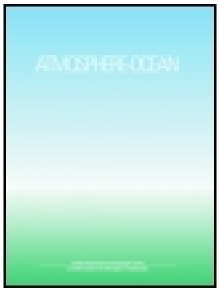

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Streamflow Modelling: A Primer on Applications, Approaches and Challenges

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Streamflow Modelling: A Primer on Applications, Approaches and Challenges

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ABSTRACT *This article examines the current practice of streamflow modelling, a field under development for over a century. A sample of the wide range of assessment and planning applications of streamflow models is presented. The diversity in the use of these models is mirrored in the diversity of model complexity, and modelling approaches ranging from empirical to physically based and from lumped to fully distributed are described with examples. Predictions derived from hydrological models are subject to many sources of error; these are discussed along with methods for error minimization or anticipation. Model error is generally quantified using an ensemble of forecasts meant to sample the range of predictive uncertainty. This ensemble can be used to generate reliable probabilistic forecasts of hydrological quantities if all sources of error are accounted for. To date, applications of ensemble methods in streamflow forecasting have typically focused on only one or two error sources. A challenge will be to develop ensemble streamflow forecasts that sample a wider range of predictive uncertainty.*

RÉSUMÉ *[Traduit par la rédaction] Le présent article examine la pratique actuelle en modélisation d'écoulement fluvial, un domaine qui évolue depuis plus d'un siècle. Nous présentons un échantillon de la vaste gamme d'applications d'évaluation et de planification des modèles d'écoulement fluvial. La diversité dans l'utilisation de ces modèles est le reflet de la diversité dans la complexité des modèles, et nous décrivons à l'aide d'exemples les approches de modélisation qui peuvent être empiriques ou basées sur la physique ou encore localisées ou entièrement réparties. Plusieurs sources d'erreur peuvent affecter les prévisions issues des modèles hydrologiques; nous discutons de ces sources d'erreur de même que des méthodes de réduction ou d'anticipation des erreurs. L'erreur du modèle est généralement quantifiée à l'aide d'un ensemble de prévisions servant à échantillonner la grandeur de l'incertitude prévisionnelle. Cet ensemble peut servir à produire des prévisions probabilistes fiables des grandeurs hydrologiques si toutes les sources d'erreur sont prises en compte. Jusqu'à maintenant, les applications des méthodes d'ensemble à la prévision des écoulements fluviaux n'ont généralement tenu compte que d'une ou deux sources d'erreur. Ce sera un défi de mettre au point des prévisions d'ensemble d'écoulement fluvial qui échantillonnent un plus large éventail d'incertitude prévisionnelle.*

KEYWORDS surface water hydrology; simulation; computational methods; watershed management; climate variability/change; ensemble forecasting; uncertainty; streamflow; numerical modelling

1 Introduction

Since the development of the first rainfall-runoff model in the late nineteenth century (Dooge, 1973; Todini, 1988), hydrological models have evolved to encompass a broad range of complexities and approaches. The many hydrological models available today reflect the diverse applications for which they were developed, such as operational forecasting of floods and streamflow in general, as planning tools in resource management, for impact assessment of past and proposed land use changes, and for assessing climate change effects.

As simplified representations of a complex physical system, hydrological model predictions carry with them a certain amount of uncertainty. This uncertainty comes not only from the simplification of hydrological process representation, but also from errors in input data, incomplete knowledge of antecedent conditions, and uncertainty in model parameters. Frameworks for anticipating these sources of uncertainty have been developed, many of which make use of ensemble forecasting methods. The diversity of the many available hydrological models lends itself well to this approach, which now represents the state of the art in hydrological modelling (Cloke and Pappenberger, 2009).

The focus of this article is on streamflow models; these are mathematical-computational models of terrestrial hydrology

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that, in effect, take weather variables over a watershed and convert them into a river flow rate generally at hourly to daily temporal resolution. Such hydrological models are increasingly being applied as components of larger modelling systems wherein they are coupled with water quality models, hydraulic models, explicit groundwater models, and so forth. While the approaches and challenges associated with these additional model types will not be covered in this article, applications of streamflow models in conjunction with such tools will be discussed.

Several in-depth reviews of hydrological models and modelling have been published, including Beven (2001) and Singh and Woolhiser (2002). In addition, Singh and Frevert (2006) present a comprehensive overview of many specific hydrological models. This article examines many of the same issues as its predecessors but with three differences. First, this paper bridges a perceived gap between introductory hydrology textbooks and highly focussed, disciplinary treatments of the subject. As such, it may be particularly useful for advanced scientists and engineers new to the specific topic of streamflow modelling. Note that meteorologists in particular are becoming more involved in hydrologic prediction. Second, unlike the reviews cited above, this primer spans both process-based watershed models and empirical approaches to streamflow prediction, such as statistical and soft-computing techniques. In this respect, its scope is considerably broader. Third, reflecting recent advances, this article places more emphasis on ensemble modelling as a tool for handling the various sources of uncertainty in model prediction—a tool which has been used in weather modelling for decades but is less completely explored in hydrological applications.

In Section 2 of this article, the many applications of hydrological models are briefly surveyed. In Section 3, some common modelling approaches are discussed and compared. Section 4 outlines sources of uncertainty in hydrological predictions, and frameworks for the anticipation of model uncertainty are described in Section 5. Based on this broad review, we conclude with a number of suggestions for future research in Section 6.

2 Uses of hydrological models

The applications of hydrological models are many and varied, ranging from the assessment of the impacts of long-term climate or land use change to operational forecasting of streamflows for flood forecasting or hydroelectric reservoir operation. Hydrological models can be used in conjunction with other modelling or assessment tools, such as hydraulic models in the design of flood control structures, models of fish production and survival, or nutrient transport models in water quality studies. They are also useful for increasing our understanding of the physical processes operating within watersheds at a variety of scales and how those processes are linked.

a *Assessing the Impacts of Land Use/Land Cover Change*

Humans are responsible for major Land Use and Land Cover (LULC) changes over a wide range of spatial scales. We have altered our landscapes through activities such as logging, mining, and urbanization, which can affect various hydrological processes (Alila and Beckers, 2001; Lin et al., 2007). Hydrological models are often used to determine to what extent LULC changes affect watershed hydrology based on observed changes. Unlike purely observational studies, the use of models permits isolating the variable whose effects are being studied. For example, long-term streamflow records in an urbanizing watershed are subject not only to changes in LULC, but also to the variability of climate. Fleming and Moore (2008) provide an example of how the commingling of effects from urban stormwater management and the Pacific Decadal Oscillation could lead to incorrect inferences when applying standard empirical data analysis methods to a hydrometric record. Driving a hydrological model for different urbanization scenarios but with constant climatological forcing allows us to discern the effects of urbanization alone on basin hydrology (Brun and Band, 2000). This ability to isolate variables by analyzing model output is an important and recurring theme in impact assessment studies.

Hydrological models are popular tools in forestry for assessing the impacts of past logging practices on flood risk and water availability. Changes in streamflow characteristics resulting from large-scale logging have been shown to result in increased flood risk (Storck et al., 1998; Whitaker et al., 2002).

Changes in LULC are not always brought on by human interaction with the natural environment. Wildfires can also have significant impacts on forest cover and subsequently on forest hydrology, and these impacts have been investigated through the use of distributed hydrological models (Rulli and Rosso, 2007). Another natural hazard for forests is the Mountain Pine Beetle (MPB). The current unprecedented outbreak of MPB in the forests of British Columbia (BC), Canada, is expected to continue for another decade, at which time at least 80% of the merchantable pine in the province will have been killed. Hydrological models have been used to assess the effects of both beetle-kill and potential salvage logging scenarios on the hydrology of the Fraser River basin (Schnorbus et al., 2010).

Hydrological models are used not only for assessing the impacts of past or ongoing LULC activities but also for aiding policy planning for future practices. Alila and Beckers (2001) note that understanding the impacts of past activities is necessary if sound decisions about optimal and sustainable forestry practices are to be made. The same can be said for the impacts of urbanization, agricultural activities, and other types of land change. For example, Brun and Band (2000) used observed land use changes with modelled soil moisture and runoff to develop a simplified model suitable for decision-making in future urbanization activities. Hydrological models can be used in conjunction with land use change models of varying complexity to predict future changes and their impacts based on land suitability for change (e.g., Niehoff et al., 2002; McColl and Aggett, 2007).

The mining industry also makes use of hydrological models, especially in reclamation studies. In the case of the oil sands of Alberta, Canada, reclamation requires that mine overburden be used to reconstruct entire landforms including their natural hydrological performance. Hydrological models are used to determine the ideal distribution of available materials, though there is an emphasis on groundwater processes as opposed to streamflow (Elshorbagy et al., 2007; Price et al., 2010). Another popular application of hydrological models in mining is for modelling stream and groundwater quality from existing or abandoned mine sites and for assessing mitigation strategies (Adams and Younger, 2001; Herr et al., 2003). It is also not uncommon for hydrological models to be employed in the pre-mining environmental assessment (EA) process as a tool for exploring the potential downstream impacts of proposed projects (e.g., Rescan, 2006).

Hydrological models are also used to assess the impacts of water management practices. Land cover changes resulting from dam construction include the flooding of large areas and changes in downstream river characteristics. Environmental impact assessments are often required prior to construction to address issues such as the conservation of fish habitats, recreational use of rivers, and water quality. Determining strategies for mitigation of these impacts requires the use of hydrological and hydraulic models as well as other tools (Hydro-Québec Production, 2004). The LULC-hydrology problem can also be inverted to determine a land use scenario that enables a particular water quantity or quality to be maintained in a stream (Kralisch et al., 2003).

b *Climate Change Impact Assessment*

Modelling studies of the impacts of anticipated global climate change on local hydrological processes involve a modelling chain. This chain extends from socioeconomic, demographic and technological scenarios, to General Circulation Models (GCM) of global climate, to downscaling procedures, and finally to hydrological models (Wilby et al., 2006). Each component in the chain involves assumptions that may not be fully valid and makes data demands that are typically not fully satisfied, resulting in the introduction of significant uncertainty.

The use of hydrological models to investigate the potential impacts of climate change can be strongly linked to their use in assessing LULC impacts. Projected climate changes are expected to affect vegetation, snow accumulation, permafrost and glaciers. Such land change scenarios should be present in hydrological models in order to comprehend the impacts of climate change fully (Beckers et al., 2009b). To date this requirement is often not met; in many such assessments, only the hydrological impacts of changed meteorological inputs are modelled. Nevertheless, hydrological modelling studies explicitly accounting for both climate change and secondary effects have indeed been performed, focusing on issues like glacier retreat (Stahl et al., 2008) and changes in vegetation leaf area and stomatal conductance (Eckhardt and Ulbrich, 2003).

Hydrological models are also used to drive hydraulic models to assess how changes in hydrological regime will impact water management practices and infrastructure. Traditionally, hydrological design rules have been based on the assumption of stationarity, which is invalid in the context of climate change. Kundzewicz et al. (2008) therefore suggest that current procedures for infrastructure design be revised. The high degree of uncertainty in climate change projections also means that adaptation procedures should not rely on precise projections.

In the state of Washington, United States, climate change may shift seasonal streamflow timing as a result of more frequent extreme precipitation events near the coast and decreased snowpack in the Cascade Mountains (Littel et al., 2009). Changes to drainage and urban stormwater infrastructure will likely be required. Peck et al. (2011) found an increased risk to bridges and flood barriers for some climate change scenarios for London, Ontario. The study recommended increased monitoring, dyke improvement, and changes to design criteria to include potential climate change impacts.

The primary challenge in linking climate model output with hydrological models is the difference in both spatial and temporal resolution of the two models. GCMs are run using a very coarse grid that is unable to resolve many of the regional and local processes important to hydrological applications. Various techniques have been developed to bridge the gap between GCMs and hydrological models. These techniques include statistical downscaling and dynamical downscaling using nested models (Xu, 1999; Wood et al., 2004; Fowler et al., 2007).

Nested model approaches often make use of Regional Climate Models (RCM), which are run on grid scales on the order of tens of kilometres and include complex physics. Nested downscaling methods result in more physically realistic output than statistical methods but are computationally demanding and often gain no skill over their statistical counterparts (Fowler et al., 2007). Jha et al. (2004) used an RCM to downscale GCM output over the continental United States and found that annual streamflows could be reproduced but seasonal variability could not. The need for removal of bias in RCM output is a commonly reported problem in such applications; it remains to be determined whether statistical corrections are valid in future climates (Hay et al., 2002; Fowler et al., 2007). Alternatively, there have been attempts to use water balance information from the land surface scheme of an RCM as a first-order estimate of streamflow responses to climate change (Rodenhuis et al., 2011), but the lack of relevant watershed process detail (e.g., routing mechanisms and cryospheric properties) is such that the results likely have a limited range of applicability.

Another potentially promising but little-used dynamic downscaling approach uses even higher-resolution physically based models that are not as physically detailed or computationally demanding as RCMs. These include orographic precipitation models (Xu, 1999) or simple boundary layer models (Kouwen et al., 2005). This "hybrid" approach may be particularly useful in complex terrain and may warrant closer attention for climate change impact studies in mountainous regions.

Statistical downscaling methods seek to determine empirical relationships between local climate and GCM-scale variables through, for example, regression (Wilby et al., 2006; Stahl et al., 2008). Artificial Neural Networks (ANN) and ensemble neural networks have also been applied to the downscaling problem and have been shown to perform better than multiple linear regression models (Cannon and Whitfield, 2002). Cannon (2008) developed a probabilistic multisite downscaling method that is able to preserve spatial patterns of precipitation important to streamflow models. The model is analogous to a regression-based downscaling model with a stochastic weather generator component. Stochastic weather generators are often used in conjunction with statistical downscaling methods to introduce spatial and temporal variability on scales smaller than GCM-scale (Wilks and Wilby, 1999; Prudhomme et al., 2002). As a result of the computational requirements of nested downscaling approaches and their other limitations, statistical downscaling methods have enjoyed greater popularity in climate change studies.

c *Aquatic Habitat Simulation*

A key use of streamflow models is to assess the possible effects on aquatic habitat of potential forcing mechanisms such as climate change, LULC changes, or existing or proposed environmental management or restoration activities. Commonly, this task is accomplished in a relatively qualitative manner, using streamflow model predictions to assess likely biological implications. However, it is not uncommon to apply streamflow models in a more quantitatively formal manner in which they are coupled with models of fish production and survival or other aspects of aquatic habitat. Such integrated approaches are useful in evaluating policies and best management practices with regard to water resources and mitigation of impacts on aquatic habitat. Larval survival and population models for various species of fish have been driven by hydrological models to assess the impacts of LULC changes and climate change, including the impacts of potential habitat restoration strategies (Anderson et al., 2006; Battin et al., 2007). Models have also been used in an operational forecast mode in support of predicting annual salmon returns and setting associated management goals, such as catch limits (Morrison and Foreman, 2005).

d *Water Quality Assessment*

Issues of water quantity and quality can be so tightly linked that several hydrological models, such as the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) and the Hydrologic Simulation Program-Fortran (HSPF; Johanson et al., 1980) include modules for modelling water quality. For hydrological models that do not include water quality, modellers can integrate an existing water quality model into the hydrological model (Mankin et al., 1999) or add to it simple equations for chemistry, mass balance and transport (Herr et al., 2003).

In addition to mitigation studies in mining, water quality models are used to assess the impacts of urbanization, agriculture and LULC changes in general, mostly in the context of planning strategies for water quality improvement. For example, Vaché et al. (2002) used SWAT to simulate nutrient export in alternative future land use scenarios in the U.S. corn belt. It was found that improvements to water quality would require major modifications to agricultural activities such as the expansion of riparian areas and reduction in the spread of agriculture. Water quantity and water quality models can also be used to complement monitoring programs in at-risk watersheds (Abbaspour et al., 2007).

Hydrological models are also coupled with hydrodynamic and water quality models in assimilative capacity studies, which seek to determine a water body's ability to accommodate toxins or wastewater while continuing to meet water quality objectives. Such integrated approaches are useful in evaluating policies and best management practices with regard to water resources and mitigation of wastewater impacts (e.g., Greenland International Consulting, Ltd., 2006; Georgia Environmental Protection Division, 2010). Similar approaches are used in water quality trading—a practice that may allow facilities to reduce the costs of compliance with water quality regulations (e.g., Obropta et al., 2008).

e *Flood Hazard Assessment and Planning*

From a land use planning perspective, hydrological models are also useful in the generation of flood maps. The use of Geographical Information Systems (GIS) in this type of work is very common, because it provides a valuable tool for communication of geographical information. The integration of hydrological and hydraulic models with GIS is becoming a common approach in flood mapping.

The typical method for integrating hydrological and hydraulic models and GIS is to run the hydrological model with meteorological and terrain inputs that are pre-processed using GIS. The results are then used as input to the hydraulic model, which propagates the flood wave down a watercourse (Dutta et al., 2000; Dal Cin et al., 2005). The water levels produced by the hydraulic model can then be used by GIS to generate flood maps. In this way, GIS functions as a pre- and post-processor for hydrological and hydraulic models. A great amount of detail can be added through GIS. For example, modellers can explicitly account for the volume of buildings and other structures for flood mapping in urban areas (Correia et al., 1998).

An integrated modelling approach is also used in testing and designing flood control structures and strategies. Dams constructed for drinking water supply can be simulated to assess their utility in flood mitigation (Gül et al., 2010). Real-time flood management strategies can be obtained by incorporating models of reservoir operation (Yang et al., 2004). Alternatively, the modelling problem can be inverted to optimize gate control strategies in order to meet multiple criteria such as flood reduction and water supply (Shim et al., 2002).

While dams can be valuable structures in flood mitigation, drinking water supply and hydropower, they can also be liabilities. For example, in the United States, many dams predate the use of probable maximum floods (PMF) in spillway design. The IVEX dam in northeastern Ohio is one such structure, and when it failed catastrophically in 1994, 38,000 m^3 of water and sediment were released in the span of two to three minutes (Evans et al., 2000). In an effort to prevent disastrous failures of this type, Hydro One (formerly Ontario Hydro) has re-evaluated the structural safety of its many dams using hydrological and hydraulic models with inflow design floods that may in some cases be much larger than those used in the original dam design (Lee, 1996).

In an urban setting, flood control is largely dependent on a sewer system's capacity for stormwater. The city of Toronto, Ontario, used output from HSPF to design a wet weather flow management plan that includes improvements to the storm sewer infrastructure as well as stream restoration (Toronto and Region Conservation, 2009). Hydrological and hydraulic models are also used in rainfall dependent inflow and infiltration studies to design sanitary sewer systems, to assess their performance and to design overflow prevention strategies under different urbanization and climate scenarios (e.g., Semadeni-Davies et al., 2008; Lowe, 2010). The Storm Water Management Model (SWMM) (US Environmental Protection Agency, 2004) is commonly applied in urban watershed modelling, because it includes hydraulic and water quality modelling components and can be used for single events or continuous simulation (e.g., Hsu et al., 2000; Lowe, 2010).

f *Operational River Forecasting*

River Forecast Centres (RFC) around the world are responsible for forecasting floods and issuing warnings for at-risk areas as needed. Additionally, hydrological models of various types have long been employed by government, academia, and industry to issue seasonal forecasts of water supply and hydroelectric power availability. For instance, the Ottawa River Regulation Planning Board uses a variety of models incorporating hydrology, hydraulics and reservoir operation to assist in reservoir operation (Environment Canada, 2010). The University of British Columbia Watershed Model (UBCWM; Quick and Pipes, 1977) has long been used operationally for forecasting daily streamflows in BC for flood and water supply forecasting by the BC Ministry of Forests, Lands and Natural Resource Operations River Forecast Centre, for hydroelectric reservoir operations planning by BC Hydro, and by Fisheries and Oceans Canada to support salmon fisheries management for the Fraser River system. The US National Weather Service River Forecast System (NWSRFS) applies snow, rainfall-runoff, and routing models among other tools in a comprehensive framework for both flood and long-term water resources planning; their system forms the basis of the US federal government's river forecasting procedures and is used all over the world (NOAA-NWS, 2004).

Originally, river forecasting models were driven by meteorological observations, yielding forecasts with a lead-time or forecast horizon on the order of hours for small catchments. The NWSRFS began using Numerical Weather Prediction (NWP) models to drive hydrological models in the late 1980s in order to extend flood forecast lead-time (Hudlow, 1988).

Relatively recent advances in computing techniques have also led to the use of so-called soft computing approaches in operational streamflow forecasting, including ANNs, fuzzy logic, and evolutionary methods such as Genetic Algorithms (GA) (Dawson and Wilby, 1999; See and Openshaw, 1999). For example, Coulibaly et al. (2000) applied an ANN to daily reservoir inflow forecasting in northern Quebec. This method outperformed the conceptual PREVIS model, which is used operationally in Quebec, and also showed a low deterioration in performance with increasing lead-time. Similarly, an ANN developed for daily inflow forecasting for a catchment in southwest BC was shown to perform better than the physically based UBCWM (Li, 2005), at least in hindcast mode. This suggests that ANNs could be a very useful tool in operational forecasting for hydropower operations. Ongoing advances in machine learning have been quickly adapted to streamflow forecasting applications; a recent example is a comparison of Bayesian Neural Network (BNN), Support Vector Regression (SVR), and Gaussian process methods for short-term forecasting in a small watershed in coastal BC (Rasouli et al., 2012).

According to Cloke and Pappenberger (2009), the state of the art in river forecasting is now represented by the move toward Ensemble Prediction Systems (EPS) in which a number of different weather forecasts are used to drive a hydrological model. This work follows on the successful use of ensemble forecasting in atmospheric science and is discussed in Sections 5 and 6 of this article.

g *Water Quantity and Resource Planning*

In addition to operational forecasting of the availability of water for drinking, agriculture, and hydroelectric generation, hydrological models are used to aid in evaluating strategies for meeting water demand as the population expands. Other important modelling tools in these applications include numerical groundwater flow models and decision support tools, such as CROPWAT, developed by the United Nations Food and Agriculture Organization for calculating crop water and irrigation requirements (Allen et al., 1998).

Cities in arid climates of the United States are increasingly using hydrological models to assess water conservation strategies in order to generate a sustainable water supply (US Environmental Protection Agency, 2002). In Albuquerque, New Mexico, for example, future demand will be met, in part, through non-potable water reclamation, the impacts of which have been assessed using coupled streamflow and groundwater models (Parsons Engineering Science, Inc., 2001; Hines and Gates, 2003). A groundwater modelling study in Sierra Vista, Arizona, has indicated that reclamation recharge basins are well situated to improve long-term local and regional groundwater elevations as well as river baseflow despite a growing demand for groundwater resources (Cain et al., 2009).

Hydrological and related models are also employed in water footprint analysis. A water footprint is defined as the total volume of water used by a consumer to produce goods and services. One of the goals of footprint analysis is to guide water use policy formulation and to use water resources more efficiently. In Spain's Guadiana basin, agriculture accounts for 95% of water use, much of which is used to generate crops with high water requirements and low economic benefit such as cereals and legumes (Aldaya and Llamas, 2009). Results of a modelling study using the CROPWAT model indicate that the use of water for low value crops is a major concern in the Guadiana basin and that future water management policy should emphasize "more cash and nature per drop" (Aldaya and Llamas, 2009, p. 2). A global water footprint study by Mekonnen and Hoekstra (2011), also using CROPWAT, suggests that crop water footprints are influenced by agricultural management practices rather than climate and that this presents an opportunity for improved water productivity. Different footprint analyses for the same area can exhibit great variability as a result of the many assumptions and uncertainties introduced to the model, especially regarding crop properties. However, even these first approximations can clearly show how water policy should evolve (Aldaya and Llamas, 2009).

h *Prediction in Ungauged Basins*

Another common use of hydrological models is in the production of synthetic flow data in basins where observations are not available. In this context, models may be used to simulate peak flows for planning purposes such as flood control design and assessment of water resources (e.g., Moretti and Montanari, 2008) or to generate synthetic data to support water licence applications (e.g., Hatfield et al., 2003).

Predictions in ungauged basins are generally based on the premise that data from a gauged basin can be applied in other locations. This kind of extrapolation carries with it considerable uncertainty (Sivapalan et al., 2003). In fact, the need to apply models to ungauged basins is so common, and the uncertainties so great, that the International Association of Hydrological Sciences (IAHS) has launched an initiative aimed at achieving advances in our ability to make Predictions in Ungauged Basins (PUB). According to Sivapalan et al. (2003), improved prediction will take place through an increased understanding of hydrological processes and the quantification and reduction of uncertainty. The IAHS PUB movement will end this year and is currently focused on finalizing and launching various reports and guidelines (IAHS, 2012).

Even physically based models that simulate known hydrological processes pose a challenge in the PUB context, as the calibration of model parameters is impossible. A common solution is to use parameter regionalization, whereby model parameters are calibrated for gauged watersheds, and the parameters are then related to watershed characteristics through regression (Cutore et al., 2007; Hundecha et al., 2008). Micovic and Quick (1999) explored the applicability of constant model parameters to different watersheds. In applying the UBCWM to twelve heterogeneous watersheds in BC, they found that for most model parameters, the ideal values showed small variation between catchments. A default set of parameters obtained by averaging the results across watersheds provided acceptable results in locations over the province.

Zhao et al. (2009) have suggested that coupling atmospheric and hydrological models could yield useful streamflow forecasts in ungauged basins, because this eliminates the need for observation of meteorological inputs. Indeed, this is the premise behind Environment Canada's Modélisation Environmentale communitaire–Surface and Hydrology (MESH) modelling system (Pietroniro et al., 2007). MESH allows for one-way and two-way coupling of atmospheric and hydrological models, using a 1-dimensional land surface scheme as the common link. Coupled modelling approaches are supported by the IAHS PUB initiative, which is also seeking to develop improved methods for downscaling NWP model output to the basin scale (Sivapalan et al., 2003).

i *Fundamental Scientific Enquiry*

Finally, and perhaps most profoundly, hydrological models can be used to test hypotheses and improve our understanding of hydrological processes and how we simulate them. For example, Wigmosta and Burges (1997) developed a hydrological model for two small watersheds in the US state of Washington. At the beginning of the exercise, it was anticipated that saturation overland flow would drive peak flows in the forested watershed, and the suburban watershed would be dominated by Horton overland flow from impervious surfaces. Through a combination of modelling and measurements, it was determined that both were dominated by subsurface flow resulting from discharge from pervious surfaces. Elshorbagy et al. (2007) have suggested that a similar approach could be used to determine the hydrological processes operating in watersheds reconstructed following mining. The lessons that can be learned through the application of hydrological models are not limited to hydrological processes; they can also be used to increase understanding of the dynamic interactions of the atmosphere and land surface (Singh and Frevert, 2006).

Sensitivity analysis is a useful tool in assessing the importance of model parameters in particular applications of

Table 1. Common approaches for hydrological modelling applications.

Modelling Applications	Considerations and Constraints	Common Modelling Approaches
Land Use/Land Cover Changes	Nonstationarity Ability to explicitly include the LULC changes taking place	Semi- and fully distributed physically oriented models e.g., VIC, DHSVM popular for forestry applications; HSPF, HEC-HMS for urbanization
Climate Change Impacts	Nonstationarity Ability to handle secondary effects such as vegetation composition	Physically oriented models Dependent on impact being studied: e.g., VIC for forestry; SWAT for water quality; HBV-EC for glacier change
Water Quality	Ability to broadly model water quality and/or specific contaminant fate and transport	Physically oriented models that include water quality modules e.g., SWAT, HSPF; SWMM for urban applications
Flood Hazard Planning	Ability to model extreme hydrometeorological events	Physically oriented hydrologic models coupled with hydraulic models (or a cascading model approach) e.g., HEC-HMS; SWMM for urban applications
Operational Forecasting	Limited time and data availability System robustness and defensibility Prediction accuracy usually valued over physical detail	All model types but dependent on institution-specific operational context(s) e.g., semi-distributed models for short-term forecasting (UBCWM, HBV, NWSRFS), empirical models for water supply forecasting
Water Quantity/Resource Planning	Long-term, often large-scale simulation Ability to model groundwater and agricultural effects	Often explicit groundwater models CROPWAT popular for agricultural studies
Prediction in Ungauged Basins	Data requirements Parameter calibration not possible	Semi-distributed physically oriented models
Scientific Enquiry	Ability to model individual components of hydrologic cycle Ability to isolate particular effects of interest	Conceptual or physically based models Empirical (e.g., regression) models for identifying particular effects using formal statistical inference Dependent on specific line of enquiry

hydrological models. Chiew and McMahon (1990) used this approach to determine parameters important to groundwater recharge by perturbing model parameters around their optimum values. They were able to find parameters that had little impact on recharge and those that were strongly correlated to other parameters. This enabled them to reduce the number of parameters requiring optimization in subsequent applications and to guide future improvements to the model.

Models can also aid in the interpretation of data; thus, field observations and modelling exercises must be closely linked in order to understand watershed processes (Alila and Beckers, 2001). In fact, modelling can even aid in determining advantageous field monitoring strategies to reduce model uncertainty (Grayson et al., 1992; Elshorbagy et al., 2007). This model-based approach to hydrological monitoring network design seems to have achieved a greater level of quantitative rigour in groundwater investigations (e.g., Fienen et al., 2010), though examples appear limited to research applications.

3 Approaches to hydrological modelling

Streamflow modelling began with simple rainfall-runoff models based on the systems approach in the late nineteenth century (Dooge, 1973; Todini, 1988). In the systems approach, inputs (for example, rainfall) are converted into outputs (runoff) without concern for the nature of the system or the physical laws acting therein. The rational method was the first model to use a transfer function based on watershed topography and the concept of travel times, and this allowed the prediction of peak flows. The development of the unit hydrograph enabled hydrologists to predict the hydrological response to any amount of rainfall. Despite the restrictive assumptions of these classical methods (namely, a linear, time-invariant system), they are still commonly used in engineering practice (e.g., Titmarsh et al., 1995; Stringer, 2000; Cleveland et al., 2008), although modified versions have been derived that relax these assumptions (e.g., Saghafian, 2006; Crobeddu et al., 2007). Still, the recognition of these limitations in the 1950s led to the development of increasingly conceptual models of the unit hydrograph relating the hydrograph shape to watershed characteristics (Todini, 1988). Conceptual watershed models handling individual components of the hydrological cycle began to appear in the 1960s and 1970s. Proposals for more physically based models representing individual hydrological components and processes through the use of differential equations also arose in the 1960s (e.g., Freeze and Harlan, 1969). As computer power has increased, so too has the complexity of these process-oriented models. Empirical techniques using soft computing have become possible as a result of advances in computer science, and these have evolved alongside physically based models during recent decades. Each modelling approach and each individual model has strengths and limitations that make it suited to particular applications. Table 1 links the modelling approaches discussed presently to modelling applications discussed in Section 2 and describes some of the associated constraints.

a *Empirical Models*

Data-driven hydrological models are essentially black-box approaches that map inputs to outputs without explicitly accounting for the physical hydrological processes responsible for that transformation. These methods fall into two broad categories: statistical methods including Box-Jenkins time series models and regression; and soft computing methods such as ANNs and support vector machines (SVM). In contrast to traditional "hard" computing methods, soft-computing approaches are tolerant of imprecision and uncertainty in order to achieve a low solution cost (Zadeh, 1994).

Box-Jenkins models are a form of univariate time series analysis in which the prediction of a particular variable is based solely on its previous evolution (Box and Jenkins, 1970). Auto-Regressive (AR) and Auto-Regressive Moving Average (ARMA) models fall into this class and have been widely used for modelling time series of runoff despite their origins in linear systems theory (e.g., Salas et al., 1980; Castellano-Méndez et al., 2004; Jain and Kumar, 2007). The AR technique produces a forecast model for a variable based on a linear function of its past values plus a white noise error term, and its common use in hydrology dates at least as far back as the early 1970s (Fiering and Jackson, 1971), with roots going back to the 1960s. The ARMA model adds to this a linear combination of past noise terms. These methods can be combined with regression models to produce ARMA models with exogenous inputs (ARMAX), which have been shown to outperform their univariate counterparts (Haltiner and Salas, 1988; Castellano-Méndez et al., 2004).

In contrast with univariate methods, linear and non-linear regression methods seek to determine how a time series (the predictand) is influenced by other variables (the predictors) (Hsieh, 2009). Note that there is overlap of the Box-Jenkins and regression approaches (e.g., Chatfield, 1996). In linear regression, the parameters of an equation describing the linear predictor-predictand relationship are determined through the minimization of differences between observations and predictions. Methods for this include ordinary least squares, weighted least squares, generalized least squares and least absolute value regression (Pandey and Nguyen, 1999). Robust regression methods based on ranking techniques are also available (for a review, see Helsel and Hirsch, 2002), and principle components regression provides a way of dealing with intercorrelation in predictor variables (Garen, 1992). Similar methods can be applied in non-linear regression, where the model parameters are allowed to be state-dependent.

As with all of the empirical methods presented in this article, it is up to the model developer to determine the appropriate predictors. Thus, even though the model does not attempt to simulate physical processes explicitly, the selection of inputs and interpretation of the model does require the modeller to have an understanding of the processes operating in the watershed. Consider, for instance, the AR with exogenous variables (ARX) model of flow in a small, rainfall-driven coastal catchment developed by Farahmand et al. (2007). The AR predictor (prior streamflow) empirically captures the effects of physical water storage within the catchment by soils, wetlands, channel storage, and so forth, and can be tied back to the physical concept of a hydrograph recession constant (James and Thompson, 1970; Tallaksen, 1995) and indeed to a governing differential equation (Fleming, 2007). By the same token, the exogenous predictor employed in the model (rainfall) obviously captures the physical driving forces behind streamflow generation. Further, it was found that changes in the impulse response functions of ARX models constructed using pre- and post-urbanization hydrometeorological data might be useful for diagnosing the hydrological impacts of LULC changes. Thus, the statistical model is able to capture significant physical meaning and relevance, even though it does not embed, a priori, a direct and detailed mathematical representation of physical hydrological processes.

In addition to conventional statistical techniques, there exists a wide range of biologically or socially inspired mathematical-computational paradigms available for empirical modelling. These often fall under such rubrics as soft computing, hydroinformatics, or computational intelligence. The leading example in hydrology and perhaps in other contexts as well is the ANN, which has been studied in the context of streamflow simulation for the past two decades. ANNs attempt to mimic the neural networks of the human brain, which has an impressive capacity for learning and pattern recognition. A common feed-forward ANN architecture, the Multi-Layer Perceptron (MLP), consists of a layer each of input and output nodes connected by one or more layers of hidden nodes. Data are fed to the input nodes and are then weighted and passed to the hidden layer by a non-linear transfer function. The input to the hidden layer is then weighted and sent to the output layer in a similar fashion. In error back-propagation training, the node weights are initially set to random values, and the network learns by passing errors back and updating weights in order to minimize a non-linear objective function. If the learning process goes on for too long, the model begins to fit to the noise in the training data. This is referred to as overfitting; the model may be able to reproduce the training data almost perfectly, but is not general enough to be applied as a forecasting tool. Methods such as cross-validation have been developed to avoid the overfitting problem (Hsieh, 2009). While ANNs have consistently been shown to outperform older, established versions of traditional Box-Jenkins methods (e.g., Castellano-Méndez et al., 2004; Jain and Kumar, 2007), it has been suggested by Lekkas et al. (2001) that state-of-the-art variants of such traditional methods can perform just as well as ANNs in some cases.

Many hydrological applications of ANNs focus on rainfall-runoff modelling in pluvial catchments, where the model is trained using rainfall and previous runoff as inputs (e.g., Minns and Hall, 1996; Shim et al., 2002; Castellano-Méndez et al., 2004). As another example, Tokar and Johnson (1999) trained a three-layer (one hidden layer) MLP with precipitation, temperature, snowmelt equivalent and discharge for daily runoff modelling. The resulting model generated better results than a physically oriented model. Rasouli et al. (2012) forced a variety of daily forecast methods, including a BNN, with antecedent hydrometric and meteorological station data, Pacific and Atlantic Basin climate indices, and meteorological states drawn directly from archived runs of an NWP model. Additionally, ANNs have been used in non-operational roles to explore the dynamics of streamflow, such as non-linear memory (e.g., Fleming, 2007). Other hydrologically relevant applications are also common. For instance, ANNs have been used as an empirical downscaling tool for the direct prediction of streamflows from GCM output (Cannon and Whitfield, 2002), and a univariate approach has been employed in some hydraulic modelling cases (e.g., Lekkas et al., 2001; Jain and Kumar, 2007). For further information on the basic principles behind ANN and some common applications see Dawson and Wilby (2001).

The MLP ANN with one hidden layer trained using error back-propagation continues to be the most widely used in hydrological applications. In some cases, the MLP architecture is chosen through trial-and-error (e.g., Jain and Kumar, 2007; Sivapragasam et al., 2007). Others adopt the MLP simply because it is considered to be the norm (e.g., Castellano-Méndez et al., 2004). Minns and Hall (1996) compared MLP ANNs with one and two hidden layers, and found that the additional computational expense required for training the second layer was not warranted. Similarly, Shim et al. (2002) found that increasing the number of nodes in the hidden layer increased training time exponentially and did little to reduce model error. Lekkas et al. (2001) compared an MLP with one hidden layer to an ANN whose architecture was allowed to evolve during training and found that the latter model outperformed the popular MLP model in simulating discharge. It is worthwhile to note that, although in practice optimal performance may obviously be more challenging to achieve, in principle an MLP with a single hidden layer can model any continuous function (Cybenko, 1989; Hornik et al., 1989)—potentially a tremendous advantage to this approach. Note, however, that distinctly different ANN architectures, such as the Kohonen network or the Self-Organizing Map (SOM), have also been applied to hydrological analysis and modelling (Kalteh et al., 2008).

Support Vector Machines (SVM) and their extension, Support Vector Regression (SVR), constitute another soft computing tool for non-linear regression and have been used in hydrological research for nearly a decade (Hsieh, 2009). The procedure is similar to ANNs, where inputs are mapped non-linearly to a hidden space and then to an output space, and the model attempts to minimize an error function through training. In SVMs, these spaces are transformed into a much higher dimension using a mathematical formula known as a kernel function. In this higher-dimensional space the mapping functions become linear and the dimensionality of the error function is similarly reduced. For an introduction to SVMs and to kernel methods in general, see Hsieh (2009).

Many of the limitations of ANNs are improved upon by SVMs, and they have been shown to outperform ANNs in many hydrological applications. For example, Behzad et al. (2009) reported that SVMs are able to generalize better than ANNs, though there is still some danger of under- or overfitting to the training data (Han et al., 2007) (true to some extent of virtually any model). The SVMs are also able to learn from a much smaller training set than ANNs, and the global minimum of the linear optimization is easily obtainable, whereas there is a risk of becoming trapped in a local minimum of the non-linear ANN objective function (Behzad et al., 2009).

Similar to the subjective architecture choice in ANNs, the performance of SVMs depends largely on the chosen kernel function. The non-linear Radial Basis Function (RBF) is the most commonly used kernel function (e.g., Asefa et al., 2006; Tripathi et al., 2006). However, as the SVM method is in its infancy in hydrological applications, there is still some debate as to which kernel function is best suited for the purpose. Han et al. (2007) compared the RBF and linear kernel functions and found that even within the same catchment, the ideal function can change under different circumstances. Despite being a relatively new approach to hydrological modelling, SVMs and SVRs have been applied to many of the same problems as ANNs, including rainfall-runoff modelling for water resources planning and flood forecasting at various lead-times (Asefa et al., 2006; Han et al., 2007; Behzad et al., 2009; Rasouli et al., 2012), hydraulic modelling (Liong and Sivapragasam, 2002) and downscaling of GCM output (Tripathi et al., 2006).

Genetic Programming (GP; Koza, 1992) is another soft computing approach to non-linear modelling and is based on Darwin's theory of evolution by natural selection. GP is a recent variant on evolutionary methods such as genetic algorithms (GA), which have been used to optimize ANN architecture and weights (Dawson and Wilby, 2001), SVM parameters (Tripathi et al., 2006), and the parameters of physically oriented hydrological models such as the UBCWM and SWAT (Lan, 2001; Zhang et al., 2009). In GP, a random initial population of equations relating predictors to predictands undergoes evolution over many generations through the sharing and mutation of genetic material (predictors and mathematical operators). The "best" individuals from each generation are selected based on some measure of fitness and go on to produce further generations. Only important variables are retained through the evolutionary process. The input variables and mathematical or logical functions that can be combined into equations are chosen by the model developer based on his or her understanding of the processes being modelled.

The use of GP in hydrological modelling is a relatively new approach and has not enjoyed a wide variety of applications. Rainfall-runoff modelling is a popular application of GP, covering a wide range of temporal scales, from sub-hourly to daily and weekly (e.g., Savic et al., 1999; Liong et al., 2002; Sivapragasam et al., 2007). GP has also shown promise in the field of downscaling GCM output, though it has not yet been directly applied in hydrological studies (Coulibaly, 2004). As with ANNs and SVMs there is a risk of overfitting to the training data (Liong et al., 2002). GP does, however, have the distinct advantage of transparently displaying the relationship between predictors and predictands, whereas this knowledge is hidden in the weights of ANN models. This allows users to gain insight into the physical processes operating in the study watershed (Liong et al., 2002; Sivapragasam et al, 2007). Comparison of ANNs and GP in daily rainfall-runoff modelling has indicated that the two approaches can yield results of similar quality (Savic et al., 1999; Sivapragasam et al., 2007). Aytek and Alp (2008) compared Gene Expression Programming (GEP) (Ferreira, 2006), a recent extension of GP, to ANNs and also found similar results between the two methods, indicating that GEP is a promising rainfall-runoff modelling tool.

Fuzzy Expert Systems (FES) are based on the method of fuzzy logic (Zadeh, 1975) and allow for lack of clarity in the modelling process. This is accomplished through simulating the process of human thought, insofar as the computer is allowed to use approximate reasoning as opposed to precise black and white (Boolean) decisions (Shu and Burn, 2004; Liao, 2005). The first step in building an FES is to choose input and output variables and for each variable to define fuzzy sets, which are expressed linguistically, along with corresponding membership functions, which are expressed quantitatively. For example, rainfall can be characterized as low, average, or high, and a given measurement may simultaneously hold partial membership in more than one of these categories. In the second step, rules that relate the membership functions to outputs are defined through simple linguistic conditional statements based on subjective expert knowledge. The third step is an iterative evaluation and tuning step that seeks to relate observations to the rules. Finally, the fuzzy rules are combined through an inference engine, and defuzzification is used to collapse the fuzzy or approximate model output into a single crisp value.

Similar to GP, FES has the advantage of transparency, as expert knowledge is used to define membership rules (Chau et al., 2005). The performance of an FES is also independent of the volume of data available for training (Mahabir et al., 2003). FES has been applied with satisfactory results to flood frequency analysis (Shu and Burn, 2004), optimal reservoir operation and flow forecasting (Russell and Campbell, 1996), seasonal water supply forecasting (Mahabir et al., 2003), and modelling of individual components of the hydrological cycle, such as infiltration and surface runoff (Bárdossy, 1996). Promising results have also been obtained through the integration of fuzzy logic with ANNs for short-term rainfall-runoff modelling (Chang and Chen, 2001).

Data-driven models require the model developer to choose suitable input variables, requiring some degree of knowledge of the important physical processes, although there are data analysis methods that can help in identifying important parameters (Cannon and Whitfield, 2002). The following discussion of physically oriented models illustrates that this kind of model subjectivity (i.e., selecting a set of predictors or hydrological processes that are optimal to a particular modelling end use in a particular watershed) is a common thread through all hydrological modelling approaches. Data-driven methods also share the risk of overfitting to the training data, which results in a loss of generality, though again this is to some degree true of many models. Other limitations include the difficulty in diagnosing the underlying processes modelled by some empirical methods. For instance, interpreting the physical meaning of the weights in ANN models is difficult, if not impossible (Minns and Hall, 1996; Hsieh, 2009), although certain techniques can in some cases be employed to extract physical understanding from an ANN (e.g., Plate et al., 2000; Cannon and McKendry, 2002; Fleming, 2007).

The primary limitation to empirical, data-driven hydrological models is that, generally speaking, they are applicable only under the same conditions under which they were originally developed. LULC or climate change modelling is therefore largely limited to process-oriented models that can account for such changes (Eckhardt and Ulbrich, 2003; Beckers et al., 2009b). In fact, Grayson et al. (1992) report that the desire to model watershed response to such planned changes has been a primary catalyst for the development of physically based models. Nevertheless, conventional statistical models can play useful, albeit subsidiary, roles in such assessments (e.g., Farahmand et al., 2007), and the assumption of strict stationarity might be relaxed for ANN models in climate change applications, where trends or seasonal variations may be accounted for by hidden layer nodes (Maier and Dandy, 1996; Poff et al., 1996).

b *Process-Oriented Models*

In contrast to the often black-box approach of empirical streamflow models, process-oriented models attempt to simulate directly the physical processes operating in the watershed. While watersheds can be conceptually compartmentalized in various ways, according to Dutta et al. (2000), a physically oriented hydrological model has five major components: interception and evapotranspiration, overland flow, river flow, subsurface flow, and groundwater flow. The simulation of the transport and storage of water through these components is accomplished through the use of basic physical equations describing conservation of various quantities. These models cover a broad spectrum of spatial and process detail, from lumped to fully distributed, and from conceptual to physically based. Because of their ability to simulate actual processes operating in the watershed, process-oriented models have

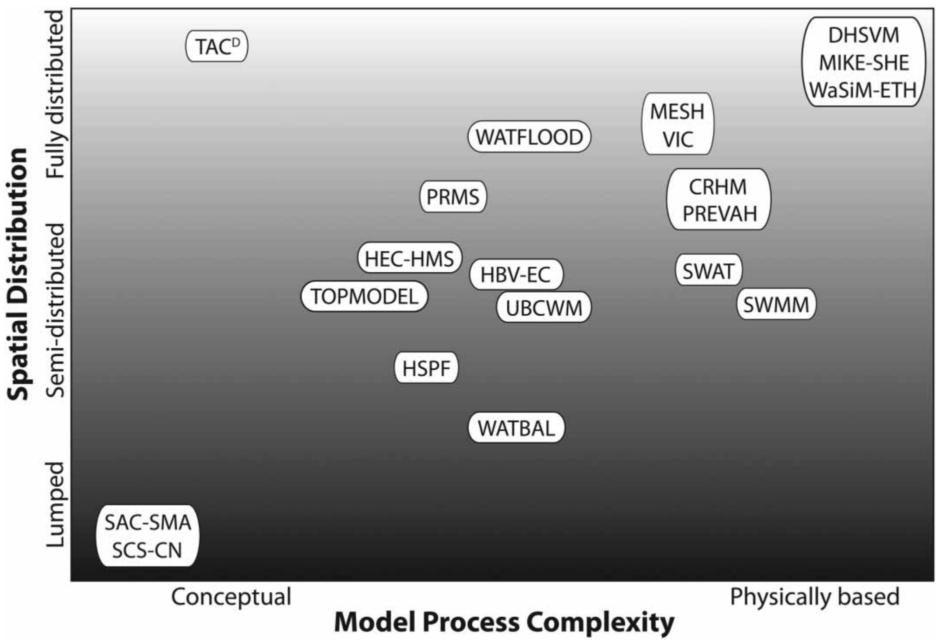

Fig. 1 Process-oriented models may be loosely classified by their degree of spatial distribution and by the sophistication of process representation. While physically complex models tend to have a higher degree of spatial discretization, the relationship between these attributes is not consistent. A given model may represent some processes in a physically detailed manner, while treating others empirically. Therefore, model classification is approximate; placement is based in part on Beckers et al. (2009c).

been employed in all applications, whereas empirical models are generally limited to simulation under conditions of unchanging watershed or climate characteristics. Note, however, that process-oriented models often retain a partially empirical character: this is an inevitable result of the inability to fully characterize all watershed properties at all space and time scales, leading to a requirement for simplified process representations, areally or volumetrically bulk parameters, and parameter calibration (e.g., Kitanidis and Bras, 1980).

As noted in Fig. 1, process-oriented models may be approximately classified by two criteria: degree of spatial distribution and degree of sophistication in process representation. Spatial distribution ranges from lumped, to semi-distributed, to fully distributed, and physical complexity ranges from relatively simple conceptual approaches to fully physically based methods. Loosely, models with simple physical representation tend toward the spatially lumped end of the spectrum, and spatially distributed models tend to be more physically rigorous. However, there is not a one-to-one ratio of spatial to process complexity in models available today. Indeed, some GIS-based water balance models use very simple representations of hydrological processes while being thoroughly spatially distributed (e.g., Olivera and Maidment, 1999), whereas some spatially simple models may incorporate complex process dynamics not included in many fully distributed models, such as seasonal shifts from snow melt to glacial melt production (e.g., Quick and Pipes, 1977). Below, we present an overview of these general approaches, building from simpler modelling structures to more complicated paradigms.

Conceptual models retain relative simplicity while incorporating physical process information not available in the empirical systems approach. This is accomplished by simplifying the mathematical representation of individual physical processes through semi-empirical rules. Despite this simplistic approach, conceptual models are not always inferior to their more physically rigorous counterparts (Ponce and Hawkins, 1996), and their simplicity often leads to both computational speed and robustness, which may be key attributes in certain operational contexts.

In spatially lumped models, one may view the model equations as being applied to a single quasi-location. Each (in general, spatially heterogeneous) characteristic of the watershed is parameterized as a single representative value. These parameters are often estimated statistically, because they cannot be directly interpreted as physically meaningful watershed characteristics that might be estimated by taking point measurements in the field, for instance (Todini, 1988). It should be noted that lumped models owe their existence to our inability to account for the spatial variability of natural phenomena properly, thus the approach is not necessarily poor (Ponce and Hawkins, 1996). In fact, Singh and Woolhiser (2002) point out that such practical limitations prevent a truly distributed approach to hydrological modelling, in which all aspects of the model should be distributed.

Semi-distributed models are intermediate complexity models, which recognize spatial heterogeneity by discretizing a watershed into sub-units. Common approaches are to break the watershed into smaller sub-watersheds, elevation bands or hydrologically homogeneous units. This avoids the need for averaging parameter values over very large heterogeneous areas while requiring less data and computational effort than fully distributed methods. In general, equations describing the hydrology of individual regions are solved for each computational unit, and an area-weighted sum over these units produces the watershed response. The semi-distributed approach essentially allows for hydrological and meteorological model inputs to be represented at the scales corresponding to their respective observations (Comeau et al., 2009). Levels of process complexity within semi-distributed models can vary widely.

Fully physically based hydrological models represent the upper end of the spectrum of process sophistication and detail, but there can be considerable ambiguity within the hydrology community as to what precisely constitutes such a model. The archetype for the fully physically based model is the "blueprint" offered by Freeze and Harlan (1969). This concept involves application of classical methods of mathematical physics to the hydrological modelling problem: definition of a governing set of (most generally, coupled) differential equations and their subsequent solution subject to specified initial and boundary conditions. In general, application of such approaches to practical problems in the geophysical and environmental sciences requires numerical methods, such as finite difference approaches. That having been said, the appropriate level of process detail within a model depends largely upon the application for which the model was originally developed and on the model developer's understanding of relevant hydrological processes. Leavesley et al. (2006) have stated that there are no universal models and that the optimal model for a given application is the one that uses the most appropriate process conceptualizations based on data availability and scale of application. This is an idea that has been repeated in the hydrological modelling literature (e.g., Jakeman and Hornberger, 1993; Elshorbagy, 2006; Maddaus, 2007; Fleming, 2009).

Spatially fully distributed models operate on a spatial grid, the cells of which are linked by fluxes of energy and mass. Fully distributed models admit the possibility of incorporating the effects of heterogeneity into the prediction of basin responses. As such, they can be amenable to modelling much larger (e.g., continental) basins than lumped or semi-distributed models, though this functionality depends in part upon the particular model. Further, fully distributed models allow the extraction of many hydrological variables across the model domain. This attribute can be a significant advantage over lumped and semi-distributed models, which generate only an overall watershed response at the basin outlet (i.e., streamflow at a single point). It is important to note, however, that while the spatial representations utilized in fully distributed models may have the appearance of finite difference grids, such as those routinely employed in groundwater flow and transport models or mesoscale models of atmospheric circulation, this does not necessarily imply that such technical approaches are in fact being employed. Some fully distributed models operate in such a way, but most do not, and as noted at the start of this section, some may be very simple in terms of process detail.

The foregoing model classifications are in common use within the hydrology community and can indeed be quite helpful. However, caution must be used in their application, because few models adhere strictly to the scheme. This is perhaps inevitable given the large number of models that have been developed; Singh and Woolhiser (2002) list over 60 process-oriented hydrological models. We give brief descriptions of a few such models below, and in doing so we hope to provide some feel for these subtleties.

Consider the conceptual and spatially lumped approaches. The Soil Conservation Service Curve Number (SCS-CN) method (Soil Conservation Service, 1956) combines spatially lumped and physically conceptual approaches using a simple mass balance equation. The model was originally developed using strictly empirical methods; however, its conceptual basis has since been explained (Ponce and Hawkins, 1996). Similarly, the Sacramento Soil Moisture Accounting (SAC-SMA) model is spatially lumped but incorporates additional physical processes, such as evapotranspiration and various forms of subsurface flow (Burnash et al., 1973). Further, it has subsequently been integrated into the NWSRFS, which additionally incorporates other modelling packages, such as snowpack and glacier melt models, as well as spatially semi-distributed modelling capabilities (e.g., Cunderlik et al., in press) The first conceptual hydrological model to attempt to simulate the entire hydrological cycle was the Stanford Watershed Model (SWM; Crawford and Linsley, 1966). Since its creation, the SWM has evolved significantly; it is now known as HSPF, which simulates a broad range of hydrological and water quality processes (Brun and Band, 2000).

Semi-distributed models can accommodate the fact that, in mountainous watersheds, elevation is one of the most important variables in the description of runoff. The UBCWM, originally developed for the complex terrain of the Fraser River system in BC, breaks a watershed into area-elevation bands to account for this (Quick and Pipes, 1977). Meteorological data at one or more points are distributed to these elevations using orographic gradients. The HBV model and its variants, such as HBV-EC, are very widely adopted models that operate on a similar philosophy (Bergström, 1976; Moore, 1993), though HBV-EC allows for further discretization of climate zones into smaller sub-units. Both the UBCWM and HBV-EC are robust, fast models for hydrological prediction in mountainous regions with limited data; conversely, these models also explicitly incorporate certain physical complexities associated with such environments that are omitted from many other models, such as a detailed model of seasonal snow melt, as well as the ability to model glacier melt contributions to flow explicitly.

Alternative approaches to semi-distributed modelling are also available. SWAT (Arnold et al., 1998) and the TOPographically based hydrological model known as TOPMODEL (Beven and Freer, 2001a) both lump processes at the

Hydrological Response Unit (HRU) level. The HRU approach divides watersheds into areas with uniform characteristics such as slope, aspect, soil type, elevation, and climate. These computational elements can be groups of grid squares, sub-basins, or elevation bands of different areas (Kite and Pietroniro, 1996). Further, the Cold Regions Hydrological Model (CRHM) also discretizes a watershed based on the HRU approach but differs from other hydrological models in its flexibility (Pomeroy et al., 2007). CRHM is essentially a platform for the development of a hydrological model, and it offers a range of spatial complexity from lumped to distributed as well as a range of physical realism from conceptual to physically based. The Precipitation-Runoff Modelling System (PRMS) also employs HRUs along with a modular approach that allows the creation of a user-defined model (Leavesley et al., 1983).

The WATer BALance (WATBAL) hydrological model was developed as a compromise between lumped, conceptual models and fully distributed physically based models (Knudsen et al., 1986). WATBAL uses a physically based HRU approach for processes affecting soil moisture where measurable parameters are available and well-proven relations exist. For subsurface flows, a lumped conceptual approach is used because of limitations on data availability. The Precipitation-Runoff-Evaporation-Hydrotope (PREVAH) model also discretizes a watershed using HRUs and uses a mix of physically based and empirical methods to model various components of the hydrologic cycle (Gurtz et al., 1997). The Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS) is semi-distributed in that it breaks a watershed into hydrological elements connected in a dendritic pattern. Available hydrological elements are sub-basins, reaches, junctions, reservoirs, diversions, sources, and sinks. Computation begins at upstream elements and proceeds in the downstream direction; therefore, its functionality is limited to relatively simple stream networks. The individual models for simulating the hydrologic cycle within HEC-HMS range from lumped to distributed and empirical to conceptual (US Army Corps of Engineers, 2000).

As noted above, distributed models divide the watershed into a grid pattern, explicitly recognizing heterogeneity in watershed processes and characteristics. By the same token, fully physically based models attempt to capture all relevant hydrological processes in a detailed way. But again, many models occupy a grey area between fully distributed and semi-distributed approaches and between physically based and conceptual or even empirical methods. The Distributed Hydrology-Soil-Vegetation Model (DHSVM) was developed specifically for the complex terrain of the Pacific Northwest (Wigmosta et al., 1994). The model accounts for snow accumulation and melt and also for the effects of forest roads on hydrological processes (VanShaar et al., 2002). The Water Flow and Balance Simulation Model (WaSiM-ETH) was originally designed to examine the effects of climate change in pre-alpine and alpine watersheds of varying size (Jasper et al., 2002). Thus, unlike DHSVM, this model simulates glacier melt (Beckers et al., 2009b). MIKE-SHE (Graham and Butts, 2006), an offshoot of the Système Hydrologique Européen (SHE) (Abbott et al., 1986), is similar to CRHM in that it is a flexible framework for modelling in lowland areas. Hydrological processes can be represented at different levels of spatial and process complexity according to the goals of the model application and the availability of data (Graham and Butts, 2006). The model is applicable from the scale of a single soil profile to large regions covering multiple river catchments. MIKE-SHE is a very advanced fully distributed, physically based hydrological model that incorporates advanced hydraulic modelling capabilities through integration with MIKE 11. However, it still includes some empirical equations, illustrating the fact that physically based models are never completely so (Abbott et al., 1986; Abu El-Nasr et al., 2005).

The WATFLOOD model (Kouwen, 2010) integrates a fully distributed grid approach with the use of the Grouped Response Unit (GRU). In this case, HRUs lying within one computational element are grouped into a GRU (Kite and Kouwen, 1992). Hydrological processes are modelled identically for each group of HRU, and the responses of each group are weighted and summed to generate a total GRU outflow (Kouwen et al., 1993). The size of the computational element is determined by the resolution of meteorological data or the desired level of detail in model output. This approach allows WATFLOOD to preserve subgrid-scale hydrological variability without sacrificing computational efficiency. WATFLOOD routing is used in the MESH regional hydrological modelling system where it is linked with a land surface scheme to enable coupling with atmospheric models (Pietroniro et al., 2007). Thus, MESH also uses the GRU approach, but the land surface model is run at a higher resolution on each GRU. The Variable Infiltration Capacity (VIC) model is a macroscale model that was developed for continental-scale basins but accounts for subgrid-scale variability of many watershed characteristics (Liang et al., 1994). While the land surface is modelled as a grid of large, flat, uniform cells, VIC can subdivide these cells into elevation bands in order to consider spatial heterogeneity in, for example, precipitation and snowmelt. The desire to apply the model to cold regions led to the addition of cold land processes such as spatially variable snow cover and frozen soils and lakes (Cherkauer et al., 2003).

In practice, there are tradeoffs between different levels of spatial or process complexity. The direct modelling of complex physical processes requires not only more computational time to run the model but also more time and effort (and therefore cost) in parameter determination. For example, in their high-resolution application of the spatially distributed conceptual Tracer-Aided Catchment (TAC^D) model, Uhlenbrook et al. (2004) found that a very small time step was required for accurate routing, which led to run times on the order of two hours for a one-year simulation. As a result of these long computation times, only a limited number of calibration runs were executed. Run times can be a mission-critical model attribute in some contexts, such as certain types of operational forecasting, and can therefore force certain model choices (e.g., Cunderlik et al., in press). Conversely, in other contexts it may be largely irrelevant, or might be mitigated by application of parallel processing resources. As another example, the lumped SCS-CN model requires the determination of a single parameter that is related to watershed characteristics, whereas the physically based WaSiM-ETH model (Schulla, 1997) requires the calibration of roughly 50 parameters (Uhlenbrook et al., 2004). When we consider spatial distribution, this number quickly increases, because many of these parameters need to be determined for each individual grid cell or watershed sub-unit. This results in an ill-posed calibration problem, as observations are not generally available at this same spatial scale.

Despite the fact that process-oriented models represent a more complex form of modelling than empirical methods, it should be emphasized that physically oriented models do not necessarily represent an evolutionary improvement over data-driven methods. In fact, soft computing methods have emerged alongside physically based models as computing power has increased in recent decades. The two approaches are competitive in terms of their quality of simulation, and offer advantages in different areas. Broadly speaking, data-driven methods are comparatively simple to implement for a particular watershed and very fast to use but are limited to unchanging watersheds and generally provide a single output such as runoff at the basin outlet. At the opposite extreme, fully spatially distributed, fully physically based models are very complex, and their high data requirements can lead to decreased accuracy (relative to data-driven approaches) in data-poor regions (Beckers et al., 2009a). Indeed, a lack of faith in the predictive abilities of these models has been reported in the past (e.g., Beven, 1989; Grayson et al., 1992). Still, it is recognized that they are useful for our increased understanding of physical processes (Woolhiser, 1996); they can also simulate these processes over long periods of time and provide a great deal of distributed model output beyond runoff (e.g., estimates of evaporative losses), although such simulation results may be challenging to verify in some cases. It has been argued that the disappointment with physically based hydrological models is a result of unrealistic expectations of the model, not of model failure itself (Smith et al., 1994). This points to an important broader lesson in hydrological modelling, namely the need to understand the capabilities and limitations of any given model, whether empirical or physically oriented, and to compare these characteristics to the problem at hand, that is, choosing the right tool for the job.

4 Uncertainty in streamflow model output

Simulations derived from both data-driven and process-oriented hydrological models are subject to various sources of uncertainty. Net model uncertainty is the product of closely linked errors in meteorological inputs, terrestrial hydrological initial conditions, and process representation or empirical relationships, as well as uncertainty in often ill-defined model parameters. Non-linearities in the model can cause the resulting errors to become amplified throughout the forecast process. The following discussion focuses on uncertainty in physically oriented model output, though much of this material applies to empirical simulation as well. Modelling frameworks have been developed to deal with some of the aforementioned error sources; these are discussed in Section 5.

a *Data Error*

The apparent quality of streamflow model output is limited by the quality of the data used to drive, calibrate, and validate the model. Inaccuracies in precipitation data are often cited as serious impediments to successful hydrological modelling (e.g., Larson and Peck, 1974; Yang et al., 2004). In addition to typically systematic instrument error, in-situ observations of liquid and especially solid precipitation can be negatively affected by deflection of particles by the wind, though this problem can be mitigated through careful site selection (Larson and Peck, 1974). Precipitation observations in mountainous terrain can be influenced by icing or blowing snow, which can also introduce huge random errors in measurement (Lapin, 1990; Yang and Ohata, 2001). Inconsistencies in an observation record can also be caused by changes in instrument type or placement.

The measurement of Snow Water Equivalent (SWE) by snow pillows or through manual snow surveys can be affected by the presence of ice layers in the snowpack that form when snow melts and then re-freezes. These ice layers can form bridges over the snow pillow, resulting in decreased pressure on the instrument and therefore unrealistic reported decreases in SWE when in fact no snowmelt has occurred (Sorteberg et al., 2001).

Although remote sensing techniques have improved in recent years, their measurements carry with them some degree of uncertainty, and improvements are needed in some applications. For example, Andreadis and Lettenmaier (2006) showed that satellite-observed snow coverage extent could be used to improve SWE estimates made by the macro-scale VIC model. Remotely sensed SWE on the other hand was consistently underestimated for deep snowpacks. Remote sensing can also be used to infer near-surface soil moisture, but vegetation and surface roughness can impact data quality (Schmugge et al., 2002). Radar has the potential to improve streamflow forecasts through the distributed nature of its precipitation observations (Yang et al., 2004). Moreno et al. (2012) compared quantitative precipitation estimates from satellite, radar, and rain gauges and found that the spatially distributed products brought more value to the forecast than rain gauge data in spite of the larger uncertainties. The added time and computational resources required for the acquisition and processing of distributed data may, however, be prohibitive in an operational forecast setting where there are significant time constraints and, in general, such distributed rainfall data may be at its most useful when applied to distributed hydrological models.

Digital Elevation Models (DEM), which are one of the most important spatial datasets for hydrological modelling, make use of remotely sensed data as well as field survey observations. DEM data contain systematic and random errors that can be reduced through filtering (Schmugge et al., 2002). Data derived from DEMs such as slope, flow direction and drainage area contain additional errors as a result of the algorithms used to derive them (Wechsler, 2006). This algorithm error becomes especially problematic with high-resolution DEM data, which can, for example, generate very high slope values. However, it has been shown that DEM accuracy is highly correlated with sampling interval and generally increases with resolution (Li, 1992). Wechsler (2006) provides a detailed review of sources of uncertainty associated with DEM and DEM-derived data.

Some information used in hydrological modelling is calculated from observable quantities based on certain assumptions. For example, a water balance approach can be used to infer reservoir inflows based on observed changes in depth and known reservoir discharges. However, failure to accurately account for components of the water balance such as seepage, percolation, or evaporation may result in erroneous inflow calculation (Guerra et al., 1990). Additionally, recorded reservoir depth and dam operation information may contain measurement errors (for example, due to seiches) that significantly affect the accuracy of inflow estimates.

Discharge is another hydrological quantity that is usually not measured directly. In this case, a rating curve describes the relationship between river stage and discharge. This curve is dependent on flow velocity and the cross-sectional area of the stream channel at a particular location. Changes in water velocity as a result of the growth of in-stream vegetation or changes in cross-sectional area as a result of scouring or deposition in the streambed can cause the rating curve to shift (Bedjaoui et al., 2008). Extrapolation of the rating curve to flows higher than those used in its derivation can also lead to a high degree of uncertainty in streamflow measurement (Clark et al., 2008). The estimation of streamflow data during periods when observation is not possible because of ice cover or instrument failure is another source of error (Stahl et al., 2008).

Finally, some data used in hydrological modelling of past events are derived from a combination of observations and model output, resulting in a combination of their respective errors. An example of such a product is the North American Regional Reanalysis (NARR) generated by the US National Centers for Environmental Prediction (NCEP). The NARR has been particularly successful in assimilation of high-quality and detailed precipitation observations, resulting in improved analysis of land hydrology. In areas where observations incorporated into the reanalysis are uncertain or sparse (in complex terrain, for example), the reanalysis itself becomes more uncertain, though the regional product does show improvement over its lower-resolution global counterparts (Mesinger et al., 2006).

b *Meteorological Representation*

Even if accurate, precipitation or other meteorological observations may not be representative of true, overall watershed conditions. This may be especially important for lumped hydrological models, where a temperature or precipitation value measured at one location is assumed to have occurred uniformly over the entire watershed, albeit generally following the application of some calibrated adjustment factor (Brun and Band, 2000; Yang et al., 2004). Localized rainfall events over a gauge site can lead to overrepresentation of precipitation within a watershed; conversely, hydrologically important precipitation events that occur away from the gauge will be overlooked.

Sparse rain gauges can also cause problems in distributed hydrological modelling, and the associated errors tend to grow more quickly in these often more complex non-linear models (Woolhiser, 1996). In some cases, precipitation observations are not available at all within the modelled catchment, and data from relatively distant gauge sites must be used, resulting in deterioration in model performance (Anderson et al., 2006). In addition, it may be difficult to account for localized meteorological effects, such as convective thunderstorm cells, within larger basins.

The process of distributing meteorological data across the watershed must account for temperature lapse rates and the rate of increase of precipitation with elevation, both of which may vary seasonally or on shorter time scales (Alila and Beckers, 2001). Mountainous terrain can also raise issues around rain shadow effects and a dependence of precipitation amount upon the relationship between storm movement and valley orientation. Thus, even a relatively dense network of measurement sites may be unable to capture the spatial distribution of precipitation and temperature.

Various interpolation methods have been developed to reproduce these patterns. Classical approaches such as Thiessen polygons (Thiessen, 1911) and inverse distance weighting (IDW; Wei and McGuinness, 1973) do not account for topography and may, therefore, be suitable only over relatively flat terrain. Regression techniques explicitly account for elevation in the interpolation process (Daly, 2006). However, single regression functions may have difficulty handling spatially varying relationships (Daly, 2006), and multiple regression models have been found to over-extrapolate and can become unnecessarily complicated (Kurtzman and Kadmon, 1999).

IDW has been incorporated into multi-step interpolation procedures in which temperature observations are normalized to sea level using a constant linear lapse rate adjustment prior to the application of IDW, and then the interpolated sea-level temperatures are adjusted back to model elevation using the same lapse rate function (e.g., Leemans and Cramer, 1991; Willmott and Matsuura, 1995). Such methods are simple to implement, computationally fast, and can produce spatial patterns very similar to more complex methods, although results are sensitive to the selected lapse rate (Dodson and Marks, 1997). Blandford et al. (2008) have recommended the use of monthly averaged lapse rates as a simple way to account for their significant variability. This method has also been applied to precipitation interpolation despite a less direct correlation with elevation (Westrick and Mass, 2001).

Recent decades have seen an emphasis on geostatistical interpolation methods such as kriging, especially for precipitation (e.g., Tabios and Salas, 1985; Dingman et al., 1988; Goovaerts, 2000). Geostatistics is based on the theory of regionalized variables; it takes advantage of knowledge of the spatial variability of the quantity in question (Matheron, 1971) and can explicitly accommodate the various forms of spatial correlation common in many geophysical quantities including surface meteorological variables. It also provides unbiased estimates and quantifies uncertainty in the interpolation (Journel and Huijbregts, 1978). For a detailed description of kriging techniques, which is beyond the scope of this paper, see Tabios and Salas (1985). Ordinary kriging has been shown to outperform classical methods such as Thiessen polygons and IDW (Tabios and Salas, 1985; Tobin et al., 2011), although the added complexity may not be warranted in regions with high-density observation sites where simpler methods perform almost as well (Goovaerts, 2000). Elevation can be incorporated through multivariate kriging methods such as co-kriging or kriging with external drift, both of which have been found to perform better than ordinary kriging at interpolating precipitation and temperature in complex terrain (Martinez-Cob, 1996; Goovaerts, 2000; Tobin et al., 2011).

Another example of geostatistical downscaling is the Statistical Interpolation (SI) technique used by the Canadian Meteorological Centre to generate initial conditions for NWP model runs (Rutherford, 1972). The method combines observations with short-term forecast fields (to fill in gaps in the observing network), weighting each data source according to their respective error statistics. The SI technique is used to produce the Canadian Precipitation Analysis (CaPA), which is available in real time at relatively fine spatial and temporal scales (Mahfouf et al., 2007). The CaPA method has been shown to perform well for summer precipitation events, but the method may not be able to produce high-quality precipitation analyses in winter or in complex terrain where observation quality is questionable.

c *Weather Forecast Uncertainty*

In an operational forecast setting, streamflow models are generally driven by weather model output. This allows for a longer forecast lead-time relative to observation-driven forecasts but introduces an additional source of uncertainty. It has been reported that the uncertainty in NWP model output is the largest source of uncertainty in NWP-driven flow forecasts with a time horizon beyond several days, whereas for shorter lead-times, uncertainties in the hydrological model dominate prediction errors (Coulibaly, 2003; Cloke and Pappenberger, 2009). However, the comparative importance of the two forms of error over the two time scales depends on context. For example, for an anticipated heavy rainstorm in a small and flashy catchment, uncertainty around the amount of rainfall expected over the next day may have considerably more impact on the quality of tomorrow's streamflow forecast than moderately incomplete or inaccurate models of the terrestrial component of the hydrological cycle.

Some of this NWP uncertainty is related to meteorological representativeness. A possible inexpensive solution to the sparseness of observations in some watersheds is provided by NWP models. Unfortunately this model output may not be representative of the true state at the ground surface. The output from the lowest horizontal slice of the weather model domain generally does not coincide with the ground surface, so meteorological variables of interest to hydrological modellers must be extrapolated to this level (Seuffert et al., 2002). Additionally, distributed hydrological models are often run with much higher spatial resolution than atmospheric models, requiring the downscaling or disaggregation of meteorological variables from NWP to hydrological model scale. The smoothing of topography in NWP models can also result in inadequate orographic enhancement of precipitation (Jasper et al., 2002). Bindlish and Barros (2000) incorporated small-scale, time-varying effects of terrain and winds in the interpolation of mesoscale NWP model precipitation fields and found improvements in forecasts of streamflow and runoff.

Deficiencies in rainfall forecasts are often cited as major challenges in the use of NWP model output for streamflow modelling. This is especially true in complex terrain where orographic effects are important and can lead to large systematic errors (Jasper et al., 2002; Pappenberger et al., 2005). An increase in NWP model resolution has improved weather forecasts greatly over the past few decades, but rainfall forecasts remain heavily dependent on subgrid-scale parameterizations of the precipitation-forming processes and are subject to additional sources of uncertainty. Also, the forecast skill of smaller scale weather features deteriorates faster than for larger scales (Stull, 2000). Thus, the location and intensity of heavy convective showers may become incorrect after approximately three hours into the future. Still, NWP has the potential to bring tremendous value to streamflow forecasts by virtue of its spatially distributed nature (Moreno et al., 2012) and its ability to increase forecast lead-time.

A common approach to overcome the shortcomings of precipitation forecasts is to remove the systematic error or bias in the forecast field. Bias correction fields can be obtained through a comparison of forecasted and observed precipitation (Westrick et al., 2002), or of forecasted and observed streamflows (Kouwen et al., 2005). The use of time-dependent bias correction factors can offer additional improvements, because precipitation biases can be highly dependent on synoptic-scale forcing, especially in complex terrain (Westrick et al., 2002; Yoshitani et al., 2009). A similar improvement may be obtained by calibrating the hydrological model using meteorological predictions rather than observations (Coulibaly, 2003; Rasouli et al., 2012). However, this approach requires a relatively long archive of NWP forecasts over which the weather model does not undergo any major changes. That requirement can be challenging, because operational NWP models are fine-tuned regularly, with more complete updates every few years. In contrast to systematic error, random errors in weather forecasts can be reduced through the use of ensemble forecasting techniques, discussed presently.

The problem of NWP representativeness becomes more difficult to solve as we move up in scale to GCMs, which do a poor job of resolving topography and other land surface related heterogeneities (Wood et al., 2002). Dynamical and statistical downscaling techniques can be used to address this challenge, as discussed previously. The use of GCM output for hydrological simulations of potential climate change scenarios carries with it great uncertainty. This includes errors in estimations of future greenhouse gas emissions, climate sensitivity, regional responses, and changes in the intensity and frequency of weather extremes (Eckhardt and Ulbrich, 2003; Wilby et al., 2006). The choices made in estimating these model parameters as well as the choice of global climate model result in a broad range of possible future scenarios (Christensen et al., 2004). Wilby et al. (2006) and Teng et al. (2012) have illustrated that uncertainty in future climate change scenarios far outweighs uncertainties associated with hydrological models. Others have found that GCM uncertainty dominates the early part of the forecast horizon, but then other sources of uncertainty become more important (Jost and Weber, 2012).

d *Model Process Uncertainty*

Hydrological models are, by definition, simplified representations of complex natural systems. Process uncertainty arises from the simplified or incorrect representation of hydrological processes or their omission entirely. Imperfect process representation may be caused by the necessary use of simplified functional relations between hydrological elements or, alternatively, by our insufficient knowledge of the physics that govern these processes (Kitanidis and Bras, 1980; Niehoff et al., 2002). As data availability and computational speed have increased, the model representation of hydrological processes has become more accurate (Kouwen et al., 2005). In some cases, however, process understanding is still so limited that we are forced into black-box approaches (Sivapalan et al., 2003). The erroneous omission of processes can be caused by the simple fact that the modeller is unaware that these processes are important to watershed response. Thus, model structure is often a quantitative expression of the modeller's experience and subjective hydrological understanding (Wagener, 2003).

The errors introduced to streamflow simulations by process uncertainty are dependent on hydrological regime. For example, Stahl et al. (2008) cited available snowmelt algorithms as an important source of uncertainty in their application of the HBV-EC model to a catchment in complex terrain in BC; this source of error would likely play a central role in overall model uncertainty during winter and the spring snowmelt period, but its importance would decrease through the summer (Götzinger and Bárdossy, 2008). Likewise, the presence of glacier melt algorithms in the WaSiM-ETH model would provide little benefit to applications in watersheds without glaciers. An understanding of the limitations and capabilities of the many hydrological models available, and the geophysical characteristics of the target watershed, will go a long way toward reducing errors introduced by process uncertainty.

e *Model Parameter Uncertainty*

The equations that govern hydrological processes contain parameters having values derived from observation, professional experience, or model calibration. A single, correct value often cannot be uniquely or reliably identified. This leads to an additional source of hydrological model uncertainty that may be closely related to process uncertainty (Götzinger and Bárdossy, 2008). When NWP output is used to drive a forecast model, parameter uncertainty may also be related to NWP uncertainty through the use of precipitation or evapotranspiration adjustment parameters (Herr et al., 2003; Carpenter and Georgakakos, 2006). Since observations of model outputs are used to calibrate model parameters, the uncertainty in these observations also affects parameter uncertainty.

As an example, GIS data can be used to generate topographical parameter sets for distributed parameter models with a spatial resolution that would be impractical for manual measurement (Wechsler, 2006). Understanding the propagation of errors from the GIS information to these parameters is an important challenge. Further, even high-resolution parameter information requires some degree of lumping, because the scale of measurement is naturally larger than the actual scale of heterogeneity in the watershed. This lumping results in effective parameter values only loosely associated with local watershed characteristics, making it very difficult to make suitable estimates of parameter values without calibration (Pappenberger et al., 2005). Parameter uncertainty is by no means a problem only of distributed models, however. Parameters that describe processes that are not well understood, that are simply impossible to measure, or that are employed in semi-empirical model components also require calibration (Niehoff et al., 2002). Alternatively, parameter values can be taken from the literature, but in some cases these may not be suitable for the region of interest (Stahl et al., 2008).

Elshorbagy (2006, p. 1) states that "in order to go beyond rainfall-runoff modelling and to reduce the parameter uncertainty, the calibration of the developed model should be based on all simulated processes … not just runoff." Unfortunately, a common impediment to the successful calibration of model parameters is the availability of observations with which to compare the various model outputs (e.g., Brun and Band, 2000; Eckhardt and Ulbrich, 2003). As hydrological models have increased in complexity, the additional parameter requirements have led to an increase in associated uncertainty despite more complete simulation of hydrological processes (Kouwen et al., 2005). Jakeman and Hornberger (1993) cite overparameterization as a major challenge in rainfall-runoff modelling, and Beven (1989) has suggested that three to five parameters should be sufficient to reproduce the hydrological record.

Parameter calibration is carried out through trial-and-error by adjusting model parameters until the model output is sufficiently close to observations. This may be done by manual iteration (in which case success is largely dependent on modeller experience and understanding) in a more automated fashion through the use of any one of a wide range of optimization algorithms or by a combination of both. A selection of parameter optimization methods providing estimates of associated predictive uncertainty are described in Section 5.

In parameter optimization or calibration, the closeness of fit is measured by an objective function, the choice of which can have an impact on the resulting optimum parameter set (Özelkan and Duckstein, 2001; Wagener, 2003), although visual hydrograph matching and other qualitative or quantitative tests of model fit also normally play important roles in practice. Different objective functions may be sensitive to different parts of the hydrograph; thus, the choice of a single function will necessarily lead to a biased calibration (Duan et al., 2007; Götzinger and Bárdossy, 2008). For example, the Nash-Sutcliffe Efficiency (NSE) emphasizes peak flow periods, whereas the NSE of the log-transformed discharge will tend to generate a parameter set with better performance during recession and low flow periods (Schnorbus et al., 2010). Multi-objective optimization algorithms, discussed in Section 5, are growing progressively more popular and generally involve the identification of a parameter set that optimally balances multiple competing objectives.

The non-unique dependence of model error upon parameter values is commonly known in the hydrological literature as equifinality. Complex models with many parameters are not the only victims of this problem; even simple models with a small number of parameters may give similarly good results with different parameter sets (Beven, 1989). The existence of multiple equally plausible parameter sets may suggest that none accurately represent watershed characteristics; the right runoff can be obtained for the wrong reasons. The non-uniqueness of parameter sets can also make it difficult to obtain well-defined relationships between mathematical model parameters and readily measured watershed characteristics.

5 Frameworks for the anticipation of forecast uncertainty

Only two decades ago, there were no ideal methods for assessing predictive uncertainty arising from parameter uncertainty, and no methods at all to account for model process uncertainty (Beven, 1989). Though the search for ideal methods still continues (Beven, 2006; Liu and Gupta, 2007), research efforts over the past two decades have led to the development of various frameworks for the minimization or estimation of the various sources of model uncertainty. Such efforts have focused primarily on uncertainties arising from NWP and hydrological model processes and parameter estimation. Hydrological state or initial condition uncertainty has gained attention relatively recently (Liu and Gupta, 2007). These frameworks generally use some sort of Monte Carlo method to produce a number of forecasts that sample the range of forecast uncertainty. This enables us to generate probabilistic forecasts from deterministic hydrological models that, on their own, neglect uncertainty (Kitanidis and Bras, 1980). Uncertainty in model predictions has led to numerous recommendations for the use of probabilistic forecasting frameworks in hydrology (e.g., Krzysztofowicz, 2001; Coulibaly, 2003; Beven, 2006; Wilby et al., 2006) and to initiatives such as the Hydrologic Ensemble Prediction Experiment (HEPEX) (Schaake et al., 2006). The following description focuses on operational river forecast applications, but many of the issues presented are strongly relevant to non-forecast applications as well.

a *Meteorological Uncertainty*

Research into probabilistic weather forecasts began in the 1960s, building on Lorenz's (1963) work in chaos theory. By the 1980s, ensembles of forecasts based on multiple initial conditions (multi-analysis ensembles) were being made in research mode; the first operational EPS was generated by NCEP in 1992 (Sivillo et al., 1997). Varied-model ensemble weather forecasts can be generated by running the same model with alternative physics schemes or parameterizations. Ensemble forecasts from the Meteorological Service of Canada combine the multi-analysis and varied-model ensemble approaches to sample a wide range of predictive uncertainty (Environment Canada, 2012). The success of ensemble weather forecasting has led to its adoption in hydrology, primarily through the use of ensemble NWP output to drive a deterministic hydrological model (Cloke and Pappenberger, 2009). That is, the hydrological model is re-run using different weather predictions to generate an ensemble of hydrographs. Ensemble methods have even been applied to capture uncertainty in observed meteorological quantities such as radar-estimated precipitation (Einfalt et al., 2010).

The first efforts in ensemble streamflow prediction (ESP) used an ensemble of meteorological observations from the climate record for long-term prediction (Day, 1985). ESP methods of this type are still routinely used for seasonal to annual water supply forecasting purposes (i.e., for forecast time scales at which NWP models do not provide useful skill). Conditioning of the ESP upon the El Niño-Southern Oscillation state by schemes involving a weighting of historical climate traces has more recently been explored for operational water supply forecasting at seasonal time scales (e.g., Werner et al., 2004). Additionally, operational weather forecast ensembles such as those distributed by the European Centre for Medium-Range Weather Forecasts (ECMWF) have recently been applied to flood forecasting in research mode (e.g., Gouweleeuw et al., 2005; Roulin and Vannitsem, 2005). Super-ensembles or grand-ensembles, derived from the combination of ensembles from each of several forecast centres, capture NWP uncertainty arising from various sources of model error in addition to initial condition error (Pappenberger et al., 2008). Uncertainty in climate change projections and their impacts on hydrology are also assessed using a multi-model approach, with GCM output from different models incorporating different emissions scenarios (e.g., Minville et al., 2008). Additional uncertainty introduced by interpolation or downscaling methods could also be incorporated into hydrological ensembles by using different downscaling methods to generate an ensemble of meteorological forcings from a single NWP or climate model run or a single set of meteorological observations.

b *State Uncertainty*

In NWP, ensembles are commonly generated by running a weather model with multiple sets of varying initial conditions. This follows naturally from the existence of deterministic chaos—a highly non-linear sensitivity to initial conditions—in the weather, as it is impossible to know the exact state of the atmosphere at any given time (Lorenz, 1963). The possible existence of chaos in hydrological processes has been investigated with inconclusive results (Sivakumar, 2000; Sivakumar et al., 2001; Khan et al., 2005). Nevertheless, errors in initial conditions are recognized as an important source of uncertainty in hydrological modelling as well (Liu and Gupta, 2007).

In order to reduce uncertainty in state variables such as soil moisture or SWE, data assimilation methods have been developed to update internal hydrological model states through an optimal combination of a model background and observations. Such methods include variational data assimilation and adaptations of the Kalman Filter (KF) algorithm (Liu and Gupta, 2007). Four-dimensional Variational data assimilation (4-D VAR) is able to account for errors in observations and initial conditions as well as model processes. This is accomplished by choosing an initial state such that an optimum fit to observations is obtained throughout an initial model run prior to the desired forecast start time. This approach has shown to be feasible in assimilation of remotely-sensed soil moisture data (Reichle et al., 2001). Unfortunately, 4-D VAR seeks only to minimize uncertainty in state estimations; it does not provide any measure of predictive uncertainty. This method also assumes that model errors have a Gaussian distribution, which is rarely true in hydrological modelling (Clark et al., 2008).

Kalman filtering is a recursive procedure for finding an unbiased and optimal estimator of a state vector that consists of two steps: prediction and update (Kalman, 1960). In the prediction step, the KF algorithm uses linear dynamics to predict the state at the current time step based on the state estimate from a previous time. In the update step, the predicted state is refined through weighted combination with observations based on relative errors. This optimal state is then used to advance to the next step, and so on. Variations on the original KF algorithm have made it suitable for use with non-linear problems such as NWP and hydrological modelling. A commonly used variant is the Ensemble Kalman Filter (EnKF; Evensen, 1994) in which an ensemble of initial conditions is used to run the (non-linear) hydrological model until an observation becomes available (e.g., Andreadis and Lettenmaier, 2006; Clark et al., 2008). At this time, the model states are updated based on relative errors in the model and observations. Model error covariances are obtained from the ensemble anomalies with respect to the ensemble mean; errors associated with observations are generally known in advance. These are perturbed to obtain an ensemble of observations such that each ensemble forecast state is updated differently, and the ensemble variance does not become reduced (Burgers et al., 1998). The EnKF has shown promise in assimilation of remotely sensed snow coverage and SWE data in complex terrain (Andreadis and Lettenmaier, 2006). Clark et al. (2008) applied the EnKF in the assimilation of streamflow data and found the method to be inappropriate because of the non-linear relationship between streamflow and the state variables. Improved results were found with a variant of the EnKF method, the Ensemble Square Root Filter (EnSRF). This method obtains a large enough analysis error covariance without adding noise to the observations. Another variant, the bias-aware Retrospective Ensemble Kalman Filter (REnKF) can successfully update state variables using observations of discharge by accounting for associated time lags (Pauwels and De Lannoy, 2006). These EnKF methods have a distinct advantage over 4-D VAR in providing estimates of predictive uncertainty through the use of ensembles; however, the assumption of a Gaussian error distribution remains an issue.

c *Parameter Uncertainty*

Minimization of parameter error is generally done through calibration. As outlined briefly above, automated procedures are often used to optimize the fit of model output to observations by repeatedly adjusting parameters until some convergence criterion is met. The non-linear nature of physically oriented (and some empirical) hydrological models makes many such procedures impractical because of the existence of local minima on the optimization function surface. Global optimization methods such as the Shuffled Complex Evolution algorithm developed at the University of Arizona (SCE-UA; Duan et al., 1992) and its extension, the Multi-Objective Complex Optimization Method (MOCOM-UA; Yapo et al., 1998) have been shown to be efficient methods for parameter calibration. They use evolutionary procedures to breed the optimal parameter set from a randomly selected original population.

The existence of equally likely sets of parameter values has long been recognized (Binley et al., 1991) and has led to the development of probabilistic and stochastic methods for estimating parameter uncertainty. As an example, adaptations of SCE-UA and MOCOM-UA have been developed, which merge their strengths with those of the Metropolis algorithm (Metropolis et al., 1953), the earliest and most general class of Markov Chain Monte Carlo samplers. The Shuffled Complex Evolution Metropolis algorithm (SCEM-UA; Vrugt et al., 2003b) and the Multi-Objective Shuffled Complex Evolution Metropolis algorithm (MOSCEM-UA; Vrugt et al., 2003a) converge to an ensemble of parameter sets that can be used to infer probabilistic uncertainty. The Simultaneous Optimization and Data Assimilation (SODA) method combines SCEM-UA with an EnKF to improve the treatment of input, output, parameter uncertainty, and structural uncertainty, resulting in "meaningful prediction uncertainty bounds" (Vrugt et al., 2005, p. 2). Fuzzy logic also provides a framework for dealing with parameter uncertainty and can be used to estimate output error (Özelkan and Duckstein, 2001).

A number of methods for estimating parameter uncertainty operate within a Bayesian framework. For example, the Generalized Likelihood Uncertainty Estimation (GLUE) method introduced by Beven and Binley (1992) can be considered a simplified Bayesian procedure (Mantovan and Todini, 2006). In GLUE, Monte Carlo sampling is used to generate different sets of parameter values from specified (typically non-informative, i.e., uniform) prior distributions. The model is then run with each set. Through comparison of model output with observations, each set is identified as "behavioural" (acceptable) or "non-behavioural" (not acceptable), and behavioural sets are assigned a likelihood that they simulate the system accurately. Each behavioural parameter set is weighted by its (rescaled) likelihood, resulting in a posterior distribution of parameter sets that provides information about parameter identifiability, uniqueness, and interrelationships (e.g., Shen et al., 2012). The suite of behavioural parameter sets may also be used to generate an ensemble of hydrological predictions. The effects of model and observation errors are handled implicitly by GLUE in the calculation of the likelihood of each parameter set given the observations (Beven and Freer, 2001b).

Another more rigorously Bayesian approach is Bayesian Recursive Estimation (BaRE; Thiemann et al., 2001). Again, sets of parameter values are chosen randomly from a prior distribution. Then the model is run using the various parameter sets until an observation becomes available. At this time, the probabilities of the parameter sets are updated, and the process repeats with this new distribution until the next observation arrives. Unlike GLUE, BaRE makes strong, explicit assumptions about observation error characteristics and, through the recursive use of observations, allows model parameters to vary in time (Liu and Gupta, 2007). Both GLUE and BaRE use Monte Carlo sampling to approximate the parameters' posterior distributions; indeed, this greatly reduces the computational effort required to implement Bayesian procedures, which otherwise require the calculation of integrals that are usually impossible to evaluate analytically. It has also been suggested that Markov Chain Monte Carlo algorithms can increase the efficiency of the search for behavioural parameter sets (e.g., Kuczera and Parent, 1998; Marshall et al., 2004; Blasone et al., 2008).

d *Model Structure Uncertainty*

Equifinality refers not only to the existence of different parameter sets within a model structure that produce acceptable simulation results but also to the existence of many possible suitable model structures. Beven and Binley (1992) define model structure as including model processes and other considerations such as spatial discretization and boundary conditions. Structural uncertainty is typically handled through the use of multiple streamflow models. The literature reveals an inclination to use model combination for minimization rather than quantification of structural uncertainty. This error minimization occurs because of the cancellation of random errors in the individual ensemble members when they are combined through averaging.

Shamseldin et al. (1997) were the first to apply the multi-model ensemble approach in rainfall-runoff modelling, using four empirical models and a simple lumped, conceptual model. Three different methods were used to combine the forecasts from these models: a Simple Average Method (SAM), Weighted Average Method (WAM), and Neural Network Method (NNM). Their results showed that, in general, better discharge predictions could be obtained through model combination. Similarly, Coulibaly et al. (2005) applied the WAM to combine forecasts from a simple regression model, an ANN model, and a lumped conceptual model. They found that the multi-model ensemble mean produced better daily reservoir inflow forecasts than the post-corrected conceptual model alone. Ajami et al. (2006) combined distributed model output and found that using uncalibrated models, the SAM streamflow forecast was superior to any individual ensemble member forecast, including the best calibrated single-model forecast. These examples clearly illustrate the power of the ensemble forecasting approach.

By way of a corollary, recall that the reason such multi-model ensembles work is that all the models within the ensemble are partly wrong, but presumably each in a different way. Thus, they span the error space, providing an effective estimate of uncertainty; and the errors they individually produce tend to mutually cancel upon averaging. This fact might have an implication for choosing the constituent models. In particular, it would seem wise to include a broad range of modelling concepts within the ensemble (e.g., a linear statistical model, a soft computing model, a lumped conceptual model, a fully distributed process model). As such, the structural errors are more likely to be different among ensemble members, relative to what might be obtained using multiple models of the same class (e.g., a number of different semi-distributed conceptual models).

e *Net Model Uncertainty*

Most of the frameworks for uncertainty estimation discussed above attempt to quantify uncertainty from one error source alone. Various methods employed to estimate streamflow model parameters and their associated uncertainties, such as GLUE, account for other sources of uncertainty only implicitly insofar as model structural errors or meteorological representation error might lead to ambiguity in the best-fit parameter set. The SODA method accounts for both state and parameter uncertainty, and the use of the EnKF algorithm means that data errors are also included (Vrugt et al., 2005). The dual state-parameter estimation method of Moradkhani et al. (2005) similarly accounts for uncertainty in model inputs, outputs, and parameters through the use of the EnKF algorithm. Krzysztofowicz (2001) states that probabilistic forecasts should, by definition, quantify *total* uncertainty and that ensembles often do not satisfy this criterion. Thus, "an ensemble forecast does not always constitute a probabilistic forecast" (Krzysztofowicz, 2001, p. 8).

A survey of recent literature reveals that this remains true today. The vast majority of the literature on the subject of predictive uncertainty in hydrology accounts for only one or two sources of uncertainty. For example, the NWSRFS ESP system generates probabilistic water supply forecasts operationally using the original method of Day (1985), whereby streamflow simulation is driven by historical sets of temperature and precipitation data (Franz et al., 2003). Thus, the ESP accounts only for uncertainty in meteorological inputs.

Research efforts into probabilistic streamflow forecasts through the use of ensembles similarly neglect some sources of uncertainty. Georgakakos et al. (2004) used multiple calibrated and uncalibrated hydrological models, some with many parameter sets to assess streamflow prediction uncertainty. Duan et al. (2007) used three hydrological models, each calibrated using three different objective functions to derive a nine-member ensemble that assessed uncertainty arising from model structure and parameter uncertainty. Carpenter and Georgakakos (2006) used a Monte Carlo sampling framework to account for both parametric and radar-rainfall uncertainty. Pappenberger et al. (2005) took this approach one step further, using ECMWF ensemble weather forecasts with the GLUE framework to cascade model uncertainty from the weather model through a rainfall-runoff model and finally through an inundation model. According to Krzysztofowicz's (2001) definition, none of the above-cited work constitutes a truly probabilistic forecast.

Ensembles are not the only way to estimate predictive uncertainty. Another common approach is to analyze the statistical properties of past forecast errors in order to determine error bounds around a single prediction (e.g., Montanari and Brath, 2004; Feyen et al., 2008; Weerts et al., 2011). By the same token, empirical hydrological modelling methods may directly generate confidence bounds, an obvious example being the standard error of a linear regression model. Error bounds of this sort would seem to come close to capturing the total modelling uncertainty, and indeed, such error estimation may often be entirely serviceable (e.g., in a seasonal water supply forecasting context). However, there are limitations to such an approach. Assumptions are generally necessary regarding the statistical properties of the predictive error, and these may be restrictive or inappropriate. Also, the advantage of the method—alleviation of the need to account for every source of predictive uncertainty explicitly—can itself be a disadvantage, as there is little or no opportunity for diagnosis of specific error sources, which can be an important step in model refinement for instance. Further, it is difficult or impossible to generate ensembles of physically realistic individual hydrograph traces using this method. This trace representation of uncertainty may be necessary in some contexts —for instance, some of the engineering models employed by BC Hydro to support hydroelectric reservoir operations in BC require an ensemble of equally likely individual hydrograph forecasts as input.

6 Concluding remarks

A survey of empirical and physically based hydrological models reveals a stark contrast between the fields of hydrology and atmospheric science. The most obvious difference is in the number of available models in the two fields. All NWP models essentially use the same set of equations to model the atmosphere. Models differ primarily in scale, the numerical approximation of the governing equations, and the parameterization of subgrid-scale processes. Global weather modelling is made possible by the fact that these models drive fluxes of various quantities through a largely homogeneous medium. In streamflow modelling, on the other hand, models move water through soils and over topography that is extremely variable over even small distances; this movement and storage is subject to many different physical and biological effects—some coupled and some independent, some present in certain catchments and absent in others—operating at a wide range of spatial and time scales that may or may not be relevant to the particular modelling application at hand. From this point of view, the practice of developing a model for specific watersheds and specific purposes with different data requirements may be warranted, if not necessary.

While the number of available models may seem problematic, this diversity in fact presents an advantage in the context of ensemble modelling. Because of the choices made by the developers of physically oriented models, each is good at simulating different parts of the hydrological cycle. In addition, the subjective choices made in soft computing approaches can result in models that perform well at different times (Han et al., 2007). By combining predictions from different models and from different modelling approaches, it is possible to take advantage of the expertise of each of them, theoretically resulting in better overall predictive capabilities.

A central theme in recent streamflow modelling research is the quantification of prediction uncertainty. We identify here some possible future directions for such work, drawing in part from the experience of the NWP modelling community but recognizing that terrestrial hydrological modelling is a distinct field presenting its own set of challenges.

First and foremost, there is a clear need for a more rigorous framework for the estimation of net model uncertainty. It is important to accept that certain errors are unavoidable and to understand how uncertainty cascades through hydrological modelling systems. This is a key aspect of the Cooperation in Science and Technology Action 731 (COST-731; see Rossa et al., 2010; Zappa et al., 2010).

Since Lorenz's (1963) work in chaos theory, the quantification of uncertainties in both initial conditions and model processes has become common practice in weather forecasting through the use of ensembles. Probabilistic weather forecast products have been largely accepted by industry and the public alike. The use of multi-model, multi-analysis super-ensembles represents a truly probabilistic approach, accounting for uncertainties in initial conditions, parameterizations, and model structure (Ross and Krishnamurti, 2005). A similar approach is needed for hydrological applications to increase ensemble spread and capture the full range of predictive uncertainty.

In NWP, the ensemble members or forecast probabilities are adjusted to make them reliable. This property ensures that an event forecast to occur with probability p will, over the course of many such forecasts, occur a fraction p of the time. For a variety of reasons, raw ensemble forecasts and their associated probabilities are not reliable and must be adjusted through processes known as ensemble and probabilistic calibration (not to be confused with hydrological model or parameter calibration). Ensemble calibration methods often focus on the bias correction and combination of ensemble members to produce reliable probabilities through, for example, Bayesian Model Averaging (Raftery et al., 2005) or Gaussian regression (Gneiting et al., 2005). Probabilistic calibration on the other hand adjusts the probabilities directly (Hamill and Colucci, 1997; Nipen and Stull, 2011). Such methods could be used to generate probabilistic forecasts that satisfy Krzysztofowicz's (2001) definition without *explicitly* accounting for all sources of error.

It has been suggested that the ensemble and probabilistic calibration methods employed in NWP are necessary because the calibration of model parameters would be too computationally intensive (Wood and Schaake, 2008). However, the idea that ensemble calibration is simply an efficient replacement for parameter optimization implies that parameter uncertainty is the greatest, if not the only, source of error in NWP model forecasts. While parameter uncertainty is undoubtedly important in NWP (as evidenced by the use of varied-model ensembles), there are many other sources of error that dominate the forecasts at different lead-times. The same is true in streamflow prediction. We have already seen that hydrological model output uncertainty is a product of many interacting sources of error. Ensemble streamflow predictions are inherently overconfident because of the deterministic treatment of these uncertainties (Wood and Schaake, 2008). Thus, even perfectly calibrated parameter sets will produce ensembles in need of further ensemble or probabilistic calibration.

Methods for the ensemble and probabilistic calibration of weather forecasts have been developed only over the past decade or so, and practitioners in hydrology have been quick to adapt these to their needs. While this is still a relatively new concept, both Bayesian Model Averaging (Duan et al., 2007) and Gaussian regression (Wood and Schaake, 2008) have been employed to produce reliable streamflow forecast probabilities. Probabilistic calibration has also been applied to improve the spread and reliability of probabilistic hydrological forecasts (Olsson and Lindström, 2008).

Effective communication of model output uncertainty is a critically important part of the hydrological modelling process. In the context of operational river forecasting, as probabilistic forecasts become more widely used, this communication will undoubtedly improve. It will require the development of methods for the display of probabilistic output that allow operational hydrologists to ascertain the uncertainty in individual forecasts quickly and to express those results in a meaningful and accessible way to their clients. A variety of visualization tools have been developed, but there is not yet a consensus on how to present this kind of information (Bruen et al., 2010). The best methods are likely to be user dependent and will require the cooperation of modellers and forecast product users.

There is also a need in hydrology for a framework for the verification and comparison of hydrological model output, both deterministic and probabilistic. There have been great steps taken toward this goal in weather forecasting (see Jolliffe and Stephenson, 2003). In hydrological modelling, a distinct lack of objectivity and consistency in verification methods has been reported in the past (Dawson and Wilby, 2001). Recently, verification frameworks developed for and used in deterministic and ensemble weather forecasting applications have been adopted by hydrologists, both in research settings (e.g., Randrianasolo et al., 2010; Van den Bergh and Roulin, 2010) and operations (Adam Gobena, BC Hydro, personal communication, 2011).

Others have recommended the increased cooperation among fields within earth sciences and the need for interdisciplinary approaches (e.g., Shapiro et al., 2010). Through increased coordination between the fields of hydrology and atmospheric science in both research and operations, we should see improvements in streamflow forecasts. This will occur through technical advances in probabilistic forecast and verification practices, through an improved understanding of hydrological client needs on the part of atmospheric scientists, and through the sharing of expertise across the division between hydrology and weather—a division that exists only in scientific practice, not in the physical world.

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