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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 the 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 characterising 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.

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 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/her own approach. Moreover, apart from the WMO inter-comparisons of conceptual models (WMO, 1975), snow accumulation and melting models (WMO, 1986) and real-time updating approaches applied to hydrological flood forecasting models (WMO, 1992) conducted in the seventies and the eighties, 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 performances 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 in practice each modeller is setting his owns.

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 quantifying predictive uncertainty and tend to describe the model sensitivity rather than the decision makers' uncertainty on the outcome of possible future values of the quantity conditional upon the model forecast.

This paper will briefly describe the historical development of the different hydrological models and will try to suggest possible approaches 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

From the Rational Method to the Linear Models (1850–1960)

The Rational Method proposed by Mulvany (1850) is a clear exposition of the concept of time of concentration and its relation to the maximum run-off;

it estimates peak flow but not flood volume and is physically meaningful only in small impervious catchments in which flow is effectively a purely kinematic process. Applications of the method to the design of sewers appeared in the literature from the end of the 19th century (Kuichling, 1889; Lloyd-Davies, 1906).

Many years later, (Sherman, 1932) introduced the concept of the Unit Hydrograph (UH) based on the principle of superposition of effects; it enabled the complete flood hydrograph to be predicted from rainfall sampled at constant intervals. With the introduction of system's theory, the unit hydrograph was then interpreted as the response of a linear, causative, dynamic stationary system and two forms of the unit hydrograph were then considered. The first one, the continuous time impulse response of a linear system, is known in hydrology as the Instantaneous Unit Hydrograph (IUH) and a second one, the response to a time discretized input, is known as the finite period unit hydrograph (TUH) (O'Donnell, 1966). Indeed, the introduction of the IUH can be viewed as the starting point that led to the separation of physically meaningful and data driven models. If the "shape" of the IUH is defined a priori by the modeller as the integral solution a set of linear or linearized differential equations and the parameter values are not estimated from the input-output historical data, but computed as a function of the physical characteristic quantities of the phenomenon, then the IUH is a physical interpretation of the phenomenon. Examples can be easily found in flood routing models. For instance, Kalinin and Milyukov (1957) demonstrated that, by linearizing the unsteady flow equations, the integral solution is a Gamma density function, namely a Nash cascade (1958; 1960) with parameters n and k, where the parameter n is now extended to the domain of real numbers, which can be expressed in terms of the Froude number, the bed slope, the velocity, etc. (Dooge, 1973). Furthermore, Hayami (1951) showed how to derive an IUH from the linear diffusion equation, while Todini and Bossi (1986) derived a TUH from the linear parabolic approximation of the unsteady flow equations, with the two parameters, celerity and diffusivity, which are recomputed at each integration time interval in terms of the hydrodynamic characteristics of the reach (discharge, the friction slope, etc.).

However, if the shape of the IUH/TUH cannot be defined a priori on physical grounds, both the shape and the relevant parameters must be derived from the measurements so, clearly, the result is a data-driven model (Natale and Todini, 1976a; 1976b).

The extension of the IUH/TUH approach to larger, not necessarily impervious catchments presented problems requiring subjective choices, such as:

- Separation of storm runoff from base flow;
- The determination of "effective" rainfall, namely that portion of the rainfall that is not lost through replenishing soil moisture etc.;
- The actual derivation of the IUH/TUH shape and/or of the IUH/TUH parameters from the measurements available.

To overcome these problems, research into non-linear or threshold-type systems led to representations based on:

1. Volterra integrals of an order greater than the first,
2. orthogonal polynomials (Amorocho and Orlob, 1961) or
3. piecewise linearisations (Todini and Wallis, 1977; Todini, 2002b), reproducing the consequences of threshold effects introduced by soil saturation.

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. Dawdy-O'Donnell (1965); Crawford and Linsley (1966)—Stanford Watershed IV; Burnash *et al.* (1973)—Sacramento (Figure 1); Rockwood, (1964)—SSARR; Sugawara, (1967, 1995)—Tank, etc.

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 that time the modellers strongly believed that the parameters of their models, such as the storage coefficients, roughness coefficients or the different thresholds were physical entities which could be inferred from the physiographic characteristics of the catchments. Due to the need to obviate a time consuming trial and error approach in parameterising these models, model parameter optimisation was introduced (Dawdy-O'Donnell, 1965). As a result, when the estimates were made on the basis of objective functions to be

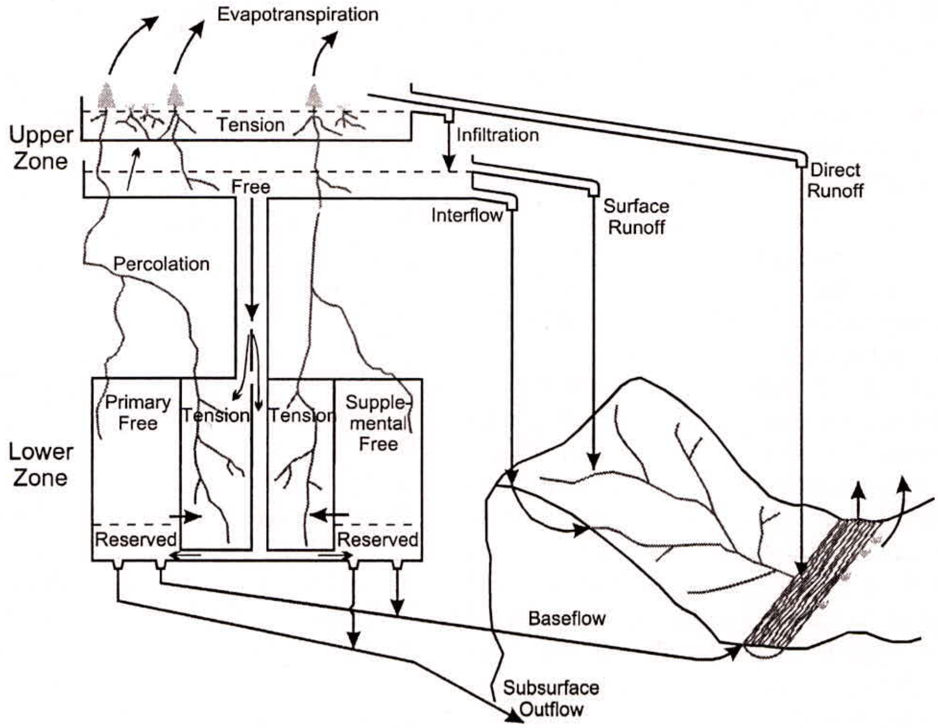

Fig. 1: Schematic representation of a typical conceptual model: the Sacramento model

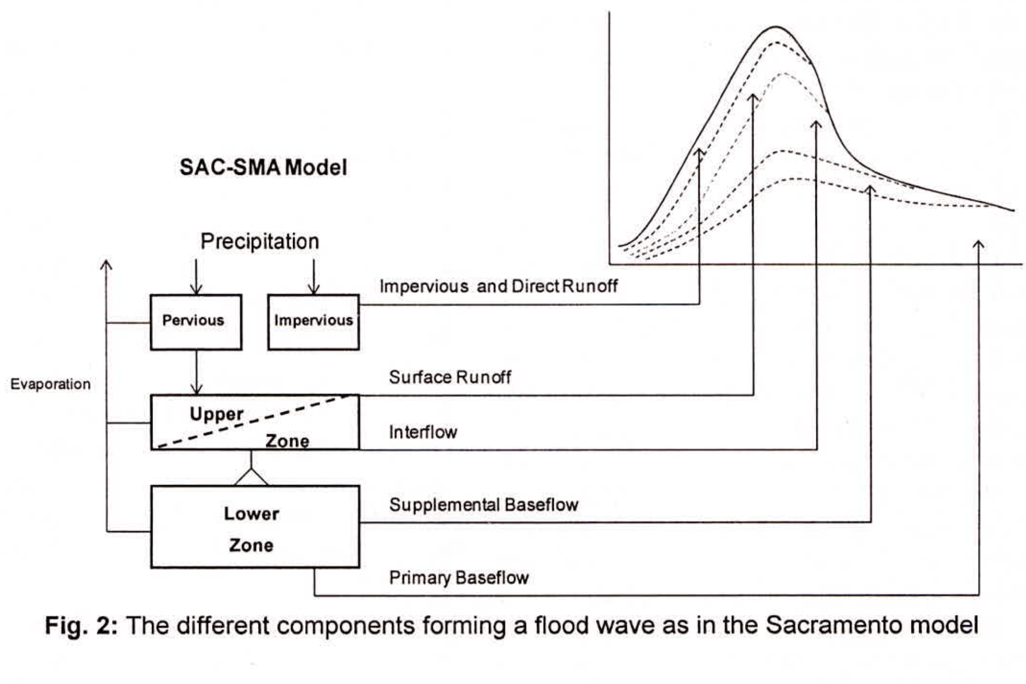

Fig. 2: The different components forming a flood wave as in the Sacramento model

minimised (for example the sum of squares criterion), the resulting parameter values were generally unrealistic, perhaps because they incorporated errors of measurements as well as those of the model itself. Also, the conditions of observability (the need for sufficient information content in the data to determine the parameter values) were not always guaranteed, particularly for multiple input-output hydrological models (Gupta and Sorooshian, 1983; Sorooshian and Gupta, 1983; Singh and Woolhiser, 2002). In essence, these models became data-driven.

At the end of the 1970s, a new type of lumped models 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 (Zhao, 1977) and the Probability Distribution (PDM) (Moore and Clarke, 1981) were characterised by few significant parameters: although expressing the physical concepts of continuity of mass they were still not entirely meaningful in their dynamics. Thereafter, Juemou *et al.* (1987) combined the Xinanjiang soil moisture distribution function with the Constrained Linear Systems (CLS) model (Natale and Todini, 1976a; 1976b; Todini and Wallis, 1977; Todini, 2002b) into the Synthesized Constrained Linear Systems model (SCLS). Later, by modifying the Xinanjiang soil moisture distribution function, Todini (1996; 2002a) developed the ARNO model, from which Wood and Lettenmaier (1992) originated the VIC model by increasing the number of soil layers (Liang *et al.*, 1996a; 1996b). The core of all these models is a two parameter distribution function curve representing the relation between the total volume of water stored in the soil and the extension of the saturated areas. Unfortunately the parameterisation of this curve, as well as of the other processes represented (drainage, percolation, groundwater flow, etc.) was based on empirical parameters to be estimated from the data. Beven and Kirkby (1979) originated a more physically-meaningful distribution function model, TOPMODEL, based on the distribution function of a topographic index. This is 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 new 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 (Saulnier and Datin, 2004), the physical meaning of parameters proved to be true only for very small hill-slope catchments represented with extremely fine meshes (Franchini *et al.*, 1996).

The Distributed Physically Meaningful Models (1965–Today)

In a further step towards a physical representation of the rainfall-runoff process, Wooding (1965a; 1965b; 1966), and Woolhiser and Liggett (1967) used kinematic models for the study of small urban basins,

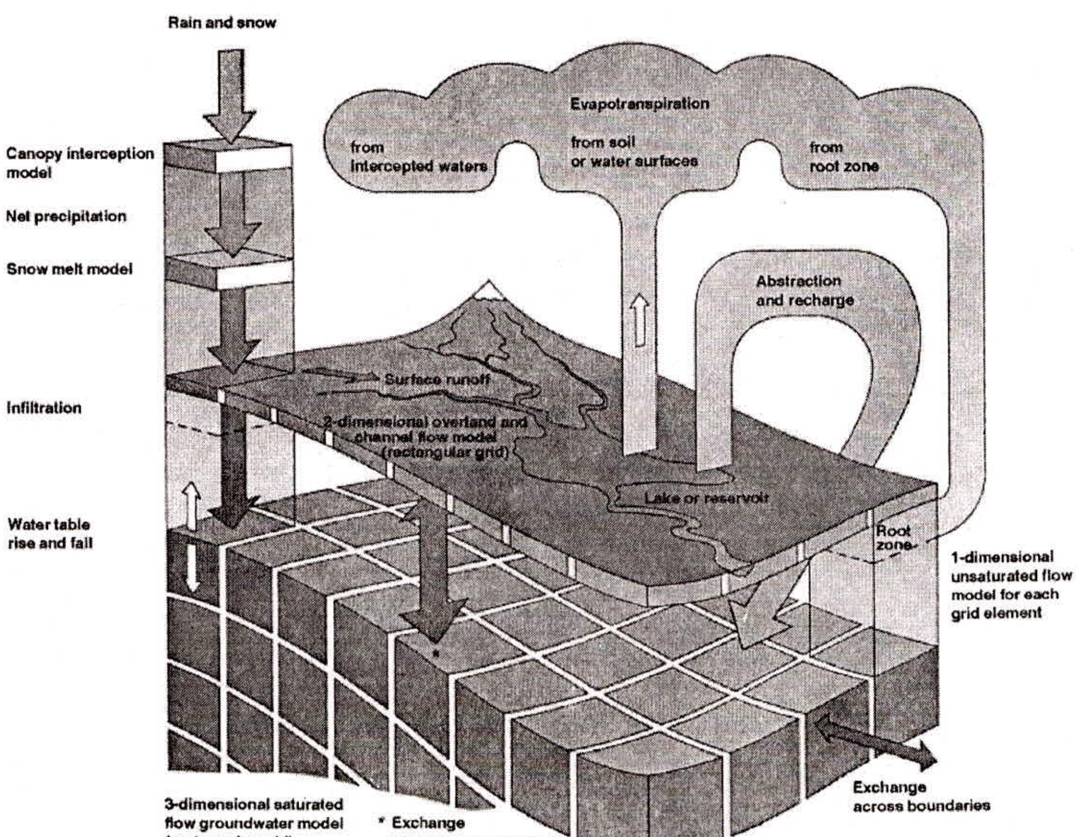

Fig. 3: Schematic representation of the SHE model

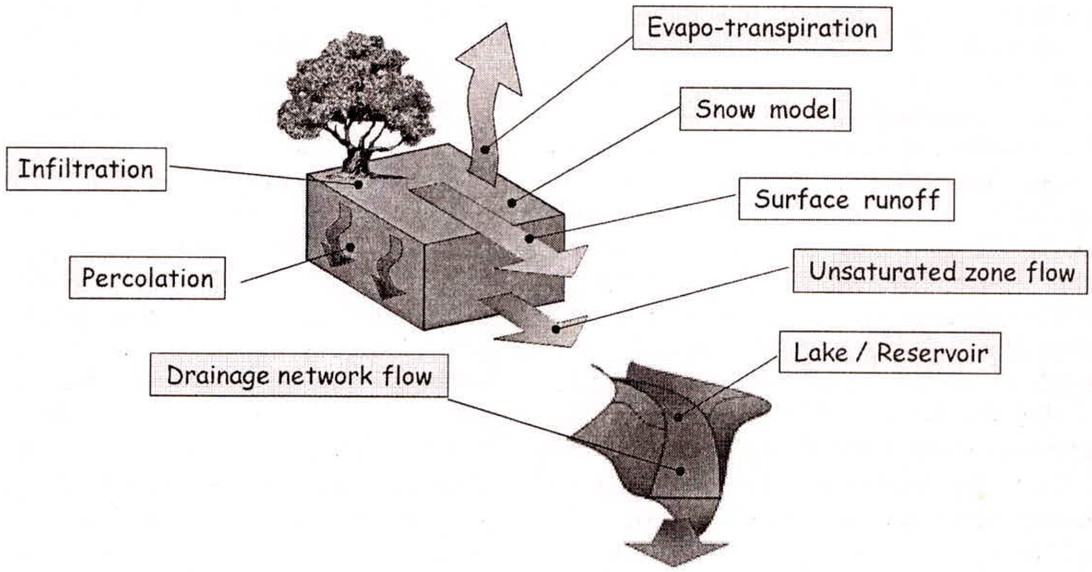

Fig. 4: Schematic representation of the TOPKAPI model

while Freeze and Harlan (1969) proposed, albeit only as a future project, the creation of 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 sub-system with the boundary conditions of another, catchment scale predictions could be produced. This concept was developed into SHE (Système Hydrologique Européen), by the Danish Hydraulic Institute (DK), the Institute of Hydrology at Wallingford (UK) and SOGREAH (France), (Abbott *et al.*, 1986a; 1986b). SHE has since evolved into a robust physically-based model, available as MIKE-SHE (Refsgaard and Storm, 1995) and SHETRAN (Ewen *et al.*, 2000).

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 simplifying assumptions, with simpler and more parsimonious parameterizations than those employed in MIKE SHE and SHETRAN, can also be applied to flood forecasting. Such models are: WATFLOOD (Kouwen, 2000), DHSVM (Wigmosta *et al.*, 1994), TOPKAPI (Todini, 1995; Todini and Ciarapica, 2002; Liu and Todini, 2002), FEWS NET Stream flow Model (Verdin and Klaver, 2002), LISFLOOD (De Roo *et al.*, 1998; 2000) and tRIBS (Vivoni, 2003), and many others that are under test within the frame of the US-NWS DMIP1 and DMIP2 projects (http://www.nws.noaa.gov/oh/hrl/dmip).

The Data-Driven Models (1970–Today)

The Sherman (1932) UH, the starting point for Data-Driven models, was expressed in discrete form by Box and Jenkins (1970), who showed the link between the Transfer Function models and the Auto-Regressive with Exogenous variables models (ARX). Following this idea, Todini (1978) used the UH in the form of an Auto-Regressive Moving-Average with Exogenous variables models (ARMAX) for the reduction of model parameters in a Kalman Filter based real-time flood forecasting system. This Box and Jenkins type modelling introduced a loss of "physicality" in the models, for instance when using the integration to eliminate cyclo-stationarities in data, with the loss of the possibility of preserving the mass balance or Intervention Analysis models, in favour of more mathematically oriented approaches. Later, system engineering approaches, including various types of input-output techniques, were applied in developing better performing and more parsimonious models to represent the hydrological behaviour of a catchment, although with a larger loss of physical interpretation.

This loss of physicality increased further with Artificial Neural Network (ANN) approaches, which can be viewed as non-linear analogues of the original linear transfer function models; unfortunately, forecasts may be poor when the events are larger than those in the training set (Cameron *et al.*, 2002; Gaume and Gosset, 2003). Although Dawson and 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); as already noted, outside of the range of the training set, the ANN may be less robust and may sometimes diverge (Gaume and Gosset, 2003). More recently, a Data Based Mechanistic (DBM) modelling approach, introduced by Young (2002), derived the model structure and the parameter values from the input and output data using system engineering identification and parameter estimation techniques that attempted to go beyond the black-box concept by selecting those (not necessarily linear) model structures that are considered physically meaningful (Young, 2001; 2002).

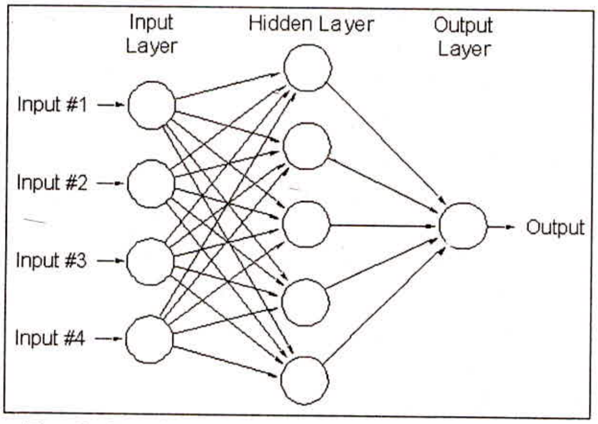

Fig. 5: A typical representation of an ANN model

ACCOMMODATING AND RECONCILING HYDROLOGICAL MODELS

Towards New Possible Classifications of Models and the Need for Test Beds

Today, users are frequently uncertain on the selection of the most appropriate hydrological model to suit their purposes given the wide variety of existing models (Singh and Woolhiser, 2002). A rather general classification of hydrological models was provided in 1988 by Chow *et al.*, as shown in Figure 6. Unfortunately, thirty 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 and Kirkby, 1979; Beven and Freer, 2001) many models, following the basic Bayesian principle, are now 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) proposed a simple classification based upon both prior knowledge and problem requirements, in order to assess the state of the art of hydrological models.

Also 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 requirements of 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.

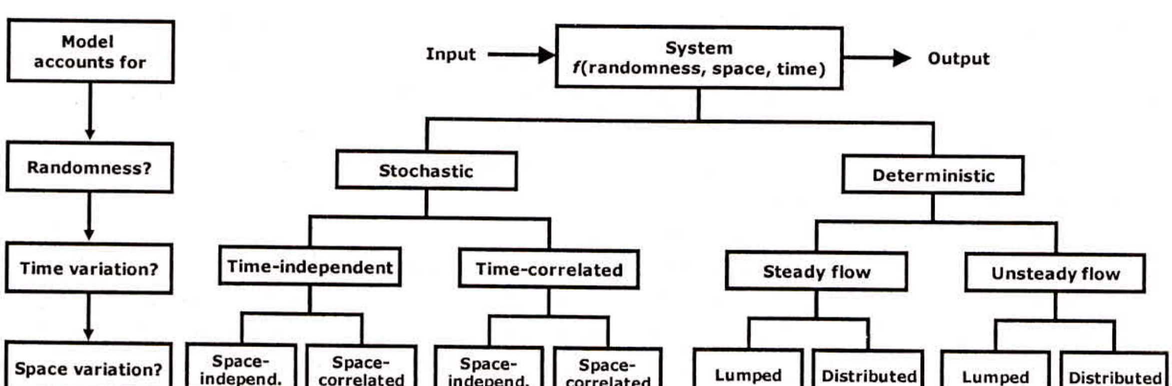

Fig. 6: The classification of hydrological models according to Chow *et al.* (1988)

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 easiness of use.

Predictive Uncertainty and the Use of Multi-Model Approaches

Since the late nineties, the 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, have created the basis for the assessment of "flood forecasting uncertainty". The interest in this subject is shown not only by the abundant available 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 with "model uncertainty". This generated, in the recent literature, a wide number of papers where the "model uncertainty" is estimated instead and is regarded as "predictive uncertainty", thus increasing the fogginess of the subject.

Flood emergency management requires operational decisions that may lead to dramatic consequences (economical losses, casualties, etc.) to be taken in real time. Knowing exactly what would actually happen in the nearby 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 managers cannot choose the right decision due to their uncertainty on the future evolution of events. Decision theory (Raiffa and Schlaifer, 1961; De Groot, 1970) studied this problem and provided solutions for decisions under uncertainty. These are generally obtained by minimising the expected value of an utility function, which represents either the actual losses (if they can be estimated) or, more in general, 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 to which a forecasting error is attached.

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.

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, 2003, 2005) and the Model Conditional Processor (MCP), more recently introduced by Todini (2008). These approaches 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 multi-model techniques is again the possibility of reconciling alternative modelling approaches, which somehow was advocated by Klemes (1983) in order to take the maximum advantage from the different characteristics of the physically 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 more comprehensive and physically based ones, gradually introducing more detailed equations in the effort of better reproducing the complex reality (Singh, 1998). 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, run-off formation processes. But the basic question is whether or not it is possible to directly set up a lumped hydrological model encapsulating the physical properties and processes that can be described at the different scales without the need of setting up distributed models.

In a recent paper, Martina *et al.* (2008) showed that unfortunately, the physical properties of the basic processes can only be retained at finer spatial scales (less than 1 km), while, due to the inherent topological non-linearity, physically based lumped models can only be derived through an averaging process conditional upon a correct representation of additional phenomena. These additional non linear phenomena, which must be reproduced when lumping at the catchment scale are: the hysteretic dependency of the saturated area on the mean soil water volume, also found by several other authors (Mishra and Seth, 1996; Niedzialek and Odgen, 2004; O'Kane and Flynn, 2007; Norbiato and Borga, 2008), and the exfiltration from the soil which continues after the end of a rainfall event (Liu and Todini, 2002). Owing to these non-linear effects, one has to realize that, as for today, only the distributed models can be exported to ungauged catchments on physical grounds, while their lumped version must be successively derived via distributed modelling simulation.

Thus, interesting research perspectives lie in the study of the non linear phenomena not resolved at the catchment scale and in the derivation of theoretical results that could overcome the need for distributed modelling simulations.

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 as 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 notice from the Figure 8, where an example of real time flood forecast at Ponte Spessa on the Po river (Figure 7) is displayed, ensemble QPF

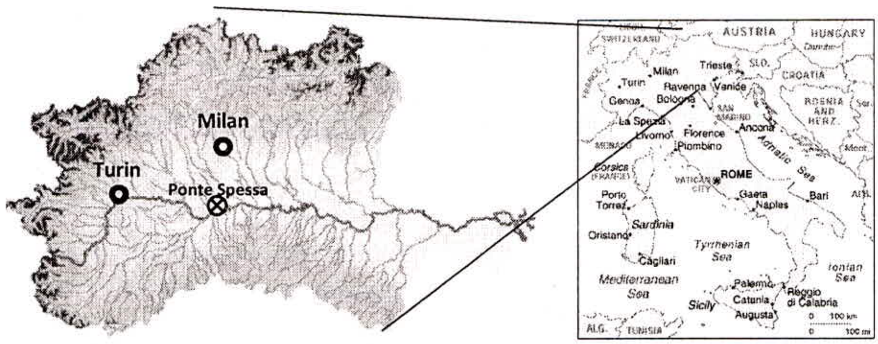

Fig. 7: The Po river basin in Italy

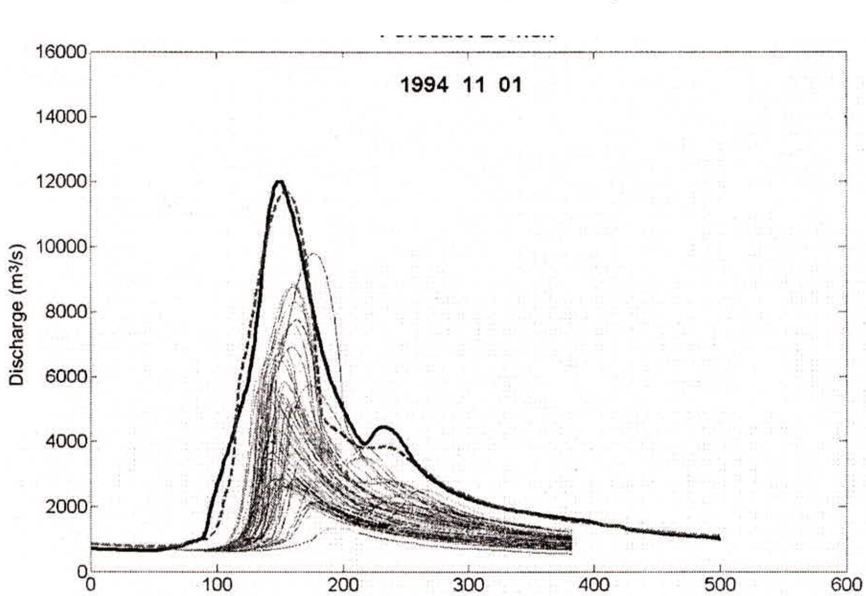

Fig. 8: Observed discharges (solid line) together with the ones simulated using observed rainfall (dashed line) and the ones resulting from ensemble forecasts of QPF (thin solid lines) for the Po river at Ponte Spessa

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 instead of the actual uncertainty of future values (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 Bayesian inferential schemes based on the uncertainty multi-model 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 and Todini (1992) who incorporated the ARNO model (Todini, 1996; 2002a) in the ECHAM GCM in place of the Manabe (1969) on-off bucket, followed by Liang *et al.* (1996a; 1996b) who used the VIC model (Wood *et al.*, 2002) in the GFDL GCM for the same purpose.

One of the reasons that motivated the interest of climatologist at 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 100×100 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 1×1 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 long way was made in terms of quantitative representation of hydrological phenomena from the Rational Method to the now-a-days available distributed physically meaningful models. Nonetheless, there is much scope in pursuing research along a number of interesting questions and problems under the pressure of climate changes or the need for correctly assessing predictive uncertainty and the possibility of reconciling alternative modelling approaches.

This paper, which aimed at presenting a historical overview and future perspective in hydrological catchment modelling, concludes with the hope of finding new young generations that will enthusiastically approach the new emerging research requests.

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