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River suspended sediment load prediction using neuro-fuzzy and statistical models: Vamsadhara river basin, India

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ABSTRACT

The present study deals with the development of Adaptive Neuro-Fuzzy Inference System (ANFIS), Multiple Linear Regression (MLR) and Sediment Rating Curve (SRC) models to estimate the suspended sediment load from Vamsadhara River basin comprising of 7820 km^2 area situated between Mahanadi and Godavari river basins. Three different inputs or cases using ANFIS, MLR and SRC were employed to find the effect of different inputs on the suspended sediment load. The developed models were trained and tested. Three statistical parameters: Root Mean Square Error (RMSE), coefficient of determination (R^2) and Coefficient of Efficiency (CE) were used to compare the results of the models. Results revealed that the neuro-fuzzy model (RMSE = 44.02 kg sec^{-1}, R^2 = 0.99 and CE = 99.06%) is in good agreement with the observed values and present better performance in suspended sediment load prediction in comparison to the traditional models like MLR (RMSE = 188.28 kg sec^{-1}, R^2 = 0.828 and CE = 82.82%) and SRC (RMSE = 331.69 kg sec^{-1}, R^2 = 0.617 and CE = 56.48%).

1. INTRODUCTION

A major problem that confronts mankind today meeting food demand of the country's growing population and sustaining our limited non-renewable natural resources. 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^{-1} (66% of total production loss) for cereals, 0.1-6.3 q ha^{-1} for oilseeds (21% of total production loss) and 0.04-4.4 q ha^{-1} for pulses (13% of total production loss) estimated across states, which has a direct bearing on food security of the country. One of the nature's greatest gifts to man is land covered by a layer of top soil extending from few centimetre to few meter. It takes hundreds to thousands of years to develop a 5 cm layer of fertile soil whereas it can be washed away in a single rainstorm event. It is estimated that Africa, Europe, and Australia have very low sediment yields less than 120 t sq mi yr^{-1} (Holeman, 1968; Gregory and Walling, 1973 and Brevik *et al.,* 2015), whereas South America's rate is low, North America's is moderate, and Asia's is high to the degree of yielding up to 80% of the sediment reaching the oceans annually (Decock *et al.,* 2015; Keesstra *et al.,* 2016 and Tallis, 1998). The sediment yield for the basins in Asia is over twice the world`s average yield of 600 t km^{-2} yr^{-1} which is four times larger than South America (Gregory and Walling, 1973). However in India soil erosion is taking place at an alarming rate of 1635 t km^{-2} yr^{-1} (ICAR and NAAS, 2010), which is not only detrimental to current agriculture production but is a serious threat to survival of mankind. Accurate estimation of sediment load carried by rivers is of utmost importance in the soil and water conservation practices in the watershed and also in large number of issues of planning, design and operations of reservoirs, dams and environmental impact assessment.

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 and Naik *et al.*, 2014 and 2015). 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 modelling a wide range of hydrologic processes like soil temperature (Bilgili, 2010; Tabari *et al.*, 2010 and Marofi *et al.*, 2011); flood flows (Engeland and Hisdal, 2009 and Eslamian *et al.*, 2010); and sediment prediction (Wang and Linker, 2008; Chang *et al.*, 2008 and Sahoo *et al.*, 1994).

Soft computing techniques are becoming a strong tool for providing civil, soil and water conservation and environmental engineers with sufficient information for design purposes and management practices. Specific applications of neuro-fuzzy system have been applied in hydrology and hydraulics including real-time flood forecasting and rainfall-runoff modelling (Zhu *et al.*, 1994; See and Openshaw, 2000; Stuber *et al.*, 2000; Hundecha *et al.*, 2001; Xiong *et al.*, 2001; Giustolisi and Lauucelli, 2005; Nayak *et al.*, 2004, 2005[a] and 2005[b]; Oinam *et al.*, 2014 and Wang *et al.*, 2015); stage-discharge relationship modelling (Lohani *et al.*, 2006 and Kisi and Cobaner, 2009); streamflow prediction (Kisi, 2004, 2007, 2008; Chang *et al.*, 2001; Chang and Chen, 2001; Cigizoglu, 2003 and Jayawardena *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 (Tayfur, 2002; White, 2005; Cigizoglu and Kisi, 2006; Tayfur and Guldal, 2006; Ardiclioglu *et al.*, 2007; Sadeghi *et al.*, 2013; Kisi, 2016 and Vercruysse *et al.*, 2017). Keeping these considerations in view, present study aims with the development, performance evaluation and validation of ANFIS, Sediment rating curve and regression models for the prediction of sediment load from the Vamsadhara River basin situated between Mahanadi and Godavari river basins.

2. MATERIALS AND METHODS

Study Area

The selected Vamsadhara river basin upto Kashinagar is located within the geographical coordinates of $18^0$15' to $19^0$55' N Latitudes and $83^0$20' to $84^0$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 location map of the study area is shown in Fig. 1.

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). It has potential to capture the benefits of both techniques in a single framework (Yurdusev *et al.*, 2009). 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. 2. The architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of five layers feed

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

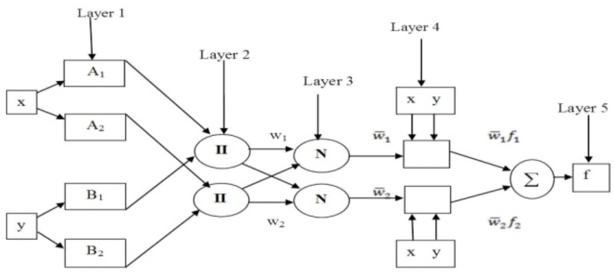

Fig. 2. Structure of adaptive neuro-fuzzy inference system

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 ith 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:

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

Where, μ_{iA} is the membership function and a_i, b_i and c_i 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:

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

Layer 3: Normalization Layer

The ith node of this layer calculates the normalized firing strengths as:

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

Layer 4: Defuzzification Layer

Node i in this layer calculates the contribution of the ith rule towards the model output, with the following node function:

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

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):

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

Multiple Linear Regression (MLR)

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 MLR analysis was performed on the same data set to estimate sediment concentration and the regression equation used is defined as:

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

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 S or load and discharge Q is of the following form:

$$S_t = a\,Q_t^b \quad ...(7)$$

Where, a and b are regression constants, Q_t is discharge (m^3 sec^{-1}) and S_t is sediment load (kg sec^{-1}) at time t.

Model Architecture

For the present study MATLAB software was used to model suspended sediment load. Four years daily data including rainfall, streamflow and sediment concentration of monsoon season from June 1, 1997 to October 31, 2000 was used. 70% data (428 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} 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 architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) networks was developed using four types: Triangular (trimf), Trapezoidal (trapmf), Gaussian (Gaussmf) and Generalized-bell (gbellmf) membership functions with number of membership functions per input varying from 3 to 5. Fuzzy model used was Takagi-Sugeno-Kang type with maximum number of epochs 1000 considering back propagation learning algorithm.

Model Performance

Three performance indicators were used to examine the goodness to fit of the ANFIS, MLR and SRC models to the testing data**.** These measures include the root mean square error (RMSE), coefficient of determination (R^2) 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:

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

2. **Coefficient of determination (R^2):** It is a measure of how well the estimated values from an estimated model fit with the real-life data. It is expressed as:

$$R^2 = \frac{\left(\sum_{i}^{N}\left(S_{o,i} - \bar{S}_{o,i}\right)\left(S_{e,i} - \bar{S}_{e,i}\right)\right)^2}{\left(\sum_{i}^{N}\left(S_{o,i} - \bar{S}_{o,i}\right)^2\right)\left(\sum_{i}^{N}\left(S_{e,i} - \bar{S}_{e,i}\right)^2\right)} \quad ...(9)$$

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:

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

Where, $S_{o,i}$ and $S_{e,i}$ are the observed and estimated sediment concentration; $\bar{S}_{o,i}$ and $\bar{S}_{e,i}$ are the average observed and estimated sediment concentration 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 ANFIS, SRC and regression models. Various performance evaluation indices of the models are given in the Tables 1, 2, 3 and 4.

ANFIS Sediment Model

Different combinations of rainfall, runoff and sediment load were considered as the inputs for ANFIS model and sediment of the present 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 (trimf), trapezoidal (trapmf), Gaussian (Gaussmf) and generalized bell (gbellmf) membership functions with number of membership functions per input varying from 3 to 5. The best model was selected based on performance indices.

Table 1 shows that results produced by ANFIS case-1 models using generalised bell membership function perform better than the other models. The RMSE, which was 249.92 kg sec^{-1} in case of ANFIS-4 model having trapezoidal membership function with three membership functions reduced to 44.02 kg sec^{-1} in case of ANFIS-12 model using generalized membership function with number of membership functions five for testing period. There is an improvement in the value of R^2 from 0.788 to 0.99 and CE from 69.76% to 99.06%. This indicates that previous day runoff and sediment load, present day rainfall and runoff have significant influence on the sediment yield.

The ANFIS case-2 models were developed to see the effect of antecedent rainfall with time step t-1 in addition to Q_t, Q_{t-1} and S_{t-1} using triangular, trapezoidal, Gaussian and generalized bell membership functions with different number of membership functions. From Table 2, it can be seen that this scenario is inferior in all aspect of statistical indicators *i.e.* RMSE, R^2 and CE. For the ANFIS-23 model the RMSE, R^2 and CE values are 52.99 kg sec^{-1}, 0.987 and 98.64%, respectively. Results reveal that previous day rainfall does not have significant influence on sediment yield from the river basin.

The ANFIS case-3 models include previous day`s rainfall and sediment load at time step t-1; and present day runoff and runoff at time step t-2. As seen from

Table: 1
Performance indicators of various ANFIS models for Case-1

Model	Network	Training			Testing		
		RMSE (kg sec^{-1})	R^2	CE (%)	RMSE (kg sec^{-1})	R^2	CE (%)
ANFIS-1	trimf-3	211.55	0.840	84.16	236.18	0.813	72.99
ANFIS-2	trimf-4	202.65	0.855	85.47	220.77	0.839	76.41
ANFIS-3	trimf-5	191.25	0.870	87.06	200.96	0.866	80.45
ANFIS-4	trapmf-3	226.25	0.819	81.88	249.92	0.788	69.76
ANFIS-5	trapmf-4	206.93	0.848	84.85	239.09	0.815	72.33
ANFIS-6	trapmf-5	192.49	0.868	86.89	205.17	0.851	79.62
ANFIS-7	Gaussmf-3	156.01	0.917	91.39	181.19	0.887	84.11
ANFIS-8	Gaussmf-4	164.68	0.906	90.40	110.37	0.941	91.68
ANFIS-9	Gaussmf-5	108.51	0.962	95.83	47.791	0.978	96.03
ANFIS-10	gbellmf-3	121.50	0.948	94.78	126.00	0.937	92.31
ANFIS-11	gbellmf-4	122.65	0.950	94.68	114.83	0.950	93.62
ANFIS-12	gbellmf-5	72.725	0.984	98.13	44.02	0.990	99.06

Table: 2
Performance indicators of various ANFIS models for Case-2

Model	Network	Training			Testing		
		RMSE (kg sec^{-1})	R^2	CE (%)	RMSE (kg sec^{-1})	R^2	CE (%)
ANFIS-13	trimf-3	207.46	0.848	84.70	207.32	0.846	79.16
ANFIS-14	trimf-4	180.06	0.886	88.53	224.40	0.840	75.63
ANFIS-15	trimf-5	153.66	0.919	91.64	162.49	0.908	87.22
ANFIS-16	trapmf-3	253.34	0.774	77.29	216.93	0.828	77.22
ANFIS-17	trapmf-4	183.54	0.885	88.08	184.94	0.868	83.44
ANFIS-18	trapmf-5	166.49	0.906	90.19	168.92	0.894	86.19
ANFIS-19	Gaussmf-3	156.49	0.915	91.33	138.75	0.952	90.68
ANFIS-20	Gaussmf-4	133.25	0.942	93.72	136.74	0.929	90.95
ANFIS-21	Gaussmf-5	98.26	0.988	98.30	84.62	0.970	96.54
ANFIS-22	gbellmf-3	99.59	0.972	96.49	129.17	0.933	91.86
ANFIS-23	gbellmf-4	71.32	0.984	98.20	52.99	0.987	98.64
ANFIS-24	gbellmf-5	79.77	0.988	97.75	132.46	0.976	91.51

the Table 3, the results produced by ANFIS models which take input-3 do not produce very satisfactory results in terms of both graphical and statistical indicators. It clearly shows that this combination of inputs cannot improve the model performance. The values of performance indicators improve as number of membership functions are increased. Considering the general case the best results were found for the models using generalized-bell membership function with number of membership functions four and five.

MLR Sediment Model

The performance criteria of the MLR models for the testing data sets are given in Table 4. 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^{-1}, R^2 = 0.828 and CE = 82.82%; for the model MLR-2 RMSE = 194.65 kg sec^{-1}, R^2 = 0.817 and CE = 81.64% while, for the model MLR-3 RMSE = 211.02 kg sec^{-1}, R^2 = 0.786 and CE = 78.44%, respectively. Based on the higher values of RMSE and lower values of R^2 and CE the MLR model performance was classified as poor.

SRC Sediment Model

From the Table 4 for the testing data set the RMSE, R^2 and CE values for sediment rating curve model are 331.69 kg sec^{-1}, 0.617 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 ANFIS, MLR and SRC Sediment Models

As observed from the Table 4, the comparative study of the three types of models shows that the ANFIS-12 model which takes present day rainfall, runoff and previous day runoff and sediment load with time step t-1 is superior to the other models in terms of all indicators. Based on the training and testing data sets, it is found that the ANFIS-12 model shows the minimum value of RMSE and maximum values of R^2 and CE. For the testing data set the RMSE, R^2 and CE values for the ANFIS-12 model are 44.02 kg sec^{-1}, 0.990 and 99.06%, respectively. In the model ANFIS-23, where present day runoff; antecedent rainfall, runoff and sediment load are considered as inputs R^2 and CE values are almost equal or slightly less than ANFIS-12, but in terms of RMSE this model is inferior. The Figures 3, 4, 5 and 6 show the comparative plots of the ANFIS-12 and ANFIS-23 models. Considering the Figures 3, 4, 5 and 6 the accuracy of the ANFIS-12 model was significantly higher than ANFIS-23 model for the sediment estimation. This was evident from the lower level of overall Scatter, greater R^2 and CE values and the better fit of the predicted data with the observed values in terms of 1:1 line of correspondence.

Based on the above discussion, it can be concluded that ANFIS models using generalized bell membership function 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 ANFIS model is quite satisfactory in this regard.

4. CONCLUSIONS

In the present study, ANFIS, MLR and SRC models were developed for simulation of suspended

Table: 4
Comparison of ANFIS models with MLR and SRC models

Model	RMSE (kg sec^{-1})	R^2	CE (%)
ANFIS-9	47.79	0.978	96.03
ANFIS-11	114.83	0.950	93.62
ANFIS-12	44.02	0.990	99.06
ANFIS-19	138.75	0.952	90.68
ANFIS-21	84.62	0.970	96.54
ANFIS-23	52.99	0.987	98.64
ANFIS-33	104.46	0.950	94.72
ANFIS-36	69.69	0.976	97.65
MLR-1	188.28	0.828	82.82
MLR-2	194.65	0.817	81.64
MLR-3	211.02	0.786	78.44
SRC	331.69	0.617	56.48

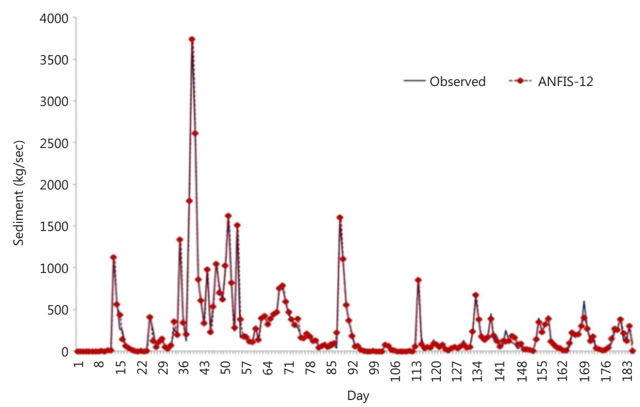

Fig. 3. Series plot of ANFIS-12 Model

Table: 3
Performance indicators of various ANFIS models for Case-3

Model	Network	Training			Testing		
		RMSE (kg sec^{-1})	R^2	CE (%)	RMSE (kg sec^{-1})	R^2	CE (%)
ANFIS-25	trimf-3	149.09	0.929	92.13	217.45	0.828	77.11
ANFIS-26	trimf-4	199.77	0.859	85.87	213.45	0.848	77.94
ANFIS-27	trimf-5	148.60	0.923	92.18	160.96	0.904	87.46
ANFIS-28	trapmf-3	211.37	0.842	84.19	271.85	0.758	64.22
ANFIS-29	trapmf-4	169.11	0.898	89.88	187.73	0.891	82.94
ANFIS-30	trapmf-5	170.35	0.901	89.73	168.25	0.887	86.28
ANFIS-31	Gaussmf-3	159.03	0.910	91.05	221.84	0.923	76.18
ANFIS-32	Gaussmf-4	113.82	0.958	95.41	151.48	0.931	88.89
ANFIS-33	Gaussmf-5	106.76	0.964	95.96	104.46	0.950	94.72
ANFIS-34	gbellmf-3	112.64	0.960	95.51	138.82	0.935	90.67
ANFIS-35	gbellmf-4	104.96	0.964	96.10	122.01	0.940	92.79
ANFIS-36	gbellmf-5	68.81	0.986	98.33	69.69	0.976	97.65

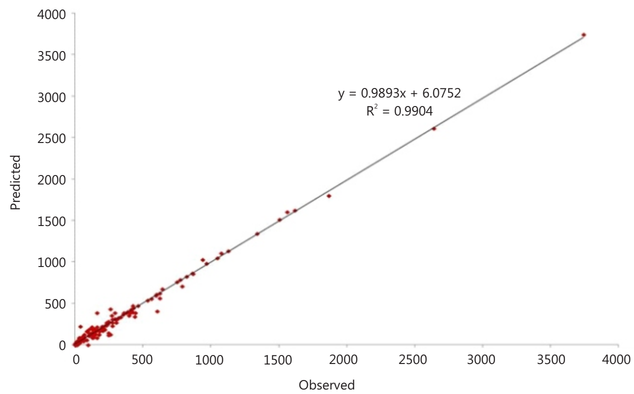

Fig. 4. Scatter plot of ANFIS-12 Model

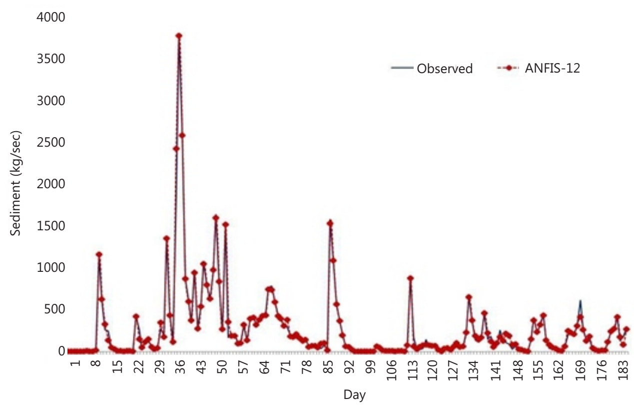

Fig. 5. Series plot of ANFIS-23 Model

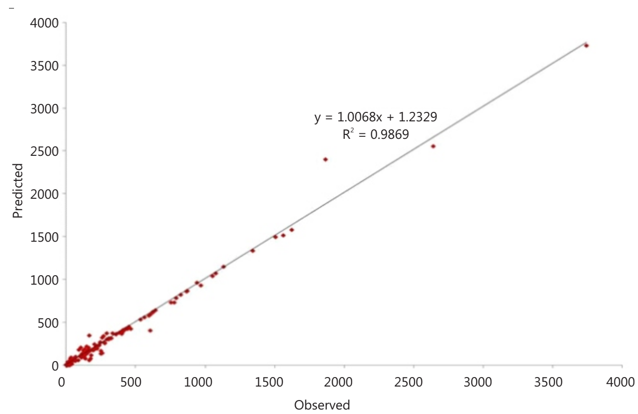

Fig. 6. Scatter plot of ANFIS-23 Model

sediment load in Vamsadhara river basin. The ANFIS-12 (RMSE = 44.02 kg sec^{-1}, R^2 = 0.99 and CE = 99.06%) and ANFIS-23 (RMSE = 52.99 kg sec^{-1}, R^2 = 0.987 and CE = 98.64%) outperformed the ANFIS, 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. The SRC model fits very poorly for the data set under study with highest value of RMSE and minimum values of R^2 and CE. The RMSE, R^2 and CE values for the sediment rating curve model are 331.69 kg sec^{-1}, 0.617 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 the soft computing models are more adequate in view of complexity and importance of the suspended sediment concentration problems in comparison to the statistical models.

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