



Hydrological modelling in a changing world

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Abstract

Changing hydrological conditions due to climate, land use and infrastructure pose significant ongoing challenges to the hydrological research and water management communities. While, traditionally, hydrological models have assumed stationary conditions, there has been much progress since 2005 on model parameter estimation under unknown or changed conditions and on techniques for modelling in those conditions. There is an analogy between extrapolation in space (termed Prediction in Ungauged Basins, PUB), and extrapolation in time (termed Prediction in Ungauged Climates, PUC) that can be exploited for estimating model parameters. Methods for modelling changing hydrological conditions need to progress beyond the current scenario approach, which is reliant upon precalibrated models. Top-down methods and analysis of spatial gradients of a variable of interest, instead of temporal gradients (a method termed 'Trading space for time') show much promise for validating more complex model projections. Understanding hydrological processes and how they respond to change, along with quantification of parameter estimation and modelling process uncertainty will continue to be active areas of research within hydrology. Contributions from these areas will not only help inform future climate change impact studies about what will change and by how much, but also provide insight into why any changes may occur, what changes we are able to predict in a realistic manner, and what changes are beyond the current predictability of hydrological systems.

Keywords

climate change, hydrological modelling, parameter estimation, Prediction in Ungauged Basins (PUB), Prediction in Ungauged Climates (PUC), uncertainty, water management

1 Introduction

Models used within hydrological research and water management communities frequently assume a stationary world. Statistical hydrological analyses commonly assume data can be modelled by a single probability distribution function with temporally fixed parameters (mean, variance, skewness, etc.). Water infrastructure critical to social and economic welfare has been designed and managed under this assumption. However, due to a combination of natural and

anthropogenic causes, Milly et al. (2008) recommend that stationarity no longer serves as the default assumption for water infrastructure planning and management. Similarly, echoing some earlier themes identified by Clifford (2002), Wagener et al. (2010: 1) have called for

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a paradigm shift in hydrology so that ‘predictions of system behaviour that are beyond the range of previously observed variability or that result from significant alterations of physical (structural) system characteristics become the new norm’. While hydrological time series may appear to be stationary at multi-annual timescales, the true nature of a series becomes more apparent over longer periods (Cohn and Lins, 2005; Koutsoyiannis, 2010). Water infrastructure designed under assumed stationarity may become stranded by subsequent climatic fluctuations, thus the issue of hydrological modelling in a changing world requires more attention than it was given in the past.

Causes of hydrological change may, or may not, be known. Although usually corrected for, errors in collection or changes in instrumentation type, location or conditions can introduce discontinuities into a data series. Teleconnection with large-scale ocean-atmosphere fluctuations, like the El Niño-Southern Oscillation, can influence hydroclimatic processes, often with varying strength over time. Largely natural climate shifts also occur – for example, the reduction in rainfall over the Sahel and southwestern Western Australia during the late 1960s (Baines and Folland, 2007). Anthropogenic causes include modification of catchments through river regulation, diversion, extractions, vegetation changes (Andréassian, 2004; Brown et al., 2005; Peel, 2009; Peel et al., 2010) and urbanization. The projected impact on hydroclimate of the enhanced greenhouse effect (Kundzewicz et al., 2008) adds another source of potential change.

From the perspective of water managers, uncertain hydrological modelling of stable or changing conditions forms part of the array of variables assessed in their quest to operate in a robust manner (Lins and Stakhiv, 1998; Power et al., 2005). The fundamentally non-linear nature of hydrological systems limits the scope for accurate prediction (Blöschl and Zehe, 2005; Koutsoyiannis, 2010). In light of this, Blöschl and Montannari (2010) call for improvements in

understanding of hydrological processes and uncertainty methods and recommend hydrological climate change impact studies be framed within the overall context of ongoing water management issues and focus more on what might change and why, rather than on the exact magnitude of any change. As Montanari et al. (2010: 169) note: ‘Offering insightful explanations for predicted changes may be more helpful than perfecting the estimates of what are inherently uncertain changes. Such a nuanced assessment will gain wider acceptance in society and will bring more credibility to the research community.’

Hydrological modelling under changing conditions is a problem familiar to hydrology. How well will a model perform when applied to conditions different from those used to estimate its parameters? This problem comes in several well-known forms – model application at: (1) the same location but under changed conditions (land use, observed climate, future climate projection); (2) a different location (gauged or ungauged catchment); and (3) a different location and time (gauged or ungauged catchment under changed conditions). The International Association of Hydrological Sciences initiative ‘Prediction in Ungauged Basins’ (PUB) is framed around these questions. Merz et al. (2010) highlight the analogy between PUB and the issue of modelling in a changing world. PUB relates to extrapolation in space while modelling in a changing world involves extrapolation in time; thus they proposed the term ‘Prediction in Ungauged Climates (PUC)’ to describe the transient prediction problem discussed in this paper.

In a changing world, model inputs, parameters and structure may all vary. This report’s focus is primarily progress in the area of model parameter estimation under unknown or changed conditions and techniques for modelling in those conditions. Progress in uncertainty of model inputs and structure will be addressed in passing. We draw upon surface water quantity research, rather than groundwater or water quality, although issues addressed here are relevant

to those areas. The following sections comprise a non-exhaustive report on progress since 2005 in estimating model parameters for ungauged or changed conditions and techniques for modelling changing conditions.

II Estimating model parameters for ungauged or changed conditions

The significant ongoing research in the area of model parameter estimation for ungauged or changed conditions is testament to the difficulty of the problem and the limited success to date. Robust methodologies to estimate model parameters for changed conditions will be critical to modelling a changing world successfully. In this section we discuss fundamental issues limiting success and highlight papers reporting progress in this area. This section largely focuses on conceptual, rather than physically based, models, as the extra data requirements and complexity of physically based models makes them an inconvenient test bed for new methodologies.

I Fundamental issues limiting success

The modelling process is beset by uncertainties that conspire against successful robust parameter estimation. Uncertainties in input data used to drive the model, output data against which the model is calibrated (e.g. streamflow), calibration method adopted, performance metric (objective function) adopted, and the model structure itself, all contribute to parameter uncertainty. In the case of parameter regionalization there are further uncertainties in the regionalization model structure, whether catchment characteristics utilized represent dominant hydrological processes and the stability of the established relationship beyond the conditions upon which it was developed. Suggested reading on the impact of these uncertainties on the modelling process and progress therein include: input data (Andréassian et al., 2004; Bárdossy and Singh, 2008; Donohue et al., 2010; Oudin

et al., 2005a, 2005b, 2006); output data (Di Baldassarre and Montanari, 2009; McMillan et al., 2010; Seibert and Beven, 2009); calibration and performance metrics (Efstratiadis and Koutsoyiannis, 2010; Gupta et al., 2009; Schaeffli and Zehe, 2009); model structure (Andréassian et al., 2009; Fenicia et al., 2008a, 2008b; Oudin et al., 2006; Vogel and Sankarasubramanian, 2003); and parameter regionalization (Wagener and Wheater, 2006; Wagener, 2007). Papers dealing with methods for estimating predictive, data and model uncertainties include Renard et al. (2010), Thyer et al. (2009), Todini (2007) and Winsemius et al. (2009).

Underlying the limited success of robust parameter estimation is the equifinality concept (reviewed by Beven, 2006). Equifinality suggests a given level of model performance can be reproduced by several, potentially quite different, parameter sets. Thus objective function optimization may identify a single parameter set, but other sets (potentially distant in parameter space) may perform similarly. Where observed input(s) and output(s) used to calibrate a model contain errors, the model is subject to equifinality (Beven, 2006). During calibration the objective function surface frequently contains multiple local optima, one of which may fractionally be the global optimum. This results in highly variable calibration parameter sets between catchments, which confound attempts at regionalization or a priori parameter estimation. Progress in the area of minimizing or removing multiple objective function optima during calibration can be found in Kavetski et al. (2006a, 2006b) and Kavetski and Kuczera (2007), while insights from calibrating in the spectral domain are reported in Montanari and Toth (2007) and Schaeffli and Zehe (2009).

2 Progress in estimating model parameters for ungauged or changed conditions

The inherent uncertainties associated with the modelling process impact to varying extent on

the success of methodologies actively being pursued in the hydrological literature.

a Estimate model parameters a priori (without calibration). A priori parameter estimation uses relationships between model parameters and catchment characteristics to estimate parameters for ungauged catchments. Physical reasoning and/or analyses of calibrated parameters from other catchments are the basis of these relationships. Duan et al. (2006) summarize results from the 2nd and 3rd workshops of the Model Parameter Estimation Experiment (MOPEX). Detailed hydrometeorological and land surface information for 12 US catchments were provided to groups running eight different models to estimate their model's parameters a priori. Model performance was assessed between a priori parameter runs and calibrated parameter runs. Overall, a priori runs indicated that existing techniques have scope for improvement relative to calibrated runs. Further work on assessing how, or whether, model parameters are related to observable catchment characteristics was recommended.

b Regionalize calibrated model parameters. While reviewing hydrological models and their application to ungauged catchments, Blöschl (2005) and Chiew (2010) note three common regionalization techniques: (1) regression relationships between individual calibrated parameters and catchment characteristics (see previous subsection); (2) catchment spatial proximity; and (3) catchment similarity of physical properties. Regionalization by spatial proximity involves either adopting a calibrated parameter set from the nearest neighbour in terms of physical distance or interpolating calibrated parameters spatially. Similarity regionalization involves adopting a calibrated parameter set from the most physically similar catchment or interpolating calibrated parameters in similarity space. Parakja et al. (2005) compared 16 regionalization methods using an 11 parameter semi-distributed

conceptual model, calibrated to daily streamflow and snow cover, across 320 Austrian catchments. Regionalization methods tested were regional averages of calibrated parameters (two methods), spatial proximity techniques (four methods), regression against catchment characteristics (three methods) and physical similarity techniques (seven methods). Overall differences between methods were small, with Kriging (spatial proximity) and combination physical similarity methods performing best. Parakja et al. (2007) used Kriging (spatial proximity) within an iterative regional calibration framework where iterations were conditioned by parameter spatial correlation. This method improved ungauged prediction relative to Kriging regionalization and generally reduced parameter uncertainty relative to local calibration.

c Multi-objective and regional calibration. In multi-objective and regional calibration the optimal parameter set is usually obtained by constraining the calibration to satisfy multiple objective functions for a catchment(s) or a single objective function across many catchments. Constraining calibration to satisfy multiple criteria, objective functions or catchments aims to limit parameter uncertainty and identify a robust set of parameters. Efstratiadis and Koutsoyiannis (2010) provide a comprehensive review of progress over the last decade in multi-objective calibration. Here we look at studies combining multi-objective and regional calibration into a single optimization. Hundecha et al. (2008) regionalize model parameters by Kriging within a physiographic-climatic space derived from canonical correlation of model parameters and catchment characteristics. The single optimization assessed model performance across several catchments while seeking to obtain well-defined spatial structures for the model parameters within the physiographic-climatic space. Zhang et al. (2008) combine multi-objective calibration and regionalization with ensemble and signature modelling (see later

subsections) to provide ensemble predictions of streamflow for three UK catchments. Reliability of the ensemble range to enclose observed streamflow at each catchment was related to the quality of hydrological signature regionalization achieved.

d Ensemble modelling. In response to the inherent uncertainties in parameter identification, ensemble modelling dispenses with finding an optimal parameter set. Instead, multiple plausible realizations from one or more models are combined to construct an ensemble of predictions. Plausible realizations can be generated by varying the input data, model initial conditions or parameter set. Viney et al. (2009) note the climate and atmospheric community have used ensemble modelling for over a decade. Furthermore ensemble modelling provides a way to assess predictive uncertainty (Blöschl and Zehe, 2005; Todini, 2007). Viney et al. (2009) report results from a range of single and multi-model ensemble combination techniques using 10 models of differing complexity on the Dill catchment in Germany as part of the ‘Assessing the impact of land use change on hydrology by ensemble modelling (LUCHEM)’ project (Breuer et al., 2009). Ensemble combination techniques were tested on calibration and validation runs. Overall, single and multi-model ensembles provided similar or better calibration and validation predictions, in terms of bias and Nash-Sutcliffe efficiency, than single realizations from each model. Weaker performing models contributed positively toward ensemble predictions and better performing models did not necessarily combine to produce the best ensembles. Many of the simple averaging combination techniques tested performed as well as, or better than, complex weighting, regression or conditional methods.

e Model (output) averaging. McIntyre et al. (2005) combined ensemble modelling and model averaging to estimate ungauged streamflow for

127 UK catchments with a catchment similarity procedure. Streamflow was estimated as the weighted average of ensemble model output for the ungauged catchment using the 10 highest performing complete parameter sets from the 10 most physically similar donor catchments. Their similarity-based output average outperformed traditional regression regionalization and a weighted ensemble average based on spatial proximity. With 913 French catchments and two hydrological models, Oudin et al. (2008) compared regression-based regionalization against model averaging using spatial proximity and physical similarity. In their dense network of catchments they found model averaging by spatial proximity performed slightly better than physical similarity and considerably better than regression regionalization. For spatial proximity and physical similarity, better streamflow estimates were achieved through averaging streamflow, modelled using donor catchment parameter sets (similar to McIntyre et al., 2005), than averaging donor parameters to then model streamflow. Oudin et al. (2008) noted a lack of consistent spatial pattern between catchments best predicted by spatial proximity or physical similarity and suggested regionalization might be improved by combining the methods. Using 95 Australian catchments, Reichl et al. (2009) optimized a physical similarity metric to maximize streamflow prediction that generally outperformed spatial proximity (nearest neighbour and model averaging of nearest neighbours) and regional regression predictions at 89 independent test catchments. Whereas Zhang and Chiew (2009), using a larger data set of 210 Australian catchments, found spatial proximity slightly outperformed physical similarity model averaging. Their combined spatial and physical similarity model averaging, following the suggestion of Oudin et al. (2008), achieved a further slight improvement in ungauged streamflow prediction.

f Hydrological signature (indices) modelling. Like ensemble modelling, hydrological signature

modelling draws upon the concept of plausible realizations to identify behavioural parameter sets, rather than an optimized parameter set. However, here a plausible realization is one that adequately reproduces one or more hydrological signatures of interest (e.g. runoff ratio, baseflow index). Shamir et al. (2005) conducted a series of three sequential Monte Carlo simulations to identify parameter sets capable of replicating hydrograph signatures at record length, annual and monthly timescales, respectively. Parameters identified in a prior simulation were used to constrain the subsequent simulation, with the final simulation identifying parameter sets capable of replicating hydrograph signatures across the three timescales better than calibrated parameters. Bárdossy (2007) and Yadav et al. (2007) introduce regionalization of hydrological signatures, rather than model parameters, to estimate signatures for ungauged catchments from catchment characteristics. The estimated signatures are used to constrain ensemble predictions into behavioural (reproduces the signatures) or non-behavioural parameter sets. Bárdossy (2007) identifies behavioural parameter sets at donor catchments using observed streamflow, transfers them to a recipient catchment and tests whether they replicate the estimated signatures. Yadav et al. (2007) dispense with the donor/recipient catchment step and directly identify behavioural parameters for the ungauged catchment using simulation. Zhang et al. (2008) introduced a multi-objective optimization to identify behavioural parameters sets and generally found more behavioural sets for a given number of simulations than uniformly distributed Monte Carlo simulation (Yadav et al., 2007). Bulygina et al. (2009) constrained randomly generated model parameter sets to replicate modified signatures of baseflow index and interception storage to assess the likely impact on streamflow of afforestation and increased grazing intensity. In summary, relationships between catchment characteristics and hydrological signatures were stronger

than between catchment characteristics and model parameters. Hydrological signature modelling is applicable to any model, is not limited by model calibration or model error issues (unless the model is unable to produce behavioural sets), and does not rely upon model parameter regionalization.

g Other methods. Bárdossy and Singh (2008) introduce the concept of parameter set depth to identify robust model parameter sets for three gauged catchments in southwest Germany. They identify randomly generated parameter sets with the highest overall performance (e.g. highest 10% of Nash-Sutcliffe efficiency values), then randomly generate new parameter sets based on the depth of the high performing sets. In two-dimensional space (a two-parameter model), a parameter set with high depth has parameter values near the middle of the cloud of better performing sets. The resultant sets are run through the model, and the process of parameter set identification, depth-based generation, and testing iterates until the difference between subsequent iteration performances is small. Bárdossy and Singh (2008) note deeper parameter sets were more robust in split sample tests and produce a narrower range of discharge estimates. Whether such sets regionalize well to ungauged conditions remains to be seen. Buytaert and Beven (2009) propose a learning process to inform how model parameters from gauged catchments should, or should not, be transformed for use in ungauged catchments. Selecting gauged catchments with different physical characteristics, like vegetation cover, they treat one catchment as gauged and the other ungauged. Based on a literature review of expected differences between the catchments (e.g. forested versus grassland), they subjectively define a parameter transformation with uncertainty and assess the transformation's ability to produce behavioural parameter sets in the 'ungauged' catchment with respect to observed flow or hydrological signatures.

III Modelling techniques for changing conditions

The methodologies in the previous section primarily aim to solve the classical ungauged catchment problem of model application to a different location. In this section, we focus on the time component of modelling changing conditions, cases 1 and 3 from the Introduction, which represent model application to a catchment for which a model has, or has not, already been calibrated that will experience a future change. For simplicity the change covered here is hydrological change due to a transient climate. Assessments of hydrological impact of climate change generally rely either on data-driven methods or on hydrological models.

I Scenario approach

Hydrological modelling techniques frequently used to assess the impact of climate change on runoff are reviewed by Chiew (2010). These include scenario modelling, where a precalibrated model is run with either of two types of input: (1) observed inputs proportionally scaled to reflect projected change (Chiew et al., 2009b); or (2) downscaled and bias-corrected global climate model (GCM) or regional climate model (RCM) projections (Christensen and Lettenmaier, 2007; Vicuna et al., 2010; Xu et al., 2005). For readers interested in the second type of input, the following papers are suggested: GCM reliability (Räisänen, 2007); methods for utilizing GCM/RCM outputs as input to hydrological models (Xu et al., 2005); and GCM selection for impact assessment (Chiew et al., 2009a; Macadam et al., 2010; Perkins and Pitman, 2009; Pierce et al., 2009; Reifen and Toumi, 2009). The issue of bias correction of GCM/RCM output for use in hydrological studies has received particular attention in recent years. In order to make climate projections more similar to observations, the former are adjusted by methods such as: (1) delta change, where only

differences between present and future climate are considered, which may be suitable for water balance estimates but might fail for extremes and highly non-linear systems (Graham et al., 2007); (2) quantile-based mapping (Li et al., 2010); and (3) power transformation, which non-linearly corrects the coefficient of variation and mean precipitation separately (Driessen et al., 2010; Leander and Buishand, 2007). However, if biases are large it is hardly plausible that bias correction methods will give realistic results for impact studies.

2 Sensitivity methods

An alternative to the scenario approach is sensitivity methods where a percentage change in input is related to a percentage change in runoff. While the scenario approach is model-based, sensitivity methods can be either model- or data-based. Model-based sensitivity methods are similar to the scenario approach with the exception that the runoff response is calculated for a spectrum of changed precipitation, air temperature, etc., values rather than for a given scenario. Data-based sensitivity methods analyse how past changes in runoff, precipitation and air temperature are related. Rainfall elasticity of streamflow, defined as the proportional change in streamflow divided by the proportional change in rainfall (Sankarasubramanian et al., 2001), provides a simple estimate of long-term streamflow sensitivity to changes in long-term rainfall, which is particularly useful as an initial estimate of likely climate change impact on water resources (Chiew, 2010). Recently, Fu et al. (2007) extended streamflow elasticity to include temperature changes as well as rainfall. The main strength of elasticity is that it is data-based. Hence no assumptions about model parameters or model structure remaining invariant under a changed climate are made. The Budyko curve (Budyko, 1974), based on similar concepts, can also be used to provide guidance on potential climate change impacts on water

resources. For example, McMahon et al. (2010) provide a simple Budyko-like method to estimate the mean and variability of annual streamflow from the aridity index, variances and covariance of annual precipitation and potential evapotranspiration for present or future climates. When combined with a simple storage-yield-reliability relationship, this method facilitates a quick assessment of the likely vulnerability of water resources infrastructure to a changed climate, without needing to run uncertain complex models or scenarios.

3 Trading space for time

This approach is based on analysis of spatial gradients of a variable of interest, instead of temporal gradients (i.e. trends). Under a changed climate, hydrological processes in a catchment may become similar to those experienced in other catchments under the current climate. For example, if winter rainfall increases under a changed climate, associated changes in flood characteristics may be similar to those currently observed in a neighbouring catchment with higher winter precipitation. Gradient methods are widely used in ecology (eg. Ter Braak and Prentice, 1988) and the authors believe they hold significant potential for analysing modified hydrological processes and providing simple estimates of likely future changes. However, using spatial gradients clearly has limitations as other relevant catchment characteristics may not be similar. Despite this, trading space for time may be an attractive alternative to the model-based scenario approach as it is data-based and hence likely to better account for possible interactions between processes in the catchment.

4 Non-stationarity of model parameters and model assumptions

Most modelling techniques implicitly assume that model parameters calibrated on observed

data remain valid under future conditions. This assumption is likely to be incorrect due to the inherent uncertainties in the modelling process and potential modification of interactions between existing catchment processes and emergence of processes not seen during calibration. For example, in snow-dominated regions warmer temperatures modify the amplitude and timing of the runoff response, moving peak melt runoff earlier into the year (Barnett et al., 2005; Woo et al., 2008) and increase the importance of processes like rain-on-snow runoff events (Sui and Koehler, 2001). Change may also nudge a catchment through a transition from one stable state into a new unknown one (Peterson et al., 2009). Merz et al. (2010) demonstrate the potential for biased runoff predictions from climate impact analyses where hydrological model parameters, calibrated against observed runoff, are assumed to be representative for future climate scenarios. Merz et al. (2010) analysed the temporal change in model parameters when a conceptual rainfall-runoff model was calibrated for six consecutive five-year periods between 1976 and 2006 for 273 catchments in Austria. Parameters representing snow and soil moisture processes showed significant temporal trends that were related to recent changes in catchment climatic conditions (eg. higher evapotranspiration and drier conditions). Their analyses suggest the impact on simulated runoff of assuming time invariant parameters can be very significant, with biases in median and high flows of about 15% and 35%, respectively. Clearly hydrological models with parameters that change with time are not accurate under transient climate conditions.

5 Bringing parameter estimation and changing condition modelling techniques together

A significant challenge for future hydrological research is to incorporate into modelling temporally changing conditions the model parameter

estimation methods for ungauged or changed conditions discussed in the previous section. To what extent parameter estimation methods like, a priori, regression-based regionalization, multi-objective, and regional calibration can overcome uncertainty issues (data, model structure, equifinality) to provide robust predictions under changing conditions is unknown. With future streamflow unavailable for model calibration at-site or in neighbouring catchments, the issue of behavioural parameter set identification required to use ensemble, model-output averaging and signature modelling techniques requires further research. The learning process suggested by Buytaert and Beven (2009) using observed catchments experiencing different conditions presents one way forward. For signature modelling significant potential exists to estimate future changes in signatures of interest through simple top-down water-energy balance models, increased understanding of how hydrological indices vary in time and space (Lima and Lall, 2010; Troch et al., 2009) and the development of catchment classification schemes (Wagener et al., 2007).

IV Conclusions

The increased importance of changing conditions in hydrology poses significant ongoing challenges to the hydrological research and water infrastructure and management community. Continued work to (1) develop techniques for non-stationary stochastic data generation, (2) increase understanding of hydrological processes and how they and their signatures respond to change, and (3) quantify uncertainty in the parameter estimation and modelling process will continue to be active areas of research within hydrology. Methods for modelling changing hydrological situations need to progress beyond the current scenario approach. Alternative simple techniques like sensitivity methods and trading space for time can provide validation of more complex model projections, thus adding

credibility to those projections. Contributions from these areas will not only help inform future climate change impact studies about what will change and by how much, but also provide insight into why any changes may occur, what changes we are able to predict in a realistic manner, and what changes are beyond the current predictability of hydrological systems.

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References

- Andréassian V (2004) Water and forests: From historical controversy to scientific debate. *Journal of Hydrology* 291: 1–27.
- Andréassian V, Perrin C, Le Moine N, Lerat J, Loumagne C, Oudin L, et al. (2009) HESS Opinions 'Crash tests for a standardized evaluation of hydrological models'. *Hydrology and Earth System Sciences* 13: 1757–1764.
- Andréassian V, Perrin C, and Michel C (2004) Impact of imperfect potential evapotranspiration knowledge on the efficiency and parameters of watershed models. *Journal of Hydrology* 286: 19–35.
- Baines PG and Folland CK (2007) Evidence for a rapid global climate shift across the late 1960s. *Journal of Climate* 20: 2721–2744.
- Bárdossy A (2007) Calibration of hydrological model parameters for ungauged catchments. *Hydrology and Earth System Sciences* 11: 703–710.
- Bárdossy A and Singh SK (2008) Robust estimation of hydrological model parameters. *Hydrology and Earth System Sciences* 12: 1273–1283.
- Barnett TP, Adam JC, and Lettenmaier DP (2005) Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature* 438: 303–309.
- Beven K (2006) A manifesto for the equifinality thesis. *Journal of Hydrology* 320: 18–36.

- Blöschl G (2005) Rainfall-runoff modeling of ungauged catchments. Article 133. In: Anderson MG (ed.) *Encyclopaedia of Hydrological Sciences*. Chichester: Wiley, 2061–2080.
- Blöschl G and Montanari A (2010) Climate change impacts – throwing the dice? *Hydrological Processes* 24: 374–381.
- Blöschl G and Zehe E (2005) On hydrological predictability. *Hydrological Processes* 19: 3923–3929.
- Breuer L, Huisman JA, Willems P, Bormann H, Bronstert A, Croke BFW, et al. (2009) Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM). 1: Model intercomparison with current land use. *Advances in Water Resources* 32: 129–146.
- Brown AE, Zhang L, McMahon TA, Western AW and Vertessy RA (2005) A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation. *Journal of Hydrology* 310: 28–61.
- Budyko MI (1974) *Climate and Life*. New York: Academic Press.
- Bulygina N, McIntyre N and Wheeler H (2009) Conditioning rainfall-runoff model parameters for ungauged catchments and land management impacts analysis. *Hydrology and Earth System Sciences* 13: 893–904.
- Buytaert W and Beven K (2009) Regionalization as a learning process. *Water Resources Research* 45: W11419.
- Chiew FHS (2010) Lumped conceptual rainfall-runoff models and simple water balance methods: Overview and applications in ungauged and data limited regions. *Geography Compass* 4(3): 206–225.
- Chiew FHS, Teng J, Vaze J and Kirono DGC (2009a) Influence of global climate model selection on runoff impact assessment. *Journal of Hydrology* 379: 172–180.
- Chiew FHS, Teng J, Vaze J, Post DA, Perraud JM, Kirono DGC, et al. (2009b) Estimating climate change impact on runoff across southeast Australia: Method, results, and implications of the modelling method. *Water Resources Research* 45: W10414.
- Christensen NS and Lettenmaier DP (2007) A multi-model ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin. *Hydrology and Earth System Sciences* 11: 1417–1434.
- Clifford NJ (2002) Hydrology: The changing paradigm. *Progress in Physical Geography* 26: 290–301.
- Cohn TA and Lins HF (2005) Nature's style: Naturally trendy. *Geophysical Research Letters* 32: L23402.
- Di Baldassarre G and Montanari A (2009) Uncertainty in river discharge observations: A quantitative analysis. *Hydrology and Earth System Sciences* 13: 913–921.
- Donohue RJ, McVicar TR, and Roderick ML (2010) Assessing the ability of potential evaporation formulations to capture the dynamics in evaporative demand within a changing climate. *Journal of Hydrology* 386: 186–197.
- Driessen TLA, Hurkmans RTWL, Terink W, Hazenberg P, Torfs PJJF, and Uijlenhoet R (2010) The hydrological response of the Ourthe catchment to climate change as modelled by the HBV model. *Hydrology and Earth System Sciences* 14: 651–665.
- Duan Q, Schaake J, Andréssian V, Franks S, Goteti G, Gupta HV, et al. (2006) Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshop. *Journal of Hydrology* 320: 3–17.
- Efstratiadis A and Koutsoyiannis D (2010) One decade of multi-objective calibration approaches in hydrological modelling: A review. *Hydrological Sciences Journal* 55(1): 58–78.
- Fenicia F, McDonnell JJ, and Savenije HHG (2008a) Learning from model improvement: On the contribution of complementary data to process understanding. *Water Resources Research* 44: W06419.
- Fenicia F, Savenije HHG, Matgen P, and Pfister L (2008b) Understanding catchment behavior through stepwise model concept improvement. *Water Resources Research* 44: W01402.
- Fu G, Charles SP, and Chiew FHS (2007) A two-parameter climate elasticity of streamflow index to assess climate change effects on annual streamflow. *Water Resources Research* 43: W11419.
- Graham LP, Hagemann S, Jaun S, and Beniston M (2007) On interpreting hydrological change from regional climate models. *Climatic Change* 81: 97–122.
- Gupta HV, Kling H, Yilmaz KK, and Martinez GF (2009) Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology* 377: 80–91.
- Hundecha Y, Ouarda TBMJ, and Bárdossy A (2008) Regional estimation of parameters of a rainfall-runoff model at ungauged watersheds using the 'spatial' structures of the parameters within a canonical physiographic-climatic space. *Water Resources Research* 44: W01427.

- Kavetski D and Kuczera G (2007) Model smoothing strategies to remove microscale discontinuities and spurious secondary optima in objective functions in hydrological calibration. *Water Resources Research* 43: W03411.
- Kavetski D, Kuczera G, and Franks SW (2006a) Calibration of conceptual hydrological models revisited: 1. Overcoming numerical artefacts. *Journal of Hydrology* 320: 173–186.
- Kavetski D, Kuczera G, and Franks SW (2006b) Calibration of conceptual hydrological models revisited: 2. Improving optimisation and analysis. *Journal of Hydrology* 320: 187–201.
- Koutsoyiannis D (2010) HESS Opinions ‘A random walk on water’. *Hydrology and Earth System Sciences* 14: 585–601.
- Kundzewicz ZW, Mata LJ, Arnell NW, Döll P, Jimenez B, Miller K, et al. (2008) The implications of projected climate change for freshwater resources and their management. *Hydrological Sciences Journal* 53(1): 3–10.
- Leander R and Buishand TA (2007) Resampling of regional climate model output for the simulation of extreme river flows. *Journal of Hydrology* 332: 487–496.
- Li H, Sheffield J, and Wood EF (2010) Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *Journal of Geophysical Research* 115: D10101.
- Lima CHR and Lall U (2010) Spatial scaling in a changing climate: A hierarchical bayesian model for non-stationary multi-site annual maximum and monthly streamflow. *Journal of Hydrology* 383: 307–318.
- Lins HF and Stakhiv EZ (1998) Managing the nation’s water in a changing climate. *Journal of the American Water Resources Association* 34(6): 1255–1264.
- Macadam I, Pitman AJ, Whetton PH, and Abramowitz G (2010) Ranking climate models by performance using actual values and anomalies: Implications for climate change impact assessments. *Geophysical Research Letters* 37: L16704.
- McIntyre N, Lee H, Wheeler H, Young A, and Wagener T (2005) Ensemble predictions of runoff in ungauged catchments. *Water Resources Research* 41: W12434.
- McMahon TA, Peel MC, Pegram GGS, and Smith IN (2010) A simple methodology for estimating mean and variability of annual runoff and reservoir yield under present and future climates. *Journal of Hydrometeorology*. doi: 10.1175/2010JHM1288.1.
- McMillan H, Freer J, Pappenberger F, Krueger T, and Clark M (2010) Impacts of uncertain river flow data on rainfall-runoff model calibration and discharge predictions. *Hydrological Processes* 24, 1270–1284.
- Merz R, Parajka J, and Blöschl G (2010) Time stability of catchment model parameters – implications for climate impact analyses. *Water Resources Research*. doi: 10.1029/2010WR009505.
- Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lettenmaier DP, et al. (2008) Stationarity is dead: Whither water management? *Science* 319: 573–574.
- Montanari A and Toth E (2007) Calibration of hydrological models in the spectral domain: An opportunity for scarcely gauged basins? *Water Resources Research* 43: W05434.
- Montanari A, Blöschl G, Sivapalan M, and Savenije H (2010) Getting on target. *Public Service Review: Science and Technology* 7: 167–169.
- Oudin L, Andréassian V, Perrin C, Michel C, and Le Moine N (2008) Spatial proximity, physical similarity, regression and ungauged catchments: A comparison of regionalization approaches based on 913 French catchments. *Water Resources Research* 44: W03413.
- Oudin L, Hervieu F, Michel C, Perrin C, Andréassian V, Anctil F, et al. (2005a) Which potential evapotranspiration input for a lumped rainfall-runoff model? Part 2 – Towards a simple and efficient potential evapotranspiration model for rainfall-runoff modelling. *Journal of Hydrology* 303: 290–306.
- Oudin L, Michel C, and Anctil F (2005b) Which potential evapotranspiration input for a lumped rainfall-runoff model? Part 1 – Can rainfall-runoff models effectively handle detailed potential evapotranspiration inputs? *Journal of Hydrology* 303: 275–289.
- Oudin L, Perrin C, Mathevet T, Andréassian V, and Michel C (2006) Impact of biased and randomly corrupted inputs on the efficiency and the parameters of watershed models. *Journal of Hydrology* 320: 62–83.
- Parajka J, Blöschl G, and Merz R (2007) Regional calibration of catchment models: Potential for ungauged catchments. *Water Resources Research* 43: W06406.
- Parajka J, Merz R, and Blöschl G (2005) A comparison of regionalisation methods for catchment model parameters. *Hydrology and Earth System Sciences* 9: 157–171.

- Peel MC (2009) Hydrology: Catchment vegetation and runoff. *Progress in Physical Geography* 33(6): 837–844.
- Peel MC, McMahon TA, and Finlayson BL (2010) Vegetation impact on mean annual evapotranspiration at a global catchment scale. *Water Resources Research* 46: W09508.
- Perkins SE and Pitman AJ (2009) Do weak AR4 models bias projections of future climate changes over Australia? *Climatic Change* 93: 527–558.
- Peterson TJ, Argent RM, Western AW, and Chiew FHS (2009) Multiple stable states in hydrological models: An ecohydrological investigation. *Water Resources Research* 45: W03406.
- Pierce DW, Barnett TP, Santer BD, and Gleckler PJ (2009) Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences of the United States of America* 106(21): 8441–8446.
- Power S, Sadler B, and Nicholls N (2005) The influence of climate science on water management in Western Australia. *Bulletin of the American Meteorological Society* 86(6): 839–844.
- Räsänen J (2007) How reliable are climate models? *Tellus* 59A: 2–29.
- Reichl JPC, Western AW, McIntyre NR, and Chiew FHS (2009) Optimization of a similarity measure for estimating ungauged streamflow. *Water Resources Research* 45: W010423.
- Reifen C and Toumi R (2009) Climate projections: Past performance no guarantee of future skill? *Geophysical Research Letters* 36: L13704.
- Renard B, Kavetski D, Kuczera G, Thyer M, and Franks SW (2010) Understanding predictive uncertainty in hydrological modelling: The challenge of identifying input and structural errors. *Water Resources Research* 46: W05521.
- Sankarasubramanian A, Vogel RM, and Limbrunner JF (2001) Climate elasticity of streamflow in the United States. *Water Resources Research* 37(6): 1771–1781.
- Schaefli B and Zehe E (2009) Hydrological model performance and parameter estimation in the wavelet-domain. *Hydrology and Earth System Sciences* 13: 1921–1936.
- Shamir E, Imam B, Gupta HV, and Sorooshian S (2005) Application of temporal streamflow descriptors in hydrologic model parameter estimation. *Water Resources Research* 41: W06021.
- Siebert J and Beven KJ (2009) Gauging the ungauged basin: How many discharge measurements are needed? *Hydrology and Earth System Sciences* 13: 883–892.
- Sui J and Koehler G (2001) Rain-on-snow induced flood events in Southern Germany. *Journal of Hydrology* 252: 205–220.
- Ter Braak CJF and Prentice IC (1988) A theory of gradient analysis. *Advances in Ecological Research* 18: 271–317.
- Thyer M, Renard B, Kavetski D, Kuczera G, Franks SW, and Srikanthan S (2009) Critical evaluation of parameter consistency and predictive uncertainty in hydrological modeling: A case study using Bayesian total error analysis. *Water Resources Research* 45: W00B14.
- Todini E (2007) Hydrological catchment modelling: Past, present and future. *Hydrology and Earth System Sciences* 11(1): 468–482.
- Troch PA, Martinez GF, Pauwels VRN, Durcik M, Sivapalan M, Harman C, et al. (2009) Climate and vegetation water use efficiency at catchment scales. *Hydrological Processes* 23: 2409–2414.
- Vicuna S, Dracup JA, Lund JR, Dale LL, and Maurer EP (2010) Basin-scale water system operations with uncertain future climate conditions: Methodology and case studies. *Water Resources Research* 46: W04505.
- Viney NR, Bormann H, Breuer L, Bronstert A, Croke BFW, Frede H, et al. (2009) Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM). 2: Ensemble combinations and predictions. *Advances in Water Resources* 32: 147–158.
- Vogel RM and Sankarasubramanian A (2003) Validation of a watershed model without calibration. *Water Resources Research* 39(10): 1292.
- Wagener T (2007) Can we model the hydrological impacts of environmental change? *Hydrological Processes* 21: 3233–3236.
- Wagener T and Wheater HS (2006) Parameter estimation and regionalisation for continuous rainfall-runoff models including uncertainty. *Journal of Hydrology* 320: 132–154.
- Wagener TM, Sivapalan M, Troch PA, McGlynn BL, Harman CJ, Gupta HV, et al. (2010) The future of hydrology: An evolving science for a changing world. *Water Resources Research* 46: W05301.
- Wagener T, Sivapalan M, Troch P, and Woods R (2007) Catchment classification and hydrological similarity. *Geography Compass* 1(4): 901–931.

- Winsemius HC, Schaefli B, Montanari A, and Savenije HHG (2009) On the calibration of hydrological models in ungauged basins: A framework for integrating hard and soft hydrological information. *Water Resources Research* 45: W12422.
- Woo M-K, Kane DL, Carey SK, and Yang D (2008) Progress in permafrost hydrology in the new millennium. *Permafrost and Periglacial Processes* 19: 237–254.
- Xu C-Y, Widén E, and Halldin S (2005) Modelling hydrological consequences of climate change: Progress and challenges. *Advances in Atmospheric Sciences* 22(6): 789–797.
- Yadav M, Wagener T, and Gupta H (2007) Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Advances in Water Resources* 30: 1756–1774.
- Zhang Y and Chiew FHS (2009) Relative merits of different methods for runoff predictions in ungauged catchments. *Water Resources Research* 45: W07412.
- Zhang Z, Wagener T, Reed P, and Bhushan R (2008) Reducing uncertainty in predictions in ungauged basins by combining hydrological indices regionalization and multiobjective optimization. *Water Resources Research* 44: W00B04.