Estimation of Land Soil Erosion Using Neural Network Model

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ABSTRACT:

The land surface erosion is controlled by multifarious of different parameters, such as slope, soil physical properties (texture, structure, permeability, etc.), rainfall, runoff, and crop cover. However, it is impossible to develop precise simplest mathematical model that can predict the values of land surface soil erosion due to the behavior of controlled parameters. This paper presents the Neural Networks Model for assessing land surface soil erosion as amass per unit area per unit of time. The model derives from the analysis data obtained from available literature and was formulated as linear regression model and back propagation algorithm neural model. Both models were built by correlating firstly five watersheds variables with land surface erosion and secondly ten watershed variables with land surface erosion. The coefficients for independent variables were highly significant for both models. The case of correlating 10- watershed variables with land surface erosion gives R=0.978 & 0.976 for both models which is higher than that for 5- watershed variables. The mean absolute relative error (MARE%) is another procedure that used in order to evaluate the accuracy of the model and The average error % is 0.025 for (5) variables and 0.0064 for (10) variables. Both the supporting practices (P) and the slope length and slope steepness (LS) coefficients have a marked effect on the amount of land surface erosion in the case of 5- watershed variables. The amount of land surface erosion show a high level of sensitivity to the content of fine sand% in soil (FS) watershed variables on The amount of land surface soil erosion.

تخمين تأكل التربة السطحية باستخدام نموذج الشبكات العصبية الصناعية

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الخلاصة:

يعتمد التآكل من سطح التربة على تنوع عدد من العوامل المختلفة مثل الميل والخواص الفيزياوية للتربة مثل (بناءها وتركيبها ونفاذيتها......الخ) والمطر والسيح والغطاء النباتي. وعلى أية حال فمن غير الممكن الحصول على نموذج رياضي بسيط يستطيع أن يعطي قيم عددية دقيقة للتآكل السطحي من التربة وذلك بفعل سلوك العوامل المسيطرة. هذا البحث يقدم محاولة لاستخدام نموذج الشبكات العصبية لإيجاد التآكل من سطح التربة بوحدات كتلة لكل وحدة مساحة لكل وحدة زمن. اشتق النموذج من تحليل معلومات جمعت من مجموعة من البحوث المتاحة وصيغت هذه المعلومات إلى نموذج للانحدار الخطي و نموذج الانحدار العكسي في تدريب الشبكات العصبية. كلا النموذجين بني من أولا ربط خمس متغيرات مع تآكل التربة السطحية وثانيا من ربط عشرة متغيرات مع تآكل التربة السطحية. المعاملات للمتغيرات الغير معتمدة المختارة ذات مغزى عالي لكلا النموذجين. في حالة ربط عشرة معاملات فان قيمة معامل الارتباط هي 0.978 و 0.976 لكلا النموذجين والتي هي أعلى منها لخمس معاملات.كما استخدمت طريقة حساب مقدار الخطأ لتقييم دقة عمل هذا النموذج وكانت مساوية إلى 0.025 لنموذج المعاملات الخمسة و 0.064 لنموذج المعاملات العشرة. كمية التآكل من التربة السطحية يتأثر بحساسية عالية جدا إلى معامل نسبة الرمل الناعم الموجود في التربة السطحية في حالة المعاملات العشرة.

Keywords: Land surface soil erosion, neural network model.

INTRODUCION:

The most harmful effects of land surface erosion occur during flooding, which is one of the world's most destructive natural disasters. A decade ago, floods in some countries cost more than (5) billions US dollars annually and since then the figure have risen steadily. In Italy catastrophic floods along the Po-River in November 1951 and the Arno- River in November 1966 left thousands of people homeless and cost more than (13) millions US dollars (Bazzoffi 2003).

Land surface erosion removes organic matter from the soil and contributes to the breakdown of soil structure that will in turn affect soil fertility and the crop yields. According to Merritt et. al. (2003), soil erosion is a three – stage process: detachment, transport, and deposition. The factors that influence the rate of soil erosion include rainfall, runoff, slope, plant cover, and the presence or absence of soil conservation strategies. It is useful to make an estimate of how fast the soil is being eroded, before implementing any conservation strategies. Thus methods of predicting the soil loss under a wide range of conditions are required. The three categories of model classifications are: empirical models, conceptual models, and physically based model.

Soil erosion models are necessary tools to predict excessive soil loss and to help in the implementation of as erosion control strategy. As part of literature review, a wide range of soil erosion models is studied which includes the universal soil loss equation USLE and its revised forms, GIS based USLE (Murimi and Prasad 1998), WEPP (Amore et. al.2004), AGNPS (Haregeweyn and Yohannes 2003), LISEM(Deroo and Jetten 1999 and Ionita and Margineanu 2000).

The Universal Soil Loss Equation (USLE) was developed by Weischmeier and Smith (1978), is the most widely used erosion prediction method (Jasmin 2008).

Predicting soil loss (A) by this method, requires the assessment of six factors (Wischmeier, 1977 and Wischmeier and Smith, (1978):

$$\mathbf{A = R \,.\, K \,.\, L.\, S \,.\, C \,.\, P}$$

Where; A=Average annual soil loss (ton/acr/year), R=Average annual rainfall erosivity factor (100 ft-ton.inch/acr.hour), which is the sum of individual storm erosivity values, EI(E is the total energy for a storm and I is the storm's maximum 30 - minute intensity), K=Soil erodibility factor (.01 ton acre hour/acre ft-ton inch), L and S = Slope length and steepness, respectively (dimensionless), C and P = Cropping system and supporting practices respectively (dimensionless).

In this paper we propose to estimate the land surface erosion through the Neural-Network Model, which was developed through data collected from available literature (Wischmeier (1977), Dehaan (1992), Cooper (1997), Nikami (1999), and Navar (2000)).

NEURAL-NETWORK MODEL:

The Neural – Network Model is implemented using neural network toolbox that is available in MATLAB program version 7.0.0.(2004). This program implements several different neural network algorithms such as back propagation and linear-regression neural models. Both models were built by correlating firstly (5) watershed variables with land surface erosion Tab.(1) and secondly (10) watershed variables with land surface erosion Tab.(2).

The most recent version of Neural- Network derives from the analysis of (85) case of data observations for (5) watershed variables and (72) case of data observation for (10) watershed variables , the watershed systems spread all over the world.

Table (1) Summary statistics of watershed variables no. (1)

Watershed variables	Unit	Mean	Min.	Max.	Std. dev.
Soil erosion (A)	ton/acr/year	4.432	0	39.96	10.3
Erosivity index (R)	100 ft-ton.inch/acr.hour	94.3	1.7	200	70.23
Erodibility index (K)	.01 ton acre hour/acre ft-ton inch	0.2021	0.03	0.37	0.09734
Slope length factor&slope steepness factor (LS)	Dimensionless	1.156	0.3	11.78	1.354
Crop factor (C)	Dimensionless	0.038	0.00325	1	0.1874
Conservation practice factor(P)	Dimensionless	0.9417	0.5	1	0.1567

Table (2) Summary statistics of watershed variables no. (2)

Watershed variables	Unit	mean	min.	Max.	Std. dev.
Soil erosion (A)	(kg/ha)	263	0	2729	555
Rainfall amount (R)	(mm)	42.64	20	70.8	19.06
Intensity (I)	(mm/hr)	40.07	12.2	63.2	17.32
Surface runoff (SR)	(mm)	0.8753	0	13.24	2.333
Slope (S)	(%)	3.75	3.5	4	0.2518
Organic matter(OM)	(%)	1.925	1.5	2.9	0.5713
Sand (SA)	(%)	17.5	16	20	1.67
Fine sand (FS)	(%)	9.275	7.4	11.7	1.657
Clay (C)	(%)	54	51	58	2.567
Silt (SI)	(%)	28.5	26	31	2.518
Bulk density (BD)	(gm/cm^3)	1.087	1.04	1.14	0.03726

The Neural Network Model independent variables are : 1-(R) erosivity index(100 ft-ton inch/acr hour); 2- (K) the soil erodibility factor(.01 ton acre hour/acr ft-ton inch); 3- (S&L) the average slope length and slope steepness factor (dimensionless) ;4- (C) crop factor (dimensionless) ; and 5- (P) conservation practice factor (dimensionless) and secondly are : 1- (R) rainfall amount (mm) ; 2- (I) intensity (mm/hr) ; 3- (SR) surface runoff (mm) ; 4- (S) slope (%) ; 5- (OM) organic matter (%) ; 6- (SA) sand content (%) ; 7- (FS) fine sand content (%) ; 8- (C) clay content (%) ; 9- (SI) silt content (%) ; 10- (BD) bulk density for depth from (1 to 10 cm).

Before constructing the Neural Network the best model search algorithm for searching the inputs for the model that best predicted land surface erosion was applied. The resilient back propagation (RPROP) is high performance algorithms that can converge from ten to one hundred times faster than the algorithms of steepest descent with momentum (GDM). In the resilient back propagation (RPROP) algorithms only the sign of the derivative is used to determine the direction of the weight update, the magnitude of the derivative has no effect on the weight update. In the (RPROP) algorithm, the individual update value, Δij , for each weight is based on the following learning rule (Bullinarai, 2004).

$$\Delta_{ij}^{h} = \begin{cases} (\eta+).\Delta_{ij}^{h-1}, & \text{if } \partial E^{h-1}/\partial w_{ij} \,.\, \partial E^{h}/\partial w_{ij} > 0 \\ (\eta-).\Delta_{ij}^{h-1}, & \text{if } \partial E^{h-1}/\partial w_{ij}.\partial E^{h}/\partial w_{ij} < 0 \\ \Delta_{ij}^{h-1}, & \text{else} \end{cases}$$

$$\Delta w_{ij}^{h} = -\text{sign}\,(\partial E^{h}/\partial w_{ij}).\Delta_{ij}^{h}$$

$$w_{ij}^{h} = w_{ij}^{h-1} + \Delta w_{ij}^{h}$$

The values of the parameters used in the (RPROP) algorithms are as follows. The decrease factor, $\eta-$, is set to 0.5 since it is not known from the gradient information by how much the minimum was missed, thus, it will be a good guess to halve the update - value. The increase factor, $\eta+$, has to be large enough to allow fast growth of the update value. On the other hand, the learning process can be disturbed if a too large an increase factor leads to persistent changes in the direction of the weight step. Therefore, $\eta+ = 1.2$ has been suggested. The range of the update value of the individual weights is restricted to an upper limit Δmax = 50 and lower limit of $\Delta min = 1*10^{6}$. The initial update value, Δ□ is set to 0.05.

To make a comparison the same training and testing sets are treated with the resilient back propagation algorithm as they are previously treated by the gradient descent back propagation for (5) variables. The comparison between the results of both algorithms related to the performance of Neural Network is summarized in table (3). It is found that the (RPROP) gives convergence faster (small number of epochs) than the (GDM) and gives a small value of mean square error (MSE).

Table (3) performance of two different algorithms for network of (5) variables.

Algorithm	Epochs	MES training	MSE testing
GDM	2000	.00881	.0097
RPROP	500	.0058	.0061

The configuration and training of Neural Network is trial and error process due to such undetermined parameters as the number of hidden layers, number of nodes in the hidden layer, and learning parameter. In testing the network at first it is necessary to run the network by using the training data to see whether the network produces good approximation to the known output for these data, and then prepare further data which have not been used in training phase and run the network with these data to check the accuracy of this net. This property of network is called generalization. This generalization depends on the size of the training data set, the architecture of the network, and the complexity of the problem. The number of testing data are taken randomly as (20%) of training data, (Steven 2006).

From table (4) and table (5) it can be seen that the network with (4) neurons in one hidden layer {(4) (tansig, purelin, purelin) }, give the best performance for both (5) and (10) variables.

Table (4) MSE for the network with different types and arrangements of transfer functions for (5) variables.

Network type	(Tansig, purelin, purelin)	(tansig, tansig, purelin)	(tansig, tansig, tansig)	(purelin, tansig, tansig)	(tansig, purelin, tansig)	(purelin, purelin, tansig)
5	.0098	.0099	.018	.022	.020	.022
6	.0091	.0093	.0098	.0098	.0079	.0092
4	.005797	.0067	.0062	.0063	.0061	.0065
3	.0079	.0082	,0086	.0091	.0081	.0085
2	.0081	.0086	.0089	.0089	.008	.0089

Table (5) MSE for the network with different types and arrangements of transfer functions for (10) variables.

Network type	(Tansig, purelin, purelin)	(tansig, tansig, purelin)	(tansig, tansig, tansig)	(purelin, tansig, tansig)	(tansig, purelin, tansig)	(purelin, purelin, tansig)
5	.00915	.033	.056	.076	.067	.054
6	.00991	.00987	.099	.059	.034	.031
4	.00889	.0094	.037	.068	.033	.035
3	.0092	.0091	.0589	.054	.035	.078
2	.0098	.136	.137	.161	.196	.099

Firstly, for 5-watershed variables after several trials, the best Neural Network was obtained by setting (4) neurons in the hidden layer. A number of nodes schematic drawing of the Neural Network is shown Fig.(1). Secondly, for 10-watershed variables and after several trials, the best Neural Network was obtained by setting also (4) neurons in the hidden layer. A number of nodes schematic drawings of the Neural Network are shown in Fig (2).

The total data (patterns) are divided into two groups; training data, and testing data. The training data are used to train the network to find the relationship between the input and output parameters. To build the model, the trying error was minimized with the addition of a theta weight associated to each hidden neuron, with the effect of the addition of one degree of freedom during training. Each hidden and output neuron was also supplemented by an additional theta like input, for feeding the sum squares of the input values to the neuron. To avoid over fitting, the early during training was adopted.

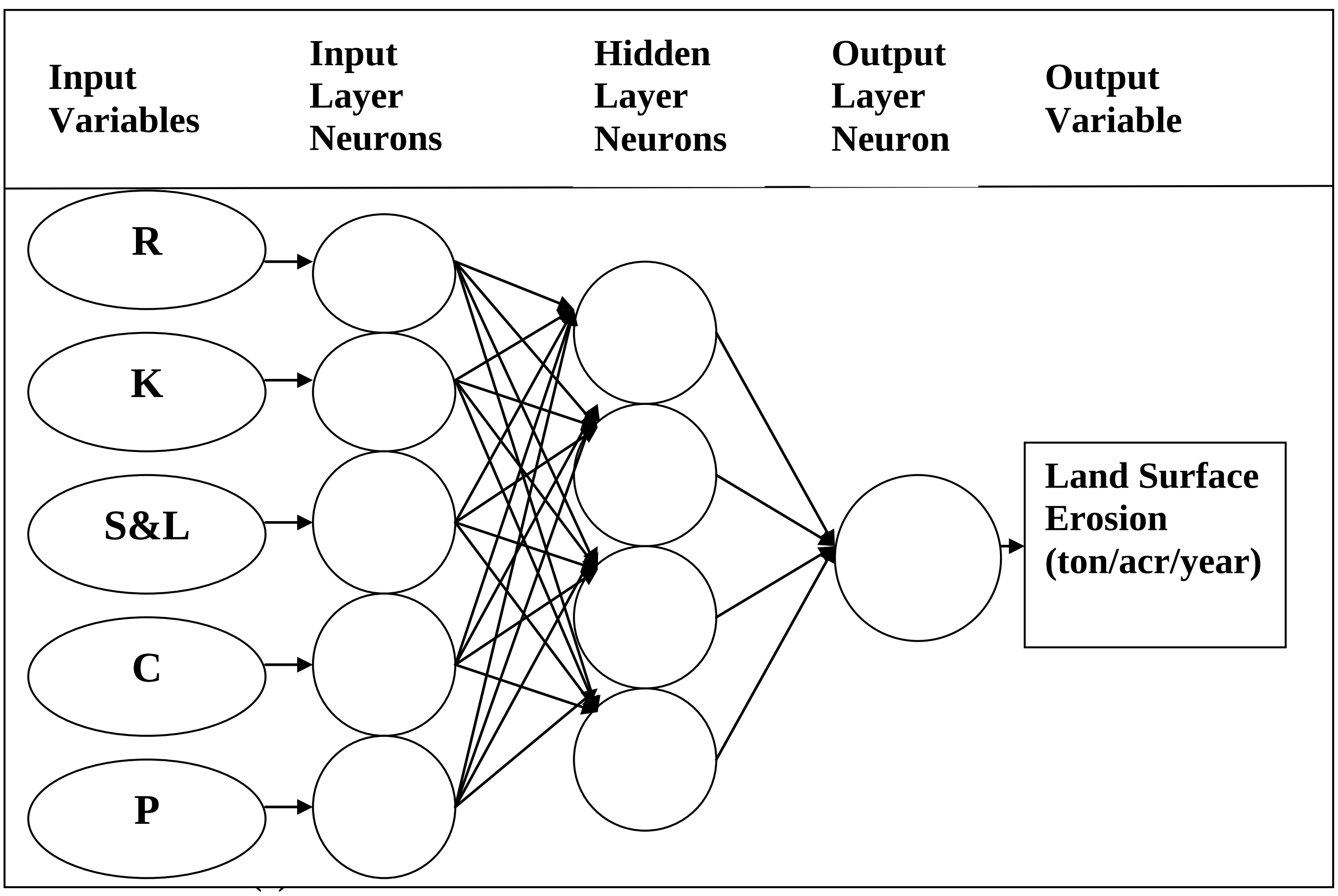

Fig. (1) schematic drawing of the neural network used to construct the test neural models for (5) variables.

After training network, the weights and biases are fixed and the network can then be run with same or fresh sets of data. In testing the network at first it is necessary to run network by using the training data to see whether the network produces good approximation to the known output for these data, and then prepare further data which have not been used in training phase and run the network with these data to check the accuracy of this net. The convergence history of training and testing data are shown in Fig. (3) for (5) watershed variables and for (85) cases and Fig. (4) for (10) watershed variables and for (72) cases.

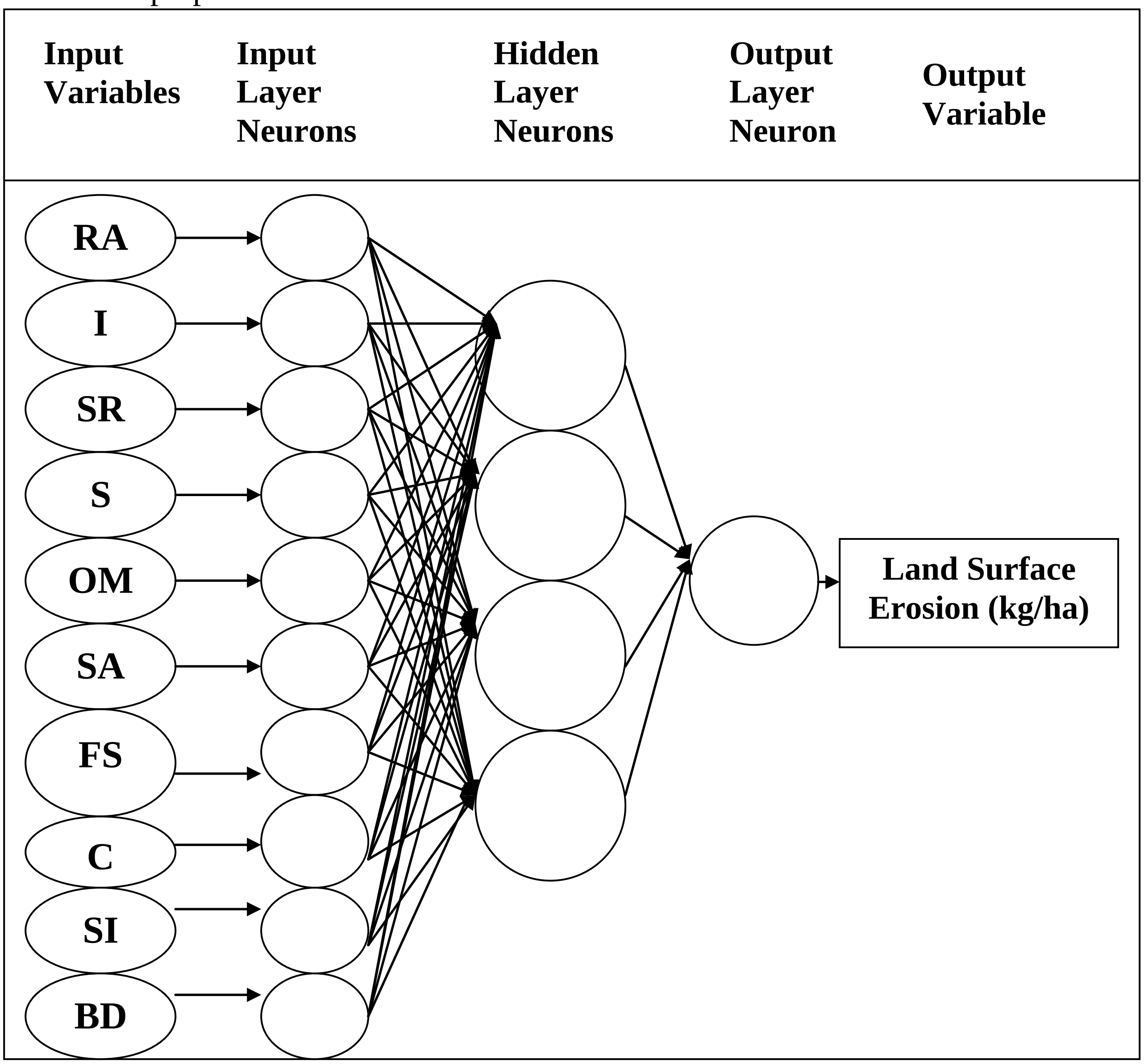

Fig. (2). Schematic drawing of the neural network used to construct the testing neural models for (10) variables.

The summary statistics for the back – error propagation model, and multiple regression model are shown in tables (6) and (7) for (5) variables and in tables (8) and (9) for (10) variables respectively.

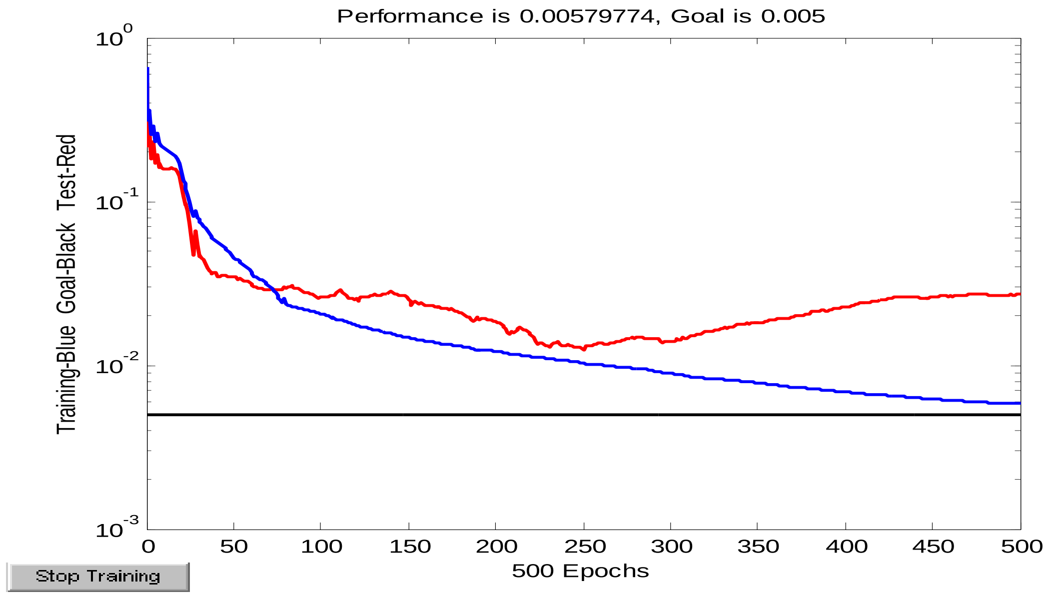

Fig.(3). Comparison between training and testing data for (5) variables.

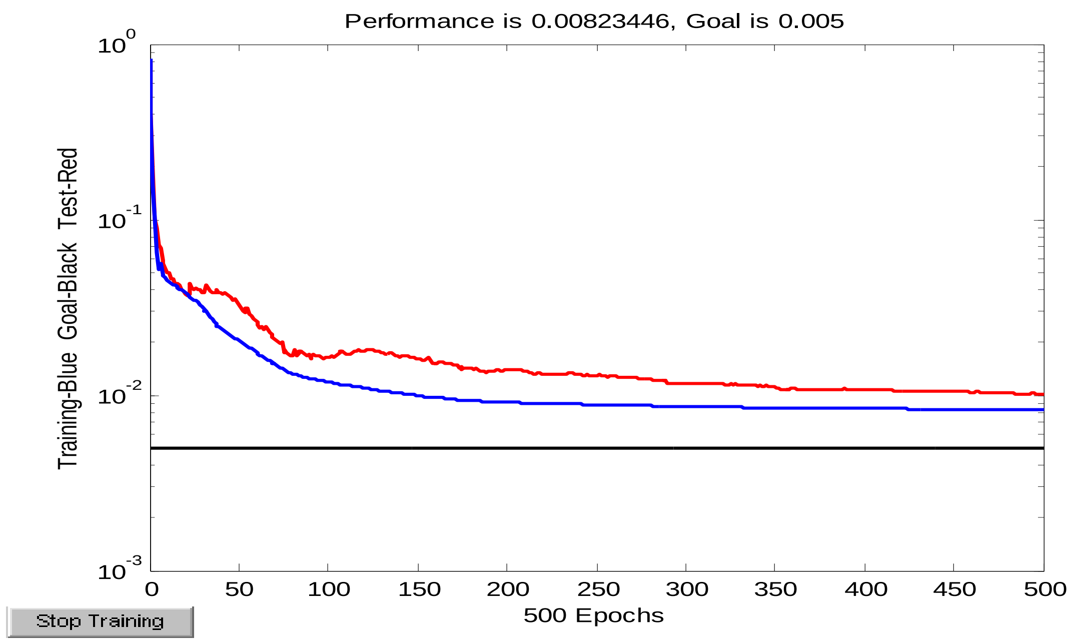

Fig.(4). Comparison between training and testing data for (10) variables.

Table (6). Summary statistics of the 85- cases neural network back-error propagation model for (5) variables.

	Mean	Std. dev.	Minimum	Maximum
Measured	4.432	10.3	0	39.96
Predicted	0.3571	10.31	-1.363	39.27
R^2	0.978			

Table (7). Summary statistics of the 85-casses neural network-multiple regression model for (5) variables.

	Mean	Std. dev.	Minimum	Maximum
Measured	4.609	8.297	0.00664	29.49
Predicted	4.432	10.3	0	39.96
R^2	0.672			

Table (8). Summary statistics of the 72-casses neural network back-error propagation model for (10) variables.

	Mean	Std. dev.	Minimum	Maximum
Measured	263	555	0	2729
Predicted	266.7	547.3	11.73	2385
R^2	0.941			

Table (9). Summary statistics of the 72-casses neural network –multiple regression model for (10) variables.

	Mean	Std. dev.	Minimum	Maximum
Measured	263	542.7	0.95	2382
Predicted	263	555	0	2729
R^2	0.957			

The performance of trained network can be measured to some extent by the errors on the training, and testing sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The routine ‘postreg’ in MATLAB program is designed to perform this analysis. The format of this routine [m,b,r] =postreg (a,t). It returns three parameters, the first two, m, and b, correspond to the slope and the y-axis intercept of the best linear regression relating targets to network outputs. If a perfect fit exists (outputs exactly equal to targets), the slope would be 1, and the y- intercept would be 0. The third variable returned by ‘postreg’ is the correlation coefficient (r-value) between the outputs and targets. It is a measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is perfect correlation between targets and outputs.

In Figures (5, 6) the observed versus predicted values of land surface erosion for (5) variables for both back-error propagation and multiple regression models the values of the slopes are 0.786 and 0.661respectivly, interception with y-axis are 0.668 and 1.68 respectively, and correlation coefficients are 0.989 and 0.82 respectively. Figures (7, 8) the observed versus predicted values of land surface erosion for (10) variables and for both back- error propagation and multiple regression models respectively. The values of the slopes are 1.01 and 0.956 respectivly, interception with y-axis is -2.65 and 11.5 respectively, and correlation coefficients are 0.976 and 0.978 respectively.

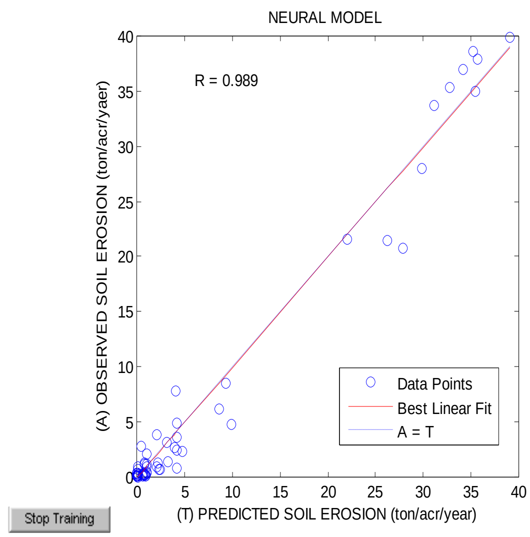

Fig.(5). Observed and predicted values by 85-casses for back-error propagation model and for 5-variables.

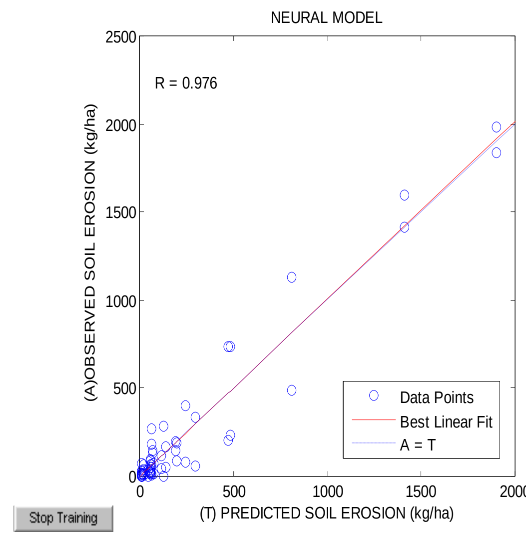

Fig.(6). Observed and predicted values by 85-casses for multiple regression model and for 5-variables.

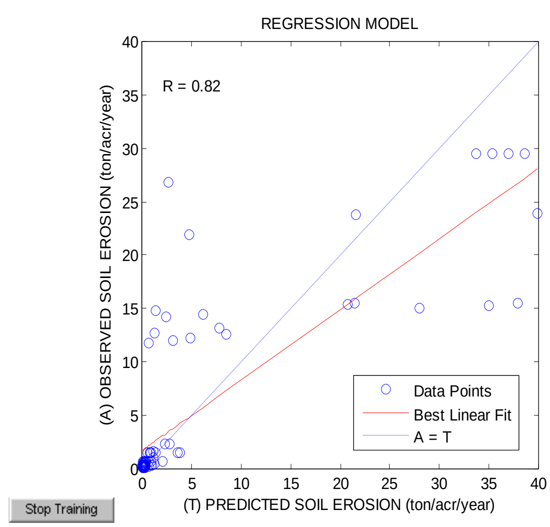

Fig. (7). Observed and predicted values by 72-casses for back-error propagation model and for 10-variables.

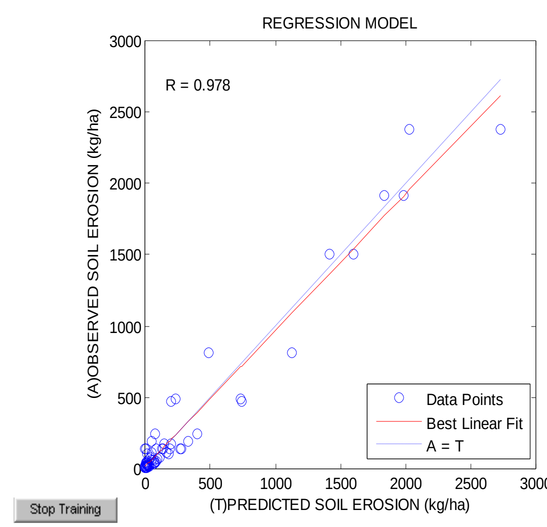

Fig. (8). Observed and predicted values by 72-casses for multiple regression model and for 10-variables.

In order to evaluate the accuracy of the model another procedure is used. The mean absolute relative error (MARE%) are computed.

$$MARE\% = 1/N \sum_{1}^{n} \left| (X1 - XT) / X1 \right| * 100$$

Where;

MARE% = mean absolute relative error

X1 = observed value

XT = predicted value

The average error% is 0.025 for (5) variables and 0.0064 for (10) variables.

The sensitivity for (85) and (72) cases of observation Neural Network model was calculated by averaging the absolute values of the change in the land surface erosion caused by moving the input variables by a small amount over the entire training set, and dividing this value by the total amount of change for all input variables. The average absolute sensitivity indexes, shown in figure (9) for (5) watershed variables and figure (10) for (10) watershed variables.

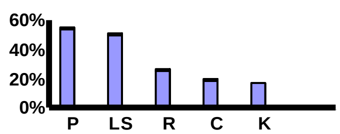

Fig. (9). Sensitivity analysis for (5) variables of the neural network model.

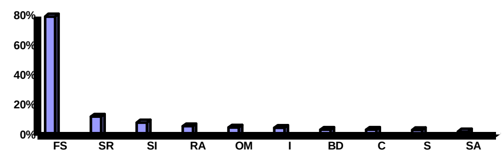

Fig. (10). Sensitivity analysis for 10-veriables of the neural network model.

Conclusions:

This work presented the Neural-Network model for the prediction of land surface soil erosion for 5-watershed variables and 10-watershed variables and in two stages model. In the first stage, using developed Back-error propagation Neural-Network model, and in the second stage the using of multiple regression Neural Network model is developed. Both back-error propagation and multiple regression Neural Network model, constructed on all the 85 case of observations and 72 cases of observations, were found to be highly significant. The coefficients for independent variables were likewise highly significant for both models. The case of correlating 10-watershed variables with land surface erosion gives R=0.978 & 0.976 for both models which is higher than that for 5- watershed variables. The mean absolute relative error (MARE%) is another procedure that used in order to evaluate the accuracy of the model and The average error is 0.025 for (5) variables and 0.0064 for (10) variables. Both the supporting practices (P) and the slope length and slope steepness (LS) coefficients have a marked effect on the amount of land surface erosion in the case of 5- watershed variables. The amount of land surface erosion show a high level of sensitivity to the content of fine sand% in soil (FS) watershed variables in the case of 10- watershed variables.

Notations:

A - soil erosion
R - erosivity index
K - erodibility index
LS-slope length and slope steepness factor
C -crop factor
P -conservation practice
RA-rainfall amount
I -intensity
SR- surface runoff
S - slope%
OM- organic matter content%
SA -sand content%
FS -fine sand content%
C -clay content%
SI -silt content%
BD-bulk density
USLE- universal soil loss equation
GIS-geographic information system
WEPP-water erosion prediction project
AGNPS-agricultural non- point source pollution model
LISEM-Limburg soil erosion model
RPROP- resilient back propagation algorithm
GDM-steepest descent with momentum algorithm
MSE-mean square error
X1- observed value
XT- predicted value

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