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Sediment prediction using generalized feed forward method for Hoshangabad, Madhya Pradesh

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Abstract
For river structures, a sediment prediction is required. The quantity of suspended sediments has been estimated using station observations and machine learning modelling approaches. The sediment concentration was measured during this research using hydrometeorlogical data such as river flow, sediment and precipitation observed between 2006 and 2015 at the Hoshangabad station in Madhya Pradesh. The generalized feed forward (GFF) approach with various learning rules and activation functions has been used to estimate the sediment load. The correlation coefficient (r), mean square error (MSE), normalized mean square error (NMSE), efficiency (CE), and coefficient of determination (R^2) were used to compare these models. When comparing the observation and model results, the GFF models provided consistent results in estimating the silt content of rivers. Even so, the overall performance of LinerAxon – Conjugate showed slightly better correlations and lower error performance than the others.

Keywords: ANN, GFF, momentum, delta-bar-delta, conjugate gradient, and Levenberg-Marquardt

Introduction
In water resources engineering; accurate estimation of sediment transported in rivers is of particular importance for the design and planning of river structures. Sediments such as rock fragments, gravel and sand carried by rivers are formed by scraping from the river basin or river bed. The sediment movement is complex and differs according to the topography, geological condition and flow characteristics of the basin. Determining the total amount of silt transported in the regulation of transportation network operations such as flood control and transportation in determining the reservoir volume, selection of water intake and type is an important engineering study. If not taken into consideration; it reduces the capacity of the hopper, leads to clogging of the mouth of the intake structure and shortens the economic life of the plants and leads to material losses. Therefore, accurate sediment observations are directly proportional to the development of soil and water resources.

It is not easy to determine because the amount of sediment varies according to many parameters. It is observed that non-linear functions are formed in the complex structure and appropriate and economical methods are used to solve them.

Usually, the amount of sediment is determined by measurements from field observation stations. Although the measured values from the station give healthy results, they are important in terms of time and cost. Even, in some rivers, when the flow rate decreases, sediment measurement is not possible. For these reasons, estimating the quantity of silt is required in the construction of water structures.

In many rivers, a major part of the sediment is transported in suspension. Recently, the importance of correct sediment prediction, mainly flood sensitive areas, has increased significantly in water resources and environmental engineering. During the previous decades, a great deal of research has been devoted to the simulation and prediction of river sediment dynamics. The daily suspended sediment load(s) process is among the most complex nonlinear hydrological and environmental phenomena to comprehend, because it usually involves a number of interconnected elements. Several studies have been undertaken to reduce the complexities of the problem by developing practical techniques that do not require much algorithm and theory. In this way, classical models such as sediment rating curve and multi linear regression are generally used for suspended sediment modelling (Kisi 2005) [1]. The last era has witnessed a huge increase in interest in the use of artificial neural networks (ANNs) to water resource and environmental concerns. The ANN, the same as the name indicates, includes the model structure of a neural network, a highly powerful computer tool used to simulate complicated nonlinear interactions, particularly when the exact form of the relationship among variables involved is unclear.

River suspended sediment load is a principal parameter in reservoir management and can serve as an index to understand the status of soil erosion and ecological environment in a watershed. Because of the regional diversity of watershed geomorphologic properties, the spatial/temporal variability of rainfall, and the participation of other physical processes, the rainfall-sediment yield process is exceedingly complicated, non-linear, dynamic, and fragmented. As a result, estimating sediment yield processes in river basins necessitates the use of a non-linear modelling technique, such as ANN, which can capture complicated temporal fluctuations within time series data. The artificial neural network (ANN) is a sophisticated soft computing technology that has been widely applied in various fields of water resource management and environmental sciences. ANN is made up of parallel systems made up of Processing Elements (PE) or neurons that are formed in layers and coupled by numerous connections or weights. After feeding input data to an input layer, it passes through the network and is processed until an output is formed at the output layer. Each neuron receives a large number of inputs via other neurons via weighted connections. These weighted inputs then are added to a standard threshold, creating the argument for a transfer function (often a linear, logistic, or hyperbolic tangent), which creates the neuron's final output.

In order to predict accurate results of rainfall forecast, several models has been created. With the advent of machine learning technologies, many researchers are trying to make predictions using the ANN method in the field of hydrology, "Researcher conducted research with ANN monthly rainfall prediction in Tengarrong station, East Kalimantan-Indonesia using back propagation neural network (BPNN) algorithm" (Mislan *et al.* 2015) [3]. "Has conducted research with ANN rainfall prediction in Udupi district of Karnataka, India" (Kumar *et al.* 2012) [2]. The results of these researches have revealed that accurate prediction of rainfall was obtained using ANN.

Study Area

The Generalized Feed-Forward Neural Network (GFF) was employed in this study to forecast silt on the Narmada River. The Hoshangabad Station in the Indian state of Madhya Pradesh was chosen as the research location. Data for this study were received from the Central Water Commission (CWC) in Bhopal.

Methods

In this work, sediment volume was estimated using hydro-meteorological indicators such as discharge, sediment, and precipitation from 2006 to 2015 at the Narmada River's Hoshangabad Station in Madhya Pradesh, India. To forecast the sedimentation, the artificial intelligence approach Generalized Feed-Forward (GFF) was utilised using different Learning rule and Transfer function.

Generalized Feed-Forward (GFF)

The GFF method is a supervised artificial neural network model that is radial-based and usually works as an estimator. The strengths of this algorithm are that they produce consistent and fast results and are easy to model. For each sample data in the training data set, one neuron is maintained in the pattern layer in this artificial neural network model. As a result, in cases where the training records set is too large, the layer structure expands in direct proportion to the quantity of sample data, raising the number of processes and memory requirements.

Learning rule

A learning rule, often known as a learning process, is a technique or a mathematical logic. It boosts the functionality of a Neural Network and applies this rule to the whole network. When a network calculates in a particular data environment, learning rules change the weights and levels of bias of the structure. This is an iterative method to apply a learning rule. It allows a neural network can learn from its surroundings and enhance its performance. Momentum, Delta-Bar-Delta, Conjugate gradient, and Levenberg-Marquardt were employed in this work.

Table 1: Details of various types of learning algorithm

Learning rule	Description
Step	Gradient information
Momentum	Gradient and weight change (momentum)
Quickprop	Gradient and rate of change of gradient
Delta-Bar-Delta	Adaptive step size for gradient plus momentum
Conjugate gradient	Second order method for gradient
Levenberg-Marquardt	Improved second order method for gradient

Activation functions

The activation function (also called transfer function or system function or network function) is used to transform the activation level of a unit (neuron) into an output signal (Patil, 2008). List of activation function is given in table 2. In this study Linear Tanh, Tanh, Sigmoid & Linear Axons these activation functions has been used.

Table 2: Details of various types of activation functions

Transfer function	Output range	Description
Linear Tanh	-1 to 1	Piecewise linear
Tanh	-1 to 1	Hyperbolic tangent
Sigmoid	0 to 1	Sigmoid
Linear Sigmoid	0 to 1	Piecewise liner
Softmax	0 to 1	Sum to one
Bias	Infinite	Add a bias
Linear	Infinite	Add a bias and scales
Axon	Infinite	Stores input

Gamma test

The concept of Gamma test was first introduced by (Stefansson *et al.* 1997) [5] to estimate the minimum standard error (SE) that can be viewed when modelling the unseen data with any continuous nonlinear models.

Table 3: Input-output combinations for GFF models for sediment concentration simulation

Model No.	Input-Output Variables	Model No.	Input-Output Variables
GFF-1	$S_t = f(R_t)$	GFF-17	$S_t= f(R_t, S_{t-1})$
GFF-2	$S_t = f(R_{t-1})$	GFF-18	$S_t= f(R_{t-1}, S_{t-1})$
GFF-3	$S_t = f(R_t, R_{t-1})$	GFF-19	$S_t= f(R_t, R_{t-1}, S_{t-1})$
GFF-4	$S_t= f(Q_t)$	GFF-20	$S_t= f(Q_t, S_{t-1})$
GFF-5	$S_t= f(Q_{t-1})$	GFF-21	$S_t= f(Q_{t-1}, S_{t-1})$
GFF-6	$S_t= f(Q_t, Q_{t-1})$	GFF-22	$S_t= f(Q_t, Q_{t-1}, S_{t-1})$
GFF-7	$S_t= f(R_t, Q_t)$	GFF-23	$S_t= f(R_t, Q_t, S_{t-1})$
GFF-8	$S_t= f(R_t, Q_{t-1})$	GFF-24	$S_t= f(R_t, Q_{t-1}, S_{t-1})$
GFF-9	$S_t= f(R_t, Q_t, Q_{t-1})$	GFF-25	$S_t= f(R_t, Q_t, Q_{t-1}, S_{t-1})$
GFF-10	$S_t= f(R_{t-1}, Q_t)$	GFF-26	$S_t= f(R_{t-1}, Q_t, S_{t-1})$
GFF-11	$S_t= f(R_{t-1}, Q_{t-1})$	GFF-27	$S_t= f(R_{t-1}, Q_{t-1}, S_{t-1})$
GFF-12	$S_t= f(R_{t-1}, Q_t, Q_{t-1})$	GFF-28	$S_t= f(R_{t-1}, Q_t, Q_{t-1}, S_{t-1})$
GFF-13	$S_t= f(R_t, R_{t-1}, Q_t)$	GFF-29	$S_t= f(R_t, R_{t-1}, Q_t, S_{t-1})$
GFF-14	$S_t= f(R_t, R_{t-1}, Q_{t-1})$	GFF-30	$S_t= f(R_t, R_{t-1}, Q_{t-1}, S_{t-1})$
GFF-15	$S_t= f(R_t, R_{t-1}, Q_t, Q_{t-1})$	GFF-31	$S_t= f(R_t, R_{t-1}, Q_t, Q_{t-1}, S_{t-1})$
GFF-16	$S_t= f(S_{t-1})$		

Performances Evaluation Indicators

In this research, a number of networks were built and trained individually, with the best network chosen based on the accuracy of the forecasts in the testing phase. The effectiveness of the created GFF models was tested using several performance assessment metrics. To evaluate and analyse the performance of the proposed model, a visual observation based on a graphical comparison of observed and anticipated values was done. Because visual observations could have personal bias, the relevant statistical indices were used to assess the performance of the GFF models for comparing observed and estimated values: mean square error (MSE), root mean square error (RMSE), coefficient of efficiency (CE), and coefficient of correlation (r).

Results

This chapter deals with the results obtained from the application of Gamma test (GT) to select appropriate input variables, and their subsequent use in training and testing of Generalized Feed-Forward (GFF) Method for the Hoshangabad catchment within M. P., India. Performance of the developed models was assessed qualitatively by visual observation, and quantitatively according to various statistical indices such as mean squared error (MSE), normalized mean square error (NMSE), coefficient of efficiency (CE), coefficient of determination (R^2) and coefficient of correlation (r).

The correlation coefficient (r) measures the strength of the linear correlation between the binary values x and y. r value closest to 1 is the most logical and appropriate. Expressions of the statistical criteria used in the study are given in equations.

$$MSE = \frac{\sum_{i=1}^{N}(X_{oi} - X_{pi})^2}{N} \quad 1$$

$$r = \frac{\sum_{i=1}^{N}(X_{oi} - \overline{X_o})(Y_{pi} - \overline{Y_p})}{\sqrt{\sum_{i=1}^{N}(X_{oi} - \overline{X_o})^2 \sum_{i=1}^{N}(Y_{pi} - \overline{Y_p})^2}} \quad 2$$

$$CE = \left[1 - \frac{\sum_{i=1}^{N}(X_{oi} - Y_{pi})^2}{\sum_{i=1}^{N}(X_{oi} - \overline{X_o})^2}\right] \quad 3$$

Where X_{oi} and X_{pi} are the observed and predicted values for i^{th} dataset, $\overline{X_o}$ and $\overline{Y_p}$ are the mean of observed and predicted values and N would be the data set in total.

Sediment modelling using GFF

GFF models (Table 3) were used to simulate current day's sediment concentration as output based on various input combinations of current and previous days' rainfall and runoff, and SC of a previous day. Five GFF models were selected after applying Gamma test Nos. - 9, 13, 14, 27, 30 Statistical indicators such as mean squared error (MSE), normalised mean square error (NMSE), coefficient of efficiency (CE), coefficient of determination (R^2), and correlation coefficient(r) were chosen for further investigation and comparison. Tables 4 to 7 provide the statistical indices results for the chosen GFF models after testing.

Table 4: Statistical indices for selected GFF (Tanh Axon – Delta Bar Delta) sediment models during the testing phase for Hoshangabad

Name of Combination			TanhAxon – DeltaBarDelta				
			Testing				
Sr. No.	Model	Combination	MSE	NMSE	r	CE	R^2
1	9	(1-2-1)	0.0003	0.0675	0.9857	0.9325	0.9717
		(1-4-1)	0.0002	0.0593	0.9897	0.9408	0.9794
		(1-6-1)	0.0003	0.0748	0.9858	0.9252	0.9718
		(1-8-1)	0.0008	0.2083	0.9816	0.7917	0.9635
		(1-10-1)	0.0013	0.3278	0.9713	0.6722	0.9434
2	13	(1-2-1)	0.0010	0.2427	0.9661	0.7573	0.9334
		(1-4-1)	0.0003	0.0730	0.9763	0.9270	0.9532
		(1-6-1)	0.0003	0.0799	0.9741	0.9201	0.9488
		(1-8-1)	0.0004	0.0870	0.9815	0.9130	0.9633
		(1-10-1)	0.0009	0.2260	0.9810	0.7740	0.9623
3	14	(1-2-1)	0.0003	0.0819	0.9789	0.9181	0.9583
		(1-4-1)	0.0003	0.0807	0.9642	0.9193	0.9298

		(1-6-1)	0.0004	0.0871	0.9617	0.9129	0.9249
		(1-8-1)	0.0003	0.0855	0.9764	0.9145	0.9534
		(1-10-1)	0.0011	0.2704	0.9716	0.7296	0.9440
4	27	(1-2-1)	0.0004	0.1007	0.9563	0.8993	0.9146
		(1-4-1)	0.0004	0.0969	0.9602	0.9031	0.9220
		(1-6-1)	0.0005	0.1115	0.9536	0.8885	0.9093
		(1-8-1)	0.0005	0.1154	0.9552	0.8846	0.9123
		(1-10-1)	0.0004	0.1095	0.9589	0.8905	0.9193
5	30	(1-2-1)	0.0004	0.1096	0.9468	0.8904	0.8965
		(1-4-1)	0.0004	0.0986	0.9545	0.9014	0.9110
		(1-6-1)	0.0004	0.1086	0.9500	0.8914	0.9025
		(1-8-1)	0.0004	0.0947	0.9582	0.9053	0.9182
		(1-10-1)	0.0004	0.0887	0.9595	0.9113	0.9206

As observed from Table 4, the increased values of CE R^2 and r during the testing period indicate good generalization capability of the selected GFF models. Based on lower values of MSE (0.0002), NMSE (0.0593) and higher CE (0.9408), R^2 (0.9794) and r (0.9897) in the testing phase, the GFF-9 was discovered to be the most effective models. Therefore, according to these models, the current day's SC can be simulated using the data of runoff of the previous day and the current day's rainfall and runoff. It was closely followed by the GFF-13 model according to which the Sc depends on the previous day's rainfall and current day's rainfall, runoff.

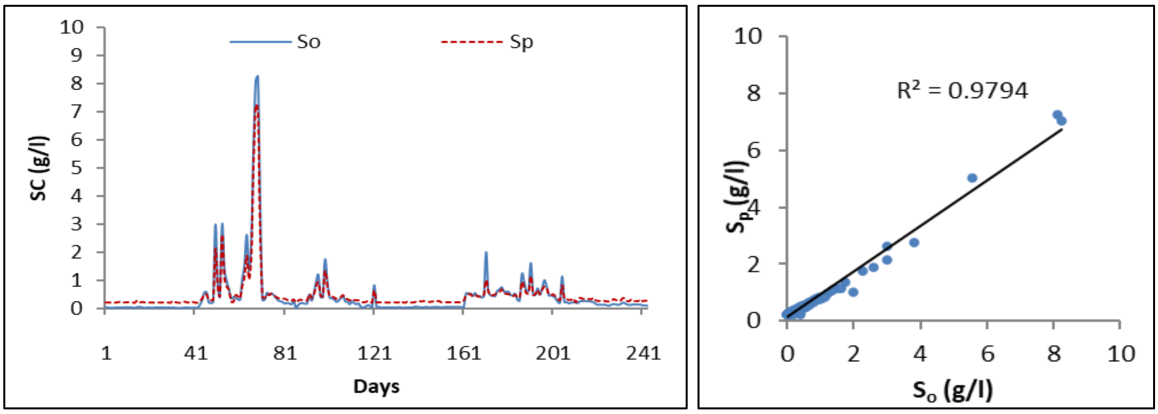


Fig 1: Comparison of observed (S_o) and predicted (S_p) SC values and corresponding scatter plot in testing period by GFF-9 (Tanh Axon – Delta Bar Delta) model for Hoshangabad

Table 5: Statistical indices for selected GFF (LinearAxon – Conjugate Gradient) sediment models during the testing phase for Hoshangabad

Name of Combination			LinearAxon – Conjugate Gradient				
			Testing				
Sr. No.	Model	Combination	MSE	NMSE	r	CE	R^2
1	9	(1-2-1)	0.0001	0.0363	0.9914	0.9637	0.9828
		(1-4-1)	0.0001	0.0363	0.9914	0.9637	0.9828
		(1-6-1)	0.0001	0.0363	0.9914	0.9637	0.9828
		(1-8-1)	0.0001	0.0363	0.9914	0.9637	0.9828
		(1-10-1)	0.0001	0.0363	0.9914	0.9637	0.9828
2	13	(1-2-1)	0.0002	0.0484	0.9829	0.9516	0.9660
		(1-4-1)	0.0002	0.0484	0.9829	0.9516	0.9660
		(1-6-1)	0.0002	0.0484	0.9829	0.9516	0.9660
		(1-8-1)	0.0002	0.0484	0.9829	0.9516	0.9660
		(1-10-1)	0.0002	0.4837	0.9829	0.9516	0.9660
3	14	(1-2-1)	0.0002	0.0467	0.9845	0.9533	0.9693
		(1-4-1)	0.0002	0.0467	0.9845	0.9533	0.9693
		(1-6-1)	0.0002	0.0467	0.9845	0.9533	0.9693
		(1-8-1)	0.0002	0.0467	0.9845	0.9533	0.9693
		(1-10-1)	0.0002	0.0467	0.9845	0.9533	0.9693
4	27	(1-2-1)	0.0001	0.0271	0.9975	0.9729	0.9949
		(1-4-1)	0.0001	0.0271	0.9975	0.9729	0.9949
		(1-6-1)	0.0001	0.0271	0.9975	0.9729	0.9949
		(1-8-1)	0.0001	0.0271	0.9975	0.9729	0.9949
		(1-10-1)	0.0001	0.0271	0.9975	0.9729	0.9949
5	30	(1-2-1)	0.0002	0.0481	0.9839	0.9519	0.9681
		(1-4-1)	0.0002	0.0481	0.9839	0.9519	0.9681
		(1-6-1)	0.0002	0.0481	0.9839	0.9519	0.9681
		(1-8-1)	0.0002	0.0481	0.9839	0.9519	0.9681
		(1-10-1)	0.0002	0.0481	0.9839	0.9519	0.9681

As observed from Table 5, the increased values of CE R^2 and r during the testing period indicate good generalization capability of the selected GFF models. Based on lower values of MSE (0.0001), NMSE (0.0271) and higher CE (0.9729), R^2 (0.9949) and r (0.9975) in the testing phase, the GFF-27 was discovered to be the most effective models. Therefore, according to these models, the current day's SC can be simulated using the data of the previous day's rainfall, runoff and sediment. It was closely followed by the GFF-9 model according to which the Sc depends on the runoff of the previous day and the current day's rainfall and runoff

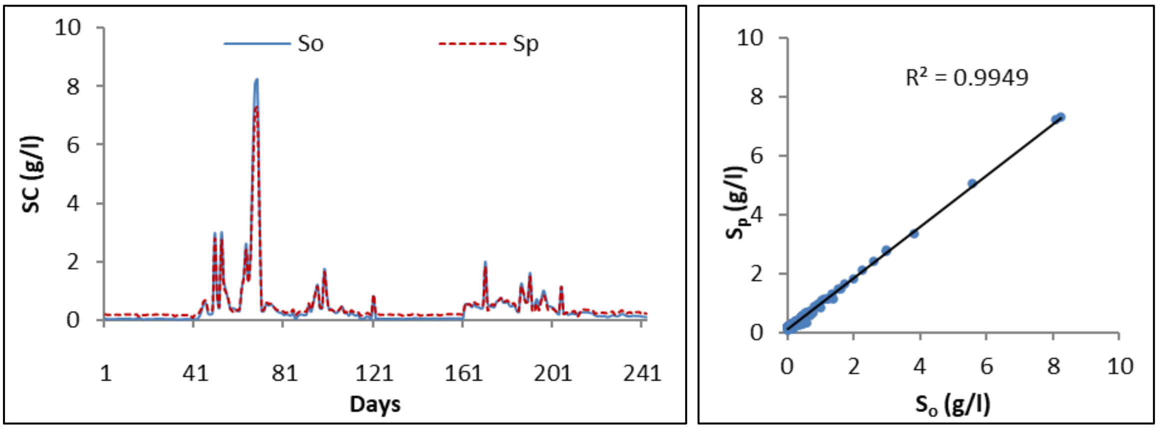
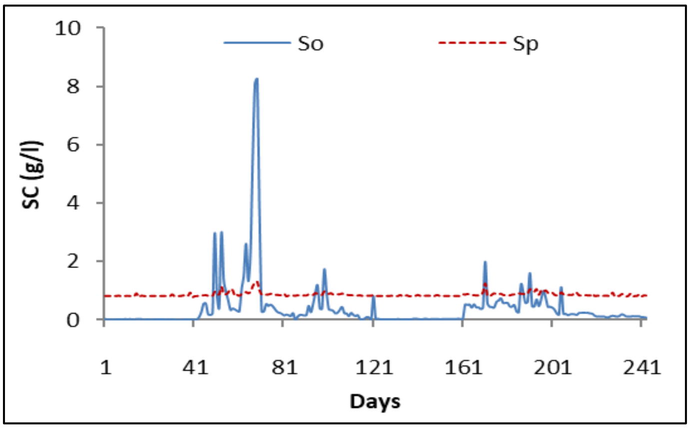


Fig 2: Comparison of observed (S_o) and predicted (S_p) SC values and corresponding scatter plot in testing period by GFF-27 (LinearAxon – Conjugate Gradient) model for Hoshangabad

Table 6: Statistical indices for selected GFF (Sigmoid Axon – Momentum) sediment models during the testing phase for Hoshangabad

Name of Combination			Sigmoid Axon – Momentum				
Sr. No.	Model	Combination	Testing				
			MSE	NMSE	R	CE	R^2
1	9	(1-2-1)	0.0013	1.2395	-0.7319	-0.2395	0.5357
		(1-4-1)	0.0012	1.1704	-0.3186	-0.1704	0.1015
		(1-6-1)	0.0012	1.1402	0.6590	-0.1402	0.4343
		(1-8-1)	0.0012	1.1552	-0.1789	-0.1552	0.0320
		(1-10-1)	0.0011	1.1090	0.7627	-0.1090	0.5818
2	13	(1-2-1)	0.0012	1.2117	-0.1920	-0.2111	0.0369
		(1-4-1)	0.0012	1.1655	-0.3818	-0.1655	0.1457
		(1-6-1)	0.0011	1.1301	0.7325	-0.1301	0.5366
		(1-8-1)	0.0012	1.1751	-0.3229	-0.1751	0.1043
		(1-10-1)	0.0011	1.0963	0.8095	-0.0963	0.6553
3	14	(1-2-1)	0.0012	1.2120	-0.2227	-0.2120	0.0496
		(1-4-1)	0.0012	1.1672	-0.3702	-0.1672	0.1370
		(1-6-1)	0.0011	1.1311	0.7153	-0.1311	0.5116
		(1-8-1)	0.0012	1.1755	-0.3336	-0.1755	0.1113
		(1-10-1)	0.0011	1.0998	0.7832	-0.0998	0.6135
4	27	(1-2-1)	0.0013	1.2319	-0.5370	-0.2319	0.2884
		(1-4-1)	0.0012	1.1670	-0.3710	-0.1670	0.1376
		(1-6-1)	0.0012	1.1366	0.7157	-0.1366	0.5123
		(1-8-1)	0.0012	1.1582	-0.2680	-0.1582	0.0718
		(1-10-1)	0.0011	1.1062	0.8227	-0.1062	0.6768
5	30	(1-2-1)	0.0127	1.2457	-0.7615	-0.2457	0.5799
		(1-4-1)	0.0012	1.1869	-0.1581	-0.1869	0.0250
		(1-6-1)	0.0011	1.1071	0.7249	-0.1071	0.5255
		(1-8-1)	0.0012	1.1566	-0.0356	-0.1566	0.0013
		(1-10-1)	0.0012	1.1472	0.0508	-0.1472	0.0026

As observed from Table 6, the increased values of CE, R^2 and r during the testing period indicate good generalization capability of the selected GFF models. Based on lower values of MSE (0.0011), NMSE (1.0963) and higher CE (-0.0963), R^2 (0.6553) and r (0.8095) in the testing phase, the GFF-13 was discovered to be the most effective models. Therefore, according to these models, the current day's SC can be simulated using the data of previous day's rainfall and the current day's rainfall and runoff. It was closely followed by the GFF-14 model according to which the Sc depends on the previous day's rainfall, runoff and current day's rainfall.



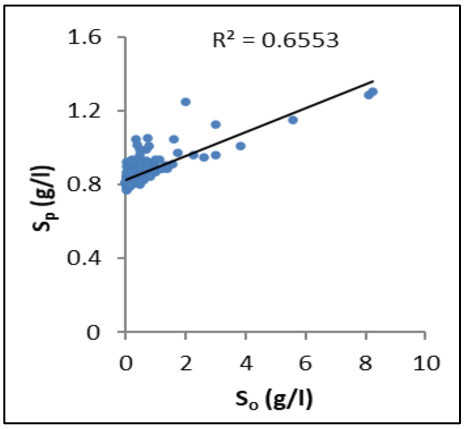


Fig 3: Comparison of observed (S_o) and predicted (S_p) SC values and corresponding scatter plot in testing period by GFF-13 (Sigmoid Axon – Momentum) model for Hoshangabad

Table 7: Statistical indices for selected GFF (Linear Tanh Axon – Levenberg Marquardt) sediment models during the testing phase for Hoshangabad

Name of Combination			LinearTanhAxon – Levenberg Marquardt				
			Testing				
Sr. No.	Model	Combination	MSE	NMSE	r	CE	R^2
1	9	(1-2-1)	0.0206	5.0704	0.0000	-4.0704	0.0000
		(1-4-1)	0.0204	5.1754	-0.0258	-4.0175	0.0007
		(1-6-1)	0.0014	0.3329	0.8546	0.6671	0.7304
		(1-8-1)	0.0135	3.3223	0.9434	-2.3223	0.8899
		(1-10-1)	0.0002	0.0443	0.9897	0.9557	0.9796
2	13	(1-2-1)	0.7510	184.7534	-0.3782	-183.7534	0.1430
		(1-4-1)	0.0011	0.2787	0.8621	0.7213	0.7432
		(1-6-1)	0.0206	5.0704	0.0000	-4.0704	0.0000
		(1-8-1)	0.0237	58.4226	0.3075	-57.4226	0.0945
		(1-10-1)	0.0003	0.0713	0.9682	0.9287	0.9374
3	14	(1-2-1)	3.5061	862.5015	0.0000	-861.5015	0.0000
		(1-4-1)	0.0082	2.0581	0.0678	-1.0058	0.0046
		(1-6-1)	0.0007	0.1686	0.9147	0.8314	0.8366
		(1-8-1)	0.0031	0.7570	0.7890	0.2430	0.6226
		(1-10-1)	0.0002	0.0586	0.9762	0.9414	0.9530
4	27	(1-2-1)	0.0003	0.0666	0.9850	0.9334	0.9702
		(1-4-1)	0.0005	0.1242	0.9665	0.8758	0.9228
		(1-6-1)	0.0206	5.0704	0.0000	-4.0704	0.0000
		(1-8-1)	0.0008	0.1935	0.9158	0.8065	0.8386
		(1-10-1)	0.0001	0.0298	0.9874	0.9702	0.9749
5	30	(1-2-1)	0.0206	5.0704	0.0000	-4.0704	0.0000
		(1-4-1)	0.0004	0.0958	0.9591	0.9042	0.9199
		(1-6-1)	0.0065	1.6079	0.6116	-0.6079	0.3740
		(1-8-1)	0.0045	1.0975	0.8088	-0.0975	0.6542
		(1-10-1)	0.0255	5.0564	-0.0033	-4.0564	0.0000

As observed from Table 7, the increased values of CE R^2 and r during the testing period indicate good generalization capability of the selected GFF models. Based on lower values of MSE (0.0001), NMSE (0.0298) and higher CE (0.9702), R^2 (0.9749) and r (0.9874) in the testing phase, the GFF-27 was discovered to be the most effective models. Therefore, according to these models, the current day's SC can be simulated using the data of previous day's rainfall runoff and sediment. It was closely followed by the GFF-9 model according to which the Sc depends on the runoff of the previous day and the current day's rainfall and runoff.

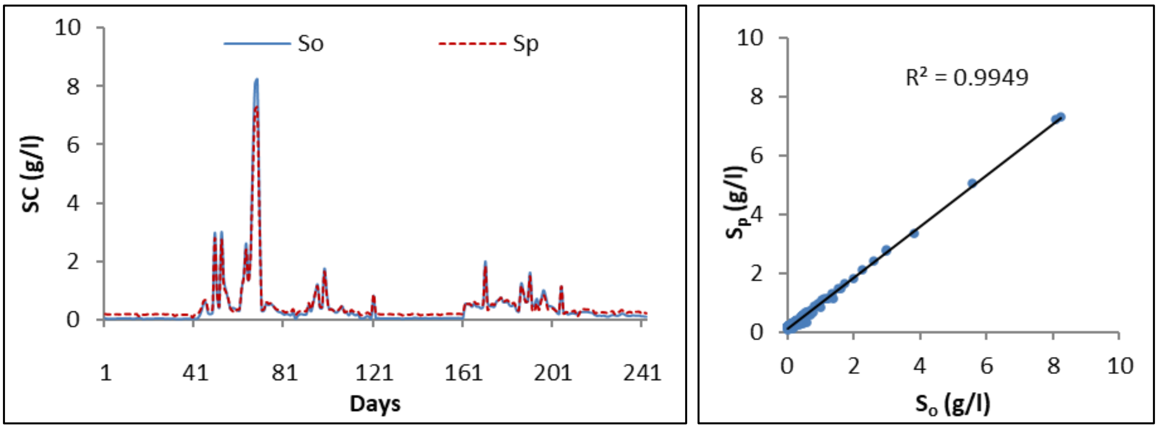


Fig 4: Comparison of observed (S_o) and predicted (S_p) SC values and corresponding scatter plot in testing period by GFF-27 (LinearTanhAxon – Levenberg Marquardt) model for Hoshangabad

Conclusion

In this study, there was an endeavor to determine a suitable architecture of ANN model and indicate the performance of ANN's application to problems concerning the estimation of sediment load from runoff, rainfall and sediment comparing with different learning rules and activation functions. It was found that an ANN model with LinearAxon – Conjugate gradient and TanhAxon – Delta-bar-Delta combination of learning rule and activation function gives the better results than other two combinations. However the values of LinerAxon – Conjugate gradient are slightly differencing as the processing element changes. It should mention that application of wide range of well-established data may lead to an increase in accuracy of ANN results.

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