Advances in the identification and evaluation of complex environmental systems models

Thorsten Wagener, Patrick Reed, Kathryn van Werkhoven, Yong Tang and Zhenxing Zhang

ABSTRACT

Advances in our ability to model complex environmental systems are currently driven by at least four needs: (1) the need for the inclusion of uncertainty in monitoring, modelling and decision-making; (2) the need to provide environmental predictions everywhere; (3) the need to predict the impacts of environmental change; and (4) the need to adaptively evolve observation networks to better resolve environmental systems and embrace sensing innovations. Satisfying these needs will require improved theory, improved models and improved frameworks for making and evaluating predictions. All of these improvements should result in the long-term evolution and improvement of observation systems. In the context of this paper we discuss current bottlenecks and opportunities for advancing environmental modelling with and without local observations of system response. More realistic representations of real-world thresholds, nonlinearities and feedbacks motivates the use of more complex models as well as the consequent need for more rigorous evaluations of model performance. In the case of gauged systems, we find that global sensitivity analysis provides a widely underused tool for evaluating models' assumptions and estimating the information content of data. In the case of ungauged systems, including the modelling of environmental change impacts, we propose that the definition of constraints on the expected system response provides a promising way forward. Examples of our own work are included to support the conclusions of this discussion paper. Overall, we conclude that an important bottleneck currently limiting environmental predictions lies in how our model evaluation and identification approaches are extracting, using and evolving the information available for environmental systems at the watershed scale.

Key words | climate change, model diagnostics, multi-objective optimization, predictions in ungauged basins, sensitivity analysis, uncertainty analysis

Thorsten Wagener (corresponding author)
Patrick Reed
Kathryn van Werkhoven
Yong Tang
Zhenxing Zhang
Department of Civil and Environmental
    Engineering,
Pennsylvania State University,
University Park, PA 16802,
USA
E-mail: *tuw4@psu.edu*

Kathryn van Werkhoven
Present address: Systech Water Resources, Inc.,
Walnut Creek CA,
USA

Yong Tang
Present address: Bechtel Corporation,
Houston TX,
USA

Zhenxing Zhang
Present address: The Susquehanna River Basin
    Commission,
Harrisburg PA 17102,
USA

INTRODUCTION

Sustaining human life as well as aquatic and terrestrial ecosystems requires the availability of sufficient quantities of freshwater of appropriate quality. The watershed provides a convenient spatial unit to define the collection, storage and release of freshwater; the provision of freshwater for a wide range of purposes can be defined as a watershed service (Wagener *et al.* 2007). Humans and ecosystems are embedded in large-scale environmental

systems that can exhibit a wide range of characteristics depending on their location and the degree of human impact. The environmental systems' internal heterogeneity leads to a complex and uncertain system, although such systems usually exhibit some level of organization (Sivapalan 2005).

An important responsibility for the hydroinformatics community is to support improvements in sustainable integrated water resource management of watershed

services using environmental models, which enable us to better understand these complex systems and to predict their response to future environmental change. This predictive capability is necessary to achieve water security for people and for the environment in an increasingly non-stationary world (Falkenmark 2001; Milly *et al.* 2008), where water security can be defined as protection from both excess water and from water scarcity (Gleick 2002) or as maximizing services and minimizing disservices (e.g. low flows or floods). Models of water-driven environmental systems at the watershed scale play a fundamental role in understanding the underlying real world system, in providing the necessary predictive power and in guiding the establishment of better observational networks.

Environmental models applied at the watershed scale originated as simple mathematical representations of the input response behaviour of catchment-scale environmental systems through parsimonious models such as the Unit Hydrograph (for flow routing) (e.g. Dooge 1959) and the Rational Formula (for excess rainfall calculation) (Dooge 1957) as part of Engineering Hydrology. Such single purpose models are still widely used to estimate design variables or to predict floods. These approaches formed the basis for a generation of more complete, but spatially lumped, representations of the terrestrial hydrological cycle, such as the Stanford Watershed Model in the 60s (which formed the basis for the currently widely used Sacramento model; Burnash 1995). This advancement enabled the continuous-time representation of the rainfall–runoff relationship and models of this type are still at the heart of many operational forecasting systems throughout the world. While the general equations of models such as the Sacramento model are based on conceptualizing plot (or smaller) scale hydrologic processes, their spatially lumped application at the catchment scale means that parameters have to be calibrated using observations of rainfall–runoff behaviour of the system under study.

Interest in predicting land use change leads to the development of more spatially explicit representations of the physics (to the best of our understanding) underlying the hydrological system in the form of the SHE model in the 80s (Abbott *et al.* 1986). The latter is an example of a group of highly complex process-based models whose development was driven by the hope that their parameters could be directly estimated from observable physical watershed characteristics, thus enabling the direct assessment of change impacts (Ewen & Parkin 1996; Dunn & Ferrier 1999). At that time, these models were severely constrained by our lack of computational power; a constraint that decreases in its severity with increases in computational resources with each passing year.

Currently available high performance computing enables us to explore the behaviour of highly complex models in new ways (Tang *et al.* 2007; Van Werkhoven *et al.* 2008*a*). However, this increased power is insufficient by itself to eliminate the problems associated with current models. Problems include those of conceptualization and parameterization of underlying processes, and of our limited ability to observe important subsurface characteristics at the scale of interest (Beven 1989). New theory and new observational capabilities will be needed to achieve better representations of environmental systems (Wagener & Gupta 2005; Kirchner 2006; Reed *et al.* 2006; Gupta *et al.* 2008). New concepts for process-based models have been put forward in recent years, but more testing is required to assess whether previous limitations of physically-based models have yet been overcome (e.g. Reggiani *et al.* 1998, 1999, 2000, 2001; Panday & Huyakorn 2004; Qu & Duffy 2007; Kollet & Maxwell 2006, 2008).

What are the main drivers for advancing environmental modelling?

We hypothesize that there are at least four distinct (but inter-related) drivers, as follows.

1. The need for understanding, estimating and communicating **uncertainty** in order to understand both the limitations of our science as well as to provide decision makers with more appropriate information (e.g. Neuman 2002; McIntyre *et al.* 2003; Wagener & Gupta 2005; Beven *et al.* 2008).
2. The need to provide guidance on the optimal *design of observational networks* at large catchment scales (Langbein 1979; Reed *et al.* 2006; National Research Council 2008).
3. The need to build *environmental models of everywhere* (e.g. Sivapalan *et al.* 2003; Wagener *et al.* 2004; Beven 2007).

4. The need to predict the impacts of *environmental change*, i.e. mainly land cover and climate change (e.g. Harbor 1994; Beven 2000; Allen & Ingram 2002; Milly *et al.* 2002, 2008; Porporato *et al.* 2004; Poff *et al.* 2006*a*,*b*; Wagener 2007).

In this article we will explore the impact of these four drivers on current research needs, bottlenecks and opportunities. We will mainly focus on the task of environmental model evaluation and identification at gauged and ungauged locations in the context of these drivers. The main challenges associated with these problems are how to extract maximum information from time-series of system responses (e.g. streamflow) and how to evaluate/identify a model at locations where such time-series are not available. We will close with a discussion of open questions and research needs.

DRIVERS OF ADVANCEMENT

First driver: uncertainty

Uncertainty analysis in environmental modelling has been investigated for many years, but recent computational advancements have significantly pushed our ability to sample from high dimensional spaces and therefore relax some of the limiting assumptions that previously had to be made in an uncertainty analysis (e.g. McIntyre *et al.* 2002; Vrugt *et al.* 2003; Wagener 2003; Marshall *et al.* 2004). The main sources of uncertainty in environmental modelling are as follows.

- *Input data uncertainty*: Uncertainties originate from both the measurement itself, but also from data processing required to translate proxy data into the variable of interest or for deriving variables at the necessary spatial and temporal scale (e.g. Kavetski *et al.* 2006*a*,*b*; Hong *et al.* 2006; Schoups & Hopmans 2006). One example is the uncertainty in precipitation, which originates for example from errors in individual raingauge observations, but also from spatial interpolation between gauges or from the translation of a radar signal to a rainfall estimate (e.g. Kavetski *et al.* 2006*a*,*b*; Yatheendradas *et al.* 2008).
- *Output data uncertainty*: Uncertainty in observations of the system response has generally received less attention since it is often assumed to be much smaller than the

uncertainty in the model input (e.g. Franks *et al.* 1998; Freer *et al.* 2004). This does not necessarily have to be the case, since uncertainties of the response in water quality studies are for example often very high (e.g. McIntyre *et al.* 2003). Problems of scale can occur similar to those present in input data.

- *Parameter uncertainty*: Many studies have focused on estimating the uncertainty in identifying the model parameters during model calibration, although significant differences in philosophy remain as will be discussed later (e.g. Beven & Binley 1992; Vrugt *et al.* 2003, 2006; Marshall *et al.* 2004; Smith & Marshall 2008).
- *Model structural uncertainty*: Recent years have seen a surge in methods to consider uncertainty in the structure of environmental models (e.g. Shamseldin *et al.* 1997; Uhlenbrook *et al.* 1999; Ajami *et al.* 2007). This surge is partially caused by findings of multiple studies that suggest the parametric uncertainty, previously thought to be dominating, can be small compared to the uncertainty introduced by the model structure (Neuman 2002). Most studies suggest the use of multiple model structures simultaneously in a Bayesian framework; however, proper statistical approaches to deal with model structural uncertainty for complex environmental models still pose a significant challenge (Clark *et al.* 2008; Beven 2009). It might be possible to include some type of 'model inadequacy function' if the model structural error is not too complex (Kennedy & O'Hagan 2001).
- *State uncertainty*: Advances in dealing with state uncertainty have been made through the introduction of new filtering techniques, such as particle filters or ensemble Kalman filters into environmental modelling (e.g. Moradkhani *et al.* 2005*a*,*b*; Vrugt *et al.* 2005; Kollat & Reed 2008).

Issues of particular interest include the search for an uncertainty estimation and propagation approach in which all sources of uncertainty can be considered simultaneously (data, model structural, parameter, state uncertainty, etc.), the need to understand and consider model structural uncertainty in general and the need for uncertainty estimation of highly complex (and therefore expensive to run) environmental models (see discussion in Neuman 2002). Several studies found that inclusion of uncertainty in

environmental modelling leads to better decision-making, which suggests that establishing uncertainty estimation as a standard for any environmental predictions (despite some remaining problems) represents an important step to make our work better suited for decision makers (Reichert & Borsuk 2005).

Second driver: observation network design

As noted by Dooge (1986) our ability to understand, predict and manage environmental systems is dependent on our ability to observe both the natural and human systems that shape their evolution. Fundamentally, the observation network design problem seeks to maximize the value of information gained with new observables. This is particularly challenging and important when seeking to detect and/or predict the impact of long-term systematic changes (non-stationarity). Reed *et al.* (2006) posit that our ability to understand human-climate impacts on environmental systems will require a paradigmatic shift away from static observation network design frameworks. Alternatively, new tools are needed for adaptively characterizing knowledge gaps and critical system gradients in both space and time. Recent work (Tang *et al.* 2007; Van Werkhoven *et al.* 2008*a*,*b*) has explicitly mapped the information content of rainfall–runoff observations. Their results demonstrate that the information content in these rainfall–runoff data is dynamic and has complex spatial variability.

The quantification of information content is a challenging problem that can be substantially biased by the models used. As a field, we must acknowledge and elucidate how our predictive modelling frameworks have shaped our historical and ongoing observation strategies for environmental systems. Information content is often quantified using model-based projections of uncertainty and sensitivity that will always be impacted by model structural errors. It has long been recognized that these structural errors can strongly bias our observation systems (Moss 1979*a*,*b*). This long-term evolution of our knowledge can be represented mathematically using Bayesian frameworks that simultaneously account for both model and observation errors to forecast how critical system gradients as well as their uncertainties vary in space and time (Evensen 1994; Miller *et al.* 1999; Christakos 2000; Neuman 2002;

Drécourt *et al.* 2006; Kollat & Reed 2008). These frameworks provide adaptivity for observation network design that can take advantage of both modelling and sensing innovations to improve our theoretical understanding. In turn, theoretical innovations will then feed forward to produce improved model-based predictions of our observational needs and uncertainties.

Third driver: models of everywhere

Historical observations of the response of environmental systems are crucial for the development of reliable environmental models due to the dependence of our models on calibration. For currently available models, some degree of parameter calibration (for at least some of the key parameters) is required to achieve reliable predictions since (at least some) model parameters cannot be estimated from measurable physical watershed characteristics (Beven 2001; Wagener *et al.* 2004; Wagener & Wheater 2006). Calibration is the process of adjusting model parameters to match the observed and simulated system response of interest (e.g. streamflow). This issue poses a significant problem due to the lack of historical observations at many places, especially the lack of streamflow observations at the watershed scale. Headwater streams, in particular, are increasingly recognized for their importance in controlling ecological and water quality functions throughout river basins (Alexander *et al.* 2007). Protection of the integrity of and services for aquatic and terrestrial ecosystems as well as for human water consumption cannot be achieved without intact and functional headwaters (Lowe & Likens 2005). The maintenance of these services will require significant advances in our understanding and in our ability to predict natural system response patterns and their controls (Palmer *et al.* 2004).

Headwaters contain over 50% of the total strength length in the Eastern US (Nadeau & Rains 2007), but are severely under-represented in operational gauging in the US in general (Freeman *et al.* 2007), where nearly 95% of smaller streams are poorly characterized with less than 3% of all gauges (Poff *et al.* 2006*a*,*b*). At the same time, processes and ecosystem habitats in headwaters are particularly sensitive to atmospheric and terrestrial disturbances (Buttle & Meatcalfe 2000), and therefore likely to be

considerably impacted in our increasingly non-stationary world (Milly *et al.* 2008). The National Research Council (2004) stresses that the lack of gauges in small streams requires research into better modelling tools for streamflow simulations across hydroclimatic and geologic settings, since "for the majority of streams that support aquatic life, a systematic understanding is lacking on water quality, habitat, biota, specific discharge…" (Bishop *et al.* 2008).

The lack of observations of environmental indicators in the vast majority of our river network and the large uncertainty associated with model predictions at these locations are seen as major limitations to solving many environmental problems today (Sivapalan *et al.* 2003; Vogel 2006). The situation is much worse in a global context where existing monitoring networks are declining in many countries (Stockstad 1999), significantly limiting the possible assessment of conditions and trends in ecosystem services (MEA 2005) and limiting the quality of hydrologic predictions for water resources applications in regions of the world where resources for hazard mitigation and for adaptation are extremely poor (GRDC 2004; Widen-Nilsson *et al.* 2007).

Of course one has to keep in mind that the lack of *in situ* observations does not mean that there are no observations at all, given the increasingly widespread availability of remotely sensed information (see the discussion in Lakshmi 2004). We can remotely obtain observations of hydrologic variables such as near-surface air temperature and precipitation, of landscape characteristics such as land cover or topography and even of watershed response characteristics such as soil moisture and surface water levels (e.g. Alsdorf & Lettenmaier 2003; Lakshmi 2004). Differences in space-time scales and frequency of measurements mean that the value of *in situ* and remotely sensed data will differ, at least for a while.

Predictions of everywhere (i.e. at any location) implies that for many of these locations no suitable or sufficiently long observations of the response variable of interest will be available–they are ungauged (Sivapalan *et al.* 2003). The modeller has to rely on a relationship between natural system characteristics (such as soils and vegetation) and model parameters to parameterize the environmental model. However, most model parameters have limited relationships to real world (measurable) characteristics

and model predictions for changed or ungauged situations are very uncertain (Wagener & Wheater 2006). The success of modelling ungauged situations therefore hinges on how well model parameters and model structure can be estimated from *a priori* information of static system characteristics (e.g. soil type, vegetation cover, etc.).

Parkin *et al.* (1996) put this to the test and performed a blind validation on the Rimbaud watershed in Southern France using the SHE model. Their model predictions were highly uncertain, and they did not meet most of their self-declared measures of success. Refsgaard & Knudsen (1996) compared both physically-based and conceptual models in ungauged watersheds in Zimbabwe. They found that a spatially distributed model structure resulted in better predictions compared to a lumped one, but could not unambiguously show that the physically based model was better than another distributed model that was more conceptual in structure.

Fourth driver: modelling change

The increasing non-stationarity of our world (largely due to increased human activity) will have significant implications for the water environment that we need to anticipate. "The United States is facing unprecedented environmental changes, but decision makers do not have the information they need to understand and respond to these changes in a timely fashion" (Heinz Center 2008). Disturbances that impact the water environment include land cover change, largely due to urbanization (DeWalle *et al.* 2000) and the increasing impacts of a changing climate (US Climate Change Science Program 2008).

The potential of developing successful strategies to deal with these changes lies in our capacity to anticipate their impact (Clark *et al.* 2001). For predictions of environmental change, assuming that the change that occurs at a study location is not too severe, this change can likely be reflected through adjusting the model parameters. If the model is to be run in predictive mode where no observations of the 'changed system response' are available, then we need to adjust the parameters based on our knowledge of how the physical characteristics of the system change (e.g. the land use). We therefore require a relationship between physical characteristics and model parameters similar to the

ungauged case discussed above. "Techniques for the analysis of the effects of land use change on modelled hydrological responses are still very much at an early stage" (Beven 2000). Origins of environmental change include deforestation and reforestation (e.g. Likens *et al.* 1977; Swank & Crossley 1988; Calder 1990); effects of fire (e.g. Parkin *et al.* 1996; Cerda 1998), urbanization (e.g. DeWalle *et al.* 2000), effects of beetle infestation, agricultural drainage (e.g. Robinson 1986; Dunn & Mackay 1996), as well as climate change (e.g. Allen & Ingram 2002; Milly *et al.* 2005; Nohara *et al.* 2006; Oki & Kanae 2006).

An environmental modelling framework

To discuss the implications of the four drivers listed above on environmental modelling, it is convenient to formalize a typical modelling framework (Figure 1). The framework separates an observation layer and a modelling layer, both consisting of three main elements represented as ovals and connections within and between layers.

The observation layer consists of an oval representing the observation of system dynamic variables (e.g. streamflow, precipitation, evapotranspiration, groundwater flow and transport, sediment fluxes or soil moisture) and one representing the observation of system static characteristics (e.g. topography, soil and vegetation characteristics or

channel network). Depending on the temporal extent of a study, several variables could be considered either as dynamic or as static, e.g. land cover or vegetation. Even topography or other geological and geomorphological characteristics could be considered dynamic if very long time-scales are to be modelled (Tucker *et al.* 2001). The third oval represents the perceptual model, which is based on (and partially limited by) our observations of real world dynamics and statics. This model represents the modeller's perception of the environmental system without a formalized mathematical abstraction. The perceptual model represents the summary of our perceptions of how the environmental system under study functions (Beven 2000). It is therefore a subjective model, depending on the individual modeller's knowledge and level of understanding.

On top of the observation layer sits a modelling layer with three components that are related to or derived from observations and perceptions. The bottom oval represents the conceptual model of our system. This is a formalization (and usually simplification) of our perceptual model. At this point, the hypotheses and assumptions being made to simplify the description of the processes need to be made explicit (Beven 2000). The modeller has to make decisions regarding the main state variables and their distribution in space, types of boundary conditions, dominant processes etc.
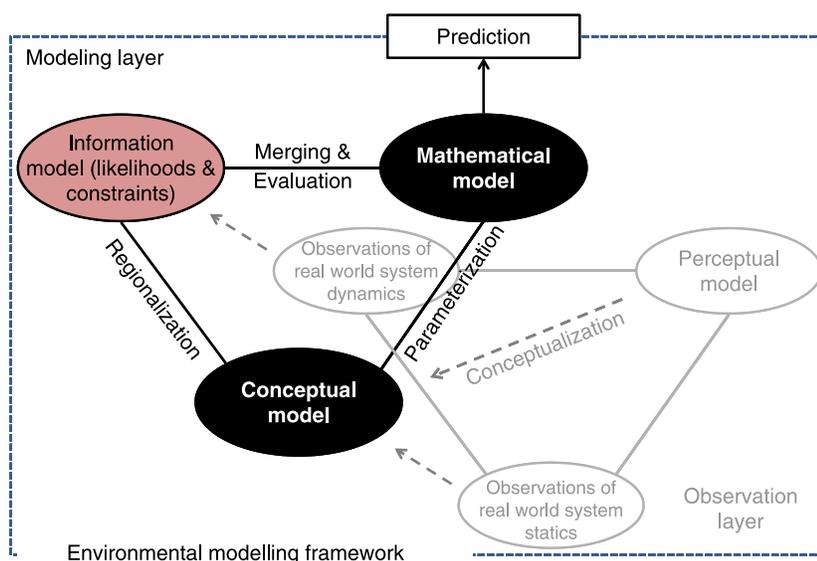

Figure 1 | Schematic representation of a typical environmental modelling framework.

This conceptualization forms the basis from which a mathematical model is built: the next oval. This mathematical model (i.e. the model equations implemented in computer code) might be impacted by the modeller's ability to translate the conceptual model into mathematical form. An additional consideration at this stage might be the purpose of our modelling exercise. For example, if one is interested in modelling the annual water balance, then the number of state variables might be very low and a spatially distributed representation of processes might be unnecessary. The third oval in the modelling layer represents what we call here the information model. This is the model used to extract information from the data and to merge (through processes of calibration, conditioning or data assimilation) this information with the mathematical model, or to evaluate the model by comparing observations and simulations. Typical examples of information models are the residual-based objective or likelihood functions used in typical model/parameter identification (calibration) procedures. The overall goal is to maximize the amount of information that can be extracted from observation data by improving the information model using a variety of methods (e.g. Wagener *et al.* 2003; Gupta *et al.* 2008).

In the following section we will discuss and provide some examples of how parts of this framework can or even need to be advanced, while largely focusing on the information model. We will concentrate on the issue of how to quantify and how to maximize extraction of information from observations of system dynamics and statics for model identification and evaluation in gauged and ungauged watersheds. This issue links to driver 1 (uncertainty) in the sense that maximal utilization of available information for model identification and evaluation will (or at least should) reduce uncertainty. It relates to drivers 3 and 4 (predictions everywhere and of environmental change impacts) in the sense that we have to find ways to develop reliable models without recourse to 'local' calibration using observations of real world system dynamics which, by definition, are not available in these circumstances. Driver 2, observational network design, is addressed in the sense that better understanding of the information content of observations, i.e. their value, as well as better quantification of the spatial and temporal extent of the information can help to enhance network design.

ADVANCES IN ENVIRONMENTAL MODEL IDENTIFICATION AND EVALUATION IN THE CONTEXT OF THESE DRIVERS

An area of active research in the framework discussed in the previous section is the information model. The main question under consideration is: how can we quantify and extract available information from observations of static and dynamic system characteristics to identify and evaluate models at gauged and ungauged locations? For ease of discussion, we will break this question into two components: the gauged and the ungauged case. Gauged in the context of this discussion refers to the availability of historical observations of the output variable(s) of an environmental system for purposes of model calibration and evaluation. We will point out some of the main research issues that require addressing and provide examples of how this could be done from our own work on modelling the rainfall–runoff relationship of watersheds.

Advances in gauged systems

An important issue in the case of gauged systems is how much information can be extracted from available observations using a particular information model as represented in a particular objective or likelihood function. Secondly, related to the first issue, we wish to determine what aspects of a model can be identified using the information provided by the observations.

A tool that has become increasingly feasible to address these two issues, due to advances in computational power and the increasing use of parallelized computing architectures, is global sensitivity analysis. Sensitivity analysis evaluates the impact of changes in selected factors (including model parameters, inputs or initial states) on the model output of interest, and can be a very valuable tool for model evaluation and identification (Demaria *et al.* 2007; Wagener & Kollat 2007). Global sensitivity analysis means that we can perform an analysis by exploring the full feasible space for all the factors considered, rather than just around some initial point (e.g. the optimum in the model parameter space). Tang *et al.* (2006) recently compared several local and global sensitivity analysis methods and found that Sobol's method
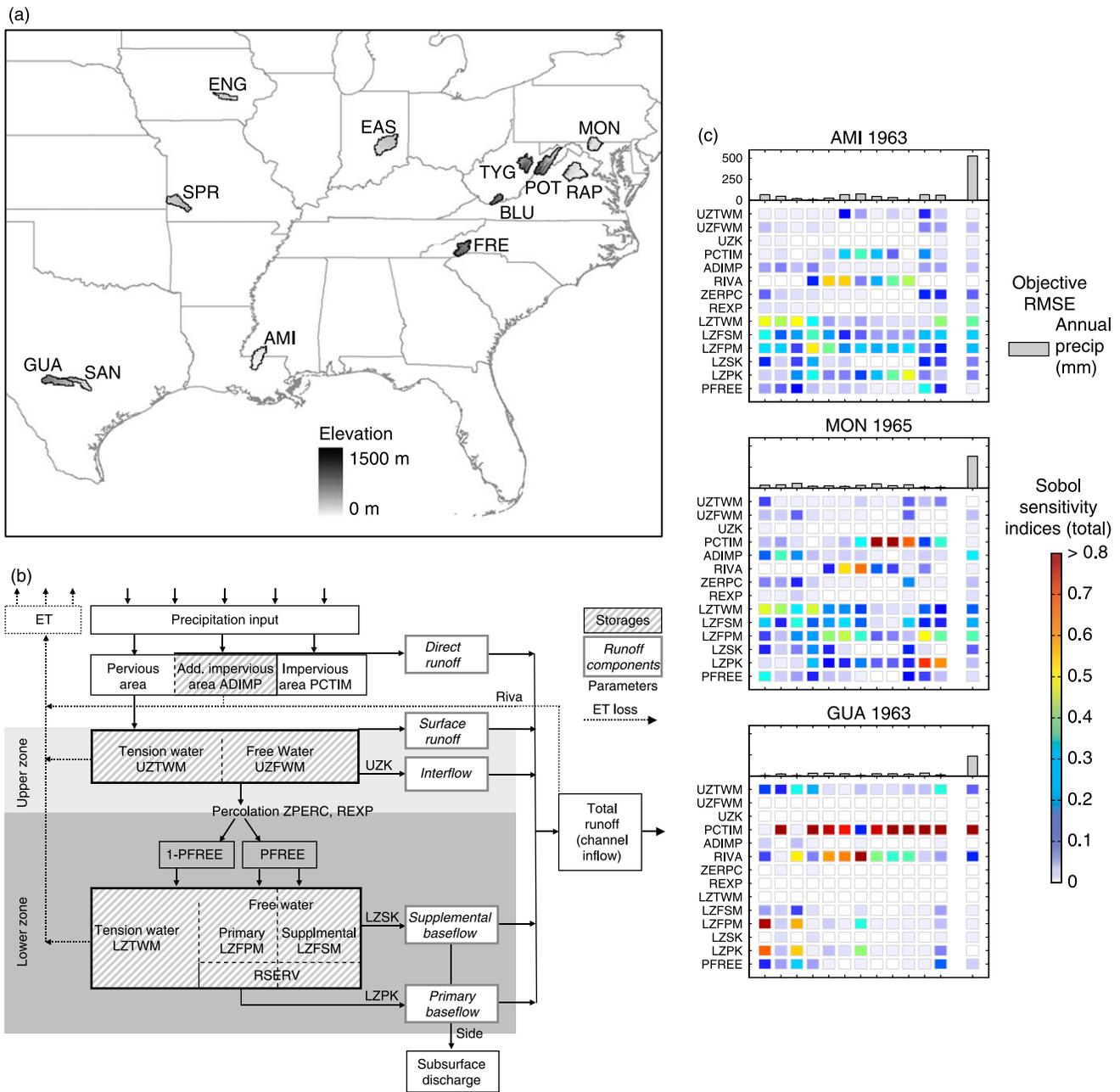
Figure 2 | (a) Map showing the locations of the 12 study basins within the US; (b) schematic figure of the Sacramento model structure; and (c) figures of the Sobol sensitivity indices (shown for each model parameter for each month of the years 1963 or 1965) for the Sacramento model parameters derived for the different study basins (ordered wet to dry from top to bottom).

(Sobol 1993; Saltelli 2002)–a variance-based global sensitivity analysis approach–provides robust and detailed sensitivity rankings. Below we will provide two examples of how this approach can be used to quantify the amount and type of information that can be extracted for both a lumped and a distributed watershed model.

Both studies utilize the Sacramento Soil Moisture Accounting (SAC-SMA) widely used by the National Weather Service (NWS) for river forecasting across the US (Figure 2(b), Table 1). We use both a lumped version of this conceptual watershed model as well as a grid-based distributed version in which a lumped SAC-SMA model is

Table 1 | Description of SAC-MCA parameters

Parameter	Units	Description
UZTWM	mm	Upper zone tension water maximum storage
UZFWM	mm	Upper zone free water maximum storage
UZK	Day^{-1}	Upper zone free water withdrawal rate
PCTIM	%/100	Percent permanent impervious area
ADIMP	%/100	Percent area contributing as impervious when saturated
RIVA	%/100	Percent area affected by riparian vegetation
ZPERC	None	Maximum percolation rate under dry conditions
REXP	None	Percolation equation exponent
PFREE	%/100	% of percolation going directly to lower zone free water
LZTWM	mm	Lower zone tension water maximum storage
LZFPM	mm	Lower zone free water primary maximum storage
LZFSM	mm	Lower zone free water supplementary maximum storage
LZPK	Day^{-1}	Lower zone primary withdrawal rate
LZSK	Day^{-1}	Lower zone supplementary withdrawal rate

used to represent each grid element with additional hillslope and channel routing through kinematic wave schemes.

In the first study, Sobol's method is applied to quantify how much information can be extracted from daily observations of streamflow for the identification of the lumped SAC-SMA model for watersheds in different hydro-climatic regions (Figure 2(b); Van Werkhoven *et al.* 2008*a*). The results shown in Figure 2(c) demonstrate how parameter sensitivities vary across hydro-climatic regimes and throughout a year with respect to the Root Mean Squared Error objective function (RMSE, a measure that emphasizes high flow performance due to the use of squared residuals in its calculation)–the chosen information model in this case.

Across watersheds (comparing across columns within each of the grids), the sensitivity differences tell us something about which parameters control the streamflow response at what time and, therefore, which parameters could be identified in a calibration process. The approach

also reveals how the model reproduces the observed system response. The modeller can use the sensitivity analysis results to judge whether the model behaviour is consistent with his/her perceptual and conceptual models. The three watersheds shown range from wet (AMI), to medium (MON) and dry (GUA). The analysis for example shows that the fast flashy response of the dry watershed is largely controlled by the percentage impervious area (PCTIM), a parameter that allows the model to produce a quick runoff contribution. The analysis also shows that flow predictions for the two wetter watersheds are more strongly controlled by lower zone model parameters (those starting with L) than the wet watershed where baseflow is much smaller. A third interesting result lies in the variability of the sensitivity throughout the year. For example, the medium watershed (MON) shows interesting behaviour during August and September. The previous months have been dry (depleting its storages) and its behaviour becomes very similar to that of the dry watershed (GUA). Other objective functions, focusing on different hydrologically relevant aspects of the watershed response (e.g. low flows or water balance) can be used to gain a more complete picture of the model behaviour and the information content of the data (Gupta *et al.* 2008; Van Werkhoven *et al.* 2008*a*).

The second study by Tang *et al.* (2007) extends the study of the lumped model to that of the distributed version of the SAC-SMA model at the event scale using hourly streamflow observations. Figure 3 shows global sensitivity maps for this model, which applies the above discussed Sacramento model structure in a distributed manner as described above. Tang *et al.* (2007) show, among other things, the impact of spatially heterogeneous forcing in creating spatial differences in sensitivity of the model parameters using this spatially distributed model. Figure 3 reveals a close link between rainfall amounts falling in a specific grid-cell and parameter sensitivity, thus indicating that the information available for model identification is a function of (or at least strongly impacted by) the space-time distribution of the model forcing. The plot shows the sensitivities for three parameters representing upper zone storage (UZTWM), percolation to the lower zone (PFREE) and lower zone storage (LZTWM). The study by Tang *et al.* (2007), however, was severely limited by computational constraints. Only two selected rainfall–runoff events could be run while
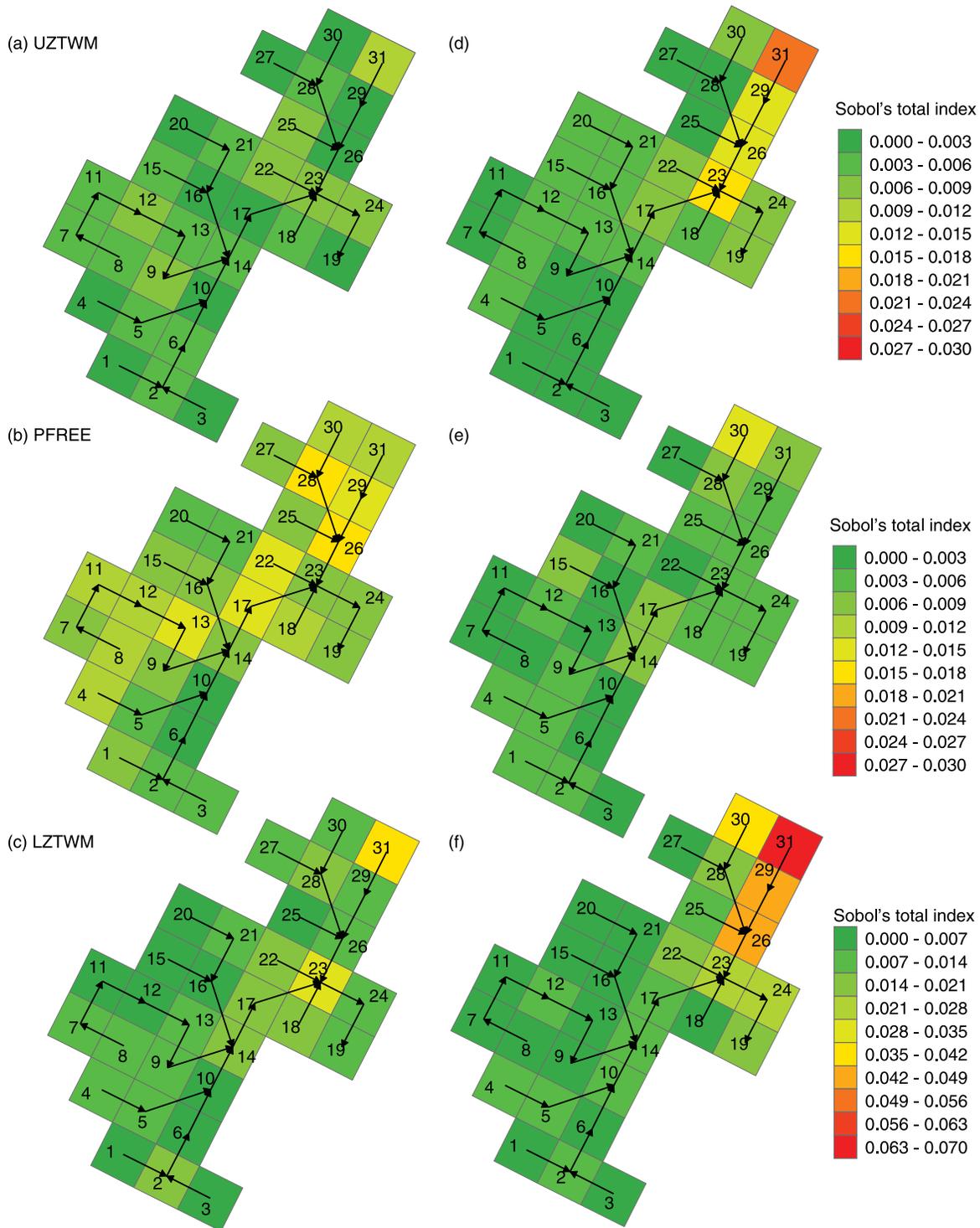
Figure 3 │ Spatial distribution of the total order sensitivity indices of the top three most sensitive parameters on each model grid cell. The spatial distributions of the May 2002 event sensitivities (caused by spatially uniform precipitation) are plotted for the model's (a) upper zone tension water storage (UZTWM); (b) fraction of percolating water (PFREE); and (c) lower zone tension water storage (LZTWM). The spatial distributions of the September 2003 event sensitivities (caused by spatially heterogeneous precipitation) are plotted for the model's (d) upper zone tension water storage (UZTWM); (e) fraction of percolating water (PFREE); and (f) lower zone tension water storage (LZTWM). The arrows in the cells designate surface flow directions.

varying all model parameters across all grid cells, even although the model was run in a parallelized version on a computing cluster.

Advances in ungauged systems

Current environmental models generally require calibration against historical observations of the system response (e.g. streamflow) in order to provide reliable predictions. As discussed above, in many cases, observations of the real world system response with respect to the variable of interest and/or at the location of interest will not be available. For example, the majority of river reaches (even in data-rich countries such as the US or the UK) are ungauged, while less-developed countries generally have much poorer observational networks (Houghton-Carr & Fry 2006). Additionally, environmental change is altering the hydrological regime of many watersheds, thus rendering historical observations less useful.

In these circumstances, alternative approaches need to be found to estimate model parameters to provide reliable predictions and to reduce model uncertainty. Past approaches to modelling the continuous hydrologic response of ungauged basins used observable physical characteristics of watersheds to either directly infer values for the parameters of hydrologic models, or to establish regression relationships between static watershed charac- teristics and model parameters (i.e. parameter regionaliza- tion). Both approaches have widely discussed limitations, like problems in measuring physical characteristics at the model scale when trying to directly measure model parameters for physically-based models. Model structural uncertainty, an ill-defined calibration problem, and our lack of understanding about how model parameters should correlate with watershed characteristics also add large amounts of uncertainty to the parameter regionalization approach (Wagener & Wheater 2006).

Yadav *et al.* (2007) recently proposed an alternative approach to the problem of modelling ungauged locations that addresses several of the above-mentioned problems. The main idea of this strategy is to formalize constraints on the feasible or expected (in their case streamflow) behaviour of ungauged environmental systems and use these constraints to reduce the uncertainty in local model

predictions. If we know how system behaviour relates to the structure and climatic conditions of a system, even if this relationship is uncertain, then we can force the behaviour of our models to be consistent with these relationships. In their particular study, Yadav *et al.* (2007) developed a model- independent approach based on empirically derived relationships between watershed response behaviour (streamflow indices), static watershed characteristics and climate characteristics. Instead of attempting to directly infer values for model parameters, different hydrologic response behaviours of the watershed, quantified through streamflow indices, are estimated and subsequently regionalized in a regression framework (see also Sanborn & Bledsoe 2006).

By including uncertainty in the form of prediction limits on the regression, we can predict ranges in which different streamflow indices are expected to fall at ungauged locations. Zhang *et al.* (2008) recently enhanced the size and scope of modelling applications where this approach can be applied. Larger, more complex models can be considered by reformulating the identification of feasible parameter sets that produce a model response within the constraints as a multi-objective optimization problem that can be solved using evolutionary algorithms. While the studies by Yadav *et al.* (2007) and Zhang *et al.* (2008) referred to the extrapolation in space, the same approach might be applicable for the extrapolation in time e.g. to address the implications of land cover change on environ- mental system behaviour (Wagener 2007).

The approach described above therefore provides a strategy to create an information model (formalized as one or more constraints) at an ungauged location that exploits commonly available data sources that provide basic watershed properties (terrain, climatology, vegetation, etc.). This strategy enables the modeller to assimilate various types of regional information to constrain or calibrate a local watershed model through this information model. Statistical hydrology has been used historically in many regions of the world to create (usually) regression- based regional models of streamflow characteristics includ- ing flood/low flow frequency analysis or flow duration curve characteristics (e.g. Fennessy & Vogel 1990; Kroll & Vogel 2002). This regional information should not conflict with the continuous simulations provided by a watershed model and can potentially reduce model uncertainty.

DISCUSSION, CONCLUSIONS AND OUTLOOK

Advances in our ability to model complex environmental systems are currently driven by at least four needs: (1) the need for the inclusion of uncertainty in observation, modelling and decision-making; (2) the need to provide environmental predictions everywhere (at any location); (3) the need to predict the impacts of environmental change (mainly land use and climate change); and (4) the need for model-guided adaptive observation network design. Satisfying these needs will require improved theory, translation of this improved theory to produce improved environmental models and enhanced observational capabilities. The latter issue is particularly important in the face of increasing budget cuts that have lead to declining observational (on-the-ground) networks in many parts of the world.

In this paper, we discuss how global sensitivity analysis can inform modellers about the information content of observations in space and time for the modelling task at hand. The study also demonstrated how widely model behaviour can vary across watersheds and even within a watershed if a spatially distributed model is used. The second example discusses how regionalized streamflow indices can be used to define constraints at ungauged locations. Feasible parameter sets can subsequently be identified using Monte Carlo sampling or, more powerfully, using evolutionary multi-objective optimization.

The hydroinformatics community is challenged to provide the scientific tools necessary to achieve water security in the 21st century by supporting sound policy making. We need to build more realistic and more integrated environmental models to represent real-world thresholds, nonlinearities and feedbacks, and which are capable of representing the implications of environmental change. Building these necessarily more complex models must also be accompanied by a development in significantly more powerful identification and evaluation algorithms. Such algorithms, combining optimization and sensitivity analysis methods while considering uncertainty, have to be able to support our analysis about how our models represent environmental systems and whether this presentation is consistent with our perception of the actual system and where (or when) models are incapable of doing so (i.e. provide model diagnostics). The work on distributed models presented here and in the references demonstrates the need for (currently unavailable) model identification procedures that account for the space-time dynamics in the precipitation forcing. This task alone is a very significant computational challenge, and presents just one of many opportunities for the hydroinformatics community to make important advancements.

Our final thought is given to the need for advancing communication and exchange within the research community and beyond. The speed in which new information and new tools are produced is accelerating continuously and better ways to share them have to be found. With respect to the free exchange of software, the Hydroarchive (www. sahra.arizona.edu/software) provides a web-based database where developers can deposit their software tools (or link their specific web-sites) while users can download them free of charge (Wagener *et al.* 2003).

REFERENCES

Abbott, M. B., Bathurst, J. C., Cunge, O'Connell, P. E. & Rasmussen, J. 1986 An introduction to the European hydrological system–systeme hydrologique Europeen, SHE. 1. History and philosophy of a physically-based, distributed modelling system. *J. Hydrol.* **87**, 45–59.

Ajami, N. K., Duan, Q. & Sorooshian, S. 2007 An integrated hydrologic Bayesian multimodel combination framework: confronting input, parameter, and model structural uncertainty in hydrologic prediction. *Water Resour. Res.* **43**, W01403.

Alexander, R. B., Boyer, E. W., Smith, R. A., Schwartz, G. E. & Moore, R. B. 2007 The role of headwater streams in downstream water quality. *J. Am. Water Resour. Assoc.* **43** (1), 41–59.

Allen, M. R. & Ingram, W. J. 2002 Constraints on future changes in climate and the hydrologic cycle. *Nature* **419**, 224–232.

Alsdorf, D. & Lettenmaier, D. 2003 Tracking fresh water from space. *Science* **301**, 1491–1494.

Beven, K. 1989 Changing ideas in hydrology: the case of physically-based models. *J. Hydrol.* **105**, 157–172.

Beven, K. 2000 *Rainfall–Runoff Modeling–The Primer*. John Wiley & Sons, Chichester, UK.

Beven, K. J. 2001 Uniqueness of place and process representations in hydrological modeling. *Hydrol. Earth Syst. Sci.* **4**, 203–213.

Beven, K. 2007 Towards integrated environmental models of everywhere: uncertainty, data and modeling as a learning process. *Hydrol. Earth Syst. Sci.* **11** (1), 460–467.

Beven, K. J. 2009 *Environmental Modeling: An Uncertain Future?* Routledge, London.

Beven, K. J. & Binley, A. M. 1992 The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Proc.* **6**, 279–298.

Beven, K. J., Smith, P. & Freer, J. 2008 So just why would a modeler choose to be incoherent? *J. Hydrol.* **354**, 15–32.

Bishop, K., Buffam, I., Erlandsson, M., Foelster, J., Laudon, H., Seibert, J. & Temnerud, J. 2008 Aqua incognita: the unknown headwaters. *Hydrol. Proc.* **22**, 1239–1242.

Burnash, R. J. C. 1995 The NWS river forecast system–catchment model. In *Computer Models of Watershed Hydrology* (ed. V. P. Singh), pp. 311–366. Water Resource Publications, Highlands Ranch, CO.

Buttle, J. M. & Meatcalfe, R. A. 2000 Boreal forest disturbance and streamflow response, northeastern Ontario. *Can. J. Fish. Aquat. Sci.* **57**, 5–18.

Calder, I. R. 1990 *Evaporation in the Uplands*. John Wiley, Chichester.

Cerda, A. 1998 Changes in the overland flow and infiltration after a rangeland fire in a Mediterranean scrubland. *Hydrol. Proc.* **12**, 1031–1042.

Christakos, G. 2000 *Modern Spatiotemporal Geostatistics*. Oxford University Press, New York, NY.

Clark, J. S., Carpenter, S. R., Barber, M., Collins, S., Dobson, A., Foley, J. A., Lodge, D. M., Pascual, M., Pielke, R., Jr, Pizer, W., Pringle, C., Reid, W. V., Rose, K. A., Sala, O., Schlesinger, W. H., Wall, D. H. & Wear, D. 2001 Ecological forecasts: an emerging imperative. *Science* **293**, 657–660.

Clark, M. P., Slater, A. G., Rupp, D. E., Woods, R. A., Vrugt, J. A., Gupta, H. V., Wagener, T. & Hay, L. E. 2008 FUSE: a modular framework to diagnose differences between hydrological models. *Water Resour. Res.* **44**, W00B02.

Demaria, E., Nijssen, B. & Wagener, T. 2007 Monte Carlo sensitivity analysis of land surface parameters using the variable infiltration capacity model. *J. Geophys. Res.–Atmos.* **112**, D11113.

DeWalle, D. R., Swistock, B. R., Johnson, T. E. & McGuire, K. J. 2000 Potential effects of climate change and urbanization on mean annual streamflow in the United States. *Water Resour. Res.* **36** (9), 2655–2664.

Dooge, J. C. I. 1957 The rational method for estimating flood peaks. *Engineering* **184**, 311–313.

Dooge, J. C. I. 1959 A general theory of the unit hydrograph. *J. Geophys. Res.* **64**, 241–256.

Dooge, J. C. I. 1986 Looking for hydrologic laws. *Water Resour. Res.* **22** (09S), 46S–58S.

Drécourt, J., Madsen, H. & Rosbjery, D. 2006 Bias aware Kalman filters: comparison and improvements. *Adv. Water Resour.* **29**, 707–718.

Dunn, S. M. & Mackay, R. 1996 Modeling the hydrological impacts of open ditch drainage. *J. Hydrol.* **179**, 37–66.

Dunn, S. M. & Ferrier, R. C. 1999 Natural flow in managed catchments: a case study of a modeling approach. *Water Res.* **33**, 621–630.

Evensen, G. 1994 Sequential data assimilation with a non-linear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *J. Geophys. Res.* **99** (C5), 10143–101624.

Ewen, J. & Parkin, G. 1996 Validation of catchment models for predicting land-use and climate change impacts.1. Method. *J. Hydrol.* **175**, 583–594.

Falkenmark, M. 2001 The greatest water problem: the inability to link environmental security, water security and food security. *Water Resour. Dev.* **17** (4), 539–554.

Fennessey, N. & Vogel, R. M. 1990 Regional flow duration curves for ungauged sites in Massachusetts. *ASCE J. Water Resour. Plann. Manage.* **116** (4), 530–549.

Franks, S. W., Gineste, P., Beven, K. J. & Merot, P. 1998 On constraining the predictions of a distributed model: the incorporation of fuzzy estimates of saturated areas in the calibration process. *Water Resour. Res.* **34**, 787–797.

Freeman, M. C., Pringle, C. M. & Jackson, C. R. 2007 Hydrologic connectivity and the contribution of stream headwaters to ecological integrity at regional scales. *J. Am. Water Resour. Assoc.* **43** (1), 5–14.

Freer, J. E., McMillan, H., McDonnell, J. J. & Beven, K. J. 2004 Constraining dynamic TOPMODEL responses for imprecise water table information using fuzzy rule based performance measures. *J. Hydrol.* **291** (3–4), 254–277.

Gleick, P. H. 2002 Soft water paths. *Nature* **418**, 373.

Global Runoff Data Centre (GRDC) 2004 Long term mean annual freshwater surface water fluxes into the world oceans. Comparison of GRDC freshwater flux estimate with the literature. http://grdc.bafg.de/servlet/is/7083/, Accessed June 2007.

Gupta, H. V., Wagener, T. & Liu, Y. 2008 Reconciling theory with observations: elements of a diagnostic approach to model evaluation. *Hydrol. Proc.* **22** (18), 3802–3813.

Harbor, J. M. 1994 A practical method for estimating the impact of land use change on surface runoff, groundwater recharge and wetland hydrology. *J. Am. Plan. Assoc.* **60** (1), 95–108.

Heinz Center 2008 *Environmental Information: A Road Map to the Future*. Heinz Center Report, Washington, DC.

Hong, Y., Hsu, K. L., Moradkhani, H. & Sorooshian, S. 2006 Uncertainty quantification of satellite precipitation estimation and Monte Carlo assessment of the error propagation into hydrologic response. *Water Resour. Res.* **42**, W08421.

Houghton-Carr, H. & Fry, M. 2006 *The decline of hydrological data collection for development of integrated water resource management tools in Southern Africa climate variability and change–hydrological impacts*. IAHS Publ. 308, 51–55.

Kavetski, D., Kuczera, G. & Franks, S. W. 2006 Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory. *Water Resour. Res.* **42**, W03407.

Kavetski, D., Kuczera, G. & Franks, S. W. 2006 Bayesian analysis of input uncertainty in hydrological modeling: 2. Application. *Water Resour. Res.* **42**, W03408.

Kennedy, M. C. & O'Hagan, A. 2001 Bayesian calibration of mathematical models. *J. R. Stat. Soc.* **D63** (3), 425–450.

Kirchner, J. W. 2006 Getting the right answers for the right reasons: linking measurements, analyses, and models to advance the science of hydrology. *Water Resour. Res.* **42**, W03S04.

Kollat, J. B. & Reed, P. M. 2008 Addressing bias and uncertainty in groundwater transport forecasts for a three-dimensional physical aquifer experiment. *Geophys. Res. Lett.* **35**, L17402.

Kollet, S. & Maxwell, R. 2006 Integrated surface-groundwater flow modeling: a free-surface overland flow boundary condition in a parallel groundwater flow model. *Adv. Water Resour.* **29**, 945–958.

Kollet, S. & Maxwell, R. 2008 Demonstrating fractal scaling of baseflow residence time distributions using a fully–coupled groundwater and land surface model. *Geophys. Res. Lett.* **35**, L07402.

Kroll, C. N. & Vogel, R. M. 2002 The probability distribution of low streamflow series in the United States. *J. Hydrol. Eng. ASCE* **7** (2), 137–146.

Lakshmi, V. 2004 The role of satellite remote sensing in the prediction of Ungauged Basins. *Hydrol. Proc.* **18** (5), 1029–1034.

Langbein, W. B. 1979 Overview of conference on hydrologic data networks. *Water Resour. Res.* **15** (6), 1867–1871.

Likens, G. E., Bormann, F. H., Pierce, R. S., Eaton, J. S. & Johnson, N. M. 1977 *Biogeochemistry of a Forested Ecosystem*. Springer-Verlag, New York.

Lowe, W. H. & Likens, G. E. 2005 Moving headwater streams to the head of the class. *BioScience* **5593**, 196–197.

Marshall, L., Nott, D. & Sharma, A. 2004 A comparative study of Markov chain Monte Carlo methods for conceptual rainfall–runoff modeling. *Water Resour. Res.* **40**, W02501.

McIntyre, N., Wheater, H. S. & Lees, M. 2002 Estimation and propagation of parametric uncertainty in environmental models. *J. Hydroinform.* **4**, 177–198.

McIntyre, N., Wagener, T., Wheater, H. S. & Siyu, Z. 2003 Uncertainty and risk in water quality modelling and management. *J. Hydroinform.* **5** (4), 259–274.

Millennium Ecosystem Assessment 2005 *Ecosystems and Human Well-being: Synthesis*. Island Press, Washington, DC.

Miller, R. N., Carter, E. F. & Blue, S. T. 1999 Data assimilation into nonlinear stochastic models. *Tellus. Ser. A Dyn. Meteorol. Oceanogr.* **51**, 167–194.

Milly, P. C. D., Wetherald, R. T., Dunne, K. A. & Delworth, T. L. 2002 Increasing risk of great floods in a changing climate. *Nature* **415**, 514–517.

Milly, P. C. D., Dunne, K. A. & Vecchia, A. V. 2005 Global pattern of trends in streamflow and water availability in a changing climate. *Nature* **438**, 347–350.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P. & Stouffer, R. J. 2008 Stationarity is dead: whither water management? *Science* **319** (5863), 573–574.

Moradkhani, H., Sorooshian, S., Gupta, H. A. & Hauser, P. R. 2005 Dual state-parameter estimation of hydrological models using ensemble Kalman filter. *Adv. Water Resour.* **28**, 135–147.

Moradkhani, H., Hsu, K. L., Gupta, H. V. & Sorooshian, S. 2005 Uncertainty assessment of hydrologic model states and parameters: sequential data assimilation using the particle filter. *Water Resour. Res.* **41**, W05012.

Moss, M. E. 1979a Some basic considerations in the design of hydrologic data networks. *Water Resour. Res.* **15** (6), 1673–1676.

Moss, M. E. 1979b Space, time, and the third dimension (model error). *Water Resour. Res.* **15** (6), 1797–1800.

Nadeau, T.-L. & Rains, M. C. 2007 Hydrological connectivity between headwater streams and downstream waters: how science can inform policy. *J. Am. Water Resour. Assoc.* **43** (1), 118–133.

National Research Council 2008 *Integrating Multiscale Observations of US Waters*. The National Academies Press, Washington, DC.

Neuman, S. P. 2002 Accounting for conceptual model uncertainty via maximum likelihood Bayesian model averaging. *Acta Univ. Carol.-Geol.* **46** (2/3), 529–534.

Nohara, D., Kitoh, A., Hosaka, M. & Oki, T. 2006 Impact of climate change on river discharge projected by multimodel ensemble. *J. Hydromet.* **7**, 1076–1089.

NRC (National Research Council) 2004 *Assessing the National Streamflow Information Program*. National Academy Press, Washington, DC.

Oki, T. & Kanae, S. 2006 Global hydrological cycles and world water resources. *Science* **313**, 1068–1072.

Palmer, M., Bernhardt, E., Chornesky, E., Collins, S., Dobson, A., Duke, C., Gold, B., Jacobson, R., Kingsland, S., Kranz, R., Mappin, M., Martinez, M. L., Micheli, F., Morse, J., Pace, M., Pascual, M., Palumbi, S., Reichman, O. J., Simons, A., Townsend, A. & Turner, M. 2004 Ecology for a crowded planet. *Science* **304**, 1251–1252.

Panday, S. & Huyakorn, P. S. 2004 A fully coupled physically-based spatially-distributed model for evaluating surface/subsurface flow. *Adv. Water Resour.* **27**, 361–382.

Parkin, G., O'Donnell, G., Ewen, J., Bathurst, J. C., O'Connell, P. E. & Lavabre, J. 1996 Validation of catchment models for predicting land-use and climate change impacts. 1. Case study for a Mediterranean catchment. *J. Hydrol.* **175**, 595–613.

Poff, N. L., Bledsoe, B. P. & Cuhaciyan, C. O. 2006a Hydrologic variation with land use across the contiguous United States: geomorphic and ecological consequences for stream ecosystems. *Geomorphology* **79**, 264–285.

Poff, N. L., Olden, J. D., Pepin, D. M. & Bledsoe, D. P. 2006b Placing global streamflow variability in geographic and geomorphic contexts. *River Res. Appl.* **22**, 149–166.

Porporato, A., Daly, E. & Rodriguez-Iturbe, I. 2004 Soil water balance and ecosystem response to climate change. *Am. Nat.* **164** (5), 625–632.

Qu, Y. & Duffy, C. J. 2007 A semi-discrete finite-volume formulation for multi-process watershed simulation. *Water Resour. Res.* **43**, W08419.

Reed, P., Brooks, R., Davis, K., DeWalle, D. R., Dressler, K. A., Duffy, C. J., Lin, H. S., Milller, D., Najjar, R., Salvage, K. M., Wagener, T. & Yarnal, B. 2006 Bridging river basin scales and processes to assess human-climate impacts and the terrestrial hydrologic system. *Water Resour. Res.* **42**, W07418.

Refsgaard, J. C. & Knudsen, J. 1996 Operational validation and intercomparison of different types of hydrological models. *Water Resour. Res.* **32** (7), 2189–2202.

Reggiani, P., Sivapalan, M. & Hassanizadeh, S. M. 1998 A unifying framework for watershed thermodynamics: balance equations for mass, momentum, energy and entropy, and the second law of thermodynamics. *Adv. Water Resour.* **22** (4), 367–398.

Reggiani, P., Hassanizadeh, E. M., Sivapalan, M. & Gray, W. G. 1999 A unifying framework for watershed thermodynamics: constitutive relationships. *Adv. Water Resour.* **23** (1), 15–39.

Reggiani, P., Sivapalan, M. & Hassanizadeh, S. M. 2000 Conservation equations governing hillslope responses: exploring the physical basis of water balance. *Water Resour. Res.* **36** (7), 1845–1863.

Reggiani, P., Sivapalan, M., Hassanizadeh, M. & Gray, W. G. 2001 Coupled equations for mass and momentum balance in a stream network: theoretical derivation and computational experiments. *Proc. R. Soc. Ser. A Math. Phys. Eng. Sci.* **457**, 157–189.

Reichert, P. & Borsuk, M. E. 2005 Does high forecast uncertainty preclude effective decision support? *Environ. Model. Softw.* **20**, 991–1101.

Robinson, M. 1986 Changes in catchment runoff following drainage and afforestation. *J. Hydrol.* **86**, 71–84.

Saltelli, A. 2002 Making best use of model evaluations to compute sensitivity indices. *Comput. Phys. Commun.* **145**, 280–297.

Sanborn, S. C. & Bledsoe, B. P. 2006 Predicting streamflow regime metrics for ungauged streams in Colorado, Washington, and Oregon. *J. Hydrol.* **325**, 241–261.

Schoups, G. & Hopmans, J. W. 2006 Evaluation of model complexity and input uncertainty of field-scale water flow and salt transport. *Vadose Zone J.* **5**, 951–962.

Shamseldin, A. Y., O'Connor, K. M. & Liang, G. C. 1997 Methods for combining the outputs of different rainfall–runoff models. *J. Hydrol.* **197** (1–4), 203–229.

Sivapalan, M. 2005 Pattern, process and function: elements of a unified theory of hydrology at the catchment scale. In *Encyclopedia of Hydrological Sciences* (ed. M. Anderson). Wiley.

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J. J., Mendiondo, E. M., O'Connell, P. E., Oki, T., Pomeroy, J. W., Schertzer, D., Uhlenbrook, S. & Zehe, E. 2003 IAHS decade on predictions in ungauged basins (PUB), 2003–2012: shaping an exciting future for the hydrological sciences. *Hydrol. Sci. J.* **48** (6), 857–880.

Smith, T. J. & Marshall, L. A. 2008 Bayesian methods in hydrologic modeling: a study of recent advancements in Markov chain Monte Carlo techniques. *Water Resour. Res.* **44**, W00B05.

Sobol', I. 1993 Sensitivity estimates for nonlinear mathematical models. *Math. Model. Comput. Exp.* **1**, 407–417.

Stockstad, E. 1999 Scarcity of rain, stream gages threatens forecasts. *Science* **285**, 1199–1200.

Swank W. T. & Crossley D. A. (eds.) 1988 *Forest Hydrology and ecology at Coweeta. Ecological Studies 66.* Springer-Verlag, New York.

Tang, Y., Reed, P. & Wagener, T. 2006 How effective and efficient are multiobjective evolutionary algorithms at hydrologic model calibration? *Hydrol. Earth Syst. Sci.* **10**, 289–307.

Tang, Y., Reed, P., Van Werkhoven, K. & Wagener, T. 2007 Advancing the identification and evaluation of distributed rainfall–runoff models using global sensitivity analysis. *Water Resour. Res.* **43**, W06415.

Tucker, G. E., Lancaster, S. T., Gasparini, N. M., Bras, R. L. & Rybarzyk, S. 2001 An object-oriented framework for distributed hydrologic and geomorphic modeling using triangulated irregular networks. *Comput. Geosci.* **27** (8), 959–973.

Uhlenbrook, S., Seibert, J., Leibundgut, Ch. & Rodhe, A. 1999 Prediction uncertainty of conceptual rainfall–runoff models caused by problems to identify model parameters and structure. *Hydrol. Sci. J.* **44** (5), 779–798.

US Climate Change Science Program 2008 Scientific assessment of the effects of global change on the United States. A Report of the Committee on Environmental and Natural Resources National Science and Technology Council, U.S. Climate Change Science Program, Washington, DC.

Van Werkhoven, K., Wagener, T., Tang, Y. & Reed, P. 2008a Understanding watershed model behavior across hydro-climatic gradients using global sensitivity analysis. *Water Resour. Res.* **44**, W01429.

Van Werkhoven, K., Wagener, T., Reed, P. & Tang, Y. 2008b Rainfall characteristics define the value of streamflow

observations for distributed watershed model identification. *Geophys. Res. Lett.* **35**, L11403.

Vogel, R. M. 2006 Regional calibration of watershed models. In *Watershed Models* (ed. V. P. Singh & D. K. Frevert), pp. 549–567. CRC Press.

Vrugt, J. A., Gupta, H. V., Bouten, W. & Sorooshian, S. 2003 A Shuffled complex evolution metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour. Res.* **39** (8), 1201.

Vrugt, J. A., Robinson, B. A. & Vesselinov, V. V. 2005 Improved inverse modeling for flow and transport in subsurface media: combined parameter and state estimation. *Geophys. Res. Lett.* **32**, L18408.

Vrugt, J. A., Gupta, H. V., Dekker, S. C., Sorooshian, S., Wagener, T. & Bouten, W. 2006 Confronting parameter uncertainty in hydrologic modeling: application of the SCEM-UA algorithm to the Sacramento soil moisture accounting model. *J. Hydrol.* **325**, 288–307.

Wagener, T. 2003 Evaluation of catchment models. *Hydrol. Proc.* **17**, 3375–3378.

Wagener, T. 2007 Can we model the hydrologic impacts of environmental change? *Hydrol. Proc.* **21** (23), 3233–3236.

Wagener, T. & Gupta, H. V. 2005 Model identification for hydrological forecasting under uncertainty. *Stoch. Environ. Res. Risk Assess.* **19**, 378–387.

Wagener, T. & Wheater, H. S. 2006 Parameter estimation and regionalization for continuous rainfall–runoff models including uncertainty. *J. Hydrol.* **320** (1–2), 132–154.

Wagener, T. & Kollat, J. 2007 Visual and numerical evaluation of hydrologic and environmental models using the Monte Carlo Analysis Toolbox (MCAT). *Environ. Model. Softw.* **22**, 1021–1033.

Wagener, T., McIntyre, N., Lees, M. J., Wheater, H. S. & Gupta, H. V. 2003 Towards reduced uncertainty in conceptual rainfall–runoff modelling: dynamic identifiability analysis. *Hydrol. Proc.* **17** (2), 455–476.

Wagener, T., Wheater, H. S. & Gupta, H. V. 2004 *Rainfall–Runoff Modelling in Gauged and Ungauged Catchments*, p. 332. Imperial College Press, London, UK.

Wagener, T., Sivapalan, M., Troch, P. & Woods, R. 2007 Catchment classification and hydrologic similarity. *Geogr. Compass* **1** (4), 901–931.

Widen-Nilsson, E., Halldin, S. & Xu, C. -Y. 2007 Global water-balance modelling with WASMOD-M: parameter estimation and regionalization. *J. Hydrol.* **340**, 105–118.

Yadav, M., Wagener, T. & Gupta, H. V. 2007 Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Adv. Water Resour.* **30**, 1756–1774.

Yatheendradas, S., Wagener, T., Gupta, H. V., Unkrich, C., Goodrich, D., Schaeffer, M. & Stewart, A. 2008 Understanding uncertainty in distributed flash-flood forecasting for semi-arid regions. *Water Resour. Res.* **44**, W05S19.

Zhang, Z., Wagener, T., Reed, P. & Bushan, R. 2008 Ensemble streamflow predictions in ungauged basins combining hydrologic indices regionalization and multiobjective optimization. *Water Resour. Res.* **44**, W00B04.