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THE STUDY OF THREE MULTIVARIATE REGRESSION, NEURAL NETWORK AND NEURO-FUZZY MODELS EFFICIENCY IN SPLASH EROSION ESTIMATION

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ABSTRACT: *The application of artificial intelligence in soil properties prediction has been progressing and developing in recent years. Determination of aggregate stability properties as indices against soil erodibility is time consuming and difficult. The predictability of three multivariate linear regression, neural network and neuro-fuzzy models efficiency in splash erosion prediction has been tested in this study. Due to low correlation of some properties of the soil, only four input parameters of Sodium Absorption Ratio (SAR), Porosity, Geometric Mean Diameter (GMD) of aggregates and runoff height have been analyzed as input variables in splash erosion prediction. The results indicated the priority of neuro-fuzzy method compared to others. Coefficient of determination of 0.798 in gauss2mf membership function with 3 membership functions and Hybrid Learning Algorithm have been obtained in adaptive neuro-fuzzy inference method. The small number of available data, in addition to samples distribution and spatial changes of samples led to low accuracy of multivariate linear regression method in splash erosion prediction.*

KEYWORDS: Aggregate Stability, Artificial Intelligence, Soil Erodibility, Geometric Mean Diameter (GMD)

INTRODUCTION

Rainfall erosivity and soil inherent erodibility are two key factors affecting splash erosion. However, there are few studies have been made to quantify the rainfall erosivity and soil properties effects on splash erosion amount (Ahmadi, 2010). Although some studies attempted to predict splash erosion based on soil particle size and soil chemical properties but due to complexity of this process, these attempts weren't universally successful (Scholten et al., 2011). Because splash erosion rate not only affected by rainfall erosivity and soil properties, but also affected by water film thickness which formed on the soil surface during rainfall event. Water film thickness is a function of the rainfall intensity, slope gradient, soil roughness and soil permeability (Ahmadi, 2010). Soil permeability affected by the soil pore size distribution and changed during rainfall event. According to the above mentioned subjects, there are complex interactions between splash erosion and its controlling factors. For this reason, there is no comprehensive model for estimation of rain splash erosion (Scholten et al., 2011).Various

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studies have reported that linear data such as soil properties may not be predicted and modeled using simple models such as regression models , and only some models such as neural network and adaptive neuro-fuzzy inference systems (ANFIS) may provide a proper prediction of these soil parameters with high reliability (Kisi et al. 2009; Huang et al. 2010). Today, the use of modeling methods such as neural network methods, fuzzy inference systems, neural network and adaptive neuro-fuzzy inference systems (ANFIS) has been developed vastly for predicting the soil properties.

On other hand, use of Artificial Neural Network (ANN) in environmental modelling has increased with recognition of its potential to solve complex problems (Chen et al., 2008). Neural networks may provide a user-friendly alternative or supplement to complex physically based models for soil erosion prediction (Licznar and Nearing, 2003). ANN model has the ability to auto-analyze the relationships between inputs by self-learning, and produce results without hypothesis.

Licznar and Nearing (2003) attempted to quantitatively predict soil loss from natural runoff plots with the ANN method. They found that correlation coefficients for predicted soil loss versus measured values were in the range of 0.7–0.9. Ahmadi (2010) also developed pedotransfer functions (PTFs) by regression and ANN methods for prediction of interrill erodibility (Ki). He showed that ANNs- PTFs are significantly more accurate and more reliable than regression-PTFs. Although ANNs based PTFs have been successfully adopted in modeling of some soil properties, but the utility of ANNs in modeling soil splash erosion hasn't been reported. So, the present study tried to investigate the application of easily found data, using soil transfer functions predictive methods, to predict rare data such as splash erosion.

MATERIALS AND METHODS

East Azarbaijan Province, which is one of the semi-arid regions of the country, and has a great potential for water erosion and especially splash erosion in terms of climatic and pedologic conditions and vegetation, was selected for conducting the study. Figure 1 shows the location of East Azarbaijan Province in Iran and sampling points.

This province with an area of 45481 km^2 dominates about 2.8% of total area of Iran. The province is located in the northwest of the country, between 36 degrees and 45 minutes to 39 degrees and 26 minutes of the northern latitudes and the meridians of 45°5′ to 48°22′ of eastern length. The East Azarbaijan climate is generally cool and dry, but it has different climates due to topographical diversity. Its average annual rainfall is 250-300 millimeters. By studying the soil map of the East Azarbaijan province and the existing pedological map studies reports, 36 areas with different soil properties, including content of organic matter, lime, gypsum or salinity were selected (Fig. 1). From these areas, 101 soil samples weighing approximately 20 kilograms were taken from Ap surface horizon (horizon for plowing cultivated soils). Soil samples were transferred to the laboratory and, after air drying, passed through a 7.54 mm sieve and stored for rainfall simulation experiments. The amount of 3 kg of each soil was stored separately to determine the physical and chemical properties.

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Measuring physicochemical properties of the soil

Measuring the soil texture was done by hydrometric method based on Stokes' law (Gee and Bauder 1979).The Soil pH has been measured in saturated paste. The pH meter electrical appliance model EYELA-2000 was used to measure pH (Sparks 1996). An electrical conductivity meter (EC meter) was used to measure electrical conductivity in soil samples saturated extract. The results were expressed in deci Siemens per meter (dS/m) and the coefficients required for converting read numbers to standard conditions (25 ° C) were applied by the machine itself (Sparks 1996). Cation Exchange Capacity (CEC) was determined by Bower (1976) method. The organic matter we measured by Walkley-Black method. The content of calcium carbonate equivalent to the samples was measured by calcimeter (or volumetric) method (Carter and Gregorich 2008).

The sodium absorption ratio (SAR) is obtained by dividing the Molar concentration of sodium monovalent cation to second root of the total Molar concentration of calcium and magnesium divalent cations (US Salinity Laboratory Staff 1954). The results of most studies conducted on water erosion confirm the importance of wet aggregate stability (Rouhipour et al. 2004; Sutherland and Zigler 1998; Agassi and Bradford 1999). Wet sieving and dry sieving method was used to measure aggregate stability, and the results were provided in the form of mean weight and geometric mean of aggregates diameter. Mean Weight-Diameter (MWD) of soil aggregates was determined by wet sieving as well as dry sieving of samples and Geometric Mean diameter (GMD) of soil aggregates was determined by wet sieving with Nimmo and Perkins (2002) method through performing sand correction.

Laboratory measurement of splash erosion rate

The artificial rain simulators are used in most of the fundamental researches used to estimate the effects of vegetation cover, stone cover and soil properties on soil erosion in order to carry out more rapid tests under controlled conditions (Rouhipour 2001).The rain simulator used in this study belonged to Research Institute of Forests and Rangelands of the country, made in French Delta Lab Co, and its nozzle is of single sweep type (Delta Lab 1992). Samples of air-dried soils (passed through 4.7mm sieve) were poured in a drainage tray (flume) of rain simulator machine with a plot with dimension of 0.5×1 m and it was saturated gradually from below during 24 hours. To start the test, the slope of the rain simulator tray was adjusted to 9%, because it was equal to standard CART slope (Lal, 1980) and most of rain-fed lands exist around this slope. The rainfall intensities of 20, 37 and 47 mm/h were applied to these soils (the mentioned intensities are equal to maximum rainfall intensity of half-hour with the return periods of 5, 25 and 100 years of the province, estimated by Vaziri (1984) with Fisher method. In order to calibrate rain simulator device, at first we adjusted the tray slope to 9%, and measured the rate of runoff accumulated over a specific time period (10 minutes), then we determined the rainfall intensity using an impenetrable tray ,without placing the soil inside it, by applying different angle of rotation to the nozzle of the machine. Afterward, we plotted the rainfall intensity graph at different angles of the nozzle rotation (Fig. 2) and used it to determine the desired rotation angle for considered rainfall intensities.

To determine the rainfall uniformity, a few (10) beakers were placed randomly as rain meter on a test tray bed and the rain was simulated with an intensity. After a specified time (10 minutes), the volume of rainfall received in each breaker was determined; after that, the rate of rainfall was determined in terms of rainfall height during the test period by dividing the rain volume to the breaker cross section, and finally the rain intensity was determined at each point of the tray bed. The test was repeated by changing the nozzle angle for all three intensities used in the test. The uniformity of rainfall intensity was obtained by the Christiansen equation (1941), quoted by Refahi (2003), as equal with 83-88% (Equation 1).

$$U_C = 100\left(1 - \frac{\sum_{i=1}^{n}\left(\left|x_i - \bar{x}\right|\right)}{\sum_{i=1}^{n} x_i}\right) \quad (1)$$

Where, UC is rain uniformity coefficient, xi is the height of accumulated rain in i^{th} breaker, $\bar{x}$ is the average rain accumulated in different breakers and n is the number of breakers used, which is equal to 10.

In order to collect the splashed material four metal sidewalls with collection troughs were attached to the flume and all of the splashed material projected over the flume sides at a height of 20 cm or less above the soil surface was collected, dried and weighed. Splash rates were determined as the mass of splashed material per unit area of the flume per unit rainfall erosivity index (EI30) in units of J mm m-2 h−1. Outflow runoff from the flume was collected separately.

Modeling and evaluating the accuracy and efficiency

Three models including 1. Multivariate regression, 2. Artificial neural network and 3. Neuro-fuzzy were used for modeling the splash erosion. The various indices such as coefficient of determination (R^2) and Root Mean Square Error (RMSE), MAPE and MAD were used to determine the value of transition functions accuracy and to evaluate it, so that, for generating functions data series, the more R^2 of the transmitting function and the less RMSE, the more precise model would be; and for evaluation data series, the more R^2 of the transmitting function and the less RMSE, the more valid model would be (2-5 equations).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[E(xi) - M(xi)]^2} \quad (2)$$

$$MAPE = \frac{\frac{\sum_{i=1}^{n}[E(xi)-M(xi)]}{\sum_{i=1}^{n} M(xi)}}{n} \times 100 \quad (3)$$

$$MAD = \frac{\sum_{i=1}^{n}[E(xi)-M(xi)]}{n} \quad (4)$$

E(xi)= Estimated value of observation i

M(xi)= Measured value of observation i

n= total number of observations

p= number of regression coefficients

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MSE= mean square error

$$R^2 = \left[\frac{\sum_{K=1}^{n}(X_k-\overline{X})(Y_k-\overline{Y})}{\sum_{K=1}^{n}(X_k-\overline{X})^2\sum_{Y=1}^{N}(Y-\overline{Y})^2}\right]^2 \qquad (5)$$

Xk= measured value

Yk= predicted value

X= mean of observed values

Y= mean of predicted values

For finding the best results, the datasets used for testing of ANN, ANFIS, and MLR.

RESULTS AND DISCUSSION

Based on Table 1, the soils had an average pH of 7.79 and the average salinity of the soils in the region was about 2.19 dS/m, indicating a low electrical conductivity of the mentioned soils. The average cation exchange capacity of the investigated soils was observed as 23.96 (centimole of positive charge per kilogram) with a minimum of 6.8 and a maximum of 90.95. The average content of organic matter in the soils of the region is about 1.9, which is comparatively high compared to arid and semi-arid soils of Iran. Idowu (2003) concluded that organic matter and pH are considered as two important properties of the soil that can play an important role to predict MWD and GMD as determinants of soil erosion and aggregate stability. The MWD index was obtained with a minimum of 0.05 and a maximum of 1.18 and an average of 0.28. Also, the values obtained from the GMD index have a minimum of 0.46, a maximum of 1.01 and an average of 0.61. The aggregate fractal dimension obtained from the Rieu and Esposito (1991) models has a minimum of 2.63, a maximum of 5.77 and average of 3.88.

The correlation between the rate of splash erosion (g per 30 minutes per square centimeter) and some soil properties is observed in Table 2. Only four parameters of porosity, GMD, runoff height and SAR value have been used as predictive and easily found parameters to predict the splash erosion due to the significant correlation. Tow indices of Geometric Mean Diameter (GMD) of aggregates and runoff height have a significant negative correlation, and tow indices of Porosity and Sodium Absorption Ratio (SAR) have a significant positive correlation with splash erosion value. Studies have shown that the ability to separate soil particles caused by rain drops depends on the height of water on the soil. If the height of water on the soil surface is more than three times of the rain drops diameter, the separation of soil particles by rain will be significantly reduced (Proffit et al. 1991; Sander et al. 1996). Therefore, given the inverse relationship between these two parameters, a significant negative correlation between runoff height and erosion would be justifiable.

Having studied the importance of soil particle adhesion and the effect of surface runoff depth on soil particles separation, Torri et al. (1987) showed that the soil particle separation

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decreases with increasing runoff depth. Therefore, the power of rain drops to separate the soil particles is nearly neutralized by the water layer. Given the relationships created, it seems that the properties mentioned can be used as easily found data to predict the rate of splash erosion. Data were divided into two parts- training (70% of the data) and test (30% of the data) - to evaluate adaptive neuro-fuzzy inference method in predicting the rate of splash erosion, and to compare it with two methods of multivariate linear regression and neural network using easily found data. Figure 3 shows the comparison and relationship between observed and predicted values of splash erosion using multivariate linear regression. The multivariate linear regression method has somehow been able to find a clear relation between input and output data, although the prediction done is not at an acceptable level due to low coefficient of determination. Table 3 shows R^2, RMSE, MAEP and MAD resulted from three methods to predict the rate of splash erosion. As observed, the adaptive neuro-fuzzy inference method has higher coefficient of determination and lower error than two other methods. The multi-layer perceptron method was used to model the neural network.

Like the estimation of building sustainability indices values, different epochs with a number of various hidden layers were investigated. The method accuracy was decreased with increasing number of hidden layers, and finally a hidden layer with the Levenberg–Marquardt algorithm (LMA) and Sigmoid functions were fitted to the data (Fig. 4). As shown in Fig. 5, the neural network method was able to predict the splash erosion somewhat better than the linear regression method (coefficient of determination of 0.709). In the neural network method, we tried to apply the best algorithms to the input data. The regression method from the neural network failed to have a good prediction of splash erosion with input data, and the coefficient of determination was obtained less than 0.4.

Since the main objective of this study was the adaptive neuro-fuzzy inference method, we used Sugeno structure with Grid partitioning at the beginning. Different membership functions were investigated with hybrid and back-propagation algorithms, and finally the relatively high coefficient of determination of 0.798 was obtained in gauss2mf membership function with 3 membership functions and the hybrid learning algorithm for predicted values (Fig. 6). We could not obtain a coefficient of determination better than 0.654 by using of Subclust method with different effect coefficients. The results of Taghizadeh Mehrjerdi et al. (2013) showed that the neuro-fuzzy model is of highest accuracy to predict soil properties, so that this model has increased the accuracy of salinity prediction up to 17 and 11%, at depths of 30 and 100 cm respectively, as compared to multiple linear regressions. Aali et al. (2009) showed that the ANFIS model has a more accurate prediction of the soil saturation moisture percentage than the artificial neural network model, which is consistent with the results of this research.

Thus, due to the uncertainty of soil-related phenomena or the approximation of measured values of different soil properties, it seems to be the reason for higher efficiency of the model based on fuzzy sets in the processing of soil transfer functions. Kalkan et al. (2009) concluded that the artificial intelligence systems could act more effectively to predict tensile strength of the soil than simple empirical methods. Overall, the results obtained from the present study show that, although multivariate linear regression may be considered as a suitable tool for quantitative evaluation of soil properties, it seems that the low number of data for regression development in addition to distribution and variation of changes in soil properties in relation to aggregates stability and splash erosion indices, may be the main reason for low accuracy of this model in the mentioned study. Therefore, it can be stated that the neural networks and neuro-fuzzy methods, compared to conventional and traditional modeling techniques such as

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linear regressions, are of high capability to diagnose complex relationships between input and output data with a small number of samples.

Neuro-fuzzy model can predict non-linear relationships and complex functions. Meanwhile, their main advantage is that they may be developed and modeled without the need to know the exact form of the analysis function, (Besalatpour et al. 2013). In fact, the neo-fuzzy model can better predict the patterns between the input and output parameters and have a better diagnosis of the parameters variation process because it has a significant ability to extract the target response from complex data. Therefore, it seems that the artificial intelligence methods such as artificial neural networks and neuro-fuzzy are superior to conventional methods of modeling in areas with environmental complexity and complex nonlinear relationships between input and output data, and with the low number of available data.

CONCLUSION

The results showed that the low number of data for regression development, in addition to the distribution and variety of changes in soil properties, have caused that multivariate linear regression fails to predict the splash erosion well. The high environmental complexity between input and output data in this study led to introduce the neuro-fuzz method as the best way to predict the aggregates stability indices as well as splash erosion. Regarding the results obtained, it is suggested that the use of other predictive methods such as genetic algorithm methods to examine the rate of splash erosion may be effective to improve these parameters modeling. Considering the coefficient of determination of 0.79 to predict splash erosion, it seems necessary to study the other physical and chemical parameters so that we can have a higher coefficient of determination for predicting these parameters.

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APPENDIX

Table 1. Minimum, Maximum, Mean, Standard Deviation (SD), Coefficient of variation (CV), skewness and Kurtosis values of some physical and chemical properties of the tested soils.

Variables	pH	EC ($dS\ m^{-1}$)	P (%)	SAR ($(mmol\ li^{-1})^{0.5}$)	CEC ($cmol_c\ kg^{-1}$)	OM (%)	Clay (%)	Silt (%)	Sand (%)	Runoff height (mm)	Splash/EI30 $gr/30min\ cm^{-2}$	MWD (mm)	GMD (mm)	Dn
Minimum	6.81	0.41	24.01	0.31	6.80	0.06	8.6	1.4	6.5	4.61	0.102	0.05	0.46	2.63
Maximum	8.30	8.56	69.08	34.72	59.90	4.38	50.2	53.0	90.1	4.47	0.079	1.18	1.01	5.77
Mean	7.79	2.19	41.81	5.84	23.96	1.91	26.00	34.6	39.4	9.08	0.357	0.28	0.61	3.88
SD	0.29	2.15	12.94	7.61	11.07	1.35	10.9	11.4	20.2	0.5	0.024	0.23	0.14	0.75
CV (%)	3.68	98.28	30.95	130.26	46.20	70.47	42.08	32.98	51.17	2.21	0.070	82.43	22.91	19.36
Skewness	-1.13	1.79	0.39	2.35	1.67	0.60	0.3	-0.71	0.28	0.16	1.66	2.6	1.17	0.71
Kurtosis	2.97	2.59	-0.81	5.86	2.90	-1	-0.85	0.70	-0.1	-1.01	2.66	7.43	0.82	0.43

Table 2. Correlation between the rete of splash erosion (g per 30 min / cm2) and some **properties**

Sand	Silt	Clay	OM	Porosity	Runoff height	GMD
0.173 ^{ns}	0.185 ^{ns}	-0.123 ^{ns}	-0.261 ^{ns}	**0.42***	**-0.593****	**-0.656****

CEC	MWD	Dn	EC	pH	SAR
-0.143 ^{ns}	-0.192 ^{ns}	0.255 ^{ns}	0.198 ^{ns}	0.161 ^{ns}	**0.341***

Table 3. Evaluation of multivariate linear regression, neural networks and adaptive neuro-fuzzy inference methods to predict the rate of splash erosion

Model	R^2	RMSE	MAEP	MAD
MLR	0.575	0.322	17.1	0.23
ANN	0.709	0.275	16.02	0.18
ANFIS	0.798	0.161	12.33	0.07

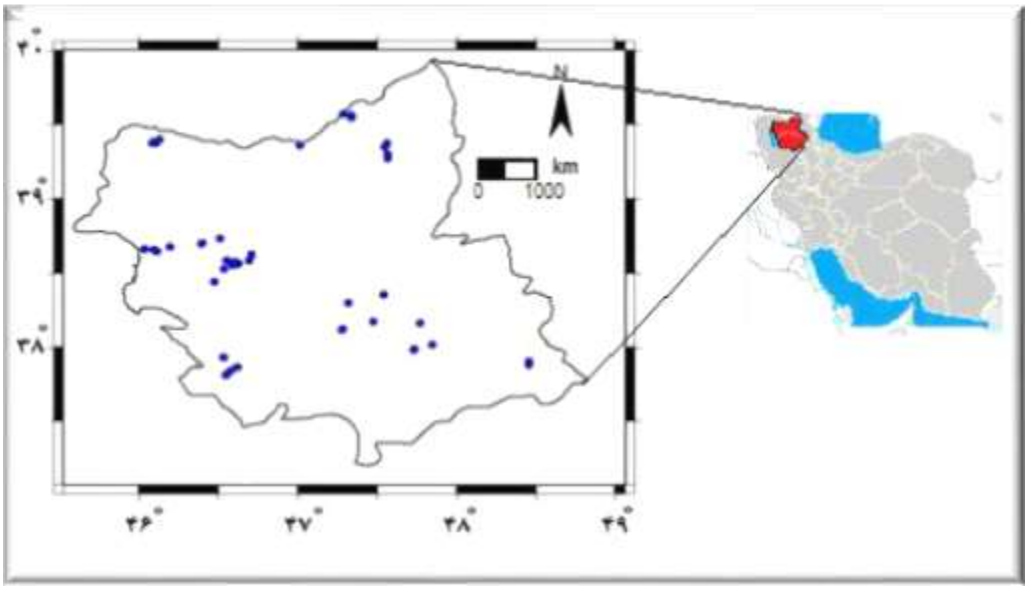

Figure 1. East Azarbaijan Province location in Iran and sampling points.

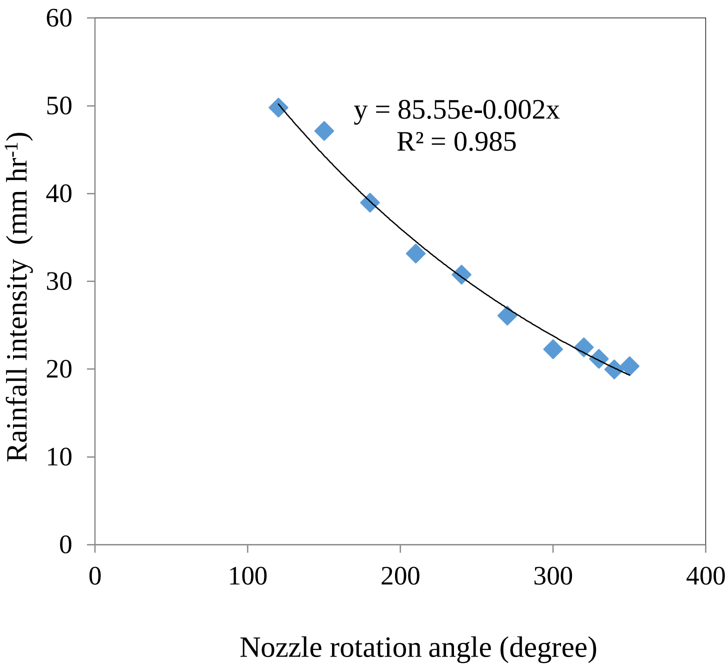

Figure 2. The calibration curve of the simulator set used in the experiments

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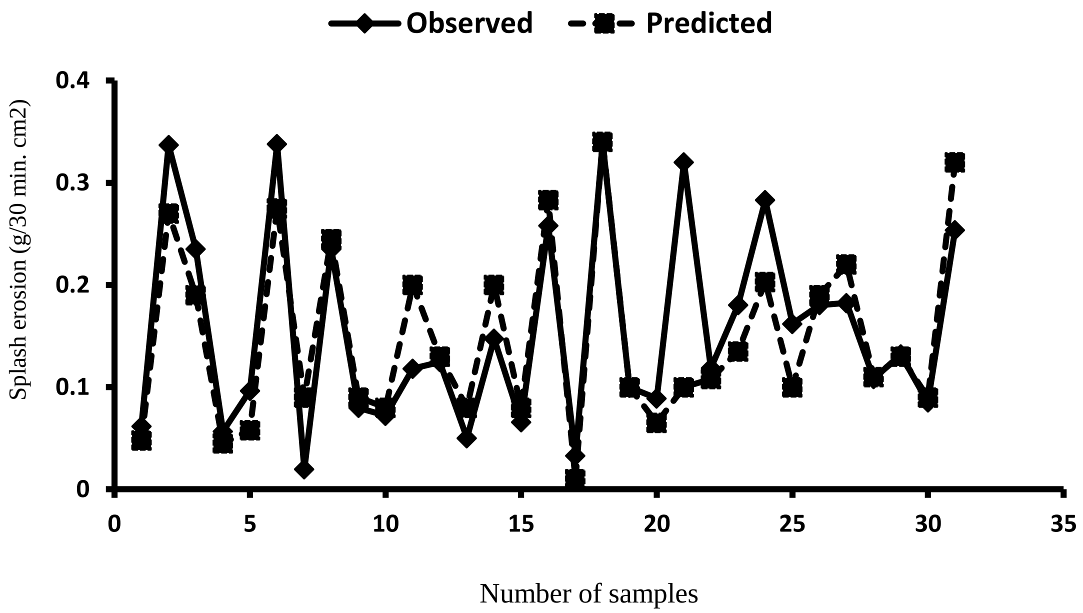

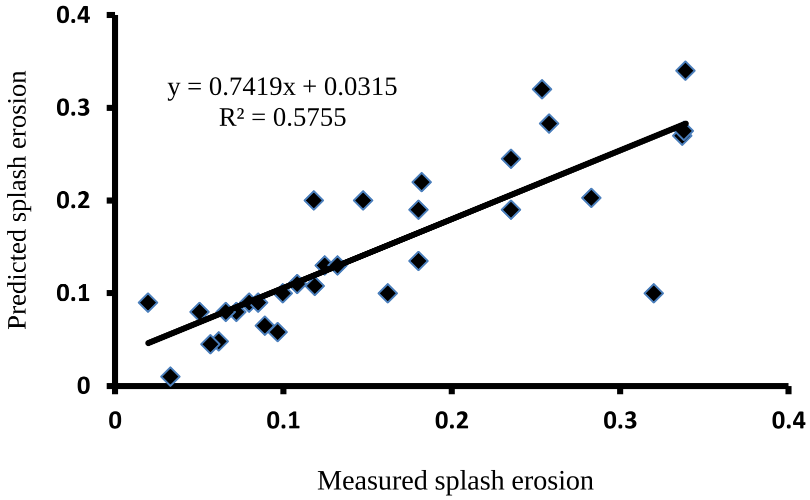

Figure 3. Comparison and relationship between observed and predicted values of splash erosion using multivariate linear regression

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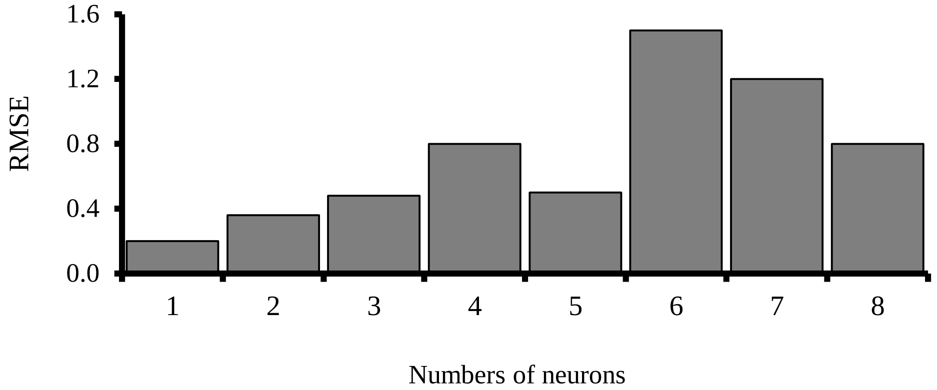
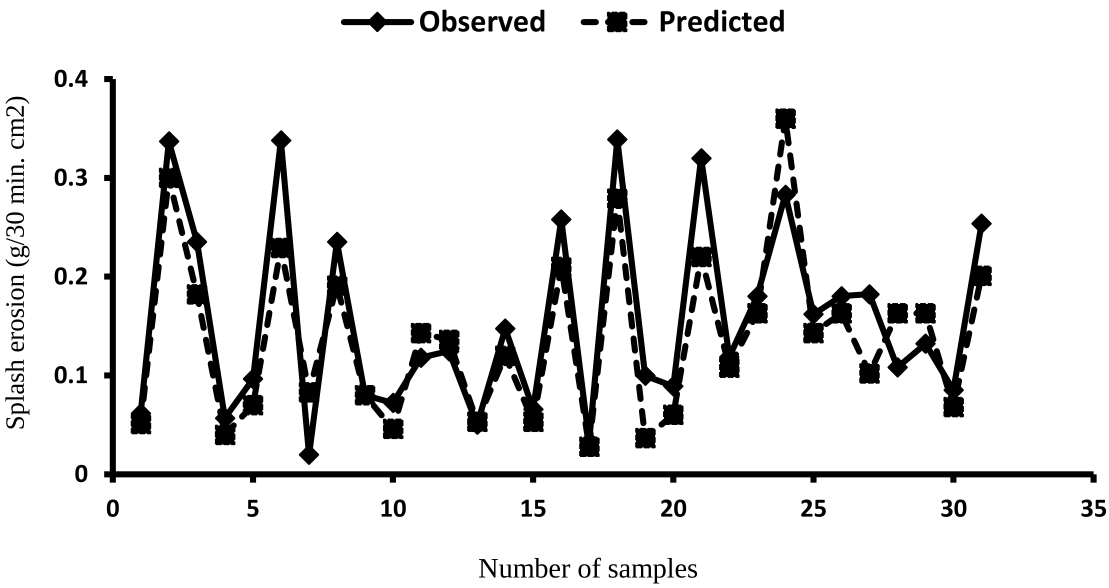


Figure 4. RMSE values to predict the rate of splash erosion by means of 1-8 hidden layers



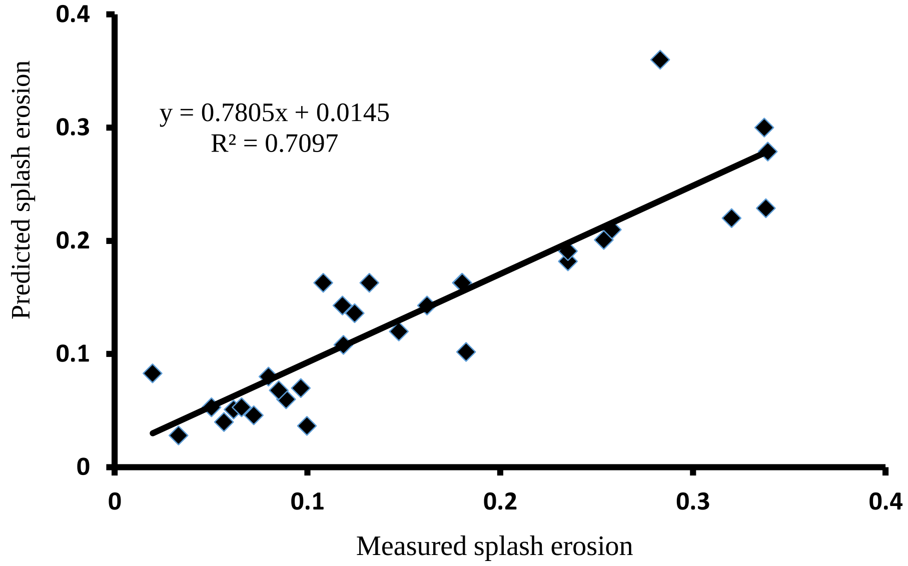
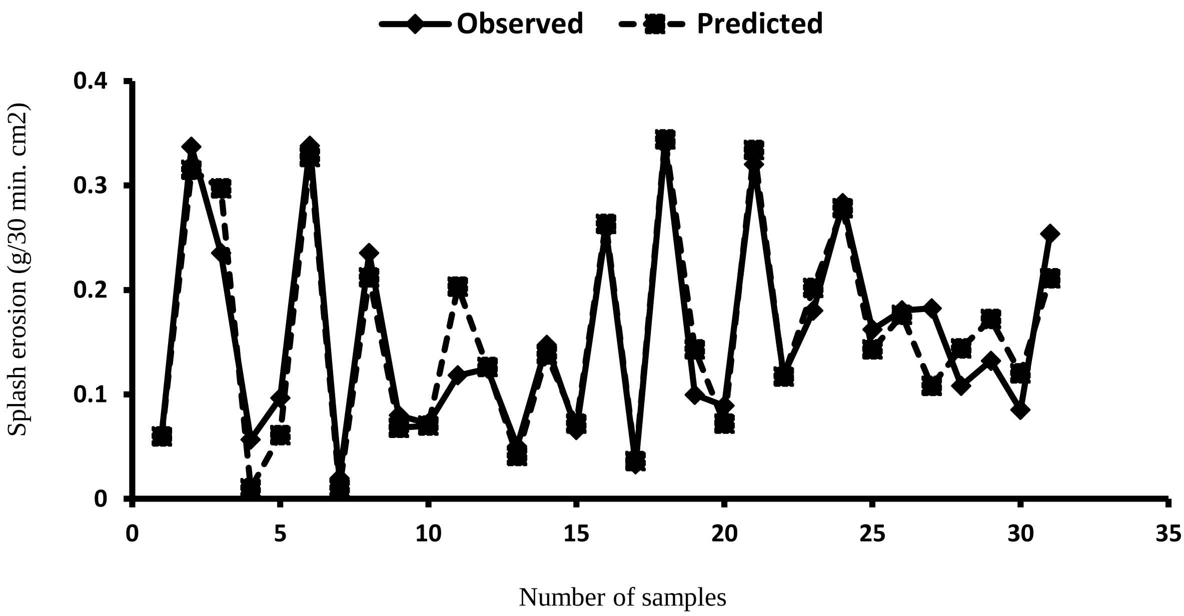


Figure 5. Comparison and relationship between estimated and predicted values of splash erosion using multilayer perceptron neural network method



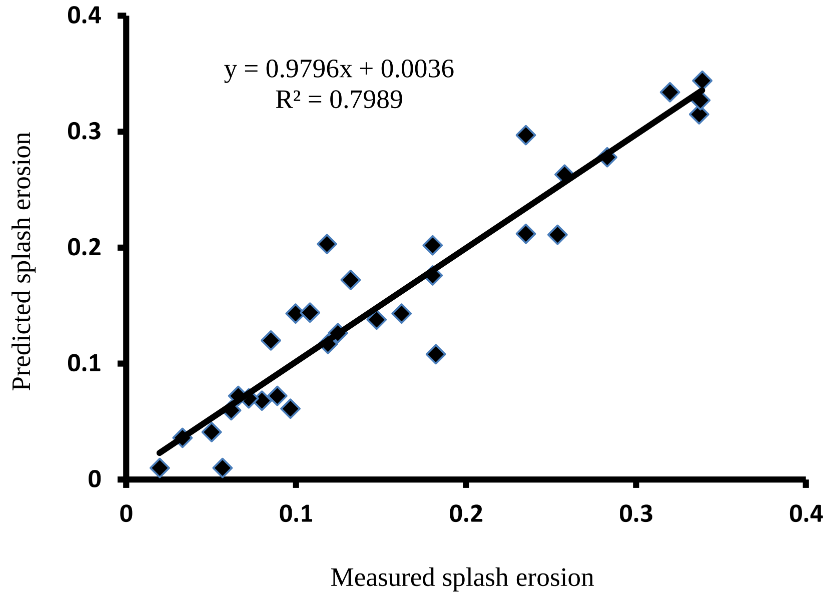


Figure 6. Comparison and relationship between observed and estimated values of splash erosion using adaptive neuro-fuzzy inference method.

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