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Challenges in Hydrological Modelling—Simplicity *vs.* Complexity

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ABSTRACT: Hydrological modeling is a challenging task nowadays because of the multi-faceted nature of the problem and the various choices available. There has been a proliferation of models and modeling techniques in the past few decades, and as a result, it is confusing even to an experienced hydrologist. There are simple models, not so simple models, complex models and more complex models with each type having its own pros and cons. There are those who consider the end result more important than the method used to arrive at it and there are also those who consider otherwise. There is no unique approach or model that suits all and all purposes. In this paper, the author attempts to highlight some criteria for the choice of a model, limitations of different types of models including calibration issues, and a comparison of a few types of models in terms of the resource costs and the marginal benefits.

Keywords: Hydrological Models, Calibration of Parameters, Optimization Techniques, Error Indicators.

INTRODUCTION

There exists a plethora of hydrological models that can be found in the literature, with each one having its own pros and cons. However, there is no hydrological model that has universal applicability, and as a result, more and more models seem to originate at a rate faster than many hydrologists can digest. The question then is what criteria should be used in selecting or developing a model that suits a particular need under a given set of conditions and constraints. The starting point should be to decide whether the model is for a practical purpose to solve a particular problem, or for an academic purpose with a view to better understand the hydrological system. The views are divided. There is a school of thought that advocates the principle that better understanding of the system is more important than the end result. There is also the other school of thought that advocates the principle that it is the end result that matters and not how it is obtained.

In developed countries where relatively more resources are available for research, the approach adopted has been to explore the hydrological system in a distributed or semi-distributed manner. As highlighted in the sections that follow, it has advantages and disadvantages. The advantages are mainly of a potential nature, meaning that it is only when all the components that constitute the model are known, or can be known, *a priori*, that there will be better understanding of the system. This condition rarely exists in the real world. On the other hand, in less developed countries where there are severe constraints in resources for research, the approach adopted is to look for simple, practical and result oriented methods that would suit the problem. In this paper, an attempt is made to highlight these and other related issues that pose as challenges to hydrological modelling. Results taken from some studies using different types of models are used as illustrations.

ISSUES TO BE CONSIDERED IN THE CHOICE OF HYDROLOGICAL MODELS

Data Issues

The accuracy and reliability of the outcome of a model depends upon the accuracy and reliability of the data used as inputs. For simple hydrological models the basic input is the rainfall which varies spatially and temporally. Present day raingauges can measure rainfall to a very high degree of accuracy, but a reasonable spatial and temporal resolution is necessary to ensure that the data are representative. Averaging out data has the tendency to smooth out variations thereby distorting the real situation. A compromise is often needed to strike a balance between the resources available and the accuracy of the expected result. The second most important hydrological variable for modelling is the discharge resulting from rainfall which can be considered as an integrator of all catchment-scale processes. Direct measurements of discharges are rarely made under normal conditions. They are derived from stage measurements using rating curves. Stage measurements can be made quite precisely, but the rating curves depend upon many factors such as the techniques and instruments used to measure velocities and channel hydraulic parameters, and whether or not measurements cover the entire range of possible values. Very often, rating curves are established under normal flow conditions, and extrapolated to obtain discharges at high flow conditions thereby introducing an uncertain error. Measurements at high flow conditions are usually not made because they are difficult, dangerous, and costly. There are other relatively less important hydrological processes such as evaporation and evapotranspiration, infiltration, interception, depression storage etc. that contribute to the basin-scale hydrological system, and their inclusion requires some approximations and assumptions while their exclusion results in over simplification.

In addition to hydrological data, geometrical and topographical data are needed for distributed type of models. On a local scale, such data can be found in limited situations. The resolutions vary and depend upon the region and the catchment. On a global or regional scale, remotely sensed topographical data are available, particularly from satellite observations. Their resolutions also vary, but the publicly available data sets do rarely have resolutions finer than 1 km x 1 km horizontally, and a few 10's of metres vertically. The results of any distributed model that uses such coarse data will have inherent errors of the same order or higher, than those of the input topographical data.

Modelling Issues

Hydrological models can be classified according to several different criteria. On a broad basis, they could be classified as data driven and physics-based. The former type includes all models that do not consider the physics of the transformation of rainfall to discharges whereas the latter type in principle considers laws of physics in the modelling process. Data driven models are relatively easy to implement but not without problems. Physics based models are much more difficult to implement and the problems are also of a higher magnitude.

Parameters and their Calibration Issues

All models need calibration before they could be applied. The normal practice is to compare the outcome of the model to the expected outcome and adjust the parameters using some optimization algorithm until the cumulative difference between the two as defined by an objective function is a minimum. For models with a small number of parameters, this is not difficult. However, as the number of parameters in the model increases, the problem of finding a global minimum of the objective function becomes difficult. The objective function often gets trapped at a local minimum.

For physics-based models which are necessarily of a distributed nature, use of optimization techniques for calibration defeats the purpose. By the nature of physics-based models, their parameters are physically identifiable and thus measurable, at least in theory. In practice however, such an exercise is not easy to implement, particularly when the catchment characteristics are heterogeneous. No distributed model which accounts for catchment heterogeneities and spatially varying hydrological inputs that has been calibrated using field measured parameter values exist at the present time. Instead, what is often done is calibrating the parameters of the model using some kind of optimization technique against a single site measured output data. As a result, most models that start with laws of physics end up as data driven models thereby defeating the purpose of adopting such an approach.

Assuming that the above is the only currently available option for calibrating distributed models, the next issue is the choice of the optimization algorithm. In addition to the problem of getting trapped at a local optimum, another problem in multi-parameter optimization is that of equi-finality—a concept originated in the general systems model of Bertalanffy (1968), meaning that the same final result may be arrived from different initial conditions and in different ways. In open systems the final state can be reached by many different ways whereas in a closed system the equi-finality principle states that there is a cause-effect relationship between the initial state and the final state. In the context of multi-parameter optimization, what this means is that there is no unique set of parameter values, but rather a feasible parameter space from which a Pareto set of solutions is sought.

SOME EXAMPLES OF SIMPLE AND COMPLEX MODELS

A simple model developed recently for forecasting the stage at Pandhare Dovan gauging station across Bagmati River in Nepal (Catchment location: 26° 42′–27° 50′ N; 85° 02′–85° 58′ E; catchment area = 2272 km^2) using the stage and rainfall values at previous time levels has been found to be of the form,

$$S_{8\text{ am}}(t) = C_1(S_{8\text{ am}}(t-1)) + C_2(S_{\text{ave}}(t-2)) + C_3(R(t-1)) \quad \ldots (1)$$

where, $S_{8\text{ am}}(t)$ is the stage at 8 am on day t, $S_{8\text{ am}}(t-1)$ is the stage at 8 am on day $t-1$, i.e. previous day, S_{ave} $(t-2)$ is the average of four measurements of stage on day t–2, i.e. two days before, and $R(t–1)$ is the mean rainfall over the area of eleven rainfall stations during the previous 24 hours. (8 am of the previous day to 8 am of the current day). The model parameter values obtained by least squares error minimization method and the error indicators during the calibration and validation periods are given in Table 1.

A similar simple model, also developed recently after several trials, for forecasting the stage at the Sivasagar gauging station across Brahmaputra River in India using upstream stage data at Dibrugarh, upstream tributary stage data at Jungaon and Nangalamora gauging stations across the tributaries Dehing and Desang respectively, and upstream rainfall data at Dibrugar, Dhemaji, North Lakshimpur and Sivasagar is of the form,

$$\begin{aligned} h_{\text{Sivasagar}}(t) = {} & a_1 h_{\text{Sivasagar}}(t-1) + a_2 h_{\text{Dibrugarh}}(t-1) \\ & + a_3 h_{\text{Dehing}}(t-1) + a_4 h_{\text{Desang}}(t-1) \\ & + a_5 r_{\text{Sivasagar}}(t-1) + a_6 r_{\text{Lakshimpur}}(t-1) \\ & + a_7 r_{\text{Dibrugarh}}(t-1) + a_8 r_{\text{Dehing}}(t-1) \end{aligned} \quad \ldots (2)$$

in which the parameters, after least squares error minimization were found to be,

$a_1 = 9.78E-01, a_2 = 8.47E-02, a_3 = -7.96E-02,$
$a_4 = 9.32E-03, a_5 = 4.03E-05, a_6 = 1.38E-03,$
$a_7 = 6.49E-04, a_8 = 8.01E-04.$

The goodness of fit of this model as indicated by the coefficient of determination (R^2) and the RMSE are given in Table 2.

Both these models are relatively simple to formulate, and require only the data normally available in any river administration office. The calibration process is quite simple and does not require much expertise. The results are reasonable for prediction purposes. As the complexity level of the model increases, the calibration process also becomes more and more complex. This is illustrated in the next two examples.

An approach that has been used for solving complex non-linear problems in recent years is Artificial Neural Networks (ANN). It has several advantages over other similar types of models, the main one being that a prior knowledge of the processes that transform the input variables to the output variables is not required. The relationship between the inputs and outputs are contained in the connection weights of the network which get adjusted incrementally to the optimal values during the calibration process that uses the backpropagation algorithm. The details of the method, the formulation, and application to hydrological modeling are well described in several references (For example, Haykin, 1999; Anmala *et al.*, 2000; Dawson and Wilby, 2001; Jayawardena and Fernando, 1998; Fernando and Jayawardena, 1998; Maier and Dandy, 2000; among others). The implementation of the ANN approach is not as simple as the two approaches described above, and requires some expertise on the part of the modeller, and the final structure of the network can only be obtained by trial and error. Furthermore, parameters that affect the rate of convergence to the optimal condition also need to be determined by trial and error.

The results of the application of an ANN to predict daily discharges in Mekong River (Basin location: 8°–34°N; 94°–110°E) at Pakse gauging station (catchment area = 545,000 km^2) for the network with the minimum error for a model which takes the form,

$$\begin{aligned} Q^{10}_{t+\gamma} = f(& Q^{10}_t, \ldots Q^{10}_{t-\beta_{10}}, Q^9_{t9}, \ldots, Q^9_{t9-\beta_9}, \ldots, \\ & Q^2_{t_2}, \ldots, Q^2_{t_2-\beta_2}, Q^1_{t_1}, \ldots, Q^1_{t_1-\beta_1}) + e \end{aligned} \quad \ldots (3)$$

where superscripts refer to the station number, $Q^{10}_{t+\gamma}$ is the discharge prediction with γ-lead time at Pakse, β is the lag time, Q^{10}_t and $Q^{10}_{t-\beta_{10}}$ are the discharges at Pakse at time t and t–β_{10}, $Q^9_{t_9}$ and $Q^9_{t_9-\beta_9}$ are the discharges at Khong Chiam at time t_9 and t_9–β_9, etc., and e is the mapping error to be minimized, are given in Table 3. The difference of the above equation from other discharge prediction formulae is that it takes into account the travel time between different stations explicitly by varying the corresponding input with flexible subscripts. As expected, the reliability of the predictions decreases with increasing lead-time.

Distributed models on the other hand become much more complex. Most of the currently available distributed models are of a conceptual nature. One such model is the VIC model (Wood, *et al.*, 1992), which is based on the Xinanjiang model (Zhao, 1992) that is widely used in China. It has undergone several

Table 1: Parameters and Error Indicators for the Stage Prediction at Pandhare Dovan in Bagmati River

Calibration Period (January 1980–December 1998)				*Model Parameters*			*Validation Period (January 1999–December 2004)*			
R^2	MSE (m)	RMSE (m)	RMSE/Average Stage (%)	C_1	C_2	C_3	R^2	MSE (m)	RMSE (m)	RMSE/Average Stage (%)
0.88	0.03	0.34	22.3	0.510	0.4124	0.016	0.88	0.05	0.33	19.51

Note: MSE – Mean Square Error; RMSE – Root Mean Square Error

Table 2: Error Indicators for the Model for the Stage Prediction at Sivasagar in Brahmaputra River

Calibration (1993–2001)		*Validation (2002–2004)*	
R^2	*RMSE (m)*	R^2	*RMSE (m)*
0.961	0.23	0.920	0.30

Table 3: Error Indicators for the ANN model for the Mekong River

Lead Time (days)	*MAE (m^3/s)*	*RMSE (m^3/s)*	*RRMSE*	*1 - NSE*
1	476.65	1028.08	0.10	0.01
7	2092.07	3806.07	0.35	0.13
14	2796.84	4887.63	0.48	0.24

Note: MAE –Mean Absolute Error; RRMSE – Relative Root Mean Square Error with respect to the average flow; NSE – Nash-Sutcliffe Coefficient of Efficiency

modifications over the years (Liang, *et al.*, 1996; Cherkauer and Lettenmaier, 1999); Jayawardena and Mahanama, 2002; Liang and Xie, 2003; among others). The most recent publicly available version is referred to as VIC-3L (Liang, *et al.*, 1996) in which three vertical soil layers are considered. The land surface is described by a given number of land cover classes each of which is empirically specified by its Leaf Area Index (LAI), canopy resistance expressed by some empirical aerodynamic relationship, and relative fraction of roots in each of the soil layers that depend upon the vegetation class and the soil type, also expressed empirically. There is also the bare soil to be considered. Surface runoff and baseflow are computed for each cover type and summed up over all cover types within a pre-specified grid. Data preparation include the delineation of the river network and the catchment boundary, catchment representation by grid cells, and determination of the flow directions based on DEM in addition to specifying the vegetation types and their respective LAI. The soil moisture is modelled statistically by a variable infiltration capacity curve, hence the name VIC. With all this information, only the runoff producing rainfall can be determined. It has to be then routed through the network of streams to estimate the flow at a given grid point. The forcing inputs are the rainfall and the evapo-transpiration. The latter, if unavailable, is estimated using some empirical equation that relates evapo-transpiration to temperature.

The point to be highlighted here is that despite the detailed description of the catchment properties, measured quantitative data on land cover, canopy resistance and fraction of roots are not available except in a few places. As a result, many hydrological modellers use default values set by the model developers and coarse data available in public domains. The validity of the use of such default values is certainly in question. Although, this kind of distributed approach is expected to produce output variable values at each grid point in the mesh, they cannot be validated due to lack of data.

There are many parameters that need to be determined in such a model. Their spatial variability is usually ignored in the calibration process in which an objective function is optimized. Very often the objective function gets trapped at a local optimum rather than reaching the global optimum. Global search techniques such as Simulated Annealing (SA), Genetic Algorithm (GA) and the Shuffled Complex Evolution algorithm (SCE) are the commonly used ones, and the SCE has been seen to be more efficient. Regardless of the algorithm used, the solution in general does not lead to a single 'best' parameter set but to a Pareto set of solutions in the feasible parameter space. A state A (a set of target parameters) is said to be Pareto optimal, if there is no other state B dominating the state A with respect to a set of objective functions. A state A dominates a state B, if A is better than B in at least one objective function and not worse with respect to all other objective functions. The SCE family of algorithms, first proposed by Duan *et al.* (1992), has undergone extensions and modifications and evolved into the Multi-Objective Complex Evolution (MOCOM) algorithm (Yapo *et al.*, 1998), the Shuffled Complex Evolution Metropolis (SCEM) algorithm (Vrugt *et al.* (2003), and the Multi-Objective Shuffled Complex Evolution Metropolis (MOSCEM) algorithm (Vrugt *et al.* (2003).

Using the VIC with six parameters to be calibrated, against the target discharge at the most downstream station at Pakse, the results for different resolutions of the Mekong River catchment are given in Table 4 which clearly illustrate the increase of computer resources required. Calibration performance in this example has been evaluated mainly in terms of normalized parameter distribution, objective function evaluation, or error indicators of the averaged simulation of the optimized parameter population.

CONCLUDING REMARKS

In this paper, an attempt has been made to highlight the various challenges in hydrological modelling given the present abundance of hydrological models and modellig techniques. The challenges arise as a result of the inadequacy of resources for research, lack of relevant data, lack of expertise and the lack of a clear understanding of the driving force for any hydrological modeling attempt. In the first place, the choice needs to be based on whether the attempt is needs driven or resources driven. When it is needs driven, simple models are adequate given the limitations arising from

Table 4: Statistics for Grid Representation of the Mekong Basin and Computation Resource Consumption for Different Grid Resolutions

Resolution	*No. of Active Grids*	*Grid Mesh Dimension*	*One Model Evaluation*		*Optimization*	
			VIC	*Routing*	*Evaluations*	*Total*
2° × 2°	37	13 × 8	2 min	5 min	1000	60 hr
1° × 1°	113	26 × 16	5 min	15 min	1000	170 hr
0.5° × 0.5°	374	51 × 31	10 min	1 hr	500	240 hr
0.25° × 0.25°	1311	102 × 61	30 min	3 hr	–	–
0.125° × 0.125°	4850	203 × 121	2 hr	9 hr	–	–

Note: Simulation period for one model evaluation of the VIC model and the linear reservoir routing is for 105 months. Grid mesh dimension is the full dimension of the grid mesh for basin grid representation. As a comparison, 100,000 model evaluations of the lumped SAC-SMA model for the Leaf River watershed use around 20 min on the *hpcpower* system for 26 month simulation period.

data inaccuracy. When it is resources driven, consideration should be given to the marginal potential benefit that may be accrued against the costs associated with uncertainties and inaccuracies of the data, model formulation and calibration issues. These issues are highlighted with results taken from four different types of hydrological models.

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