Environmemtal Resources Research (ERR)
Print ISSN: 2783-4832
Online ISSN: 2783-4670

Prediction of daily suspended sediment load using the Genetic Expression Programming and Artificial Neural Network models

Adele Alijanpour Shalmani[1]*, Ali Reza Vaez[2], Mahmoud Reza Tabatabaei[3]

[1] Ph.D., Soil Science. Department, University of Zanjan, Zanjan, Iran. Email: Adele.alijanpour@gmail.com
[2] Professor, Soil Science. Department, University of Zanjan, Zanjan, Iran. Email: vaezi.alireza@gmail.com.
[3] Associate Professor, Soil Conservation and Watershed Management Research Institute, Agricultural Research, Education and Extension Organization (AREEO), Tehran, Iran.Email: taba1345@hotmail.com

Article Info

Article type:
Research Article

Article history:
Received: 4 may 2021
Accepted:15 December 2021

Corresponding author:
Adele.alijanpour@gmail.com

Keywords:
Daily discharge
Daily precipitation
Clustering
Gamma test
Self-organizing map
Smart model

Abstract

Because of the quantitative and qualitative problems of Daily Suspended Sediment Load (SSL) data with direct measurement, it is important to use methods for predicting it in watersheds. In this research, two methods consisting of the artificial neural network (ANN) and Genetic Expression Programming (GEP) were used to predict SSL. The studied area was a watershed in north of Iran. Input data included instantaneous flow discharge (Q), average daily flow discharge (Qi), average daily precipitation (Pi) and the output was SSL. A clustering method was used to homogenize data for the self-organizing map (SOM) method and then, all data were divided into three groups including 70, 15 and 15% for training, validating and testing, respectively. Also, the gamma test method was used to determine the best combination of input variables. In all combinations of inputs to the ANN and GEP models, the ANN model with tangent sigmoid activation function and input variables combination including Q, Q_i, Q_{i-2}, Q_{i-3}, P_i, P_{i-2}, P_{i-3} was the best for estimating SSL in the area with a root mean square error of 1995.3 (ton day $^{-1}$) and the Nash-Sutcliff efficiency of 0.96. In general, the results of this study showed that intelligent models are capable of accurately estimating the SSL value. Also, using SOM preprocessing techniques and gamma tests increased the generalization power of the models. We also found that choosing the most influential variables and their best combination increased the modeling power and accuracy of SSL estimation, respectively.

Cite this article: Adele Alijanpour Shalmani, Ali Reza Vaez and Mahmoud Reza Tabatabaei. 2022. The effect of exclosure on cultural services of semi-arid shrublands of Kerman province, Iran. *Environmental Resources Research*, 10 (1), 115-132. DOI: 10.22069/ijerr.2022.6056

© The Author(s).
DOI: 10.22069/ijerr.2022.6056
Publisher: Gorgan University of Agricultural Sciences and Natural Resources

Introduction

Soil erosion by water results in the loss of fertile agricultural soil and useful foodstuffs such as clay and organic matter, which are transported in sediments by heavy metal elements and contaminated water (Kisi et al., 2012; Chen and Chau, 2016). Soil erosion by water is the major factor controlling sediment production in the watersheds (Wang et al., 2016; Ochoa et al., 2016). The sediment yield of a catchment represents only a part of the total soil erosion within the watersheds (Li and Yang, 2010; Masselink et al., 2016). It is dependent on all variables that control erosion and sediment delivery in the catchment (Baartman et al., 2013; Marchamalo et al., 2016). This variable is as an effective factor in understanding the process of aggravation of erosion and sediment and essential in the management and planning of soil and water resources particularly in arid areas. The Daily Suspended Sediment Load (SSL) is the weight of materials that pass through a given cross-section at a given time, which is ton day^{-1}. The optimal design and proper operation of water resources structures require accurate estimates of SSL and sediment load (Tayfur, 2012).

The soil erosion (harvesting) cycle, the transport and sediment that controls the sediment yield of a watershed, includes a set of complex and highly nonlinear processes (Azamathhulla et al., 2013; Kaveh et al., 2017). All stages of this cycle are influenced by natural factors and human interactions. Therefore, it is very difficult to quantitatively and accurately describe all the important factors that cause measurement and prediction of the sediment (Li et al., 2010). Therefore, due to the uncertainty in the full knowledge of the processes affecting the erosion and sedimentation of watersheds, it seems that in modeling SSL, instead of focusing on presenting a quantity equation in this case, pay attention to the response of the watershed for the inputs to it (Such as dynamic variables of watershed such as precipitation) which creates different behaviors in the watershed, is important. In this regard, the use of soft computing methods such as artificial neural networks and Genetic Expression Programming can be good tools for quantifying SSL in the watershed. In this method, the main focus is on determining the response of the watershed to the inputs rather than on the detailed description of the processes in the watershed and its physical characteristics (Tayfur, 2012).

Extensive efforts have been made by researchers to estimate the SSL worldwide. Melesse et al. (2011) used the Multilayer Perceptron Neural Network Model to estimate the suspended sediment using daily and lag time discharge and sediment data in the three major rivers in the United States. The results showed that the accuracy of MLP in estimating the sediment load of the rivers (R^2=0.97) was higher than the regression (linear and nonlinear) models. Mustafa et al. (2012) used a MLP in an investigation to estimate the suspended sediment in the Peri River in Malaysia. They used four different methods Gradient Descent, Gradient Descent with Momentum, Scaled Conjugate Gradient and Levenberg Marquardt (LM) to learning the neural network. The results showed that LM method (with R^2=0.99) and combined gradient method (with R^2=0.98) were better than other methods to estimating suspended sediment. The LM method was faster than the combined gradient method resulting in network convergence. Wolfs et al. (2014) compared the linear regression method with sediment rating curve, ANN model and M50 tree methods using discharge and SSL data in the Marc and Dener rivers in Belgium. The results showed that all models except to linear regression method were more accurately with the least estimation error (RMSPE=6.34) and the highest degree of fit for predicting SSL (R^2= 0.99). Tfwala and Wang (2016) compared the two models: Sediment Rating Curve and artificial ANN for more accurate estimation of sediment load in Taiwan's shion River. They used 170 suspended sediment and flow discharge data to estimate sediment load and developed new models using 80 percentages of data. The results showed that the ANN model with a R^2 of 0.903 had more power in estimating the SSL compared to the Sediment Rating Curve (R^2= 0.76). Emamgholizadeh and Karimi Demneh (2018) estimated the amount of the SSL using the GEP, ANFIS and ANN methods in the Telar watershed. The GEP with R^2=0.75 and MAE=1269.7 was more accurate method than other methods. Norouzi et al. (2021) to estimate the suspended sediment load in the Kasilian watershed in Mazandaran, used one-line, two-line and mean-load rating curves methods. The variables used in this study were discharge and suspended sediment load, during the statistical period of 13 years (2006-2015). The results showed that the mean-load method with R^2=0.89 and NSE=1 had better performance compared to other methods in estimating suspended sediment load.

The selecting inputs from all variables affecting SSL variables are an essential step in the modeling using soft computing method. Additionally, performing preprocessing and find out a suitable combination of variables is very important in nonlinear modeling. The genetic algorithm and principal components analysis are methods for extracting major factors controlling the study variable. One of the methods that have recently been taken up by the hydrologists is the gamma test method (Ghabaei Sough et al., 2010; Shamim et al., 2016).

One of the other important issues in modeling is data clustering. The clustering data plays an important role in generating homogeneous and similar data sets (such as calibration, cross validation and test data sets) for use in the models (such as regression and ANN). Failure to use similar and homogeneous data in three sections will affect negatively on the accuracy and performance of the designed models and will reduce considerably their generalization power (May, 2010). Less information exists on the homogeneity of data and the selecting as well as combination of variables in the ANN model and others (Tayfur, 2012). Little studies have been done in this way. Bowden et al. (2002) used self-organizing map method (SOM) and the neural network to predict the amount of salt in the Murray River in southern Australia. The results of the research showed the superiority of the performance of the neural network model with clustered data compared to when the data were randomly categorized. Tabatabai et al. (2019) proposed a multi-objective optimization approach using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to increase the efficiency of the SRC model in estimating the suspended sediment load in the Ramian watershed River in northern Iran. The input data was instantaneous flow discharge and SSL data. Data clustering was performed using self-organizing map (SOM) and SRC model including conventional SRC models and optimized models (single-objective and multi-objective optimization algorithms) were evaluated. Comparative analysis of the results showed that the optimal SRC model obtained through NSGA-II algorithm with R^2=0.84 and NSE=0.83 was superior to the SRC models in daily SSL estimation for the data used in this study. Nour et al. (2006) used artificial neural network and SOM clustering methods to estimate daily suspended sediment and phosphorus concentration in rivers of two forest areas in northern Canada. In a similar study, Li et al. (2010) used the SOM and the neural network to estimate nitrogen released from the five forest areas in northern Canada. These studies indicated that the homogeneity causes the data used in all three training, cross validation and test data sets to be representative of all data during a given statistical period and in consequence can improve the efficiency and accuracy of modeling (Tokar and Johnson, 1999). For this purpose, the self-organizing map neural network (SOM) and data clustering (Zhu, 2007) along with the gamma test will be used to predict SSL. In humid and cold areas at high altitudes, due to mountainous and slope of the area, severe storms and flooding, soils with low to moderate organic matter, degradation or weakness of vegetation and incorrect use of land, are the causes of erosion and sediment production and the accurate analysis of SSL is the basis for knowing these factors. Therefore this study was conducted to evaluate some methods consisting of self-organizing map, ANN with log sigmoid and tangent sigmoid activation functions and Genetic Expression Programming and gamma test for estimating SSL in a humid watershed.

Materials and Methods

Study Area

The study area was Karaj watershed which covers the Amirkabir dam in north of Iran, installed to supply drinking water for Tehran, the capital of Iran. The watershed is located in 51°3’ - 51° 35’ E longitude and 35°53’–36°11’ N latitude about 50 kilometer away from northwest of Tehran (Figure 1). The watershed surface area is

842 square kilometer with a perimeter of 274 kilometer, mean elevation of 2899 meter above sea level, length of Major River of 47 kilometer and medium river slope of 37.4 percentages. With regarding to a Gravelius factor of 2.68 and form factor of 2.69, the watershed is long shape and noncircular indicating longer concentration time. The climate is humid type with a mean annual precipitation of 671 mm and temperature of 8.24 °C. The soils are mostly Entisols and Inceptisols according to the Soil Taxonomy classification (Soil survey staff, 2010).

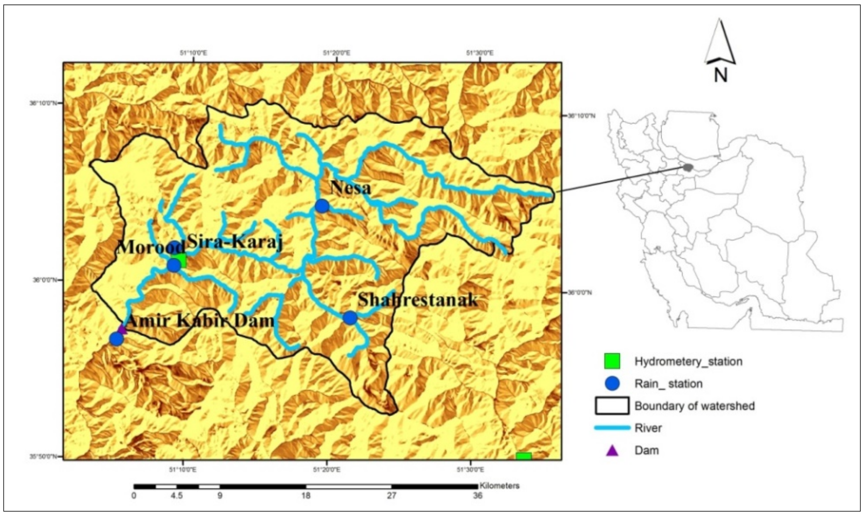

Figure 1. Location of the Karaj watershed in north of Iran

Data Used

The Sira hydrometric station located in south west of the Karaj Watershed was used to estimate SSL in the area. The data used in this research included 624 information records for a- 31 year from 1981 to 2011. Input data to the models included instantaneous flow discharge (Q), average daily flow discharge (Q_i), average daily flow discharge for one day ago (Q_{i-1}), average daily flow discharge for two day ago (Q_{i-2}), average daily flow discharge for three day ago (Q_{i-3}), average daily precipitation (P_i), average daily precipitation for one day ago (P_{i-1}), average daily precipitation for two day ago (P_{i-2}) and average daily precipitation for three day ago (P_{i-3}) and output data was daily suspended sediment load (SSL). The lowest instantaneous flow discharge was 2.63 m^3 sec^{-1} and its maximum value was 136.17 m^3 sec^{-1}.The lowest SSL was 0.74 ton $day^{-1}$and the highest value is 62958.91 ton day^{-1}.

Input variable selection

Gamma test estimates the minimum mean squared error that can be obtained in continuous nonlinear models with unobserved data (Chaudhary et al. 2014). Suppose there is a series of observational data of the Equation 1:

$$((x_1 \ldots x_m), y) = (X, y) \qquad (1)$$

where; $(x_1 \ldots x_m)$: is the input vector at the range of $C \in R^m$, and y is the output vector. If Equation 2 exists between members of the community:

$$y = f(x_1 \ldots x_m) + r \qquad (2)$$

r is the random variable. Gamma test is an estimate for the output variance of a non-uniform model. Gamma test is based on N [i, k] which contains a list of k ($1 \le k \le p$) neighbors for each vector X_i ($1 \le i \le M$). The delta function calculates the mean square of Kth distance the nearest neighbors (Equation 3):

$$\delta_m(k) = \frac{1}{M}\sum_{i=1}^{M}\left|X_{N[i,k]} - X_i\right|^2 \qquad (3)$$

where; |.| indicates the Euclidean distance. Corresponding gamma function is shown in Equation 4:

$$\gamma_m(k) = \frac{1}{2M}\sum_{i=1}^{M}\left|y_{N[i,k]} - y_i\right|^2 \quad (4)$$

where; $y_N[i,k]$: is the corresponding value for the Kth nearest neighbor of Xi in Equation (3). For calculate Γ, a linear regression line of P points is fitted on values of $\delta_m(k)$ and $\gamma_m(k)$ (Equation 5):

$$\gamma = A\delta + \Gamma \quad (5)$$

Intercept vertical axis (δ= 0) is the Γ value which represents the portion of the output data variance that cannot be predicted by the model and $\gamma_m(k)$ is equal to variance errors which illustrates the complexity of a model made up of an input and output data set and the slope the faster it is shows the complexity of the model.

Another important criterion that can be obtained using gamma test is the v_{ratio} dimensionless criterion (Equation 6) that has values between 0 and 1 (Chaudhary et al., 2014).

$$V_{ratio} = \frac{\Gamma}{\sigma^2(y)} \quad (6)$$

where; $\sigma^2(y)$: is output variance of y. And the closer this criterion to zero, it represents the high accuracy of the model to find the optimal outputs of inputs. In fact, if the value of v_{ratio} is reduced from the number one then the value of the coefficient of explanation is shown (Moghaddamnia et al., 2009).

If we assumed that n as the input parameter is effective on the occurrence of a phenomenon; the number 2^n-1 is created a significant combination of input parameters. For modeling this phenomenon using ANN and GEP models, it is a very time-consuming and boring to check all the compounds created to find the best combination. Therefore, when the number of effective parameters in a phenomenon is high, we can use the gamma test to arrange the importance of the input parameters and the best combination of all possible combinations (Shamim et al., 2016). In order to obtain the best combination of input into ANN and GEP models, in the WinGamma™ software, the full embedding and Genetic Algorithm commands were used.

Self-organizing map (SOM) clustering method

For the power of generalization of Artificial Neural Networks and Genetic Expression Programming models, it was necessary that the samples used in models (train, cross validation and test data in terms of characteristics), be representative for all samples during the statistical period. For this purpose, Self-organizing map (SOM) clustering method was used for data clustering. Also to ensure the homogeneity of the three data groups of clustering, proportional allocation method was used (Zhu, 2007).

An artificial neural network of self-organizing map was an uncontrollable neural network and its training algorithm is competitive. The basis of the SOM was the Euclidean distance. The value of the Euclidean distance was obtained from equation 7 (Chaudhary et al., 2014).

j=1,2,…, M

$$D_j = \left|x - w_j\right| = \sum_{i=1}^{N}\left[(x_i - w_{ji})^2\right]^{\frac{1}{2}} \quad (7)$$

where; Dj: Distance of neuron j of output layer from input vector x (X=(xi;i=1,2,3,.,N) ∈ R^n), N: Number of input vector variables, M: The number of neurons in the output layer, W_{ij}: Weight of the output neuron (Wji; j=1,2,…, M; i=1,2,…, n) and sing $|x - w_j|$ represents distance (Bowden et al., 2002).

This network consists of an input layer and an output layer. The number of input neurons was equal to the number of input variables and the output layer was a network of neurons each neuron of which connects to all neurons in the input layer. The output layer neurons enters three phases of competition, collaboration and matching with the input layer neurons and finally, the best overlapping network with neurons of input layer is created.

Validation of clusters by Davies Bouldin Index

Validation indicators Davies Bouldin Index to determine the optimal number of cluster moods is used. Davies Bouldin Index uses the similarity between two clusters (R_{ij})

based on the dispersion of a cluster (s_i) and the lack of similarity between two clusters (d_{ij}).

Usually, similarity between two clusters is defined from equation 8 (Bolboaca et al., 2006):

$$R_{ij} = \frac{s_i + s_j}{d_{ij}} \quad (8)$$

Where, R_{ij}: similarity between i and j clusters; S_i and S_j: dispersion of i and j clusters; and d_{ij}: the distance between the center of two clusters.

The index actually calculates the average of similarity between each cluster with the closest cluster to it. The lower the index, the better clusters are produced. Finally, the clusters are created where the data in each cluster is homogeneous and representative of the total data (Fort, 2006). Thus, the data are divided into three groups of homogeneous train, validation and test, respectively 70 percent for train data, 15 percent for validation data and 15 percent for test data.

Feed-forward Multi-layer Perceptron (FFMLP) of ANN

Neural Networks inspired by biological neurons have the ability to learn the relationships between inputs and outputs of a process according to the previous data set of that process without knowing the set of hidden rules governing that process. Artificial neural network of the perceptron consists of three layers of input, hidden and output. Input layer neurons are the location of input parameters and the number of input and output layer neurons is equal to the number of input and output variables of the model, respectively. The number of hidden layer neurons is also selected by the designer due to the complexity of the model and the output variables (He et al., 2014; Zounemat-Kermani et al., 2016). The function of the neural network is determined by the way of connecting the components by setting the values of each connection which is called the weight of the connection (Kaufman et al., 2009).

One of the useful types of networks used in hydrology and sediment was Feed-forward Multi-layer Perceptron Neural Networks With the training pattern of Back Propagation error. In this kind of neural networks, for streaming data, from the input layer to the hidden layer and from the hidden layer to the output layer and in this sense, they are referred to as Feed-forward neural networks (Tayfur, 2012). In order to train the neural network, the error value is calculated in the direction of the maximum tilt of the error function and this value is sent to the previous layers (layers or hidden layers) to reduce the error value by resetting the values of the neurons (Tayfur, 2012). Delta law is defined from equation 9:

$$W_{ij}^{new} = W_{ij}^{old} - \eta \frac{\partial E}{\partial W_{ij}} \quad (9)$$

Where; W_{ij}^{old} and W_{ij}^{new}: respectively the weight between the neurons i and j before and after the specified repetition, η: the learning rate and E is the error function.

Network learning and error reduction continue to create network convergence. For learning of neural network, Lewenberg Marquardt method was used. The activation functions in the hidden layer neurons and the output layer were respectively considered log sigmoid or tangent sigmoid and linear. In this research, MATLAB R2013a software used for ANN modeling and, clustering and calculate cluster validity index.

Genetic Expression Programming (GEP)

The Gene Expression Programming model is a combination of Genetic Algorithm (GA) and Genetic Programming (GP) developed by Ferreira in 1999 and introduced in 2001 (Ferreira, 2001). GEP's structure is based on evolutionary calculations inspired by natural evolution in which both genotypes and phenotypes act independently. In this method, the chromosome genotype is similar to the genetic algorithm with a linear structure and the chromosome phenotype is a tree structure of variable length and size similar to the genetic programming algorithm (Baylar et al. 2011). Thus, the GEP algorithm by overcoming the dual role of chromosomes in its predecessor algorithms allows the application of multiple genetic operators with a permanent health guarantee for child's chromosomes and At a faster pace than GP, because of structural variation above GA, it searches for more possible responses (Cevik, 2007). In GEP, the processes of mutation, inversion, reproduction and selection of the best gene in a linear structure are performed and then expressed as a tree structure which makes it possible for the only modified genome to be transmitted to the next generation (Ferreira, 2001; Teodorescu and Sherwood, 2008). In the GEP method, variable modeling with a set of terminals (variables used in the model and constant values) and functions can be simple functions such as the main operators(+ - × /) or trigonometric functions such as (x2, exp, log) and etc. (Kayadelen et al., 2009). Functions are determined by the user according to the type of variable. In this research, GEPXpro Tools5.0 software was used for GEP modeling.

Standardization of data

Data standardization is done to reduce the data in the calculation of data entry into the WinGamma™ software or to avoid excessive weighing of neurons in neural network models. In this study, for data entry into the WinGamma™ software the standardization of data between [0 1] and the use of activation functions log sigmoid or tangent sigmoid in artificial neural networks, data standardization was performed between [0.1 0.9] and [-0.9 0.9].

$$Z = \frac{(X_i - X_{imin})}{(X_{imax} - X_{imin})} \quad (10)$$

$$Z = 0.1 + 0.8 * \frac{(X_i - X_{imin})}{(X_{imax} - X_{imin})} \quad (11)$$

$$Z = \left(1.8 * \frac{(X_i - X_{imin})}{(X_{imax} - X_{imin})}\right) - 0.9 \quad (12)$$

Where; Z is a standardized variable, X_i is the initial variable, X_{imin} is the minimum value and X_{imax} is is the maximum value.

Evaluating the performance of models

To assess the accuracy and validity of the calculated data using models relative to observational values, factor statistics Contains Coefficient of Determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and Nash-Sutcliffe (NS) were used, which was shown in equations 13, 14, 15 and 16 respectively were used.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(s_O - \overline{s_O})(s_M - \overline{s_M})}{\sqrt{\sum_{i=1}^{n}(s_O - \overline{s_O})^2 \sum_{i=1}^{n}(s_M - \overline{s_M})^2}}\right]^2 \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_M - s_O)^2} \quad (14)$$

$$MAE = \frac{\sum_{i=1}^{n}|(s_O - s_M)|}{n} \quad (15)$$

$$NS = 1 - \frac{\sum_{i=1}^{n}(s_M - s_O)^2}{\sum_{i=1}^{n}(s_O - \overline{s_O})^2} \quad (16)$$

Where; s_O and s_M respectively: observed and predicted suspended sediment load, $\overline{s_O}$: Average of observed suspended sediment load, $\overline{s_M}$: Average of predicted suspended sediment load and n is number of data. In this research, MATLAB R2013a software and SPSS22 software used for statistically analyzed.

Results and Discussion

Selected and combined variables for models

The test of all possible combinations based on the input variables for using in were the ANN and GEP models indicated there are five groups of variable combinations with the lowest gamma statistics standard error and V_{ratio}. Table 1 shows the results of the best combinations of input variables in the models with V_{ratio}, gamma statistics and standard error for both gamma test groups and genetic algorithms. According to Table 1, model 1 with input variables including Q, Q_i, Q_{i-2}, Q_{i-3}, P_i, P_{i-2}, P_{i-3}. Model 1 with the least amount of gamma statistics (0.0002), the standard error (0.0003) and V_{ratio} (0.0216) was the best and most efficient combination of input variables for smart models. Malik et al. (2017) used a smart and regression model for modeling the suspended sediment concentration in the Parnhita River in India. They used gamma test method to obtain optimal variable components for models, and the results showed that intelligent models with the best combination of input variables provide a more accurate estimate of sediment concentration compared to regression methods. Also, avoiding our results, Kumar Singh et al. (2018) and Shamim et al. (2016) also used gamma test for selecting the optimal variable composition for estimating daily solar radiation and daily volume of the reservoir.

The results showed that the use of these compounds with the coefficient R^2 is 0.88 and 0.90 accurate estimates of daily solar radiation and daily volume of the reservoir. These results correspond with the results of this research.

Table 1. The results of the best combination of input variables to the models.

Number of model	input variables combination	V_{Ratio}	Gamma	standard error
1	$Q,Q_i,Q_{i-2},Q_{i-3},P_i,P_{i-2},P_{i-3}$	0.0216	0.0002	0.0003
2	$Q,Q_i,Q_{i-1},P_i,P_{i-1},P_{i-2},P_{i-3}$	0.0734	0.0005	0.0005
3	$Q,Q_i,Q_{i-2},P_i,P_{i-2},P_{i-3}$	0.1012	0.0007	0.0006
4	$Q,Q_i,Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	0.0888	0.0006	0.0005
5	$Q_i,Q_{i-1},Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	0.1453	0.0011	0.0006

Clustered data with the SOM

Data clustering was performed using a Self-organizing map neural network (SOM). The optimal number of clusters with the lowest Davis Bouldin index (1.01) was 33 clusters (Figure 2). Then homogeneous data were divided into three groups: 70 percentage training data, 15 percentage validation data and 15 percentage test data. Table 2 shows the minimum (X_{min}), maximum (X_{max}), mean (X_{mean}), coefficient of variation (C_v) and skewness (X_s) of the three sets of training, validation and test data sets. The results of the three groups of training cross validation and test data showed the distribution of data homogeneously in three sets. The results showed that the data obtained from clustering in each set that will eventually be used in the model represent a representative of the total statistical period. This can increase the accuracy and efficiency of the models in estimating the suspended sediment load. Chen et al. (2017) used the SOM method to map the interaction between surface and underground waters in the Cooping Watershed area in southern Taiwan. The results showed a decrease in the complex data dimensions and the role of spatial distribution and seasonal variations in the relationship between surface water and underground water in preparing the topological map of the area. These results correspond with the results of this research.

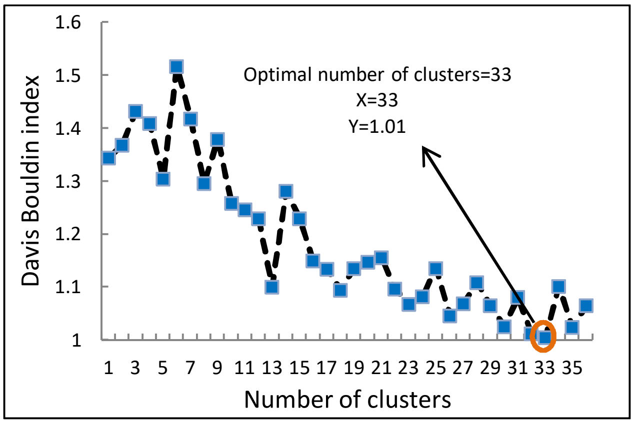

Figure 2. Davis Bouldin index Chart to determine the optimal number of clusters

Results of ANN models

Compounds of optimal variables obtained from gamma test and genetic algorithm were introduced into ANN models with two activation functions: log sigmoid and tangent sigmoid. The structure of neural networks for the activation function of log sigmoid and tangent sigmoid and the performance evaluation indicators for the test data sets for each model are presented in Tables 3 and 4, respectively. In Table 3, the result of test showed that MAE is 605.81 ton day-1, RMSE is 2204.42 ton day-1, NSE is 0.95 and R2 is 0.92 was the best model of ANN with log sigmoid activation function for estimating SSL. Also, in table 4, the results of test showed that MAE is 500.05 ton day^{-1}, RMSE is 1995.33 ton day^{-1}, NSE is 0.96 and R^2 is 0.96 was the best model of ANN with tangent sigmoid activation function for estimating SSL. Also, this model is the best input variables combination obtained from the gamma test and genetic algorithm method which appeared the least the gamma statistics (0.0002), standard error (0.0003) as well as V_{ratio} (0.0216). Therefore, the use of the gamma test preprocessing method has been able to discover the variables that affect the proper estimation of SSL and provide the best combination for entering models. In a similar study in this study, Rashidi et al. (2016) used an artificial neural network model in Korkorsar watershed in northern Iran to estimate SSL. The researchers used gamma test method to obtain the best combination of variables for entering the model. The results showed that the use of gamma test method increased the accuracy of the model in SSL estimation with R^2= 0.86 and NSE=0.88 compared to input compounds, without pre-processing with R^2=0.79 and NSE=0.73.

Table 2. Statistical parameters from clustered data using the SOM in three groups: training, validation and test

Data set	Data type	X_{min}	X_{max}	X_{mean}	C_v	X_s
Training	Q (m^3/s)	2.63	136.17	17.19	95.25	2.19
	Qi (m^3/s)	2.05	84.29	16.34	91.24	1.68
	Pi (mm)	0.00	72.28	4.88	206.93	2.78
	SSL (ton/day)	1.10	62958.91	1548.67	358.37	7.11
	Q_{i-1} (m^3/s)	1.95	87.16	14.77	85.34	1.54
	Q_{i-2} (m^3/s)	1.95	87.16	14.49	90.06	1.84
	Q_{i-3} (m^3/s)	2.14	87.95	14.21	87.73	1.65
	P_{i-1} (mm)	0.00	52.54	2.93	215.22	3.30
	P_{i-2} (mm)	0.00	72.28	2.36	288.48	5.61
	P_{i-3} (mm)	0.00	36.04	1.95	263.90	3.62
Cross validation	Q (m^3/s)	2.67	109.24	18.05	109.91	2.15
	Qi (m^3/s)	2.75	86.78	17.92	100.42	1.61
	Pi (mm)	0.00	57.50	5.12	205.99	2.85
	SSL (ton/day)	1.41	30048.52	1760.57	271.04	3.90
	Q_{i-1} (m^3/s)	2.76	54.60	15.34	90.68	1.18
	Q_{i-2} (m^3/s)	2.76	52.60	14.54	89.05	1.13
	Q_{i-3} (m^3/s)	2.76	52.20	13.99	90.19	1.23
	P_{i-1} (mm)	0.00	39.45	2.94	230.86	3.38
	P_{i-2} (mm)	0.00	22.46	2.37	223.62	2.51
	P_{i-3} (mm)	0.00	29.09	2.17	241.21	2.89
Test	Q (m^3/s)	2.82	102.19	16.58	109.91	2.39
	Qi (m^3/s)	2.90	87.95	15.32	100.42	2.21
	Pi (mm)	0.00	52.54	4.49	205.99	2.91
	SSL (ton/day)	0.74	49578.99	1564.17	271.04	6.65
	Q_{i-1} (m^3/s)	3.08	53.88	13.90	90.68	1.50
	Q_{i-2} (m^3/s)	2.92	56.27	13.25	89.05	1.53
	Q_{i-3} (m^3/s)	3.16	56.27	13.30	90.19	1.48
	P_{i-1} (mm)	0.00	31.22	2.38	230.86	3.35
	P_{i-2} (mm)	0.00	25.96	1.89	223.62	3.33
	P_{i-3} (mm)	0.00	27.66	1.40	241.21	4.53

Table 3. Results of ANN models with log sigmoid activation function

Number of model	input variables combination	Network structure	MAE	RMSE	NSE	R^2
1	$Q,Q_i,Q_{i-2},Q_{i-3},P_i,P_{i-2},P_{i-3}$	1:8:1	1020.65	3093.94	0.78	0.80
2	$\mathbf{Q,Q_i,Q_{i-1},P_i,P_{i-1},P_{i-2},P_{i-3}}$	**1:11:1**	**605.81**	**2204.42**	**0.95**	**0.92**
3	$Q,Q_i,Q_{i-2},P_i,P_{i-2},P_{i-3}$	1:11:1	984.32	2596.26	0.85	0.86
4	$Q,Q_i,Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	1:9:1	967.05	2684.87	0.84	0.86
5	$Q_i,Q_{i-1},Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	1:11:1	1146.64	3411.42	0.73	0.76

Table 4. Results of ANN models with tangent sigmoid activation function

Number of model	input variables combination	Network structure	MAE	RMSE	NSE	R^2
1	$\mathbf{Q,Q_i,Q_{i-2},Q_{i-3},P_i,P_{i-2},P_{i-3}}$	**1:11:1**	**500.05**	**1995.33**	**0.96**	**0.96**
2	$Q,Q_i,Q_{i-1},P_i,P_{i-1},P_{i-2},P_{i-3}$	1:10:1	984.41	2730.73	0.83	0.88
3	$Q,Q_i,Q_{i-2},P_i,P_{i-2},P_{i-3}$	1:11:1	957.56	2499.50	0.86	0.88
4	$Q,Q_i,Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	1:12:1	974.83	2689.36	0.84	0.89
5	$Q_i,Q_{i-1},Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	1:11:1	810.51	2917.90	0.75	0.88

Figure 3 and 4, respectively; show the scatter plot of the results of prediction SSL by ANN model with the activation function of log sigmoid and tangent sigmoid versus the observed values for test data set (15%). In figure 4, Model 2 was developed using the combination of variables including Q, Qi, Q_{i-1}, P_i, P_{i-1}, P_{i-2} and P_{i-3} following as:

$y = 0.8553x - 118.08.$

where y is predicted SSL (ton day^{-1}) and x is observed SSL (ton day^{-1}). The coefficient of explanation is 0.92. According to Figure 4, model 1 was developed using the combination of variables including Q, Q_i, Q_{i-2}, Q_{i-3}, P_i, P_{i-2}, P_{i-3}, following as:

$y = 0.9851x - 89.76.$

where y is predicted SSL (ton day^{-1}) and x is observed SSL (ton day^{-1}). The coefficient of explanation is 0.96. The proximity of the line slope of this model to number one indicates that the observed and estimated values of SSL are in high match with each other and the model has been able to accurately estimate SSL. This indicates the proper selection of input variables using the genetic algorithm and gamma test to estimate SSL. Kakaei Lafdani et al. (2013) investigated the ability of ANN model and Support Vector Machines (SVM) method to estimate SSL in the Duiraj River in western Iran. They used the flow discharge data as inputs and the sediment discharge as output. The best input variables for both models were determined using Genetic Algorithm and Gamma test. The results indicated that the models were superior to SSL estimates as compared to regression models.

Figure 5 and 6, respectively; show the results of the best model for prediction SSL by ANN models with the activation function of log sigmoid and tangent sigmoid versus the observed values for test data set. The use of data clustering and optimal combination of variables could predict SSL for low and high values with high accuracy. According this, Talebi et al. (2016) estimated SSL using the ANN model and Sediment Rating Curve (SRC) method in the Heydarabad watershed in western Iran for a-20 year from 1985 to 2006. The analysis of 233 data showed that an ANN model with back propagation algorithm had the most accurate estimation of SSL, especially in high values of sediment. Ulke et al., (2009) investigated on the estimation of SSL using the discharge and sediment variables in the Gediz River in Turkey. The results showed that the neural network (ANN) method had a more accurate estimate of the SSL (RMSE=1692 ton day^{-1}, R^2=0.92) rather than the multivariate regression. Kisi and Ozkan (2017) studied two stations data in the years 1966 to 1977 for modeling SSL on El River in California using three methods: least squares support vector machine (LSSVM), ANN and SRC models were compared. The results showed that ANN model had a more accurate estimate of suspended sediment (39%) compared to other models. These results correspond with the results of this research. Abbaspour et al. (2015) applied daily flow discharge and daily SSL data using the ANN and Sediment Rating Curve models in the Cham Anjir catchment in Lorestan, west Iran. The results indicated that ANN model had more accuracy in estimating sediment discharge with mean square error of 0.02 compared to Sediment Rating Curve. According this result, our findings confirmed the ANN model can reliably estimate SSL in a humid watershed. In fact, the ANN model, as an evolutionary and exploratory method, could, based on learning, discover the hidden relationships between the variables well and store the set of these relations as weights in the system, and ultimately, the corresponding response is similar to the output of the observation as the output Computational presentation. Therefore, the ANN model, with parallel processing of information similar to the human brain, is capable of estimating appropriate environmental variables such as SSL.

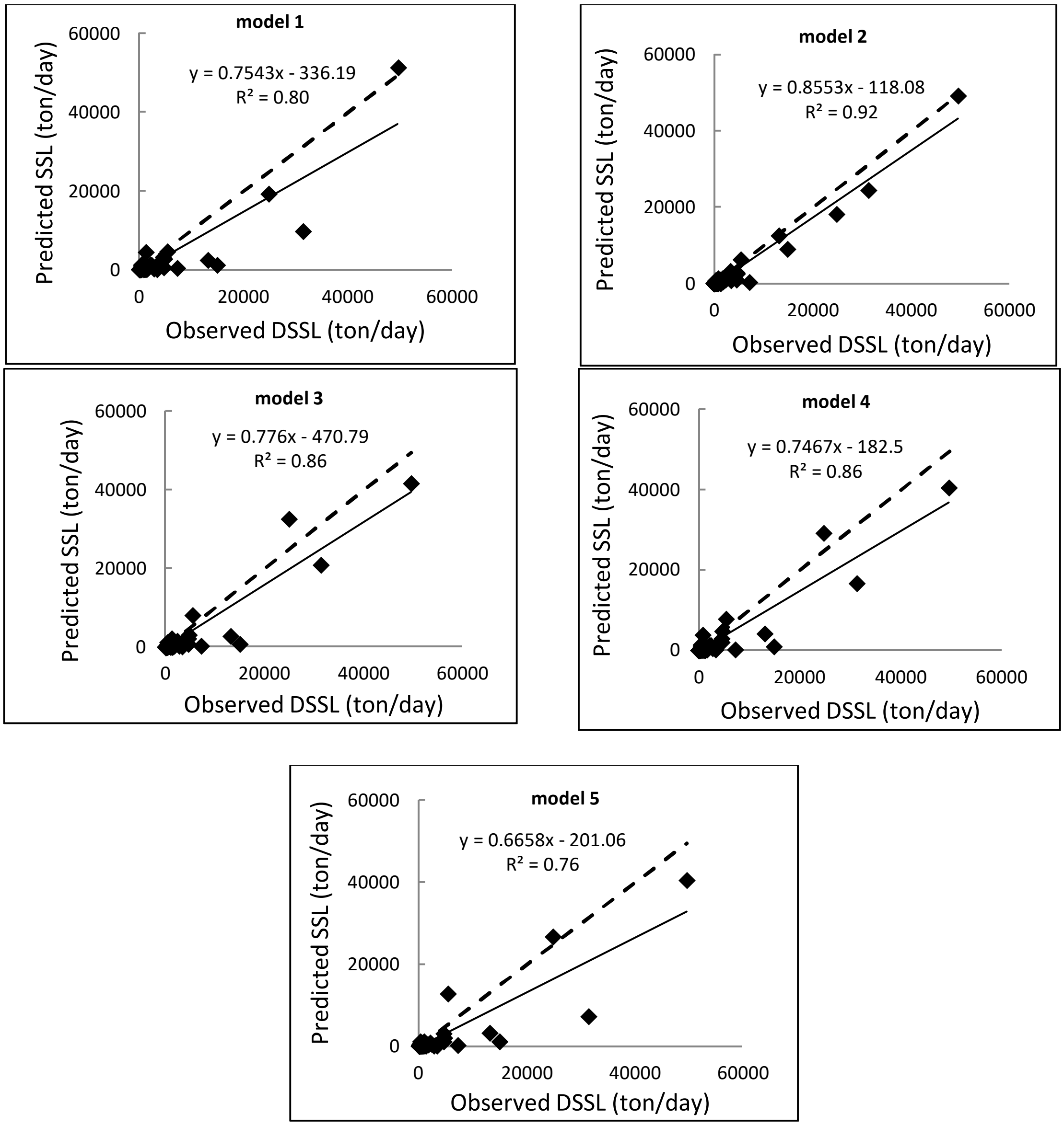

Figure 3. Values of SSL predicted by ANN with activation function of log sigmoid versus the observed values for test data for a 30-year period from 1980 to 2011

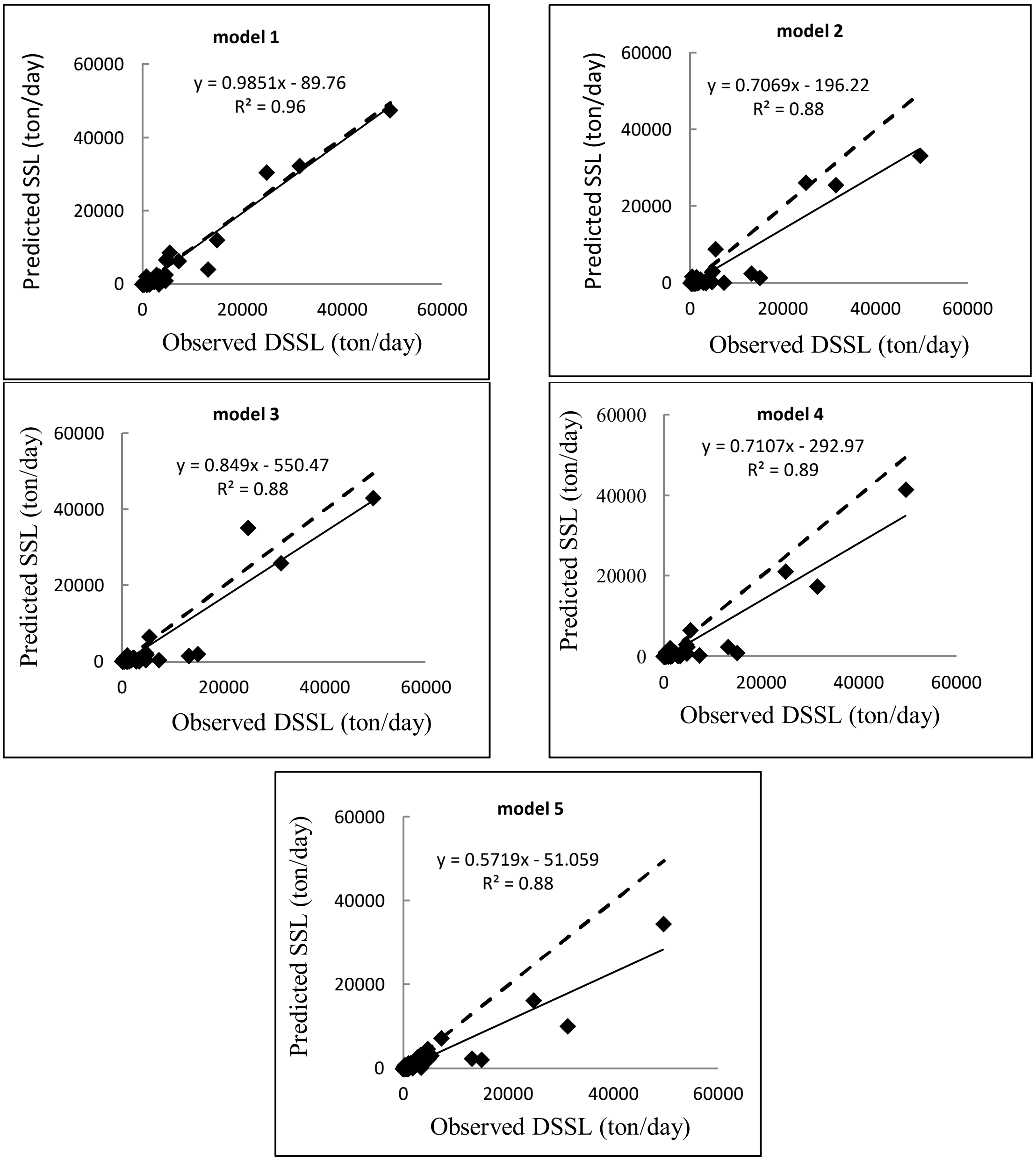

Figure 4. Values of SSL predicted by ANN with activation function of tangent sigmoid versus the observed values for test data for a 30-year period from 1980 to 2011

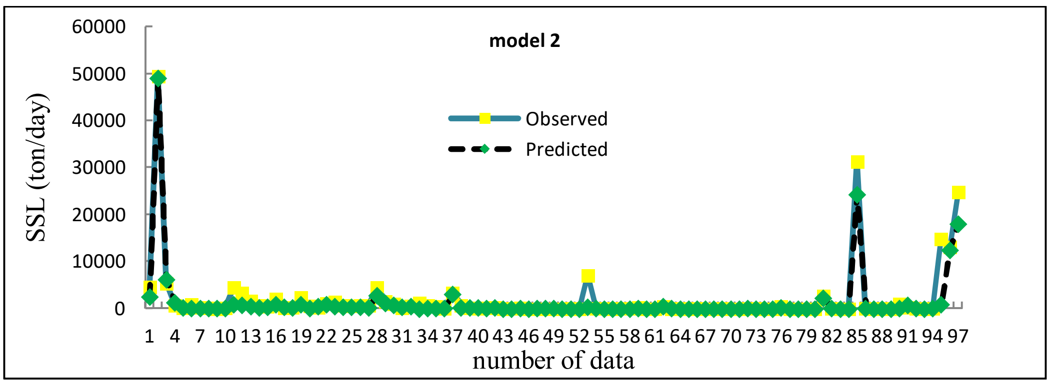

Figure 5. The results of the best model for prediction SSL versus observational values by ANN-log sigmoid model

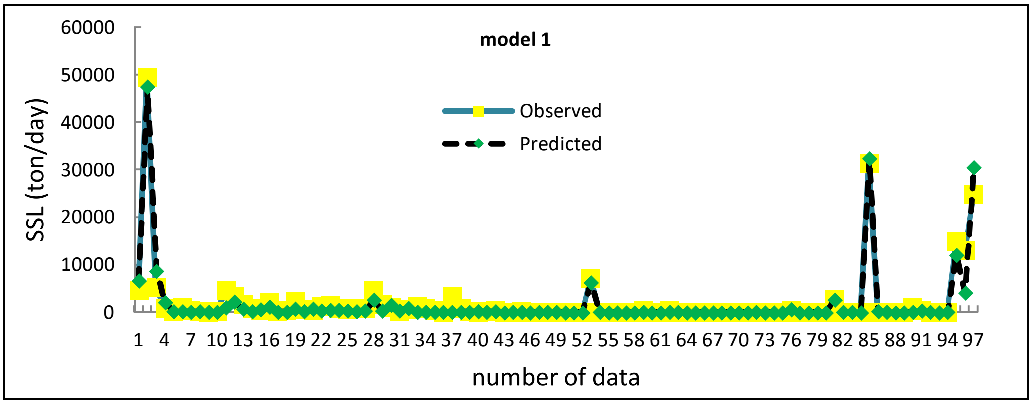

Figure 6. The results of the SSL estimated values by the Model 1 (ANN- tangent sigmoid model) for various data during a-31- year study period from 1980 to 2011.

Results of GEP models

The parameters and results of the GEP model for estimating SSL are shown in Tables 5 and 6, respectively. According to Table 5, the GEP model has the same length genes. The number of genes for the optimal response in this model was three and the number of chromosomes was thirty. Also, Fitness function for this model was considered RMSE.

Table 5. Parameters used by GEP model

Parameter	Setting of parameter	Parameter	Setting of parameter
Number of chromosomes	30	One-point recombination rate	0.3
Number of Genes	3	Two-point recombination rate	0.3
Linking function	+	Gene recombination rate	0.1
Mutation rate	0.044	Number of head	10-18
Inversion rate	0.1	Production population	1000
Number of Genes	3	Gene transposition rate	0.1

Table 6. Results of GEP models

Number of model	Input variables combination	MAE	RMSE	NSE	R^2
1	**$Q,Q_i,Q_{i-2},Q_{i-3},P_i,P_{i-2},P_{i-3}$**	**880.64**	**2385.72**	**0.88**	**0.88**
2	$Q,Q_i,Q_{i-1},P_i,P_{i-1},P_{i-2},P_{i-3}$	991.11	2919.77	0.82	0.83
3	$Q,Q_i,Q_{i-2},P_i,P_{i-2},P_{i-3}$	978.22	2616.59	0.83	0.83
4	$Q,Q_i,Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	960.41	2500.72	0.84	0.85
5	$Q_i,Q_{i-1},Q_{i-2},P_i,P_{i-1},P_{i-2},P_{i-3}$	1200.39	3214.84	0.71	0.72

Scatter plot of the results of estimating SSL versus the observed values for the test data sets by GEP models is shown in Figure 7. According to Table 6 and Figure 7, model 1 was developed using the combination of variables including Q, Q_i, Q_{i-2}, Q_{i-3}, P_i, P_{i-2}, P_{i-3}, following as:

$y = 0.8664x + 297.12$.

Where y is predicted SSL (ton day^{-1}) and x is observed SSL (ton day^{-1}). The coefficient of explanation is 0.88. The results of test showed that MAE is 880.64 ton day^{-1}, RMSE is 2385.72 ton day^{-1}, NSE is 0.88 and R^2 is 0.88. This model was the best model of GEP for estimating SSL. Sheikhipour et al. (2013) examined the SSL using GEP in the Sistan River. Results for test data with RMSE = 2305.45, MAE =1400.12 and R^2 = 0.88 showed that sediment can be estimated using high-accuracy GEP model. These results and Emamgholizadeh and Karimi Demneh (2018) results correspond with the results of this research.

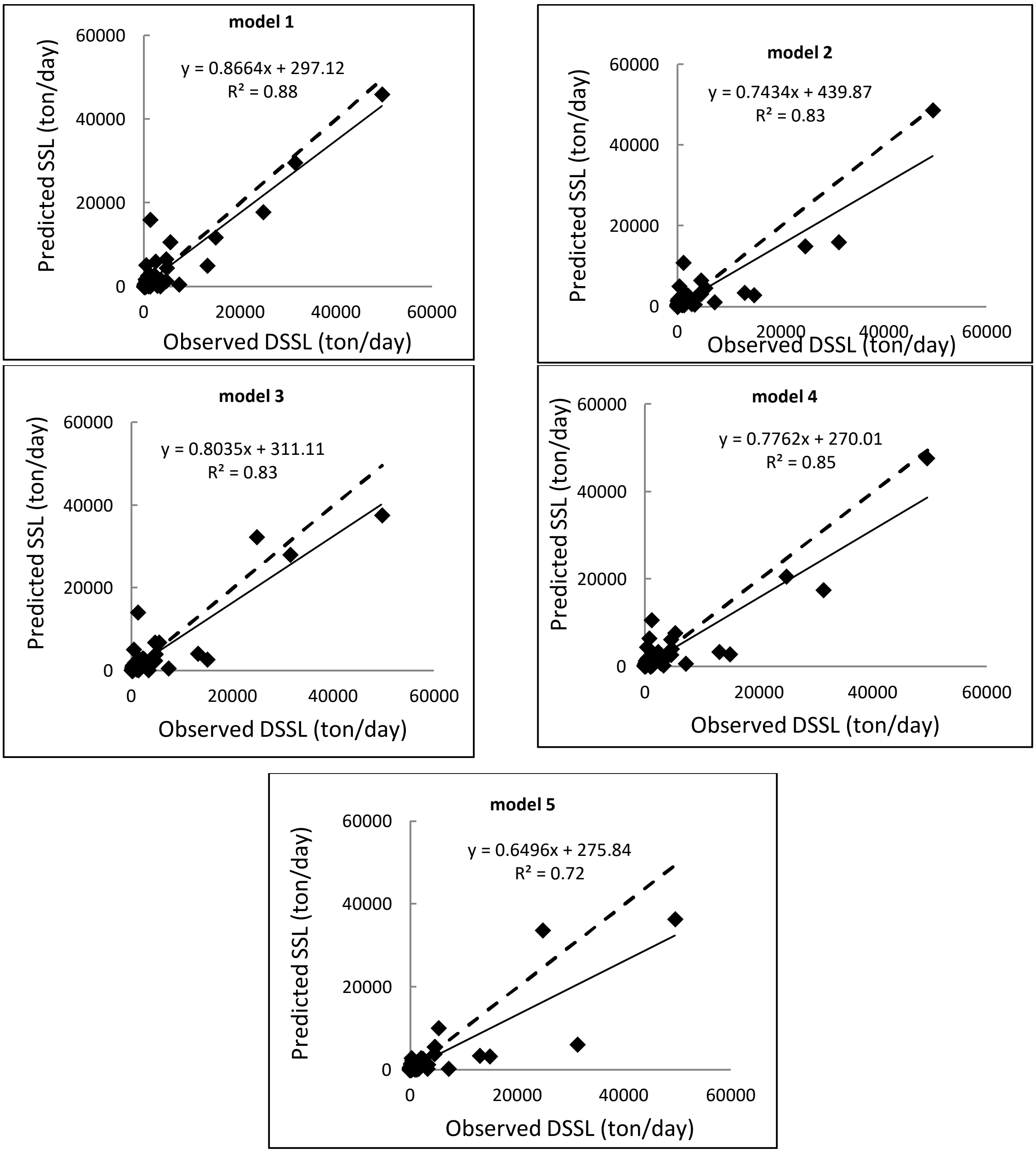

Figure 7. Scatter plot of prediction versus observed SSL for the test data sets by GEP model

Figure 8 show the results of the best model derived from the SSL estimate versus the observation values by GEP. By observing the data process in this figure, it is deduced that the GEP model has been able to perfectly match the data which illustrates the efficiency of this model in prediction of SSL. In this research, observed and predicted SSL adaptation in low and high values, in addition to the ability of intelligent models such as GEP in SSL estimating power, is related to clustering and the use of the SOM method. So, in using data clustering, watershed conditions are understood to model, and this makes the data in the three training, cross validation and test groups representative of the data in the entire statistical period. As a result, with clustered data, the model is well-trained and provides a desired output in test conditions by entering data. Tabatabaei and Salehpour Jam (2017) calibrate the SRC model using evolutionary algorithm to estimate the suspended sediment load in Shalman Rood watershed in north of Iran. In order to increase the generalizability of models, they used clustering methods using SOM neural network. The results indicate the effect of these methods on reducing the amount of RMSE from 5754 to 1681 tons per day.

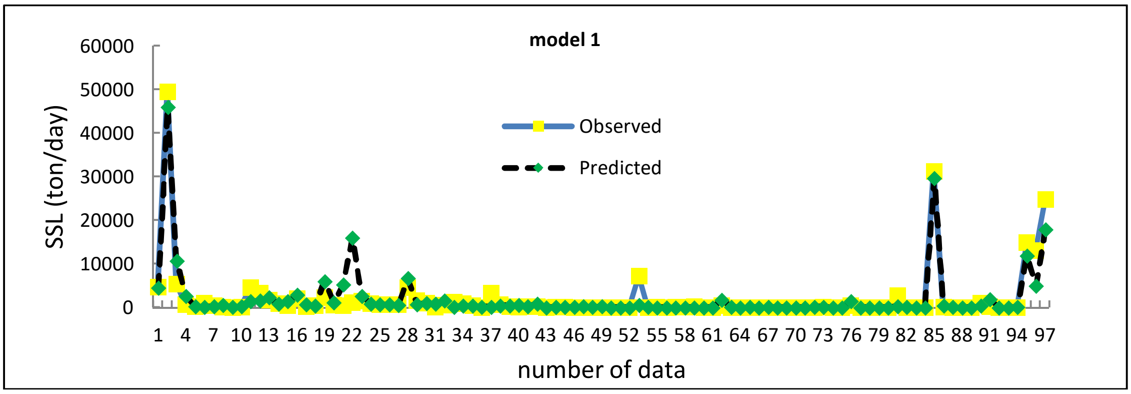

Figure 8. Graph of the results of the best model for prediction SSL versus observational values by GEP model

Conclusion

In this study, daily SSL of Karaj watershed was estimated by using the Genetic Expression Programming and Artificial Neural Network models. In this research, 512 combinations of inputs were obtained using nine input variables. The result indicated that the use of all possible input variables for ANN modeling with the log sigmoid and tangent sigmoid activation function and GEP modeling can be very difficult and tedious. So we used the gamma test and genetic algorithm methods to obtain the best combinations of the input variables. Using the gamma test and genetic algorithm methods, as a data preprocessing method, was able to reduce the estimation error by selecting combinations of appropriate input variables and by increasing the similarity between the values of observational data and computational data, increase the model performance in estimation SSL. The use of the self-organized mapping neural network (SOM) method in this research for data clustering enhanced the homogeneity of data in three sets of training, validation and test data sets for entering models. The use of the self-organized mapping neural network (SOM) method, made the distribution of data uniform in all three groups which could improve the accuracy and efficiency of the models in the SSL prediction. Among the methods of modeling (ANN models with log sigmoid and tangent sigmoid activation function and GEP model), the combination 1 with input variables of Q, Q_i, Q_{i-2}, Q_{i-3}, P_i, P_{i-2}, P_{i-3}, was the best model for estimating SSL in GEP and ANN- tangent sigmoid models. The ANN- tangent sigmoid model was able to predict the SSL value with a higher accuracy than the GEP model. In general, the use of modern modeling tools such as the ANN, GEP, SOM and the gamma test and genetic algorithm methods can be an important step in improving the performance of SSL estimator models. Given the uncertainty in the data and the multivariate space governing the input pattern of models, the use of smart models is inevitable. The structure and results of the models developed in this research can be tested for their usefulness in estimating evapotranspiration, nitrate and other variables in the watershed. It is suggested that other watershed dynamics variables such as temperature, snow cover and NDVI index be used in SSL modeling and its effect be seen in the output. And other intelligent methods such as artificial neural networks wavelet and support vector machine, etc., by considering the pre-processing methods of data clustering by SOM method and obtaining effective variables in modeling by Gamma test method is used for SSL modeling.

References

Abbaspour, B., and Haghiabi, A.H. 2015. Comparing the estimation of suspended load using two methods of sediments rating curve and artificial neural network (A Case Study: Cham Anjir Station, Lorestan Province). J. Environ. Treat. Tech. 3(4), 215-222.

Baartman, J.E.M., Masselink, R., Keesstra, S.D., and Temme, A.J.A.M. 2013. Linking landscape morphological complexity and sediment connectivity. Earth Surf. Process. Landf. 38(12), 1457–1471.

Baylar, A., Unsal, M., and Ozkan, F. 2011. GEP modeling of oxygen transfer efficiency prediction in aeration cascades. KSCE Journal of Civil Engineering. 15(5), 799–804.

Bolboaca, S.D., Jantschi, L. 2006. Pearson versus Spearman, Kendall's tau correlation analysis on structure-activity relationships of biologic active compounds. Leonardo Journal of Sciences. 5(9), 179-200.

Bowden, G.J., Maier, H.R., and Dandy, G.C. 2002. Optimal division of data for neural network models in water resources applications. Water Resources Research. 38(2), 1-2.

Cevik, A. 2007. A new formulation for longitudinally stiffened webs subjected to patch loading. Journal of Constructional Steel Research. 63(10), 1328–1340.

Chaudhary, V., Bhatia, R.S., and Ahlawat, A. 2014. The self-organizing map learning algorithm with inactive and relative winning frequency of active neurons. Journal HKIE Transactions. 21(1), 62–67.

Chen, I.T., Chang, L.C., and Chang, F.J. 2017. Exploring the spatio-temporal interrelation between groundwater and surface water by using the Self-Organizing Maps. Journal of Hydrology. 556, 131-142.

Emamgholizadeh, S., and Karimi Demneh, R. 2018. The comparison of artificial intelligence models for the estimation of daily suspended sediment load: a case study on Telar and Kasilian Rivers in Iran. Water Science and Technology: Water Supply. 1-14.

Ferreira, C. 2001. Gene Expression Programming: A New Adaptive Algorithm for Solving Problems. Complex Systems. 13(2), 87-129.

Fort, J.C. 2006. SOM's mathematics. Neural Networks. 19, 812–816.

Ghabaei Sough, M., Mosaedi, A., Hesam, M., and Hezarjaribi, A. 2010. Evaluation effect of input parameters preprocessing in artificial neural networks (ANNs) by using stepwise regression and Gamma Test techniques for fast estimation of daily evapotranspiration. Journal of Water and Soil. 24(3), 610-624.

He, Z., Wen, X., Liu, H., and Du, J. 2014. A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountainous region. Journal of Hydrology. 509(4), 379–386.

Kakaei Lafdani, E., Moghaddam Nia, A., and Ahmadi, A. 2013. Daily suspended sediment load prediction using artificial neural networks and support vector machines. Journal of Hydrology. 478(4), 25-50.

Kaufman, L., and Rousseeuw, P.J. 2009. Finding Groups in Data: An Introduction to Cluster Analysis. Hoboken, New Jersey: John Wiley and Sons.

Kaveh, K., Duc Bui, M., and Rutschmann, P. 2017. A comparative study of three different learning algorithms applied to ANFIS for predicting daily suspended sediment concentration. International Journal of Sediment Research, 32(3), 340-350.

Kayadelen, C., Gunaydin, O., Fener, M., Demir, A., and Ozvan, A. 2009. Modeling of the angle of shearing resistance of soils using soft computing systems. Expert Systems with Applications. 36(9), 11814–11826.

Kişi, O. 2012. Modeling discharge-suspended sediment relationship using least square support vector machine. Journal of Hydrology. 456(5), 110–120.

Kisi, O., and Ozkan, C. 2017. A new approach for modeling sediment-discharge relationship: Local weighted linear regression. Water Resources Management. 30(2), 1-23.

Kumar Singh, V., Kumar, D., Kashyap, P.S., and Kisi, O. 2018. Simulation of suspended sediment based on gamma test, heuristic, and regression-based techniques. Environmental Earth Sciences. 77, 708.

Li, X., Nour, M.H., Smith, D.W., and Prepasc, A.A. 2010. Neural networks modeling of nitrogen export: model development and application to unmonitored boreal forest watersheds. Environmental Technology. 31(5), 495–510.

Li, C. and YANG, S. 2010. Is chemical index of alteration (CIA) a reliable proxy for chemical weathering in global drainage basins?. American Journal of Science. 310(10), 111–127.

Malik, A., Kumar, A., and Piri, J. 2017. Daily suspended sediment concentration simulation using hydrological data of Pranhita River Basin, India. Computers and Electronics in Agriculture. 138, 20–28.

Marchamalo, M., Hooke, J.M., and Sandercock, P.J. 2016. Flow and sediment connectivity in semi-arid landscapes in SE Spain: patterns and controls. Land Degrad. Dev. 27(4), 1032–1044.

Masselink, R.J.H., Keesstra, S.D., Temme, A.J.A.M., Seeger, M., Giménez, R., and Casalí, J., 2016. Modelling discharge and sediment yield at catchment scale using connectivity components. Land Degradation and development. 27(4), 933–945.

May, R.J., Maier, H.R., and Dandy, G.C. 2010. Data splitting for artificial neural networks using SOM-based stratified sampling. Neural Networks. 23(2), 283-294.

Melesse, A.M., Ahmad, S., McClain, M.E., Wang, X., and Lim, Y.H. 2011. Suspended sediment load prediction of river systems: An artificial neural network. Agricultural Water Management. 98(5), 855-866.

Moghaddamnia, A., Ghafari Gousheh, M., Piri, J., Amin, S., and Han, D. 2009. Evaporation estimation using artificial neural networks and adaptive neurofuzzy inference system techniques. Advance Water Res. 32, 88-97.

Mustafa, M.R., Rezaur, R.B., Saiedi, S., and Isa, M.H. 2012. River suspended sediment prediction using various multilayer perceptron Neural Network training Algorithms—A case study in Malaysia. Water Resources Management. 26(7), 1879-1897.

Norouzi, A., Pajouhesh, M., Abdollahi, K., and Esmali Ouri, A. 2021. Estimating the Suspended Sediment Load and Evaluating the Homogeneity and Heterogeneity of Water and Sediment (Case Study: Kasilian watershed, Mazandaran). Iranian Journal of Echo Hydrology. 7(4), 1099-1112. (In Persian).

Nour, M., Smith, D., El-Din, M., and Prepas, E. 2006. Neural networks modeling of stream flow, phosphorus, and suspended solids: application to the Canadian Boreal forest. Water Science and Technology. 53(10), 91-99.

Rashidi, S., Vafakhah, M., Kakaei Lafdani, E. and Javadi, M.R. 2016. Evaluating the support vector machine for suspended sediment load forecasting based on gamma test. Arabian Journal of Geosciences. 9(11), 583.

Shamim, M.A., Hassan, M., Ahmad, S., and Zeeshan, M. 2016. A comparison of Artificial Neural Networks (ANN) and Local Linear Regression (LLR) techniques for predicting monthly reservoir levels. KSCE Journal of Civil Engineering. 20(2), 971–977.

Sheikhalipour, Z., and Hassanpour, F. 2013. Estimation of suspended sediment load using genetic expression programming. Journal of Civil Engineering and Urbanism. 3(2), 292-299.

Soil survey staff. 2010. Keys to soil Taxonomy USDA-NRCS. 327 pages.

Tabatabaei, M. and Salehpour Jam, A. and Hosseini S.A. 2019. Suspended Sediment Load Prediction Using Non-Dominated Sorting Genetic Algorithm II. International Soil and Water Conservation Research. 7(2), 119-129.

Tabatabaei, M., and Salehpour Jam, A. 2017. Optimization of sediment rating curve coefficients using evolutionary algorithms and unsupervised artificial neural network. Caspian Journal of Environmental Sciences. 15(4), 387-401.

Talebi, A., Mahjoobi, J., Dastorani, M.T., and Moosavi, V. 2016. Estimation of suspended sediment load using regression trees and model trees approaches (Case study: Hyderabad drainage basin in Iran). Journal of Hydraulic Engineering. 21(3), 1-8.

Tayfur, G. 2012. Soft computing in water resources engineering - Artifical Neural Networks, Fuzzy Logic and Genetic Algorithms. WIT Press, Southampton, England, UK.

Teodorescu, L., and Sherwood, D. 2008. High energy physics event selection with gene expression programming. Computer Physics Communications. 178(6), 409–419.

Tfwala, S.S., and Wang, Y.M. 2016. Estimating sediment discharge using Sediment Rating Curves and Artificial Neural Networks in the Shiwen River, Taiwan. Water. 8(53), 1-15.

Tokar, A., and Johnson, P. 1994. Rainfall-runoff modeling using Artificial Neural Networks. Journal of Hydrologic Engineering. 4(3), 232–239.

Ulke, A., Tayfur, G., and Ozku, S. 2009. Predicting suspended sediment loads and missing data for Gediz River, Turkey. Journal of Hydrologic Engineering. 14(9), 954-965.

Wolfs, V., and Willems, P. 2014. Development of discharge-stage curves affected by hysteresis using time varying models, model trees and neural networks. Environmental Modelling and Software. 55(4), 107-119.

Zhu, Y.M., Lua, X.X., and Zhoub, Y. 2007. Suspended sediment flux modeling with Artificial Neural Network: An example of the Longchuanjiang River in the Upper Yangtze Catchment, China. Geomorphology. 84(2), 111–125.

Zounemat-Kermani, M., Kişi, O., Adamowski, J., and Ramezani-Charmahineh, A. 2016. Evaluation of data driven models for river suspended sediment concentration modeling. Journal of Hydrology. 16(2), 1-40.