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Comparative Evaluation of Neural Network and Regression Based Models to Simulate Runoff and Sediment Yield in an Outer Himalayan Watershed

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ABSTRACT

The complexity of rainfall-runoff-sediment yield hydrological processes remains a challenge for runoff and sediment yield prediction for large mountainous watersheds. In this study, a simple Non-Linear Dynamic (NLD) model has been employed for predicting daily runoff and sediment yield by considering the watershed memory based rainfall and runoff, and rainfall-runoff and sediment yield, respectively. The results were compared with two commonly used Artificial Neural Network (ANN) and Wavelet based ANN (WNN) models by taking maximum input parameters of values of time memory for rainfall, runoff, and sediment yield derived from the developed NLD model through step-wise regression. The feed forward ANN models with back propagation algorithm was used. Twenty-six years' daily rainfall, runoff, and sediment yield data of Bino Watershed, Uttarakhand, were used in this study. The coefficient of determination, root mean square error, and model efficiency were adopted to evaluate the model's performance. The results revealed a better performance by the ANN and WNN rainfall-runoff models compared to the NLD, however, NLD rainfall-runoff-sediment model showed higher efficiency than the ANN and WNN models in case of considering whole time series data. Under-prediction of sediment yield by all the models resulted from sudden landslides/flash floods in Himalayan Watersheds. The study showed that though WNN was better than ANN and NLD, its application cannot be generalized for entire mountainous watersheds. Again, criteria for successful selection of a useful sub-component in WNN need to be developed. The study also indicates the greater capturing power of WNN for simulation of extreme flows with lowest percent-error-peak-flow values.

Keywords: Dynamic, Mountainous watershed, Neural networks, Peak flow, Time lag.

INTRODUCTION

The runoff and sediment generation processes in watersheds are very complex in nature involving a number of variables pertaining to rainfall, physiography, soil, cropping system, and management practices. The rainfall-runoff-sediment yield is the most complex hydrological phenomenon to comprehend. Therefore, accurate modeling of these hydrological processes will be helpful in land use planning, flood and water resource management on watershed basis. Since 1930s, a number of models have been developed for the simulation of processes of rainfall-runoff, runoff-sediment yield, and rainfall-runoff-sediment yield in a watershed fluvial system. These models have been broadly classified into regression, stochastic, conceptual or parametric, and system (dynamic) models (Agarwal *et al.,* 2006). However, use of soft computing and data mining tools offers alternative to the distributed and physical based modeling approaches. The Artificial Neural Network

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(ANN), a soft computing tool belonging to black-box modeling category, has attracted researchers due to its capability of correlating large and complex multi-parameter data sets (Rao *et al.,* 2014). However, one of the essential steps when using any mathematical tool is to determine dominant input variables of the process. Many researchers have demonstrated the potential applications of ANN in different hydrological processes and water resources by taking different input parameters. It is also reported that ANN models are not very satisfactory in terms of precision. Most of the models available for analyzing and simulating the rainfall-runoff and rainfall-runoff-sediment processes involve hydrological time series with the original data only. From a time-frequency perspective, each hydrological time series includes several frequency components that satisfy various rules and constraints. Using the components without resolution to model hydrological process makes the internal mechanism difficult to understand. Therefore, application of wavelet-based multi-resolution analysis can provide efficient tools to increase the precision for modeling hydrological processes at various resolution levels.

Many researchers have demonstrated the potential applications of ANN and wavelet analysis to hydrology and water resources (Agarwal and Singh, 2003; Wang and Ding, 2003; Cannas *et al,* 2005; Agarwal *et al*., 2006; Tewari, 2007; Sachan, 2008; Rathinasamy and Khosa, 2012). Although the ANN has the advantage of being able to establish the linear as well as the non-linear relationships, the ANN models are limited in their ability to deal with non-stationary data. The wavelet transform, developed in the mathematics community, appears to be an effective tool in analyzing non-stationary time series (Partal and Kisi, 2007; Adamowski and Chan, 2011). It is an important derivative of the Fourier transform and consists of a multi-resolution analysis in the time and frequency domains (Tiwari and Chatterjee, 2010). Wavelet transforms provide a useful decomposition of a time series for better revealing and handling by data-driven models (Murtagh *et al*., 2004; Rathinasamy and Khosa, 2012). Several studies have shown that data preprocessing using wavelet transforms improves ANN performance e.g. for monthly reservoir inflow (Coulibaly *et al*., 2000); drought forecasting (Kim and Valdés, 2003); precipitation forecasting (Partal and Kisi, 2007); suspended sediment forecasting (Partal and Cigizoglu, 2008); river flow forecasting (Sivakumar *et al.*, 2002; Adamowski, 2008; Adamowski and Sun, 2010), and groundwater level forecasting (Adamowski and Chan, 2011, Taormina *et al.,* 2012). Remesan *et al.* (2009) used the wavelet transform in runoff prediction. Tiwari and Chatterjee (2010) developed a hybrid Wavelet–Bootstrap–Artificial Neural Network (WBANN) model to explore the potential of wavelet and bootstrapping techniques for developing an accurate and reliable ANN model for hourly flood forecasting. Nourani *et al.* (2011) introduced two hybrid artificial intelligence approaches, including wavelet-Adaptive Neuro-Fuzzy Inference System (ANFIS) model for developing a rainfall–runoff model. Selection of the most relevant and appropriate wavelet- based features is an important step in modeling of the above processes when various data sources are available over the watershed. Liu *et al*. (2013) used Wavelet-artificial Neural Network model (WNN) to predict suspended sediment concentration in a hyper-concentrated river of China by simulating daily Suspended sSediment Concentration (SSC) and water discharge data. Muttil and Chau (2006) used ANN and genetic programming for modeling algal biomass by taking different water quality, rainfall and other climatological parameters as input. Rao *et al.* (2014) used ANN and WNN for daily stream flow forecasting by taking runoff with lag values of five days as input parameter. Agarwal *et al.* (2006) used ANN for rainfall-runoff and rainfall-runoff-sediment modeling using lag values of three

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for daily, weekly, ten-daily and monthly forecasting. It was reported that the feed forward ANN, without time-delayed input, did not provide a significant improvement over other regression techniques. A detail explanation of different properties of ANN and WNN is beyond the scope of this paper which has already been discussed by the above researchers. Again, Kisi (2011), and Tiwari and Chatterjee (2010) discussed in detail the application of ANN and WNN for river stage and flood forecasting. Kumar (1993) also discussed the importance of regression models (linear and non-linear) taking watershed memory based runoff and sediment as input for prediction of sediment yield in mountainous watersheds. The review showed that the models have been built by using runoff and sediment yield only; however, other factors like rainfall and vegetation should be adopted to improve the model performance (Liu *et al.,* 2013). Again, little research has been reported to estimate daily runoff and sediment yield by taking watershed memory based rainfall and runoff, and rainfall-runoff and sediment, respectively, and particularly for large mountainous watersheds.

Keeping in view the above points, the work reported in this paper was for the large mountainous watersheds, in which the hydrologic processes are really conspicuous and also the rainfall-runoff-sediment process was highly dynamic in nature. To model these processes, consideration of antecedent status of input and output variables is important, and this status depends to a great extent on the memory content of watershed system which is generally non-linear (Kumar, 1993). Therefore, it necessitates a testing of data mining approach and its utility in prediction of surface runoff and sediment yield. In order to improve the prediction accuracy, the aim of this study was to develop a rainfall-runoff and rainfall-runoff-sediment yield model using Non-Linear Dynamic (NLD), Artificial Neural Network (ANN) and hybrid Wavelet Neural Network (WNN) models considering runoff and sediment yield for a specified time delayed inputs, taking whole time-series and peak values separately, and further evaluating their effectiveness in mountainous watershed.

MATERIALS AND METHODS

Study Area and Data Used

The study was conducted at Bino Watershed under River Ramganga, a major tributary of the River Ganga, which originates in the outer Himalayas of Uttarakhand and drains into River Bino. It is situated at 79° 6′ 14.4″ to 79° 17′ 16.8″ E longitude and 29° 47′ 6″ to 30° 02′ 9.6″ N latitude in Almora and Pauri Garhwal districts (Figure 1) having geographical area of 296.75 km^2. Climate of the watershed varies from Himalayan sub-tropical to sub-temperate with mean annual maximum and minimum air temperature of 30 and 18°C, respectively, and mean annual rainfall of 931.3 mm. The daily mean temperature remains high during months of May and June, and minimum in December and January. The daily rainfall in the watershed was measured by non-recording rain gauge at four raingauge stations *viz.* Bungidhar, Jaurasi, Tamadhaun and Kedar, runoff at the outlet by stage level recorder, and sediment yield (suspended) were collected from Divisional Forest Office, Ranikhet, Uttarakhand. Weighted average values of daily rainfall for the watershed were estimated by Thiessen polygon method using ArcGIS 9.3 software. The runoff and sediment yield collected have been reported in hectare-meter (ham). Further, runoff was converted into millimetre (mm) by dividing with the area of the watershed and sediment load into kg sec^{-1} by multiplying with bulk density of silt as 1.4 gm cm^{-3}.

Model Development

Three models, namely, Non-Linear Dynamic model (NLD), Artificial Neural Network (ANN) model, and Wavelet

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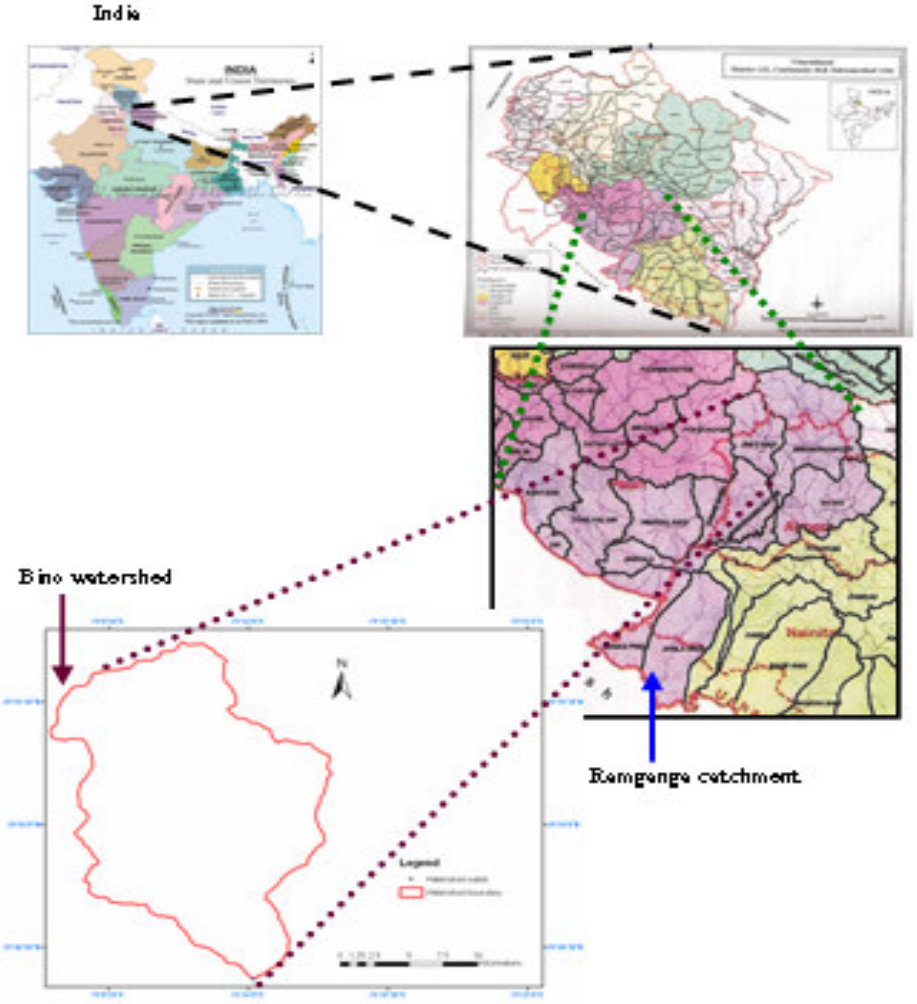

Figure 1. Location map of the study area.

artificial Neural Network (WNN) model were developed for predicting runoff and sediment yield using daily data of rainfall (P), runoff (Q) and sediment yield (S) of monsoon period (June1st to September 30th) from 1983 to 2008. The functional presentations of dynamic- invariant models for rainfall-runoff [Equations (1) and (2)] and rainfall-runoff-sediment yield [Equations (3) and (4)] are as follows:

$$Q_t = f(P_t, P_{t-1}, P_{t-2}, \ldots, P_{t-n}. Q_{t-1}, Q_{t-2}, \ldots, Q_{t-n}) \quad (1)$$

In the logarithmic form,

$$\ln Q_t = \ln K_0 + \sum_{i=0}^{n} K_{P_i} \ln P_{(t-i)} + \sum_{i=1}^{n} K_{Q_i} \ln Q_{(t-i)} \quad (2)$$

$$S_{yt} = f(P_t, P_{t-1}, P_{t-2} \ldots P_{t-n}. Q_t, Q_{t-1}, Q_{t-2} \ldots Q_{t-n}, S_{y(t-1)}, S_{y(t-2)}, \ldots, S_{y(t-n)}) \quad (3)$$

In the logarithmic form,

$$\ln S_t = \ln K_0 + \sum_{i=0}^{n} K_{P_i} \ln P_{(t-i)} + \sum_{i=0}^{n} K_{Q_i} \ln Q_{(t-i)} + \sum_{i=1}^{n} K_{S_i} \ln S_{(t-i)} \quad (4)$$

Where, K is the respective coefficient representing the lumped effects of the watershed parameters. The subscript 't' represents the present time value of the parameter, and t-1, t-2…, *t-n* are the previous values of the parameters at the 1, 2…, *n* time lags in days. For finding the sensitivity of the variables, the values of these K coefficients were determined by the

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multiple step-wise regression analysis and variables found significant at 5% level were only retained in the model. Any model development means it should be used by the end-users. In India particularly, most of the watershed managers are Departmental organizations. The employees are not well versed with modern tools which needs skill. But, non-linear dynamic models can be run by simply using statistical software SPSS and/or also excel sheet. Therefore, in this study, a greater emphasis was given to simple non-linear dynamic method. For ANN and WNN, the predictor variables were chosen by taking different combinations of number of input parameters equal or less than the maximum number of model parameters determined through step-wise regression tried in non-linear dynamic model. Then, the two models were compared with non-linear dynamic model for both rainfall-runoff and rainfall-runoff-sediment processes to get a better option.

An ANN is an information-processing system composed of many nonlinear and densely inter-connected processing elements or neurons. The main function of the ANN paradigms is to map a set of inputs to a set of outputs. Sigmoid function is the most commonly used non-linear activation function in ANN. In the present study, multilayer feed-forward networks which are made up of multiple layers of neurons with supervised learning using Back-Propagation (BP) were used due to its simplicity and effectiveness. The Haar-A-Trous wavelet transform based Multi-Resolution Analysis (MRA), which helps in an efficient modeling of hydrological processes, was used in this study (Maheswaran and Khosa, 2012). It provides a convincing and computationally very straightforward solution while, at the same time, avoiding the troublesome boundary effects (Rathinasamy and Khosa, 2012); Murtagh *et al.*, 2004) and Wang and Ding, 2003). Wavelet transform was used to decompose the rainfall and runoff time series at level 3 into four sub-series (one approximation and three details). This appropriate decomposition level was determined using the formula:

$$L = int\,(log(N)) \quad (5)$$

Where, L indicates decomposition level and N refers to the number of time series data (Nourani *et al.*, 2011; Adamowski and Chan, 2011), which is 6,403 in this case study. Due to proportional relationship between amount of rainfall, runoff and sediment load, they are supposed to have the same seasonality levels. Therefore, all the time series were decomposed at the same level.

Input-Output Data Preparation and Selection of Network Architecture

Daily rainfall, runoff, and sediment flow data were used for training and testing of the models. Analysis of daily surface runoff and sediment yield revealed that past hydrologic values of more than five days have no significant effect on present day runoff or sediment yield. Therefore, in this study a maximum value of lag was taken as five and multiple regression equations were developed for runoff and sediment prediction, respectively. The data in multiple layer networks is divided into training, validation, and testing (Liu *et al.,* 2013) and the ratio of partitioning taken as 60, 20, and 20%, respectively (Tiwari and Chatterjee, 2010). Therefore, 21 years' (1983-2003) daily records of the rainfall, runoff, and sediment yield data were used for non-linear dynamic model calibration and 5 years' (2004-2008) data for testing. However, daily data of 16 years (1983-1998), 5 years (1999-2003), and 5 years (2004-2008) were used for the training (calibration), validation, and testing of ANN and WNN models, respectively. For resolving daily data of rainfall, runoff, and sediment yield, a program developed in C++ language (Tewari, 2007) and individual wavelet and scale coefficients were calculated and used for further analysis.

One of the most important attribute of a layered neural network design is the

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architecture. The size of the hidden layer(s) is the most important consideration when solving the actual problems using multilayer feed-forward neural networks. However, Shu and Ouarda (2007) recommended that the number of hidden nodes should be less than twice the number of input nodes. In this study, the number of hidden nodes was determined based on a trial-and-error process that involved varying the number of nodes from one to double the number of input variables. There are several types of ANNs but the major advantage of feed forward back propagation ANN is that it is less complex than other ANNs (Tiwari and Chatterjee, 2010). Therefore, here sigmoid feed forward activation function was used for training ANN and WNN (Khalil *et al.*, 2011; Kisi, 2011). The Levenberg–Marquardt methodology was used for adjusting weights of the models due to its being more powerful than conventional gradient descent technique (Hagan and Menhaj, 1994; Nakhaei and Nasr, 2012). The training of ANN and WNN models is similar to the calibration of conceptual models. In the present study, input-output pairs in the training and validation data sets were applied to the network of a selected architecture and training was performed. Validation data set was used to apply an early stopping approach related to epoch size in order to avoid over training or over fitting of the training data sets. Epoch is the number of sets of training data and it is recommended that the number of epochs should be less than the number of input data sets. Various networks of single and two hidden layers were trained up to maximum iterations or epochs of 2000, with different combinations of hidden neurons and the best suited network was selected based on the minimum values of Root Mean Square Error (RMSE), Akaike's Information Criterion (AIC) and maximum value of Coefficient of determination (R^2) (Agarwal *et al.,* 2006). Once the training process was satisfactorily completed, the network was saved, the test data sets were used for studying the best performed model by the observed and simulated values of runoff and sediment yield. The normalized output values were reconverted to give the predicted values of runoff and sediment yield for comparison with the corresponding observed values. The analysis of ANN and WNN was performed for predicting the runoff and sediment yield by using *NeuroSolutions 5.0* software. The performance of the developed models was assessed in terms of their R^2, (RMSE) (Agarwal, 2007), and model Efficiency (E) (Nash and Sutcliffe, 1970; Rao *et al.,* 2014). In hydrological modeling, one of the major concerns is estimating the flow or sediment in extreme cases. Therefore, the models in estimating the extreme values were evaluated using Percent Error in Peak Flow (PEPF) which measure only the magnitude of peak flow and does not account for total volume or timing of the peak (Asadi, 2013).

$$PEPF = 100\left|\frac{Qo(peak) - Qs(peak)}{Qo(peak)}\right| \quad (6)$$

Where, Qo= Observed, Qs= Simulated peak values.

RESULTS AND DISCUSSION

For rainfall-runoff modeling, based on the step-wise regression, the Non-Linear Dynamic (NLD) model with highest R^2 (0.676) was built as follows:

$$\ln Q_t = 0.338 + 0.117 \ln P_t - 0.044 \ln P_{(t-1)} + 0.575 \ln Q_{(t-1)} + 0.07955 \ln Q_{(t-2)} + 0.124 \ln Q_{(t-3)} \quad (7)$$

Where, Q and P are in mm. It was observed that, independent variables of rainfall of present and previous day and runoff of first, second, and third previous days as the input to predict runoff on any day was the best among the lag days tried. As explained earlier, these five independent variables are selected as the maximum number of input to ANN and WNN models (Tiwari and Chatterjee, 2010). Therefore, different combinations of inputs *viz.* (i) P_t, P_{t-1}, Q_{t-1}, Q_{t-2}, Q_{t-3} i.e., 5 inputs+1 output for ANN and resolved 20 inputs+1 output for WNN, (ii) P_t, P_{t-1}, Q_{t-1}, Q_{t-2} i.e., 4 inputs+1

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output for ANN and resolved 16 inputs+1 output for WNN, and (iii) P_t, Q_{t-1}, Q_{t-2} i.e., 3 inputs+1 output for ANN and 12 inputs+1 output for WNN were tried to get another option of better combinations with minimum inputs. A few of the networks with single layer having very low values of *RMSE, AIC*, and higher value of R^2 are shown in Table 1. Inclusion of two hidden layers increased the model running time significantly and also had higher value of *RMSE* and low value of R^2, hence, not considered and the results are not shown here. In ANN model, it was observed that among 5 inputs, network structure 5-6-1 (i.e. 5 inputs, 1 hidden layer with 6 neurons and 1 output) with epochs of 1,000 was better as compared to the other networks based on the performance criteria. Similarly, among 4 inputs, networks, 4-8-1 and among 3 input, 3-4-1 networks with epochs of 2000 were better having higher R^2 and minimum *RMSE* and *AIC*. Out of these ANN network structures; 5-6-1 network structure was selected as the best performing ANN model for prediction of daily runoff. However, in case of WNN model, on the basis of overall performance of the attempted network structures, 20-21-1, 16-19-1 and 12-14-1 were found to be performing better at epochs of 355, 304 and 325, respectively. From these better performing network structures, the 20-21-1 was finally selected as the best WNN model with higher R^2 and minimum *RMSE* and *AIC* during training and testing periods at epoch 355 (Table 1).

For rainfall-runoff-sediment modeling, the NLD model with highest R^2 (0.872) was built as:

$$\ln S_t = -0.427 + 0.056 \ln P_t + 0.949 \ln Q_t - 0.420 \ln Q_{(t-1)} - 0.231 \ln Q_{(t-2)} + 0.824 \ln S_{(t-1)} \quad (8)$$

Where, Q and P are in mm and S in kg s^{-1}. In the development of ANN and WNN models for sediment prediction, the input status was kept the same as in the above dynamic sediment model. As explained earlier, various inputs parameters (i) P_t, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1} i.e., 5 inputs and 1 output for ANN and resolved 20 inputs and 1 output for WNN, (ii) Pt, Q_t, Q_{t-1}, S_{t-1} i.e., 4 inputs and 1 output for ANN and resolved 16 inputs and 1 output for WNN were used for prediction of sediment load. Different combinations of input and hidden layer neurons were tried for developing the model after selection of the best network architecture. On the basis of overall performance of the attempted network structures, 5-6-1 and 4-5-1 network structures with epochs 375 and 564, respectively, were found to be performing better. From these better performing network structures, the 5-6-1 network structure was finally selected as the best ANN model having maximum R^2 and minimum *RMSE* and *AIC* (Table 1). In case of WNN, among 20 inputs, the maximum R^2, minimum RMSE and AIC were observed in 20-15-1 with epochs of 172 during both training and validation period, whereas among 16 inputs, the maximum R^2, minimum *RMSE* and AIC were observed in 16-15-1 during training, and higher R^2 and minimum *RMSE* in 16-14-1 were observed at epochs of 79 during validation period. Therefore, 16-14-1 was selected among 16 inputs. After comparison with the maximum R^2, minimum *RMSE* and *AIC* during both training and validation periods, 20-15-1 network was found to be better.

All R^2 and model Efficiency (%E) from the ANN and WNN for runoff prediction during testing period were much higher than those from the NLD. Whereas, *RMSE* value (1.287) from the NLD model during this testing period was much lower than those for the ANN and WNN, and the respective R^2 (0.834) and E (83.113%) values were higher in case of sediment yield prediction (Table 2). A visual assessment of the predicted and observed runoff (Figure 2) shows that the ANN predicted runoff had the best fit, followed by WNN, and that the NLD fit was the worst. Figure 3 shows the scatter plot between the observed and predicted values of NLD, ANN and WNN for sediment yield and shows that the prediction of daily

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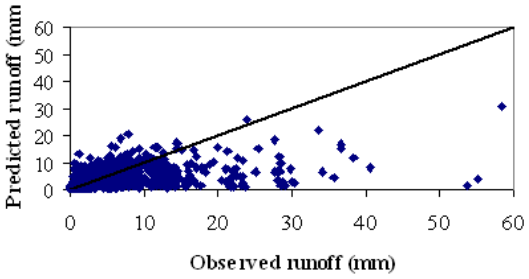
Table 1. Selection of various ANN and WNN architectures for daily runoff and sediment yield prediction**.**

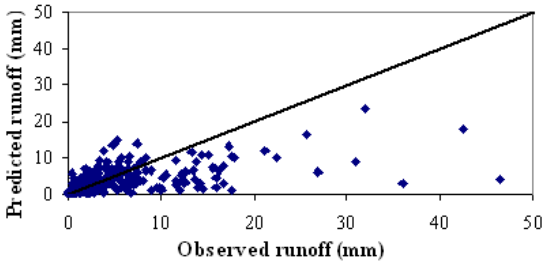
Network	Epoch	Training period			Validation period		
		R^2	RMSE (mm)	AIC	R^2	RMSE (kg s^{-1})	AIC
				Runoff (mm)			
				(A) ANN			
5-6-1	1000	0.829848	0.032342	-12761.28019	0.754292	0.013229	-3980.72819
4-8-1	2000	0.829484	0.032373	-12745.85659	0.740271	0.033151	-3887.95372
3-4-1	2000	0.814199	0.033792	-12640.85729	0.742062	0.032326	-3973.26144
				(B) WNN			
20-21-1	355	0.813748	0.03366	-11988.31810	0.704257	0.033332	-3711.11960
16-19-1	304	0.811008	0.033912	-12199.84062	0.703401	0.033675	-3349.15126
12-14-1	325	0.811963	0.033823	-12501.86442	0.704055	0.033481	-3647.95701
				Sediment load (kg sec^{-1})			
				(A) ANN			
5-6-1	375	0.890777	0.052849	-15233.02936	0.829885	0.00728	-5696.33270
4-5-1	564	0.907161	0.015427	-15554.11817	0.799290	0.00800	-5567.66402
				(B) WNN			
20-15-1	172	0.851375	0.019442	-14343.78800	0.645452	0.013342	-4575.37633
16-14-1	79	0.803676	0.022361	-13966.72537	0.636166	0.014387	-4540.40422

Table 2. Performance evaluation statistics of developed runoff and sediment models during testing period.

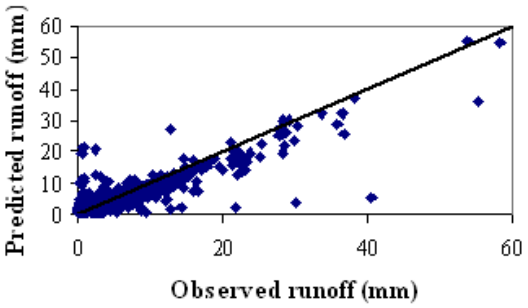
Model	Rainfall-Runoff				Rainfall-runoff-sediment			
	RMSE (mm)	R^2	E (%)	PEPF (%)	RMSE (kg s^{-1})	R^2	E (%)	PEPF (%)
Non-Linear Dynamic (NLD)	0.742	0.700	69.838	49.691	1.287	0.834	83.113	37.495
ANN	2.141	0.837	81.356	22.071	5.536	0.770	76.705	15.877
WNN	2.215	0.831	79.787	20.024	6.197	0.704	70.323	12.094



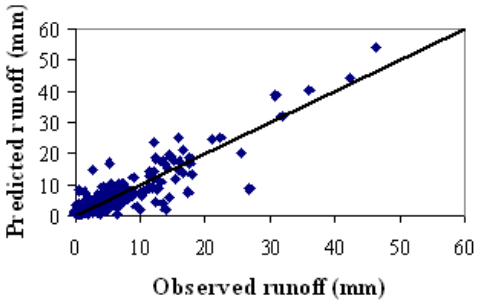
(a) Scatter plot for Calibration period of NLD (5-1) model.



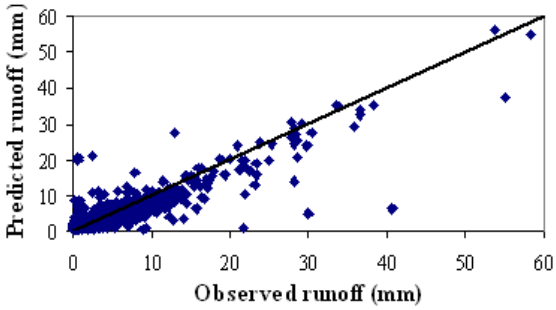
(b) Scatter plot for Testing period of NLD (5-1) model.



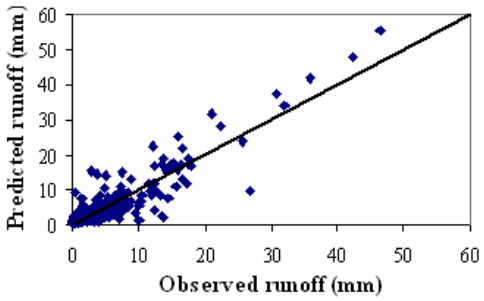
(c) Scatter plot for Calibration period of ANN (5-6-1) model.



(d) Scatter plot for Testing period of ANN (5-6-1) model.



(e) Scatter plot for Calibration period of WNN (20-21-1) model.



(f) Scatter plot for Testing period of WNN (20-21-1) model.

Figure 2. Scatter plot between observed and predicted daily runoff.

sediment from NLD model was close to the observed values, whereas ANN and WNN under-predicted the sediment loads. In case of runoff prediction, the developed models performed well, but they under-predicted sediment yield in all cases. This under-prediction might be due to unexpected (random) heavy sediment outflow caused by sudden landslides. This randomness in sediment outflow was not taken into account by the developed models and, hence, it resulted in under-prediction. Again, negative values predicted by the ANN and WNN model are obviously not realistic, for the observed runoff and sediment may be close to zero but can never be negative. The occurrence of negative values with this type of model is not unusual (Kisi, 2010). But as

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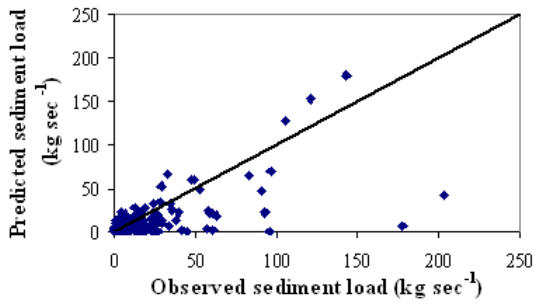
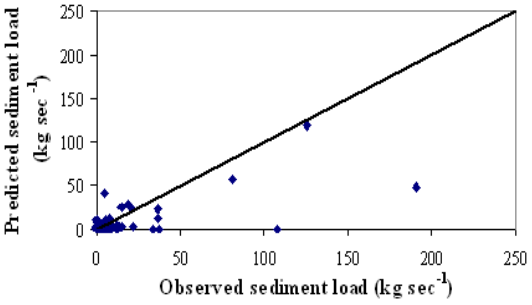
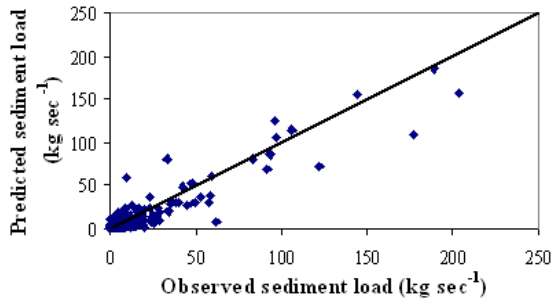


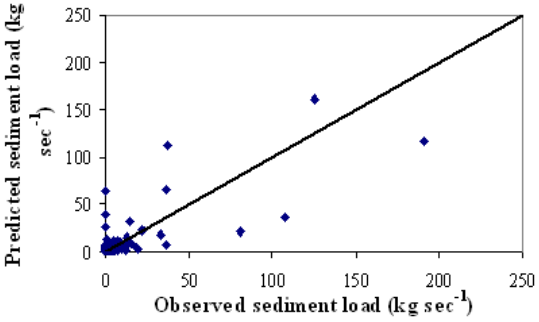
(a) Scatter plot for Calibration period of NLD (5-1) model.



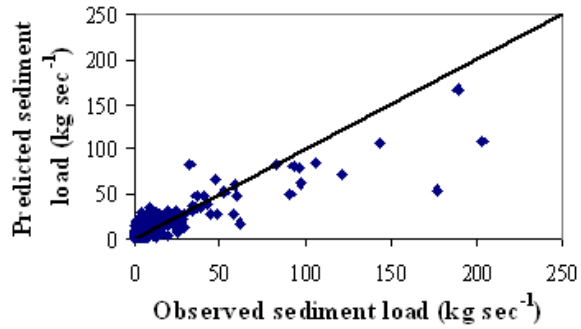
(b) Scatter plot for Testing period of NLD (5-1) model.



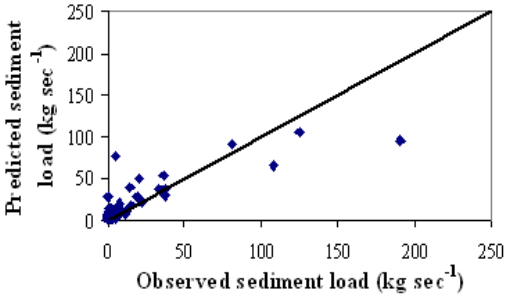
(c) Scatter plot for Calibration period of ANN (5-6-1) model.



(d) Scatter plot for Testing period of ANN (5-6-1) model.



(e) Scatter plot for Calibration period of WNN (20-15-1) model.



(f) Scatter plot for Testing period of WNN (20-15-1) model.

Figure 3. Scatter plot between observed and predicted daily sediment load.

predictions, they serve no purpose. Therefore, here, negative values change to zero values which increase the R^2 of the ANN and WNN by 2.43% and 3.54%, respectively. Thus, an appropriate way of dealing with negative values remains a challenge for future ANN and WNN-based model construction (Liu *et al.,* 2013). Again, the decomposition level for WNN was taken as 3 by using the formula, but criteria for successful selection of a useful sub-component need to be developed.

Though many researches have proved that WNN model predicted better than simple ANN model, but in this analysis, both of the models gave almost on par predictions for

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runoff and sediment yield. This may be due to the fact that large mountainous catchment runoff and the sediment yield generated are discontinuous for so many days and again the lag values were fixed for both of the models, taking into account the resulting lag values through simple and easily computable non-linear dynamic model by simple software or excel sheet. Peak value is a key point in the time series modeling. The results reported here are based on the whole time series data. Since the WNN model is a multi-scaled and seasonal model and ANN is autoregressive model, it is expected that WNN has a better ability to capture peak values. Therefore, analysis was done for peak flows. *PEPF* values of 20.024 and 12.094 were observed for runoff and sediment yield, respectively, which are less than that of ANN and NLD (Table 2). This indicates the greater capturing power of WNN for simulating extreme flows (Rao *et al.,* 2014; Tiwari and Chatterjee, 2010). This under-prediction may be due to unexpected (random) heavy sediment outflow due to sudden landslides. This randomness in sediment outflow is not taken into account by the developed models and, hence, it results in under-prediction.

CONCLUSIONS

In this work, performance of feed forward ANN and Wavelet based ANN (WNN) has been reported, taking the input parameters obtained through step-wise regression done for Non-Linear Dynamic (NLD) model for predicting daily runoff and sediment yield considering the memory system of a Himalayan Mountainous Watershed in Uttarakhand, India. Twenty-six years' of daily rainfall, runoff and sediment yield data of monsoon period of Bino Watershed under Ramganga catchment were used for the analysis. The performance of a developed model was assessed in terms of its coefficient of determination, root mean square error, and model efficiency. The results revealed superior performance of the ANN and WNN models in comparison to the NLD model in case of rainfall-runoff process, whereas NLD model performed well compared to ANN and WNN models in case of rainfall-runoff-sediment process. The comparison revealed that, for runoff modeling, ANN and WNN performed at par, whereas for sediment yield prediction, NLD model performed well. However, the models under-predicted sediment yield. This could be due to not considering randomness in values resulting from sudden landslides and flash floods in Himalayan Watersheds. Again, criteria for successful selection of a useful sub-component in WNN need to be developed. Further, the WNN performance was evaluated for peak flows, which revealed that WNN performed better compared to ANN and NLD. Therefore, this study suggests that, in mountainous watershed, due to more dynamic nature of hydrologic events, it is very difficult to generalize that WNN is better than ANN and/or non-linear models. This indicates the capturing power of WNN model for simulation for extreme flows in mountainous watershed compared to whole time series data.

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ارزیابی تطبیقی مدل های شبکه عصبی و مبتنی بر رگرسیون برای شبیه سازی رواناب و تولید رسوب در یک حوضه آبریز بیرون از هیمالیا

س. سودهیشری، ا. کومار، و ج. ک. سینک

چکیده

در پیش بینی رواناب و تولید رسوب در حوضه های کوهستانی وسیع، پیچیدگی فرایند هیدرولوژیکی بارندگی–رواناب–تولید رسوب همچنان به عنوان یک چالش باقی مانده است.در پژوهش حاضر، یک مدل ساده وغیر خطی پویا (simple non-linear dynamic, NLD) برای پیش بینی رواناب و تولید رسوب روزانه و با در نظر گرفتن تاریخچه بارندگی و رواناب حوضه آبریز و رابطه بارندگی–رواناب و تولید رسوب به کاررفت. نتایج به دست آمده با دو مدل شبکه عصبی مصنوعی (ANN) و ANNموجک (wavelet based ANN, WNN) که رایج هستند مقایسه شدند و این کار با استفاده از مقدار حد اکثر پارامترهای نهاده ای (maximum input parameters of values) مربوط به حافظه زمانی (time memory) برای بارندگی، رواناب، و تولید رسوب به دست آمده از مدل توسعه یافته NDL و از طریق رگرسیون گام به گام انجام شد.مدل های ANN از نوع feed forward با الگوریتم تکثیر پسین (back propagation) مورد استفاده قرار گرفت. در این پژوهش از آمار روزانه بارندگی، رواناب، و تولید رسوب یک دوره ۲۶ ساله حوضهBino درایالت آتاراخند استفاده شد. برای ارزیابی عملکرد مدل ازضریب تبیین، ریشه میانگین مربعات خطا و کارآیی مدل

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استفاده شد. نتایج به دست آمده حاکی از عملکرد بهتر برای مدل های بارندگی-رواناب ANN و WNN در مقایسه با NLD بود، هرچند که در حالتی که تمام داده های سری زمانی در نظر گرفته شد مدل بارندگی-رواناب-تولید رسوب NLD کارآیی بیشتری از ANN و WNN داشت. دلیل این که همه مدل ها تولید رسوب را کم پیش بینی می کردند وقوع ناگهانی زمین لغزه و سیل های شدید در حوضه های هیمالیا بود. نتایج پژوهش نشان داد که هرچند WNN بهتر از ANN و NLD بود، کاربرد این مدل را برای همه حوضه های کوهستانی نمی توان تعمیم داد. مجددا یاد آوری می شود که ضوابط انتخاب موفق یک زیر-جزء در WNN می بایست فراهم آید. همچنین، این پژوهش چنین اشاره دارد که مدل WNN با کمترین درصد اشتباه در مورد جریان اوج (peak flow) توانایی بیشتری برای شبیه سازی جریانات فوق العاده را دارد.

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