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Estimation of basin sediments using regression analysis and artificial neural network- A case study in Kordan Basin

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Abstract

Soil is an essential natural resource for life that provides the required substrate on which plants grow and flourish. One of the challenges for environmental specialists is to accurately estimate and control soil erosion. MPSIAC (Modified model of Pacific Southwest Inter-Agency Committee) is a common model for estimating erosion and sedimentation rate. In this study, we used MPSIAC, regression and artificial neural networks (ANN) to estimate sediment yield in Kordan Basin, a region in Alborz Province of Iran. The erosion and sedimentation data of the region were collated using the opinions of sedimentation experts. A linear regression was performed in Weka software to determine the factors influencing the sedimentation rate. Based on the results and the opinion of the experts, the factors with less impact on the sedimentation were removed. ANN was implemented using NeuroSolutions and Matlab software. The neural network was a Multi-Layer Perceptron (MLP) with one hidden layer and five neurons. The hidden layer consisted of tan-sigmoid activation function, and the output layer had a linear-sigmoid activation function. The algorithm used for training the neural network was Levenberg-Marquardt. The ANN results were superior to that of regression and the Matlab's output was more accurate than that of NeuroSolutions, with a mean square error of 0.009 for sediment yield. Finally, Matlab's neural network was extracted in the form of a function for later applications without the need to further training.

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Introduction

Today, preserving the soil and preventing its erosion is one of the basic duties of every country. Soil erosion causes huge and irreparable damage that not only leads to soil depletion and abandonment of agricultural lands, but also to sedimentation in canals, reservoirs, dams and ports, as well as reduction of water holding capacity 0 . According to the estimates by Food and Agriculture Organization (FAO), to maintain current food consumption standards, production in developing countries must double the amount produced in the year 1975. This will be achieved by increasing the area under cultivation, planting more crops per year and increasing productivity per unit area (Khalilmoghadam et al., 2009). Any mistake in using soil can cause irreversible damage, and the soil formed over many years will be destroyed in a short period of time. For example, each year, more than seven billion metric tons of fertile soil in Asian countries is washed into the sea in the form of sediment. If an average of 0.2 to 0.8 mm of soil is produced annually worldwide, at the current erosion rate, the soil loss rate will be 3 to 10 times that of the produced soil.

The main motivation in this paper is to present an artificial neural network approach to estimate basin sediment and to compare the results with existing approaches. The structure of the remaining sections is as follows. In Section 2, the basic concepts are briefly explained, and then we review the related work on the matter. Section 3 proposes the method and shows implementation of the regression algorithm and MLP neural network in Weka and NeuroSolutions and Matlab software, respectively. In Section 4, the results are analyzed, and the sediment yield values provided by Weka, NeuroSolutions, and Matlab are compared with that of MPSIAC. Section 5 comprises summary and conclusion of the paper.

Fundamental Concepts and Related Work

In this section, we review the fundamental concepts related to the neural network. After that, the latest research on the matter is reviewed.

Fundamental Concepts

Several important basic concepts require explanation. These concepts are PSIAC Model, MPSIAC Model, Artificial Neural Network, and Multi-Layer Perceptron (MLP), which are described below.

- **PSIAC Model**: This model was introduced in 1968 by the Pacific Southwest Inter-Agency Committee (PSIAC) in the United States (Vente and Poesen, 2005; Mansouri Daneshvar and Bagherzadeh, 2012). It is used to estimate soil erosion in drainage basins without any stations for measuring sediment yield. In this model, estimation of soil erosion is based on an appraisal of nine factors: geology, soil, climate, runoff, topography, vegetation, land use, existing erosion, and channel erosion.
- **MPSIAC Model:** In 1982, Johnson and Gembhart modified PSIAC and renamed it Modified PSIAC or MPSIAC. Briefly, the main modification was the change from the qualitative approach to a quantitative approach. In this model, to estimate erosion and sedimentation rates in a land component or hydrological unit, each of the nine factors mentioned above for PSIAC is calculated carefully based on the extent of its impact on soil erosion and sedimentation rates. The final result, taking into account all the nine factors, shows the rates of soil erosion and sedimentation in that unit (see Vente el al., 2005 and 0, 2012) for more details).
- **Artificial Neural Network (ANN)**: ANN is a data processing model imitating the human brain's neural network. Given their remarkable ability to derive conclusions from complex and vague data, various ANN’s can be used to detect patterns and trends that are extremely difficult for humans and computers to detect0. There are different neural network structures in terms of layers. In the simplest form of the neural network, there is one layer of input neurons connected to the neurons of the output layer through the weights assigned to them. In a multi-layer neural network, there is at least one intermediate layer called a hidden layer. With more hidden layers, the neural network gains the ability to analyze more complicated problems. Figure 1 shows a single-layer neural network (left-side) and a multi-layer artificial neural network (right-side).
- **Multi-Layer Perceptron (MLP)**: The concept of perceptron network was introduced by Rosenblatt in 1958. This network has three layers, with an intermediate layer known as the association layer. This network can learn to assign a random output to every given input. In 1974, Werbos developed the back-propagation (BP) training method, which was a multi-layer perceptron network with more powerful training rules 0. In MLP networks, every neuron has a nonlinear activation function. MLP networks are most useful in solving engineering problems, using the back-

propagation training rule. In the structure of MLP networks, every neuron in each layer is connected to every neuron in the next layer. This layout forms a fully connected network.

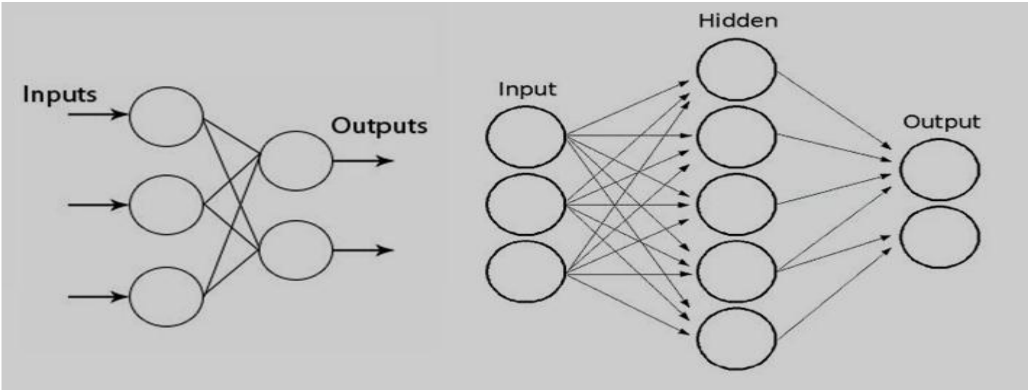

Figure 1. A single-layer neural network (left-side) and neural network with one hidden layer (right-side)

Related Work

In this section, we review the latest research on the matter, implemented in different regions of the world. In a study, the rainfall and runoff from a land application site near Lincoln, Nebraska, USA, a model was extracted from the neural network designed by Kim and Gilley (Kim and Gilley, 2008)0. The first specific objective of this study was to relate soil erosion, dissolved phosphorus (DP) and NH4–N concentrations in the runoff to selected hydrologic and water quality factors. The second objective was to evaluate artificial neural networks model performance for predicting soil erosion and runoff nutrient transport. This model showed that the quantity of eroded soil is positively correlated with rainfall and runoff.

In a study in the Juniata basin in Pennsylvania, US, the multi-layer feed-forward and radial basis function networks were compared with the multiple regression in estimating the daily suspended load of the region (Alp and Kerem Cigizoglu, 2007). The inputs of the artificial neural network model were slope percentage, ground cover and rainfall intensity, which were superior in terms of statistical parameters required for training and testing datasets. The results confirmed that artificial neural networks could estimate sediment concentration more accurately than conventional multiple linear regression models.

In another study on the Eel river watershed located in California, two neural network models were developed for modeling the partial distribution of suspended sediment load0. In the first model, which was an integrated neural network model, the training process was performed using data from several stations inside the drainage basin. The second model was a geomorphology-based neural network, in which the sub-basins location-dependent geomorphological parameters and time-dependent meteorological data were used as input. The results showed that although the time series of suspended sediment load predicted by both models were satisfactorily consistent with the observations, the geomorphological neural network model performed better because of using location-dependent factors.

Another research focused on the coastal waters of Singapore, in the Johor Strait in the north and the Singapore Strait in the south, to study the amount of sediment entering dam reservoirs, the erosion rate function of the upstream basin, and the ability of the river to transport eroded material to the dam reservoir (Palani et al., 2008). The objective of this research was to provide a comprehensive review of the application of the smart methods of artificial neural network and support vector machine in the field of water resources. The results of this research showed that the advanced smart methods were more efficient, accurate, economical, and faster than other computational methods to predict the quantitative and qualitative parameters of water resources.

In another study, the amount of suspended sediment in the Mississippi, Missouri, and Rio Grande rivers in the United States was estimated through a multiple linear regression neural network model (Melesse et al., 2011). The daily and weekly precipitation and discharge data for the day under study and the day before as well as the amount of sediment for the day before, were used to predict each day's suspended sediment. The results of the neural network model were compared with those of the multiple linear regression showing the neural network model was more accurate than the regression model.

In another research in Firat Basin of Turkey, the suspended sediment prediction was conducted using complex nonlinear equations (Ardiclioglo et al., 2007). In this research, two different feed-forward back-propagation neural network algorithms, Levenberg - Marquardt and Gradient - Descent, were utilized for the 0. To create dataset, the monthly streamflow and suspended sediment data from two stations, Palu and Çayağzi, were used. Then sediment data for the two stations were predicted. Afterwards, sediment data for downstream station using upstream data were predicted. The effect of the periodicity on the model performance was also investigated. The results were compared with the evaluation of multiple linear regression and showed that the feed-forward neural network had better performance.

To study the monthly flow data from a river in Turkey, the flow of the river was modeled by an artificial neural network (Kisi et al., 2015)0. The models used for prediction were back-propagation neural network and autoregressive (AR) model. The results showed that the neural network predictions were better than those of the auto-regression model. The accuracy of artificial neural networks algorithm was examined for the modeling discharge-suspended sediment relationship using the artificial bee colony (ABC). The ANN–ABC was compared with the neural differential evolution, adaptive neuro-fuzzy, neural networks, and rating curve models. As two case studies, the daily streamflow and suspended sediment concentration data from two stations including Rio Valenciano Station and Quebrada Blanca Station were used. For evaluating the capability of the models, the mean square error and determination coefficient criteria were used. The experimental results, along with comparisons, showed that the ANN–ABC was able to provide better results than that of the neural differential evolution, neuro-fuzzy, neural networks, and rating curve models. Moreover, the logarithm transformed data were also used as input to the proposed ANN–ABC model. It was found that the logarithm-transform significantly improved the accuracy of the models in suspended sediment estimation.

Another research focused on urban areas in Canada and Spain, to study erosion and sedimentation rates0. The results of showed that the linear regression and neural network models were suitable at estimating erosion and sedimentation rates. In the research, several models were presented with an improved accuracy to advance the design of erosion and sediment controls for construction sites. The models were developed based on multiple linear regression (MLR) on event-based permutations of the universal soil loss equation and artificial neural networks (ANN). In the models, the authors considered surface runoff monitoring datasets obtained from three sites, including Greensborough, Cookstown, and Alcona. The datasets were mined from the additional sites- Treynor, Iowa, Coshocton in Canada and Cordoba in Spain. The main advantages of the research were that the predictive MLR and ANN models could act as both diagnostic and design tools for adequate sizing of erosion and sediment controls on active construction sites. Moreover, researchers claimed that the developed method could be used for forecasting dynamic scenario when examining rapidly changing lands use in different stages of construction.

Another research studied the capability and effectiveness of simulating a complex nonlinear on real-world river system processes in the Himalayan location0. The time-series data were gathered from January to December (2008–2010) for water discharge and suspended sediment concentration (SSC). Three ANNs with different network structures were developed and trained using the Levenberg Marquardt Back Propagation Algorithm in Matlab software. The networks were optimized by the enumeration technique, and, finally, the best network was employed to predict the SSC values for the year 2011. The values obtained through the ANN model were compared with the observed values of SSC. The coefficient of determination for the optimal network was estimated at 0.99. This research not only provided insight into ANN modeling in the Himalayan river scenario, but also it showed the importance of the factors that affect the SSC. Despite the temporal variations in the study area, the model successfully predicted the SSC values with very simple artificial neural networks.

Another research studied sediment of the region of Salebhata, a village located in the Balangir district of Orissa state, India (Khan et al., 2019). The research used three methods with considerable differences and benefited from the experimental observations. The equations relating to sediment transport were used in estimating sediment load. The sediment measures had certain limits and a black-box model of ANN was used for simulation of the suspended sediment load. The models that provided the lowest RMSE and highest R^2 were considered as the best. The lowest values of RMSE based on the normalized data for Feedforward back-propagation method, Cascade forward back-propagation, and neural network fitting were 0.0087, 0.0083, and 0.0119, respectively. The corresponding values of R^2 were 0.93, 0.97, and 0.98, respectively. The research showed that the Neural Network Fitting model was superior to the other models, and produced few pessimistic estimates.

Proposed Method

In this section, we describe the method implemented in Matlab for calculating sediment yield. Currently, the sediment yield in the area is calculated using the MPSIAC-a Modified model of Pacific Southwest Inter-Agency Committee- model (Jafarzadeh et al., 2021; Layeghi et al, 2020). Here we attempted to apply regression analysis and artificial neural networks to process data and to estimate sediment yield. To evaluate the proposed method in a case study, the Kordan basin located in Alborz Province was selected. A map of the provinces in Iran (left) and Alborz Province with the study area (right) is illustrated in Figure 2. Additionally, Figure 3 shows a map of the Kordan village in Alborz Province and the river, where this study was conducted. Kordan is a village in Chendar Rural District, Savojbolagh County, Alborz Province.

Firstly, the erosion and sedimentation maps were entered into a Geographic Information System (GIS) software, and eight features were obtained. Then, eleven more features were obtained through reports by a sedimentation expert adding the features up to nineteen features in total. The values of these nineteen features were used as raw data.

Then we determined the factors affecting erosion using regression and ANN approaches in Weka, NeuroSolutions, and Matlab.

Figure 2. A map of the Provinces in Iran (left) and Alborz Province with the study area (right)

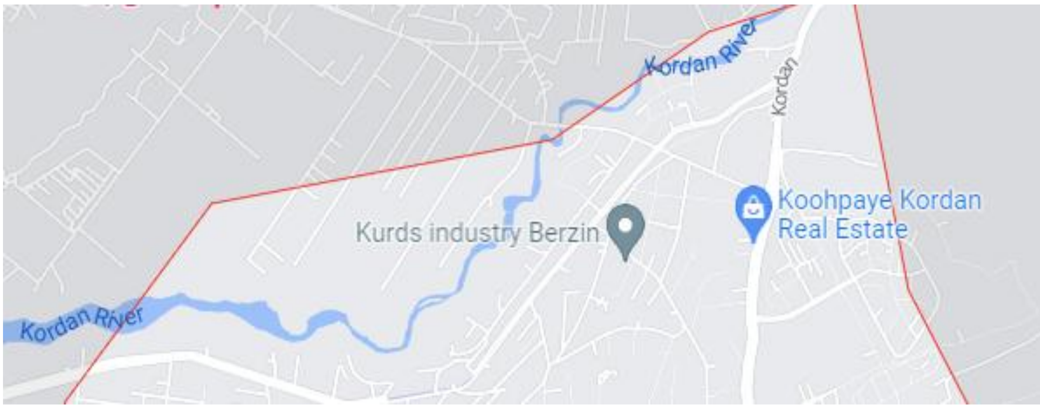

Figure 3. A map of Kordan village in Alborz Province of Iran and the river where the study was conducted

Factors Influencing Erosion

Nineteen factors influence erosion, including crown canopy, bare soil, gravel, leaf litter, precipitation, discharge, flow intensity, slope, soil erodibility, land use, infiltration, gully erosion, flow pattern, grooves, degradation effects, pavements, leaf litter based on soil surface factors (SSF), soil movement with regard to SSF, and river based on SSF.

In the MPSIAC model, there are nine formulas used to estimate sediment yield. Given the parameters required by this model, the estimation process is extremely time-consuming. In Section 4, the calculation process is explained and compared with the proposed method. The Kordan Basin was divided into 1766 polygons; therefore, there were 1766 samples in this dataset.

Regression Implemented in Weka

Weka is a software tool for classification and prediction in data mining. It performs classifications and predictions using algorithms such as decision tree, Bayesian, linear regression, ID3, J48, and k-NN. In this section, the implementation of linear regression in Weka and the results are explained.

Regression analysis is a statistical method for estimating the relationships between variables. In this method, there are many techniques for modeling and analyzing specific variables when the purpose is to determine relationship between a dependent variable and one or more independent variables. Regression analysis is very useful in estimating the conditional expectation of the dependent variable with respect to the independent variables. Moreover, regression analysis can help in finding the dispersion of the dependent variable around the regression function, which can be explained through a probability distribution0.

In this study, the numerical values of the nineteen factors influencing sedimentation were entered into the software as inputs, and sediment yield was selected as the output. The inputs with smaller effects on sediment yield estimation were removed, and each of the remaining inputs was assigned a weight. Table 1 shows the inputs and their weights. The factors flow intensity and slope were not sufficient in our calculations. In the calculation process, the value for each input are multiplied by the corresponding weight, and then the weighted values are added together. In addition to the inputs and their weights, there will be another value in the bottom row that shows the results of inputs being added to the other inputs.

Table 1. Estimation of sediment yield using regression in *Weka*

Factor	Weight	Factor	Weight
Crown Canopy	-0.59	Flow Pattern	0.9082
Bare Soil	-0.3712	Groove	12.1674
Gravel	-0.2921	Degradation Effects	0.9118
Precipitation	-0.5641	Pavement	0.9081
Discharge	73.084	Leaf Litter SSF	0.9089
Soil Erodibility	64.4276	Soil Movement SSF	0.9082
Land Code	1.7347	River SSF	-1.9576
Infiltration	-2.7867	Outcome Of Inputs	109.5521
Gully	1.4204		

Implementation of MLP Neural Network in Neuro Solutions

NeuroSolutions is a powerful software tool for applying artificial neural networks. It is used in conjunction with Microsoft Excel. This tool can perform cluster analysis, prediction, and classification.

To implement the MLP Neural Network in NeuroSolutions, the elements in the dataset were set randomly. Then, the nineteen features were specified as the neurons of the input layer. After that, the column for the final sediment yield was specified as the neuron in the output layer. Once the neuron of the output layer had been specified, it was time to determine the percentages of the samples to be used for the processes of training, validation, and testing. Out of 1766 samples, 75% were allotted to training, 10% to validation, and 15% to testing. Through trial and error and observation of mean square error (MSE) values, it was decided that one hidden layer with five neurons would be enough for this dataset.

In the hidden layer, a hyperbolic tangent was selected as the activation function. The training rule of the selected network was the momentum parameter with a default step size one. In the output layer, a linear sigmoid was selected as the activation function, and the selected network training rule was the momentum parameter with a default step size 0.1. Once the neural network is designed, it must be trained. The number of training epochs was set at three. After completing the training process, the graphs for mean cost and mean square error were drawn for both training and validation.

Figure 4 shows the results of the neural network for the difference between the real sediment yield values and the values estimated in 265 samples. In this figure, the X-axis shows the sample number and the real values are represented by blue, while the values estimated by the neural network are represented by red color.

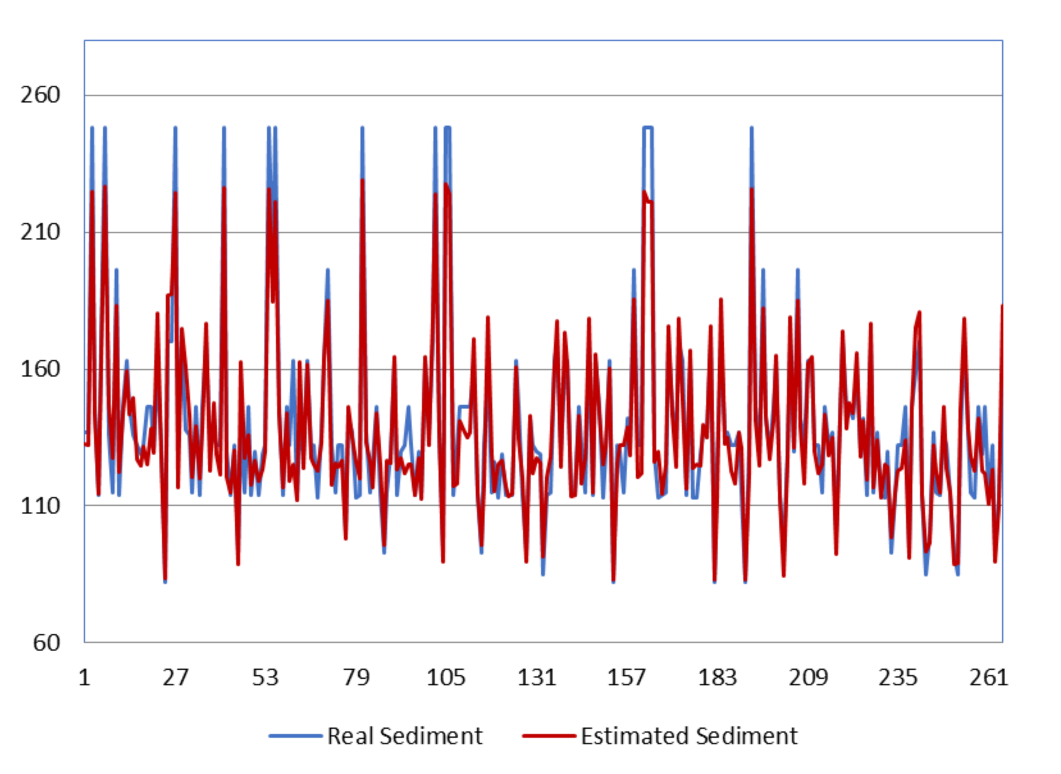

Figure 4. The observed and the estimated sediment using neural network in NeuroSolutions

MLP Neural Network Implemented in Matlab

Matlab is a high-level programming language with common features of most programming languages. These features include flow control, functions, input/output, and object-oriented capability. Matlab allows technical calculations, displaying information, and programming, all in a simple environment using many mathematical instructions. It provides many toolkits, each of which works as an application with matrix/array. One of these toolkits is simulating artificial neural networks (Marvin, 2016; Afrakhteh et al., 2020).

In the present study, we used Matlab to simulate an MLP neural network. First, the input and output of the neural network were specified. Two Excel files named ‘Inputs’ and ‘Output’ were created. The first nineteen columns were entered into the ‘Inputs file’, and the 20th column was entered into the ‘Output file’. Then, the percentages of the data to be used for each of the processes of training, validation, and testing were determined. Out of 1766 samples, 75% (1324 samples) were used for training, 10% (177 samples) for validation, and 15% (265 samples) for testing. This neural network has two layers-hidden layer and output layer. A tan-sigmoid function and a linear sigmoid function were selected for the hidden layer and the output layer, respectively. The Levenberg-Marquardt algorithm was selected for training the neural network. After that, the number of neurons in the hidden layer was set to 5 and the training process was begun.

Figure 5 shows a performance diagram, illustrating the output of the neural network during training, validation, and testing. As can be seen in the figure, the best performance occurred at the 61st epoch with a mean square error of 0.009, and the training process was terminated at the 67th epoch. Since the mean square error had not decreased for six successive epochs during the validation process, the training was terminated.

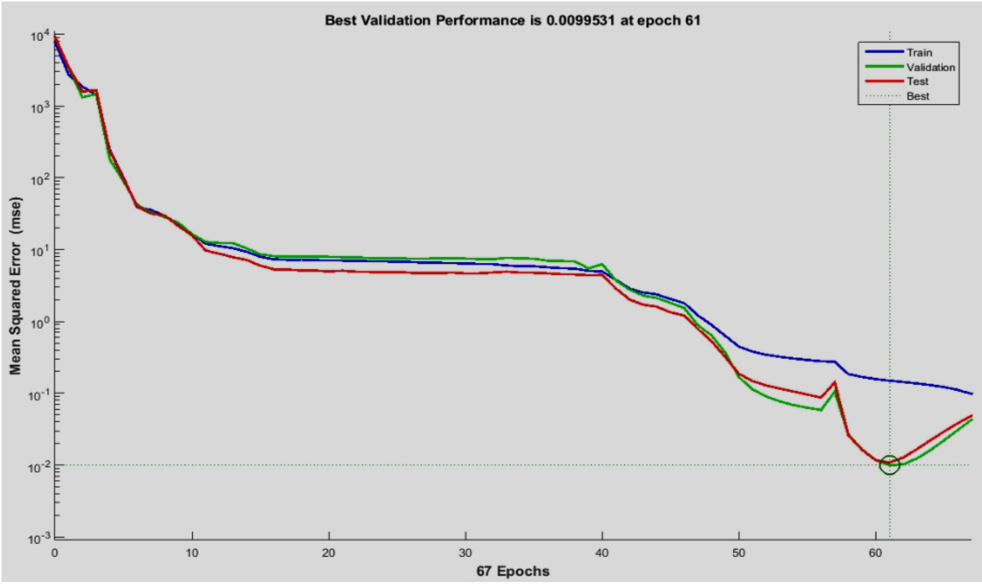

Figure 5. ANN Performance diagram in Matlab

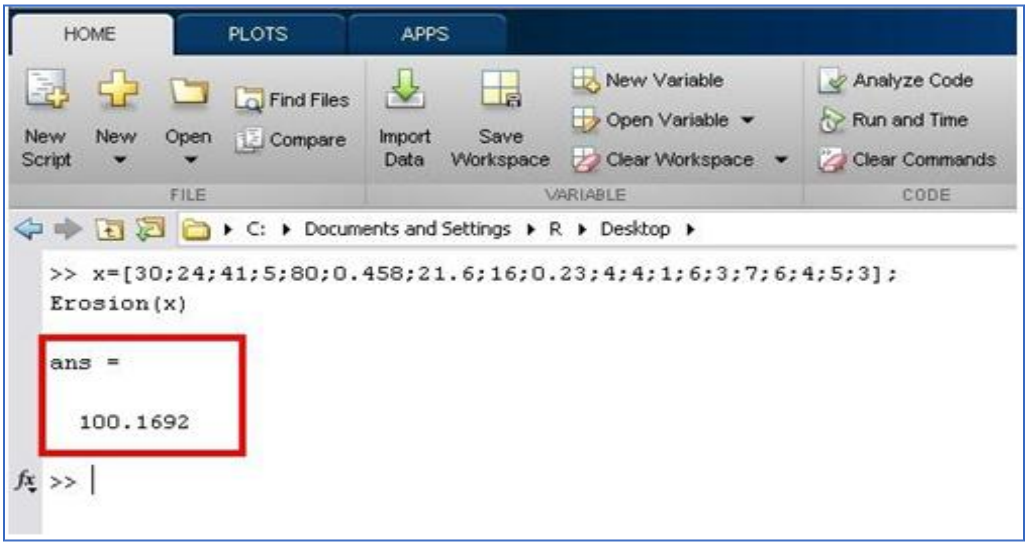

Figure 6. Creating a function for the neural network in Matlab

Extracting a Function from the Neural Network

Matlab provides a facility to extract a function from the constructed neural network. The advantage of this facility is that the neural network can be used repeatedly on subsequent occasions without the need for further training. To extract a function from the neural network, we named this function as 'Erosion'. For our purpose, an array had to be created in Matlab. The number of elements in this array had to be equal to the number of inputs in the neural network. Since the neural network in this study had nineteen inputs, the array was supposed to have nineteen elements. The name of the array can be arbitrary; and for the purposes of the present study, it was named 'x'. The 'Erosion' function provides a value, which is the output of the neural network. Figure 6 shows the results of execution of the function 'Erosion'. Under the inputs shown in the figure, the output of the neural network was 100.1692. In this study, the final sediment yield was 100, and the value estimated by the neural network was 100.16; thus the error was only 0.16, and the estimated value was very close to the real value.

Analysis of Results

In this section, we describe how the dataset is created. Then, the process of calculating sediment yield through the MPSIAC model is explained. After that, the results obtained from the simulation software tools are compared with the values obtained from the MPSIAC model.

The Dataset

To create the dataset, the maps of the drainage basin were combined in the GIS, and a total of 1766 samples and nineteen features were obtained. Table 2 shows the nine formulas to calculate the factors in the left column. The second and third columns show the weights and a brief description of the factors, respectively.

After obtaining the numerical values of the nine factors, the values obtained from these formulas were added together to obtain ‘R’, as the erosion parameter. The erosion severity and the annual sediment yield are estimated based on the values of all factors, indicated by the R-value. So, the ‘R’ is the total value of nine factors of MPSIAC model (in cubic meters per square kilometer per year). Finally, the value of ‘R’ was substituted in the MPSIAC formula, and the sediment yield was calculated by Eq. (1).

$$QS=18.6\times e0.0353\times R \quad (1)$$

where the QS is sediment yield and ‘e’ is the Euler's number, which is approximately 2.71.

The Comparison

In this section, we compare the sediment yield values provided by Weka, Neurosolutions, and Matlab in 20 samples. Table 3 shows the comparison of sediment yield values provided by regression in Weka and ANN in NeuroSolutions and Matlab. The values showed that the software tools are able to predict erosion and sedimentation rates with good accuracy.

Figure 7 shows the sediment yield values provided by Weka, NeuroSolutions, and Matlab, compared with MPSIAC. We calculated the percentage of the difference between the values provided by those three methods. Table 4 shows the percentage of the difference between the values in Table 3. The first rows of Table 4 show how these percentages are calculated, based on the label assigned to the columns in Table 3. Figure 8 illustrates the percentage of the difference between the values provided by Weka, NeuroSolutions, and Matlab.

Table 2. Explanation of the factors influencing soil erosion in the MPSIAC method (Vente and Poesen, 2005)

	Factor	Weight	Explanation
1	Surface Geology	$Y_1=X_1$	X_1 is the susceptibility of geological formations to erosion.
2	Soil	$Y_2=16.67\times X_2$	X_2 is the same as soil erodibility (K) in the USLE method.
3	Climate	$Y_3=0.2\times X_3$	X_3 is precipitation for six hours with a return period of two years.
4	Runoff	$Y_4=0.2\times X_4$	X_4 is 0.03×annual wastewater volume+50×annual peak discharge (cubic meter per second per square kilometer) [(m3/s)/km2]
5	Topography	$Y_5=0.33\times X_5$	X_5 is the average slope percentage of the drainage basin.
6	Vegetation	$Y_6=0.2\times X_6$	X_6 is the vegetation percentage of the drainage basin.
7	Land Use	$Y_7=20-0.2\times X_7$	X_7 is the percentage of the crown canopy.
8	Soil Surface and Erosion	$Y_8=0.25\times X_8$	X_8 is the state of the soil surface and erosion using the BLM (Bureau of Land Management) method. It is the sum of the outcome of the seven factors in the BLM method.
9	Stream Erosion	$Y_9=1.67\times X_9$	X_9 is channel erosion in low-slope areas next to a river.

From Figures 7 and 8, together with the values in Table 4, we can see that the neural network in Matlab provides sedimentation values that are very close to the actual values obtained through the MPSIAC model. The neural network constructed in NeuroSolutions, too, provides acceptable results but is less accurate. The regression algorithm in Weka can also predict sediment yield to some extent, but with a greater error. We, therefore, propose the method implemented in Matlab for calculating sediment yield.

Table 3. Comparison of sediment yield values provided by Weka, NeuroSolutions, and Matlab

Sample No.	MPSIAC	Weka-Regression	NeuroSolutions-Neural Network	Matlab-Neural Network
1	100	127.82	110.70	100.16
2	100	121.26	112.52	100.10
3	100	119.41	99.87	100.09
4	82	101.35	100.03	81.90
5	82	86.98	87.89	81.91
6	93	98.54	98.84	92.97
7	93	94.46	96.93	93.36
8	93	100.59	99.31	93.02
9	93	103.77	95.05	92.94
10	136	151.69	138.80	136.06
11	146	152.86	148.30	146.02
12	159	178.73	184.65	158.82
13	248	230.39	232.62	248.02
14	248	237.66	232.02	248.01
15	248	232.45	231.43	247.95
16	248	240.62	238.71	248.05
17	170	177.13	173.34	169.87
18	132	124.86	123.81	132.04
19	163	163.92	156.05	163.09
20	163	170.86	160.33	163.08

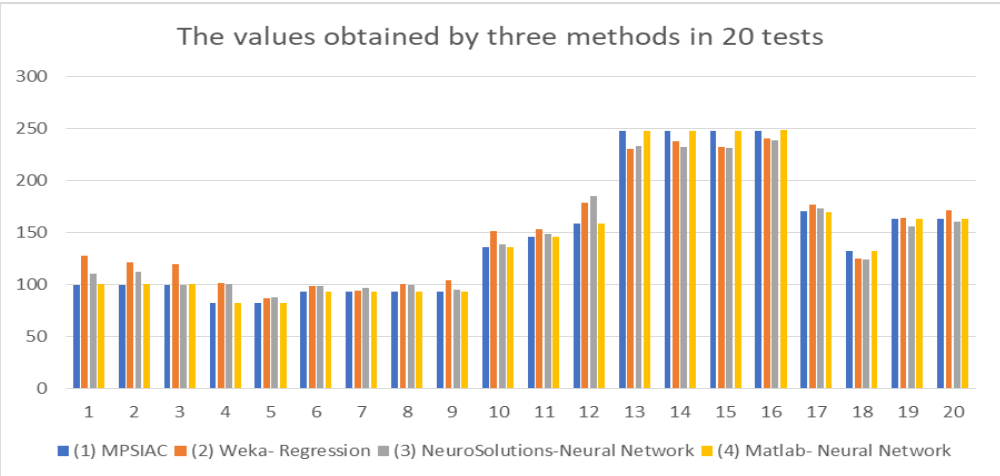

Figure 7. The sediment yield values provided by Weka, NeuroSolutions, and Matlab, compared with MPSIAC

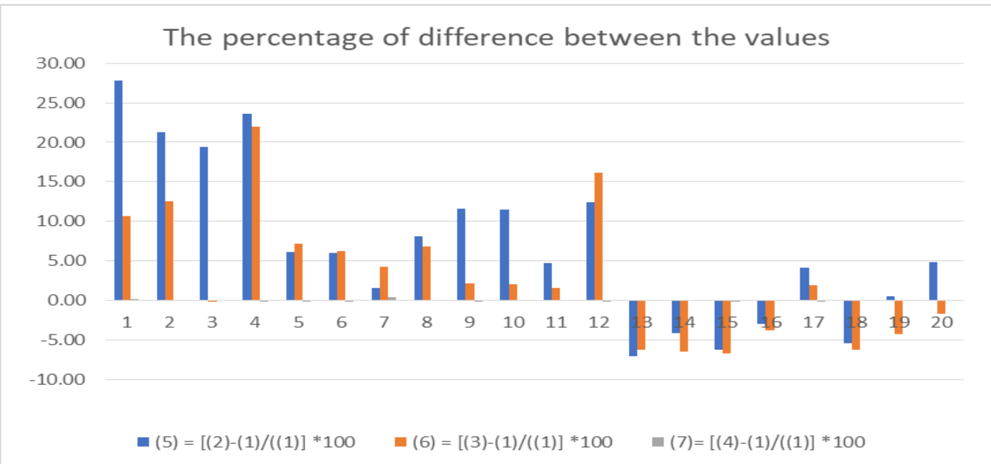

Figure 8. The percentage of the difference between the values provided by Weka, Neurosolutions, and Matlab

Table 4. Percentages of the difference between the values provided by Weka, NeuroSolutions, and MATLAB

Sample No.	(5) = (2)-(1)/((1) *100	(6) = (3)-(1)/((1)*100	’)= (4)-(1)/((1) *100
1	27.82	10.70	0.16
2	21.26	12.52	0.10
3	19.41	-0.13	0.09
4	23.60	21.99	-0.12
5	6.07	7.18	-0.11
6	5.96	6.28	-0.03
7	1.57	4.23	0.39
8	8.16	6.78	0.02
9	11.58	2.20	-0.06
10	11.54	2.06	0.04
11	4.70	1.58	0.01
12	12.41	16.13	-0.11
13	-7.10	-6.20	0.01
14	-4.17	-6.44	0.00
15	-6.27	-6.68	-0.02
16	-2.98	-3.75	0.02
17	4.19	1.96	-0.08
18	-5.41	-6.20	0.03
19	0.56	-4.26	0.06
20	4.82	-1.64	0.05

Summary and Conclusion

The purpose of this study was to select a method for calculating erosion and sedimentation rate. For this purpose, we used regression and artificial neural networks in three software tools Weka, NeuroSolutions, and Matlab. The results of all three software tools were satisfactory, but the MLP neural network designed in Matlab could predict the amount of sediment more accurately. In the design of this neural network, two layers were used and in its hidden layer with five neurons. In this study, a function of the neural network was extracted so that it could be easily used in future applications without the need for further training.

The proposed method has three advantages. Firstly, it eliminates the need for the complicated and time-consuming processes of the MPSIAC formulas. Secondly, it predicts sediment yield with more accuracy. Thirdly, it can quickly obtain sediment yield values from its output without the need to repeat the training process. Additionally, the function extracted from the neural network can be used in many organizations that conduct environmental studies and research with negligible requirements for preparing data and implementation of the model.

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