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Assessment of soft computing and statistical approaches for suspended sediment load estimation: Vamsadhara river basin, India

Shreya Nivesh, Pravendra Kumar, Bhagwat Saran, Pragati N Sawant and Ramesh Verma

Abstract
The present study was undertaken to estimate the suspended sediment load from the Vamsadhara river basin comprising of 7820 km^2 area, situated between Mahanadi and Godavari river basins. Three daily input data groups or cases were employed using Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Logic (FL), Multiple Linear Regression (MLR) and Sediment Rating Curve (SRC) to find the effect of different inputs on the suspended sediment load. Input 1 consists of P_t, Q_t, Q_{t-1}, S_{t-1} as inputs to the model to predict S_t. Input 2 consists of P_{t-1}, Q_t, Q_{t-1}, S_{t-1} and Input 3 consist of P_{t-1}, Q_t, Q_{t-2}, S_{t-1}. The developed models were trained and tested. Three statistical parameters: root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency (CE) were used to compare the results of the models. Based on the performance analysis results revealed that the ANFIS model (RMSE-44.02 kg/sec, r-0.995 and CE-99.06%) outperformed other soft computing and conventional models. It can be concluded that the ANFIS models are more preferable and can be applied successfully for the estimation of the suspended sediment concentration for the study area.

Keywords: Artificial neural network, adaptive neuro-fuzzy inference system, fuzzy logic, multiple linear regression, sediment rating curve.

1. Introduction

The accelerated erosion and the sediment outflow from agricultural lands is a serious global problem. Mankind will be facing great challenges in the next few decades. The sediment yield for the basins in Asia is over twice the world`s average yield of 600 t/km^2/year which is four times larger than South America (Gregory and Walling, 1973) [16]. However, in India soil erosion is taking place at an alarming rate of 1635 t/km^2/year (ICAR and NAAS, 2010), which is not only detrimental to current agriculture production but is a serious threat to survival of mankind. Out of the total degraded area of 1965 Mha, over 300 Mha of land constituting about 57% of the total geographical area suffers from deleterious effects of soil erosion and other forms of degradation (Sehgal and Abrol, 1994) [43]. Active erosion caused by water and wind alone accounts for 150 Mha of land, whereas 25Mha has been degraded due to ravines/gullies, shifting cultivation, salinity/alkalinity and water logging (Reddy, 1999; Meiaraj and Sundararajan, 2007) [40, 31]. Surface runoff one of the main causes for soil erosion, leads to sedimentation of reservoirs, loss of plant nutrients, and deterioration of river water quality (Verma *et al.*, 2010; Balasaheb *et al.*, 2016) [51, 4]. The world population reached 7 billion in 2012 and is expected to exceed 9 billion by 2050 (FAO, 2015) [13]. A global demand for food will increase with expected population (Ray *et al.*, 2013) [39]. Hence this necessitates the simulation of processes like runoff and transport of sediment from watersheds through hydrological modeling (Pandey *et al.*, 2008) [38]. A number of linear and non-linear models have been developed since 1930's to simulate and forecast various hydrological processes and variables (Yang, 1996; Verstraeten and Poesen, 2001) [57, 52]. Hydrologic simulation models are rapidly being improved with increased advances in computer techniques that facilitate their capability to interface with emerging technologies to provide more powerful tools for operational applications. 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 modeling a wide range of hydrologic processes like soil temperature (Bilgili, 2010; Tabari *et al*., 2010; Marofi *et al*., 2011) [5, 46, 29]; flood flows (Hazra and Avishek, 2010; Engeland and Hisdal, 2009; Eslamian *et al*., 2010) [17, 11, 12]; and sediment prediction (Wang and Linker, 2008; Chang *et al*., 2008) [53, 6]. Soft computing techniques such as artificial neural networks and adaptive neuro-fuzzy inference system and fuzzy logic are becoming a strong tool for providing civil, soil & water conservation and environmental engineers with sufficient information for design purposes and management practices. Specific applications of Soft computing techniques such as ANNs, ANFIS and fuzzy logic including time series prediction of runoff or discharge (Jain, 2001) [20], water table management, estimation of runoff hydrograph parameters, water quality management, estimating water quality parameters, sediment prediction (Alp and Cigizoglu, 2007; Chang *et al.*, 2008; Dehgani, 2009; Melesse *et al.*, 2011; Shabani *et al.*, 2012; Olyaie, 2015) [2, 6, 32, 45, 37]; real-time flood forecasting and rainfall-runoff modelling (Zhu *et al.*, 1994; See and Openshaw, 2000; Stuber *et al.*, 2000; Hundencha *et al.*, 2001; Xiong *et al.*, 2001; Giustolisi and Lauucelli, 2005; Nayak *et al.*, 2004, 2005 and 2005) [60, 42, 44, 56, 15, 33-35]; stage–discharge relationship modelling (Lohani *et al.*, 2006; Kisi and Cobaner, 2009) [28, 23]; streamflow prediction (Kisi, 2004, 2007 and 2008; Chang and Chen, 2001; Chang *et al.*, 2001; Cigizoglu, 2003; Jayawardne *et al.*, 2006) [24-26, 8] ; reservoir inflow forecasting (Bae *et al.*, 2007) [3]; river flow modeling (Zounemat-Kermani and Teshnehlab, 2008) [61] ; estimation of suspended sediment and scour depth near pile groups (Tayfur, 2002; White, 2005; Cigizoglu and Kisi, 2006; Tayfur and Guldal, 2006; Ardiclioglu *et al.*, 2007; Sadeghi *et al.*, 2013; Oinam *et al.*, 2014; Wang *et al.*, 2015; Kisi, 2016; Vercruysse *et al.*, 2017) [48, 55, 9, 49, 1, 41, 36, 54, 27, 50]. Keeping the above views in mind, the present study has been undertaken for the development, validation, performance evaluation and comparison of the models using artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic (FL), multiple linear regression (MLR) and sediment rating curve (SRC) to estimate the daily suspended sediment concentration.

2. Materials and Methods
2.1 Study Area
The selected Vamsadhara River basin up to Kashinagar is located within the geographical coordinates of 18˚ 15’ to 19˚ 55’ N latitudes and 83˚ 20’ to 84˚ 20’ E longitudes between Mahanadi and Godavari River basins, Odisha. Hydrological data were collected from India Meteorological Department (IMD) and Central Water Commission (CWC), Godavari Mahanadi Circle Division, South Eastern Region, Bhubaneswar, Odisha at six sites: Kutraguda, Mohana, Gudari, Mohandragarh, Gunpur, and Kashinagar. The data include rainfall, discharge and sediment concentration. The map of the study area is shown in Fig. 1.

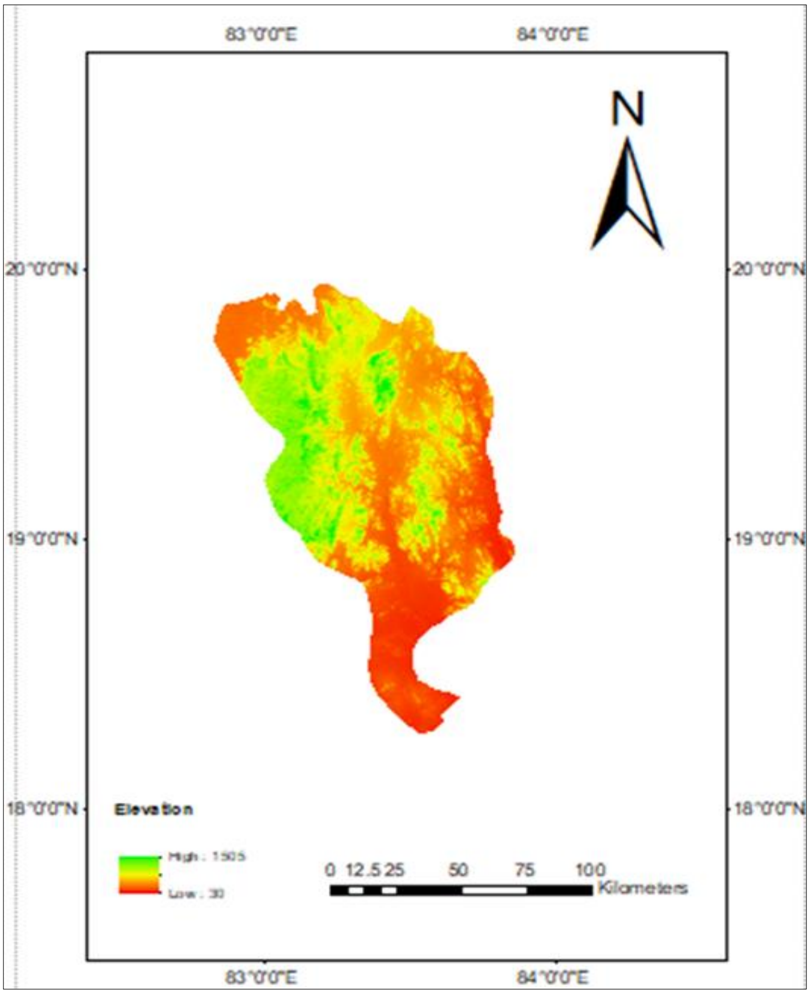


Fig 1: Map of Vamsadhara River Basin, India

2.2 Methodologies

Artificial Neural Network

Artificial neural networks are parallel information processing systems consisting of a set of neurons arranged in layers (McClelland and Rumelhart, 1988). The multilayer feed-forward perceptron (MLP) consists of an input layer and an output layer with Levenberg- Marquardt back propagation learning algorithm and is one of the popular ANN`s architectures as shown in Fig. 2. The neurons are connected by a weight in each layer to the neurons in subsequent layer during training. The sigmoid and linear activation functions were used in the hidden and the output layer, respectively (Ghorbani *et al.*, 2013) [14].

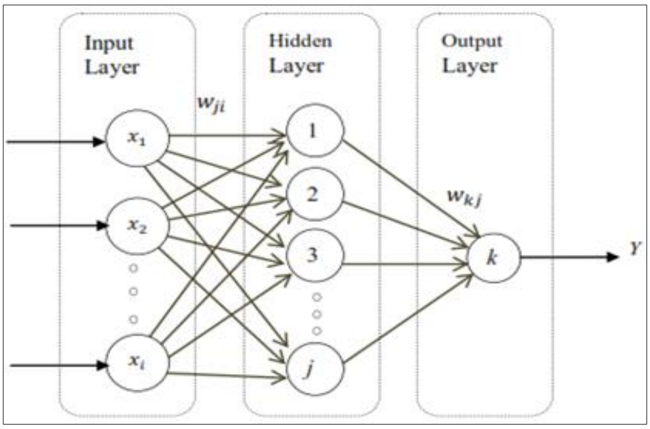


Fig 2: Single hidden layer feed-forward neural network

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 (Takagi and Sugeno, 1985) [47]. It has potential to capture the benefits of both techniques in a single framework (Yurdusev *et al.*, 2009) [58]. 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. Structure of ANFIS is shown in Fig. 3. The architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of 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 l is denoted as O^1_i.Assuming a generalized bell function as the membership function, the output O^1_i can be computed as:

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

Where μ_{A_i} the membership function and ai, bi and ci is are the adaptable variables known as premise parameters.

Layer 2: Rule Layer

Every node in this layer multiplies with the incoming signals, the outputs of this layer called firing strengths:

$$O_i^2 = w_i = \mu_{Ai}(x)\ \mu_{Bi}(y),\ i = 1, 2 \ \text{…. (2)}$$

Layer 3: Normalization Layer

The i^{th} node of this layer calculates the normalized firing strengths as

$$O_i^3 = \overline{w}_i = \frac{w_1}{w_1 + w_2} \quad i=1, 2 \text{ …. (3)}$$

Layer 4: Defuzzification Layer

Node i in this layer calculates the contribution of the i^{th} rule towards the model output, with the following node function:

$$O_i^4 = \overline{w_i f_i} = \overline{w_i}(p_i x + q_i y + r_i) \quad \text{…. (4)}$$

Where $\overline{w_i}$ is the output of layer 3 and p_i, q_i and r_i are 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, 1995

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum_i w_i} \quad \text{…. (5)}$$

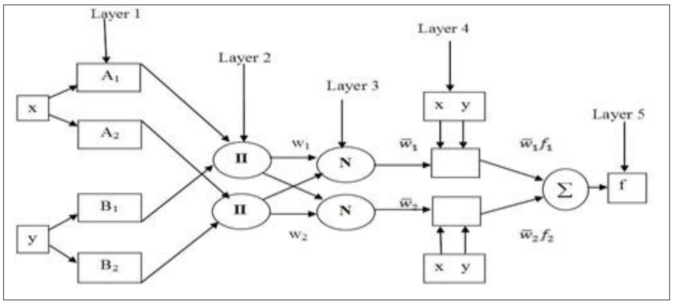


Fig. 3 Structure of Adaptive Neuro-Fuzzy

Fuzzy Logic

The idea of fuzzy logic was given by Zadeh (1965) [59], a computer scientist of the University of California at Berkeley. It is a convenient way to map an input space to an output space. Fuzzy logic provides a remarkably simple way to draw definite conclusion from vague, ambiguous or imprecise information. Fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions. Fuzzy Logic (FL) modeling refers to process whereby dynamical system is modeled not in the form of conventional differential and difference equations but in the form of set of fuzzy rules and corresponding membership function. Therefore, it is often called "fuzzy expert system.

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 the problems in which records have been kept of one variable S_t the dependent variable and several other variables P_t, Q_t, Q_{t-1} and S_{t-1} the independent variables, and in which the objective requires the relationship between the variable S_t and the variables P_t, Q_t, Q_{t-1} and S_{t-1} to be investigated. In the present study the multiple linear regression analysis was performed on the same data set to estimate sediment concentration and the regression equation used is defined as

$$S_t = a + bP_t + cQ_t + dQ_{t-1} + eS_{t-1} \ldots (6)$$

where a, b, c, d and e are constants and P_t, Q_t, Q_{t-1} and S_{t-1} are the variables; P_t, Q_t are the rainfall and discharge at time t; Q_{t-1} and S_{t-1} are the discharge and sediment at the time t-1.

Sediment Rating Curve

The sediment rating curve is a relationship between the river discharge and sediment load. Such curves are widely used to estimate the sediment load being transported by rivers. 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 or load S and discharge Q is of the following form

$$S_t = aQ_t^b \ldots (7)$$

Where a and b are regression constants, Q_t is discharge (m^3/sec) and S_t is sediment load (kg/sec) at time t.

2.3 Model Architecture

For the present study MATLAB (R2009a) 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 were used. 70% data (248 data sets) were used for training and 30% data (184 data sets) were used for testing. Three daily input data groups or cases were employed in this study. Input 1 consists of P_t, Q_t, Q_{t-1}, S_{t-1} as inputs to the model to predict S_t. Input 2 consist of P_{t-1}, Q_t, Q_{t-1}, S_{t-1}. Input 3 consist of P_{t-1}, Q_t, Q_{t-2}, S_{t-1}. The details of different ANN, ANFIS, FL and MLR models are shown in Tables 1 and 2. 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. The fuzzy logic based models were formulated to estimate the suspended sediment concentration from Vamsadhara river basin. Rainfall, stream flow and sediment concentration were fuzzified into fuzzy subsets in order to cover the whole range of changes during training period and were sub-divided into nine subsets as extremely low (EL), very low (VL), low (L), Quite low (QL) medium (M), Quite high (QH), high (H), very high (VH) and extremely high (EH) and were considered to have triangular membership functions. The most common `centroid` method of defuzzification was adopted.

Table 1: Details of various ANN, ANFIS and FL models

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

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	$S_t = a_3+b_3P_{t-1}+c_3Q_t+d_3Q_{t-2}+e_3S_{t-1}$

2.3 Model Performance

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_{o,i} - S_{e,i})^2}{N}} \quad \ldots (8)$$

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:

$$r = \frac{\sum_{i}^{N} ((S_{o,i} - \bar{S}_{o,i})(S_{e,i} - \bar{S}_{e,i}))}{\sqrt{\sum_{i}^{N} (S_{o,i} - \bar{S}_{o,i})^2 \sum_{i}^{N} (S_{e,i} - \bar{S}_{e,i})^2}} \quad \ldots (9)$$

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:

$$CE = \left\{ 1 - \frac{\sum_{i}^{N} (S_{o,i} - S_{e,i})^2}{\sum_{i}^{N} (S_{o,i} - \bar{S}_{o,i})^2} \right\} * 100 \quad \ldots (10)$$

Where, $S_{o,i}$ and $S_{e,i}$ are the observed and estimated suspended sediment concentration;

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

3. Results and Discussion

Different types of graphical and statistical indicators were used to evaluate the performance of the developed ANN, ANFIS, FL, MLR and SRC models. Based on 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) and three FL models were selected for comparison. Various performance evaluation indices of the models are given in the Tables 3 and 4.

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

Model	RMSE	r	CE (%)
ANN-2	110.15	0.971	94.13
ANN-11	118.72	0.967	93.18
ANN-17	135.38	0.957	91.13
ANFIS-12	44.02	0.995	99.06
ANFIS-23	52.99	0.993	98.64
ANFIS-36	69.69	0.988	97.65
FL-1	138.64	0.970	92.45
FL-2	145.09	0.965	91.38
FL-3	169.65	0.959	88.69
MLR-1	188.28	0.910	82.82
MLR-2	194.65	0.904	81.64
MLR-3	211.02	0.880	78.44
SRC	331.69	0.786	56.48

ANN sediment model

The artificial neural network (ANN) based sediment models were developed on daily basis using sigmoid as an activation function considering the normalization of the data with maximum value of input variables. A number of structures were tried to obtain the best generalization. Finally, a three layered structure obtained as the best generalized model. The performance evaluation indices of the ANN models for the testing data sets are represented in Table 3. The results show that the model ANN-2 performs better than ANN-11 and ANN-17 respectively. For the model ANN-2 RMSE=110.15 kg/sec, r=0.971 and CE=94.13%; for the model ANN-11 RMSE=118.72 kg/sec, r=0.967 and CE=93.18% while, for the model ANN-17 RMSE=135.38 kg/sec, r=0.957 and CE=91.13% respectively. Based on the higher values of RMSE and lower values of r and CE the ANN model performance was classified as good.

ANFIS sediment model

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. As observed from the Table 3 for the model ANFIS-12 RMSE=44.02 kg/sec, r=0.995 and CE=99.06%; for the model ANFIS-23 RMSE=52.99 kg/sec, r=0.993 and CE=98.64% while, for the model ANFIS-36 RMSE=69.69 kg/sec, r=0.988 and CE=97.65% respectively. The results indicate that for the testing period the estimated suspended sediment concentration values result in better agreement with the observed values using ANFIS model.

FL sediment model

The fuzzy logic based models were formulated to estimate the suspended sediment load using triangular membership functions, considering the number of membership functions nine per input and output variables. The fuzzy rule base was created on the basis of historical data and intuition. The centroid method of defuzzification was adopted to obtain crisp output value. Various indices were used to evaluate the performance of the models. As reveled from the Table 3 for the model FL-1 RMSE=138.64 kg/sec, r=0.970 and CE=92.45%; for the model FL-2 RMSE=145.09 kg/sec, r=0.965 and CE =91.38% while, for the model FL-3 RMSE=169.65 kg/sec, r=0.959 and CE =88.69% respectively. Thus, the results of the FL model indicate satisfactory overall prediction of the suspended sediment load during the testing period.

MLR sediment model

The performance criteria of the MLR models for the testing data sets are shown in Table 3. The performance criteria show that the regression model MLR-1 performs better than MLR-2 and MLR-3 respectively. For the model MLR-1 RMSE=188.28 kg/sec, r=0.910 and CE =82.82%; for the model MLR-2 RMSE=194.65 kg/sec, r=0.904 and CE =81.64% while, for the model MLR-3 RMSE=211.02 kg/sec, r=0.88 and CE =78.44% respectively. Based on the higher values of RMSE and lower values of r and CE the MLR model performance was classified as poor.

SRC sediment model

From the Table 3 for the testing data set the RMSE, r and CE values for sediment rating curve model are 331.69 kg/sec, 0.786 and 56.48% respectively. This implies that for the study river basin runoff information alone is not sufficient to compute sediment load as the state of basin plays an important role in determining the sediment yield.

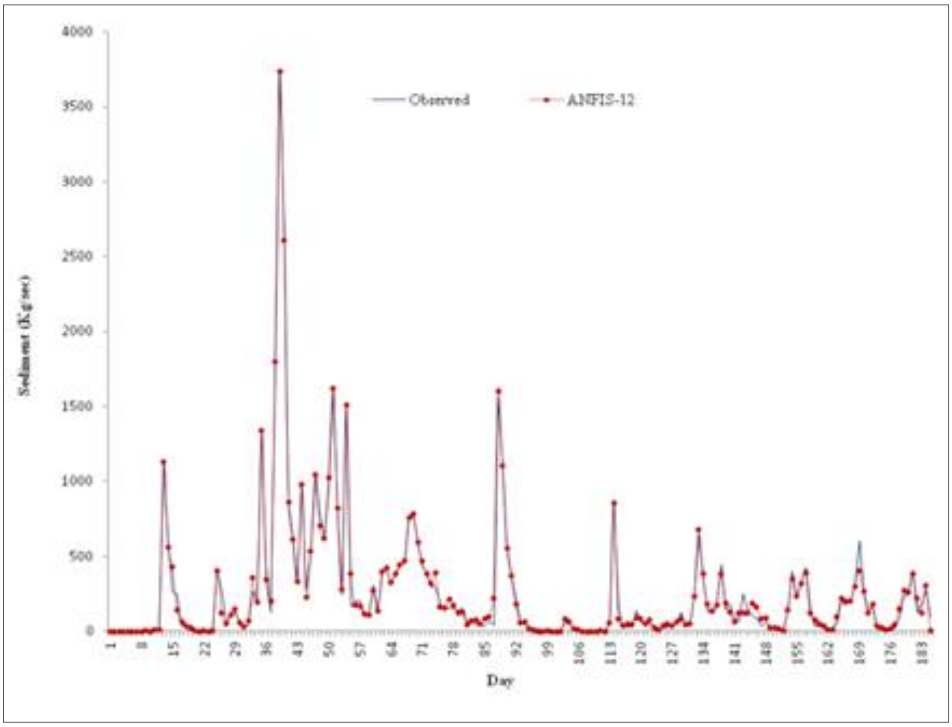
Comparison of ANN, ANFIS, FL, MLR and SRC sediment models

As observed from the Table 4, the comparative study of the five types of models shows that ANN-2 model with network 4-6-1 which takes concurrent rainfall, runoff; and antecedent runoff and sediment load with time step t-1 performed better than other models in terms of all indicators. The RMSE, r and CE values for ANN-2 model are 110.15 kg/sec, 0.971 and 94.13% respectively. Among the FL models the estimated values matched consistently well with the observed values while estimating sediment concentration throughout the testing period. RMSE, r and CE values for FL-1 model were found to be 138.64 kg/sec, 0.970 and 92.45% respectively. As depicted from the Table 4 for the ANFIS-12 model which takes present day rainfall, runoff and previous day runoff & sediment load with time step t-1 is superior to the other models in terms of all indicators. Based on the testing data sets, it is found that the ANFIS-12 model shows the minimum value of RMSE and maximum values of coefficient of correlation (r) and coefficient of efficiency (CE). For the testing data set the RMSE, r and CE values for the ANFIS-12 model are 44.02 kg/sec, 0.995 and 99.06% respectively. In the models ANFIS-23 and ANFIS-36 where present day runoff; antecedent rainfall, runoff and sediment load are considered as inputs r and CE values are almost equal or slightly less than ANFIS-12, but in terms of RMSE these models are inferior. The figures 4, 5 and 6 show the comparative plots of the ANFIS-12 ANFIS-23 and ANFIS-36 models. Considering the figures 4, 5 and 6 the accuracy of the ANFIS-12 model was significantly higher than ANFIS-23 and ANFIS-36 models for the sediment estimation. This was evident from the lower level of overall Scatter, greater r and CE values and the better fit of the predicted data with the observed values in terms of 1:1 line of correspondence.

So, based on the above discussions, 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 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 performance of the soft computing models is quite satisfactory in this regard.

Table 4: Comparison among the selected ANN, ANFIS, FL, MLR and SRC models

Model No.	Network	Input	RMSE	r	CE (%)
ANN-2	4-6-1	P_t, Q_t, Q_{t-1}, S_{t-1}	110.15	0.971	94.13
ANFIS-12	gbellmf-5	P_t, Q_t, Q_{t-1}, S_{t-1}	44.02	0.995	99.06
ANFIS-23	gbellmf-4	P_{t-1}, Q_t, Q_{t-1}, S_{t-1}	52.99	0.993	98.64
ANFIS-36	gbellmf-5	P_{t-1}, Q_t, Q_{t-2}, S_{t-1}	69.69	0.988	97.65
FL-1	trimf-9	P_t, Q_t, Q_{t-1}, S_{t-1}	138.64	0.970	92.45



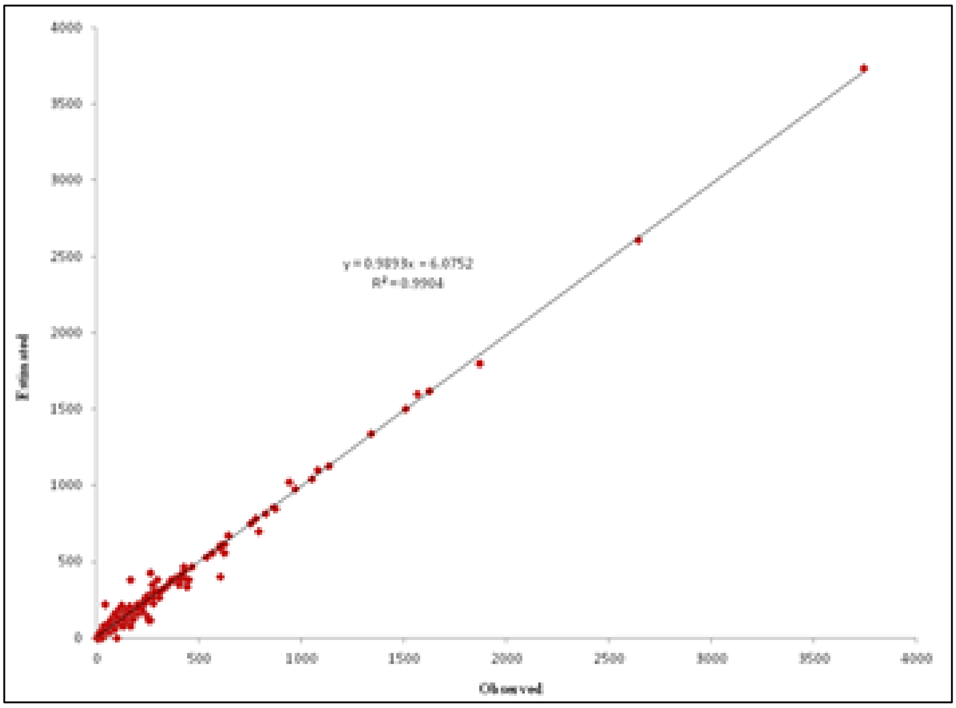
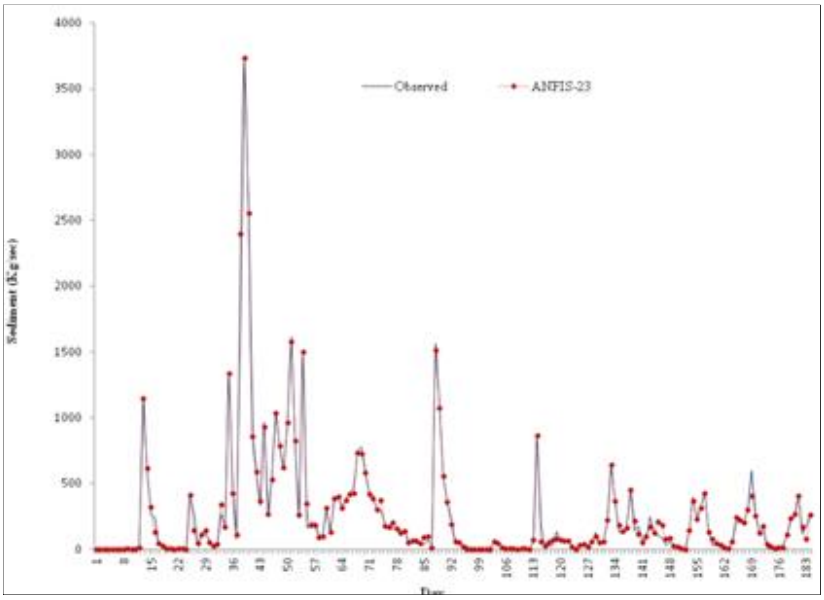


Fig 4: Series and scatter plots of ANFIS-12 model for testing period



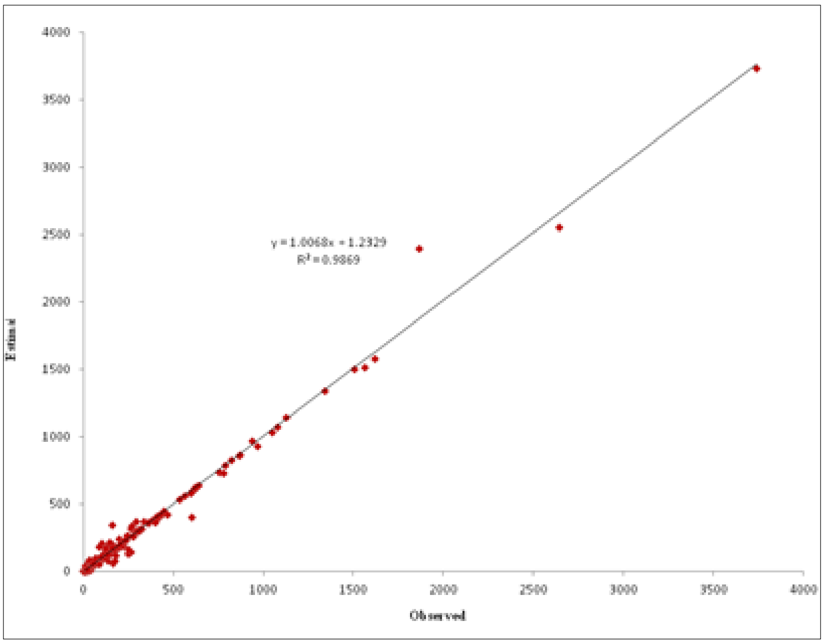
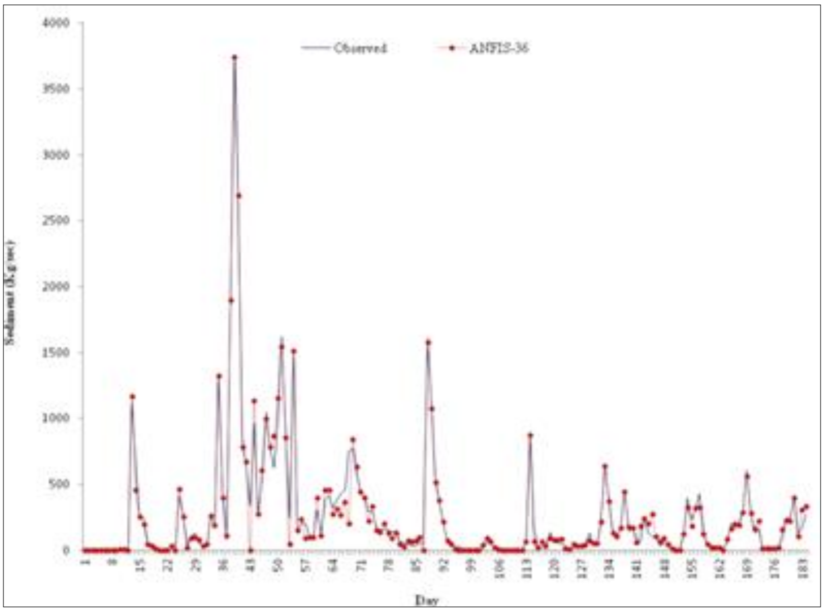


Fig 5: Series and scatter plots of ANFIS-23 model for testing period



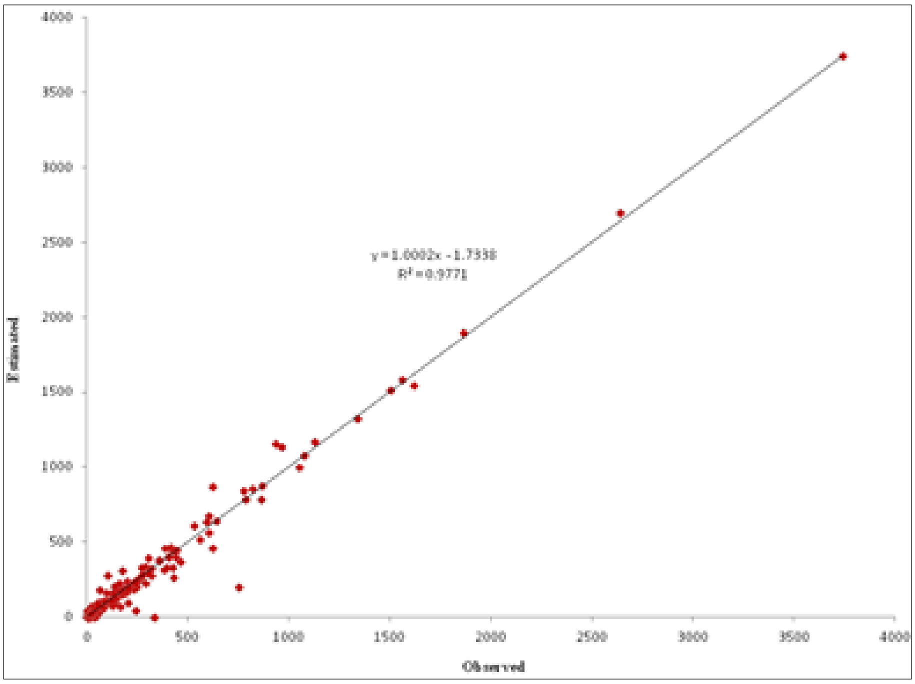


Fig 6: Series and scatter plots of ANFIS-36 model for testing period

4. Conclusions

The prime natural resources such as soil and water are deteriorating fast due to improper utilization, assessment and management. A proper watershed management plan can be developed and implemented effectively only when availability and outflow of water and loss of sediment from the watershed can accurately be assessed for future. In the present study ANN, ANFIS, FL, MLR and SRC models were developed for simulation of suspended sediment load in Vamsadhara River Basin. Based on the performance evaluation indices different Conclusions were drawn from the study. The ANFIS-12 (RMSE=44.02 kg/sec, r=0.995 and CE=99.06%), ANFIS-23 (RMSE=52.99 kg/sec, r=0.993 and CE=98.64%) and ANFIS-36 (RMSE=69.69 kg/sec, r=0.988 and CE=97.65%) outperformed the ANN, FL, MLR and SRC models for estimating suspended sediment load for the study area. The ANFIS model with membership function generalized-bell and inputs as present day 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. ANN and FL simulated daily suspended sediment concentration is more reliable than MLR and SRC simulated sediment concentration. The SRC model fits very poorly for the data set under study with highest value of RMSE and minimum values of r and CE. The RMSE, r and CE values for the sediment rating curve model are 331.69 kg/sec, 0.786 and 56.48% respectively. Overall, the result indicates a greater accuracy with ANFIS model compared with MLR and SRC models and this indicates potential utility of Soft computing models compared with the traditional models like MLR and SRC. It can be concluded that Neuro-Fuzzy model is superior to ANN, FL, MLR and SRC models for simulating daily sediment concentration in Vamsadhara river basin India. Therefore, the use of ANFIS model is recommended for future studies on hydrological modeling in this basin.

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