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Summary of Pattern Comparison and Concluding Remarks

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14.1 INTRODUCTION

> It also seems obvious that search for new measurement methods that would yield areal distributions, or at least reliable areal totals or averages, of hydrologic variables such as precipitation, evapotranspiration, and soil moisture would be a much better investment for hydrology than the continuous pursuit of a perfect massage that would squeeze the nonexistent information out of the few poor anaemic point measurements . . . Klemeš (1986a, p. 187S)

> . . . the collection of data without the benefit of a unifying conception (embodied in a model or theory) may submerge us in an ever deepening sea of seemingly unrelated facts. Hillel (1986, p. 38)

These two wonderful quotes from 1986 encapsulate the motivation for the work presented in this book. Just what was so special about 1986 is difficult to say, perhaps it was to do with the combined developments in computer technology and the desire for a sounder scientific base for hydrology. In any case, while these calls were not new, they were restated in a powerful way. Progress was being stymied by a lack of appropriate data and the often weak links between those who undertook the modelling and measurement. Careful observation and measurement is of course the foundation on which science is built and hydrology is not short of striking examples. Pioneering observations of runoff processes in the 1960s and early 70s by Emmett (1970), Betson (1964), Dunne and Black (1970a,b) and others, expanded the view of how runoff was produced (although many ideas were established much earlier, e.g. Hursh and Brater, 1941). But as noted by Betson and Ardis (1978) these new concepts took a long time to be explicitly incorporated into hydrological models, although their bulk effects could be represented implicitly via calibration of parameters that the modeller probably did not associate with the process. Interest lay primarily in getting the catchment runoff right and the simpler a model the better, when this is the aim

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(Dawdy, 1969). But when used for investigative purposes, the need for models to mimic the real processes and be "right for the right reasons" (Klemeš, 1986a) becomes paramount. However, mimicking real processes adds complexity, which in turn expands the amount and type of data needed for testing.

In the early chapters of this book we argued that in catchment hydrology, the measurement of *spatial patterns* is necessary to further our understanding of hydrological processes and to properly test and develop spatially explicit hydrological models. The case studies represent some of the few attempts to test this assertion by combining detailed spatial observations and modelling in a catchment hydrology context. The studies also serve to test whether the response of funding agencies and organisations to those powerful calls, that continued through to the 90s, can be vindicated. The case studies cover an extraordinary range of dominant processes, catchment sizes, data types and modelling approaches. Environments range from the semi-arid, convective storm dominated region of Arizona, through the tropical forests of the Amazon, to catchments in Australia, France, Belgium, Norway, Denmark and Canada; from the steep mountains of Austria to the rolling country of Idaho. Catchment sizes range from less than 1 hectare to more than 10,000. Data types include simple nested stream gauging data, numerous point samples of soil moisture using a number of methods, piezometric level, snow water equivalent, runoff detectors, soil chemical and vegetative indicators of recharge and discharge, and a range of remote sensing techniques (satellite SAR, airborne passive microwave, multispectral data, RADAR precipitation, and aerial photography). Most measurements have been quantitative but some have been descriptive or binary. The models have also covered a wide range of dynamic modelling approaches with different distributed structures, as well as stochastic and distribution function approaches. The one thing all of these studies can claim in common is the rare honour of comparing *observed* to *simulated* patterns.

14.2 WHAT HAVE WE LEARNED FROM THE COMPARISONS OF OBSERVED AND SIMULATED PATTERNS?

All case studies of this book have been concerned with comparing simulated and observed patterns of hydrologic variables to inform modelling. A summary of the most important conclusions reached on the basis of these comparisons in each of the chapters is given in Table 14.1.

In the following section, we attempt to compile a bigger picture from the outcomes of these studies in terms of the more general contributions to hydrological science. These fall into three main categories related to *processes*, *data*, and *modelling*.

Processes

A number of the studies have shown that often, a single process dominates hydrological response in a particular catchment. This dominant process depends on the climate and other environmental factors. In the arid/semi-arid climate of

Table 14.1. Summary of findings from the patterns comparisons

Chapter	Pattern comparison	What was learnt from the comparison
4. Patterns and organisation in precipitation	RADAR precipitation versus downscaled (statistically disaggregated) simulations based on large scale patterns from both RADAR data and atmospheric model output. (Figs 4.7, 4.9)	Spatio-temporal rainfall patterns exhibit dynamic scaling behaviour. With appropriate normalisation and dynamic scaling methods, both space and space-time variability can be simulated using stochastic simulation. Storm scale atmospheric models were found to simulate patterns that showed less variability in space and time than observed, indicating that the models *may* need some modification.
5. Patterns and organisation in evaporation	Point flux measurements of evaporation versus simulations from models based on remotely sensed surface temperature and surface cover. (Fig. 5.2)	Reasonable agreement with surface flux stations obtained. Uncertainty in effect of heterogeneity on flux measurements and lack of directly measured patterns of evaporative flux prevented detailed analysis of predictive capability or possible model errors. State of data and knowledge of spatial interactions insufficient at present for confident spatial evaporation estimation.
6. Runoff, precipitation and soil moisture at Walnut Gulch	Rainfall interpolated from dense rain-gauge network versus estimated from remotely sensed surface brightness temperature (ESTAR). (Fig. 6.12) Soil moisture measured by passive microwave versus simulated using various sources of variability and different amounts of data assimilation in a distributed model. (Figs 6.13, 6.15)	Remotely sensed brightness temperature looks to be a promising estimator of precipitation patterns in semi-arid environments. Rainfall patterns are the dominant control on soil moisture patterns and must be represented to model hydrological response in this environment. Spatial variability at the sub-hectare scale was influential on runoff processes. Estimating soil properties from soil type *deteriorated* simulations of soil moisture by a distributed model as compared to using uniform soil properties. Newtonian nudging was best able to assimilate PBMR soil moisture estimates with model estimates to correct spatial simulations. The representation of channel losses is critical to predicting runoff accurately in this environment.
7. Spatial snow cover processes at Kühtai and Reynolds Creek	Aerial photographs of snow cover versus simulations from a distributed model. (Figs 7.3, 7.4, 7.5)	Inclusion of topographically varied energy inputs and wind drift in a distributed model enabled the spatial variability of basic cover patterns to be reproduced. Refined representations of avalanching, wind drift and reflected and emitted radiation from adjacent areas are needed to further improve simulated patterns.

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Table 14.1 (*continued*)

Chapter	Pattern Comparison	What was learnt from the comparison
	Observed snow water equivalent from intensive point measurements versus simulations from a distributed model. (Fig. 7.12)	Patterns of SWE could be reproduced only when the process of wind drift was simulated – this process dominates spatial patterns in a rangeland environment. Other factors such as topographic variations in energy inputs were insignificant compared to drift.
8. Variable source areas, soil moisture and active microwave observations at Zwalmbeek and Coët-Dan	A field survey of saturated area versus estimated pattern from the standard deviation, and from PCA, of multi-temporal SAR images. (Figs 8.5, 8.11) Mapped soils that are characteristic of wet areas versus estimated patterns from the standard deviation, and from PCA, of multi-temporal SAR images. (Figs 8.6, 8.8)	Soil moisture and wet areas cannot be retrieved from single images on vegetated surfaces. The hypothesis that wet areas should be identifiable as areas of low variance in multi-temporal SAR images was confirmed. In areas where terrain variability is high, it dominates the SAR response. PCA applied to multitemporal images can be used to isolate the component of the backscatter coefficient that is dominated by variations in soil moisture, providing qualitative patterns of areas likely to be wet.
9. Soil moisture and runoff processes at Tarrawarra	Soil moisture in the top 30 cm from intensively sampled point measurements versus simulated soil moisture from a distributed model. (Figs 9.6, 9.9, 9.10, 9.11, 9.12)	A distributed model that represented the effect of spatial variability in topography on lateral surface and subsurface flow, and radiation exposure on evaporation, was able to represent the spatial and temporal variation in soil moisture. Introduction of variability in soil properties via mapping of soil type did not improve simulations. Preferential flow through cracks in the soil in Autumn needs to be represented to improve observed spatial patterns during this period. An additional soil layer needs to be represented, and better ET procedures included to further improve soil moisture estimates in the Spring.
10. Storm runoff generation at La Cuenca	Runoff occurrence from intensive network of runoff detectors versus simulated runoff occurrence from a distributed model (Figs 10.15, 10.16)	Simulations using deterministic patterns of soil hydraulic properties could not reproduce observed patterns of runoff occurrence. Distributed models in this tropical environment could represent the functional behaviour of spatial runoff response only by combining deterministic patterns and random realisations of soil hydraulic properties.

Table 14.1 (*continued*)

Chapter	Pattern comparison	What was learnt from the comparison
11. Shallow groundwater response at Minifelt	Water levels from a dense network of piezometers versus simulations from a quasi distributed model. (Figs 11.4, 11.12)	Topography and soil depth alone could not reproduce observed patterns. Measured patterns of piezometric level could be simulated only through the use of spatially variable soil porosity and hydraulic conductivity. These soil parameters needed to be "back-calculated" from spatial water table response and their patterns could not be interpreted physically. Model structure uncertainty complicated the assessment of the value of different data types for constraining the uncertainty in simulations. In the dry parts of the catchment, patterns were more useful than times series at a point for constraining the uncertainty in simulations but the reverse was true in the wet parts of the catchment.
12. Groundwater–vadose zone interactions at Trochu	Observations of long term recharge and discharge locations based on piezometric levels and vegetative, biological and soil chemical indicators, versus simulations from an equilibrium vadose zone model linked to a distributed groundwater model. (Figs 12.6, 12.7, 12.8, 12.9, 12.10)	Coupling of the vadose zone and groundwater behaviour was able to reproduce observed patterns of recharge and discharge. Recharge/discharge patterns are more dependent on local topography when strong coupling exists and on regional topography when weak coupling exists. Low bedrock transmissivities increase the area of a catchment over which coupling is important
13. Towards a formal approach to calibration and validation of models using spatial data	Multiple point observations of ground-water level and stream flow versus simulations from a large scale distributed model (Figs 13.5, 13.6, 13.7)	Predictive performance for stream gauges and wells that were not used for calibration was poor due to problems with the simulated groundwater divide. Use of even limited spatial data provides a severe test for distributed models and should become part of modelling practice of credibility of results is to be assured.

Walnut Gulch (Chapter 6) rainfall space-time variability was vastly more important than other controls, based on an analysis of rainfall data at the sub-hectare scale and a sensitivity analysis using the KINEROS model. For the very different climate of Reynolds Creek (Chapter 7) it was demonstrated that wind drift is by far the most important process affecting space-time patterns of snow water equivalent, by comparing observed snow water equivalent patterns with two simulated scenarios, with and without a representation of snow drift. In the humid climate of the Tarrawarra catchment (Chapter 9) saturated source area runoff was the dominant runoff mechanism as concluded from simple initial analyses of the observed TDR soil moisture patterns and later confirmed by Thales simulations. The simulations also confirmed that subsurface water movement changes abruptly in spring and autumn. During summer (dry), vertical water movement was dominant while in winter (wet), lateral water movement was dominant. Finally, a comparison of simulated and observed recharge/discharge patterns in the Prairie climate of Trochu (Chapter 12) indicated that recharge and discharge patterns were controlled by the coupling of the regional aquifer with the surface through the unsaturated zone, which dominated the local water budget. This finding was corroborated by a sensitivity study comparing scenarios with and without coupling to observed recharge/discharge patterns. The scenario without coupling could be made to match observed patterns only when unrealistically high values of recharge were assumed.

Comparisons of simulated and observed patterns have also shed light on the *nature* of space-time variability of hydrologic variables that probably would not have been possible by simple visualisation of the data alone. For example, analyses of RADAR rainfall data in Chapter 4 suggested that the space-time variability of rainfall is characterised by dynamic scaling, i.e. the rainfall fluctuations in space and time can be represented by a power law when plotted against scale after appropriate renormalisation. This property was used for generating rainfall patterns by means of stochastic simulations (downscaling) that when compared to RADAR rainfall patterns, looked realistic. Analyses of remotely sensed (ESTAR) soil moisture patterns in Walnut Gulch (Chapter 6) indicated that, following a rainstorm, these patterns were organised but this organisation faded away after the storm, and the pattern became random. The authors suggested that this change-over is a reflection of the changing control on soil moisture of rainfall versus patterns of surface soil characteristics. A similar change-over in the variability of soil moisture, however this time on a seasonal basis, was identified at Tarrawarra (Chapter 9). Spatially organised patterns that were related to terrain occurred in winter while spatially random patterns occurred in summer. This change-over was identified by visual inspection of the TDR measurements and further explained by comparison with model results. In La Cuenca (Chapter 10) where infiltration excess and pipe flow were important runoff mechanisms, the type of spatial variability in soil hydraulic conductivity was inferred from a comparison of observed patterns of frequency of runoff occurrence with a number of scenarios with different types of soil variability represented. It was found that a combined deterministic (by soil type) and stochastic pattern of conductivity produced patterns of runoff occurrence that were most similar to the observed patterns.

Clearly, the detail of these insights into catchment behaviour was made possible by the availability of measured patterns.

Data

While it is clear that the patterns were useful in their own right, several studies showed that they are even more useful if used in combination with time series data. Patterns and time series are therefore complementary and the case studies have shown that these different types of data (space variability and time variability, respectively) can be used to identify different properties of the catchment behaviour. In Chapter 7 conventional runoff hydrographs were used to identify the snow melt runoff *volume* from the catchment. In a similar fashion, runoff was used to close the water balance of the Tarrawarra catchment (Chapter 9) by enabling an estimation of deep drainage into bedrock. In La Cuenca (Chapter 10) runoff hydrographs were used to complement the spatial patterns, but this time at the event scale, to calibrate the Manning roughness parameter. In each of these cases, the information available in the time series was used for things that could not be well identified from the spatial data. Use of the two types of information together was the key to realistic simulation of space-time patterns of processes in each study. Similarly, in Minifelt (Chapter 11) soil porosity (related to the dynamics) was calibrated from mainly time series data (borehole data of the shallow groundwater table), while hydraulic conductivity was calibrated from mainly snapshots of spatial patterns of the groundwater table. It was the complementary nature of spatial pattern and time series data that enabled successful modelling.

Perhaps surprisingly, patterns of binary data were used in about half of the case studies; i.e. in the trade off between spatial resolution and information from a particular point (discussed in Chapter 2), the scales were tipped towards spatial resolution. All of these studies showed that a wealth of information can be revealed from a binary pattern. In Kühtai (Chapter 7) snow cover patterns (snow/no snow) were used; in Zwalmbeek and Coët-Dan (Chapter 8) patterns of saturated source areas (saturated/not saturated) were used; in La Cuenca (Chapter 10) patterns of runoff occurrence (for a single event, runoff occurred/did not occur) were used; and in Trochu (Chapter 12) patterns of recharge/discharge (either recharge or discharge) were used. The data used at Trochu are particularly interesting as they have been derived from qualitative observation including chemical/vegetation indicators. These indicators integrate over time so are representative of the long-term mean of recharge/discharge conditions (Tóth, 1966). Although water tables for a given point in time (snap shots) would have been easier to measure, the binary recharge/discharge data were much more appropriate to test the equilibrium vadose zone model used in Chapter 12.

The spatial variability of physical soil properties is particularly critical in catchment hydrology, yet we have relatively poor ways of estimating them at the catchment scale. It is therefore not surprising that a number of case studies in this book have scrutinised the reliability of soils data and their effect on the representation of catchment response. For Walnut Gulch (Chapter 6), where the infiltration excess runoff mechanism dominates, TOPLATS was used to simulate scenarios of soil moisture patterns. One of the scenarios was based on uniform soil hydraulic properties, while the other scenario used pedotransfer functions from the literature to estimate the soil hydraulic properties from mapped soil type. A comparison of the soil moisture patterns from the two scenarios with observed soil moisture patterns from airborne PBMR, indicated that the one based on soil type was too patchy and the scenario using uniform soil properties was more consistent with the observations. At Tarrawarra (Chapter 9) one scenario used soil type to spatially distribute hydraulic conductivity measurements, assuming uniform conductivity within each soil type zone. This scenario produced artificially high soil moisture values at the interface of the soil types that could be identified by comparisons with observed soil moisture patterns. A similar comparison at La Cuenca (Chapter 10) indicated that the assumption of uniform conductivity in each of their three land types was not appropriate and a random component had to be added to the deterministic pattern imposed by land type. Clearly, the variability of soil physical properties within soil types can be as large or larger than the variability between soil types. This suggests that the widespread practice in distributed modelling of allocating soil hydraulic properties on the basis of soils type (using either pedo-transfer functions or typical measurements from each soil) is likely to result in poor simulations of patterns in soil moisture and runoff.

With respect to data issues, the case studies have highlighted the value of *complementary* data (spatial patterns and time series), the utility of *binary* patterns (which are often simple to collect compared to quantitative patterns) and some particular problems in representing soil properties in models. We next address the utility of these data for informing model development.

Modelling

An important reason for comparing simulated and observed patterns was to assess the credibility of the distributed catchment models, i.e. how well can they represent individual processes that operate in the catchment, and which processes are perhaps not represented very well? This assessment resulted in suggestions for changes in model structure or model parameters (or perhaps inputs) that are needed to refine the model simulations.

Most of the chapters in this book concluded that the models worked quite well, albeit after calibration, and that the main processes were very well represented. However, they also concluded that it is possible to use subtle differences between simulated and observed patterns to inform us about how the models could be improved. At Kühtai (Chapter 7), for example, the comparison of snow cover patterns suggested that the model underestimated snow water equivalent in cirques. This was traced back to not representing emitted radiation from surrounding terrain. Similarly, a tendency to overestimate (and underestimate) snow cover on south facing (and north facing) slopes, was interpreted as evidence that the model should account for the dependence of snow albedo on energy input. At Reynolds Creek (Chapter 7) the comparison of simulated and observed patterns of snow water equivalent suggested that the simulated drift is more sharply defined than the observed drift. This was traced back to differences in the wind conditions between the year used for calibrating the model and the year where the model was tested. A suggested remedy was to use a more sophisticated deterministic wind drift model that takes into account differences in wind conditions from year to year, although more data would probably be needed to properly test this idea. At Tarrawarra (Chapter 9) subtle differences between simulated and observed rates of the temporal change in soil moisture patterns in autumn suggested that the lateral soil hydraulic conductivity may in fact change with time. This was indicated by faster subsurface redistribution in early autumn than in late autumn. It was suggested that this was due to temporal changes in conductivity caused by the closing of cracks that had formed over summer, thereby reducing lateral conductivity. However, testing of this would need additional data. At Minifelt (Chapter 11) where shallow water table patterns were used to calibrate the spatial patterns of soil physical properties in TOPMODEL, it was difficult to physically interpret the calibrated patterns. This was suggested to be evidence that there may be structural problems with the TOPMODEL approach for Minifelt, and relaxing the TOPMODEL assumptions may improve spatial predictions. Also, the uncertainty analysis based on spatially uniform soils parameters (which is a more common TOPMODEL application) gave different predictions and different uncertainty bounds depending on whether time series of borehole data or patterns of piezometer data were used to constrain the model parameters. This also suggested that there may be substantial structural uncertainty with TOPMODEL as applied in the Minifelt example.

In about half of the case studies (Reynolds Creek, Tarrawarra, La Cuenca, Minifelt) comparisons of simulated and observed patterns were used not only to assess the reliability of the model, but also to calibrate some of the model parameters as mentioned above. Both assessment and calibration were done by a visual pattern comparison. Some of the case studies, however, used more objective and sophisticated methods for model testing and parameter identification. At Walnut Gulch (Chapter 6) four-dimensional data assimilation (4DDA) methods were used to update the model state variables of the TOPLATS model by using remotely sensed (PBMR) and in situ point measurements of soil moisture. It was concluded that 4DDA (already being in operational use in atmospheric modelling) holds substantial promise for operational use in spatially distributed hydrological modelling. There is an obvious parallel with operational runoff forecasting, where updating model state variables (albeit in the time domain) is common practice today. A formal parameter uncertainty analysis was performed in Chapter 11 based on the GLUE procedure which gave a very useful assessment of the reliability of model parameters and helped define the value of various data types in constraining the model parameter uncertainty. Although the method is computationally demanding it can handle nonlinear models and it can make use of observed spatial patterns. In Chapter 11, parameter uncertainty was plotted against the topographic wetness index, which allowed differences in uncertainty between the gully and ridge areas of the catchment to be examined. The validation tests were taken even further in Chapter 13 for the Karup catchment. This was a significantly larger application than the case study chapters in the book and focussed on use of models in a more practical context. The MIKE-SHE model was calibrated and than validated based on a formal procedure presented by the author, using data from a number of internal stream gauges and boreholes. In this respect it was more typical of what may be possible in practical applications of spatially distributed models outside small research catchments. The author concluded from the comparisons of observed and simulated hydrologic variables at a number of locations, that when a formal framework of validation tests is set a priori, it may be difficult to meet the validation criteria in practice. He concluded that formal protocols are needed for model validation and that implementation of these for practical applications will require more dialogue between model developers, users and the managers who use simulations in their decision making, so that capabilities and limitations are clearly articulated.

In this section, we have summarised in some detail, the conclusions of the case studies, highlighting where the use of measured patterns, often in combination with more traditional measurements, were useful in explaining processes and developing models within relatively small research catchments. As discussed in Chapter 13, the larger scale, more practically oriented problems to which distributed models are applied can also benefit from the use of pattern data, but that such data are much less common in the ‘‘real world’’. We predict that in the coming years, more effort will be placed on collecting and using patterns at the larger scale so that the benefits discussed in the case studies can be realised in more practical applications.

14.3 OUTLOOK

The use of spatial patterns in catchment hydrology is in its infancy, but initial results are encouraging and provide sound reasons to believe that there are great improvements to be made in our understanding of catchment hydrological processes; and in quantifying the way they affect, and are affected by, spatial variability across a range of scales. More specifically, the work presented in this book illustrates that to realise these improvements, we need *appropriate* data. *Appropriate* meaning that it tells us about system behaviour, tests critical assumptions in our understanding and in our models of that understanding, and provides enough information to resolve the problems of non-uniqueness and parameter identifiability inherent in complex models. Spatial patterns of hydrological response are an *appropriate* data source in this respect. So while collecting and collating large spatial data sets will be important to the development of spatial models and improved process understanding, just where are the specific areas where significant progress can be made? In the following few paragraphs we provide a brief assessment of key areas.

14.3.1 Improvements to Model Inputs

Numerous hydrological studies spanning over many decades have shown the importance of precipitation on hydrological response. Now with RADAR estimates of spatial patterns in precipitation and new methods such as those described in Chapter 4 for characterising space-time variability, we are on the threshold of a major advance in the use of spatial precipitation information in distributed models. To fully realise the potential of this information, we may well need changes to model structure, and will certainly need changes in the attitudes of hydrological modellers who have been firmly wedded to the use of raingauge data for calibration and testing. Several of the case studies showed that simple binary patterns can be powerful tests of distributed models and provide useful information on threshold phenomena such as saturated source areas. There would appear to be further scope for use of this type of data, but again some changes in attitude towards ‘‘non-quantitative’’ data, and possibly changes to model structure, may be needed. At least in the immediate future, remotely sensed (RS) data can be thought of in this context and might be best used to assist in reducing the degrees of freedom in distributed hydrological models by providing *patterns,* rather than absolute values, of important inputs and parameters. Model structures are being improved to better exploit pattern data via improved software engineering (such as integration with GIS platforms) and this should serve as encouragement for the development of hydrological algorithms that are specifically intended for the scale and nature of RS data. Chapter 5 clearly illustrated that we have a long way to go in fully understanding and being able to represent spatial patterns of evaporation. Given that evaporation can be over 90 % of the water budget in some environments, it is obvious that studies into dealing with spatial measurement and the role of land surface heterogeneity will continue to be critical to improvements in, particularly, large-scale models.

Spatially distributed modelling requires the use of interpolation for a number of purposes, including the matching of model and measurement scales of information used for input and testing. There is a need for improved interpolation methods that better enable us to incorporate our understanding of physical phenomena. While there are a range of methods already available, these need to be improved in their ability to represent organisation in spatial patterns of hydrological importance.

14.3.2 Improvements to Model Testing

It is envisaged that comparisons between observed and simulated patterns will eventually become part of standard procedures for model testing. As well as needing the observed patterns, we also need improved quantitative techniques for comparing the similarities and differences between patterns. Some simple methods have been presented at the end of Chapter 3, but few of these have so far been used in practice. With rich areas of research on topics such as pattern recognition, we expect that the sophistication of pattern comparisons will greatly increase as hydrologists come to realise the value of patterns for model development and testing. Comprehensive uncertainty analysis also needs to be further developed for spatially distributed models. The potential of these methods for assessing the separate sources of uncertainty (input information, parameter values, model structure and data used in testing) is large, but at present they are not computationally tractable for most distributed models. Methodological developments as well as improvements in computer power are likely to lead to wider use of such techniques.

14.3.3 Challenges for Model Conceptualisation

The primary challenge of hydrologists has been, and remains, the prediction of hydrological response in "ungauged" areas – i.e. areas for which we have no hydrological response information. There is still a need to improve methods for generalising results from small catchments such as those described in this book, to other catchments; from small catchments to large catchments; and for being able to predict hydrological response under changed land use and climatic conditions in catchments of all sizes. All of these needs can be met only with better understanding and representation of fundamental processes, and their spatial variability across a range of scales. Distributed modelling generally has moved beyond just trying to scale up small catchment models to large scales because of problems with identifiability and scale dependence. As has been suggested for some time by many authors, we need models for a range of scales that are parsimonious, but that reflect the manifestation of important processes at those different scales. In moving beyond the notion of "trying to model everything" we should be developing methods to identify dominant processes that control hydrological response in different environments (landscapes and climates) and at different scales, and then develop models to focus on these dominant processes (a notion we might call the "Dominant Processes Concept" (DPC)). This would provide a framework for the development and application of techniques specially designed to deal with those controls and help to avoid some of the overparameterisation problems that occur when processes that are not important are represented in models. Developments along the lines of the DPC may help with the generalisation problems that have haunted hydrologists since the science began.

14.4 FINAL REMARKS

As mentioned in the introduction, there have been many calls for data collection and analysis to go hand in hand, for improved understanding of processes, and for the scientific endeavour of measurement to be recognised. There is a range of evidence that these calls have elicited a response. For example, Water Resources Research has had "data notes" for some time (Hornberger, 1994) and the number being published is increasing. There is an increasing awareness that the development of a spatial model is not of itself useful, unless it can be properly tested so that it can provide more credible predictions, or more insight into process understanding. Large field campaigns are continuing and the valuable role of smaller catchment, process-focussed, studies is being recognised as the researchers have integrated their work with theoretical and modelling developments to ensure the results contribute to a wider understanding of patterns of hydrological variability. We hope that the case studies presented in this book, and the broader conclusions from this extraordinary range of studies, have unequivocally illustrated the value of this investment, and act as encouragement for more, and more innovative, studies into spatial patterns in catchment hydrology.