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Comparison of Lumped Rainfall-Runoff Modelling Approaches for a Semiarid Basin

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ABSTRACT: This study compares three different approaches to continuous-time modelling of the daily rainfall-runoff response of the Dedtalai basin, India. The main objective is to compare the modelled response of the watershed using a Conceptual Rainfall-Runoff (CRR) model, a Data-Based Mechanistic (DBM) model, and an Artificial Neural Network (ANN) model. The Dedtalai watershed is a large semiarid basin (6,705 km^2) with ephemeral rivers and it is located within the Tapi basin (65,145 km^2). Daily forcing climate and discharge data are available from 1990 to 1998, although with very limited spatial coverage. The CRR model is based on a deterministic model chosen subjectively based on modeller experience. The DBM modelling philosophy identifies a rainfall-runoff transfer function using only the input-output data, with no prescribed conceptual structure. The physical interpretation of the transfer function, in terms of conceptual stores, is compared with the simplified hydrological representations of the applied CRR models. The ANN model is a three layer back propagation ANN, with observed climate and streamflow data as inputs. The models are identified and validated using two periods each of about four years. The estimate flows are compared visually and using least-squares objective functions. The ANN and DBM models performed best in validation, with NSE values of 0.95 and 0.64 compared to 0.41 for the CRR model. However the CRR model has wider applicability to simulation because it does not need observed flow inputs. This paper concludes by providing discussion and guidance about how the different approaches can be used in a complementary manner for modelling rainfall-runoff response in large semi-arid areas.

INTRODUCTION

Numerous modelling options are available for continuous-time modelling of rainfall-runoff relationships (Wheater, *et al.*, 1993), with conceptual modelling being by far the most common approach. However, for some modelling tasks data-based methods, specifically data-based mechanistic modelling and neural network modelling, may be more useful. This may be especially true in arid and semi-arid catchments, which have presented particular challenges for conceptual type of models.

This study compares three different approaches to lumped modelling of the daily rainfall-runoff response of the 6,705 km^2 Dedtalai catchment, located in the semi-arid Tapi basin, India. The main objective is to compare the accuracy of simulated response of the watershed using: Conceptual Rainfall-Runoff (CRR) models, Data Based Mechanistic (DBM) models, and Artificial Neural Networks (ANNs). In each case, the model structures are different, and parameters are identified using different techniques. The paper also discusses the tasks for which the different approaches may be preferable, and how the different approaches could be used in a complementary manner for modelling large semi-arid areas.

CONCEPTUAL RAINFALL-RUNOFF MODELLING (CRR)

CRR models are an established way of simulating streamflow time-series as a function of climate inputs.

They aim to represent the physical rainfall-runoff processes in a simplified manner. Conceptual models range from relatively complex models which attempt to explicitly represent all known components of the system including equations of water balance and conservation of energy (sometimes called 'physically-based' models), to simple models which lump many of the components into a small number of conceptual storages considering only water balance and may have as few as two parameters (Wagener, *et al.*, 2004; Singh and Frevert 2005). CRR models may be applied in a spatially distributed manner, with different parameter sets or even different model structures being employed for different parts of the catchment, however here we limit our discussion and application to lumped modelling.

Typically, a lumped CRR model includes a loss model or soil moisture accounting (to generate effective rainfall from total rainfall) and a routing model (to route effective rainfall to the catchment outlet).

DATA-BASED MECHANISTIC RAINFALL-RUNOFF MODELLING (DBM)

The DBM modelling is introduced and described by Young (1998), Young (2001), Young (2005) and references therein. This is an inductive approach to modelling stochastic, dynamic systems. One important generic model class that facilitates the DBM approach is the Transfer Function (TF) class of model. TFs are simple and convenient representations of continuous-time, stochastic differential equation models, or their discrete-time equivalents. They provide a useful interpretation of the input-output dynamics of the system under study that can be decomposed straight-forwardly into physical meaningful sub-systems (Young, 2005). Young (2005) includes discussion of other potential advantages over more conventional methods of rainfall-runoff modelling and flow routing, in the context of real-time flow forecasting. These advantages include: the DBM model is not biased by prior perceptions of how a particular catchment functions, however the model structure can be constrained to those structures which are physically plausible; the method is essentially stochastic thereby inherently allowing for input-output errors; it is statistically rigorous if implemented using Instrumental Variable methods and allows statistically-founded estimates of uncertainty; it sits easily within an adaptive mode of modelling, where parameters and/or states are updated by real-time data; although normally linear TFs are employed to represent routing, non-linearities can easily be introduced using state-dependent parameters . A case study of the semi-arid ephemeral Canning catchment (544 km^2) in Australia is used by Young (2005) to demonstrate the power of the DBM method for identifying dominant hydrological modes and non-linearities in continuous-time runoff generation, and impressive performance in real-time forecasting of daily flows. Other applications of the DBM method to runoff forecasting include Mwakalila *et al.* (2001), Young (2002), and Romanowicz *et al.* (2006).

The DBM method, in application to rainfall-runoff modelling (e.g. Young 2005), generally consists of a filter to transform catchment-average rainfall, r_k, to effective rainfall, u_k (e.g. Eqn. 1), followed by a linear TF to represent flow routing Eqn. 2. The filter is a non-linear empirical function in which the (time-dependent) effective rainfall is a function of an index of catchment wetness. In the case of Eqn. 1, y_k is the observed discharge which acts as a surrogate variable for the antecedent moisture status of the catchment, α is a scalar factor to force a water balance between effective rainfall and streamflow, λ a parameter to be optimised, and r_k is the rainfall, where subscript k represents the discrete time-step. The estimated runoff, $\hat{y}_k$, is represented in Eqn. 3,

$$u_k = \alpha \cdot r_k \cdot {y_k}^{\lambda} \qquad \text{... (1)}$$

$$x_k = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \ldots + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_n z^{-n}} \cdot u_{k-\delta} \qquad \text{... (2)}$$

$$\hat{y}_k = x_k + \xi_k \qquad \text{... (3)}$$

The discrete linear TF may be any combination of linear reservoirs in parallel and in series, represented in general form by Eqn. 2. The TF model parameters are estimated using the Refined Instrumental Variable (RIV) method (Young, 1984) or the Simplified RIV (SRIV) method (Young *et al.*, 1996), which identify the models by using overall statistics such as the Coefficient of determination (CD)[1] or the Young's Information Criterion (Young, 1989), among others.

DBM modelling has so far been applied to lumped catchment modelling due to the underlying philosophy of statistical efficiency and hence the need to avoid using correlated sets of rainfall inputs. Potential limitations of DBM modelling compared to conceptual modelling are discussed later in this paper in the context of our case study results. The major differences

[1]The CD used here is a normalised measure based on the variance of the error between the sample output data and the simulated model output, which is equivalent to the Nash-Sutcliffe efficiency measure. CD should not be confused with the classical Coefficient of Determination used in classical regression and time-series analysis.

are: (1) a conceptual model has a prescribed model structure according to prior perception of what structure is suitable (or convenient) whereas the DBM approach avoids this; (2) a conceptual model generally has loss and runoff thresholds and other non-linearities which mean that non-linear optimisation methods are required and that formal stochastic treatment of errors in rainfall and flow is very difficult; (3) conceptual models are not generally parsimonious and therefore have inherent parameter non-identifiability problems.

ARTIFICIAL NEURAL NETWORK MODELLING (ANN)

A number of researchers have investigated the potential of ANNs, also called artificial neural nets, in modelling the rainfall runoff process (e.g. Nazemi *et al.*, 2003; Imrie *et al.*, 2000; Campolo *et al.*, 1999, among many others). The non-linear nature of the rainfall-runoff relationship and the complexity of physically–based models are some of the reasons that have caused researchers to look at alternative models being ANNs a logical choice. An excellent overview of the preliminary concepts and hydrologic applications of ANNs was provided by the ASCE (2000a,b). The ANN models essentially belong to black box model category and due their lack of physical basis, and lack of parsimony there is usually a sceptical attitude towards this methodology.

An ANN model has an input, hidden and output layer, being each one made up of several nodes, also called neurons, which are interconnected by sets of correlation weights, see Fig. 1. In most applications, the input (first) layer receives the input variables for the problem at hand and the output (last) layer consists of values predicted by the network, representing the model output. The number of hidden layers and the number of nodes in each hidden layer are usually determined by a trial-and-error procedure. The architecture that represents the pattern of connection between nodes can be defined using different network trainings or learning processes, such as, back-propagation, conjugate gradient algorithms, a radial basin function, recurrent ANNs, among others.

The most popular and commonly used ANN is a feedforward propagation with an error back-propagation training algorithm, which is the algorithm used in this study to simulate daily streamflow. The interconnections between neurons defined using an error back propagation consist of two phases: a feed forward phase that propagates forward the observed input variables (rainfall etc.) at the input nodes, computing estimated discharge at the output node; and a backward phase in which modifications to the connections strengths are made based on the difference between the estimated and observed streamflow. Initially, random values are assigned to the connection strengths. The optimization process modifies the weights in each iteration until convergence based on Eqn. 4 is achieved, where $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are the weight increments between node i and j during the nth and $(n+1)$th pass. The variables ε and α are called learning rate and momentum, respectively,

$$\Delta w_{ij}(n) = -\varepsilon \cdot \frac{\partial E}{\partial w_{ij}} + \alpha \cdot \Delta w_{ij}(n-1) \qquad \text{... (4)}$$

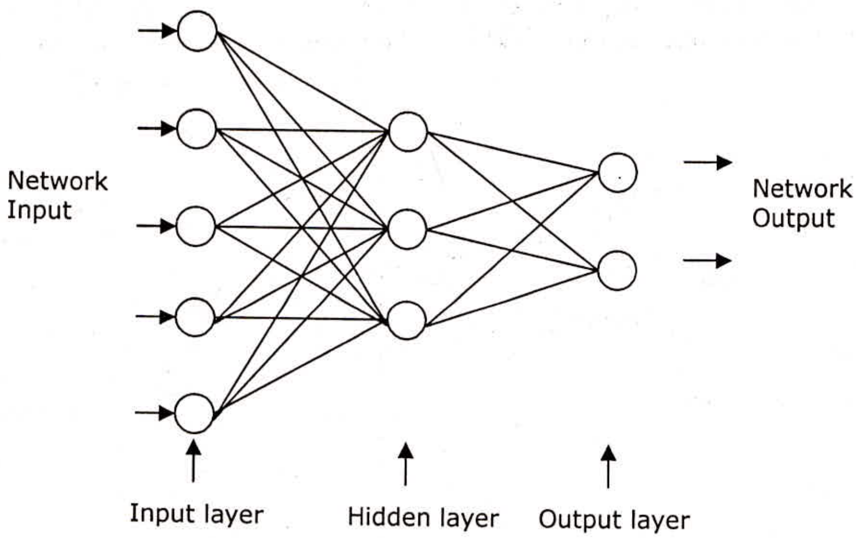

Fig. 1: Configuration of Feed Forward Three-Layer ANN, (ASCE, 2000a)

STUDY AREA

The study area is the Dedtalai catchment (6,705 km^2) located within the Tapi River basin (65,145 km^2) in India, see Fig. 2. The Dedtalai catchment has an elongated shape with two well defined physical regions, hillslopes and the plains. The area is dominated by forest (59%) followed by agricultural (16%), pasture/ fallow land (14%) and barren lands (11%).

The climate of the region is characterised by a dry summer and winter, and the South-West monsoon which breaks by the middle of June and withdraws by the middle of October. The basin receives around 90% of the annual average rainfall during the monsoon period, with the average annual rainfall equal to 1300 mm. The rivers are ephemeral; measures of discharge at the catchment outlet are smaller than 0.25 mm/day for approximately 58% of the time from 1990 to 1998.

Daily time series (precipitation, streamflow, mean temperature and potential evaporation) from the 1st of January 1990 to the 31st of December 1998 are available for this study. The rainfall data correspond to average precipitation based on seven rain gauges within the area. The streamflow, temperature and potential evaporation time-series have missing data. The potential evaporation data correspond to pan evaporation measures applying a correction factor equal to 0.7 and missing values are completed using estimated mean daily values. Missing streamflow and temperature data are not filled in.

METHODS AND RESULTS

CRR

A simple nonlinear CRR model composed of a probability-distributed soil moisture model (PDM) [Moore 2007 and references therein] and two parallel linear reservoirs routing is used to model the daily streamflow response at the outlet of the basin. This CRR model is referred as PDM-2PAR. The PDM model assumes that runoff production is a saturation excess process and detailed explanation of its formulation can be found in the previous reference. The evaporation is modelled as directly proportional to soil wetness, reaching a maximum of potential evaporation at soil saturation.

The PDM-2PAR model has five parameter values to be estimated via calibration: the maximum storage capacity in the catchment, *cmax*, the degree of spatial variability of the soil moisture capacity within the catchment, *b*, the factor distributing the flow between the two parallel reservoirs, *%(q)*, and the residence times of the fast and the slow response of the catchment, *k(q)* and *k(s)* respectively.

Table 1: Range of Parameter Values Used in Calibration, PDM-2PAR

Parameters	*Lower*	*Upper*	*Units*
cmax	100	1000	mm
b	0.01	2	–
k(q)	0	10	day
k(s)	10	300	day
%(q)	0.01	0.99	%

Calibration is performed using Uniform Random Search (URS) with 100,000 parameter samples, and four years of data (1990–1994). The best out of all these samples in terms of model performance in the calibration period (neglecting a warm-up period of one year) is selected to identify the model, parameter set. Two criteria are used the Nash-Sutcliffe Efficiency

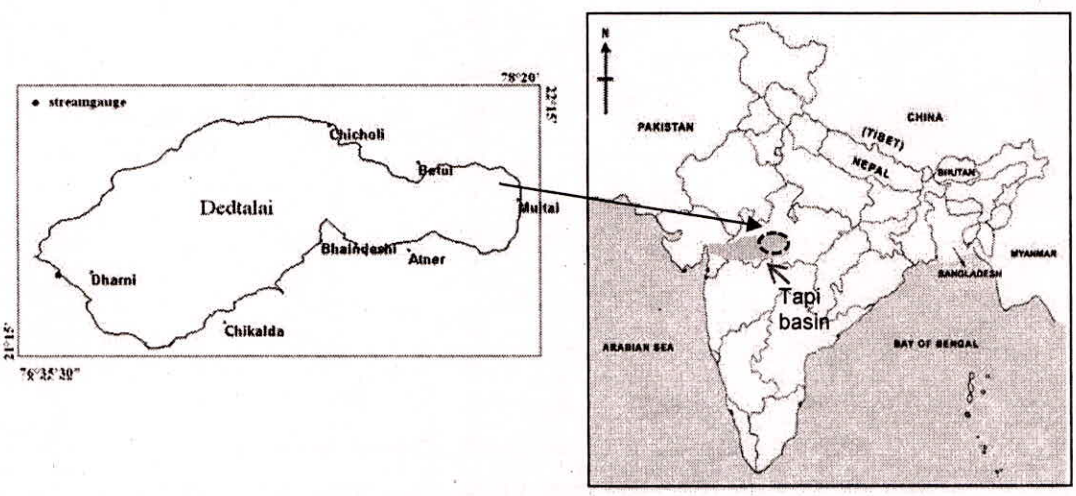

Fig. 2: Location of the study area, Dedtalai subcatchment, India

(NSE) and the root mean square of the log transformed streamflow (RMSELOG).

Calibration of the PDM-2PAR model using the NSE and RMSELOG objective functions generate reasonable values of efficiency between the observed and the simulated discharge (NSE = 0.83, RMSELOG = 1.12). However when comparing the observed and estimated hydrographs, see Figure 4 and Fig. 5, the model is not able to predict well the low flows in the recession part. This situation has been recognized in the literature, as overall functions try to fit the high peaks overestimating the lower streamflow. The estimated parameter values using each criterion are summarized in Table 2.

Table 2: Calibrated Parameter Values, pdm-2par

Parameters	*NSE*	*RMSELOG*
cmax	915	743
b	0.49	0.01
k(q)	0.24	0.18
k(s)	94.4	38.4
%(q)	85.5	86.2

Validating the model structures from 1995 to 1998, and using a year as warm-up period, provides a significant deficit in performance on the NSE criteria but improved simulations using the RMSELOG criterion. Table 3 summarises the criteria values for the two models using the parameter sets shown in Table 2.

DBM

For this study, DBM modelling functions available in the CAPTAIN toolbox (Taylor *et al.*, 2006) were integrated into the Rainfall Runoff Modelling Toolbox (RRMT) developed by Wagener *et al.* (Wagener *et al.*, 2002). Instrumental variable methods were used to identify parameter values for a series of possible transfer function polynomials (i.e. subsets of Eqn. 2). The criterion used to evaluate the relative efficiencies of the models is CD; but the NSE and RMSELOG values are calculated to compare streamflow simulations to the other modelling approaches. Based on the rainfall-streamflow input-output data, a second-order TF model with zero time delay between the estimated effective rainfall and streamflow was selected from the identified models, see Fig. 3. The upper reservoir represents relatively fast runoff responses (e.g. overland flow and throughflow) while the slow pathway represents the base-flow behaviour. This structure was also found to be optimally efficient in other studies which used daily data (e.g. River Hodder catchment (Young, 2003). The selected model had values of NSE and CD equal to 0.93 and 0.94, and RMSELOG equal to 4.91. The fit to the observed data is shown in Figure 4 and Figure 5,

$$u_k = 0.16 \cdot r_k \cdot y_k^{0.448}$$

$$\hat{y}_k = \frac{\hat{b}_0 + \hat{b}_1 \cdot z^{-1}}{1 + \hat{a}_1 \cdot z^{-1} + \hat{a}_2 \cdot z^{-2}} \cdot u_{k-\delta} + \xi_k \qquad \text{... (5)}$$

being $\hat{a}_1$ = –0.920 (0.024), $\hat{a}_2$ = 0.044 (0.010), $\hat{b}_0$ = 0.572 (0.004), $\hat{b}_1$ = –0.465 (0.013), $\delta = 0$

The numbers in parentheses represent the approximate standard deviations on the parameter estimates (obtained from RIV estimation). The parallel decomposition of the TF in Eqn. (5) yields to the following description of the two buckets:

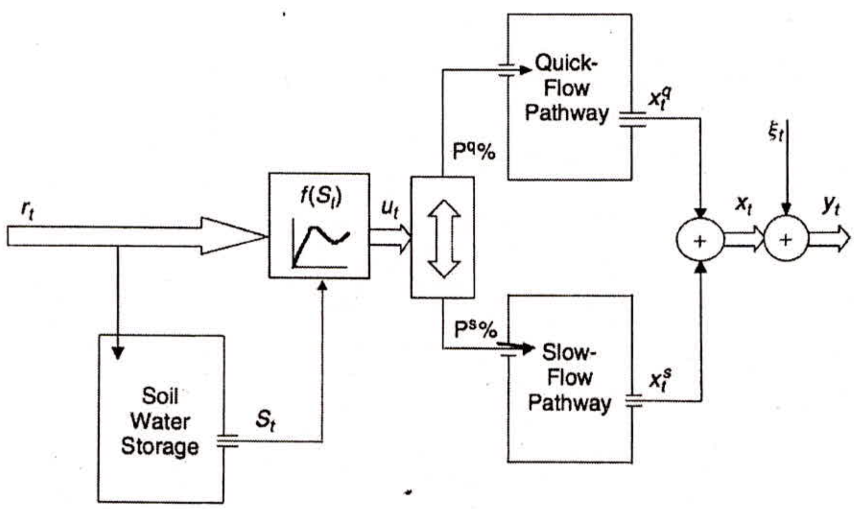

Fig. 3: Two-bucket diagram of second-order, parallel pathway DBM model (Young, 2003)

Quick Flow:

$$y_k^q = \frac{0.5333}{1-0.0510} \cdot u_k \quad T_q = 0.34 \text{ days} \quad P_q = 65.40\% \ \ldots (6)$$

Slow Flow:

$$y_k^s = \frac{0.0391}{1-0.8686} \cdot u_k \quad T_s = 7.09 \text{ days} \quad P_s = 34.60\% \ \ldots (7)$$

Where y_t^q and y_t^s are the partitioned quick and slow-flow components, respectively; T denotes the mean residence time and P the partition percentage of generated runoff i.e. the estimated percentage of flow of water down each pathway.

Using the parallel decomposition of the estimated linear TF model over the remaining validation period (1995–1998) the model performance decreased compared with the calibration period, obtaining NSE and CD criteria values of 0.64, but there is a slight increase in the RMSELOG criterion.

ANNs

Input variables used were rainfall, average temperature, potential evaporation. The lead-time of the ANN model has been considered as one day, i.e. observed streamflow for the previous day was also included as input. Thus four nodes were considered for the input layer.

A three layer error back propagation ANN was used as non-linear sigmoid activation function uniformly between the layers. The number of nodes in the input layer are equal to the number of input variables; in the hidden layer the number of nodes varies between the number of inputs to approximately double of input nodes (Zhao *et al.*, 1980); and in the output layer there is one node. All the inputs and output variables were re-scaled to values between 0 to 1 using the maximum value of the variables to avoid any saturation effect that may be caused by the use of the sigmoid function. All interconnection weights between nodes of successive layers were initialised at random values between +0.5 to –0.5 (Dawson and Wilby, 1998). Constant values of 0.15 and 0.75 were considered for the learning rate η and momentum term α (Lorrai and Sechi, 1995; Raman and Sunilkumar, 1995). The learning process, i.e. the process applied to find the optimal weight matrices, minimized the error of each pattern, one by one in sequence, and the weights continuously being updated with the processing of each pattern. The nodes in the hidden layer were equal to the number of inputs and were increased if the sensitivity of the error of each weight was check and the nodes in hidden layer were increased if required. At the end of the learning process five nodes were used in the hidden layer.

For the calibration period the ANN model achieved values of NSE and CD equal to 0.98 and RMSELOG of 2.39; for the validation period of the NSE performance was slightly decreased (0.95) but there was an improvement in the RMSELOG value (1.94).

Results

The estimated streamflow at the Dedtalai catchment using the three different methodologies during wet seasons for the calibration and validation period are shown in Figures 4 and 5. The streamflow are plotted using a flow transformation suggested by Hogue *et al.* (2000) for visualization purposes. In terms of the shape of the hydrograph all models seem to predict well the time to peak and the peak flows. However, the fit to the recession part of the hydrograph is less accurate.

The DBM model identified a routing structure similar to the subjectively chosen routing in the CRR model. Both, the calibrated routing parameter values and the parallel decomposition of the identified TF, Equation (5) and (6), identified a residence time of the fast reservoir less than a day but the percentage of flow acting as quick response is higher in the CRR model than in the DBM estimation. There is also a clear difference in the residence time of the slow response of the catchment, using the NSE and RMSELOG criteria. The mean residence time is at least 5 times higher than the physical TF decomposition of the DBM approach.

Table 3: Efficiency Measures, Calibration and Validation Periods

Model	*Calibration*		*Validation*	
	NSE	*RMSELOG*	*NSE*	*RMSELOG*
pdm_2par (NSE)	0.83	2.17	0.41	1.77
pdm_2par (RMSELOG)	0.77	1.12	0.29	1.07
DBM	0.93	4.91	0.64	3.42
ANN	0.98	2.39	0.95	1.94

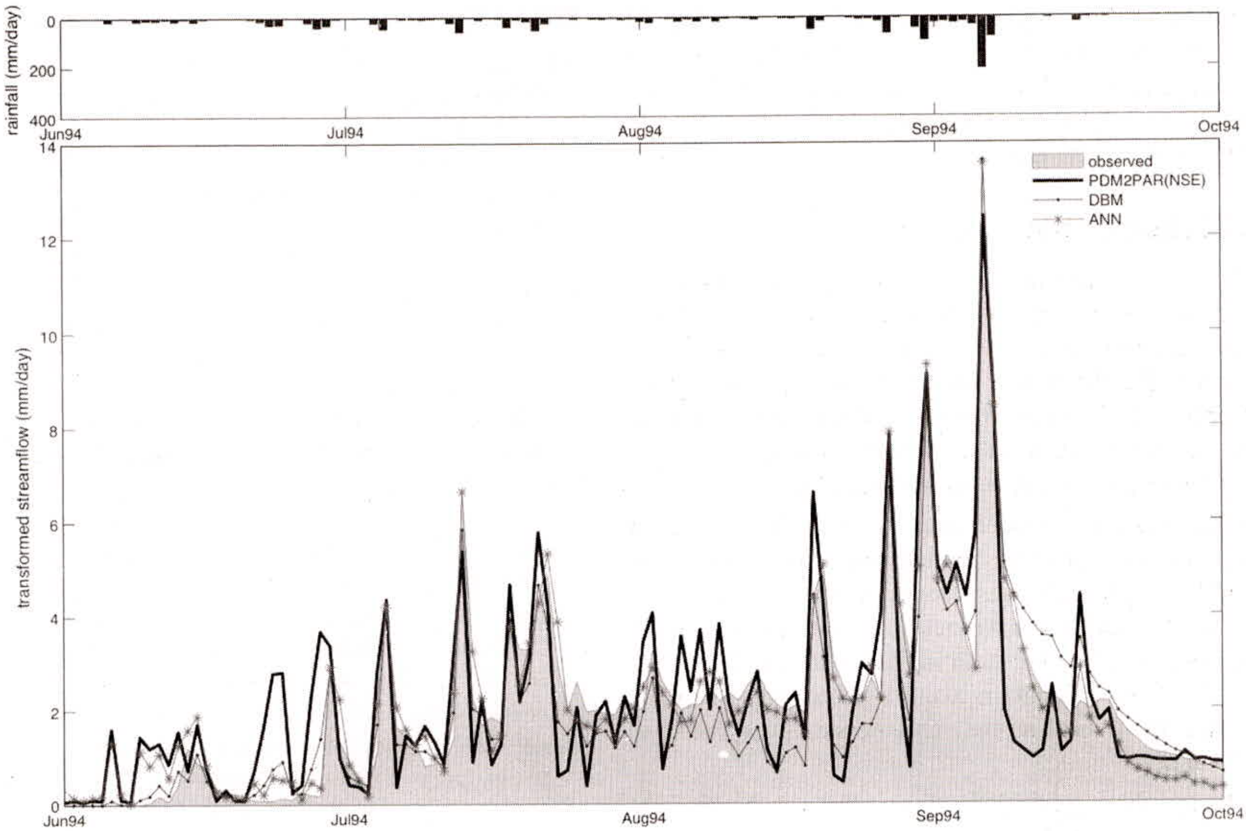

Fig. 4: Observed and estimated streamflow, part of the calibration period (1990–1994)

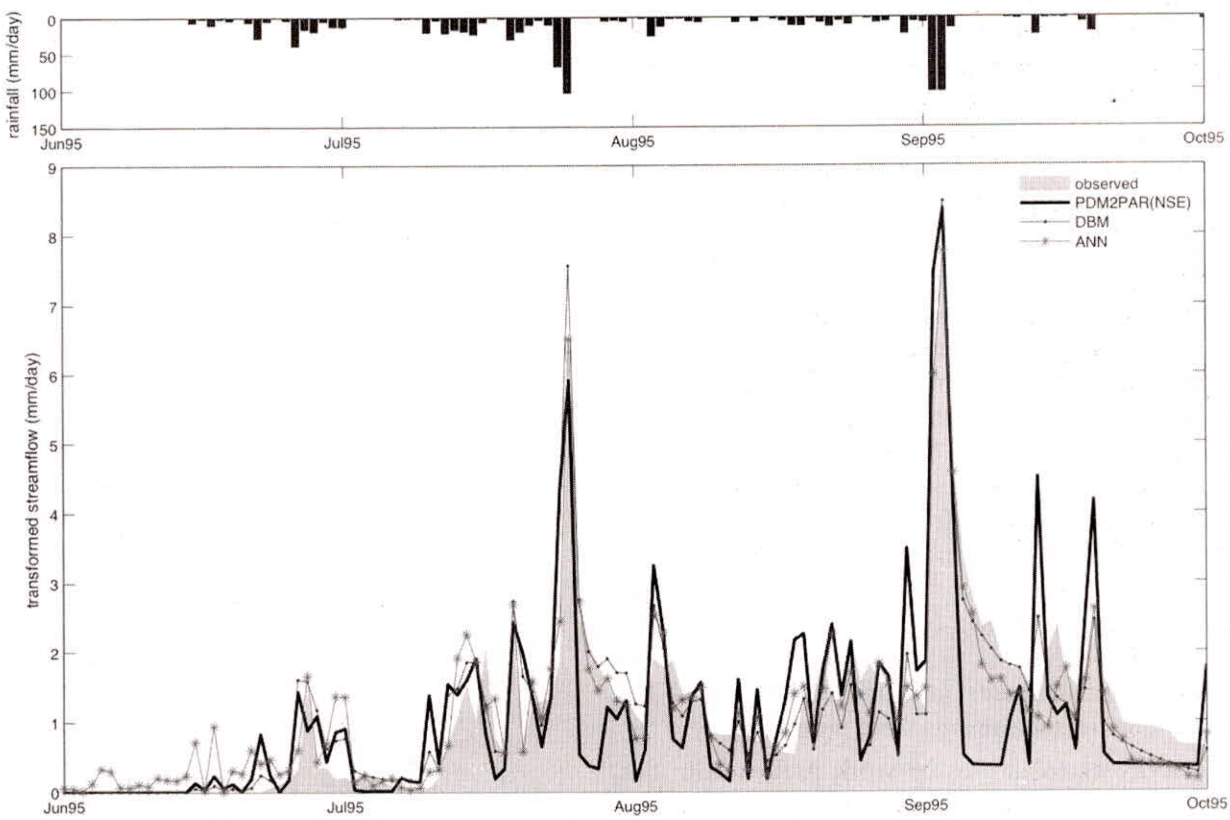

Fig. 5: Observed and estimated streamflow, part of the validation period (1995–1998)

In terms of the two criteria used, the ANN model is the one which performs better in both calibration and validation periods. But this model uses temperature as information which is not included neither in the CRR model or the DBM approach.

CONCLUDING DISCUSSION

The Dedtalai catchment is not an ideal case study for comparing rainfall-runoff methods because it is a large basin with limited data (e.g. only seven rain gauges). However the ANN and DBM modelling approaches perform well. Reasons why the CRR performs poorly may be due to systematic rainfall errors, which the other methods may better compensate for.

Also, the CRR model does not use flow as input data, so errors are compounded over time. The DBM modelling approach uses observed flow as an input, but only to represent a wetness index in the non-linear filter, not to update the state in the linear TF. The ANN uses flow as an input in a more direct role, being a one-step prediction model, and hence is expected to perform best.

Hence, although CRR performs the worst, the facts that it is a simulation method based around physics-based conceptualisations and does not require observed flow as an input except for calibration, it is potentially a more flexible method for different types of application. For example, it could be more suitable than the DBM and ANN methods for evaluation of land-use impacts on hydrological processes, while DBM and ANN are expected to perform better for real-time forecasting. Also, the DBM and potentially the ANN methods can be used to identify the principal response components.

There is a potential scope to integrate the CRR and DBM modelling approaches to combine their strengths, using the information extracted from the data by the DBM approach. The transfer function identified as optimal by the DBM method, can be used in the conceptual model, and the non-linear filter can be used to remove noise from the rainfall data. The CRR and ANN methods may also be integrated. For example, Chen and Adams (2006) suggest a hybrid model structure composed of a semi-distributed CRR model and an ANN to transform runoff from individual subcatchments into the total runoff at the catchment outlet; their results were promising.

A priority extension to the work presented in this paper is the inclusion of uncertainty analysis, to estimate confidence intervals on the results in Figure 4 and Figure 5.

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