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Estimation of sediment load using ANN, ANFIS, MLR and SRC Models in Vamsadhara River Basin, India

SHREYA NIVESH AND PRAVENDRA KUMAR

Department of Soil and Water Conservation Engineering, College of Technology, G. B. Pant University of Agriculture and Technology, Pantnagar (U. S. Nagar), Uttarakhand India – 263145

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ABSTRACT

One of the nature`s greatest gifts to man is land, covered by a layer of top soil extending from few centimetres to few meters. It takes hundreds to thousands of years to develop a 5 cm layer of fertile soil where as it can be washed away in a single rainstorm event. Soil erosion by rainfall and runoff is the most serious form of land degradation resulting in loss of crop productivity by 0.2-10.9 q/ha (66% total production loss) for cereals, 0.1-6.3 q/ha for oilseeds (21% total production loss) and 0.04-4.4 q/ha for pulses (13% total production loss) estimated across states, which has a direct bearing on food security of the country. One viable approach to this challenge is the use of suitable hydrological models for efficient management of watersheds and ecosystems. The present study deals with the suspended sediment estimation for the Vamsadhara river catchment comprising of 7820 km^2 area, situated between Mahanadi and Godavari river basins in south India. Considering the active monsoon period, 70% data were used for model development and remaining 30% data were used for validation. Three daily input data groups or cases were employed using Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference System (ANFIS), Multiple Linear Regression (MLR) and Sediment Rating Curve (SRC) to find the effect of different inputs on the suspended sediment concentration in MATLAB (R2009a) for identification of most efficient model type. Three different types of performance indicators viz. root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency (CE) were used to evaluate the accuracy of various models. Based on the performance analysis a SRC model, three MLR models, three ANN models out of eighteen (six for each case) and three ANFIS models out of thirty-six (twelve for each case) were selected for comparison. Comparison results indicated that Neuro-Fuzzy model (RMSE-44.02 kg/sec, r-0.995 and CE value 99.06%) is superior to SRC, ANN and MLR models for simulating daily sediment concentration in Vamsadhara river basin India. Results also, revealed that the Neuro-Fuzzy models are in good agreement with the observed values and present better performance in comparison to the statistical models.

Key Words: Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System, Multiple Linear Regression, Sediment Rating Curve

INTRODUCTION

Conservation of land and water resources is among the most important issues related to the watershed management. Spatially and temporally unbalanced distribution of water, along with rapid population growth and negative impacts of human activities on the quality of water resources, has created significant problems in hydrological management in recent decades (Akhbari and Grigg 2013). Soil erosion by rainfall and runoff is a major threat to productivity of agriculture. Soil erosion is associated with adverse environmental impacts and crop productivity loss that makes its understanding important in assessing food security and environmental safety (Matson *et al.,* 1997). Hence this necessitates the simulation of processes like runoff and transport of sediment from watersheds through hydrological modelling (Pandey *et al.* 2008). A number of linear and non-linear models have been developed since 1930's to simulate and forecast various hydrological processes and variables (Verstraeten and Poesen, 2001). The sediment-rating curve is a relationship between the discharge of river and sediment load. Practically a rating curve can be constructed by log transforming the data and using a linear least squares regression to determine the best-fit line. Multiple linear regression (MLR) is a statistics based technique that uses several independent variables to predict the outcome of a dependent variable. MLR takes a group of variables selected randomly and tries to find a linear relationship among them. In recent years, regression models have been successfully employed in modelling a wide range of hydrologic processes like soil temperature (Bilgili, 2010; Marofi *et al.*, 2011); flood flows

Corresponding author e-mail: shreyanivesh@gmail.com

(Eslamian *et al.*, 2010); and sediment prediction. Soft computing techniques such as artificial neural networks and adaptive neuro-fuzzy inference system and fuzzy logic are becoming a strong tool for providing environmental, irrigation and drainage, soil and water conservation, and civil engineers with sufficient details for design purposes and management works. Specific applications of Soft computing techniques such as ANNs, ANFIS and fuzzy logic including time series prediction of runoff or discharge (Chakravati *et al.,* 2015; Noori and Kalin*,* 2016), water table management (Yang *et al.,* 1998), estimation of runoff hydrograph parameters (Ahmad and simonovic, 2005), water quality management (Wen and Lee, 1998), estimating water quality parameters (Zhang and Stanley, 1997; Melesse *et al.,* 2008), sediment prediction (Shabani *et al.,* 2012; Olyaie, 2015; Buyukyildiz and Kumcu, 2017); real-time flood forecasting and rainfall-runoff modelling (Giustolisi and Lauucelli, 2005; Nayak *et al.*, 2004, 2005 and 2005); stage–discharge relationship modelling (Lohani *et al.*, 2006; Kisi and Cobaner, 2009); streamflow prediction (Cigizoglu, 2003; Jayawardne *et al.*, 2006); reservoir inflow forecasting (Bae *et al.*, 2007); river flow modelling (Zounemat-Kermani and Teshnehlab, 2008); estimation of suspended sediment and scour depth near pile groups (Ardiclioglu *et al.,* 2007; Sadeghi *et al.,* 2013); fuzzy rule base approach for developing soil a protection index map: a case study in the upper awash basin, Ethopian highlands (Oinam *et al.,* 2014); Fuzzy intelligence system for land consolidation-a case study for Shunde, China (Wang *et al.,* 2015) and a new approach for modelling suspended sediment using evolutionary fuzzy approach (Kisi, 2016); Suspended sediment transport dynamics in rivers : Multi-scale driver of temporal variation (Vercruysse *et al.,* 2017). Keeping the above views in mind, present study has been undertaken to develop artificial neural network (ANNs), adaptive neuro-fuzzy inference system (ANFIS), multiple linear regression (MLR) and sediment rating curve (SRC) models on daily basis for Vamsadhara river catchment. For establishing the compatibility and applicability of soft computing models, their performance was compared with the sediment models developed by using statistical techniques.

MATERIALS AND METHODS

Study Area

The present study was undertaken in Vamsadhara river basin comprising of 7820 km^2, situated within the geographical coordinates of 18˚15’ to 19˚55’ N latitudes and 83˚20’ to 84˚ 20’ E longitudes in between Mahanadi and Godavari river basins falls in the state of Orissa and the remaining 26% in Andhra Pradesh. Hydrological data were collected by India Meteorological Department (IMD) and Central Water Commission (CWC), Godavari Mahanadi Circle Division, South Eastern Region, Bhubaneswar, Orissa at six sites: Kutraguda, Mohana, Gudari, Mohandragarh, Gunpur, and Kashinagar. The measurements include rainfall in the units of millimetres, discharge in the units of m^3/sec and sediment concentration in the units of kg/m^3. The location of the study area is shown in Fig. 1.

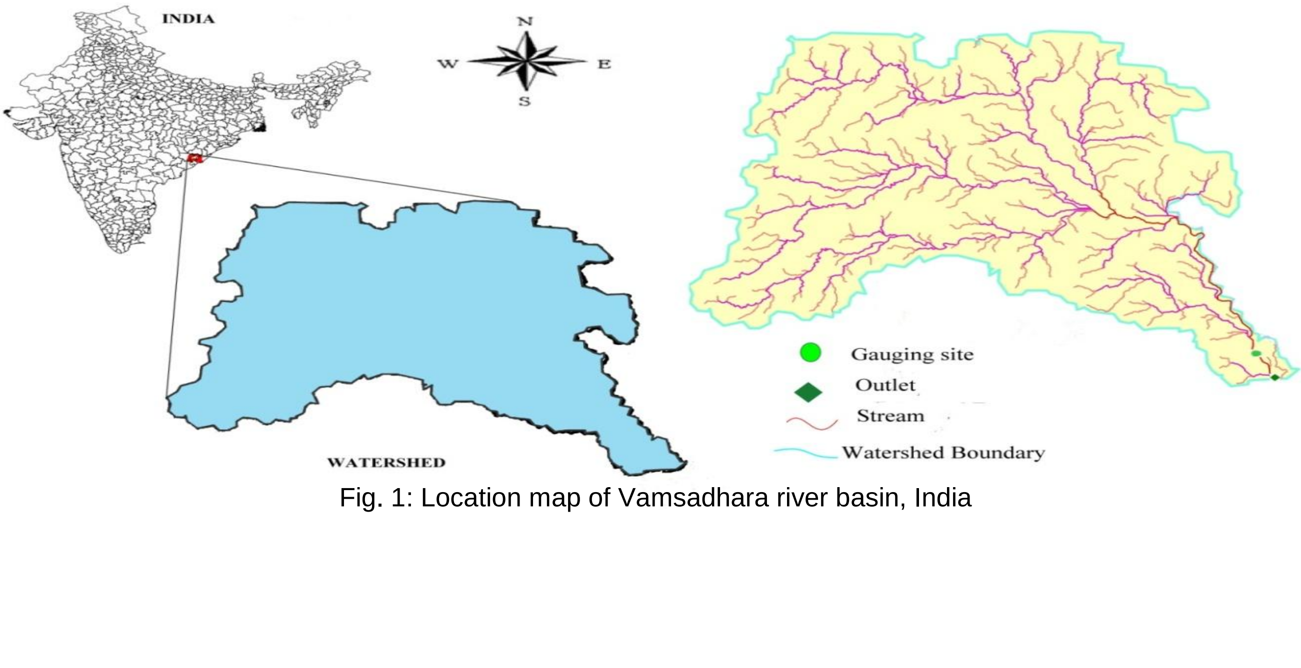

Fig. 1: Location map of Vamsadhara river basin, India

Artificial Neural Network

A neural network is a technique that establishes the relationship between a set of inputs and desired output without giving any information about the actual processes involved. Neural networks have a natural tendency for storing experiential knowledge and making it available for utilization. Artificial neural network (ANN) is a type of Artificial Intelligence technique that mimics the behaviour of the human brain. Neural networks do not need an algorithm to perform various tasks. These networks are well suitable for real time systems because of their fast response and computational times. Fundamental to the operation of a neural network is an information-processing unit i.e. called a neuron. Combinations of synapses or connecting links are defined by its weight or strength. A signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}. In artificial neural network an adder is used for adding the input signals, weighted by the different synapses of the neuron it is a linear combiner. An activation function for limiting the amplitude of the output of a neuron also called squashing function which squashes (limits) the permissible amplitude range of the output signal to some finite value. Typically, the amplitude range of the output of a neuron is normalized and is taken to be in the interval 0 to 1 or alternatively –1 to +1. The activation function adopted in this study is log-sigmoid (range 0 to 1). An external bias, denoted by b_k, has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively. In mathematical form, a neuron k may be described by the equations:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j$$

$$y_k = \varphi(u_k + b_k)$$

where x_1, x_2, x_3………..x_m are the input signals; w_{k1}, w_{k2},…….,w_{km} are the synaptic weights of neuron k; u_k is the linear combiner output due to the input signal; b_k is the bias; φ(.) is the activation function; and y_k is the output signal of the neuron k. Here

$$v_k = \varphi(u_k + b_k)$$

where, v_k is called the induced local field or activation potential. Above three equations can also be combined as follows:

$$v_k = \sum_{j=0}^{m} w_{kj} x_j$$

and $y_x = \varphi(v_k)$

In above equation, a new synapse with input x_0 = +1 is added having weight $w_{k0} = b_k$.

The propagation law of a neural system describes the way by which net input of a neuron is calculated from several outputs of neighbouring neurons. The most commonly used algorithm for multi-layer feed forward artificial neural network is back-propagation algorithm and has been adopted in this study. The back propagation computation is derived using chain rule of calculus. It involves adjustment of weight to minimize error i.e. performance by calculating gradients of the error function.

Adaptive Neuro-Fuzzy Inference System

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. It integrates both neural networks and fuzzy logic principles. It has potential to capture the benefits of both techniques in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have capability to learn to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. The architecture of adaptive neuro-fuzzy inference system (ANFIS) shown in Fig. 2 consists of a five layers feed forward neural network. Description of each layer is given as follows:

Layer 1: Fuzzification Layer:

Each node in this layer produces membership grades of an input variable. The output of the i^{th} node in layer I is denoted as O_i^1. Assuming a generalized bell function as the membership function, the output O_i^1 can be computed as:

$$O_i^1 = \mu_{A_i}(x) = \frac{1}{1 + ((x - c_i)/a_i)^{2b_i}}$$

where {a_i, b_i, c_i} are adaptable variables known as premise parameters.

Layer 2: Rule Layer:

Every node in this layer multiplies with the incoming signals:

$$O_i^2 = w_i = \mu_{Ai}(x)$$

$\mu_{Bi}(y)$, i =1, 2

Layer 3: Normalization Layer:
The i[th] node of this layer calculates the normalized firing strengths as

$$O_i^3 = \overline{w}_i = \frac{w_1}{w_1 + w_2}$$

i=1, 2

Layer 4: Defuzzification Layer:
Node i in this layer calculate the contribution of the i[th] rule towards the model output, with the following node function:

$$O_i^4 = \overline{w_i}\, f_i = \overline{w_i}\,(p_i x + q_i y + r_i)$$

where $\overline{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: Single Summation Neuron:
The single node in this layer calculates the overall output of the ANFIS as reported by Jang and Sun, 1993

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum_i w_i}$$

Multiple Linear Regression

Regression analysis is used when two or more variables are thought to be well connected by a linear relationship systematically. MLR applies to problems in which records have been kept of one variable, *y*, the dependent variable, and several other variables $x_1,..., x_k$, the independent variables, and in which the objective requires the relationship between the variable *y* and the variables $x_1, ..., x_k$ to be investigated. In the present study the multiple linear regressions analysis was performed on the same data set to estimate sediment concentration and the regression equation used is defined as

$$S_t = a + bP_t + cq_t + dq_{t-1} + es_{t-1}$$

where a, b, c, d and e are constants and P_t, Q_t, Q_{t-1}, and S_{t-1} are the variables.

Sediment Rating Curve

The sediment rating curve is a relationship between the river discharge and suspended sediment load. Such curves are widely used to estimate the sediment load being transported by river. In this study sediment rating curve was developed for Vamsadhara River basin using daily data of stream flow and suspended sediment concentration. The relationship between the sediment concentration S or load and discharge Q is of the following form

$$S_t = aQ_t^b$$

Where, a and b are regression constants, Q_t is discharge and S_t is suspended sediment load at time t.

Model development

For the present study MATLAB (R 2009a) software was used to model suspended sediment load. Four years daily data of rainfall, stream flow and sediment concentration of monsoon season from June 1, 1997 to October 31, 2000 was used. 70% data (248 data sets) were used for calibration and 30% data (184 data sets) were used for validation. Three daily input data groups or cases were employed in this study. Input 1 consists of P_t, Q_t, Q_{t-1}, and S_{t-1} as inputs to the model to predict S_t. Input 2 consist of P_{t-1}, Q_t, Q_{t-1}, and S_{t-1}. Input 3 consist of P_{t-1}, Q_t, Q_{t-2}, and S_{t-1}. The details of different ANN, ANFIS and MLR models are shown in Table 1 and 2 respectively. Six ANN structures were tried for each model using Levenberg-Marquardt as a training function with sigmoid as an activation function and subjected to maximum 1000 iterations, were trained with the help of back propagation learning algorithm. The highest value of respective variable in series was considered for normalisation of input and output variables. The architecture of ANFIS networks was developed using triangular, trapezoidal, Gaussian and generalized bell membership functions with number of membership functions per input varying from 3 to 5. Fuzzy model used was Takagi-Sugeno-Kang type with maximum epochs 1000 considering back propagation learning algorithm, was applied to identify the network which trains the model more efficiently.

Model performance

Three statistical measures were used to examine the goodness to fit of the ANN, ANFIS, MLR and SRC models to the testing data**.** These measures include the root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency (CE).

1. Root mean square error (RMSE)
   It yields the residual error in terms of the mean square error expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_{o,i} - S_{e,i})^2}{N}}$$

2. Correlation coefficient (r)
   It is a measure of how well the estimated values from an estimated model fit with the real-life data. It is expressed as:

$$r = \frac{\sum_{i}^{N}((S_{o,i} - \overline{S}_{o,i})(S_{e,i} - \overline{S}_{e,i}))}{\sqrt{\sum_{i}^{N}(S_{o,i} - \overline{S}_{o,i})^2 \sum_{i}^{N}(S_{e,i} - \overline{S}_{e,i})^2}}$$

3. Coefficient of efficiency (CE)
   The Nash–Sutcliffe model efficiency coefficient is used to assess the predictive power of hydrological models and is expressed as:

$$CE = \left\{1 - \frac{\sum_{i}^{N}(S_{o,i} - S_{e,i})^2}{\sum_{i}^{N}(S_{o,i} - \overline{S}_{o,i})^2}\right\} * 100$$

where, $S_{o,i}$ and $S_{e,i}$ are the observed and estimated suspended sediment concentration; $\overline{S}_{e,i}$ and $\overline{S}_{o,i}$ are the average observed and estimated suspended sediment concentration respectively for the i^{th} data set and N is the total number of observations.

RESULTS AND DISCUSSION

Various graphical and statistical indicators were used to evaluate the performance of the sediment ANN, ANFIS, MLR and SRC models. Based on different performance evaluation criteria, a SRC model, three MLR models, three ANN models out of eighteen (six for each case), three ANFIS models out of thirty six (twelve for each case) were selected among the different types of models for comparison. Various statistical performance evaluation indicators of the models are given in the Tables 3.

Table 1: Details of various ANN and ANFIS models

Model Type	Output	Input-Variables
ANN-Case-I, ANFIS-Case-I	S_t	P_t , Q_t , Q_{t-1}, S_{t-1}
ANN-Case-II, ANFIS-Case-II	S_t	P_{t-1} , Q_t , Q_{t-1}, S_{t-1}
ANN-Case-III, ANFIS-Case-III	S_t	P_{t-1} , Q_t , Q_{t-2}, S_{t-1}

The artificial neural network (ANN) based sediment concentration models on daily basis using sigmoid as an activation function were developed considering the normalization of the data with maximum value of input variables and generalization of the model for maximum 1000 iterations. A number of structures were tried to obtain the best generalization. Finally a three layered structure obtained as the best generalized model. For the selected ANN models the root mean square error (RMSE) varied from 110.15 kg/sec to 135.38 kg/sec. The correlation coefficient (r) varied from 0.957 to 0.971 while, the coefficient of efficiency (CE) varied from 91.13% to 94.13%. However, the best results were shown by ANN-2 model with RMSE, r and CE values 110.15 kg/sec, 0.971 and 94.13% respectively.

Table 2: Details of various MLR models

Model	Input-output Variables
MLR-1	$S_t = a_1+b_1P_t+c_1Q_t+d_1Q_{t-1}+e_1 S_{t-1}$
MLR-2	$S_t = a_2+b_2P_{t-1}+c_2Q_t+d_2Q_{t-1}+e_2S_{t-1}$
MLR-3	$S_t = a_3+b_3P_{t-1}+c_3Q_t+d_3Q_{t-2}+e_3S_{t-1}$

Different combinations of rainfall, runoff and sediment load were considered as the inputs for ANFIS models and sediment of the concurrent day as the output. Back-propagation algorithm was used to train the models for the prediction of suspended sediment concentration. The optimal learning parameters were tried using triangular, trapezoidal, Gaussian and generalized-bell membership functions with number of membership functions per input varying from 3 to 5. The best model was selected based on performance indices. For the selected ANFIS models the RMSE varied from 44.02 kg/sec to 69.69 kg/sec. The correlation coefficient (r) varied from 0.988 to 0.995 whereas, the coefficient of efficiency (CE) varied from 97.65% to 99.06%.

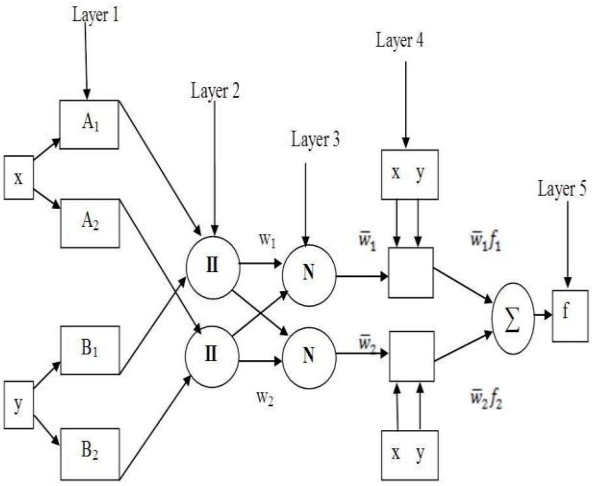

Fig. 2 Structure of Adaptive Neuro-Fuzzy Inference System

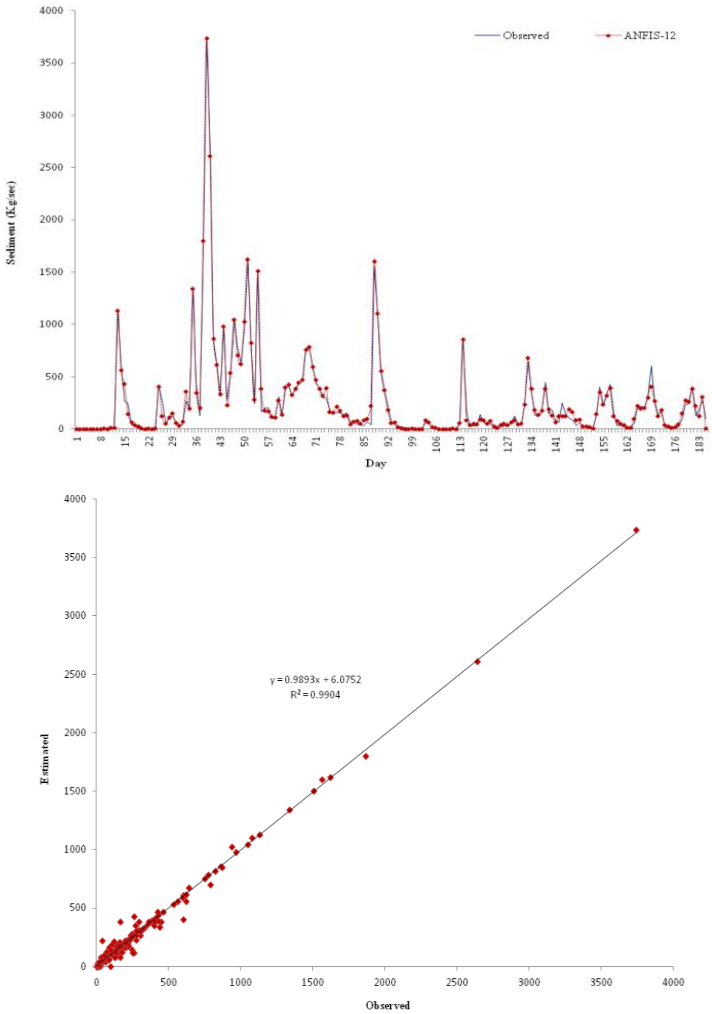

Fig. 3 Series and scatter plots of ANFIS-12 model for testing period

Various graphical and statistical indicators were used to evaluate the performance of the sediment yield regression models as shown in Table 3. It has been found that for the selected MLR models the RMSE varied from 188.28 kg/sec to 211.02 kg/sec. The correlation coefficient (r) varied from 0.88 to 0.91 whereas, the coefficient of efficiency (CE) varied from 78.44% to 82.82%.

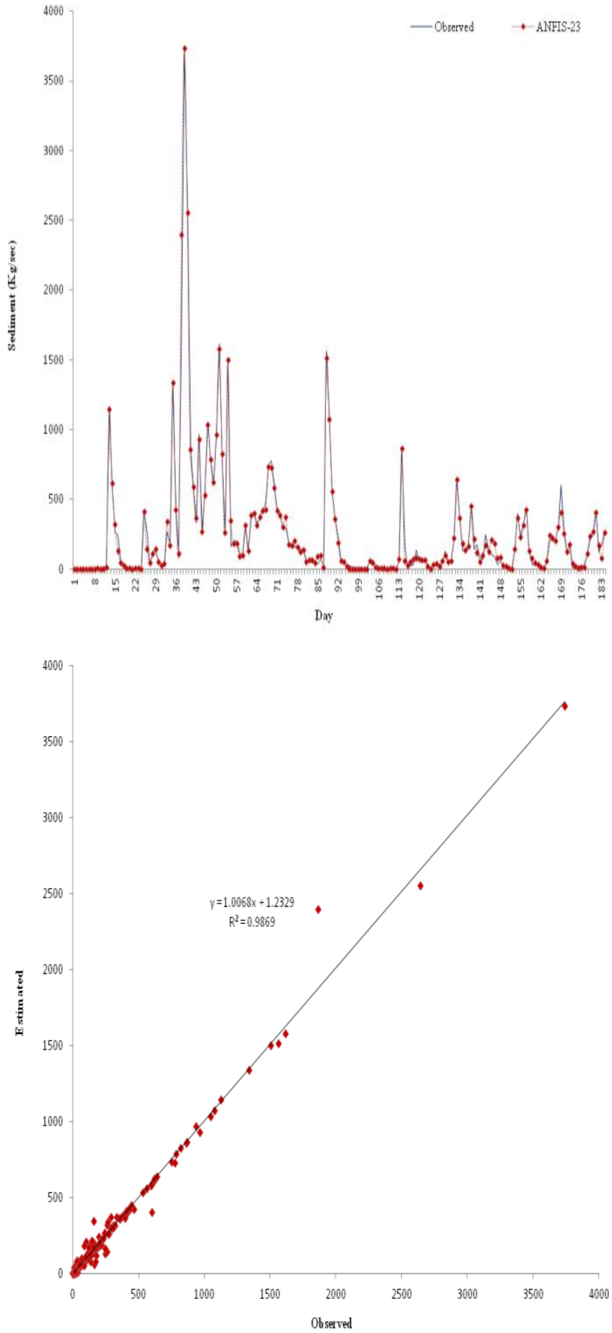

Fig. 4 Series and scatter plots of ANFIS-23 model for testing period

Table 3: Performance indicators of various ANN, ANFIS, MLR and SRC models

Model	Input	RMSE	r	CE (%)	Network
ANN-2	P_t , Q_t , Q_{t-1}, S_{t-1}	110.15	0.971	94.13	4-6-1
ANN-11	P_{t-1} , Q_t , Q_{t-1}, S_{t-1}	118.72	0.967	93.18	4-12-1
ANN-17	P_{t-1} , Q_t , Q_{t-2}, S_{t-1}	135.38	0.957	91.13	4-12-1
ANFIS-12	P_t , Q_t , Q_{t-1}, S_{t-1}	44.02	0.995	99.06	gbellmf-5
ANFIS-23	P_{t-1} , Q_t , Q_{t-1}, S_{t-1}	52.99	0.993	98.64	gbellmf-4
ANFIS-36	P_{t-1} , Q_t , Q_{t-2}, S_{t-1}	69.69	0.988	97.65	gbellmf-5
MLR-1	P_t , Q_t , Q_{t-1}, S_{t-1}	188.28	0.910	82.82	-
MLR-2	P_{t-1} , Q_t , Q_{t-1}, S_{t-1}	194.65	0.904	81.64	-
MLR-3	P_{t-1} , Q_t , Q_{t-2}, S_{t-1}	211.02	0.880	78.44	-
SRC	Q_t	331.69	0.786	56.48	-

As revealed from the Table 3 the values of performance evaluation indices viz. RMSE, r and CE for sediment rating curve model which takes concurrent runoff as input does not produce satisfactory results. The values of performance evaluation indices viz. root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency (CE) using sediment rating curve model during testing period were found to be 331.69 kg/m^3, 0.786 and 56.48% respectively. It can be seen from the Table-3 the ANFIS-12 model with network gbellmf-5 which takes concurrent rainfall, runoff; antecedent runoff and sediment load with time step t-1 is superior to the other models in terms of all indicators. The RMSE, r and CE values are 44.02 kg/sec, 0.995 and 99.06 % respectively. In the models ANFIS-23 and ANFIS-36 with network gbellmf-4 and gbellmf-5 respectively, where concurrent runoff; antecedent rainfall, runoff and sediment load were considered as input the r and CE values are almost equal or slightly less than ANFIS-12, but in terms of RMSE these model are inferior. The graphical representation along with corresponding scattered plots for the models ANFIS-12, ANFIS-23 and ANFIS-36 are shown in figures 3 to 5.

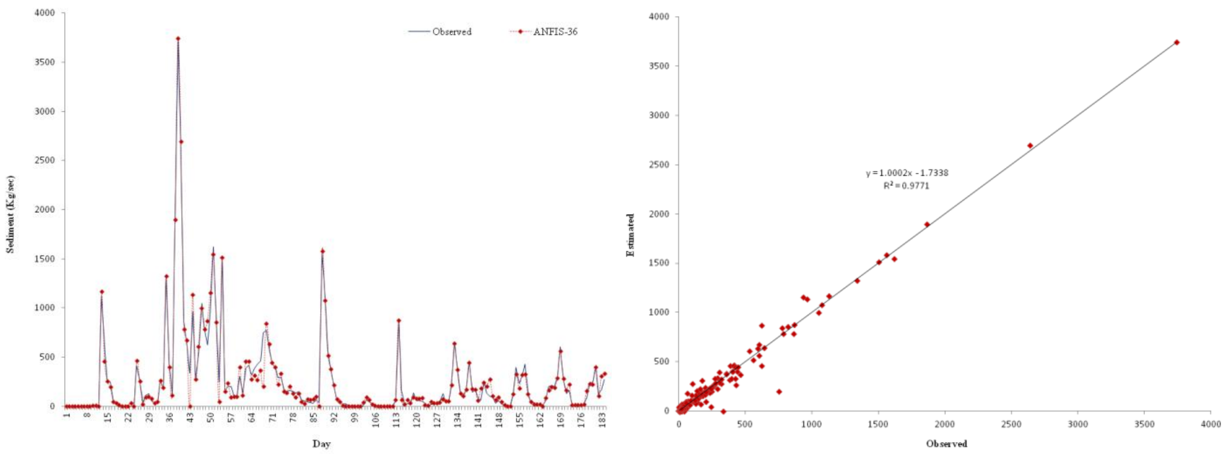

Fig. 5 Series and scatter plots of ANFIS-36 model for testing period

Based on the above discussion it can be concluded that ANFIS models with input variables as P_t, P_{t-1}, Q_t, Q_{t-1}, Q_{t-2} and S_{t-1} and membership function generalized bell (gbellmf) with number of membership functions per input 4 and 5 can best simulate the sediment load in Vamsadhara River basin. It can also be concluded that statistical or traditional models are not capable of simulating complex and non-linear sediment yield processes whereas the performance of the soft computing models is quite satisfactory in this regard.

Conclusions

In the present study, ANN, ANFIS, MLR and SRC models were developed for simulation of suspended sediment load in Vamsadhara River basin. Based on the performance evaluation indices the following conclusions were drawn from this study.

1. The ANFIS-12, ANFIS-23 and ANFIS-36 outperformed the ANN, MLR and SRC models for estimating suspended sediment load for the study area.
2. The ANFIS model with membership function generalized-bell and inputs as concurrent rainfall and runoff, antecedent runoff and sediment load was found to be the best among the selected models for predicting suspended sediment load for the Vamsadhara River basin.
3. Performance of the ANN models is satisfactory.
4. The SRC model fits very poorly for the data set under study.
5. It can be concluded that Neuro-Fuzzy models are superior to ANN, MLR and SRC models in predicting suspended sediment load in all respects.

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