Research Journal of Recent Sciences ISSN 2277-2502
Vol. 4(**ISC-2014),** 120-130 **(2015)** *Res. J. Recent. Sci.*

Sediment Yield Modelling of Kal River in Maharashtra Using Artificial Neural Network Model

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Available online at: www.isca.in, www.isca.me
Received 30th November 2014, revised 7th January 2015, accepted 17th January 2015

Abstract

The sediment yield is important factor concern with erosion rate from the catchment which is caused the problems of reducing the storage capacity of reservoirs, creating delta at mouth of rivers and reduces capacity of streamflow, etc. There are several models developed for estimation of sediment yield like USLE, RUSEL and physical based models like SWAT, but they required rigours series of data. In present study artificial neural network model is non linear Black box model used to forecast the sediment yield of Kal river in Maharashtra using the streamflow, stream flow lag by one or two day, rainfall and sediment yield lag one or two day as input to the model. In present study multi layers feed forward back propagation neural network model with one to three input layers, one hidden layers and one output layers were developed. The models were adopted by changing numbers of neuron in hidden layers and epoch. The models performance was evaluated by statistical indices such as R, RMSE, CE, VE, MAD, and MAPE. The study reveal that, ANN model with single input as streamflow and 10 neuron in hidden layer found R values 0.92 and 0.85 during training and cross validation respectively and other indices such as RMSE, CE, VE, MAD and MAPE were 91.58 tons/day, 84.16 per cent, 2.28 per cent, -4.52 per cent and 98.07 per cent during training period where 110.35 ton/day, 76.82 per cent, 0.1 per cent, 10.62 per cent and 20.91 per cent during cross validation period, respectively. It is also observed that, the performance of model increase with increases input parameter and changing combination inputs parameters. The linear regress model developed to compare the performance, found the ANN model performance were better and overall ANN model performance were satisfactory for prediction of sediment yield.

Keywords: Black box, performance, sigmoidal function, streamflow.

Introduction

Sediment yield is defined as the total sediment outflow from the catchment or watershed at a point of reference during specific time period. The sediment from the watershed is induced by the process of detachment, transportation and deposition of soil materials by rainfall and runoff [1,2]. The quantity of sediment yield deposited or transported is totally dependant of rainfall i.e. rainfall amount, intensity, duration and distribution besides that, other parameter such as soil type, vegetation cover, soil moisture and slop of land, etc. The sediment transports caused to reduce the capacity of rivers and reservoirs. The sediment also carried the pollutant such as radio active material, soil nutrients and pesticides, etc. The wide variety of linear and non linear model has been developed since long for forecasting runoff, sediment yield and rainfall runoff sediment yield in hydrology. These models are classified into lumped, conceptual, hydrological and hydraulic model. The physical based model (such as ArcSWAT, HSP, ANSWER, etc.) required wide range of input data related to land used, soil properties, soil slope, man med activities, topographic data etc. These are spatial and significant over time and these are very difficult to monitored and collect over period of time. Stochastic model required time series but need to made some assumption and found not more reliable in estimation of sediment[3]. The assumptions creased lumpiness in stochastic process. It is therefore important to develop a model that can predict accurately the suspended sediments concentration from continuous water data set where typhoon and tropical storms exist.

The Artificial Neural Network (ANN) approach comprises linear and non- linear concepts in model building, and can be operated with the dynamic or memory less input-output system. The ASCE Task Committee on the application of ANNs for its application in mapping from one multivariate space to another without providing the physics of the process[4]. It has the following major advantages as: i. An ANN model does not require a prior knowledge of the system and, therefore, can be applied to solve the problems not clearly defined[5]. ii. The model has more tolerance to noise and incomplete data, and thus, requires less data for model development and the results are the out-come of the collective behaviour of data, and thereby, the effect of outlier is minimized. iii. In ANN, the gradient de-scent search optimization embedded with back propagation algorithm is quite popular in ANN for exploring diverse areas such as bio-medical, engineering, image processing, water resources, and others[6,7,8]. Artificial neural network (ANN) approaches to model the streamflow–suspended sediment relationship were investigated by Kisi at Rio Valenciano station operated by US Geological survey[9]. Agarawal *et al.* carried out the study of sediment yield using back propagation ANN model at Vamsadhara river basin, India[10]. Jha and Jain investigated the use of ANNs in rainfall-runoff modelling in Kentucky River basin, USA[11]. Raghuwanshi *et al.* investigated the performance of ANN in predicting runoff and sediment yield at Upper Siwana River, India[12]. Several regression models for rainfall-runoff and sediment yields are available in literature[13]. Thus the present study was undertaken to develop memory based feed forward linear transfer function back propagation neural network model for forecasting the sediment yield on daily time periods and evaluate the model performance for their forecasting abilities using the data of the Kal river catchments in Maharashtra of India.

Material and Methods

Study area and data used: The Present study was conducted for the Kal river is the tributary of Savitri river basin comes under the western part of Sahayandri Ghat part of Konkan region located in Maharshtra State in India (figure-1). The latitude and longitude of the study area is $17^0 51'$N to $18^0 20'$N and $73^0 22'$ E to $73^0 41'$E respectively and elevation ranges from 10.50 m to 1366.23 m above mean sea level**.** The Kal river comprises catchments area 354 Sq. Km and hydrologic and meteorological station located at Birwadi outlet of Kal river to Savitri river basin. The mean average daily rainfall, streamflow and mean daily sediment yield were collected from Hydrologic project, data storage centre, Nashik for duration of 7 years (2003 to 2009) of Birwadi station.

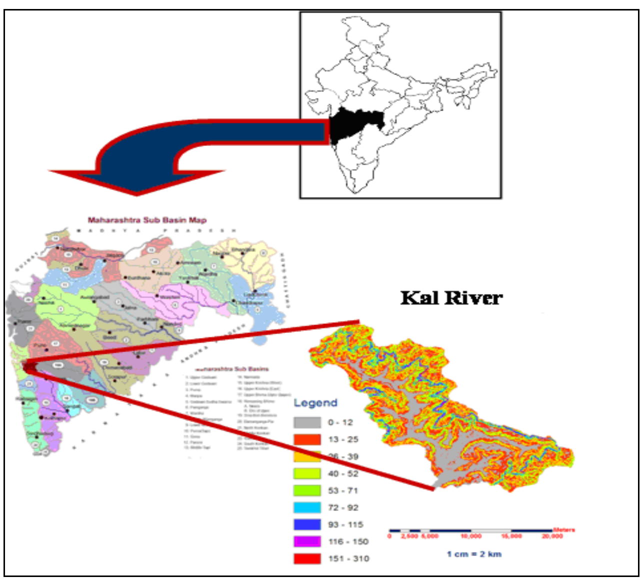
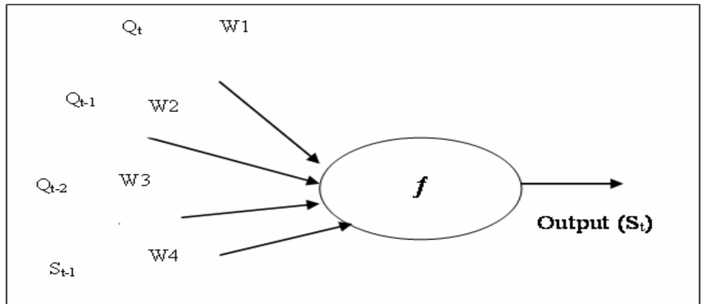


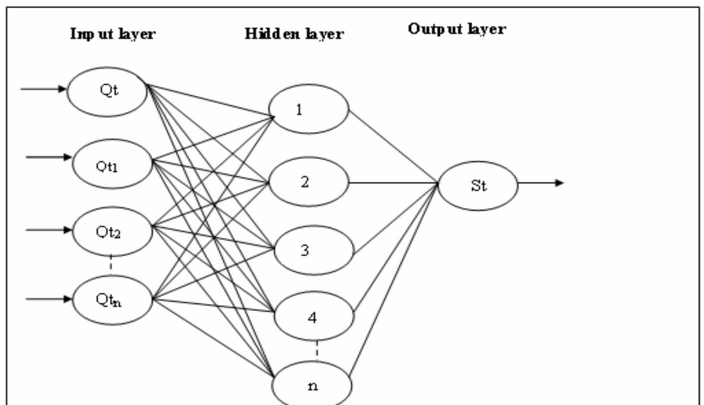
Figure-1
Location of study area

Input to the models: The ANN models used in this study are multi layer feed forward backpropagation networks with one to three input layers, one hidden layer with different combination of neuron and one output layer (figure-2a-b). The different combination of inputs layers were adjusted and check the performance of modes. The combinations of inputs parameters are presented in table-2 for identification of best model. The 6 models were developed for Kal river to forecast sediment yield from streamflow, rainfall and sediment yield lag by one or two days as input.



Where,
Q_t = input streamflow, cumecs,
Q_{t-1} = input stream flow lag by one day,
S_t = input sediment yield, tons/ha,
Q_{t-2} = input streamflow lag by two day, cumec,
W_1, W_2, W_3, W_4---W_n= weight to input
St = output sediment yield, ton/ha,
f = logistic sigmodal function.

Figure- 2(a)
Architecture of an artificial neuron I ANN Model



Where,
Q_1, Q_2, Q_3, Q_4… Q_n = rainfall inputs to ANN in input layer.
1, 2, 3, 4, 5 ….n = number of neurons in hidden layers.
St = Sediment yield as output of neuron.

Figure-2(b)
Architecture of feed forward multilayer artificial neuron network model for forecasting sediment yield

Artificial neural network: An ANN is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Neurons having similar characteristics in an ANN are arranged in groups called layers (figure-2a). The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is represented by what is known as a 'connection strength' or 'weight'. An ANN normally consists of three layers, an input layer, a hidden layer and an output layer. In a feed-forward network, the weighted connections feed activations only in the forward direction from an input layer to the output layer. On the other hand, in a recurrent network additional weighted connections are used to feed previous activations back to the network. The application of a function newff in relation to inputs, target, and number of neurons has created a feed-forward network. The principle of this function was to use the units where each performed a biased weighted sum of their inputs. Then, these units passed this activation level through a transfer function to produce their output, and the units were arranged in a layered feed-forward topology (figure-2b). Once the number of layers and number of units in each layer, has been selected, set so as to minimize the prediction error made by the network. This was the role of the training algorithms. The used function 'newcf' has created cascade-forward networks. The CF included a three-layer network that has connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3 (figure-2b). The three-layer network also has connections from the input to all three layers. In this study, Tan-sigmoid (tansig) and pure linear (pureline) transfer functions were selected for both forward backpropagation networks to reach the optimized status. The operational schematic representation of ANN models is given figure-3.

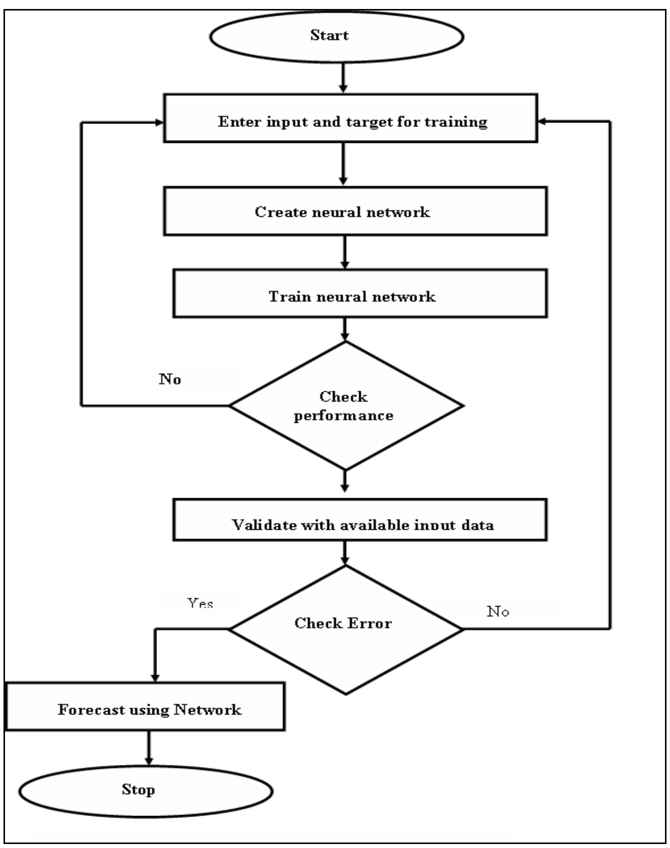


Figure-3
Schematic representation of MLFFBANN model

In the present study the back propagation algorithm is used in multi layered feed-forward ANNs[6]. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) was calculated. The idea of the back propagation algorithm was to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal was to adjust them so that the error will be minimum. The activation function of the artificial neurons in ANNs implementing the back propagation algorithm is a weighted sum (the sum of the inputs Pt-1 multiplied by their j-i respective weights w), Architecture of artificial neural network is as shown in figure-2b. The expression can be written in the mathematical form for ANN model given by following equation.

$$S(t) = f(SR, Q(t_l), Q(t_{l-1}), Q(t_{l-2}, P(t_{s-1}), St(t_{s-2}))$$

Where: t =time of prediction, days (24 hrs), t_l = time to incorporate rainfall (in this case, $t_l = t_{l-2}$), t_{l-1} = time period, (24hrs), P = daily rainfall (mm), P_{t-1}= daily rainfall lag by one day, mm (24 hr), Q_t = daily stream flow (cumecs), Q_{t-1}= stream flow lag by one day, cumecs (24 hr), Q_{t-2}= stream flow lag by two day, cumecs (48 hr), St = sediment yield (Output) ton/day, SR = summation of rainfall value from t_l to t_{l-2} ,(mm).

Transfer function: The transfer function of a neuron in a neural network is only processing function. It is utilized for the limiting the amplitude of the output of a neuron. Also known as activation function is referred to as squashing function as squashes (limits) the permissible amplitude range of the output signal to some finite values. It gives output in a range of 0 to 1. This transfer function is commonly used in the hidden layers of multilayer ANN networks as given in Figure-4 and it is represented by equation- 2. The symbol in the square to the right of each transfer function graph shown above represents the associated transfer function. These icons replace the general *f*(α) in the network diagram blocks to show the particular transfer function being used. The mathematical expression of the logistic sigmoid function is given by following equation.

$$f(\alpha) = \frac{1}{1+e^{-\alpha}}$$

An attempt to improve the accuracy is to use data on discharge excess and sum of rainfall during the last one day (24 hours) from the prediction time as additional input to the network model.

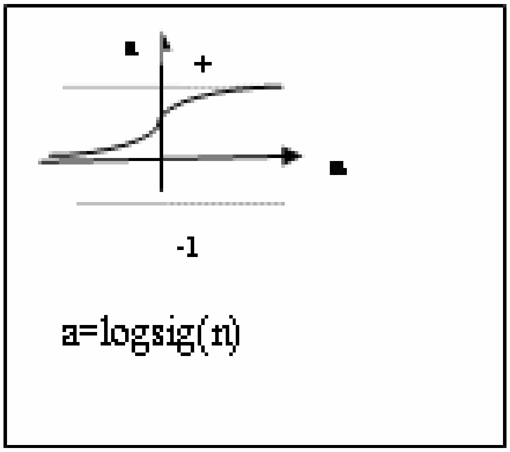


Figure-4
Log Sigmodal transfer function

Data Division: It is common practice to split the available data into two subsets; a training set and independent validation set. Typically, ANNs are unable to extrapolate beyond the range of the data used for training[14,15]. In present study, total data of sediment yield measured at Birwadi station from 2003 to 2009 (740 sets) used for development of ANN model. The data from 2003 to 2007 (584 sets) were adopted for training, testing and validation. Out of the 584 data set 60 per cent (350 sets) were adopted for training and remaining for testing and validation under the training mode. The cross validation is the techniques that is used frequently in ANN modelling and has a significant impact on the way of available data are divided[16]. It can used to determine when to terminate training and to compare the generalization ability of different models. The output in training data was cross validated using data sets of year 2008 to 2009 (171 sets).

Data Pre-processing for ANN model: A logistic sigmoid is used here as the transfer function and the observed input parameters (daily mean rainfall, daily mean streamflow, and daily mean sediment yield) are normalized using The transformation bounded the in the ranges of 0.1 to 0.99.

$$X_n = 0.1 + 0.8\mathrm{X}\left(\frac{X_{value} - X_{\min}}{X_{\max} - X_{\min}}\right)$$

Where: X_n = normalized data set, X_{value} = original data set, X_{min} = minimum value of data set, X_{max} = maximum value of data set.

Training of ANN: ANN models are trained based on a so-called supervised training procedure which allows the network to simulate the hydrological system by examining input-output examples from it. Work by Samani et al. (2007) show that the popular steepest-descent back propagation algorithm is sometimes easily out performed by second-order gradient algorithms and a wider consensus has been reached that such algorithms are therefore preferable over first-order methods[17]. Randomness is introduced in the ANNs initialization, in which normally distributed random values for the network weights are generated. This variability in parameter estimates can be interpreted as a measure of uncertainty of the combination of ANN model and training algorithm.

Statistical sensitivity analysis of ANN model: A number of statistical criteria have been suggested by researchers to evaluate the performance of rainfall runoff models[18-22]. To assess the accuracy of a rainfall-runoff model, more than one criterion should be used. The model performance were evaluated using following statistical parameters such as Correlation coefficient (R), Root mean square error (RMSE), Mean Absolute Deviations (MAD), Coefficient of efficiency (CE), Volumetric Error (EV) and Mean Absolute Percentage Error (MAPE) The details of each criterion are as follows:

Correlation coefficient (R)

$$\mathrm{R} = \frac{\sum_{i=1}^{N}\left\{(Q_{obs,i} - \overline{Q_{obs,i}})(Q_{sim,i} - \overline{Q_{sim,i}})\right\}}{\sqrt{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q_{obs,i}})^2 . \sum_{i=1}^{N}(Q_{sim,i} - \overline{Q_{sim,i}})^2}}$$

Where: Q_{obs} = the observed runoff, cumecs, Q_{sim} = the simulated runoff, cumecs, N = the number of observations.

The correlation coefficient is described in Equation-4. The correlation coefficient measures how well each observed discharge value correlates with the simulated discharge. The value is between -1 and 1. The value of one means perfect correlation, whereas zero means that there is no correlation. This criterion can be used to measure the agreement between the overall shape of the observed and simulated hydrographs.

Root mean square error (RMSE): The root mean square error as shown in Equation-5 measures the average error between the observed and simulated discharges. The lesser the RMSE value, the better the performance of the model. The RMSE can be used to measure the agreement between the observed and simulated water balance.

$$\mathrm{RMSE} = \left(\frac{\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2}{N}\right)^{\frac{1}{2}}$$

Mean absolute deviation (MAD): It is measure of mean absolute deviation of the observed values from the simulated values. Its value nearer to one indicate best computation and mean or to zero giver less accurate predictions given by following equation.

$$MAD = \frac{\sum_{i=1}^{N}\left|Q_{obsj} - Q_{simj}\right|}{N}$$

Coefficient of efficiency (CE): Nash and Sutcliffe proposed the criterion on the basis of standardization of the residual variance with initial variance and named it as coefficient of efficiency[20] and is give by following equation.

$$CE = 1 - \left(\frac{\sum_{i=1}^{N} \left(Q_{obs,i} - Q_{sim,i}\right)^2}{\sum_{i=1}^{N} \left(Q_{obs,i} - \overline{Q}_{obs}\right)^2} \right)$$

The coefficient of efficiency or Nash-Sutcliffe criterion as shown in Equation-7 is often used to measure the performance of a hydrological model. The value is in the range of [-∞, 1]. The zero value means that the model performs equal to a naive prediction; that is, a prediction using an average observed value. The value less than zero means the model performs worse than the average observed value. A value of one is a perfect fit.

Volumetric error (EV): It is also termed as absolute prediction error and it is estimated by following equation.

$$EV = \left\{ \frac{\sum_{i=1}^{n} (Q_{sim,i} - Q_{obs,i})}{\sum_{i=1}^{n} Q_{obs,i}} \right\} x100$$

Mean average per cent error (MAPE): It is also the criteria for evaluation of the hydrologic models. It is given in following equation.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{Q_i - \hat{Q}_i}{Q_i}}{n}$$

Results and Discussion

MLP neural networks with back propagation method has been investigated to forecast sediment yield data for Kal river measured at Birwadi Hydrologic station.The three layers network structure which was shown in Figugre-2b was applied. The network was developed by using Matlab (7.2b) neural networks tools. For investigating the suitability of ANN, a ratio of 60:20:20 for training, validation and testing was considered. Different models were tried with different number of neurons in the hidden layer. To evaluate neural networks performance initialization of connection weights, training, validation and testing has been performed with the independent random trails. A three layer back propagation network model trained by Levenberg-Marquardt optimization algorithm is chosen for this study. The advantage of MLP is the shorter time span during the training process. It is to note that, the level of non-linearity and the selection of training data have no direct influence on the performance of the model. However, the accuracy of the model is largely dependent on the size of the training data sets.

Identifying the architecture of the used ANN for modelling sediment yield process is primary and important aspect of the modelling. In this study considering network, e.g. number of hidden layers (one layer), learning rate (α = 0.6), activation function (tansig) and number of output layer neurons (just one), were assumed as the constant and on the other hand, some other parts, e.g. number of the neurons in input and hidden layers and number of training epochs, are counted as dynamic parameters which must be optimized through a trial-error process. The number of neurons in input layer varies from 1 to 3 which represents the amount of streamflow (Q_t) at the current day, one day lag (Q_{t-1}) and two days lag (Q_{t-2}) and current day rainfall (p_t) before the date of observed sediment load (S_t) data. Number of hidden layer's neurons varies from 2 to 15. Using available data at Birwadi station (2003 to 2009) of the study watershed, the network architecture that yielded the best results in terms of determination coefficient (R) and MSE on the training (using training data set) and verifying (using verifying data set) steps, determined through trial and error process for Kal rive is presented in Table-1. In Present study total six models were identified on trial and error basis. The numbers neurons in hidden layers were selected with best combination of R and RMSE value during training data sets.

Model performance: The developed six models for predicting sediment yield were evaluated for their performance using statistical indices during training and cross validation period. And the performance of developed models during training and cross validation is presented in table-2. From table-2 observed that, values of R during training are 0.0.92, 0.93, 0.93, 0.93, 0.95 and 0.96 for model M1, M2, M3, M4, M5, and M6 respectively whereas in cross validation period 0.87, 0.92, 0.92, 0.93, 0.93, 0.93 respectively. Kachroo reported that a model can be considered satisfactory if R value exceeds 90 per cent and considered fairly good for R in the range of 80 per cent to 90 per cent[23]. This indicates that model's performance very good in predicting the sediment yield during training and cross validation except model 1 during cross validation. From table-2 observed that, RMSE for all models under training phase varies from 91.58 to 67.49 t/ha/day, whereas under cross validation phase varies from 110.35 to 83.59 t/ha/day. The minimum values of RMSE indicate the model performance is good and higher values reduce the performance. The RMSE values are in acceptable range. It is also observed that, M5 and M6 are performed well compared with other model adopted for the study in consideration of RMSE. Other performance indices such as CE, EV, MAD and MAPE of Model M5 and M6 were 91.55per cent and 91.49 per cent, 1.46 per cent and 3.62 per cent, -2.90 per cent and -7.16 per cent, and 28.05 per cent and 39.17 per cent respectively under training period whereas, for cross validation period were 84.48 per cent and 83.59 per cent, 86.31 per cent and 86.60 per cent, 0.12 per cent and 0.14v, 0.080 and 3.12 per cent, and 23.67 per cent and 28.61 per cent, respectively. Hence, it concluded that, model with input as sediment load of lag by one or two day improved the performance of ANN model over the other model. But it is also observed that, performance of model M1 to M4 is very good and satisfactory results for predicting the sediment yield of Kal river. The negative value of MAD indicated that ANN model over predict the sediment load under training period as compared to the cross validation period. The same results were reported for the prediction of sediment yield using ANN models by Agrawal *et al.*[3].

The scatter plot of observed and estimated sediment yield (t/ha/day) during training and cross validation phase for different model under consideration are presented in figure-5(a-f). It observed from the scatter plots of all the models that, the performance of models increases with addition of sediment yield lag by one or two days. It also concluded that, the sediment yield predicting with developed by different inputs parameter are performing better and closely matched with observed data sets. The linear regressive model developed with observed and estimated ANN model sediment yield is presented in Table 3. It observed that linear relationship between the observed and predicted sediment yields Regression coefficient(R^2) ranges between 84.1 to 91.6 per cent during training period whereas during cross validation 76.2 to 91.56 per cent for all models. The less intersection of regressive models was observed for Model 6 and high regression coefficient was 91.2 during training period and also during cross validation intersection less (15.719) with regression coefficient of 91.6 per cent for same model. Hence, it concluded that, comparatively the ANN model and regressive model performance were observed very better for prediction of sediment yield. The Model 5 and 6 found to better perform and closed fitted with above R^2 as 91.2 per cent. Whereas other models show comparatively less fit to model 5 and 6.

The comparative performance of daily observed and estimated sediment yield hydrograph plotted for all models are presented in Figure-6(a-f). From Figure-6(a-f) observed that, all models are performing very better during training and cross validation and are acceptable range.

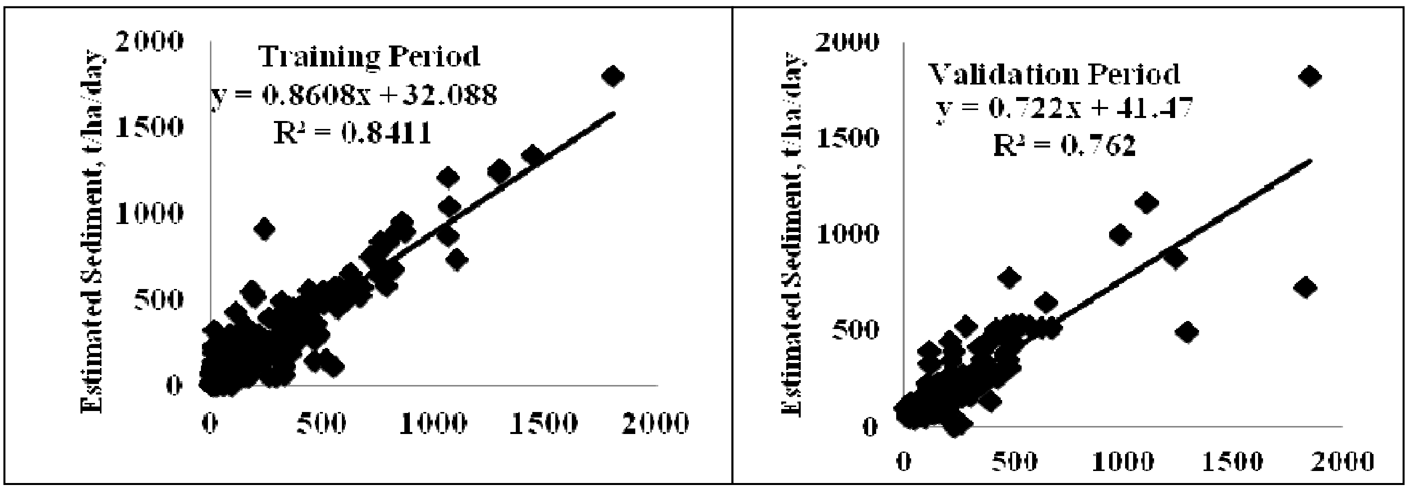


Figure-5(a)
Scatter plot of observed and estimated sediment yield during training and validation period for M1(1 2 10 1)

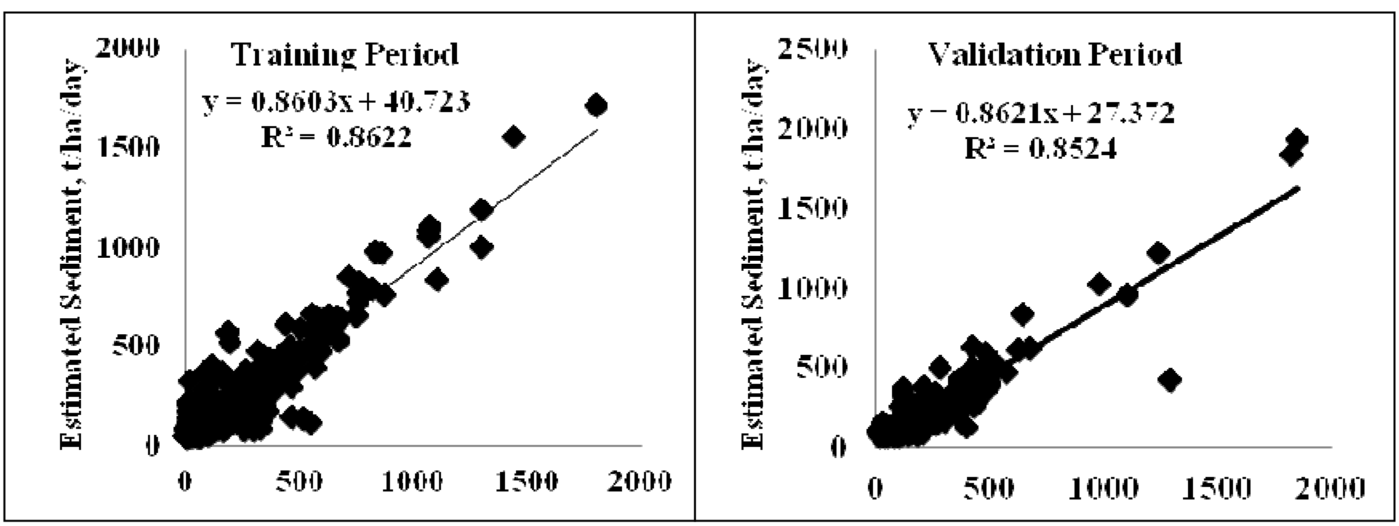


Figure-5(b)
Scatter plot of observed and estimated sediment yield during training and validation period for M2 (2 2 10 1)

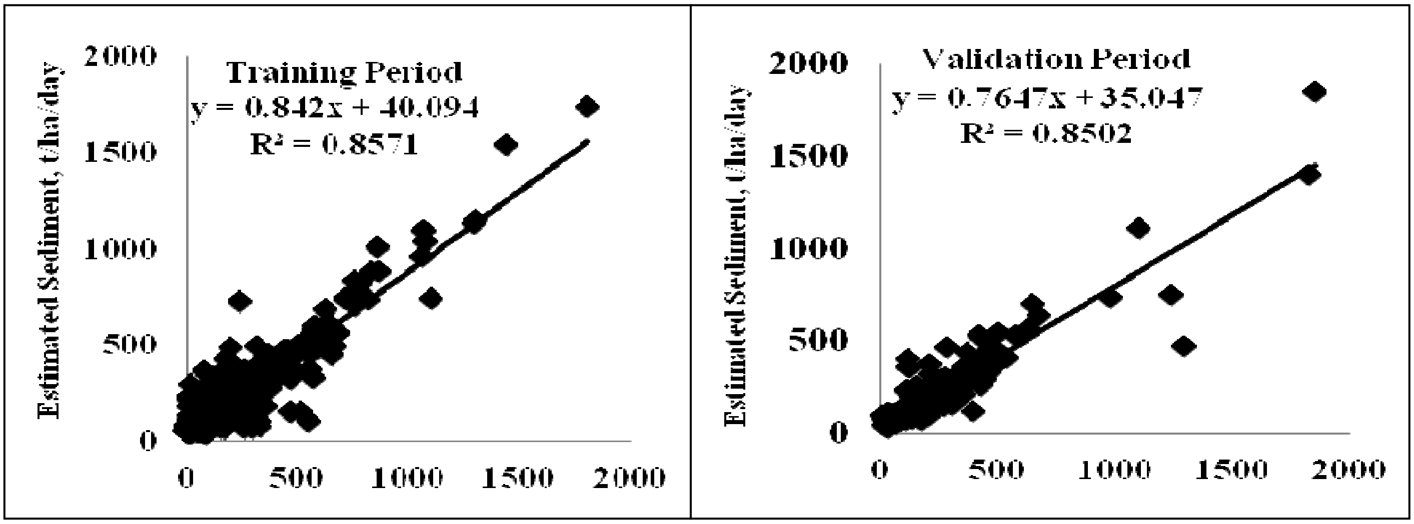


Figure-5(c)
Scatter plot of observed and estimated sediment yield during training and validation period for M3(3 2 10 1)

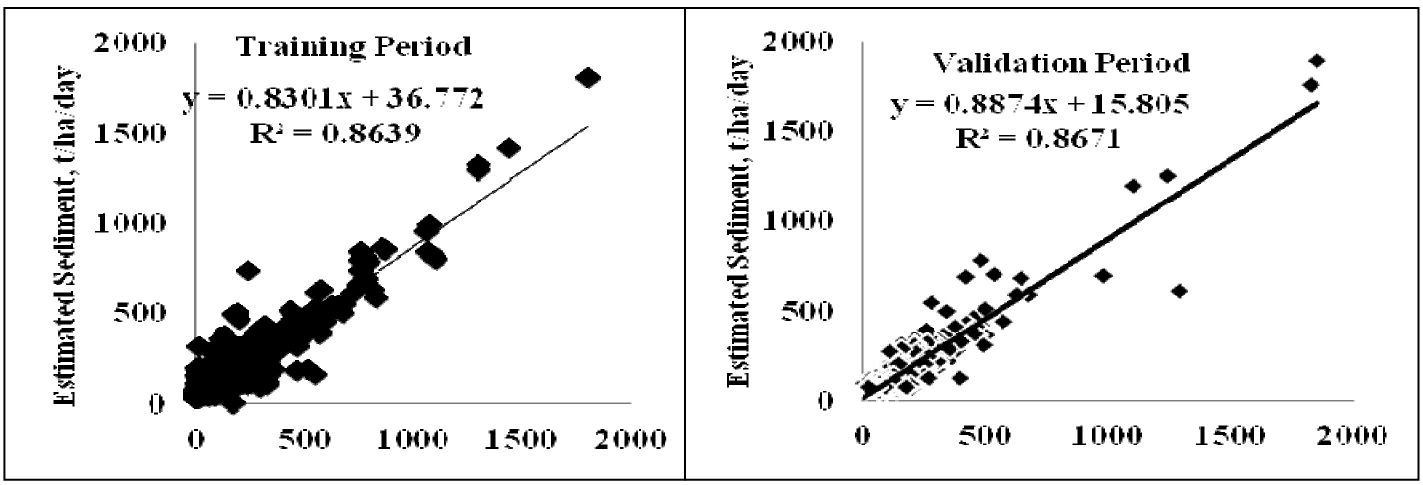


Figure-5(d)
Scatter plot of observed and estimated sediment yield during training and validation period for M4 (2 2 10 1)

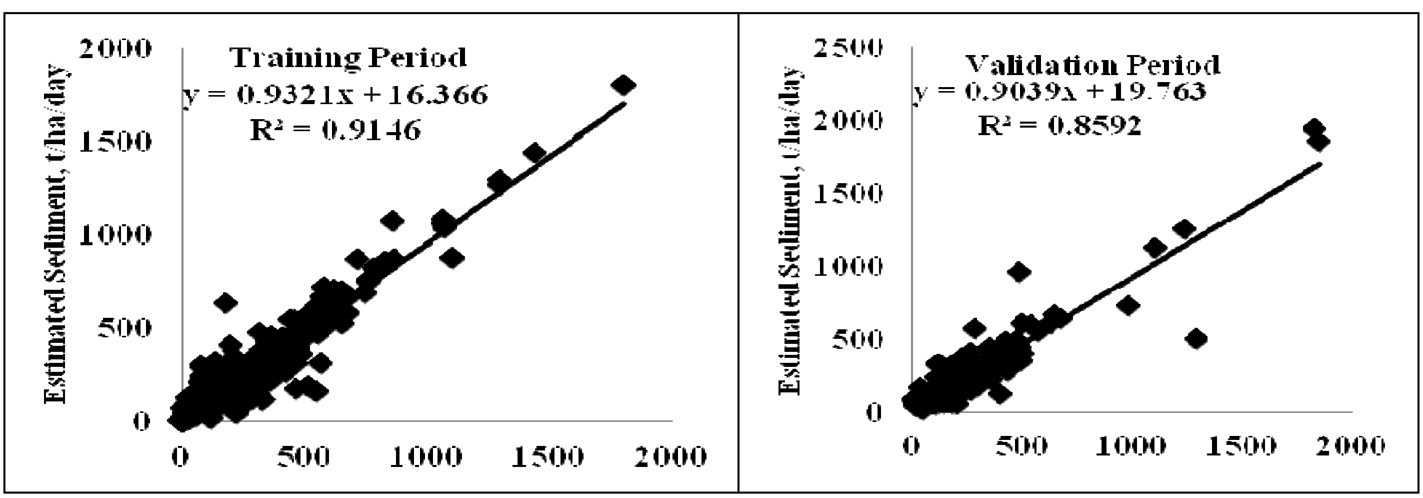


Figure-5(e)
Scatter plot of observed and estimated sediment yield during training and validation period for M5(2 2 10 1)

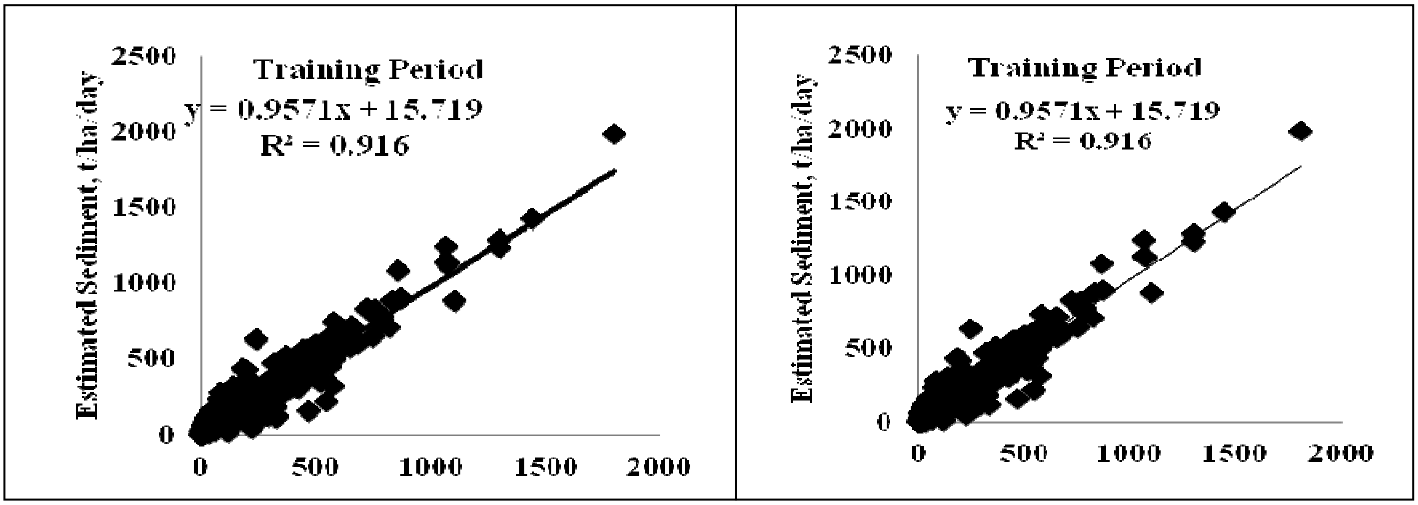


Figure-5(f)

Scatter plot of observed and estimated sediment yield during training and validation period for M6(3 2 10 1)

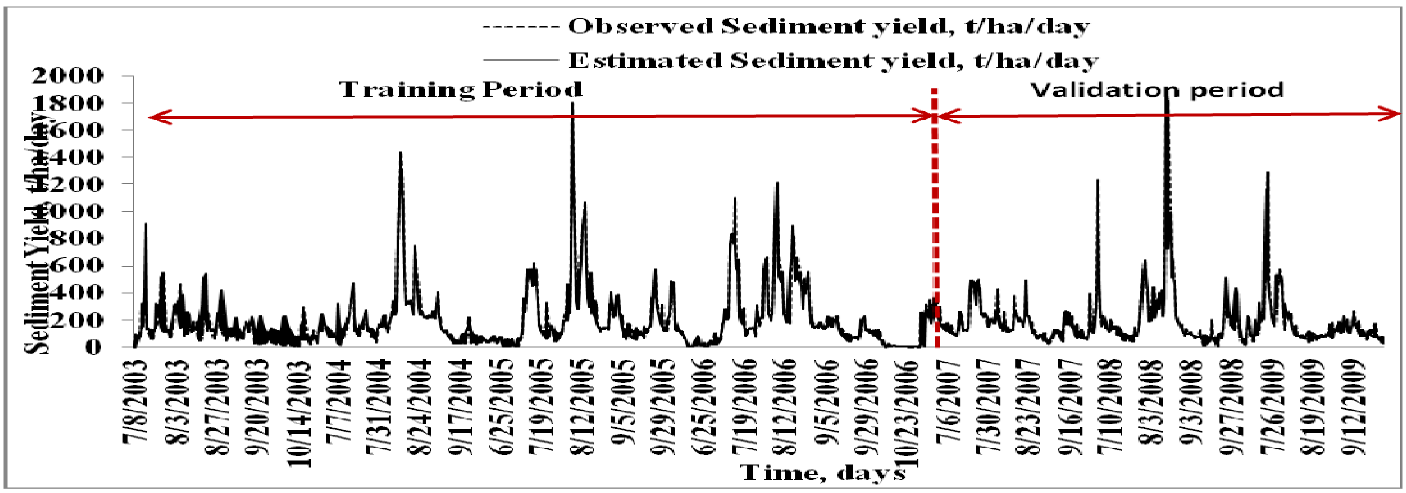


Figure-6(a)

Comparison of observed and estimated Sediment yield for M1 (1 2 10 1) during training and validation period

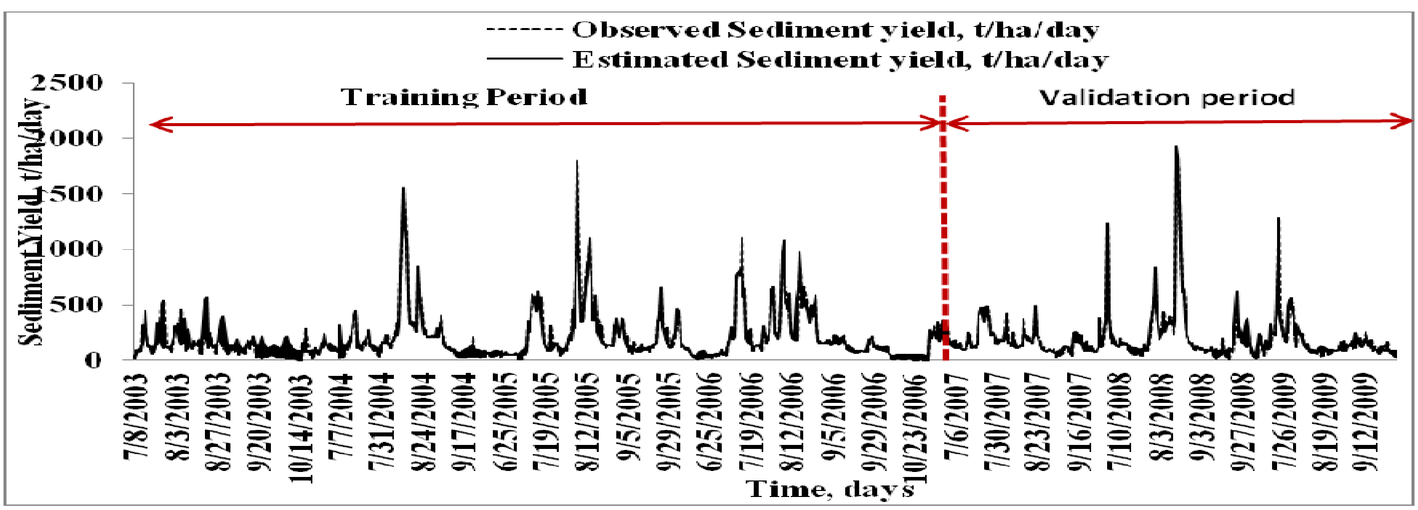


Figure-6(b)

Comparison of observed and estimated Sediment yield for M2 (2 2 10 1) during training and validation period

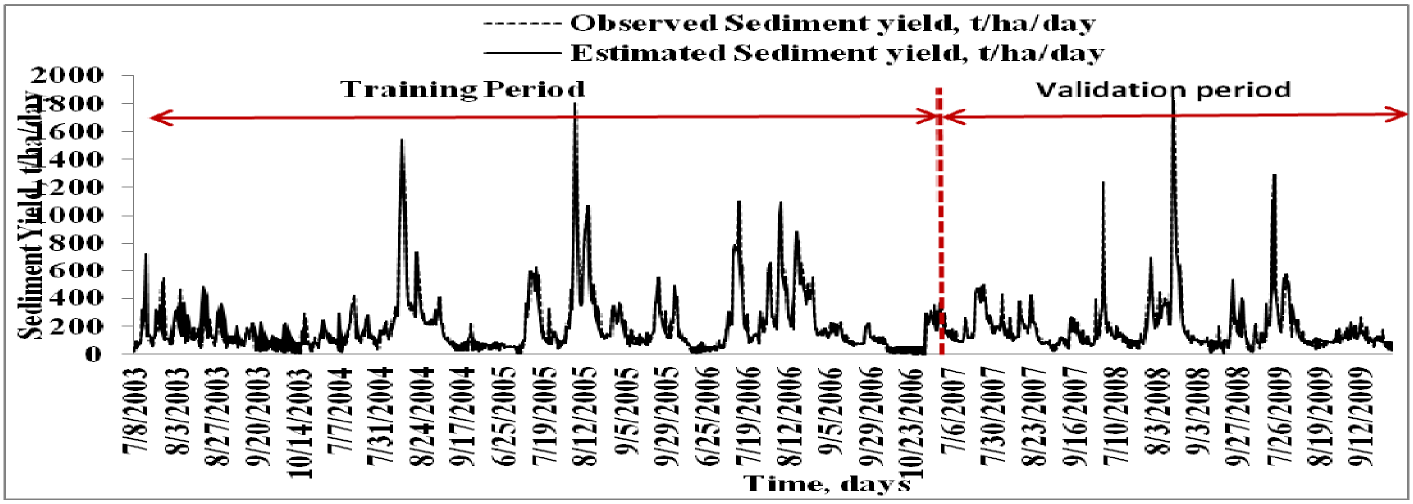


Figure-6(c)

Comparison of observed and estimated Sediment yield for M3 (3 2 10 1) during training and validation period

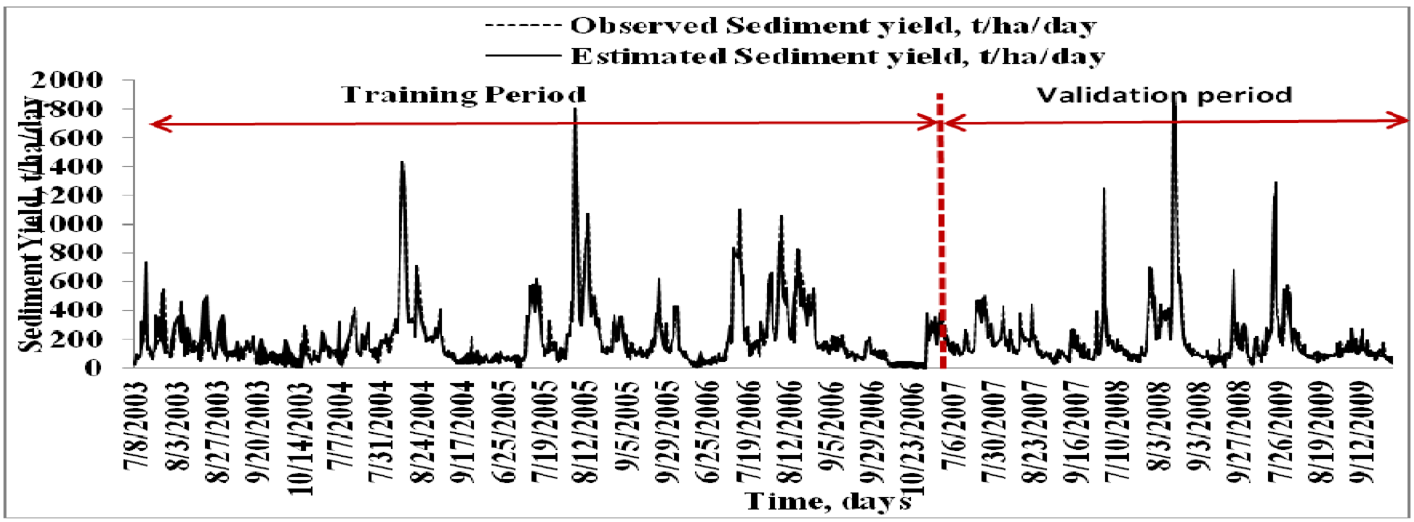


Figure- 6(d)

Comparison of observed and estimated Sediment yield for M 4 (2 2 10 1) during training and validation period

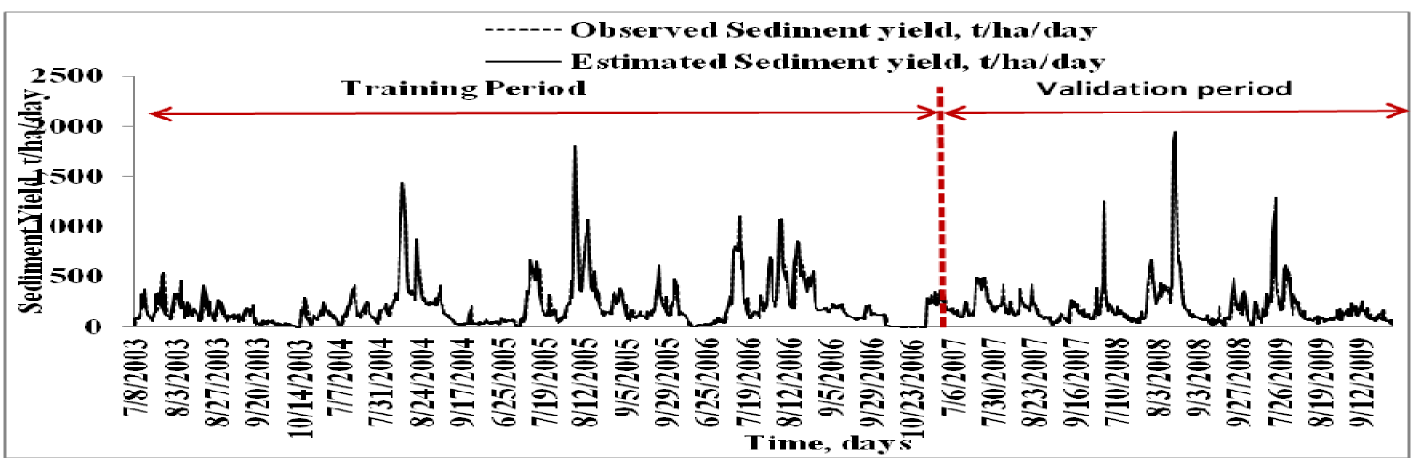


Figure-6(e)

Comparison of observed and estimated Sediment yield for M5 (2 2 10 1) during training and validation period

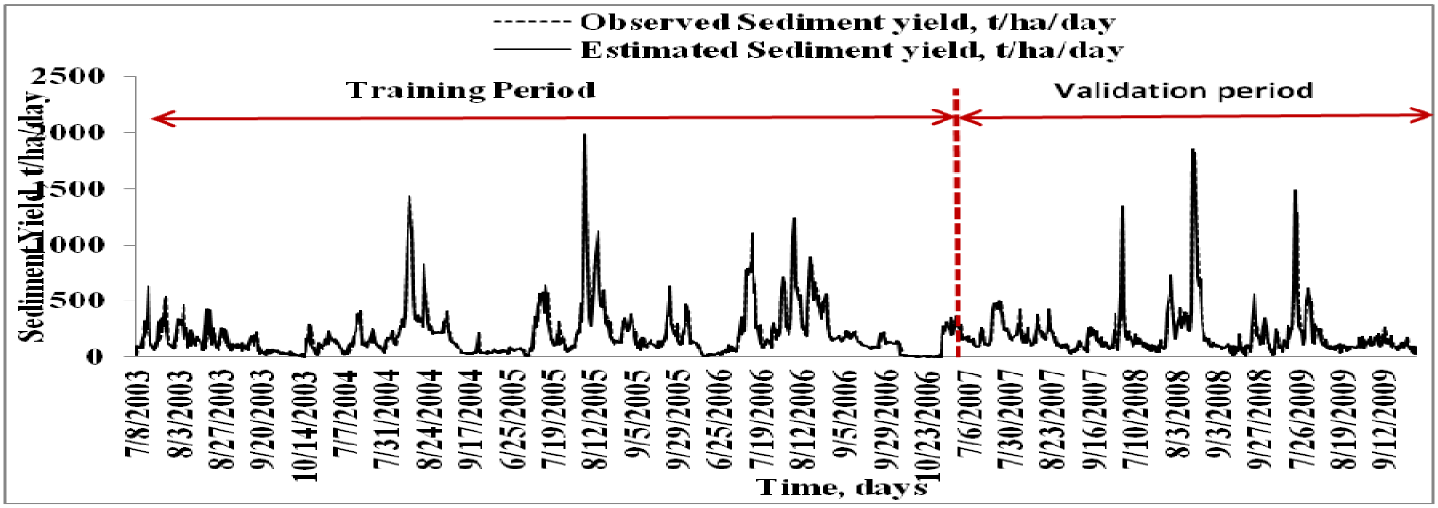


Figure- 6(f)
Comparison of observed and estimated Sediment yield for M6 (3 2 10 1) during training and validation period

Table-1
Input parameters and identified ANN Structure of different model for Sediment modelling of Kal river

Model No	Models input parameters	No. of input parameters	No of Hidden layers	No of neurons in the hidden layer	Output layer	Model structure
M1	St = Qt	1	1	10	1	1 1 10 1
M 2	St =Qt, Qt-1	2	1	10	1	1 1 10 1
M 3	St = Qt, Qt-1, Qt-2	3	1	15	1	3 1 15 1
M 4	St = Qt, Pt	2	1	10	1	2 1 10 1
M 5	St =Qt, St-1	2	1	10	1	2 1 10 1
M 6	St Qt, St-1, St-2	3	1	10	1	3 1 10 1

Table-2
Statistical Performance of developed ANN models of Kal river for sediment yield forecasting

Model No.	Training Period (1992-2004)						Validation Period (2005-2011)					
	R	RMSE	CE	EV	MAD	MAPE	R	RMSE	CE	VE	MAD	MAPE
M1	0.92	91.58	84.16	2.28	-4.52	98.07	0.87	110.35	76.85	0.10	15.62	20.91
M2	0.93	86.02	86.12	6.54	-12.95	201.41	0.92	85.78	85.22	0.17	3.11	35.20
M3	0.93	87.09	85.77	4.39	-8.70	206.97	0.92	89.81	84.53	0.12	13.42	25.48
M4	0.93	84.98	86.46	1.53	-3.04	159.58	0.93	81.87	87.15	1.97	7.45	23.02
M5	0.95	67.13	91.55	1.46	-2.90	28.05	0.93	84.48	86.31	0.12	0.080	23.67
M6	0.96	67.49	91.46	3.62	-7.16	39.17	0.93	83.59	86.60	0.14	3.12	28.61

Table-3
Regression model for estimated and observed ANN model for sediment yield prediction

Models	During training Period (2003 to 2007)		During cross validation period (20008-2009)	
	Regressive Model	R^2	Regressive Model	R^2
M1	S_{tp} = 0.8608St + 40.087	84.21	S_{tp} = 0.722 St + 41.47	76.60
M2	S_{tp} = 0.8603St + 40.723	86.2	S_{tp} = 0.8621 St + 27.37	85.2
M3	S_{tp} = 0.842 St + 40.09	85.70	S_{tp} = 0.8647 St + 35.647	85.56
M4	S_{tp} = 0.8261St + 36.77	86.90	S_{tp} = 8874St + 15.805	86.71
M5	S_{tp} = 0.9321St + 16.36	91.46	S_{tp} = 0.9089 St + 19.76	85.92
M6	S_{tp} = 0.9571St + 15.719	91.6	S_{tp} = 0.9571 St + 15.719	91.6

Conclusions

The present study was conducted to developed multilayer feed forward artificial neural network for prediction of sediment yield using stream flow, rainfall and sediment yield lag by one or two day as inputs. The six modelled identified with bets combination of inputs and number of neurons in hidden layers using Metlab 2.9b software and data were analysed. The performance of the developed models for prediction of sediment yield found very satisfactory on the basis of statistical indices. The model R values ranges in between 0.92 to 0.96 during training period whereas during cross validation 0.87 to 0.93. The model M5 and M6 are found highest R values compared to other adopted ANN structures. Other statistically parameters also found in the satisfactory ranges. The regressive model also developed to check and compare the performance of ANN model which show the ANN model performance very better compared to the regressive models. Hence, overall the ANN model found better for prediction of sediment yield form stream flow for Kal river.

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