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Prediction of suspended Sediment Yield using soft computing approaches of Mahanadi River

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ABSTRACT

Understanding the mass balance between the ocean and the land requires estimating sediment yield. Direct measurement of suspended sediment is challenging considering the time and money required. The suspended sediment yield is influenced by several variables, all of which have non-linear and complex interrelationships. This study proposed artificial intelligence algorithms such as Artificial Neural Networks (ANN) to estimate the suspended sediment yield in Mahanadi River Basin. The hydro-climatic parameters, namely precipitation, stage, and discharge as the direct influencing parameters, temperature, and soil moisture were taken as the indirect influencing parameters to estimate the suspended sediment yield at the Tikarapada gauging station of the Mahanadi River Basin the AI models were compared with the conventional mathematical models of Sediment Rating Curve (SRC) and Multiple Linear Regression (MLR) models. The results demonstrated that the ANN model l has the highest coefficient of determination for the testing data the and least root mean squared error value (RMSE = 0.005) for the testing data. It was followed by ANN, MLR, and finally SRC. ANN model had the least underestimated values of the estimated yield, and these two models were very close to estimating the peak sediment yield values. SRC was the least accurate model, which heavily underestimated the peak yield values. Hence, the ANN model will be beneficial to estimate the yield where suspended sediment yield values are unavailable.

Keywords: Mahanadi River; Sediment yield; ANN; Rating curve

1. Introduction

Direct estimation of sediment load is a great challenge because it requires an adequate amount of time and technical resources. Assessment of sediment yield is consistently a vital issue during the assessment of the plan for various developmental structures in water resources engineering like dams and reservoirs, transport of sediment particles inside the natural river, streams, and lakes, plan of stable channels, assurance of the importance of water resources management, protection of aquatic animals, environment and climatic impact assessment and evaluation and hydroelectric equipment life span (Cigizoglu, 2004a; Cobaner et al., 2009). The testimony of sediment load has a great impact on the flooding effects as well which influences the farming and agricultural region and the soil disintegration process of that region. The productivity of dams has likewise decreased because of sedimentation. With the above-mentioned issues, the estimation of suspended sediment yield is becoming a fundamental requirement in natural river management.

Recent research shows that change in river sediment pattern is greatly affected by discharge (Bürger & Menzel.2002.; Nijssen et al., 2001; Yadav et al., 2018a), soil erosion (Michael et al., 2005; Pruski & Nearing, 2002), and the sediment movement (Duan. et al., 2013). Apart from discharge other agents are also indirectly contributing to the river sediment yield. Most influencing parameters have been analyzed in the present study to check the interdependency with sediment patterns for the Mahanadi River Odisha. The river Mahanadi is the second-largest and one the most significant streams in Peninsular India after the Godavari River (India-WRIS 2021). Subsequently, the fundamental goal of this paper is to assess the different algorithms like ANN model and the traditional strategies like the MLR model and rating curve approach for the sediment load prediction in the Mahanadi stream.

2. Selection of data and description of Study area.

The Mahanadi River system is a significant stream in eastern India. The overall river length from the starting point to the endpoint is around 850 km. Around 356 km stretch length of river was in Chhattisgarh state and 494 km is in the state of Odisha. The Mahanadi basin is located between the longitudes of 80°30' - 86°50' east and the latitudes of 19°20' - 23°35' north. The total catchment area of the river is 141,700 square kilometres. The largest drainage area of the basin is covered by the Tikarapara gauging station i.e., 124,450 km^2, while the smallest area of 1100 km^2 is covered by the Mahendragarh site. The name of the research station from which the data set was collected is the Tikarapada gauging station which is the last measuring point for sediment yield for the entire Mahanadi basin after that the sediment gets deposited to the Bay of Bengal. Because of the location of the Tikarapada and the accessibility of hydro-meteorological data at this measuring site, Tikarapada has been chosen as the research site. Monthly based rainfall intensity, temperature, stage (water level), sediment concentration, discharge, and soil moisture, data were gathered at the Tikarapada gauging station from 1990–2010 to generate all the models which are to be used for the prediction of the sediment yield concentration. All these five input parameters have different contributions to the performance of the model which has been seen during the application of each parameter individually as input to the model.

3. Methodology, Results and discussions

3.1 Sediment Rating Curve based on Nonlinear Regression model

The non-linear model which was developed for this research was the SRC model which is a traditional sediment rating curve. A non-linear relationship was created between the input parameters and the sediment load using the non-linear approach or rating curve model. The SRC model was used by many researchers like (Jain, 2001b) (Zhu et al., 2007)(Yadav et al., 2018c). The equation for the SRC model developed for this research is presented as follows

$$\boldsymbol{Q_s = 0.532436\ Q^{1.44767}} \qquad (1)$$

Where Q_s *is* Suspended Sediment Yield (t/d), Q is the Water Discharge (m^3/s). The values were derived by regression analysis using the least square approach. Only one input data i.e., discharge, is employed in the SRC model to forecast sediment concentration (Jansson, 1997). The error matrix for the model is designated in Table 1.

Table 1 Error Statistics of NLR Model

Error Statistics	Training	Testing
RMSE	0.035	0.031
R^2	0.948	0.949
MAE	0.017	0.014
MSE	0.0012	0.0009
NSE	0.948	0.933

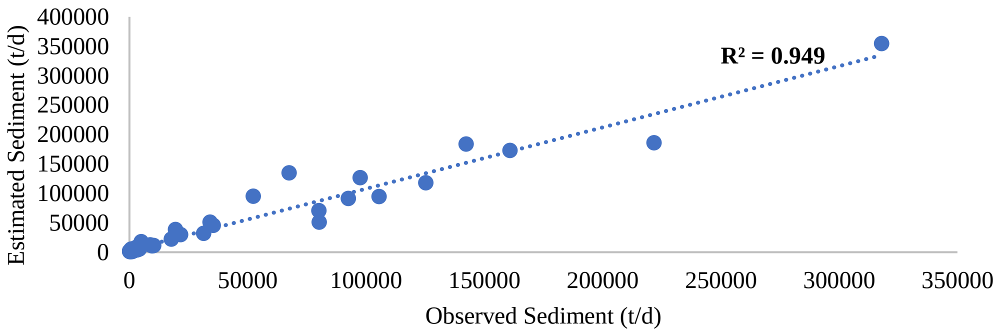

Fig 1. Scatter plot of actual data and predicted sediment yield data of testing phase of NLR Model

3.2 Multiple linear regression (MLR) models

The MLR is a widely used regression model for predicting the linear connection between input parameters and sediment load. The equation of the MLR model developed for this research site by using all the five parameters is presented as:

$$Q_s = 20691 - 2799y - 1966T + 8962V_w - 2240\,i + 37.944\,Q \qquad (2)$$

Where Q_s is the Suspended Sediment Yield (t/d), y is the Water stage (m), T is the Temperature (°C), and V_w is the soil moisture, i is the Rainfall Intensity (mm/d), Q is the Water Discharge (m^3/s). With the input and observed output data, the values were determined using a least-squares approach of regression. Thirty-one possible models of MLR were analyzed using all the possible input combinations and the best model was selected based on minimum error statistics. The error matrix for the MLR model for all the input parameters is represented in Table 2.

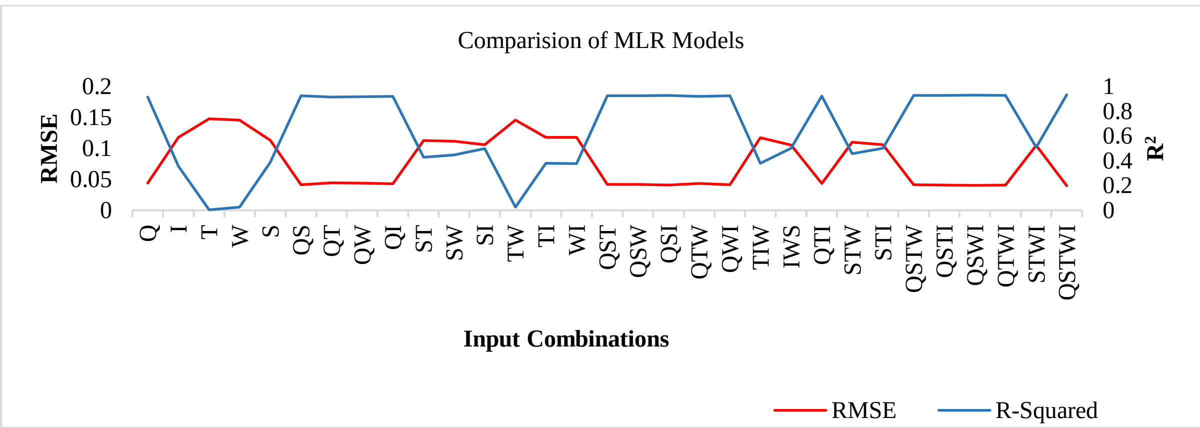

Fig. 2 Plot of RMSE and R^2 obtained for MLR models

Table 2 Error Statistics of MLR Model

Error Statistics	Training	Testing
RMSE	0.038	0.041
R^2	0.938	0.936
MAE	0.022	0.024
MSE	0.0014	0.0016
NSE	0.937	0.909

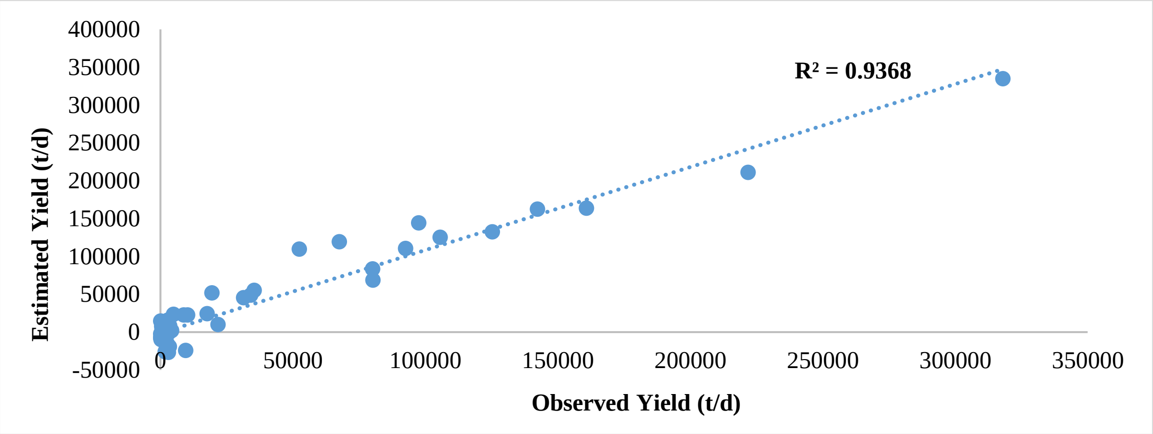

Fig 3. Plot between the actual data and predicted sediment data of the testing period of the MLR Model

3.3 ANN MODEL or Feedforward back-propagation neural network (FFBP) model with Levenberg- Marquardt algorithm (FEBP-LM) approach.

The ANN-based FFBP-LM model was created by choosing all the thirty-one possible combinations of input parameters of the five hydroclimatic parameters considered for this study i.e., discharge (Q), stage (S), rainfall intensity (I), Temperature (T), and soil moisture (W). Fig.4 represents the RMSE error for the sediment yield prediction for all the possible models. From Fig. 4, it can be seen that the QSTWI model is producing the lowest RMSE error of 0.0108 by taking all five hydro-climatic datasets as input parameters for the sediment load prediction. There were 1000 iterations (epochs) taken to get the optimized model. To achieve optimal performance in the hidden layer, the number of neurons changed from 1 to 60. In the FFBP-LM model, the learning parameter (µ) values were changed from 0.001 to a maximum of 10^9. The calculation values increased by 10 and decreased by a factor of 0.1. To increase model performance, the value of µ changes in each epoch of the algorithm. Grid search algorithm techniques were used to select the µ value and the number of hidden nodes. Fig 5 shows the Scatter plot of observed and predicted values of sediment yield in the ANN Model.

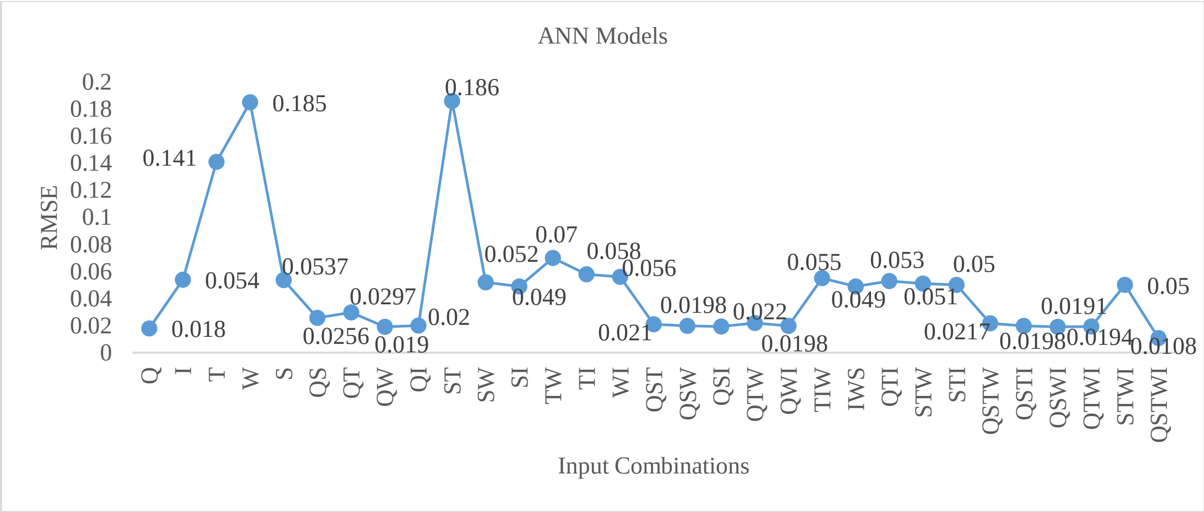

Fig. 4 Plot of RMSE obtained for ANN (FFBP-LM) models

Table 3 Error Statistics of FFBP-LM Model

Statistics	Training	Validation	Testing
RMSE	0.020	0.011	0.010
R^2	0.981	0.963	0.988
MAE	0.013	0.008	0.009
MSE	0.0004	0.0001	0.0001
NSE	0.982	0.99	0.981

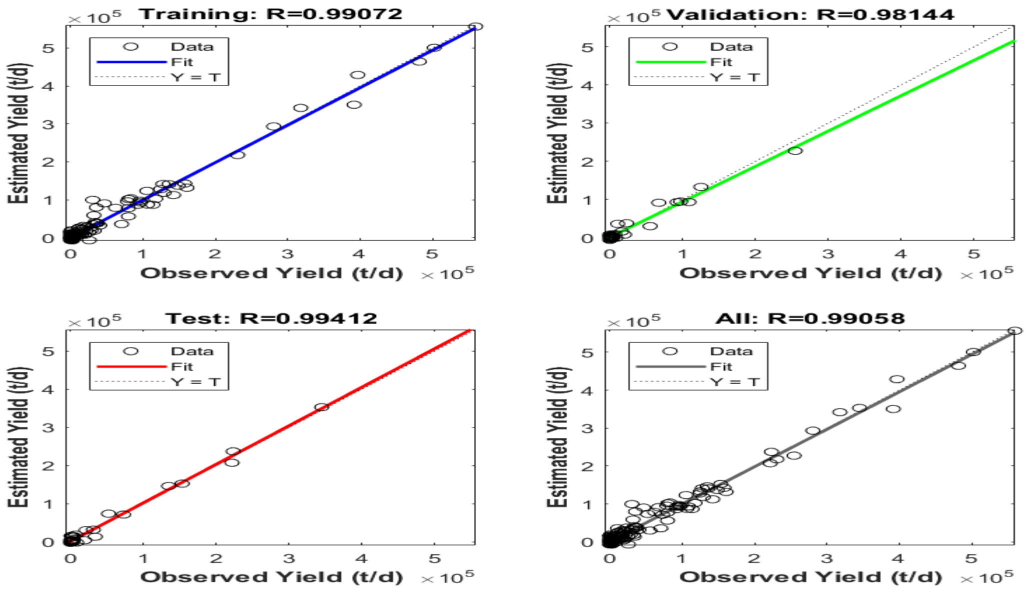

Fig 5 Scatter plot of observed and predicted values of sediment yield in ANN Model

For the ANN-based FFBP-LM model. For the development of the model, 70% of data (Jan 90-Jul 04) was used for training, 15% (Aug 04-Aug 07) for validation, and 15% (Sep 07-Sep 10) for testing the model. The error matrix in Table 3, shows different trends for the MAE and RMSE errors. The RMSE during validation was 0.011 and during testing, the data were 0.0108. Similarly, MAE were 0.008 and 0.009 during testing and validation respectively. The results indicate that it is a better model among MLR and SRC for sediment yield prediction for the lower Mahanadi River, India.

4. Conclusions

In the present work, the suspended sediment yield has been predicted at the Tikarapada gauging station downstream of the Mahanadi River. The potential of all four models was examined in terms of their capacity to estimate the Mahanadi River's suspended sediment output. The prime performance indicators were based on the R^2 values and RMSE values of the test parameters for the comparative assessment of sediment yield. The capacity of the NLR model to estimate sediment yield was found to be much lower than the other models. The standard mathematical model with extended data sets also failed to estimate sediment yield as intended. The MLR model had the most underestimated yield values, while the ANN model had the highest inflated yield points. Significant contributing parameters to the sediment yield were not included in the SRC algorithm. Despite the fact that the ANN models produced positive sediment values even when suspended sediment levels were low, they outperformed the SRC and MLR models in terms of output potential. The ANN model was improved by the inclusion of temperature, stage, and soil moisture as the hydro-climatic parameters influencing the suspended sediment yield. Therefore, it can be concluded that ANN or soft computing-based model can be an improvement over the existing methods in terms of sediment yield prediction ability. Although there is no such significant variability in the model output but few have been observed by the model. This is due to may the effects of a few unknown factors contributing to the sediment yield and is not considered as input but those are needs to be addressed in future research. This study may be a major contribution to hydrological studies where the sediment values are not accessible or easily available.

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