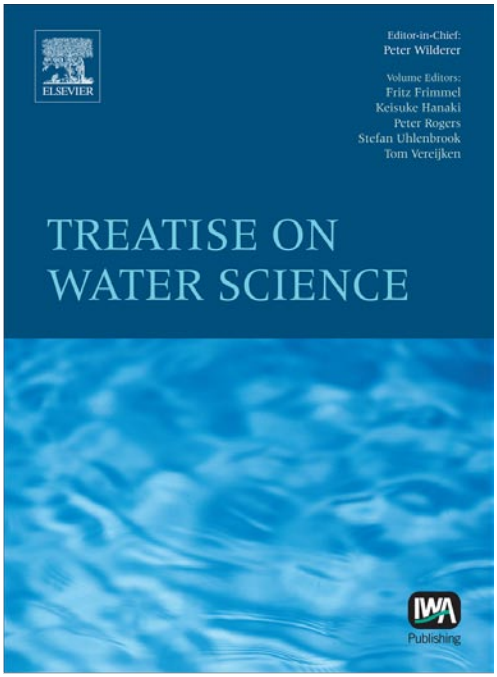

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2.16 Hydrological Modeling

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2.16.1 Introduction

Hydrological models are simplified representations of the terrestrial hydrological cycle, and play an important role in many areas of hydrology, such as flood warning and management, agriculture, design of dams, climate change impact studies, etc. Hydrological models generally have one of two purposes: (1) to enable reasoning, that is, to formalize our scientific understanding of a hydrological system and/or (2) to provide (testable) predictions (usually outside our range of observations, short term vs. long term, or to simulate additional variables). For example, catchments are complex systems whose unique combinations of physical characteristics create specific hydrological response characteristics for each location (Beven, 2000). The ability to predict the hydrological response of such systems, especially stream flow, is fundamental for many research and operational studies.

In this chapter, the main principles of and approaches to hydrological modeling are covered, both for simulation (process) models that are based on physical principles (conceptual and physically based), and for data-driven models. Our intention is to provide a broad overview and to show current trends in hydrological modeling. The methods used in data-driven modeling (DDM) are covered in greater depth since they are probably less widely known to hydrological audiences.

2.16.1.1 What Is a Model

A model can be defined as a simplified representation of a phenomenon or a process. It is typically characterized by a set of variables and by equations that describe the relationship between these variables. In the case of hydrology, a model represents the part of the terrestrial environmental system that controls the movement and storage of water. In general terms, a system can be defined as a collection of components or elements that are connected to facilitate the flow of information, matter, or energy. An example of a typical system considered in hydrological modeling is the watershed or catchment. The extent of the system is usually defined by the control volume or modeling domain, and the overall

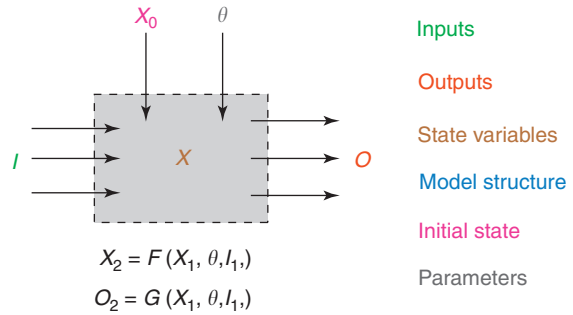

Figure 1 Schematic of the main components of a dynamic mathematical model. I, inputs; O, outputs; X, state variables; X_0, initial states; and θ, parameters.

modeling objective in hydrology is generally to simulate the fluxes of energy, moisture, or other matter across the system boundaries (i.e., the system inputs and outputs). Variables or state variables are time varying and (space/time) averaged quantities of mass/energy/information stored in the system. An example would be soil moisture content or the discharge in a stream [L3/T]. Parameters describe (usually time invariant) properties of the specific system under study inside the model equations. Examples of parameters are hydraulic conductivity [L/T] or soil storage capacity [L].

A dynamic mathematical model has certain typical elements that are discussed here briefly for consistency in language (Figure 1). Main components include one or more inputs I (e.g., precipitation and temperature), one or more state variables X (e.g., soil moisture or groundwater content), and one or more model outputs O (e.g., stream flow or actual evapotranspiration). In addition, a model typically requires the definitions of initial states X_0 (e.g., is the catchment wet or dry at the beginning of the simulation) and/or the model parameters θ (e.g., soil hydraulic conductivity, surface roughness, and soil moisture storage capacity).

Hydrological models (and most environmental models in general) are typically based on certain assumptions that make them different from other types of models. Typical assumptions that we make in the context of hydrological modeling include the assumption of universality (i.e., a model can represent different but similar systems) and the assumption of physical realism (i.e., state variables and parameters of the model have a real meaning in the physical world; Wagener and Gupta, 2005). The fact that we are dealing with real-world environmental systems also carries certain problems with it when we are building models. Following Beven (2009), these problems include the fact that it is often difficult to (1) make measurements at the scale at which we want to model; (2) define the boundary conditions for time-dependent processes; (3) define the initial conditions; and (4) define the physical, chemical, and biological characteristics of the modeling domain.

2.16.1.2 History of Hydrological Modeling

Hydrological models applied at the catchment scale originated as simple mathematical representations of the input-response behavior of catchment-scale environmental systems through parsimonious models such as the unit hydrograph (for flow routing) (e.g., Dooge, 1959) and the rational formula (for excess rainfall calculation) (e.g., Dooge, 1957) as part of engineering hydrology. Such single-purpose event-scale models are still widely used to estimate design variables or to predict floods. These early approaches formed a basis for the generation of more complete, but spatially lumped, representations of the terrestrial hydrological cycle, such as the Stanford Watershed model in the 1960s (which formed the basis for the currently widely used Sacramento model (Burnash, 1995)). This advancement enabled the continuous time representation of the rainfall–runoff relationship, and models of this type are still at the heart of many operational forecasting systems throughout the world. While the general equations of models (e.g., the Sacramento model) are based on conceptualizing plot (or smaller) scale hydrological processes, their spatially lumped application at the catchment scale means that parameters have to be calibrated using observations of rainfall–runoff behavior of the system under study. Interest in predicting land-use change leads to the development of more spatially explicit representations of the physics (to the best of our understanding) underlying the hydrological system in form of the Systeme Hydrologique Europeen (SHE) model in the 1980s (Abbott *et al.*, 1986). The latter is an example of a group of highly complex process-based models whose development was driven by the hope that their parameters could be directly estimated from observable physical watershed characteristics without the need for model calibration on observed stream flow data, thus enabling the assessment of land cover change impacts (Ewen and Parkin, 1996; Dunn and Ferrier, 1999).

At that time, these models were severely constrained by our lack of computational power – a constraint that decreases in its severity with increases in computational resources with each passing year. Increasingly available high-performance computing enables us to explore the behavior of highly complex models in new ways (Tang *et al.*, 2007; van Werkhoven *et al.*, 2008). This advancement in computer power went hand in hand with new strategies for process-based models, for example, the use of triangular irregular networks (TINs) to vary the spatial resolution throughout the model domain, that have been put forward in recent years; however, more testing is required to assess whether previous limitations of physically based models have yet been overcome (e.g., the lack of full coupling of processes or their calibration needs) (e.g., Reggiani *et al.*, 1998, 1999, 2000, 2001; Panday and Huyakorn, 2004; Qu and Duffy, 2007; Kollet and Maxwell, 2006, 2008).

2.16.1.3 The Modeling Process

The modeling process, that is, how we build and use models is discussed in this section. For ease of discussion, the process is divided into two components. The first component is the model-building process (i.e., how does a model come about), whereas the second component focuses on the modeling protocol (i.e., a procedure to use the model for both operational and research studies).

The model-building process requires (at least implicitly) that the modeler considers four different stages of the model

(see also Beven, 2000). The first stage is the perceptual model. This model is based on the understanding of the system in the modeler's head due to both the interaction with the system and the modeler's experience. It will, generally, not be formalized on paper or in any other way. This perceptual model forms the basis of the conceptual model. This conceptual model is a formalization of the perceptual model through the definition of system boundaries, inputs–states–outputs, connections of system components, etc. It is not to be mistaken with the conceptual type of models discussed later. Once a suitable conceptual model has been derived, it has to be translated into mathematical form. The mathematical model formulates the conceptual model in the form of input (–state)–output equations. Finally, the mathematical model has to be implemented as computer code so that the equation can be solved in a computational model.

Once a suitable model has been built or selected from existing computer codes, a modeling protocol is used to apply this model (Wagener and McIntyre, 2007). Modeling protocols can vary widely, but generally contain some or most of the elements discussed below (**Figure 2**). A modeling protocol – at its simplest level – can be divided into model identification and model evaluation parts. The model identification part mainly focuses on identifying appropriate parameters (one set or many parameter sets if uncertainty in the identification process is considered), while the latter focuses on understanding the behavior and performance of the model.

The starting point of the model identification part should be a detailed analysis of the data available. Beven (2000) provided suggestions on how to assess the quality of data in the context of hydrological modeling. This is followed by the model selection or building process. The model-building process has already been outlined previously. In many cases, it is likely that an existing model will be selected though, either because the modeler has extensive experience with a particular model or because he/she has applied a model to a similar hydrological system with success in the past. The universality of models, as discussed above, implies that a typical hydrological model can be applied to a range of systems as long as the basic physical processes of the system are represented within the model. Model choice might also vary with the intended modeling purpose, which often defines the required spatio-temporal resolution and thus the degree of detail with which the system has to be modeled.

Once a model structure has been selected, parameter estimation has to be performed. Parameters, as defined above, reflect the local physical characteristics of the system. Parameters are generally derived either through a process of calibration or by using *a priori* information, for example, of soil or vegetation characteristics. For calibration, it is necessary to assess how closely simulated and observed (if available) output time series match. This is usually done by the use of an objective function (sometimes also called loss function or cost function), that is, a measure based on the aggregated differences between observed and simulated variables (called residuals). The choice of objective function is generally closely coupled with the intended purpose of the modeling study. Sometimes this problem is posed as a multiobjective optimization problem. Methods for calibration (parameter estimation) are covered later in Section 2.16.5. Further, the model

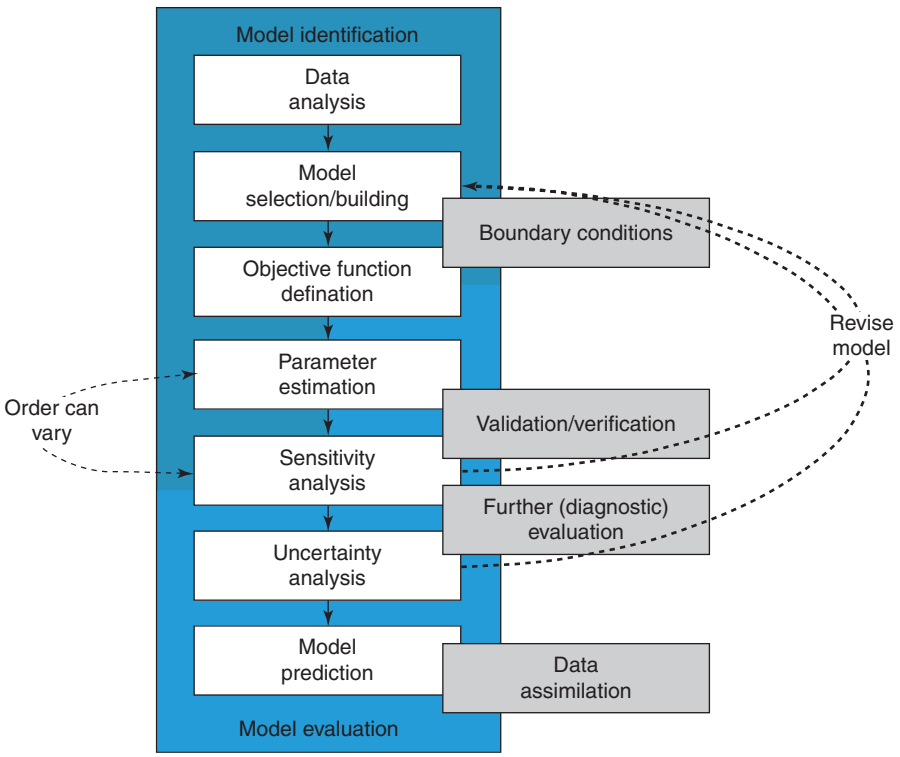

Figure 2 Schematic representation of a typical modeling protocol.

should be evaluated with respect to whether it provides the right result for the right reason. Parameter estimation (calibration) is followed by the model evaluation, including validation (checking model performance on an unseen data set, thus imitating model operation), sensitivity, and uncertainty analysis. A comprehensive framework for model evaluation (termed diagnostic evaluation) is proposed by Gupta *et al.* (2008).

One tool often used in such an evaluation is sensitivity analysis, which is the study of how variability or uncertainty in different factors (including parameters, inputs, and initial states) impacts the model output. Such an analysis is generally used either to assess the relative importance of model parameters in controlling the model output or to understand the relative distributions of uncertainty from the different factors. It can therefore be part of the model identification as well as the model evaluation component of the modeling protocol.

The subsequent step of uncertainty analysis – the quantification of the uncertainty present in the model – is increasingly popular. It usually includes the propagation of the uncertainty into the model output so that it can be considered in subsequent decision making (see Section 2.16.7).

When a model is put into operation, the data progressively collected can be used to update (improve) the model parameters, state variables, and/or model predictions (outputs), and this process is referred to as data assimilation.

One aspect needs mentioning here. Due to the lack of information about the modeled process, a modeler may decide not to try to build unique (the most accurate) model, but rather consider many equally acceptable model parametrizations. Such reasoning has led to a Monte-Carlo-like method of uncertainty analysis called Generalised Likelihood Uncertainty Estimator (GLUE) (Beven and Binley, 1992), and to research into the development of the (weighted) ensemble of models, or multimodels (see e.g., Georgakakos *et al.*, 2004).

2.16.2 Classification of Hydrological Models

2.16.2.1 Main types of Hydrological Models

A vast number of hydrological model structures has been developed and implemented in computer code over the last few decades (see, e.g., Todini (1988) for a historical review of rainfall–runoff modeling). It is therefore helpful to classify these structures for an easier understanding of the discussion.

Many authors present classification schemes for hydrological models (see, e.g., Clarke, 1973; Todini, 1988; Chow *et al.*, 1988; Wheater *et al.*, 1993; Singh, 1995b; and Refsgaard, 1996). The classification schemes are generally based on the following criteria: (1) the extent of physical principles that are applied in the model structure and (2) the treatment of the model inputs and parameters as a function of space and time. According to the first criterion (i.e., physical process description), a rainfall–runoff model can be attributed to two categories: deterministic and stochastic (see **Figure 3**). A deterministic model does not consider randomness; a given input always produces the same output. A stochastic model has outputs that are at least partially random.

Deterministic models can be classified based on whether the model represents a lumped or distributed description of the considered catchment area (i.e., second criterion) and whether the description of the hydrological processes is empirical, conceptual, or more physically based (Refsgaard, 1996). With respect to deterministic models, we will distinguish three classes: (1) data-driven (also called data-based, metric, empirical, or black box models), (2) conceptual (also called parametric, explicit soil moisture accounting or gray box models), and (3) physically based (also called physics-based, mechanistic, or white box models) models. The two latter classes are sometimes referred to as simulation (or process) models. **Figure 4** provides some guidelines on estimation of structure and parameters for various types of deterministic models.

Note that the distinction between deterministic and stochastic models is not clear-cut. In many modeling studies, it is

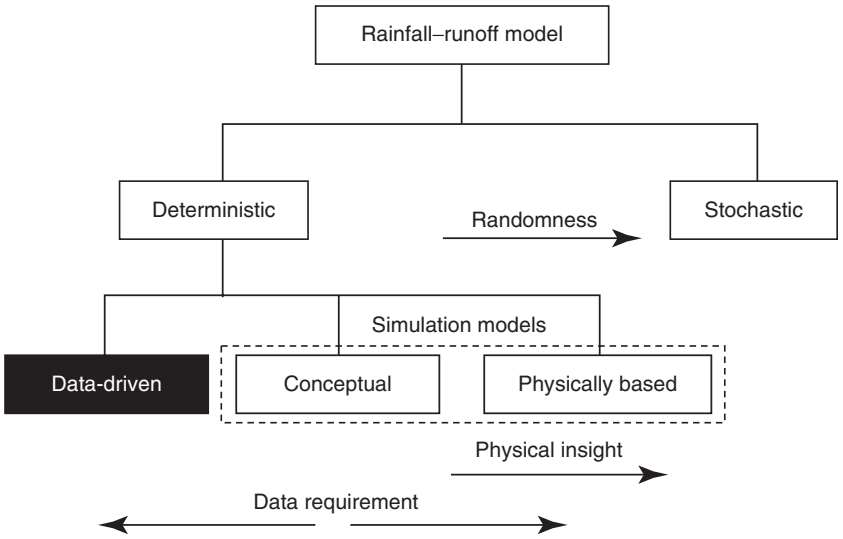

Figure 3 Classification of hydrological models based on physical processes. Adapted from Refsgaard JC (1996) Terminology, modelling protocol and classification of hydrological model codes. In: Abbott MB and Refsgaard JC (eds.) *Distributed Hydrological Modelling*, pp. 17–39. Dordrecht: Kluwer.

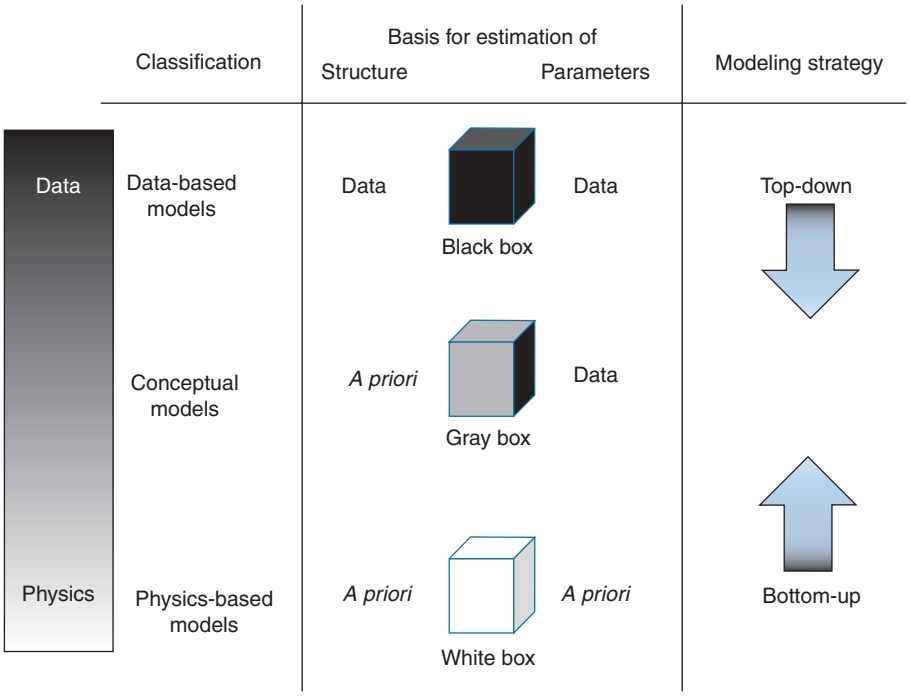

Figure 4 Estimation of structure and parameters for various types of deterministic models.

assumed that the modeled variables are not deterministic, but still more developed apparatus of deterministic modeling is used. To account for stochasticity, additional uncertainty analysis is conducted assuming probability distributions for at least some of the variables and parameters involved.

2.16.3 Conceptual Models

Conceptual modeling uses simplified descriptions of hydrological processes. Such models use storage elements as the main building component. These stores are filled through fluxes such as rainfall, infiltration, or percolation, and emptied through processes such as evapotranspiration, runoff, and drainage. Conceptual models generally have a structure that is specified *a priori* by the modeler, that is, it is not derived from the observed rainfall–runoff data. In contrast to empirical models, the structure is defined by the modeler's understanding of the hydrological system. However, conceptual models still rely on observed time series of system output, typically stream flow, to derive the values of their parameters during the calibration process. The parameters describe aspects such as the size of storage elements or the distribution of flow between them. A number of real-world processes are usually aggregated (in space and time) into a single parameter, which means that this parameter can therefore often not be derived directly from field measurements. Conceptual models make up the vast majority of models used in practical applications. Most conceptual models consider the catchment as a single homogeneous unit. However, one common approach to consider spatial variability is the segmentation of the catchment into smaller subcatchments, the so-called semi-distributed approach.

One typical example of a conceptual model – Hydrologiska Byråns Vattenbalansavdelning (HBV) – (Bergström, 1976) as rainfall–runoff model is given below. The HBV model was developed at the Swedish Meteorological and Hydrological Institute (Hydrological Bureau Water balance section). The model was originally developed for Scandinavian catchments, but has been applied in more than 30 countries all over the world (Lindström *et al.*, 1997).

A schematic diagram of the HBV model (Lindström *et al.*, 1997) is shown in **Figure 5**. The model of one catchment comprises subroutines for snow accumulation and melt, soil moisture accounting procedure, routines for runoff generation, and a simple routing procedure. The soil moisture accounting routine computes the proportion of snowmelt or rainfall P (mm h^{-1} or mm d^{-1}) that reaches the soil surface, which is ultimately converted to runoff. If the soil is dry (i.e., small value of SM/CF), the recharge R, which subsequently becomes runoff, is small as a major portion of the effective precipitation P is used to increase the soil moisture. Whereas if the soil is wet, the major portion of P is available to increase the storage in the upper zone.

The runoff generation routine transforms excess water R from the soil moisture zone to runoff. The routine consists of two conceptual reservoirs. The upper reservoir is a nonlinear reservoir whose outflow simulates the direct runoff component from the upper soil zone, while the lower one is a linear reservoir whose outflow simulates the base flow component of the runoff. The total runoff Q is computed as the sum of the outflows from the upper and the lower reservoirs. The total runoff is then smoothed using a triangular transformation function.

Input data are observations of precipitation and air temperature, and estimates of potential evapotranspiration. The

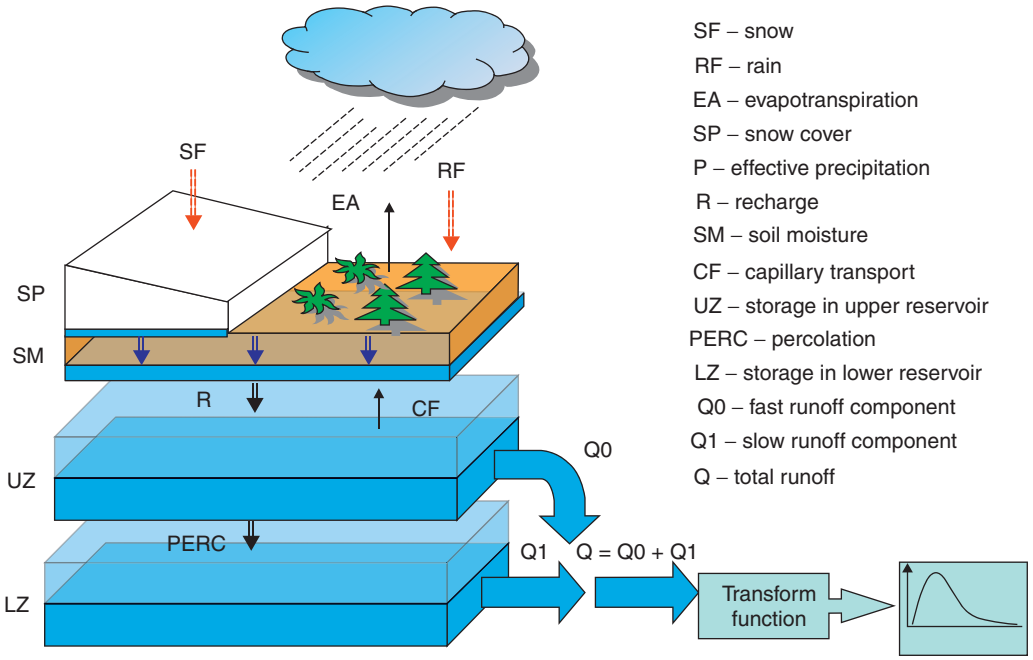

Figure 5 Schematic representation of the HBV-96 model with routines for snow, soil, and runoff response. Modified from Lindström G, Johansson B, Persson M, Gardelin M, and Bergström S (1997) Development and test of the distributed HBV-96 hydrological model. *Journal of Hydrology* 201: 272–228.

time step is usually 1 day, but it is possible to use shorter time steps. The evaporation values used are normally monthly averages, although it is possible to use the daily values. Air temperature data are used for calculations of snow accumulation and melt. It can also be used to adjust potential evaporation when the temperature deviates from normal values, or to calculate potential evaporation.

Note that the software IHMS-HBV allows for linking several lumped models and thus making it possible to build separate models for sub-basins, which are integrated, so that the overall model is the semi-distributed model.

The HBV model is an example of a typical lumped conceptual model. Other examples of such models differ in the details of describing the catchment hydrology. The following examples can be mentioned: Sugawara's tank model (Sugawara, 1995), Sacramento model (Burnash, 1995), Xinanjiang model (Zhao and Liu, 1995), and Tracer Aided Catchment (TAC) model (Uhlenbrook and Leibundgut, 2002).

2.16.4 Physically Based Models

Physically based models (e.g., Freeze and Harlan, 1969; Beven, 1996, 1989, 2002; Abbott *et al.*, 1986; Calver, 1988) use much more detailed and rigorous representations of physical processes and are based on the laws of conservation of mass, momentum, and energy. They became practically applicable in 1980s, as a result of improvements in computer power. The hope was that the degree of physical realism on which these models are based would be sufficient to relate their parameters, such as soil moisture characteristic and unsaturated zone hydraulic conductivity functions for subsurface flow or friction coefficients for surface flow, to physical characteristics of the catchment (Todini, 1988), thus eliminating the need for model calibration. However, mechanistic models suffer from high data demand, scale-related problems (e.g., the measurement scales differ from the simulation model (parameter) scales), and from over-parametrization (Beven, 1989).

One consequence of the problems of scale is that (at least not all of) the model parameters cannot be derived through measurements; physically based models structures, therefore, still require calibration, usually of a few key parameters (Calver, 1988; Refsgaard, 1997; Madsen and Jacobsen, 2001). The expectation that these models could be applied to ungauged catchments has, therefore, not yet been fulfilled (Parkin *et al.*, 1996; Refsgaard and Knudsen, 1996). They are typically rather applied in a way that is similar to conceptual models (Beven, 1989), thus demanding continued research into new approaches to merge these models with data. Physically based models often use spatial discretizations based on grids, triangular irregular networks, or some type of hydrologic response unit (e.g., Uhlenbrook *et al.*, 2004). A typical model of this kind is, for example, a physically based model based on triangular irregular networks – the Penn State Integrated Hydrologic Model (PIHM) (Qu and Duffy, 2007); its simplified structure is presented in **Figure 6**.

Such models are therefore particularly appropriate when a high level of spatial detail is important, for example, to estimate local levels of soil erosion or the extent of inundated areas (Refsgaard and Abbott, 1996). However, if the main interest simply lies in the estimation of stream flow at the catchment scale, then simpler conceptual or data-driven models often perform well and the high complexity of physically based models is not required (e.g., Loague and Freeze, 1985; Refsgaard and Knudsen, 1996). Regarding the results of

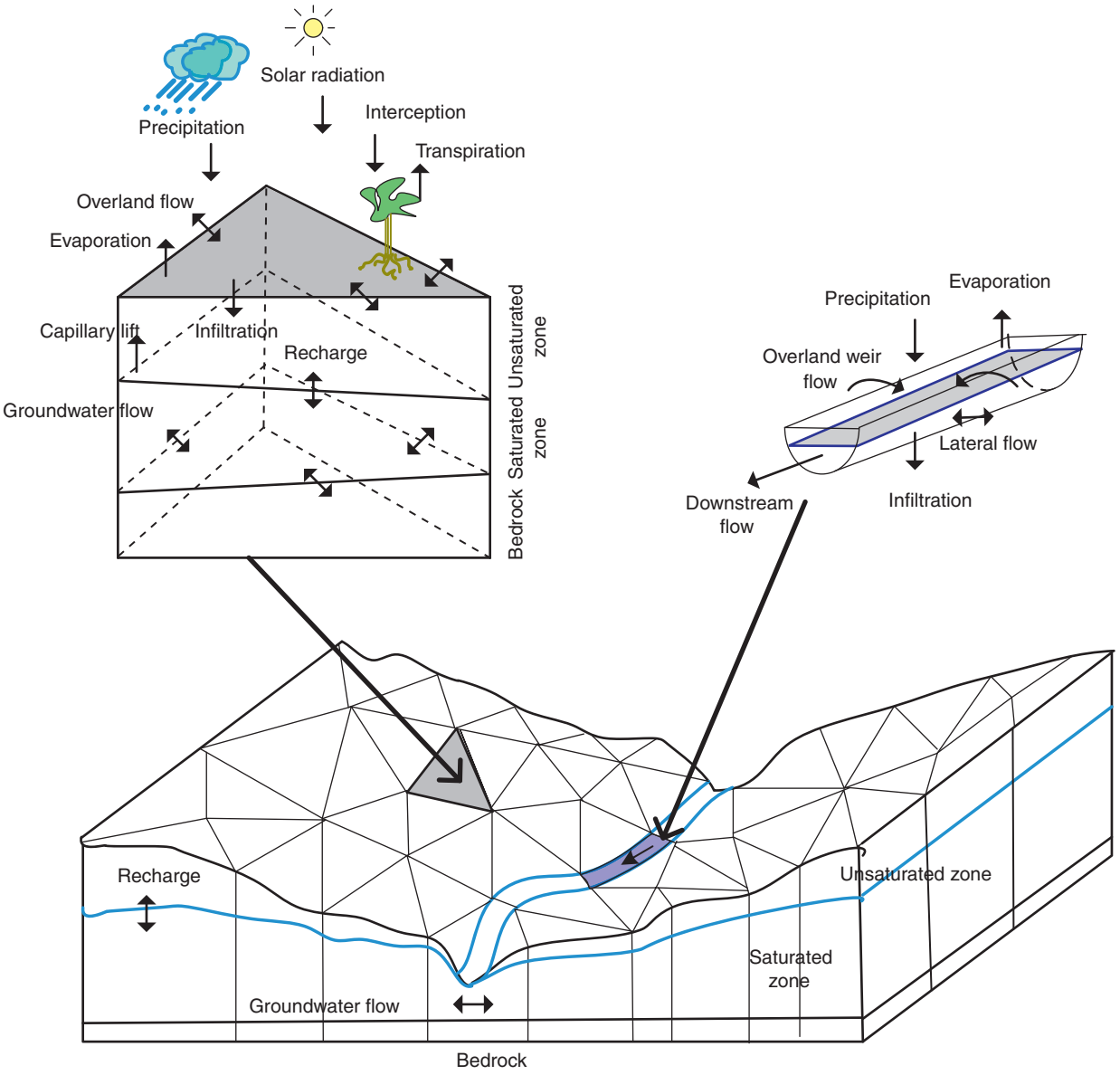

Figure 6 Schematic representation of the PIHM model, an example of a TIN-based physically based hydrological model (Qu and Duffy, 2004).

a comprehensive experiment to compare lumped and distributed models, the reader is referred to Reed *et al.* (2004). This experiment has shown that due to difficulties in calibrating distributed models, in many cases, conceptual models are in fact more accurate in reproducing the resulting catchment stream flow than the distributed ones.

2.16.5 Parameter Estimation

Many, if not most, rainfall–runoff model structures currently used to simulate the continuous hydrological response can be classified as conceptual, if this classification is based on two criteria (Wheater *et al.*, 1993): (1) the model structure is specified prior to any modeling being undertaken and (2) (at least some of) the model parameters do not have a direct physical interpretation, in the sense of being independently measurable, and have to be estimated through calibration against observed data. Calibration is a process of parameter adjustment (automatic or manual), until catchment and model behavior show a sufficiently (to be specified by the hydrologist) high degree of similarity. The similarity is usually judged by one or more objective functions accompanied by visual inspection of observed and calculated hydrographs (Gupta *et al.*, 2005).

The choice of such objective functions has itself been the subject of extensive research over many years. Traditionally, measures based on the mean squared error (MSE) criterion were used, for example, root mean squared error (RMSE) or Nash–Sutcliff efficiency (NSE). Appearance of the squared errors in many formulations is the result of an assumption of the normality (Gaussian distribution) of model errors, and

using the principle of maximum likelihood to derive the error function. Calibration includes the process of finding a set of parameters providing the minimum of RMSE or the maximum value of NSE. For more information on the formulations of these and other error function, the reader is referred to, for example, Gupta *et al.* (1998). In a recent paper, Gupta *et al.* (2009) showed certain deficiencies of MSE-based objective functions and suggested possible remedies.

Often a single measure may not be enough to capture all the aspects of the system response that the model is supposed to reproduce, and several criteria (objective functions) have to be considered simultaneously so that multiobjective optimization algorithms have to be used. Examples of such multiple objectives include the RMSE calculated separately on low and high flows, timing errors, and error in reproducing the water balance. The models constituting the Pareto in criteria space should be seen as the best models, since there are no models better than these on all criteria.

If a single model is to be selected from this set, it is done either by a decision maker (who would use some additional criteria that are difficult to formalize), or by measuring the distance of the models to the ideal point in criteria space, or by using the (weighted) sum of objective functions values. This section covers single-objective optimization; for the use of multiobjective methods, the reader is directed to the papers by Gupta *et al.* (1998), Khu and Madsen (2005), and Tang *et al.* (2006) (with the subsequent discussion).

Hydrological model structures of the continuous watershed response (mainly stream flow) became feasible in the 1960s. They were usually relatively simple lumped, conceptual mathematical representations of the (perceived to be important) hydrological processes, with little (if any) consideration of issues such as identifiability of the parameters or information content of the watershed response observations. It became quickly apparent that the parameters of such models could not be directly estimated through measurements in the field, and that some sort of adjustment (fine-tuning) of the parameters was required to match simulated system responses with observations (e.g., Dawdy and O'Donnell 1965). Adjustment approaches were initially based on manual perturbation of the parameter values and visual inspection of the similarity between simulated and observed time series. Over the years, a variety of manual calibration procedures have been developed, some having reached very high levels of sophistication allowing hydrologists to achieve very good performing and hydrologically realistic model parameters and predictions, that is, a well-calibrated model (Harlin, 1991; Burnash, 1995). This hydrological realism is still a problem for most automated procedures as discussed in van Werkhoven *et al.* (2008).

Necessary conditions for a hydrological model to be well calibrated are that it exhibits (at least) the following three characteristics (Wagener *et al.* 2003; Gupta *et al.* 2005):

1. the input–state–output behavior of the model is consistent with the measurements of watershed behavior;
2. the model predictions are accurate (i.e., they have negligible bias) and precise (i.e., the prediction uncertainty is relatively small); and
3. the model structure and behavior are consistent with a current hydrological understanding of reality.

This last characteristic is often ignored in operational settings, where the focus is generally on useful rather than realistic models. This will be an adequate approach in many cases, but will eventually lead to limitations of potential model uses. This problem is exemplified in the current attempts to modeling watershed residence times and flow paths (McDonnell, 2003). This aspect of the hydrologic system, though often not crucial for reliable quantitative flow predictions, is however relevant for many of today's environmental problems, but cannot be simulated by many of the currently available models.

The high number of nonlinearly interacting parameters present in most hydrological models makes manual calibration a very labor-intensive and a difficult process, requiring considerable experience. This experience is time consuming to acquire and cannot be easily transferred from one hydrologist to the next. In addition, manual calibration does not formally incorporate an analysis of uncertainty, as is required in a modern decision-making context. The obvious advantages of computer-based automatic calibration procedures began to spark interest in such approaches as soon as computers became more easily available for research.

In automatic calibration, the ability of a parameter set to reproduce the observed system response is measured (summarized) by means of an objective function (also sometimes called loss or cost function). As discussed above, this objective function is an aggregated measure of the residuals, that is, the differences between observed and simulated responses at each time step. An important early example of automatic calibration is the dissertation work by Ibbitt (1970) in which a variety of automated approaches were applied to several watershed models of varying complexity (see also Ibbitt and O'Donnell, 1971). The approaches were mainly based on local-search optimization techniques, that is, the methods that start from a selected initial point in the parameter space and then walk through it, following some predefined rule system, to iteratively search for parameter sets that yield progressively better objective function values. Ibbitt (1970) found that it is difficult to conclude when the best parameter set has been found, because the result depends both on the chosen method and on the initial starting parameter set. The application of local-search calibration approaches to all but the most simple watershed models has been largely unsuccessful. In reflection of this, Johnston and Pilgrim (1976) reported the failure of their 2-year quest to find an optimal parameter set for a typical conceptual rainfall–runoff (RR) model. Their honesty in reporting this failure ultimately led to a paradigm shift as researchers started to look closely at the possible reasons for this lack of success.

The difficulty of the task at hand, in fact, only became clear in the early 1990s when Duan *et al.* (1992) conducted a detailed study of the characteristics of the response surface that any search algorithm has to explore. Their studies showed that the specific characteristics of the response surface, that is, the $(n+1)$-dimensional space of n model parameters and an objective function, of hydrological models give rise to conditions that make it extremely difficult for local optimization strategies to be successful. They listed the following characteristics commonly associated with the response surface of a

typical hydrological model:

- it contains more than one main region of attraction;
- each region of attraction contains many local optima;
- it is rough with discontinuous derivatives;
- it is flat in many regions, particularly in the vicinity of the optimum, with significantly different parameter sensitivities; and
- its shape includes long and curved ridges.

Concluding that optimization strategies need to be powerful enough to overcome the search difficulties presented by these response surface characteristics, Duan *et al.* (1992) developed the shuffled complex evolution (SCE-UA) global optimization method (UA, University of Arizona). The SCE-UA algorithm has since been proved to be highly reliable in locating the optimum (where one exists) on the response surfaces of typical hydrological models. However, in a follow-up paper, Sorooshian *et al.* (1993) used SCE-UA to show that several different parameter combinations of the relatively complex Sacramento model (13 free parameters) could be found which produced essentially identical objective function values, thereby indicating that not all of the parameter uncertainty can be resolved through an efficient global optimizer (see discussion in Wagener and Gupta (2005)). Similar observations of multiple parameter combinations producing similar performances have also been made by others (e.g., Binley and Beven, 1991; Beven and Binley, 1992; Spear, 1995; Young *et al.*, 1998; Wagener *et al.*, 2003). Part of this problem had been attributed to overly complex models for the information content of the system response data available, usually stream flow (e.g., Young, 1992, 1998).

It is worth mentioning that practically any direct search optimization algorithm can be used for model calibration. The reason of using direct search (i.e., the search based purely on calculation of the objective function values for different points in the search space) is that for most calibration problems computation of the objective function gradients is not possible, so the efficient gradient-based search cannot be used. (Another name for this class of algorithms is global optimization algorithms since they are focused on finding the global minimum rather than a local one.) For example, in many studies a popular genetic algorithm (GA) is used.

If a model is simple and fast running, then it is really not important how efficient the optimization algorithm is. Here, efficiency is measured by the number of the model runs needed by an optimization algorithm to find a more-or-less accurate estimate of the parameter vector leading to the minimum value of the model error. However, if a model is computationally complex, as is the case for physically based and distributed models, efficiency of the optimization algorithm used becomes an issue. With this in mind, the so-called adaptive cluster-covering algorithm (ACCO) was developed (Solomatine, 1995; Solomatine *et al.*, 1999, 2001), and it was shown that on a number of calibration problems it is more efficient than GA and several other algorithms.

A large number of other algorithms has been applied to hydrological models, including a multialgorithm genetically adaptive method (AMALGAM) (Vrugt and Robinson, 2007) and epsilon-NSGA-II (NSGA, nondominated sorting genetic algorithm; Tang *et al.*, 2006), and different algorithms have come out as most effective or most efficient depending on the study. A range of algorithms for model calibration can be obtained from the Hydroarchive website.

As mentioned above (**Figure 2**), once parameters are estimated, the model has to be validated, that is, the degree to which a model is an accurate representation of the modeled process has to be determined.

Case of ungauged basins. A different problem has to be solved in the case of the so-called ungauged basins, that is, watersheds for which none or insufficiently long observations of the hydrological response variable of interest (usually stream flow) are available. The above-discussed strategy of model calibration cannot be used under those conditions. Early attempts to model ungauged catchments simply used the parameter values derived for neighboring catchments where stream flow data were available, that is, a geographical proximity approach (e.g., Mosley, 1981; Vandewiele and Elias, 1995). However, this seems to be insufficient since nearby catchments can even be very different with respect to their hydrological behavior (Post *et al.*, 1998; Beven, 2000). Others propose the use of parameter estimates directly derived from, among others, soil properties such as porosity, field capacity, and wilting point (to derive model storage capacity parameters); percentage forest cover (evapotranspiration parameters); or hydraulic conductivities and channel densities (time constants) (e.g., Koren *et al.*, 2000; Duan *et al.*, 2001; Atkinson *et al.*, 2002).

The main problem here is that the scale at which the measurements are made (often from small soil samples) is different from the scale at which the model equations are derived (often laboratory scale) and at which the model is usually applied (catchment scale). The conceptual model parameters represent the effective characteristics of the integrated (heterogeneous) catchment system (e.g., including preferential flow), which are unlikely to be easily captured using small-scale measurements since there is generally no theory that allows the estimation of the effective values within different parts of a heterogeneous flow domain from a limited number of small-scale or laboratory measurements (Beven, 2000). It seems unlikely that conceptual model parameters, which describe an integrated catchment response, usually aggregating significant heterogeneity (including the effect of preferential flow paths, different soil and vegetation types, etc.), can be derived from catchment properties that do not consider all influences on water flow through the catchment. Further fine-tuning of these estimates using locally observed flow data is needed because the physical information available to estimate *a priori* parameters is not adequate to define local physical properties of individual basins for accurate hydrological forecasts (Duan *et al.*, 2001). However, useful initial values might be derived in this way (Koren *et al.*, 2000). The advantages of this approach are that the assumed physical basis of the parameters is preserved and (physical) parameter dependence can be accounted for, as shown by Koren *et al.* (2000).

Probably, the most common apprnoach to ungauged modeling is to relate model parameters and catchment characteristics in a statistical manner (e.g., Jakeman *et al.*, 1992; Sefton *et al.*, 1995; Post *et al.*, 1998; Sefton and Howarth, 1998; Abdullah and Lettenmaier, 1997; Wagener *et al.*, 2004;

Merz and Bloschl, 2004; Lamb and Kay, 2004; Seibert, 1999; Lamb *et al.*, 2000; Post and Jakeman, 1996; Fernandez *et al.*, 2000), assuming that the uniqueness of each catchment can be captured in a distinctive combination of catchment characteristics. The basic methodology is to calibrate a specific model structure, here called the local model structure, to as large a number of (gauged) catchments as possible and derive statistical (regression) relationships between (local) model parameters and catchment characteristics. These statistical relationships, here called regional models, and the measurable properties of the ungauged catchment can then be used to derive estimates of the (local) model parameters. This procedure is usually referred to as regionalization or spatial generalization (e.g., Lamb and Calver, 2002). While this approach has been widely applied, it still does not constrain existing uncertainty sufficiently in many cases (Wagener and Wheater, 2006).

Recent approaches also used regionalized information about stream flow characteristics to further reduce this uncertainty (Yadav *et al.*, 2007; Zhang *et al.*, 2008). It seems as if the most promising strategies for the future lie in combining as much information as possible to reduce predictive uncertainty, rather than relying on a single approach.

2.16.6 Data-Driven Models

2.16.6.1 Introduction

Along with the physically based and conceptual models, the empirical models based on observations (experience) are also popular. Such models involve mathematical equations that have been assessed not from the physical process in the catchment but from analysis of data – concurrent input and output time series. Typical examples here are the unit hydrograph method and various statistical models – for example, linear regression, multilinear, ARIMA, etc. During the last decade, the area of empirical modeling received an important boost due to developments in the area of machine learning (ML). It can be said that it now entered a new phase and deserves a special name – DDM.

DDM is based on the analysis of all the data characterizing the system under study. A model can then be defined based on connections between the system state variables (input, internal and output variables) with only a limited number of assumptions about the physical behavior of the system. The methods used nowadays can go much further than the ones used in conventional empirical modeling: they allow for solving prediction problems, reconstructing highly nonlinear functions, performing classification, grouping of data, and building rule-based systems.

It is worth mentioning that among some hydrologists there is still a certain skepticism about the use of DDM. In their opinion, such models do not relate to physical principles and mathematical reasoning, and view building models from data sets as a purely computational exercise. This is true, and indeed DDM cannot be a replacement of process-based modeling, but should be used in situations where data-driven models are capable of generating improved forecasts of hydrological variables.

There are cases where the traditional statistical models (typically linear regression or ARIMA-class models) are accurate enough, and there is no need of using sophisticated methods of ML. Some of the concerns of this nature are discussed, for example, by Gaume and Gosset (2003), See *et al.* (2007), Han *et al.* (2007), and Abrahart *et al.*, 2008. Abrahart and See (2007) also addressed some of these problems, however, demonstrated that the existing nonlinear hydrological relationships, which are so important when building flow forecasting models, are effectively captured by a neural network, the most widely used DDM method. In this respect, positioning of data-driven models is important: they should be seen as complementary to process-based simulation models; they cannot explain reality but could be effective predictive tools.

2.16.6.2 Technology of DDM

2.16.6.2.1 Definitions

One may identify several fields that contribute to DDM: statistical methods, ML, soft computing (SC), computational intelligence (CI), data mining (DM), and knowledge discovery in databases (KDDs). ML is the area concentrating on the theoretical foundations of learning from data and it can be said that it is the major supplier of methods for DDM. SC is emerging from fuzzy logic, but many authors attribute to it many other techniques as well. CI incorporates two areas of ML (neural networks and fuzzy systems), and, additionally, evolutionary computing that, however, can be better attributed to the field of optimization than to ML. DM and KDDs used, in fact, the methods of ML and are focused typically at large databases being associated with banking, financial services, and customer resources management.

DDM can thus be considered as an approach to modeling that focuses on using the ML methods in building models that would complement or replace the physically based models. The term modeling stresses the fact that this activity is close in its objectives to traditional approaches to modeling, and follows the steps traditionally accepted in (hydrological) modeling. Examples of the most common methods used in data-driven hydrological modeling are linear regression, ARIMA, artificial neural networks (ANNs), and fuzzy rule-based systems (FRBSs).

Such positioning of DDM links to learning which incorporates determining the so far unknown mappings (or dependencies) between a system's inputs and its outputs from the available data (Mitchell, 1997). By data, we understand the known samples (data vectors) that are combinations of inputs and corresponding outputs. As such, a dependency (mapping or model) is discovered (induced), which can be used to predict (or effectively deduce) the future system's outputs from the known input values.

By data, we usually understand a set K of examples (or instances) represented by duple $\langle x_k, y_k \rangle$, where $k = 1, \ldots, K$, vector $\mathrm{x}_k = \{x_1, \ldots, x_n\}_k$, vector $y_k = \{y_1, \ldots, y_m\}_k$, $n =$ number of inputs, and $m =$ number of outputs. The process of building a function (or mapping, or model) $y = f(x)$ is called training. If only one output is considered, then $m = 1$. (In relation to hydrological and hydraulic models, training can be seen as calibration.)

In the context of hydrological modeling, the inputs and outputs are typically real numbers ($x_k, y_k \in \geq \mathscr{R}^n$), so the main

learning problem solved in hydrological modeling is numerical prediction (regression). Note that the problems of clustering and classification are rare but there are examples of it as well (see, e.g., Hall and Minns, 1999; Hannah *et al.*, 2000; Harris *et al.*, 2000).

As already mentioned, the process of building a data-driven model follows general principles adopted in modeling: study the problem, collect data, select model structure, build the model, test the model, and (possibly) iterate. There is, however, a difference with physically based modeling: in DDM not only the model parameters but also the model structure are often subject to optimization. Typically, simple (or parsimonious) models are valued (as simple as possible, but no simpler). An example of such parsimonious model could be a linear regression model versus a nonlinear one, or a neural network with the small number of hidden nodes. Such models would automatically emerge if the so-called regularization is used: the objective function representing the overall model performance includes not only the model error term, but also a term that increases in value with the increase of model complexity represented, for example, by the number of terms in the equation, or the number of hidden nodes in a neural network.

If there is a need to build a simple replica of a sophisticated physically based hydrological model, DDM can be used as well: such models are called surrogate, emulation, or metamodels (see, e.g., Solomatine and Torres, 1996; Khu *et al.*, 2004). They can be used as fast-working approximations of complex models when speed is important, for example, in solving the optimization or calibration problems.

2.16.6.2.2 Specifics of data partitioning in DDM

Obviously, data analysis and preparation play an important role in DDM. These steps are considered standard by the experts in ML but are not always given proper attention by hydrologists building or using such models.

Three data sets for training, cross-validation, and testing. Once the model is trained (but before it is put into operation), it has to be tested (or verified) by calculating the model error (e.g., RMSE) using the test (or verification) data set. However, during training often there is a need to conduct tests of the model that is being built, so yet another data set is needed – the cross-validation set. This set serves as the representative of the test set. As a model gradually improves as a result of the training process, the error on the training data will be gradually decreasing. The cross-validation error will also be first decreasing, but as the model starts to reproduce the training data set better and better, this error will start to increase (effect of over fitting). This typically means that the training should be stopped when the error on cross-validation data set starts to increase. If these principles are respected, then there is a hope that the model will generalize well, that is, its prediction error on unseen data will be small. (Note that the test data should be used only to test the final model, but not to improve (optimize) the model.)

One may see that this procedure is more complex than the standard procedure of the hydrological model calibration – when no data are allocated for cross-validation, and, worse, often the whole data set is used to calibrate the model.

Note that in an important class of ML models – support vector machines (SVMs) – a different approach is taken: it is to build the model that would have the best generalization ability possible without relying explicitly on the cross-validation set (Vapnik, 1998).

In connection to the issues covered above, there are two common pitfalls, especially characteristic of DDM applications where time series are involved, that are worth mentioning here.

The desired properties of the three data sets. It is desired that the three sets are statistically similar. Ideally, this could be automatically ensured by the fact that data sets are sufficiently large and sampled from the same distribution (typical assumption in machine and statistical learning). However, in reality of hydrological modeling, such situations are rare, so normally a modeler should try to ensure at least some similarity in the distributions, or, at least, similar ranges, mean and variance. Statistical similarity can be achieved by careful selection of examples for each data set, by random sampling data from the whole data set, or employing an optimization procedure resulting in the sets with predefined properties (Bowden *et al.*, 2002).

One of the approaches is to use the 10-fold validation method when a model is built 10 times, trained each time on 9/10th of the whole set of available data and validated on 1/10th (number of runs is not necessarily 10). A version of this method is the leave-one-out method when K models are built using $K-1$ examples and not using one (every time different). The modeler is left with 10 or K trained models, so the resulting model to be used is either one of these models, or an ensemble of all the built models, possibly with the weighted outputs.

Strictly speaking, for generation of the statistically similar training data sets for building a series of similar but different models, one should typically rely on the well-developed statistical (re)sampling methods such as bootstrap originated by Tibshirani in the 1970s (see Efron and Tibshirani, 1993) where (in its basic form) K data are randomly selected from K original data.

For many hydrologists, there could be a visualization (or even a psychological) problem. If one of these procedures is followed, the data will not be always contiguous: it would not be possible to visualize a hydrograph when the model is fed with the test set. There is nothing wrong with such a model if the time structure of all the data sets is preserved. Such models, however, may be rejected by practitioners, since they are so different from the traditional physically based models that always generate contiguous time series. A possible solution here is to consider the hydrological events (i.e., contiguous blocks of data), to group the data accordingly, and to try to ensure the presence of statistically similar events in all the three data sets.

This is all possible of course, if there is enough data. In the situations when the data set is not large enough to allow for building all three sets of substantial size, modelers could be forced not to build cross-validation set at all with the hope that the model trained on training set would perform well on the test set as well. An alternative could be performing 10-fold cross-validation but it is somehow rarely used.

2.16.6.2.3 Choice of the model variables

Apart from dividing the data into several subsets, data preparation also includes the selection of proper variables to represent the modeled process, and, possibly, their transformation (Pyle, 1999). A study on the influence of different data transformation methods (linear, logarithmic, and seasonal transformations, histogram equalization, and a transformation to normality) was undertaken by Bowden *et al.* (2003). On a (limited) case study (forecasting salinity in a river in Australia 14 days ahead), they found that the model using the linear transformation resulted in the lowest RMSE and more complex transformations did not improve the model. Our own experience shows that it is sometimes also useful to apply the smoothing filters to reduce the noise in the hydrological time series.

Choice of variables is an important issue, and it has to be based on taking the physics of the underling processes into account. State variables of data-driven models have nothing to do with the physics, but their inputs and outputs do have. In DDM, the physics of the process is introduced mainly via the justified and physically based choice of the relevant input variables.

One may use visualization to identify the variables relevant for predicting the output value. There are also formal methods that help in making this choice more justified, and the reader can be directed to the paper by Bowden *et al.* (2005) for an overview of these.

Mutual information which is based on Shannon's entropy (Shannon, 1948) is used to investigate linear and nonlinear dependencies and lag effects (in time series data) between the variables. It is the measure of information available from one set of data having knowledge of another set of data. The average mutual information (AMI) between two variables X and Y is given by

$$\mathrm{AMI} = \sum_{i,j} P_{XY}(x_i, y_j) \log_2 \left[\frac{P_{XY}(x_i, y_j)}{P_X(x_i) P_Y(y_j)} \right] \qquad (1)$$

where $P_X(x)$ and $P_Y(y)$ are the marginal probability density functions (PDFs) of X and Y, respectively, and $P_{XY}(x,y)$ the joint PDFs of X and Y. If there is no dependence between X and Y, then by definition the joint probability density $P_{XY}(x,y)$ would be equal to the product of the marginal densities ($P_X(x)$ $P_Y(y)$). In this case, AMI would be zero (the ratio of the joint and marginal densities in Equation (1) being 1, giving the logarithm a value of 0). A high value of AMI would indicate a strong dependence between two variables. Accurate estimate of the AMI depends on the accuracy of estimation of the marginal and joint probabilities density in Equation (1) from a finite set of examples. The most widely used approach is estimation of the probability densities by histogram with the fixed bin width. More stable, efficient, and robust probability density estimator is based on the use of kernel density estimation techniques (Sharma, 2000).

It is our hope that the adequate data preparation and the rational and formalized choice of variables will become a standard part of any hydrological modeling study.

2.16.6.3 Methods and Typical Applications

Most hydrological modeling problems are formulated as simulation of forecasting of real-valued variables. In terminology of machine (statistical) learning, this is a regression problem. A number of linear and (sometimes) nonlinear regression methods have been used in the past. Most of the methods of ML can also be seen as sophisticated nonlinear regression methods. Many of them, instead of using very complex functions, use combinations of many simple functions. During training, the number of these functions and the values of their parameters are optimized, given the functions' class. Note that ML methods typically do not assume any special kind of distribution of data, and do not require the knowledge of such distribution.

Multilayer perceptron (MLP) is a device (mathematical model) that was originally referred to as an ANN (Haykin, 1999). Later ANN became a term encompassing other connectionist models as well. MLP consists of several layers of mutually interconnected nodes (neurons), each of which receives several inputs, calculates the weighted sum of them, and then passes the result to a nonlinear squashing function. In this way, the inputs to an MLP model are subjected to a multiparameter nonlinear transformation so that the resulting model is able to approximate complex input–output relationships. Training of MLP is in fact solving the problem of minimizing the model error (typically, MSE) by determining the optimal set of weights.

MLP ANNs are known to have several dozens of successful applications in hydrology. The most popular application was building rainfall–runoff models: Hsu *et al.* (1995), Minns and Hall (1996), Dawson and Wilby (1998), Dibike *et al.* (1999), Abrahart and See (2000), Govindaraju and Rao (2001), Coulibaly *et al.* (2000), Hu *et al.* (2007), and Abrahart *et al.* (2007b). They were also used to model river stage–discharge relationships (Sudheer and Jain, 2003; Bhattacharya and Solomatine, 2005). ANNs were also used to build surrogate (emulation, meta-) models for replicating the behavior of hydrological and hydrodynamic models: in model-based optimal control of a reservoir (Solomatine and Torres, 1996), calibration of a rainfall–runoff model (Khu *et al.*, 2004), and in multiobjective decision support model for watershed management (Muleta and Nicklow, 2004).

Most theoretical problems related to MLP have been solved, and it should be seen as a quite reliable and well-understood method.

Radial basis functions (RBFs) could be seen as a sensible alternative to the use of complex polynomials. The idea is to approximate some function $y = f(x)$ by a superposition of J functions $F(x, \sigma)$, where σ is a parameter characterizing the span or width of the function in the input space. Functions F are typically bell shaped (e.g., a Gaussian function) so that they are defined in the proximity to some representative locations (centers) w_j in n-dimensional input space and their values are close to zero far from these centers. The aim of learning here is to find the positions of centers w_j and the parameters of the functions $f(x)$. This can be accomplished by building an RBF neural network; its training allows the identification of these unknown parameters. The centers w_j of the RBFs can be chosen using a clustering algorithm, the parameters of the Gaussian can be found based on the spread (variance) of data in each cluster, and it can be shown that the weights can be found by solving a system of linear equations. This is done for a certain number of RBFs, with the

exhaustive optimization run across the number of RBFs in a certain range.

The areas of RBF networks applications are the same as those of MLPs. Sudheer and Jain (2003) used RBF ANNs for modeling river stage–discharge relationships and found out that on the considered case study RBF ANNs were superior to MLPs; Moradkhani *et al*. (2004) used RBF ANNs for predicting hourly stream flow hydrograph for the daily flow for a river in USA as a case study, and demonstrated their accuracy if compared to other numerical prediction models. In this study, RBF was combined with the self-organizing feature maps used to identify the clusters of data. Nor *et al*. (2007) used RBF ANN for the same purpose, however, for the hourly flow and considering only storm events in the two catchments in Malaysia as case studies.

Regression trees and M5 model trees. These models can be attributed simultaneously to (piece-wise) linear regression models, and to modular (multi)models. They use the following idea: progressively split the parameter space into areas and build in each of them a separate regression model of zero or first order (**Figure 7**). In M5 trees models in leaves are first order (linear). The Boolean tests a_i at nodes have the form $x_i < C$ and are used to progressively split the data set. The index of the input variable i and value C are chosen to minimize the standard deviation in the subsets resulting from the split. *Mn* are models built for subsets filtered down to a given tree leaf. The resulting model can be seen as a set of linear models being specialized on the certain subsets of the training set – belonging to different regions of the input space. M5 algorithm to build such model trees was proposed by Quinlan (1992).

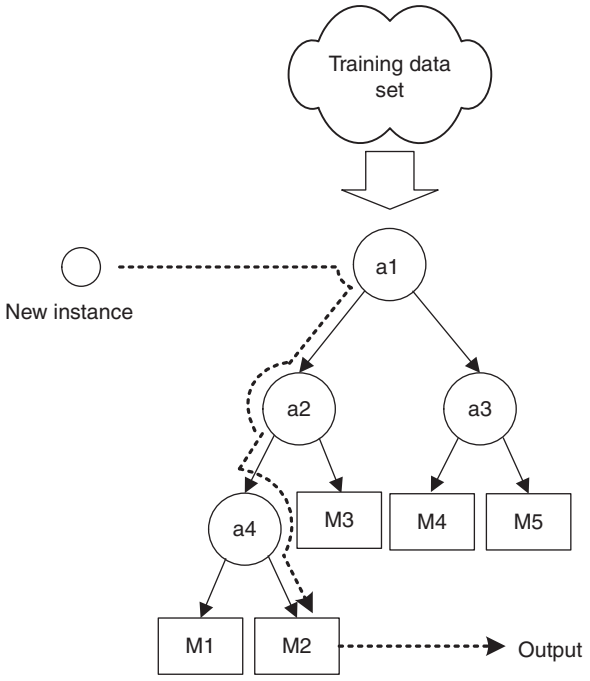

Figure 7 Building a tree-like modular model (M5 model tree). Boolean tests a_i have the form $x_i < C$ and split data set during training. Mn are linear regression models built on data subsets, and applied to a new instance input vector in operation.

Combination of linear models was already used in dynamic hydrology in the 1970s (e.g., multilinear models by Becker and Kundzewicz (1987)). Application of the M5 algorithm to build such models adds rigor to this approach and makes it possible to build the models automatically and to generate a range of models of different complexity and accuracy.

MTs are often almost as accurate as ANNs, but have some important advantages: training of MTs is much faster than ANNs, it always converges, and the results can be easily understood by decision makers.

An early (if not the first) application of M5 model trees in river flow forecasting was reported by Kompare *et al*. (1997). Solomatine and Dulal (2003) used M5 model tree in rainfall–runoff modeling of a catchment in Italy. Stravs and Brilly (2007) used M5 trees in modeling the precipitation interception in the context of the Dragonja river basin case study.

Genetic programming (GP) and evolutionary regression. GP is a symbolic regression method in which the specific model structure is not chosen *a priori*, but is a result of the search (optimization) process. Various elementary mathematical functions, constants, and arithmetic operations are combined in one function and the algorithm tries to construct a model recombining these building blocks in one formula. The function structure is represented as a tree and since the resulting function is highly nonlinear, often nondifferentiable, it is optimized by a randomized search method – usually a GA. Babovic and Keijzer (2005) gave an overview of GP applications in hydrology. Laucelli *et al*. (2007) presented an application of GP to the problem of forecasting the groundwater heads in the aquifer in Italy; in this study, the authors also employed averaging of several models built on the data subsets generated by bootstrap.

One may limit the class of possible formulas (regression equations), allowing for a limited class of formulas that would *a priori* be reasonable. In evolutionary regression (Giustolisi and Savic, 2006), a method similar to GP, the elementary functions are chosen from a limited set and the structure of the overall function is fixed. Typically, a polynomial regression equation is used, and the coefficients are found by GA. This method overcomes some shortcomings of GP, such as the computational requirements – the number of parameters to tune and the complexity of the resulting symbolic models. It was used, for example, for modeling groundwater level (Giustolisi *et al*., 2007a) and river temperature (Giustolisi *et al*., 2007b), and the high accuracy and transparency of the resulting models were reported.

FRBSs. Probability is not the only way to describe uncertainty. In his seminal paper, Lotfi Zadeh (1965) introduced yet another way of dealing with uncertainty – fuzzy logic, and since then it found multiple successful applications, especially in application to control problems.

Fuzzy logic can be used in combining various models, as done previously, for example, by See and Openshaw (2000) and Xiong *et al*. (2001), building the so-called fuzzy committees of models (Solomatine, 2006), and also the instrumentarium of fuzzy logic can be used for building the so-called FRBSs which are effectively regression models. FRBS can be built by interviewing human experts, or by processing historical data and thus forming a data-driven model. These

rules are patches of local models overlapped throughout the parameter space, using a sort of interpolation at a lower level to represent patterns in complex nonlinear relationships. The basics of the data-driven approach and its use in a number of water-related applications can be found in Bárdossy and Duckstein (1995).

Typically, the following rules are considered:

$$IF\ x_1\ is\ A_{1,r}\ AND \ldots AND\ x_n\ is\ A_{n,y}\ THEN\ y\ is\ B$$

where $\{x_1, \ldots, x_n\} = x$ is the input vector; A_{im} the fuzzy set; r the index of the rule, $r = 1, \ldots, R$. Fuzzy sets A_{ir} (defined as membership functions with the values ranging from 0 to 1) are used to partition the input space into overlapping regions (for each input these are intervals). The structure of B in the consequent could be either a fuzzy set (then such model is called a Mamdani model) or a function $y = f(x)$, often linear, and then the model is referred to as Takagi–Sugeno–Kang (TSK) model. The model output is calculated as a weighted combination of the R rules' responses. Output of the Mamdani model is fuzzy (a membership function of irregular shape), so the crisp output has to be calculated by the so-called defuzzification operator. Note that in TSK model, each of the r rules can be interpreted as local models valid for certain regions in the input space defined by the antecedent and overlapping fuzzy sets A_{ir}. Resemblance to the RBF ANN is obvious.

FRBSs were effectively used for drought assessment (Pesti *et al.*, 1996); reconstruction of the missing precipitation data by a Mamdani-type system (Abebe *et al.*, 2000b); control of water levels in polder areas (Lobbrecht and Solomatine *et al.*, 1999); and modeling rainfall–discharge dynamics (Vernieuwe *et al.*, 2005; Nayak *et al.*, 2005). Casper *et al.* (2007) presented an interesting study where TSK type of FRBS has been developed using soil moisture and rainfall as input variables to predict the discharge at the outlet of a small catchment, with the special attention to the peak discharge. One of the limitations of FRBS is that the demand for data grows exponentially with an increase in the number of input variables.

SVMs. This ML method is based on the extension of the idea of identifying a hyperplane that separates two classes in classification. It is closely linked to the statistical learning theory initiated by V. Vapnik in the 1970s at the Institute of Control Sciences of the Russian Academy of Science (Vapnik, 1998). Originally developed for classification, it was extended to solving prediction problems, and, in this capacity, was used in hydrology-related tasks. Dibike *et al.* (2001) and Liong and Sivapragasam (2002) reported using SVMs for forecasting the river water flows and stages. Bray and Han (2004) addressed the issue of tuning SVMs for rainfall–runoff modeling. In all reported cases, SVM-based predictors have shown good results, in many cases superseding other methods in accuracy.

Instance-based learning (IBL). This method allows for classification or numeric prediction directly by combining some instances from the training data set. A typical representative of IBL is the k-nearest neighbor (k-NN) method. For a new input vector x_q (query point), the output value is calculated as the mean value of the k-nearest neighboring examples, possibly weighted according to their distance to x_q. Further extensions are known as locally weighted regression (LWR) when the regression model is built on k nearest instances: the training instances are assigned weights according to their distance to x_q and the regression equations are generated on the weighted data.

In fact, IBL methods construct a local approximation to the modeled function that applies well in the immediate neighborhood of the new query instance encountered. Thus, it describes a very complex target function as a collection of less complex local approximations, and often demonstrates competitive performance when compared, for example, to ANNs.

Karlsson and Yakowitz (1987) introduced this method in the context of water, focusing however only on (single-variate) time-series forecasts. Galeati (1990) demonstrated the applicability of the k-NN method (with the vectors composed of the lagged rainfall and flow values) for daily discharge forecasting and favorably compared it to the statistical autoregressive model with exogenous input (ARX) model, and used the k-NN method for adjusting the parameters of the linear perturbation model for river flow forecasting. Toth *et al.* (2000) compared the k-NN approach to other time-series prediction methods in a problem of short-term rainfall forecasting. Solomatine *et al.* (2007) explored a number of IBL methods, tested their applicability in rainfall–runoff modeling, and compared their performance to other ML methods.

To conclude the coverage of the popular data-driven methods, it can be mentioned that all of them are developed in the ML and CI community. The main challenges for the researchers in hydrology and hydroinformatics are in testing various combinations of these methods for particular water-related problems, combining them with the optimization techniques, developing the robust modeling procedures able to work with the noisy data, and in developing the methods providing the model uncertainty estimates.

2.16.6.4 DDM: Current Trends and Conclusions

There are a number of challenges in DDM: development of the optimal model architectures, making models more robust, understandable, and ready for inclusion into existing decision support systems. Models should adequately reflect reality, which is uncertain, and in this respect developing the methods of dealing with the data and model uncertainty is currently an important issue.

One of the interesting questions that arise in case of using a data-driven model is the following one: to what extent such models could or should incorporate the expert knowledge into the modeling process. One may say that a typical ML algorithm minimizes the training (cross validation) error seeing it as the ultimate indicator of the algorithms performance, so is purely data-driven – and this is what is expected from such models. Hydrologists, however, may have other consideration when assessing the usefulness of a model, and typically wish to have a certain input to building a model rightfully hoping that the direct participation of an expert may increase the model accuracy and trust in the modeling results. Some of the examples of merging the hydrological knowledge and the concepts of process-based modeling with those of DDM are mentioned in Section 2.16.8.2.

Data-driven models are seen by many hydrologists as tools complementary to process-based models. More and more practitioners are agreeing to that, but many are still to be convinced. Research is now oriented toward development of

the optimal model architectures and avenues for making data-driven models more robust, understandable, and very useful for practical applications. The main challenge is in the inclusion of DDM into the existing decision-making frameworks, while taking into consideration both the system's physics, expert judgment, and the data availability. For example, in operational hydrological forecasting, many practitioners are trained in using process-based models (mainly conceptual ones) that serve them reasonably well, and adoption of another modeling paradigm with inevitable changes in their everyday practice could be a painful process. Making models capable of dealing with the data and model uncertainty is currently an important issue as well.

It is sensible to use DDM if (1) there is a considerable amount of observations available; (2) there were no considerable changes to the system during the period covered by the model; and (3) it is difficult to build adequate process-based simulation models due to the lack of understanding and/or to the ability to satisfactorily construct a mathematical model of the underlying processes. Data-driven models can also be useful when there is a necessity to validate the simulation results of physically based models.

It can be said that it is practically impossible to recommend one particular type of a data-driven model for a given problem. Hydrological data are noisy and often of poor quality; therefore, it is advisable to apply various types of techniques and compare and/or combine the results.

2.16.7 Analysis of Uncertainty in Hydrological Modeling

2.16.7.1 Notion of Uncertainty

Webster's Dictionary (1998) defines uncertain as follows: not surely or certainly known, questionable, not sure or certain in knowledge, doubtful, not definite or determined, vague, liable to vary or change, not steady or constant, varying. The noun uncertainty results from the above concepts and can be summarized as the state of being uncertain. However, in the context of hydrological modeling, uncertainty has a specific meaning, and it seems that there is no consensus about the very term of uncertainty, which is conceived with differing degrees of generality (Kundzewicz, 1995).

Often uncertainty is defined with respect to certainty. For example, Zimmermann (1997) defined certainty as "certainty implies that a person has quantitatively and qualitatively the appropriate information to describe, prescribe or predict deterministically and numerically a system, its behaviour or other phenomena." Situations that are not described by the above definition shall be called uncertainty. A similar definition has been given by Gouldby and Samuels (2005): "a general concept that reflects our lack of sureness about someone or something, ranging from just short of complete sureness to an almost complete lack of conviction about an outcome."

In the context of modeling, uncertainty is defined as a state that reflects our lack of sureness about the outcome of a physical processes or system of interest, and gives rise to potential difference between assessment of the outcome and its true value. More precisely, uncertainty of a model output is the state or condition that the output cannot be assessed uniquely. Uncertainty stems from incompleteness or imperfect knowledge or information concerning the process or system in addition to the random nature of the occurrence of the events. Uncertainty resulting from insufficient information may be reduced if more information is available.

2.16.7.2 Sources of Uncertainty

Uncertainties that can affect the model predictions stem from a variety of sources (e.g., Melching, 1995; Gupta *et al.*, 2005), and are related to our understanding and measurement capabilities regarding the real-world system under study:

1. Perceptual model uncertainty, that is, the conceptual representation of the watershed that is subsequently translated into mathematical (numerical) form in the model. The perceptual model (Beven, 2001) is based on our understanding of the real-world watershed system, that is, flowpaths, number and location of state variables, runoff production mechanisms, etc. This understanding might be poor, particularly for aspects relating to subsurface system characteristics, and therefore our perceptual model might be highly uncertain (Neuman, 2003).
2. Data uncertainty, that is, uncertainty caused by errors in the measurement of input (including forcing) and output data, or by data processing. Additional uncertainty is introduced if long-term predictions are made, for instance, in the case of climate change scenarios for which as per definition no observations are available. A hydrological model might also be applied in integrated systems, for example, connected to a socioeconomic model, to assess, for example, impacts of water resources changes on economic behavior. Data to constrain these integrated models are rarely available (e.g., Letcher *et al.*, 2004). An element of data processing, that is, uncertainty, is introduced when a model is required to interpret the actual measurement. A typical example is the use of radar rainfall measurements. These are measurements of reflectivity that have to be transformed to rainfall estimates using a (empirical) model with a chosen functional relationship and calibrated parameters, both of which can be highly uncertain.
3. Parameter estimation uncertainty, that is, the inability to uniquely locate a best parameter set (model, i.e., a model structure parameter set combination) based on the available information. The lack of correlation often found between conceptual model parameters and physical watershed characteristics will commonly result in significant prediction uncertainty if the model is extrapolated to predict the system behavior under changed conditions (e.g., land-use change or urbanization) or to simulate the behavior of a similar but geographically different watersheds for which no observations of the variable of interest are available (i.e., the ungauged case). Changes in the represented system have to be considered through adjustments of the model parameters (or even the model structure), and the degree of adjustment has so far been difficult to determine without measurements of the changed system response.
4. Model structural uncertainty introduced through simplifications, inadequacies, and/or ambiguity in the description

of real-world processes. There will be some initial uncertainty in the model state(s) at the beginning of the modeled time period. This type of uncertainty can usually be taken care of through the use of a warm-up (spin-up) period or by optimizing the initial state(s) to fit the beginning of the observed time series. Errors in the model (structure and parameters) and in the observations will also commonly cause the states to deviate from the actual state of the system in subsequent time periods. This problem is often reduced using data assimilation techniques as discussed later.

Figure 8 presents how different sources of the uncertainty might vary with model complexity. As the model complexity (and the detailed representation of the physical process) increases, structural uncertainty decreases. However, with the increasing complexity of model, the number of inputs and parameters also increases and consequently there is a good chance that input and parameter uncertainty will increase. Due to the inherent trade-off between model structure uncertainty and input/parameter uncertainty, for every model there is the optimal level of model complexity where the total uncertainty is minimum.

2.16.7.3 Uncertainty Representation

For many years, probability theory has been the primary tool for representing uncertainty in mathematical models. Different methods can be used to describe the degree of uncertainty. The most widely adopted methods use PDFs of the quantity, subject to the uncertainty. However, in many practical problems the exact form of this probability function cannot be derived or found precisely.

When it is difficult to derive or find PDF, it may still be possible to quantify the level of uncertainty by the calculated statistical moments such as the variance, standard deviation, and coefficient of variation. Another measure of the uncertainty of a quantity relates to the possibility to express it in terms of the two quantiles or prediction intervals. The prediction intervals consist of the upper and lower limits between which a future uncertain value of the quantity is expected to lie with a prescribed probability. The endpoints of a prediction interval are known as the prediction limits. The width of the prediction interval gives us some idea about how uncertain we are about the uncertain entity.

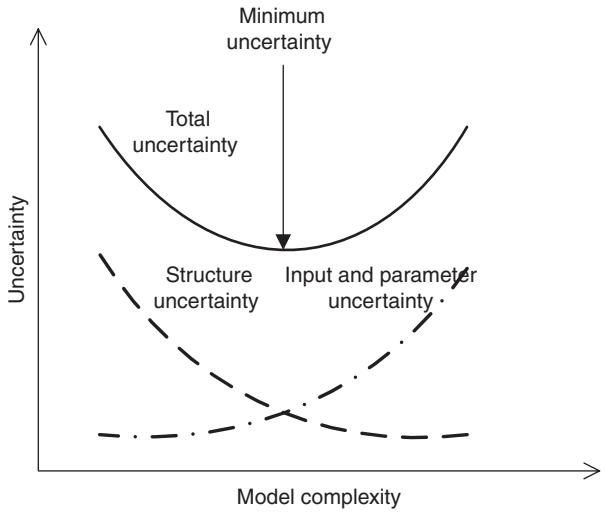

Figure 8 Dependency of various sources of uncertainty on the model complexity.

Although useful and successful in many applications, probability theory is, in fact, appropriate for dealing with only a very special type of uncertainty, namely random (Klir and Folger, 1988). However, not all uncertainty is random. Some forms of uncertainty are due to vagueness or imprecision, and cannot be treated with probabilistic approaches. Fuzzy set theory and fuzzy measures (Zadeh, 1965, 1978) provide a nonprobabilistic approach for modeling the kind of uncertainty associated with vagueness and imprecision.

Information theory is also used for representing uncertainty. Shannon's (1948) entropy is a measure of uncertainty and information formulated in terms of probability theory. Another broad theory of uncertainty representation is the evidence theory introduced by Shafer (1976). Evidence theory, also known as Dempster–Shafer theory of evidence, is based on both the probability and possibility theory. In hydrological modeling, the primary tool for handling uncertainty is still probability theory, and, to some extent, fuzzy logic.

2.16.7.4 View at Uncertainty in Data-Driven and Statistical Modeling

In DDM, the sources of uncertainty are similar to those for other hydrological models, but there is an additional focus on data partitioning used for model training and verification. Often data are split in a nonoptimal way. A standard procedure for evaluating the performance of a model would be to split the data into training set, cross-validation set, and test set. This approach is, however, very sensitive to the specific sample splitting (LeBaron and Weigend, 1994). In principle, all these splitting data sets should have identical distributions, but we do not know the true distribution. This causes uncertainty in prediction as well.

The prediction error of any regression model can be decomposed into the following three sources (Geman *et al.*, 1992): (1) model bias, (2) model variance, and (3) noise. Model bias and variance may be further decomposed into the contributions from data and training process. Furthermore, noise can also be decomposed into target noise and input noise. Estimating these components of prediction error (which is however not always possible) helps to compute the predictive uncertainty.

The terms bias and variance come from a well-known decomposition of prediction error. Given N data points and M models, the decomposition is based on the following equality:

$$\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(t_i-y_{ij})^2=\frac{1}{N}\sum_{i=1}^{N}(t_i-\bar{y}_i)^2+\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(\bar{y}_i-y_{ij})^2 \qquad (2)$$

where t_i is the ith target, y_{ij} the ith output of the jth model, and $\bar{y}_i=1/M\sum_{j=1}^{M}y_{ij}$ the average model output calculated for input i.

The left-hand-side term of Equation (2) is the well-known MSE. The first term on the right-hand side is the square of bias and the last term is the variance. The bias of the prediction errors measures the tendency of over- or under-prediction by a model, and is the difference between the target value and the model output. From Equation (2), it is clear that the variance does not depend on the target, and measures the variability in the predictions by different models.

2.16.7.5 Uncertainty Analysis Methods

Once the uncertainty in a model is acknowledged, it should be analyzed and quantified with the ultimate aim to reduce the impact of uncertainty. There is a large number of uncertainty analysis methods published in the academic literature. Pappenberger *et al.* (2006) provided a decision tree to help in choosing an appropriate method for a given situation. Uncertainty analysis process in hydrological models varies mainly in the following: (1) type of hydrological models used; (2) source of uncertainty to be treated; (3) the representation of uncertainty; (4) purpose of the uncertainty analysis; and (4) availability of resources. Uncertainty analysis has comparatively a long history in physically based and conceptual modeling (see, e.g., Beven and Binley, 1992; Gupta *et al.*, 2005).

Uncertainty analysis methods in all the above cases should involve: (1) identification and quantification of the sources of uncertainty, (2) reduction of uncertainty, (3) propagation of uncertainty through the model, (4) quantification of uncertainty in the model outputs, and (6) application of the uncertain information in decision-making process.

A number of methods have been proposed in the literature to estimate model uncertainty in rainfall–runoff modeling. Reviews of various methods of uncertainty analysis on hydrological models can be found in, for example, Melching (1995), Gupta *et al.* (2005), Montanari (2007), Moradkhani and Sorooshian (2008), and Shrestha and Solomatine (2008). These methods are broadly classified into several categories (most of them result in probabilistic estimates):

1. analytical methods (see, e.g., Tung, 1996);
2. approximation methods, for example, first-order second moment method (Melching, 1992);
3. simulation and sampling-based (Monte Carlo) methods leading to probabilistic estimates that may also use Bayesian reasoning (Kuczera and Parent, 1998; Beven and Binley, 1992);
4. methods based on the analysis of the past model errors and either using distribution transforms (Montanari and Brath, 2004) or building a predictive ML of uncertainty (Shrestha and Solomatine, 2008; Solomatine and Shrestha, 2009); and
5. methods based on fuzzy set theory (e.g., Abebe *et al.*, 2000a; Maskey *et al.*, 2004).

Analytical and approximation methods can hardly be applicable in case of using complex computer-based models. Here, we will present only the most widely used probabilistic methods based on random sampling – Monte Carlo simulation method. The GLUE method (Beven and Binley, 1992), widely used in hydrology, can be seen as a particular case of MC approach. MC simulation is a flexible and robust method capable of solving a great variety of problems. In fact, it may be the only method that can estimate the complete probability distribution of the model output for cases with highly nonlinear and/or complex system relationship (Melching, 1995). It has been used extensively and also as a standard means of comparison against other methods for uncertainty assessment. In MC simulation, random values of each of uncertain variables are generated according to their respective probability distributions and the model is run for each of the realizations of uncertain variables. Since we have multiple realizations of outputs from the model, standard statistical technique can be used to estimate the statistical properties (mean, standard deviation, etc.) and empirical probability distribution of the model output. MC simulation method involves the following steps:

1. randomly sample uncertain variables X_i from their joint probability distributions;
2. run the model $y = g(x_i)$ with the set of random variables x_i;
3. repeat the steps 1 and 2 s times, storing the realizations of the outputs $y_1, y_2, \ldots, y_s$; and
4. from the realizations $y_1, y_2, \ldots, y_s$, derive the cdf and other statistical properties (e.g., mean and standard deviation) of Y.

When MC sampling is used, the error in estimating PDF is inversely proportional to the square root of the number of runs s and, therefore, decreases gradually with s. As such, the method is computationally expensive, but can reach an arbitrarily level of accuracy. The MC method is generic, invokes fewer assumptions, and requires less user input than other uncertainty analysis methods. However, the MC method suffers from two major practical limitations: (1) it is difficult to sample the uncertain variables from their joint distribution unless the distribution is well approximated by a multinormal distribution (Kuczera and Parent, 1998) and (2) it is computationally expensive for complex models. Markov chain Monte Carlo (MCMC) methods such as Metropolis and Hastings (MH) algorithm (Metropolis *et al.*, 1953; Hastings, 1970) have been used to sample parameter from its posterior distribution. In order to reduce the number of samples (model simulations) necessary in MC sampling , more efficient Latin Hypercube sampling has been introduced (McKay *et al.*, 1979). Further, the following methods in this row can be mentioned: Kalman filter and its extensions (Kitanidis and Bras, 1980), the DYNIA approach (Wagener *et al.*, 2003), the BaRE approach (Thiemann *et al.*, 2001), the SCEM-UA algorithm (Vrugt *et al.*, 2003), and the DREAM algorithm (Vrugt *et al.*, 2008b), a version of the MCMC scheme.

Most of the probabilistic techniques for uncertainty analysis treat only one source of uncertainty (i.e., parameter uncertainty). Recently, attention has been given to other sources of uncertainty, such as input uncertainty or structure uncertainty, as well as integrated approach to combine different sources of uncertainty. The research shows that input or structure uncertainty is more dominant than the parameter uncertainty. For example, Kavetski *et al.* (2006) and Vrugt *et al.* (2008a), among others, treat input uncertainty in hydrological

modeling using Bayesian approach. Butts *et al.* (2004) analyzed impact of the model structure on hydrological modeling uncertainty for stream flow simulation. Recently, new schemes have emerged to estimate the combined uncertainties in rainfall–runoff predictions associated with input, parameter, and structure uncertainty. For instance, Ajami *et al.* (2007) used an integrated Bayesian multimodel approach to combine input, parameter, and model structure uncertainty. Liu and Gupta (2007) suggested an integrated data assimilation approach to treat all sources of uncertainty.

Regarding the sources of uncertainty, Monte-Carlo-type methods are widely used for parameter uncertainty, Bayesian methods and/or data assimilation can be used for input uncertainty and Bayesian model averaging method is suitable for structure uncertainty. The appropriate uncertainty analysis method also depends on whether the uncertainty is represented as randomness or fuzziness. Similarly, uncertainty analysis methods for real-time forecasting purposes would be different from those used for design purposes (e.g., when estimating design discharge hydraulic structure design).

It should be noted that the practice of uncertainty analysis and the use of the results of such analysis in decision making are not yet widely spread. Some possible misconceptions are stated by Pappenberger and Beven (2006):

> a) uncertainty analysis is not necessary given physically realistic models, b) uncertainty analysis is not useful in understanding hydrological and hydraulic processes, c) uncertainty (probability) distributions cannot be understood by policy makers and the public, d) uncertainty analysis cannot be incorporated into the decision-making process, e) uncertainty analysis is too subjective, f) uncertainty analysis is too difficult to perform and g) uncertainty does not really matter in making the final decision.

Some of these misconceptions however have explainable reasons, so the fact remains that more has to be done in bringing the reasonably well-developed apparatus of uncertainty analysis and prediction to decision-making practice.

2.16.8 Integration of Models

2.16.8.1 Integration of Meteorological and Hydrological Models

Water managers demand much longer lead times in the hydrological forecasts. Forecasting horizon of hydrological models can be extended if along with the (almost) real-time measurements of precipitation (radar and satellite images, gauges), their forecasts are used. The forecasts can come only from the numerical weather prediction (NWP; meteorological) models.

Linking of meteorological and hydrological models is currently an adopted practice in many countries. One of the examples of such an integrated approach is the European flood forecasting system (EFFS), in which development started in the framework of EU-funded project in the beginning of the 2000s. Currently, this initiative is known as the European flood alert system (EFAS), which is being developed by the EC Joint Research Centre (JRC) in close collaboration with several European institutions. EFAS aims at developing a 4–10-day in-advance EFFS employing the currently available medium-range weather forecasts. The framework of the system allows for incorporation of both detailed models for specific basins as well as a broad scale for entire Europe. This platform is not supposed to replace the national systems but to complement them.

The resolution of the existing NWP models dictates to a certain extent the resolution of the hydrological models. LISFLOOD model (Bates and De Roo, 2000) and its extension module for inundation modeling LISFLOOD-FP have been adopted as the major hydrological response model in EFAS. This is a rasterized version of a process-based model used for flood forecasting in large river basins. LISFLOOD is also suitable for hydrological simulations at the continental scale, as it uses topographic and land-use maps with a spatial resolutions up to 5 km.

It should be mentioned that useful distributed hydrological models that are able to forecast floods at meso-scales have grid sizes from dozens of meters to several kilometers. At the same time, the currently used meteorological models, providing the quantitative precipitation forecasts, have mesh sizes from several kilometers and higher. This creates an obvious inconsistency and does not allow to realize the potential of the NWP outputs for flood forecasting – see, for example, Bartholmes and Todini (2005). The problem can partly be resolved by using downscaling (Salathe, 2005; Cannon, 2008), which however may bring additional errors. As NWP models use more and more detailed grids, this problem will be becoming less and less acute.

One of the recent successful software implementations of allowing for flexible combination of various types of models from different suppliers (using XML-based open interfaces) and linking to the real-time feeds of the NWP model outputs is the Delft-FEWS (FEWS, flood early warning system) platform of Deltares (Werner, 2008). Currently, this platform is being accepted as the integrating tool for the purpose of operational hydrological forecasting and warning in a number of European countries and in USA. The other two widely used modeling systems (albeit less open in the software sense) that are also able to integrate meteorological inputs are (1) the MIKE FLOOD by DHI Water and Environment, based on the hydraulic/hydrologic modeling system MIKE 11 and (2) FloodWorks by Wallingford Software.

2.16.8.2 Integration of Physically Based and Data-Driven Models

2.16.8.2.1 Error prediction models

Consider a model simulating or predicting certain water-related variable (referred to as a primary model). This model's outputs are compared to the recorded data and the errors are calculated. Another model, a data-driven model, is trained on the recorded errors of the primary model, and can be used to correct errors of the primary model. In the context of river modeling, this primary model would be typically a physically based model, but can be a data-driven model as well.

Such an approach was employed in a number of studies. Shamseldin and O'Connor (2001) used ANNs to update runoff forecasts: the simulated flows from a model and the current and previously observed flows were used as input, and the corresponding observed flow as the target output. Updates of daily flow forecasts for a lead time of up to 4 days were

made, and the ANN models gave more accurate improvements than autoregressive models. Lekkas *et al.* (2001) showed that error prediction improves real-time flow forecasting, especially when the forecasting model is poor. Abebe and Price (2004) used ANN to correct the errors of a routing model of the River Wye in UK. Solomatine *et al.* (2006) built an ANN-based rainfall–runoff model whose outputs were corrected by an IBL model.

2.16.8.2.2 Integration of hydrological knowledge into DDM

An expert can contribute to building a DDM by bringing in the knowledge about the expected relationships between the system variables, in performing advanced correlation and mutual information analysis to select the most relevant variables, determining the model structure based on hydrological knowledge (allowed, e.g., by the M5flex algorithm by Solomatine and Siek (2004)), and in deciding what data should be used and how it should be structured (as it is done by most modelers).

It is possible to mention a number of studies where an attempt is made to include a human expert in the process of building a data-driven model. For solving a flow forecasting problem, See and Openshaw (2000) built not a single overall ANN model but different models for different classes of hydrological events. Solomatine and Xue (2004) introduced a human expert to determine a set of rules to identify various hydrological conditions for each of which a separate specialized data-driven model (ANN or M5 tree) was built. Jain and Srinivasulu (2006) and Corzo and Solomatine (2007) also applied decomposition of the flow hydrograph by a threshold value and then built the separate ANNs for low and high flow regimes. In addition, Corzo and Solomatine (2007) were building two separate models related to base and excess flow which were identified by the Ekhardt's (2005) method, and used overall optimization of the resulting model structure. All these studies demonstrated the higher accuracy of the resulting models where the hydrological knowledge and, wherever possible, models were directly used in building data-driven models.

2.16.9 Future Issues in Hydrological Modeling

Natural and anthropogenic changes constantly impact the environment surrounding us. Available moisture and energy change due to variability and shifts in climate, and the separation of precipitation into different pathways on the land surface are altered due to wildfires, beetle infestations, urbanization, deforestation, invasive plant species, etc. Many of these changes can have a significant impact on the hydrological regime of the watershed in which they occur (e.g., Milly *et al.*, 2005; Poff *et al.*, 2006; Oki and Kanae, 2006; Weiskel *et al.*, 2007). Such changes to water pathways, storage, and subsequent release (the blue and green water idea of Falkenmark and Rockstroem (2004)) are predicted to have significant negative impacts on water security for large population groups as well as for ecosystems in many regions of the world (e.g., Sachs, 2004). The growing imbalances among freshwater supply, its consumption, and human population will only increase the problem (Vörösmarty *et al.*, 2000). A major task for hydrologic science lies in providing predictive models based on sound scientific theory to support water resource management decisions for different possible future environmental, population, and institutional scenarios.

But can we provide credible predictions of yet unobserved hydrological responses of natural systems? Credible modeling of environmental change impact requires that we demonstrate a significant correlation between model parameters and watershed characteristics, since calibration data are, by definition, unavailable. Currently, such *a priori* or regionalized parameters estimates are not very accurate and will likely lead to very uncertain prior distributions for model parameters in changed watersheds, leading to very uncertain predictions. Much work is to be done to solve this and to provide the hydrological simulations with the credibility necessary to support sustainable management of water resources in a changing world.

The issue of model validation has to be given much more attention. Even if calibration and validation data are available, the historical practice of validating the model based on calculation of the Nash–Sutcliffe coefficient or some other squared error measure outside the calibration period is inadequate. Often low or high values of these criteria cannot clearly indicate whether or not the model under question has descriptive or predictive power. The discussion on validation has to move on to use more informative signatures of model behavior, which allow for the detection of how consistent the model is with system at hand (Gupta *et al.*, 2008). This is particularly crucial when it comes to the assessment of climate and land-use change impacts, that is, when future predictions will lie outside the range of observed variability of the system response.

Another development is expected with respect to modeling technologies, mainly in the more effective merging of data into models. One of the aspects here is the optimal use of data for model calibration and evaluation. In this respect, more rigorous approach adopted in DDM (e.g., use of cross-validation and optimal data splitting) could be useful. Modern technology allows for accurate measurements of hydraulic and hydrologic parameters, and for more and more accurate precipitation forecasts coming from NWP models. Many of these come in real time, and this permits for a wider use of data-driven models with their combination with the physically based models, and for wider use of updating and data assimilation schemes. With more data being collected and constantly increasing processing power, one may also expect a wider use of distributed models. It is expected that the way the modeling results are delivered to the decision makers and public will also undergo changes. Half of the global population already owns mobile phones with powerful operating systems, many of which are connected to wide-area networks, so the Information and communication technology (ICT) for the quick dissemination of modeling results, for example, in the form of the flood alerts, is already in place. Hydrological models will be becoming more and more integrated into hydroinformatics systems that support full information cycle, from data gathering to the interpretation and use of modeling results by decision makers and the public.

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