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Modelling river suspended sediment load using artificial neural network and multiple linear regression: Vamsadhara River Basin, India

Shreya Nivesh and Pravendra Kumar

Abstract
Accurate estimation of suspended 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 hydro-environmental issues such as planning, design and operations of reservoirs, dams and environmental impact assessment. This study explores the abilities of statistical models to improve the accuracy of rainfall-streamflow-suspended sediment relationships in daily suspended sediment estimation. In this study, a comparison was made between multiple linear regression and artificial neural networks (ANNs) for the Vamsadhara river catchment. Daily rainfall-runoff and suspended sediment data were used as inputs and outputs. The performance results based on three different types of indicators viz. root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency (CE) revealed that ANN (RMSE-110.15 kg/sec, r-0.97 and CE value 94.22 %) can predict sediment load more efficiently than traditional models like multiple linear regression.

Keywords: Artificial Neural Networks (ANNs), Multiple Linear Regression (MLR), Calibration and Validation.

1. Introduction
Soil and water one of the nature`s greatest gifts to man. It takes thousands of years to develop a 5 cm layer of fertile land where as it can be washed away in a single rainstorm event. Water is a precious natural resources a basic human needs and a prime national asset. The relentless increase in human population and changes of life style have put tremendous pressure on the land and water resources causing their degradation and posing a global threat. It is estimated that Africa, Europe, and Australia have very low sediment yields, less than 120 tons per square mile per year (Holeman, 1968; Gregory and Walling, 1973; Brevik *et al.*, 2015) [25, 24, 10], 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; Tallis, 1998) [17, 52]. 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) [24]. However in India soil erosion is taking place at an alarming rate of 1635 t/km^2/year (ICAR and NAAS, 2010) [28]. The problem of soil erosion is prevalent over about 53% of the total land area of India (Narayana and Ram Babu, 1983), which is not only detrimental to current agriculture production but is a serious threat to survival of mankind Therefore, accurate estimation of suspended sediment concentration carried by rivers is of utmost importance in the soil and water conservation practices in the watershed and also in large number of hydro-environmental issues 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) [63, 57]. 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. Multiple linear regression (MLR) is a statistics based technique that uses several independent variables to predict the outcome of a dependent variable. 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; Marofi *et al.*, 2011) [7, 51, 37]; flood flows (Engeland and Hisdal, 2009; Eslamian *etal.*, 2010) [21, 22]; and sediment prediction (Wang and Linker, 2008;

Chang, *et al*., 2008) [58, 12]. 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 (Bonafe *et al.,* 1994; Hsu *et al.,* 1995; Shamseldin, 1997; Zealand *et al.,* 1999; Elshorbagy *et al.,* 2005; Jain, 2001; Agarwal *et al.,* 2003; Melesse and Wang, 2006; El-shafie, 2011; Chakravati *et al.,* 2015; Noori and Kalin, 2016) [8, 26, 65, 29, 2, 38, 19, 43], water table management (Yang *et al.,* 1998), estimation of runoff hydrograph parameters (Ahmad and simonovic, 2005) [3], water quality management (Wen and Lee, 1998) [60], estimating water quality parameters (Zhang and Stanley, 1997; Melesse *et al.,* 2008) [67, 39], sediment prediction (Abrahart and white, 2001; Yitian and Gu, 2003; Alp and Cigizoglu, 2007; Dehgani, 2009; Shabani *et al.,* 2012; Olyaie, 2015; Buyukyildiz and Kumcu, 2017) [1, 64, 4, 18, 48, 45, 9]; 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) [66, 47, 50, 27, 62, 23, 40-42]; stage–discharge relationship modelling (Lohani *et al.*, 2006; Kisi and Cobaner, 2009) [36, 31]; streamflow prediction (Kisi, 2004a, 2007, 2008a; Chang and Chen, 2001; Cigizoglu, 2003; Jayawardne *et al.*, 2006) [33, 32, 34, 13, 14, 16]; reservoir inflow forecasting (Bae *et al.*, 2007) [6]; river flow modelling (Zounemat-Kermani and Teshnehlab, 2008) [68]; 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) [54, 61, 15, 5, 46]; 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) [44]; Fuzzy intelligence system for land consolidation-a case study for Shunde, China (Wang *et al.,* 2015) [59] and a new approach for modelling suspended sediment using evolutionary fuzzy approach (Kisi, 2016) [35]; Suspended sediment transport dynamics in rivers : Multi-scale driver of temporal variation (Vercruysse *et al.,* 2017) [55]. The present paper deals with the development, performance evaluation and validation of ANNs, and regression models for predicting sediment load from the Vamsadhara river basin situated between Mahanadi and Godavari river basins in south India.

2. 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˚15′ to 84˚ 20′ E longitudes in between Mahanadi and Godavari river basins falls in the state of Orissa and the rest 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 daily weighted rainfall for the study area was found by considering the Theissen polygons. The location of the study area is shown in Fig. 1.

2.1 Methodologies

Artificial neural networks

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 $w_{k0} = b_k$.

Thus, the model representative of equations 4 and 5 is as shown in Fig. 2. 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.

Multiple linear regression

Regression analysis is a linear relationship between two or more variables. MLR applies to problems in which records have been kept of the dependent variable, y and independent variables $x_1, x_2, x_3 ... x_n$, 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 regression analysis was performed on the same data set to estimate sediment concentration and the regression equation used is defined as

$S_t = a + bP_t + cQ_t + dQ_{t-1} + eS_{t-1}$

Where a, b, c, d and e are constants and P_t, Q_t, Q_{t-1}, and S_{t-1} are the variables. A major limitation of this approach is that it is not able to take into account the hysteresis effect that gives a looping rating curve.

Model development

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 was 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}.

Model Performance

Three performance indicators were used to examine the goodness to fit of the ANN and MLR 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 provides 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 predicted 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 determine 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; and are the 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

Various graphical and statistical indicators were used to evaluate the performance of the sediment artificial neural network and regression models. Various performance evaluation parameters of the models are given in the Tables 1, 2, 3 and 4.

ANN sediment model

Six ANN models were tried for each case using Levenberg-Marquardt as a training function with sigmoid as an activation function, subjected to maximum 1000 iterations and were trained with the help of back propagation learning algorithm. Highest value of respective variable in series was considered for normalization of input and output variables. First and last numeric values of ANN structure represent the number of input and output parameters in input and output layer respectively while, the middle value represents the number of neurons in the hidden layer. For developing multiple linear regression models, the sediment load at time step t is regressed against precipitation, discharge and previous sediment with specified lag time i.e. P_t, P_{t-1}, Q_t, Q_{t-1}, Q_{t-2}, and S_{t-1}. Various statistical performance evaluation indicators of the models are given in the Tables 1, 2, 3 and 4.The graphical representations along with corresponding scattered plots of developed ANN and MLR models are shown in figures 3 to 5. Table 1 reveals that results produced by ANN case-1 models which take concurrent rainfall and runoff; and antecedent runoff and sediment load of time step t-1 considering 4-6-1 network perform better than the other models. The RMSE, which was 251.758 kg/sec in case of ANN-6 model having single hidden layer with 14 neurons reduced to 110.154 kg/sec in case of ANN-2 model having 4-6-1 network for testing period. There is an improvement in the value of correlation coefficient (r) from 0.838 to 0.971 and coefficient of efficiency from 69.318% to 94.219%. This indicates that previous day runoff and sediment load; concurrent day rainfall and runoff have significant influence on the sediment yield.

The ANN 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}, S_{t-1} using single hidden layer with different neurons varying from 4 to 14. From Table 2, it can be seen that this scenario is inferior in all aspect of statistical indicators i.e., root mean square error, correlation coefficient and coefficient of efficiency. For the ANN-11 model the RMSE, r and CE values are 118.725 kg/sec, 0.967 and 93.177 % respectively. Results reveal that previous day rainfall does not have significant influence to sediment yield from the river basin.

The ANN case-3 models include previous day`s rainfall and sediment load at time step t-1; and concurrent runoff and runoff of time step t-2. As seen from the Table 3, the results produced by ANN models which take input-3 do not produce very satisfactory results in terms of both graphical and statistical performance indicators. It clearly shows that this combination of inputs cannot improve the model performance.

Considering the values of various performance indicators the best results were found in case of models with inputs P_t, Q_t, Q_{t-1}, S_{t-1} and output S_t.

MLR sediment model

The Table 4 reveals the performance of regression model. It has been found that the MLR-1 model is better than the other MLR-2 and MLR-3 models in terms of RMSE, r and CE. This clearly implies that regression model cannot be applied in this catchment for predicting sediment yield.

Comparison of ANFIS and MLR sediment models

It can be seen from the Table 4, for the selected ANN models the root mean square error (RMSE), correlation coefficient (r) and coefficient of efficiency values vary from 110.15 kg/sec to 135.38 kg/sec, 0.96 to 0.97 and 91.13 % to 94.22 % respectively; for the MLR models vary from 188.28 kg/sec to 211.02 kg/sec, 0.88 to 0.91 and 78.44 % to 82.82 %.

The ANN-2 model which takes concurrent rainfall, runoff; and 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 110.15 kg/sec, 0.97 and 94.22 % respectively. In the model ANN-11, where concurrent runoff; antecedent rainfall, runoff and sediment load were considered as input r and CE values are almost equal or slightly less than ANN-2, but in terms of RMSE this model is inferior. The reason for this discrepancy may be the imprecise representation of spatial distribution of rainfall within the watershed by estimated mean areal rainfall used as input (Verma *et al*., 2010) [56]. The graphical representation along with corresponding scattered plots for the models ANN-2, ANN-11 and ANN-17 are shown in figures 3, 4 and 5.

So, based on the above discussions, it can be concluded that ANN models with input variables as P_t, Q_t, Q_{t-1} and S_{t-1} with network 4-6-1 with number of neurons 4 in input layer, 6 in hidden layer and having one output 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 ANN models is quite satisfactory in this regard.

Table 1: Performance indicators of various ANNs model for Case-1

Model	Network	RMSE	r	CE
ANN-1	4-4-1	244.617	0.852	71.034
ANN-2	4-6-1	110.154	0.971	94.219
ANN-3	4-8-1	227.124	0.872	91.122
ANN-4	4-10-1	198.710	0.910	80.886
ANN-5	4-12-1	169.748	0.929	86.052
ANN-6	4-14-1	251.758	0.838	69.318

Table 2: Performance indicators of various ANNs model for Case-2

Model	Network	RMSE	r	CE
ANN-7	4-4-1	203.443	0.910	79.965
ANN-8	4-6-1	185.516	0.918	83.340
ANN-9	4-8-1	188.992	0.923	82.710
ANN-10	4-10-1	172.879	0.930	85.532
ANN-11	4-12-1	118.725	0.967	93.177
ANN-12	4-14-1	228.801	0.888	74.659

Table 3: Performance indicators of various ANNs model for Case-3

Model	Network	RMSE	r	CE
ANN-13	4-4-1	301.418	0.847	56.020
ANN-14	4-6-1	207.628	0.890	79.132
ANN-15	4-8-1	204.727	0.911	79.711
ANN-16	4-10-1	172.525	0.933	85.592
ANN-17	4-12-1	135.383	0.957	91.128
ANN-18	4-14-1	293.025	0.826	54.262

Table 4: Comparison of ANN and MLR models

Model	RMSE	r	CE
ANN-2	110.15	0.97	94.22
ANN-11	118.72	0.97	93.18
ANN-17	135.38	0.96	91.13
MLR-1	188.28	0.91	82.82
MLR-2	194.65	0.90	81.64
MLR-3	211.02	0.88	78.44

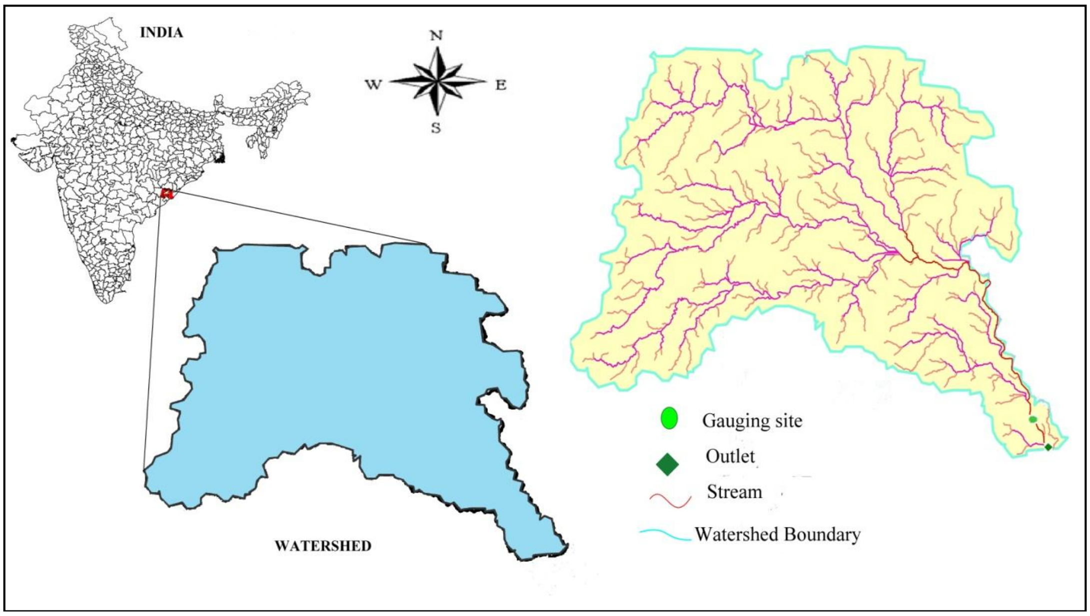

Fig 1: Location map of Vamsadhara river basin, India

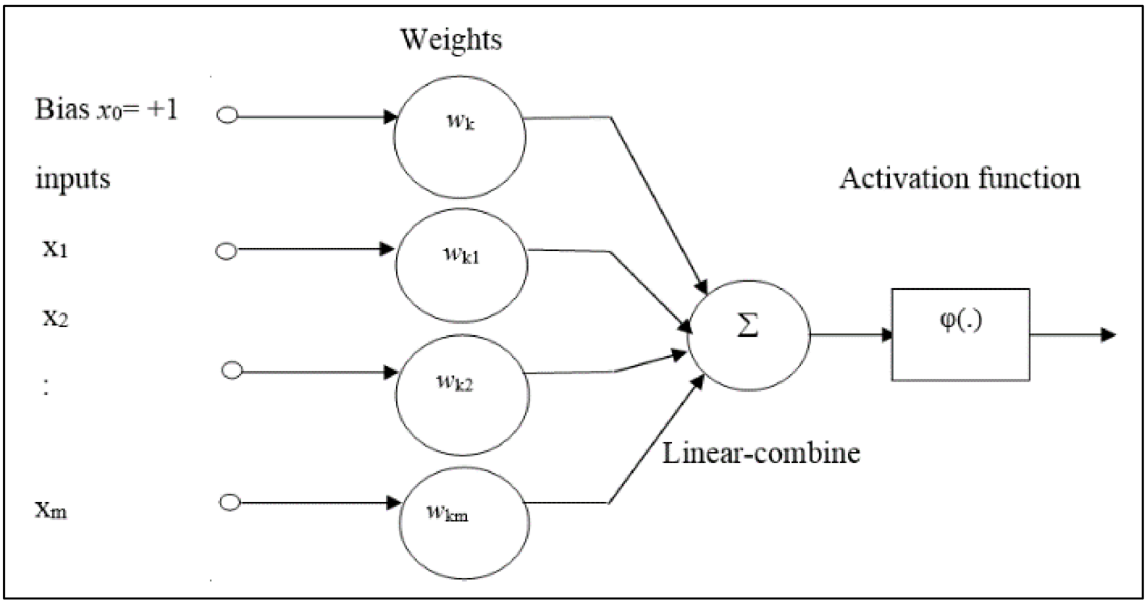

Fig 2: A reformulated model of a non-linear neuron

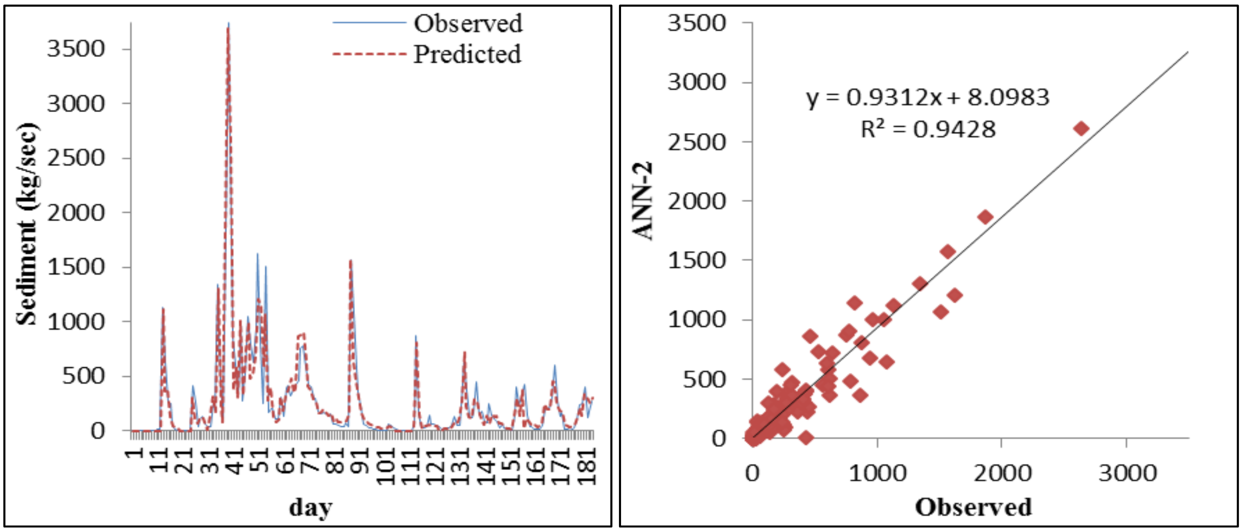

Fig 3: Series and Scatter plots of observed and estimated suspended sediment load for ANN-2 model.

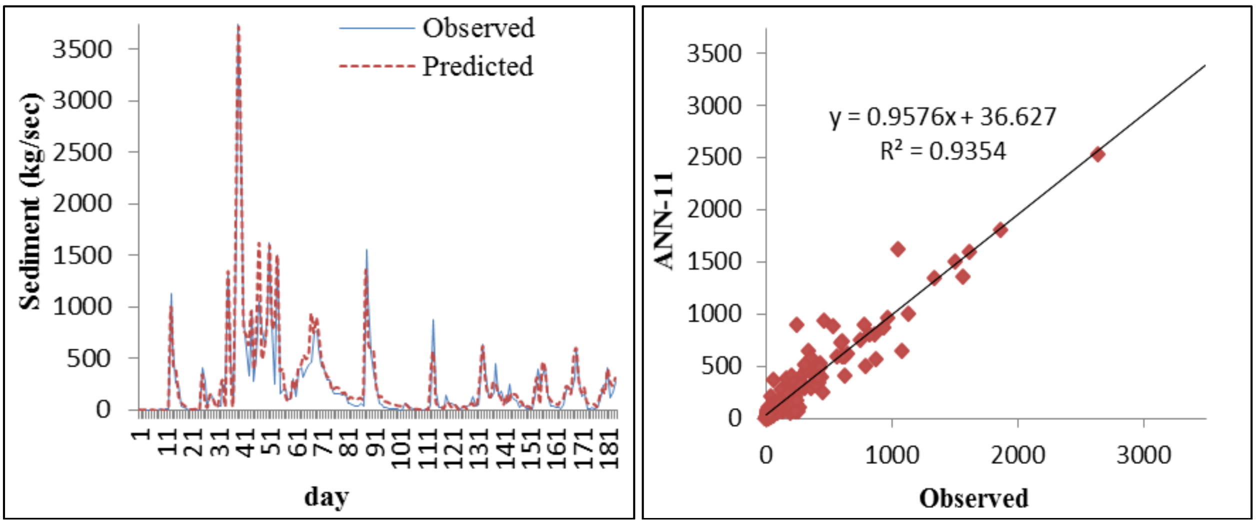

Fig 4: Series and Scatter plots of observed and estimated suspended sediment load for ANN-11 model.

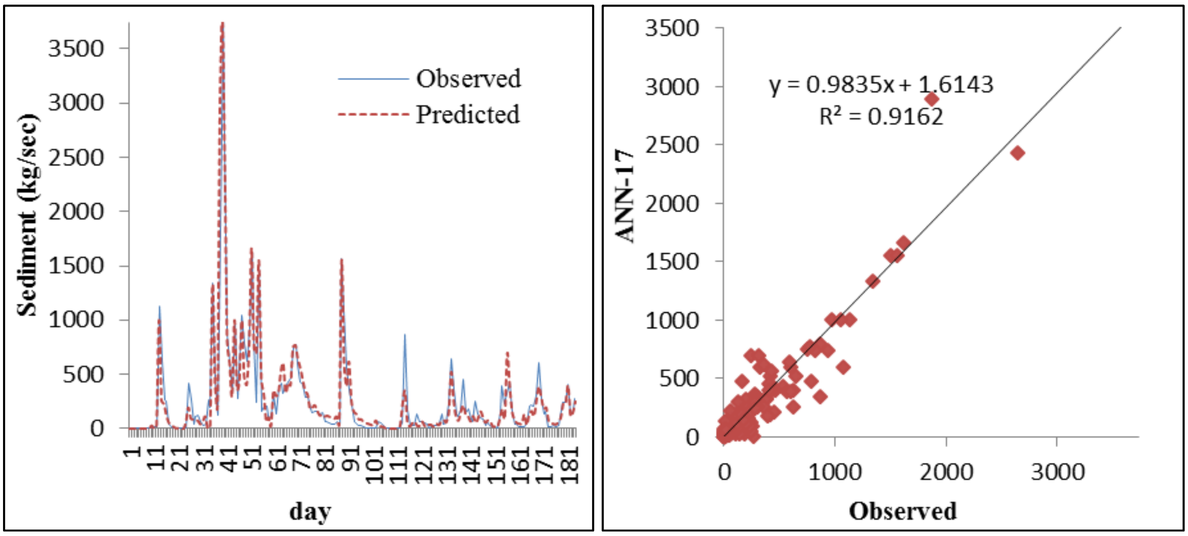

Fig 5: Series and Scatter plots of observed and estimated suspended sediment load for ANN-17 model

4. Conclusions

In the present study, ANN and MLR 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 ANN-2 outperformed the ANN and MLR models for estimating suspended sediment load for the study catchment.
2. The ANN model with network 4-6-1 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. The MLR models fit poorly for the data set under study.
4. It can be concluded that Artificial Neural Network models are superior to regression models in predicting suspended sediment load in all respects.

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