Proceedings of H04, IAHS-IAPSO-IASPEI Assembly, Gothenburg, Sweden, July 2013 (IAHS Publ. 361, 2013).

Suspended sediment flux modelling in a transboundary Himalayan river basin

ARCHANA SARKAR[1], R.D. SINGH[1] & NAYAN SHARMA[2]

1 National Institute of Hydrology, Roorkee-247667, India

2 Indian Institute of Technology, Roorkee-247667, India

Abstract Artificial neural network (ANN) models have been developed for simulation of daily suspended sediment flux in the Subansiri River basin, which is a transboundary eastern Himalayan basin and the biggest sub-basin of the Brahmaputra River in India. Modelling was conducted on two datasets: (1) daily discharge and suspended sediment concentration data of 15 years (1993–2007) and (2) daily data of climate (rainfall, temperature) and snow cover area along with discharge and suspended sediment concentration for six years (2001, 2003–2007). The performance of ANN models has been compared with conventional sediment rating curves (SRC) and multiple linear regression models (MLR) having similar input data. ANN models were found to be considerably better than the SRC and MLR models. This paper concludes by providing discussion about how the different type of input data, length of input data and lagging of input data affects the accuracy of sediment flux estimation in a large Himalayan River basin and also provides guidance on the types of tasks for which different types of input data may be preferable.

Key words suspended sediment flux; artificial neural networks; multiple linear regression; Himalaya; Brahmaputra River; Subansiri River; India

INTRODUCTION

Rigorous assessment of sediment fluxes in rivers is required in a wide spectrum of problems such as design of reservoirs and dams; hydroelectric power generation and water supply; water quality and pollution and environmental impact assessment (Singh *et al*., 1998). Himalayan rivers transport sediment at a very high rate and in the Himalayan and Tibetan region, they supply about 25% of the dissolved load to the world oceans (Raymo & Ruddiman, 1992). Among Himalayan rivers, the Brahmaputra is a major international river, ranking second in the world with respect to sediment load (Rao, 1984). The Brahmaputra flows across four countries, including India. Within India, the Subansiri River is the biggest tributary of Brahmaputra and it has tremendous potential for hydropower (22 projects having potential of 15 191 MW already proposed/in progress). Therefore, accurate estimation of sediment fluxes of the river is of vital importance for the design and management of water resources projects. In the past few decades, great strides have been made in conceptualizing the process of runoff generation and sediment yield/flux from catchments through varying modelling approaches (Flaxman, 1972; Walling, 1983; Wicks & Bathurst, 1996; Van Oost *et al.,* 2000; Verstraeten *et al*., 2003). Models are classified according to their degree of representation of the physical processes involved in abstraction of the real sediment flux phenomenon. They are classified as physically-based distributed models, conceptual models, empirical models and black-box models in a decreasing degree of representation and increasing degree of application simplicity.

The physically-based distributed models attempt to represent the spatial heterogeneity of variables by dividing the catchment into grids and describe the processes of the sediment transport from grid to grid with simplified partial differential equations (Wicks & Bathurst, 1996). These models can provide satisfactory simulation and prediction for small and heavily instrumented catchments (<100 km^2). However, their applications at regional and larger scales are unrealistic because the quantity and quality of necessary input data are usually insufficient. Lumped conceptual models are favoured in terms of their limited data requirements and inclusion of a conceptual framework. However, lumped conceptual models also require a lengthy calibration and parameterization process. Empirical models estimate suspended sediment flux by relating it to catchment characteristics such as drainage area, topography, land cover and climate (Walling, 1983). They are widely used because of their relatively simple structure and ability to work with limited input data. However, empirical models are unable to represent the spatial variability of

Copyright © 2013 IAHS Press

hydrological processes and catchment parameters that influence the suspended sediment flux in a river. Black-box models in the form of regression models can simulate the highly nonlinear suspended sediment flux with limited accuracy, due to their simple model structure and underlying distribution assumptions. In this context, use of soft computing techniques offers an alternative modelling approach.

In recent years, artificial neural network (ANN) models have attracted researchers in hydrology and water resources (ASCE, 2000) since they are capable of approximating any arbitrary continuous function, simulating a nonlinear system without *a priori* assumption of processes involved, and giving a good solution even when input data are incomplete or ambiguous. The application of the ANN approach for modelling sediment flux is very recent and has already produced encouraging results. Jain (2001) applied ANN to establish an integrated stage–discharge–sediment concentration relation for two sites on the Mississippi River. Tayfur (2002) used ANN to simulate experimentally observed sediment fluxes from different slopes under various rainfall intensities. Kisi (2004) used ANN to simulate daily suspended sediment concentration at two stations on the Tongue River in Montana, USA. Sarkar (2005) and Sarkar *et al*. (2008, 2010) applied the ANN technique to model the sediment–discharge relationship of Satluj River of western Himalaya in India, Kosi River of the Ganges River system in northern India, and Pranhita River of the Godavari River system in southern India. The above studies demonstrate that the modelling of sediment, including its concentration in a river and flux from a slope or a watershed, is possible through the use of ANN. A common approach adopted was that discharge and suspended sediment flux at previous time steps were used as inputs. Although it may increase the accuracy of the simulation, ANNs established by this method are unable to explain the contribution from climatic variables. Therefore, in the study presented in this paper, instead of using only discharge and suspended sediment concentration as inputs, we relate the suspended sediment flux to the original driving forces (i.e. rainfall and temperature) to develop an ANN model that can be used to explore the relationships between climate inputs and sediment responses.

This paper presents development of an ANN model based on daily sediment flux simulation models for the Subansiri basin up to Chouldhuaghat gauging site. The advantages of ANN models have been evaluated by comparing its performance with that of conventional sediment rating curves (SRC) and multiple linear regression (MLR) models. Two types of daily ANN models have been developed, one with a longer length of input data (15 years) consisting of only discharge and suspended sediment concentration; and a second with shorter length input data (6 years) of the original driving forces, i.e. rainfall and temperature along with data of snow cover area in the catchment and water discharge. For comparison, RCs having data similar to the first type of ANN models and MLR models having data similar to second type of ANN models have been developed.

METHODS

Study area and data availability

The study area is located in the Subansiri River basin (Fig. 1). The Subansiri River is the biggest north bank tributary of the Brahmaputra River in India. It originates in Tibet beyond the Great Himalayan Range at an altitude of around 5340 m and joins the Brahmaputra in the plains of Assam State in India. The region of Subansiri basin has three distinct parts: (1) the great Himalayan range, (2) the Sub-Himalayas, and (3) fertile plains of Assam. In the mountainous terrain, the river has a total length of about 208 km and falls from 4206 to 80 m a.s.l. near Dulangmukh in the foothills. As it flows across the central Himalaya to the Arunachal foothills, the Subansiri receives discharge from numerous streams. The total length of known and well-defined tributaries of Subansiri is 1960 km. The Subansiri River contributes about 10.7% of the total discharge of the Brahmaputra at Pandu near Guwahati in India. The catchment area of Subansiri basin up to the outlet at Chouldhuaghat is approx. 26 419 km^2 from SRTM data, of which about 10 237 km^2 (38.75%) lies in Tibet and the remaining 61.25% in India.

The Sub-Himalayan range of Subansiri generally consists of soft sandstones and weathered rocks. During the period May to October, the intensity of precipitation is high and sediment is deposited in areas nearer to and along the foot hills are easily eroded. Daily suspended sediment (SS g/L) and discharge (Q m^3/s) data were available at the Choulduaghat gauging site for the period 1993–2007. However, meteorological data were available only after the year 2000, in the form of daily observed rainfall in the Indian part of basin at Gerukamukh and Daporizo raingauge stations (RG and RD, mm); daily gridded rainfall data from APHRODITE (Yatagai, 2009) at $0.25° \times 0.25°$ for the Tibetan part of basin at three grids (R1, R2 and R3, mm); daily observed temperature at Gerukamukh station (T°C) and daily snowcover area as a percentage of total basin area (SCA1 up to an elevation of 4800 m, and SCA2 for elevations >4800 m) computed from MODIS data. MODIS snow data (Riggs *et al.*, 2007) are Aqua/Terra satellite data products available from February 2000 to the present date. In the present research, MOD10A2 8-day composite snow data products at a resolution of 500 m were used to estimate the snow cover in Subansiri basin. The details of snow cover area estimation are given in Sarkar *et al.* (2010).

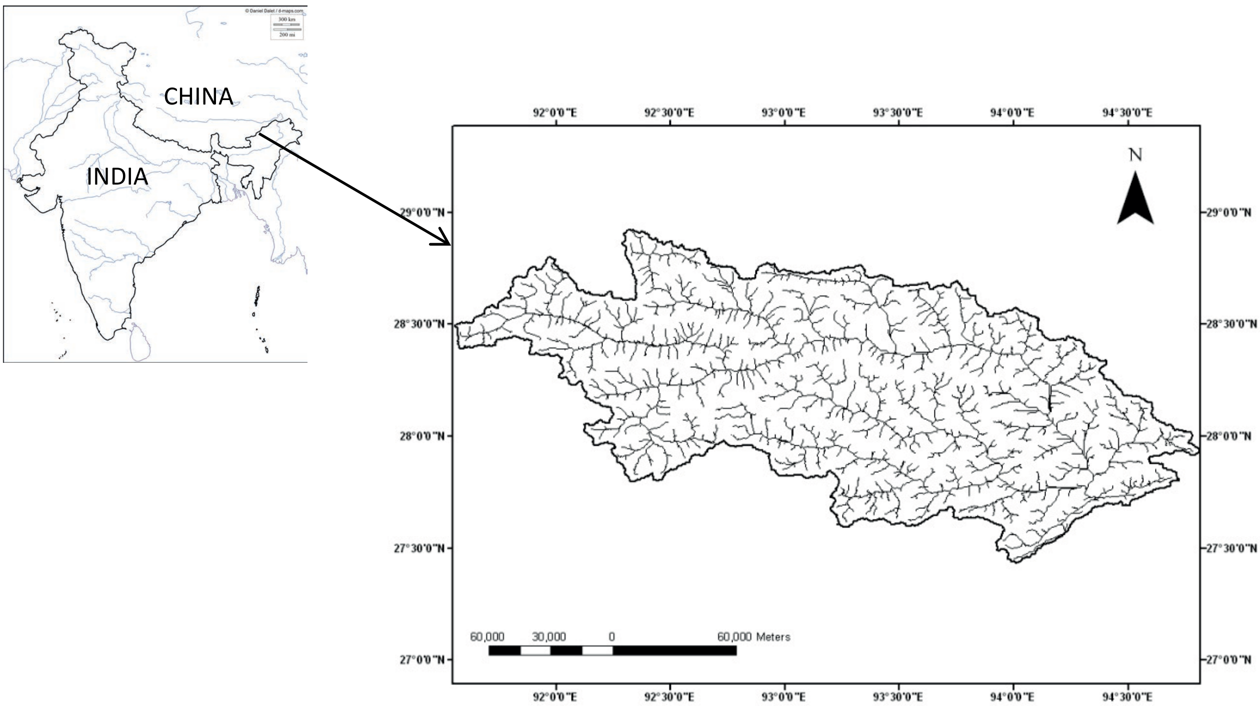


Fig. 1 Index map of the study area.

Selection of input/output data variables

The input/output variables for the two types of ANN models that use data with different periods of record (15 *vs* 6 years of data) were designed separately.

The ANN models for 15 years of data consist of daily Q (m^3/s) and S (mg/L) at Chouldhuaghat site for 1993 to 2007 which gave a total of 5478 patterns (data sets). Out of this, nine years (1993–2001) consisting of 3287 patterns were used for training, three years (2002–2004) consisting of 1096 patterns for validation and three years (2005–2007) consisting of 1095 patterns for cross-validation. Various combinations of input data (considering lagged inputs) used for training of ANN models are given in Table 1.

The ANN models with six years (2001, 2003–2007) of daily rainfall data at RG, RD, R1, R2 and R3; daily mean temperature T and daily snowcover area as SCA1 and SCA2 comprised 2191 patterns (data sets). Out of this, four years (2001, 2005–2007) consisting of 1460 patterns were used for training, one year (2003) consisting of 366 patterns for validation and one year (2004) consisting of 365 patterns for cross-validation. Various combinations of input data were considered in three groups, viz, Group I: A simple model was selected by representing suspended sediment concentration at the present time, t, as a function of rainfall and mean temperature at time t; Group II: The snow cover area and discharge at the present time, t, were added as additional input variables to the model of Group I; Group III: The suspended sediment concentration at the previous time step, t – 1 was added as an additional input variable to the model of Group II. Within these three groups of ANN models, three models each were considered: (i) with input variables at current time, t; (ii) with input variables at the previous time step, (t – 1) in addition to (i); and (iii) with input variables at two time steps earlier, (t – 2) in addition to (ii). However, in the last group of models, the first sub-group already has the suspended sediment concentration at t – 1. The various ANN models considered for training are given in Table 1.

Models with different lengths of data were designed to evaluate the effect of data length on model accuracy. Models in different groups were designed to compare the performance of different sets of input variables, while those in the same group were designed to assess the degree of lag-effect between the inputs and outputs through addition of lagged data, one by one.

Table 1 Input/ouput variables of ANN models.

ANN model	No. input variables	Input variables	Output variable
ANN models with 15 years data			
ANN15-1	1	Q_t	S_t
ANN15-2	3	Q_t, Q_{t-1}, S_{t-1}	S_t
ANN15-3	5	Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}	S_t
ANN15-4	7	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, S_{t-1}, S_{t-2}, S_{t-3}	S_t
ANN15-5	9	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, S_{t-1}, S_{t-2}, S_{t-3}, S_{t-4}	S_t
ANN models with 6 years data			
Group I:Input variables with rainfall and mean temperature only			
ANN6-1	6	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, T_t,	S_t
ANN6-2	12	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, T_t, T_{t-1}	S_t
ANN6-3	18	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, RG_{t-2}, RD_{t-2}, $R1_{t-2}$, $R2_{t-2}$, $R3_{t-2}$, T_t, T_{t-1}, T_{t-2}	S_t
Group II: Input variables with rainfall, mean temperature, snow cover area and runoff (discharge)			
ANN6-4	9	RG_t, RD_t, $R2_t$, $R5_t$, $R6_t$, T_t, $SCA1_t$, $SCA2_t$, Q_t	S_t
ANN6-5	18	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, T_t, T_{t-1}, $SCA1_t$, $SCA2_t$, $SCA1_{t-1}$, $SCA2_{t-1}$, Q_t, Q_{t-1}	S_t
ANN6-6	27	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, RG_{t-2}, RD_{t-2}, $R1_{t-2}$, $R2_{t-2}$, $R3_{t-2}$, T_t, T_{t-1}, T_{t-2}, $SCA1_t$, $SCA2_t$, $SCA1_{t-1}$, $SCA2_{t-1}$, $SCA1_{t-2}$, $SCA2_{t-2}$, Q_t, Q_{t-1}, Q_{t-2}	S_t
Group III: Input variables with rainfall, mean temperature, snow cover area and runoff (discharge)			
ANN6-7	10	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, T_t, $SCA1_t$, $SCA2_t$, Q_t, S_{t-1}	S_t
ANN6-8	19	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, T_t, T_{t-1}, $SCA1_t$, $SCA2_t$, $SCA1_{t-1}$, $SCA2_{t-1}$, Q_t, Q_{t-1}, S_{t-1}	S_t
ANN6-9	29	RG_t, RD_t, $R1_t$, $R2_t$, $R3_t$, RG_{t-1}, RD_{t-1}, $R1_{t-1}$, $R2_{t-1}$, $R3_{t-1}$, RG_{t-2}, RD_{t-2}, $R1_{t-2}$, $R2_{t-2}$, $R3_{t-2}$, T_t, T_{t-1}, T_{t-2}, $SCA1_t$, $SCA2_t$, $SCA1_{t-1}$, $SCA2_{t-1}$, $SCA1_{t-2}$, $SCA2_{t-2}$, Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}	S_t

TRAINING OF ANN MODELS

The process of determining ANN weights is called learning or training and it is similar to calibration of a conceptual/mathematical model. The ANN package Neural Power (2003) was used for ANN model development, training as well as testing. The structure for all simulation models was a three layer back-propagation ANN which utilizes a non-linear sigmoid activation function uniformly between the layers. Nodes in the input layer were equal to the number of input variables, nodes in the hidden layer were varied from the number of input nodes to approximately double the input nodes (Zhu *et al*., 1994) and the nodes in the output layer was one as the models provide single output.

The modelling of ANN initiated with the normalization (re-scaling) of all inputs and output with the maximum value of the respective variable, reducing the data to the range 0 to 1 and 0.1 to 0.9, respectively, to avoid any saturation effect that may be caused by the use of a sigmoid function. All interconnecting links between nodes of successive layers were assigned random values called weights. Constant values of 0.15 and 0.75, respectively, were considered for the learning rate α and momentum term β, selected by trial and error. A quick propagation (QP) learning algorithm was used, which is a heuristic modification of the standard back propagation and is very fast (NeuralPower, 2003). The criterion selected to avoid over training was generalization of the ANN through cross-validation (Haykin, 1994). Training data were used for estimation of weights of the ANN model and validation data for evaluation of the performance of the ANN model during training. Training was stopped when the error for the validation dataset started increasing. In this way, the training and validation datasets were used to assess the performance of various candidate model structures, and thereby choose the best one. The ANN model with the best performing parameter values was chosen and the generalized performance of the resulting network was measured on the cross-validation data set to which it had never before been exposed.

RESULTS AND DISCUSSION

Performance indices of the various daily ANN models developed based upon the input data structure are presented in Table 1. The SRC and MLR are presented in Table 2. SRC has input/output variables similar to ANN15-1. MLR models in each group have input/output variables similar to the best performing ANN model in that group. Statistical criteria, namely the root mean square error (RMSE), correlation coefficient (R) and determination coefficient (DC) were used to evaluate the performance of the models. The criterion for selection of the best model in different groups was based on the performance of the various models in validation and cross-validation phases.

Among the 15 year data ANN models, ANN15-3, which consisted of two antecedent discharges and two antecedent sediment concentrations in input, had the best overall performance (Table 2). The RMSE value of ANN15-32 is slightly higher during training compared to ANN models based on more input data, but is lowest during validation and cross-validation phases, which indicates a better generalization capability of the model.

Among ANN models based on six years of data, Group I models based only on rainfall and mean temperature show relatively poor performances (Table 2). The best performing model in this group is ANN6-2, with the lowest RMSE and highest R & DC in the validation as well as cross-validation phases. ANN6-2 model has 12 input variables comprising five rainfall values and one mean temperature value of the current day as well as the previous day. It is evident from Table 1 that with the addition of one previous day's data in the input variables, the model performance improves.

However, with addition of another lagged input variable set, i.e. previous two day data, model performance declines. In Group II models, the best performing model is ANN6-4 with nine input variables comprised of five rainfall data, one mean temperature data, two snow cover area data and one discharge data, all for the current day. Group II models do not exhibit any improvement of model performance with addition of lagged input variables. It is observed that all the Group II models show an improved performance over the corresponding (with respect to data lagging) models in Group I. Looking at the performance of Group III models, it can be seen that there is a dramatic improvement in the performance of all the models of this group compared to Groups I and II. In Group III models, the best performing model is ANN6-7 with 10 input variables comprising of five rainfall data, one mean temperature data, two snow cover area data, one discharge data, all of current day and one suspended sediment concentration data of previous day.

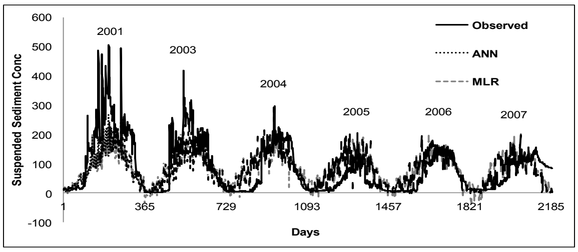
Table 2 Comparative performance of various ANN models and SRC/MLR models.

Model	Training			Validation			Cross-Validation		
	RMSE	R	DC	RMSE	R	DC	RMSE	R	DC
ANN models with 15 years data									
ANN15-1	157.60	0.633	0.400	117.62	0.631	0.286	126.98	0.601	–6.07
ANN15-2	60.604	0.955	0.911	52.545	0.928	0.858	8.347	0.985	0.969
ANN15-3	*59.455*	*0.956*	*0.915*	*50.450*	*0.933*	*0.869*	*9.234*	*0.982*	*0.964*
ANN15-4	53.895	0.964	0.930	50.493	0.935	0.869	12.692	0.982	0.929
ANN15-5	51.826	0.968	0.935	50.521	0.934	0.869	9.556	0.981	0.930
SRC	164.26	0.631	0.349	588.69	0.637	–16. 9	624.88	0.602	–170.2
ANN models with 6 years data									
Group I: Models with only rainfall and mean temperature as input									
ANN6-1	65.852	0.618	0.381	66.361	0.784	0.524	57.124	0.737	0.515
ANN6-2	*63.271*	*0.655*	*0.429*	*62.353*	*0.787*	*0.582*	*54.588*	*0.765*	*0.556*
ANN6-3	60.894	0.687	0.547	64.267	0.785	0.552	56.497	0.751	0.526
MLR6-I	66.243	0.611	0.373	66.403	0.741	0.521	57.899	0.731	0.501
Group II: Models with rainfall, mean temperature, snow cover area and discharge as input									
ANN6-4	*56.39*	*0.748*	*0.550*	*55.709*	*0.855*	*0.664*	*47.221*	*0.829*	*0.666*
ANN6-5	56.61	0.737	0.543	58.129	0.805	0.636	47.896	0.813	0.659
ANN6-6	55.76	0.746	0.556	56.394	0.818	0.657	47.654	0.807	0.660
MLR6-II	63.645	0.649	0.422	56.439	0.815	0.658	52.506	0.770	0.590
Group III: Models with rainfall, mean temperature, snow cover area, discharge and previous day sediment concentration as input									
ANN6-7	*19.861*	*0.971*	*0.944*	*23.000*	*0.975*	*0.948*	*16.988*	*0.984*	*0.968*
ANN6-8	19.293	0.973	0.947	23.717	0.972	0.939	18.593	0.977	0.949
ANN6-9	19.035	0.974	0.948	24.787	0.969	0.934	18.810	0.976	0.948
MLR6-III	21.181	0.967	0.936	23.743	0.971	0.943	17.729	0.979	0.957

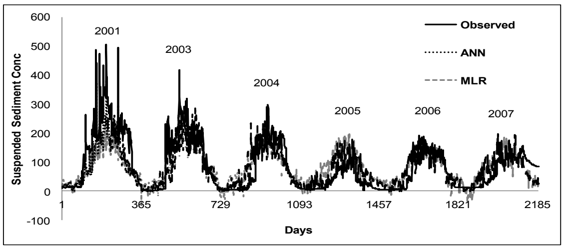
Group III models also do not exhibit any improvement of model performance with addition of more lagged input variables. Through comparison of SRC and MLR model performance with corresponding ANN models (Table 2), it can be seen that both SRC and MLR models perform less well than ANN models in all the three phases.

A comparison of the time series of observed suspended sediment flux and model simulated sediment flux based on ANN models namely, ANN6-2, ANN6-4, ANN6-7, ANN15-2 with corresponding MLR/SRC models during all three phases except training phase of ANN15-2 are presented in Fig. 2 (units of sediment data have been omitted because of data secrecy issues). The figure shows that suspended sediment flux time series generated using ANN models are closer to the observed series compared to the corresponding MLR/SRC model series, especially for the peak and low flows. The MLR models of Group I and II estimate negative suspended sediment flux values when there is no rainfall/low runoff during the periods selected in the input model structure.

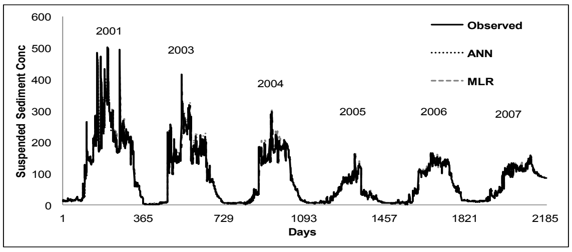
The most important issue in sediment flux modelling is selection of input variables which play an important role in determining the accuracy of the developed models. Rainfall and temperature were selected because they are closely correlated with the sediment flux and can be used to represent the influence of climate. While rainfall is the main driving force of sediment flux, the close relationship between temperature and sediment flux may be a result of two mechanisms. First, about 30% of the study area lies in cold arid deserts of the Tibetan Plateau where the average annual potential evaporation is generally higher than that of the annual rainfall, and temperature, to some degree, affects the potential evaporation. Second, temperature is an index of soil moisture, which significantly affects soil erosion processes and resultant sediment supply to rivers. The inclusion of discharge has improved the performance of ANN models because of the close relationship between suspended sediment flux and discharge. Inclusion of antecedent sediment flux has further enhanced the performance of the models. The results show that selection of input variables also overcomes the limitation of data length. ANN model, ANN6-7, with six years data



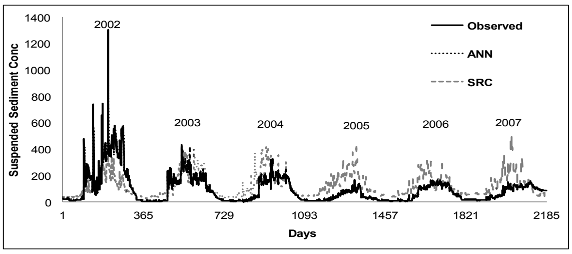
(a) ANN6-2: Only R & T input



(b) ANN6-4: R, T, SCA & Q input



(c) ANN6-7: R, T, SCA, Q & S_{t-1} input



(d) ANN15-2: Q & S_{t-1} input

Fig. 2 Comparative performance of observed and simulated sediment flux series.

performs much better than model ANN15-2 with 15 years data, because the previous model has rainfall, mean temperature and snowcover data in addition to discharge and previous day suspended sediment concentration data.

Among the various groups of ANN models, Group I models have the lowest data requirement and relatively simple structure. However, their accuracy is lower than the others. Group II ANNs have higher accuracy than Group I ANNs because snowcover area and discharge are used as additional inputs; however, such models cannot be used to predict sediment flux directly from the climate input. Therefore, in ungauged catchments, one extra step is required to predict the discharge before the sediment flux can be predicted. The error may become cumulative in such a case and final accuracy may be lower than those of the present ANNs with observed discharge data as input. Group III ANNs have much higher accuracy than the Group II ANNs. This type of ANN actually estimates the difference between values of the dependent variable at current and previous time steps thereby making them suitable for applications focusing on the status of water or sediment. Even with more accurate results, such models do not provide any information about the contribution of driving forces, such as climate.

The lag effect of input variables is another issue that should be taken into account in developing ANN models. The best performing ANN in Group I is the one with input data of the current day and previous one day, suggesting that a 1-day lag-effect exists between the climate inputs and sediment flux. In Group II, when R, T, SCA and Q are used as inputs, the current time information is good enough for the estimation of the sediment flux, reflecting the strong influence of Q without lag time. The degree to which the input information from previous time steps should be involved can be decided from the physical relationship between the inputs and the output. When the inputs are directly or closely related to the output, no or only a shorter lag effect should be considered. In other cases a longer lag effect may be required, as for rainfall and temperature.

CONCLUDING REMARKS

The suspended sediment flux modelling in the transboundary Subansiri basin of the Himalayas is necessary for development and management of the upcoming water resources projects in the catchment. In this study, the ANN methodology was applied to simulate the daily suspended sediment flux of the catchment using different lengths of data and different types of input data. The results of the ANN models were compared with conventional SRC as well as MLR models. Although ANNs showed better performance in estimating sediment flux with a large magnitude, especially for records higher than 200 compared to MLRs and SRC, in general they showed weak robustness in estimating sediment flux with a large magnitude. Such limitations in the application of ANNs are commonly attributable to scarcity of large observed values in the training dataset. In other words, this inefficiency can be attributed to different non-linear relationships governing the process of sediment detachment and final sediment flux generated from a catchment. For example, the mechanism of sediment flux generation induced by a low flow event is obviously different from the sediment flux produced by a storm event in which a significant amount of wash load enters the catchment drainage network and passes the outlet. Therefore, due to different mechanisms, a single ANN, which may produce satisfactory results for the simulation of medium and low fluxes, may not simulate large sediment flux events with the same accuracy. In the present data set, there were inadequate data corresponding to high sediment flux events to train a separate ANN model for simulating these high values. Therefore, more input data would enhance the accuracy of ANN models for a large basin.

Acknowledgements This study was funded by the National Institute of Hydrology, Roorkee, India. The authors would like to extend their appreciation to Central Water Commission (CWC), India and National Hydro Power Corporation (NHPC), India for providing the hydrological and meteorological data used in the study. The lead author is thankful to Prof. D.E. Walling, University of Exeter, UK for sharing his ideas regarding sediment response of large Asian catchments and data-related issues. The authors would also like to thank the Reviewer for his comments which helped to improve the paper.

REFERENCES

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. (2000) Artificial neural networks in hydrology II: Hydrologic applications. *J. Hydrol. Engng ASCE* 5(2), 124–137.

Flaxman, E.M. (1972) Predicting sediment yield in western United States. *Proc. of the American Society of Civil Engineers Journal of the Hydraulics Division, ASCE* 98(HY12), 2073–2085.

Jain, S.K. (2001) Development of integrated sediment rating curves using ANNs. *J. Hydrol. Engng ASCE*, 127(1), 30–37.

Haykin, S. (1994) *Neural Networks – A Comprehensive Foundation*. Macmillan, New York.

Kisi, O. (2004) Multi-layer perceptrons with Levenberg-Marquardt optimization algorithm for suspended sediment concentration prediction and estimation. *Hydrol. Sci. J.* 49(6), 1025–1040.

Rao, K.L. (1984) River basins of India. In: *Contributions to Indian Geography: Resource Geography, 5* (ed by A. Ramesh), Heritage Publishers.

Raymo, M.E. & Ruddiman, W.F. (1992) Tectonic forcing of Late Cenozoic climate. *Nature* 359, 117–122.

Riggs, G.A., Hall, D.K. & Salomonson, V.V. (2007) MODIS snow products user guide to collection 5. doi:modis-snow-ice.gsfc.nasa.gov/sug_c5.pdf.

Sarkar, A. (2005) Sediment runoff modeling using ANNs in a western Himalayan basin, India. *Proc Intl conf on Headwater control VI: Hydrology, Ecology and Water Resources in Headwaters,* June 2005, Bergen, Norway.

Sarkar, A., Kumar, R., Jain, S.K. & Singh, R.D. (2008) Artificial neural network models for estimation of sediment loads in an alluvial river in India. *Journal of Environmental Hydrology* 16, 1–16.

Sarkar, A., Raju, M.M., & Kumar, A. (2010) Sediment runoff modeling using artificial neural networks. *J. Indian Water Resources Society IWRS* 30(1), 39–45.

Sarkar, A., Singh, R.D. & Sharma, N. (2010) Spatio-temporal variation of snow cover in a part of Brahmaputra basin based on MODIS/Terra. *Proc. International Symposium on "Benefiting from Earth Observation: Bridging the Data Gap for Adaptation to Climate Change in the Hindu Kush-Himalayan Region*, 4-6 October 2010, Kathmandu, Nepal.

Singh, V.P., Krstanovic, P.F. & Lane, L.J. (1988) Stochastic models of sediment yield. In: *Modeling Geomorphological Systems* (ed by M.G. Anderson), John Wiley & Sons Ltd.

Tayfur, G. (2002) Artificial neural networks for sheet sediment transport. *Hydrol. Sci. J.* 47 (6), 879–892.

Walling, D.E., (1983) The sediment delivery problem. *J. Hydrol.* 65, 209–237.

Wicks, J.M. & Bathurst, J.C. (1996) SHESED: a physically based, distributed erosion and sediment yield component for the SHE hydrological modeling system. *J. Hydrol.* 175, 213–238.

Van Oost, K., Govers, G. & Desmet, P. (2000) Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. *Landscape Ecology,* 15, 577–589.

Verstraeten, G., Poesen, J., de Vente, J. & Koninckx, X. (2003) Sediment yield variability in Spain: a quantitative and semiqualitative analysis using reservoir sedimentation rates. *Geomorphology* 50, 327–348.

Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N. & Kitoh, A. (2009) APHRODITE: Constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Bulletin of American Meteorological Society*, doi:10.1175/BAMS-D-11-00122.1.