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Estimation of Daily Suspended Sediment Yield Using Artificial Neural Network and Sediment Rating Curve in Kharestan Watershed, Iran

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Abstract: The objective of current study is to find out the capability of artificial neural networks method for estimation of daily suspended sediment in Kharestan Watershed located in the northwest of Fars province, Iran. For this purpose, 25 years of water and sediment discharge of Shoor Kharestan River were considered. Then the estimation was done based on artificial neural networks and sediment rating curve and were compared based on RMSE, MAE and R^2. The results showed that estimation of artificial neural network is more accurate than sediment rating curve. The estimations of RMSE, MAE and R^2 for method neural networks method was 19.27, 12.14 and 0.98 respectively while these values for sediment rating curve were 36.84, 20.75 and 0.74 which showed the lower errors of artificial neural networks method compared sediment rating curve.

Key words: Suspended sediment yield, artificial neural network, sediment rating curve, Kharestan Watershed.

INTRODUCTION

Estimation of suspended sediment yield in river is an important parameter for reservoirs and dams management, environmental impact assessment and it is an index for the status of soil erosion and ecological environment of a watershed. Increase of suspended sediment concentration has negative influence on biological life in river, on economic use of water and on recreation conditions of reservoirs. It may degrade aquatic ecosystems by increasing turbidity, reducing light penetration and may damage habitats by sedimentation. Therefore, it is important to develop a model that can predict accurately the suspended sediment concentration from continuous water data set. The sediment load process is a highly nonlinear and complex system. However, the classical regressions despite of their inability to represent successfully the nonlinear complex system have been widely used in sediment process to establish continuous relationship between water discharge, turbidity and suspended sediment (Lewis and Eads, 1996; Wang *et al*., 2006). One of the new methods used in hydrology and water resources problem is artificial neural networks (ANNs). The last two decades have seen increasing popularity of artificial neural network based models for simulation of hydrological process (Singh and Panda, 2011). Artificial neural network is a flexible mathematical structure, having strong similarity to the biological brain and therefore a great deal of the terminology is borrowed from neuroscience (Haghizade *et al*., 2010). In recent years, using artificial neural networks in water resource engineering and hydrology modeling is increased in different parts around the world (Sudheer *et al*., 2003; Mustafa *et al*., 2012) and it has shown acceptable results (Imrie *et al*., 2000; Mohan Raju *et al*., 2011). The use of artificial neural networks in simulating many hydrological processes with high speed and accuracy such as evapotranspiration (Kisi 2007; Kumar *et al*., 2011), flood (Topaloulu 2002; Viviroli *et al*., 2009), runoff (El-Shafie *et al*., 2011) and sediment yield (Jothiprakash and Garg 2009; Rezapour *et al*., 2010) has tunred it into a useful and powerful tool for professionals and engineers of water resources. Many studies on application of ANNs in sediment yield simulation and forecasting has been presented. Tayfur (2002); Nagy (2002); Cigizoglu (2004); Agarwal *et al*., (2005); Koutsoyiannis (2007); Rai and Mathur (2008); Wang and Traore (2009); Melesse *et al*., (2011) focused on ANN for sediment yield modeling and sediment concentration. bhattacharya *et al*., (2005) sed a feed–forward three layer back propagation (BP) ANN model to predict the sediment concentration in rivers using eight input parameters reflecting sediment and riverbed information. The ANN approach provided better results than other formulas used for estimation of sediment concentration. Kisi (2008) suggested ANN model to estimate sediment yield using a data driven algorithm in USA. The result of his study indicated that the statistical pre-processing of the data could significantly reduce the effort and computational time required in developing an ANN model. Haghizadeh *et al*., (2010) used artificial neural network to estimating of sediment yield in Dez basin, Iran. Their results showed that estimated rate of sediment yield by ANN is much better fits with the observed data in comparison to multiple regression (MR) model. Singh and Panda (2011) modeled daily sediment yield with artificial neural network using 10-fold cross validation method in India. The results of the study revealed that models considering both rainfall and temperature as inputs performed better than those considering rainfall alone as input. This study has been carried out in Kharestan Watershed, located in Fars

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province, Iran. The specific objective of present study was evaluation of artificial neural network model for estimation of daily suspended sediment.

MATERIALS AND METHODS

Study Area:

This study was conducted in Kharestan Watershed located in upstream of Doroodzan Dam in Fars province, Iran. It extends between 30°35' to 30°47' N latitude and 51°47' to 52°00' E longitude and covers an area of 14685 ha (Fig. 1). The average yearly precipitation is 580 mm in a Mediterranean and semi-wet climatic condition. Maximum, minimum and average elevations are 3040, 1900 and 2337 m above sea level and average land slope is 25.67%.

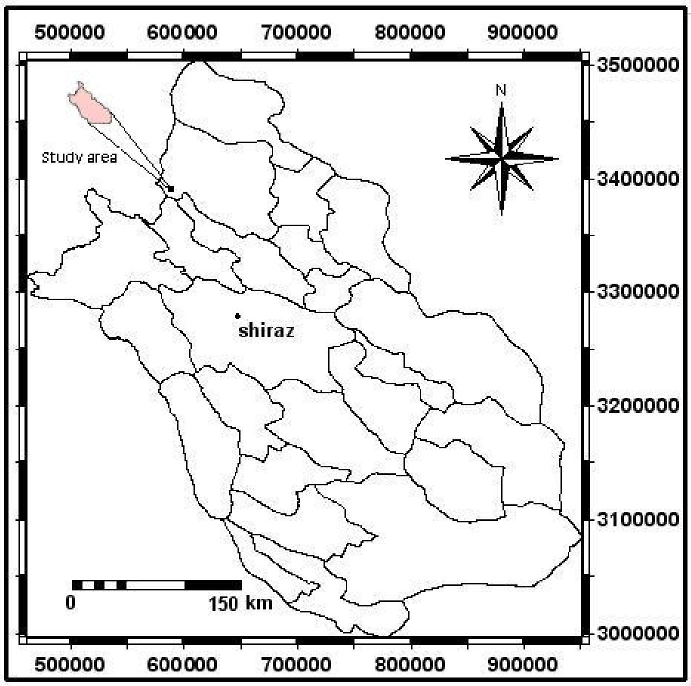

Fig. 1: Location of study area on the Iran map.

Preparation of Sediment Rating Curve:

One of the most important tasks in hydrological study is estimation of suspended sediment yield. The estimation of it in a time step, is conducted base on the relationship between sediment and water discharge in every hydrological station. The regression relationship between sediment and water discharge was named sediment rating curve. In this study, data of suspended sediment concentration (gr/lit) and discharge (m^3/s) in a 25 years period (1985-2009) in Jamal beig station at outlet of Shoor Kharestan River, were collected and the sediment concentration were changed to sediment discharge (ton/day) using equation 1.

$$Q_s = 0.0864\, C\, Q_W \tag{1}$$

Where, C = concentration of suspended sediment (gr/lit), Q_W = water discharge (m^3/s) and Q_s = sediment discharge (ton/day). The regression relationship between suspended sediment and water discharge was established to prepare sediment rating curve. The equation of sediment rating curve can be written in the following form:

$$Q_S = a\, Q_w{}^b \tag{2}$$

Where, Q_s = suspended sediment discharge (ton/day), Q_W = water discharge (m^3/s) and a and b are constants.

Architecture of Artificial Neural Network Model (ANN):

Artificial neural networks (ANNs) are based on the present understanding of biological nervous system, though much of the biological detail is neglected (Kisi, 2008). An artificial neural network has an input layer, a hidden layer and an output layer. Each layer is made up of several nodes, and layers are interconnected by sets of correlation weights. A popular architecture used with artificial neural networks is the multi layered perceptron (MLP), witch can be trained by an error back propagation algorithm (BP) (Kim and Gilley, 2008; Agarwal *et al*., 2005). In a multi layer back propagation artificial neural network (BPANN), the nodes of input layer receive the in put data, process it and pass the out put to the nodes of subsequent hidden layer(s), and from last hidden layer to the output layer. In this study, multi layer perceptron neural networks with error back propagation algorithm were used to predict and simulate suspended sediment yield from water discharge. Simplified model of an artificial neural network is shown in Fig. 2.

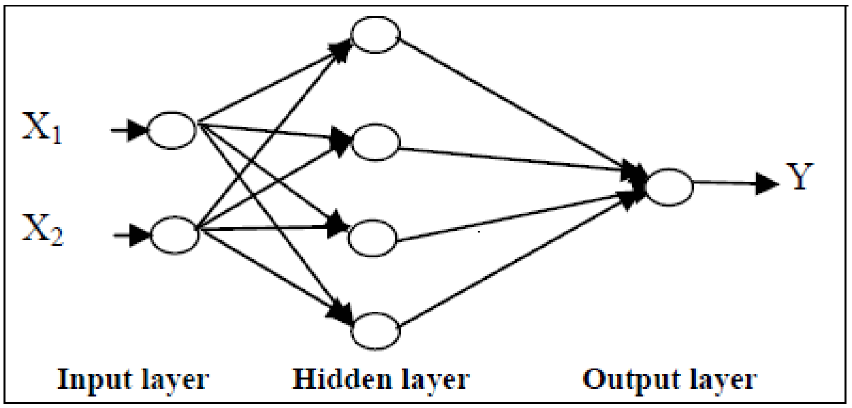

Fig. 2: Structure of an artificial neural network.

To estimate daily suspended sediment yield using artificial neural network, at first, observed water discharge (Q_w) and suspended sediment discharge (Q_s) data were collected in a 25 years period (1985-2009). To prevent the effect of extreme values in the data sets, the input and output data are normalized between 0 and 1 before entering to the ANN model using the equation 3 (Yeh, 1997; WANG, 2009).

$$Y_{norm} = \frac{Y_i - Y_{\min}}{Y_{\max} - Y_{\min}} \quad (3)$$

Where, Y_{norm} is the normalized dimensionless variable; Y_i is the observed value of variable; Y_{min} and Y_{max} are the minimum and maximum values of the variables, respectively. After normalizing, the data sets are divided into tow packages of test and train so that 80% of data were chosen as train data and remaining 20% were selected as network test data. Qnet-2000 software was used for information modeling. With a change in hidden layers and combining different equations, a different structure is created for artificial neural network that optimum structure is selected from them. Try and error method was used to select optimum structure. After selecting optimum structure and its training, network was assessed by test package data.

Evaluation Criteria:

The capability of artificial neural network model for sediment estimation was evaluated and compared with sediment rating curve method. The results were compared based on root mean squared error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) (Eq. 4 to 6).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left[Z^*(x_i) - Z(x_i)\right]^2}{n}} \quad (4)$$

$$MAE = \frac{\sum_{i=1}^{n}\left|Z^*(x_i) - Z(x_i)\right|}{n} \quad (5)$$

$$R^2 = \frac{\sum_{i=1}^{n}\left[Z^*(x_i) - \bar{Z}(x_i)\right]^2}{\sum_{i=1}^{n}\left[Z(x_i) - \bar{Z}(x_i)\right]^2} \tag{6}$$

Where, n= number of observed data, $Z^*(x_i)$ = the estimated value in point i, $Z(x_i)$ = the observed value for each point i and $\bar{Z}(x_i)$ = average of the observed values.

Results:

The results of some parameters related to suspended sediment and water discharge of Shoor Kharestan River are provided in Table 1. Fig.3 shows the sediment rating curve and regression relation between water and sediment discharge. Characteristics of optimum structure of artificial neural network used in study are given in Table 2.

Table 1: The values of some parameters of suspended sediment and water discharge in Shoor Kharestan River.

Parameter	Water discharge (m^3/s)	Sediment discharge (ton/day)
Mean	2.68	74.88
Standard deviation	2.97	130.50
Maximum	17.79	714.22
Minimum	0.18	0.730

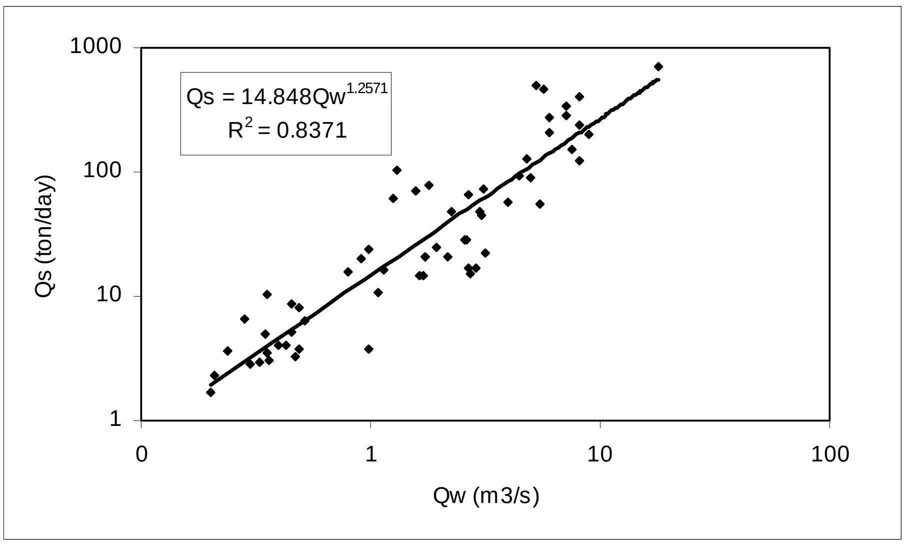

Fig. 3: Sediment rating curve of Shoor Kharestan River.

Table 2: Characteristics of optimum structure of artificial neural network in study area.

Number of input layer neuron	1
Number of first hidden layer neurons	20
Number of second hidden layer neurons	7
Number of output layer neuron	1
Transfer function	Gaussian-Sigmoid-Sigmoid
Learning rate	0.01
Momentum coefficient	0.8
Iteration	200000

Table 3 describes the results of artificial neural network and sediment rating curve based on RMSE, MAE and R^2. Comparison diagrams of estimated and observed sediment yield by ANN and sediment rating curve methods are shown in Figurs 4 and 5, respectively.

Table 3: Evaluation of the results related to ANN and sediment rating curve.

Factor / Method	R^2	MAE	RMSE
Sediment rating curve	0.74	20.75	36.84
ANN	0.98	12.14	19.27

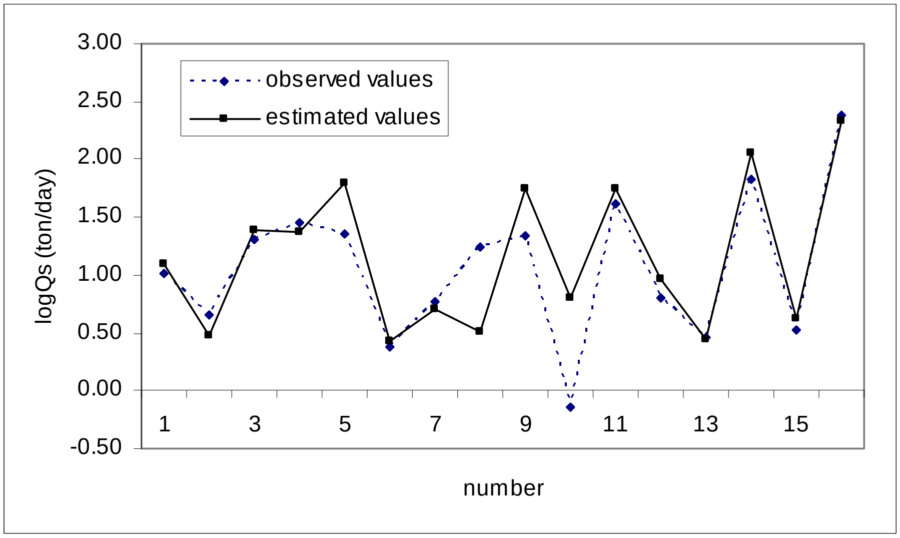

Fig. 4: Comparison diagram of estimated and observed sediment yield by ANN model.

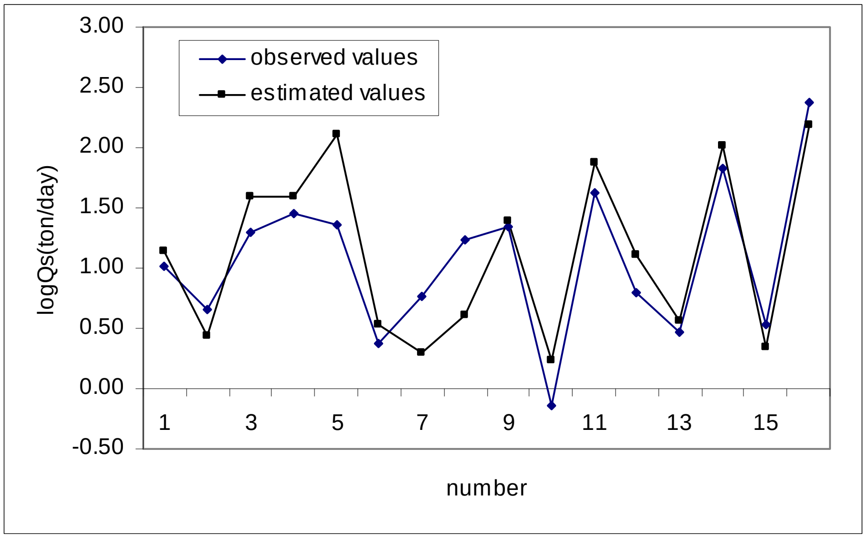

Fig. 5: Comparison diagram of estimated and observed sediment yield by sediment rating curve.

Figs. 6 and 7 show the correlation between estimated and measured values of sediment rating curve and artificial neural network model, respectively.

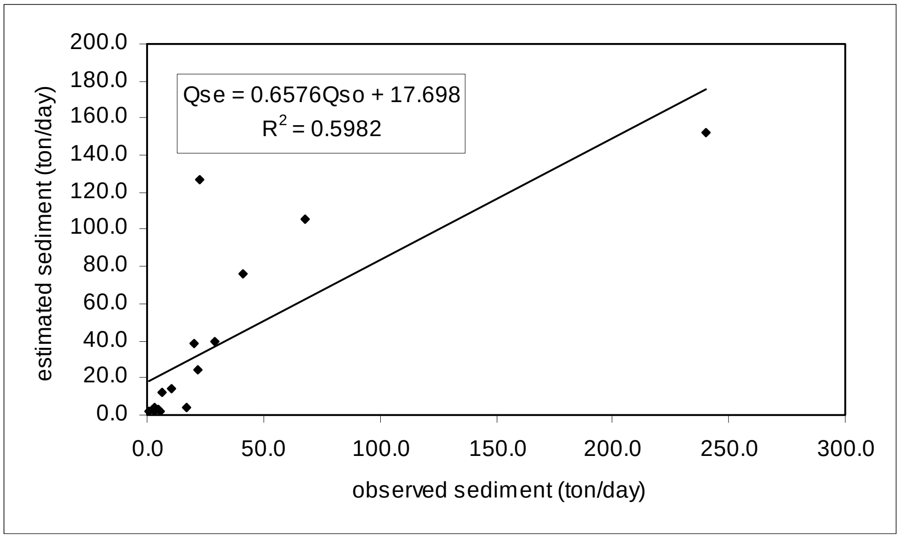

Fig. 6: Correlation between observed and estimated sediment of sediment rating curve.

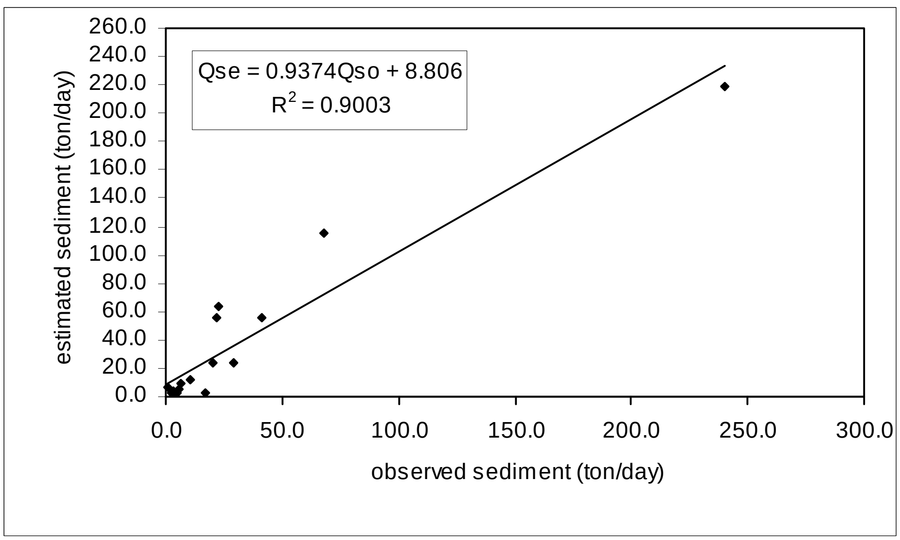

Fig. 7: Correlation between observed and estimated sediment of ANN model.

Discussion and Conclusion:

Direct measurement of sediment yield is difficult and needs sufficient time and money. However estimation methods have long error and different accuracy. This research was conducted in Kharestan Watershed for accuracy evaluation of artificial neural network model and sediment rating curve. Results of Table 2 showed that optimal structure of artificial neural network used in this study contains 4 layers perceptron construction with 1 neuron in input layer, 20 neurons in first hidden layer, 7 neurons in second hidden layer and 1 neuron in output layer so that it could pass training and make network mean error acceptable using learning law of error back propagation after 200000 iteration. The comparisons results of two methods showed that the values of RMSE, MAE and R^2 for artificial neural network are 19.27 , 12.14 and 0.98 respectively. While these values for sediment rating curve are 36.84, 20.75 and 0.74 respectively (Table 3). Since selection criteria for an appropriate method in suspended sediment estimation is lower RMSE and MAE and higher R^2, it is therefore concluded that artificial neural network estimations compared with sediment rating curve have more accuracy and lower error, they could estimate suspended sediment yield changes in Kharestan Watershed better than sediment rating curve method (Figs. 4 and 5). Also the comparison of Figures 6 and 7 showed that the determination coefficient of artificial neural network model is R^2=0.90 while for sediment rating curve is R^2= 0.58. This shows higher accuracy artificial neural network model than sediment rating curve for suspended sediment estimation.

Therefore, results showed that artificial neural network model is a useful tool for estimation of hydrologic parameters such as daily suspended sediment in Kharestan Watershed in a higher accuracy.

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