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Daily Suspended-sediment Concentration simulation using ANN and Wavelet ANN models

Manish Kumar[1*]and Pravendra Kumar[2]
[1]Dept. of SWCE, G.B.P.UA.T, Pantnagar, Uttarakhand-263145,
[2] Dept. of SWCE, G.B.P.UA.T, Pantnagar, Uttarakhand-263145
*Corresponding author:- manishcae2k11@gmail.com

ABSTRACT
The heterogeneity of the interrelations between suspended sediment concentration (SSC) and river discharge (Q) remains a challenge for SSC prediction in a hyper-concentrated river. Therefore, it is necessary to acquire knowledge about sediment concentration in the river to give a way to watershed management. In the present study, artificial neural networks (ANNs) and wavelet-based artificial neural networks (WANN) models were considered for time series modeling of suspended sediment concentration (SSC) in the Ghatshilasitewithin a Subernrekha river basin of Jharkhand. The observed daily time series for discharge and suspended sediment concentration data of 3649 days (from 2004 to 2013) were used for simulation of input and output data in which 70% of data were used for train the model while 30% were used for test the model. The input for modeling were selected from different combination made from lagging the Q and SSC data by using gamma test. The best input combination with least gamma value were used as input for both the models. The correlation coefficient (r) and root-mean square error (RMSE, g/l) were adopted to evaluate the model's performance. For the best WANN model, the value for 'r' and RMSE is 0.786664and 0.067243 g/l respectively. For best ANN model, the value for 'r' and RMSE is 0.643837 and 0.090106respectively. Therefore, the study shows that the performance of WANN model is better than ANN model. The study also depicts that more acquiring power of WANN for simulation of extreme flows with the lowest percentage of error.
Keywords: Gamma Test, ANN, Wavelet ANN, Ghatshila, Combinations

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INTRODUCTION

Generally, suspended sediment concentration (SSC) is expressed as the ratio of the mass of sediment to the volume of the water–sediment mixture [28]. The SSCalong with sediment yield, suspended load, and grain size – is a prompt river characteristic in hydrology and geomorphology and which is closely related to the river's geological and geographical settings [19, 21, 4]. The SSC is dependent on erosion processes [27]. The rate of change in sediment concentration can influence the river's morphology of scouring, transportation and deposition thatdetermine changes in river channel morphology. Mechanics of erosion and sediment transport phenomena in streams, rivers and watershed are heterogeneous hydrological and environmental problems [15, 16].Many models have been proposed to simulate these phenomena [25]. Due to a large number of obscure parameters involved in this phenomenon, the theoretical governing equations may not be of many advantages in gaining knowledge of the overall process.Suspended sediment in water carries pollutants, e.g., phosphorous and heavy metals that may influence water quality [13]. Therefore, the accuracy in estimation of SSC is also adistinctive issue in hydrologic, hydraulic and drainage engineering.

ANN's employ in estimation and prediction of suspended sediment has recently been worked out [10, 1, 7]. Nagy *et al.* [17] simulated an ANN model to estimate and predict SSC in rivers, achieved by training the ANN model to extrapolate several stream data collected from reliable sources.Raghuwanshi *et al.* [20] employed an ANN model to simulate runoff and sediment yield in Nagwan watershed in India. Seven year data was used for simulation in which fiveyeardata set was employed for training while two-year data set was considered for testing the model. Using the above training data set linear regression based daily and weekly runoff and suspended sediment yield prediction models were also developed and were tested using the testing data set. It was found that the ANN models performed better than the linear regression models in predicting both runoff and sediment yield on a daily and weekly simulation scale.

Many number of studies have applied wavelet analysis and ANN for hydrological engineering problems. Kim and Valdes [11] proposed a wavelet based ANN model to predict droughts in Mexico. Tantanee *et al.* [24] studied a coupled wavelet-autoregressive model for annual rainfall prediction. Cannas *et al.* [5] studied a hybrid wavelet based ANN model for monthly rainfall-runoff modeling in Italy. Kisi [13] studied the accuracy of WANN and ANN models in monthly stream flow prediction and proposed that the WANN performs much better than ANN. Cannas *et al.* [6] investigated the consequences of preprocessing of data on the ANN model performance by using continuous and discrete wavelet transforms. Each of these studies exhibit that ANNs calibrated with preprocessed data resulted in higher efficiency than ANNs that were calibrated with an undecomposed, noisy, raw time series.

Artificial neural network may not be able to perform with non-stationary data if preprocessing of the input-output data is not performed. Therefore, in this study, a combined model was developed for daily suspended sediment concentration prediction based on wavelet decomposition and ANN techniques. The aim of combining the wavelet and ANN models is to improve the precision of suspended sediment prediction.

MATERIAL AND METHODS

Study Area and Data Collection

Ghatshila is a town situated in East Singhbhum, Jharkhand. It is 45 km from Jamshedpur. The town is located on the bank of the Subarnarekha River, and it is situated in a forested area. It contains a railway station on the main line of the South Eastern Railway. The site of the study area lies onlatitude 22°35'14.31"N and longitude 86°28'27.77"E. It has an average elevation of 103 m.The location site of the study area is shown in Fig. 1.

Fig. 1. Location map of the study area

The hydrological data i.e. discharge (m^3/s) and suspended sediment concentration (SSC,g/l) was collected from www.india-wris.nrsc.gov.in /. The ten years (2004-2013) daily data of discharge and SSC was taken for analysis. The total data (i.e. 3649) was divided into two set: (i) training data set consists 70% (i.e. 2554) of total data which was used for development of the model and rest 30% (i.e.1095) of total data was used for testing to check the prediction capability of models used in the study.The time series graphical representation of total available data sets of discharge and SSC versus time shown in Fig. 2.

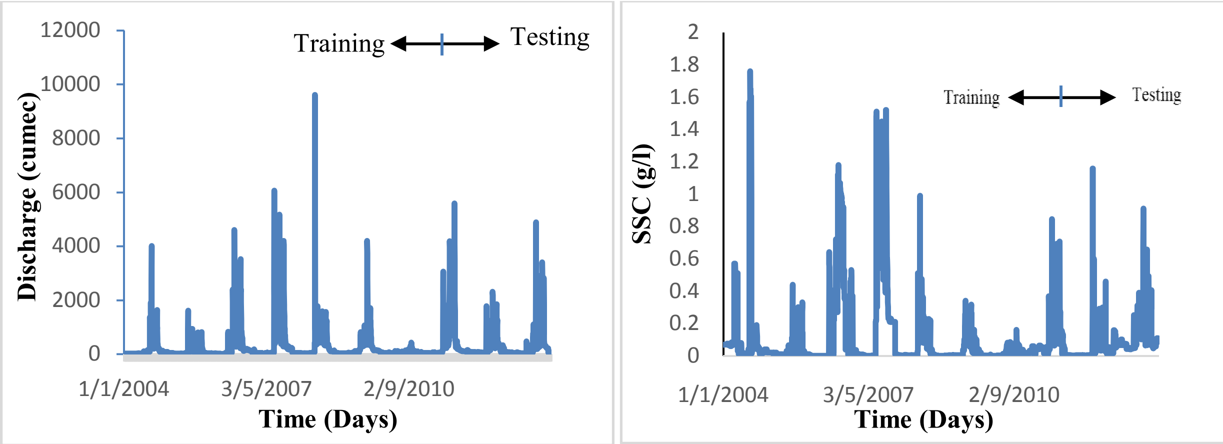


Fig. 2. Discharge and SSC time series (10 years) for Ghatshila, Jharkhand.

Statistical analysis

The statistical analysis of discharge (Q, m^3/s) and suspended sediment concentration (g/l) of all data, training and testing sets are shown in Table 1 which include various parameters like mean, median, minimum, maximum, standard deviation (Std. Dev.), coefficient of variance (C.V.) and skewness.When dividing the data set into training and testing subsets, it is essential to check that the data subsets represent the same statistical population. From Table 1, it is observed that the statistical parameters are approximately the same for training and testing sets for the givenstation.Because of high skewness coefficient, there has been a considerable negative effect on ANN performance. Therefore,skewness coefficients are low for both calibration and validation sets for the given station and this is appropriate for simulation of given data sets.

Table 1. Statistics analysis for training, testing and all data set

Statistical parameter	**Training Data**		**Testing Data**		**All Data**	
	Q(m^3/s)	**SSC(g/l)**	**Q(m^3/s)**	**SSC(g/l)**	**Q(m^3/s)**	**SSC(g/l)**
Mean	226.06	0.10214	310.91	0.081319	251.57	0.095880
Median	43.633	0.010000	72.987	0.052000	54.605	0.020000
Minimum	0.39900	0.0000	16.938	0.0010000	0.39900	0.0000
Maximum	9609.0	1.7600	5580.3	1.1590	9609.0	1.7600
Std. Dev.	547.47	0.23013	600.71	0.10877	565.26	0.20169
C.V.	2.4218	2.2531	1.9321	1.3375	2.2470	2.1035
Skewness	7.0962	3.4284	4.0817	4.1087	5.9976	3.8204

Artificial neural networks

Generally, ANN models are effective approaches to treat nonlinear and noisy data, especially in conditions where the relationships among physical processes are not fully understood. On real time basis, particularly they are also well suited for modeling complex systems. In this study,among the applied neural networks (i.e. Multilayer Perceptron Neural Network, MLNN), the feed forward neural networks (FFNN) with back-propagation (BP) algorithm was used as network type.The MLP consists of an input layer, a hidden layer, and an output layer. Each neuron was connected to all neurons in the adjacent layers in each layer but the information flowed only in one direction, from the input side to the output side. The inputs values pass the signal values to the hidden layer with their respective weight. In the hidden layer,the values are distributed to all the nodes which depend on the connection weights between the input and hidden layers. The weights are assignedfor all connections. Detailed information about MLP is found in the literature [22].The Levenberg–Marquardt training function algorithm was operated to train ANN models [9]. The application of ANN for simulating Q andSSC consists of two steps. The first is to train ANN models and the second one is to test the models. ANN architecture and training iteration number (epoch) are two important points used inappropriate selectionin ANN modeling can progress the model efficiency in both steps of calibration and verification. In this study, hyperbolic tangent sigmoid transfer function was used to calculate a layer's output from its net input.

Wavelet analysis

The purpose of the wavelet transform is to preprocess of the data in order to improve the performanceof the models [5, 6]. In this study, the Haar-à trous wavelet transform has been used. The number of resolution level used in the wavelet decomposition should not be much or too few. Here, a resolution is the separation of data into different frequency components. Xu *et al.* [27] suggested that three to five resolution level be kept is sufficient for the preprocessing of the data. In the present study, three resolution level has been taken.

The original discrete time series series C_0 (t) can be resolved by Haar à trous decomposition algorithm (Wang and Ding, 2003) as:

$C_r(t) = \sum_{l=0}^{+\infty} h(l) C_{r-1}(t+2^r)$ (r = 1, 2, 3,.....,n) ... (1)

$W_r(t) = C_{r-1}(t) - C_r(t)$ (r = 1, 2, 3,...,n) ... (2)

in which, h(l) is the discrete low pass filter, C_r (t) and W_r (t) (r = 1, 2, 3, ...) are scale coefficient (background information) and wavelet coefficient (detailed information) at resolution level respectively.

Murtagh et al., (2001) used non decimated haar algorithm which is exactly same as the Haar-à trous algorithm, except that the low pass filter h(l) (1/16, 1/4, 3/8, 1/4,1/16) , is replaced by simpler filter (1/2, 1/2) and named it as Haar à trous algorithm.

Accordingly on substituting, h (l) = $\begin{cases} \frac{1}{2}; & l = -1 \\ \frac{1}{2}; & l = 0 \end{cases}$ in Eqn (1), it becomes to,

$C_r(t) = \sum_{l=0}^{+\infty} h(l) C_{r-1}(t+2^r) + 1/2 C_{r-1}(t)$ ... (3)

Or

$C_r(t) = ½[C_{r-1}(t) + C_{r-1}(t-2^r)]$ ... (4)

Let the original (zero resolution level) discrete data sets of rainfall of the daily events is represented by C_0(p, t), using Eqn. (3) the scale coefficients and wavelet coefficients [C_r (p, t), W_r (p, t)], for original rainfall discrete time series C_0 (p, t) were resolved as,

$C_r(p, t) = 1/2 [C_{r-1}(p, t) + C_{r-1}(p, t-2^r)]$ (r = 1, 2, 3, ...,n) ... (5)

$W_r(p, t) = C_{r-1}(p, t) - C_r(p, t)$(r = 1, 2, 3, ...,n) ... (6)

It is possible to reconstruct the original hydrological time series in term of sub-time series of wavelet and scale coefficient {W_1(t), W_2(t), W_3(t)......W_r(t), C_1(t), C_2(t),...C_r(t)}. The wavelet reconstruction of the original time series, in term of obtained coefficients, is given by (Wang and Ding, 2003) as;

$C_0(t) = C_r(t) + \sum_{p=1}^{r} W_p(t)$ ... (7)

Eqn. (7) provides a reconstruction formula for original time series, called as Haar-à trous reconstructing algorithm. It is clear from the equation (6) that except the scale coefficient C_r(t), r represents resolution level, other scale coefficients, i.e C_1(t), C_2(t)......C_r(t) does not have any significance in original data. That is for r = 3, the obtained sub time series coefficients for observed time series will comprise the time series of [{W_1(t)},{W_2(t)},{W_3(t)},{C_3(t)}] and for r = 4, the obtained sub-time series coefficient will comprise the time series of [{W_1(t)},{W_2(t)},{W_3(t)},{W_4(t)},{C_4(t)}] for the development of the model.

Gamma Test

Gamma test is a versatile and impartial technique to identify the significant potential of each input parameter. The concept of gamma test in modeling was first discovered by Stefansson *et al.* (1997), which was modified by other researchers (Remesan*et al.,* 2009; Malik *et al.,* 2017). To estimate the minimum standard error between each input-output dataset with continuous nonlinear models gamma test was used. In order to calculate gamma, a linear regression line is constructedas:

$$\mathbf{Y} = \mathbf{A}\,\Delta + \Gamma \quad ...(8)$$

Where, *Y*is the output vector of the regression line, Δis gradient and Γ is the intercept of the regression line. The value of Γ is corresponding to the output at Δ = 0. The smaller value of Γ (close to zero), is acceptable.

Model development

In this study, daily suspended sediment concentration (SSC_t) was predicted with the help of various combinations of current discharge (Qt) along with three days lag discharge (Q_{t-1}, Q_{t-2} andQ_{t-n}) and three days lag suspended sediment concentrations (S_{t-1}, S_{t-2}andS_{t-3}) for the study area. In designing all mathematical and artificial intelligencemodeling,selection ofan appropriate combination of input parameters is the most sensible phases. The best input combination for the model development was selected on the basis of gamma test in which least gamma value assign best input combination. The value of various input combination of different parameters like gamma value, standard error (SE) and $V_{ratio}$is given in Table 2 which was computed using Wingamma software. The best input combination was used for modeling. Two model artificial neural network (ANN) and wavelet based artificial neural network (WANN) was developed for predicting daily suspended sediment concentration. Their performance evaluation of above two modelswas evaluated by two indices using correlation coefficient (r) and root mean square error (RMSE). The equation for correlation coefficient (r) and root mean square error (RMSE) is given in the equation

$$r = \frac{\sum_{i=1}^{n}(S_{oi}-\bar{S}_o)(S_{pi}-\bar{S}_p)}{\sqrt{\sum_{i=1}^{n}(S_{oi}-\bar{S}_o)^2}\sqrt{\sum_{i=1}^{n}(S_{pi}-\bar{S}_p)^2}} -1< r < 1 \quad \ldots(9)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{Soi}-\mathrm{Spi})^2}{N}}\; 0 < RMSE < \infty \quad \ldots(10)$$

Where, S_{oi} and $S_{pi}$are the observed and simulated suspended sediment concentration values (SSC_t) for i^{th}dataset.N is the total number of observations while$\bar{S}_o$and $\bar{S}_p$are the mean of observed and simulated (SSC_t)values, respectively.

Table 2. Results for Gamma test of various combinations of input variables

Model No.	Combinations	Gamma test statistics		
		Gamma (Γ)	SE	V_{ratio}
1	Q_{t-1} Q_{t-2} Q_{t-3} $S_{t-1}S_{t-2}$ S_{t-3}	0.043935	0.0048639	0.17574
2	Q_{t-2} Q_{t-3} $S_{t-1}S_{t-2}$ S_{t-3}	0.10739	0.012347	0.42954
3	Q_{t-2} Q_{t-3} S_{t-2} S_{t-3}	0.061651	0.0057241	0.2466
4	Q_{t-1} Q_{t-3} $S_{t-1}S_{t-2}$ S_{t-3}	0.075019	0.010193	0.30008
5	Q_{t-1} Q_{t-2} Q_{t-3} $S_{t-1}S_{t-3}$	0.044482	0.0042441	0.18015
6	Q_{t-1} Q_{t-2} $S_{t-1}S_{t-2}$ S_{t-3}	0.063487	0.011546	0.25395
7	Q_{t-1} Q_{t-2} Q_{t-3} $S_{t-1}S_{t-2}$	0.046632	0.0025767	0.18654
8	Q_{t-3} $S_{t-1}S_{t-2}$ S_{t-3}	0.12078	0.011676	0.48312
9	**Q_{t-1} Q_{t-2} S_{t-1} S_{t-2} S_{t-3}**	**0.043339**	**0.004157**	**0.17336**

RESULTS AND DISCUSSION

This section deals with the predictions performed by the ANN and WANN models for best input combinations. From Table 2, combination 9 (Q_{t-1} Q_{t-2} S_{t-1} S_{t-2} S_{t-3}) has least value i.e. 0.043339 was selected for input for the models. The results for the ANN and WANN are tabulated in Table 3 provided details of performance indices of various models obtained in WANN and ANN.

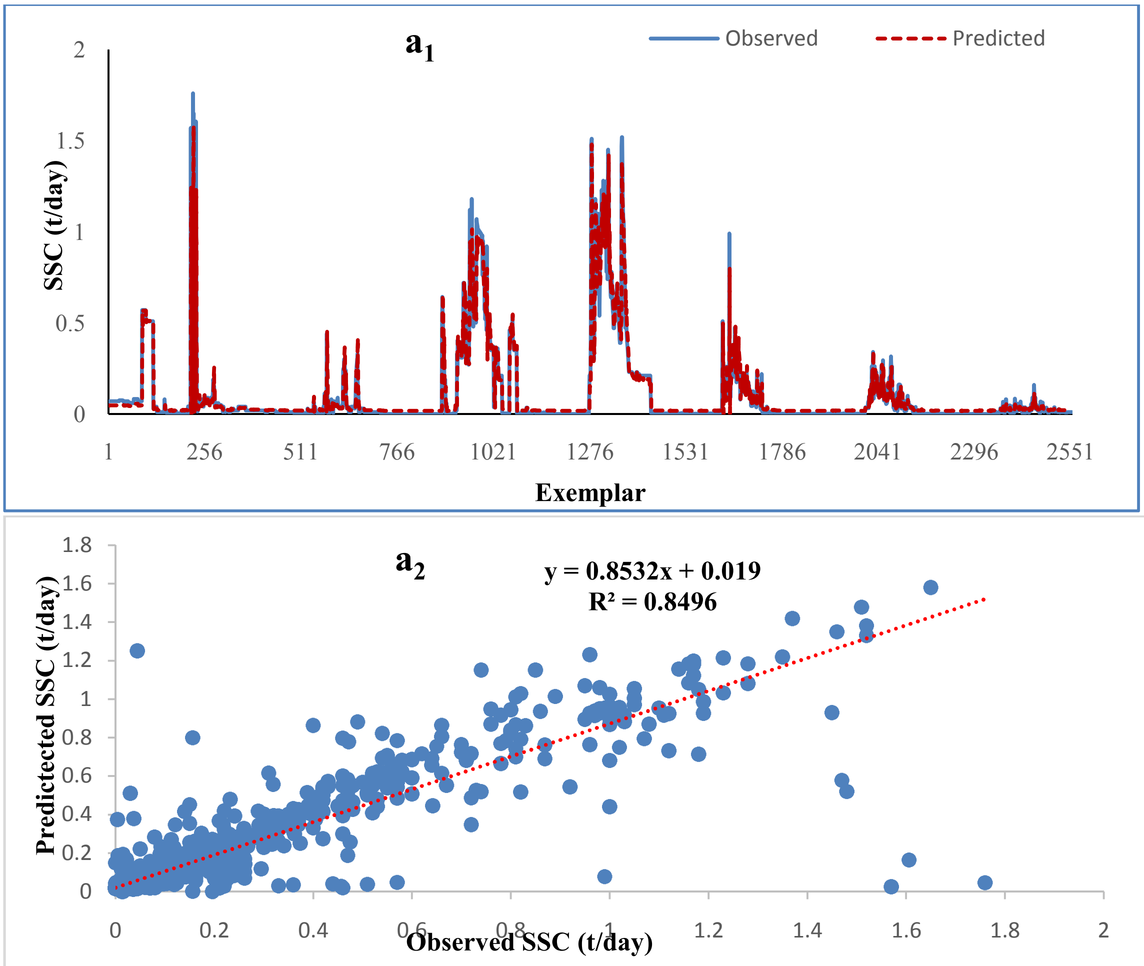
Table 3. The correlation coefficient (r) and RMSE in SSC prediction

Model	Training		Testing	
	r	RMSE(g/l)	r	RMSE(g/l)
Wavelet				
WANN1	0.964729	0.060807	0.785868	0.068911
WANN2	0.951209	0.07263	**0.786664**	**0.067243**
WANN3	0.946571	0.075289	0.734326	0.075749
ANN				
ANN1	0.921762	0.089319	**0.643837**	**0.090106**
ANN2	0.907996	0.097162	0.605752	0.089308

Model Performance

Artificial Neural Network(ANN)

Two models were obtained in ANN model which was ANN1 and ANN2 denotes5-5-1 and 5-10-1 respectively. Here, three sections represent inputs, a hidden layer with neurons and output. Consider the structure 5-10-1, 5 represents numbers of input for the model, 10 represents number of neurons in one hidden layer and 1 represents the output of the model. The value of the correlation coefficient for ANN1 and ANN2 model was obtained as 0.921762 and 0.907996 respectively for training data set. While for testing data set the value of correlation coefficient for ANN1 and ANN2 model was 0.643837 and 0.605752 respectively. The value for root mean square error (RMSE, g/l) for training data set was obtained 0.089319 and 0.097162 respectively for model ANN1 and ANN2. Similarly, the value was 0.090106 and 0.089308 respectively for testing data sets. Hence, on comparison of these two models on the basis of performance evaluation, it is seen that ANN1 model performed better than ANN2 model. Since, the value of correlation coefficient for testing for Ann1 model is greater than ANN2 model and also along with its RMSE value is comparable. A visual assessment of the predicted and observed SSC is shown in Fig. 3. It is seen that model consistently underestimated or overestimated the high amount of observed SSC.



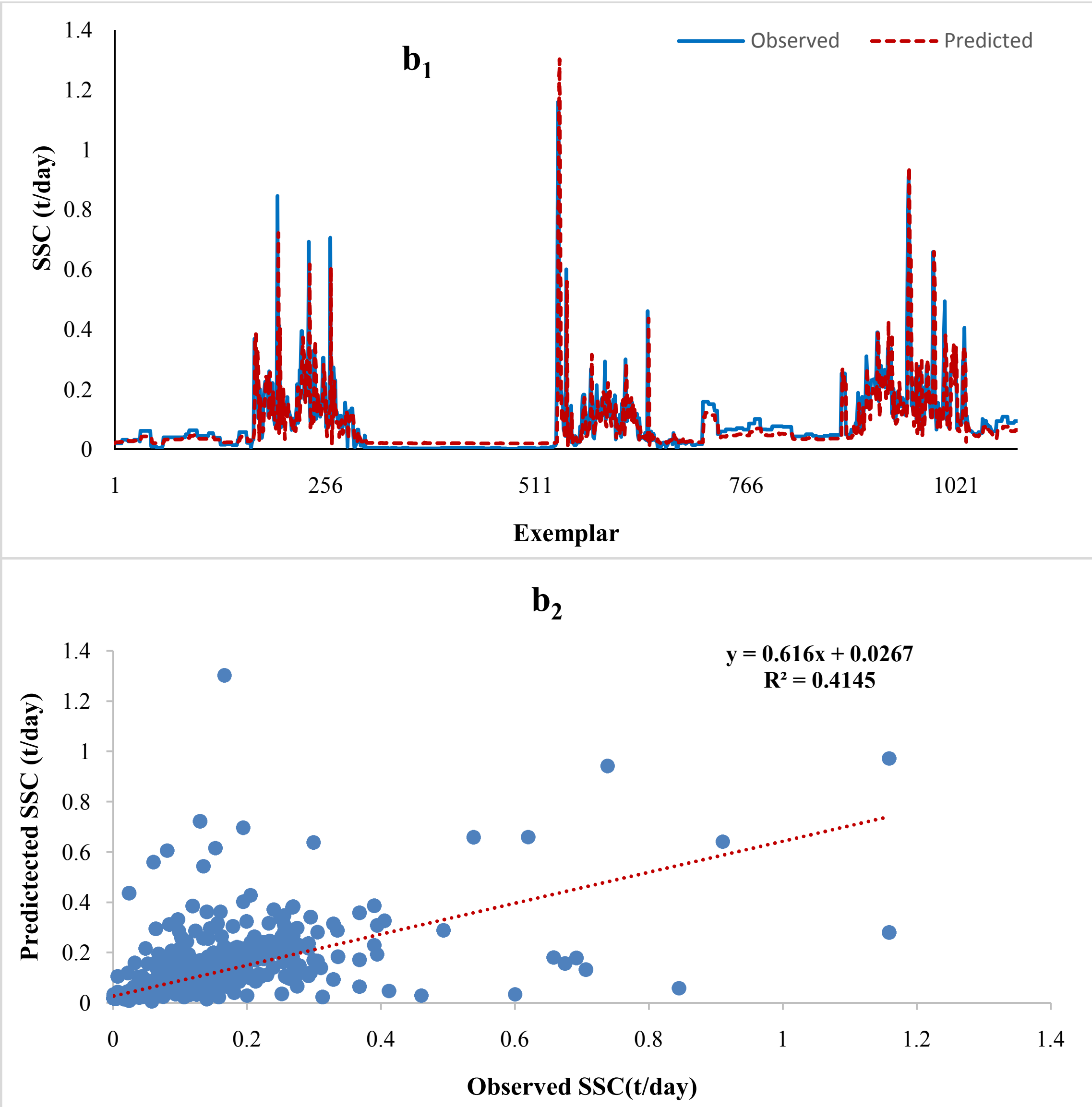
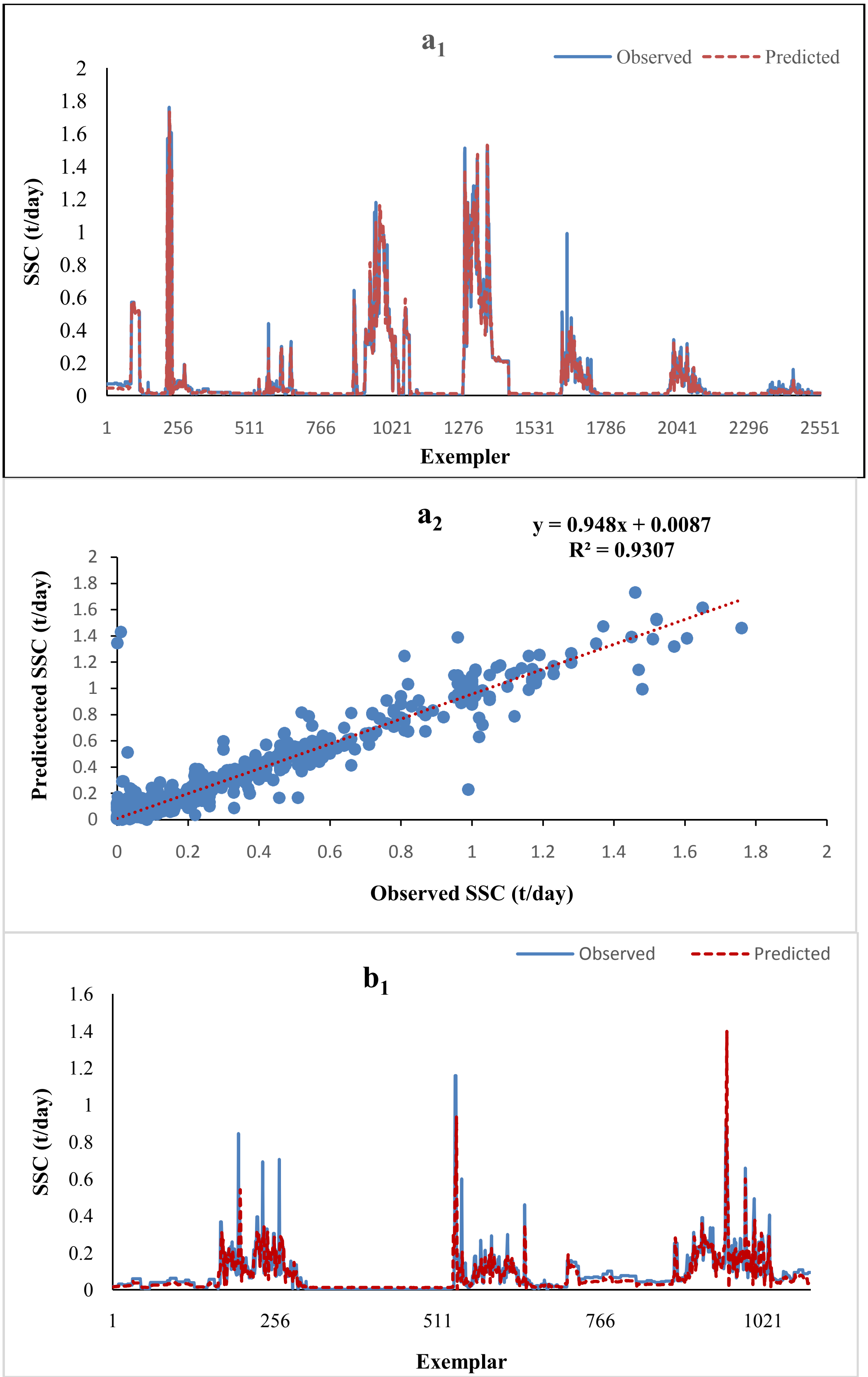


Fig. 3.SSC prediction by ANN model for training data set (a_1, a_2) and testing data set (b_1, b_2)

WaveletArtificial Neural Network (WANN)

Three models were obtained in WANN model which was WANN1 WANN2 and WANN3 denotes 24-5-1, 24-10-1 and 24-5-5-1 respectively. Due to the decomposition of input data by wavelet algorithm, the number of input data get increased to 24. Consider the structure 24-5-5-1, 24 represents numbers of input for the model, 5-5 represents two hidden layer in which each layer have 5 neurons and 1 represents output of the model. The value of correlation coefficient for WANN1 WANN2 and WANN3 model was obtained as 0.964729, 0.951209and 0.946571respectively for training data set. While for testing data set value of correlation coefficient for WANN1 WANN2 and WANN3 model was 0.785868,0.786664and 0.734326 respectively. The value for root mean square error (RMSE, g/l) for training data set was obtained 0.060807, 0.07263and 0.075289 respectively for model WANN1 WANN2 and WANN3. Similarly, the value was 0.068911, 0.067243and 0.075749respectively for testing data sets. Hence, on comparison of these above three models on the basis of performance evaluation, it is seen that WANN2 model performs better than other two model as the value for testing data set of correlation coefficient is higher and that of RMSE is lower than other models. A visual assessment of the predicted and observed SSC is shown in Fig. 4. It is seen that model consistently underestimated or overestimated the high amount of observed SSC.


a1
Observed
Predicted
SSC (t/day)
Exempler
a2
y = 0.948x + 0.0087
R² = 0.9307
Predictected SSC (t/day)
Observed SSC (t/day)
b1
Observed
Predicted
SSC (t/day)
Exemplar

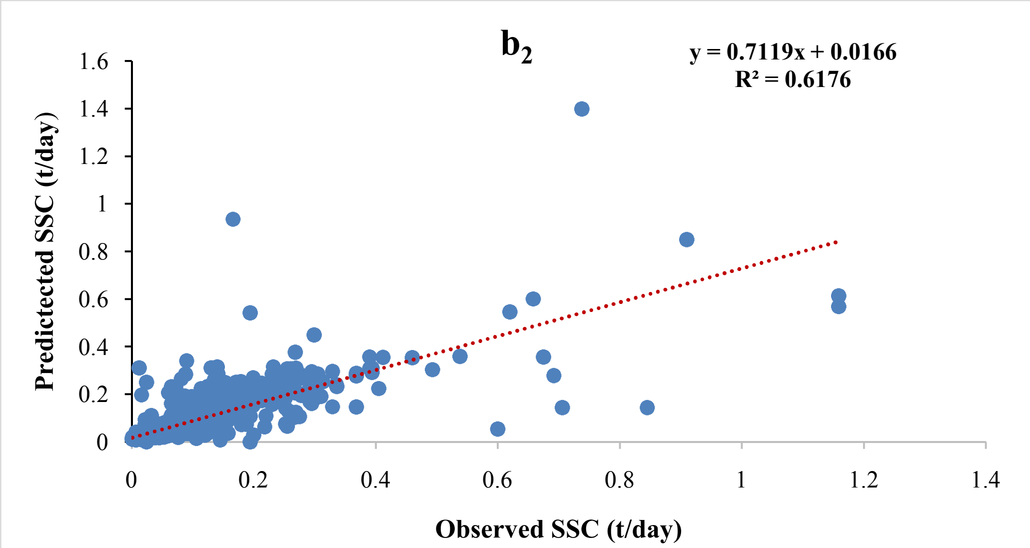


Fig. 4.SSC prediction by WANN model for training data set (a_1, a_2) and testing data set (b_1, b_2)

Comparison of WANN and ANN models

On comparison of the best model of both ANN and WANN model on the basis of performance evaluation indices i.e. correlation coefficient and root mean square error presented in Table 3, the WANN model predicted more comparable than the ANN model. Since, the value for correlation coefficient (r) lie in the range 0.785868- 0.734326, meanwhile, the value of RMSE lie in the range 0.075749-0.067243 for WANN model. While,the value for correlation coefficient (r) lie in the range 0.643837-0.605752, meanwhile, the value of RMSE lie in the range 0.090106-0.089308 for ANN model. The WANN model raised the predictive performance correlation coefficient by 23.57% and decreased RMSE by 25.37% compared with the ANN model. The advantage of the WANN model over ANN is that the input data are pre-processed using wavelet analysis to eliminate noise.Therefore, it is clear that WANN predicted better than ANN model.

CONCLUSION

In this present study, there was an endeavor to estimate an accurate suspended sediment load model for Ghatshila site within Subernrekha river basin, Jharkhand. Two modelsANN and WANN are employed to estimate sediment load. The multilayer feed forward with back propagation algorithm of neural network was used to run the model. The observed daily time series for discharge and suspended sediment concentration data of 3649 days (from 2004 to 2013) were used for simulation of input and output data in which 70% of data were used for train the model while 30% were used for test the model. The input for modeling was selected from different combination made from lagging the Q and SSC data by using gamma test. The best input combination (Q_{t-1} Q_{t-2} S_{t-1} S_{t-2} S_{t-3}) with least gamma value (0.043339) was used as input for both the models.The correlation coefficient (r) and root-mean square error (RMSE, g/l) was adopted to evaluate the model's performance.For the best WANN model, the value for 'r' and RMSE is 0.786664and 0.067243 g/l respectively. For best ANN model, the value for 'r' and RMSE is 0.643837 and 0.090106g/lrespectively. The WANN model raised the predictive performance correlation coefficient by 23.57% and decreased RMSE by 25.37% compared with the ANN model. The advantage of the WANN model over ANN is that the input data are pre-processed using wavelet analysis to eliminate noise.From the result, the comparison results indicated that WANN model has superior performance than ANN model in estimating daily sediment load.

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