:

1. to maintain continuity, and validate new methods during implementation.
2. to provide better interfaces to the complex datasets that are needed.

3. for openness and transparency in all predictive approaches.
4. for common operating platforms.
5. for better outreach to practitioners.

The legacy of the PUB decade includes significant advances in the understanding of hydrological processes and development and testing, in research settings, of revised or new methods for PUB. The challenge remains to address the need to adopt standards and globally generalized approaches for practitioners to make predictions in ungauged basins; the participants in the workshop portion of this meeting have suggested approaches that will address this situation. Three participants in the workshop, Denis Hughes, Ross Woods, and Chris Spence, were tasked with providing a synthesis and summary of the major findings of the workshop. They suggest that the key themes to emerge were [1] the need to decrease the gap between process understanding and model structure, [2] the need to constrain uncertain model inputs and outputs, and [3] the need to address the barriers that exist to adoption of new approaches by practitioners (Hughes *et al*., Chapter 21).

It was clear from the workshop discussions that a major divide exists between the hydrological research and water resource applications communities. Some divide is inevitable, due to the translation time of research results and techniques into accepted practical methods. It is hoped that the workshop helped to narrow the divide amongst participants and that this monograph will do the same for a wider audience. Still, there must be diligence and efforts to continue to narrow the divide. Whilst research, innovation and development must continue, hydrological researchers must also ensure that advances are readily and rapidly available to those who work to improve the resilience, sustainability, and security of water resource systems. The successes of the PUB decade in improving the understanding of hydrological processes, the increased availability of spatially distributed hydrometeorological data, the development of more robust physically based and statistical prediction tools, and the transfer of this information to the water resources practitioner community should be built upon. The process of researcher-practitioner engagement, information and technology transfer, and the development of new and relevant scientific tools for prediction must be an ongoing feature of hydrology and water resource science and application.

While the progress made during the PUB decade was critically evaluated, the outcome provides guidance for continued innovation now that the PUB decade has ended. The principal aim of the workshop was to make progress towards a crystallization of the 'state of the art' of predicting in ungauged basins. This "snapshot" could then support the further development of techniques that would contribute directly to the practical solution of real-world challenges in water resources management. It is hoped that this monograph forms part of that progress.

1.10 ACKNOWLEDGEMENTS

The editors of this monograph would like to express their appreciation to all the authors of the papers presented in this volume for both their contributions to the workshop and for the additional time they invested in preparing and revising their papers. We also need to express our thanks to all the participants in the workshop whose ideas and suggestions were valuable directly within the workshop, but also in the preparation of this monograph. The list of participants in the workshop is provided at the end of the monograph.

2

HOW TO MAXIMIZE THE PREDICTIVE VALUE OF AVAILABLE DATA IN UNGAUGED BASINS? – CHINESE LESSON

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2.1 ABSTRACT

Based on research results available from the literature and authors' experiences in PUB (IAHS Decade for Predictions in Ungauged Basins), a methodology framework on how to maximize the predictive value of available data in ungauged basins is proposed. It includes three methodological categories: "Borrowing", "Substituting", and "Generating", according to the logic of a Chinese saying: "Even a clever housewife cannot cook a meal without rice." The Borrowing method is defined as a method to use other data by transplanting the data from a nearby region, or extrapolating and/or interpolating among the data from the adjacent catchments. The Substituting method is the method to obtain the necessary data from the related information either from the same area by simulation and assimilation or from another area by for example upscaling and/or paired-catchment analysis. Generating is a method to obtain the data from field or laboratory experiments. Based on these three methods, there are at least three ways to promote the values of available data for the predictions in ungauged basins, including the further study of hydrological prediction theory, application of innovative and comprehensive methods for prediction, and making use of advances in technology for applications in hydrological prediction research. This methodology framework, summarized from a Chinese lesson, can be a reference for maximizing the predictive value of available data in ungauged basins.

2.2 RÉSUMÉ

D'après les résultats de recherche disponibles dans la documentation et en fonction des expériences des auteurs dans le cadre de l'initiative Décennie de prévisions en bassins non jaugés (PBNJ) de l'AISH, un cadre méthodologique est proposé quant à la manière de maximiser la valeur prédictive des données disponibles dans les bassins non jaugés. Ce cadre englobe trois catégories méthodologiques : « Emprunter », « Substituer » et « Générer », selon la logique d'un dicton chinois : « Même la meilleure des ménagères ne peut pas, si elle n'a pas de riz, préparer son repas ». La méthode de l'emprunt est définie comme étant une méthode qui consiste à se servir d'autres données en transposant les données d'une région à proximité, ou en extrapolant ou en interpolant les données de bassins adjacents. La substitution est une méthode qui consiste à obtenir les données nécessaires à même des données connexes soit de la même région au moyen de la simulation et de l'assimilation, soit d'une autre région, par exemple grâce à la mise à l'échelle supérieure ou au moyen de l'analyse à base de bassins versants appariés. La génération est une méthode qui consiste à obtenir des données à partir d'expériences sur le terrain ou en laboratoire. Suivant ces trois méthodes, il existe au moins trois moyens de promouvoir les valeurs des données disponibles pour les prévisions dans les bassins non jaugés, y compris l'étude plus poussée de la théorie de la prévision hydrologique, l'application de méthodes innovatrices et exhaustives pour les prévisions et le recours aux percées technologiques pour les applications de recherches sur les prévisions hydrologiques. Ce cadre méthodologique, résumé à partir d'un précepte chinois, peut servir de référence pour maximiser la valeur prédictive des données disponibles dans les bassins non jaugés.

2.3 INTRODUCTION

China is a country with climates ranging from arid to humid, with a population that reached 1.35 billion in 2012. It is undergoing rapid social change and economic growth, but maintains a low density of hydrological gauges; lower than that recommended by the World Meteorological Organization (Figure 2.1a) and in western China, for example the western sub-basins of the Yellow River Basin even lower densities than the national average (Figure 2.1b). China started to consider predictions in ungauged basins as early as the 1950s (Liu *et al*., 2005). Many achievements have

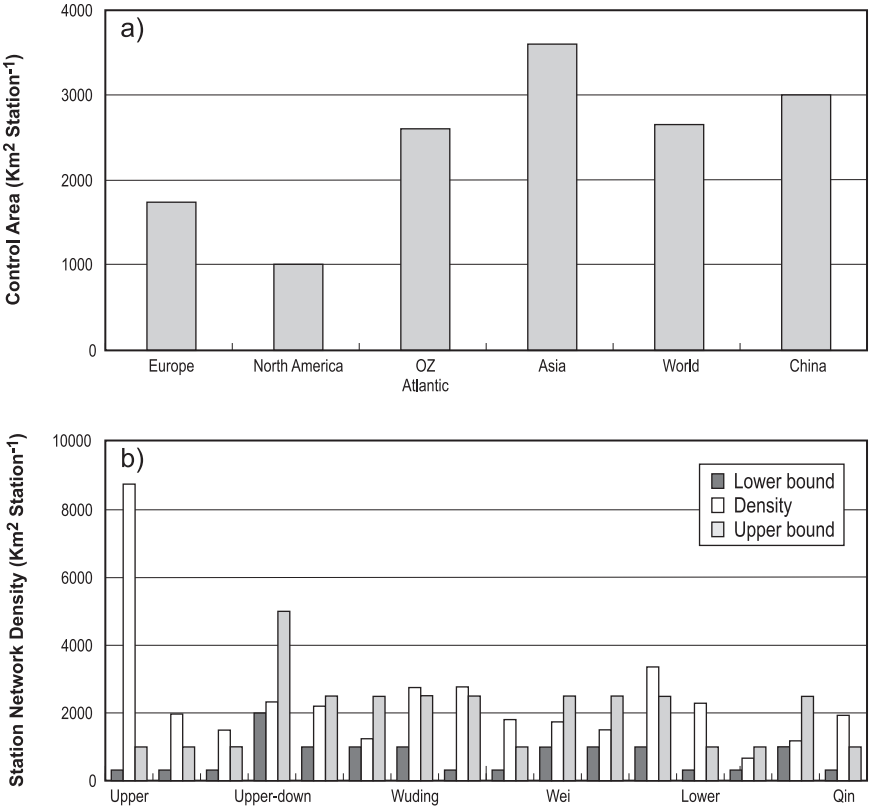

Figure 2.1 ***a)*** *The controlled area per station (km²) in China and other places in the world provided by the World Meteorological Organization;* ***b)*** *The station network density of each sub-catchment of the Yellow River Basin, the second largest river in China (Liu* et al.*, 2010), the basins are ordered by location from west to east.*

been made in hydrological prediction by overcoming the problems of lack of data. Recent efforts in predicting in ungauged basins (PUB) has focused on [1] process studies, modelling approaches and applications (Yang *et al*., 2008), [2] hydrological modelling and integrated water resources management in ungauged mountainous watersheds (Xu *et al*., 2009), and [3] bringing new PUB theories into practice (Liu *et al*., 2010).

One of the important tasks of predicting in ungauged basins is to maximize the predictive value of available data in ungauged basins. Here it is generalized to include "borrowing", "substituting", and "generating" methods according to the logic of a Chinese saying: "even a clever housewife cannot cook a meal

without rice" (Liu *et al*., 2010). Borrowing is defined as a method to use other data by transplanting the data from a nearby region or doing interpolation and/or extrapolating among the data from the adjacent watersheds. Substituting is the method to obtain the necessary data from the related information either from the same area by simulation and/or assimilation or from another area by for example upscaling and paired-catchment analysis, both based upon similarity of geographic characteristics. Generating is a method to obtain the data from field or laboratory experiments. While the methodology framework presented here is based mainly on Chinese research it serves as a representative framework of how to maximize the predictive value of available data in ungauged basins in general.

2.4 THREE METHODS TO MAXIMIZE THE PREDICTIVE VALUE OF AVAILABLE DATA IN UNGAUGED BASINS

"Borrowing"

When faced with the difficulty of a shortage of rice, the first method the clever house wife may think about is to borrow some food from neighbours. This is also a good strategy for people beginning to get the data in ungauged basins; it is a simple and sometimes very effective way to maximize the value of available data from other basins for doing hydrological prediction in the ungauged basin. This method can be divided into either direct borrowing or indirect borrowing. When there are no data in the study basin, the first thing usually is to look at the adjacent basins. If there is a gauged basin nearby which is similar in geographic environment to the study basin, a good starting place is to directly borrow the data from this basin. Direct borrowing is simple, but very difficult as it is unusual to find two identical basins.

The more common form of borrowing is indirect borrowing. When there are no data in the study basin, the search needs to be extended in other directions. Using a rule of thumb that the closer the distance the closer the geographic similarity, it is possible to get the information for the study basin by synthesizing based on the information borrowed from nearby basins. There are some cautions for using this rule; nearby basins do not always have the same runoff generating mechanisms. Therefore before borrowing, doing necessary hydrological field investigation is highly recommended. Some common methods include interpolating, averaging,or inverse distance weighting of the borrowed data.

Indirect borrowing was widely used in the 1950s and 1960s in China in the classification and investigation to Chinese rivers (Guo and Tang, 1980; Liu, 1986), and resulted in products such as [1] Hydrological Maps and Hydrological Handbooks, [2] Storm-runoff Calculation Books (Yang, 1999; Ministry of Water Resources of China, 2002), [3] Estimated unit hydrograph (Li and Shen, 1996), and [4] Hydrological responses to climate change (Guo *et al*., 2002).

"Substituting"

A second method to maximize the predictive value of available data in ungauged basins is substituting. Instead of borrowing some food from the neighbours, the clever house wife may try her own means to find some substitutes to feed her family. Finding appropriate substitutes is also an important way to maximize the predictive value of available data in ungauged basins. There are also two categories; from the study basin and from other basins.

The substitution method using data from the study basin uses modelling to generate the desired hydrological information for the ungauged basin. There are many hydrological models used for prediction in China; the earliest modelling used the rational model and the formula for the estimation of small-watershed peak flow (The research group of small-watershed peak flow estimation, 1978; Liu and Wang, 1980). Peak flow was estimated based on land surface features such as basin area, slope, slope length, roughness, and rainfall parameters (Figure 2.2a). Following the well-known Chinese Xinanjiang model (Zhao, 1984), other models have been developed that have different features, such as Hydro-Informatic Modelling System (HIMS) (Liu *et al*., 2008), DTVGM model (Xia *et al*., 2005), and Vegetation Interface Processes model (VIP) (Mo and Liu, 2001; Mo *et al*., 2012); each of these used substitution of hydrological information.

Liu *et al*. (2009a) explored the change pattern and trend of soil moisture (SM) in the Wuding River basin, Loess Plateau, China based on the simulated long-term SM data from 1956 to 2004 using the VIP model. *In-situ* SM observations together with a remotely sensed SM dataset were used to validate the model. Trend analysis showed that SM is decreasing, confirming a drying of northern China (Liu *et al*., 2009a). The availability of long term SM information for the basin supports early detection of desertification, ecosystem recovery, and also improved soil and water management.

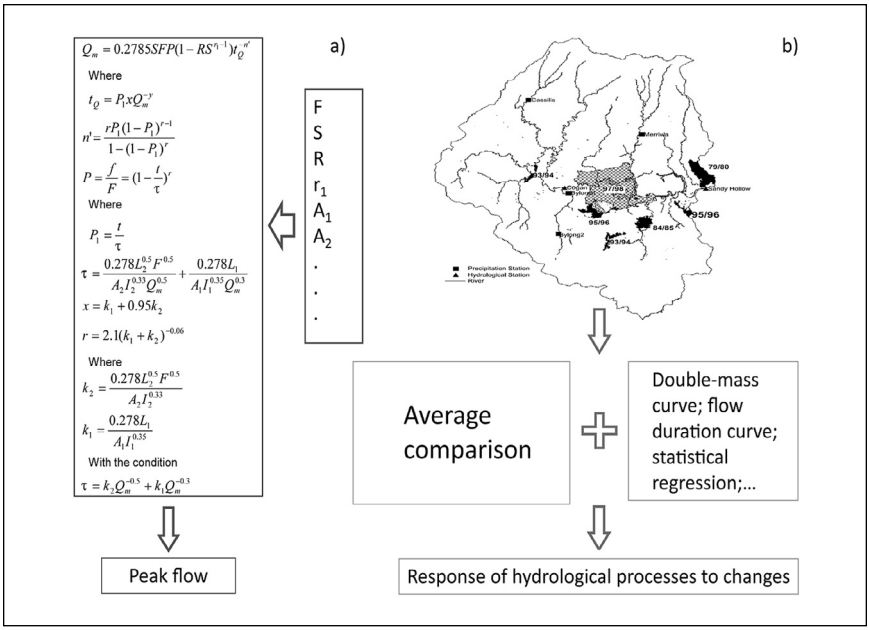

Figure 2.2 *Examples of tools to substitute of hydrological information for ungauged basins:* ***a)*** *rational model to estimate peak flow; and,* ***b)*** *paired-catchment analysis to explore the response of flow change to a bushfire (Liu* et al*., 2004).*

Parameters sometimes are not fixed values and may vary significantly at a seasonal and inter-annual scale. It was shown that with observed eddy covariance fluxes, data assimilation with an ensemble Kalman filter can successfully retrieve the seasonal and inter-annual variations of parameters related to photosynthesis and respiration of a boreal ecosystem site (Mo *et al*., 2008), a good way to increase the modelling efficiency in the substitution.

Uncertainty analysis is very important for predicting in ungauged basins by modelling. Hydrological simulation often pays insufficient attention to uncertainty (Krzysztofowicz, 2001; Marshall *et al*., 2005; Sharma and Chowdhury, 2011); however, Chinese authors have recently explored the uncertainty of model inputs (Shi and Zhou, 1995; Liu and Zhang, 2011), structure (Cai *et al*., 2000), and model parameters (Shu *et al*., 2000; Mo and Beven, 2004).

The substituting method can also use data from other basins, for example, by using upscaling and paired-catchment analysis. For the upscaling, gauged catchments are modelled using calibration against measured flow data,

whereas streamflow in the ungauged sub-catchments is simulated by a disaggregation procedure deriving measured streamflow data from a gauged catchment in which the ungauged sub-catchment may be nested. The method is based on the assumption that the streamflow contribution from each sub-catchment to the total catchment yield is proportional to a ratio of the catchment area and its average slope (Schreider *et al*., 2002). Obviously interflow and groundwater inputs depend more on flow paths than on the catchment area, and so upscaled model results may not reach high model prediction efficiencies when the ratio of surface runoff to total runoff is low.

Paired-catchment analysis (Figure 2.2b) is used to explore the response of a catchment to changes. When the control and treated parts of the catchment are calibrated against each other using the data before and after the treatment, the catchment response to the changes can be evaluated by employing techniques of analysis such as double-mass curves, flow duration curves, statistical regression, and other methods. There is a caution when analyzing the responses by using paired-catchment analysis. For example, for a catchment incurring a fire, the response might be greatly delayed following the treatment (Liu *et al*., 2004). After the fire, new forest grows. Usually regrowth young trees "drink" more water than the mature trees before the fire. The height of the mature trees and consequent low leaf water potential could be increasing the stomatal resistance to the diffusion of water vapour; differences in transpiring biomass and energy exchange within the canopy could also cause important differences between the water consumption of mature and regrowth forests (Langford, 1976). Due to these complicated influences, it may be hard to explain the results from paired-catchment analysis. More capable of exploring the response perhaps is with the combination between paired-catchment analysis and physically based ecohydrological modelling (Vertessy, *et al*., 1998; Mo *et al*., 2012). There are many documented studies and reviews of paired-catchment methods (Liu *et al*., 2004; Vanclay, 2009; Bart, 2010); paired-catchment analysis is both a field within comparative hydrology and within PUB (Falkenmark and Chapman, 1989; Woo and Liu, 1994; Granger and Pomeroy, 1997; Sivapalan *et al*., 2003; McDonnell and Woods, 2004; Blöschl and Merz, 2008; Wagener *et al*., 2010).

In China, the essential ideas of the substituting method from other basins belong to the regional synthesis method. It is routinely used in designing storm-floods by local water resources sectors (e.g., Yangtze Valley Planning Office,

1982; Hydrology and Water Resources Survey Bureau of Liaoning Province, 1998) and is written into many post-graduate textbooks (e.g. Ye, 1991).

"Generating"

When the above methods have failed, a clever wife still does not give up. She will go to the field, dig a hole, and plant a seed to generate the food for her family. Correspondingly, observation is always a solution to the problem of data scarcity, which is an indirect way to maximize the predictive value of available data in ungauged basins. Observation includes field observation and laboratory experiments.

China has been making field observations for 4000 years. For 2000 years, the observations have included water levels, precipitation, velocities, discharges and sediment; however the equipment was poor. Only in the middle of the 19th Century, more advanced hydrological observation in China began. At the end of 2011, there were 46,783 hydrometeorological stations of various kinds in China, including 3,219 basic hydrological

Figure 2.3 *The early artificial rainfall-runoff laboratory in China.*

stations, 1,523 water level stations, 19,082 precipitation stations, 19 evapotranspiration stations, 1,648 soil moisture stations, 7,750 water quality stations, 13,489 groundwater stations, and 53 specific experimental stations. Among them, there are 12,444 stations reporting hydrological information routinely to their upper sectors and 1,005 stations issuing hydrological predictions as required (Deng, 2012).

In addition to these stations operated by the Ministry of Water Resources, there are also other stations observing hydrological elements, including China Meteorological Administration, Chinese Ecosystem Research Network, Ministry of Environmental Protection, Ministry of Agriculture, and others. Setting up these stations is a good example of generating. The earlier the station was started, the more valuable the data are. With the social development in the areas around the hydrological stations in recent years, it has posed serious challenges for data from these gauges to reflect what the hydrological world really is.

Setting up the stations to acquire the information usually takes money, time, and effort to maintain. Doing laboratory experiments is another important generating method. One of the earliest rainfall-runoff laboratories in China was established in the Institute of Geography, Chinese Academy of Sciences in Beijing in the 1960s, as the photo shown in Figure 2.3. Since then more such laboratories have been established in Xi'an, Nanjing, and other cities in China.

Artificial rainfall-runoff experiments, conducted both in field and laboratory, provided the parameters of runoff formation and runoff in areas which had not been gauged: deserts, Qinghai-Tibet plateau, high-altitude alpine areas, and the loess plateau (The research group of small-watershed peak flow estimation, 1978). A general relationship amongst precipitation (P), runoff (R), and evapotranspiration (ET) provides a general formula to deduce storm peak runoff for ungauged basins (Liu, 1986). By doing field experiments and interdisciplinary investigations, minimum ecological instream flow requirements (environmental flows) were estimated for the donating rivers for the Western Route South-to-North Water Transfer project, which are ungauged, remote, and alpine (Liu *et al*., 2008a). Additional new methods were proposed to estimate environmental flows including the Hydraulic Radius method (Liu and Men, 2007), the LiHaFloVa method (Liu *et al*., 2007), the Analytical Wetted Perimeter method (Liu *et al*., 2009b), and the principle of scaling (Liu *et al*., 2008b).

2.5 WHAT IS BEYOND?

Strengthen PUB theoretical study

To maximize the predictive value of available data for ungauged basins, it is necessary to borrow, substitute, or generate information capitalizing upon PUB-related research such as regional hydrology and comparative hydrology; however, it is not simply streamflow but other hydrological cycle components such as precipitation, soil moisture, snow, and evapotranspiration that need to be adequately predicted for ungauged basins. Further, this need not be just the quantity of these components, but also the change patterns, to make full use of the predictive value of available data.

Keep an eye on innovative and comprehensive methods and increase use of advances in methods

With a denser observation network, remote sensing, and process-based models, it is increasingly easier to draw isoline maps for hydrological quantities. In addition to spatial runoff maps, China uses similar maps for actual evapotranspiration, soil moisture, precipitation, radiation, sunshine duration, aridity index, and other elements. These scientifically based products are helpful for hydrological and water resources variability studies in ungauged basins.

Find more applications for PUB research results

With the PUB decade ending, how will these PUB research results be used to address real problems? PUB needs to contribute to hydraulic engineering design, and to improved risk assessment. The 2010 Zhouqu mudflow in Gansu Province provides a reminder of the important role that prediction in ungauged basins needs to fill.

2.6 ACKNOWLEDGEMENTS

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3

MAXIMIZING THE PREDICTIVE VALUE OF INFORMATION FROM DIFFERENT SOURCES: AN AMAZON CASE STUDY

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3.1 ABSTRACT

Precipitation estimation is crucial for hydrological prediction in ungauged and gauged basins. This paper uses a parametric geostatistical model to estimate the Gumbel distribution of annual maximum one-day rainfall at sites without rain gauges in the Amazon and Tocantins basins of Brazil. Analyses showed that the model y ~ N($D\beta$, $\tau^2 I + \sigma^2 R$) – denoted the 'full' model – is acceptable for predicting the first two L-moments L_1 and L_2 of a Gumbel distribution at an ungauged site. The predictor variables used in the matrix D were estimates of L_1 and L_2 derived from two satellite product datasets, CMORPH and TRMM 3B42 at spatial scale 0.25°×0.25°, with three-hourly rainfalls accumulated to give annual maximum one-day rain. Using rain gauge data from 366 sites in these basins with 15 or more years of record between 1970 and 2005, Root Mean Square Errors (RMSEs) of estimated L_1 and L_2 were calculated when the model was fitted to data from the 365 sites remaining after each site was omitted in turn. For comparison, RMSEs were calculated when the same 'leave-one-out' procedure was used with four other interpolation procedures to obtain estimates of L_1 and L_2: namely, (i) simply using the CMORPH as estimates; (ii) simply using the TRMM 3B42 estimate; (iii) using a simple trend-surface estimate; and, (iv) using a weighted mean value of L_1 or L_2, with inverse-squared-distances as weights. In all cases, the full model described above gave much smaller RMSEs, confirming the utility of the parametric geostatistical model for this application.

3.2 RÉSUMÉ

L'estimation des précipitations est cruciale pour les prévisions hydrologiques dans les bassins jaugés et non jaugés. La présente communication porte sur un modèle géostatistique paramétrique pour estimer la loi de Gumbel relativement à une pluie journalière maximale annuelle à des sites sans pluviomètre dans les bassins de l'Amazone et du Tocantins au Brésil. Les analyses ont révélé que le modèle $y \sim N(D\beta, \tau^2 I + \sigma^2 R)$ – désigné comme étant le modèle « intégral » – est acceptable pour la prédiction des deux premiers L-moments L_1 et L_2 de la loi de Gumbel à un site non jaugé. Les variables explicatives utilisées dans la matrice D consistaient en des estimations de L_1 et de L_2 dégagées de deux ensembles de données tirées des produits satellites de précipitations CMORPH et TRMM 3B42 à une échelle spatiale de 0,25°×0,25°, avec trois précipitations horaires accumulées pour donner une pluie journalière maximale annuelle. À l'aide des données de pluviomètre de 366 sites dans ces bassins correspondant à 15 ans ou plus d'enregistrement entre 1970 et 2005, les écarts-types des valeurs L_1 et L_2 estimatives ont été calculés lorsque le modèle a été ajusté aux données des 365 sites restants une fois que chaque site a été omis tour à tour. À des fins de comparaison, les écarts-types ont été calculés lorsque la même procédure (méthode du « leave-one-out » qui consiste à extraire un seul élément) a été employée de concert avec quatre autres procédures d'interpolation en vue d'obtenir des estimations de L_1 et de L_2 : à savoir (i) simple utilisation de l'estimation du produit CMORPH; (ii) simple utilisation de l'estimation du produit TRMM 3B42; (iii) utilisation de l'estimation reposant sur une simple analyse par surfaces de tendance et (iv) recours à une valeur moyenne pondérée de L_1 ou de L_2 faisant appel, comme facteur de pondération, à la loi de l'inverse du carré de la distance. Dans tous les cas, le modèle intégral décrit ci-dessus a donné lieu à des écarts-types beaucoup moindres, ce qui confirme l'utilité du modèle géostatistique paramétrique pour cette application.

3.3 INTRODUCTION

When estimating characteristics of the water cycle at ungauged sites within drainage basins, many candidate variables are commonly available for use as predictors. One early example, showing how such candidate predictors were identified for estimating flow characteristics at ungauged sites, was

given in the Natural Environment Research Council's Flood Study Report of 1975 (Natural Environment Research Council, 1975) and its successor the UK Flood Estimation Handbook (Institute of Hydrology, 1999). Since that time, many other such studies have been reported, and the number of statistical procedures used for selecting and using predictors has increased to include classification and regression trees, random forests, self-organizing maps, neural networks, and radial basis functions (Taylor and Silverman, 1993; Hastie *et al*., 2009; Breiman *et al*., 1984; Breiman, 2001). There are also analytical procedures for generalized linear models (GLMs) such as log-linear models and logistic regression (McCullagh and Nelder, 1989) and, in multivariate analyses, canonical variate analysis and cluster analysis (e.g., Johnson and Wichern, 2007). Other predictors may come from satellite data-products such as those for mapping terrain (e.g. the Shuttle Radar Topographical Mission's digital elevation model) and vegetation (e.g. Normalized Difference Vegetation Index); for estimating rainfall (rainfall products from the Tropical Rainfall Measuring Mission (TRMM), and the Climate Prediction Center Morphing technique (CMORPH)); and, for estimating other components of regional water and energy balance (e.g. the Moderate Resolution Imaging Spectro-radiometer (MODIS)). These are all possible sources of predictor variables.

Basic difficulties confronting an analyst wishing to infer the hydrological characteristics at a location in a catchment without observations are therefore (i) how to select the best predictor variables from those available; (ii) how to select the predictive model that will best use them; and (iii) how the uncertainty in the predictions should be evaluated. This paper discusses such issues in terms of experience with a parametric geostatistical model (Diggle *et al*., 1998, 2003; Diggle and Ribeiro, 2007) used as part of a wide-ranging hydrological study of the Amazon and Tocantins basins of Brazil which are poorly instrumented in comparison with Europe and North America. Figure 3.1 shows the position of the study region within the South American landmass.

This paper describes a procedure for estimating rainfall intensity-duration-frequency (IDF) curves at sites without rainfall records. More specifically, and for limitations of space, we consider here the estimation of the first two *L*-moments, at ungauged sites, of annual maximum one-day rainfalls; a similar procedure to that illustrated can be used for different rainfall durations (e.g. Clarke and Buarque, in press), from which IDF curves can be constructed.

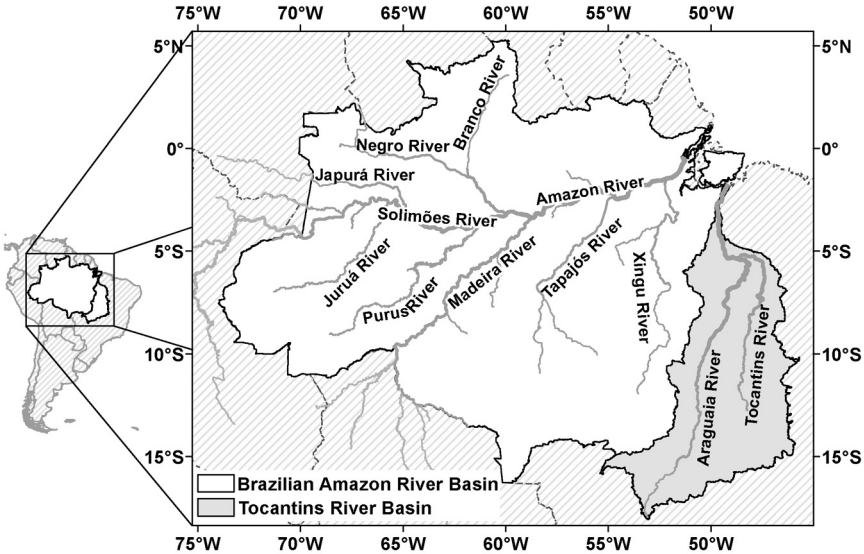

Figure 3.1 *Location of the Brazilian Amazon-Tocantins basins within the South-American landmass.*

A parametric geostatistical model (Diggle and Ribeiro, 2007) is used to relate rainfall characteristics derived from ground-level data (rain gauges) with those derived from satellite-derived data sets (TRMM 3B42 and CMORPH). Spatial correlation is common in many hydrological variables (Buarque *et al*., 2010); when calculating the precision of any quantities estimated from hydrological data, the spatial correlation must be accounted for. Geostatistical models have commonly been used for interpolation by universal kriging with spatial coordinates as predictor variables (e.g. Cressie, 1993). Their use with other predictors, and for selecting between predictors, has been less widely explored. It is a straightforward extension of parametric geostatistical models for use with non-Gaussian data, and in Bayesian contexts (Diggle and Ribeiro, 2007); but here the emphasis is on how they can improve estimates of rainfall characteristics extrapolated to ungauged sites. Therefore, since the method transfers rainfall information from sites where gauges exist to ungauged sites, it is directly relevant to the aims of PUB.

3.4 METHODS

Data

Data from 750 rain gauges in the region, an area about 4.7 million km^2, were provided by the Brazilian Water Agency (ANA), and 366 gauge sites were selected, of which 209 sites were in the Brazilian Amazon and 157 in the adjacent Tocantins basin (Figure 3.2). All 366 selected sites had 15 or more years of complete data during the period 1970-2005 (unless otherwise stated, 'complete' in this paper refers to the years in which rain gauge readings were available for more than 80% of days in the year). Fragmented records are a common problem in the statistical analysis of extreme values of environmental variables, particularly in developing countries, but procedures have been described which show how information about extremes in fragmented records can be recovered (Jones, 1997; Svensson *et al*., 2007; Clarke *et al*., 2009). In each 'complete' year of data, the annual maximum one-day rainfall was abstracted, and L_1 and L_2 statistics were calculated (the L_1 statistic is, of course, simply the sample mean) using the expressions given by Hosking and Wallis (1997).

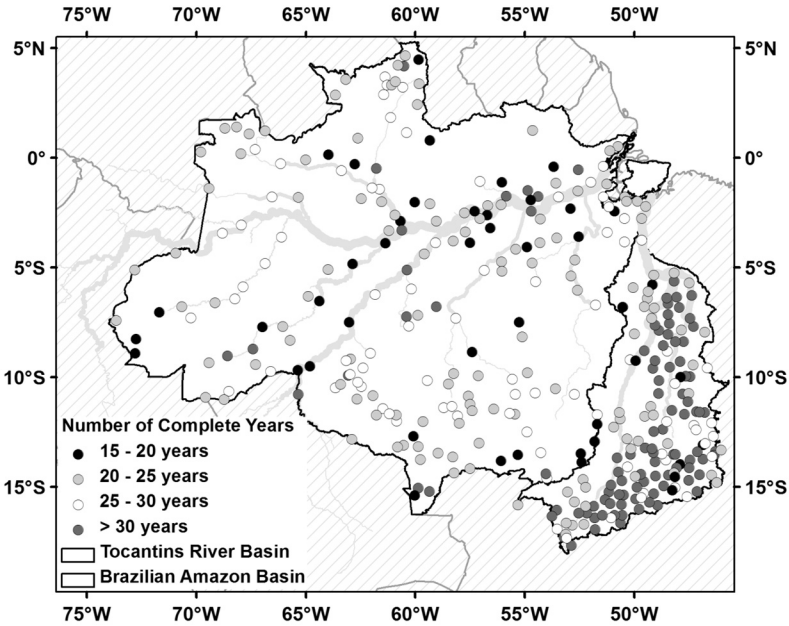

Figure 3.2 *Locations and lengths of record of the 366 rain gauge sites in the Brazilian Amazon-Tocantins basins.*

Given the spatial coordinates of these 366 rain gauges, points of intersection on the CMORPH (Joyce *et al*., 2004) and TRMM 3B42 (Huffman *et al*., 2007) grids were then identified which were nearest to each rain gauge site. CMORPH records were abstracted for the seven-year period 2003-2009, and TRMM records for the twelve-year period 1998-2009. Three-hour rainfalls given by both satellite data-products were totalled over 24-hour periods that corresponded most nearly to the 24-hour period of rain gauge totals, which are recorded at 07:00, local time, daily. For each selected TRMM or CMORPH record, L_1 and L_2 statistics were calculated from the annual maximum one-day rainfalls, over the 12 years of TRMM record and the 7 years of CMORPH record.

Analytical procedure

Research on the region's rainfall characteristics has shown that with records from N rain gauge sites, the $N \times N$ variance-covariance matrix Σ can commonly be represented by a three-parameter model of the form

$$\Sigma_{ii} = var[y_i] = \tau^2 + \sigma^2 \qquad i = 1 \ldots N \tag{1a}$$

$$\Sigma_{ij} = \Sigma_{ji} = cov[y_i, y_j] = \sigma^2 \, exp(- d_{ij} / \varphi) \qquad (i \neq j) \tag{1b}$$

where y_i, y_j are the numerical values of the rainfall characteristic Y at sites i and j with spatial coordinates x_i, x_j, $d_{ij} =| x_i - x_j |$ is the distance separating them, and τ^2, σ^2, and φ are parameters. Thus Σ has the form $\sigma^2 R(\varphi) + \tau^2 I$, where I is an $N \times N$ unit matrix and R (also $N \times N$) has ones on its leading diagonal and $exp(- d_{ij} / \varphi)$ as its (i,j)-*th* element. The variance-covariance structure given in (1a) and (1b) corresponds to a semivariogram with exponential form

$$\mathrm{V}(d) = \tau^2 + \sigma^2 \, \{1 - exp\,(-d / \varphi)\} \tag{1c}$$

with 'nugget' variance τ^2 and 'sill' variance $\tau^2 + \sigma^2$ (Diggle and Ribeiro, 2007).

Having specified the variance-covariance matrix for the rainfall characteristic of interest (L_1 or L_2, in the present context), its value y_i recorded at a rain gauge site is related to the value C_i and T_i of that rainfall

characteristic found from the CMORPH and TRMM records, for the grid-point nearest to the rain gauge site. Thus the predictive model estimating the desired rainfall characteristic y at an ungauged site (site k say) using CMORPH and TRMM as predictor variables, is

$$y_k = \beta_0 + \beta_1 C_k + \beta_2 T_k + \varepsilon_k. \tag{2}$$

When the observed y_i are mean values over the period of record, it is reasonable to assume that they are approximately normally distributed. In matrix form, the model is then:

$$\mathrm{Y} \sim \mathrm{N}(D\beta, \sigma^2 R(\varphi) + \tau^2 I) \tag{3}$$

where D is an N×3 matrix with ones in its first column, and the values of C_k and T_k in its second and third columns; $\beta = [\beta_0\ \beta_1\ \beta_2]^{\mathrm{T}}$; and Y is the N×1 vector of the rainfall characteristic (L_1 or L_2). For more or fewer predictor variables, dimensions of the matrix D and the vector β are modified accordingly. The assumption of Normality can be relaxed through the use of Generalised Linear Models (GLMs) in which the predicted variable y has any distribution belonging to the exponential family (McCullagh and Nelder, 1989) which includes the binomial, exponential, gamma, and inverse gamma distributions, amongst others. GLMs can be fitted with the geoRglm package (Diggle and Ribeiro, 2007).

Diggle and Ribeiro (2007) describe a straightforward way of estimating the parameters β, σ^2, φ and τ^2 by maximum likelihood. Since

$$V = R(\varphi) + v^2 I \tag{4}$$

where $v^2 = \tau^2/\sigma^2$, then for given V the log-likelihood function is maximized at

$$\hat{\beta}(V) = (D^T V^{-1} D)^{-1} D^T V^{-1} y \tag{4a}$$

and

$$\hat{\sigma}^2(V) = N^{-1}\{y - D\hat{\beta}(V)\}^T V^{-1}\{y - D\hat{\beta}(V)\}. \tag{4b}$$

Substituting (4a) and (4b) in the log-likelihood function gives $log\ L\ (v^2, \varphi)$, where

$$log\ L\ (v^2, \varphi) = -\ (0.5)\{N\ log\ (2\pi) + N\ log\ [\hat{\sigma}^2(V)] + log\ |V| + N\} \quad (5)$$

which is maximized with respect to v and φ, followed by back-substitution to give $\hat{\sigma}^2$ and $\hat{\beta}$. Maximization of (5) was achieved by the Nelder-Mead procedure, with four convergence criteria: the maximum number of iterations and the maximum number of function (log-likelihood) evaluations (both of which were required to be less than 400 for convergence); the tolerance allowed for each parameter, and the tolerance allowed for evaluating (5), the latter two criteria were both required to be less than 10^{-4}.

Given estimates of the first two L-moments L_1 and L_2, Gumbel distributions can be fitted in which the position and dispersion parameters ξ and α are estimated as $\alpha = L_2/log\ 2$, $\xi = L_1 - 0.5772\alpha$ (Hosking and Wallis, 1997). To estimate L_1 and L_2 at sites without rain gauges, estimates of L_1 and L_2 calculated from rain gauge records were combined with estimates of L_1 and L_2 derived from two satellite product datasets TRMM 3B42, and CMORPH, both at grid-spacing 0.25°×0.25°, but with different periods of record. These satellite products were selected because they have been extensively used in the rainfall-runoff model MGB-IPH (Collischonn *et al*., 2007) applied to many South American watersheds, and the Amazon and Tocantins basins in particular (Collischonn *et al*., 2008; Paiva, 2009; Paiva *et al*., 2011; 2012; 2013a; 2013b).

Values of the first L-moment L_1, calculated at 5983 grid points within the study area for the period of their common record 2003-2009 are shown in the Figures 3.3(a) and 3.3(b) for TRMM 3B42 and CMORPH, respectively; the shades of grey classify the L_1 values according to the class intervals shown in the figure legends (with white lowest, black highest). Although the quantiles shown in Table 3.1 are fairly similar for TRMM and for CMORPH, the spatial distribution of L_1 is very different between the two datasets. It is the differences between predictors of L_1 that the predictive model (given in its matrix form by equation 3 above) aims to exploit. When L_1 is calculated (a) from the full available period of TRMM, 1998-2009, (b) from CMORPH data for the period 2003-2009, and (c) for the 15 (or more) complete years of record calculated from rain gauge data for the period 1970-2005 at the 366 sites used in the present work, the summary statistics for L_1 are in Table 3.2. The correlations between the L_1's from (a), (b), and (c) are presented in Table 3.3.

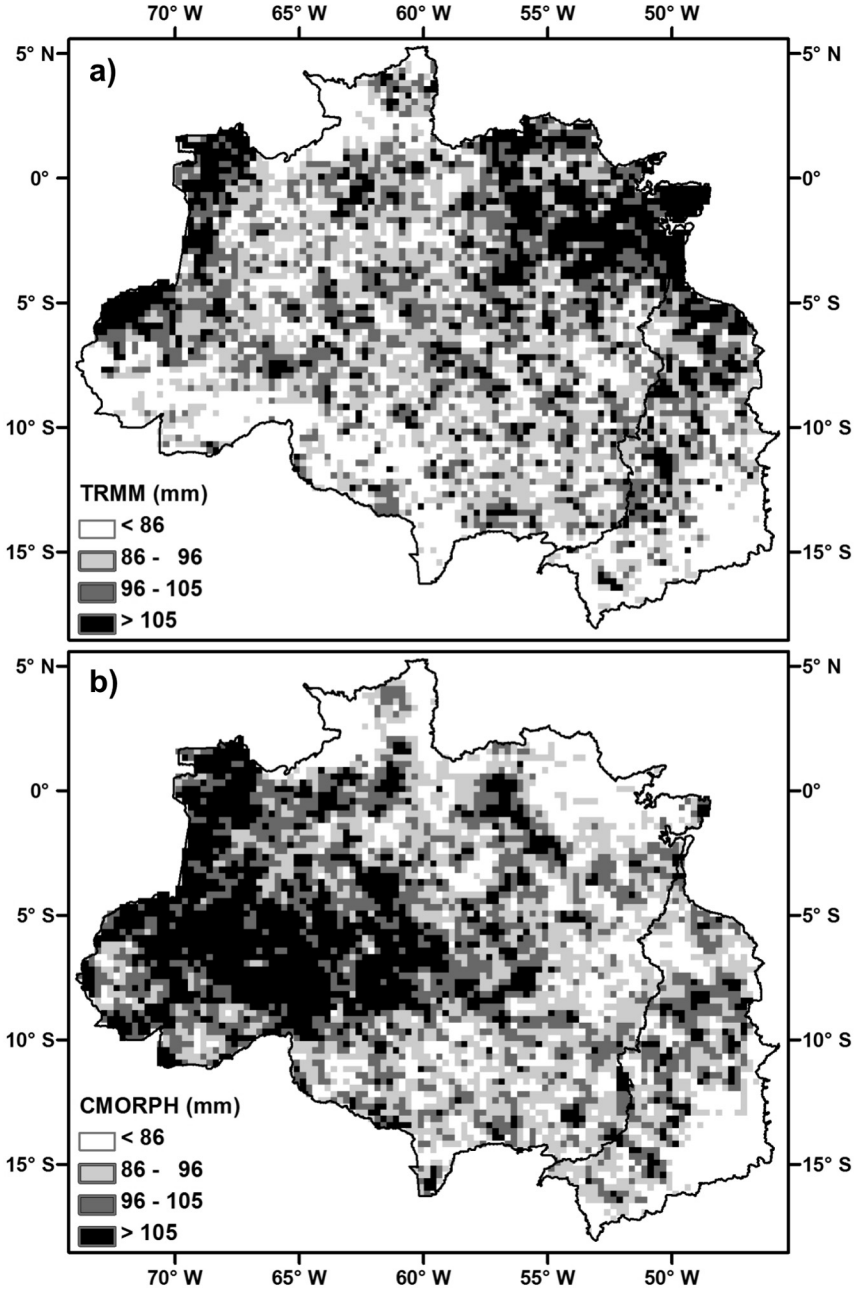

Figure 3.3 *L-Moment L_1, the mean annual maximum one-day rainfall (mm) for the period 2003-2009, at 5983 grid points within the study area, calculated from the* ***(a)*** *TRMM 3B42 dataset, and* ***(b)*** *the CMORPH dataset.*

Table 3.1 *Summary statistics (mm) for means, over the period 2003-2009, of annual maximum one-day rainfalls at 5983 grid points lying within the Brazilian Amazon and Tocantins basins, derived from TRMM and CMORPH datasets. Q1 and Q3 are the first and third quartile. Units are in mm. (Mean for TRMM: 94.24 mm; mean for CMORPH: 96.41 mm).*

	Min	Q1	Median	Q3	Max
TRMM	51.3	84.9	93.2	102.3	167.6
CMORPH	44.2	86.7	95.6	105.5	156.1

Table 3.2 *Summary statistics for one-day rainfall L_1 at 366 rain gauge sites in the Brazilian Amazon-Tocantins basin, over 15 years minimum record between 1970-2005, together with 366 TRMM L_1 values for 1998-2009, and 366 CMORPH L_1 values for 2003-2009, at grid points nearest to the gauge sites. Q1 and Q3 are the first and third quartile. Units are in mm. (Mean for TRMM: 92.5 mm; mean for CMORPH: 91.4 mm; mean for gauges: 91.4 mm).*

	Min	Q1	Median	Q3	Max
TRMM	55.2	81.1	91.6	102.1	145.9
CMORPH	54.0	81.6	91.8	101.6	135.5
Rain Gauges	61.8	84.4	91.8	98.0	120.2

Table 3.3 *Correlations between L_1 values of CMORPH, rain gauge and TRMM, for the periods defined in Table 3.2(a).*

	TRMM	CMORPH	Rain Gauges
TRMM	1	0.482	0.348
CMORPH	0.482	1	0.334
Rain Gauges	0.348	0.334	1

When the CMORPH and TRMM data are used to derive the predictor variables C and T in (2), it is not necessary for them to be calculated from the same period of record as the variables L_1 and L_2 obtained from rain gauge data. It is not even necessary for the annual maxima from which the

predictor variables C and T are calculated to be accumulated over the same 24-hour periods that are used when calculating the response variables L_1 and L_2 from rain gauge data (although it is likely that the variables to be predicted, L_1, L_2, will be more closely correlated with the predictor variables C and T when they are). It is the information content in the predictor variables CMORPH and TRMM that is important.

The Gumbel distribution was selected only as a 'demonstration of concept' and the L-moments could be used to obtain parameters of any other distribution. There is no reason why the first three L-moments should not each be modelled using (2) above for the purpose of obtaining a three-parameter GEV, or any other distribution, at an ungauged site. The question might be asked, however, 'why use the model in (2) to obtain estimates of L_1 and L_2 at an ungauged site, instead of predicting maximum likelihood estimates of the Gumbel parameters ξ and α for the site directly?' The answer to this is two-fold: (a) the first L-moment is just the arithmetic mean of the annual maximum one-day rainfalls at a site, and therefore has a very simple and direct interpretation, whilst the maximum likelihood estimate of ξ is not directly equivalent (although its numerical value will be similar); (b) the maximum likelihood iterative calculation yielding estimates of ξ and α at a gauged site may not always converge, whereas calculation of L_1 and L_2 does not involve convergence of an iterative procedure.

3.5 RESULTS

The results from using the model are described in two parts, dealing with the estimation at ungauged sites of L_1 and L_2 respectively.

Extrapolation of L_1 (i.e. mean annual maximum one-day rainfall)

As a first step, the model was fitted without using any predictors, so that (3) became simply $Y \sim N(\beta_0, \sigma^2 R(\varphi) + \tau^2 I)$, where Y is the (366×1) vector of L_1 values obtained from rain gauge data. The four model parameters β_0, τ^2, σ^2, φ were estimated as 91.09, 57.85, 47.35, and 0.4785 respectively, with which the maximized log likelihood was $log\ L = -1333.38$. This value of $log\ L$ is the measure against which the utility of predictors can be assessed; a model with one parameter added for each and every observation in Y would give a perfect fit (just as a quadratic curve fitted to three points will give a perfect fit). Fitting any alternative model having more parameters than the β_0, τ^2, σ^2, φ given above will always increase $log\ L$, and statistical analysis

(specifically, a likelihood ratio test: e.g. Johnson and Wichern, 2007) will show whether the increase is sufficiently large to justify inclusion of the additional parameters, thus giving a more complex model. When TRMM is included in the model as a predictor, the value of *log L* increases from -1333.38 to -1324.64: an increase of 8.74. The likelihood ratio test showed whether this increase in *log L* is statistically significant; since one additional parameter β_1 has been included in the model (3), the difference 8.74 was compared with tabulated values of the χ^2 distribution with one degree of freedom (1 d.f.). This table shows that to be statistically significant at the 5% and 1% levels, the increase in *log L* should exceed 3.841 and 6.635 respectively, so that the utility of the TRMM estimate of L_1, as a predictor of rain gauge L_1, is established. When CMORPH is included in the model as the only predictor, the value of *log L* also increases, but the increase of 4.53 is smaller than that given by using only TRMM as predictor; however, the increase is statistically significant at the 5% level. Thus, the use of TRMM alone in the model as predictor will provide a better estimate of rain gauge L_1 than when CMORPH alone is used, since the increase in *log L* has greater statistical significance.

If CMORPH is added to a model which already has TRMM as one predictor, the value of *log L* increases to -1323.51, so that the increase – relative to that given by the use of TRMM alone is only 1.13. TRMM therefore contributes most to any prediction, as shown above; however, inclusion of both predictors increases *log L* by -1223.51 + 1333.38 = 9.87, significant at the 1% level (for 2 d.f., the tabulated χ^2 value is 9.21) so both are retained. Values calculated for the model parameters, and for *log L*, are shown in Table 3.3.

There are gradients in mean annual rainfall in both west-east and north-south directions (Clarke and Buarque, in press); so one question is whether there is value to be gained by using latitude and longitude as predictors to estimate L_1 of annual maximum one-day rainfall at an ungauged site. To answer this question, the model was fitted using both latitude and longitude as predictors. This calculation is then equivalent to universal kriging with an exponential spatial correlation function (or, equivalently, an exponential semivariogram) fitted by maximum likelihood. The log likelihood then becomes -1332.60, only very slightly greater than the *log L* = -1333.28 found for the "null" model (Table 3.3). It is concluded that latitude and longitude as spatial predictors are less useful as predictors of L_1 than the TRMM and CMORPH estimates of L_1.

Extrapolation of *L*-moment dispersion L_2

The correlations between L_2 calculated from rain gauge data, and L_2 calculated from TRMM and CMORPH data, are smaller than those for L_1; the correlation between CMORPH L_2 and gauge L_2 is 0.093, between TRMM L_2 and rain gauge L_2 is 0.121, and between CMORPH L_2 and TRMM L_2 is 0.275. For the "null" model, without any predictors, the value of *log L* was -978.32; when L_2 calculated from TRMM, and L_2 calculated from CMORPH, were included as predictors of rain gauge L_2, the value of *log L* increased to -975.14. With these two parameters included the increase in *log L* is compared with the χ^2 distribution for 2 d.f. (5.991, $p<0.05$). Thus the increase of 3.18 in *log L* shows that TRMM and CMORPH estimates of L_2 are not useful for predicting rain gauge L_2. Therefore only the null model $L_2 \sim N(\beta_0, \sigma^2 R(\varphi) + \tau^2 I)$ was used, for which estimates of the four parameters β_0, τ^2, σ^2, and φ were 14.09, 10.54, 1.766, and 2.916.

The next section describes how the models for L_1 and L_2 performed when used for extrapolation to sites without rain gauge records, using a "leave-one-site-out" procedure.

Model performance when predicting *L*-moment position L_1 at ungauged sites: assessment using a "leave-one-site-out" procedure

A "leave-one-site-out" procedure was used to find out how well the model performed when used to predict L_1 at any site without a rain gauge. Each one of the 366 sites with a rain gauge record was omitted in turn; data from the remaining 365 sites were used to fit the model given by (3) above (i.e. estimate the parameters β, τ^2, σ^2, φ). The model was then used to predict the value of L_1 at the omitted site. Repeating this procedure for each of the 366 sites gave 366 predicted values of L_1, which were compared with the values of L_1 derived from the rain gauge records at those sites.

To obtain the predicted value at each site for which the L_1 values from TRMM and CMORPH are known, the "trend" value was obtained by substituting them in $\hat{\beta}_0 + \hat{\beta}_1 L_{1,CMORPH} + \hat{\beta}_2 L_{1,TRMM}$, where the quantities with "hats" were estimated as shown in equations (4) and (5) above. It was then necessary to predict the value of the residual component e at the omitted site, and the procedure for this has been described, for example, by Cressie (1993). Dropping the 'hats' from the calculated residuals to simplify

presentation, the required residual ε was $\lambda^T\varepsilon$, where the dimensions of λ and ε are 365×1 and λ^T is given by

$$\lambda^T = \{c + 1\ [1 - 1^T S^{-1} c] / 1^T S^{-1} 1\}^T\ S^{-1} \qquad (7)$$

where $\boldsymbol{S}$ is the 365×365 matrix with $\tau^2 + \sigma^2$ on its leading diagonal and σ^2 exp $(-d_{ij} / \varphi)$ in its off-diagonal elements (calculated from the remaining 365 rain gauges after one had been omitted); $\boldsymbol{c}$ is the 365×1 vector with elements $\sigma^2\ exp\ (-d_{0j} / \varphi)$, where the suffix zero refers to the omitted rain gauge site; and $\boldsymbol{1}$ is a 365×1 vector of ones. Thus using (7), the residual ε was estimated for the omitted site; it was then added to $\beta_0 + \beta_1\ L_{1,\ CMORPH} + \beta_2\ L_{1,\ TRMM}$ (where, for convenience, the "hats" have been omitted) to give the "full" estimate. The estimates $\beta_0 + \beta_1\ L_{1,\ CMORPH} + \beta_2\ L_{1,\ TRMM}$, without the estimated residual added, are termed the "trend" estimate; if the predictors had been latitude and longitude instead of $L_{1,\ CMORPH}$ and $L_{1,\ TRMM}$, the predicted value of L_1 would be that given by fitting a planar trend surface to the 366 rain gauge coordinates.

Having predicted the value of L_1 at each omitted site using the "full" model, a Root Mean Square Error (RMSE) was calculated from the differences between predicted and "observed" values of L_1 ("observed" in the sense that they were calculated from the rain gauge data at the omitted site). For purposes of comparison, the following were also calculated: (i) the RMSE when the L_1 obtained from CMORPH data was simply taken as an estimate of the rain gauge L_1 at each of the 366 sites, denoted by RMSEL1,CMORPH; (ii) the same, but with $L_{1,\ TRMM}$ instead of $L_{1,\ CMORPH}$, giving $RMSE_{L1,\ TRMM}$; (iii) the RMSE calculated when the "trend" estimate $\beta_0 + \beta_1\ L_{1,\ CMORPH} + \beta_2\ L_{1,\ TRMM}$ was taken as an estimate of L_1, denoted by $RMSE_{L1,\ Trend}$; and (iv) the RMSE obtained when each omitted L_1 was estimated by a weighted mean of the remaining 365 L_1's, using squared inverse distances as weights, denoted by $RMSE_{L1,\ Weighted}$. The values of the five RMSEs are shown in the first two columns of Table 3.4.

Columns 1 & 2 of Table 3.4 shows that simple substitution of CMORPH- and TRMM-derived values of L_1, as estimates of the L_1 that a rain gauge would have given if one had been present, had the largest RMSEs. The weighted-mean estimate, using only the L_1 values at the 365 rain gauge sites that were not omitted, performed slightly better than the "trend" estimate

Table 3.4 *Estimates of parameters β, τ^2, σ^2, φ in the model $L_1 \sim N(D\beta, \sigma^2 R(\varphi) + \tau^2 I)$, and the maximized log likelihood $\log L$, when using: no predictors ("Null" model); only TRMM (T); only CMORPH (C); and, both TRMM and CMORPH (T-C) as predictors.*

Parameter	"Null" Model	TRMM alone	CMORPH alone	TRMM and CMORPH
β_0	91.09	75.96	78.12	71.44
β_1	–	0.165	0.142	0.138 (T)
β_2	–	–	–	0.077 (C)
τ^2	57.84	58.87	61.09	60.12
σ^2	47.35	34.93	32.89	29.86
φ	0.478	0.536	0.578	0.606
$\log L$	-1333.38	-1324.64	-1328.85	-1323.51

$\beta_0 + \beta_1 L_{1,\,CMORPH} + \beta_2 L_{1,\,TRMM}$. The best estimation procedure, in terms of giving the smallest RMSE, was the "full" model in which a predicted residual was added to the "trend" estimate.

Model performance when predicting L-moment dispersion L_2 at ungauged sites: assessment using a "leave-one-site-out" procedure

A similar procedure to that described for L_1 was also used to predict the L-moment dispersion L_2 at an omitted site, when each of the 366 sites was omitted in turn; calculation of the five RMSEs followed the same procedure, and the right-hand side of Table 3.5 shows $RMSE_{L2,\,TRMM}$, $RMSE_{L2,\,CMORPH}$, $RMSE_{L2,\,Trend}$, $RMSE_{L2,\,Weighted}$ and $RMSE_{L2,\,Full}$. These broadly follow the same pattern as for L1; the "full" model shows a particularly good performance.

3.6 DISCUSSION

The use of L_1 and L_2 calculated from CMORPH and TRMM to predict rain gauge derived L_1 and L_2 gave the poorest predictions; predictions given by "trend" ($\beta_0 + \beta_1 L_{1,\,CMORPH} + \beta_2 L_{1,\,TRMM}$ in the case of L_1; β_0 in the case of L_2) performed less well than weighted-mean predictions, although the difference in performance was not large. The best predictions for both of L_1 and L_2 were those given by the "full" models.

Table 3.5 *RMSEs calculated from differences between "observed" and predicted values of L_1, for five different prediction procedures (for explanation of symbols, see text). and for the L-moment dispersion L_2.*

First L-moment L_1		Second L-moment L_2	
$RMSE_{L1, TRMM}$	14.348	$RMSE_{L2, TRMM}$	6.046
$RMSE_{L1, CMORPH}$	16.080	$RMSE_{L2, CMORPH}$	11.985
$RMSE_{L1, Trend}$	9.470	$RMSE_{L2, Trend}$	4.044
$RMSE_{L1, Weighted}$	9.064	$RMSE_{L2, Weighted}$	3.680
$RMSE_{L1, Full}$	2.603	$RMSE_{L2, Full}$	0.042

The model $Y \sim N(D\beta, \sigma^2 R(\varphi) + \tau^2 I)$ assumes that the variable to be predicted, y, is normally distributed, but this will not always be a reasonable assumption. Extension using GLMs is possible, for which the expected value of y_i, $E[y_i] = \mu_i$, where μ_i is linked to the predictor variables by means of a known function h(.), so that $h(\mu_i) = D\beta$; the normal distribution is then replaced by whatever other distribution from the exponential family is deemed appropriate. It was assumed that there is no trend over the period 1970-2005 in annual maximum one-day rainfall and, in fact, Buarque *et al*. (2010) have shown that trends in annual maximum rainfalls for durations from one to five days are small. Where trends are thought to exist it would be possible to adapt the model by including a parameter to represent trend; but since this may be different for different sites, and since the mean value y_i at the i-th site would be replaced by y_{ij} (the value at the i-th site in the j-th year of record) the dimensionality of the model would be very greatly increased. While conceptually simple, numerical difficulties could arise.

In this paper, the geostatistical model given by (3) has been illustrated solely to estimate two selected rainfall characteristics (L_1 and L_2) at ungauged sites, but in principle it would be possible to apply the same procedure to construct fine grid estimates of seasonal or monthly rainfall (whether as time series, or as seasonal or monthly averages), by supplementing the information given by a limited rain gauge network with the seasonal or monthly totals obtained from satellite datasets. Fitting and using the model season by season, or month by month, would not reproduce any serial correlation existing in seasonal or monthly totals (or to be more explicit, annual fluctuations in seasonal or

monthly rainfall would be reproduced, but serial correlations between residuals about these annual fluctuations would not). Also, applying the modelling procedure to derive sequences of daily rainfall would be problematical because the spatial and temporal correlation structure of daily rainfall would not be reproduced; simply using the model on a day-by-day basis would not necessarily yield the alternating runs of wet and dry days. Extension to the combination of ground level information on monthly or seasonal climate variables, measured at ground level, with satellite derived counterparts would also be possible, provided that the density of surface climate stations is sufficient to enable parameters in the spatial correlation model to be estimated.

3.7 CONCLUSIONS

A modelling procedure is illustrated in which the first two *L*-moments of annual maximum one-day rainfall are estimated at sites without rainfall records, by combining limited information from existing rain gauge networks with information contained in datasets derived from satellite mounted instrumentation (or derived from any other remote sensing procedure). Extending the analysis to annual maximum rainfalls accumulated over different periods yields estimates of IDF curves at ungauged sites. Essential characteristics of the procedure are: (i) where a number of candidate satellite derived predictors of rainfall characteristics exist for the ungauged sites, the most useful predictors can be identified; (ii) the candidate satellite datasets need not be of equal length, nor of equal spatial scale, nor contemporaneous with the limited records from any existing rain gauge network. In the case of the first two *L*-moments, a "leave-one-site-out" analysis showed that the modelling procedure gave smaller RMSEs than a number of interpolation procedures in common use. The procedure is also applicable for predicting other variables of hydrological interest (seasonal and monthly average rainfall; seasonal and monthly time series of rainfall; …) at ungauged sites, whether as monthly or seasonal averages or as time series of seasonal or monthly totals.

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4

PREDICTING IN UNGAUGED BASINS USING PHYSICAL PRINCIPLES OBTAINED USING THE DEDUCTIVE, INDUCTIVE, AND ABDUCTIVE REASONING APPROACH

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4.1 ABSTRACT

At the beginning of the PUB Decade the process approach to hydrological prediction was proposed as part of the solution to the problem of predicting in ungauged basins; however, persistent errors in model process descriptions continue to hamper the progress of hydrology as a science and in the development of solutions for PUB. Process algorithms developed in the last three decades of research in Canada and elsewhere provide solutions to most of these errors for cold regions environments, but the implementation of these algorithms within a predictive model is nontrivial. An approach combining deductive, inductive, and abductive reasoning for developing appropriate model process structure, basin discretization and parameterization is applied to the ungauged portion of the Smoky River Basin in Alberta, Canada. Deductive reasoning uses known physical laws and relationships to derive information from existing basin inventories and satellite imagery. Inductive reasoning is used to calibrate a small selection of sub-surface model parameters using discharge measured in a local sub-basin. Abductive reasoning is used to borrow parameters from a suite of process and modelling research basins in western Canada. The model predicted the peak spring flows on the Smoky River over several years and at two different scales with reasonable accuracy. This suggests that prediction in ungauged basins using physical principles is possible and indeed a viable alternative in regions of the world where stream gauges are

sparse or non-existent. Since hydrology is a science, prediction in both gauged and ungauged basins using physical principles is not only possible, but should be the preferred approach to simulating the hydrological cycle.

4.2 RÉSUMÉ

Au début de la décennie de PBNJ, l'approche processus de la prévision hydrologique a été proposée comme élément de solution au problème qui consiste à formuler des prévisions en bassins non jaugés; toutefois, des erreurs persistantes dans les descriptions du processus du modèle continuent d'entraver les progrès de l'hydrologie en tant que science ainsi que l'élaboration de solutions pour les PBNJ. Les algorithmes de processus mis au point au cours des trois dernières décennies de recherches au Canada et ailleurs offrent des solutions à la plupart de ces erreurs pour les milieux situés en régions froides. Cependant, la mise en œuvre de ces algorithmes dans le cadre d'un modèle de prévision est non triviale. Une approche qui combine un raisonnement déductif, inductif et abductif pour l'élaboration d'une structure de processus de modèle appropriée, la discrétisation et la paramétrisation à l'échelle du bassin, est appliquée à la partie non jaugée du bassin de la rivière Smoky en Alberta, au Canada. Le raisonnement déductif fait appel aux relations et aux lois physiques connues pour extraire l'information des inventaires existants des bassins et de l'imagerie satellitaire. Le raisonnement inductif sert à l'étalonnage d'une petite sélection de paramètres de modèle de subsurface au moyen du débit mesuré dans un sous-bassin local. Le raisonnement abductif est utilisé pour emprunter des paramètres d'un ensemble de processus et à des fins de modélisation des bassins de recherche dans l'Ouest canadien. Le modèle a permis de prédire avec une exactitude raisonnable les débits de pointe du printemps de la rivière Smokey sur plusieurs années et à deux différentes échelles. Cela donne à penser que les prévisions en bassins non jaugés au moyen de principes physiques est possible et constitue en fait une solution de rechange viable dans les régions du monde où les fluviomètres sont peu abondants ou inexistants. Étant donné que l'hydrologie est une science, la prévision à la fois en bassins jaugés et non jaugés à l'aide de principes physiques est non seulement possible, mais elle devrait être l'approche privilégiée pour ce qui est de simuler le cycle hydrologique.

4.3 INTRODUCTION

Prediction in ungauged basins (PUB) has been hampered by both a lack of information on the basin and its hydrological characteristics (Sivapalan *et al*., 2003a), and by ubiquitous misconceptions on the operation of the hydrological cycle that have persisted in many hydrological models. Almost a decade ago, the process approach to hydrological prediction was proposed as a solution to the problem of PUB (Pomeroy *et al*., 2005); however, persistent errors in model process descriptions continue to hamper the progress of hydrology. These misconceptions cause systematic deviations of model simulations from actual hydrological processing. Calibration to streamflow observations has been used to "correct" these deviations; however, problems of equifinality cause uncertainty in parameter identification (Bevan and Freer, 2001). These create an artificial dilemma. The reliance on calibration, when streamflow observations are missing, creates the problem of predicting in ungauged basins; when observations are available the reliance on calibration supports the continuing persistence of deficient modelling approaches. This dilemma is artificial as the need for calibration is partly due to conceptual errors in hydrological model structure, form, and resolution; and partly due to an inability to identify values for certain parameters. Making progress in reducing the problems of PUB requires advances on both aspects of this problem. The objective of this paper is to demonstrate using a three-stage approach of deduction, induction, and abduction of information to identify some common misconceptions in hydrological models and how they might be readily corrected, and to show how appropriate model structure and parameters can be identified. The procedures are demonstrated in the development of a predictive system for the ungauged portions of the Smoky River Basin, Alberta, Canada.

Persistent misconceptions in hydrological modelling

Many older hydrological concepts, sometimes called "hydromythologies", often persist in hydrological models despite being dismissed by more recent scientific investigations. This situation is not new (e.g. Klemeš, 1986). Predictive problems caused by these misconceptions are particularly evident for cold and sub-humid regions that are outside of the primary regions of hydrological model conceptualization and development, but are found in all regions. The following are but a few examples of misconceptions that are found in many hydrological models in current use; specific models using

various hydromythological algorithms are not mentioned by name, but the knowledgeable reader will easily identify many examples for each point; the corrections are noted in italics and in references cited following the hydromythology.

1. Solar and net radiation are impossible to estimate with normal meteorological data and so energy balance formulations for evapotranspiration, sublimation, soil thaw, snowmelt, and glacier melt cannot be operated in hydrological models and must be replaced by empirical temperature index formulations. [*There are several relationships to estimate solar and long-wave radiation from latitude, time of year, air temperature, and humidity which can be used to drive energy balance snowmelt and combination type evapotranspiration algorithms, (Walter et al., 2005; Sicart et al., 2006; Shook and Pomeroy, 2011a).*]

2. Vegetation is not a dynamic mediator of hydrology and can be represented by simple fixed boundary conditions or constant unresponsive functions. [*There are many dynamic vegetation growth and rooting algorithms available to provide resistance to potential evaporation, and complementary feedback relationships are available for when vegetation, roots, and soils are relatively unknown (Granger and Gray, 1990; Brimelow et al., 2010; Armstrong et al., 2010).*]

3. Snowfall and rainfall can be distinguished by a simple temperature threshold. Snowfall gauge undercatch is not important, and most snow that falls is the snowpack available for melt because sublimation losses are negligible. [*Precipitation phase is controlled by the psychrometric equation, snowfall gauge undercatch can be very substantial but is correctable, and sublimation can consume a substantial proportion of snowfall in dry environments. Sublimation can be estimated using energy balance and aerodynamic approaches (Pomeroy and Gray, 1995; Goodison and Metcalfe, 1992; Harder and Pomeroy, 2013).*]

4. Soils can be adequately represented by a fully-connected uniform porous media with horizontally layered properties, and without macropores and vertical structure. The hydraulic properties of soils change with scale by some unknown scaling mechanism, but are temporally invariant, fixed over hillslopes and little affected by vegetation, animals, and tillage. [*Macropores caused by plants, animal and mankind can provide a primary soil flowpath and infiltration equations can be modified for macropore flow. The*

variance of soil properties over a hillslope is a critical influence on variable contributing areas, fill and spill mechanisms control saturated flow at the soil-bedrock interface (Beven and Kirkby, 1979; Beven and Germann, 1982, 1985; Tromp-van Meerveld and McDonnell, 2006; Craig et al., 2010).]

5. Drainage basins are definable in that sub-surface flow drains within the drainage basin, all land surfaces can always drain freely to a stream, and all parts of the basin are always fully contributing to streamflow via overland or sub-surface flow. As a result, drainage of stored water produces basin discharge via unique functions that are often linear. [*Contributing areas expand and contract as depressional storage and saturated flow pathways fill and empty; the relationship between contributing area and storage is non-linear hysteretic but can be modelled using network connectivity concepts (Spence and Woo, 2003; Phillips et al., 2011; Shook et al., 2013).*]
6. Overland flow is the dominant runoff mechanism and so open channel hydraulic equations can be used to calculate the celerity of runoff from land. [*Sub-surface flow abounds and its velocity is controlled by soil and topographic parameters (Henderson and Wooding, 1964; Sabsevari et al., 2010).*]
7. Water movement into, through, and above frozen soils behaves in a similar manner to unfrozen soils. [*Infiltration and soil hydraulics are controlled by the interaction of soil ice content and porosity over time which is controlled by coupled energy and mass balance equations and influenced by the depth of freezing and the presence of permafrost (Zhao and Gray, 1999; Gray et al., 2001; Quinton and Gray, 2001).*]

The Cold Regions Hydrological Modelling platform (CRHM) was created as a set of algorithms that could be used to address such problems in a flexible, modular hydrological modelling context (Pomeroy *et al*., 2007). The application of CRHM in this paper shows how most of these hydromythologies can be overcome with modern, flexible, modelling technologies, based on scientific principles.

Deduction, induction, and abduction and the cold regions hydrological model

Inductive (bottom up) and deductive (top down) approaches to environmental prediction have abounded for many years and the application of these approaches to hydrology are reviewed in Dornes (Chapter 10).

Philosophically, they go back to the reasoning of Ancient Greece, but similar concepts can be found in Chinese philosophy (Liu *et al*., Chapter 2) and are perhaps common to the experience of humanity in solving problems. Unfortunately in hydrology, there has been persistent confusion about what these terms mean and they have been commonly misapplied in the field. For instance, Sivapalan *et al*. (2003a) and Littlewood *et al*. (2003) define the top down or downward approach in hydrology to be driven by observation and moving from general observations to specific rules and therefore deductive, whilst in the study of scientific philosophy it is accepted that data driven approaches are inherently inductive and bottom up (Vickers, 2013). Physics-based approaches are in fact deductive and top down as they derive from application of accepted rules (Holyoak and Morrison, 2005). Further, what has been referred to in the PUB decade as the top down approach in hydrology, is not only inductive and empirical, but can lead to serious errors in conclusions, the dangers of which have been known since the writings of the classical philosopher Sextus Empiricus in the 3rd C AD (Romesburg, 1981; Popper and Miller, 1983). Dornes (Chapter 10) shows the benefits of combining top down and bottom up approaches for hydrological prediction. In this paper, deductive and inductive approaches follow the accepted conventions of philosophy (Vickers, 2013) and correspond to physics-based and empirical approaches respectively.

Whilst it has become clear in PUB that both induction and deduction are needed to develop robust and appropriate hydrological models, the role of abduction (inference) has not been widely discussed despite its great utility to PUB and heretofore unrecognized use in hydrology (Magnani, 2001; Couclelis, 2003). Abduction follows a logic where the major premise is true but the minor premise is probable; here it begins with an incomplete set of observations from a wide range of sources and proceeds to the likeliest possible explanation. It does its best with the information at hand which is often incomplete – a typical situation that hydrologists face. Combining the three approaches in hydrology can be termed the "DIA Approach" and can be quite powerful. A simple example of the DIA approach applied to snowmelt runoff follows:

1. Deduction (rule based / top-down): allows deriving *b* from *a* only where *b* is a formal logical consequence of *a*. Given a rule, based on the continuity equation, that whenever the snow melts in a basin that streamflow must result, the deductive statement is: snow is melting in a basin, therefore there must be streamflow.

2. Induction (observation based / bottom-up): allows inferring *b* from *a*, where *b* does not follow necessarily from *a*. Given the observation that the stream flows only when there is snowmelt in a particular basin, the inductive statement is: the stream is observed to be flowing, therefore there must be snowmelt in the basin.
3. Abduction (opportunistic / lateral): allows inferring to the best explanation even when information is incomplete. Given the inference that when the regional snowcover melts there is streamflow in many local streams in springtime and that this can occur without rainfall, the abductive statement is: streamflow is observed without rainfall in springtime, therefore it is likely that snow is melting in the basin.

A weakness of the inductive approach in this example is that streamflow can be derived from sources other than snowmelt in the spring, and a weakness of the deductive approach is that the rule might be misapplied and snowmelt water might evaporate, infiltrate, or form depressional storage, rather than forming streamflow. The flexibility and ability to bring in auxiliary information of the abductive approach is appealing for complex hydrological problems, but it also has weaknesses, such as the situation where the basin of interest is not like others in the region. Clearly, the use of any reasoning approach by itself can lead to misconceptions and errors, but the combined DIA approach can be powerful when the availability of observations, the applicability of rules, and the reliability of regional inference are limited, as is often the case in hydrology. The application of physical laws by deduction permits rigorous enforcement of continuity of mass and energy and the laws of thermodynamics and kinematics. Using fundamental observations by induction to develop rules of hydrological behavior is how hydrological science often advances. Inferring missing observations or unknown hydrological behavior by abduction of rules or induced behavior is how the hydrological response can be determined with inadequate knowledge or information. There are clearly parallels between the DIA approach and the traditional Chinese housewife approach outlined by Liu *et al*. (Chapter 2).

CRHM is a modular modelling system that permits appropriate hydrological processes for the basin, selected from a library of process modules, to be linked to simulate the hydrological cycle as a purpose-built model (Pomeroy *et al*., 2007). CRHM is very well suited for the DIA approach as an initial selection

of process laws can be considered deduction, the evaluation of process performance, inclusion and model redesign based on learning from model failure can be considered induction, and the use of regional analogues for structure and parameters from research basins can be considered abduction.

From its inception, CRHM has focused on the modular incorporation of physically based descriptions of cold regions hydrological processes, but it also includes a full range of temperate regions modules. Recent developments include options for treeline forest effects from alpine blowing snow (MacDonald *et al*., 2010), improved soil moisture accounting and fill and spill depressional storage (Fang *et al*., 2010), variable rooting zones for evapotranspiration calculations (Armstrong *et al*., 2010) and enhanced forest canopy interception and radiation modules (Ellis *et al*., 2010). CRHM has a suite of process modules including calculation of solar radiation using diurnal temperature ranges, direct and diffuse radiation to slopes, long-wave radiation in complex terrain, intercepted snow, blowing snow, sub-canopy turbulent and radiative transfer, sublimation, energy balance snowmelt, infiltration to frozen and unfrozen soils, rainfall interception, combination-type evapotranspiration, sub-surface flow, depressional storage fill and spill, saturation excess overland flow, and separate routing of surface, sub-surface, and streamflow. The selection of modules is an inductive exercise, depending on the biophysical environment and data availability. CRHM uses an object-oriented structure to develop, support, and apply dynamic model routines. Existing algorithms can be modified or new algorithms can be developed and added to the module library, which are coupled to create a purpose-built model, suited for the specific application. It is particularly useful to replace hydromythologies with modules based upon physical principles.

CRHM operates on the spatial discretization of the hydrological response unit (HRU) which has been found optimal for modelling in basins where there is a good conceptual understanding of hydrological behaviour, but incomplete detailed information to permit a fully distributed fine scale modelling approach (Dornes *et al*., 2008). The level of disaggregation into HRUs is guided not only by the spatial variability of biophysical attributes and drainage conditions in the basin, but by the available information to describe these attributes as parameters and so is simultaneously an inductive and deductive exercise. Being physically based, the majority of CRHM modules do not require calibration against gauged flows and therefore are suitable for parameterization in ungauged basins. Parameters are typically selected *a*

priori from soil/land cover characteristics, vegetation cover, drainage networks, and other basin information – a deductive exercise. Some unmeasured parameter values can be transferred from hydrologically similar basins – an abductive exercise. Calibration of unknown parameters against gauged flows is possible using trial and error methods – an inductive exercise.

4.4 APPLICATION OF THE DIA APPROACH TO HYDROLOGICAL PREDICTION FOR THE SMOKY RIVER BASIN

The Province of Alberta needs to predict spring streamflow for the ungauged portion (46%) of the 51 839 km^2 Smoky River Basin as the ungauged flows have been implicated in exacerbating river ice jams and floods on the Peace River, downstream. The Smoky River flows north out of the Canadian Rocky Mountains into the Peace River lowlands which are the northernmost agricultural region in Canada. The region is remote; weather and climate stations are sparse in the basin and require substantial interpolation and infilling of data for use in hydrological modelling. There are 26 ungauged and 14 gauged sub-basins in the Smoky River Basin and these vary from mountain headwater basins dominated by alpine tundra and sub-alpine forest, upland boreal forest sub-basins to lowland agricultural and forested sub-basins.

Model process structure by deduction

Known hydrological characteristics of the region are long periods of winter (usually five months) and snowcovers heavily modified by wind redistribution and sublimation of blowing snow (Pomeroy and Gray, 1995). The blowing snow process is affected by the interaction of local topography and surficial vegetation cover with regional wind flow patterns (Pomeroy *et al*., 1993; Fang and Pomeroy, 2009). High surface runoff derives from spring snowmelt, which is 80% or more of annual local surface runoff in the Prairies (Gray and Landine, 1988), and occurs as a result of frozen mineral soils at the time of melt and a relatively rapid release of water from melting snowpacks (Gray *et al*., 1985). Snowmelt timing and meltrate are primarily controlled by the net inputs of solar radiation, thermal radiation, energy advected from rainfall, and turbulent transfer of sensible and latent heat. These net inputs are controlled by the storage of internal energy in the snowpack and the snow surface albedo, both of which change rapidly in the pre-melt and melt period. Meltwater infiltration into frozen soils can be restricted, limited, or unlimited depending on soil infiltrability (Gray *et al*., 1985; Zhao and Gray, 1997).

Frozen mineral soils usually have limited infiltration characteristics, which means that the infiltrability is controlled by the degree of saturation of the soil pores with water and ice. The degree of saturation can be estimated from the soil porosity and the volumetric moisture content of the preceding fall if overwinter soil moisture changes are minimal. Substantial mid-winter melts or rain events can cause restricted infiltration, in which most snowmelt water goes directly to runoff (Gray *et al*., 2001) due to the presence of ice layers at the snow-soil interface. Heavy clay soils can crack when frozen, resulting in nearly unlimited infiltration; hence little to no runoff generation (Pomeroy *et al*., 1990). Deep prairie soils are characterized by good water-retaining capacity and high unfrozen infiltration rates (Elliott and Efetha, 1999). Most rainfall occurs in spring and early summer from large frontal systems and the most intense rainfall in summer is associated with convective storms over small areas (Gray, 1970). During summer, most rainfall is consumed by evapotranspiration associated with the growth of crops and perennial grasses (Armstrong *et al*., 2008). Evapotranspiration occurs quickly from wet surfaces such as water bodies, wetted plant canopies, and wet soil surfaces, but relatively slowly from unsaturated surfaces such as bare soils and plant stomata (Granger and Gray, 1989). Any physically based runoff model for this region must correctly resolve these hydrological processes.

Deduction based on the experience of the modellers in constructing models in western Canada with the known physical processes in the region, informed the construction of a model using physically based modules in a sequential manner to simulate the dominant hydrological processes for the Smoky River. Appropriate modules were selected that could be run to robustly forecast the hydrological cycle of the region in a physically based manner. Figure 4.1 shows the schematic setup of these modules. The following list describes the methods that are included in each module:

1. Observation module: reads the meteorological data (temperature, wind speed, relative humidity, vapour pressure, precipitation, and radiation) used to operate CRHM, adjusting temperature with environmental lapse rate and precipitation with elevation and wind-induced undercatch, and providing these inputs as the "driving meteorology" to other modules as required by the module calculations.
2. Radiation module based upon Garnier and Ohmura (1970): calculates the theoretical global clear-sky radiation as direct and diffuse solar radiation to slopes based on latitude, elevation, ground

slope, and azimuth, providing radiation inputs to the energy-budget snowmelt module, and the net all-wave radiation module. Transmittance is estimated using a diurnal temperature range method (Annandale *et al*., 2002; Shook and Pomeroy, 2011).

3. Long-wave radiation module based upon Sicart *et al*. (2006): estimates incoming long-wave radiation using vapour pressure, air temperature, and the short-wave transmittance estimated from the short-wave radiation module. This feeds into the energy-balance snowmelt module.
4. Albedo module based upon Gray and Landine (1987): estimates areal snow albedo throughout the winter and into the melt period and also indicates the beginning of melt for the energy-balance snowmelt module.
5. Canopy module based upon Ellis *et al*. (2010): estimates the snowfall and rainfall intercepted by the forest canopy and updates the under-canopy snowfall and rainfall and calculates short-wave and long-wave sub-canopy radiation. This module has options for open environment (no canopy adjustment of snow mass and energy), small forest clearing environment (adjustment of snow mass and energy based on diameter of clearing and surrounding forest height), and forest environment (adjustment of snow mass and energy from forest canopy).
6. Blowing snow module based upon the method of Pomeroy and Li (2000): simulates the inter-HRU wind redistribution of snow transport and blowing snow sublimation losses throughout the winter period.
7. Energy-Budget Snowmelt Model based upon Gray and Landine (1988): estimates snowmelt by calculating the energy balance of radiation, sensible heat, latent heat, ground heat, advection from rainfall, and change in internal energy.
8. All-wave radiation module using the method of Granger and Gray (1990): calculates the net all-wave radiation from short-wave radiation for input to the evaporation module for snow-free conditions.
9. Infiltration module using Gray's snowmelt infiltration algorithm (Gray *et al*., 1985): estimates snowmelt infiltration into frozen soils; Ayers' infiltration (Ayers, 1959): estimates rainfall infiltration into unfrozen soils based on soil texture and ground cover. Both infiltration algorithms link moisture content to the soil column in the soil module. Surface runoff forms when snowmelt or rainfall exceeds the infiltration rate.

10. Fall soil moisture module: sets the fall soil moisture status for running multiple-year simulations. The amount of soil moisture and the maximum soil moisture storage in the soil column are used to estimate the fall soil moisture status, which provides the initial fall soil saturation for the infiltration module.

11. Evaporation module using Granger's evaporation expression (Granger and Gray, 1989; Granger and Pomeroy, 1997): estimates actual evapotranspiration from unsaturated surfaces using an energy balance and extension of Penman's equation to unsaturated conditions; Priestley and Taylor evaporation expression (Priestley and Taylor, 1972): estimates evaporation from saturated surfaces such as stream channels. Both evaporation algorithms modify moisture content in the interception store, ponded surface water store, and soil column and are restricted by water availability to ensure continuity of mass; the Priestley and Taylor evaporation also updates moisture content in the stream channel.

12. Soil & Hillslope module: calculates sub-surface flow and simulates groundwater-surface water interactions using physically based parameters. The present module was revised from an original soil moisture balance routine developed by Leavesley *et al*. (1983) and modified by Pomeroy *et al*. (2007), Dornes *et al*. (2008), Fang *et al*. (2010), and Fang *et al*. (2013) and now calculates the soil moisture balance, groundwater storage, subsurface and groundwater discharge, depressional storage, and runoff for control volumes of two unsaturated soil layers, the groundwater layer and surface depressions. Groundwater recharge occurs via percolation from the soil layers or directly from depressional storage via macropores. Subsurface discharge occurs via horizontal drainage from either soil layer; groundwater discharge takes place through horizontal drainage in the groundwater layer. Surface runoff occurs when inputs from snowmelt or rainfall exceed subsurface withdrawals from saturated soils or if the rate of snowmelt or rainfall exceeds the infiltration rate. The drainage factors for lateral flow in soil layers and groundwater layer (i.e. subsurface and groundwater discharges) as well as vertical flow of excess soil water to groundwater (i.e. groundwater recharge) are estimated based on Darcy's flux. The Brooks and Corey (1964) relationship is used to calculate the unsaturated hydraulic conductivity.

13. Routing module: the Muskingum method is based on a variable discharge-storage relationship (Chow, 1964) and is used to route

runoff between HRUs in the sub-basins. The routing storage constant is estimated from the average distance from the HRU to the main channel and average flow velocity; the average flow velocity is calculated by Manning's equation (Chow, 1959) based on the average HRU distance to the main channel, average change in HRU elevation, overland flow depth, and HRU roughness.

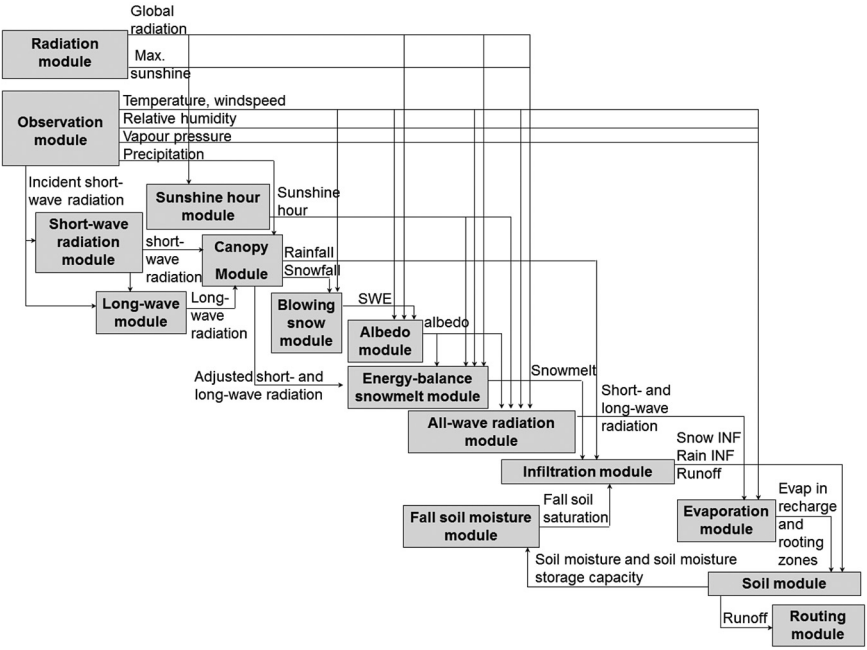

Figure 4.1 *Flowchart of physically based hydrological module used in the Lower Smoky River Model created using CRHM.*

Model HRU structure by induction

Hydrological response units (HRU) are based on combinations of vegetation, soils, drainage, waterbody, and topographic parameter information. Sub-basins of the Smoky River Basin span the mountains and foothills, boreal forest, boreal forest – agricultural transition, and agricultural ecoregions. The boreal forest has been heavily impacted by forest harvesting and disturbance for oil and gas production platforms and pipelines, and agricultural regions are heavily cultivated to cereal and oilseed crops. HRU delineation varied by ecoregion; in all areas land cover

and drainage were important; however, in alpine areas slope, aspect, and elevation were included whereas in the flatter agricultural areas soil texture was used. Figure 4.2 shows how an overall delineation of land cover from a satellite image classification was used to delineate HRU specific to each ecoregion, by induction informed by a site visit and field observation of how satellite-derived land cover classifications corresponded to suitable landscape units for hydrological simulation. Figure 4.3 presents a map of the HRUs for the ungauged portion of the basin and of the drainage pattern.

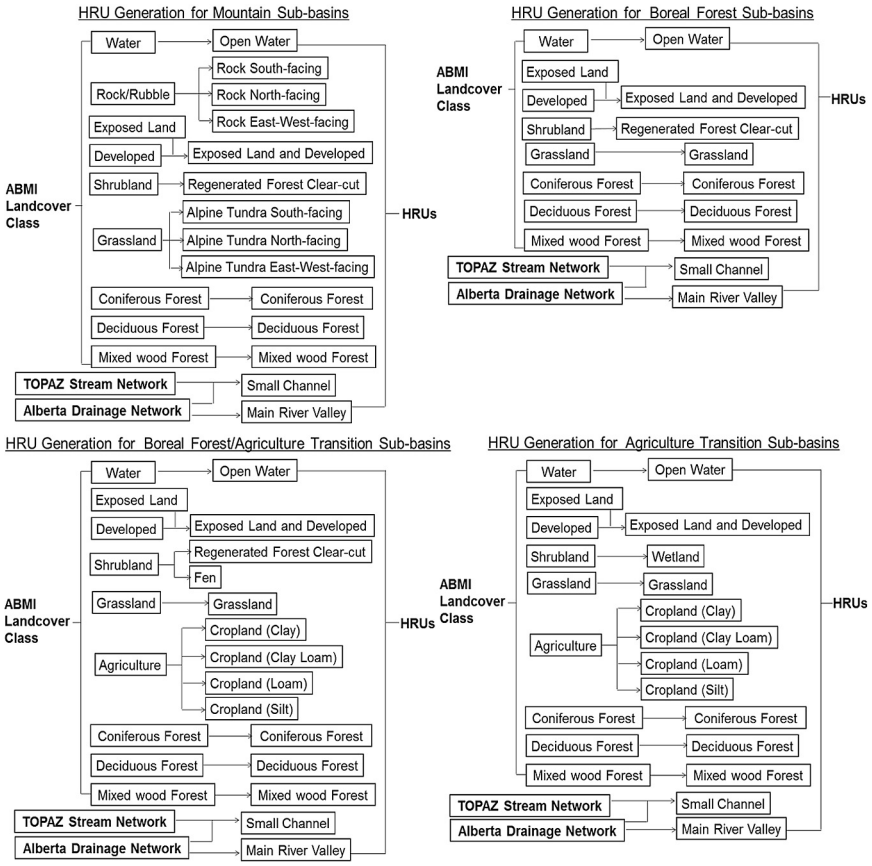

Figure 4.2 *HRU generation for the Smoky River modelled sub-basins.*

Model parameterization by DIA

Deduction

The sub-basin network was extracted using an automated basin delineation tool, TOPAZ, which uses rules to decide on drainage patterns from the digital elevation model (Garbrecht and Martz, 1997). For HRU, the corresponding area, elevation, aspect, and slope for the HRUs were

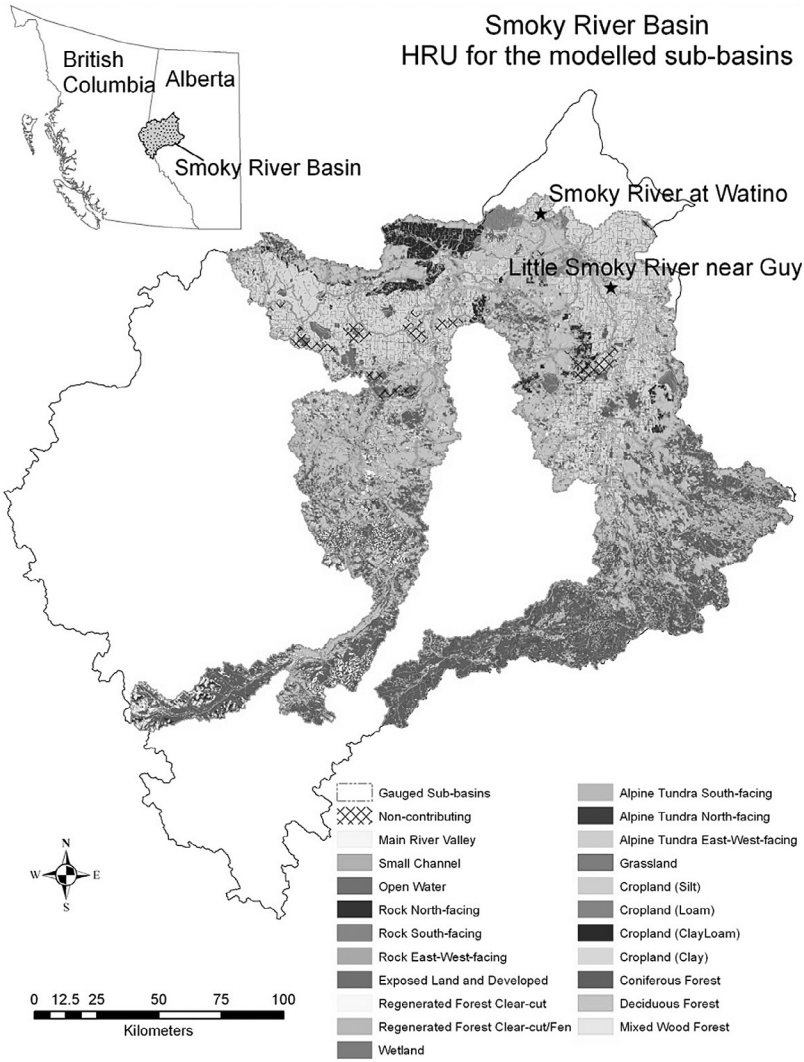

Figure 4.3a *HRU for the modelled sub-basins in the Smoky River Basin.*

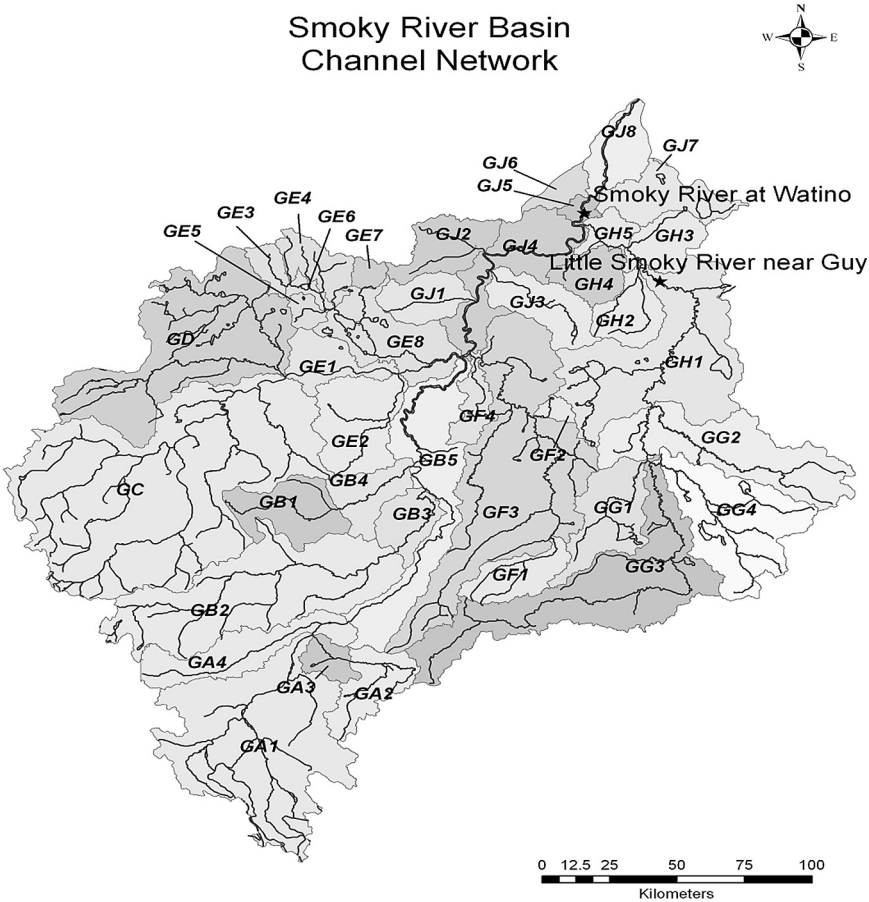

Figure 4.3b *Smoky River Basin channel network and sub-basins.*

computed using the SAGA GIS (Conrad, 2006) terrain "analysis profile tool" and the ArcGIS (Environmental Systems Research Institute, 2012) "extract by mask" tool, as described by Fang *et al*. (2010). This was largely a deductive exercise obtained from existing information using rules. Vegetation and soils were determined by Alberta Biodiversity Monitoring Institute satellite remote sensing vegetation classifications and soil surveys and were interpreted to leaf area index, vegetation height, and soil texture classes using rules developed from field studies in western Canada over many years (e.g. Pomeroy and Gray, 1995; Pomeroy and Brun, 2001;

Pomeroy *et al*., 2002). These rules were modified by ecoregion as it is understood from ecological principles that a "grass" classification in an alpine ecoregion corresponds to tundra, whilst in a prairie ecoregion it corresponds to grassland. Hydraulic parameters such as Manning's n and channel shape were estimated from observations made during site visits.

Induction

The need to adjust some model parameters was informed by induction since the initial sub-basin modelled flows matched observed streamflows very poorly. Induction with respect to sub-basin streamflow was used to adjust the vertical profile of saturated hydraulic conductivity in soil, and the sub-surface travel time parameter, as these parameters were not measured. No other parameters were calibrated.

Abduction

As local measurements of many parameters were not available, their values were abducted from detailed observations in four Canadian ecoregions as explained in Pomeroy *et al*. (2005). For instance, abduction was used to set fall soil moisture parameters to address the impact of macropores in soil (Darwent and Baily, 1982) and the snow interception parameters to address the effects of strong winds on interception efficiency (Pomeroy and Gray, 1995). Additional information was extracted from studies of Prairie agricultural fields (Knapik and Lindsay, 1983; Pomeroy *et al*., 2007; Armstrong *et al*., 2008; Fang and Pomeroy, 2009; Fang *et al*., 2010; Pomeroy *et al*., 2010); from alpine tundra in Alberta and Yukon (MacDonald *et al*., 2009; 2010; Fang *et al*., 2013), and from boreal forest in Saskatchewan and Yukon (Granger and Pomeroy, 1997; Hedstrom and Pomeroy, 1998; Pomeroy *et al*., 2002). The set of model parameters and the parameterization process are described in detail by Pomeroy *et al*. (2013).

4.5 IMPLICATIONS OF MODELLING RESULTS

Simulations of ungauged streamflows are by definition impossible to evaluate directly. In an attempt to evaluate the model against gauged flows, nine years of local simulated ungauged inflows were added to routed gauged upstream flows and compared to the gauged downstream flows on the Little Smoky River at Guy and the Smoky River at Watino in Figure 4.4. The

gauged upstream flows were routed so that the discharges of gauged and modelled flows were synchronized. The predicted seasonal spring discharges (modelled plus routed gauged flows) from 15 March to 31 May were compared to the gauged flows for both rivers for nine spring periods and are shown in Figure 4.5. For the Little Smoky River simulations, the mean bias ranged from -0.60 in 2007 to 0.76 in 2010, indicating the cumulative spring discharge ranged from 60% underestimation to 76% overestimation with an average seasonal underestimation of 3%. Cumulative spring flows were underestimated by 18.5% over the nine springs. For the Smoky River simulations, the mean bias ranged from -0.07 in 2008 to 0.41 in 2009, indicating the cumulative spring discharge ranged from a 7% underestimation to a 41% overestimation with an average seasonal overestimation of 12%. Cumulative spring flows were overestimated by 9.7% over the nine springs. These statistics, when evaluated along with the Nash-Sutcliffe coefficient for the Little Smoky River and Smoky River daily hydrographs of 0.41 and 0.87, suggest good model performance in hydrograph prediction and in estimating the water balance, with model performance improving with increasing basin size and distance downstream. This is partly due to the contribution of the routed gauged flows to the modelled flows and partly due to the effect of increasing basin size on masking unmeasured and missing precipitation data and errors in parameterization and model structure. Overall, it is a confirmation that a physically based model with minimal calibration can provide good simulations of ungauged basins when the DIA approach is used to develop and parameterize the model.

The success of the abductive approach to model development and parameterization in this example was due to the availability of information from intensive research basins in similar ecoregions to those occurring in the basin (Pomeroy *et al*., 2005). These research basins were not nearby, in some cases being over 1000 km away from Alberta, in Saskatchewan and the Yukon Territory, but the similarity of vegetation form and structure, soil structure, drainage basin spatial arrangement, and climate across these biomes permitted the transfer of certain conceptual approaches and physically identifiable parameters over vast distances. Kouwen *et al*. (1993) suggested this approach for parameterization of grouped response units in large scale hydrological models, and Pietroniro and Soulis (2003) demonstrated application of the parameter regionalization concept to water

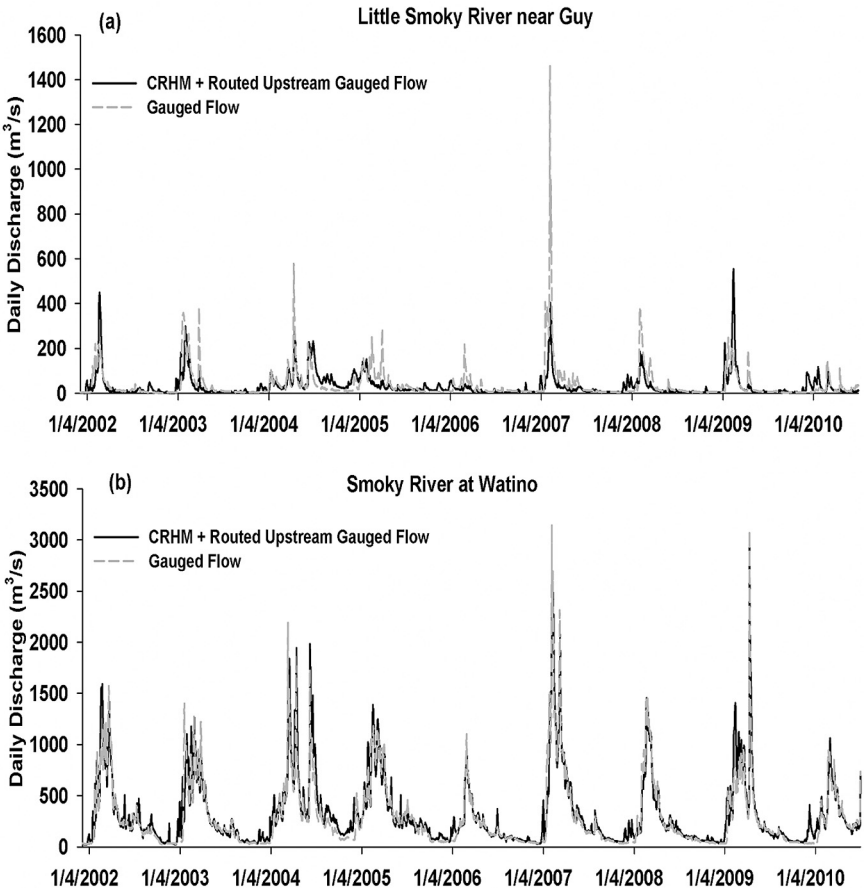

Figure 4.4 *Comparisons of CRHM simulated plus routed real-time upstream gauged streamflows and gauged daily streamflows from 4 March 2002 to 30 September 2010 for:* ***(a)*** *Little Smoky River near Guy and* ***(b)*** *Smoky River at Watino.*

and energy cycle calculations over large areas of Canada. This suggests that regionalization of modelling approaches on ecological, hydrological, and climatic principles is viable and that this abductive approach can be employed where there are networks of research basins from which detailed hydrological relationships and parameter values can be obtained. These research basins were established around the world in the International Hydrological Decade of 1964-1975, and archives or recent studies from those basins that still exist are invaluable resources for abductive contributions to PUB.

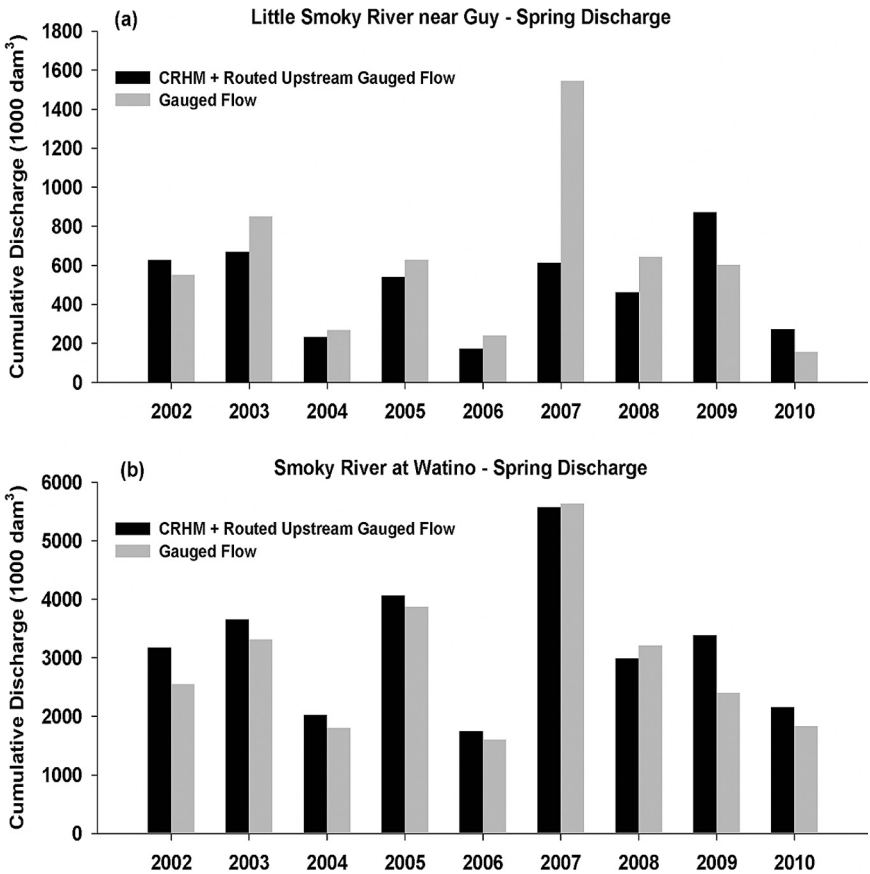

Figure 4.5 *Comparisons of CRHM simulated plus real-time upstream gauged streamflow and observed gauged cumulative spring discharge from during 15 March-31 May in nine springs from 2002 to 2010 for:* ***(a)*** *Little Smoky River near Guy and* ***(b)*** *Smoky River at Watino.*

4.6 CONCLUSIONS

Persistent errors in model process descriptions have hampered the progress of hydrological prediction as has the over reliance on either data-driven inductive approaches or physically prescribed deductive approaches to model derivation. Modelling errors can be corrected using process algorithms developed from the last three decades of integrated, strategic field and modelling research. Models including these process descriptions may be capable of prediction in ungauged basins with minimal calibration if parameters can be identified and appropriate model structures created. The use of a combination of deductive, inductive, and abductive reasoning is recommended for prescribing both an appropriate level of complexity and process inclusion in model structure and in parameterizing process algorithms. An example of the deduction, induction, and abduction approach was shown in the development of model process structure, basin discretization and parameterization and was applied to the ungauged portion of the Smoky River Basin in Alberta, Canada. Deductive reasoning used known laws to deduce information from existing basin maps and satellite imagery. Inductive reasoning was used to calibrate certain model parameters from a test sub-basin. Abductive reasoning was used to borrow parameters from a suite of intensive research basins in western Canada. The model was able to achieve good performance in predicting the peak spring flows on the river over several years and at two different scales. This suggests that in remote regions of the world where stream gauges are sparse or non-existent, prediction in ungauged basins using physical principles is a possible, viable, and preferable alternative.

4.7 ACKNOWLEDGEMENTS

The authors would like to acknowledge funding provided by NSERC, CFCAS, Environment Canada, Canada Research Chairs, the Global Institute for Water Security and the Province of Alberta and model support from Mr. Tom Brown. The inspiration that hydrological prediction based on physical principles is not only possible but preferable comes from the late Professor Donald M. Gray to whom this paper is dedicated.

5

FLOOD RISK ASSESSMENT IN A POORLY GAUGED BASIN

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5.1 ABSTRACT

An approach for flood risk assessment in a poorly gauged basin has been proposed and tested for the Sosna River basin in European Russia. The approach involves searching a data-rich small proxy basin which is hydrologically similar to the poorly gauged study basin, developing a physically based model of flood generation in the proxy basin, and transferring the developed model with adjustments to the study basin. In this case study, the adjustment was carried out through the model calibration against snow and soil freezing survey data in the study basin; streamflow data were not used for the calibration. Long-term artificial time series of daily weather variables were Monte Carlo simulated and input to the hydrological model to generate a corresponding series of snowmelt flood hydrographs in the study basin. Frequency distributions of flood characteristics (volume and peak discharge) were derived from the long-term series of the modelled hydrographs. The approach allows the derivation of frequency distribution of flood volume without utilizing any streamflow observations in the study basin; however, in order to obtain reliable frequency distribution of flood peak discharge, several years of streamflow observations should be used for the additional calibration of the model. The proposed approach is targeted for hydrological engineering practice and considered as a suitable alternative to the traditional methods of flood risk assessment in ungauged or poorly gauged basins.

5.2 RÉSUMÉ

Une approche d'évaluation des risques d'inondation dans un bassin fluvial avec un nombre insuffisant de limnimètres a été proposée et essayée pour la rivière de Sosna située dans la partie européenne de Russie. Cette approche

comprend une recherche d'un petit basin témoin riche en données qui est semblable du point de vue hydrologique au basin exploré mal calibré, un development d'une modèle physiquement justifiée de la formation des inondations dans le bassin témoin ainsi qu'un transfert de la modèle développée avec les ajustements dans le bassin exploré. Dans cette étude de cas l'ajustement a été fait par le moyen d'étalonnage du modèle contre les données d'un sondage sur la couverture de neige et congélation du sol dans le bassin exploré. L'étalonnage n'a pas utilisé les données sur le débit d'eau fluvial. Monte Carlo simulation a été effectuée pour obtenir des séries de temps artificielles à long terme des variables météorologiques quotidiens qui ont été entrées dans la modèle hydrologique afin de générer des séries correspondantes d'hydrographes d'inondation de la fonte des neiges dans le bassin exploré. Distributions de fréquence des caractéristiques d'inondation (volume et débit de pointe) ont été dérivées de séries à long terme des hydrographes modelés. Cette approche permet de dériver les distributions de fréquence du volume de l'inondation sans utiliser aucunes observations sur le débit de l'eau fluvial dans le bassin exploré. Pourtant, pour obtenir les données fiables sur la distribution de fréquence du débit de pointe de l'inondation, plusieurs années d'observations sur le débit de l'eau fluvial doivent être utilisées pour avancer l'étalonnage du modèle. L'approche proposée est axée sur la pratique d'ingénieur hydrologique et est considérée une alternative convenable à méthodes traditionnelles d'évaluation des risques d'inondation dans les bassins manquants ou sans limnimètres.

5.3 INTRODUCTION

Planning and design of water resources systems, flood management, and protection are fundamentally dependent on reliable estimates of flood risk. Most countries use a set of empirical methods for flood risk assessment, and among these methods the flood frequency analysis (FFA) is the most commonly used one for over a century. The standard at-site FFA is based on acquisition of data of flood extremes, computation of observed probabilities of occurrence, fitting of the appropriate probability distribution to the observed probabilities with use of an appropriate parameter estimation technique, and, finally, estimation of flood quantiles of the desired probabilities. The fundamental weakness of the FFA is widely known (see, for example, discussions in Klemeš, 1986; Singh and Strupczewsky, 2002) and arises, first of all, from lack of available streamflow data for the

overwhelming majority of river basins. This is the case especially when the interest is in the assessments of extreme floods with return periods of hundreds of years, i.e. much longer than the period of flood observations. The data deficit results in increasing uncertainty of assessments for the desired extreme floods that can negate the practical value of these assessments. Moreover, in many countries, the gauging network has been reduced for the past few decades. Presently, the number of stream gauges in Russia, for instance, is about 70% of the density of the hydrological network that existed during the 1980s. The density of the hydrological network is about an order of magnitude less than the minimum density recommended by WMO (1994), and one can assume that the difference between the number of gauged basins and ungauged basins is of the same order. Regional statistical analyses of flood frequency can to some extent compensate for the lack of temporal data, but an additional, spatial dimension is introduced (Bobée and Rasmussen, 1995) that leads to increasing uncertainty of the desired estimates.

Attempts at improving the FFA so far have been focused on the statistical aspects, such as improvement of the parameter estimation techniques, seeking probability distribution for improving goodness of fit, etc. Lack of knowledge about the form of the parent distribution limits these attempts; however, even if one assumes that the distribution form is known, the paucity of the available observations *per se* leads to the unreliable results of the extrapolation above the maximum observed flood. As an example, Figure 5.1 presents the annual maximum peak discharges of the Seim River (centre of European Russia) observed during 61 years (beginning from 1928) and fitted by a three-parameter gamma-distribution curve. Note that in the range of the available observations, this distribution is indistinguishable from the other distributions typically used for FFA of annual maximum discharge, e.g. Log-Pearson type III distribution. Another gamma-distribution curve is fitted to a 56-year sample obtained by exclusion of the first five years of discharge (from 1928 to 1932) from the original, 61-year sample. The legitimacy of the fitted curves cannot be doubted, but there is an obvious difference between these curves when extrapolated to extreme floods. The exceedance probability of the maximum observed discharge (2230 m^3/s), estimated by the 61-year sample, is 0.012 (83-year return period). If, for some reason, the observations began 5 years later (in 1933 instead of 1928), the corresponding exceedance probability of the same discharge would be four times less (0.003, i.e. 333-year return

period). This presents a major difficulty in applying such statistical techniques with limited time series for flood prediction purposes in ungauged basins.

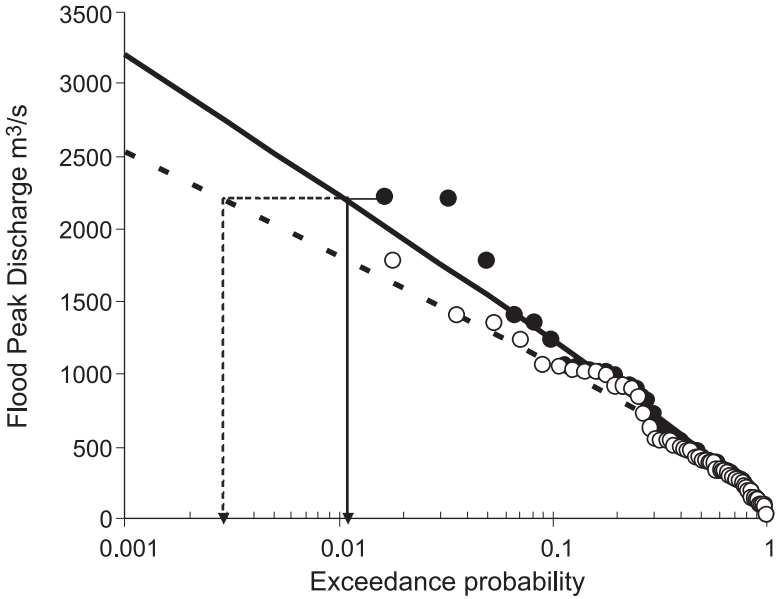

Figure 5.1 *Gamma-distribution curves fitted to 61-year (solid line; solid circles) series of observations at the Seim River beginning from 1928 and 56-years (dashed line; open circles) series beginning from 1933 (explanations are in the text).*

An opportunity for refinement of the extreme flood frequency assessment is associated with the inclusion of deterministic, physical information in addition to statistical information extracted solely from the runoff observation series. As Klemeš (1993) states: "if more light is to be shed on the probabilities of hydrological extremes, then it will have to come from more information on the physics of the phenomena involved, not from more mathematics." Such additional information may be both *a posteriori*; empirical information about factors affecting flood generation (e.g., meteorological factors, watershed conditions), and *a priori* information, reflecting accumulated knowledge on flood generation physics. In other words, lacking homogeneous runoff data for the standard FFA, the data deficit may be partly compensated by deterministic information on physical processes and stochastic information on better defined forcing variables, e.g. meteorological variables.

Development of such a model which is based on the deterministic description of the hydrological processes and takes into account available stochastic information on input meteorological variables is the subject of the dynamic-stochastic approach to flood risk assessment (Kuchment and Gelfan, 1991). The resulting dynamic-stochastic model integrates two components: a physically based deterministic model of runoff generation and stochastic models of the meteorological variables which are the inputs into the deterministic model. The integration of dynamic and stochastic approaches opens an opportunity for assessment of magnitude/frequency of extreme floods in the basins where series of streamflow data are too short and/or statistically non-homogeneous due to anthropogenic pressure on environment and climate change ("virtually ungauged basins" (He *et al*., 2011)), in other words, in the basins where the standard FFA is ineffective.

Eagleson (1972) was the first who proposed a dynamic-stochastic model based on the physically based description of hydrological processes of rainfall flood generation; he derived a distribution function of flood peak discharge through integration of joint probability distribution of rainfall intensity and duration over the domain determined from the analytic solutions of the kinematic wave equation. Eagleson's (1972) approach to flood frequency estimation has been used and extended by Carlson and Fox (1976), Chan and Bras (1979), Hebson and Wood (1982), Diaz-Granados *et al*. (1984), Bras *et al*. (1985), Blöschl and Sivapalan (1997), and others.

Bras *et al*. (1985) compared abilities of the models of Eagleson (1972), Hebson and Wood (1982), and Diaz-Granados *et al*. (1984) to derive flood frequency distribution for ungauged basins. Five river basins located in the different physiographic and climatic conditions with catchment areas from 100 to 1000 km^2 were selected and it was assumed that no streamflow data were available, so that the parameters of the rainfall-runoff components of the models were assigned *a priori*. The return periods of flood peak discharges derived by each of the models for the five basins were compared with the return periods estimated from the available data of observations. The comparison has shown that none of these models agreed well with the observations. Bras *et al*. (1985) concluded that performance of these models could be significantly improved if some observation data could be used for calibration of the rainfall-runoff models.

Blöschl and Sivapalan (1997) used the derived distribution approach in order to test the "index flood" concept underlying the standard procedure of determination of homogeneous geographical regions in regional FFA often used for ungauged basins. The authors interpreted data from hundreds of catchments in Austria and showed that the coefficient of variation of peak discharge depends on the basin area, which contradicts the principal "index flood" assumption of independence of variation of peak discharge.

An alternative, numerical technique for deriving flood frequency is a Monte Carlo simulation-based dynamic-stochastic modelling allowing one to combine a sophisticated model of runoff generation with a stochastic weather generator. A physically based model of rainfall flood was first combined with the Monte Carlo continuous simulation of precipitation and air humidity series by Kuchment *et al*. (1983); they showed for small basins that extreme flood frequency numerically derived by the use of the available short series of streamflow data for the model calibration is more reliable than flood frequency obtained by the standard statistical analysis of that series. Recently, the numerical dynamic-stochastic approach has been applied, for example, by Franchini *et al*. (1996), Blazkova and Beven (1997), Hashemi *et al*. (2000), Sivapalan *et al*. (2005), Fiorentino *et al*. (2007), and Haberlandt *et al*. (2008) who used different deterministic models (TOPMODEL, ARNO, HEC-HMS and others) for derivation of rainfall flood frequency.

Considerably fewer authors have applied the numerical dynamic-stochastic approach to derive the frequency of extreme snowmelt floods (Kuchment and Gelfan, 2002; Blazkova and Beven, 2004; Gelfan, 2010), and there are no publications regarding snowmelt flood frequency assessment for ungauged or poorly gauged basins. This is rather surprising, given (1) the dominant role of snowmelt in the flow regime of rivers over vast cold regions and the associated high cost of snowmelt flood events for the economy of cold-region countries (e.g. in Russia more than 65% of the disastrous floods are of snowmelt origin) and (2) the sparse gauge network in most cold regions.

The objective of this study was to develop an approach for assessment of snowmelt flood risk in the basins where no streamflow data are available or data are too scarce for application of the FFA but for which long-term meteorological data are assumed to be available. The developed approach consists of the following steps:

1. Select a data-rich small proxy-basin which is hydrologically similar to the ungauged study basin; the criteria of similarity proposed by Kuchment and Gelfan (2009) are used for the selection (details about the criteria are presented in the next section).
2. Develop a physically based model of snowmelt flood generation for the proxy-basin and "transpose" the model to the study basin without use of the streamflow data in the latter basin.
3. Construct a stochastic weather generator using long-term meteorological observations in the study basin.
4. Assess flood risk in the study basin on the basis of the dynamic-stochastic approach combining the "transposed" model with the weather generator.

In the next sections, the proposed approach is demonstrated by the example of the Sosna River basin as the study basin.

5.4 STUDY BASIN AND PROXY-BASIN: BRIEF DESCRIPTION AND CRITERIA OF SIMILARITY

The Sosna River basin is located in the centre of European Russia, draining west into the Don River. The study area of approximately 16 300 km^2 (up to the outlet at Elets town, 52°37'N, 38°28'E) is situated at the steppe-forest physiographic zone (Figure 5.2). The basin terrain is a smooth plain. Soils in the area belong to a steppe type of soil formation, being mainly represented by common chernozem (black soils) and podzol with a texture varying from heavy loam to clay. About 80% of the basin area is farmed; of the remainder, pastures take up about 10%, ravines and gullies occupy 8%, and forest about 2% of the basin area. Annual air temperature is +5.9 °C, the mean air temperature in the coldest month (January) is -7.0 °C and +19.5 °C in the warmest month (July). Annual precipitation is 475 mm, about 29% of which falls as snow. The maximum snow water equivalent (SWE) varies significantly from year to year (mean SWE is 69 mm with a maximum observed value of 180 mm and minimum of 17 mm). The mean date of the beginning of snowmelt is March 27. During the snowmelt period, which averages 26 days, from 39% to 73% of annual runoff is generated (55% on average). The snowmelt runoff coefficient varies from year to year over a wide range: from 0.21 to 0.88. Mean snowmelt runoff is 72 mm; the mean peak discharge of snowmelt floods is 1783 m^{3}s^{-1} which is much greater than

the highest observed peak discharge of rainfall flood, 388 m^3s^{-1}. The highest peak discharge from a snowmelt flood was 4950 m^3s^{-1} on April 5, 1970. The Sosna River basin will be considered hereafter as an ungauged basin, a so-called "pseudo-ungauged basin" (He *et al*., 2011).

Kuchment and Gelfan (2009) suggest that small experimental basins, particularly those included in the network of the Russian water balance stations (WBS), can be considered as good proxy-basin candidates. The network of WBS was created in different physiographic zones over the former USSR in the 1930s-1950s; more than 20 WBS existed at the end of the 1980s. Presently, the number of Russian WBS sites is shrinking significantly, but they are still a source of the unique long-term detailed data including measurements of streamflow, meteorological and snow characteristics, soil properties, hydrothermal regime of vadose zone, evaporation, groundwater, etc. (Kane and Yang, 2004).

A number of hydrological similarity criteria have been proposed in the literature (e.g. Wagener *et al*., 2007). Beginning from the simplest criterion of spatial proximity, the Yasenok Creek experimental basin located within the territory of the Nizhnedevitskaya WBS (51°33'N, 38°22'E), near the south-eastern boundary of the Sosna River catchment (Figure 5.2) was considered as the initial choice of the proxy-basin for the Sosna River basin.

The Yasenok Creek catchment (22 km^2) is located in the upper part of the Devitsa River basin draining east into the Don River. Relief is flat and the dominant soils are chernozems with some podzol. The bottom water-bearing horizon of 25-30 m depth is the main aquifer, which is drained only by main watercourses. The vegetation cover of the station belongs to a band of steppes rich in herbs with oak forests. Forests cover 4% of the catchment. The main part of the Yasenok Creek basin is occupied by arable lands. The mean annual temperature is 5.8°C; the mean annual precipitation is 507 mm. The maximum SWE varies considerably from year to year, from 34 to 124 mm. Location of the measurement gauges within the catchment area is shown in Figure 5.2.

Comparing the above descriptions one can see that the Sosna River and the Yasenok Creek basins have similar catchment attributes, such as topographic characteristics, soil and vegetation type, etc. This likeness allows one to expect that the catchments behave in a hydrologically similar manner.

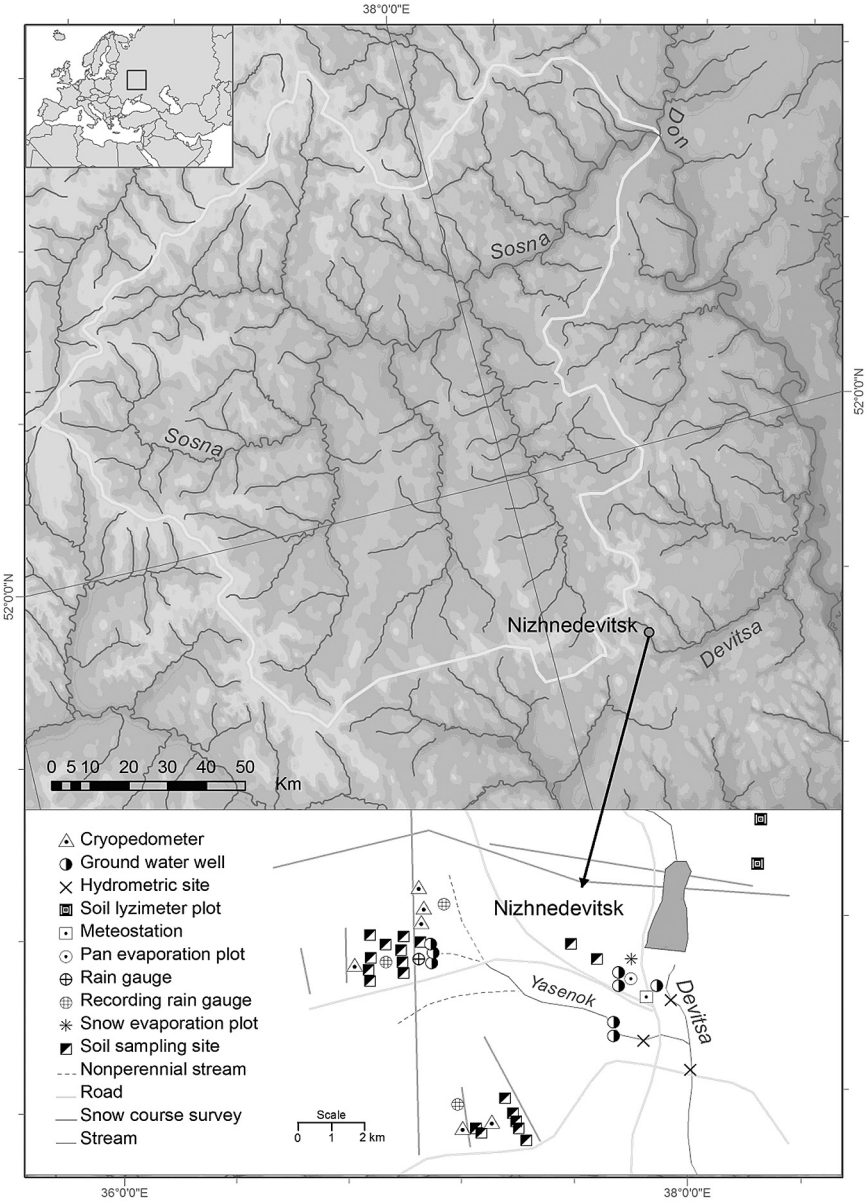

Figure 5.2 *Location of the study basin (Sosna River) and the proxy-basin (Yasenok Creek).*

Measures of hydrological similarity (such as aridity index, topographic wetness index, runoff coefficient, bifurcation ratio, etc.) differ in terms of the processes they aim to represent (Blöschl, 2005) and a reasonable choice of the measures depends on the understanding of the dominant runoff generation mechanism in both gauged and ungauged catchments. In other words, one can talk about the similarity of the prevailing features of runoff generation rather than similarity of hydrological systems as a whole. Kuchment and Gelfan (2009) found that the dimensionless indices derived from the Richards' equation work well as similarity measures for the arid steppe region where the infiltration excess mechanism of runoff generation is dominated. Four dimensionless similarity indices proposed by Kuchment and Gelfan (2009) were used here as the criteria of hydrological similarity: (1) the Peclet number, which is the ratio of the rates of moisture transfer by gravitational filtration and capillary diffusion; (2) the index of maximum soil capacity, which is the ratio of the infiltration to water-bearing capacities of soil; (3) the gravitational filtration efficiency, which is the ratio of the saturated hydraulic conductivity to the mean precipitation rate; and (4) the capillary filtration efficiency which is the ratio of the mean rate of capillary filtration to the mean precipitation rate. Hydraulic properties of soils needed for calculation of the above indices were adopted from the soil survey data (Department of Hydrometeorological Service for the Central-Chernozem Regions, 1975) as well as the data of the experiments made in the Hydrophysical Lab. of the State Hydrological Institute (SHI) published in (Kalyuzhny *et al*., 1988). For the Sosna and Yasenok catchments, the following values of the similarity indices were obtained: the Peclet numbers are 0.43 and 0.38, the free soil capacity criteria are 1.59 and 1.78, the gravitational filtration efficiencies are 81.0 and 66.7, and the capillary filtration efficiencies are 277.9 and 215.1, respectively. Taking into account a large spatial variability of the hydraulic soil properties, the differences between the similarity indices for the catchments are insignificant. Thus, the closeness of the indices was interpreted as similarity of the processes of runoff generation in the basins, and the data-rich Yasenok basin was assigned as the proxy-basin for the Sosna River basin.

5.5 MODEL OF SNOWMELT FLOOD GENERATION

Description of the model and its development for the proxy-basin

The model of snowmelt flood generation used in this study presents a modification of the model version reported in Gelfan (2010). The model

describes processes of snow accumulation and melt, water and heat transfer in a soil during its freezing and thawing, infiltration into frozen and unfrozen soil, detention of meltwater by basin storage, and overland and channel flow. Below the main equations are shown; algorithms of their solution as well as relationships for the parameters are presented in Gelfan (2010).

Dynamics of snow depth, water/ice content of snow are calculated by the equations:

$$\frac{dH_s}{dt} = \rho_w \left[X_s \rho_0^{-1} - (M + E_s)(\rho_i I_s)^{-1} \right] - V \tag{1}$$

$$\frac{d}{dt}(\rho_i I_s H_s) = \rho_w (X_s - M - E_s) + F_i \tag{2}$$

$$\frac{d}{dt}(\rho_w \theta_s H_s) = \rho_w (X_l + M - E_l - R_s) - F_i \tag{3}$$

where H_s is the snow depth; I_s and θ_s are the volumetric content of ice and liquid water, respectively; X_s and X_l are the snowfall rate and the rainfall rate, respectively; M is the melt rate; E_l and E_s are the evaporation and sublimation rates, respectively; F_i is the rate of refreezing of meltwater in snow; R_s is the meltwater outflow from snowpack calculated taking into account the maximum liquid water-retention capacity; V is the snowpack compression rate.

Water and heat transfer in a soil during the processes of soil freezing, thawing and infiltration of water are described by the following equations:

$$\frac{\partial W}{\partial t} = \frac{\partial}{\partial z}\left(D \frac{\partial \theta}{\partial z} + D_I \frac{\partial I}{\partial z} - K \right) \tag{4}$$

$$c_T \frac{\partial T}{\partial t} - \rho_w LH \frac{\partial W}{\partial t} = \frac{\partial}{\partial z}\left(\lambda \frac{\partial T}{\partial z} \right) + \rho_w c_w \left(D \frac{\partial \theta}{\partial z} + D_I \frac{\partial I}{\partial z} - K \right) \frac{\partial T}{\partial z} \tag{5}$$

where W, θ and I are the total water content, liquid water content, and ice content of soil, respectively; $K = K(\theta, I)$ is the hydraulic conductivity of soil; T is the temperature of soil; $\lambda = \lambda(\theta, I)$ is the thermal conductivity; D and D_I are the diffusivities under the constant values of I and θ, respectively; $c_T = c_T(\theta, I)$ is the heat capacity of soil; LH is the latent heat of ice fusion.

The hydraulic parameters of Equations (4) - (5) for a frozen soil are calculated from the relationships (Gelfan, 2010) derived from van Genuchten's (1980) formulae for an unfrozen soil.

Cumulative detention, DET_Σ, of meltwater by surface depressions is calculated by the formula assuming exponential distribution of the storage capacity:

$$DET_\Sigma = DET_0 \left[1 - \exp\left(-\frac{R_\Sigma}{DET_0} \right) \right] \tag{6}$$

where DET_0 is the mean value of the free storage capacity before the beginning of melt; R_Σ is the cumulative snowmelt outflow from snowpack.

The rate of evaporation, E, from an unfrozen, snow-free soil is calculated as:

$$E = K_E \, d_a \, S_1 \tag{7}$$

where S_1 is the relative saturation of the upper soil layer; d_a is the air humidity deficit; K_E is an empirical coefficient.

Runoff excess over the rectangular reaches is calculated taking into account the variability of snow water equivalent before spring melt and saturated hydraulic conductivity of soil. The same scheme was used and described in detail by Kuchment and Gelfan (2002) for simulating sub-grid variability within the finite-elements.

To simulate overland flow over the Yasenok Creek catchment, its area was schematized as a series of 18 rectangular reaches located along the main channel. Overland flow along each of the schematized reaches was described by the length-integrated kinematic wave equation written as:

$$L \frac{dh}{dt} = RL - q_l \tag{8}$$

$$h = \frac{m}{m+1} \left(\frac{q_l n_l}{i_l^{0.5}} \right)^{\frac{1}{m}} \tag{9}$$

where h is the average flow depth; L is the length of the reach; R is the rate of water inflow per unit length of the reach; q_l is the lateral overland inflow rate per unit length of the channel; i_l is the slope of the overland flow; n_l is the Manning's roughness coefficient for slope; m is equal to 5/3.

Equations (8) and (9) were used instead of the quasi two-dimensional description of the overland flow used previously Gelfan (2010) in order to make simulations more computationally fast. Overland flow is the main mechanism of water inflow to the Yasenok Creek; subsurface contribution is negligible, so it is not considered in the model. To simulate channel flow, the one-dimensional kinematic wave equation is applied.

The procedure used for the assessment of the soil parameters of Equations (4) - (5) was described in (Gelfan, 2006) and illustrated, partially, by the measurements in the Nizhnedevitskaya WBS; only the essence of the parameterization procedure utilized in that paper is shown below.

Parameters of the van Genuchten's formulae for the hydraulic soil properties, as well as of the formulae for the thermal conductivity and the heat capacity of soil were calculated from their dependences on the measurable soil characteristics (bulk density, porosity, field capacity, and wilting point). Saturated hydraulic conductivity K_s and the coefficient K_E (Eq. 7) were adjusted through calibration against the measured soil moisture profiles over 5 warm seasons, as well as measurements of soil evaporation. In addition, the coefficient K_E was refined with the use of the evaporation measurements for the same seasons. The parameters of the snow model (1) - (3) were adjusted through calibration against the available snow measurements at the NWBS for 5 cold seasons. To test an ability of the model (4) - (5) to reproduce the hydrothermal regime of a frozen soil during the melt season, the measurements of the infiltration-excess overland flow, which were carried out at bounded rectangular 100 m^2 plots representing sections of the watershed slope, were used. Runoff excess simulated for four spring melt periods was compared satisfactorily with the observations. In this study, snow and soil parameters were taken the same as found in Gelfan (2006). The remaining 3 parameters (DET_0, n_l, and the Manning's roughness coefficient for channel, n_r) were adjusted through calibration against observed discharge in the Yasenok Creek for the period 1970-1974. In Figure 5.3, the simulated hydrographs of snowmelt floods are compared with those observed. Figure 5.3 shows that the model better reproduced large floods than the small ones; however, generally the obtained results can be interpreted as satisfactory: Nash and Sutcliffe's (1970) efficiency criterion $E_{discharge} = 0.69$. The complete list of the model parameters is presented in Table 5.1.

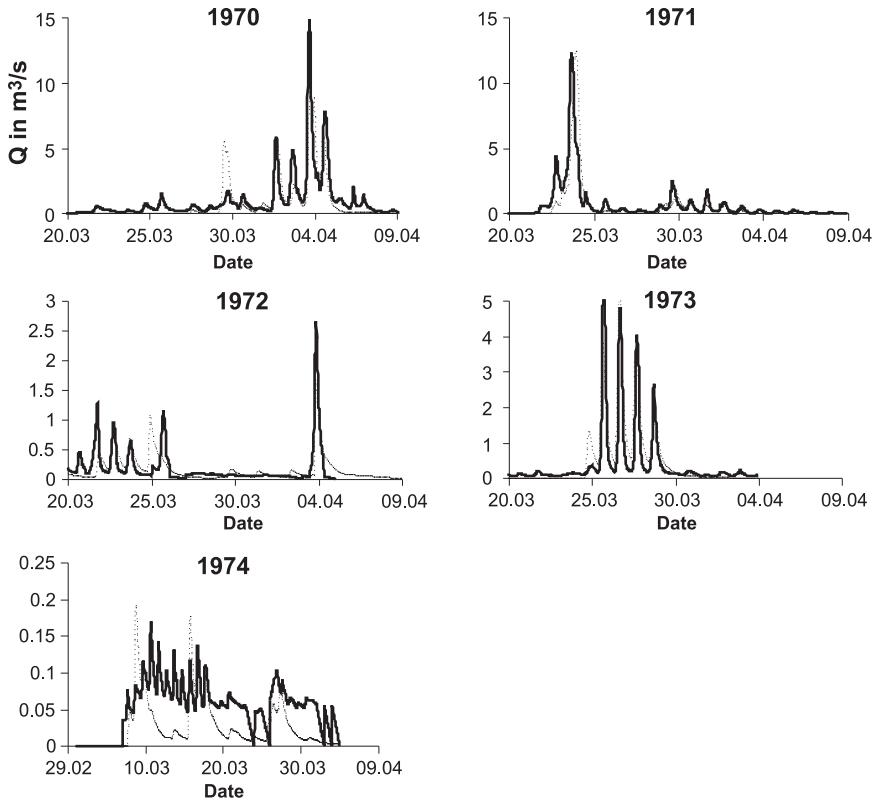

Figure 5.3 *Comparison of observed (bold line) and simulated hydrographs of snowmelt floods in the Yasenok Creek.*

The next step is to transfer the model developed for the proxy-basin (Yasenok Creek) to the study basin (Sosna River) considered as an ungauged basin. The transferring procedure is described below.

Transferring the developed model to the study basin

In order to apply the developed model to the study basin, the latter was schematized as a series of 91 rectangular reaches located along the main channel and along the main tributaries and completely covered the catchment area. Each reach is characterized by the set of the topography parameters for simulation of overland flow by Equations (8) - (9). Hydraulic constants of soil (porosity, density, field capacity, and wilting point) were adopted from the catalog (Department of Hydrometeorological Service for the Central-Chernozem Regions, 1975) containing data of measurements at the agrometeorological stations located in the study basin.

Table 5.1 *Parameters of the model of runoff generation in the Yasenok Creek basin.*

Physical meaning	Numerical value	
Hydraulic and thermal parameters of soil		
	Type of soil	
	Podzol	Chernozem
Volumetric porosity	0.510	0.490
Bulk density, kg m^{-3}	1260	1100
Volumetric field capacity	0.289	0.310
Volumetric wilting point	0.126	0.165
Parameters of the formulae of van Genuchten $\alpha, cm^{-1}/n$	0.088/1.219	0.063/1.136
Specific heat capacity of ground matrix, J kg^{-1} $°C^{-1}$	Depends on soil temperature and moisture content (Gelfan, 2006)	
Thermal conductivity, J m^{-1} s^{-1} $°C^{-1}$	Depends on soil temperature and moisture content (Gelfan, 2006)	
Saturated hydraulic conductivity, m/s	0.3×10^{-5}	1.6×10^{-5}
Snow parameters		
Density of fresh fallen snow, kg m^{-3}	Depends on air temperature (Pomeroy, Hedstrem, 1998)	
Coefficient of snow evaporation rate, m hPa^{-1} s^{-1}	2.9×10^{-8}	
Coefficient of melt rate, m^4 $°C^{-1}$ kg^{-1} s^{-1}	1.8×10^{-10}	
Soil evaporation and water detention parameters		
Coefficient of soil evaporation rate formula, m hPa^{-1}	4.4×10^{-8}	
Mean value of the free storage capacity, m	0.008	
Roughness coefficients		
Manning's coefficient of roughness for the river channels, s $m^{-1/3}$	0.04	
Manning's coefficient of roughness for the slope surface, s $m^{-1/3}$	0.15	

Parameters of van Genuchten's formulae were calculated from these soil constants as before. The evaporation coefficient K_E , as well as Manning's coefficients of roughness were assigned the same as obtained for the proxy-basin. The other 4 parameters listed in Table 5.1 (the saturated hydraulic conductivity, K_s, two snow parameters, namely the coefficients of melt, β and snow evaporation, K_E^*, and the mean value of the free storage capacity, DET_0) were assumed to be refined in comparison with their values obtained for the proxy-basin.

The procedure of the parameter refinement was designed as if no streamflow data measurements are available in the Sosna River basin. The data sets used for the refinement were obtained from the following sources: the hydrometeorological archive of the World Data Centre in Obninsk, Russia (http://www.meteo.ru/data_b/); the published materials of the field experiments of SHI in the 1960s-1970s (Vershinina *et al*., 1985); and catalogue (Morduhy-Boltovsky and Zubchenko, 1971). The archive, materials, and catalogue summarize a vast amount of information on the Don River basin (where both the Yasenok and Sosna basins are located), its physiographic peculiarities and hydrological behavior, regionalized values of the hydrological characteristics, etc. The data used included: (1) maximum SWE and maximum soil freezing depth measured at four meteorological stations before the beginning of the melt seasons for 25 years (1952-1976); (2) snow and soil freezing depths measured once per 10 days at the Livny meteorological station for 17 years (1965-1981); and (3) regionalized value of the long-term mean of snowmelt runoff obtained by interpolation from the large-scale runoff maps presented in Morduhy-Boltovsky and Zubchenko (1971).

Initially, the snow model (Equations (1) - (3)) was calibrated against the maximum SWE and snow depth data. Then the model of heat and moisture transfer (Equations (4) - (5)) was calibrated against the freezing depth data; the calibrated snow model was utilized to assign the upper boundary conditions for Equations (4) - (5). In both cases, daily meteorological data (air temperature and humidity, precipitation) measured at 4 meteorological stations located within the study area were used for 30 years (1952-1981) as the inputs into the models. The manual calibration procedure was used and a search of the optimal parameter values was carried out within the intervals specified *a priori* on the basis of the simulations in the proxy-basin. In addition, to specify the intervals for K_s, the data of the field infiltration experiments (Nazarov, 1970) made in the steppe-forest zone of European Russia were utilized. As a result of the calibration, three aforementioned parameters (K_s, β, and K_E^*) were refined in comparison with ones obtained for the proxy-basin. As an example, Figure 5.4 shows the maximum values of SWE and freezing depth measured at the Livny station versus the corresponding ones calculated under the following values of the refined parameters: K_s (podzol) = 0.8×10^{-5} m s^{-1}; K_s (chernozem) = 2.9×10^{-5} m s^{-1}; $\beta = 0.1 \times 10^{-9}$ m^4 °C^{-1} kg^{-1} s^{-1}; $K_E^* = 4.5 \times 10^{-8}$ m hPa^{-1} s^{-1}. Nash and Sutcliffe's (1970) efficiency of simulations of the maximum SWE and the maximum

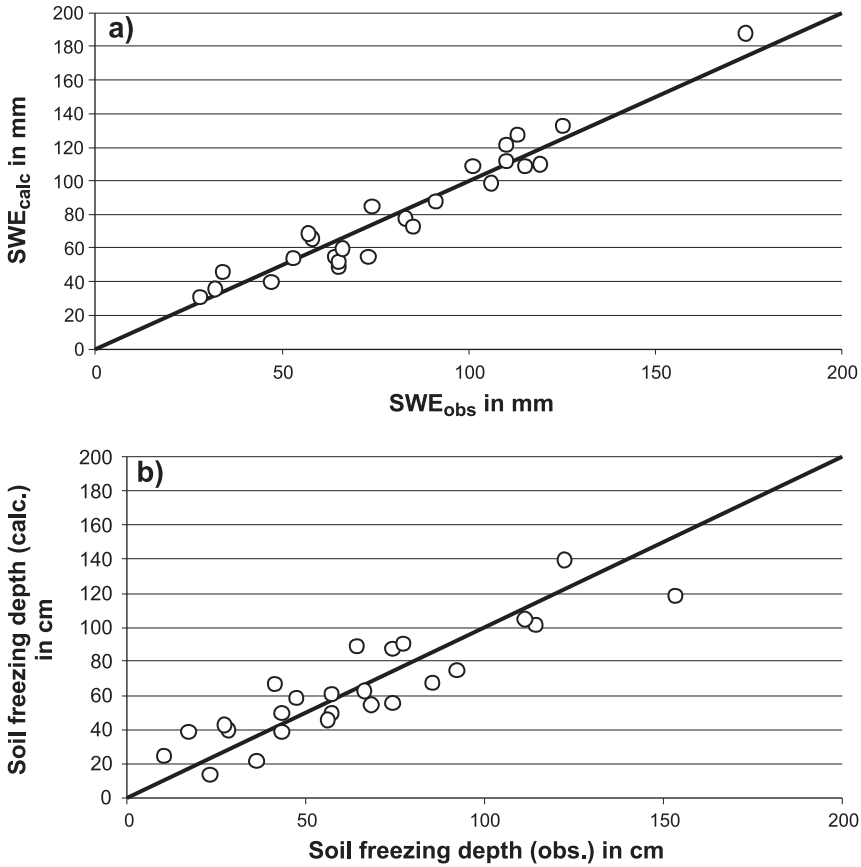

Figure 5.4 *Calculated vs. observed values of maximum SWE* ***(a)*** *and soil freezing depth* ***(b)*** *(Sosna River basin, meteorological station Livny, 1952-1976).*

freezing depth equals $E_{SWE} = 0.92$ and $E_{FD} = 0.80$, respectively. The listed values of the parameters were assumed as the final ones for the Sosna River basin.

Long-term (climatic) mean snowmelt runoff volume averaged over the Don River basin (where the Sosna basin is located) is 75 mm (Morduhy-Boltovsky and Zubchenko, 1971). This information was used for calibration of the parameter DET_0 that is one of two key-parameters controlling runoff losses during a melt period (K_s is the second one). Snowmelt runoff volume for 30 years (1952-1981) was calculated by the model and the value of DET_0 was adjusted under the unchanged, listed above values of other parameters. Mean 30-year snowmelt runoff of 75 mm was calculated under $DET_0 = 0.014$ m.

5.6 STOCHASTIC WEATHER GENERATOR FOR THE SOSNA RIVER BASIN

The weather generator (WG) is a set of stochastic models that use existing weather records to produce long series of synthetic daily weather variables, for which statistical properties are expected to be similar to those of the actual data. The WG used includes stochastic models of daily precipitation, air temperature, and the air humidity deficit. To represent the tendency of wet or dry weather spells to persist, the widely used two-state, first-order Markov chain was applied. Daily precipitation amount was considered as a gamma distributed random variable with different parameters for the cold season and the warm season. For the dry spell, the average air humidity deficit is considered as a lognormal variable; for the wet spell, the air humidity deficit was set equal to zero. In order to simulate the daily air temperature occurrences, the method of fragments (Srikanthan and McMahon, 1985) was applied.

Table 5.2 *Stochastic weather generator parameters estimated by the long-term meteorological observations in the Sosna River basin (standard deviations of the estimations are shown in brackets).*

Model of Daily Precipitation		
Parameter	Period of simulation	
	May-October	November-April
Probability of dry day after dry day	0.70 (0.08)	0.60 (0.08)
Probability of wet day after wet day	0.54 (0.07)	0.75 (0.08)
Mean daily precipitation amount, mm	4.10 (1.08)	2.00 (0.86)
Coefficient of variation of daily precipitation amount	1.31 (0.35)	1.06 (0.25)
Model of daily air temperature		
	November-April	
Mean seasonal temperature, °C	-3.55 (0.28)	
Standard deviation of mean seasonal temperature, °C	1.89 (0.16)	
Model of daily air humidity deficit		
	May-October	
Mean air humidity deficit for the dry spell, mb	7.482 (0.89)	
Standard deviation of mean air humidity deficit, mb	2.31 (0.33)	

Time series of daily precipitation, air temperature, and humidity deficit observed in the Livny meteorological station located at the Sosna catchment for 54 years from 1949 to 2005 (3 years containing long periods of missed data were removed) were utilized for estimating the parameters of the developed stochastic models on mean areal basis. Parameters of the precipitation model were estimated by the methods presented by Katz (1977). Parameters of the air temperature and humidity models are estimated by the method of moments. The complete list of the weather generator parameters is presented in Table 5.2.

The stochastic models were comprehensively tested through their ability to reproduce the main features of meteorological processes at the Sosna River basin. For testing, only those characteristics of the observed and simulated time series which are neither the parameters of the models nor a single-valued function of the parameters were compared. The following characteristics of the observed and simulated time series of precipitation were compared: histograms of wet and dry spell durations, autocorrelation functions of precipitation occurrence and daily precipitation series, variance of precipitation sum for 30 and 365 successive days, and distribution of maximum daily precipitation for 30 and 365 successive days. For the model of air temperature we tested how

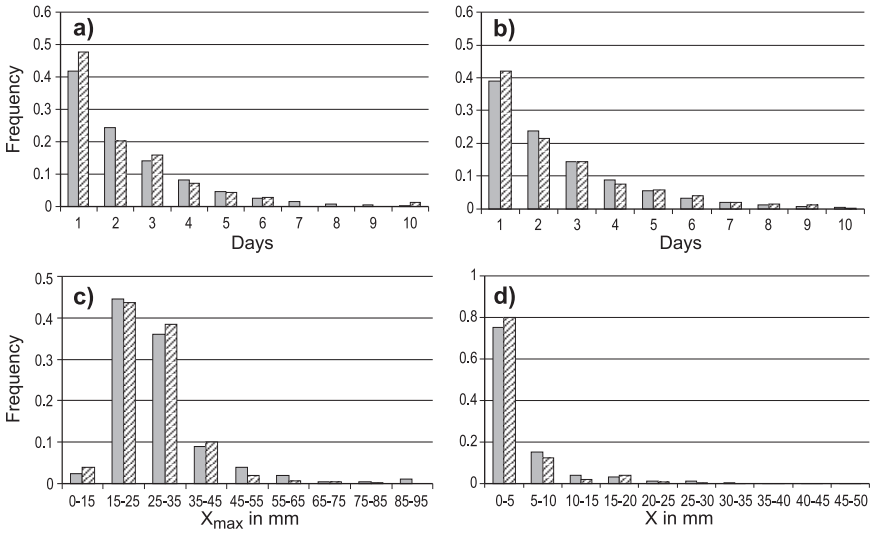

Figure 5.5 *Frequency histograms of the observed (gray columns) and calculated (striped columns) characteristics of precipitation:* ***(a)*** *- duration of a wet-day sequence;* ***(b)*** *- duration of a dry-day sequence;* ***(c)*** *- annual maximum of daily precipitation;* ***(d)*** *- daily precipitation.*

the model reproduces mean value and variance of air temperature for 30 successive days and autocorrelation function of temperature time series. Histograms of mean air humidity deficit for dry spell intervals of different duration were compared for testing the model of air humidity deficit. Some results demonstrating comparison between statistical properties of the observed and simulated precipitation series are shown in Figure 5.5.

5.7 ASSESSING PROBABILITY DISTRIBUTION OF SNOWMELT FLOOD CHARACTERISTICS FOR THE PSEUDO-UNGAUGED BASIN

The dynamic-stochastic model consisting of the runoff generation model and the stochastic weather generator described in sections 5.4, and 5.5, respectively, is applied to the assessment of flood frequency in the pseudo-ungauged Sosna River basin.

Five thousand weather scenarios were Monte Carlo generated (hereafter, the weather scenario is determined as the 1-year, from May 1 to April 30, time series of daily generated meteorological data) (Gelfan, 2010). The weather scenario was used as an input into the hydrological model to simulate a single snowmelt flood hydrograph, i.e. each simulated hydrograph was in accordance with the respective weather scenario. Thus, the series of 5000 hydrographs of snowmelt flood were simulated at first by the model parameterized without using streamflow data measurements. The assessed exceedance probabilities of flood volume and peak discharge were calculated from the series and are shown in Figure 5.6a, b, respectively.

In order to estimate the accuracy of the assessments we need “to remember” the available runoff data in the Sosna River basin which we ignored so far. So, the exceedance probabilities assessed from the artificial hydrograph series are compared in Figure 5.6a, b with the probabilities of the available 61-year series of the observed flood volume (1927-1989) and the 49-year series of the observed peak discharges (1936-1989). Statistical characteristics of the simulated and the observed series are compared in Table 5.3.

Flood volume statistics are satisfactorily reproduced by the dynamic-stochastic model as it follows from Figure 5.6a and Table 5.3 and, importantly, this result was obtained without use of the streamflow data measurements. At the same time, the model overestimates both mean peak discharge and its year-to-year variation.

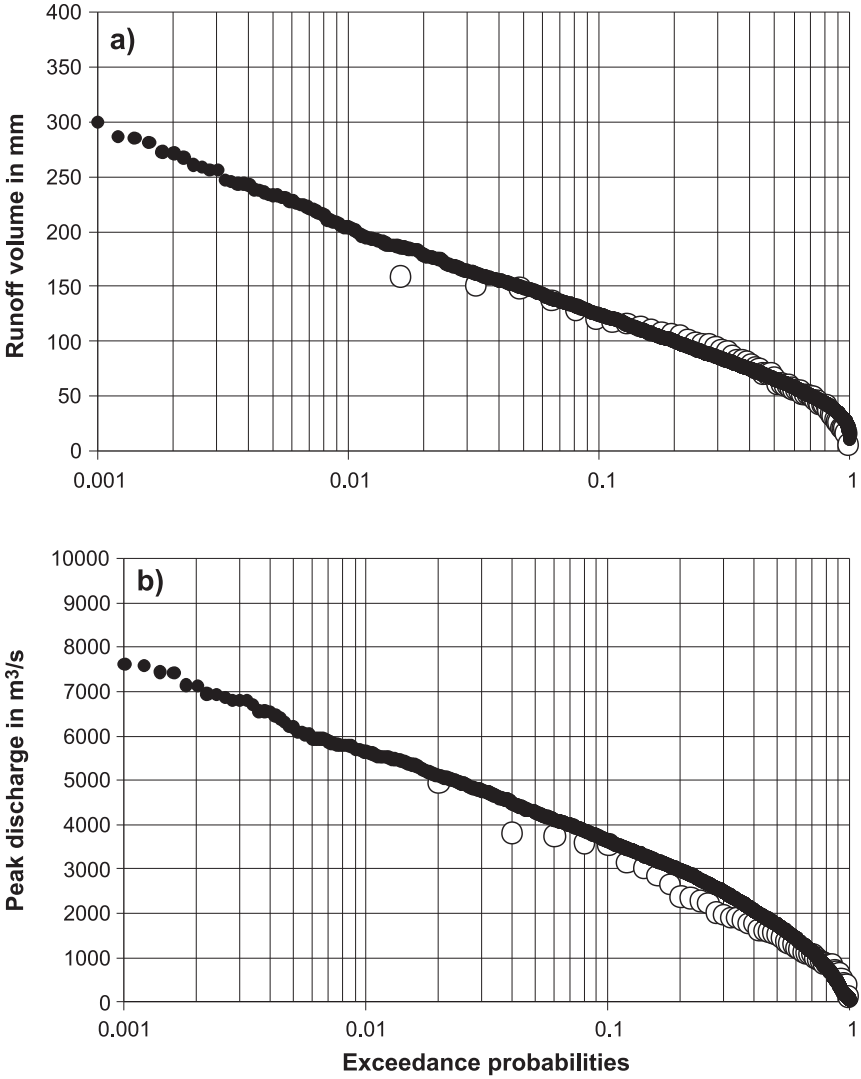

Figure 5.6 *Exceedance probabilities of the observed snowmelt floods (open circles) and ones simulated (solid circles) without use of streamflow data for the model calibration:* ***(a)*** *- flood volume,* ***(b)*** *- flood peak discharge.*

Inaccuracy in reproduction of the flood peak discharge statistics is caused by the errors in the roughness parameters, which were transposed from the proxy-basin as are, without any refinement through the local calibration. Let us assume now that we have a few observed values of annual peak discharge in the study basin and use these data for adjustment of Manning's roughness

Table 5.3 *Statistical characteristics of the measured and calculated flood characteristics of the Sosna River.*

	Mean	Standard Deviation	Coefficient of Variation	Quantiles of Exceedance Probabilities				
				0.001	0.005	0.01	0.05	0.1
Flood Volume, mm								
Observation Data (1927-1989)	72.5	36.4	0.50	-	-	-	149	121
Simulation Data	73.7	38.3	0.52	300	233	204	149	125
Flood Peak Discharge, m^3/s								
Observation Data (1936-1989)	1727	1031	0.60	-	-	-	3795	3570
Simulation Data	1991	1354	0.68	7632	6221	5647	4291	3656

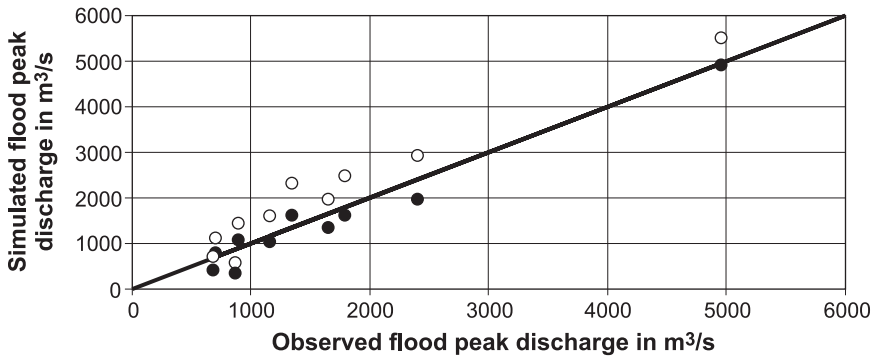

Figure 5.7 *Simulated vs. observed flood peak discharge at the Sosna River basin: open circles – roughness parameters are transferred from the proxy-basin; solid circles – roughness parameters are refined through calibration against 10 observed values of annual peak discharge in the Sosna River basin.*

coefficients for channel and overland flow. The coefficients were adjusted through the kinematic wave model calibration against annual flood peak discharge data for the period of 1965-1974. The adjusted coefficients turned to be equal to 0.17 s $m^{-1/3}$ for overland flow and 0.07 s $m^{-1/3}$ for channel flow.

Figure 5.7 shows flood peak discharge calculated before and after the calibration procedure versus the observed discharges. The refinement of the parameter values in comparison with ones obtained for the proxy-basin has lead to removing positive bias in the peak discharge simulations (Figure 5.7).

Five thousand generated weather scenarios were used once again as the inputs into the model with the refined parameters of roughness. The exceedance probabilities of flood peak discharge assessed from the simulated 5000-year hydrograph series are compared in Figure 5.8 with the corresponding probabilities obtained from 49-year observations.

Comparison of Figure 5.8 with Figure 5.6b suggests that use of even a relatively short series of the hydrograph observations to calibrate the parameters improved the simulation results regarding estimates of both mean peak discharge and its year-to-year variation. Mean flood peak discharge was found to be 1767 m^3s^{-1}, while the coefficient of variation equals 0.64. Comparing these values with those in Table 5.3, the calibration error of the mean value was reduced from 15% to 2% and error of coefficient of variation was reduced from 13% to 6%.

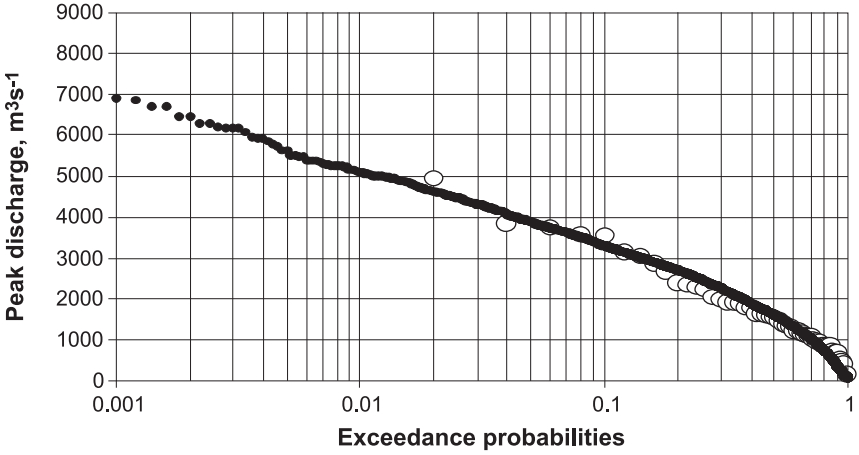

Figure 5.8 *Exceedance probabilities of the observed peak flood discharge (open circles) and the probabilities of the discharge simulated by the calibrated model (solid circles).*

5.8 CONCLUSION

Hydrological models are widely recognized as the main tool for prediction of streamflow time series from meteorological data and are used for a huge range of scientific and engineering applications. Applicability of models is dramatically reduced when the basin in question is ungauged, i.e. there are no past streamflow observations, so the model parameters can not be adjusted through calibration against streamflow data. In this case, as well as in the cases of poorly gauged basins and virtually ungauged ones (when the available observation series are inhomogeneous because of the changes that occurred), data-based models become inapplicable. Kuchment and Gelfan (2009) argued that the physical foundation of the model, particularly, *a priori* information, reflecting accumulated knowledge on runoff generation mechanisms in the basin under consideration, can compensate, to some extent, for the lack of homogeneous streamflow observation data. Kuchment and Gelfan (2009) suggested a methodology of assessing the parameters of the physically based model from both the observations in the hydrologically similar proxy-basin and the observations in the poorly gauged study basin. They then concluded that 3-4 years of streamflow observations in the poorly gauged basin are enough for obtaining stable results of hydrograph simulation by the model used in the study.

The methodological approach developed by Kuchment and Gelfan (2009) was extended here and applied for the classical problem of the engineering design – flood risk assessment in a poorly gauged basin; this is among the most crucial problems of putting the PUB-decade achievements into the practice.

The essence of the approach suggested in this paper is the following. In order to assess extreme snowmelt flood magnitude and frequency in a study basin where streamflow data are assumed to be unavailable, a data-rich small proxy-basin which is hydrologically similar to the study basin is selected. A physically based model of snowmelt flood generation was developed for the proxy-basin and then “transposed” to the study basin. Thereafter, some key parameters of the model were refined by the use of the snow and soil freezing survey data available for the study basin. At last, the deterministic hydrological model was linked to the developed stochastic weather generator and forced by the long series of the artificial meteorological data simulated by this generator. As a result of the applied

dynamic-stochastic approach, multi-year hydrograph series were calculated and the exceedance probability curves for flood volume and peak discharge were constructed for the study basin without using any streamflow data. It was found that flood volume statistics (mean and coefficient of variation) were satisfactory reproduced by the applied approach but the corresponding statistics of flood peak discharge were overestimated. In order to remove the detected bias, we had to adjust flow roughness parameters of the model through its calibration against annual peak discharge values registered for the 10-year period of observations.

After calibration of the model, both the calculated mean value and variance of the annual flood peak discharge turned much closer to the corresponding values obtained from the long-term observations: error of mean value reduced from 15% to 2%, error of coefficient of variation reduced from 13% to 6%. One can consider this approach as a suitable alternative to the traditional engineering methods of flood risk assessment in the ungauged or poorly gauged basins.

5.9 ACKNOWLEDGEMENTS

I am sincerely grateful to Professor John Pomeroy for many helpful discussions on PUB problems and their peculiarities for cold region hydrology, and I thank him for inviting me to present this paper for the PUB monograph. I wish to express my appreciation to my teacher, Professor Lev Kuchment: some ideas of this paper are the continuation of our cooperative works.

6

CHOOSING AND ASSIMILATING FORCING DATA FOR HYDROLOGICAL PREDICTION

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6.1 ABSTRACT

Developing meteorological forcing data for input to hydrological models is an essential first step in modelling and prediction, whether for gauged or ungauged basins. The most common source of forcing data is meteorological stations. There are different constraints on station selection depending on the purpose of the modelling, whether the simulation is for model experimentation and testing, estimating hydrograph changes due to watershed or climate changes, or real-time streamflow forecasting. Considerations in station selection include data quality, timeliness, and spatial representativeness. Real-time forecasting poses particularly stringent requirements of station data timeliness and quality. To use station data as model input, they must be spatially interpolated over the watershed. One useful technique to do this is elevationally detrended kriging, which involves computing relationships of meteorological quantities (specifically precipitation and temperature) with elevation to describe vertical variability, subtracting this from the data to obtain residuals, then applying ordinary kriging to describe horizontal variability. The interpolation produces spatial (i.e., gridded) fields of precipitation and temperature at a daily or smaller time step, which can then be input directly to fully distributed hydrological models, or they can be averaged over the watershed or sub-areas thereof for lumped or semi-distributed models. Other interpolation techniques are usually required for other meteorological variables due to insufficient stations being available or due to the physical characteristics of the quantity not lending themselves to a kriging type of spatial interpolation (e.g. wind). Although preparation of forcing data can require significant database and

software infrastructure, especially for real-time forecasting, any hydrological modelling exercise must begin with good forcing data. In ungauged basins, without streamflow measurements to use as a check on simulation skill, it is especially critical to ensure that model forcings are accurately prepared.

6.2 RÉSUMÉ

La création de données de forçage météorologique comme données d'entrée dans les modèles hydrologiques constitue un premier pas essentiel dans la modélisation et la prévision, que ce soit pour les bassins jaugés ou les bassins non jaugés. Les stations météorologiques constituent la source la plus courante de données de forçage. Il existe différentes contraintes quant au choix de la station suivant le but de la modélisation, selon que la simulation soit faite à des fins d'expérimentation de modèle et d'essais, d'estimation des changements hydrographiques en raison de changements climatiques ou au niveau du bassin ou de prévision des débits en temps réel. Les facteurs à considérer dans le choix d'une station englobent la qualité des données, la rapidité de production des données et la représentativité spatiale. La prévision en temps réel pose des exigences particulièrement rigoureuses en fait de qualité et de rapidité de production des données de la station. Pour que l'on puisse se servir des données de la station en tant que données d'entrée du modèle, celles-ci doivent être interpolées spatialement à l'échelle du bassin hydrographique. Un moyen utile pour y arriver est d'employer la méthode du krigeage avec modèle de tendance, qui suppose le calcul des relations des quantités météorologiques (en particulier les précipitations et la température) avec recours à l'altitude pour décrire la variabilité verticale, en soustrayant ces valeurs des données en vue d'obtenir des données résiduelles, puis en appliquant le krigeage ordinaire pour décrire la variabilité horizontale. L'interpolation produit des champs spatiaux (c. à-d. sur une grille) de précipitations et de température à un intervalle de temps quotidien ou plus petit, qui peuvent ensuite être entrés directement dans les modèles hydrologiques entièrement distribués. Il est également possible d'en établir la moyenne en fonction de l'ensemble du bassin ou de certaines de ses sous-zones pour des modèles localisés ou semi-distribués. D'autres techniques d'interpolation sont habituellement nécessaires pour d'autres variables météorologiques en raison d'un nombre insuffisant de stations disponibles ou du fait des caractéristiques physiques de la quantité qui ne se prêtent pas à une interpolation spatiale par krigeage (p. ex. le vent). Bien que la préparation des données de forçage exige parfois une infrastructure logicielle et des bases de

données considérables, en particulier pour la prévision en temps réel, tout exercice de modélisation hydrologique doit commencer par de bonnes données de forçage. Dans les bassins non jaugés, sans mesures de débit à utiliser pour la vérification des compétences liées à la simulation, il est particulièrement essentiel de veiller à ce que les forçages de modèle soient préparés avec exactitude.

6.3 INTRODUCTION

An initial step of fundamental importance in hydrological prediction is developing the meteorological forcing data to be used as model input. Even if the stream to be modelled and predicted is ungauged, forcing data must still be used to define the system inputs. Without good inputs, either due to the lack of sufficient meteorological stations or due to poor processing and utilization of the station data available, one cannot expect to achieve accurate predictions. Good estimates of inputs, therefore, are essential to the success and usefulness of any system simulation exercise.

In most hydrological modelling applications, forcing data are taken from measurements at meteorological stations. While there are some examples of the use of forcings from radar, remote sensing, or atmospheric modelling (e.g., Mahfouf *et al*., 2007; Pietroniro *et al*., 2007), these are not yet common and, in some regions of high spatial variability (e.g., mountainous areas), not yet feasible. Issues relating to the use of station data in hydrological modelling, then, are of central importance. These issues include data quality, timeliness, spatial representativeness, and spatial interpolation.

These issues often do not receive thorough attention in hydrological model documentation and user manuals, giving the hydrologist rather incomplete immediately available guidance. Data quality, timeliness, and spatial representativeness are generally not addressed explicitly, presumably assuming that the hydrologist has already done a screening of stations based on these considerations and knows how to do so. Regarding spatial interpolation, sometimes models provide built-in methods for interpolating / extrapolating / averaging station data to model spatial computational units, but these tend to be very simple or based on certain assumptions about the station network that may or may not be valid (e.g., Anderson, 1973; Leavesley *et al*., 1983). For example, some built-in techniques either compute a weighted average or make a one-to-one assignment of stations to the model spatial computational units

and/or require the specification of (time-invariant) elevation lapse rates (for either precipitation or temperature). Such a technique could be appropriate in a given basin, or it may be excessively rigid, incomplete, or oversimplified. Sometimes, models offer little flexibility in how the forcings are to be prepared, requiring the selection of one of the built-in methods rather than allowing the user to prepare forcings in any way desired external to the model in a pre-processing step and then supplying them to the model as input. The latter, of course, would allow the user to tailor the processing of station data into forcings for model spatial computational units, but it does put more burden on the user to have an appropriate technique at hand. In any case, the user should pay very close attention to how the station data are utilized so as to be conscious of how the forcings are prepared rather than uncritically choosing some pre-existing technique offering simply because it is convenient.

This paper presents some thoughts, ideas, considerations, and techniques for using station data in hydrological modelling and prediction. These topics apply equally to gauged and ungauged basins.

6.4 DATA REQUIREMENTS FOR DIFFERENT TYPES OF PREDICTION AND MODELS

Hydrological prediction can have different meanings. Three categories of what might be considered "prediction" would be: (1) Simulating the hydrograph to reproduce it as best as possible (e.g. comparing the accuracies of different models or calibrations thereof); (2) Estimating changes in the hydrograph due to past or anticipated watershed or climate changes; and (3) Real-time streamflow forecasting. All of these applications require forcing data, although there are some differences in the constraints in station usage for each application. Note that while these types of prediction are typically made in gauged basins (allowing model calibration and prediction verification), the same need exists in ungauged basins for high-quality forcings, for without this, neither of the two settings will produce successful results.

There are different types of models that can be applied for these prediction categories. The primary distinction to be made here is between statistical models and continuous process simulation models. Statistical (or empirical) models are often regression-based, such as those commonly used for long-range streamflow volume forecasts (e.g. Garen, 1992), although they could also include, for example, neural network models, where physical

hydrological processes are not explicitly represented in the model structure. Process simulation models, in contrast, operate on a daily or shorter time step and have mathematical representations of a greater or lesser level of detail to represent the major hydrological water storages and fluxes that affect the flow of water into and out of the watershed.

For statistical models, the station data requirements are less stringent than for process simulation models. For the former, station data need only be good indices of the target flow to be predicted; absolute magnitudes of measured quantities do not have to be correct but only need to have a consistent relationship with the target. On the other hand, for process simulation models, the station data have to have accurate measurements in terms of absolute amounts so that the inputs to the watershed (mass and energy) are quantitatively correct. This is a much more demanding requirement than just being a consistent index.

Another difference is that for statistical models, not necessarily all stations must or even should be used. Optimization algorithms are often applied to search for combinations of predictor stations that minimize forecast error. Not all stations are necessarily required to minimize the error. In contrast, all stations, except anomalous ones with unrepresentative microclimate effects (Figure 6.1), would generally be used to define the input (e.g., precipitation, temperature) fields for process simulation models. The example shown in Figure 6.1 illustrates the importance of understanding the spatial variability of precipitation and temperature, determining if the available stations are capable of representing them, and recognizing (and perhaps excluding) stations that are not spatially representative.

An important consideration in streamflow forecasting is the real-time availability of station data. For research-mode studies, such as historical simulation or impact assessment studies, real-time station data availability is not an issue, and any stations with sufficient data can be used. This might also include discontinued stations. For forecasting, however, a more stringent data availability criterion must be applied. It does the forecaster no good to use stations in the model forcing data setup that will not be available when they are needed in forecast mode. For forecasting, then, forcing fields and model calibrations should be based only on those stations that will actually be available and usable in real-time. This places a limitation on the stations that can be selected.

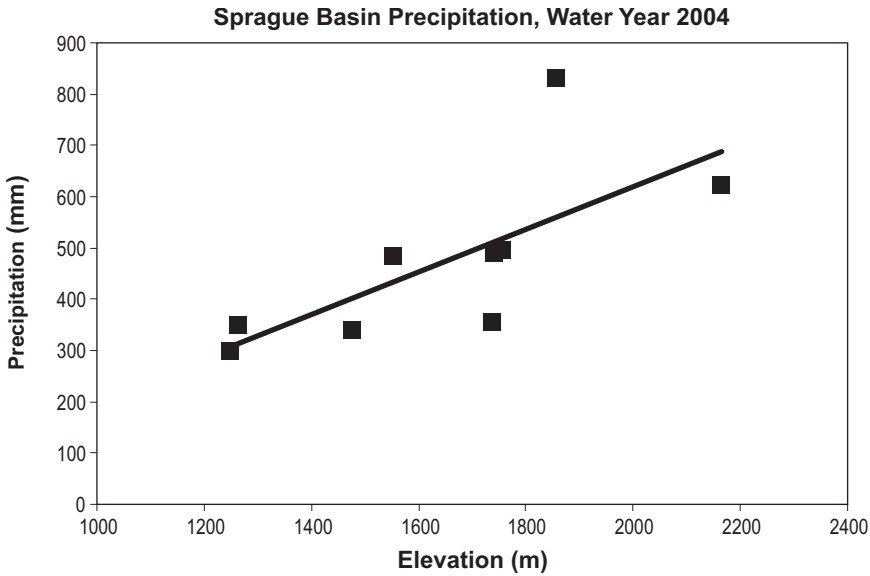

Figure 6.1 *Precipitation-elevation relationship for annual total precipitation in water year 2004 at meteorological stations in the watershed of the Sprague River in southern Oregon, USA. Deciding whether the anomalous station lying far above the regression line should be used for spatial interpolation of precipitation fields requires some investigation regarding the spatial representativeness of this station.*

Data quality and continuity is also important in all applications, although perhaps more critically in real-time forecasting. This issue manifests itself most commonly in missing values. It is troublesome to try to use a station in research simulation studies that has many missing values, as these must either be filled in with estimates, excluded from calculating forcing fields when missing, or the station not used at all. For real-time forecasting, these issues exist as well, but missing value detection and estimation also have to be done in real-time via an automated process for expediency and timeliness.

In fact, automated processing for input data preparation in real-time forecasting is a major requirement. Automated processing includes the following activities that must be done unattended: data retrieval from sources; data quality checks; estimation of missing data (could be optional depending on model setups); pre-processing (such as spatial interpolation); and formatting for model input. Human review of the results of this automated processing is also advisable. The rapid and automated execution of these functions is a non-trivial task requiring much database and software infrastructure.

6.5 SPATIAL INTERPOLATION

The use of station data for hydrological model application leads immediately to a spatial interpolation task of generalizing meteorological station data collected at a point scale to the spatial domain of a watershed. There are many ways to do this, some simple and some complex, and the technique used depends to a large degree on the number of stations available and the characteristics of the quantity being interpolated. Although some simple station weighting and averaging techniques are sometimes offered in hydrological models, more modern and complete techniques are available.

One general spatial interpolation technique that has found widespread usage in hydrology and other fields in recent years is the geostatistical procedure called kriging. Kriging is essentially a station weighting scheme. An estimate of a quantity at a spatial location is a weighted sum of the measurements at stations in its vicinity. The station weights are determined for each spatial location (most commonly grid cells in a geographic information system) in the domain to be interpolated via the kriging algorithm. The weights are a function of distance and the spatial correlation structure of the variable as represented by the semivariogram, which describes how the difference between values of the quantity at two spatial locations increases with distance between the locations (which is equivalent to, but the inverse of, a spatial correlation function, which decreases with distance). The station weights are greater for the nearest stations and smaller for the more distant stations, with the station weights summing to 1.

There are many flavours and variations of kriging, depending on specific characteristics of the data to be interpolated. One of the main issues is whether the data exhibit systematic trends in space related to a geographical characteristic, such as elevation or latitude and longitude. If this is the case, these systematic trends must either be removed from the data before applying the kriging algorithm, or the kriging framework must otherwise be designed to account for this factor affecting the spatial distribution of the quantity. Recent reviews and algorithm comparisons include Goovaerts (2000), Zhang and Srinivasan (2009), Ly *et al*. (2011), Tobin *et al*. (2011), and Feki *et al*. (2012). One such technique, elevationally detrended kriging, as applied to precipitation and temperature data is described below. This technique is highlighted here because it has been shown in the comparison studies to perform well, is conceptually straightforward, and is operationally practicable.

Garen and Marks (2005) selected this technique for use in snowpack simulations after a review of previous literature on kriging techniques.

Elevationally detrended kriging (Garen *et al*., 1994) is appropriate where elevation is the primary deterministic external factor affecting the behaviour of a meteorological variable. This is the case for precipitation, which generally increases with elevation due to orographic processes, and for temperature, which decreases with elevation. Detrended kriging divides the spatial variability of the meteorological quantity into two components: vertical and horizontal. The vertical component is described by a linear regression relationship of the quantity with elevation, which is subtracted from the data. The horizontal component is described by ordinary kriging of these detrended residuals.

The steps in the algorithm are shown in Figure 6.2. In this implementation of detrended kriging, a simplification is made by using a linear semivariogram. Doing so makes the kriging station weights invariant in time because the weights are independent of the slope and intercept of the semivariogram line. (Without this simplification, a separate semivariogram would have to be specified for each time step, greatly increasing the complexity and computational cost of the processing.) With the linear semivariogram, the kriging station weight calculation is made for all grid cells in the domain once at the beginning of the processing. From this point, the algorithm enters a loop for each time step in the time series of data to be interpolated. While a daily time step is common, shorter or longer time steps can also be accommodated in the algorithm. The calculations for each time step consist of: calculating the linear regression elevation relationship; subtracting this from the data to obtain residuals; kriging of the residuals for each grid cell in the domain; computing the deterministic elevational trend at each grid cell; and, adding the deterministic trend to the kriged residual for each grid cell to obtain the final interpolated field.

There are some implicit assumptions in this implementation. One is that the domain to be interpolated has a relatively homogeneous precipitation and temperature regime; for example, there are no strong orographic barriers within the domain that would create very different elevation relationships for different sub-areas. Another assumption is that the station density is sufficient to give a reasonable representation of the essential vertical and horizontal distribution of the precipitation and temperature fields. A final assumption is

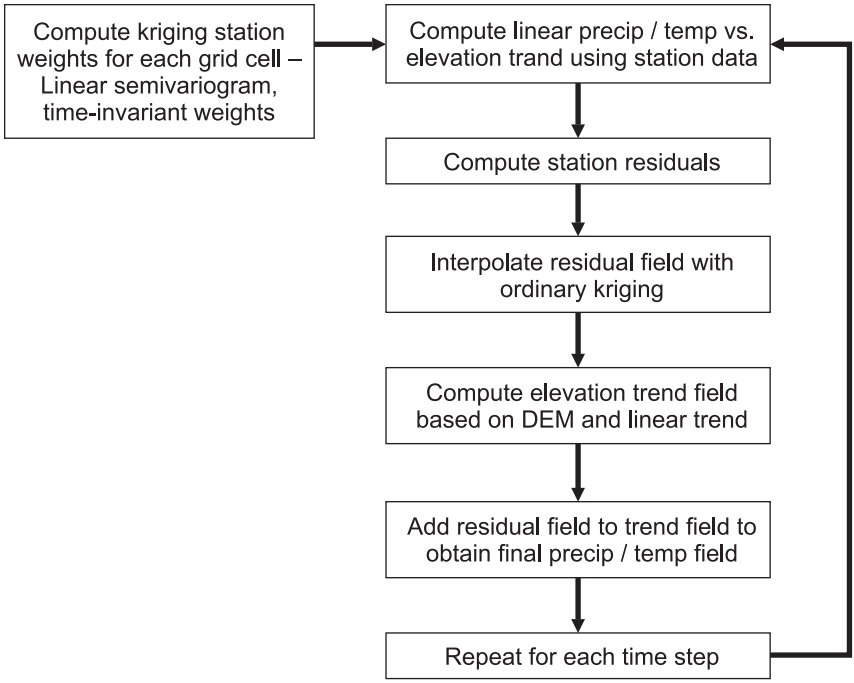

Figure 6.2 *Detrended kriging flowchart (DEM = digital elevation model).*

that the length and width of the spatial domain is moderate enough in size that the spatial correlation structure is reasonably represented by a linear semivariogram. This would imply that the domain to be interpolated should be "mesoscale" in size, perhaps on the order of 100 to 10 000 km^2.

Examples of interpolations of precipitation and temperature are given in Figures 3 and 4. These figures show both the elevation detrending relationship and the final interpolated field. In Figure 6.3, note that the Silver Creek site, lying well above the detrending line, exerts a significant influence on the interpolated precipitation in the northern part of the basin. Its large positive detrending residual causes grid cells in its vicinity also to have a large positive residual due to the kriging spatial interpolation, resulting in these cells also having precipitation above that estimated for their respective elevations by the detrending line. Similarly, the Gerber Reservoir and Quartz Mountain sites lie well below the detrending line, causing the kriging interpolation to calculate negative detrending residuals for grid cells in their vicinity in the southern part of the basin, and leading

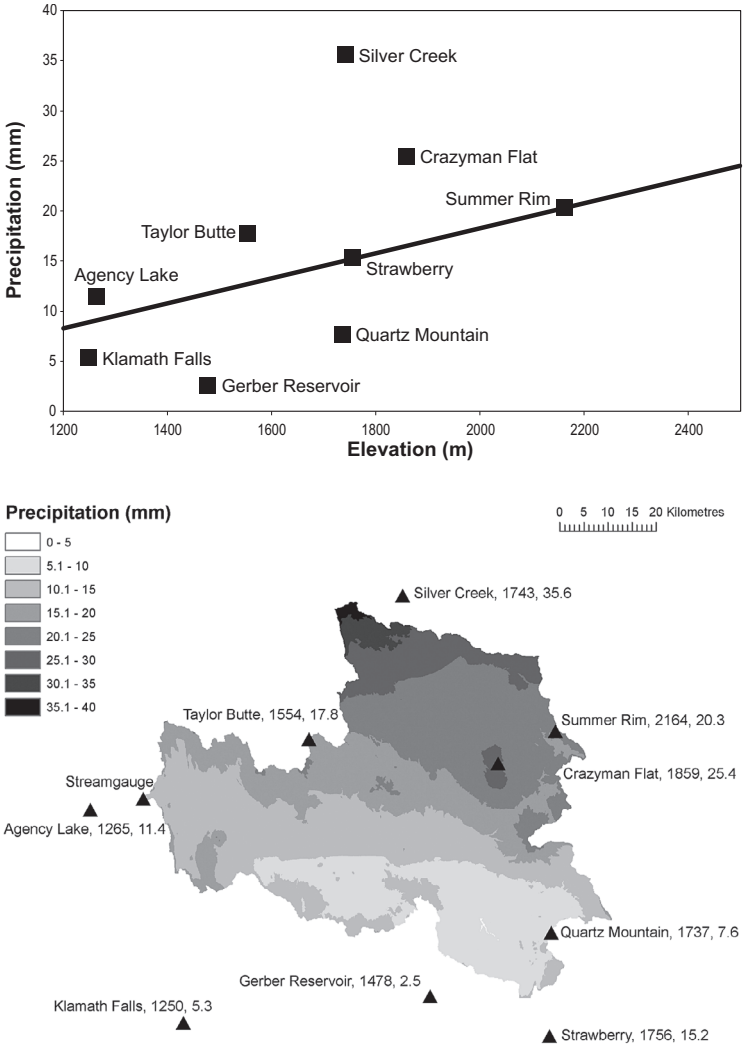

Figure 6.3 *Precipitation-elevation relationship and interpolated daily precipitation spatial field for 1 January 2004, Sprague River basin, southern Oregon, USA. On the map, values after the station names are, respectively, the elevation and the observed precipitation amount.*

to the final precipitation estimates being drier for their respective elevations than estimated by the detrending line. In Figure 6.4, the detrending residuals for temperature are smaller than for precipitation, so the influence of positive or negative residuals are less noticeable, and the final interpolated

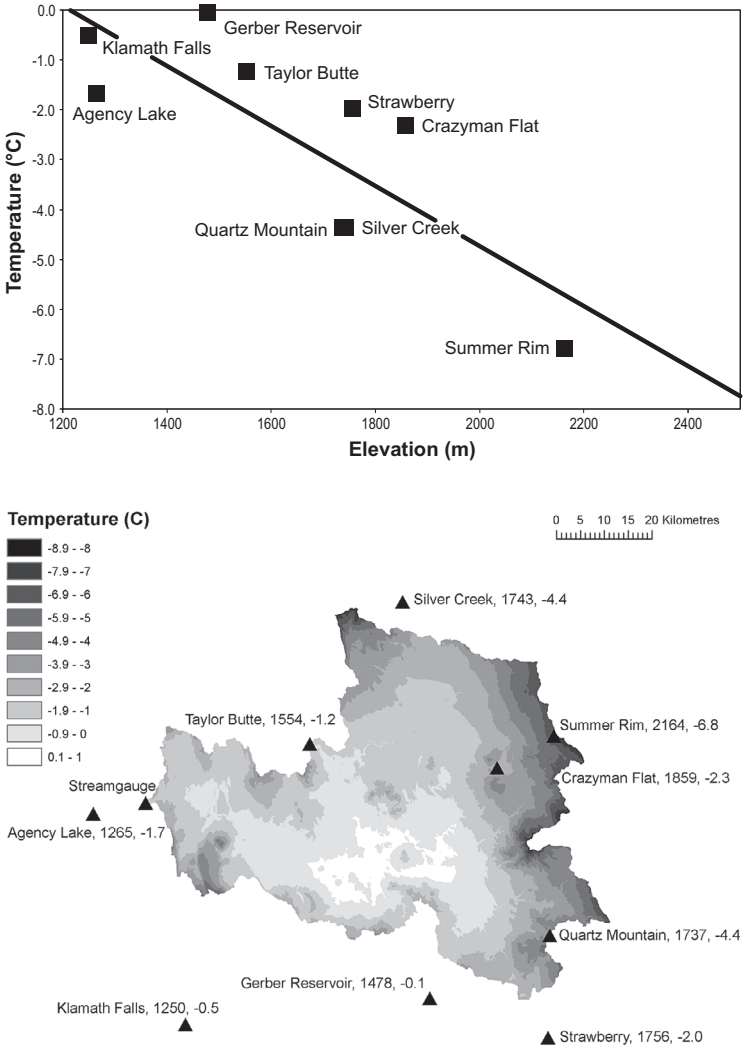

Figure 6.4 *Temperature-elevation relationship and interpolated temperature spatial field for the hours of 12:00-15:00 on 1 January 2004, Sprague River basin, southern Oregon, USA. On the map, values after the station names are, respectively, the elevation and the observed average temperature for the three-hour period.*

temperature follows the elevation field quite closely. Nevertheless, the residuals still have local influence, making the temperature estimates greater or less than the estimates from the detrending line for the respective grid cell elevations.

The results of such interpolations, for each time step (e.g. day) in the historical period to be simulated, can either be used directly as input to a fully distributed hydrological simulation model (requiring grid-based inputs), or the whole watershed or sub-areas thereof can be spatially averaged over the appropriate grid cells and used as input for a spatially lumped or a semi-distributed model. Note that the spatial interpolation process requires the hydrologist to consider carefully the station representativeness and data quality issues mentioned previously to ensure that the interpolation and the resulting model forcings are the best that can be done with the available information.

6.6 CONCLUDING REMARKS

This discussion and these examples illustrate the major considerations in selecting and interpolating data for the preparation of time series of hydrological model forcings. Careful station selection, attention to data quality, and the use of a robust and conceptually solid spatial interpolation technique are all prerequisites for a successful hydrological modelling effort.

As demonstrated, some essential meteorological station data can be spatially interpolated, but it must be remembered that the adequacy of the result is strongly dependent on station density and spatial representativeness. Precipitation and temperature are the easiest to interpolate; other meteorological variables, such as humidity, wind, and solar radiation, do not lend themselves as readily to the detrended kriging method due to sparse station density and other deterministic geographical factors for these quantities, hence other methods must be used if the model requires these additional variables (Garen and Marks, 2005). In any case, the hydrologist must establish that the station network can indeed support the preparation of adequate forcing data; if not, then there is little reason to proceed with a modelling effort, as no system can be simulated well without good estimates of the inputs.

Preparation of model forcings in a manner such as that described here gives the hydrologist confidence in the appropriateness of the system inputs given the station network and the terrain. The hydrologist can then trust the forcings and look to other model components and parameters for refining model skill. Whether in a gauged or ungauged basin, high-quality forcings are essential. Indeed, in an ungauged basin, the forcings may take on even greater importance than in a gauged basin, because there is no opportunity to use streamflow observations as a check on the adequacy of the forcings. In any case, it is evident that preparation of forcings is worth significant care and effort as the first prerequisite for successful hydrological modelling.

7

HOW TO USE NEW INFORMATION TECHNOLOGIES FOR PREDICTION: ENSEMBLE FLOW FORECASTING, VERIFICATION AND POST-PROCESSING

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7.1 ABSTRACT

Hydrological ensemble forecasting is increasingly used in scientific and in operational modes. Generally, a hydrological ensemble of forecasts is created by forcing hydrologic models with meteorological ensemble forecast input or by running multiple hydrological models; however, although the resulting spaghetti plots provide some feeling of future variability, it may be difficult to interpret except for experienced operational forecasters. Verification and post-processing of either archived forecasts or hindcasts can be used to create probabilistic forecasts that represent the predictive uncertainty of future flows and are thus useable by decision makers. Useful techniques are illustrated through a hindcast study of the operational flow forecasting system of the River Rhine. The forecast horizon in combination with basin characteristics such as size and travel time, determine the relative contribution of different sources of uncertainty. Understanding these dominant sources of uncertainty is crucial when using the probabilistic forecast in informing a decision, both in gauged and ungauged basins.

7.2 RÉSUMÉ

Les prévisions hydrologiques d'ensemble sont de plus en plus utilisées dans les modes scientifiques et opérationnels. En général, un système de prévisions

hydrologiques d'ensemble est créé en forçant les modèles hydrologiques à l'aide de données d'entrée de prévisions météorologiques d'ensemble ou en exécutant de multiples modèles hydrologiques. Cependant, même si les schémas spaghetti qui en résultent donnent une idée approximative de la variabilité future, ils peuvent être difficiles à interpréter sauf pour les prévisionnistes opérationnels expérimentés. Il est possible d'avoir recours à la vérification et au post-traitement soit des prévisions archivées, soit des prévisions a posteriori afin de créer des prévisions probabilistes qui représentent l'incertitude prédictive des débits futurs et dont les décideurs peuvent par conséquent s'inspirer. Des techniques utiles sont illustrées au moyen d'une étude de prévision a posteriori du système de prévision opérationnelle des débits du Rhin. L'horizon de prévision, combiné aux caractéristiques du bassin comme la taille et le temps de parcours, déterminent l'apport relatif des différentes sources d'incertitude. La compréhension de ces sources principales d'incertitude est cruciale lorsque la prévision probabiliste sert à éclairer une décision, à la fois dans les bassins jaugés et non jaugés.

7.3 INTRODUCTION

Hydrological forecasts are used to mitigate damage due to flooding, but also provide relevant information for various other purposes, including river navigation, power plant management and water supply management. Unfortunately, forecasts of future water levels or discharges can be quite uncertain and in some cases the cost of taking action in response to a warning in comparison to the loss avoided that the cost of false alarms may be more expensive than when no warning is provided at all (Verkade and Werner, 2011). Not only does the uncertainty inherent in hydrological modelling contribute to uncertainty in the forecast, to a large degree meteorological conditions of the (recent) past, present, and especially future also carry significant uncertainty; however, both hydrological and meteorological models are improving, and increasingly provide forecasts that are acceptably close to observations. Despite this, these forecasts will always have some uncertainty, and the confidence in a prediction should be expressed with a probability. With this information a risk based decision using the probability of the predicted event can be made by a decision maker based on a deterministic forecast, rather than the forecaster making the decision (Weerts *et al*., 2011).

Ensemble forecasting is a technology to assess the variability of predictions in future conditions by sampling of the probabilities of the most relevant sources of uncertainty. A first step is to identify these sources, defining the locations, variables, and more importantly the lead time (i.e. the forecast horizon) of the forecast. Generally, the uncertainty within the model and the present conditions dominate the forecast uncertainty for short lead times, while for longer lead times the future meteorological conditions tend to dominate (Werner *et al*., 2005). The knowledge of the relevant sources of uncertainty and their relative contribution at different lead times will help the forecaster interpret the (probabilistic) information, and thus lead to reducing the forecast decision uncertainty (Nester *et al*., 2012) .

Regarding the larger lead times (medium range forecasts) it has been demonstrated that meteorological ensemble forecast products are very useful inputs for hydrological models (Roulin, 2007). These numerical weather prediction products are globally available and provide fields of precipitation, temperature, and other meteorological variables (Molteni *et al*., 1996; Bartholmes and Todini, 2005).). Such global resolution ensemble numerical weather prediction products should, however, be downscaled according to the size, topography, and model resolution of the forecasting basin (Renner *et al*., 2009). For short lead times, it can be useful to run an ensemble of models resulting from sampling from probability distributions of e.g., parameter distributions of a hydrologic model (Kuczera and Parent, 1998), the observed meteorological inputs (Vrugt *et al*., 2008), or to run different hydrological models (multi-model ensemble) (Georgakakos *et al*., 2004; Velázquez *et al*., 2011), or use additional observations fed into the forecasting chain through a data assimilation procedure (Weerts and El Serafy, 2006; Weerts *et al*., 2010). Combining all these sources of uncertainty into the forecast chain can be computationally demanding, however, and does not necessarily improve forecast accuracy (Velázquez *et al*., 2011).

If an ensemble is expected to be a good representation of the predictive uncertainty (Wilks, 2006; Krzysztofowicz, 2002), then this implies that the ensemble is drawn from the same distribution as the true uncertainties. Having a set of forecasts and observations, these assumptions can be checked and the accuracy of the forecast assessed. Where an archive of operational forecasts is not available, a set of hindcast runs could be considered. Further, the knowledge of specifically the bias in the mean and the variability of past forecasts that is gained can be used to calibrate new

forecasts. This is referred to as post-processing, giving a statistical means to objectively judge forecasts based on previous performance.

Hydrological forecasts for ungauged catchments provide further challenges because the lack of data to calibrate hydrological models and to verify forecasts adds significant uncertainty. Generally, model parameters are taken from similar catchments or these are derived by regression approaches linking catchment properties with model parameters (e.g. Merz and Blöschl, 2004). Thereby, the use of distributed hydrological models seems to outperform simulations with conceptual model approaches for ungauged catchments (Reed *et al*., 2007). While the uncertainty of hydrological models can change with the respective known or unknown properties of a catchment, the uncertainty of meteorological forecasts can be considered rather independent. Ensemble flow forecasts of hydrological models forced with meteorological ensembles can provide essential information on the expected forecast discharge variability even in ungauged basins.

The purpose of this paper is to address three questions:

1. How can the relevant sources of uncertainty of flow forecasts for a given forecast horizon and different basin properties be identified?
2. How can the accuracy and skill of an ensemble prediction be assessed?
3. How can ensemble forecasts using post-processing methods be improved?

The operational flow forecasting system of the River Rhine is used to illustrate how an ensemble prediction system can be set up to generate an archive of forecasts through hindcasting. The Rhine basin is a reasonably well gauged basin and the results of the verification of ensemble flow forecasts comprise many different sub-catchments, with different sizes, hydrological regimes, and rainfall runoff characteristics. Then the potential of the ensemble flow forecasting method for ungauged basins is discussed. In particular, the most important catchment properties are highlighted for the purpose of transferring verification metrics to ungauged basins.

The paper is structured as follows. First the operational forecasting suite of the River Rhine is presented. Then useful statistical forecast verification methods to assess the accuracy of ensemble forecasts are reviewed. Different sources of uncertainty dominate the forecast accuracy, and how forecasts can be improved at various catchment scales using post-processing

methods is demonstrated. Finally, recommendations for improving hydrological forecasts in ungauged basins are provided.

7.4 CASE STUDY: MEDIUM RANGE FLOW FORECASTING AT RIVER RHINE

The River Rhine is the third largest river (1 233 km long, 170 000 km^2) in Europe; in economic terms it is the most important river and waterway in Europe. Data from an operational forecast system that provides short to medium range forecast with a lead time from 2 to 10 days is used as an example in forecasting flood levels, and for low water levels for river navigation, where forecasts are used by ship captains to plan loading and travel routes. Figure 7.1 displays the basin boundaries, the main rivers, and primary forecast locations used for verification and post-processing.

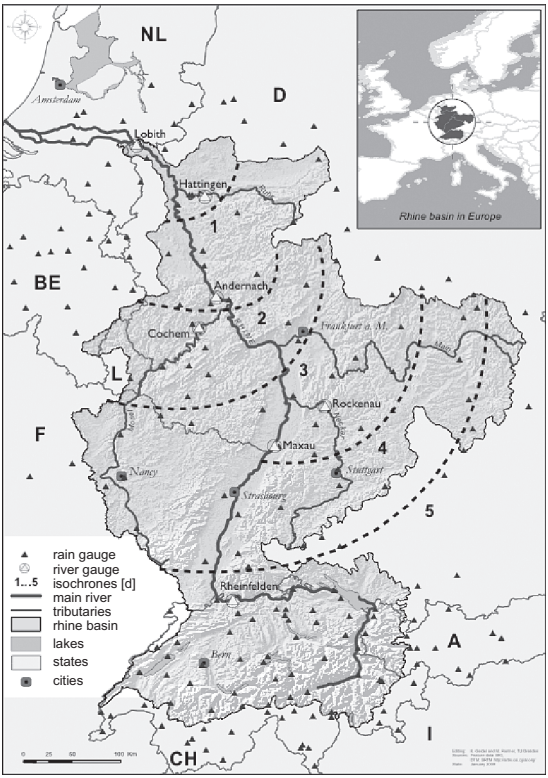

Figure 7.1 *Map of the Rhine River basin and the stations used. Hillshading is used to display the topography. Reprinted from Renner* et al. *(2009) with permission from Elsevier.*

Forecast and model set up

The operational flow forecasting system is embedded in the data management environment Delft-Flood Early Warning System (FEWS), (Werner *et al*., 2013). This system serves to assist the forecasting departments of the Federal Institute of Hydrology (Bundesanstalt für Gewässerkunde - BfG) in Koblenz, Germany as well as the Centre for Water Management of Rijkswaterstaat, The Netherlands. A reduced forecasting scheme is used, consisting of the conceptual hydrological HBV-96 model (Bergström, 1995), which has been set up and calibrated for the 134 sub-basins (Eberle *et al*., 2005). The sub-basins are connected by a simple routing routine. For the purpose of this study, the detailed hydrodynamic routing models used to predict levels are not considered due to computational constraints. Forecast results are primarily evaluated in terms of discharge accuracy.

In historical simulation mode, the model is forced with observed, i.e. spatially interpolated fields of precipitation and temperature (Figure 7.2). In forecast mode, the model is forced with meteorological forecast products. In the case of ensembles, the HBV model is run for each ensemble member, which results in an ensemble flow forecast. The results of such a forecast run can be seen in the spaghetti plot of simulations in Figure 7.2.

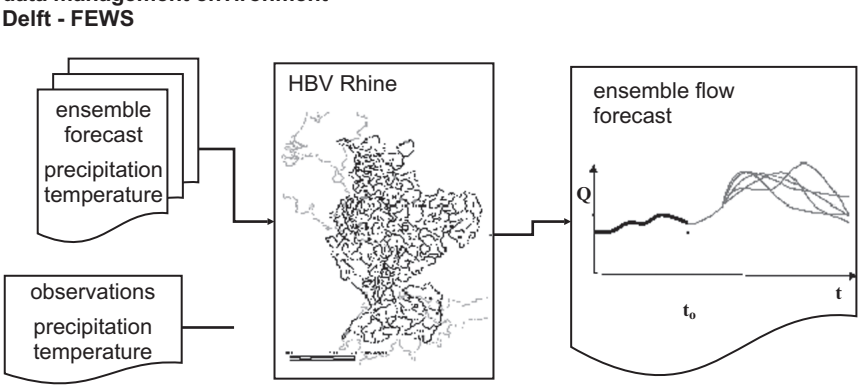

Figure 7.2 *Scheme of producing an ensemble flow forecast based on observed and forecast meteorological input to a hydrological model of the River Rhine. The resulting flow simulation consists of a simulated part using observed meteorological inputs and the ensemble of flow forecasts through running the model for each meteorological forecast input.*

Hindcast set up

Because an archive of ensemble flow forecasts from the operational forecast was not available, a hindcast study was conducted. For this purpose a baseline simulation forcing HBV with observed meteorological inputs was performed. Daily hindcasts, where HBV is forced with meteorological forecasts using the initial conditions of the baseline simulation, were run. The ensemble product of the European Center for Medium Range Forecasts (ECMWF EPS), a global circulation model (GCM) with a resolution of approximately 50 km and 51 ensemble members was used. The hindcast period consisted of more than 1000 daily forecasts over the period June 2004 to October 2007. The system is described in detail in Renner *et al*. (2009) and references therein.

7.5 ENSEMBLE FORECAST VERIFICATION

Forecast verification is concerned with the question of how well do the forecasts agree with observed data? Verification is essential to improve forecasts and provides metrics to compare forecast performance over different locations. The verification methods reviewed here are widely applied in meteorology (Wilks, 2006), and these can be extended to hydrological forecasting. There is, however, some need to adapt these for hydrological predictions. Here verification measures useful to hydrological forecasting are presented, and it is illustrated how ensemble forecasts are transformed to actually compute the selected verification measures.

A scalar accuracy measure

A single ensemble flow forecast including observations over time is shown in Figure 7.3. The forecast is based on a hydrologic simulation with meteorological inputs. The grey bold line depicts the simulation being forced by observed meteorological inputs. After the start of the forecast at time t_0 (vertical dashed line) the model is forced with meteorological ensemble forecasts. Further, knowing the difference of simulation and observation (black dots), the resulting hydrological ensemble forecast (grey thin lines) is corrected using a simple Auto-Regressive (AR) error model, such that the forecast continues the observation. This has shown to improve forecast accuracy at short lead times (Broersen and Weerts, 2005).

Usually the forecast accuracy is estimated at a predefined lead time (vertical dashed line in Figure 7.3) from a set of ensemble forecasts. This disregards any information of the shape of the hydrograph of each ensemble member. A further reduction is done when computing the mean absolute error MAE of a set of n forecasts (y_i) and observations (o_i):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - o_i| \tag{1}$$

Here y_i is a deterministic forecast issued at day i for some lead time. In the case of ensembles, the ensemble mean and sometimes the median is used; however, this deterministic score does not consider the ensemble spread.

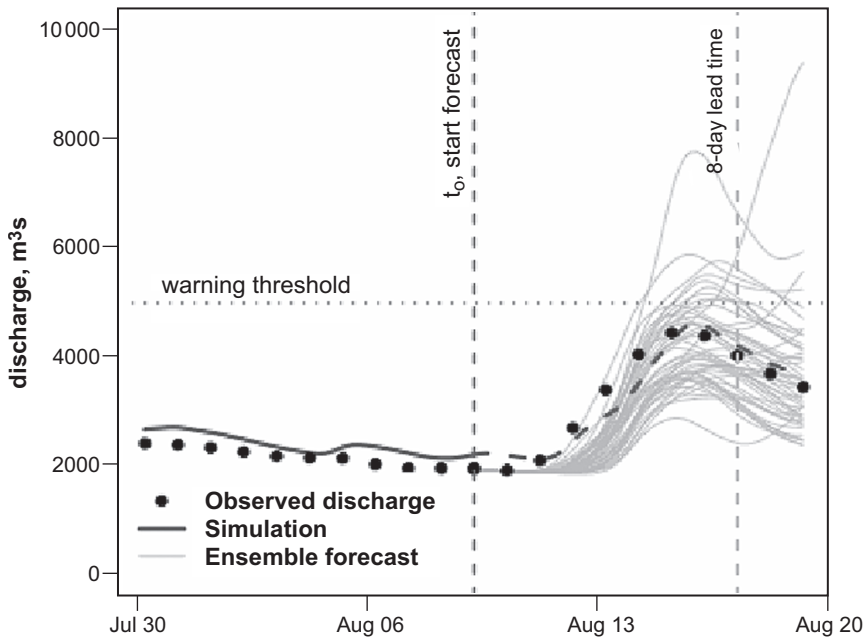

Figure 7.3 *One single ensemble forecast, with observations, simulation, and ensemble forecast simulations. For illustration a warning threshold is shown as horizontal line, and the start of the forecast at time t0 the forecast horizon at a given lead time as vertical dashed line.*

Verification Rank Histogram

For the assessment of the ensemble spread and its reliability, the visual measure of the rank histogram, (a Talagrand Histogram) is useful (Hamill, 2001). It addresses the question, "is the ensemble drawn from the same

distribution as the predictive uncertainty" (Wilks, 2006). The rank histogram is constructed by sorting a single ensemble forecast (such as the one shown in Figure 3) and the respective observation in order of their value. Then the rank of the observation within the ensemble is computed, as shown by the black bar in Figure 7.4a. Repeating this step for a set of forecasts, one can construct a histogram of these ranks, as shown in Figure 7.4b. If the ensemble characterizes the uncertainty well, then all ranks would occur at the same frequency, resulting in a uniform histogram, which is an indication of a reliable ensemble forecast. The example shown in the right panel of Figure 7.4 displays frequent very low and high ranks and thus indicates that the ensemble forecast does not show enough spread, because in the example shown the whole ensemble was either above or below the observation most of the time. An analogue method for probabilistic forecasts is also available, the probability integral transform (PIT) (Casella and Berger, 1990; Gneiting *et al*., 2007), which is interpreted similarly.

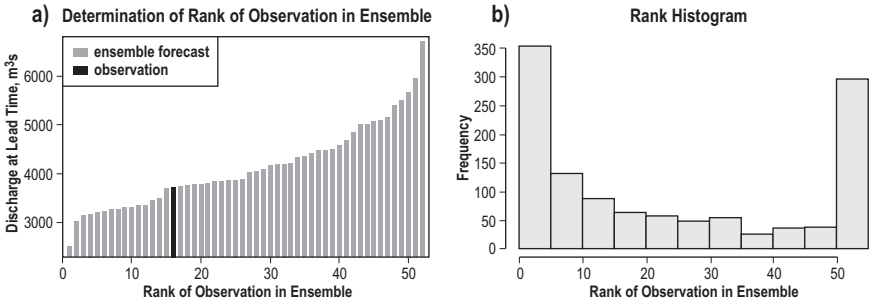

Figure 7.4 *Constructing a rank histogram, in* ***(a)*** *an observation is compared to the ensemble members, and its rank determined,* ***(b)*** *a rank histogram.*

There are many ways to interpret ensemble forecasts and thus many suitable probabilistic verification scores. Common transformations are threshold scores where the exceedance of some predefined threshold is evaluated. Examples are the Brier score (Brier, 1950), the reliability diagram or the Receiver Operating Characteristic; Wilks (2006) provides an overview. Threshold scores are highly relevant for assessing the forecast accuracy at warning thresholds, such as the exceedance of a water level resulting in inundation. Although important in flood warning, the evaluation of such thresholds is statistically problematic, given that the thresholds that are interesting typically represent extreme events, which means the sample size

is generally too small. This could be improved by assessing lower, more frequent thresholds, but the performance at these low thresholds may not be representative of that at the higher thresholds.

7.6 DOMINANT SOURCES OF UNCERTAINTY

It is common sense, that predictions are more uncertain with increasing forecast horizon because as lead time increases future meteorological conditions will increasingly dominate the forecast. In larger river basins, such as the lower Rhine, however, we can assume that most of the water in the river that will pass a downstream forecast point in the coming days has already been observed as precipitation, melted snow, or observed flow. Thus that water is already in the system and therefore, the observed model states and the simulation model are highly relevant for the predictive uncertainty. Through this analysis the simulation uncertainty representing water which is already in the system at the onset of the forecast can be distinguished from the meteorological forecast uncertainty, which reflects all water that will enter the system after the start of the forecast (Werner *et al*., 2005).

The current set up of the forecasting suite allows an estimate of the contribution of both types of uncertainty to the resulting forecast. Comparing a forecast (with error correction) with the observation includes both the uncertainty of the meteorological forcing and of the model, while comparing the forecast (without error correction) with the simulation only includes the meteorological forecast uncertainty. Computing the ratio of both errors:

$$\frac{MAE\ (\text{forecast, simulation})}{MAE\ (\text{forecast, observation})} \tag{2}$$

yields a measure of the relative contribution of the meteorological forecast error on the total error. Here, a value of zero means no contribution and a value of 1 full contribution. This ratio is shown in Figure 7.5 for 10 different river gauging stations on the Rhine and its tributaries ranging from 900 km^2 to 160 000 km^2. Clearly, the relative contribution increases with lead time, but there are distinct differences in the different (tributary) river basins.

The three small basins located in the hilly North of the Rhine basin (forecast points at Altenahr, Grolsheim, and Hattingen) show similar behaviour. After

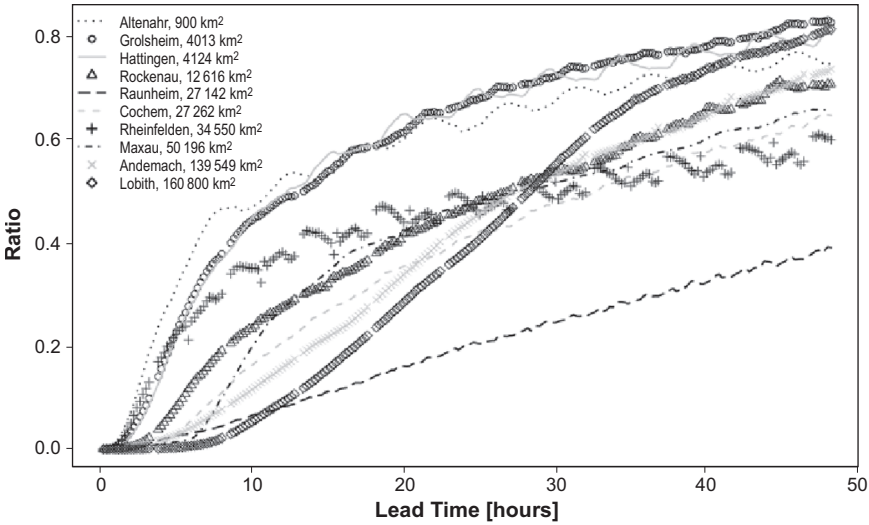

Figure 7.5 *Ratio of MAE (forecast - simulation) over MAE (forecast - observation) against lead time. Here the ensemble forecast mean of ECMWF-EPS forecasts has been used. The points are computed from hourly forecasts issued daily between June 2004 and October 2007.*

a lead time of only two days, the future meteorological conditions already introduce 50% of the total uncertainty and then approach about 80% at 10 days lead time. For larger river basins (> 12 000 km²) the increase is less steep and reaches 50% contribution between 4 to 6 days lead time. There are three remarkable deviations from this expected behaviour, each of which can be attributed to the respective basin characteristics.

The first is the river gauge at Rheinfelden, which is located on the Swiss-German border, at the outlet of the Alpine part of the basin. Here the contribution to the error of the meteorological forecast rises quickly to about 40% percent in two days lead time, but then rises markedly slower to only 60% after ten days. This may be attributed to the quick response of the Aare tributary (about 50% of the total flow at Rheinfelden) and the slow response due to the large lakes upstream, especially Lake Bodensee.

The second interesting station is Lobith at the border between the Netherlands and Germany. There is almost no contribution of meteorological forecast uncertainty up to 2 days lead time. That means for lead times smaller than 2 days there is no reason to use meteorological forecasts as input; however, at higher lead times the contribution increases with a larger slope than at

comparable, but small river stations. This behaviour is eventually caused by the large uncertainty in tributaries close to the river gauge. So, while one part of the water in the system has already been observed, a significant part of the water originating in the meteorological forecast may have entered the system.

The last anomalous station is Raunheim on the Main tributary, where the contribution increases linearly with time. Two reasons for this behaviour are suspected: (a) water level regulation for navigation resulting in controlled streamflow, and (b) inaccurate streamflow measurements due to backwater effects (computed by water levels and a rating curve).

To summarize, the expected behaviour with increasing contribution of meteorological forecast uncertainty to the total prediction uncertainty with lead time was generally observed. Basin characteristics such as basin size and travel time estimates can be used to regionalize the meteorological uncertainty. A simple linear regression model shows that the lead time at which 40% of the error is due to meteorological forecast uncertainty can be predicted by the logarithm of the basin area with an explained variance of $R^2 = 0.7$ ($N = 9$, without the outlier of the Raunheim/Main). This estimate could potentially be improved by using further catchment properties, such as topography or hydro-climatic properties like the runoff ratio. Hence the important information of uncertainty contributions of hydrological model or meteorological forecast uncertainty can also be easily obtained for ungauged basins.

7.7 IMPROVING FORECASTS WITH POST-PROCESSING

A thorough verification study, comparing past forecasts with observations, could reveal certain inaccuracies of the forecasts such as bias or discrepancies in the reliability of the assigned probability. There may be underdispersion (i.e. the ensemble does not display enough spread) or a lack of resolution (i.e. two different forecast probabilities result in indistinguishable outcomes). Post-processing is a means to calibrate forecasts, given previous forecast errors, i.e. the joint probability distribution of forecast and observations $P(y;o)$. The great advantage is that errors and the uncertainties of the entire forecast chain can be corrected, but with the forecast error conditioned on observations. The drawbacks are clear; (i) observations are needed, and (ii) characteristics of $P(y;o)$ are assumed stationary and especially do not change for the upcoming forecast being considered.

Recent research has established some post-processing methods that are able to deal with ensemble forecasts; examples are Ensemble Bayesian Model Averaging (EBMA) (Raftery *et al*., 2005), an extension of the Hydrological Uncertainty Processor framework (Krzysztofowicz, 1999) to ensemble forecasts (Reggiani *et al*., 2009), or the use of quantile regression (Weerts *et al*., 2011).

An application of EBMA in a Rhine case study is shown here. The method has the advantage that it is able to deal with ensembles arising from different models (multi-model ensembles) and ensembles arising from meteorological ensemble products. In multi-model ensembles, each ensemble member represents a unique entity, and can be recognized as such in subsequent ensemble forecasts, while in meteorological ensembles this is not the case and ensemble members cannot be discerned from one forecast to the next. Thereby the EBMA forecast model uses mixture distributions where each ensemble reflects a component (Fraley *et al*., 2010). The parameters of these distributions are estimated from the forecast ensembles and the respective observations.

The setup for the EBMA computation was chosen as follows: data for the verification period January 2007 to October 2007 and subsequently for each lead time, fitted the parameters (mean and standard deviation) of a Gaussian distribution using the expectation maximization algorithm available in the R package "ensembleBMA" (Fraley *et al*., 2010; R Development Core Team, 2012). Initially assigned equal weights were assigned to all ensemble members, where these weights are subsequently trained by evaluating the performance of the different models in a suitably selected training period prior to the start of the forecast. For the case study and at lead times where the meteorological forecast uncertainty is dominant, a training period of 30 days yielded best results.

To demonstrate the value of the post-processing step, Figure 7.6 shows the Rank histogram of the ensemble flow forecasts forced with ECMWF-EPS and the PIT of the calibrated forecasts using EBMA. While the original ensemble flow forecasts are under-dispersed and not reliable (U-shaped histogram), the EBMA flow forecasts show a more uniform distribution, indicating a better representation of the predictive uncertainty. Moreover, this improvement is found at both the small scale (Hattingen, River Ruhr, 4100 km^2) and at the large scale (Lobith, River Rhine, 160 000 km^2).

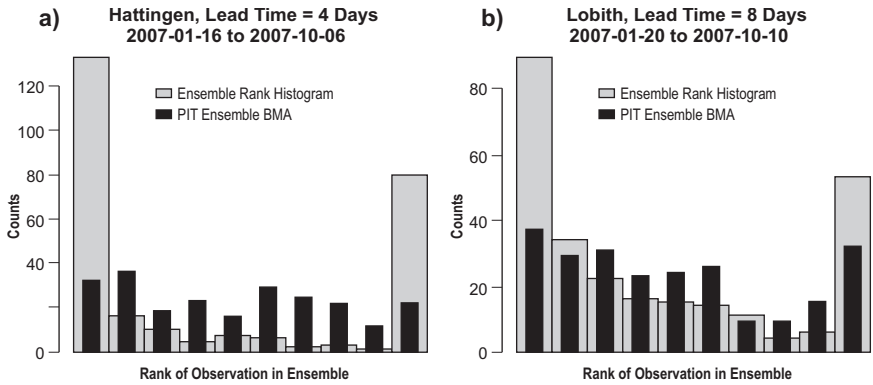

Figure 7.6 *Rank Histogram of ensemble flow forecasts overlaid with the Probability Integral Transform (PIT) for two different river gauges* ***(a)*** *Hattingen at the River Ruhr and* ***(b)*** *Lobith at the River Rhine.*

To summarize, post-processing methods are available and can be employed to improve the uncertainty representation of ensemble forecasts. Post-processing should naturally be applied at the end of the forecast chain to avoid possible non-stationarity due to combining different methods. Also the selection of the training period requires some understanding of the given forecast situation (lead time, travel times of the river, previous processing methods, such as data assimilation, which are likely to change the error characteristics of the forecasts). It does not make sense to use a long training period of more than half a year to improve daily forecasts at the medium range because the systematic bias, e.g. in the model simulation, may change its sign over longer periods. In the case of ungauged basins, geostatistical methods have been suggested to perform local post-processing steps by Kleiber *et al*. (2011) for temperature forecasts. This might also be a prospective method for hydrological forecasts. A successful example for a geostatistical treatment of forecast errors of hydrological forecasts was presented by Roscoe *et al*. (2012). It must be noted, however, that for spatial transfer of postprocessing results to be useful, similar travel time dynamics must be present. So it has been found that transferring EBMA weights to other stations can eventually improve the forecast, but when transferring weights of stations with different temporal dynamics (e.g., Maxau, Upper Rhine with Cochem, River Mosel) this can easily introduce biased outcomes with lower predictive value than the original ensemble forecast.

7.8 CONCLUSIONS AND RECOMMENDATIONS

Ensemble forecasting is a means to reflect the uncertainty of a forecast by running a forecast model for a series of different conditions, such as different inputs, initial conditions, models, or parameters. There are two different sources of uncertainty in flow forecasting; simulation uncertainty arising from modelling the flow of observed water, and; meteorological forecast uncertainty which regards future model inputs. The forecast horizon, and the travel time of a given basin determines the relative effect of these uncertainties on the flow forecast error. This information is crucial when trying to improve flow forecasts. For ungauged basins it is recommended to estimate the relative effect of different sources of uncertainty by basin characteristics such as travel times. The verification of ensemble forecasts is the key to compare and improve forecast accuracy; therefore, an archive of forecasts is needed. Such an archive allows calibration of (probabilistic) forecasts to improve forecast accuracy and reliability based on previous forecast errors. The use of a post-processing method such as EBMA can improve the reliability of flow forecast at the small and large scale.

The results discussed here are based on a case study of the well gauged Rhine basin. The basin includes different hydrological regimes (snow dominated, rainfall dominated, and mixed), and sub-basins of differing catchment sizes. This allows some recommendations for improving forecasts in ungauged basins to be inferred.

In the case where meteorological forecast uncertainty is relevant, for example if travel times are shorter than the forecast horizon, then it is recommended to use meteorological forecast ensembles as input to a hydrological model. In the case of short term forecast the recommendations will depend on the data available. In data-poor regions, it is recommended that the most relevant uncertainties, which are the simulations and their input data, be sampled. The uncertainty in simulation may be reflected by so-called hydrological multi-model ensembles (Georgakakos *et al*., 2004; Velázquez *et al*., 2011). Also sampling of the input uncertainty is important (Vrugt *et al*., 2008). For ungauged basins the uncertainty arising from transferring model parameters should also be sampled (McIntyre *et al*., 2005); however, the uncertainties should ideally be constrained by additional data sources. For example model states can be updated by using

other data (e.g. remote sensed soil moisture (Komma *et al*., 2008)). If some data are available, e.g. flow observations along the river stream or similar catchments in the neighborhood of the respective forecast location, then other possibilities arise, such as the regionalization of forecast accuracy or of post-processing parameters through geostatistical interpolation methods (Kleiber *et al*., 2011; Roscoe *et al*., 2012).

Where there are data available, the forecasts can be improved by error correction methods using observations at the forecast location. These methods can be statistical, such as the post-processing methods shown in this article, or they may include some physical basis where model states are updated through data assimilation methods (Weerts and El Serafy, 2006; Vrugt and Robinson, 2007). With the advances in hydrological modelling, meteorological forecasting, and earth observations, it is possible to provide hydrological forecasts anywhere in the world (Fortin, 2011). It is important to emphasize that such forecasts are inherently uncertain and without reliable observations it is impossible to verify and calibrate forecasts, which is essential when using these to provide guidance to decision makers.

7.9 ACKNOWLEDGMENTS

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8

PREDICTION IN UNGAUGED BASINS – THE CHALLENGE OF CATCHMENT NON-STATIONARITY

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8.1 ABSTRACT

Prediction of the effects of changing land use and land management practices (i.e. catchment non-stationarity) for ungauged catchments is an issue of considerable practical importance for catchment planning and management. While improved understanding of model strengths and limitations has led in recent years to major progress in the regionalization of continuous simulation rainfall-runoff models under the assumption of catchment stationarity, the issues of non-stationarity raise difficult methodological challenges. In this paper we report on a) the development and application of detailed physics-based models, with and without local data, to represent field scale effects of land management practices in the UK uplands, b) the use of simpler meta-models to upscale the results to catchment scale, c) the use of regionalized indices of catchment response to constrain conceptual model parameterizations for ungauged application, and d) the mapping of land management effects on soil structure and runoff processes to extend the use of regionalized indices to address impacts of land management practice. Finally we point to future developments in which various data sources can be combined to address these issues.

8.2 RÉSUMÉ

La prédiction des effets des pratiques changeantes d'utilisation et de gestion des terres (c.-à-d. la non-stationnarité du bassin) pour les bassins non jaugés

constitue un enjeu d'une importance pratique considérable pour la planification et la gestion du bassin. Même si une meilleure compréhension des forces et des limitations des modèles au cours des dernières années a donné lieu à des progrès majeurs entourant la régionalisation des modèles de simulation continue du ruissellement pluvial, en posant comme hypothèse la stationnarité du bassin, les problèmes de non-stationnarité constituent des défis méthodologiques de taille. Dans la présente communication, nous abordons a) la création et l'application de modèles détaillés à base physique, avec et sans données locales, pour représenter les effets pleine échelle des pratiques de gestion des terres dans les hautes-terres du Royaume-Uni, b) l'utilisation de méta-modèles plus simples pour extrapoler les résultats à l'échelle du bassin, c) le recours à des indices régionalisés de réponse du bassin pour limiter les paramétrisations de modèle conceptuel pour toute application liée à un bassin non jaugé et d) le mappage des effets de la gestion des terres sur la structure des sols et sur les processus de ruissellement afin d'étendre l'utilisation des indices régionalisés pour tenir compte des impacts des pratiques de gestion des terres. Enfin, nous traitons des développements futurs suivant lesquels diverses sources de données peuvent être combinées en vue de s'attaquer à ces problèmes.

8.3 INTRODUCTION

The ability to predict the hydrological response of ungauged basins remains a critical test of the state of hydrological science. In recent years, with improved understanding of the strengths and weaknesses of different model types, and the increased computer power to explore in depth issues of model performance and parameter identifiability, hydrological modelling has been developing from an art, based on user expertise and experience, into a science, in which more formal and objective analysis of model performance is possible. As a consequence, important progress has been made in prediction of the response of ungauged basins. Whereas, in the 1970s, estimation of flows for ungauged basins was limited to simple event-based rainfall-runoff methods and flow statistics regressed on catchment characteristics, continuous simulation modelling of the precipitation-runoff response of ungauged catchments is now a practical tool for use in many hydrological environments. The representation of catchment change for ungauged basins remains a difficult challenge, however, and one which requires careful reflection on, and critical analysis of, the roles of different types of hydrological models.

In this chapter, we first briefly review rainfall-runoff model types and report on recent progress on the regionalization of hydrological rainfall-runoff models for catchments under the assumption of unchanging catchment properties (catchment stationarity). We then discuss the modelling of the effects of catchment change, reporting results of a major UK study to address the impacts of changing rural land use and land management. We consider the potential of physically based models (with and without detailed supporting data), the use of simpler 'meta-models' to represent detailed model performance at catchment-scale, and the use of conceptual models conditioned on regionalized indices.

8.4 RAINFALL-RUNOFF MODEL TYPES AND MODEL REGIONALIZATION

It is helpful to set the context for understanding the modelling challenges of prediction in ungauged basins to introduce briefly a classification of hydrological model types and their historical development, after Wheater *et al*. (1993). We focus on dynamic models of the relationship between precipitation and runoff. More detailed background can be found in Wheater (2002), Wagener *et al*. (2004), and Beven (2011).

Metric models

One of the simplest and most widely used rainfall-runoff models is the unit hydrograph, which can be seen as a precursor to more powerful methods of time series analysis (see, for example, Young (2005)). First developed in the 1930s to represent stream response to individual storm events, the model consists of a loss function and a linear transfer function. The simplicity of the method provides a powerful tool for data analysis. Once a set of assumptions has been adopted (separating the streamflow hydrograph into fast and slow components and allocating rainfall losses), rainfall and streamflow data can be readily analyzed, and a unique 'unit hydrograph' determined. This is an example of a class of models known as 'metric' or 'black box', in which the model functional form is derived primarily from input-output observations (Wheater *et al*., 1993).

This analytical capability has been widely used for regional analysis of catchment response. An example is the 1975 UK Flood Studies Report (FSR) (Natural Environment Research Council (NERC), 1975). Rainfall loss and transfer functions were derived from 138 UK catchments, and

subsequently, regression relationships were defined between the parameters of the loss and routing models and storm and catchment characteristics, providing a method for flood estimation on ungauged catchments.

In principle, metric models are limited to the range of observed data; effects such as catchment change cannot be directly represented (Wheater *et al*., 1993). In practice, the analytical power of the method has enabled some gross effects of change to be quantified. For example, the extent of urban development was found to be an important explanatory variable for determining both rainfall losses and the unit hydrograph, and this provided the basis of a design method to predict potential impacts of urbanization within the observed range in the UK (NERC, 1975).

The unit hydrograph therefore provides a practical tool for prediction of response to storm events on ungauged basins. While its strength is its simplicity, this is also its weakness. The focus on individual events for flood estimation has important limitations. One example is in application to groundwater-dominated catchments, where seasonally varying groundwater discharge is often the dominant streamflow contribution (see e.g. Wheater *et al*., 2007). More generally there is a problem of representing the effects of antecedent conditions due to snow accumulation, surface water storage or sub-surface storage on runoff generation, particularly where, as in the case of climate change, these can be expected to change. Hence there has been a need to develop more powerful methods for prediction in ungauged basins, which can incorporate the full range of hydrological processes, and provide a capability for continuous simulation.

Conceptual models

By the 1960s, available computing power was sufficient to support the first integrated representation of catchment hydrological processes in models which could generate continuous flow sequences from inputs of precipitation and potential evaporation. These 'conceptual' models represent component processes using simplified relationships between storages, defined by parameters with no direct, physically measurable identity. The best known early example is the Stanford Watershed Model (Crawford and Linsley, 1966), currently available as the USEPA-supported HSPF model. This requires some 16-24 parameters to be specified to define the model inter-relationships. Hence, for application to a particular catchment, calibration is required, i.e. fitting to observed input-output data to obtain an appropriate set of parameter

values. In the 1960s this was done manually and subjectively; over succeeding decades, automatic optimization procedures have increasingly been applied.

A basic problem arises in the fitting of the many parameters in these models to observed data (typically streamflow), denoted by Beven (1993) as "equifinality". For a given model, many combinations of parameter values may give similar performance, as indeed may different model structures. This gives rise to two important limitations. If parameters cannot be uniquely identified, then they cannot be linked to catchment characteristics, and there is a major problem in application to ungauged catchments. Similarly, it is difficult to represent catchment change if the physical significance of parameters is ambiguous.

Developments in computing power, linked to an improved understanding of modelling limitations, have led to some important theoretical and practical developments for conceptual modelling. It is generally recognized that there is no simple best fit parameter set for such models, rather an ensemble of 'behavioural' parameter sets, for which the 'likelihood' that a parameter set is consistent with the available data can be defined (see, for example, the Generalised Likelihood Uncertainty Estimation (GLUE) procedure (Beven and Binley, 1992; Freer *et al*., 1996)).

A second area of development is based on the recognition that much more information is available within an observed flow time series than is indicated by a single performance criterion, and that different segments of the data contain information of particular relevance to different modes of model performance (Wheater *et al*., 1986). As a result, multi-criterion optimization has been widely applied for rainfall-runoff modelling (e.g., Gupta *et al*., 1998; Wagener *et al*., 2000a; 2000b). Tool kits for model building and analysis using these and other methods are currently available (e.g. Wagener *et al*., 1999).

Use of these tools has led to the understanding that there are trade-offs between model complexity and parameter identifiability that need to be explored. If we are interested in model application to ungauged catchments, it is desirable that those parameter sets considered as behavioural are contained within a limited range of the feasible parameter space. In general, improved parameter identifiability is associated with parsimonious conceptual models (i.e. models with few parameters). These have been termed Hybrid Metric Conceptual, or HMC, models, because while they retain a conceptual form, the aim is to achieve the analytical capability of metric models (Wheater *et al*., 1993).

HMC models have therefore been widely used in regionalization studies. Wagener *et al*. (2004) provide a detailed discussion of the underlying theory, tools, and example applications. A basic approach to the regionalization problem is to search for relationships between model parameters and catchment characteristics through the regional analysis of large numbers of catchments. For example, regression relationships for ungauged application of continuous simulation rainfall-runoff models in the UK have been developed by Lamb and Kay (2004) and Lee *et al*. (2005). Alternative approaches are based on the concept of 'donor' catchments (McIntyre *et al*., 2005). Multiple parameter sets can be transposed from multiple donor catchments, with relative weighting of donor parameter sets based on some measure of similarity of the donor catchment to the target catchment (based on a set of catchment characteristics), and on the quality of fit (or likelihood) of the parameter set to the donor catchment. Thus some 40 years after the first development of conceptual models, their application to ungauged catchments, at least in certain hydrological environments, has been established to the point that they can be considered as suitable tools for routine application in hydrological practice.

Physics-based models

The third and final element in our model typology is the category of "physics-based models." Such models are explicitly based on the physics of hydrological processes, using a continuum representation of catchment processes in which the equations of motion of the constituent processes are solved numerically using a regular or irregular grid. They first became feasible in the 1970s when computing power became sufficient to solve the relevant coupled Partial Differential Equations for surface and subsurface flow (Freeze and Harlan, 1969; Freeze, 1972). The models are characterized by parameters that are (in principle) measurable and have a direct physical significance. An important theoretical advantage is that if the physical parameters can be determined *a priori*, such models can be applied to ungauged catchments, and the effects of catchment change can be explicitly represented; however, whether this theoretical advantage is achievable in practice remains an open question at present, particularly in the context of subsurface processes.

One of the best known models is the Systeme Hydrologique Europeen (SHE) model (Abbott *et al*., 1986a; 1986b), currently available commercially from DHI; a subsequent development is reported by Ewen *et al*. (2000). The

catchment is discretized, on a square grid basis, for the representation of land surface and subsurface processes, creating a column of finite difference cells, which interact with cells from adjacent columns to represent lateral flow and transport. River networks are modelled as networks of stream links, with flow again represented by finite difference solution of the governing equations. The resulting model is complex, computationally demanding, and data intensive.

In practice, two fundamental problems arise with such models. The underlying physics has generally been derived from small scale, mainly laboratory-based, process observations. Hence, the processes may not apply under field conditions and at field scales of interest. There is, for example, numerical evidence that the effects of small scale subsurface heterogeneity may not be captured effectively by spatially aggregated properties (Binley and Beven, 1989). Secondly, although the parameters may be measurable at small scale, they may not be measurable at the scales of interest for application. An example of both is the representation of soil water flow at hillslope scale. Field soils are characterized by great heterogeneity and complexity. Macropore flow is ubiquitous, yet neglected in physics-based models, for lack of relevant theory and supporting data; the Richards' equation commonly used for unsaturated flow depends on strongly non-linear functional relationships to represent physical properties, for which there is no measurement basis at the areal scales of practical modelling interest; and field studies such as those of Pilgrim *et al*. (1978) demonstrate that the dominant modes of process response cannot be specified *a priori*. For more detailed discussion see, for example, Beven (1989).

Physics-based models, therefore, have important strengths and weaknesses. When applied at catchment scale, with limited data to support the parameterization, a user is faced with a model with thousands of parameters, each of which may be associated with a high degree of uncertainty. Due to the numerical complexity of the model, rigorous exploration of the parameter space is generally not feasible, so the scientific developments discussed above for conceptual models can only be applied in a limited sense (for example, by restricting the spatial variability of parameters to provide a much smaller number). On the other hand, the fact that parameters can notionally be associated with physical properties provides a strong foundation for exploring effects of catchment change as well as application to data-sparse regions, in particular where cold region processes occur. In that latter context, we note that there has been widespread use of a class of

model that represents the physical processes in a parsimonious framework that seeks to balance process emergence, complexity and parameter realism; however such models have as yet received little formal analysis of output and parameter uncertainty. We return to this discussion below.

8.5 BASIN NON-STATIONARITY – MODELLING THE EFFECTS OF LAND USE AND LAND MANAGEMENT CHANGE

Modelling the effects of changing catchment properties for ungauged basins is an important practical issue for policy and management, but raises major challenges for hydrological science. For example, in the UK, following a set of major floods (in 2000, 2004, 2005, and 2007), questions were asked concerning the effects of agricultural intensification on flood risk (Wheater *et al*., 2008; 2010). Changing agricultural practices include, for arable agriculture, changing cropping patterns (leaving soils bare at vulnerable times of the year) and the use of heavy machinery, and for pastures, increased stocking density and animal weights. It was thought that these may cause higher flood peaks in streams and rivers due primarily to their impacts on soil structure and runoff processes (e.g., Heathwaite *et al*., 1990; Holman *et al*., 2003; O'Connell *et al*., 2007). This issue is not confined to the UK; similar concerns have been raised across northern Europe (Boardman *et al*., 1994; Boardman, 1995; Savenije, 1995; Bronstert *et al*., 2002; Pinter *et al*., 2006; Evrard *et al*., 2007). If agricultural intensification were to have significant impacts on flood risk, this would have major implications for rural land management policy, including the potential for using land management practices beneficially to mitigate flood risk. Although the risk of flooding is mainly concentrated in lowland regions, catchment headwaters, with their generally higher precipitation rates and flashier response, are important source areas for runoff generation, and hence are of particular interest.

Although land use and land management changes have been observed to change local runoff (O'Connell *et al*. 2004; Marshall *et al*., 2008), quantification of catchment scale effects has proved elusive. A UK programme of catchment scale data analysis was undertaken in an attempt to identify effects of land management intensification (Beven *et al*., 2008). This proved unsuccessful due to the heterogeneity of land use practices at the catchment scale, lack of information about the local detail of land

management practices for a given land use type, variability of response with climate, and data error. In a review of the current state of knowledge about the effects of land use and management change on flood risk, O'Connell *et al*. (2004) concluded that new modelling techniques were needed in order to predict the impacts of land management on flood risk.

The application of physics-based models with intensive data support

We consider first the role of physics-based models as a tool to address land management change in a relatively data-rich environment, in particular an extensive field experimental program established at Pontbren, in the headwaters of the River Severn in Wales. The aim of the experiment was to provide multi scale data on the effects of land management practices for a typical set of upland land management issues and interventions, to support development of the new modelling approaches needed for flood risk policy and management (Wheater *et al*., 2008; 2010).

Pontbren is a farmers' cooperative, involving 10 farms covering 1000 ha of agriculturally improved upland pasture (drained, ploughed, re-seeded, and fertilized) and woodland. Elevations range from 170 to 438 m above sea level, and the soils are clay-rich, with low permeability subsoil overlying glacial drift deposits, and are seasonally wet or water-logged. Field drainage is ubiquitous where pasture has been improved. The predominant land use is grazing, mainly for sheep.

The Pontbren experiment arose as a result of farmers' concerns that changes to land management, and in particular changes to grazing densities and animal weights, had changed runoff response. Between the 1970s and 1990s, sheep numbers increased by a factor of 6 and animal weights doubled (R. Jukes, pers. comm.). Recent farmers' initiatives have included the reduction of grazing densities and reinstatement of woodland areas and hedgerows. Research on the infiltration rates of the grazed hillslopes and woodland buffer strips (e.g. Carroll *et al*., 2004) demonstrated a significant change in soil response to rainfall. Infiltration rates on the grazed pastures were extremely low, but within a few years of tree planting, soil structure and permeability in buffer strips showed significant improvement, with mean permeability more than doubling.

Details of the multi scale experiment can be found in Wheater *et al*. (2008) and Marshall *et al*. (2008). Replicated manipulation plots were instrumented

to observe the plot scale effects of land management change, instrumented fields and hillslopes provided data on soil water response and runoff processes (overland and drain flow) at larger scale, and multiple flow monitoring installations provided data on stream flows at scales ranging from ditches and drains to second order catchment response (12 km^2). In addition, soil physical properties were derived from extracted soil cores and *in situ* infiltration tests.

The modelling challenges include representing the effects of soil compaction and tree buffer strips on soil properties and runoff processes, as well as the effects of agricultural field drainage, at the scale of individual fields, and at the whole catchment scale.

A detailed, physics-based model was developed, capable of representing the important hydrological processes operating at Pontbren and similar catchments, at the scale of individual fields and hillslopes. A model was developed based on Richards' equation for saturated/unsaturated soil water flow, and including macropore processes and overland flow. It incorporated vegetation processes (such as interception), could represent associated effects such as changing root depths and soil hydraulic properties, and was capable of being run in 1, 2, or 3 dimensions (Jackson *et al*., 2008). The model was conditioned, within a Monte Carlo based framework of uncertainty analysis, using physically determined soil hydraulic properties and continuous measurements of climate inputs, soil water states, and runoff (as overland flow and drain flow) from the Pontbren experimental sites. Due to the highly non-linear dynamics, individual fields and hillslopes were represented at fine resolution (1cm vertical and 1m horizontal resolution), although spatial heterogeneity on soil properties was not explicitly represented.

The detailed model can be used to simulate scenarios of interest, including the planting of strips of woodland within a hillslope, and the associated changes to soil structure, evaporation processes, overland flow, and drainage. Figure 8.1 illustrates the simulated response for a representative hillslope (100 m x 100 m) using the detailed model for a range of land management types, including grazed and ungrazed drained grassland, grassland with tree shelter belts (80 m length, 15 m width) in different locations, and full tree cover. The envelopes of response represent the range of parameter uncertainty.

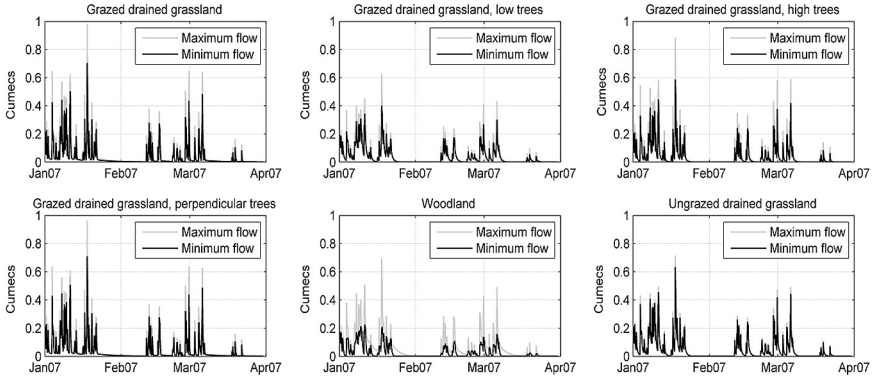

Figure 8.1 *Physics-based model: Field scale runoff for different land use types, with uncertainty bounds.*

While these results are instructive, some caveats remain. For example, despite the extensive field program, there are residual uncertainties in the perceptual model (i.e. the characterization underlying the physics-based model) concerned with the fate of subsurface water in the tree planted areas. We assume here that connection to field drainage systems exists; and while the modelling allows for uncertainty in soil properties, and the model has been conditioned on field scale data, the effects of spatial heterogeneity have not been explicitly evaluated. Another notable effect was non-stationarity in observed response associated with a hot dry summer (2006) in which soils cracked and only gradually returned to normal over the following autumn and winter. These effects have not been represented in the modelling. Nevertheless, the model provides a relatively sound basis for the quantification of field scale effects of these complex and spatially localized land management options, particularly given the absence of viable alternatives.

Upscaling for catchment scale application

The detailed model is highly computationally intensive and not suitable for direct application at catchment scale. A strategy was therefore developed to upscale the results in a computationally-efficient procedure, using meta-modelling. The detailed model is used to train a simpler, conceptual model (i.e. of the HMC class as discussed above) that represents the response in a parsimonious and computationally efficient manner, using basic hydrological components of loss and routing functions. This requires classification of the landscape into hydrological response units, based for example on soils, land

use, and existing/proposed interventions. Each field in the Pontbren catchment is classified into a land use/management type; so that the corresponding set of field scale models can be applied. 9 field types were chosen based on dominant land use types currently within the catchment and those management changes that were perceived as likely to have an impact on flood peaks, including grazed improved and unimproved grassland, tree shelter belts with different orientations, woodland, and marsh/wetland.

The detailed model is run for each member of a library of hydrological units, and hence a meta-model parameterization is obtained for each member through the model training process. Uncertainty in parameter values is carried forward to this stage via Monte Carlo analysis. Figure 8.2 illustrates the performance of the meta-model in emulating the detailed model response for a grazed hillslope with a woodland buffer strip at the base of the slope.

With a library of meta-models, the final element of the procedure is a catchment scale semi-distributed model. We use a modular modelling structure, based on a semi-distributed version of the Rainfall-Runoff Modelling Toolbox

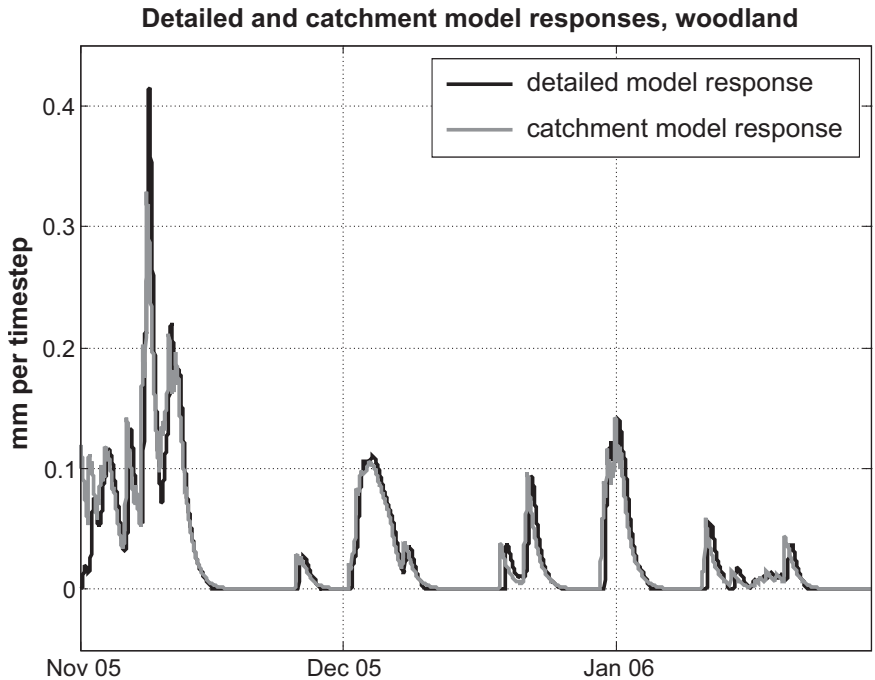

Figure 8.2 *Meta-model performance (woodland response) – meta-models can match the hydrographs of detailed physics-based models.*

(RRMT) (Wagener *et al*., 1999), in which the meta-model elements represent individual hydrological elements, and their outflows are routed down the stream network. Using the semi-distributed model, the meta-model can be further conditioned on catchment scale data to reduce parameter uncertainty.

The hydrological processes and climatological forcing data within the sub-areas are considered to be homogeneous; the degree of spatial distribution is represented mainly through the number of sub-areas. These can represent subcatchments or hydrological response units, and can incorporate the meta-model structures discussed above. Fields were chosen to be the individual response units in this application, and as the appropriate land management unit. They also generally form sensible hydrological units due to the tendency of farmers to set ditches and drainage outlets at field boundaries.

The simulated impacts of land management change at the catchment scale are illustrated in Figure 8.3, for a 4 km^2 Pontbren sub-catchment. The baseline is the present land use at Pontbren, the first scenario removes the effect of the recent Pontbren tree plantings (and hence takes the catchment back to something approximating the intensive use of the early 1990s), the second adds buffer strips to all grazed grassland sites, and the third assumes the entire catchment is woodland. The median changes in flood peaks observed for the three scenarios are: removing all the trees causes up to 20% increase in flood peaks from the baseline condition, adding tree shelter belts

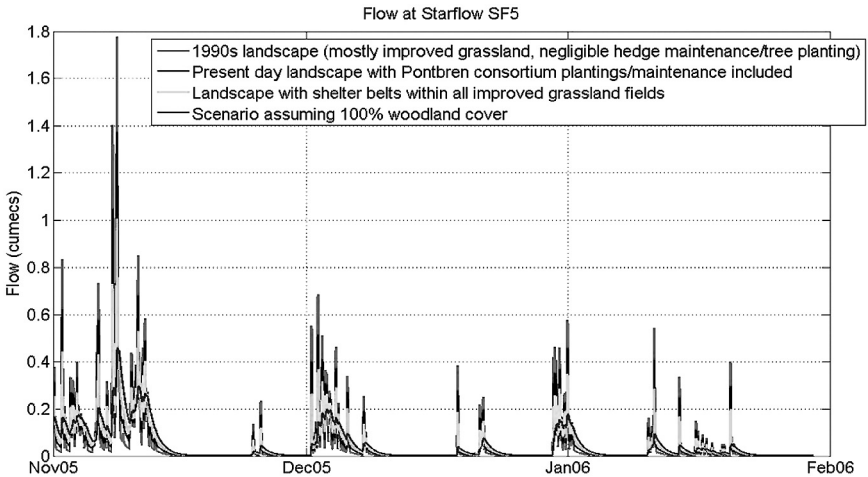

Figure 8.3 *Scenario comparisons of present day landscape, more intensified 1990s land use, and the implementation of shelter belts and woodland cover.*

to all grazed grassland sites causes up to 20% decrease in flood peaks from the baseline condition, and full afforestation causes up to 60% decrease in flood peaks from the baseline condition. These effects, however, decrease with increasing storm return period (Wheater *et al*., 2008; 2010).

The application of physics-based models with limited data support

Having considered physics-based models applied to simulate land management change in a data-rich environment, we now consider the role of physics-based models in a data-poor environment. Even without hydrological measurements for a site of interest, physics-based models can be developed and tested using information about small scale hydrological processes and properties from the literature, or possibly from surrogate sites, as well as qualitative information about responses through engagement with field researchers. By using such data to parameterize the physics-based models, uncertainty in prior parameters is likely to increase greatly. Limited data also implies that there is a greater chance that the model structures will be poorly defined (Ebel and Loague, 2006), thereby adding additional uncertainty to the model predictions (Butts *et al*., 2004). Therefore the extent to which uncertainty can be constrained by such data is a key research question. We also note that physics-based models have the power to support the development of improved conceptual understanding of runoff processes and the dominant physical controls, and can thereby provide qualitative insights that may be of value when considering the effects of land management change. They may also assist in the design of more effective monitoring programs in order to reduce model uncertainty.

The context for this discussion is an application to the problem of peatland management in the UK uplands, and in particular to the Hodder catchment in NW England. Almost half of the UK's upland blanket peatlands were drained, typically by open ditch drainage, during a period of agricultural intensification in the 1960s and 70s (Milne and Brown, 1997). The intention was that water tables would be reduced, to create conditions more suitable for livestock grazing (Stewart and Lance, 1983); however, the reality has been that drainage generally causes only localized drawdown of the water table, while also acting as a rapid conduit for runoff. In most reported cases, the runoff response from drained blanket peats is found to have reduced times to peak, increased peak flows, led to greater erosion, and increased DOC in runoff (Ahti, 1980; Conway and Millar, 1960;

Robinson, 1986; Stewart and Lance, 1991; Holden *et al*., 2006, 2007; Worral *et al*., 2007). Hence, beginning in the 1980s, a program of blocking peatland drains was started.

Due to the complex process interactions and relatively limited observations, there are large uncertainties about the best management practices for upland blanket peatlands, and therefore suitable process-based models can potentially aid our understanding of impacts of management interventions. Following a modelling philosophy similar to that of Weiler and McDonnell (2004), we developed *a priori* model structures where the key hydrological processes were included whilst working to maintain an appropriate level of complexity relative to the detail of available information concerning the system hydrological processes. A schematic of the model is shown in Figure 8.4. Full details are available in Ballard *et al*.(2012a; 2012b).

In the absence of local data, the drained blanket peatland model was tested against data from a surrogate experimental site. The model was found to perform well (Ballard *et al*., 2012b), which provided a degree of confidence that the *a priori* model structure captured the key hydrological processes for drained peatlands, particularly for peak flows. All calibrated parameters were found to be identifiable within the *a priori* parameter ranges, although some more strongly than others. This suggests that the physical interpretation of these parameters is reasonable.

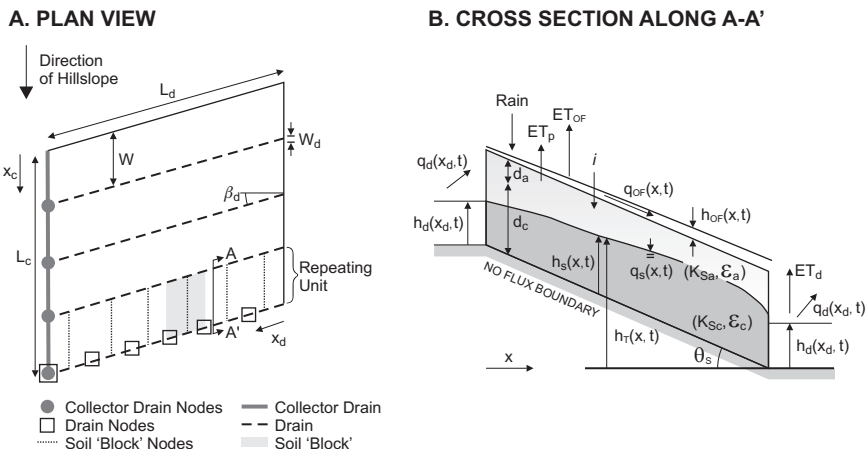

Figure 8.4 *Drained Peatland Detailed Model.*

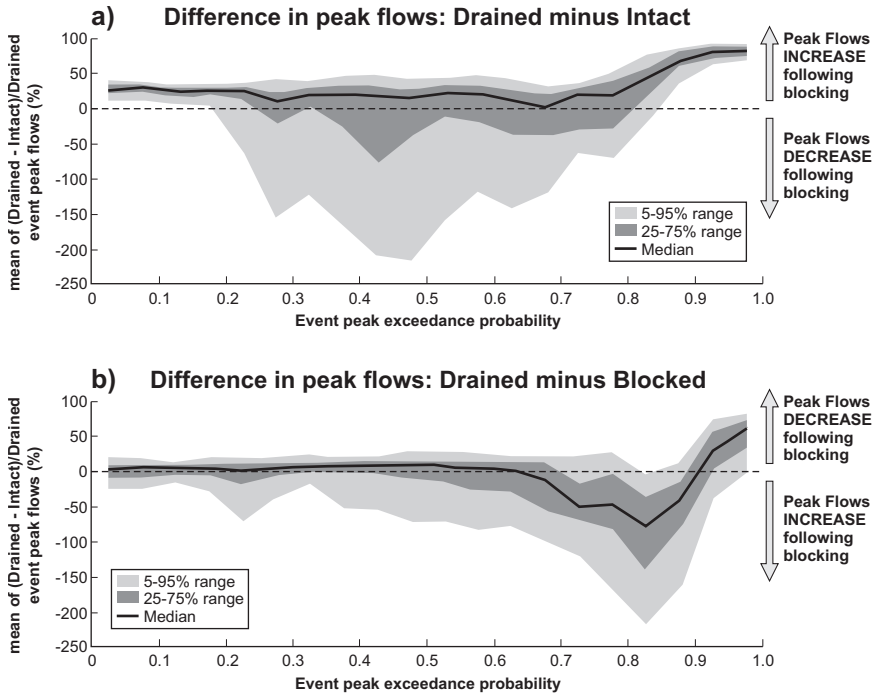

Figure 8.5 *Comparison of change in peak flows as a function of event exceedance probability.*

The model was used to perform "virtual experiments" to explore aspects of hydrological response to a range of storm events throughout the potential parameter space of UK blanket peatlands. Figure 8.5 shows results obtained for hypothetical 200 m x 200 m hillslope elements for a range of events of different occurrence frequency (details are provided in Ballard, 2011). The results provide important insights into the variability of magnitude and sign of response with event frequency for the different management practices (intact and drained peat, and the case of drains that were retrospectively blocked).

The peatland model was then used to perform simulations of intact, drained and blocked drained blanket peatlands for the Hodder upland catchment in North-West England. 100 parameter sets were selected from *a priori* parameter ranges that were restricted based on specific site knowledge (drainage maps and DEMs) and information from the literature. For the largest runoff event, the mean increase in peak flow from intact to drained peatland was 25%, and the mean decrease in peak flow from drained to blocked drained peatland was 3%; the range in responses was 4-42%

increase and 16% increase to 25% decrease, respectively. The change in runoff response was highly dependent on local conditions, and peak flow changes from drained to blocked were also dependent on the flow magnitudes, with simulations with the largest runoff in the drained simulations most likely to give larger percentage reductions in flows following drain blocking. Despite parameter uncertainty, the ensemble responses of the different land management types were found to be distinct; this suggests that even scarce data can be used to reduce ensemble uncertainty sufficiently to allow meaningful insights into the changes in runoff response related to land management.

As in the Pontbren example, the problem of upscaling results from hillslope scale arises. A set of meta-models was developed to describe the management of upland blanket peat, representing intact, drained and blocked drained blanket peatlands. These have been incorporated into a catchment scale semi-distributed model, along with other elements, collectively representing the soils and management practices of interest in the catchment.

8.6 REGIONALIZATION OF CONCEPTUAL MODELS

In the application of physics-based models for catchment scale simulation, we introduced the use of conceptual models (meta-models) to emulation of their performance. In this section the potential use of conceptual models as an alternative (or complementary) approach to the problem of estimating land use change effects in the absence of detailed data is explored more generally. In particular, the use of regionalized indices of hydrological behaviour to constrain model parameters in a formal Bayesian framework is assessed.

In this section, two regionalized indices are considered: the Base Flow Index (BFI) and the US Soil Conservation Service Curve Number (CN). BFI is the proportion of the catchment discharge hydrograph that can be considered as base flow. For the UK, BFI has been successfully regionalized based on the Hydrology of Soil Types (HOST) classification (Boorman *et al*., 1995). HOST is based on the soil characteristics of depth to gleyed / slowly permeable layer, depth to ground water, presence of a peaty surface layer, and soil substrate. CN relates rainfall volume to corresponding storm runoff volume (Hawkins, 1993; van Mullem *et al*., 2002). Based on data from experimental catchments, estimated values of CN were regionalized for the USA (United States Department of Agriculture (USDA), 1986) based on hydrological soil group, land use, and land management classification.

The essence of our method, as described in Bulygina *et al*. (2009, 2011), is that for a given conceptual model, large numbers of parameter sets are sampled from the feasible parameter space. Those parameter sets that provide simulations for which derived BFI and CN values are consistent with the regionalized estimates of these indices are retained, with a weighting dependent on an appropriate likelihood function. Thus the posterior likelihood of a sampled parameter set is proportional to the consistency of simulated BFI, considered alone, or BFI and CN values considered together, with the values predicted by the regionalization method for those indices. The simulated BFI values are calculated from the continuous time simulations using the hydrograph separation procedure of Gustard *et al*. (1992), and the simulated CN values are calculated following Hawkins (1993) and van Mullem *et al*. (2002).

Two case studies are presented. The first, based on Pontbren, uses only information contained in BFIHOST. Land use effects are represented using changes in BFIHOST value (see below), and in interception and evapotranspiration losses. Two types of land use effects are evaluated: afforestation, and increased stocking density. The second study, based on the Plynlimon experimental catchments, also in Wales, additionally includes information from the Curve Number method, which in principle provides the capability to represent a much wider variety of land use/management types (Bulygina *et al*., 2011).

The first study relies on the following assumptions, which are necessarily of a speculative nature. Afforestation is assumed to lead to higher BFI, through changes to soil structure and hence hillslope runoff processes, while keeping the same HOST soil type. We therefore select for the posterior only those parameter sets that lead to a base flow increase (with respect to the unforested BFI). Changes in interception losses associated with afforestation are estimated using a simple hard threshold bucket model, with canopy storage capacity depending on species, leaf area index, canopy cover, vegetation structure, and density (David *et al*., 2005). Increased stocking density leads to soil structural degradation. Following the approach of Hollis (Packman *et al*., 2004), degraded soil is assigned an appropriate analogue HOST class to represent the change. The rationale for the proposed changes is that soil structural degradation, in the form of topsoil and upper subsoil compaction and seasonal ‘capping’ and sealing of soil surfaces, causes a reduction in the effective soil storage, which in turn results in increased surface runoff.

The second study adds CN information to BFI information to represent effects of different land uses and managements. To assign CN to each considered soil – land use combination, the British HOST soil classification (29 types) is mapped into the American USDA soil classification (4 classes) (Bulygina *et al*., 2011). Thus, an important assumption is that the CN index can be used under conditions other than those from which it was derived, with correspondence derived from a subjective mapping process.

The chosen rainfall-runoff model is the probability distributed moisture (PDM) model with two parallel linear routing stores (Bulygina *et al*., 2009; Moore, 2007). Its structural simplicity is thought appropriate given the data limitations (i.e. the information used to condition the model comes from only one or two flow indices), and it has been extensively applied to other catchments in upland Wales and other UK regions (Calver *et al*., 2005; Lamb and Kay, 2004; Lee *et al*., 2005). This model has five parameters: C_{max} is the maximum soil water storage capacity within the modelled element, b is a shape parameter defining the storage capacity distribution, k_f and k_s are fast and slow routing store residence times, and α is the proportion of the total flow going through the fast routing store. Model inputs are hourly precipitation and potential evaporation; the latter calculated using a Penman-Monteith formulation allowing for explicit representation of canopy interception.

Pontbren application

A 15-minute time resolution rainfall-runoff model was developed for the Pontbren catchment, which was discretized into 100 m x 100 m runoff generating elements, integrated using a simple constant velocity routing to generate catchment scale response. Each element is represented using the PDM model (see above), which allows element scale land management changes to be represented within the catchment scale model. Potentially, the catchment model needs a separate set of parameters for each element. Here, it is assumed that all elements with the same BFI_{HOST} have the same set of parameter values.

The posterior parameter distributions were found to restrict two (out of the five) model parameters, the slow flow residence time k_s and runoff partitioning coefficient α. Low k_s values have low posterior probability, and the runoff partitioning coefficient distribution is concentrated around a value of (1-BFI_{HOST}). Model performance was estimated over a highly variable flow period of 1 January, 2007 to 31 March, 2007. Results showed that the posterior prediction uncertainty was significantly reduced when compared

to prior predictions, based on the feasible parameter space. Nash-Sutcliffe statistics for the expected values of probabilistic flow predictions varied between 0.7 and 0.85 for different Pontbren subcatchments, supporting the view that BFI_{HOST} is an effective response index.

Application of the speculative relationships between BFI_{HOST} and land management practices is illustrated in Figure 8.6, which shows the predicted impacts of full afforestation and increased stocking density on runoff at the most downstream Pontbren flow gauge, for 18 January 2007. The solid lines represent the 90th percentile simulation range for current conditions and the dashed lines are the corresponding results for full afforestation and soil degradation. The uncertainty in the peak flow is high compared to the expected changes, suggesting that more information about the model parameter values would be beneficial. The afforestation delayed the highest peak arrival by 15 minutes (one simulation time step), and the soil degradation scenario did not show any difference in peak flow arrival time. Full afforestation decreased peak flow by 8% (median value), and stocking intensification increased peak flow by 11% (median value).

Plynlimon application

The Plynlimon catchments comprise the headwaters of the rivers Wye and Severn (Marc and Robinson, 2007; Robinson and Dupeyrat, 2005). The Wye (10.55 km^2) is almost exclusively under extensively grazed grassland, while the Severn (8.7 km^2) is mostly covered with mature coniferous forest. Both catchments are extremely humid; the ratio of long term precipitation to potential evapotranspiration is about 5, with similar, slowly permeable soils. Because of soil similarity, geographical proximity, and qualitatively

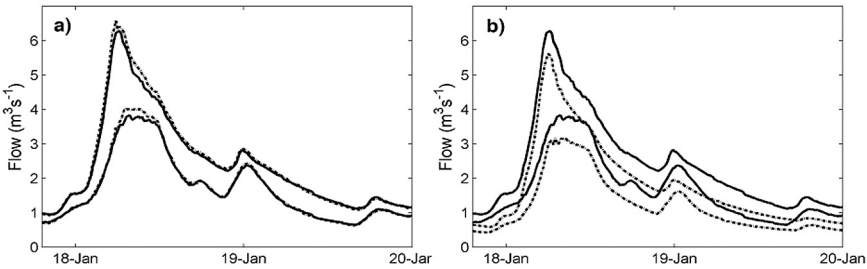

Figure 8.6 *Prediction uncertainty bounds for flows at gauge 10 due to the 18th of January, 2007 rainfall event:* ***a)*** *afforestation,* ***b)*** *soil degradation.*

different land uses in the catchments, the Wye and Severn catchments are ideal for application and testing of land use change simulation methodologies.

Given the physical scale of the catchments, and the use of hourly data, the catchment response was simulated using the PDM model (for the period May 1980 through June 1981) without explicit flow routing, i.e. the average of the responses for all relevant soil type/land use/land management combinations weighted by their relative contributing areas was used; this might introduce at most a one hour timing error.

As in the previous case study, it was observed that only two parameters, the slow flow residence time k_s and runoff partitioning coefficient α, were restricted by the information available (BFI and CN); however, different land use/management types (as represented by CN) introduced shifts in the parameter distributions – mainly, for parameter α. Performance with respect to observed flow in all 8 subcatchments was considered generally good: the prior uncertainty was reduced by a large degree throughout the simulated periods; and probabilistic NS values (Bulygina *et al*., 2009) ranged from 0.70 to 0.81.

As an illustration of the potential applicability of the method, two simple land use change scenarios were considered: a) the upper Severn becomes pasture in good condition; and b) the upper Wye becomes forest in good condition. Figure 8.7 shows predictions for the event with the highest flow peak (5-6 October, 1980). Here, black lines represent 95% confidence intervals for the existing land use conditions and grey lines represent 95% confidence intervals for the scenario. The median peak flow in the Severn increases by 9% when the afforested area becomes pasture; in the Wye it reduces by 13% when the pasture land is afforested.

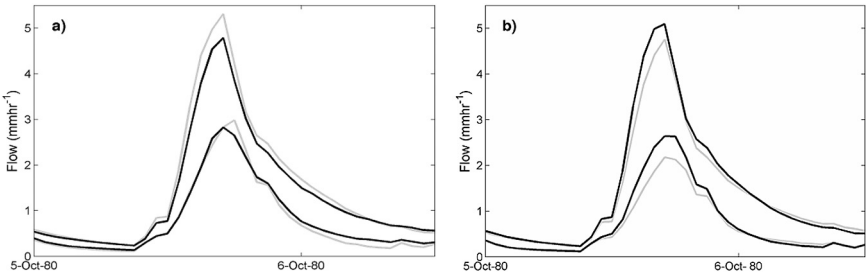

Figure 8.7 *Predictions during a large flood event.* ***a)*** *Severn becomes pasture in good condition;* ***b)*** *Wye becomes forest in good condition.*

8.7 SUMMARY

In parallel with the development of improved understanding of and insights into the application of hydrological models, there has been major progress over the last 40 years in the capability for prediction of flows in ungauged basins. A key aspect of this has been the use of models as a tool for regional analysis. Simple metric models, in particular the unit hydrograph method, provided the capability to analyze event response in terms of simple loss and routing functions in certain conditions. Regional application of this type of analysis to large numbers of catchments provided relationships between the parameters of these models and catchment characteristics that could be used in ungauged catchment application. Such methods have been widely used as the basis of much hydrological practice, in particular for flood design.

The use of event-based methods has important limitations (Wheater, 2002). Conceptual models provide a more powerful set of tools, incorporating the full set of hydrological processes and providing a capability for continuous simulation. Advantages include applicability to a wider range of catchment types, and the capability to represent explicitly effects of sequences of weather events on runoff generation, including the potential effects of climate change. Until relatively recently, problems of equifinality of parameter sets have limited the regional application of conceptual models; however, increasing understanding of the relationship between model complexity and parameter identifiability has led to the use of parsimonious HMC models in regional analysis of large sets of catchments. This has resulted in the availability of regionalized continuous simulation models, in which parameter sets are derived either from regression relationships between model parameters and catchment characteristics or from the direct use (with appropriate weighting functions) of parameter sets from donor catchments.

The representation of effects of land use and land management change adds an additional dimension to the problem of modelling ungauged basins. The ability of models to discriminate such effects through regional analysis is limited. While gross effects, such as urban development, have been identified as significant factors in regional analysis, more subtle effects, such as rural land management practices, have not. This is not surprising, as discussed above, and does not mean that such effects do not exist. Rather, the data available are generally insufficient to detect such signals. In this context, we consider the role of models in synthesis, rather than analysis, and turn to physics-based models.

The applications reported here, for Pontbren and the Hodder, demonstrate the strengths of physics-based models in representing catchment non-stationarity, in particular their ability to represent explicitly the effects of changing physical properties, such as soil compaction, and spatially-localized management interventions, such as tree shelter belts and buffer strips. The Pontbren study builds on a detailed multi scale data set, and it is important to note in passing that few such data sets exist, but that detailed and long term monitoring and experimentation are absolutely necessary to understand the effects of land management changes. Nevertheless, the Hodder example shows that useful insights can be obtained even in the absence of local data (though surrogate data were available to give confidence in the model and its parameterization).

The very detailed physics-based models necessarily require high spatial resolution to represent the effects of soil structural changes and spatially-localized interventions. We therefore used the concept of meta-modelling, to emulate the response of the detailed models using simpler conceptual model structures, more readily suited to catchment scale application. Results were presented for Pontbren to demonstrate the ability of meta-models to emulate the response of detailed physics-based models, and hence to simulate catchment scale effects.

The application of detailed physics-based models and the development of a library of meta-models represents a relatively complex and time-consuming process. While this methodology is suitable for detailed studies of specific issues on specific catchments, and can provide important insights, it could not readily be extended to broad scale (e.g. national) application (although catchment classification could provide one potential approach for generalization). We therefore considered the potential role of hydrological indices in conditioning conceptual models.

In the UK, the Base Flow Index has consistently been shown to be a powerful descriptor of hydrological response in regionalization studies (e.g. Lee *et al*., 2005). Our results from both Pontbren and Plynlimon show that the use of BFI to condition the PDM model gives a remarkable level of performance in the absence of any other data; however, to represent the effects of land management change, some subjective interpretation was needed. For CN this required mapping of SCS soil types onto HOST soil types, and the presumption that a US regionalization could have relevance and value in a UK application. For BFI, soil structural degradation was

related to an effective change in soil class, and effects of afforestation on soil structure and runoff processes were simply represented by imposing the constraint that BFI would be expected to while the HOST class remained unchanged. We can state that the method is readily applicable, and gives plausible results. Clearly, a more extensive evaluation that introduces more sources of information and covers a wider range of UK conditions is strongly recommended.

While the issues of model regionalization have been presented in the context of the historical development of alternative model types, an additional theme running through the paper is the use of alternative sources of information in the conditioning of parameter sets. We see this as an important generic methodology, with the power to combine alternative sources of information to address complex modelling issues of this kind. We note that a first step in that direction is reported by Bulygina *et al*. (2012), in which information from small scale physical properties, regionalized signatures of flow, and available flow measurements is combined in a Bayesian framework and applied to a distributed model for the Hodder catchment in the UK. Interestingly, the physics-based information contributed most to improving model performance, followed by local flow data (used to define peak travel times), and lastly the regionalized signatures.

8.8 ACKNOWLEDGEMENTS

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9

REGIONALIZING HYDROLOGICAL RESPONSE UNDER A CHANGING CLIMATE

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9.1 ABSTRACT

Regionalizing hydrological response to ungauged catchments is a difficult problem. It is typically expressed as Prediction in Ungauged Basins (PUB). The typical practical application of the PUB problem involves not just predicting the historical hydrological response of a catchment, but also requires a prediction of the hydrological response of a catchment into the future. This is particularly true in large-scale water assessment studies, which are typically initiated and funded to not only understand how much water is currently available in any particular (typically, at least in part, ungauged) region, but also to determine how much water will be available for both water users and the environment into the near (1-5 years) and more distant (5-50 years) future. This problem is compounded by the potential for changes in catchment hydrological functioning, modifying the climate-runoff-streamflow-water availability relationship. Changes in catchment hydrological functioning can be brought about through changes in land use and land management, or through changes due to a changing climate. To solve this latter issue, some fairly intuitive solutions are postulated. Firstly, the hydrological functioning of a catchment under historical conditions must be understood; secondly, the models used to represent this hydrological functioning must be improved through improving the model calibration procedures and parameter estimation; and thirdly, the model structure must be modified to incorporate hydrological processes which are assumed to change under a changing climate. It must be recognized, however, that water managers require estimates of current and future water availability now in order to more effectively manage water resources. Solutions to the problem of non-stationarity need to be found, but assessments of water availability will continue using whatever methods and models are available.

9.2 RÉSUMÉ

La régionalisation de la réaction hydrologique aux bassins non jaugés pose un problème délicat. Elle est en général exprimée en tant que prévisions dans les bassins non jaugés (PBNJ). Cependant, l'application pratique type du problème lié aux PBNJ n'implique pas uniquement la prévision de la réaction hydrologique historique d'un bassin versant, mais exige également la prévision de la réaction hydrologique future d'un bassin. Cela est particulièrement vrai dans les études d'évaluation de l'eau à grande échelle, qui sont en général entamées et financées non seulement afin de comprendre combien d'eau est disponible à ce stade dans une région en particulier (en général non jaugée, du moins en partie), mais également afin de déterminer combien d'eau sera disponible à la fois pour les utilisateurs d'eau et pour l'environnement dans un avenir prochain (d'ici 1 à 5 ans) et dans un avenir plus lointain (d'ici 5 à 50 ans). Ce problème est aggravé par la possibilité de changements touchant le fonctionnement hydrologique du bassin, ce qui modifie la relation climat-débit de ruissellement-disponibilité de l'eau. Les changements qui touchent le fonctionnement hydrologique d'un bassin peuvent être entraînés par des changements dans l'utilisation et dans la gestion des terres, ou par des changements attribuables au changement climatique. Pour résoudre ce dernier problème, certaines solutions hypothétiques passablement intuitives sont avancées. Tout d'abord, le fonctionnement hydrologique d'un bassin dans des conditions historiques doit être compris; deuxièmement, les modèles servant à représenter ce fonctionnement hydrologique doivent être améliorés grâce à l'amélioration de la procédure d'étalonnage du modèle et à l'estimation de paramètres et, troisièmement, la structure du modèle doit être modifiée afin d'intégrer les processus hydrologiques censés évoluer dans des conditions de climat changeant. Toutefois, il faut reconnaître que les gestionnaires des eaux ont besoin maintenant d'estimations de la disponibilité de l'eau actuelle et future pour pouvoir gérer les ressources en eau de manière plus efficace. Des solutions au problème de la non-stationnarité doivent être trouvées. Cependant, les évaluations de la disponibilité de l'eau continueront de reposer sur les méthodes et les modèles disponibles, peu importe lesquels.

9.3 INTRODUCTION

The Prediction in Ungauged Basins (PUB) initiative seeks to extrapolate hydrological response spatially. This has proven to be a difficult problem to tackle and has rightly received much attention; however, the problem

becomes even more difficult when the temporal dimension is added. That is, more than predicting the hydrological response of an ungauged catchment historically, there is a need to predict the hydrological response of an ungauged catchment into the future. Were a catchment to behave the same in the future as it did historically, then this would not be a problem; however, this is most frequently not the case, and it is this non-stationarity in catchment hydrological response which adds an additional layer of complexity.

It has long been recognized that the assumption of stationarity in hydrological time series is questionable. Milly *et al*. (2008) argue that not only is stationarity of hydrological time series a poor assumption, but that anthropogenic warming of the climate is the root cause of this. This assumption is also questionable given the evidence of palaeoclimate records; for instance, those for south-eastern Australia as presented in Gergis *et al*. (2011) show that the range of conditions encountered prior to the 20th century indicate that the assumption of stationarity prior to significant anthropogenic warming is a poor one; however, Milly *et al*. (2008) also point out that the available information base is rapidly changing, and the inability to assume that future conditions will fall within the range of those encountered historically means that it is now more important than ever for information to pass rapidly from climate scientists to water managers. The most efficient and logical conduit for this communication to occur is through the hydrological community. The potential for this to occur in a successful way is demonstrated in Post and Moran (2011).

Many factors can produce non-stationarity in catchment hydrological response. These include changes in land use (e.g. replacing forest with pasture), changes in land management (e.g. increasing the number of farm impoundments), and changes in vegetation functioning (e.g. wildfire replacing mature forest with regrowth forest). In addition to these 'land' changes, climate change may also introduce further non-stationarity. This can happen through changes in vegetation type (e.g. due to higher temperatures), changed vegetation functioning (e.g. due to enhanced CO_2 conditions), or through modifications to the hydrological functioning of a catchment. This could include modifications to the dominant hydrological processes occurring in a catchment (e.g. a deepening ground water table may lead to a stream gaining water from ground water discharge and becoming a stream losing water to ground water recharge), or through fundamentally new hydrological processes (e.g. the inability of a seasonal snowpack to form may lead to a complete loss of spring snowmelt).

It is important to remember that non-stationarity of hydrological response due to climate change is only one of many factors that influence future water availability. In general, changes in future runoff due to changes in rainfall will be more important than the impact of non-stationarity, as will secondary impacts on hydrology such as changes in runoff due to changes in potential evapotranspiration; however, not accounting for changed hydrological processes under a changing climate may lead to a consistent over or under-estimation of water availability and a consistent error of this type is of great importance for water managers.

One of the key aims of PUB is to improve the ability of existing hydrological models to generate reliable predictions in ungauged basins. In Section 9.3 of this paper, differences in catchment behaviour under different climatic inputs are illustrated; to do this requires a consideration of the impacts of climate non-stationarity on hydrological response. A second key aim of PUB is to develop innovative new models which are able to represent the spatial and temporal variability of hydrological processes. In Section 9.4 of this paper, the processes believed to be responsible for the changed hydrologic regime during the recent drought in south-eastern Australia are described and those processes that may need to be better represented in hydrological models are discussed. Finally, in Section 9.5, an example of how to effectively communicate the uncertainties in projections of future water availability based on the outcomes of a recent project carried out in Tasmania is given.

9.4 CHANGES IN HYDROLOGICAL FUNCTIONING

Changes in hydrological functioning due to changes in climate are more likely to lead to changes in water availability across a large region when they occur in energy limited catchments rather than water limited catchments. This is because across a large region, more water is likely to be sourced from energy limited rather than water limited catchments. This is particularly true in Australia, where the vast majority of the country falls into the water limited category. For example, in the important agricultural Murray-Darling Basin in south-eastern Australia, 80% of the water is sourced from 20% of the catchment area, and although only 0.3% of the total Murray-Darling Basin is energy limited, it yields 9% of the total runoff (McVicar *et al*., 2010). Donohue *et al*. (2011) attempted to quantify the magnitude of this effect using a simple, Budyko approach and found that basin-wide, an

increase in rainfall of 10 mm/year only led to a modelled increase in runoff of 1 mm/year; however, over the high yielding catchments (which are predominantly energy limited), an increase in rainfall of 10 mm/year led to a much greater modelled increase in runoff of 7 mm/year.

A number of recent papers have assessed how the climate-hydrology relationship may change under a future climate, and how models calibrated to historical conditions may perform when attempting to predict runoff under a future climate displaying different climate characteristics. Key results of these papers are summarized in this section. In general, these studies are limited to examining historical rainfall-runoff relationships; however, they may offer some useful insights. Vaze *et al*. (2010) examined 61 unregulated catchments from south-eastern Australia with at least 60 years of streamflow records. They conclude that in general, models can be used to predict the hydrological response of a future period as long as the rainfall in the two periods differs by less than about 15%. They also found a degradation of model performance when the model was applied to a period which was wetter or drier than the calibration period. Additionally, this degradation was found to be greater when the period to be predicted (representing a future period) was drier than the calibration period. This can be seen in Figure 9.1 which shows the reduction in simulation efficiency when a calibrated model is applied to a drier (or wetter) validation period. The line of best fit shows that the degradation in model efficiency is consistently larger when a model is applied to a drier period of record (left-hand side of the y-axis), compared to when it is applied to a wetter period of record (right-hand side of y-axis).

Of greater concern for water availability studies however, is the fact that Vaze *et al*. (2010) show that not only is this degradation in model performance also seen in the model bias, but that again, the degradation in streamflow bias estimates is much greater when a model is applied to a drier period than when it is applied to a wetter period (Figure 9.2). Interestingly, three of the rainfall-runoff models examined (IHACRES, SMARG, and to a lesser extent Sacramento) show a general under-estimation of streamflow when they are applied to a drier period, while the other model (SIMHYD) shows an over-estimation when it is applied to a drier period. As the vast majority of global climate models predict a drier future for this part of south-eastern Australia (Post *et al*., 2012b) the choice of rainfall-runoff model used in the analysis may therefore lead to either a consistent over or under-estimation of future water availability.

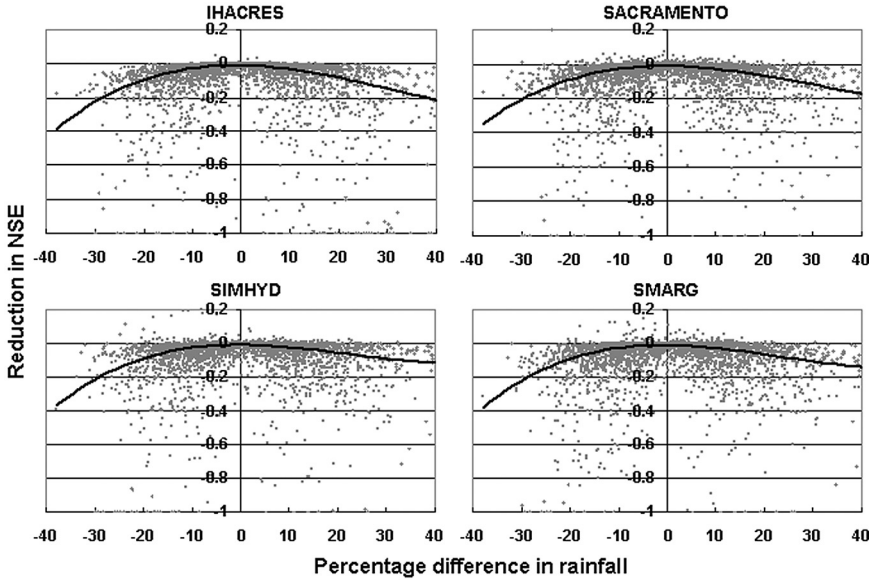

Figure 9.1 *Reduction in goodness-of-fit (as measured by the Nash-Sutcliffe Efficiency, NSE) when a calibrated hydrological model is applied to a validation period which is drier (left-hand side of y-axis) or wetter (right-hand side of y-axis) than the calibration period. (Vaze* et al.*, 2010).*

In other regions of the world, the impacts of a changing climate on the hydrological response of catchments might be even greater than those of Vaze *et al*. (2010). This will be particularly true in areas subject to a seasonal snowpack, where a warming climate may change a snow dominated regime into a rainfall dominated one. This was examined by Merz *et al*. (2011) who found that some of the model parameters of the HBV model were strongly related to the climate of the calibration period. As a result, when predicting the runoff of a future, warmer period, there was a consistent bias. This was particularly true for wetter catchments, and also for the prediction of peak streamflows. They attribute this consistent bias to the observed increase in mean annual air temperature across the catchments of nearly 2 °C between 1976 and 2006 resulting in higher evapotranspiration and drier catchment conditions in more recent years. They suggest that explicitly accounting for non-stationary model parameters or relying less on calibration of model parameters may help, but conclude that identifying model structures that are able to reliably represent hydrological processes in a changing world is a more promising solution.

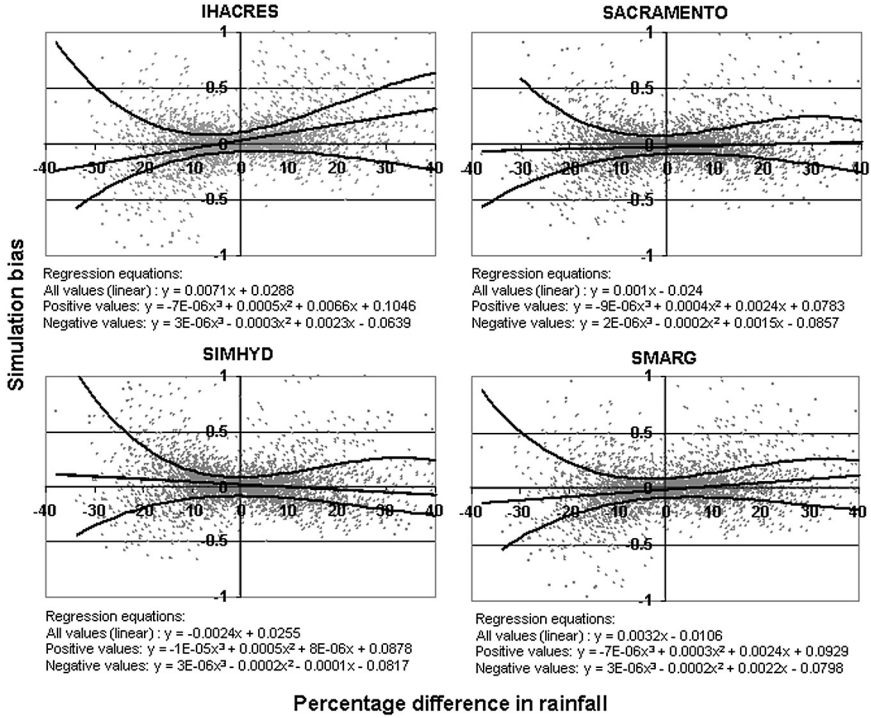

Figure 9.2 *Degradation in simulation bias (as a fraction of runoff) when a calibrated hydrological model is applied to a validation period which is drier (left-hand side of y-axis) or wetter (right-hand side of y-axis) than the calibration period. Lines of best fit are shown for all values as well as for just those points with a positive and negative bias. (Vaze* et al.*, 2010).*

One possible way of determining how a catchment may behave outside the climatic conditions encountered historically is to examine, by analogy, how other catchments behave under these different climatic conditions. Obviously, this is limited by the differences in catchment hydrological response due to other than climatic factors; however, this can provide adequate predictions of at least the long-term runoff ratio. This technique is exploited by Singh *et al*. (2011) who use a Budyko approach to trade space for time and thus assess the response of catchments to a range of potential future climates which fall outside those encountered historically. Interestingly, this completely different approach reached similar conclusions to those reached by Vaze *et al*. (2010) in that the current generation of rainfall-runoff models produced adequate representations of future

streamflow if the rainfall changed by between -10% and +20%. This result is reinforced by Bastola *et al*. (2011) who concluded that time invariance in parameter values has a minimal impact if the change in precipitation is less than 10%. Outside this range of future conditions therefore, a different approach may be warranted.

9.5 POSSIBLE SOLUTIONS

This problem of how to address the potential non-stationarity of rainfall-temperature-runoff relationships under a variable or indeed a changing climate has been recognized as a major issue in water resource planning. For example, the South Eastern Australian Climate Initiative (SEACI) recently reported results from a project designed to examine the changing relationship between rainfall, temperature, and runoff (CSIRO 2012a, 2012b). The outcomes of this work show that during the recent 'Millennium Drought' in south-eastern Australia, the extended dry conditions led to fundamental changes in the rainfall-runoff relationship in some catchments, with the same amount of annual rainfall during the latter stages of the drought leading to much less runoff than was produced prior to the commencement of the drought (Figure 9.3). In addition, as shown for the Axe Creek catchment, a stream that was essentially perennial before the commencement of the drought became ephemeral, flowing for only 20% of the year in 2008. Much of this change in behaviour can be attributed to lower ground water levels (Figure 9.3), leading to a previously gaining stream becoming a losing stream (Chiew *et al*., 2011).

Petheram *et al*. (2011) extended this analysis to 34 catchments across south-eastern Australia; low relief, moderate rainfall catchments showed statistically significant reductions in runoff coefficient, slow flow, and hydrograph recession constants during the drought, while high relief, high rainfall catchments did not. They contend that this reflects the greater importance of ground water connectivity in low relief catchments. Petheram *et al*. (2011), however, also caution about the interaction between changed processes due to climate variability and those due to land use and land use change. In particular, they found that it was far more difficult to detect a changed runoff response in those catchments with very few farm dams, compared to those with many. Whether this reflects an increase in the number of farm dams during the drought, or it reflects the impacts of the surface

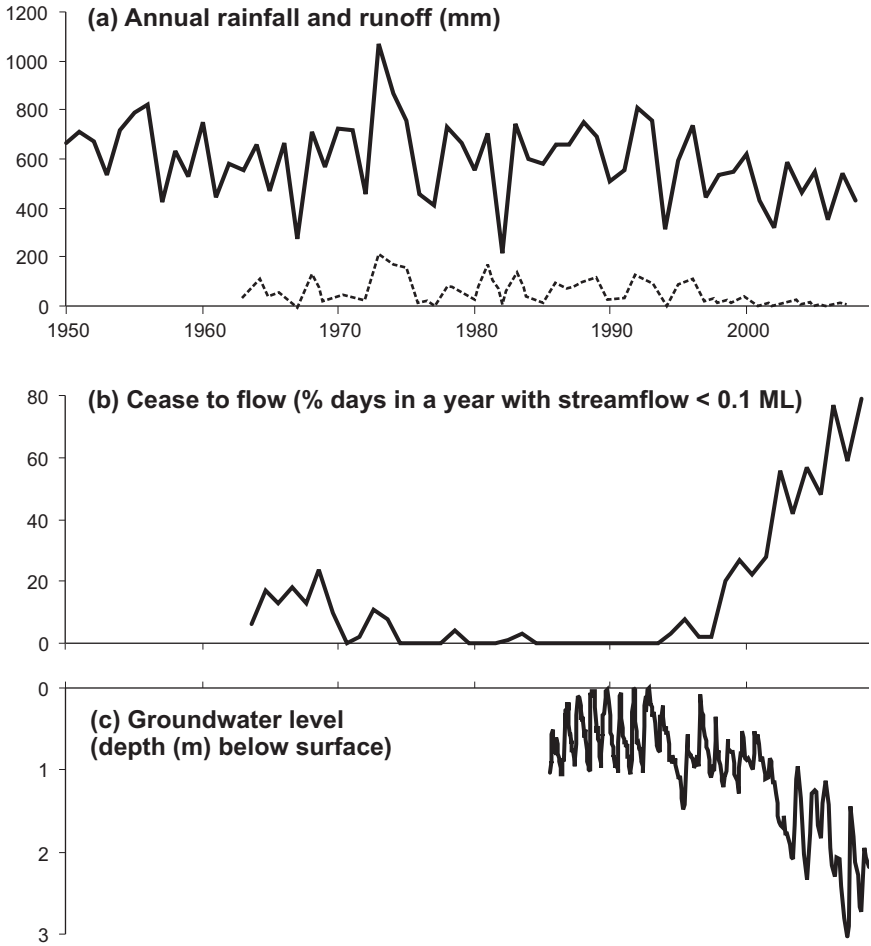

Figure 9.3 *Hydroclimate time series for the Axe Creek catchment in south-eastern Australia showing* ***(a)*** *rainfall (solid line) and runoff (dashed line),* ***(b)*** *cease to flow, and* ***(c)*** *ground water level. (Chiew* et al.*, 2011).*

water storage capacity in those catchments with pre-existing farm dams is not easy to determine, although McGee *et al*. (2012) suggest that farm dams can have a significant impact on streamflow response in the Canadian prairies.

Clearly for a rainfall-runoff model to adequately represent the hydrological behaviour of these catchments during the recent drought, it would need to have a reasonably sophisticated ground water - surface water module. It may also need to account for farm dam storages explicitly. Most current rainfall-runoff models would be unable to represent these behaviours. As the

Millennium Drought has recently ended in south-eastern Australia, it will be interesting to observe whether the changed rainfall-runoff relationship continues and if so, for how long. This, coupled with observations of ground water levels will guide the development of improved rainfall-runoff models able to represent these processes.

In addition to falling ground water levels, other studies have attributed changes in the hydrological response of catchments in south-eastern Australia during the Millennium Drought to other factors. Potter *et al*. (2011) report changes in the rainfall-temperature-streamflow relationship for 34 catchments across south-eastern Australia. They attribute around two-thirds of the observed reduction in streamflow to a reduction in mean annual rainfall and around 7% to increased temperatures experienced across the region during the drought. Potter and Chiew (2011) also show that it is not simply changes in mean annual rainfall which are important, with around 15% of the observed streamflow reduction in the Campaspe catchment in south-eastern Australia being due to a reduction in rainfall variability (lack of very wet months) and another 12% due to a change in rainfall seasonality (with most of the rainfall reduction occurring in autumn). Clearly, rainfall-runoff models used in climate change impact studies also need to be able to reflect the impact of these changed inputs on catchment hydrological functioning.

Given the issues raised here, three steps are proposed which should allow for the impacts of a change in hydrological processes under a changed or variable climate to be assessed:

1. Understand the dominant hydrological processes occurring in a catchment.
2. Improve model calibration and parameter estimation.
3. Change hydrological model structure to incorporate hydrological processes which are assumed to change under a modified climate.

9.6 CONCLUDING REMARKS

While it is important to continue to develop hydrological model structures which can account for changed hydrological processes, it is important to reiterate the comment made in the Section 9.2 that a rapidly changing information base means that it is more important than ever for information to pass rapidly from climate scientists to water managers. In addition, water

managers have decisions to make, and will use whatever information is readily available *in a short time frame* in order to make these decisions.

An example of this is provided by the recent expansion of the irrigation industry in Tasmania. Here, decision makers required an assessment of the impacts of climate change on water availability out to the year 2030 in order to determine which irrigation projects to implement. At the time of carrying out this assessment, a methodology to adequately account for the effects of climate non-stationarity on water availability in the region had not yet been developed. In order to make an informed decision however, water managers required whatever information was available in a short time frame. In order to deliver the information required to expand the irrigation industry in a sustainable way, Post *et al*. (2012a) adapted a methodology developed in the Murray-Darling Basin (CSIRO, 2008) to the Tasmanian context.

Determining the impacts of climate change on future water availability was achieved through the application of multiple rainfall-runoff models combined with numerous global warming scenarios and the output of 15 AR4 global climate models. Obviously such a methodology produced many scenarios of future water availability. Communicating these scenarios in a way that allowed the decision makers to understand the range of uncertainty inherent in the projections while still providing them with the data they needed to reach a decision was a difficult task. Ultimately, presenting the 10th and 90th percentile of results was chosen as the most appropriate method; however, the importance of labeling them as 'dry' and 'wet' projections rather than 10th and 90th percentiles of projected changes is not to be underestimated. Effective communication of the outputs of sometimes complex scientific investigations can allow the results of these investigations to be more readily adopted by the water industry (Post and Moran, 2011).

In attempting to refine our hydrological models in order to better account for non-stationarity under climate change, it is important to also continue to deliver information to stakeholders in a timely fashion. It is always important to quantify the uncertainty in this information. Uncertainties due to changed hydrological response in a changing climate are just one of many, and the impact of climate change on water resource availability is just one piece of information used by water planners and policy makers in reaching their decisions. It is prudent for climate scientists and hydrologists to remember this.

10

HOW TO COMBINE INDUCTIVE AND DEDUCTIVE APPROACHES TO PREDICTION?

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10.1 ABSTRACT

The implementation of a new modelling philosophy based on the combination of inductive and deductive reasoning approaches for predicting snowcover ablation and snowmelt runoff is illustrated. An inductive (i.e. top-down) modelling approach was used for representing landscape heterogeneity, whereas a deductive (i.e. bottom-up) approach was applied for detailed snowmelt process descriptions. Physically based hydrological land surface simulations, using distributed initial conditions of snowcover and incoming solar radiation, showed an appropriate representation of both the basin hydrographs and the snowcover ablation. Aggregated simulations were unable to describe the dynamics of the basin streamflow when the runoff response was largely governed by solar radiation. When temperature was a key factor in the onset of melt, the differences were less. Results indicate that the number of model units should be in concordance with the association between initial snow water equivalent (SWE) and melt energy to adequately represent the landscape heterogeneity in subarctic environments. The modelling methodology capitalizes on the strength of both modelling approaches, and appears to be an effective method to reduce the size of the parameter sets and still retain physical consistency. Therefore it is an appropriate methodology for applying physically based hydrological models in poorly or ungauged basins such as complex subarctic environments.

10.2 RÉSUMÉ

La mise en œuvre d'une nouvelle philosophe de modélisation basée sur la combinaison d'approches de raisonnement inductif et déductif pour la prévision de l'ablation nivale et du ruissellement nival est illustrée. Une approche de modélisation inductive (c.-à-d. descendante) a été utilisée pour représenter l'hétérogénéité du paysage, tandis qu'une approche déductive (c. à d. ascendante) a été appliquée pour les descriptions détaillées du processus de fonte nivale. Des simulations hydrologiques à la surface des sols, à base physique et reposant sur des conditions initiales distribuées de manteau neigeux et de rayonnement solaire incident, ont révélé une représentation appropriée à la fois des hydrogrammes de bassin et de l'ablation nivale. Les simulations globales n'ont pas permis de décrire la dynamique du débit du bassin versant lorsque la réaction de ruissellement était en grande partie dictée par le rayonnement solaire. Lorsque la température était un facteur clé au début de la fonte, les différences étaient moindres. Les résultats indiquent que le nombre d'unités de modèle devrait correspondre à l'association entre l'équivalent en eau de la neige (EEN) initial et l'énergie de la fonte pour représenter de manière suffisante l'hétérogénéité du paysage en milieu subarctique. La méthode de modélisation mise sur la force des deux approches de modélisation et semble constituer une méthode efficace pour réduire la taille des séries de paramètres tout en conservant une cohérence physique. Par conséquent, il s'agit d'une méthode appropriée pour l'application de modèles hydrologiques à base physique aux bassins non jaugés ou pauvrement jaugés, par exemple en milieu subarctique complexe.

10.3 INTRODUCTION

Making reliable statements about modelling hydrological processes at different spatial and temporal scales is a crucial aspect to hydrology and remains a major challenge in hydrological research. The main constraint is to consider and evaluate the effects of the numerous complex interactions among hydrological inputs, landscape properties, and initial conditions. Over the years there have been attempts to make modelling tools more rigorous and representations of hydrological processes more realistic, through incorporation of spatial and physical descriptions. While more sophisticated models result, they continue to suffer from restrictive assumptions, particularly the representation of landscape heterogeneity and

both parameter and modelling equifinality that result from transferring point scale observations and process descriptions to basin scales (Beven, 2002).

Traditionally, two main approaches to model building have been applied, deductive and inductive. The deductive or bottom-up approach, conceptualizes a model structure that is based on the belief that the physical system can be described by deterministic mathematical equations (Young, 2003). This deductive approach assumes that process knowledge acquired on small spatial and temporal scales can be used to predict the overall basin response by means of up-scaling small-scale process understanding. This was first outlined by Freeze and Harlan (1969) for a distributed physically based hydrological model. Typically, this means that physically based equations developed at laboratory or point-scale are usually applied to describe hydrological processes at larger scales (i.e. basin models).

Conversely, the inductive or top-down approach avoids theoretical preconceptions as much as possible in the initial stages of the analysis (Klemeš, 1983). The model structure is not pre-specified; rather it is inferred from the observational data. The approach consists of deriving behaviour through an analysis of its response based on the rationale that information or model complexity should be only added when the prior conceptualization was not able to describe the processes of interest. The inductive approach therefore has a model structure which is inferred from the data, whereas the model conceptualization is based on the predominant processes at the catchment scale (Sivapalan *et al*., 2003a; Littlewood *et al*., 2003).

Both approaches are challenged by scaling issues related to the nonlinearity of the hydrological processes (Beven, 2001). Limitations of the deductive approach are [1] that processes important at one scale may not necessarily be important at other scales (Blöschl and Sivapalan, 1995), and [2] the problems of model equifinality and parameter identifiability that result from explicit landscape representations and incorporation of detailed process descriptions (Beven, 2000; 2006). Distributed physically based models have large degrees of freedom since many parameters and initial conditions need to be set, and consequently, these models rely on calibration to account for the lack of knowledge in representing the landscape heterogeneity and to compensate for the insufficient understanding of physical processes and their interactions (Beven, 2006; Kirchner, 2006; McDonnell *et al*., 2007). Thus, fully distributed physically based models are usually restricted to small areas due

to their large requirements for data and computational time (Todini, 2007). Limitations of the inductive modelling approach are [1] it attempts to identify processes directly at the scales of interest, [2] it interprets these in terms of properties and processes occurring at finer scales, and [3] since data are usually rather limited, only simple and often physically unrealistic models can be inferred solely from the data (Sivapalan *et al*., 2003a).

Aided by increased computing power, increased process understanding, and the availability of digital terrain attributes, the most widely used modelling philosophy is the deductive approach describing a hydrological system by deterministic mathematical equations founded on well-known scientific laws (Beven, 2002; Ratto *et al*., 2007). Though these models have complex process descriptions, they often do not properly account for landscape heterogeneity and drainage basin hydrological dynamics (Beven, 1989; Kirchner, 2006; Savenije, 2009).

One challenge for the hydrological modelling community is to produce accurate and reliable predictions in ungauged or poorly gauged basins. The challenge is even more difficult in areas with limited data, such as in cold regions due to the limited gauging of subarctic and arctic environments. While the application of distributed and physically based models in such environments is restricted due to the lack of data, models based upon physically based process descriptions offer a valid approach to extrapolation beyond available observations.

Both inductive and deductive modelling methodologies have limitations when scaling is needed to adapt the model structure, the process descriptions, and the observational data. The methodology of this study seeks to combine the strengths of the two approaches used in hydrological modelling. The objective of this work is to demonstrate this combined modelling approach for predicting snowcover depletion and snowmelt runoff in cold region environments with limited input data while retaining physical integrity within the processes representation. In order to reduce the predictive uncertainty of physically based models in ungauged basins, this study seeks an appropriate model complexity, one that is physically based and parametrically efficient, for an area with limited data and that would allow both the scaling from point scale observations to catchment scale models and the identification of stable landscape based model parameterizations.

10.4 STUDY AREA

The study area is the Wolf Creek Research Basin (WC) which lies on the interior edge of the Coast Mountains at approximately 61° N latitude, 155° W longitude (Figure 10.1). The WC basin encompasses an area of 195 km^2 and is located in the northwest of Canada 15 km south of Whitehorse. The basin is part of the southern mountainous headwaters of the Yukon River Basin and has a generally northeasterly aspect with elevations ranging from 800 to 2035 m a.s.l. and a median elevation of 1325 m a.s.l. The climate is sub-arctic continental which is characterized by a large variation in temperature, low relative humidity, and relatively low precipitation. Mean annual temperature is in the order of -3°C with summer and winter extremes of 25° and -40°C respectively. Mean annual precipitation is 300 to 400 mm with approximately 40 percent falling as snow (Pomeroy *et al*., 1999). The

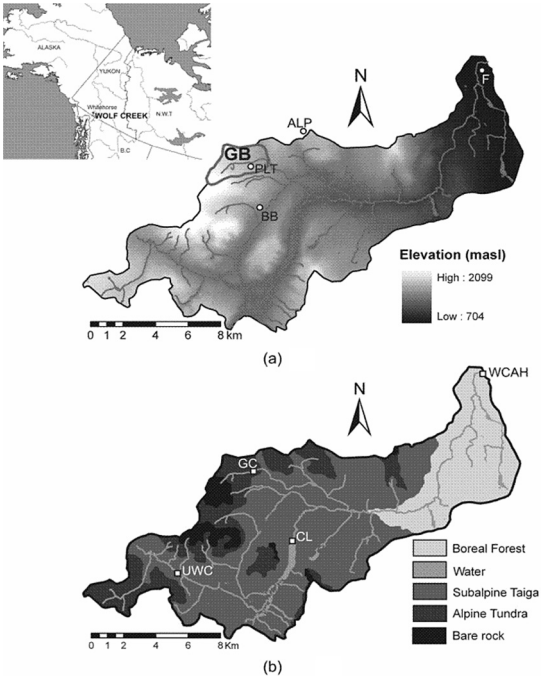

Figure 10.1 *Wolf Creek Research Basin (WC).* ***(a)*** *Topographic map. GB: Granger Basin. Circles indicate meteorological stations (PLT: Plateau, ALP: Alpine, BB: Back-brush, and F: Forest),* ***(b)*** *Land-cover map. Squares indicate streamflow gauge stations. (UWC: Upper Wolf Creek, GC: Granger Creek, CL: Coal Lake, and WCAH: Wolf Creek Alaska Highway). Inset shows the location in Canada.*

WC basin is within the sporadic discontinuous permafrost zone, and permafrost is present in north facing (NF) slopes, poorly drained areas, or areas with significant organic layers. In permafrost areas and the riparian zones, soils are capped by an organic layer up to 0.4 m thick consisting of peat, lichens, mosses, sedges, and grasses (Carey and Quinton, 2005).

The WC basin spans three major environments separated primarily on a gradient of elevation (Figure 10.1b). The boreal forest (spruce, pine, aspen) is found in lower areas (800-1300 m a.s.l.), subalpine taiga (shrub tundra) is found at mid-elevations (1300-1800 m a.s.l.), while alpine tundra (short shrubs, forbs, and bare rock) dominates high elevation areas (1800-2035 m a.s.l.). These ecological zones cover 22, 58 and 20% of the basin area respectively (Francis, 1997). Granger Basin (GB) is a small 8 km^2 sub-basin located in the northwest edge of WC basin (see Figure 10.1a) drained by Granger Creek with a length of approximately 3 km. Physiographically, GB is characterized by a northeasterly aspect and ranges in elevation from 1310 to 2035 m a.s.l; it encompasses the alpine tundra and shrub tundra environments. The selection of GB resulted from the extensive existing field observations of the WC research project (Janowicz, 1999) which included landscape snow survey transects measured on a daily basis during snowmelt, meteorological and soil moisture observations performed in different landscapes (e.g., UB: upper basin, PLT: plateau area, NF and SF: north and south facing slopes, and VB: valley bottom) within the basin (Janowicz, *et al*., 2002; Pomeroy *et al*., 2003; McCartney *et al*., 2006; Bewley *et al*., 2007).

10.5 MODELLING STRATEGY

Prediction of snowcover depletion and spring melt runoff in subarctic and arctic basins is challenging due to the combination of their remote location and the importance of the winter processes (e.g. snow accumulation and redistribution). Streamflow in these regions is generally difficult to gauge well due to winter inaccessibility (Pomeroy *et al*., 2007).

The conceptual methodology of this study is based on combining the strengths of the two approaches used in hydrological modelling. An inductive approach was used for the identification of the spatial model units (i.e. basin segmentation) based on a basin wide understanding of the main hydrological responses, while a deductive modelling approach, based on a

detailed process description, was applied in each of the model units to generate the physically based forcing data and process representations. This approach follows those ideas proposed by Dooge (1986) about the need to define parameterization of microscale effects and the search for macroscale laws to properly describe the dynamics of intermediate size systems categorized by both high complexity and degree of organization.

The modelling methodology of this study consists of distributed landscape based simulations of snowcover ablation and snowmelt runoff using a land surface hydrological (LSH) model in the WC basin. The simulation period included the 2002 and 2003 snowmelt seasons. The modelling techniques involved up-scaling exercises from landscape based simulations performed with two models, a small-scale hydrological model, and a land surface scheme (LSS) (Dornes *et al*., 2008a; 2008b) in GB. These models were used to investigate the effects of including explicit landscape representation and the effects of varying degrees of spatial complexity in the initial conditions and forcing data on snowmelt simulations. In order to evaluate the performance of the distributed landscape based model in WC, model results were compared to simulations using an aggregated modelling approach assuming a basin average initial SWE and incoming solar radiation which was not corrected for slope and aspect effects.

Model description

As part of the MEC (Modélisation Environmentale Communautaire) developed by Environment Canada, the MEC – Surface and Hydrology (MESH; Pietroniro *et al*., 2007) is a stand-alone LSH model configuration that couples an LSS, specifically the Canadian Land Surface Scheme (CLASS) with hydrological routing schemes. Representation of spatial heterogeneity is based on a mosaic approach using the Group Response Unit (GRU) concept (Kouwen *et al*., 1993) where areas with similar land cover, soils, etc., are grouped with no requirement for grids or sub-basins to be hydrologically homogenous. The implicit assumption is that each individual component of the land surface mosaic has the same response for given inputs of energy and water. GRUs are grouped together into predefined square model grids where energy and mass balances are calculated, whereas the runoff generated from the different groups of GRUs is summed together and then routed to the stream and river system. This approach has the advantage that the location of the GRU within a grid is not important in the

routing scheme and that the parameters are landscape dependent rather than sub-basin based. Since the location of the landscape element within the calculation unit is not critical, the size of the area of each of these elements is controlled by only the input data heterogeneity. This spatial aggregation is appealing because it reduces the total number of model elements but retains an adequate representation of the landscape heterogeneity (e.g., Pietroniro *et al*., 1996; Pohl *et al*., 2005; Davison *et al*., 2006). The routing scheme (Soulis *et al*., 2000; 2005) includes the adaptation of CLASS to sloped terrain drainage functions and its coupling to the routing scheme of the WATFLOOD model (Kouwen, 1988). This involved the inclusion of physically based transfer functions between the soil column and the micro-drainage system within each GRU. The fundamental drainage element is conceptualized by an assembly of sloped blocks connected to a stream and with the drainage system. Excess surface water drains to the micro-drainage system as overland flow.

The horizontal near-surface flow, called interflow, q_{int}, occurs through the soil matrix and the macropore structure, leaving the control volume through the seepage face. It is conceptualized as a shallow aquifer flow model assuming that q_{int} occurs almost entirely when soil moisture is between saturation and field capacity (Soulis *et al*., 2000).

Routing in MESH is based on a storage routing method (Kouwen *et al*., 1993). Inflow for each river reach consists of overland flow, interflow, baseflow, and channel flow from all contributing upstream basin elements, whereas outflow is related to the storage through the Manning formula.

In this study, the CLASS version 3.3 coupled into MESH 1.0b was used. CLASS (Verseghy 1991; Verseghy *et al*., 1993) includes a physically based treatment of energy and moisture fluxes between the vegetation canopy, the snowcover, and the soil layers. Vegetation canopies in CLASS can be represented by four main vegetation types. Energy fluxes are determined by summing component contributions along a flat horizontal plane that is assumed to have zero thickness and therefore no heat storage capacity. The resulting surface flux is directed either to the ground, snow pack, or canopy. CLASS has a three layer soil representation where textural contents are explicitly set. Additionally, surface parameters for each model tile such as soil drainage index, DNR, and soil permeable depth, SDEP [m], control the drainage through the bottom of the soil profile, and the depth of the soil. The

flux of energy across each soil layer boundary is evaluated using the flux-gradient relation for heat conduction in one dimension. Moisture fluxes through the soil layers are calculated using one-dimensional unsaturated Darcian flow in the case of gravitational drainage, and the Green-Ampt method for infiltration.

The snow model uses a coupled energy and mass balance at the top and bottom of the snow pack to calculate an internal energy state. When the surface or average layer temperature rises above 0°C, this excess energy is used to melt part of the snow pack and the temperature is set back to 0°C. Snow albedo and density vary with time according to exponential functions. Snowcover is assumed to be complete above a limiting depth of 0.10 m (D_{100}); otherwise fractional snow coverage is calculated through the employment of a snowcover depletion curve. Meltwater from the surface percolates through the snow pack and refreezes until the temperature of the snow pack reaches the freezing point, upon which any further melt reaches the base of the snow pack.

The Cold Regions Hydrological Model (CRHM; Pomeroy *et al*., 2007) was used to generate the distributed solar forcing for MESH. Incoming solar radiation was corrected by slope and aspect (Dornes *et al*., 2008a; 2008c) and applied to NF and SF slopes. This is accomplished by the modular features of CRHM that allow for the partitioning of the incoming solar radiation into direct beam and diffusive components and the corrections for slope, aspect, and cloudiness conditions. To include the corrected incoming short-wave radiation in the MESH model, the forcing-data scheme was modified to include the independent allocation of the solar forcing for each GRU.

Spatial model representation

The definition of the spatial model elements is an arbitrary criterion given the difficulty, or impossibility, of finding an optimum element size that can represent measurements, processes, and modelling scales (Blöschl, 1999). The choice of a model resolution determines what variability can be explicitly and implicitly represented (Grayson and Blöschl, 2001). The representation of the landscape heterogeneity was based on intense field observations during several years of research in WC and in arctic environments of snow accumulation, ablation regimes, and runoff generation processes. GRU delimitation was based on landscape tiles defined according to their distinct parameters that are relevant for snowmelt such as initial

conditions (i.e. end of winter snowcover characteristics), vegetation cover (i.e. alpine, shrubs, and forest), and topographic characteristics (i.e. slope and aspect) (Figure 10.2a). Slopes with angles lower than 20° were assumed to be equivalent to horizontal terrain. The exposures explicitly considered were those relevant to both snow accumulation and ablation processes. Therefore, NF and SF slopes were included due to their distinct energy and snow accumulation regimes as a result of redistribution of snow by wind, whereas the EF slopes were explicitly included due to the typical presence of snow drifts as a result of their lee location with respect to the dominant western wind direction (McCartney *et al*., 2006). Vegetation types, alpine tundra, shrubs, and boreal forest were also explicitly considered due to their important role in snowfall interception, snow accumulation regimes, and

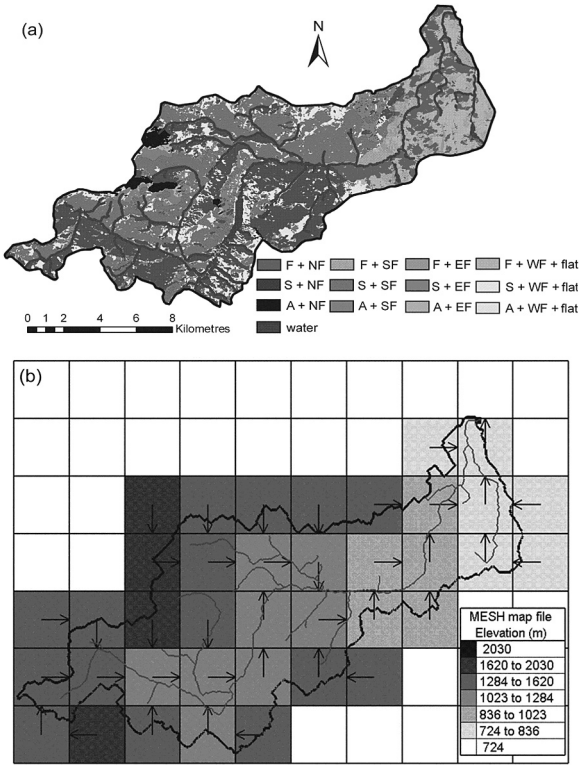

Figure 10.2 ***(a)*** *Illustration of the GRUs used for landscape model representation of WC in the MESH model. F: Forest, S: Shrub, A: Alpine, NF: North facing slope, SF: South facing slope, EF: East facing slope, and WF: West facing slope.* ***(b)*** *Illustration of the model grid used to aggregate runoff calculations. Arrows represent flow direction and internal lines the drainage network.*

snow pack energetics (Pomeroy *et al*, 1999; Carey and Woo 2001a; McCartney *et al*., 2006). Shrub areas developed the deepest snowcovers whereas shallow and wind-eroded snowcovers formed at the forest and alpine sites respectively. In the shrub area, snow is blown from short shrubs and exposed areas to sheltered and tall shrub sites resulting in very heterogeneous snowcovers (McCartney *et al*., 2006; MacDonald *et al*., 2009). In the forest site, intercepted snow is mostly retained in the canopy from where it sublimates resulting in shallow snowcovers (Pomeroy *et al*., 1999). At the alpine site, the lack of a conspicuous vegetation cover and its exposed location due to the elevation, lead to eroded snowcovers as a result of its source role in the snow transport process (Pomeroy *et al*., 1999).

A model grid of 3 x 3 km was used to aggregate runoff calculations from GRUs (Figure 10.2b). Thus, the 195 km^2 basin was divided into a 10 by 7 square grid. The grid size was selected to approximate the area of GB in order to compare the distributed results of a single 9 km^2 grid cell with the GB observations.

The spatial variability of the available snowmelt energy is also related to topography and vegetation. Pomeroy *et al*. (2003) found substantial differences in energetics and rates of snow ablation over shrub tundra surfaces of varying slope and aspect. Incoming solar radiation on SF slopes was substantially higher that on the NF. These differences in solar radiation on NF and SF slopes were reduced with cloudiness conditions, and caused small differences in net radiation in early melt; however, as shrubs and bare ground emerged due to faster melting on the SF slope, the albedo differences resulted in large positive values of net radiation to the SF, whilst the NF fluxes remained negative. The presence of shrubs also has important influences in driving ablation regimes; decreasing the albedo values and governing snowmelt energy (Sturm *et al*., 2001; Pomeroy *et al*., 2006). Further, McCartney *et al*. (2006) observed that the greatest snow accumulation in tall shrubs plays a key role in the snowmelt streamflow regime.

Observations, data, and initial conditions

Four meteorological stations were used to generate the distributed forcing data for the MESH model. The stations are located in the three major environments (forest, shrubs, alpine), covering not only the different landscape types but also the basin elevation ranges (see Figure 10.1). Table 10.1 describes the location variables observed at 30 minute intervals at the meteorological stations.

Table 10.1 *Meteorological stations within Wolf Creek basin.*

Station ID	UTM location		Elevation (m a.s.l.)	Meteorological and state variable measured*
	Northing (km)	Easting (km)		
Forest (F)[1]	6718	503	750	K↓,K↑, T_a, RH, U, P, S_d, T_s, S_m
Alpine (ALP)[2]	6715	492	1616	K↓,K↑, T_a, RH, U, P_{atm}, P, S_d, T_s, S_m
Buck Brush (BB)[2]	6710	489	1250	K↓,K↑, T_a, RH, U, P, S_d, T_s, S_m, SP
Plateau (PLT)[2]	6712	490	1460	K↓,K↑, L↓,T_a, RH, U, P, S_d, T_s, S_m

[1,2]Elevation from ground surface for meteorological sensors:
1 is 10 m (above canopy), 2 is 2 m.
*Incoming (K↓) and outgoing (K↑) short-wave radiation, incoming long-wave radiation (L↓), air temperature (T_a), relative humidity (RH), wind speed (U), precipitation (P), barometric pressure (P_{atm}), snow depth (S_d), soil temperature (T_s), soil moisture (S_m), and snow pillow (SP).

Distributed values of each forcing variable for the model domain were obtained by linear interpolation values from the four stations based on the model domain. Since the snowmelt season is a relatively short period, a constant environmental lapse-rate correction (-7.65°C/km), was used to compensate for elevation effects on T_a values. The atmosphere pressure (P_{atm}) values were distributed by calculating for each grid element the values measured at the ALP station using a barometric equation. Atmospheric long-wave radiation (L↓) values measured at the PLT station were uniformly distributed over the model domain. Due to uncertainties in the precipitation (P) values recorded using unheated tipping bucket devices at the F, PLT, and ALP stations, P values measured at the BB station using an automatic precipitation gauge, consisting of a storage bin filled with antifreeze used to convert snow to liquid water, were corrected for wind-induced undercatch. The P values were uniformly distributed over the basin since no consistent relationship between snowfall and elevation was observed in the basin (Pomeroy *et al*., 1999).

Soils types can be related to the three principle ecosystems of WC basin (Francis, 1997; Janowicz *et al*., 2003). Forest soils are coarse consisting of loamy sand and sandy loam with a thin organic layer. Shrub tundra soils are medium to coarse textured consisting of silty loam in the upper horizons (0 to 18 cm) with sandy loam in the lower horizons. The organic layer is usually

less than 10 cm thick with the exception of the NF slopes where it is usually well defined with depths of about 18-25 cm (Carey and Woo, 2001b). Alpine tundra soils are primarily silty loam with a very thin (< 2 cm) or nonexistent organic layer. Presence of boulders of up to 1 m is frequent and scattered about the landscape. Since soils are fully frozen at the time of snowmelt, initial soil moisture content was based on fall observations at different depths using Time-Domain Reflectometry (TDR) sensors at the A, BB, and F sites. As for pre-melt conditions, no ponded water was considered and minimal liquid water content (0.04) was assumed for the entire soil column; however, these values are indicative since soil moisture content can potentially be affected by sporadic melt or infiltration events during winter. Initial soil temperatures were obtained from observations at the same sites using buried thermocouples with the same reading depths. Temperatures of the canopy were set to match the air temperature, following Sicart *et al*. (2004).

Snowcover conditions prior to the onset of melt were set from snow survey transects located in different locations (UB, NF, SF, VB, PLT) of the shrub and forest sites. To account for snowcover redistribution, field observations describing the typical presence of snowdrifts on the NF and EF slopes (Pomeroy *et al*., 2003; 2004; McCartney *et al*., 2006) were considered. As a result, SWE values corresponding to snowdrift conditions were assigned to the GRUs with NF and EF slopes in the shrub landscape area. In the forest landscape, the same initial snowcover was applied to all GRUs reflecting interception rather than wind redistribution of SWE. The alpine environment was initialized with values from the ALP station and UB snow survey in GB.

Distributed simulations of MESH were validated where data were available. Thus, snowcover ablation was evaluated in GB using snow survey data (Dornes *et al*., 2008b), at BB station using snow pillow data, and at the F site for 2003 using snow survey data from a snow grid of 21 by 21 points. Streamflow model performance was analyzed at four stations within the WC basin (see Figure 10.1) and subject to different flow regimes during the melt season.

Model calibration

Automatic calibration of the MESH model was performed using the Dynamically Dimensioned Search (DDS) global optimization algorithm (Tolson and Shoemaker, 2007). The calibration problem was solved using a single objective function by maximizing the Nash Sutcliffe Efficiency (E)

coefficient (Nash and Sutcliffe, 1970) between simulated and observed streamflow values at the WC basin outlet (WCAH). Since the snowmelt runoff is described by a relatively well-defined single hydrograph, the *E* coefficient was selected due to its simplicity and because it is the most widely used reliable statistic for assessing the goodness of fit of hydrological models.

The 2002 snowmelt season was used as the calibration year while the 2003 snowmelt season was selected as the validation period. Since the modelling of the entire WC basin is an up-scaling exercise of the results found in GB, calibration was restricted to the hydrological parameters that describe flow routing at the landscape or GRU scale (i.e. overland, subsurface flow) and streamflow, while the values of the parameters that describe snowmelt were set according to the optimum values found for CLASS in GB (Dornes *et al*., 2008b). Parameter ranges were restricted according to both distributed

Table 10.2 *Optimized flow routing parameter values for MESH in WC basin. Forest, Shrub, and Alpine GRUs include the NF, SF, EF, and WF-flat landscape units. Parentheses indicate parameter bounds.*

	GRU			River network
	Forest	**Shrubs**	**Alpine**	
DRN - Drainage index	0.500 (0-1)	0.615 (0-1)	0.817 (0-1)	
Dd - Drainage density [m^{-1}]	2.765 (0-5)	2.324 (0-5)	3.350 (0-5)	
XSLP - Average GRU slope [m m^{-1}]	0.015 (0.01-0.05)	0.047 (0.01-0.05)	0.005 (0.01-0.05)	
GRKF - Coef. K_{sat} change in 1st metre of soil	0.22 (0.2-1)	0.40 (0.2-1)	0.92 (0.2-1)	
MANN - Manning's n overland flow	0.034 (0.025-1)	0.040 (0.025-1)	0.046 (0.025-1)	
WFCI - Surface K_{sat} [m s^{-1}]	5.9E-6 (1E-9-1E-5)	0.040 (0.025-1)	0.046 (0.025-1)	
wf_r2 - River roughness				0.792 (0.1-0.95)
ZPLIMS - Lower limit ponding water [m]				0.078 (0.02-0.015)
ZPLIMG - Upper limit ponding water [m]				0.176 (0.15-0.19)

observations at GB (e.g., McCartney *et al*., 2006; Bewley *et al*., 2007) and prior information (e.g., Verseghy *et al*., 1993; Davison *et al*., 2006) for similar environments. Figure 10.3 shows the CLASS landscape based simulations of the snowcover ablation when distributed and solar forcing and initial conditions are considered. Forest parameters not included in the simulations of GB were set to the default values used in the Global Environmental Multi-scale (GEM) model of Environment Canada.

Calibration was constrained by assigning the same parameter value to all GRUs within each main vegetation cover. For example, NF slope, SF slope, EF slope, and WF slope and flat landscape units in the shrub area each shared the same parameterization. Similar approaches were applied in the alpine and forest area. Table 10.2 illustrates the parameters values defined using the DDS algorithm.

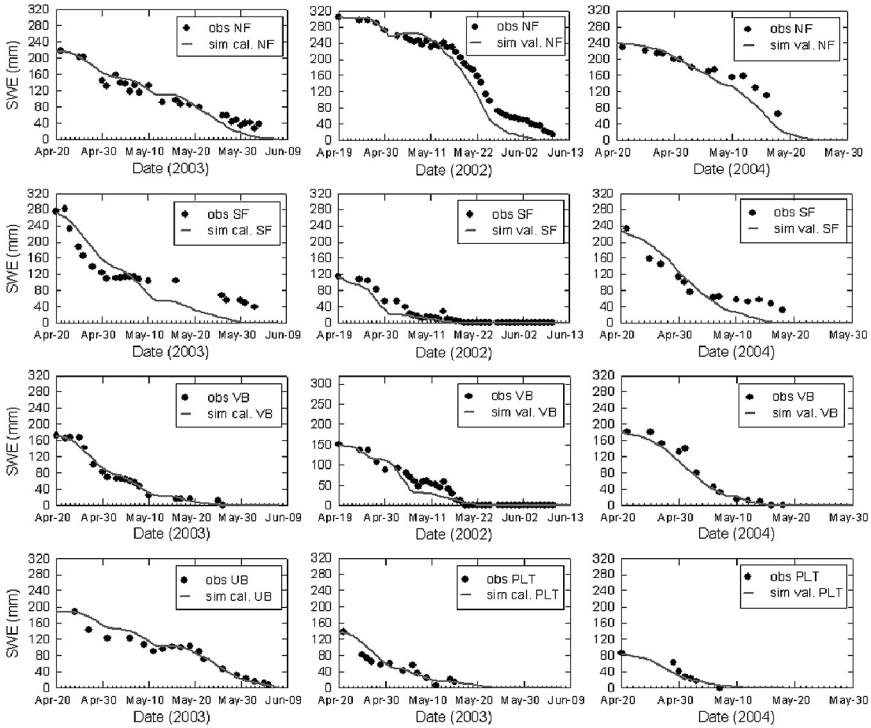

Figure 10.3 *Observed and simulated landscape SWE values with CLASS in Granger Basin (GB) using distributed initial conditions (SWE) and incoming short-wave radiation (K↓). Cal. and Val: calibrated and validated simulations. NF and SF: north and south facing slopes, VB: valley bottom, UB: upper basin, PLT: plateau area. (Adapted from Dornes* et al.*, 2008b)*

10.6 MODELLING RESULTS

Figure 10.4 shows the streamflow simulations at the WCAH station, at the outlet of the basin, for the 2002 and 2003 snowmelt seasons using distributed and aggregated approaches respectively. Overall, an accurate representation of the observed hydrograph was seen when the distributed approach (i.e. using distributed initial conditions and solar forcing) was applied in both the calibration and the validation periods (Table 10.3). Simulated values adequately described the different dynamics of the observed streamflow that resulted in a steady and late hydrological response in 2002 with a gradual rise and recession of the hydrograph limbs compared to the early, sharp, and ephemeral peak observed in 2003. The model efficiency resulted in *E* coefficients of 0.88 and 0.68 for 2002 and 2003 respectively. Although underestimation of the hydrograph peak degraded the model performance in the validation period in 2003, an appropriate representation of both the timing of the peak and the recession was seen.

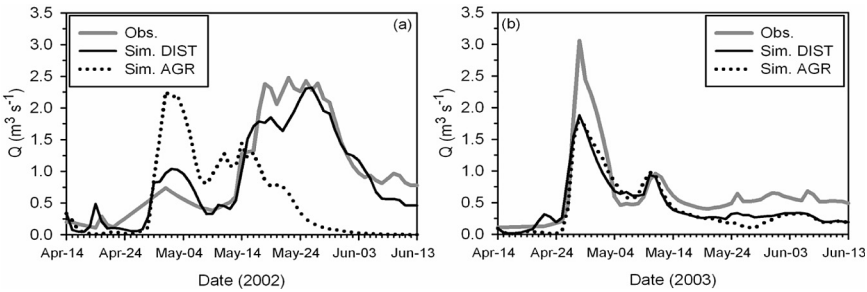

Figure 10.4 *Comparison between observed and simulated hydrographs at the Wolf Creek Alaska Highway (WCAH) gauge station. DIST and AGR: distributed and aggregated modelling approaches.* ***(a)*** *2002 calibration,* ***(b)*** *2003 validation.*

Table 10.3 *Streamflow model performance (E, Nash-Sutcliffe coefficient) obtained at the WCAH gauge station in Wolf Creek basin. DIST. and AGR: Distributed and aggregated modelling approaches. 2002 was the calibration year.*

Year	Modelling approach	
	DIST	AGR
2002	0.88	-1.06
2003	0.68	0.67

Conversely, when the aggregated approach was applied by assuming a basin-wide average initial snowcover and uniform (i.e. over horizontal terrain) incoming solar radiation, the model performance was drastically degraded in 2002 with a less noticeable effect in 2003 compared to the distributed approach. To avoid the possible influence of calibration in the comparison between distributed and aggregated approaches, simulations using the aggregated approach were also calibrated in 2002 using the DDS algorithm. The inappropriate prediction of the observed hydrograph that resulted in a negative *E* coefficient highlighted the importance of considering the spatial distribution of initial conditions and solar forcing in model performance.

Reasons that might explain the different model performance from using both distributed and aggregated approaches can be found by analyzing the basin streamflow response. Typically, the streamflow response of the WC basin is controlled by sequential melt timing between the different ecosystems and by the shrub tundra zone due to its larger extent, central location, and deeper snow packs compared to the forest and alpine areas. Melt starts around the middle of April in the forest area, followed by the shrub tundra zone with an onset of melt around April 20, whereas melt in the alpine area starts around the end of April. Furthermore, streamflow dynamics can by affected by warm air advection over the melting snowcover, enhancing melt, and accelerating streamflow response. A combination of these processes can lead to synchronized or unsynchronized melt events between the different landscapes resulting in different basin streamflow responses. For the 2002 snowmelt season, the onset of melt was rather late and driven by increases in both air temperature and incident solar radiation. These atmospheric factors, combined with large snowdrifts observed on NF slopes, resulted in a late and single peak streamflow response. The aggregated model using a basin average initial SWE and incoming solar radiation not corrected by topography, simulated melts earlier than occurred. The 2003 snowmelt season showed an onset of melt as a consequence of above freezing air temperatures earlier in the season that stopped as the temperatures fell below the freezing point on May 2 (Figure 10.5). This phenomenon generated a sharp and early streamflow response. Later in the season, the increasing air temperatures and solar radiation combined with lower amounts of initial snow on the NF slopes and comparatively larger snowcovers on the SF slopes resulted in a steady streamflow response. Simulations using the aggregated approach at the basin

outlet did not differ from those using the distributed approach and both replicated the observed peak hydrograph, although the model performance degraded as the season progressed. Moreover, simulated streamflow values in 2003 showed an early melt event in concordance with an air temperature increase around April 20 that was not recorded in the observed hydrograph presumably due to the delay of streamflow as a result of snow dam effects.

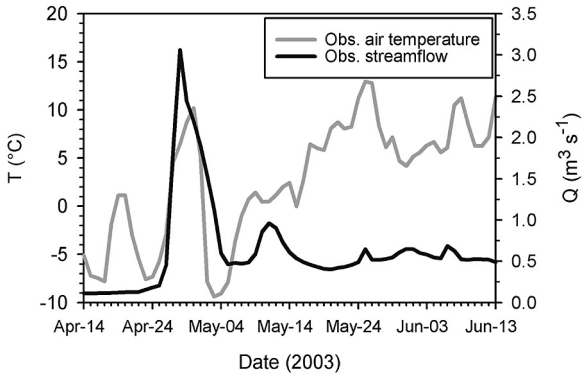

Figure 10.5 *Illustration on a daily basis of the incidence of air temperatures in the dynamics of the streamflow response observed at WCAH gauge station in the 2003 snowmelt season.*

Distributed streamflow simulations are displayed in Figure 10.6 in CL, GC, and UWC gauge stations for 2002 and 2003 respectively. The main contribution of Coal Lake is the maintenance of a base flow. This situation was observed in 2003 where the flows at CL did not influence the peak hydrograph at the Wolf Creek outlet; however, a larger contribution to the basin response was observed in 2002, where both hydrographs showed the same shape and timing. Simulated values for the 2002 snowmelt season at the GC station (Figure 10.6c) showed an appropriate timing of the peak; however, an underestimation of the observed hydrograph peak value was seen. Simulated streamflow values in 2003 (Figure 10.6d) showed a lack of agreement with the observed hydrograph resulting in earlier runoff volumes and lower peak estimations.

Simulated values at the UWC gauge station in 2002 (Figure 10.6e) showed early runoff volumes that were not recorded in the observed hydrograph. Despite the differences between the observed and the simulated hydrograph shapes, spring runoff volumes were reasonably close. Similarly, for the 2003

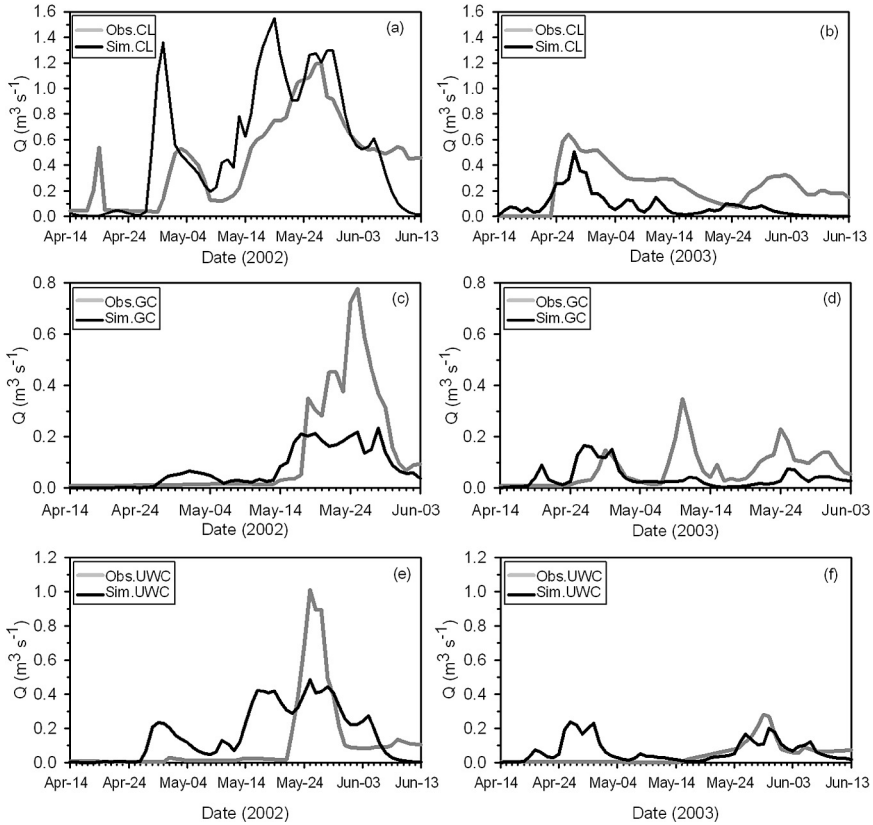

Figure 10.6 *Comparison between observed and validated simulated hydrographs.* ***(a)*** *and* ***(b)*** *at the Coal Lake (CL) gauge station (drainage area: 71 km²),* ***(c)*** *and* ***(d)*** *at the Granger Creek (GC) gauge station (drainage area: 6 km²), and* ***(e)*** *and* ***(f)*** *at the Upper Wolf Creek (UWC) gauge station (drainage area: 15 km²) for 2002 and 2003 respectively within each pair.*

snowmelt season, simulated values showed an earlier snowmelt runoff response (Figure 10.6f). Overall, differences between distributed simulated and observed streamflow values illustrate that the model with the given spatial resolution is not able to accurately replicate the complexity of small-scale snowmelt runoff processes. Good agreement of simulated and observed runoff volumes and less important differences in replicating the runoff dynamics were seen in 2002 when the snowmelt runoff response was characterized by a single peak event. Larger differences in describing both the observed dynamics and runoff volumes were observed in 2003 as a result of the complex runoff response that resulted in lower flows and multi-peak

hydrographs. The inherent observation errors of low flow volumes, and the inaccessibility of the gauge stations early in the melt season, could also contribute to observational uncertainty.

Distributed simulated values of snowcover depletion were extracted in those places where distributed observations were available. Figure 10.7 illustrates the comparison between simulated snowcover depletion values with snow pillow observations at the BB station for 2002 and 2003 and with snow survey values measured at the F station in 2003. Evaluation of the model performance against snow pillow data was conducted by comparing the simulations against the 5-day average of the observational data. Overall, there is reasonable agreement between simulations of the snowcover depletion and observed snowcover values for both years (Figures 10.7a and b), particularly since the snow pillow data represents the melting of an unvegetated snow pack. Differences were more evident in 2003, where the model results were not totally able to describe the observed fast depletion of the snow pack. In the forested area (Figure 10.7c), an adequate description of the early stages of melt was seen despite the sparse data through the snowmelt period.

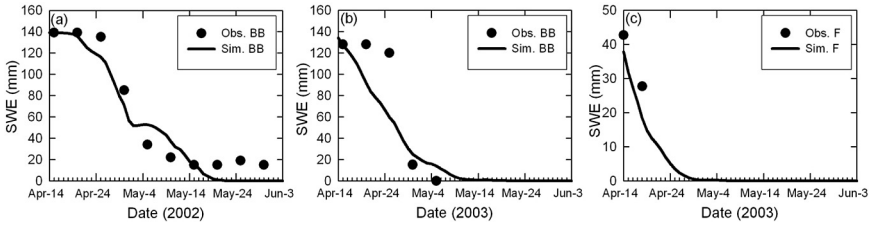

Figure 10.7 *Comparison between observed and validated simulated snowcover depletion.* ***(a)*** *and* ***(b)*** *Buck-brush (BB) site (snow pillow data), and* ***(c)*** *Forest (F) site (snow survey data).*

Limitations to this approach were i) coarse scale of modelling compared to small sub-basins with stream gauges in WC prevented small scale validation of the model, ii) non-physical snowcover depletion and vegetation parameters were present that could not be related to field observations, and iii) calibration of shrub and vegetation parameters may have masked effects of shrub emergence, small-scale advection, and micrometeorological differences between tiles. There needs to be further assessment of whether to include these in the model.

10.7 CONCLUSIONS

This study illustrates an example of a new approach for physically based modelling of snowcover ablation and snowmelt runoff in complex subarctic environments with limited data while retaining integrity in the process representations. This modelling methodology is based on the combination of inductive and deductive reasoning approaches. The inductive (i.e. top-down) modelling approach, based on a basin-wide understanding gained from observations of the main factors that drive the snowmelt processes in northern mountainous areas, was used for representing the landscape heterogeneity, hence the spatial model representation was based on landscape units. The deductive (i.e. bottom-up) modelling approach was applied for detailed process descriptions that incorporated physically based algorithms with *a priori* parameter sets describing snowmelt. The philosophical basis of the modelling approach is the desire to describe the processes in as physically realistic a manner as possible, given the availability of data and parameters to run the model.

Simulated streamflow values using distributed initial conditions of snowcover and incoming solar forcing were able to describe the different timing and magnitude of the basin responses observed in both of the study years. When the aggregated approach was applied, the model was unable to simulate the dynamics of the basin streamflow in 2002 when the runoff response was largely governed by solar radiation and the negative association between snow accumulation and melt energy observed in the shrub tundra area. Conversely, the differences between the distributed and aggregated approaches were less important when temperature was a key factor as in the onset of melt in 2003. Melt synchronicity was reduced with greater incoming short-wave radiation, so the more clear skies prevailed, the greater the duration of melt over the basin. The distributed modelling approach was able to properly describe the sequential melt timing, whereas the aggregated approach failed. Under conditions with greater cloudy skies, both modelling approaches had a very similar performance as a result of a less important effect of the initial conditions and solar forcing on the onset of melt.

The selection of landscape units defined according to premelt snowcover conditions, vegetation cover, and topographic characteristics appears to be an effective method to reduce the size of the parameter sets and still retain

physical consistency. These model units can be viewed as signatures of hydrological variability or predictor variables (Sivapalan *et al*., 2003b; Sivapalan, 2005) which have a significant importance for accurate predictions in northern and mountain basins typically characterized as ungauged or poorly gauged basins and for land surface-atmospheric interactions at both small and larger scales.

11

PUB IN PRACTICE AT THE NATIONAL SCALE: THE CASE OF SOUTH AFRICA

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11.1 ABSTRACT

The extent to which some of the achievements of the PUB decade can be applied in practice is discussed in the context of South Africa. The country has a long history of using hydrological models for practical water resources assessment, but their application has been largely based on traditional, pre-PUB approaches using calibration in gauged basins and rather subjective parameter transfer approaches to ungauged basins. This chapter outlines some of the more recent advances that have been made in the use of uncertainty approaches in South Africa and identifies some of the issues with implementing these in practice. The general conclusion is there is much to be gained from the further implementation of PUB principles in practice, but greater efforts are required to convince practitioners and decision makers of the advantages.

11.2 RÉSUMÉ

La mesure suivant laquelle certains des accomplissements de la décennie de prévisions en bassins non jaugés (PBNJ) peuvent être appliqués dans la pratique est traitée dans le contexte de l'Afrique du Sud. Ce pays possède une longue histoire d'utilisations de modèles hydrologiques pour l'évaluation pratique des ressources en eau, mais leur application a été largement basée sur les approches traditionnelles, pré-PBNJ, faisant appel à l'étalonnage dans les bassins jaugés et à des approches plutôt subjectives de transfert des paramètres aux bassins non jaugés. Le présent chapitre décrit certains des progrès les plus récents ayant été accomplis dans l'utilisation d'approches d'incertitude en Afrique du Sud et cerne certains des problèmes

liés à leur mise en œuvre dans la pratique. La conclusion générale qui se dégage est qu'il y a beaucoup à gagner de l'adoption plus poussée des principes de PBNJ dans la pratique, mais qu'il faut déployer davantage d'efforts pour convaincre les professionnels en exercice et les décideurs des avantages offerts.

11.3 INTRODUCTION

A large proportion of the research undertaken as part of the PUB decade has been directed at developing the science of hydrological modelling, including such topics as parameter estimation, scale and regionalization issues, model structures and, of course, various aspects of uncertainty quantification and assessment. The use of hydrological models for practical water resources assessments has a much longer history than the recent PUB decade. Within South Africa, the WR90 reports (Midgley *et al*., 1994) represented the first attempt in the region at using a hydrological model (the Pitman model: Pitman, 1973) to generate time series of monthly streamflows for each of 1946 so-called "quaternary" catchments (varying in area from approximately 50 km^2 to over 10 000 km^2) covering the whole of South Africa, Lesotho, and Swaziland. These are the fourth, and most detailed, level of catchment definition used for making important water resources management and planning decisions. This study has been recently updated as WR2005 (Bailey and Pitman, 2005), while a further review of some of the data, model approaches, and model results is currently under way.

The WR90 simulations were based on the calibration of the model against a limited number of naturalized (development impacts removed) and patched (missing data values infilled) observed streamflow records, followed by regionalization of the model parameters based on somewhat subjective assessments of catchment similarity. The WR2005 update adopted the same approach but using a more recent version of the model that more explicitly accounts for surface and groundwater interactions and is similar to the method in Hughes (2004). While these studies can claim to represent examples of PUB in practice, they have not had the opportunity to incorporate many of the advances in model application that have resulted from the contributions to the PUB decade (Sivapalan *et al*., 2003). Unfortunately, the proposals for the future updating of the simulations remain based on the same basic techniques that were used during the first

study, and the implications are that the scientific advancements made internationally during the PUB decade will not become part of hydrological modelling practice in the region.

Some of the potential problems with the approaches that were previously used, and which are continuing to be used include:

1. The Pitman model is a conceptual type model with many interacting parameters such that equifinality issues (Beven, 2006) can be very problematic during manual calibration. This problem is potentially exacerbated when the calibration and parameter regionalization tasks are performed separately by different groups in different parts of the country. Even though the calibration teams are expected to operate with similar calibration principles, it is likely that some variations in the calibration approach will exist between teams. The implication is that the calibrated parameter sets will be inconsistent across the country and that there is a need for a more objective approach to establishing parameter sets for both gauged and ungauged catchments.

2. There are relatively few streamflow gauges in the country and many of these are impacted by upstream developments that are not adequately quantified. The process of naturalizing streamflow records will clearly influence the calibrated parameter sets and therefore the regional parameter sets used for ungauged sites. Many users in South Africa have preferred to use naturalization methods, while others have included the human activities as part of the model and compared the results with the existing observed streamflow data. Both approaches are very uncertain when faced with poor water use data and human effects that are highly non-stationary. It is therefore difficult to determine if the parameter sets used to represent the natural hydrological response are appropriately quantified (i.e. behavioural).

3. There are some parts of the country (notably the areas of steep topography) where rainfall patterns are highly spatially variable and where rain gauge network densities are low. Any errors in the rainfall estimates will clearly impact on the calibration parameter sets in the various regions.

4. The overall result is that the input data and the parameter sets established for both gauged and ungauged catchments are very uncertain, and no attempts have yet been made to quantify the uncertainty and to include it as part of the estimation process.

All of these issues have been recurring themes within the international literature that has been generated as part of PUB. The real question is therefore – how can these scientific developments be properly incorporated into the type of practical modelling approaches being used in (for example) South Africa?

11.4 INCORPORATING SCIENCE INTO PRACTICE

Figure 11.1 illustrates an uncertainty framework that has been proposed (Kapangaziwiri *et al*., 2009) for South Africa and which is based on some of the developments that have emerged from PUB (e.g., Wagener *et al*., 2001; Seibert and McDonnell, 2002; McIntyre *et al*., 2005; Wagener and Wheater, 2006; Yadav *et al*., 2007; Wagener *et al*., 2007; Wagener and Montanari, 2011). The starting point is to replace the traditional use of single parameter sets with parameter uncertainty distributions based on a more objective estimation method that can be applied to both gauged and ungauged basins (Kapangaziwiri and Hughes, 2008; Kapangaziwiri *et al*., 2012). These would be coupled with uncertain estimates of the climate (precipitation and evaporation demand) through an appropriate sampling scheme to provide multiple inputs into the hydrological model. If the model contains components to simulate development impacts (abstractions, return flows, etc.), uncertainty in the parameters used to quantify these can also be included (Hughes and Mantel, 2010). The uncertainty ensembles generated by the model would then be subjected to a constraint analysis using either local observed data (which might also be considered uncertain) or regional indices of hydrological response behaviour (Yadav *et al*., 2007; Kapangaziwiri *et al*., 2012). The ensembles could be either accepted as all behavioural (and representative of the real uncertainty in the parameter or climate input estimates) or some could be considered to be non-behavioural and therefore not used in further water resources assessment analyses (Figure 11.1). The distinctions between behavioural and non-behavioural ensembles could also be used in a feedback loop to identify which parameter sets (or climate inputs) can be considered more representative than others using some of the methods of sensitivity analysis (Saltelli *et al*., 2008).

There are two main messages resulting from the recent research work that has been completed in South Africa: first, it is possible to develop an uncertainty framework for the application of hydrological models that is aligned with

current practices used for water resources estimation in South Africa, and; second, the uncertainty framework (and many of its components) are based on the scientific developments that have resulted from the PUB decade.

There remain a number of issues associated with the practical application of the framework, many of them associated with reluctance by some practitioners to change to new methods and the need to incorporate changes into existing software products; however, there is a general acceptance by the community of practitioners in South Africa that the framework represents a valuable approach for the future, and several practitioners are engaging with the research community to find suitable ways in which it can be implemented in practice. This is an important step that provides further opportunities for incorporating more of the recent PUB scientific developments into the practice of hydrological modelling for the purposes of water resources assessment.

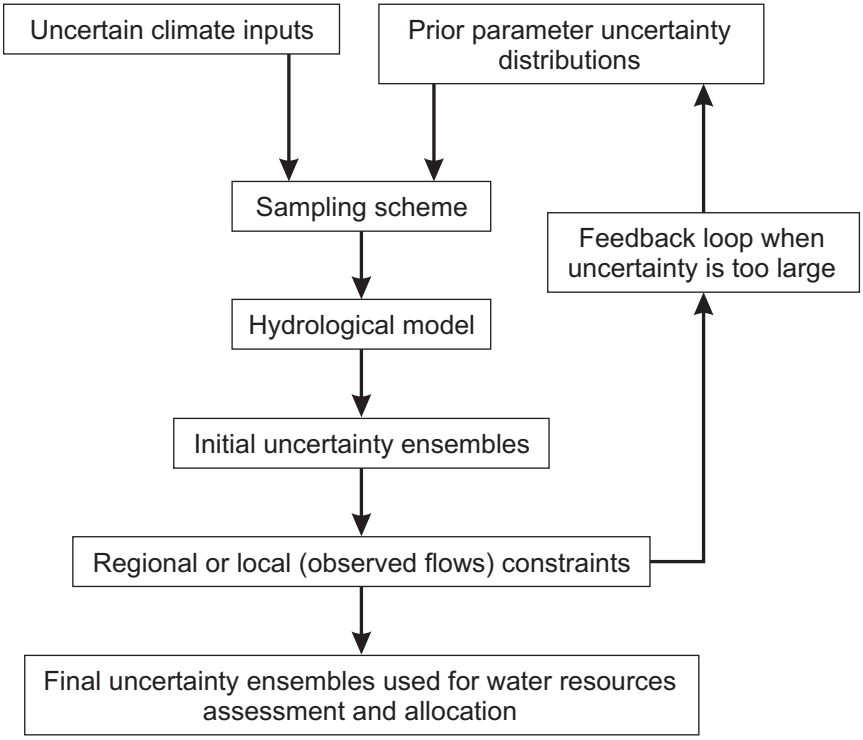

Figure 11.1 *Uncertainty framework for hydrological modelling.*

11.5 PUB SUPPORT FOR THE PRACTICAL APPLICATION OF THE FRAMEWORK

There were a number of developments that have been part of the PUB contributions to hydrological modelling over the last decade or so, that have the potential to contribute to the practical application of the proposed framework.

Parameter estimation procedures

One of the contributions that PUB has made is promoting the need for understanding processes at the catchment scale and how hydrological processes are distributed across complex landscapes. Specific topics include the estimation of residence times and flow paths using isotope data, improving our understanding of storages and fluxes under different landscape conditions, and scaling rules that apply in different sized catchments. While many of these advances in hydrological science remain within the research domain, there is a great deal of potential for them to be used in practice. Arguably, one of the critical issues is making the links between process understanding (at different scales) and the structure of any specific model being used in practice.

One of the important problems that has always been central to either research or practice has been the transfer of parameters from donor catchments (gauged) to other areas (ungauged). The principles of uncertainty and the use of parameter value probability distributions are not new to hydrological science, but it seems to be taking a long time for these to be used in routine practice.

Constraining uncertain model ensemble outputs

Perhaps one of the major stumbling blocks to the use of uncertainty approaches in practical hydrological modelling is the reliance on traditional model calibration and validation approaches that are not applicable in ungauged basins. The framework that has been proposed for South Africa attempts to overcome this problem by adopting a common uncertainty approach to all simulations and constraining the ensembles based on whatever information is available. In a well-gauged catchment this would mean that the final ensemble set would have a very narrow band of uncertainty, while in other areas the uncertainty band would be much greater and depend on the availability of information used as constraints.

Developing a suitable suite of constraints therefore represents a potentially more critical step in the process than defining the prior parameter distributions. Developing constraints is also a field of research that has enormous potential to be useful in practice. An important issue in any practical uncertainty assessment is not only to try and reduce the uncertainty, but also to ensure that the uncertainty is properly represented.

The basic concept of using constraints is to make use of information from data-rich situations for use in data-poor situations and could include a wide variety of different approaches including:

- Using hydrological indices based on some established approaches that have proven value in the region of interest (e.g. SCS curve numbers estimated from regional soils and land use data).
- Using hydrological state variables as well as streamflow data to condition the model outputs, where estimates of the temporal change in state variables are based on readily available remote sensing data (GRACE, MODIS, etc.). Some of these techniques have been applied within South Africa to a limited extent, but their full potential has yet to be realized.
- Developing regional signatures of catchment response based on a sound understanding of hydrological processes and readily available physical catchment property data (soils, geology, land cover and use, topography, etc.). The regional signatures could be related to any component of the model output, such as mean runoff ratio, residence times, catchment storage, ground water recharge or discharge, etc.
- Using focused short-term field campaigns to improve understanding and reduce the uncertainty in some of the model inputs or outputs.

Feedback loops from constraint analysis to parameter estimation

Figure 11.1 offers two options to follow after the initial uncertainty ensemble outputs from the model are assessed. The first is simply to reject non-behavioural ensembles (identified as those that fall outside the constraint boundaries referred to above and in Figure 11.1), while the second is to feed information back to the parameter estimation process and try and reduce the initial uncertainty in the parameter estimation process. This feedback loop may be useful to identify critical processes or parameters that generate most of the output uncertainty (sensitivity analysis) and this represents an approach that uses model outputs to evaluate conceptual

process understanding. The feedback loop may also be used to identify parameter redundancy and contribute to more parsimonious models in future applications. Alternatively, the feedback loop may also help to identify critical deficiencies in the structure of a specific model.

Other issues

Some of the initial applications of the framework in South Africa have found that the design of the parameter sampling approach is not a trivial issue if realistic expressions of output uncertainty are to be achieved with models having different complexities (Hughes *et al*., 2010, 2011) Even with a relatively simple conceptual model, applied in a semi-distributed (sub-catchment) format in a large basin, the sampling space is huge, and designing an approach that efficiently (from a practical perspective) and effectively samples that space does not appear to be straightforward (Hughes *et al*., 2011).

The use of alternative sources of model forcing data (e.g. satellite rainfall or evapotranspiration) is an important issue in data-scarce regions, particularly given the shrinkage in ground-based observation networks that is being experienced in many countries of the world (World Water Assessment Programme, 2009). These data sources have been the subject of many PUB related contributions to the scientific literature, but evidence of their successful use in practice is relatively scarce (Sawunyama and Hughes, 2010).

Demonstrating that uncertainty approaches are possible, practical, and essential (Pappenberger and Beven, 2006) and communicating uncertainty to hydrological model practitioners and water resources managers are essential components of effectively putting PUB into practice. The reluctance of some practitioners to adopt new approaches (that might complicate their professional lives) is something that has to be overcome. It is therefore the responsibility of the PUB science community to demonstrate to the practitioners, as well as decision makers, that new approaches which are scientifically sound, can be applied in practice and should result in more informed water resources management decisions being made (Pappenberger and Beven, 2006).

11.6 CONCLUSIONS

There are certainly many PUB contributions that could be almost immediately applied in practice with relatively small changes to either the models or the methods of applying them used currently by practitioners. There are many more PUB contributions that have the potential to improve the practical use of hydrological models. Realizing that potential requires further work to move the scientific developments from the research domain into the domain of practice. It is unlikely that the initiative to achieve this will come from the practitioners (with some exceptions) and therefore any translation of research methods into practice will, by necessity, have to be driven by those members of the PUB research community who are interested in seeing their scientific developments applied. South Africa has been used as a specific example in this document, but the general experiences and concepts are arguably applicable to many other countries of the world and particularly developing countries with sparse data sources.

12

ESTIMATING MEAN MONTHLY STREAMFLOW IN THE LUGENDA RIVER, NORTHERN MOZAMBIQUE

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12.1 ABSTRACT

In many regions, there are not sufficient observational records to support water resources planning efforts. In northern Mozambique, there are limited observations of streamflow in the Lugenda River, a major tributary to the Rovuma River. Four methods are evaluated for extending these observations to produce a longer time series of mean monthly flow estimates in the Lugenda River. The methods, three index-gauge methods and the historic seasonality of flows by month, are evaluated using limited mean monthly streamflow estimates based on *in situ* stream stage observations and streamflow rating curves. Of these methods, the mean flow ratio provides the best performance based on mean monthly flow, inclusion of interannual variability, and Nash-Sutcliffe efficiency ratios. Gaps in the mean flow ratio estimates due to lack of data at the index gauge are filled in using the historic seasonality by month. This combination provides a 53-year time series of 640 mean monthly flow estimates for the Lugenda River. While water resources planning efforts in this region will benefit from additional *in situ* observations, these estimates provide a starting point for current planning efforts and for future assessment of changes in water resource availability under climate uncertainty.

12.2 RÉSUMÉ

Dans de nombreuses régions, il n'existe pas suffisamment de dossiers d'observation pour soutenir les efforts de planification des ressources en eau. Dans le nord du Mozambique, il existe des observations limitées du débit de la rivière Lugenda, affluent majeur du fleuve Ruvuma. Quatre méthodes sont évaluées en vue d'étendre ces observations dans le but de

produire une série chronologique plus longue des estimations des débits moyens mensuels dans la Lugenda. Les méthodes, trois méthodes de la jauge-indice et le cycle saisonnier historique des débits par mois, sont évaluées à l'aide d'estimations limitées du débit mensuel moyen basées sur des observations *in situ* de la hauteur d'eau et des courbes des débits jaugés. De ces méthodes, le coefficient de débit moyen offre le meilleur rendement basé sur le débit mensuel moyen, l'inclusion de la variabilité interannuelle et le coefficient d'efficacité de Nash-Sutcliffe. Les lacunes statistiques dans les estimations du coefficient de débit moyen attribuables à un manque de données à la jauge indice sont comblées grâce à la saisonnalité historique par mois. Cette combinaison offre des séries chronologiques, échelonnées sur 53 ans, de 640 estimations de débit mensuel moyen pour la rivière Lugenda. Même si d'autres observations *in situ* s'avéreront utiles pour les efforts de planification des ressources hydriques dans la région, ces estimations offrent un point de départ pour les efforts de planification en cours et pour l'évaluation future des changements touchant la disponibilité des ressources hydriques dans un contexte d'incertitude climatique.

12.3 INTRODUCTION

Water resources development planning is dependent on estimates of historic and future streamflow conditions. The government of Mozambique is considering water resources development in the Lugenda River basin, potentially including medium-scale irrigated agriculture and hydropower. They only have sporadic historic *in situ* observations of streamflow, however, which can limit water resources planning. The purpose of this work is to extend the time series of mean monthly streamflow estimates in the Lugenda River to sufficiently support initial water resources planning efforts. The streamflow extension method must be accessible to local water resources planners, scientifically robust, and relevant to regional water resources planning goals.

The optimal streamflow record extension method for estimating a time series of streamflow in any river depends on several factors, including the availability of *in situ* observations and the goal(s) of the record extension exercise. For water resources planning, including water supply strategy, reservoir design, and land management, 10-50 years of data is required to account for the impact of climate variability on various timescales (Ziervogel *et al*., 2010). Examples in the literature suggest 25 years of monthly flow data

can be sufficient for reservoir storage-yield design (McMahon *et al*., 2007) or 30 years of baseline historic data can be used to evaluate future climate impacts on water resource availability (Charlton *et al*., 2006). In at least one study, a 22 year historic streamflow record that was being used by water resources planners for designing water management strategy was shown to be insufficient because longer historical records show a wider range of hydrologic conditions that impacts design and system performance (Vano *et al*., 2010). In contrast to these studies, mean monthly flow estimates are available in the Lugenda River for only 169 out of 276 months over a 23-year period (~60%). This is insufficient for most water resources planning goals.

In rivers with insufficient *in situ* observations, regionalization of data from nearby basins can be used to supplement those *in situ* observations in the river of interest (e.g. Yadav *et al*., 2007). Most regionalization methods require dense observations relative to what is actually available in poorly gauged regions (Özçelik and Bayakan, 2009). If sufficient local data for model parameterization, calibration, and hydrometeorological inputs are available, hydrological models can be useful tools for streamflow estimation (Abdulla and Lettenmaier, 1997; Xu and Singh, 2004). In data-sparse regions, a potentially useful streamflow record extension approach is to use an index gauge. Index gauge methods transfer information from a nearby stream gauge to the location of interest using a relationship such as the ratio of drainage areas or the ratios of mean annual flow (Xu and Singh, 2004).

12.4 STUDY AREA, DATA, AND METHODS

Study site description

The Lugenda River lies in northern Mozambique and is a major tributary to the Rovuma River (Figure 12.1). The watershed is about 40,300 km^2 and is located between -12° and -14° latitude and 35° and 38° longitude. About 800 mm to 1200 mm of precipitation falls annually, mostly between November and March; annual runoff is 200-600 mm. Higher precipitation and runoff rates are typically found in the western, higher elevation portions of the watershed, and lower rates are found in the eastern portion, closer to the sea. The strong seasonality of the precipitation is reflected in the streamflow seasonality. The watershed is covered with forests and some open grassland areas with dispersed trees. Temperatures typically fall in the range of 15°C to 30°C with lower temperatures observed during the southern hemisphere

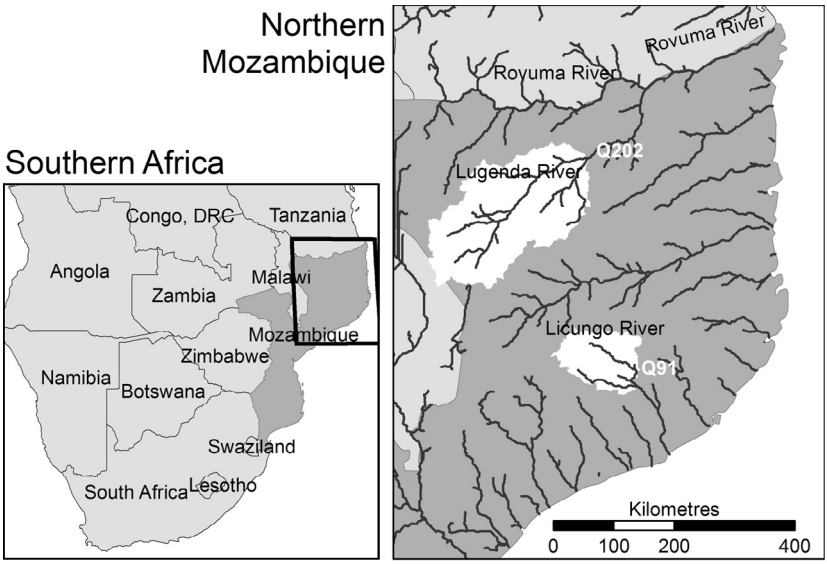

Figure 12.1 *Location map showing the Licungo and Lugenda Rivers, the stream gauges Q202 and Q91, and the respective drainage basins.*

winter months. There is a stream gauge, Q202, at which observations were taken sporadically between 1960 and 1982. The Directorate National de Agua, Moçambique (DNA) converted daily stage observations to monthly streamflow estimates using rating curves developed in the 1950s through the 1970s. The Licungo River is located to the south of the Lugenda basin and experiences similar hydrometeorological seasonality and climate. The gauge in this river, Q91, is selected as the index gauge because it is the only gauge in the region with regular observations over the period 1955-present.

Data sources

Mean monthly streamflow estimates for select Mozambique rivers were estimated by DNA based on *in situ* stage data and streamflow rating curves. There are 166 mean monthly flow estimates based on *in situ* stream stage observations in the Lugenda River and 618 mean monthly flow estimates in the Licungo River over the period 1957-2010. The gauges began operations in 1960 and 1957, respectively for the Lugenda River at Q202 and the Licungo River at Q91; however, while the most recent observation at Q202 was taken in 1982, DNA is still actively recording gauge measurements in the Licungo River at Q91.

Lugenda streamflow estimation methods

For this work, mean monthly streamflow in the Lugenda River is estimated using the drainage area ratio method, the mean flow ratio method, historic seasonality of flows by month, and a statistical index gauge method. Other regionalization methods and hydrological modelling both require more hydrological data than is available in this region. The streamflow estimates generated from a 20 year calibration period (1963-1982) are evaluated based on observational estimates for the validation period of 1960-1962.

The drainage area ratio method (Equation 1) is a simple index method that scales the flow at the index gauge by the ratio of the drainage areas for the two basins to estimate the flow in the basin of interest.

$$Q_j(t) = Q_i(t)\frac{A_j}{A_i} \tag{1}$$

where $Q_j(t)$ is the mean monthly estimated streamflow at the location of interest, $Q_i(t)$ is the mean monthly streamflow at the index gauge, and A_i and A_j are the areas of the index gauge drainage basin and the drainage basin of interest, respectively. The drainage area ratio streamflow estimation method can be used in the absence of any hydrologic information from the basin of interest. This method works best when the two basins have the same runoff ratio and similar precipitation events or similar seasonal streamflow patterns.

The next method is the mean flow ratio method (Equation 2), in which flows at the index site are scaled by the ratio of mean annual flows for the station of interest and the index station.

$$Q_j(t) = Q_i(t)\frac{\overline{Q_{aj}}}{Q_{ai}} \tag{2}$$

where $\overline{Q_{ai}}$ and $\overline{Q_{aj}}$ are the mean annual flows at the index station and at the station of interest, respectively. The mean flow ratio method assumes hydrologic similarity between the index basin and the basin of interest, particularly in the timing of precipitation and runoff. This method does require an estimate of mean annual flow, which can be limiting in ungauged basins and data-poor regions.

The third streamflow estimation method, seasonal flows by month, uses long-term mean monthly flow by month (e.g., Jan., Feb., Mar., etc.) to estimate the flow in that month for any given year.

$$Q_i(t) = \left\{ \left[Q_j \right]_{m=1}^{12} \right\}_{y=1}^{n} \tag{3}$$

where the expression in the curly braces {} indicates a repeating sequence of 12 numbers, each of which is the mean monthly flow rate for one of the 12 calendar months (m = 1 to 12), for *n* years of the estimation period, and Q_{jm} is the mean monthly flow rate for each calendar month defined as $Q_{jm} = \frac{\sum_{obs.m} Q_j}{n_{obs.m}}$ where the summation subscript *obs.m* indicates all observations for month *m*, and $n_{obs.m}$ is the number of observations for that month. This requires sufficient historical observations in the basin of interest, which can be problematic in ungauged regions. An advantage of this method is that it does not require an index gauge and therefore does not assume hydrologic similarity between two basins; however, it does not provide information about interannual variability, which is an important factor for water resources planning.

The final streamflow estimate comes from the Maintenance of Variance Extension 3 (MOVE3) method, a statistical streamflow record extension algorithm. MOVE3 is described by Vogel and Stedinger (1985) and implemented in the Streamflow Record Extension Facilitator program published by the U.S. Geological Survey (Granato 2009). MOVE3 is a statistical method that provides a long streamflow time series with an unbiased mean and variance based on a shorter streamflow time series at the location of interest, and a longer time series of observations at an index gauge. This method requires a significant number of *in situ* observations in the river of interest as well as at an appropriate index gauge.

Metrics for comparison

In-channel observations for the Lugenda River are compared to the record extension streamflow estimates using a set of performance metrics. The comparison is done for a 3-year validation period (1960-1962) in which there were observations for most months. Performance metrics include the bias in average estimated monthly flow over the validation period, the representation

of interannual variability, and the efficiency ratios defined below. The Nash-Sutcliffe (N-S) efficiency ratio (Nash and Sutcliffe, 1970) is used in two forms. First, the conventional N-S efficiency ratio is summarized in Equation 4.

$$\text{N - S efficiency ratio} = 1 - \frac{\sum \left(Q_{obs}(t) - Q_{est}(t)\right)^2}{\sum \left(Q_{obs}(t) - \overline{Q_{obs}}\right)^2} \tag{4}$$

where $Q_{obs}(t)$ represents the time series of observed mean monthly flows, $Q_{est}(t)$ represents estimated mean monthly flows using one of the methods described here, and $\overline{Q_{obs}}$ represents the long-term average of the observed monthly flows.

In addition, since squaring the terms in the N-S ratio has been criticized for over-penalizing high flow estimates (e.g., McCuen, *et al*., 2006; Garrick *et al*., 1978), an alternate form using only absolute values is also provided. This alternate efficiency ratio is summarized in Equation 5.

$$\text{alternative efficiency ratio} = 1 - \frac{\sum abs\left(Q_{obs}(t) - Q_{est}(t)\right)}{\sum abs\left(Q_{obs}(t) - \overline{Q_{obs}}\right)} \tag{5}$$

In both cases, efficiency ratio values greater than zero indicate that the estimate is an improvement over using the mean monthly streamflow over the entire historic record to estimate monthly flows. Values closer to one indicate estimates that are closer to the observed values, and efficiency ratio values less than zero indicate estimates that are worse than using the mean monthly flow rate.

12.5 RESULTS AND DISCUSSION

Lugenda River streamflow estimates

Streamflow estimates from four different estimation methods are evaluated in comparison to observed gauge data. A calibration period of 1963-1982 with a total of 143 monthly observations at each gauge is used for methods that require calibration data (mean flow ratio, seasonal flows by month, MOVE3). The validation period for comparing streamflow estimates to the *in situ* observations is 1960-1962, which includes 26 observations at each gauge. During the validation period, when observations are available at both gauges,

those values are used to calculate the mean annual flow ratio used to estimate mean annual flow at Q202 in the Lugenda River for all other months. The four streamflow estimation methods are evaluated based on their performance compared to these 26 validation period observations. The index gauge methods require observations in the index gauge to estimate flows at the point of interest (i.e. observation at Q91 required to estimate streamflow at Q202); missing data is shown as a gap in the streamflow estimation time series.

Comparison of streamflow estimation methods

The comparisons of performance metrics for streamflow estimation methods (Table 12.1 and Fig. 2) suggest that the seasonal flows by month and the mean flow ratio outperform the drainage area ratio and MOVE3 methods. The use of seasonality by month from the calibration period to predict flows during a validation period scores the highest efficiency ratios with the smallest deviation from the observation-based mean monthly flow rate; however, this method does not provide any indication of inter-annual variability, which is a key consideration for water resources planners. In comparison, the mean flow ratio method has similar efficiency ratios but does provide information about the inter-annual variability. As evident from the table, the drainage area ratio method does not perform well by the metrics used. In particular, the mean flow bias is greater and the efficiency

Table 12.1 *Comparison of performance metrics for streamflow estimation methods.*

Streamflow estimation method	Mean flow (m^3/s)	Runoff ratio	Mean flow difference	N-S efficiency ratio	Alternate efficiency ratio	Inter-annual variability
Observations (validation period only)	221	0.17	-	-	-	-
Drainage area ratio	381	0.30	+72%	-1.1	-0.34	Yes
Mean annual flow ratio	160	0.13	-27%	0.47	0.40	Yes
Seasonal flows by month (calibration period)	183	0.14	-17%	0.56	0.43	No
MOVE3	497	0.39	+125%	-3.2	-0.50	Yes

ratios are negative. This is due to different drainage densities in the Lugenda and Licungo River basins. The MOVE3 statistical method is not effective either, as is evident by the negative efficiency ratios and the mean flow bias. The MOVE3 performance might improve with additional observations, though those observations are not available at this time.

Effective water resources planning requires consideration of interannual variability in addition to a low bias and high efficiency ratio. The mean flow ratio outperforms the other three methods based on these comparison criteria. Therefore, the mean flow ratio is selected as the primary method to extend the mean monthly flow record in the Lugenda River.

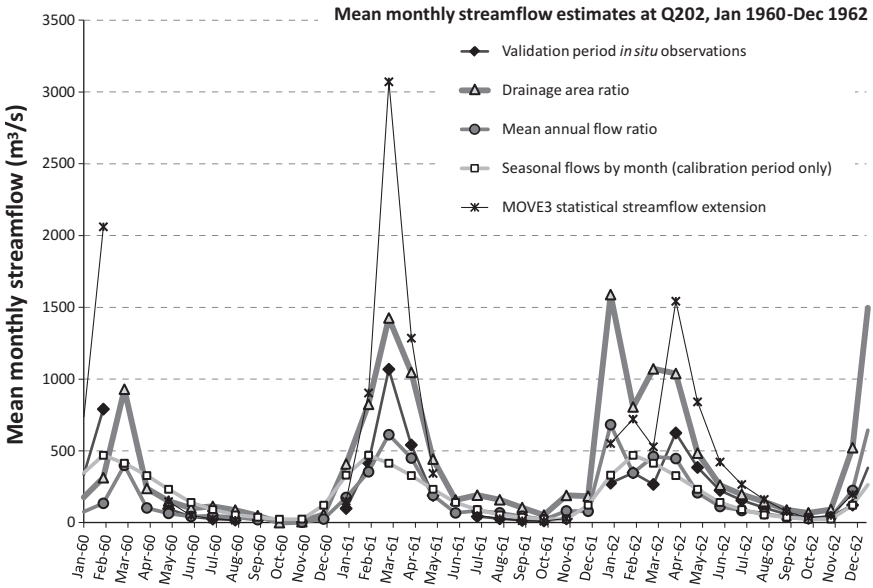

Figure 12.2 *Estimated mean monthly streamflow in the Lugenda River at gauge Q202 for the validation period using: in situ stage observations, the drainage area ratio, the mean flow ratio, seasonal flows by month (from calibration period), and the MOVE 3 statistical method.*

Lugenda River streamflow record extension

The mean flow ratio index gauge at Q91 in the Licungo River extends the 169 mean monthly flow observations at Q202 in the Lugenda River to 618 mean monthly flow estimates; however, since the MFR relies on observations at the index gauge, there are months for which the MFR

method cannot be used to estimate flows in the Lugenda River. In fact, by definition, none of the index gauge methods can estimate flows in the basin of interest in the absence of streamflow estimates at the index gauge. Therefore, the seasonal flows by month are used to fill the gaps in the MFR time series. This combination of methods produces a 53 year times series with 640 mean monthly flow estimates at Q202 in the Lugenda River (Figure 12.3).

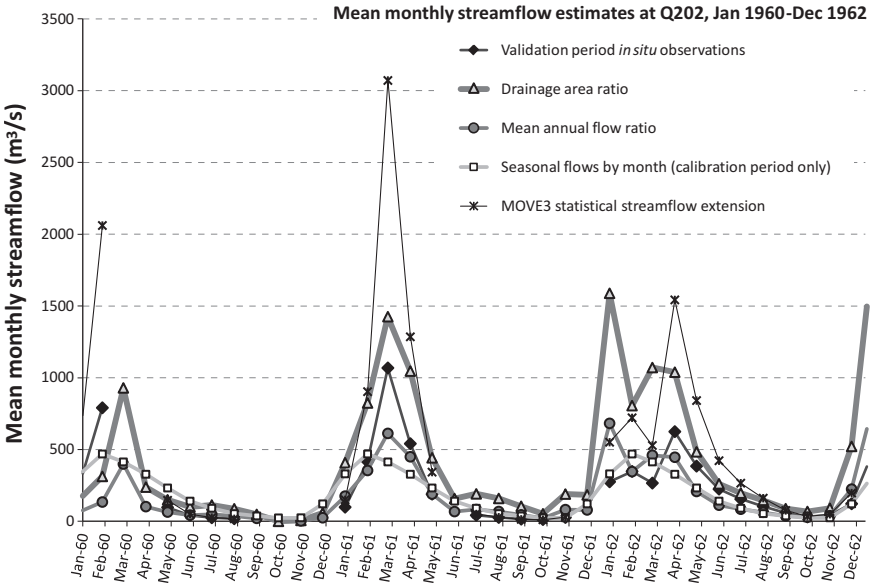

Figure 12.3 *Mean monthly flow observations (black diamonds) and estimates for the Lugenda River over the period January 1957-April 2010: MFR estimates (grey line with circles) with time series gaps filled by seasonal flows by month (grey line with triangles).*

12.6 CONCLUSIONS

Sparse, historic *in situ* observations in the Lugenda River combined with more consistent monthly observations in the Licungo River provide a time series of 640 estimated mean monthly flows in the Lugenda River for a period of over 53 years. Both the mean flow ratio method and the seasonal flows by month are straightforward methods that are accessible to local and regional water resources planners. Using conventional performance metrics of bias and efficiency ratios demonstrates that the methods are effective for estimating flows in the Lugenda River based on historic flows and an index gauge in the Licungo River. A monthly streamflow time series of this length can be used for investigating water supply strategy, reservoir design, land management, and as a starting point for evaluating possible future impacts of climate change on water resource availability. These estimates are only preliminary and should be supplemented by current *in situ* measurements before water resources investments are made. These results, however, provide a useful starting point for water resources planning and development in the Lugenda River in northern Mozambique.

12.7 ACKNOWLEDGEMENTS

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13

CREATING A RUNOFF RECORD FOR AN UNGAUGED BASIN: PEYTO GLACIER, 2002-2007

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13.1 ABSTRACT

Peyto Glacier basin runoff was gauged by the Water Survey of Canada during the 1965-74 International Hydrological Decade (IHD), but the gauge was removed soon after. In 1989, the first year-round automatic weather station was installed in the basin, the scope and quality of sensors improving over the years, so that hourly records of solar radiation, air temperature, humidity, wind speed, and precipitation have been available since 2002. These data are the forcing function of a distributed basin model that generates potential runoff due to snow and ice melt for each element of a 25 m resolution grid. Basin discharge is the aggregate of yield from storage in each element of the grid, using a delay constant of 100 h for snow, 11.25 h for ice, where ice cover increases over the melt season. An interesting feature of model development is the use of runoff measurement data from the IHD archive to find a suitable delay constant for ice, a value that is consistent with the ~0.5 d used for ice by other modellers. Also of interest is recent supraglacial runoff work on Peyto, for which a 10.5 h delay constant is obtained, thus raising the possibility of significant storage in the weathering crust of the ice surface. Past association of runoff measurements with weather data pointed to the growing importance of solar radiation as the melt season progressed, air temperature being important throughout. Similar associations are evident for discharge estimates from this model.

13.2 RÉSUMÉ

L'écoulement du bassin du glacier Peyto a été mesuré par la Division des relevés hydrologiques du Canada au cours de la Décennie hydrologique internationale (DHI) de 1965 à 1974. Cependant, la jauge a été retirée peu

de temps après. En 1989, la première station météorologique automatique exploitée à longueur d'année a été installée dans le bassin, la portée et la qualité des capteurs étant améliorées au fil des ans, si bien que des enregistrements horaires du rayonnement solaire, de la température de l'air, de l'humidité, de la vitesse du vent et des précipitations sont disponibles depuis 2002. Ces données constituent la fonction de forçage d'un modèle distribué à l'échelle du bassin versant qui génère un écoulement potentiel en raison de la fonte de la neige et de la glace pour chaque élément d'une grille d'une résolution de 25 m. Le débit du bassin correspond au total du produit de l'emmagasinement dans chaque élément de la grille, une constante de temps de 100 h étant utilisée pour la neige et de 11,25 h pour la glace là où la couverture de glace augmente pendant la saison de fonte. Une caractéristique intéressante du développement de modèle est le recours à des données de mesure de l'écoulement tirées des archives DHI pour trouver une constante de temps appropriée pour la glace, soit une valeur conforme à la valeur ~0,5 jour utilisée pour la glace par d'autres modélisateurs. Il est également intéressant de noter les travaux récents portant sur l'écoulement supraglaciaire dans le bassin du glacier Peyto, pour lequel une constante de temps de 10,5 h est obtenue, ce qui soulève par conséquent la possibilité d'un emmagasinement considérable dans l'écorce d'altération de la surface de glace. L'association passée des mesures d'écoulement avec des données météorologiques a fait ressortir l'importance croissante du rayonnement solaire au fur et à mesure que la saison de fonte progressait, la température de l'air étant importante tout au long de cette période. Des associations similaires sont évidentes pour les estimations de débit tirées de ce modèle.

13.3 INTRODUCTION

The problem of prediction in ungauged basins (PUB) addresses the many cases of basins that have never been gauged. But what of PUB where there are only past runoff records? How can the past inform the present in such a case? The question is explored here with respect to the Peyto Glacier basin.

Peyto Glacier supplies runoff to Peyto Creek, which was gauged during much of the International Hydrological Decade (IHD), but not long after. The first automatic weather station (AWS) was installed in the basin 15 years after the end of the IHD, but without restoring the gauge. Thus one is

presented with an excellent data input set for distributed basin runoff modelling and an excellent validation data set, neither of which are from corresponding time periods.

Given a recent AWS input record for the Peyto Glacier, the problem arose of creating a matching runoff output record from a distributed model of its ungauged basin. This raised the question of what role the IHD runoff data could play in obtaining a plausible result. The purpose of this paper is to show that a plausible outflow record can be created by tuning the model flow response time to the IHD data set, using five-year hourly mean values as the basis for comparison. This type of model could be applied to other ungauged glacierized basins which abound in the Canadian Rockies.

13.4 BACKGROUND AND DATA RESOURCES

The Peyto Glacier basin (51°40' N, 116°33' W) covers a 22 km^2 area on the eastern side of the continental divide in Alberta, Canada. The basin outflow was gauged from 1970-77, the 1971-74 period producing sufficiently long continuous records from which to calculate hourly means. Glacier diminution since then has reduced glacier area from approximately 60% of the basin area to 50%, the most noticeable changes being to the tongue, which has receded by nearly 1000 m and lost approximately 100 m of elevation. The current glacier elevation range is 2200 to 3100 m above sea level.

The first AWS was installed at a base camp adjacent to the glacier tongue in 1989, at 2300 m above sea level. Improvements to the station have been made over time such that recent records comprise hourly solar radiation, air temperature, humidity, wind speed, and precipitation: the essential data inputs for a distributed mass balance and melt runoff model. Precipitation data are corrected for signal noise and gauge catch error, then partitioned into rain or snow according to a 1.5 °C threshold. The part of the AWS record used here covers six years from 2002-07.

A LiDAR based digital elevation model (DEM), with 25 m grid resolution, was obtained in 2002 (Hopkinson *et al*., 2010). Slope and aspect were determined for each grid element and used to make adjustments to the direct and diffuse components of the solar radiation input, as described in Munro and Young (1982). Elevation adjusted temperature and precipitation from the AWS was applied to each grid element, such that it was possible for the precipitation record to simultaneously distribute rain over the lower

elevations of the basin, snow over the higher elevations. The distribution of melting and non-melting conditions was similarly controlled, the threshold temperature being 0 °C.

13.5 MODELLING APPROACH

The key component of the model is the change in surface mass balance, $\delta M_{i,j}$, which is driven in hourly time steps, i, through each element, j, of the DEM:

$$\delta M_{i,j} = \left\{ P_{rain/snow} - \frac{\mathrm{K}\downarrow(1 - \alpha_{i/s}) + L_* + Q_H + Q_E}{\rho_{ice/snow} L_f} \right\}_{i,j} \quad (1)$$

where the main driving variables are precipitation, $P_{rain/snow}$, global radiation, $K\downarrow$, air temperature and relative humidity, the latter two used to model net long-wave radiation, L_*, sensible heat flux, Q_H, and latent heat flux, Q_E. Application of density, $\rho_{\mathrm{ice/snow}}$, and latent heat of fusion, L_f, allow conversion of energy to water equivalent. In winter, $\delta M_{i,j}$ accumulates to form the snowpack that ablates over the summer, resulting in surface meltwater production, $q_{M_{i,j}}$.The glacier soon becomes partitioned into snow and ice melt elements, the latter increasing in number as the snow line migrates up the glacier.

In each time step, $q_{M_{i,j}}$, is accumulated over j elements of ice and snow to produce q_{M_i} for each cover type, each of which, following Hannah and Gurnell (2001) is routed through a linear flow reservoir, S_i:

$$q_i = \frac{S_i}{K_{ice/snow}} \; ; S_i = S_{i-1} + q_{M_i} - q_{M_{(i-1)}} \quad (2)$$

Thus, aggregate grid element runoff yields total basin discharge, $q = q_{i,ice} + q_{i,snow}$. The delay constant, $Kice/snow$, is set to 100 h for the snow reservoir throughout the modelling exercise, but the ice reservoir value is obtained by maximizing the correlation between modelled q and q from the IHD data set. To do so, four-year hourly averages from the 2003-2007 modelled runoff series were calculated for each new value of K_{ice} to provide a sample size to match that of the IHD data. The strongest correlation between the two data sets, $r^2 = 0.73$, was achieved with $K_{ice} = 11.25$ h.

13.6 RESULTS AND DISCUSSION

Measured and modelled basin discharge values are displayed in Figure 13.1, where the four-year means and their constituent years are plotted. Notable in the comparison is that inter-annual variability is smaller for modelled than for measured *q* due to smoothing by the model. A range of approximately 1-25 m^3s^{-1} contains the measured runoff variation over the years (Figure 13.1a) while a 1-12 m^3s^{-1} range applies to modelled runoff limits (Figure 13.1b). Four-year mean values are mainly contained within a 2-10 m^3s^{-1} range for both types of runoff, though with more variability in the measured four-year mean (Figure 1a). A mid-June runoff 'spike' that appears in the measurement record is not replicated in the model record, possibly because of the changes to the glacier that have occurred since measurements ended.

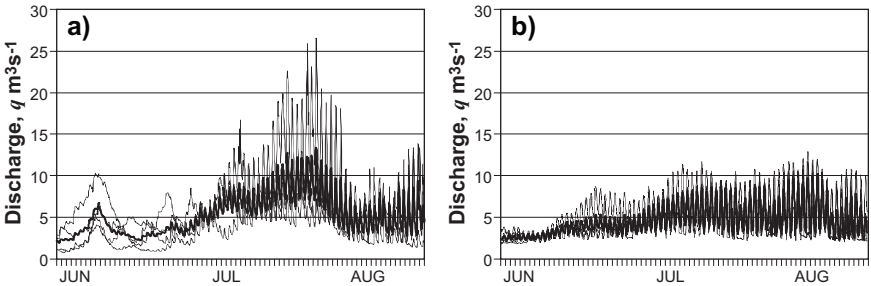

Figure 13.1 *Hourly discharge:* ***a)*** *measured q for 1971-74 and* ***b)*** *modelled q for 2003-06. Four-year mean values are the heavy line plot in each panel.*

The suitability of an 11.25 h delay constant to model discharge is consistent with other distributed modelling work (Baker *et al*., 1982; Hock and Noetzli, 1997; Yong *et al*., 2007). It is also comparable to a delay constant of 10.5 h recently reported by Munro (2011) for supraglacial runoff, albeit based on a small number of samples. The comparison is consistent with the idea of most runoff delay being generated in the ice surface itself, with little additional delay as a consequence of englacial and sub-glacial flow regimes (e.g. Flowers, 2008). This requires the creation of significant storage capacity in the ice surface, a requirement that is possibly met by the development of a substantial surface weathering crust during the melt period, as suggested in Munro (2011).

To judge the importance of radiative and temperature forcing of the model during the melt season, linear regressions of modelled q against these variables were done for the months of May to September (Table 13.1). Turning first to α, which may be associated with baseflow, the global radiation results are remarkably similar to those for temperature in showing July-August maxima, when glacier runoff is expected to peak due to a combination of strong solar energy input and extensive ice exposure. Taking β as an indicator of runoff sensitivity to forcing, it appears that while q is sensitive to air temperature forcing throughout the summer, sensitivity to global radiation does not appear until July, when ice exposure becomes important. This is also expressed in the value of r^2 which is above 0.2 for July and August, when r^2 for temperature has doubled in value. The mid to late summer emergence of global radiation as a factor in runoff prediction is

Table 13.1 *Linear regression results of $Y = \alpha + \beta X$, where Y is model q (m^3s^{-1}) and X is measured global radiation or air temperature.*

		May	June	July	August	September
Global Radiation ($W\ m^{-2}$)	r^2	0.003	0.001	0.037	0.205	0.213
	β ($m^3s^{-1}/W\ m^{-2}$)	-0.000	0.000	0.004	0.011	0.012
	α (m^3s^{-1})	1.471	2.602	3.754	2.788	0.887
Air Temperature (°C)	r^2	0.336	0.293	0.376	0.582	0.621
	β ($m^3s^{-1}/°C$)	0.048	0.096	0.233	0.306	0.246
	α (m^3s^{-1})	1.452	2.203	3.057	3.342	2.250

to be expected from the model structure, but it also replicates what Young (1982) found when using measured q as the dependent variable.

The degree of correspondence between the two types of discharge record was further explored by first normalizing q according to the mean daily discharge, q_{24}, thus removing the effects of day-to-day runoff variations. The four-year mean values from each data set show comparable normalized diurnal hydrograph ranges for q/q_{24} over much of the melt season (Figure 13.2), though correspondence is not as good in the early melt period (Figure 13.2b) as in the late melt period (Figure 13.2c). This is reflected in the contrasting r^2 values for the two periods (Figure 13.2a).

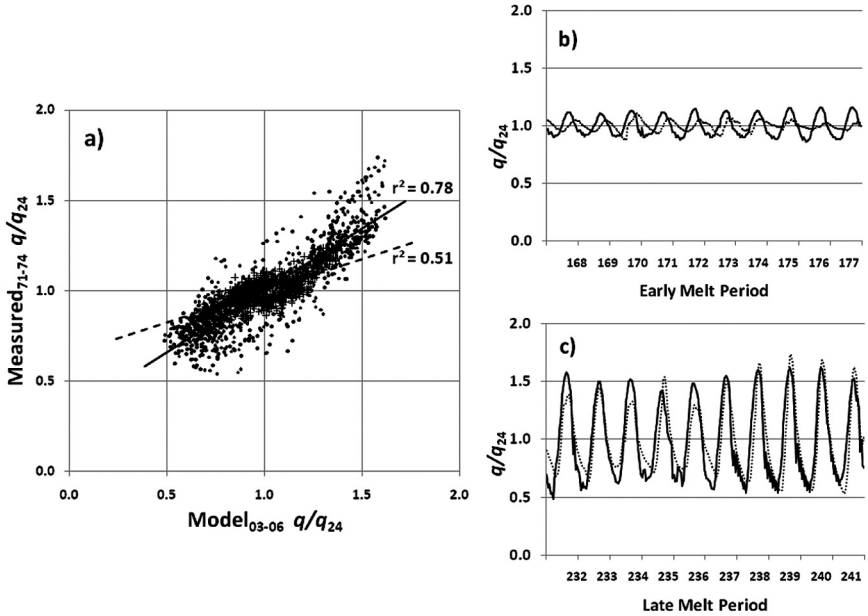

Figure 13.2 *Normalized discharge comparisons:* ***a)*** *point comparisons for early (crosses, $r^2=0.51$) and late (dots, $r^2=0.78$) melt season and* ***b), c)*** *day of year comparisons, where solid lines are model values.*

The poor correspondence in the early melt period, due to relatively small diurnal variation in measured q/q_{24}, probably reflects development of the englacial-subglacial drainage system, which is not a component of the model used here. The observation that $r^2 = 0.78$ for the late summer melt period is close to $r^2 = 0.73$ for the whole melt period, however, suggests that sub-surface drainage develops to maturity fairly quickly, and thus allowed a surface runoff model to yield plausible estimates of basin discharge.

13.7 CONCLUDING REMARKS

Although the model discharge record is not real, it is plausible in comparison to earlier runoff measurements for the Peyto Glacier basin, thus indicating capture of the key driving mechanisms. The fact that the model works as well as it does suggests a glacier hydrologic system that is strongly driven by glacier surface processes, notably seasonal snow line migration and weathering crust development, the latter of which itself merits further study. Because this modelled runoff record seems to capture the features of

a measured runoff record, despite it being from far in the past, it may be useful as an assessment tool for other hydrological models that use different approaches and spatial resolutions.

13.8 ACKNOWLEDGEMENTS

Research funding for this work over the years has been provided by the Canada Foundation for Climate and Atmospheric Science through its Improved Processes, Parameterizations and Predictions (IP3) in Cold Regions Network support, Environment Canada support of the Cryospheric System (CRYSYS) in Canada program, and the Natural Sciences and Engineering Research Council of Canada Discovery Grants program. Material and infrastructure support has been supplied by Natural Resources Canada as part of its Geological Survey Canada – Canadian Glacier Variations Monitoring and Assessment Network, and the University of Toronto Mississauga. Gratitude is expressed to the University of Waterloo for providing access to the Peyto Glacier runoff data archive.

14

PARAMETERIZATION OF A PHYSICAL HYDROLOGICAL MODEL FOR A MOUNTAIN REGION IN ALBERTA

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14.1 ABSTRACT

The primary objective of the IAHS initiative "Predictions in ungauged basins (PUB)" was to reduce uncertainty in hydrological predictions and to avoid the need for statistical analyses and model calibration. This can be achieved by calculating spatially explicit hydro-climatological parameters, such as spatially explicit precipitation and air temperatures, and the integration of high resolution solar radiation calculations. This case study describes some important methods developed by the author over recent years to provide the hydrological modeller with spatially explicit and physically based hydrological parameters. Results for an application of the ACRU agro-hydrological modelling system in the upper North Saskatchewan River Basin are described, where daily variables of air temperature and snow water equivalent are compared against observed data.

14.2 RÉSUMÉ

Le principal objectif de l'initiative Décennie de prévisions en bassins non jaugés (PBNJ) de l'AISH consiste à réduire l'incertitude liée aux prévisions hydrologiques et à éviter le besoin d'analyses statistiques et d'étalonnage de modèle. Il est possible d'y arriver en calculant des paramètres hydroclimatologiques spatialement explicites, comme les données spatialement explicites sur les précipitations et les températures de l'air, et grâce à l'intégration de calculs du rayonnement solaire à haute résolution. La présente étude de cas décrit certaines méthodes importantes élaborées par l'auteur au cours des dernières années afin de fournir au modélisateur

hydrologique des paramètres hydrologiques spatialement explicites et basés sur des critères physiques. Les résultats d'une application du système de modélisation agro-hydrologique ACRU dans le bassin du cours supérieur de la rivière Saskatchewan-Nord sont décrits, les variables quotidiennes de la température de l'air et de l'équivalent en eau de la neige étant comparés par rapport aux données observées.

14.3 INTRODUCTION

Many important watersheds are ungauged, and only physically based, spatially distributed, or semi-distributed hydrological simulation models can provide estimates of streamflow time series and other hydrological processes, such as soil moisture dynamics, under historical and a range of future environmental change conditions, as they are able to capture the spatial variability of hydrological processes throughout complex watersheds (Bathurst *et al*., 2004). In hybrid watersheds both snowmelt and rainfall events occur, and consequently the watershed behaviour is dominated by contrasting hydrological processes, and may respond uniquely to changes of the future climate (Loukas and Quick, 1996; Whitfield *et al*., 2003). While models are simplifications of reality, they are important tools in assessing future scenarios for water management strategies if accurately parameterized and verified (Beven, 1989). Rigorous parameterization of a model is a crucial step to avoid problems during the model verification process (Refsgaard and Storm , 1996). Parameters should be based on observed data, or should be estimated within a physically acceptable range based on available data and literature sources.

The primary objective of the IAHS initiative "Predictions in ungauged basins (PUB)" was to reduce uncertainty in hydrological predictions and to avoid the need for statistical analyses and model calibration. This can be achieved by calculating spatially explicit hydro-climatological parameters, such as spatially explicit precipitation and air temperatures, and the integration of high resolution solar radiation calculations. The ACRU agro-hydrological modelling system (Schulze, 1995) is a physical-conceptual, semi-distributed hydrological modelling system designed to be responsive to changes in land use and climate. The model has been updated to include specific high-mountain and cold climate routines and is applied to simulate impacts of land cover and climate change on the hydrological behaviour of numerous Rocky Mountain watersheds. The challenges of setting up a physically based

hydrological model are usually similar for ungauged and gauged watersheds, as the governing elements of the hydrological cycle (precipitation, actual evapotranspiration, soil moisture, and groundwater storage) can typically not be verified against observed data (with the exception of research watersheds). Therefore, in all hydrological simulations, it is important to maximize the predictive value of available information (climate, soils, and vegetation) by applying GIS techniques combined with improved hydrological process algorithms, thus reducing the predictive uncertainty of the simulations. The objective of this case study is to describe some of the more important methods developed by the author over recent years to provide the hydrological modeller with spatially explicit and physically based hydrological parameters, and to showcase a study where these methods have been applied.

14.4 METHODS

The procedures described here were applied for the parameterization and verification analyses of the Cline River watershed, the headwater of the North Saskatchewan River Basin, using the ACRU agro-hydrological modelling system. The Cline River watershed has an area of 3856 km^2 and consists of alpine, sub-alpine, and foothills landscapes located on the eastern slopes of Alberta's Rocky Mountains. The study area was divided into hydrological response units (HRUs), which were delineated based on 100 m elevation bands, nine land cover classes, four mean annual radiation classes, and watershed boundaries. GIS overlay analysis resulted in 308 HRUs, with an average HRU area of 12.5 km^2. Each HRU was parameterized to have a unique combination of hydrological variables. The area of each HRU was calculated based on its true, sloped area, as the planimetric area derived from a GIS is underestimated in steeply sloped terrain. The omission of correcting for sloped areas would result in incorrect calculations of interception volumes, soil moisture storages, groundwater recharge rates, actual evapotranspiration volumes, and runoff coefficients (Kienzle, 2010).

To appropriately transfer daily climate time series observed at a climate station situated in a valley at the outlet of the watershed to all the HRUs, monthly normal climate surfaces were required to calculate monthly precipitation and temperature correction factors. As the climate data in the study area were too sparse and incomplete to be able to interpolate a meaningful climate surface, the Parameter-elevation Regressions on Independent Slopes Model (PRISM),

developed by Daly *et al*. (2008), was used. The 1971-2000 monthly normal PRISM surfaces of minimum and maximum temperature and precipitation were available at a 2 km resolution. A smoothing algorithm was implemented to avoid potentially large jumps in precipitation values along the edges of the PRISM grid cells. The smoothing was achieved by using the centroids of each 2 km spaced raster cell value as input for a spline with tension spatial interpolation with a spatial resolution of 100 m.

Daily short-wave radiation and mean monthly potential sunshine hours were calculated for each DEM grid cell (100 m resolution) by calculating daily short-wave radiation using the Area Solar Radiation tool in ArcGIS (Environmental Systems Research Institute, 2008). Incoming radiation is calculated over an entire year using 1/2 hour time increments in a GIS, based on latitude, topography, hemispherical viewshed, atmospheric transmissivity, proportion of diffuse radiation, and elevation (Fu and Rich, 2000). Mean monthly atmospheric transmissivity and diffuse radiation were based on observations from the three nearest climate stations (located at Ellerslie, Edmonton City Centre Airport, and Edmonton International Airport) up to 350 km northeast of the center of the study site.

When temperature values are required where no measurements are available, lapse rates are commonly used to adjust the minimum and maximum temperatures measured at the nearest climate stations to the location under consideration (e.g., Martinec and Rango, 1986; Ahl *et al*., 2008). The use of mean annual lapse rates must be avoided, as lapse rates typically fluctuate strongly during the course of a season. Mean monthly lapse rates can be estimated from surrounding climate stations and their associated elevations, or from the available PRISM temperature surfaces. In this updated version of ACRU, the lapse rate adjusted daily air temperatures from the base station are only used for the separation of precipitation into snow and rain. Snowmelt, sublimation, and evapotranspiration are understood to depend on near-ground temperatures (Bowling *et al*., 2004), influenced by the local characteristics. In order to enable different daily air temperatures as a function of exposition, i.e. north vs. south facing slopes, or valleys that rarely receive direct incoming radiation, the lapse rate adjusted air temperatures are further corrected according to daily incoming radiation and land cover. A variation of an approach described by Glassy and Running (1994) and used in MTCLIM (Thornton *et al*., 1997) is applied.

For the calculation of the slope and exposure adjusted daily temperature, mean monthly incoming radiation was calculated in the GIS twice: once for flat topography, and once for sloped topography (Fig. 1). The first assumes that DEM grid cells have a slope of zero, thus still adjusting incoming radiation for elevation, atmospheric transmissivity, diffuse radiation, and shading effects; the second addresses slope and aspect. The ratio between the two radiation surfaces is then calculated (Kienzle, 2010). In ACRU, daily minimum and maximum temperatures are then adjusted using that ratio (Figure 14.1). In a second step, radiation adjusted daily minimum and maximum temperatures are further adjusted as a function of the leaf area index (LAI), as suggested by Hungerford *et al*. (1989). As the LAI varies seasonally, the LAI is changed on a monthly basis. The source for LAI data was MODIS (National Snow and Ice Data Center, 2009). The result of these complex calculations is that each combination of elevation, slope, and land cover has a unique, and fairly realistic, set of daily minimum and maximum temperatures. This is considered to be a critical step towards realistic evapotranspiration calculations.

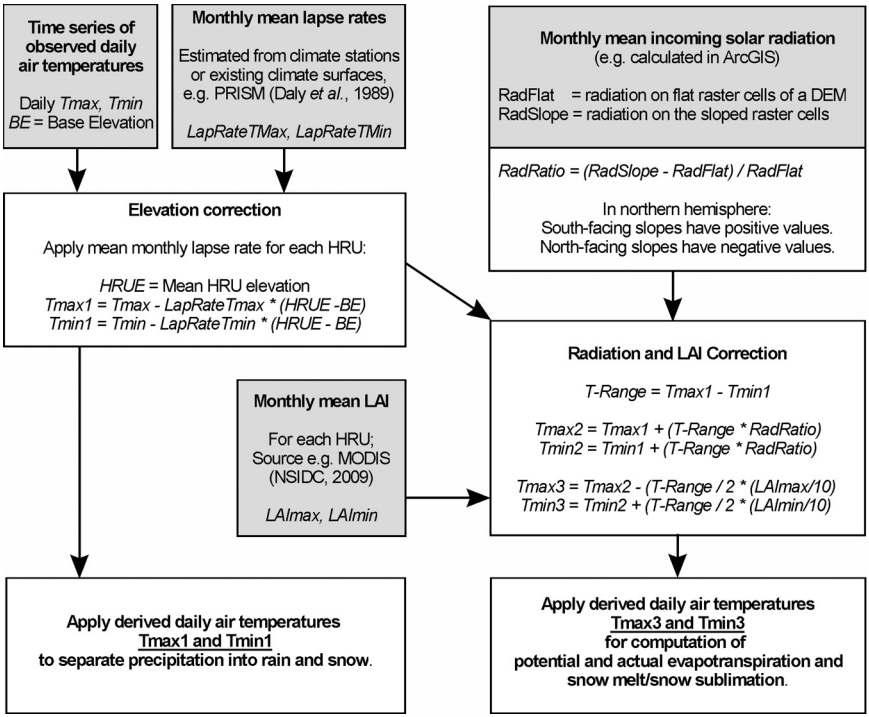

Figure 14.1 *Flowchart of temperature correction in ACRU. The grey boxes are data inputs.*

Similar in principle to the spatial estimation of air temperature, other climate variables such as daily observed (or estimated) radiation, relative humidity, and wind speed, can be transferred from the best suitable climate station to each HRU by calculating correction factors between the climate station and each HRU. Where no observations are available, mean monthly estimations of those variables for the region can be used. Daily sunshine hours are also estimated from the DEM using GIS functions, and are then reduced for all days with precipitation.

The threshold temperature that determines whether precipitation falls as rain or snow, as well as the temperature range within which a proportion of precipitation falls as rain, were calculated for each HRU, based on its average elevation and an empirical equation developed for the study area (Kienzle, 2008) which was based on a curvi-linear relationship between mean daily air temperature and the proportion of precipitation that falls as snow. Snow canopy interception and melt, snowpack evolution, rain on snow events, snow density, and the areas covered by snow during the melting phase of snow are all simulated in a physically explicit manner. The snowmelt simulation is based on an empirically derived dynamic and HRU specific snowmelt factor, which is determined for each day using a regression equation. This equation was established using mean monthly net radiation and albedo estimates (calculated in ACRU) and observed snowmelt from snow course and snow pillow data in two Rocky Mountain watersheds (St. Mary's watershed in Montana, and the upper North Saskatchewan River basin in Alberta – UNSRB). In ACRU, snow water equivalent (SWE) is simulated differently in forested HRUs than in non-forested HRUs. When an HRU is predominantly forested, estimations of HRU specific canopy cover percentages are required, which affect calculations of daily snow interception, and subsequently albedo, net radiation, and snowmelt.

14.5 VERIFICATION OF AIR TEMPERATURE ESTIMATES AND SNOW WATER EQUIVALENT

Observed daily maximum and minimum temperature data from ten short-term and seasonal climate stations (Environment Canada, 2008) within the UNSRB were used to verify that the daily air temperatures for the HRUs were estimated correctly. Between five and 42 years of observations were available, totaling 37 604 days. Figure 14.2(a) shows a scatter plot for

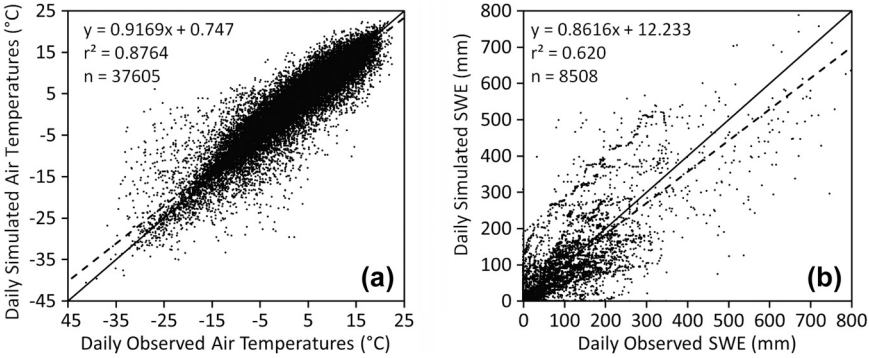

Figure 14.2 *Scatter plots for simulated and observed mean daily* ***(a)*** *air temperature and* ***(b)*** *snow water equivalent (SWE). Solid line is 1:1 line, the dashed line is the regression equation shown.*

simulated and observed mean daily air temperature values. Monthly mean air temperatures are slightly over-simulated, but are statistically not different. Monthly differences between variances were low (-3.79%), and the coefficient of determination was 0.98, with a regression slope of 0.97.

Figure 14.2(b) shows a scatter plot for daily simulated and observed snow water equivalent (SWE) values. The 15 available snow courses had a total of 882 observations, and the two snow pillows had a total of 7625 observations, resulting in a total of 8507 days with observed data. The coefficient of determination was 0.63, with a slope of the regression line of 0.81, indicating a systematic and overall under-simulation. The difference in simulated and observed variances was 4%. When compared to all observed SWE values, overall SWE depths were simulated fairly well, considering the geographical extent of the watershed, and the few climate base stations available to drive the model. One major challenge in snow simulations is the comparison with observed data, as both observed snow course and snow pillow data are not necessarily representative of a larger, forested area, such as an HRU. The major problem is that both snow courses and snow pillows measure snow in clearings, where snow accumulation and snowmelt are influenced by snow redistribution and solar radiation, which are not representative of closed forest stands (Gary, 1974; Brown and Braaten, 1998; Pomeroy *et al*., 2002). Taking into account the difficulties of representative snow measurements within a watershed due to very diverse forests in terms of local tree density, snow interception, and snowmelt dynamics, SWE was reasonably well simulated, as was the timing of snowmelt.

Annual potential evapotranspiration (PET) was simulated to range from about 500 mm to 1000 mm and compared very well, both spatially and in magnitudes, against values mapped in the Hydrological Atlas of Canada (1978). The seasonality of PET was validated against a total of 100 months (May to October) of observations at three A-pan stations in the vicinity of the watershed (r^2 of 0.78, difference in variance of 2.5%, slope of the regression line 0.87).

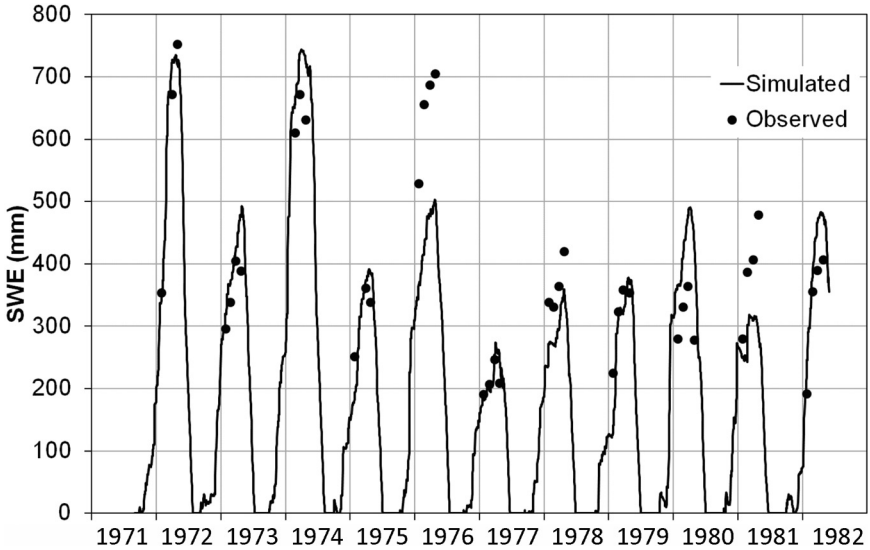

Figure 14.3 *Eleven years of simulated and observed SWE at Nigel Creek snow course, in the western part of the UNSRB.*

14.6 CONCLUSIONS

The spatially explicit parameterization and verification of air temperature, SWE and PET facilitated the successful simulation of both historical and future streamflow under a range of climate change conditions, described in detail by Nemeth *et al*. (2012) and Kienzle *et al*. (2011). Whilst other hydrological models would likely apply different approaches, this brief case study demonstrated the potential of sophisticated spatial analyses in the parameterization of both gauged and ungauged watersheds, thus enabling the hydrological modeller to estimate important, usually not readily available, climate variables for the hydrological simulation of ungauged hybrid mountain watersheds.

15

REGIONALIZATION OF RAINFALL-STREAMFLOW MODELS FOR ESTIMATING FLOWS IN UNGAUGED BASINS: TOWARDS REDUCING UNCERTAINTY

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15.1 ABSTRACT

Published statistical relationships linking physical basin attributes to calibrated parameters of rainfall-streamflow models (regionalization) are typically based on analysis of daily hydrometric data and often exhibit large uncertainty. The paper draws upon earlier work to discuss the component of this uncertainty caused by loss of information when model parameters are calibrated using data that are too coarse temporally to capture the rainfall-streamflow dynamics of a basin. Although a model parameter might be calibrated with good precision from daily data it can be massively inaccurate, especially if it relates to a quick-response component of streamflow. For a 10.6 km^2 basin in Wales, a quick-flow model parameter calibrated using daily data has a precision of +/-2% and an inaccuracy of +430% relative to it being calibrated using hourly data. About 42% of the absolute inaccuracy in this case is accounted for by loss of information in daily effective rainfall, leaving 58% caused by loss of information in daily streamflow data. Inaccurate model parameters employed as the dependent variable in regression analyses contribute to poor precision of regionalization equations. The paper argues for the use of sub-daily data when necessary, in pursuit of reductions in the uncertainties associated with regionalization equations and related estimation of flows at ungauged sites.

15.2 RÉSUMÉ

Les relations statistiques publiées qui relient les caractéristiques physiques du bassin hydrographique aux paramètres calibrés des modèles pluie-débit (régionalisation) sont en général basées sur l'analyse des données

hydrométriques quotidiennes et affichent souvent une grande incertitude. L'article s'inspire de travaux antérieurs pour aborder l'élément de cette incertitude causé par la perte d'information lorsque les paramètres du modèle sont étalonnés à l'aide de données considérées comme trop brutes d'un point de vue temporel pour capter la dynamique pluie-débit d'un bassin. Même si les paramètres du modèle peuvent être étalonnés avec une bonne précision à partir des données quotidiennes, ils peuvent être massivement inexacts, en particulier s'ils se rapportent à une composante de réponse rapide du débit. Pour un bassin de 10,6 km^2 au Pays de Galles, un paramètre de modèle de débit rapide calibré à l'aide de données quotidiennes offre une précision de +/-2 % et une inexactitude de +430 % relativement au même modèle calibré à l'aide de données horaires. Environ 42 % de l'inexactitude absolue dans ce cas s'explique par la perte d'information relativement à la pluie efficace quotidienne, ce qui laisse un pourcentage de 58 % attribuable à la perte d'information liée aux données quotidiennes sur les débits. Les paramètres de modèle inexacts employés en tant que variable dépendante dans les analyses de régression contribuent à une piètre précision des équations de régionalisation. L'article préconise l'utilisation de données infra-quotidiennes en cas de besoin, à des fins de réduction des incertitudes associées aux équations de régionalisation et à l'estimation connexe des débits à des sites non jaugés.

15.3 INTRODUCTION

For the purposes of this article, gauged basins are those for which rainfall and streamflow time series data are available, allowing rainfall-streamflow conceptual modelling. Secondary hydrometeorological data required for the modelling, e.g. air temperature, are also available for gauged basins. Ungauged basins do not have streamflow data, but they do have time series data for rainfall, air temperature, etc. Measures of uncertainty associated with statistical relationships for gauged basins, between a given parameter of a rainfall-streamflow model and physical basin characteristics (slopes, drainage density, etc.), are typically and disappointingly large. This article describes a method by which it should be possible to reduce this uncertainty. This, in turn, would improve estimates for ungauged basins (using regionalized statistical relationships for gauged basins) of (a) model parameters from physical basin characteristics, and (b) streamflow time series generated from the regionalized model parameters and recorded rainfall time series.

As data time-step increases (e.g. from hourly to daily), information is lost from rainfall and streamflow time series. This loss of information can be a dominant contributor to uncertainty (a combination of precision and accuracy) in calibrated rainfall-streamflow model parameters for gauged basins. For example, as will be seen, calibrated model parameters can become increasingly inaccurate as data time-step increases, even if their precision is good. Model parameters that can be shown to be more accurate should lead to an increase in the precision associated with regionalization equations used for estimating model parameters from the physical characteristics of ungauged basins.

For the 10.6 km^2 Wye at Cefn Brwyn research catchment in Wales, Littlewood and Croke (2008) show that each of the five parameters of a discrete-time IHACRES model (e.g., Jakeman *et al*., 1990; Jakeman and Hornberger, 1993) can be calibrated with good, to very good, precision from daily data; however, the accuracies of these parameters can be poor or extremely poor. The five model parameters in the version of IHACRES applied by Littlewood and Croke (2008) are (with dimensions in square brackets): a catchment drying time constant, τ_w [T]; the depth of a conceptual catchment wetness store, c [L]; a quick-flow decay time constant, $\tau^{(q)}$ [T]; a slow flow time constant, $\tau^{(s)}$ [T]; and, a slow flow index, SFI [-] analogous to well-known baseflow indices. The Wye at Cefn Brwyn is a grassland upland basin and one of the wettest gauged catchments in England and Wales (annual precipitation is about 2487 mm and streamflow is about 2182 mm, or 85% of precipitation). It has a flashy flow regime; hydrographs plotted using daily data are smoothed versions of the real thing and therefore information is lost, especially at and near streamflow peaks. Similarly, information is lost in daily rainfall data. In the worst case of IHACRES model parameter inaccuracy for Cefn Brwyn, although $\tau^{(q)}$ was calibrated using daily data by Littlewood and Croke (2008) with a precision of about +/-2%, its inaccuracy (relative to the value of $\tau^{(q)}$ calibrated using hourly data) was about 430%. The other four model parameters calibrated using daily data had poorer precision but better (though still poor) accuracy.

Daily data are likely to be too coarse to capture the dynamics of flashy catchments included in a set of gauged basins employed for model parameter regionalization. Inaccurate model parameters for basins in this category will cause some of the imprecision associated with regionalization

equations that link model parameters with physical catchment descriptors and, therefore, some of the uncertainty associated with streamflow predictions, based on those regionalization equations, for ungauged basins.

The objective of this paper is to develop the hypothesis that by using appropriately standardized values of discrete-time rainfall-streamflow model parameters (gauged basins) it should be possible to increase the precision associated with regionalization equations used for estimating model parameters from the physical characteristics of ungauged basins.

15.4 EFFECTS OF DATA TIME-STEP ON THE VALUES OF CALIBRATED, DISCRETE-TIME, RAINFALL – STREAMFLOW MODEL PARAMETERS

The accuracy of a given model parameter calibrated using *n*-hourly data ($n > 1$ hour) is defined here for Cefn Brwyn as the difference between the values of that parameter calibrated using (a) the *n*-hourly, and (b) hourly data. Figure 15.1 shows the trajectories of calibrated Cefn Brwyn IHACRES model parameter values as the logarithm of data time-step changes (Littlewood and Croke, 2008); it also illustrates the definition of accuracy used here and gives accuracy and precision values associated with each of the model parameters when calibrated using daily data. In Figure 15.1, the horizontal dashed lines represent the standardized model parameter, i.e. calibrated using hourly data, and the vertical arrows indicate the inaccuracy in a model parameter calibrated using daily data. In Figure 15.1, "pp" for SFI means percentage points. The error bars on each point in Figure 15.1 indicate the precision on a calibrated model parameter (e.g. +/-10% for τ_w calibrated using daily data). The precision on a model parameter (Littlewood and Croke, 2008) is the 95% confidence interval derived from a fine search in the vicinity of the optimized set of parameter values, selecting model parameter sets that gave a coefficient of determination (comparing modelled and observed streamflow) of more than 99.9% of its maximum value. Figure 15.1 shows that each of the five Cefn Brwyn IHACRES parameters approaches a stable value as the logarithm of data time-step decreases to 1 hour, providing a reference point for assessing the accuracy of that parameter calibrated using *n*-hourly data ($n > 1$ hour). IHACRES calibrated for catchments with more, or less, dynamic streamflow responses than at Cefn Brwyn may exhibit parameter value stability at a data time-step of less, or more, than 1 hour respectively.

Littlewood *et al*. (2010) used the continuous-time, data-based mechanistic, modelling methodology (e.g., Young and Romanowicz, 2004; Young and Garnier, 2006) to corroborate the stability of the Cefn Brwyn IHACRES parameters calibrated using hourly data. Extrapolation of the model parameter trajectories to a data time-step of zero (data time-step plotted arithmetically – not shown) gives estimates of the parameters of an instantaneous rainfall-streamflow model comprising an instantaneous loss module that generates effective rainfall input to an instantaneous unit hydrograph module.

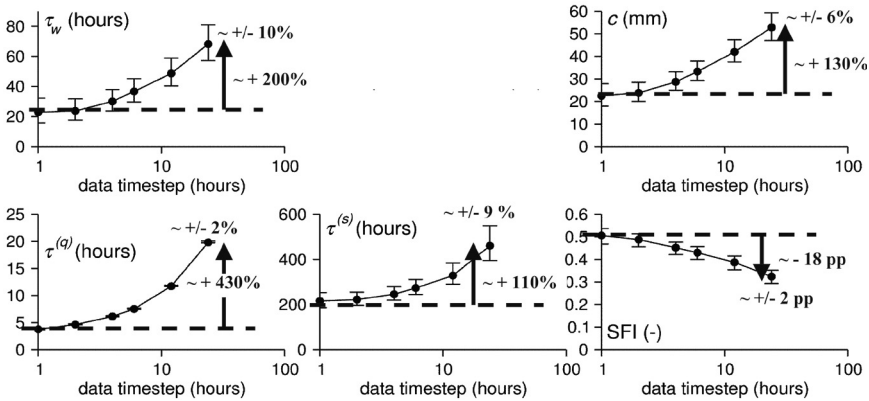

Figure 15.1 *Trajectories of Cefn Brwyn IHACRES parameters showing model parameter precisions for each data time-step and accuracies for a daily data time-step.*

The trajectories shown in Figure 15.1 correspond to a 210-day calibration period (6 December, 1987 to 2 July, 1988). IHACRES and other discrete-time, rainfall-streamflow models with about the same number of parameters can be expected to exhibit similar model parameter trajectories when calibrated for basins with a dynamic streamflow response comparable to that for Cefn Brwyn. Less dynamic catchments than Cefn Brwyn may not exhibit such well defined trajectories, especially if the quality of the hydrometric data is not as good as it is for Cefn Brwyn. Catchment scale rainfall-streamflow models with more than about 6 parameters (Perrin *et al*., 2001) are likely to be over-parameterized when calibrated using rainfall and streamflow data (and perhaps an additional evapotranspiration surrogate variable, e.g. air temperature), so may not produce such well-defined and well-behaved trajectories as those shown in Figure 15.1.

Employing the same model calibration period (6 December 1987 to 2 July 1988), Littlewood and Croke (2013) present estimates of the separate contributions to Cefn Brwyn IHACRES model parameter inaccuracy caused by loss of information in the daily rainfall and streamflow data respectively. To facilitate this investigation the hourly rainfall and streamflow data were assumed to be perfect. About 42% of the inaccuracy in $\tau^{(q)}$ calibrated using daily data (19.9 - 3.76 = 16.1 hours, +430% in Figure 15.1) is accounted for by loss of information in the effective rainfall, leaving 58% caused by loss of information in daily streamflow data. For $\tau^{(s)}$, which has an inaccuracy of 455 - 216 = 239 hours (+110% in Figure 15.1), the corresponding values are 85% and 15%. So, for $\tau^{(q)}$ calibrated using daily data, the very large inaccuracy is due slightly more to loss of information in daily streamflow than in effective rainfall, whereas for the corresponding $\tau^{(s)}$, the lower (but still large) inaccuracy is, as expected, caused largely by loss of information in the effective rainfall data rather than in the streamflow data.

15.5 REGIONALIZATION OF DISCRETE-TIME MODEL PARAMETERS

Several rainfall-streamflow model regionalization schemes have employed daily rainfall and streamflow data to calibrate discrete-time models for sets of gauged basins. For any flashy catchments in these sets, daily data are likely to be too coarse temporally to allow accurate calibration of each of the model parameters, especially parameters associated with quick-response components of streamflow. Whatever discrete-time rainfall-streamflow model is used, the flashier the streamflow response, the more inaccurate some of the model parameters are likely to be when calibrated using daily data, even if they are estimated with good precision. Qualitatively, the parameter inaccuracy, which will be different for different catchments, will contribute to the imprecision associated with model parameter regionalization equations, as follows.

For each gauged catchment considered in a regionalization study, a given discrete-time rainfall-streamflow model calibrated using daily data provides model parameter values (P_1, P_2, …, P_n; n = number of model parameters). The P_n are regressed (usually individually) on catchment descriptors (X_1, X_2, … X_m; m = number of catchment descriptors for a given P). Equation 1 is then available for estimating a model parameter ($\hat{P}_n$) from X_1, X_2, … X_m.

$$\hat{P}_n = f\,(X_1,\ X_2,\ ...,\ X_m) \qquad (1)$$

When similar relationships for all n model parameters have been established, flow hydrographs can be estimated using (a) model parameters estimated from the relationships, and (b) time series of rainfall and whatever other hydrometeorological variables are used to drive the rainfall-streamflow model (e.g., air temperature, soil moisture content). A plot of P_n against $\hat{P}_n$ for gauged basins might exhibit a scatter as illustrated schematically in the left-hand side of Figure 15.2.

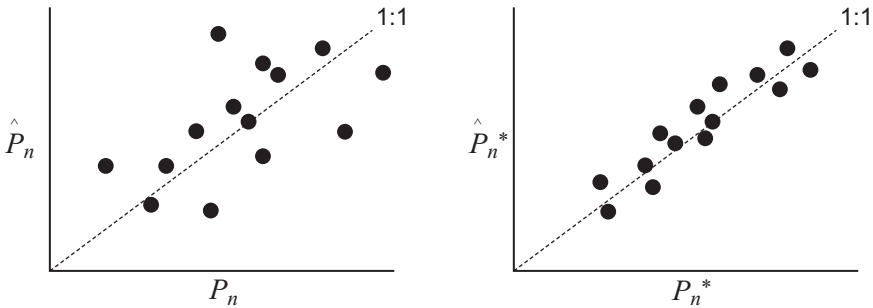

Figure 15.2 *Schematic of expected improvement in rainfall-streamflow model parameter regionalization* ***(a)*** *non-standardized parameters and* ***(b)*** *standardized parameters (see text for further explanation).*

If, however, standardized values of model parameters are used ($P_1^*, P_2^*, \ldots, P_n^*$) instead of ($P_1, P_2, \ldots, P_n$), where P^* means a model parameter value that can be shown to be accurate and essentially independent of the data time-step used for its calibration, e.g. using hourly data for the Cefn Brwyn IHACRES model (Figure 15.1), then a reasonable hypothesis is that the scatter between P_n^* and $\hat{P}_n^*$ for gauged basins should be less than between correponding P_n and $\hat{P}_n$, as illustrated in Figure 15.2.

15.6 CONCLUDING REMARKS

Subject to the availability of suitable sub-daily flow data (from which archived daily flows are usually derived) and sub-daily basin rainfall data, a testable hypothesis has been developed. It is expected that the precision associated with rainfall-streamflow model parameter regionalization relationships will improve when demonstrably accurate model parameters are used for all the gauged basins considered rather than using some likely

to be inaccurate for flashy catchments. For cases where daily data have been used for all basins in the set of gauged basins considered, the magnitude of the improvement in precision associated model parameter regionalization is expected to be dependent on the number of flashy basins in the set and the different degrees to which daily data adequately capture the dynamics of each of those flashy catchments.

A reviewer of this article asked, very reasonably, about work that quantified this hypothesized improvement in precision associated with rainfall-streamflow model parameter regionalization equations. Unfortunately, the necessary work has yet to be undertaken. It would be necessary to re-run a well-documented model parameter regionalization exercise that had used daily (for example) data for each of the gauged catchments (during which inaccurate model parameters for flashy basins were probably generated), this time using sub-daily data to calibrate more accurate model parameters for any flashy catchments included in the set of gauged basins employed. Then, new relationships between each model parameter and physical catchment descriptors would need to be established and their associated precisions compared with those of the previous relationships. This substantial task is beyond the scope of this paper, the purpose of which is to expose the issue so that others might consider it in the context of their rainfall-streamflow model parameter regionalization studies. Better regionalization equations obtained through using demonstrably accurate estimates of rainfall-streamflow model parameters for flashy gauged catchments should lead to better predictions of streamflow for ungauged basins.

15.7 ACKNOWLEDGEMENTS

This paper is based upon the author's poster "Don't forget – uncertainty comprises imprecision AND inaccuracy" presented at the PUB-P3 workshop, Canmore, Alberta, May 2011.

16

PREDICTION OF NEAR REAL TIME NATURAL FLOWS IN GAUGED AND UNGAUGED WATERSHEDS OF SOUTH SASKATCHEWAN RIVER BASIN – WHAT ARE OUR OPTIONS?

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16.1 ABSTRACT

Two different approaches to estimate the natural streamflow at both gauged and ungauged sites in Alberta are described. The first method uses the physically based distributed model MIKE SHE/MIKE 11 and the other makes use of flow duration curves (FDC). These methods are practical only where flow measurements are available.

16.2 RÉSUMÉ

Sont décrites deux différentes approches visant à estimer l'écoulement naturel à des sites jaugés et non jaugés en Alberta. La première méthode fait appel au modèle à paramètres physiques distribués MIKE SHE/MIKE 11 et l'autre fait appel aux courbes des débits classés (CDC). Ces méthodes sont pratiques seulement lorsque des mesures du débit sont disponibles.

16.3 INTRODUCTION

Knowledge of how much water is naturally available, when it is available, and its variability is important for planning and operational purposes including regulatory aspects such as water licensing and compliance. Quantification of these natural water supplies is often hindered by the lack of hydrological, climatic, and other relevant data. Monitoring every single stream to support

water licensing and compliance is impractical (due to lack of funding), which means that hydrologists often do not have the ongoing streamflow time series required for planning and operations (Metcalfe *et al*., 2005). Alternatively, hydrological modelling can be employed to estimate the natural streamflow which is then used to estimate flow characteristics at gauged or ungauged sites. Estimates of natural streamflow at both gauged and ungauged sites can be generated either by [i] deterministic rainfall-runoff models, or [ii] making use of spatial interpolation and hydrological regionalization. If robust, these two methods may enhance the current capabilities and reduce uncertainties in quantifying water availability that would contribute to water management in Alberta. This paper describes the application of two different approaches to estimate the natural streamflow at both gauged and ungauged sites, one using the physically based distributed model MIKE SHE/MIKE 11 and the other, a Pragmatic Method (PM) which makes use of flow duration curves (FDC).

Outputs from spatially-distributed hydrological models that are based on physical processes and parameters are expected to produce more detailed and realistic results compared to outputs from lumped models (Graham *et al*., 2005); however, these models require the adequate quantification of a large number of parameters, reliable climate inputs, and are generally a time consuming, labor intensive approach (Graham *et al*., 2005). The inclusion of such models as predictive tools has been identified as part of the long-term research objectives of Alberta Environment and Sustainable Resource Development (AESRD).

As an alternative, applied research suggests that in many parts of the developing world a spatial interpolation and regionalization methods using FDC would offer an initial, parsimonious approach for simulating natural flow regimes at gauged and ungauged sites (Metcalfe *et al*., 2005). This approach may not be adequate for predicting flows in intermittent/ephemeral streams; therefore, the Province of Alberta is pursuing a pilot project to test the applicability of a fully distributed hydrological model capable of coupling surface-ground water interaction to enhance the capability of predicting flows in intermittent/ephemeral streams. This paper describes the development and application of two different approaches for predicting natural flows in gauged and ungauged streams representing the two ends of the hydrological modelling spectrum – from a simple pragmatic hydrological model to a comprehensive spatially-distributed, physically based hydrological model.

AESRD has initiated two pilot projects to test these two distinct methodologies to estimate natural flows at both gauged and ungauged watersheds in the South Saskatchewan River Basin (SSRB). One project involves the application of PM in the SSRB within Alberta (includes Red Deer River, Bow River, Oldman River, and South Saskatchewan River basins) while the second project involves the application of the MIKE SHE/MIKE 11 model in the Elbow River watershed which is located in the Bow River Basin (Figure 16.1). Complexity and computational burden increase with a physically based fully distributed hydrological model like MIKE SHE, which may be best suited for operational needs that warrant relatively more certainty in model outputs. Conversely, conceptual and

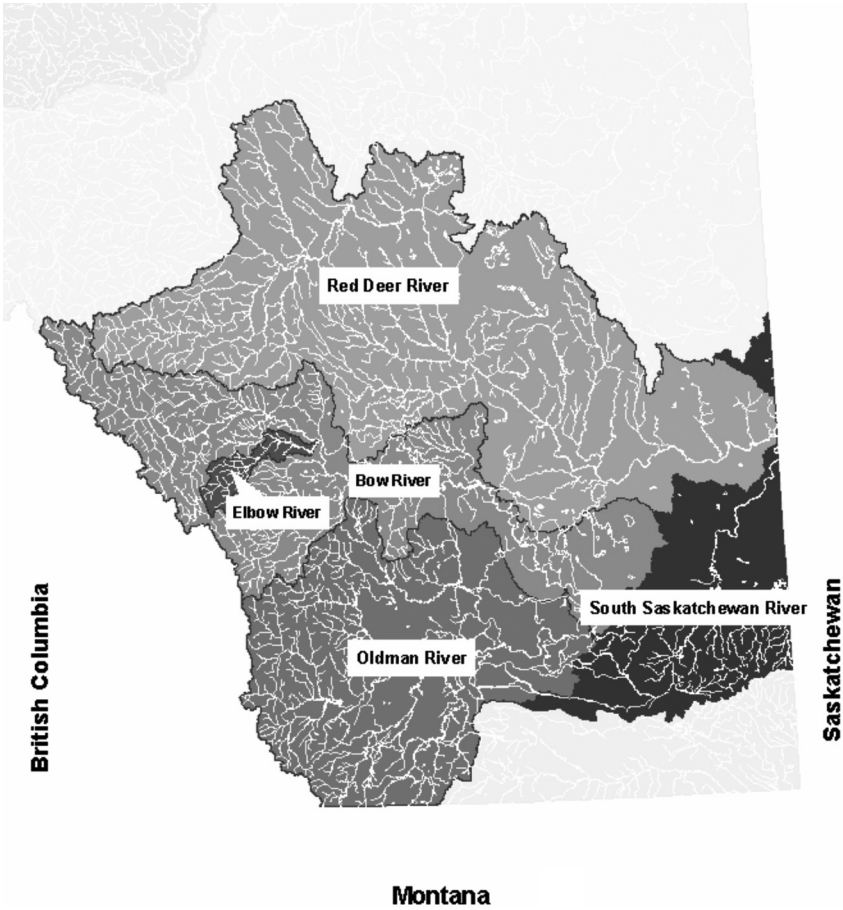

Figure 16.1 *Map of the South Saskatchewan River Basin.*

lumped modelling like the PM is rather simple, requires less computational time, and is best suited for basin level water management planning. It is expected that at the end of these pilot projects the province would be able to implement these models in the entire Province of Alberta to enhance water management (planning and operation) by enabling near real time computation of natural flows in gauged and ungauged watersheds.

MIKE SHE hydrological model

MIKE SHE, a physically based distributed hydrological model was used to simulate hydrological processes in the Elbow River watershed (Figure 16.1 and 16.2). It was dynamically linked to the one-dimensional hydrodynamic surface water model MIKE 11 for a complete representation of the river network within the watershed. The configuration includes comprehensive surface water and groundwater components. A detailed description of the relevant data, parameters, and methods used for the model setup can be found in Wijesekara *et al*. (2012, 2013). The sensitivity of the model to surface water and geological

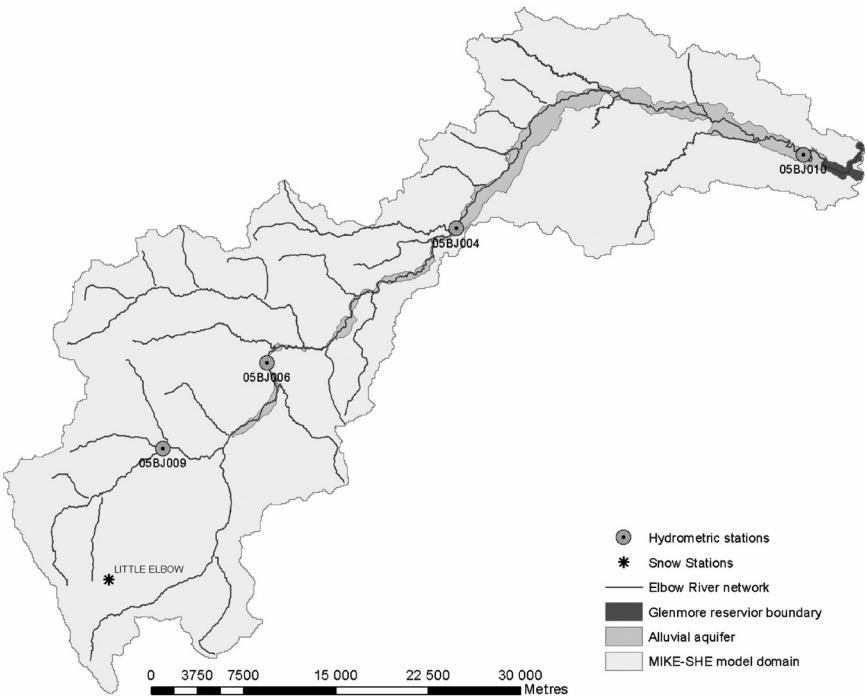

Figure 16.2 *Map of the Elbow River watershed and MIKE SHE model domain (from Wijesekara and Marceau, 2012).*

parameters required for the 3D groundwater module was evaluated by changing the values of each parameter at a time and running simulations. With each run, the goodness of fit of the model was evaluated by comparing observed and simulated total snow storage and streamflow data. Based on the results obtained from this analysis, a rigorous calibration and validation procedure was applied using the split-sample, multi-criteria, and multi-point procedure recommended by Refsgaard (1997).

Pragmatic Method based hydrological model

The PM is a simple yet robust approach (Metcalfe *et al*., 2005) based on spatial interpolation and hydrological regionalization methods to generate natural flows in ungauged watersheds. The hydrological regionalization project was completed in 2006 (Golder Associates, 2006) and is not part of this paper. One of the outcomes of the hydrological regionalization project was a set of hydrological region boundaries within the province of Alberta which have been used in the PM spatial interpolation analysis (Figure 16.3).

Prior to any interpolation, data collected from the hydrometric stations were analyzed to determine the period of record and whether or not the data are collected on an annual or seasonal basis (typically April to October). During this step, the data were also analyzed to ensure that they are truly natural flow stations (McGee *et al*., 2012). For any interpolation run the associated drainage area polygon of each selected hydrometric station was used to establish the centroid of the watershed. This was done because basin specific yield values are better represented spatially at the centroid of each watershed than at the gauge location (Krug *et al*., 1990). A variety of analytical tools used in conjunction with the project were created to facilitate the development of a PM hydrological model for the entire SSRB watershed.

Continuous interpolated surfaces of annual yield and dimensionless flow exceedance percentage points for each hydrological region in Alberta were created (Figure 16.3). Although the tool is designed to calculate any percent exceedance point (user defined), the defaults are 31 percent exceedance surfaces (0.01, 0.05, 0.5, 1, 2.5, 5, 7.5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 92.5, 95, 97, 99.45, 99.9, 99.95 and 99.99).

The combination of all interpolated surfaces generates a dimensionless percent exceedance curve for any drainage area within the SSRB. At the same time, the annual yield can also be computed for the drainage area in question.

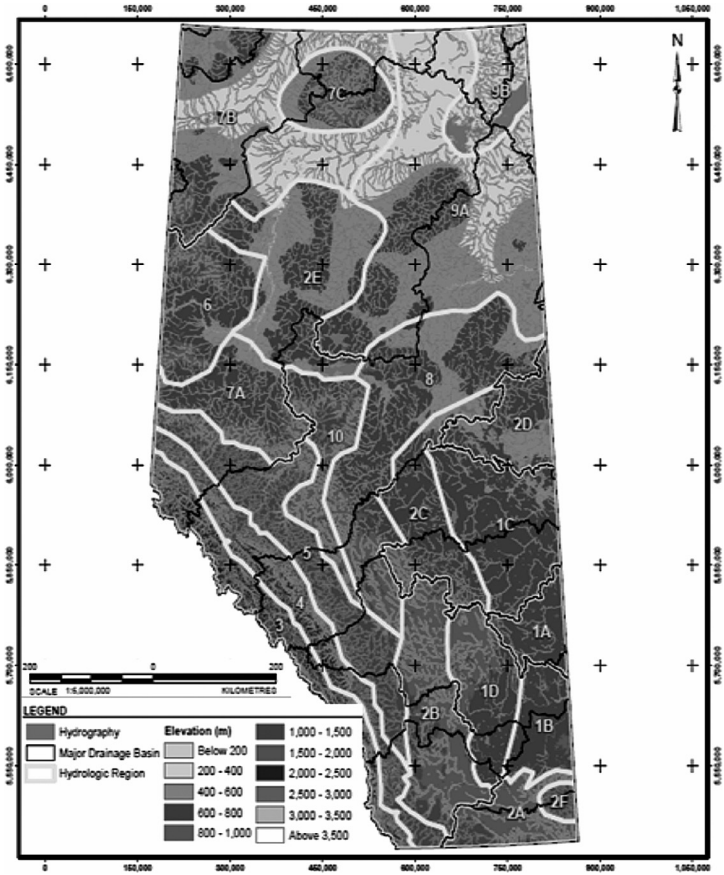

Figure 16.3 *Hydrological regions of Alberta.*

Combining the dimensionless percent exceedance points and annual yield results in an FDC for the selected watershed. With any point and click watershed delineation tool (in this project ArcHydro), the estimation of the FDC for ungauged watersheds is relatively easy. The applied methodology was adopted as outlined by Metcalfe *et al*. (2005), where known key hydrometric stations and/or regional FDCs are used to compute the near real time flows at ungauged watersheds.

The PM is simple in theory where known flows from key hydrometric stations are transferred to an ungauged watershed using FDCs (Figure 16.4). At key hydrometric stations, two things are required: (i) availability of real time flow data, and (ii) a derived FDC using historical data. When flows are

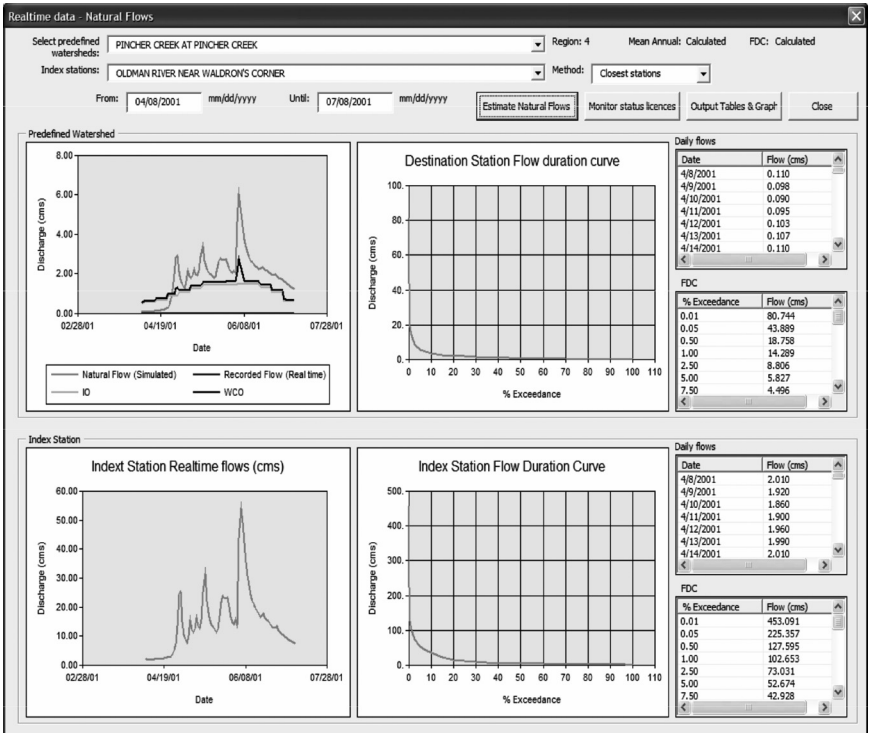

Figure 16.4 *Estimation of near real time natural flow using the Pragmatic Method.*

required to transfer from a key station to an ungauged station, a percent exceedance is obtained from the key hydrometric FDC. For the ungauged watershed, an FDC is derived from the aforementioned continuous interpolated surfaces. The key assumption is that, at the time of transfer the ungauged watershed is flowing at the same percent exceedance as the key hydrometric station, and therefore it is possible to compute near real time natural flows at ungauged watersheds.

16.4 RESULTS AND DISCUSSION

MIKE SHE Hydrological Modelling

This section describes the performance of the MIKE SHE/MIKE 11 model. The total water balance error during all model runs was less than 1% and considered an adequate model performance. The differences in accumulated flow volumes between observed and simulated flows at Bragg Creek (05BJ004) hydrometric station during the simulation period of 1982-91 are

Table 16.1 *Accumulative flow volume at Bragg Creek (05BJ004) hydrometric station Creek during the simulation period of 1982-91.*

	Accumulated		
	Simulated volume (Mm^3)	Observed volume (Mm^3)	Difference (%)
Total volume	2359	2200	7
High flow volume	1586	1496	6
Low flow volume	773	705	10

listed in Table 16.1. A seven percent difference was found at Bragg Creek flow gauge station between the simulated and observed total accumulated volume for the period of 1982 to 1991. The difference in accumulated flows during the open water (high flow) periods and the winter (low flow) periods were found to be six percent and ten percent, respectively. The comparison of simulated and observed hydrographs (Figure 16.5) shows that the trends of flow changes are reasonably simulated for the calibration period from 1982 to 1991. The calculated Nash-Sutcliffe Efficiency (NSE) values were between 0.52-0.94 and the correlation coefficients were between 0.52-0.97

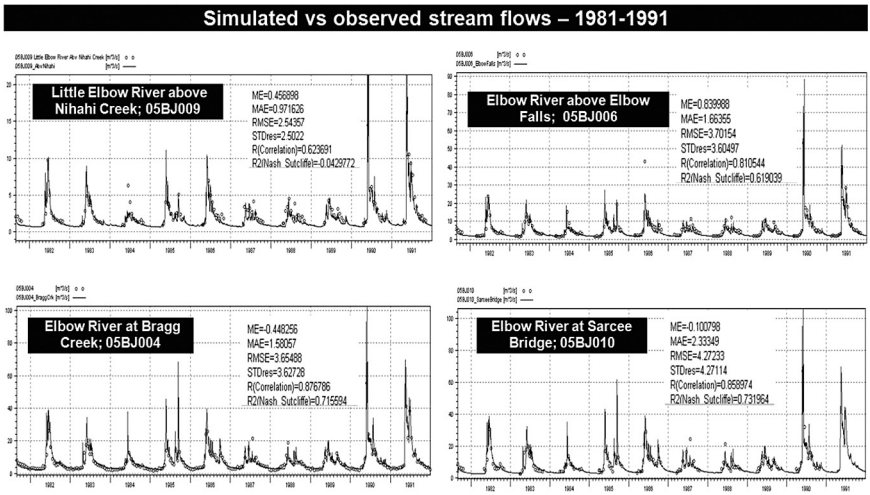

Figure 16.5 *Comparison of simulated and observed flow data at various hydrometric stations in the Elbow River watershed.*

based on monthly flow data at the four hydrometric gauging stations located on the main stem of the Elbow River (Figure 16.2). According to model evaluation guidelines mentioned by Moriasi *et al*. (2007), an NSE value above 0.5 for a monthly time step in hydrological modelling is considered satisfactory. Therefore, the performance of the MIKE SHE model as configured for the Elbow River watershed was considered sufficient to reasonably estimate the required natural streamflow series in the watershed.

Pragmatic Method based Hydrological Model

The developed PM based hydrological model for the Alberta portion of the SSRB is currently being calibrated. Even though the methodology is robust and has been applied in various parts of the world (Metcalfe *et al*., 2005), comprehensive calibration and testing are required. The initial results are promising and will be published in the near future. Moreover, further testing is being conducted to identify any limitations with respect to drainage size and spatial representation of key hydrometric stations. This methodology depends on the availability of near real time flow data at key hydrometric stations which makes it difficult to apply in watersheds where there are no hydrometric measurements.

16.5 ACKNOWLEDGEMENTS

We thank the Government of Alberta (Alberta Environment and Sustainable Resource Development Department) for providing funding and the Danish Hydrological Institute (DHI) for providing technical expertise in debugging the MIKE SHE model.

17

TOWARDS IMPROVED HYDROLOGIC MODEL PREDICTIONS IN UNGAUGED SNOW-DOMINATED WATERSHEDS UTILIZING A MULTI-CRITERIA APPROACH AND SNODAS ESTIMATES OF SWE

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17.1 ABSTRACT

In the mountainous regions in the western United States, much of the annual streamflow runoff originates as meltwater from snow. Hydrologic models used for water supply forecasting in these regions use a wide range of algorithms to simulate the snow water equivalent (SWE) throughout the accumulation and depletion processes of the snowpack; obtaining accurate estimates of the spatial and temporal distribution of SWE, however, is a challenge due to the limited number of point observations of SWE. Thus, the calibration of these models generally focuses on fitting simulated streamflow to observed streamflow data. In this study, SWE estimates obtained from the Snow Data Assimilation System (SNODAS) product are investigated as a surrogate for observation data to perform a multi-objective, multi-behaviour calibration of a hydrologic model. When the hydrologic model is calibrated using the SNODAS SWE estimates (and the streamflow observations are not used in the calibration process) the resulting simulation of streamflow compares reasonably well with the observed streamflow values. This suggests SNODAS estimates of SWE may contain information that, in the absence of any streamflow observations, may be very useful for improving model predictions in ungauged basins.

17.2 RÉSUMÉ

Dans les régions montagneuses de l'ouest des États-Unis, une bonne partie de l'écoulement annuel provient de l'eau de fonte de la neige. Les modèles hydrologiques servant à la prévision des réserves d'eau dans ces régions reposent sur un vaste éventail d'algorithmes pour simuler l'équivalent en eau

de la neige (EEN) tout au long des processus d'accumulation et de diminution du manteau neigeux; cependant, l'obtention d'estimations exactes de la distribution spatiale et temporelle de l'EEN constitue un défi vu le nombre limité de points d'observation de l'EEN. Par conséquent, l'étalonnage de ces modèles met en général l'accent sur l'ajustement de l'écoulement simulé en fonction des données observées sur le débit. Dans la présente étude, les estimations de l'EEN obtenues à partir du produit du système de données SNODAS (SNOw Data Assimilation System) sont étudiées en tant que substituts des données d'observation pour l'exécution d'une calibration multi-objectifs et multi-comportements d'un modèle hydrologique. Lorsque le modèle hydrologique est étalonné à l'aide des estimations de l'EEN basées sur les données de SNODAS (et que les observations entourant le débit ne sont pas utilisées dans le processus d'étalonnage), la simulation de l'écoulement qui en résulte se compare raisonnablement bien aux valeurs d'écoulement observées. Cela porte à croire que les estimations de l'EEN tirées des données SNODAS peuvent contenir de l'information qui, en l'absence de toute observation entourant les débits, peut s'avérer très utile pour l'amélioration des prédictions de modèle dans les bassins non jaugés.

17.3 INTRODUCTION

There have been a wide range of different modelling approaches for ungauged watersheds planned, developed, and tested over the last decade through the International Association of Hydrologic Sciences (IAHS) effort focused on Predictions in Ungauged Basins (PUB) (Sivapalan *et al*., 2003). Some of the more common approaches include regionalization methods based on physical and/or hydrological similarities between an ungauged study area and a gauged basin or geographical region, nearest neighbour methods which infer parameter values based on gauged watershed models in close geographical proximity to the study area (Vandewiele and Elias, 1995; Parajka *et al*., 2007), and other methods with regression based algorithms like the simple linear parametric (Seibert, 1999) and the more complex multivariate semi-parametric (Li *et al*., 2010) algorithms which establish relationships between model parameters and variables such as watershed characteristics or climate.

More traditional model calibration approaches involve the selection of values for parameters so that the model matches the observed behaviour of the watershed system as closely as possible. The observed behaviour is most

often the streamflow, which is, by definition, not available in PUB applications. In the absence of observed streamflow, other observations or estimates of important watershed behaviours related to the water and energy balance may be available to improve the performance of the model. Hay *et al*. (2006) used a multistep calibration procedure with readily available estimates of average monthly solar radiation and Potential Evapotranspiration (PET) to improve the simulation of streamflow observations. While this procedure is a promising advance in hydrologic model calibration, two of the four calibration steps require the availability of streamflow measurements, thus a limitation for applying the procedure to ungauged basins that lack observed data.

In this chapter, a hydrologic model is applied to a snow dominated mountainous watershed to simulate daily streamflow values at the outlet. While daily observations of streamflow are available, they are not used to estimate model parameter values (i.e. a typical PUB situation) but are used to evaluate model performance. The method developed by Hay *et al*. (2006) is used to investigate the value of an operational daily SWE product to estimate snow related model parameters and improve the simulation of streamflow. The SWE product is not a direct observation; rather, it is a surrogate for spatial and temporal SWE observations throughout the study watershed.

17.4 METHODS

Study Area

This study was conducted on the West Walker River watershed as defined by the area contributing to the United States Geological Survey (USGS) surface water station (USGS gage #10296500) located near Coleville, CA (Figure 17.1). The watershed is approximately 630 km^2 and the elevation ranges from 1,700 m a.s.l. to 3,500 m a.s.l.. The average precipitation varies with elevation from 535 mm to 1,550 mm and occurs primarily in the winter as snow. There are four Natural Resource Conservation Service (NRCS) snow-telemetry (SNOTEL) sites located in the headwaters of the Walker River basin (Figure 17.1).

SNOw Data Assimilation System (SNODAS) (Carroll *et al*., 2001) is a modelling and data ingestion product of the U.S. National Oceanic and Atmospheric Administration (NOAA) National Operational Hydrologic

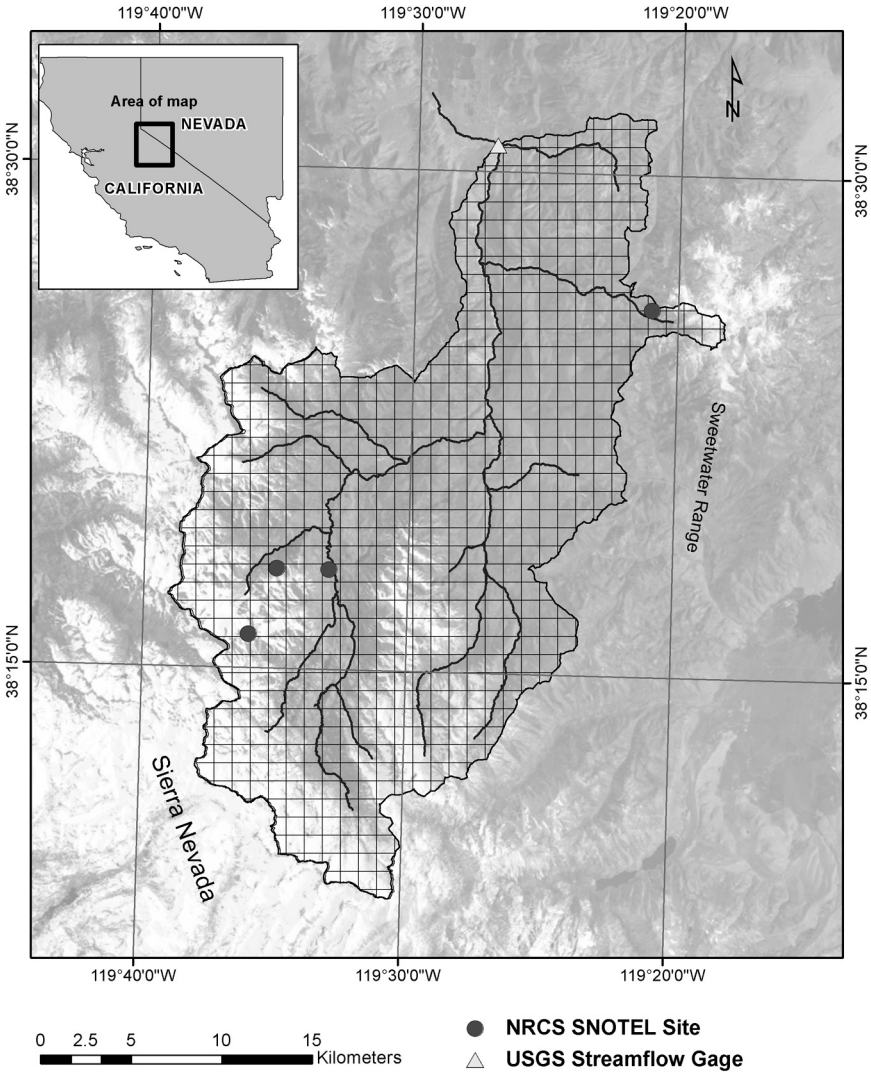

Figure 17.1 *Location of West Walker River study area.*

Remote Sensing Center (NOHRSC) that provides "best possible estimates" of hydrologic variables related to snowcover for the continental United States in high spatial (1 x 1 km) and temporal (daily) resolution (Barrett, 2003). The main component of the system is a spatially distributed, multi-layered snow mass and energy balance model that uses input such as

temperature, precipitation, and wind analyses from NOAA and National Centers for Environmental Prediction (NCEP) operational Rapid Update Cycle 2 (RUC2) numerical weather prediction model. Differences between model estimates and ground measurements as well as remotely sensed data of snow covered area, snow depth, and snow water equivalent are compared on a daily basis, and, if necessary, used to rerun the model and nudge estimated variables to match observed data more closely. The SNODAS product is updated daily and can be downloaded cost-free from the National Snow and Ice Data Center, for the period since 1 October, 2003.

Hydrologic Model

The Precipitation Runoff Modeling System (PRMS) is a hydrologic model that uses both empirical relationships and physical relationships to represent the water and energy balances within a watershed (Leavesley *et al*., 1983). PRMS is widely used in mountainous, snow-dominated watersheds, to simulate the streamflow response due to changes in precipitation, temperature, and snowmelt.

In this study, the PRMS model was applied at a daily time step over the period 1 October, 2003 through 30 September, 2009 at a hydrologic response unit (HRU) and SNODAS grid resolution of 1 km^2 (Figure 17.1). A time series of daily precipitation and minimum and maximum air temperature were estimated for the centroid of each HRU using the observations at each SNOTEL site and a relationship based on the location of each SNOTEL site and each HRU derived from an analysis of long-term average monthly values of precipitation, minimum temperature, and maximum temperature from the Parameter-elevation Regression on Independent Slopes Model (PRISM) (Daly *et al*., 1994). Initial estimates of all model parameters were set to default values except those that could be estimated from GIS information (e.g., topography, soil and vegetation type, etc.); the resulting parameter set is referred to from here on as the default parameters (Table 17.1).

Parameter Estimation

The PRMS model was calibrated using a three-step automatic calibration approach based on the approach presented by Hay *et al*. (2006). Step one involves using the Shuffled Complex Evolution-University of Arizona (SCE-UA) genetic optimization algorithm developed by Duan *et al*. (1993) to locate optimal values of the monthly solar radiation parameters (*dd_intcp*

Table 17.1 *PRMS parameters adjusted in steps 1-3.*

Parameter	Description	Source	
		Method[1,2]	GIS derived
mix_rain	Monthly factor to adjust rain proportion in a rain/snow event	X(3)	
cecn_coef	Monthly convection energy coefficient	X(3)	
covden_sum	HRU vegetation cover density (summer)		X
covden_win	HRU vegetation cover density (winter)		X
cov_type	HRU vegetation type (bare, grass, scrub, and tree)		X
dday_intcp	Monthly intercept temperature degree – day relationship	X(1)	
emis_noppt	Emissivity of air on days without precipitation	X(3)	
freeh2o_cap	Free water holding capacity of snowpack	X(3)	
hru_area	HRU area		X
hru_aspect	HRU aspect		X
hru_elev	HRU elevation		X
hru_lat	HRU latitude		X
hru_slope	HRU slope		X
jh_coef	Monthly coefficient used in Jensen – Haise PET computations	X(2)	
jh_coef_hru	HRU coefficient used in Jensen – Haise PET computations		X
potet_subllim	Proportion of PET that is sublimated from snow surface	X(3)	
rad_trncf	Transmission coef. for sw radiation through winter canopy		X
snarea_thresh	Maximum SWE below which SCA depletion curve is applied		X
snow_intcp	HRU snow interception capacity for the major vegetation type		X
soil_type	HRU soil type (clay, loam, sand)		X
srain_intcp	HRU summer rain interception capacity for the major veg. type		X
tmax_adj	HRU max temp. adjust. based on slope and aspect		X
tmax_index	Monthly index temp. used to determine precip. adjust. to solar rad.	X(1)	
tmax_allrain	Monthly max. temp. above which all precip. is simulated as rain	X(3)	
tmax_allsnow	Max. temp. below which all precip. is simulated as snow	X(3)	
tmin_adj	HRU min. temp. adjust. based on slope and aspect		X
wrain_intcp	HRU winter rain interception capacity for the major veg. type		X

[1]All parameters not included in Table 17.1 were set to PRMS default values.
[2]Parameters identified with X() were initially set to PRMS default values. The number in parentheses corresponds to the calibration step in which the parameter was optimized.

and *tmax_index*) while leaving the remaining model parameters at their default values. In this step, the monthly values of each parameter were adjusted by the SCE-UA algorithm until the error between the model estimates of mean monthly solar radiation and those from long-term average solar radiation resource maps (http://rredc.nrel.gov/solar/old_data/nsrdb/1961-1990/redbook/) was minimized based on the log of the absolute difference as recommended by Hay *et al*. (2006):

$$OBJ_{solrad} = \sum_{m=1}^{12} |log(EST_m) - log(SIM_m)| \quad (1)$$

where OBJ_{solrad} is the objective function, m is the month, and EST and SIM are the basin average estimated and PRMS simulated values of mean monthly solar radiation, respectively.

In step two the monthly solar radiation parameters found in step one were set to the optimized values from step one and the remaining model parameters were set to their default values except one related to the mean monthly PET (*jh_coef*). In this step, the monthly values of the parameter were adjusted by the SCE-UA algorithm until the error between the model estimates of mean monthly PET and those estimated from Farnsworth *et al*. (1982) was minimized based on the log of the absolute difference as recommended by Hay *et al*. (2006):

$$OBJ_{pet} = \sum_{m=1}^{12} |log(EST_m) - log(SIM_m)| \tag{2}$$

Where OBJpet is the objective function, m is the month, and EST and SIM are the basin average estimated and PRMS simulated values of mean monthly PET.

Step three involves setting the solar radiation and PET parameters to the values found in steps one and two; the remaining parameters are set at their default values except for parameters related to the snow accumulation and melt processes (*adjmix_rain, cecn_coef, emis_noppt, freeh2o_cap, potet_sublim, tmax_allrain, and tmax_allsnow*). In this step, the values of these parameters were adjusted by the SCE-UA algorithm until the error between the model estimates of daily SWE and those estimated from the SNODAS product was minimized based on the following objective measure:

$$OBJ_{SWE} = 0.3 \cdot OBJ_{overall} + 0.1 \cdot OBJ_{nosnow} + 0.3 \cdot OBJ_{accum} + 0.3 \cdot OBJ_{depl} \tag{3}$$

Where $OBJ_{overall}$, OBJ_{nosnow}, OBJ_{accum}, and OBJ_{depl} are the objective measures of the entire time series, the periods of no snow, snow accumulation, and snow depletion, respectively. The no snow period is weighted with 0.1 while the other behaviours received weights of 0.3, to give emphasis to behaviours in which snow is physically present according to the SNODAS product. Each of these four objective functions is calculated using the normalized root-mean-squared error (NRMSE):

$$OBJ = \sqrt{\frac{\sum_{n=1}^{ndays} (SNOD_n - SIM_n)^2}{\sum_{n=1}^{ndays} (SNOD_n - MN)^2}} \tag{4}$$

Where ndays is the number of days in the time series that fall in the individual SWE period, n is the number of days in the period, SNOD and SIM are the SNODAS and PRMS simulated time series values of the respective period, and MN is the mean daily SWE value associated with an individual period. This step is different from the procedure outlined in Hay *et al*. (2006) since our approach takes advantage of the SNODAS estimates of SWE and assumes no streamflow observations exist to perform their steps three and four.

17.5 RESULTS

The results for steps one and two are shown in Figure 17.2 and Table 17.2. The mean monthly solar radiation and mean monthly PET estimates resulting from the default parameter set tend to slightly underestimate the values in October through April and overestimate June through September while those resulting from the calibration procedure are a near perfect fit for all months.

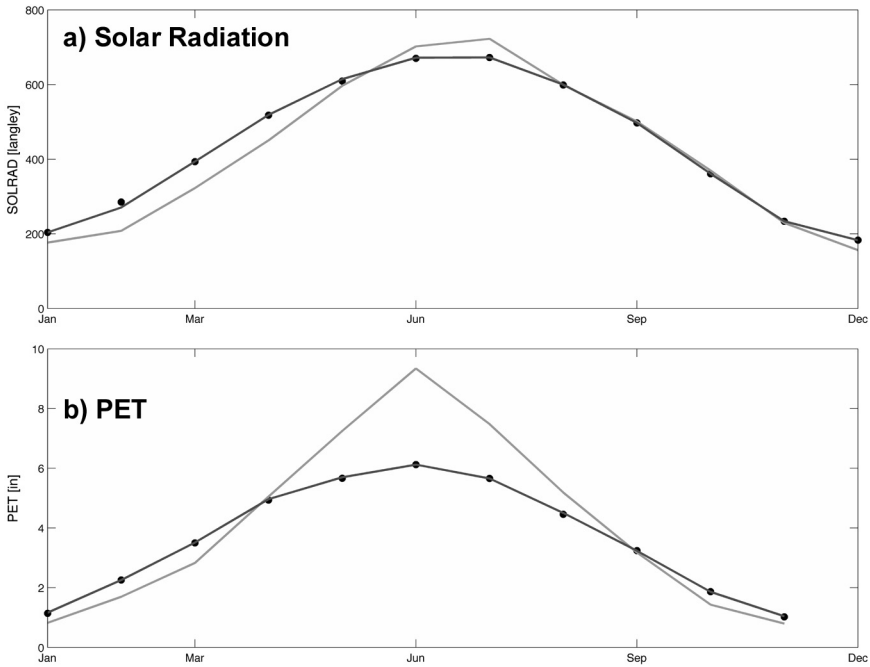

Figure 17.2 *Calibration results for step 1* ***(a)*** *and step 2* ***(b)****. Observations are indicated by black dots, simulated results using default parameters by grey lines, and calibrated results by black lines.*

Table 17.2 *Objective measures obtained for the first and second calibration step.*

PRMS	Step 1 ($absLogDiff_{solrad}$)	Step 1 ($absLogDiff_{PET}$)
Default	0.50	1.08
Calibrated	0.03	0.03

The results for step three are shown in Figure 17.3 and Tables 3 and 4. A visual inspection of Figure 17.3a reveals the improvement in the model's ability to fit the SNODAS SWE estimates with the parameters obtained after step three of the calibration procedure. The objective measures shown in Table 17.3 also provide a means to assess the improvement in the model's ability to fit all defined behaviours of the SWE (i.e. overall, no snow, accumulation, and depletion).

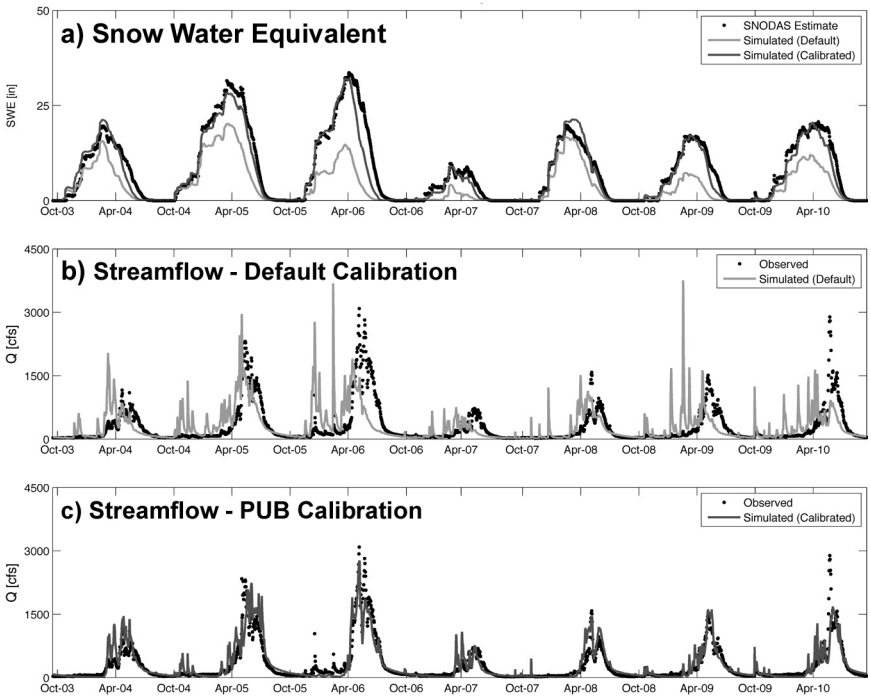

Figure 17.3 *Results from step 3 for SWE **(a)** and streamflow **(c)**; results for streamflow using default values are shown **(b)** for comparison. Observations are indicated by black dots, simulated results using default parameters by grey dashed lines, and calibrated results by black lines.*

Table 17.3 *Objective measures for SWE corresponding to third calibration step.*

Objective Measures[1]	Default	Step 3
Weighted $NRMSE_{SWE}$	0.75	0.26
$NRMSE_{overall}$	0.7	0.25
$\%BIAS_{overall}$	-50	-6
$NRMSE_{nosnow}$	0.47	0.18
$\%BIAS_{acn}$	-42	20
$NRMSE_{accumulation}$	0.72	0.19
$\%BIAS_{accumulation}$	-41	3
$NRMSE_{depletion}$	0.92	0.38
$\%BIAS_{depletion}$	-59	-18

[1]The objective measure used for calibration in step 3 was the weighted $NRMSE_{SWE}$. The remaining objective measures are shown in the table to provide a quantitative measure of closeness for each of the defined behaviours of the watershed in terms of SWE.

Visual inspection of Figures 3b and 3c reveals the improvement of the model's performance in terms of observed streamflow. In general, the results appear to be much closer to the observed streamflow in terms of dynamics and bias; however, there are still two short duration, high flow rain on snow events that the calibrated model is significantly overestimating. The poor performance for these two events is most likely related to errors in temperature observations and the process of partitioning precipitation into rain and snow. The values of NRMSE and percent bias presented in Table 17.4 were computed for the overall time series of simulated and observed streamflow and individual streamflow behaviours defined by Boyle *et al*. (2000) as rising limb, falling limb, and baseflow. Both measures show a quantifiable improvement for all behaviours for the calibrated model.

17.6 DISCUSSION AND CONCLUSIONS

While the results presented in this paper are for only one watershed using one hydrologic model, they demonstrate at a proof of concept level the potential value in incorporating estimates of SWE from the operational SNODAS product into the calibration process. There was an improvement in the model's ability to simulate observed streamflow compared to the results obtained using default parameter values. This is particularly relevant

Table 17.4 *Objective measures of streamflow corresponding to third calibration step.*

Objective Measures[1]	Default	PUB Calibration
$NRMSE_{overall}$	0.89	0.46
$\%BIAS_{overall}$	8.28	7.55
$NRMSE_{baseflow}$	8.24	3.17
$\%BIAS_{baseflow}$	99	24
$NRMSE_{risingLimb}$	1.35	0.64
$\%BIAS_{risingLimb}$	84	7
$NRMSE_{fallingLimb}$	0.79	0.47
$\%BIAS_{fallingLimb}$	-48	6

[1]The objective measure used for calibration in step 3 was the weighted $NRMSE_{SWE}$.
The objective measures shown in this table were calculated to provide a quantitative measure of closeness for each of the defined behaviours of the watershed in terms of streamflow.

to PUB applications where there are no observations of streamflow. A general evaluation of the value of this approach, however, would require a much more comprehensive evaluation over a large number of watersheds in different regions (e.g., Sierra Nevada, Rocky Mountains, Wasatch, etc.).

It would also be useful to better understand the relationship between the SWE estimates and the observed streamflow and how these relationships change for different regions. It is very important to remember that the SNODAS estimates of SWE are not direct observations of SWE, rather they are a product based on a modelling process that is evaluated and influenced by point observations of meteorological and snowpack information where available. The watershed selected in this study contained four NRCS SNOTEL stations that are used by the SNODAS product. A similar study is currently being performed by our team in a mountainous study area in central Nevada with no point observations of meteorological and snowpack information to expand our understanding of the value of SNODAS in PUB applications. Clearly, this specific methodology will not work in areas outside the U.S. where SNODAS SWE products are generally unavailable (though southern Canada also has SNODAS coverage). The general approach of using independently derived estimates of important hydrologic variables to estimate relevant model parameters in the calibration process could be useful, and will be a focus of future work.

17.7 ACKNOWLEDGEMENTS

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18

USING SATELLITE IMAGERY AND THE DISTRIBUTED ISNOBAL ENERGY BALANCE MODEL TO DERIVE SWE HETEROGENEITY IN MOUNTAINOUS BASINS

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18.1 ABSTRACT

A novel reconstruction method that estimates the spatial distribution of snow water equivalent (SWE) in mountainous areas is presented. This model is based on remote sensing imagery and energy balance calculations only and allows us to compute the SWE distribution at sub-pixel resolution for any day during the melt season. No precipitation input is needed to drive this model; hence it could be a valuable addition to the existing tool boxes of hydrologic modelling researchers and practitioners.

18.2 RÉSUMÉ

Une nouvelle méthode de reconstruction permettant d'estimer la distribution spatiale de l'équivalent en eau de la neige (EEN) dans les régions montagneuses est présentée. Ce modèle est basé sur l'imagerie de télédétection et sur des calculs du bilan énergétique seulement et il nous permet de calculer la distribution EEN à une résolution sous-pixel pour n'importe quel jour pendant la saison de la fonte. Aucune donnée d'entrée sur les précipitations n'est nécessaire pour exécuter ce modèle. Par conséquent, il pourrait s'agir d'un ajout précieux à la boîte à outils existante des professionnels en exercice et des chercheurs du domaine de la modélisation hydrologique.

18.3 INTRODUCTION

Spatial variability in snow water equivalent (SWE) plays an important role in the prediction of a basin's streamflow at both daily and seasonal times scales, because it affects the timing and magnitude of daily and annual melt; areas of heterogeneous SWE will cause patchy snow coverage during the melt season. This heterogeneity reduces the surface-to-volume ratio of the remaining snow, compared to homogeneous snowcover, because the same amount of snow has a smaller surface. Consequently, the snow will persist longer into the melt season and sustain stream discharge into the summer months. In addition to the effect on streamflow, SWE heterogeneity also affects soil moisture and vegetation; areas of high accumulation produce quasi-riparian zones of increased soil moisture that remain wet longer into the dry season.

Spatial patterns of snow heterogeneity are expected to be similar between years, since they are related to interannually invariant parameters like topography, vegetation, and prevailing wind direction. Capturing these patterns, even by a retrospective method, could improve predictive modelling. It is also important to evaluate just how similar these spatial patterns are.

Remote sensing can give us a good measurement of the areal extent of snowcover, but quantifying the depth of snow from remote sensing is very difficult. Snowmelt and energy balance models can estimate the daily melt, but capturing the progression of spatial heterogeneity of SWE throughout the water year exceeds most models' capabilities. Combining the strengths of both methods will enable us to predict snowmelt runoff most effectively.

18.4 METHOD

SWE reconstruction from snowcover depletion was first proposed by Martinec and Rango (1981) and further developed by others (Cline *et al*., 1998a, 1998b; Molotch *et al*., 2004; Molotch and Bales, 2005). Martinec and Rango (1981) reconstructed basin SWE backward in time using estimates of snow covered area from Landsat and aerial photography combined with daily melt computed by a temperature-index model. The basic idea was both simple and clever: starting at peak snow accumulation, the potential melt is summed up daily for each pixel until the remote sensing imagery shows that this pixel is snow-free. The sum yields the total amount of SWE per pixel. The novelty of the model presented here is that it does not just sum up the

pixel SWE to a grand total, but instead determines the distribution of SWE within each pixel in order to study the degree of heterogeneity.

The temporal resolution of MODIS allows tracking of daily changes in fractional snowcover area (f_{SCA}). Using this record, the reconstruction model follows the pixel fractions and the time when each of them melts out. From this the snowpack is reconstructed day by day as shown in Figure 18.1.

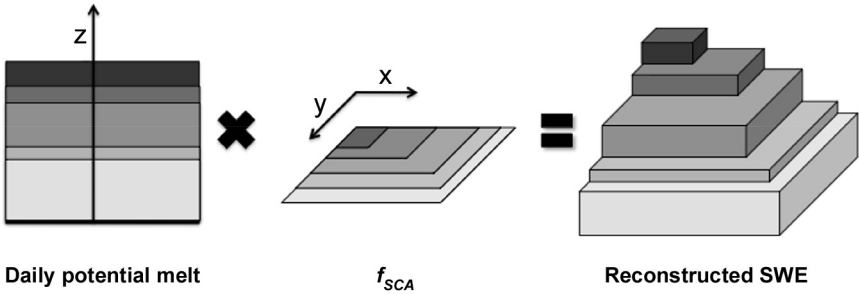

Figure 18.1 *Conceptual model to estimate heterogeneous snow water equivalent (SWE) in a MODIS grid cell.*

The potential melt estimates snow in the vertical dimension and f_{SCA} masks out the fraction of the pixel to which this snow is added. The product of these will give us a SWE volume for one day. This calculation is done each day until we reach the end of the melt season; the final product yields the distribution of SWE for one day within one pixel and can be plotted as a histogram of SWE values. Since visual inspection of histograms is impractical for the study of an entire watershed, statistical measures are used to represent the distributions instead. The median is chosen to represent pixel average and the percentile range from 25th to 75th percentile, referred to as C50, quantifies the spread. C50 scales with the pixel's average SWE value, because precipitation increases towards higher elevations. To eliminate this dependence, C50 can be normalized by the median to represent SWE heterogeneity by the coefficient of variation of the pixels' SWE distribution. For direct quantitative comparison with the heterogeneity from melt, however, C50 is better suited.

Fractional snow covered area is derived from spectral-mixture analysis of daily MODIS data at 500 m resolution (Painter *et al.*, 2009). The daily f_{SCA} estimates are modelled to interpolate and smooth across data gaps and errors, such that the final product is continuous in time and space (Dozier

et al., 2008). The potential daily melt is modelled with the snowmelt model Isnobal (Marks *et al*., 1999; Garen and Marks, 2005) at 30 m resolution. The model assumes a two-layer snowpack and computes the full mass and energy balance at hourly steps. To simulate a full water year, input of distributed radiation and meteorological data, as well as precipitation maps for each storm event are required. Alternatively the melt season can be modelled by itself, without the need for any precipitation input. In that case the snowpack is simply initialized with the appropriate amount of SWE, and subsequent melt can be computed from radiation, temperature, and humidity alone. For the reconstruction model, only the melt output of Isnobal is needed, and it is aggregated at the MODIS resolution to combine it with the previously described f_{SCA} data.

Heterogeneity from melt is derived from modelled 30 m Isnobal melt. It is computed as the standard deviation of the cumulative melt within the larger region of the 500 m MODIS pixels. Since melt is a surface effect without strong dependence on the depth of the snowpack, normalization by average SWE values is not appropriate.

18.5 RESULTS

SWE reconstruction

Heterogeneity from accumulation:

- derived from reconstructed SWE at peak accumulation (the point in time when snow melt has not begun)
- inter-annually consistent
- highest above the timberline (effects of redistribution and sublimation)
- used C50 here (not coefficient of variation) to allow quantitative comparison with heterogeneity from melt in Figure 18.2 below

Vegetation cover plays an important role, because it provides shelter from wind, the main driver of sublimation and redistribution. Histograms of individual pixels around the transition zone from forest to open illustrate the resulting SWE distributions (Figure 18.3). The three example pixels are located in close spatial proximity at elevations between 2600 m and 3000 m (Table 18.1; Figure 18.3). Pixel 132 is in the forest, pixel 136 at the timberline and pixel 138 in the open. Forested and open pixels have similar

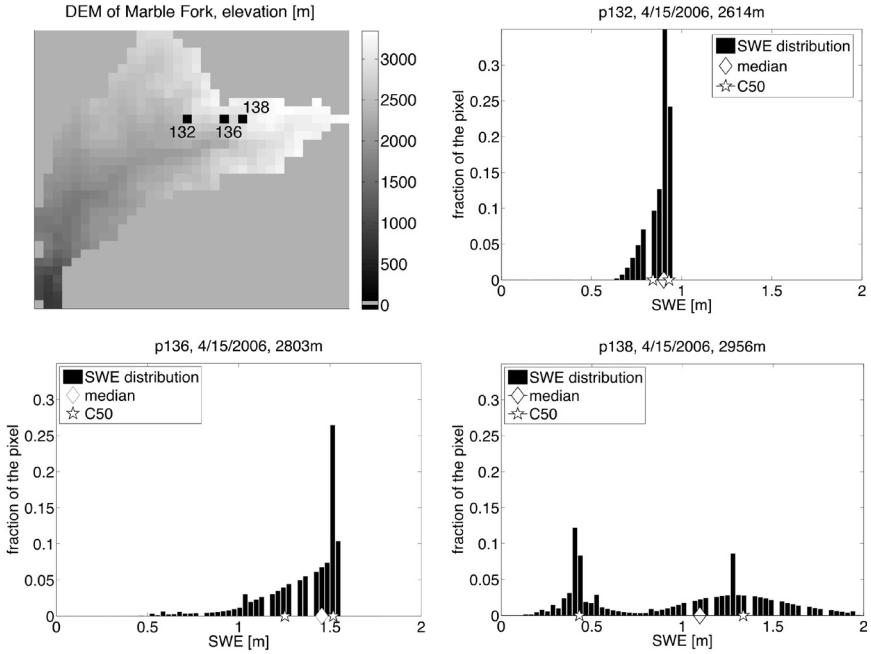

Figure 18.2 *Basin location (within 500 m DEM) and SWE histograms of three example pixels, with different distributions, pixel statistics in Table 18.1.*

average SWE values, but their distributions are distinctly different, leading to an order of magnitude difference in coefficient of variation. The pixel with dense canopy is an example of a homogeneous snowpack, while the pixel in the open exhibits a heterogeneous snowpack.

Pixel 136 at the transition between forest and open is closer to the open pixel, both in terms of horizontal and vertical distance, but the shape of its SWE distribution resembles that of the forested pixel. Pixel average SWE

Table 18.1 *Statistics of SWE distribution from the three example pixels in Figure 18.3.*

pixel ID	elev (m)	fveg	Med (mm)	C50 (mm)	Cov
132	2614	0.8	888	89	0.10
136	2800	0.4	1341	265	0.20
138	2957	0	949	903	0.95

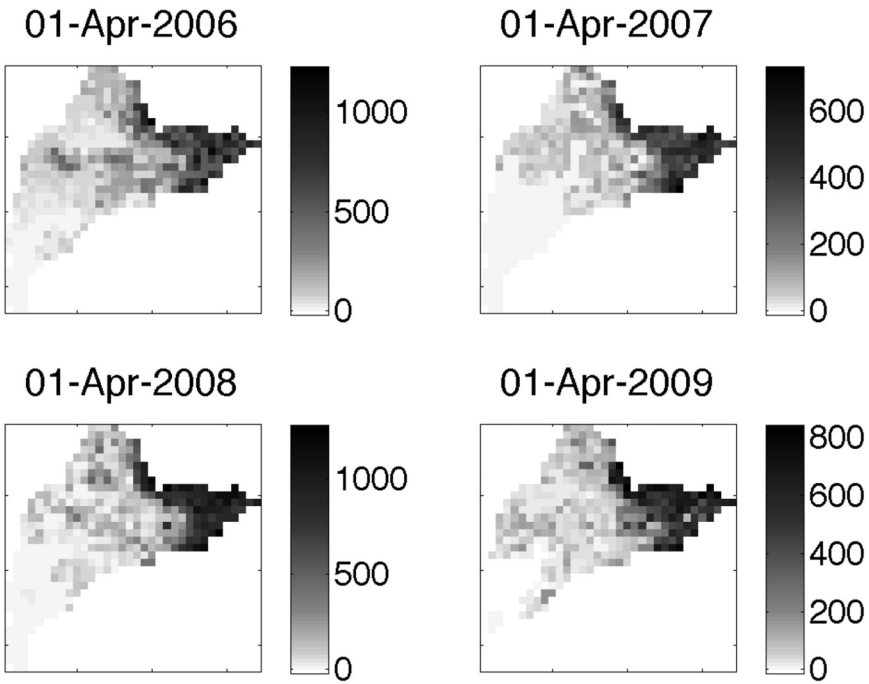

Figure 18.3 *Heterogeneity in SWE from the accumulation period of water year 2006-2009 quantified as C50 values (mm) of reconstructed SWE at peak accumulation.*

values tend to increase toward the upper elevations since precipitation is higher there; however, this trend halts at the timberline, probably due to sublimation and scouring effects, which deplete the snowpack during the accumulation period. As a result pixel 138 has less SWE than pixel 136.

The spatial patterns of SWE heterogeneity from melt are similar in 2007-2009. During 2006 the relative distribution is distinctly different. Heterogeneity values are lower and more uniform throughout the basin. April 2006 had several storms, hence new snow accumulated and very little melted. Since April is the month with the highest spatial variability in melt, the 2006 snowpack does not pick up much of that and remains more homogeneous for the rest of the season.

The consistency of the spatial patterns in the remaining years suggests spatial correlation with other invariant basin characteristics. A comparison of a typical pattern of SWE heterogeneity with a map of fractional vegetation cover reveals a number of spatial similarities (Figure 18.4).

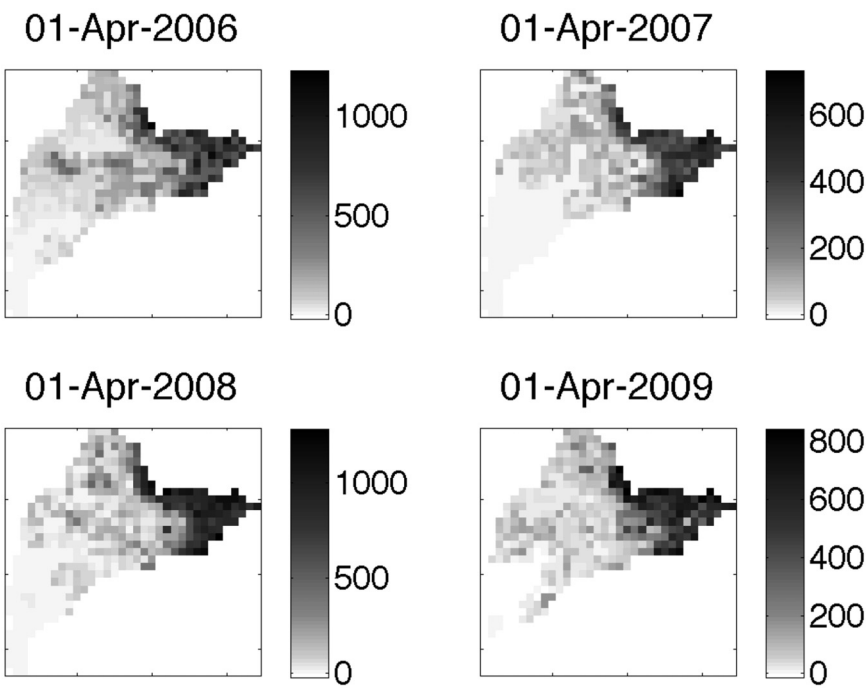

Figure 18.4 *Heterogeneity in SWE due to melt towards the end of the melt seasons 2006-2009. Heterogeneity is computed at standard deviation of cumulative 30 m melt within 500 m MODIS pixels, (mm).*

There are three zones of high heterogeneity. The first is a thin line of high heterogeneity along the southeastern edge of the basin, which coincides with the park road (depicted with black line in Figure 18.5). The road runs in a forest aisle representing an abrupt change in the vegetation cover, which causes a high change in melt and thus high heterogeneity. Another zone of high heterogeneity is outlined with dotted blue ovals across the northwest corner of the basin. In some years the heterogeneity is higher in the north, in others in the south. This zone lies along the timberline so again there is a relatively rapid change in vegetation cover. The southern end of this oval shows particularly high values of heterogeneity. It coincides with a narrow valley where south-facing and north-facing slopes meet, so topography accentuates the SWE heterogeneity. The third zone of high heterogeneity approximately forms a cross at mid-elevations. The 500 m map of fractional canopy cover derived from a binary map at 30 m resolution indicates values of around 0.5 for these pixels. By the nature of this derivation, 0.5 does not

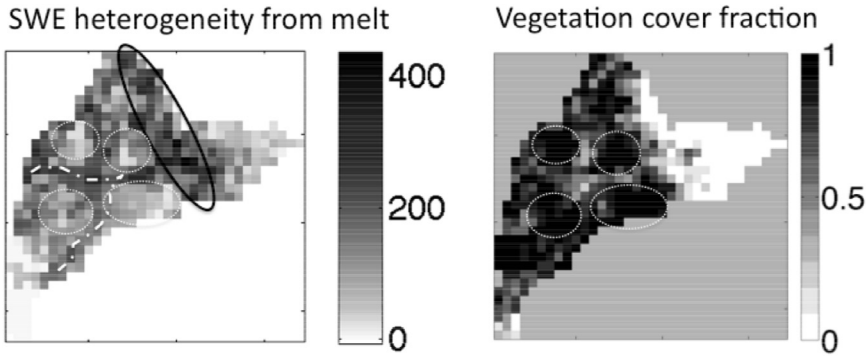

Figure 18.5 ***left:*** *Typical pattern of heterogeneity in SWE (mm) due to melt (June 1st, 2007);* ***right:*** *Vegetation cover fraction derived from binary vegetation cover based on NLCD at 30 m resolution. Black oval: high SWE heterogeneity around timberline, dashed line: National Park Road in a forest aisle, dotted circles: zones of low heterogeneity in pixels with vegetation cover fraction near 1.*

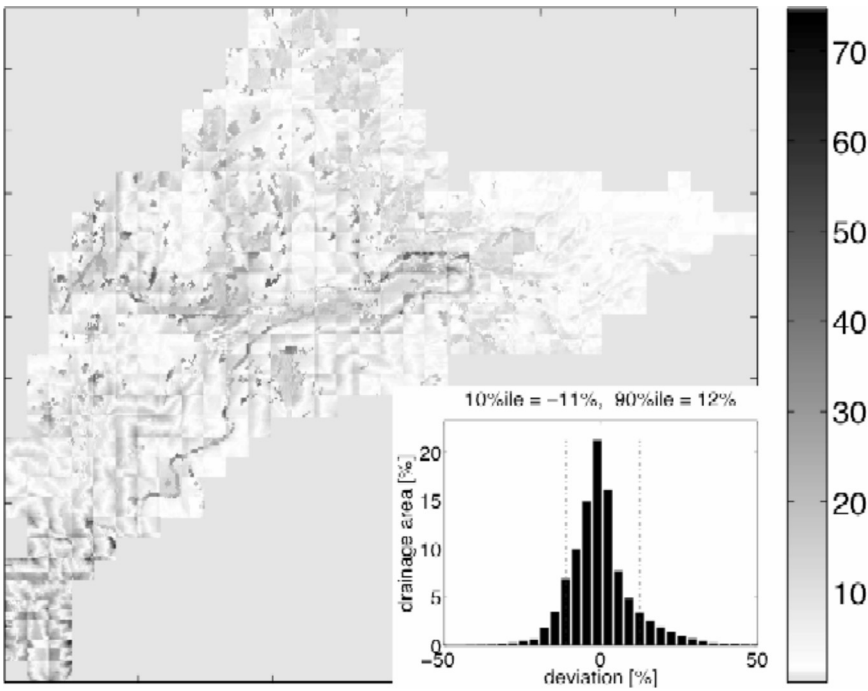

Figure 18.6 *Spatial distribution of absolute values of total annual deviation between $Melt_{500\,m}$ and $Melt_{30\,m}$ (%). Inset: distribution of the deviation values.*

refer to the density of evenly spaced trees, but to the fraction of 30 m pixels in the 500 m pixel that has trees in it. Thus, as for the previous two zones, this group of pixels represents a heterogeneity canopy cover. The zones of low SWE heterogeneity coincide with pixels of homogeneous vegetation cover. The four zones below the timberline (circled in Figure 18.5) include almost no open pixels, and the vegetation fraction is near 1.0. Above the timberline the SWE heterogeneity is also low, but here the homogeneous lack of vegetation cover is the reason.

Heterogeneity from melt:

- Comparison of the two patterns show high persistence between years, but heterogeneity from melt depends on timing of onset of melt.
- Location of high values in the two components do not coincide spatially, but both are correlated with vegetation cover: Accumulation = above timberline; Melt = transition zone between forested and open.
- Maximum heterogeneity caused by accumulation is higher than the one caused by melt.

Limitations

Currently the reconstruction model is still limited in the extent of heterogeneity that can be captured during the melt season. Potential melt is simulated at 30 m resolution, but f_{SCA} only provides one scalar per 500 m MODIS pixel to indicate the snow covered fraction. How much of the pixel is covered is known, but location within the pixel is not. Consequently, transferring the full information of the potential melt from Isnobal to the reconstruction is not possible and the melt is assumed to be uniform within a MODIS pixel. Figure 18.6 shows that this might be an acceptable assumption, but that it is not completely true; it shows the deviations of total annual melt at 30 m resolution from the total annual melt averaged over 500 m resolution. Deviations range from -40% to 60%, but these extreme values occur only rarely as shown in the inset in Figure 18.6. Most of the large deviations occur at lower elevations or along the National Park road where snow is only present for a few days of the year. 80% of the pixels deviate by less than 12% from the 500 m average.

18.6 SUMMARY AND CONCLUSIONS

A new approach to characterize the snowpack in mountainous basins using minimal ground-based measurements is proposed. The SWE reconstruction method presented does not require precipitation input, which makes it a highly attractive method to improve predictions in ungauged basins. In addition to pixel total SWE, which was estimated in previous reconstruction efforts, this model also captures the variability in SWE distribution within each modelling unit. It combines the daily change in fractional snow covered area with cumulative daily melt, computes the distribution of SWE, and summarizes its spread as the range between 25th and 75th percentile of the distribution, normalized by the median SWE.

This study further demonstrates how to separate and locate the two contributions to SWE heterogeneity: During accumulation, heterogeneity is highest in the open areas above the tree line. Once melt sets in, the heterogeneity increases also at the transition between forested and open areas.

In winter, snow accumulation is heterogeneous because of wind (Winstral *et al*., 2013); however, reconstruction accounts for the results of wind-redistributed snow at the beginning of the melt season, even though it does not model the actual distribution processes. Thus it provides an independent method of examining the spatial distribution of snow, which is useful to validate models of snow accumulation, either owing to redistribution (Elder *et al*., 1991) or to precipitation itself, such as PRISM (Daly *et al*., 2001; Davis *et al*., 2001). It is also useful in evaluating other methods to measure snow accumulation and its spatial variability, for example passive microwave. Not only does reconstruction match streamflow better than other methods (Rittger, 2012), it shows the significant negative bias of passive microwave measurements (Vander Jagt *et al*., 2013).

The measurement of heterogeneity can improve the way we model snowmelt. When the snowcover becomes patchy, uncovered ground will alter the advective energy exchange with the snowpack. Usually in our models, we refine the grid size down to the point where we make the cells individually homogeneous, but this strategy drives consumption of computational resources. Can we instead develop our distributed hydrologic models to account for heterogeneity in each cell (Luce and Tarboton, 2004)? This issue becomes particularly important when we incorporate snow into

land-surface interactions for climate models, because in addition to the obvious processes like snowmelt, the distribution of snow affects biogeochemical fluxes like carbon exchange (Pitman, 2003) and other elements of the land-surface interaction (Giorgi and Avissar, 1997; Liston, 2004; Swenson and Lawrence, 2012). Snow is therefore a general example of the importance of spatial patterns in the hydrologic response of catchments (Grayson *et al*., 2002). Improvements needed include better quantitative methods for pattern comparisons and better use of pattern information in data assimilation and modelling.

Finally, snow heterogeneity is important for a wide range of animal behaviour and vegetation patterns in the mountain environment; for example, caribou eat not the most nutritious lichen, but the lichen that are beneath the shallow snow patches (Johnson *et al*., 2001). Snow heterogeneity also affects the response of ecosystems to climate change, for example plant growth, arthropod communities, and carbon cycling. Winter snowcover and depth will add to spatial patterns in vegetation heterogeneity (Bokhorst *et al.*, 2012).

19

USING THE WETLAND DEM PONDING MODEL AS A DIAGNOSTIC TOOL FOR PRAIRIE FLOOD HAZARD ASSESSMENT

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19.1 ABSTRACT

On the Canadian Prairies the vulnerability of rural municipalities, their infrastructure, and economies to flooding has become a concern in recent years. The usual modelling approaches to assessing flood hazards are unsuitable for Prairie landscapes because of invalid assumptions and their focus on river reaches and the adjacent flood plain rather than the entire landscape. Prairie landscapes, being recently deglaciated, are comprised of complexes of wetlands which can contribute to flooding and are also ungauged. The Wetland DEM (Digital Elevation Model) Ponding Model (WPDM) is a tool that has been introduced to the Land and Infrastructure Resiliency Assessment (LIRA) project to provide improved flood hazard information for Prairie landscapes. The application of the WDPM to LiDAR (Light Detection and Ranging) DEMs has been particularly useful for Prairie landscapes where filling of wetlands is a dominant factor contributing to flooding. The accuracy of spatially distributed runoff information has been verified against ground and aerial photographs, remote sensing imagery, and most importantly community stakeholder experience. The results for two recent LIRA case studies are presented which show the value of this simple, spatially focused approach to assessing flood hazards across wetland dominated landscapes. Stakeholders have used this spatially distributed runoff information for assessing community planning and development, and for considering potential response strategies where flooding has occurred.

19.2 RÉSUMÉ

Dans les Prairies canadiennes, la vulnérabilité aux inondations des municipalités rurales, de leur infrastructure et de leurs économies est devenue un sujet de préoccupation ces dernières années. Les approches de modélisation habituelles de l'évaluation des risques d'inondation ne sont pas appropriées pour les paysages des Prairies en raison des hypothèses non valides qu'elles formulent et de l'accent qu'elles mettent sur les tronçons de rivière et sur les plaines d'inondation adjacentes plutôt que sur le paysage dans son ensemble. Les paysages des Prairies, ayant récemment connu une déglaciation, sont composés de complexes de milieux humides pouvant contribuer à des inondations et ils sont également non jaugés. Le modèle altimétrique numérique (MAN) relatif aux zones humides « Wetland Digital Elevation Model (DEM) Ponding Model (WDPM) » a été intégré au Projet d'évaluation de la résilience des terres et des infrastructures (LIRA) pour offrir de meilleures données sur les risques d'inondation pour les paysages terrestres des Prairies. L'application du modèle WDPM aux MAN du LIDAR (détection et localisation par la lumière) a été particulièrement utile pour les paysages des Prairies où le remplissage des milieux humides constitue un facteur dominant qui contribue aux inondations. L'exactitude des données d'écoulement spatialement distribuées a été vérifiée à la lumière des photographies terrestres et aériennes, de l'imagerie de télédétection et, qui plus est, de l'expérience des intervenants communautaires. Les résultats de deux récentes études de cas LIRA sont présentés. Ils témoignent de la valeur de cette approche spatiale simple de l'évaluation des risques d'inondation dans les paysages dominés par les terres humides. Les intervenants ont utilisé ces données d'écoulement spatialement distribuées pour l'évaluation de l'urbanisme et du développement des collectivités et pour la prise en considération des éventuelles stratégies d'intervention là où des inondations se sont produites.

19.3 INTRODUCTION

The Land and Infrastructure Resiliency Assessment (LIRA) is a systematic methodology consisting of a land use inventory and benefit-cost analysis designed to assist local and regional municipalities, watershed groups, and other decision makers identify effective adaptation strategies to address the risks due to extreme runoff events (Agriculture and Agri-Food Canada, 2013).

A key input for the economic modelling is a geospatial flood hazard assessment that can help identify urban and rural regions vulnerable to flooding and their intersection with economic infrastructure and/or areas of social or environmental importance. In Prairie landscapes these regions often include hydrological interactions within ungauged basins.

Canadian Prairie hydrology is complicated by the nature of Prairie landscapes (Winter, 1989; Shook and Pomeroy, 2011b; Shaw *et al*., 2011). The Prairie Pothole Region (PPR), which includes the Canadian Prairies, is marked by numerous wetland depressions capable of receiving and storing runoff and groundwater discharge, recharging groundwater, or functioning as flow-through systems (Euliss *et al*., 1999). Wetlands can interact hydrologically by connecting and disconnecting, which are complex processes that are influenced by the internal state of the system (the storage water levels and the antecedent soil moisture conditions) and by the local meteorological forcings (Shook and Pomeroy, 2011b; Shaw *et al*., 2011).

Complexes of wetland depressions may contribute runoff to larger systems when a series of interconnected depressions drains into a waterway. As a result, Prairie floods are due both to rising streams and to the fill-and-spill of interconnected depressions. Therefore the 'basins' that require modelling include those of the interconnected wetland depressions, whose size and connectivity change dynamically with the changes to the water stored within them.

Although some Prairie streams are gauged, the complexes of wetlands and the ephemeral streams which connect them are not, so the hydrological responses of complexes of Prairie wetlands depend upon the prediction of ungauged basins. The ability to model the interactions among wetlands is critical for determining runoff contributing areas, estimating discharge rates and runoff volumes, and identifying potential flood hazard zones. Unfortunately, standard hydrologic and hydraulic practices lack consideration of the wetland-dominated Prairie hydrology. Conventional hydrological models cannot reproduce the dynamic contributing fractions of Prairie basins, and hydraulic models are generally only applicable for connected channelized water flows.

Therefore current methods cannot generate geospatial flood hazard assessments that consider potential flood zones, for both rural and urban landscapes, within ungauged Prairie basins. Nevertheless, this type of

assessment is a key input to LIRA case studies in the Prairie region of Canada (Agriculture and Agri-Food Canada, 2013). LIRA required a diagnostic tool to provide estimates of the spatial distributions of runoff and the possible extents of flood hazards over entire landscapes.

19.4 METHODS

The Wetland DEM Ponding Model (WDPM)

The Wetland DEM Ponding Model (WDPM) was developed at the Centre for Hydrology of the University of Saskatchewan (Shook and Pomeroy, 2011b; Shook *et al*., 2013). The original purpose of the program was to model changes in the contributing area of wetland-dominated Prairie basins, due to the changes in the states of wetland storage; however, as the WDPM computes the spatial distribution of ponded runoff on a Prairie landscape, it has also been applied as a diagnostic tool to identify areas within the landscape vulnerable to runoff / flooding hazards.

The WDPM models the destination of surface runoff by applying the algorithm of Shapiro and Westervelt (1992) to a depth of water which is added to the entire DEM. The depth of water may be chosen arbitrarily; however, reference water depths have been applied to examine the potential spatial limits of runoff and flooding boundaries within the entire landscape. The reference depths applied are generally equivalent to annual extreme 24 hour return-period rainfall totals (e.g., 1:100 yr, 1:200 yr) and to other extreme rainfall cases that can contribute to flooding on the Prairies. The Vanguard, SK flood in July 2000, in which 300 mm of rainfall fell in 8 hours (Hunter *et al*., 2003), is of great interest in the Prairies, and was used as reference depth of water in the runoff simulations. Because the model assumes that all of the applied water runs off, the simulations exaggerate the extent of actual flooding that would be due to rainfall events; however, the simulations are still considered to be useful as a qualitative description of the location of the destination of runoff, as they represent worst-case scenarios.

The WDPM is well suited to routing runoff throughout Prairie landscapes and basins. Conventional overland flow models are limited to identifying runoff directions from a DEM cell to the single direction having the steepest slope; the Shapiro and Westervelt (1992) algorithm allows water to drain in all downhill directions, simulating the convergence and divergence of fractional flow, which generates realistic runoff patterns. The algorithm is also useful in

that the water is moved physically between cells across the entire DEM. The iterative nature of the algorithm allows the runoff paths to change dynamically as wetlands fill and connect, but it can be very slow to converge, typically requiring hundreds of thousands of iterations. Although the WDPM is written in Fortran 95 for speed, very large DEMs have resulted in model runs lasting many hours or days. Improved coding and parallel processing have subsequently reduced computation times by more than order of magnitude.

19.5 DIGITAL ELEVATION MODELS

The WDPM requires a digital elevation model (DEM) formatted as a gridded 2D ESRI ASCII file as input. In Canada, freely available elevation data products with moderate spatial resolutions of 30 m or 90 m include Canadian Digital Elevation Data (CDED), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Shuttle Radar Topography Mission (SRTM) data surveyed in February 2000.

All surface elevation datasets contain errors and / or artefacts which limit their potential suitability for derivative analysis. Deep holes and trenches in the 30 m ASTER data (attributed to the limited contrast in relief), contour artefacts embedded in the 30 m CDED data, and the coarser spatial resolution of SRTM V4 (90 m) rendered these data unsuitable for WDPM simulation purposes. A second source of SRTM data considered was SRTM V3 which is a global void-filled downscaled (re-interpolated) version of the SRTM 90 m elevation data having a horizontal resolution of 30 m. The suitability of SRTM V3 data for any given application will generally depend on the backscatter noise in the DEM due to topographic and vegetation characteristics (Bhang and Schwartz, 2008; Hancock *et al*., 2006).

Remotely sensed LiDAR survey data, although costly, provide the greatest level of surface elevation detail and accuracy possible for producing a DEM. This method generates massive point clouds from measured laser pulses reflected (returned) from any contacted surface objects. A general limitation of LiDAR is that due to the size and detail, the data can be difficult to work with, and may require conditioning to enhance the hydrological connectivity of infrastructure such as culverts.

Two sources of elevation data were considered for the LIRA case studies in Prairie locations. Not surprisingly, the WDPM simulations based on LiDAR provided the most accurate and useful information. Simulations based on

SRTM V3 data were useful in some areas but were not nearly as accurate or as detailed as the LiDAR simulations. Visual inspections of runoff simulations based on SRTM V3 suggest that the lower resolution data are generally more useful in areas characterized by undulating topography where drainage into wetlands, lakes, and along channels is relatively well defined, and tall vegetation is sparse.

Less information is generally obtained from areas of relatively low relief, where drainage is poorly defined and vegetation is dense, obscuring the underlying topographic variability (Bhang and Schwartz, 2008). Due to the timing of the SRTM data capture (during the winter in Canada) and to processing (downscaling), and where the topographic relief is low or vegetation is dense, the SRTM V3 dataset may not be suitable for WDPM in some Prairie locations.

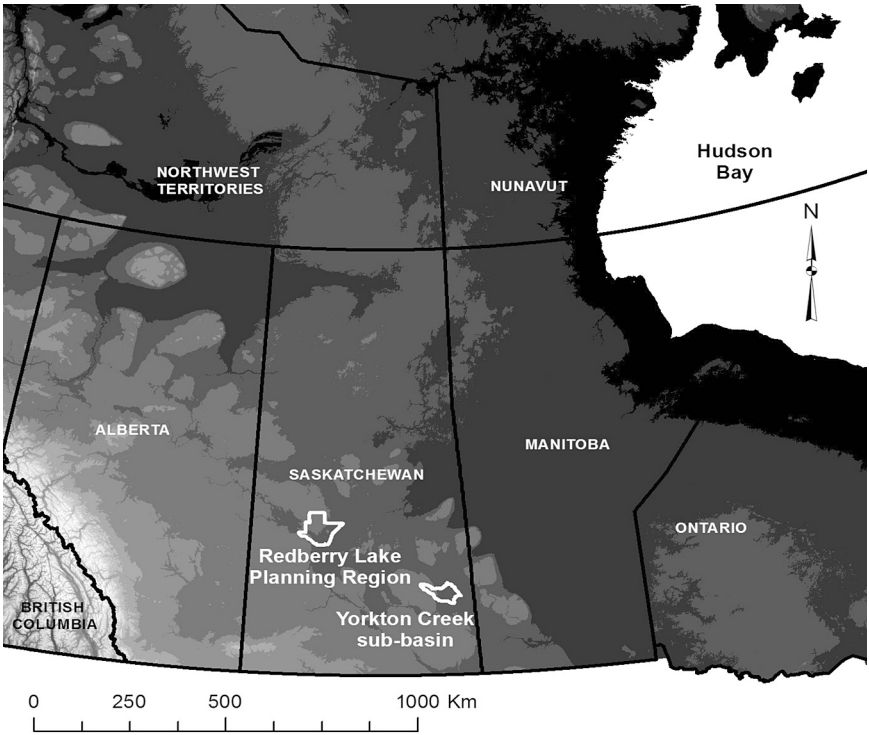

Figure 19.1 *Locations of Redberry Lake Planning Region and Yorkton Creek sub-basin in Saskatchewan, Canada. Shaded relief is based on Canada 3D DEM obtained from Natural Resources Canada.*

For the purpose of this paper, LiDAR survey data with a vertical accuracy of ±15 cm were available for a portion of the Redberry Lake planning region located in Saskatchewan. The accumulated water depths generated from LiDAR based analysis are more likely to be correctly resolved than outputs generated from SRTM V3 which has a vertical accuracy of 16 m.

19.6 EXAMPLES OF FLOOD HAZARD ASSESSMENT

LIRA has been involved in three case studies within the Prairie region of Saskatchewan; at Corman Park, SK from 2006-2009 (Agriculture and Agri-Food Canada, 2013), and in the case studies presented here. The flood hazard assessment methodology which was initially developed for the Corman Park study was improved by the introduction of the WDPM. As described above, for simplicity the soil surface was assumed to be impervious to infiltration for the runoff simulations, which maximizes the assessment of the flood hazard. The cases presented are for a coarse DEM simulation in the Yorkton Creek sub-basin, which is located within the Assiniboine watershed in eastern Saskatchewan, and a fine DEM simulation for the Redberry Lake Planning Region, which is located in central Saskatchewan. The locations of these regions are shown in Figure 19.1.

Assiniboine case study: Yorkton Creek sub-basin

In the Yorkton Creek region, the simulation was performed using SRTM V3 data, as no LiDAR data were available. An example of the runoff simulation output for Yorkton Creek is shown in Figure 19.2. This simulation used a reference water depth of 110 mm applied to the DEM. The reference depth was derived using Environment Canada's (2012) Gumbel distribution of annual maximum rainfalls (1:200 year, 24 hour rainfall depth). The spatial pattern of accumulated runoff is generally realistic, as it coincides with the large streams and accumulation zones within lakes and larger wetland areas depicted in the overlaid hydrography in Figure 19.2. Although the information is derived from coarse DEM data, the runoff simulation can provide some useful flood hazard information.

Figure 19.2 indicates that the simulated runoff accumulates in two large depressional features in the city of Yorkton, which are where storm water retention ponds were built in 2011 in response to the storm water flooding that occurred in July 2010. The general agreement between simulated runoff and real flood hazard zones within Yorkton and the surrounding area is

encouraging. A key limitation of this relatively coarse dataset, is that the simulation may cause water to accumulate at locations that may not be real features. Also roads cannot be resolved at the scale of this DEM, so the influences of roads on drainage patterns cannot be considered directly. Therefore the simulation outputs must be used with caution, and the

Figure 19.2 *Yorkton Creek region. Gray shaded areas indicate accumulated runoff from the runoff simulation model (WDPM) output based on 110 mm of water added to the SRTM 30 m DEM. Black outlines are the surface hydrography blue lines and water bodies from the National Hydrography Network.*

personal experiences of stakeholders are crucial to verifying the general accuracy and usefulness of the information.

Redberry Lake planning region case study

Rural municipalities within the Redberry Lake planning region are currently engaged in studies for future planning and development. Through consultations with project proponents and community stakeholders, a region that included the town of Radisson and village of Borden was identified as being vulnerable to runoff flooding. This region was considered to be a logical site for testing the utility of WPDM on a fine scaled LiDAR DEM that could be verified by the personal experiences of stakeholders. The location of the study and of the LiDAR survey data are indicated in Figure 19.3.

For comparative purposes, runoff simulation results are presented in Figure 19.4 for both the SRTM V3 and the LiDAR survey DEM data. The maps demonstrate the differences in the outputs when 100 mm of water was

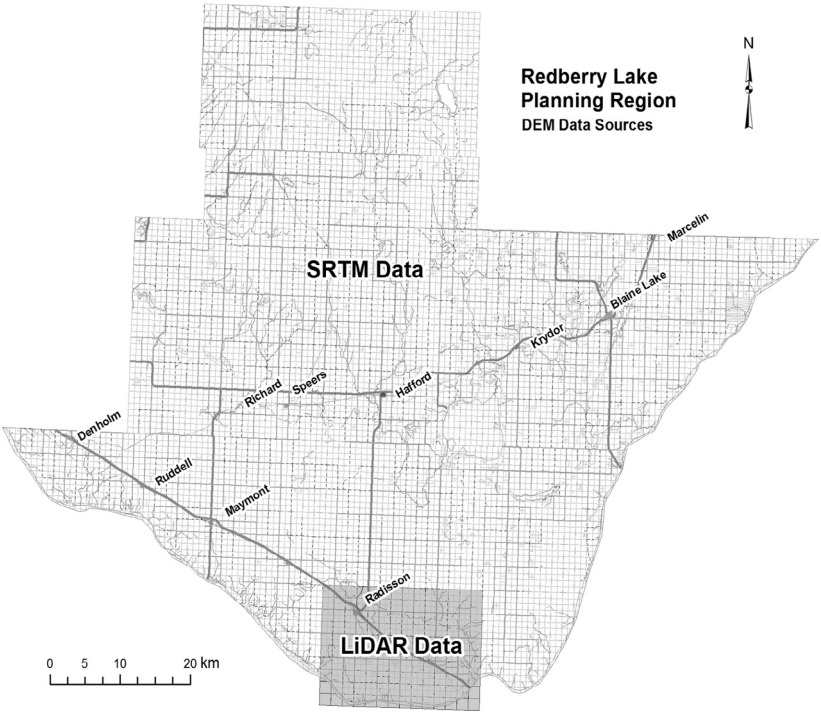

Figure 19.3 *Redberry Lake planning region. Extent of SRTM 30 m and 5 m LiDAR data surveyed in October, 2011.*

added to each DEM; approximately the 1:100 year, 24 hour rainfall amount for this region. The improvement in the diagnostic level for a flood hazard assessment is demonstrated by the detailed results for the simulations using the 5 m LiDAR DEM and the SRTM V3 30 m DEM in the Redberry Lake planning region plotted in Figure 19.4.

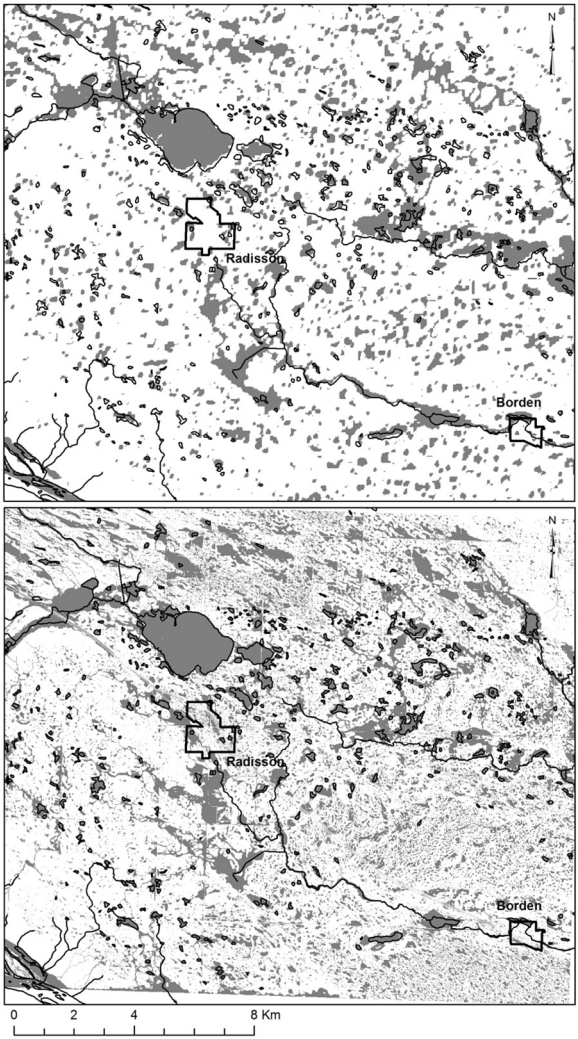

Figure 19.4 *Radisson and Borden area. Runoff simulation model (WDPM) output based on 100 mm of water added to the SRTM 30 m (top) and LiDAR 5 m (bottom) DEM data. Gray shaded areas indicate accumulated runoff. Black outlines are the surface hydrography blue lines and water bodies from the National Hydrography Network.*

In general, the spatial water extent and connectivity of surface water, produced by the simulations using the detailed LiDAR data, cannot be matched by those using the SRTM V3 data. The higher-resolution LiDAR simulation indicates greater potential for water ponding within the landscape, and for backflooding influenced by roads. Based on a visual inspection of the outputs, it is asserted that the spatial extent of runoff for the SRTM V3 data is overestimated in some areas compared to the LiDAR derived spatial extents, and underestimated in other areas. These simulation maps are valuable for identifying locations where more detailed hydrologic or hydraulic analysis may be required to assess areas affected by changes to a drainage design, or areas of inundation associated with rising water levels.

Verification of WDPM Runoff Simulation Output

In late April 2013, the town of Radisson and the village of Borden declared a state of emergency due to large depths of spring melt runoff which resulted in rising flood waters. Aerial photos taken during the flooding are related to WDPM outputs for verification purposes for both the Borden (Figure 19.5) and the Radisson (Figure 19.6) regions. For each region, results for the application of 100 mm (Figure 19.5a and Figure 19.6a) and 300 mm (Figure 19.5b and Figure 19.6b) of water to the DEMs are presented. Both sets of simulations are included to demonstrate the differences in the estimated spatial extents of the outputs, the magnitudes of the hazards depicted, and whether either scenario is realistic. Overlaying the township fabric onto the respective flood hazard assessment maps allows users to trace the location of water movement through the towns and along the roads and evaluate possible intersections with economically or socially important receptors.

For the village of Borden (shown in Figure 19.5) various portions of the 100 and 300 mm water depth simulation results appear to agree with flooding observed in photos 5c - 5e (outlined in black); for example, the extent of flooding outlined in photo 5c flowing into Borden from the west, appears to be better represented by the results for the 300 mm simulation (Figure 19.5b). By comparison, the majority of flooding outlined in photo 5d (through and around the village) appears to be better reflected by the 100 mm simulation results (Figure 19.5a); and a smaller portion in the upper right of the photo, by the 300 mm simulation. Similarly, the area of high water outlined in photo 5e (east of the village) appears to be better reflected by the spatial extent of runoff in the 100 mm simulation results.

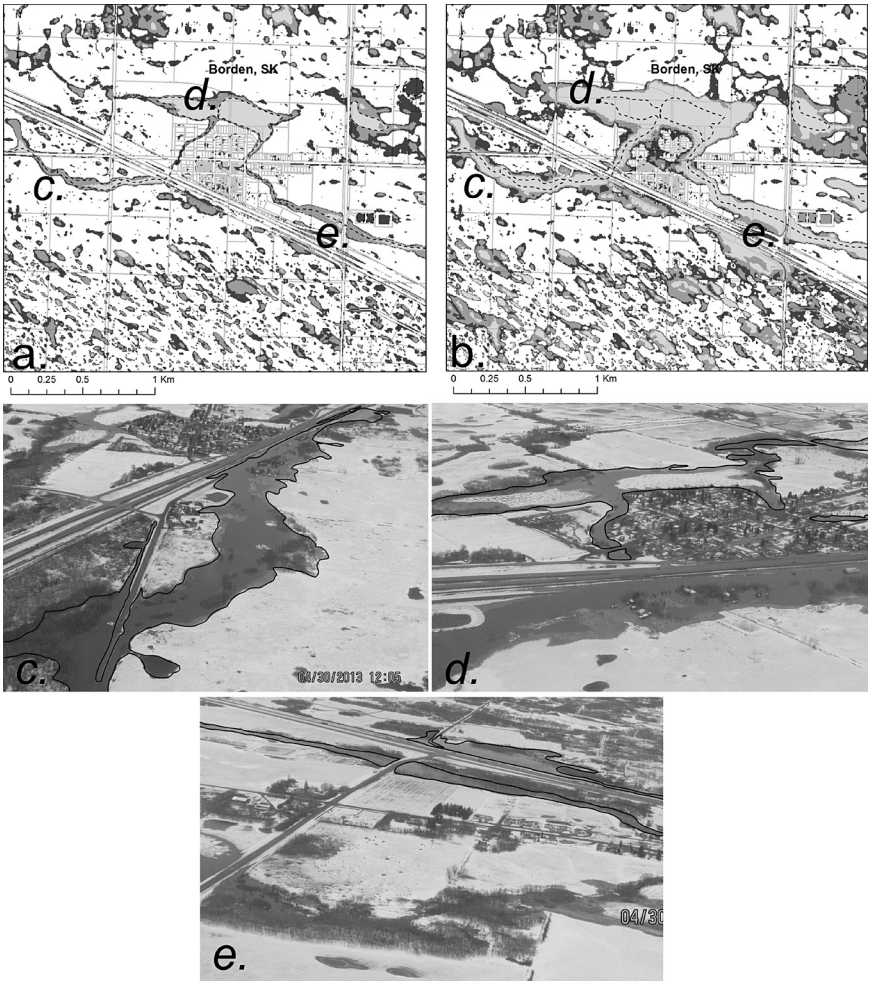

Figure 19.5 *Example of WDPM output for the Borden area from applying,* ***(a)*** *100 mm water depth and* ***(b)*** *300 mm water depth. Photos* ***(c - e)*** *link the WDPM output to verified areas of flooding outlined in black. Aerial photos were provided courtesy of Frank Fox, Saskatchewan Water Security Agency.*

For the town of Radisson the general shapes of the flooded areas surrounded by higher land features can be visually compared with the WDPM output in Figure 19.6a. The flooding observed in photos 6c - 6f appears to better capture the results for the 100 mm simulation (Figure 19.6a). The respective high water outlines (in black) in the photos have been linked to the outputs; land marks in the photos and runoff output serve as useful references for navigation purposes. It should be noted that flood waters shown in photo 6c

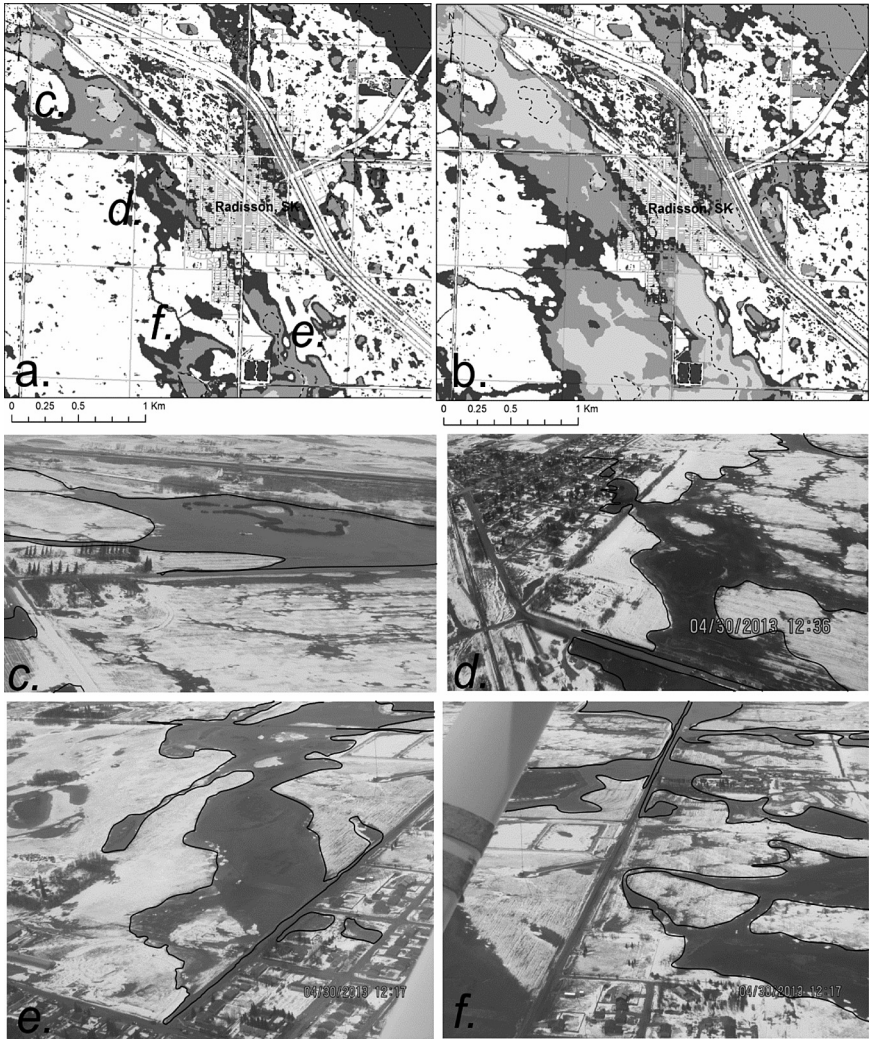

Figure 19.6 *Example of WDPM output for the Radisson area from applying,* ***(a)*** *100 mm and* ***(b)*** *300 mm of water. Photos* ***(c - f)*** *link the WDPM output to verified areas of flooding outlined in black. Aerial photos were provided courtesy of Frank Fox, Saskatchewan Water Security Agency.*

were being pumped into the natural wetland area shown in photo 6d which artificially increased the area being actively flooded in that region.

Based on the available observations, the flood hazard information provided by the 300 mm simulation generally appears to be unrealistic for the Radisson area, which illustrates a limitation of the modified LIRA methodology for

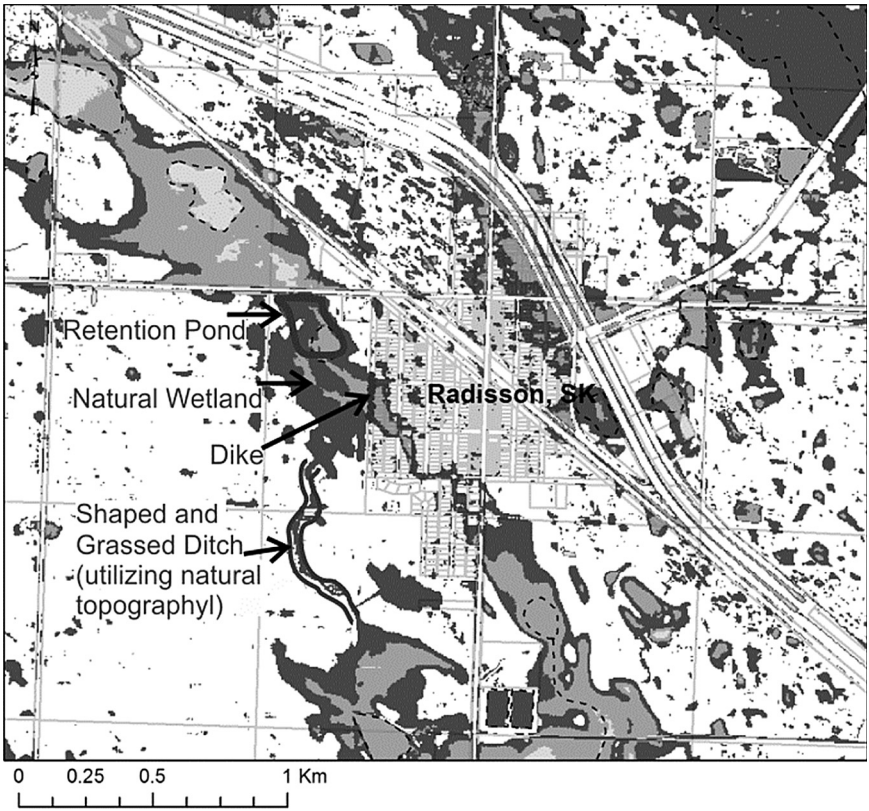

Figure 19.7 *Example of potential adaptation option based on a flood hazard assessment and elevation profiles generated from LiDAR data (courtesy Frank Fox, Saskatchewan Water Security Agency).*

assessing flood hazards in Prairie landscapes. Although the simulations based on reference values have provided useful information to stakeholders, the scientific and technical rigor could be enhanced by linking the spatial simulations to runoff estimates provided by a hydrological model that considers a full range of Prairie processes. The Cold Regions Hydrological Modelling (CRHM) platform, which was also developed at the Centre for Hydrology, has been developed to model the full range of hydrological processes that are responsible for producing runoff on the Canadian Prairies (Pomeroy *et al*., 2007). Work is ongoing on uniting the physical process simulations of CRHM, with the spatial representation of the WDPM.

Input for Potential Adaptation Strategies

Stakeholder and community feedback has been valuable for verifying the accuracy of runoff outputs; particularly their personal accounts of where past flooding has occurred (or not) and where it might occur in future events. The runoff simulation maps can be useful for stakeholders in rural communities to assess their vulnerability to flood hazards without increasing the danger of their doing nothing, based on a probabilistic assessment of a flood occurrence.

The simulation outputs allow decision makers to trace the pathways of surface water over the landscape, which can aid in the development of adaptation strategies. Figure 19.7 shows an example of one adaptation option generated for the town of Radisson (through LIRA) that might include building a retention pond, dike, and grassed ditch along a natural drainage pathway. Stakeholders have indicated that a well-drained area exists further south where surface water does not generally accumulate, and that this location may be able to absorb the redirected runoff. Of course, the potential hydrological and hydraulic impacts of any adaptation strategy also need to be assessed.

19.7 CONCLUSIONS

The recent large-scale flooding events in the Prairie Provinces have demonstrated the need for better flood protection and mitigation strategies in the region, which includes many ungauged basins. Conventional flood hazard modelling approaches are generally unsuitable for assessments in Prairie landscapes that are dominated by complexes of wetlands. A new diagnostic runoff simulation tool, the WPDM, was used to generate estimates of runoff flood hazard locations in Prairie landscapes.

The accuracy of the spatially distributed runoff map is partly dependent on the quality and scale of the input digital elevation model (DEM) and also on the depth of water applied to the DEM. LiDAR derived runoff maps provide the greatest detail and also include the influence of roads on water accumulation. Verification of runoff map outputs using ground and aerial photographs, and stakeholder experience demonstrated that the runoff maps, despite their inaccuracies, can be useful for assessing flood hazards in ungauged Prairie basins where fill-and-spill flooding is of key concern.

The methods applied here for the purpose of LIRA rely on the application of reference water depths which are generally equivalent to return-period rainfall amounts and the historical Vanguard event. The technical rigor of the method could be improved by using runoff water depths provided by a physically based Prairie hydrological model. Nevertheless, when verified against recent flooding events in the spring of 2013, the ponding model depicted the observed paths of rising waters and flood zones through the communities and the surrounding landscape surprisingly well.

Conventional flood plain hazard assessments generally show the inundation areas only along river reaches. Comprehensive flood hazard maps for the Prairies should include entire landscapes, and could be generated by combining estimated flood plain hazard zones and spatially distributed runoff information provided by the WDPM. Specifically, combining the spatial runoff modelling of the WDPM and a hydrological model capable of simulating the unique aspects of Prairie hydrology may allow the generation of spring melt runoff maps that are based on return-period runoff events.

19.8 ACKNOWLEDGEMENTS

Funding for the Land and Infrastructure Resiliency Assessment project was provided by Agriculture and Agri-Food Canada (AAFC), Natural Resources Canada, and the former Saskatchewan Watershed Authority (now the Water Security Agency of Saskatchewan). Access to the LiDAR DEM data for the Radisson and Borden area was provided by Agriculture and Agri-Food Canada. The authors would like to thank Cam Kenny (AAFC) who was helpful with figures and Frank Fox (Saskatchewan Water Security Agency) for providing aerial photographs of the April 2013 flood events in the Radisson and Borden areas.

20

SUMMARY AND SYNTHESIS OF WORKSHOP BREAK OUT GROUP DISCUSSIONS

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20.1 ABSTRACT

The workshop discussions about making predictions in ungauged basins in different hydrological landscapes with different states of data availability are summarized. While the science underlying hydrological prediction has advanced considerably during the past decade, implementing the new

science into practice remains a challenge. The workshop participants identified a number of opportunities for addressing this challenge and recommended developing a watershed classification system with a generalized diagnostic to facilitate the transfer of results from research catchments and other gauged watersheds to ungauged systems. These tools should be developed adopting an open source framework with better outreach to enhance the accessibility and adoption by practitioners.

20.2 RÉSUMÉ

Sont résumées les discussions de l'atelier quant aux prévisions en bassins non jaugés dans différents paysages hydrologiques comportant différentes situations de disponibilité des données. Bien que la science qui sous-tend les prévisions hydrologiques ait fait des progrès considérables au cours de la dernière décennie, la mise en pratique de la nouvelle science représente encore un défi. Les participants à l'atelier ont cerné un certain nombre d'occasions de composer avec ce défi et ont recommandé l'élaboration d'un système de classification des bassins hydrographiques favorisant un diagnostic généralisé pour faciliter le transfert des résultats des bassins de recherche et autres bassins jaugés aux bassins non jaugés. Ces outils doivent être conçus en adoptant un cadre de source ouverte d'une meilleure portée afin d'en accroître l'accessibilité et l'adoption par les professionnels en exercice.

20.3 INTRODUCTION

This paper provides a summary of the break out sessions from the Putting PUB into Practice [P3] meeting in Canmore, Alberta, in 2011. At the workshop, issues related to prediction in ungauged basins were discussed in relation to (1) type of landscape (e.g., high mountain, boreal), and (2) data availability (data-rich, data-sparse, and data-poor). This summary focuses on commonalities and differences of PUB challenges across landscapes and data richness. Through this comparison, we seek to share and consolidate between and across:

- The PUB themes and working groups,
- The variety of regional efforts and perspectives,
- The different approaches that maximize the predictive value of streamflow data, other data, and their use,

- The approaches that maximize the use of physically based theory and process structure, process variability, and their emergence into predictive approaches,
- The inclusion of new measurement and information technologies for meteorological inputs, process verification, and catchment characterization, and
- The continuation of the exploration of improved models and tools that reflect improved hydrological understanding and their use in practice.

One key task was to identify opportunities for future developments or new perspectives that would contribute to the main issue of turning research into accessible tools that improve the practice of making predictions in ungauged basins. In particular, could approaches developed and validated for data-rich areas be adapted as prediction tools for data-sparse and data-poor areas?

All of the break out groups addressed common discussion points, but each focused on a different hydrological landscape. The participants represented a broad cross section of researchers and practitioners having a range of experience and expertise in hydrology and in different landscapes. Table 21.1 contains the guidance that was provided to each of the six break out groups over the three days of the meeting. A list of the workshop participants is provided in the Appendix to this volume.

This summary begins with a brief description of the attributes and monitoring issues associated with the six hydrological landscapes upon which the discussions were focused. Then, the scales and methods of hydrological analysis being used in predictions in ungauged basins are addressed. The barriers to adoption and implementation of new methods as identified by the participants are described. Following on these commonalities, the specific issues characterizing the hydrological landscapes are provided. The summary ends with a series of recommended actions, research, and tools for future work.

20.4 HYDROCLIMATIC / LANDSCAPE REGIONS

The key attributes of the hydrological landscapes considered by the break out groups are given in Table 21.2. The key types of predictions required in ungauged basins are also identified. Water supply is an issue common to all landscapes, but each landscape has a specific set of relevant hydrological attributes.

Table 20.1 *The guidance provided to each of the break out groups during the workshop. The three parts took place on successive days.*

a) Data-Rich

The PUB issue in "Data-Rich" areas is not whether good predictions can be made for ungauged sites as both empirical and deterministic modelling approaches are likely to be successful. The challenge in these situations is to learn about how to use those methods to reduce the uncertainty of predictions in ungauged basins.

1) How can the various approaches for hydrological prediction in this hydroclimatic region be implemented given the availability of meteorological and catchment data and current understanding of hydrology?
   - -small spatial scales, short time scales
   - -large scales, longer time scales
2) How can PUB predictive approaches be improved? Is there additional process understanding required or additional data required?
3) How can the available hydrological tools contribute to products usable by practitioners? ***How can we address practitioners' needs for tools to do PUB?***
4) How can information gleaned from data-rich regions be applied to more data-poor regions? ***How can we extend the information based upon data-rich PUB to other areas?***

b) Data-Sparse

The PUB issue in "Data-Sparse" areas is whether good predictions can be made for ungauged sites using modelling approaches that are 'likely' to be successful. How can empirical information be used to extract sufficient information from the limited observation records to validate models where data are sparse? The challenge in these situations is to learn about how to use those methods to understand the uncertainty of predictions in ungauged basins.

1) How can the various approaches for hydrological prediction in your hydroclimatic region be implemented given the availability of meteorological and catchment data and current understanding of hydrology?
   - -small spatial scales, short time scales
   - -large scales, longer time scales
2) How can PUB predictive approaches be improved? Is there additional process understanding required or additional data required?
3) How can the available hydrological tools contribute to products usable by practitioners? ***How do we address practitioners' needs for tools to do PUB?***
4) How can information gleaned from data-sparse regions be applied to more data-poor regions? ***How can we extend the information based upon data-sparse PUB to other areas?***

Table 20.1 *(cont'd)*

c) Data-Poor

The PUB issue in "Data-Poor" areas is whether good predictions can be properly validated. How can empirical information be used to extract sufficient data coverage from the limited observation records to validate models where data are poor? The challenge in these situations is to learn about how to use those methods to understand the uncertainty of predictions in ungauged basins.

1) How can the various approaches for hydrological prediction in your hydroclimatic region be implemented given the availability of meteorological and catchment data and current understanding of hydrology?
   - -small spatial scales, short time scales
   - -large scales, longer time scales
2) How do predictive approaches need to be improved? Are there options other than additional process understanding required or additional data required?
3) How can the available hydrological tools contribute to products usable by practitioners? ***How do we address practitioners' needs for practical tools to do PUB in data-poor areas? Tools for validating or confirming predictions?***
4) How can information gleaned from data-poor regions be better applied to other data-poor regions? ***How can we extend the information based upon data-poor PUB to provide feedback to the developments made in data-rich and data-sparse areas?***

Arid and semi-arid

A semi-arid (sub-polar) region receives precipitation equal to or less than the potential evapotranspiration. Many semi-arid areas are characterized by high spatial variability in rainfall making it difficult to quantify areal rainfall inputs into hydrological and water resource simulation models (Paturel *et al*., 1995; Andréassian *et al*., 2001; Fekete *et al*., 2004).

Semi-arid areas exist in both cold (e.g. Tundra) and warm (e.g. Prairie) regions, and groundwater may be more important than rivers as a water resource. Temporary streams are common in semi-arid regions (Buttle *et al*., 2012). Intensive agriculture and irrigation are often widespread in warm semi-arid regions. Hence, in semi-arid regions the effect of land use may overshadow those of climate and weather, increasing the complexity of modelling and analysis.

Table 20.2 *Summary of the main attributes of the hydrological regions used in the discussions. The text in italics indicates the predominant needs for predictions in ungauged basins in the region.*

Type	Sub-Type	Characteristics & PUB Connection
Arid & Semi-arid	Warm Cold	Potential Evaporation exceeds precipitation Groundwater plays an important role Extensive grasslands *Drought, flooding, and water supply*
Mountains	Warm Cold	Steep elevation and vegetation gradients Snow, snowpack development, and melt processes High watershed gradients Glaciers and glaciation features *Hydropower, fish habitat, water supply, and flooding*
Temperate Agriculture	Warm Cold	Extensive soils Large conversion of landscape through tillage and modifications Hydrological modifications also extensive; storages, abstractions *Drought, wetlands, and ecological values*
Temperate Forests		Evaporation Large conversion of original forests Insects, deforestation, and forest rotation Sediment transport *Hydropower, fish, aquatic habitats, and flooding*
Arctic & Boreal	Taiga Tundra	Long, extremely cold winters Latitudinal vegetation gradients Low station densities and bias towards very large basins >100 000 km^2 *Hydropower, resource development, and ecological values*
Tropical	Humid Semi-arid	High rainfall intensity and depth Strong seasonal rainfall regime Seasonally hydrophobic soils Large surface runoff components and high sediment loads *Drought, flooding, sediment transport, water supply, and groundwater*

Streamflow records are often sparse in semi-arid regions as many watercourses lack continuous flow. In many jurisdictions, gauges are operated seasonally or only during short periods of the year. Rainfall networks are too sparse to adequately observe precipitation processes that are strongly convective in summer and predominantly snowfall during winter.

Mountains

Mountainous areas generally receive greater precipitation than lowland areas and have low evapotranspiration, and thus are efficient generators of streamflow that is a critical water resource in densely populated downstream areas. Much of the precipitation is stored as snow or ice for periods of time (months in the case of snow, many years in the case of ice) and is later released during the spring-summer melt period. In many high mountain regions, glaciers play an important role in supplementing streamflow in late summer and early autumn and regulating the interannual variability of streamflow (Fountain and Tangborn, 1985; Stahl and Moore, 2006).

Mountainous areas generally have low population densities and are poorly gauged outside of research basins. Weather stations tend to be located in valley bottoms and do not represent the higher elevations due to orographic effects. In addition to this dependence on elevation, key hydroclimatic variables (temperature, precipitation, solar radiation, humidity, wind speed) also vary strongly with slope and aspect and as a result of complex interactions between weather systems and topography, such as seeder-feeder precipitation processes and rain shadow effects. Extrapolation of hydroclimatic information from weather stations to account for this spatial variability is a key challenge in making hydrological predictions in mountain regions.

Gauging stations are also predominantly located in valley bottom sites on main stem channels. As a consequence, streamflow records integrate runoff from a broad range of elevations, and measured streamflow may not represent the quantity and timing in smaller headwater catchments. Due to the combination of sparse monitoring networks and biased station locations, almost every water resource analysis in mountainous areas is an exercise in PUB.

Temperate forests

This landscape comprises the forested areas between the tropics and the boreal forest. In this landscape there have been conversions of large areas of the original forests through harvesting and subsequent replanting or

regeneration for repeated harvesting cycles. These areas are also subject to changes that accompany natural disturbances such as wildfire and insect infestations, as well as deforestation associated with conversion of land to agricultural, urban, and other non-forest land use. The hydrological variables being predicted in ungauged temperate forest basins are principally runoff and evaporation. The types of hydrological predictions required in these areas are wide ranging, from water supply estimates to hydrological variables that support protection of ecological values.

As this landscape contains highly populated settlements, temperate forests are generally better monitored than other regions with respect to both climate and streamflow; however, monitoring networks for climate and streamflow are generally disconnected from each other as the networks developed separately to meet different needs. This often results in practitioners having access to local observations (e.g., of precipitation and streamflow) but not from the same watersheds, so that data extrapolation is a key challenge in PUB applications.

Temperate agricultural

Temperate agricultural landscapes are typified by extensive well developed soils. Typical of these areas is the extensive conversion of landscape through tilling, draining, and other modifications. Hydrological modifications are also extensive. Drainage alterations, drainage of natural storages such as wetlands and creation of artificial storages, and water abstraction and augmentations through irrigation result in watersheds with altered hydrological responses. In addition, drainage areas may become disconnected for periods of time resulting in variable watershed contribution areas.

With these extensive and complex modifications of the landscape and water on the landscape, monitoring and process-based observations alone will not be sufficient to model these systems; effective models for prediction in ungauged basins must take into consideration these landscape changes.

Arctic and boreal

The boreal forest is a circum-global ecozone dominated by long cold winters, peat deposits, and coniferous forests. North of this is the arctic region; above treeline the vegetation is tundra. Evapotranspiration is the dominant hydrological flux in the boreal and arctic region. A key feature of the region is the importance of storage of water on the landscape both in

shallow lakes and in frozen form as seasonal snowpacks, and in some mountainous catchments, as multiple-year to decadal storage as glaciers. Outside of research basins, forcing data are only available at a coarse scale.

Hydrometric gauge density in the Arctic Ocean drainage basin has remained static at ~1 per 10^4 km^2 (Shiklomanov *et al*., 2002). While ~70% of the pan-arctic area is gauged, most of that area is observed only at the mouths of very large rivers, such as the Mackenzie (1.8 million km^2) and Lena (2.5 million km^2) basins (Prowse and Flegg, 2000). Even though most of the largest basins are gauged, data collected at the mouths of these major river systems does not adequately provide a representative picture of the flow regime characteristics of the smaller watersheds that feed into these large systems. Processes operating at small spatial scales generally differ from those found within the large river systems. The fraction of small catchments (i.e. less than 10 000 km^2) that are gauged remains unacceptably small (e.g. 0.8% in the Mackenzie). Region-specific flow characteristics that are critical to ecosystem health (Poff *et al*., 1997) are masked in the flows of the larger system and often require decades of times series data to understand (Burn *et al*., 2008).

Without the benefit of local, region-specific monitoring, important annual and inter-annual flow variation of the smaller river systems is not well observed and is often not understood; this can have substantial importance to local and regional communities. Because few small basins are monitored, the current sample of gauges cannot be assumed to be representative of the range of basin characteristics across the arctic and boreal landmass – thus there remain many catchment types (particularly those that are small and/or glacier fed) for which there is little to no data (Spence and Saso, 2005; Spence and Burke, 2008). The small sample and inherent spatial and temporal variability in runoff response from these catchments increases uncertainty in hydrological prediction for this region.

Tropics

The humid tropics and semi-arid tropics have distinctive hydrological characteristics that distinguish them from each other and from other hydroclimatic zones. The humid tropics are characterized by high rainfall intensity and depth, generally with a well-defined seasonal rainfall regime. These characteristics can lead to high volumes of surface runoff, high sediment loads, and seasonally hydrophobic soils. Temperatures are warm year-round. The semi-arid tropics are much drier than the humid tropics, but

also exhibit strong rainfall seasonality. In the humid tropics, large scale land use change is one of the major water management issues (Eden and Parry, 1996), as conversion of forested lands to agricultural use can result in changes to the seasonal distribution of runoff. This, in turn, can have significant effects on water use and availability, water quality, sediment loads, and ecology. In the semi-arid tropics, the main water management issues are somewhat different, instead focusing on drought prediction and management (Mishra and Singh, 2011). Prediction of droughts and drought frequency, estimating yields from reservoirs or other small scale water resource structures, and efficient conjunctive use of surface water and groundwater are all important water management objectives.

Hydrological processes of particular importance in the tropics include: interception loss, especially within the dense multi-layered canopy of tropical rain and cloud forests; vegetation-atmosphere, surface water-groundwater, and soil-atmosphere interactions; and changing land use, especially given very high rainfall intensities. The latter is important in the semi-arid tropics as mentioned previously. Understanding these important processes in the catchment of interest goes hand in hand with data collection since the data help to illuminate important processes, and an understanding of the important processes can inform what data are needed.

Throughout the tropics, data availability is limited and the reliability of data can be problematic, making prediction of flow difficult for large ungauged areas (Hughes, 2006). Data-rich areas are generally limited to a small number of well-resourced areas, and extrapolation to the majority of the catchments which are ungauged represents a serious challenge for both science and practice. Many areas also lack centralized water resource management institutions, which further exacerbates the problems of data access and contributes negatively to the sharing of expertise in water resources estimation methods.

20.5 METHODS FOR PUB APPLICATIONS

The methods currently in use for prediction in ungauged basins are varied. Simple approaches that are in common use include data transfer methods and techniques such as rule curves and the rational method, in addition to field-based methods based on channel morphology. In areas with sufficient data, statistical approaches such as regional regression analysis are popular

among practitioners. Process-based models, both conceptual and physically based, are rarely applied, although substantial research effort has focused on developing and testing them.

Data transfer

A common approach is to identify a gauged catchment that is judged to be similar to the target catchment, and then to adjust flows to account for differences in drainage area. Back-of-envelope adjustments can be made to account for differences in glacier cover or other attributes. This approach can be improved upon by installing a short-term gauge on the target stream to verify any empirical relationship between the target stream and the gauged stream. In regions where the basin contributing areas are not constant, this method can be very difficult to apply.

Geomorphic approach

Where no usable streamflow or weather records are available, a geomorphic approach can be used to estimate design peak flows. In this approach, a channel survey is conducted to determine bankfull channel geometry and roughness. Manning's equation is then used to estimate velocity and bankfull discharge, which is often assumed to coincide with a return period of two years; however, in some landscapes the bankfull return period may be greater.

Generalized rainfall-runoff relations

A number of approaches have been developed to predict runoff response from rainfall at a range of temporal resolutions. Many of these methods are popular in engineering applications, and involve the use of tables or diagrams to estimate parameters based on catchment characteristics such as topography and vegetation cover. For example, synthetic unit hydrographs can be used to estimate stormflow response during an individual storm event. The rational method is commonly used to compute design floods in cases where no usable streamflow records are available, but rainfall intensity has been recorded at a weather station in or near the target catchment; however, because most precipitation gauges are in valley bottoms, measured rainfall will typically underestimate actual rainfall over the catchment. A fundamental criticism of these rainfall-runoff relations is that peak flows in regions with cold winters typically occur as a result of spring-summer snowmelt or mid-winter rain-on-snow events and not simply rainfall.

Statistical modelling

Where a sufficient number of gauges are available, it may be possible to derive statistical relations between streamflow metrics or flow duration curves and predictor variables based on catchment characteristics such as drainage area, geology, land cover, and elevation. These relations are commonly derived using techniques such as multiple regression. In addition, geostatistical methods such as kriging can be used either on their own or in conjunction with multiple regression (e.g. by using kriging to interpolate prediction errors to account for any spatial autocorrelation). In British Columbia, for example, Eaton *et al*. (2002) used geostatistical interpolation to map a "k factor" computed from gauged basins as $k = Q_{ma}/A^{0.75}$, where Q_{ma} is the mean annual flood and A is the drainage area (km^2). The k factor represents the mean annual flood for a catchment with a drainage area of 1 km^2. To compute the mean annual flood for an ungauged basin, the k factor is extracted from the map and then multiplied by the drainage area raised to the power 0.75. An advantage of these statistical methods is that they can provide estimates of the prediction error.

Process-based modelling

Data-based and field-based methods as described above cannot account for changing climatic conditions or changes in land cover. For example, forest recovery following the extensive tree mortality associated with the recent outbreak of mountain pine beetle in western North America will fundamentally change the water balance of affected catchments over the coming decades. In contrast, process-based models have the potential to address all of the weaknesses associated with currently used methods. Their temporal resolution can match the resolution of available forcing data, and models can, in principle, explicitly represent the effects of changes in land cover (e.g. Koboltschnik *et al*., 2007). Despite their potential advantages, process-based models are not routinely used in water resource analyses. A major challenge to the use of process-based models in PUB applications is their need for input data. A complete suite of weather forcing data for physically based simulation of melt and evapotranspiration would include air temperature, precipitation, humidity, solar radiation, and wind speed. At minimum, process-based models require air temperature and precipitation at daily or higher temporal resolution; humidity and solar radiation can be estimated from temperature and precipitation, if required (Walter *et al*.,

2005). In addition to weather forcing data, state variables such as snowcover and snowpack water equivalent can be valuable for model development and testing.

Considerations in the choice of PUB method

Depending on the application, a range of prediction targets may be of interest. For example, broad scale screening assessments may require only mean annual runoff. For the planning of large reservoirs, annual runoff and its interannual variability may be relevant. For many infrastructure design needs, a flow extreme associated with a specific return interval may suffice, such as the 200-year flood or the 10-year 7-day low flow. In other cases, time series of discharge at daily or shorter time intervals may be required.

In principle, a process-based hydrological model that runs at a daily or sub-daily time step, in combination with an appropriately long time series of input data, could be used to generate the full range of prediction targets. In practice, however, simpler methods that are less expensive to apply could be appropriate if their predictions were sufficiently accurate for the project requirements. As an example, consider mean annual runoff as a prediction target. It can be predicted using statistical relations with drainage area defined using a regional monitoring network, which can generally provide estimates within an order of magnitude. While this approach is efficient, it does not necessarily provide estimates within an acceptable level of uncertainty, nor does it provide information about seasonal patterns (Whitfield and Spence, 2011). In order to provide bounds for these estimates and extreme values, we can use a combination of traditional knowledge (Woo *et al*., 2007), hydraulic geometry measurements (McNamara and Kane, 2009), and paleo-records (Fortin and Lamoureux, 2009). Vegetation and animal species diversity regimes can also be indicators of floodplain extent and, in turn, of the extent and duration of extreme high flows. Statistical regression techniques can be robust (Lee and Ouarda, 2010), but if the regional monitoring network does not include physioclimatically and/or hydrologically similar gauging sites to those of the target catchment, the results may be dubious (Spence and Burke, 2008). An alternative is to use catchment classification indices (Quinton *et al*., 2003). Where time and financial resources permit, short term gauges can be installed in the basins of interest and the resulting datasets can be used to develop relationships with long-term operational gauges.

In New Zealand, mean annual discharge is estimated from maps of mean annual precipitation and evapotranspiration. This estimate is checked for consistency with nearby gauged catchments, and is then prorated to monthly flows on the basis of maps of monthly flow proportions.

Deterministic models are often used by electrical utilities for short-term forecasting (e.g. St. Hilaire *et al*., 2010) and to simulate streamflow under climate change scenarios (Kattsov *et al*., 2007); however, they are not necessarily the most feasible tool to determine long-term streamflow regimes because the length of climate data required to force them rarely exists. Stochastic weather generators (Srikanthan and McMahon, 2001) that mimic observed or potential climate regimes have been used as an alternative.

Snowcover and snowpack water equivalent

The availability of snowcover information from the Moderate Resolution Imaging Spectrometer (MODIS) platform and other distributed snow products are potentially valuable targets for model calibration. Finger *et al*. (2011) used MODIS snowcover information along with streamflow to calibrate a catchment hydrology model. Boyle *et al*. (*this volume*) found that the use of the SNODAS product as the sole calibration target generated a parameter set that also performed well for simulating streamflow. A weakness with MODIS and other optical remote-sensing products is the effect of cloud cover, which can severely limit the completeness of snowcover scenes in mountain regions.

Snow water equivalent is more difficult to sense than the snow extent. Natural gamma emissions measured from low flying aircraft can provide estimates of SWE, although the measurements can also be affected by the presence of ice lenses or liquid water in the snowpack or underlying soil (WMO, 2008). In North America, NOAA conducts airborne gamma snow surveys over many northern states as well as portions of Canada.

Other passive measurements, generally made from satellites, are also used to estimate SWE. These measurements may use a wide variety of electromagnetic frequencies, including microwaves. The condition of the snowpack (crystal size, wetness) and blocking/shading due to vegetation or topography can cause large errors in the magnitudes of the estimated SWE.

Evapotranspiration

Evapotranspiration is often only treated in terms of estimations and general classes. There are problems of availability of validation data, in particular at

different temporal scales, e.g. monthly versus daily. Methods are available for regionalization in space and time, e.g. via PRISM. It is possible to model solar radiation reliably for monthly data as an input to evapotranspiration, but cloud cover remains an obstacle at shorter time intervals. Sometimes this can be overcome by using weather satellites. Alternatively, daily air temperature range can be used to model the effects of cloud cover on incident solar radiation at a daily time-step (e.g. Bristow and Campbell, 1984). It is also important to define actual versus potential evapotranspiration. Techniques such as the scintillometer are available for this. Global estimates of evapotranspiration are available at the 1 km grid, for example from MODIS, AIRS, and CERES. Although this resolution is too coarse for complex terrain, it may be useful in semi-arid regions without too much variability in vegetation or in any region without complex topography. The effects of climate change on evapotranspiration remain difficult to evaluate, in particular when long-term projections on the variability of evapotranspiration are required. Projecting vapour pressure changes in the atmosphere remains a substantial challenge.

20.6 COMPARISONS ACROSS LANDSCAPES

Process Understanding

The need for process understanding is common to all landscapes. Before selecting any conceptual model, a basic understanding of the important processes that play a dominant role within the catchment is needed (Weiler and McDonnell, 2004; Abesser *et al*., 2008), along with knowledge of how the dominant processes change between the seasons and how they vary spatially. Put simply, scientists and practitioners both need to understand the water balance, in particular how water storages, fluxes, and pathways are affected by landscape factors including:

- seasonality of precipitation and evaporative demand
- groundwater
- surface water impoundments
- soil moisture and storage
- wetlands
- vegetation – interception, transpiration
- other development, including urban areas

Data-rich regions

Spatially, the definition of "data-rich" depends on the density of meteorological and hydrological (surface) as well as groundwater (subsurface) stations. It also depends on the diversity of data types and the degree of connection between different scales of data. Temporally, "data-rich" depends on the time-step between observations in relation to the time scale of the hydrological processes, and the length and resolution of data record. It is important to consider the applicability of data from data-rich catchments and whether the full range of available variables can be exploited in models, including the following:

- weather stations at high and low elevations
- streamflow
- topography and land cover
- soil information
- glacier mass balance
- snowpack SWE

We need to consider that developing understanding in the application of conceptual or process-based models in a data-rich situation should contribute heavily to predictions in ungauged basins where data are not available. While practitioners in data-rich areas may face less uncertainty than those in other areas, they have the opportunity to document the limits of statistical, conceptual, and process models and thus can potentially contribute to quantifying uncertainty in the data-sparse and data-poor contexts. Restated, models developed in data-rich areas need to be fully explored and exploited before applying them to areas where supporting data are not as available.

In all landscapes, data-rich areas are primarily associated with experimental watersheds or long-term ecological research areas. These research sites are generally small in area (i.e. less than 100 km^2) but frequently have data for long periods of time for many relevant variables.

Data-sparse regions

Any definition of "data-sparse" depends on the type of landscape being considered, e.g. homogenous plains vs. highly variable mountain terrain; it also depends on the representativeness of the scale of variability. Spatially,

"data-sparse" was considered to include only one or two observation locations within a basin, thereby excluding the ability to resolve spatial variations. Temporally, in "data-sparse" areas, observations cover only short periods of time (i.e. one or two years) or are inhomogeneous data series where data overlap only during relatively brief periods. Measuring stations are spaced at intervals of at least 400 km or are situated out of the basin in similar regions. Only limited variables are available and the data are insufficient for both calibration and validation of predictive models. The data-sparse classification could also apply to basins that are covered by remote sensing data, but no monitoring stations to ground truth these data.

In data-sparse regions, complex questions cannot be answered using available data and current PUB methods. Management decisions, however, do not always require complicated models and equations; rather they rely on confident predictions. Scientists are often asked how to reduce uncertainty of forecasts or predictions. This is frequently a question of the amount of time or money that can be invested with relation to actual improvement. The reduction of uncertainty also depends on how to determine the best location for answering the question. Managers in these situations need to make decisions that consider or tolerate irreducible uncertainty. From this perspective, social adaptation or risk based decision making may be a better alternative.

Understanding and modelling in data-sparse areas may be difficult to validate as fully as might be possible in data-rich situations. Here the practitioner needs to accept being dependent upon a combination of good judgement in selecting models and reasonable scales (temporal and spatial) and in choosing how to use the available data, either in calibration or validation. At the same time, a similar level of judgement needs to be applied to interpretation of the results. The quality of predictions in data-sparse applications is necessarily of lower confidence and resolution than in data-rich applications. It would be useful to develop a nomograph or index table that would assist the practitioner in this effort; such an approach might relate the hydrological attribute to the available data. Simply put, the annual mean flow can be predicted in a data-rich area with more precision than in a data-sparse area; monthly or daily flows that could be predicted with some accuracy in a data-rich application might be unreasonable to generate where insufficient data exists.

Data-sparse areas are often the result of the uncoordinated interests of resource and management agencies. Frequently, meteorological and climate networks were located in relation to settlements and to aviation facilities. Water networks, specifically for water levels and streamflows, developed in relation to resource development (railways, hydropower) and concerns over flooding (floodplain settlements). Soils and soil moisture were observed within agricultural and forestry agencies. The net result is that in most data-sparse landscapes the lack of coordination and exchange is a factor in the availability and/or complementarity of data.

Data-poor regions

While data-poor regions, by definition, lack sufficient ground-based information for hydrological prediction, there is potentially a wealth of usable information from remote-sensing platforms (particularly in the form of digital elevation models and maps of land use and land cover) and output from global and regional climate models. The main obstacles to providing this information to users, beyond lack of data availability, are restrictions in data processing capacity and the lack of graphical interfaces, user manuals, and documentation. For example, remote sensing data such as MODIS are widely available but often lack an interface to help with transferring it into GIS for use by practitioners. The North American Regional Reanalysis (NARR) product provides spatially distributed weather information at daily or sub-daily time scales, but is difficult for practitioners to use since it requires an interface or specialized programming skills to access and manipulate. One reason for the difficulty is that gridded data are generally organized as temporal snapshots and consequently require the user to download, disaggregate, and combine many large individual files to produce time series for specific locations or catchments.

It is an open question whether the practitioners or the scientists should be responsible for developing easy-to-use tools for accessing and processing gridded data sets. Scientists generally do not feel responsible for translating their research results into practical tools or lack the motivation to do so as their reward system is based on scientific publications, not practical application; but on the other hand, practitioners often do not have the money or time to invest in developing tools for accessing and processing the available information. There is a clear need for someone to operate at the interface between scientists and end-users, e.g. from technical colleges and governments.

Data-poor areas exist within all landscape types but are particularly prevalent in arctic, arid, and semi-arid regions, which are also commonly water-poor unpopulated regions. This leads to a reliance on predictions in ungauged basins in these water sensitive landscapes, which are increasingly the focus of resource development. Lack of information and data leads to greater uncertainty for any predictions made for these sensitive regions.

Differences among landscapes

Two factors strongly affect how much data are available in a given country: the density of population and the economic status. There are generally more data available in populated areas of developed countries than in unpopulated areas or developing countries. Within any of these contexts, data are likely to be more available in areas where water issues such as flooding and drought are recurrent. There may also be a cultural bias, as data seem to be more available where there has been an influence from the historical situations; British Empire military installations, for example, often provided detailed observations of weather and climate. The distribution of data networks is also affected by economic interests related to potential development, such as wind power and hydropower, and potential risk, such as flood prone areas. In many areas there are more monitoring data available where there are more people and water than in areas where there are fewer people and less water.

20.7 BARRIERS BETWEEN RESEARCH AND PRACTICE

The break out group discussions illustrated a divide that presently exists: researchers are focused on methods that are dynamic, detailed, information-rich, and rely on extensive observations; practitioners are using simple user-friendly methods that can be applied in areas with sparse monitoring, and that sometimes involve soft data or subjective judgement. The time scales of the predictions are also often different. The scale of hydrological predictions required ranges from simple annual values to seasonal, monthly, and finer time scales and also includes extreme events. The types of predictions that are needed or expected also vary from water rich to water poor areas. The variables to be predicted can be fluxes, states, or storages.

Researchers continue to contribute to all areas needed to improve predictions in ungauged basins, including process understanding and development and testing of empirical, statistical, conceptual, and process models. These developments continue, not always linearly, but are highly

influenced by observation technology and computer capability and capacity. While these tools have promise for improving predictions for ungauged basins, their uptake by practitioners does not automatically follow.

Practitioners need to be provided with modelling tools and once researchers have developed effective tools, there needs to be uptake by the user community. Users need to be provided with the tools and required data products in a manner that minimizes their investment of time and resources. In research, data sources such as gridded fields of driving variables can be accessed via the internet, sometimes along with software tools for extracting the information required in a specific application and exporting it to a format required by a model. Such tools could be better suited for use by practitioners in the form of a graphical user interface or a simple scripting language; however, practitioners are not in a position to adopt tools that require intensive relearning and technical support, while the research community is unlikely to put a high priority on developing such tools or to provide training to the practitioner community. One existing solution would be research partnerships, possibly funded by regulatory or government agencies, focused on technology transfer that supports implementation of research and development, and on providing a level of training commensurate with the need for practitioners to use the appropriate tools.

An important issue with obtaining data from the internet and agency databases is fitness for purpose (Whitfield, 2012). Data which are available may, or may not, be suitable for supporting predictions in ungauged basins. Practitioners need tools and guidance that support them in making effective and appropriate decisions about the use of such data in their application. One consequence of data becoming widely available on the internet has been a decline in the professional guidance available to ensure the user understands the nature of the data. Tools that better communicate metadata and inform the user of data quality and its representativeness are needed.

The adoption of new approaches, including process-based models, is generally constrained by cost and aversion to change: clients are typically unwilling to invest in new tools when simpler methods are acceptable or required by regulators. There is a need to weigh the lower cost of analysis associated with simple methods against their risk of failure. It is conceivable that, in some cases, the risk of an erroneous analysis may be sufficiently low that there is no economic incentive to pursue application of model-based approaches. In other cases, there may be clear economic arguments in favour

of model-based analyses; however, it is expected that everyone would rely on getting the right answer for the right reasons. Other barriers expressed by practitioners include the following:

- Lack of awareness of emerging approaches and model developments. Some of these are related to the cost of accessing journal articles, as well as limited time to devote to professional development activities, such as attending conferences
- Cost of purchasing another model and the cost of retraining
- Aversion to the risk of investing time in learning an approach that may not be widely accepted, especially to regulators
- Familiarity with existing models and tools and project timelines that are too tight to allow for alternatives to be implemented

One possible approach that was identified is not to build a model and then customize data inputs and model outputs to it. Rather the focus should be to develop a platform where data and output handling is conducted through a standard interface. Models should be supported by complete documentation and either a graphical user interface and/or a straightforward scripting language to facilitate training and application. An example of a relatively easy-to-use platform is Green Kenue. Green Kenue™ (formerly EnSim Hydrologic) is an advanced data preparation, analysis, and visualization tool for hydrological modellers. It provides a platform that integrates environmental databases and geospatial data with model input and output. Green Kenue provides pre- and post-processing for the WATFLOOD and HBV-EC hydrological models. It can be downloaded without cost at: http://www.nrc-cnrc.gc.ca/eng/solutions/advisory/.

Potential barriers to the adoption and development of these resources by model developers include the following:

- Lack of skill in software applications implementation
- Lack of awareness of user environment and needs
- Lack of forward planning in model development that ensures linkages with existing tools
- Competition and aversion to risk in participating in applied research which may not be recognized in academic/research career promotions
- Lack of a reward system for researchers, thus no motivation to make models user-friendly or to offer training

Potential barriers to the adoption of these resources by practitioners include the following:

- Lack of awareness of the existence of the tools
- Inertia, particularly when considering new tools
- Dedication to familiar tools, particularly those used during university training, or commonly used for other applications (e.g., Excel, MATLAB, ArcView)
- Vendor lock-in, where the customer is dependent on a commercial program, and switching to another program incurs costs
- Lack of technical support in dealing with onerous data requirements, data handling, and requirements for specific programming skills.

20.8 RESEARCH NEEDS AND EMERGING METHODS

Many research and application needs and opportunities were identified in the workgroup discussions. In this section those which were common to several groups are described.

Catchment characterization

One way to strategically choose and collect transferable data is the development of a classification system for watersheds. Catchment classification has been advocated within the Predictions in Ungauged Basins initiative for some time (McDonnell and Woods, 2004). While there have been streamflow regime classifications for some regions (e.g. Church, 1974), a general catchment classification system has not yet been developed. While basin-scale classification systems exist for particular regions, a general system should be based on physioclimatic characteristics to enable the prediction of the streamflow regime and other hydrological behaviour (Wagener *et al*., 2007). Basin classification can be based upon several traits, including topography (e.g. relief), hydraulic geometry (e.g. channel morphology), vegetation (e.g. NDVI distribution), or response units (e.g. hydrological function and distribution). Several classification schemes may need to be developed and/or combined so that the most appropriate transfer mechanisms are available for individual indices, parameters, or indicators. While one size may not fit all, it will be important to avoid applying an existing regional classification too widely. This is a classic hydrology trap; develop locally and then apply globally.

An approach would be to identify several representative basins and develop appropriate classification schemes. Building from that, developing and testing index, parameter, or indicator transferability across a range of space and time scales is needed. This process must incorporate a feedback mechanism to improve the design and implementation of research basins and the activities therein. This will also assist in guiding research and monitoring efforts that can continue to support the development of transferable data and information. In every region where data availability is at a premium, parsimony, in both data collection and modelling, must remain a key consideration.

Catchment characterization will be an important tool in transferring parameterizations. Characterization schemes will need to account for climatic thermal and moisture regimes (particularly the seasonality of precipitation), land cover, topographic complexity, and geology. Tague and Grant (2009) illustrated the profound influence that the underlying geology can have on streamflow variability and the response to climate variability. Geological maps are generalized, and it may be difficult to translate geological information from maps into hydrologically relevant parameters related to storage and transport dynamics. Research that extends the work of Tague and Grant (2009) to a wide range of geological and hydroclimatic contexts is needed.

For the foreseeable future, semi-distributed models will likely dominate over fully distributed models due to their lower computational demands. Current semi-distributed models use either a Grouped Response Unit (GRU) or a Hydrological Response Unit (HRU) approach.

In the GRU approach, a catchment is normally represented using gridded maps of various boundary conditions, including elevation, slope, aspect (derived from the elevation grid), underlying geology and/or soil types, and land cover (e.g., forest/open/water/glacier). Individual grid cells are categorized and cells with similar characteristics are grouped; heat and water fluxes are then modelled for each GRU rather than each individual cell. The delineation of cells is presently constrained, in part, by the resolution of digital maps. Digital elevation models are increasingly available with grid resolutions less than 100 m. Land cover maps are also available at increasing resolution. Characterizing land cover, particularly accurate land use information, is difficult. Rapid and widespread land use or land cover changes such as agriculture, irrigation, or forest disturbance (e.g. Mountain Pine Beetle) add a considerable challenge.

An important difference between HRUs and GRUs is that GRUs do not normally incorporate any information on lateral interactions between grid cells. On the other hand, HRUs are defined in consideration of their relative position within the cascade of lateral water transfers by, e.g., elevation, blowing snow, and subsurface flow, in addition to the types of criteria used to define GRUs. Delineation of HRUs is normally guided by land cover and geomorphology that guide the modeller's understanding of the dynamics of storage, connectivity, and thresholds in a landscape. The delineation process is subjective: two modellers are likely to generate different catchment descriptions, which contributes yet another dimension to the issue of equifinality.

Clearly, there is scope for research to further develop the understanding of the consequences of the HRU/GRU strategies and alternative hybrid approaches. Does the routing present in the HRU approach realistically capture the flux of water in the watershed? Does this perform significantly better that a GRU approach at some space and time scales? For example, would the GRU approach be suitable for annual fluxes and the HRU for finer time steps? Are there alternative approaches where the routing can be better captured within a GRU type of approach? Can the definitions of HRUs be made to be more objective, or even automated?

Processes and parameterizations

In principle, gridded models can be transferred in time or space if they incorporate the appropriate physics. The predominant challenge with complex models is that their numerical solution schemes can be costly in terms of computer processing time. To address physical processes that are unresolved at the model scale, processes are parameterized; however, highly parameterized models can be sensitive to errors in input variables. Simpler highly parameterized process-based models require fewer computer resources than detailed processed models; however, robust parameterizations of the processes that facilitate the transferability of parameter sets must be developed. A globally applicable model may not be appropriate. Instead, the development of modular modelling platforms such as Cold Regions Hydrological Model (Pomeroy *et al*. 2007)) and Raven (Craig *et al*., 2011) may be a more appropriate and useful approach. Such models would incorporate only those processes and representations that are relevant and limited by available data sources. In such a modelling

environment the onus is on the hydrologist to understand the dominant processes in the target catchment to ensure they are incorporated in the chosen model.

Calibration or parameter estimation will likely always be required in modelling applications, either to estimate parameters in process representations or to correct biases in fields of driving variables. The ultimate objective is to develop parameterizations that are transferable in time and space and that do not require site-specific calibration. This would be consistent with the trend for modellers to move away from using streamflow as the sole calibration target and incorporating additional variables such as glacier mass balance (e.g., Konz and Seibert, 2010; Schaefli and Huss, 2011) and other "soft" data (Seibert and McDonnell, 2002). Bias-correcting meteorological fields derived from products such as NARR or MERRA could be approached by using them to drive a process-based snow model and forcing it to reproduce snowcover patterns as derived, e.g. from the MODIS products.

Research opportunities in process-based modelling are extensive. Robust and consistent methods for assessing the suitability of physically based models or parameterizations in model performance for site-specific field studies and for supporting scaling will continue to be a focus (Wagener and Wheater, 2006). Research tools are needed to support communicating uncertainty. New approaches for allocating model resources and supporting appropriate decision making in model implementation (i.e. should the process be in the model physics or simply a parameterization) are needed to guide which approach is more suitable.

Scale considerations

Because data products are available over many differing spatial resolutions, converting them to a common scale requires degrading high resolution data to a coarser scale and/or interpolating coarser resolution products to higher resolutions. Degrading the resolution of a more finely resolved product to a coarser scale destroys information. Interpolation of coarse-scale data carries the risk of introducing artifacts of the interpolation procedure and may not accurately represent the true spatial pattern. Research that assesses the trade-offs in these approaches and their influence on model performance is needed as either approach may introduce additional uncertainties and bias.

Assessment of model output

Assessment of the uncertainty of model results is essential for understanding the applicability of the output to water management and the risks associated with making decisions with uncertain data (Pappenberger and Beven, 2006). An assessment of the potential to reduce uncertainty is also valuable in determining where additional resources may be best spent.

Practitioners and researchers would be well served by adopting a common framework for model assessment. As seen previously, modellers and analysts make assumptions, parameterize, and simplify as a matter of course, often without explicit explanation or justification. A standard framework that allows common interpretation of these decisions would be widely useful. Since everyone must make assumptions, simplifications, and parameterizations, the uncertainty induced by these simplifications needs to be adequately communicated. As a hypothetical example, a modeller might argue that, since glaciers are less than 5% of the given basin's area, glacier-related processes are not modelled; this choice might induce an uncertainty of < 5% in the annual runoff, but can produce a major error in predictions of late summer discharge, particularly during hot, dry weather.

Communicating uncertainty is a core issue for predicting in ungauged basins. Frameworks such as GLUE (Generalized Likelihood Uncertainty Estimation) (Beven and Freer, 2001) provide guidance for scientists, practitioners, and decision makers who need both tools and training that support their use of this information. Too often, decision makers fail to interpret uncertainty in terms of confidence intervals; rather they perceive it as lack of knowledge. At the same time, a single number may be perceived as "better" than numbers with confidence intervals or as the "right" answer. Client expectations may result in practitioners simplifying results (e.g. removing confidence intervals) resulting in information loss.

Research basins

Given that many areas are generally poorly monitored, research basins will be critical in the development and testing of simplified but robust representations of processes, for determining the appropriate scales for process representation, and for testing alternative approaches to the definition of HRU/GRUs. With increasing pressures on hydrometric network managers to reduce costs, it is crucial to maintain the data-rich infrastructure at research sites, especially at

sites with relatively long periods of record, where the effects of climatic variability can be separated from other impacts and can be more readily assessed. Reference hydrological networks play a key role in this (Whitfield *et al*., 2012; Burn *et al*., 2012).

Putting PUB advances into wide practice will require research to progress on a number of academic fronts, especially (1) generation of spatial fields of meteorological variables, (2) characterization of catchments and delineation of HRUs so as to capture the range of hydrological behaviour in a parsimonious yet robust manner, and (3) development of approaches for transferring information about processes and parameterizations from data-rich research catchments to ungauged catchments. Researchers should engage in a series of PUB emulation exercises to demonstrate the improvement in predictive capability asociated with newly developed modelling approaches. The following basic steps incorporate the scientific principles associated with predicting flows in ungauged basins, but also recognize the limitations that exist in practice:

- basic process understanding
- data assessment and compilation
- model selection based on processes and data
- model parameterization
- assessment of model output

An important consideration is that not all applications require or provide the same level of accuracy; accordingly, there may be a demand for a range of modelling approaches to suit the needs and data availability in specific applications. Researchers will need to continue to engage with practitioners in workshops like "Putting PUB into Practice" to gain a better understanding of their needs.

Dealing with change

Climate change is generally being approached by variability and trend studies of climate and streamflow, but largely tied to temperature and precipitation. Data from research basins and reference hydrological networks can be used to define 'natural' types and their attributes. Presently, we are not in a position to provide long term projections without making large simplifying assumptions such as lack of landscape or vegetative change. Projecting future

streamflows is a complex process and there are multiple GCMs, RCMs, and many equally likely future scenarios that could be considered. Hydrology models (statistical, conceptual, and physical) could all be driven by climate model outputs, possibly downscaled (dynamically or statistically), for any number of possible cases. Research in data-rich areas will need to provide insight to the direction and scale of potential changes in order for there to be confidence in the outcomes. PUB in data-sparse and data-poor situations will need to develop much further before the methods can be considered adequate for projections that address changes in climate, land use, and vegetation.

20.9 KEY OPPORTUNITIES

Standardized protocols

The hydrological community must recognize and adopt standard protocols or best management practices for both data collection and data extrapolation across all regions for hydrological prediction. This would help reduce uncertainty in decision making and data transferability during the tool evaluation process. For instance, the Canadian oil and gas industry is currently developing standard protocols for stream gauging in collaboration with the British Columbia Ministry of the Environment and the Water Survey of Canada. This example of co-operation illustrates the objective to ensure inter-industry comparability in order to facilitate the more widespread use of data already being collected and, thereby, assist the development of more robust models of water availability for management and allocation purposes. These types of activities help improve the appetite for non-hydrometric service data and encourage a two-way transfer of information on how to optimize data collection. In addition, inherent benefits of this multi-agency approach are improved data transferability and reduced redundancy among different groups. Instead, time and finances can be applied to other knowledge gaps. Important results of the above, of course, are more cost-effective data collection and hydrological model development protocols.

Protocol for a catchment function diagnostic

When faced with a diversity of choices and an even greater range of potential outcomes, a tool of increasing popularity is the decision tree (Bosch *et al*., 1996). This is a simple decision support tool that uses a tree-like graph or model of decisions and their possible outcomes, and it can help in the design of a strategy most likely to aid in meeting a specific goal. The decision tree

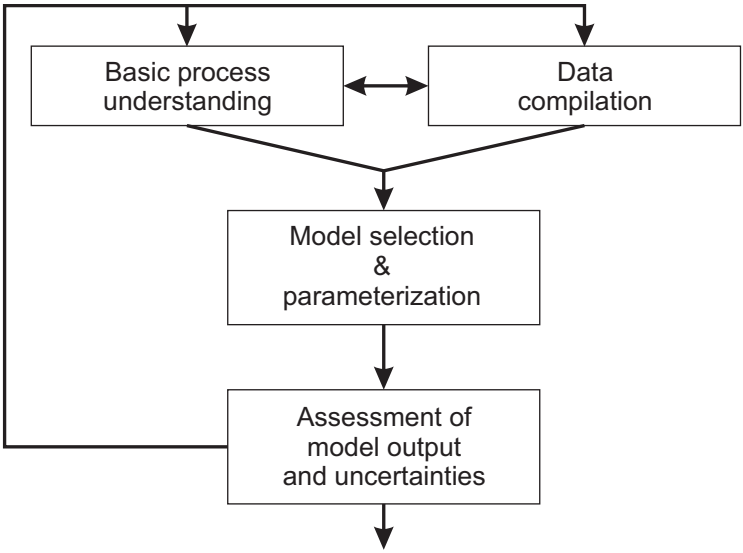

Figure 20.1 *Schematic showing the flow of process-based hydrologic modelling under uncertainty.*

could be used to identify the most suitable approach to hydrological prediction given the parameters of a particular situation. Figure 20.1 illustrates a possible decision tree based on the methods summarized above, that includes the spatial and temporal nature of the question being posed, the level of acceptable uncertainty, and the time and financial constraints for use by hydrological practitioners. This was envisaged as a decision tree approach that would use available information, assess process understanding, direct data assessment and compilation, and guide model selection and model parameterization. Basic process understanding could be determined from available information on climate, topography, land use, regionally generated streamflow predictions, and experience in data-rich contexts. This information could be incorporated in the decision tree to identify and differentiate processes and their linkages, and would be needed to develop tools, guidelines, and thresholds. The process must not be a single entry key; rather it should [1] identify the main processes and pathways including groundwater and landscape storages, [2] identify the landforms and topography, the existence and extent of wetlands and flood plains, slopes, and drainages, [3] identify the vegetation, soils, including interception and evaporation, and [4] address the heterogeneity of the mosaic. Ultimately, any classification needs to be accessible based upon the available information.

A well-constructed decision tree available to both academics and practitioners, indicating both traditional and ground-breaking methodologies, may provide insight into which methods could and should be implemented. We recommend that a decision tree for prediction in ungauged basins should be constructed and made publicly available as it would be a valuable means of both knowledge and technology transfer, and it would serve as a 'handbook on a page'.

Better outreach

Developing tools like decision trees or comprehensive handbooks (e.g. Pike *et al*., 2010) depends on good and ongoing communication between researchers and practicing hydrologists. Thematic meetings and workshops have proven to be very successful for information and idea exchange in Canada (Spence *et al*. 2005, Spence *et al*., 2008) as they bring together a diversity of attendees, increase awareness and conversation, and develop trust, the value of which cannot be underestimated.

In most data-sparse and data-poor regions, academics, practitioners, and governments must work together in data collection, research, and the development of predictive tools. Unfortunately, a good communication strategy to advertise the availability of new data or technologies to the practicing water resource community is generally lacking. A website that provides a conduit for research and development notes would be widely valuable. Such a website would include required metadata that would accompany the tools and would include details of the technical workings and the broader relevance for hydrological prediction. This would assist both technicians and managers in appreciating the value of the information. Active and up-to-date, online resources used as tools for the dissemination of valuable information to the hydrological community would support the traditional peer-reviewed literature medium for research results by acting as the key outlet for up-to-date development results. Furthermore, on-line sources support sustainable linkages among academia, government, practitioners, and the public, each of whom have a stake in the development and understanding of water resources in ungauged remote areas. Hosting of such a site presents several challenges as there is no single entity that has that mandate. A shared approach where individual agencies share their information through a single portal may be a workable system. Most likely, success would rely on an open source approach.

Open source solutions

Much of the development of improved tools to date has been top-down, with the concerns of users often an afterthought. To make the uptake of improved tools successful, not only do the tools need to be useful to practitioners but practitioners need to be informed about the existence of new tools, the nature of the improvements, and that the resulting tools implement these changes. An advantage of open source methodologies is that they potentially increase the number of people developing the project and those testing the code, contributing to improvements in development speed and code reliability. The best way to ensure the engagement of users is to involve them in the development of tools, preferably from an early stage in the development. In open source projects, this can be done by soliciting the participation of end users at the beginning and throughout the project. In all cases there needs to be extensive collaboration between researchers and end users. Stakeholders can be involved in research projects and in the training of students. While financial contributions from the users give them a stake in a project, it is critical to keep expectations clear.

One opportunity is to develop an open-access database of standardized watershed variables which is routinely updated. Standardized open source clustering of the database records would be updated and 'published' on a timely basis perhaps based upon growth in the size of the database. At each iteration, new records would be tested to see if they "fit" the classification (high similarity); if they do not (low similarity), a rule based new generation would be generated, reviewed, and released as a new version by a peer team. Each new version would require a description to be published in a public forum such as a peer-reviewed international journal. The editorial board of the journal would need to be approached to create an ongoing relationship. It is expected that the classification and the diagnostic should co-evolve, but be done separately.

Since every watershed is unique, the classification needs to simultaneously deal with the common attributes upon which similar hydrological landscapes are grouped at a high level while allowing more separation based upon additional attributes. This should provide a system where the major processes and timing are captured for any ungauged basin, but with the additional information available to increase resolution.

It is recognized that all new tools need to better incorporate user/practitioner needs. Projects also need to include better communication plans and training of end users. Practitioners make it clear that the initial adoption of a new technology has both a risk and a cost; hydrology will be well served if new developments in the science are incorporated into a limited number of tools. All developments being implemented for professional practice need to be accompanied by training which could include webinars, podcasts, and other forums where the needs of the users, and not the developers, are best addressed.

20.10 CONCLUDING REMARKS

The lack of data with which to inform any type of predictive model, in combination with the wide diversity of hydrological landscapes, make prediction in ungauged basins challenging. The PUB Decade has seen the development of research that has a great potential to advance the practice of hydrological prediction in ungauged basins, particularly thanks to the development of gridded hydrometeorological products and research activities in relatively data-rich research basins. Support for research basins needs to continue as these basins provide the testing grounds for new hypotheses, statistical, conceptual, and deterministic models, and reanalysis tools. By clearly determining the scales at which the data and information produced would be applicable, possibly through a basin classification system, the value of these sites would be enhanced. Practitioners and managers also need such a classification system and other tools designed to enhance the development of transferable data, indices, parameters, and indicators. It is recommended that standardized and generalized physiographic information be collected using the same set of tools that are widely used by practicing hydrologists. The classification system should link landscape attributes to these more intensive and detailed measurements. As predictive tools develop, updated decision trees may prove to be valuable to practicing hydrologists. Development and maintenance of these types of tools require ongoing communication and collaboration among all hydrologists. The existing newsletters, journals, and websites of professional and learned societies are well suited for the spreading of such information and would complement the traditional peer-reviewed literature conduit for information dissemination. An open source approach to the classification system and the diagnostic protocol is recommended so these will have widespread application and acceptance.

20.11 RECOMMENDATIONS AND ISSUES

1. Address the need to maintain continuity. What would be the appropriate mechanism for validating new methods, and bringing them into practice? It is not obvious who should be responsible for the ongoing need to convert research into practice. New approaches and improved methods deliberately result from research; moving such new developments into professional practice is an apparent gap in our community, although at different times government, practitioners, and software developers have played important roles. Some guidance with respect to this has been provided above.
2. Address the need for interfaces to complex datasets. How can complex datasets be made widely accessible to practitioners? Researchers commonly use a diverse mixture of complex datasets from remote sensing, climate models, and reanalysis products. While these datasets are readily accessible, they are not readily put into practice, and if they are used in practice, the access methodology is not always clear.
3. Address the need for open source approaches. Are we getting the right answers for the right reasons? With increasing complexity of models and analysis there is a responsibility for transparency. The community needs to be certain that models and methods properly capture the science, the uncertainty, and the quality of inputs. This is particularly true for regulatory agencies that make key decisions based upon outputs from models and analysis.
4. Address the need for common operating platforms. Can the community adopt a common framework that would improve upon the current situation? With the increasing diversity of models and tools there is a growing risk that the users will use tools that they have available, that they are familiar with, or that cost less, rather than ones where the science matches the information needs. The growing gap needs to be made much smaller. Modelling environments such as Green Kenue have demonstrated the value of creating a common framework that supports model development, hydrological modelling, and the display of results. Green Kenue was recently made freely available with the intent of it being used in training students in the practice of hydrological modelling.

5. Address the need for better outreach. Is the community taking the correct actions to support the transfer of science into practice? Adopting an open source approach with a generalized classification and diagnostic scheme are key steps; making training and support readily available to practitioners will also be important. Tools that are unsupported or left up to the users to discover and apply will be unsuccessful. Practitioners often prefer tools where support is available on demand, or just in time, rather than "do it yourself".

The legacy of the PUB decade includes significant advances in the understanding of hydrological processes and development and testing, in research settings, of revised or new methods for PUB. The challenge remains to address the need to adopt standards and globally generalized approaches for practitioners to make predictions in ungauged basins; the participants in the workshop portion of this meeting have suggested approaches that will address this situation.

20.12 ACKNOWLEDGEMENTS

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SYNTHESIS OF MAJOR FINDINGS AT PUB 2011 AND RECOMMENDATIONS FOR FUTURE DIRECTIONS

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21.1 ABSTRACT

This chapter discusses three tasks that are considered necessary to advance improvements in prediction in ungauged basins in applied situations. First, incorporation of new hydrological process understanding into predictive models needs to continue. This should enable models to predict more than the traditional end point; streamflow, and expand into others such as storage in the snowpack and subsurface. It will also reduce uncertainty when dealing with non-stationarity. Second, methods need to be introduced that help constrain, rather than calibrate, model parameters. Traditional calibration could be used to solve for these parameters; but there are reasons to avoid this approach, non-stationarity being only one. Constraining parameters is useful as it helps locate uncertainty, and how it could be addressed. Information for constraining parameters can come from a wealth of sources, including existing hydrological indices, independent measurements from remote sensing, or research catchments. Third, work must continue to encourage the adoption and implementation of robust tools by practicing hydrologists. Unfamiliarity and adhering to accepted standards of practice are two reasons why practitioners are sometimes hesitant to adopt new approaches. Time limitations and a lack of easy access to new tools are significant logistical impediments to adoption as well. Some countries have addressed these problems with training courses as a means of technology and knowledge transfer. Such collaborative efforts are crucial to improve water management and prediction systems.

21.2 RÉSUMÉ

Le présent chapitre traite de trois tâches jugées nécessaires pour l'avancement des initiatives d'amélioration de la prévision dans les bassins non jaugés dans des situations appliquées. Tout d'abord, l'intégration de la compréhension des nouveaux processus hydrologiques aux modèles de prévision doit se poursuivre. Cela devrait permettre aux modèles de prédire davantage que l'écoulement fluvial, point terminal traditionnel, et d'étendre la capacité des modèles à d'autres prévisions, notamment l'emmagasinement de l'eau dans le manteau neigeux et la subsurface. Cela réduira aussi l'incertitude lorsqu'il faut composer avec la non-stationnarité. En deuxième lieu, des méthodes doivent être adoptées afin de restreindre, plutôt que d'étalonner, les paramètres du modèle. Il est possible d'avoir recours à l'étalonnage traditionnel pour la résolution de ces paramètres. Cependant, il existe des raisons d'éviter cette approche, la non-stationnarité étant l'une d'elles. La restriction des paramètres est utile, car elle aide à localiser l'incertitude et elle facilite la manière de l'aborder. Les données pour la restriction des paramètres peuvent provenir d'une myriade de sources, entre autres des indices hydrologiques existants, des mesures indépendantes de la télédétection ou des bassins de recherche. Troisièmement, le travail doit se poursuivre en vue d'encourager l'adoption et la mise en œuvre d'outils robustes par les hydrologues en exercice. L'inexpérience et le fait de devoir adhérer à des normes de pratique acceptées constituent deux raisons pour lesquelles les professionnels en exercice hésitent parfois à adopter de nouvelles approches. De plus, les délais fixés et un manque d'accès simple aux nouveaux outils constituent d'importants obstacles logistiques à l'adoption. Certains pays se sont attaqués à ces problèmes en offrant des cours de formation comme moyen de transfert de technologie et de connaissances. De tels efforts de collaboration sont indispensables à l'amélioration des systèmes de prévision et de gestion de l'eau.

21.3 INTRODUCTION

The organizers of the Putting PUB into Practice Workshop of 2011 challenged the participants to develop innovative answers to the following question: How can the practice of prediction in ungauged basins be successful in areas where it is hard to do so, during changing environmental regimes, and when multiple end points are needed? The solution seems straightforward – build tools capable of the task - but the implementation is not simple. The content

presented earlier in this volume summarizes the research and development efforts specifically presented and discussed at PUB 2011 that can lead towards building and implementing improved predictive tools. Beyond the scope of PUB 2011, there have been a large number of published contributions over the PUB decade, (see Hrachowitz *et al.*, 2013 for examples) that when implemented will contribute to the practice of prediction in ungauged basins. At this stage, near the end of the PUB decade, there is still progress to be made. The discussion at PUB 2011, with its focus on improving prediction by practicing hydrologists and water resource managers, provided key insight into where this progress is needed so that society can benefit from the increased knowledge that came from research conducted during the PUB decade. Rapid improvements in prediction could now come from a concerted effort on two sequential fronts; first, ensure that new hydrological process understanding is incorporated into predictive models; second, ensure successful application of enhanced predictive models by implementing methods to constrain parameterization of these new process algorithms as they are incorporated into the models; however, even if the water resource research and management communities are successful in achieving these goals, they may be moot. The full potential of this knowledge, research, and development will only be ensured by having them adopted and enacted by practicing hydrologists. Each of these three tasks is addressed in turn.

21.4 DECREASE THE GAP BETWEEN PROCESS UNDERSTANDING AND MODEL STRUCTURE

Deterministic hydrological models are traditionally designed to predict one end point; streamflow. More needs to be demanded from these models. Society is no longer only asking about the statistical properties of the quantity of water in the stream; they are asking much more complicated questions about water; for example, how might the volume and timing regimes of streamflow and lake levels change in the future, and how might this affect the quality of the water? This requires models that properly predict streamflow by correctly simulating other parts of the hydrological cycle. For the distribution of water storage or water chemistry, for instance, to be correctly simulated, there needs to be proper representation of runoff processes and pathways. In order to have confidence that models are correctly simulating all aspects of the water cycle and runoff pathways, they should perform well at not just the catchment outlet, but also at sub-catchment scales.

Dornes *et al*. (*this volume*) provide an example to model developers and users of how a distributed model can be structured to ensure important components of the water cycle are properly simulated. The authors applied knowledge of how snowmelt energy is distributed across a mountainous subarctic watershed and structured how energy was distributed in the model accordingly. As a result, simulations of both snow ablation and streamflow were improved from when aggregated approaches were used. New algorithms were not necessarily required, but wise application of existing knowledge and tools was. The lesson for practitioners is to apply models appropriate to the level of landscape complexity and true to the predominant processes.

Via hydrometric (Tromp van Meerveld and McDonnell, 2006) and hydrochemical techniques (Tetzlaff *et al*., 2007), one of the major contributions from the research community to PUB was identifying that previous theories of runoff generation and pathways are not necessarily as widely applicable as expected. This was a problematic finding, as these theories have provided the foundation for the algorithms in many commonly used numerical models. New algorithms have proved successful in research models (Soulsby *et al*., 2006), but this type of information has not generally made its way into models commonly used by practitioners.

There is a firm belief in the research community now that models must encapsulate the proper processes and fluxes of water within the catchment and not just from the catchment. This is because of growing understanding of the role of sub-catchment units in complex landscapes in catchment runoff generation (Spence and Woo, 2006; Jencso *et al*., 2009). Because of these developments during the PUB decade that show that sub-catchment storage states and thresholds are crucial to runoff generation, attendees at PUB 2011 encouraged the development of models that can predict both hydrologic state and storage (e.g. Seyfried, *et al*., 2009). This would be complementary to the development of research models that can properly simulate how storage is converted to discharge via simulating the correct source areas, flowpaths, and residence times (Soulsby *et al*., 2006).

Developing robust model structures is a means to an end, the latter being improved prediction in ungauged basins and better information for decision makers; however, building such models should also be an end unto itself. Doing so is necessary to ensure the continued relevance of predictive models, in a post-stationary world (Milly *et al*., 2008). The issue with non-

stationarity is pervasive. Post (*this volume*) implies that non-stationarity could result in a change in predominant hydrological processes in a given region. This would imply that a more adaptive (i.e. more endpoints, less calibration) model structure is required for predictions to be relevant into the future. Furthermore, physically lumped catchment-scale signatures and diagnostics (Wagener *et al*., 2007), and the empirical relationships that come from them, are also vulnerable to non-stationarity. Hydrologists leading research into these types of "top-down" models need to consider the role of non-stationarity, so as to build resiliency into these types of predictive tools. Practicing hydrologists also need to consider this and implement best practices to ensure the tools they are using remain resilient before being used to generate information used by decision makers.

21.5 CONSTRAINING UNCERTAIN MODEL INPUTS AND OUTPUTS

Perhaps one of the major stumbling blocks to improving confidence in new algorithms and schemes in hydrological models is the reliance on traditional model calibration and validation approaches. New algorithms require new parameters, information on which is unlikely to have been collected. Traditional calibration could be used to solve for these parameters, but there are two reasons to avoid this approach. First, calibration is not suitable for ungauged basins because of the absence of streamflow data with which to calibrate models. Furthermore, one of the key tenets of the PUB initiative was to progress away from calibration (Sivapalan *et al*., 2003) and build tools that did not need observed hydrological response data. A framework has been proposed in South Africa that promotes a focus on constraining model parameters within a range defined with as much information as is available (Kapangaziwiri *et al*., 2012). In a well-gauged and measured catchment model, parameters may be constrained well because of the generous amount of information and there may be a very narrow band of uncertainty. In poorly or ungauged catchments, the uncertainty band would be much greater and depend on the availability of information used to constrain parameters. Developing a suitable suite of constraints, therefore, represents an equally critical step in the process as defining parameters and their distributions. As such, understanding parameter distributions and how to constrain the possible range for an ungauged basin is also a field of research that has enormous potential to be useful in practice (Seibert and McDonnell, 2002).

The exercise of constraining parameters within specific ranges is one of using information from data-rich situations and transferring them to data-poor situations and could include a wide variety of different approaches including:

- Applying hydrological indices based on some established approaches that have proven valuable in the region of interest (e.g. SCS curve numbers estimated from regional soils and land use data).
- Assimilating independent measurements of hydrological state variables (e.g. storage from GRACE (e.g. Ramillien *et al*., 2008)) as well as stream flow data to condition model outputs.
- Evaluating how regional catchment response (e.g., mean runoff ratio, residence time) varies with catchment properties such as soils, geology, land cover and use, and topography. This would help provide information on expected parameter values for different catchment classes (Yadav *et al.*, 2007).
- Using focused, short-term field campaigns to confirm or constrain and reduce the uncertainty in some of the model inputs or outputs (Pomeroy *et al*., 2005; Hughes *et al*., 2013).

Figure 22.1 outlines the steps in an ensemble approach to assessing uncertainty in model parameters. There are two options to follow after the initial uncertainty ensemble outputs from the model are assessed. The first is simply to reject non-behavioural ensemble members, while the second is to feed information back to the parameter estimation process and try to reduce the initial uncertainty in the parameter values. This feedback loop may be useful to identify critical processes or parameters that generate most of the output uncertainty (sensitivity analysis), and this represents an approach that uses model outputs to evaluate conceptual process understanding (Beven, 2012). The feedback loop may also be used to identify parameter redundancy and contribute to more parsimonious models in future applications. Alternatively, the feedback loop may also help to identify critical deficiencies in the structure of a specific model.

Research basins provide a wealth of parameter information that can be used for model applications; however, end-members and gradients within individual and networks of research basins need to be captured in order for the spectrum of relevant hydrological processes and parameters to be sampled. There is a huge body of literature on the network design of

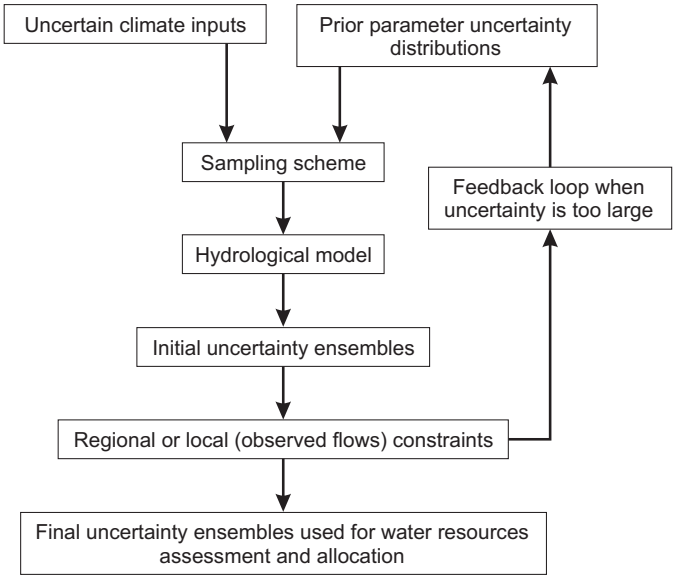

Figure 22.1 *Uncertainty framework for hydrological modelling.*

sampling sites in stream gauging networks (e.g., Langbein, 1954; Dawdy, 1979; Moss, 1979), but there has been very little development of methods with which to ensure research basins are representative and fit for purpose. Process level classification schemes from Winter (2001) and Buttle (2006) could be used to evaluate research basin representativeness. Because catchments are selected as intense research sites for logistic reasons as much as anything else, this could be crucial work.

Nonetheless, measurements in research catchments should and will continue to include those necessary to research hydrological processes and characterize both regional hydrological and physiographic parameters. Sound management of these sites, however, should include scale appropriate measurements with tools that facilitate transferring this information to ungauged basins. Furthermore, research hydrologists should strive to develop predictive techniques that will still perform well when driven with regionally available data. This includes considering the type, scale, and resolution of data that exists outside the research catchment. Sivapalan *et al*. (2005) and Wagener *et al*. (2007) promote the use of diagnostics of hydrological behaviour, catchment function, and hydrological signatures because these emerge at larger scales.

Traditional signatures used to estimate ungauged basin behaviour and hydrological regimes use climate, topography, vegetation, and geological characteristics. Wagener *et al*. (2007), Kuchment and Gelfan (2005), and Woods (2003, 2009) provide excellent reviews of similarity indices that encapsulate how catchments function. In light of new research, McNamara *et al*. (2011) and Spence (2010) have suggested that diagnostics should include those measures that characterize storage mechanisms, hydrological connectivity, and controls on threshold properties. This research is relatively young and the catchment diagnostics that will prove successful are not fully known or tested. A key first step could be catchment classification and mapping as a means to quickly identify the most important controls on water fluxes (McDonnell and Woods, 2004). Therefore, coordinated efforts to map regional catchment function diagnostics using measurement tools already adopted by practicing hydrologists would be a useful exercise. The benefits of mapping catchment function diagnostics in ungauged basins would be twofold. First, a broad scale spatial dataset could encourage testing by researchers of the usefulness of these diagnostics for prediction. Second, using established measurements could encourage adoption of the new diagnostics by practicing hydrologists.

21.6 ADOPTION OF NEW APPROACHES BY PRACTITIONERS

Unfamiliarity and adhering to accepted standards of practice are two reasons why practitioners are sometimes hesitant to adopt new approaches. Time limitations and a lack of easy access to new tools are significant logistical impediments to adoption as well. There are current models and new data sources (e.g., satellite rainfall or evapotranspiration) for data-scarce regions that are an important contribution from the PUB decade to the scientific literature, but evidence of their successful use in practice is relatively scarce to date. Demonstrating that uncertainty approaches are possible, practical and essential (Pappenberger and Beven, 2006) and communicating how to manage uncertainty to practicing hydrologists and water resources managers are essential components of effectively moving these models and data sources into practice. The reluctance of some practitioners to adopt new approaches or data sources is a shared challenge which needs to be addressed by all members of the hydrological community. It is therefore the responsibility of the PUB science community to demonstrate to the practitioners that new approaches are scientifically sound, can be applied in

practice, and should result in more informed water resources management decisions being made. Researchers and practitioners could test a variety of old and new techniques in collaborative exercises, within the uncertainty framework in Figure 22.1, to demonstrate the advantages or disadvantages of new tools and data sources developed during the PUB decade.

Model structure selection is often ad hoc because there is often no guidance in data-poor and sparse regions (McDonnell and Woods, 2004). Research on how to objectively select appropriate model structures for ungauged catchments remains a challenging research problem in hydrology (McMillan *et al*, 2011). Sound catchment classification and mapping would contribute much to the availability of spatial information on catchment diagnostics useful for selecting the most appropriate predictive tools. Working in snow-dominated environments, Clark *et al*. (2011) provide an example of using research to guide the selection of model structure at varying spatial scales. This type of information could assist in the application of decision trees (Whitfield *et al*., *this volume*). It would reduce uncertainty around choices of the most suitable model structure given a particular ungauged basin and the financial and time limitations within which the practitioner must operate. This would provide the practitioner with some insight into how useful different model structures are in particular landscapes.

Some countries have had particular success with training courses as a means of technology and knowledge transfer. Short, intense courses can expose early and mid-level career hydrologists to recent research and new data, theories, models, and techniques. Courses can focus on physical principles, field instrumentation, model application, and data sources. Courses on hydrological principles provide participants with information on relevant hydrological processes, very useful when selecting appropriate tools for specific landscapes. Field courses teach participants established and new ways to obtain data and information; for example, the rise in popularity of acoustic velocity measurements or the introduction of field deployable water isotope analyzers can provide data and information previously unavailable. Modelling courses familiarize students with new models and algorithms which is an important element in the uptake of new technologies. There are new data, especially gridded meteorological data being made available, but the practitioner needs to be made aware of their existence. A good course on models and data can provide guidance for which tasks the tool or data source are appropriate. These types of courses have been successful in New

Zealand (http://www.niwa.co.nz/education-and-training/training-courses) and Canada (www.cwra.org) in recent years. Whatever the focus of an individual course, communication via courses is a long-term generational approach to the adoption of new methodologies.

21.7 CONCLUDING REMARKS

There were certainly many advances developed during the PUB decade that can be easily applied in practice with relatively small changes to models used currently by practitioners. There are many more contributions that have the potential to improve the practical use of hydrological models. Realizing this potential requires further work to move the scientific developments from the research domain into the practical domain. It is likely that the initiative to achieve this will come from small victories among those practitioners wishing to expand their horizons and members of the PUB research community who are interested in seeing their scientific developments applied; however, prediction becomes increasingly difficult with non-stationarity in hydroclimatic regimes, and the associated risk to society rises accordingly. In order to ensure societies are resilient to water related stress, it is becoming imperative that all researchers, practitioners, and decision makers strive to work together to improve our water management and prediction systems.

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Ric Soulis	University of Waterloo	Waterloo, Ontario
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The Columbia Icefield in Jasper National Park – triple point headwater of the Columbia, Athabasca, and Saskatchewan Rivers and location of the workshop field trip

P.K. Gregory

Athabasca Glacier

P.K. Gregory

Mount Athabasca

P.K. Gregory

View from the Icefields Parkway

P.K. Gregory

Canmore, Alberta, Canada – Location of the Workshop

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Canmore, Alberta, Canada – Location of the Workshop

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