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History and perspectives of hydrological catchment modelling

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ABSTRACT

This paper presents a brief historical excursus on the development of hydrological catchment models together with a number of possible future perspectives. Given the wide variety of available hydrological models which, according to the embedded level of prior physical information, vary from the simple input–output lumped models to complex physically meaningful ones, the paper suggests how to accommodate and to reconcile the different approaches. This can be performed by better clarifying the roles and the limitations of the different models through objective benchmarks or test-beds characterizing the diverse potential hydrological applications. Furthermore, when dealing with hydrological forecasting, the reconciliation can be obtained in terms of forecasting uncertainty, by developing Bayesian frameworks to combine together models of different nature in order to assess and reduce predictive uncertainty.

Key words | conceptual, data-driven, hydrological models, physically based, predictive uncertainty, validation uncertainty

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INTRODUCTION

The history of hydrological modelling ranges from the Rational Method to recent distributed physically meaningful models. Over the same period of time, starting from the simple Unit Hydrograph, input–output models, now called data-driven models, have evolved into artificial neural network (ANN) models and data-based mechanistic (DBM) models. From the wide range of models available, the choice of the one most appropriate for any specific task is difficult, particularly as each modeller tends to promote the merits of his own approach. Moreover, apart from the WMO (1975) inter-comparison of conceptual models, the WMO (1986) inter-comparison of snow accumulation and melting models and the WMO (1992) inter-comparison of real-time updating approaches applied to hydrological flood forecasting models, no further objective comparisons using benchmarks or standard data sets have been proposed or effected in the last decades. Only recently an inter-comparison of distributed model was started by the US-NWS (http://www.nws.noaa.gov/oh/hrl/dmip) in order to assess the performance of distributed hydrological models.

Today the plethora of available models has grown beyond any possible limit and the need for accommodating under a unifying view and reconciling the different approaches has become of great priority. Unfortunately, hydrology is one of the few scientific branches where standards on the use and development of models are difficult to set and, although there is an increasing awareness at developing standards for calibration and verification (Refsgaard *et al.* 2005; Jakeman *et al.* 2006), there is still a long way to go.

Moreover, hydrological models serve many purposes, one of the most important applications being flood forecasting where uncertainty plays a major role. Unfortunately, the implication of using uncertainty in the decision-making process and even the concept of uncertainty seem to deter hydrologists from addressing the problem. Indeed, many hydrologists do not appear to be aware of the need to

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quantifying predictive uncertainty and tend to describe the model sensitivity rather than the decision makers' uncertainty on the outcome of possible future occurrences given (or conditional upon) the model forecasts.

This paper will briefly describe the historical development of the different hydrological models and will try to suggest possible ways to reconcile the different approaches both on the basis of their potential use as well as in terms of their Bayesian combination aimed at benefiting of all possible information generated by the use of alternative models within the frame of the decision making process. Finally, the paper concludes with an overview of possible future perspectives in hydrological research.

A BRIEF HISTORY OF QUANTITATIVE HYDROLOGICAL MODELS

Although a more detailed overview of the historical development of hydrological models was given in an earlier paper (Todini 2007), a brief historical description was deemed necessary to better understand the development of thought and the future perspectives in hydrological modelling.

From the rational method to the conceptual models (1850–1960)

It must be acknowledged that from the onset, the development of hydrological models has always been motivated by practical engineering problems. For instance, the generally recognised first hydrological model, the Rational Method, proposed by Mulvany (1850) came as a response to the need for designing sewers, to which it was extensively applied (Kuichling 1889; Lloyd-Davies 1906), or dam spillways in small, practically impervious catchments. The Rational Method, uses the concept of time of concentration to estimate the peak flow in small impervious catchments, such as the urban or mountain catchments, where flow can be well assimilated to a purely kinematic process.

Also, the development of the unit hydrograph (UH), introduced by Sherman (1932), was motivated by the need for providing not only the peak flow, but the shape and the volume of the flood wave to improve the design of reservoirs and flood defences. From its original triangular shape, the UH, with the advent of system's theory, was then extended to a variety of shapes in the form of impulse responses of causative linear dynamic systems, known in the literature as the "linear models" (Dooge 1973; Nash 1958, 1960).

Initially, the need to extend the results obtained with the linear models to larger and non-entirely impervious catchments prompted the separation of the "effective rainfall", namely the component of rain that would generate surface runoff (Chow *et al.* 1988), to be then modelled using the linear models. Further on, with the advent and the wider availability of digital computers "conceptual models" started to appear (Dawdy & O'Donnell 1965) with the aim of modelling the complex interdependence of soil-surface runoff generating mechanisms.

From conceptual to variable contributing area models (1960–2000)

To achieve a better physical interpretation of catchment response, the 1960s saw the development of models in which individual components in the hydrological cycle were represented by interconnected conceptual elements; each of these represented, in the hydrological model, the response of a particular subsystem: for example Dawdy & O'Donnell (1965), Crawford & Linsley (1966) – Stanford Watershed IV; Burnash *et al.* (1973) – Sacramento (Figure 1); Rockwood (1964) – SSARR; Sugawara (1967, 1995) – Tank.

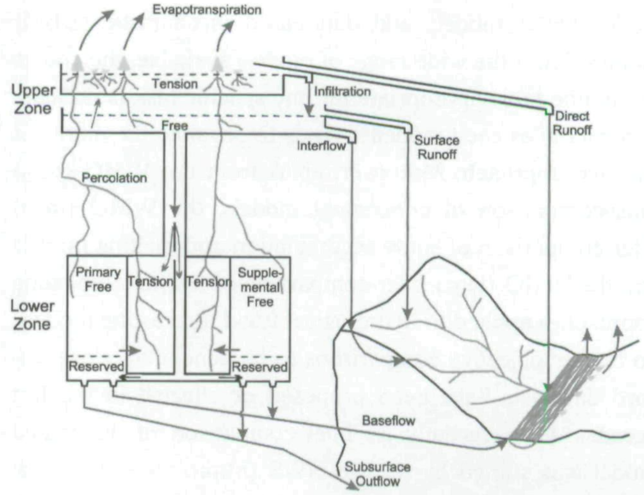

Figure 1 | Schematic representation of a typical conceptual model: the Sacramento model.

All these models, also known as Explicit Soil Moisture Accounting (ESMA) models, represented in different ways the responses of, and the interconnections between, the various subsystems from which the overall catchment response could originate (see Figure 2); at the time, they were regarded as the very best that could be achieved with the then current data and computational resources.

At the end of the 1970s, a new type of lumped model was introduced, based on the idea that the rainfall runoff process is mainly dominated by the dynamics of saturated areas, which can be related to the soil moisture storage using a simple monotone function, thus leading to the variable contributing area models. These models generally employed the Dunne (1978) assumption that all precipitation enters the soil and that surface runoff originates by saturation of the upper soil layer. These variable contributing area models, the Xinanjiang due to Zhao (1977) and the Probability Distribution (PDM) proposed by Moore & Clarke (1981), the ARNO (Todini 1996) were characterized by few significant parameters, which unfortunately could not be directly derived, but needed to be estimated during model calibration.

More recently, Beven & Kirkby (1979), with the increased availability of digital terrain models (DTM), originated the TOPMODEL, based on the distribution function of a topographic index, that can be derived from the DTM. Based on the assumption that the accumulation of soil moisture can be approximated by successive steady states of the water table originating in the upper soil layer, they derived a relation between the volume of water stored in the soil and the extent of saturated areas (the topographic index function) on the basis of physically meaningful parameters. Unfortunately, also due to a water balance error which was present in the original TOPMODEL, recently detected and corrected by Saulnier & Datin (2004), the physical meaning of parameters proved to be true only for very small hill-slope catchments represented with extremely fine meshes as found by Franchini *et al.* (1996).

The distributed process models (1965–today)

As an alternative to conceptual models several authors aimed at improving the physical representation of the rainfall-runoff process. For instance, Wooding (1965*a*, *b*, 1966) and Woolhiser & Liggett (1967) used kinematic models for the study of small urban basins, while Freeze & Harlan (1969) proposed a mathematical model based on distributed physical knowledge of surface and subsurface phenomena. By numerical integration of the coupled sub-systems of partial differential equations describing surface flow and flow in the unsaturated and saturated zones, and by matching the solutions of each subsystem with the boundary conditions of another, catchment scale predictions could be produced. This concept was then developed into SHE (Système Hydrologique Européen) (Abbott *et al.* 1986*a*, *b*), by the Danish Hydraulic Institute (DK), the Institute of Hydrology at Wallingford (UK) and SOGREAH (France). Figure 3 shows a sketched representation of the SHE model.

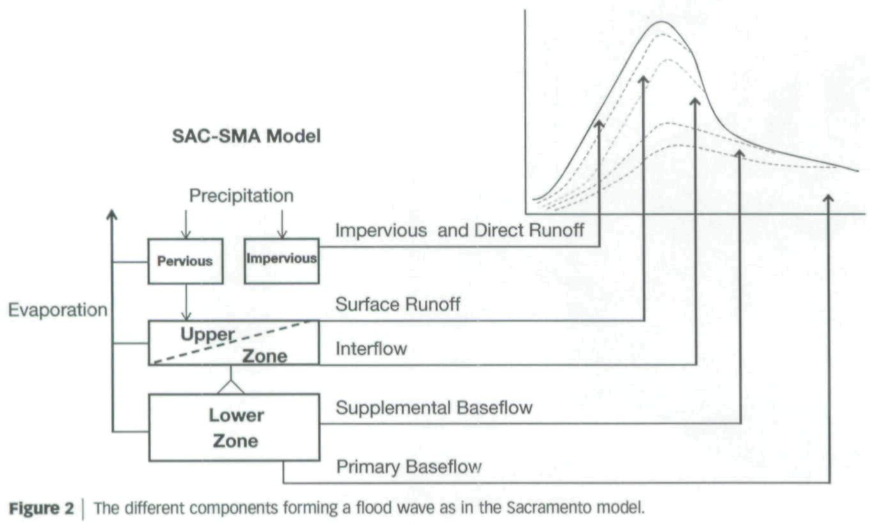

Figure 2 | The different components forming a flood wave as in the Sacramento model.

The limitation to its practical use is the large requirement for data and computational time which restrict its use to small extensively instrumented catchments.

More recently, the wider availability of distributed information, ranging from soil types and land use to radar rainfall, have facilitated the production of simplified physically meaningful distributed hydrological models. These models, based on the upscaling of point process equations to finite-dimension pixels, with simpler and more parsimonious parameterizations than those employed in MIKE SHE (Refsgaard & Storm 1995) and SHETRAN (Ewen *et al.* 2000), can also be applied to operational flood forecasting. This is the case of TOPKAPI (Todini 1995; Liu & Todini 2002; Todini & Ciarapica 2002), LISFLOOD (De Roo *et al.* 1998, 2000) and TETIS (see Figure 4) (Vélez 2001; Francés *et al.* 2007).

The data-driven models (1970–today)

The Sherman (1932) UH together with all the "linear models" (Nash 1958, 1960; Dooge 1973) can be viewed as the first data-driven models in hydrology. Box & Jenkins (1970) showed in fact the link between the Transfer Function or Impulse Response models and the Auto-Regressive with Exogenous variables models (ARX). Later, system engineering approaches, including various types of input–output techniques, were applied to develop better performing and more parsimonious models to represent the hydrological behaviour of a catchment, at the expense of a larger loss of physical interpretation.

This loss of physicality increased further with ANN approaches, which can be viewed as nonlinear analogues of the original linear transfer function models. Although Dawson & Wilby (2001) and Shamseldin (1997) review applications of ANN to rainfall-runoff modelling, few operational forecasting systems are presently based on ANN (Garcìa-Bartual 2002) since outside of the range of the training set, the ANN may be less robust and may sometimes diverge (Gaume & Gosset 2003).

More recently, there is an interesting return to the need for justifying the identified models on physical grounds. The DBM modelling approach, introduced by Young (2002), is a tentative attempt to go beyond the black-box concept by selecting, among the resulting model structures, those that

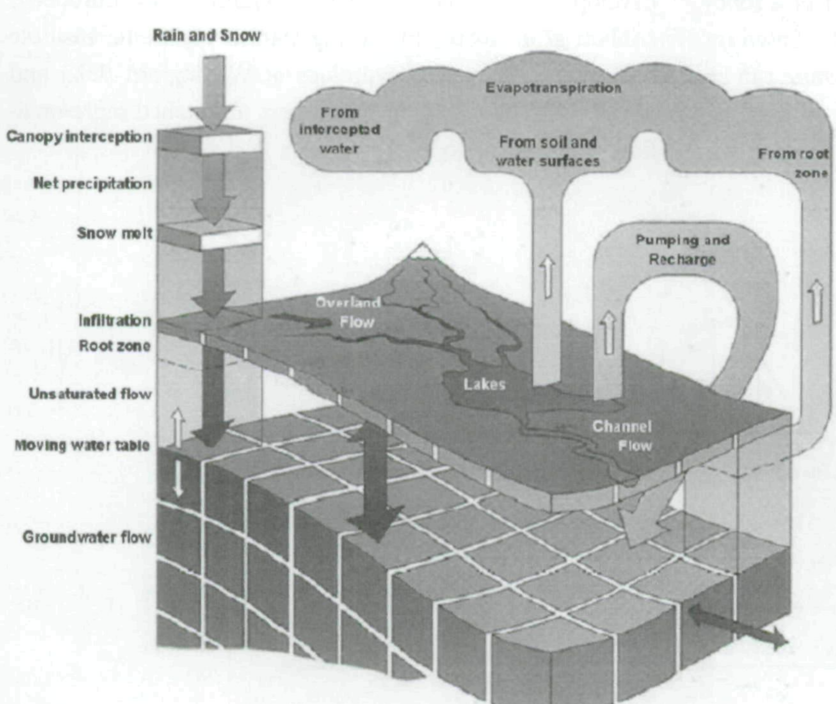

Figure 3 | Schematic representation of the SHE model.

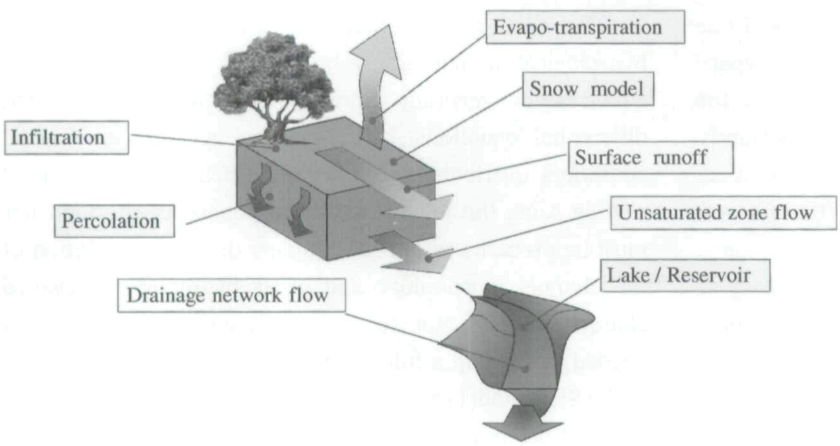

Figure 4 | Schematic representation of the TOPKAPI model.

are considered physically meaningful (Young 2001, 2002). Unfortunately, apart from simple routing models, scant examples of this modelling approach are presently available in operational hydrology.

ACCOMMODATING AND RECONCILING HYDROLOGICAL MODELS

Data-driven or physics-based models

The dichotomy between the two lines of thought on the one hand of hydrologists aiming at understanding and improving the physical representation of processes in their models and on the other hand at successfully modelling the relations between inflow and outflow regardless of the complexity of phenomena, is still an unresolved problem. Needless to say, no model is either fully data driven or entirely physically based; nonetheless, a discussion on these two lines of thought is essential, given the practical implication that they have over the present and future development and availability of hydrological models. In broad terms, the development of a model is the synthesis of what the modeller assumes to know with what he regards as unknown, to be derived from data and, in principle, the modeller should introduce as prior knowledge all the information he or she is sure of or comfortable with, unless this results in excessive data demand.

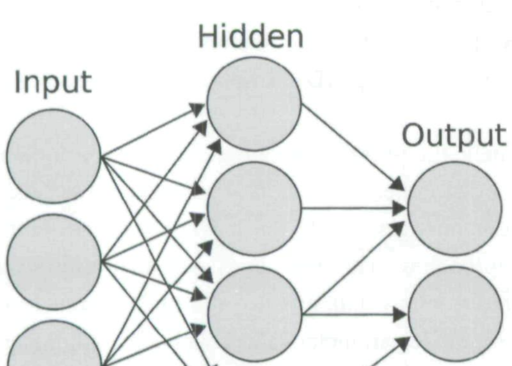

Figure 5 | A typical representation of an ANN model.

From the lower end a modeller may assume to know virtually nothing and statistical as well as system engineering or ANN approaches will provide him the techniques to identify at the same time the structure of the model and the relevant parameters. The structure of the model will be then based upon one or more simple model forms, a typical representation of which is given in Figure 5, such as for instance the negative exponential (linear reservoir) in impulse response models, the polynomial ratio forms in the Laplace or Z transformed spaces or the Logistic function in the case of the ANN approaches.

But, regardless to the simplicity of the lumped input–output model, when dealing with physical systems, a modeller would like to build in some lumped form of the obvious physical laws such as, for instance, water mass balance or some simple form of energy or momentum balance. Therefore, to introduce this prior information into the model one must either introduce it in terms of constraints over the space of parameters (Natale & Todini 1976*a*, *b*) or to justify the shape of the selected impulse response on physical grounds. For instance, Kalinin & Milyukov (1957) demonstrated that, by linearizing the unsteady flow equations, the integral solution (the impulse response of the system) has the shape of a Gamma density function, better known in hydrology as the Nash (1958, 1960) cascade with parameters n and k, where the parameter n is now extended to the domain of real numbers.

At this point the modeller has two choices: either to estimate the model parameters by matching the results of the model to a set of historical observations or, if he believes in the physical approximation, he can relate the parameters to measurable quantities. For instance, in the case of the above-mentioned routing problem the parameters can be expressed in terms of the Froude number, the bed slope, the velocity, etc., as shown by Dooge (1973).

Another step, towards increasing the complexity of prior information to be introduced in a model, arises when the modeller wants to reproduce not only the outflow, but also the state of the internal state variables, such as for instance the state of soil moisture in a hydrological model. The modeller will then have to specify the structure and the interlinks of "sub-models" such as evapo-transpiration, soil moisture infiltration and balance, overland and channel flow. This was in fact done in the conceptual models where each component of the hydrologic cycle was represented in the form of buckets, thresholds, connections, etc., but the resulting models became dependent on far too many parameters to be estimated with input (rainfall) and overall output (discharge in the river). Using this approach it was virtually impossible to relate the parameters to measurable quantities for many reasons: the "sub-models" were mostly coarse bucket analogues of the processes involved; validation of the assumed internal structure was not possible due to the fact that only precipitation and flow in the channel were available. Also, calibration could be extremely difficult due to the large number of parameters and their interdependence (Gupta & Sorooshian 1983; Sorooshian & Gupta 1983), which resulted into a loss of confidence in "complex physically based" models as the conceptual models were considered in the 1970s and 1980s.

The next step in increasing prior knowledge into a hydrological model not only involves model complexity, which is now generally expressed in the form of distributed differential equations, but also a tremendous amount of additional distributed information. When performing flood routing using the full Saint Venant equations, the modeller must be prepared to introduce a very detailed description of the channel morphology and of its hydraulic conveyance characterization. Not to say the amount of information needed to develop a fully distributed catchment model such as the SHE model (Abbott *et al.* 1986*a*, *b*). In this case a major problem lies in the fact that the original process differential equations were studied and are valid at the infinitesimal scale, while in the model their validity is extended up to the pixel scale (from metres to hundreds of metres), without taking into account the obvious spatial averaging effect that occurs in the upscaling process. This in turn impacts on the validity of the used "physically meaningful" parameter values: these values may be correct at a point, but, due to the not infrequent high spatial variability, they are not necessarily true or valid at the pixel scale over which the model is discretized. Therefore, effective parameters have again to be calibrated using series of available historical data. This is why a more realistic approach seems then, starting from the same point process equations, to derive their average behaviour over the finite pixel scale, as for instance in TOPKAPI (Todini 1995; Liu & Todini 2002; Todini & Ciarapica 2002). This allows one to use representative average parameter values (such as hydraulic conductivity, porosity, slope) at the pixel scale up to scales of the order of a few hundred metres without losing model performance, as shown by Martina *et al.* (2009), with the additional advantage that these parameters can be reasonably derived from available maps (DTM, soil maps and land-use maps).

Unfortunately, the proponents of the data-driven models and the fans of distributed differential models do not discuss in terms of the advantages and the fields of applications of the alternative approaches. The first ones say that complex models require too many data and are still undetermined in terms of representative parameter values, while the others say that the data-driven models can hardly be extrapolated beyond the range of the historical data used for calibration. It is therefore hoped that efforts will be made towards a reconciliation of the two lines of thought, since they are both valid and fruitful for the improvement of the quality of representation of hydrological systems.

Towards new possible classifications of models and the need for test beds

Today, users are frequently uncertain about the selection of the most appropriate hydrological model to suit their purposes given the wide variety of existing models (Singh & Woolhiser 2002). A rather general classification of hydrological models was provided in 1988 by Chow *et al.* (1988), as shown in Figure 6. Unfortunately, 30 years later this classification does not seem to be fully satisfactory. With the introduction of the concepts of "predictive uncertainty" (de Finetti 1975) and "equifinality" (Bertalanffy 1968; Beven & Binley 1992; Beven & Freer 2001) many models, following the basic Bayesian principle, are now more correctly viewed as a combination of what is assumed to be known and what is derived from the observations. Under these new concepts, it is difficult to classify even a routing component of a hydrological model. This could in fact be interpreted as physically based when using the Saint Venant equations with known boundary conditions, but, at the same time, as stochastic since all the uncertainty (model structure, parameters, initial and boundary conditions, input and output measurement errors) would be taken to be concentrated in the roughness coefficient, which becomes now an uncertain (stochastic) parameter only characterized by its posterior probability density. Therefore it is evident that the classification proposed by Chow *et al.* (1988) becomes more and more difficult to actually represent the wide variety of available models.

As an alternative, Todini (1988), in order to assess the state of the art of hydrological models, proposed a simple classification based upon the level of prior knowledge introduced in the model and assumed for the parameter values.

This classification, which was just sketched in the referenced paper, is not conclusive, but it is probably along these lines that the models should be assessed and classified with the aim of clarifying to possible users, in relation to the problem to be solved, the quantity and quality of assumptions made; the need for geo-morphological information; the role of uncertainty and the calibration requirements.

This implies the definition of a number of standard test beds, covering a wide variety of engineering and water resources problems, in order to operationally compare the models also in relation to their declared objectives, their performances and their ease of use.

Predictive uncertainty and the use of multi-model approaches

Flood emergency management requires operational decisions that may lead to dramatic consequences (economic losses, casualties, etc.) to be taken in real time. Knowing exactly what would actually happen in the near future (next few hours or days), emergency managers could safely take, by the book, the best possible decisions on the basis of pre-defined operational plans. Unfortunately, in real situations the

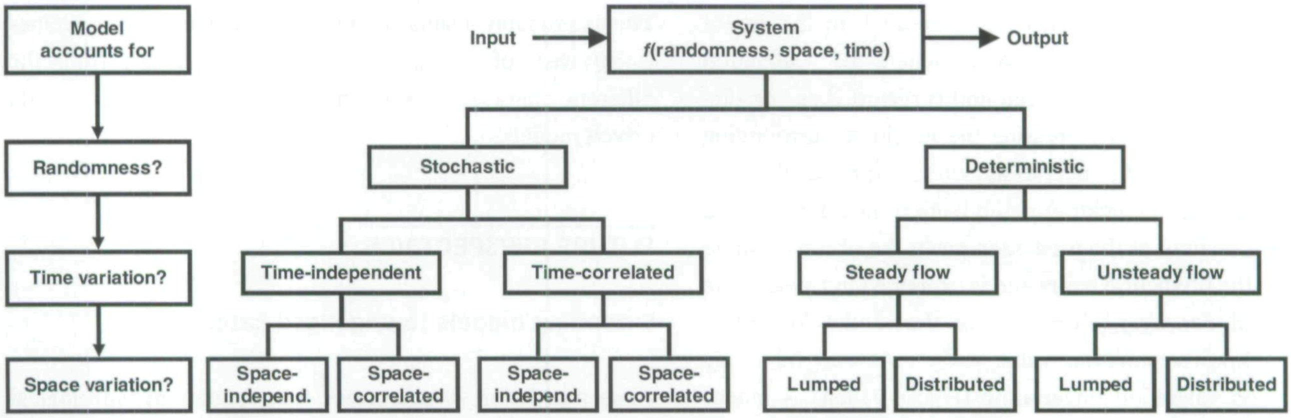

Figure 6 | The classification of hydrological models according to Chow *et al.* (1988).

managers cannot choose the right decision due to their uncertainty on the future evolution of events. As described by Raiffa & Schlaifer (1961) and De Groot (1970), decision theory studied this problem and provided solutions for decisions under uncertainty. These are generally obtained by minimizing the expected value of an utility function, which represents either the actual losses (if they can be estimated) or, more generally, the manager perception of losses, as a function of a quantity that may occur at a future time, such as the discharge or the water stage that will be reached at a given cross-section. This quantity, which is called "predictand" in the statistical literature, is not known when issuing the forecast, but can be evaluated as an expected value conditional to one or more model forecasts, to which a predictive uncertainty is attached.

Since the late 1990s, interest in assessing "uncertainty" in models has grown exponentially within the scientific communities of meteorologists and hydrologists. In particular, the introduction, on the one hand, of meteorological ensembles, aimed at assessing meteorological meso-scale models forecasting uncertainty (Molteni *et al.* 1996; Buizza *et al.* 1999; Stephenson *et al.* 2005), and on the other hand, of the Hydrological Uncertainty Processor (Krzysztofowicz 1999), aimed at assessing predictive uncertainty in hydrological forecasts, has created the basis for the assessment of "flood forecasting uncertainty". The interest in this subject is shown not only by the abundant literature, but also by the establishment of the International Research Programme HEPEX (2004). Unfortunately, the statistical background of far too many meteorologists and hydrologists was insufficient to really appreciate the definition of "predictive uncertainty" and its subtle difference from what could be defined as "validation uncertainty". This has generated, in the recent literature, a large number of papers where the "validation uncertainty" is estimated instead and is regarded as "predictive uncertainty", thus increasing the fogginess surrounding the subject. Validation uncertainty, which expresses the ability at emulating (mimicking) reality with a model, is defined as the uncertainty of the prediction given the observed value to which the prediction refers and is expressed in terms of the conditional density $f_{\hat{y}|y^*}(\hat{y}|y = y^*)$ of the model forecast $\hat{y}$ about a known observed value $y = y^*$. As can be easily understood validation uncertainty (Figure 7, left) is fundamental to assess the quality and to improve a given model: the aim in this case is to reduce validation uncertainty in order to improve model structure, model parameterization and parameter estimation. In contrast, predictive uncertainty (Figure 7, right) expresses the uncertainty on what may happen at a future stage when the available information is provided by a model forecast, which at the time of the forecast is a known value. In this case, it is what will actually occur which is unknown. Predictive uncertainty is expressed in terms of the conditional density $f_{\hat{y}|y^*}(\hat{y}|y = y^*)$ of a future unknown value y given its prediction $\hat{y} = \hat{y}^*$ provided by a model, which is evidently known when issued.

In the case of flood forecasting, predictive uncertainty can thus be defined as the uncertainty that a decision maker has on the future evolution of a predictand that he uses to trigger a specific decision, such as issuing a flood warning or opening the gates of a water detention area or activating a bypass, conditional on all the model(s) forecasts he can be aware of. Today, basically three approaches are available in the literature for the assessment of predictive uncertainty, the Hydrological Uncertainty Processor (HUP) introduced by Krzysztofowicz (1999), the Bayesian Model Averaging (BMA) promoted by Raftery (1993) and Raftery *et al.* (2003, 2005), and the Model Conditional Processor (MCP), more recently introduced by Todini (2008). All these approaches, and in particular the last two, aim at assessing and reducing predicting uncertainty by combining together one or more than one predictive model.

One of the major benefits arising from the use of the multi-model techniques is the possibility of reconciling alternative modeling approaches in terms of the estimation of a unique predictive uncertainty, conditional upon all the models, which will then be used in the decision making process. This is probably a satisfactory way of replying to Vit Klemes (1983) wish of taking the maximum advantage from the different characteristics of the physics based and the data driven models.

FUTURE PERSPECTIVES

Extending models to ungauged catchments

As seen in the previous sections, the evolution of hydrological models proceeded from the simple conceptual models to the

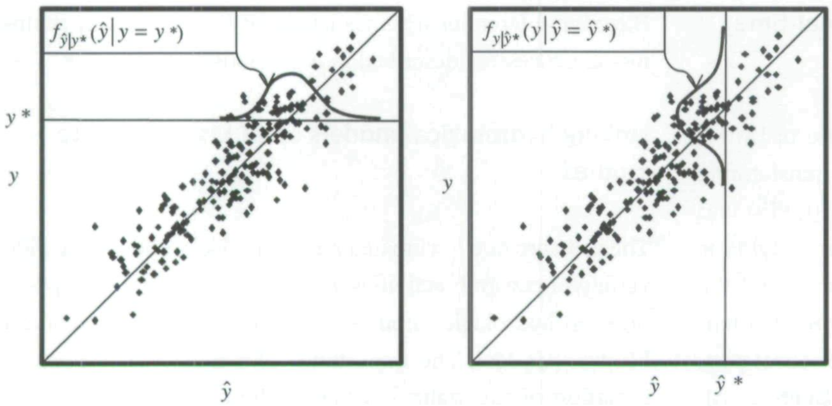

Figure 7 | Graphical representation of validation and predictive uncertainty. Validation uncertainty (left) is expressed in terms of the conditional density $f(\hat{y}|y = y^*)$ of the model forecast $\hat{y}$ about a known observed value $y = y^*$, while predictive uncertainty (right) is expressed in terms of the conditional density $f(\hat{y}|y = y^*)$ of a future unknown value y given its prediction $\hat{y} = \hat{y}^*$ provided by a model, which is evidently known when issued.

more comprehensive and physically based ones, gradually introducing more detailed equations in the effort of better reproducing the complex reality (Singh 1988). At the same time, several lumped models have been proposed, which tend to represent reality with widely different parameterisations of the infiltration, soil saturation, drainage, runoff formation processes. But, given the present (as well as near-future expected) availability of detailed spatial information such as for instance DTMs at tenths of metres, radar precipitation estimates at few hundred metres, the basic question in order to be able to accurately extrapolate models to ungauged catchments, is whether or not it is possible or worthwhile to directly set up lumped hydrological models encapsulating the physical properties and processes that can be described at the different scales without the need of setting up distributed models. The reason for this question lies in the fact that the statistical approaches to extrapolate information from one catchment to another have mostly failed at providing efficient models that can benefit from the large amount of available distributed and detailed geomorphological information, today available through remote sensing.

In a recent paper, Martina *et al.* (2009) showed that, unfortunately, the physical properties of the basic soil and surface processes (such as hydraulic conductivity, soil moisture content, slope, overland friction) can only be retained at finer spatial scales (up to few hundred metres), due to the inherent topological nonlinearities of the hydrological processes at the catchment scale that hide the small scale ones, which directly depend on the parameters. Physics-based lumped models can only be derived through an averaging (lumping) process conditional upon a correct representation of these additional nonlinear phenomena at the catchment scale, which are automatically resolved when using distributed finer scales models but are not resolved by the present generation of lumped models. These phenomena are the hysteretic dependency of the saturated area on the mean soil water volume, also found by several other authors (Mishra & Seth 1996; Niedzialek & Ogden 2004; O'Kane & Flynn 2007; Norbiato & Borga 2008), and the exfiltration from the soil which continues after the end of a rainfall event (Liu & Todini 2002). Owing to these nonlinear effects, one has to realize that, currently, only the distributed models can be used if one wants to use the available distributed maps to extrapolate on physical grounds the hydrological parameters to ungauged catchments, while lumped version retaining the physical information can be successively derived via distributed modelling simulation.

Thus, interesting research perspectives lie in the study (from their experimental analysis to their conceptualisation in hydrological models) of the macro nonlinear phenomena that can be observed when aggregating from the pixel to the catchment scale, but not directly at this latter scale, since they cannot be not resolved in lumped form. Furthermore, additional research should be concentrated in the derivation of theoretical results that could overcome this need for distributed modelling simulations, by more directly finding the nonlinear relations occurring through different scales as a function of the different available maps.

Linking hydrological models to LAMs for real-time and flash flood forecasting

Another important area of development is the use of hydrological models as part of a chain aimed at transforming meteorological quantitative precipitation forecasts (QPFs) into flood forecasts at given river cross sections. The use of QPFs is common when one wants to extend the forecast beyond the characteristic concentration time of a catchment. Several tentative case studies have been implemented in the recent past, particularly within EU funded projects such pas EFFS (2003), which have not lead to satisfactory results. In addition, the use of meteorological ensemble predictions, namely predictions based not on a single future precipitation scenario, but on a set of 20–50 scenarios (members of the ensemble), has additionally complicated the problem.

As one can see from Figure 8, for an example of real-time flood forecast at Ponte Spessa on the Po river in Italy, ensemble QPF forecasts tend to generate ensembles of predicted discharges and water levels that hardly embed the observed ones. This is due to the fact that meteorological ensembles represent an envelope of model, parameter and boundary conditions uncertainty, the validation uncertainty, instead of the predictive uncertainty, namely the uncertainty on future values given the model forecasts (Todini 2008).

Therefore, current research, particularly within the frame of HEPEX, aims at finding the most appropriate ways of making use of QPF ensembles by incorporating them into

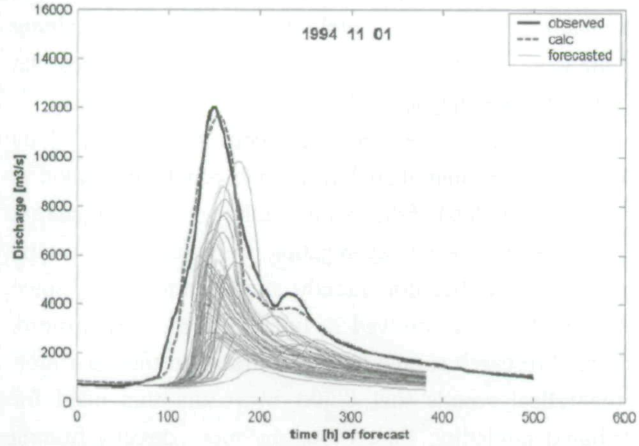

Figure 8 | Observed discharges (solid line) together with the ones simulated using observed rainfall (dashed line) and the ones resulting from ensemble forecasts of QPF (thin solid lines) for the Po river at Ponte Spessa.

Bayesian inferential schemes based on the uncertainty multimodel processors described in a previous section.

Linking hydrological models to GCMs for climate studies

The pressure due to climate changes is also motivating a wide variety of research activities and in particular the incorporation of hydrologic models into the General Circulation Models (GCMs). The importance of a more realistic representation of the water balance at the catchment scale was recognized by Dümenil & Todini (1992) who incorporated the ARNO model (Todini 1996, 2002) in the ECHAM GCM in place of the Manabe (1969) on–off bucket, followed by Liang *et al.* (1996*a*, *b*) who used the VIC model (Wood *et al.* 1992) in the GFDL GCM for the same purpose.

One of the reasons that motivated the interest of climatologists in using more realistic surface schemes, rather than the simple on–off bucket, to represent the formation of runoff is tied to the possibility of using river discharges, now available for most of the largest rivers of the world, to assess the response of the GCMs not only in terms of average climatology, but also in terms of actual monthly water volumes delivered to the oceans.

What appeared immediately evident was the need for a lumped hydrological model that could be applied to all the GCM pixels which were, at that time, of the order of magnitude of $100 \times 100\ \text{km}^2$. Neither the ARNO nor the VIC schemes could be extended on physical grounds to the different pixels, taken as ungauged catchments, due to the lack of physical meaning of their parameters. This motivated the interest in possible hydrological model parameterizations which parameters could be derived from digital elevation maps, land use maps and soil type maps that are now available for the entire globe at pixels of the order of $1 \times 1\ \text{km}^2$.

As described in a previous section, results in this area are promising but not yet conclusive and additional research is still needed.

CONCLUSIONS

A significant advance has been made in terms of quantitative representation of hydrological phenomena from the Rational

Method to the nowadays available distributed physics-based models. Nonetheless, there remains much scope in pursuing research into a number of interesting questions and problems under the pressure of climate change and the need to correctly assess predictive uncertainty and the possibility of reconciling alternative modelling approaches.

This paper, which aimed to present a historical overview and future perspective of hydrological catchment modelling, concludes with the hope that future generations of hydrologists will enthusiastically approach the new emerging research needs.

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