Catena 111 (2013) 72–79

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

Estimating wet soil aggregate stability from easily available properties in a highly mountainous watershed

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ARTICLE INFO

Article history:
Received 25 March 2013
Received in revised form 25 June 2013
Accepted 1 July 2013

Keywords:
Intelligence systems
Neuro-fuzzy inference system
Artificial neural networks
Conventional regression models
Mean weight diameter

ABSTRACT

A comparison study was carried out with the purpose of verifying when the adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), generalized linear model (GLM), and multiple linear regression (MLR) models are appropriate for prediction of soil wet aggregate stability (as quantified by the mean weight diameter, MWD) in a highly mountainous watershed (Bazoft watershed, southwestern Iran). Three different sets of easily available properties were used as inputs. The first set (denoted as SP) consisted of soil properties including clay content, calcium carbonate equivalent, and soil organic matter content. The second set (denoted as TVA) included topographic attributes (slope and aspect) and the normalized difference vegetation index (NDVI). The third set (denoted as STV) was a combination of soil properties, slope, and NDVI. The ANN and ANFIS models predicted MWD more accurately than the GLM and MLR models. Estimation of MWD using TVA data set resulted in the lowest model efficiency values. The observed model efficiency values for the developed MLR, GLM, ANN, and ANFIS models using the SP data set were 60.76, 62.98, 77.68 and 77.15, respectively. Adding slope and NDVI to soil data (i.e. STV data set) improved the predictions of all four methods. The obtained correlation coefficient values between the predicted and measured MWD for the developed MLR, GLM, ANN, and ANFIS models using STV data set were 0.24, 0.35, 0.84 and 0.73, respectively. In conclusion, the ANN and ANFIS models showed greater potential in predicting soil aggregate stability from soil and site characteristics, whereas linear regression methods did not perform well.

1. Introduction

Soil aggregate stability is a key factor of soil resistivity to mechanical stresses, including the impacts of rainfall and surface runoff, and thus to water erosion (Canasveras et al., 2010). When soil aggregates break down, finer particles are produced, which are easily carried away by wind and water flow and which upon re-sedimentation tend to clog soil pores, leading to the formation of soil crusts (Kirkby and Morgan, 1980; Renard et al., 1997; Yan et al., 2008). Reducing infiltration, this sealing effect enhances surface runoff and thus promotes further water erosion. Hence, aggregate stability is an important factor in soil erosion.

Various indicators have been proposed to characterize and quantify soil aggregate stability, for example percentage of water-stable aggregates (WSA), mean weight diameter (MWD) and geometric mean diameter (GMD) of aggregates, and water-dispersible clay (WDC) content (Calero et al., 2008; Le Bissonnais, 1996). Unfortunately, the experimental methods available to determine these indicators are laborious, time-consuming and difficult to standardize (Canasveras et al., 2010). Therefore, it would be advantageous if aggregate stability could be predicted indirectly from more easily available data.

General soil properties most closely correlated with soil aggregate stability are the contents of clay, calcium carbonate, and organic matter (Canasveras et al., 2010). Clay particles are considered as cementing agents for aggregation because of their high specific surface area, high cation exchange capacity (CEC), and consequently, high physical and chemical activity. Soil organic matter content can affect soil structure as well as soil aggregate stability in different ways: the transient aggregating effect of polysaccharides on micro-aggregates, increased aggregate coherence against slaking due to hydrophobic materials, the temporarily stabilizing effect of roots and hyphae on macro-aggregates, and the persistent effect of polymers and aromatic compounds on micro-aggregates. Calcium carbonate contents also influence soil aggregation through their cementing effects and preventing aggregate dispersion (Amezketa, 1999).

Indirectly, also topography and vegetation characteristics affect aggregate stability, in particular through their influence on the dynamics of soil structure and soil properties such as clay mineralogy,

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0341-8162
http://dx.doi.org/10.1016/j.catena.2013.07.001

SOM, carbonate concentration, texture, soil water content, and plant development (Canton et al., 2009). Furthermore, slope and aspect may influence the rate of weathering and erodibility of soils and thus soil aggregate stability (Bronick and Lal, 2005).

Functions translating such data into predictions of soil aggregate stability can be derived by a variety of methods. In contrast to widespread applications of conventional regression models to predict soil aggregate stability indirectly from other data; artificial intelligence systems such as artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) have not been exploited for this purpose, although they have shown much potential in similar applications (Azamathulla et al., 2009; Bocco et al., 2010; Gago et al., 2010; Huading et al., 2007; Huang et al., 2010; Kisi et al., 2009; Uno et al., 2005).

ANNs are computing systems made up of a number of simple, highly interconnected processing elements, also called neurons. Generally, an ANN is made of an input layer, one or several hidden layers (HLs), and an output layer of neurons (Tracey et al., 2011). The input layer neurons receive the input information from the outside environment and transmit it to hidden layer. Each neuron of a subsequent layer first computes a linear combination of the outputs from all neurons of the previous layer and then adds a bias to it. Furthermore, each neuron of a HL applies a specific nonlinear function, called *activation function*, to this linear combination plus bias. The coefficients of the linear combinations and the biases are called weights (Bocco et al., 2010; Saridemir, 2009; Sobhani et al., 2010; Turan et al., 2011).

ANFIS is a scheme that uses the learning capability of ANNs to derive fuzzy IF–THEN rules with appropriate fuzzy set membership functions (Jang and Sun, 1995; Tay and Zhang, 1999). The main strength of ANFIS in comparison with ANNs is that it generates linguistically interpretable IF–THEN rules (Sobhani et al., 2010). ANFIS models capture the relationship between input and output data by establishing fuzzy language rules, while ANNs do so in form of trained connection weights. Furthermore, it is reported that constructing an ANFIS model is less time-consuming than an ANN model (Azamathulla et al., 2009).

The objectives of this study were to: i) compare the capabilities of ANFIS, ANN, generalized linear model (GLM), and multiple linear regression (MLR) to derive pedotransfer functions (PTFs) between soil aggregate stability and various sets of input variables, and ii) use the PTFs for prediction of aggregate stability using another set of soil samples collected from the same area. For this purpose, three different sets of easily available data including soil properties alone, topographic attributes and vegetation index, and a combination of soil properties and topographic and vegetation attributes were used as inputs. The current comparison study in using different soft computing techniques and also different data sets for MWD estimation can be a valuable source of information for other modelers. Discussions of advantages and disadvantages are also given in different point of view for all the methods.

2. Materials and methods

2.1. Study area description

The study area was part of the Bazoft watershed (31° 37′ to 32° 39′ N and 49° 34′ to 50° 32′ E), which is located in the northern part of the Karun river basin in central Iran. The major river in the watershed is the Ab-Bazoft, which joins the Karun River at the outlet of the watershed. The elevation ranges from 880 m a.s.l. in the south of the watershed to 4300 m a.s.l. on the Zardkuh Mountain in the north. The long-term average rainfall of the region varies between 500 and 1400 mm per year, and the average temperature varies between 8 and 20 °C. The watershed is highly mountainous where the most slopes are between 40 and 70%, covering about 46% of the watershed. The dominant slope shape is convex. Approximately 56% of the watershed area is covered by pastures, the rest by forests and bare lands. *Quercus brantii* is the dominating forest tree species, and *Astragalus* sp. is the most abundant pasture plant.

Old terrace deposits (Qt1) are dominant geological unit having moderate susceptibility to weathering and erosion with some marls enrichment with gypsiferous and sandstone (mp1) (Iranian Geological Organization, 2006). Majority of the soils include Calcic Argixerolls, Typic Calcixerepts, Typic Xerorthents, Typic Cryorthents, and Typic Haploxerolls in the watershed (Soil Survey Staff, 2006) which are dominated by calcareous materials. Soils are less than 5 cm deep on steep slopes and more than 150 cm deep in the valley bottoms. The main textural classes are silt loam, loam, silty clay loam, clay loam, and silty clay. The dominant physiographic units are mountains, hills, plateaus and upper traces, alluvial plains, and gravelly colluvial fans.

2.2. Soil sampling and measurements

A stratified random sampling was designed using digital geology, topography, and land use maps in the environment of ILWIS 3.4 software (ITC, University of Twente, Netherlands) for proper selection of soil sampling locations in all of the land uses. Thus, land use type was indirectly taken into account in the soil sampling. In other words, the land use directly or indirectly affects the soil properties (like texture, calcium carbonate, and organic matter) as well as vegetation cover (as quantified by NDVI) which were used as predictors in the PTFs. A total of 160 soil samples were collected from the top 5 cm of soil surface from all major land unit tracts. The positions of the sampling points were identified in the field using GPS (model: 76CSx).

The soil samples were air-dried and ground to pass a 2-mm sieve. Soil organic matter (SOM) content was determined by the Walkley–Black method with dichromate extraction and titrimetric quantization (Nelson and Sommers, 1986). Clay content (<2 μm) was measured by means of sieving and sedimentation using the procedure described by Gee and Bauder (1986), and calcium carbonate equivalent (CCE) was determined by the back-titration method (Nelson, 1982).

The soil samples for aggregate stability assessment were taken from the same locations and brought to the laboratory in such a way that minimum structural deformation and/or destruction occurred. Following van Bavel (1950) method, as modified by Kemper and Rosenau (1986), was used to parameterize the mean weight diameter (MWD) of wet-sieved aggregates. Briefly, 50 g of the <4.75 mm aggregates were placed on the topmost of a stack of sieves with descending mesh size (2, 1, 0.5, and 0.25 mm) from top to bottom. The samples were first immersed in distilled water and then sieved by moving the sieve set vertically. The soil retained by each sieve was dried at 105 °C for 24 h, weighed and corrected for sand/gravel particles to obtain the proportion of water-stable aggregates. The MWD (mm) of water-stable aggregates was calculated using the following equation:

$$\mathrm{MWD} = \sum_{i=1}^{n} w_i \overline{X}_i \tag{1}$$

where $\overline{X}_i$ is the arithmetic mean diameter of each size fraction (mm) and w_i the proportion of the total water-stable aggregates in the corresponding size fraction after deducting the weight of sand/gravel particles (upon dispersion and passing through the same sieve) as indicated above.

2.3. Topographic and vegetation attributes

The topographic attributes, including slope and aspect, were determined using a 20 m by 20 m digital elevation model (DEM). The slope of each cell represents the maximum rate of elevation change between the cell and its neighbor cells. The aspect represents the direction of slope, i.e. of the maximum rate of elevation change in down-slope direction. The normalized difference vegetation index (NDVI) was used to quantify the vegetation cover. It was derived from an IRS-1D satellite photo taken in April 2008 with a spatial resolution of 24 m by 24 m (Indian Space Applications Centre, 2002).

2.4. Data sets

The following three data sets were used as model inputs for predicting soil aggregate stability (Table 1). The first set (denoted as SP) consisted of the soil properties CCE, SOM, and clay content, the second data set (denoted as TVA) included the topographic attributes slope and aspect and the vegetation index (NDVI), and the third data set (denoted as STV) was constructed using additional topographic and vegetation attributes slope and NDVI along with soil properties CCE, SOM, and clay content.

Descriptive statistics of the experimental data including mean, minimum, maximum, range, standard deviation (SD), variance, and skewness were determined using the statistical software SPSS (IBM Com., Chicago, USA). Scatter plot matrices, displaying relationships among the data (i.e. clay, SOM, CCE, NDVI, slope, aspect, and MWD), were obtained using VisuLab (ETH University, Zurich, Switzerland). All input data were normalized to a range of 0.1–0.9 using the following equation:

$$x_i = 0.8 \times \left[\frac{(x - x_{\min})}{(x_{\max} - x_{\min})}\right] + 0.1. \tag{2}$$

Each data set was then divided into three subsets of training, testing, and verification. The training subset was randomly chosen from 60% of the total set of the data and the remaining samples (40% of the data) were used equally in two parts as the testing and validation sets.

2.5. Multiple linear regression (MLR)

Linear regression is one of the oldest statistical techniques, and has long been used in many researches (Guisan et al., 2002). The basic linear regression model has the form:

$$Y = \alpha + X^T\beta + \varepsilon \tag{3}$$

where Y denotes the dependent variable, α is a constant called the intercept, $X = (X_1,\dots,X_n)$ is a vector of explanatory variables, $\beta = \{\beta_1,\dots,\beta_n\}$ is the vector of regression coefficients (one for each explanatory variable), and ε represents random measured errors as well as any other variation not explained by the linear model. When calibrating a regression model, one tries to minimize the unexplained variation by the use of one of the estimation techniques such as the least-squares (LS) algorithm (Guisan et al., 2002). In this study, the statistical software SAS (Cary, NC., USA) was used to develop the MLR models.

2.6. Generalized linear model (GLM)

GLMs are one of the mathematical extensions of linear regression models that account for nonlinearity and inhomogeneous variance structures in the data (Hastie and Tibshirani, 1990). In concept, a GLM is based on an assumed relationship (called a link function, see below) between the mean of the dependent variable and the linear combination of the explanatory variables. Data may be assumed to be from several families of probability distributions, including binomial, Poisson, negative binomial, or gamma distribution, many of which better fit the non-normal error structures of most data (Guisan et al., 2002).

Table 1
Input data sets used in developing the MWD prediction models using MLR, GLM, ANN, and ANFIS techniques.

Input data set name	Inputs
SP	Clay, SOM, and CCE
TVA	Aspect, Slope, and NDVI
STV	Clay, SOM, CCE, Slope, and NDVI

Clay: clay content, SOM: soil organic matter content, CCE: calcium carbonate equivalent content, and NDVI: normalized difference vegetation index.

In GLMs, the predictor variables X_j, ($j = 1, \dots, n$) are combined to produce a linear predictor LP which is related to the expected value $\mu = E(Y)$ of the response variable Y through a link function $g(E(Y))$, such as:

$$g(E(Y)) = LP = \alpha + X^T\beta \tag{5}$$

where α, X, and β are those previously described in Eq. (3).

In contrast to classical linear models, which presuppose a Gaussian (i.e. normal) distribution and an identity link, the distribution of Y in a GLM may be any of the exponential family distributions (e.g. Gaussian, Poisson or binomial) and the link function may be any monotonic differentiable function like logarithm or logit (McCullagh and Nelder, 1989). The variance of Y depends on $\mu = E(Y)$ through the variance function $V(\mu)$, giving $Var(Y) = \varphi V(\mu)$, where φ is a scale (also known as a dispersion) parameter. When the scale parameter is expected to be higher than the value anticipated under the chosen distribution (i.e. over-dispersion), it can be estimated using the quasi-likelihood which is an extension of generalized least-squares (Davison, 2001). In this study, the SPSS Clementine (IBM Com., Chicago, USA) software was used to develop the GLM models.

2.7. Artificial neural networks (ANNs)

For neural network analysis, we used the multilayer perceptron (MLP) with back-propagation (BP) learning rule, which is the most commonly used neural network structure in ecological modeling and soil science (Bocco et al., 2010; Tracey et al., 2011). As the output of the MLP network, the MWD, was calculated as (Juang et al., 1999):

$$\mathrm{MWD} = f_2\left\{B_0 + \sum_{k=1}^{n}\left[w_k f_1\left(B_{Hk} + \sum_{i=1}^{m}[w_{ik}P_i]\right)\right]\right\} \tag{6}$$

where B_0 is the bias at the output layer; w_k is the weight of connection between neuron k of the hidden layer and the single output layer neuron; B_{Hk} is the bias at neuron k of the hidden layer ($k = 1,\dots,n$); w_{ik} is the weight of connection between input variable i ($i = 1,\dots, m$) and neuron k of the hidden layer; P_i is the input variable i; $f_1(h_k)$ is the transfer function of the neurons in the hidden layer; and $f_2(h_k)$ is the transfer function of the neuron in the output layer. Both transfer functions $f_1(h_k)$ and $f_2(h_k)$ adopted were sigmoid functions in this study given by:

$$f_N(\lambda) = \frac{1}{1 + e^{-\lambda}} \quad N = 1, 2 \tag{7}$$

The numbers of neurons and epochs were determined by trial and error. For the constructed ANN model using SP data set, 6 hidden neurons and an epoch set number at 50000 gave a satisfactory result (evaluated in term of network performance). Five hidden neurons and an epoch set number at 25000 for the TVA data set and 9 hidden neurons and an epoch set number at 5000 for the STV data set also gave satisfactory results. Neural network analyses were performed using MatLab 7.6, Neural Networks Toolbox (Mathworks, Inc., Natick, MA, USA).

2.8. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a hybrid scheme that uses the learning capability of the artificial neural network to derive the fuzzy IF–THEN rules with appropriate membership functions worked out from the training pairs, which in turn leads to the inference (Jang and Sun, 1995; Tay and Zhang, 1999). In fact, ANFIS incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF–THEN fuzzy rules. The difference between the common neural networks and the ANFIS is that, while the former captures the underlying dependency in the form of the trained connection weights, the latter does so by establishing the fuzzy language rules. The main strength of ANFIS models is that they are universal approximators with the ability to solicit interpretable IF–THEN rules (Sobhani et al., 2010). Detailed description of ANFIS theory is discussed more in reviews (Azamathulla et al., 2009; Jang and Sun, 1995; Sobhani et al., 2010; Takagi and Sugeno, 1985; Tay and Zhang, 1999).

In a preliminary analysis, we evaluated a command genfis1 with different types of membership functions (including gbellmf, gaussmf, gauss2mf, psigmf, dsigmf, pimf, trapmf, and trimf) and different numbers of epochs to get the best training performance with minimum squared error. The command genfis1 generates a Sugeno-type FIS structure as initial conditions (initialization of the membership function parameters) for ANFIS training. Hybrid learning algorithm was also employed to optimize the learning procedure of the ANFIS models in each trial. The hybrid learning algorithm is a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters in emulating a training data set. Finally, the generalized bell-shape fuzzy membership function (i.e. gbellmf) with 3 numbers of membership functions was used for the adaptive system analysis.

2.9. Statistical parameters

The performances of the developed models were evaluated using various standard statistical performance evaluation criteria. The statistical measures were included the root mean square error (RMSE), model efficiency factor (MEF), absolute error percentage (AEP), and correlation coefficient (R) between the measured and predicted MWD values. The RMSE, MEF, and AEP statistics are defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[P(x_i) - M(x_i)\right]^2} \tag{17}$$

$$\mathrm{MEF} = 1 - \frac{\sum_{i=1}^{n}\left[P(x_i) - M(x_i)\right]^2}{\sum_{i=1}^{n}\left[M(x_i) - \overline{M}(x_i)\right]^2} \tag{18}$$

$$\mathrm{AEP} = \frac{\sum_{i=1}^{n}\left|P(x_i) - M(x_i)\right|}{\sum_{i=1}^{n}M(x_i)} \times 100 \tag{19}$$

where $P(x_i)$ denotes the predicted value of observation i, $M(x_i)$ is the measured value of observation i, $\overline{M}$ is the mean of measured values, and n is the total number of observations.

3. Results and discussion

3.1. Descriptive statistics

Table 2 revealed that there was little variability in the sample distributions of the variables used in this study to develop the MWD prediction models, indicating that their values were all normally distributed. Fig. 1 also shows the scatter plot matrices displaying interrelations between the input variables (i.e. Clay, SOM, CCE, slope, and NDVI) and MWD. This figure revealed the dependencies between the MWD and input variables; however, the existing patterns and trends seem to be relatively complex and intricate. In other words, although variation in change of MWD seems to be depended on the changes in the other investigated characteristics, the nature of the relationships is not simply understandable. Nevertheless, it appears that the investigated soil properties, topographic and vegetation attributes may directly or indirectly affect the aggregate stability in the studied sites and thus soft computing techniques might be useful to be used to derive the functions translating such data into predictions of soil aggregate stability.

Table 2
Summary statistics of soil properties, topographic and vegetation attributes used in developing the MWD prediction models.

Parameter	Descriptive statistics					
	Mean	Minimum	Maximum	Variance	SD	Skewness
Clay (%)	31.07	8.0	53.60	70.91	8.42	−0.23
SOM (%)	2.57	0.22	6.33	1.69	1.30	0.49
CCE (%)	25.29	0.25	80.65	447.06	21.14	0.61
Slope (%)	28.33	3.10	80.61	237.09	15.40	0.62
NDVI	0.13	−0.31	0.47	0.006	0.08	−0.66
Aspect	171.82	8.87	356.85	10162.83	100.81	−0.03

Clay: clay content, SOM: soil organic matter content, CCE: calcium carbonate equivalent content, NDVI: normalized difference vegetation index, MWD: mean weight diameter, and SD: standard deviation.

3.2. Soil aggregate stability prediction

3.2.1. MLR model

The MLR model had lower prediction efficiency in comparison with the other investigated methods. Using MLR with only topographic attributes and vegetation index as input data (i.e. TVA data set) resulted in the lowest correlation coefficient (R) between the measured and predicted MWD values among the other proposed MLR models (Figs. 2, 3, and 4). Prediction capability of the constructed MLR model using SP data was better than that using TVA data and a higher R and MEF values obtained (Figs. 2 and 3; Tables 3 and 4). The AEP value for the constructed MLR model using TVA data set was 16.20% (Table 4). Addition of slope and NDVI to soil properties (i.e. STV data set) had no considerable effect on the prediction accuracy, however, a slightly higher R value of 0.24 obtained and AEP was lower than the proposed MLR models using SP and TVA data sets (Fig. 4 and Table 5). According to the evaluation indices, it appears that the conventional regression models were to some extent poor in predicting soil aggregate stability in the studied region.

3.2.2. GLM model

The MEF, AEP, and RMSE values for the constructed GLM model using SP data set were 62.98, 15.93, and 10.45%, respectively (Table 3). The proposed GLM model using topographic and vegetation properties alone (i.e. TVA data set) had the lowest R and MEF among the other proposed generalized linear models similar to the obtained results for MLR technique (Figs. 2, 3, and 4; Tables 3, 4, and 5). Furthermore, the coefficient of correlation between the measured and predicted MWD values for the constructed GLM model using STV data set was 0.34 and a higher MEF value of 64.23 obtained (Fig. 4 and Table 5). These results suggest a relatively better performance of GLM technique for predicting MWD in comparison with MLR technique. However, it appears that this technique also fail to be reliable for predicting soil aggregate stability in the study area.

3.2.3. ANN model

The best developed ANN model using different input data sets was the constructed model using a combination of soil properties, topographic and vegetation attributes together (i.e. STV data set) which had the highest model efficiency factor (MEF = 89.10) among the developed neural network models (Table 5). It also gave a greater correlation coefficient of 0.84 and lower AEP and MSE values of 10.04 and 6.26%, respectively (Fig. 4 and Table 5). Using the soil information alone (i.e. SP data set) resulted in a higher model efficiency and R values than that using the information from topographic and vegetation attributes alone (i.e. TVA data set). The observed MEF, AEP, RMSE, and R values for the constructed ANN model using SP data were 77.68,

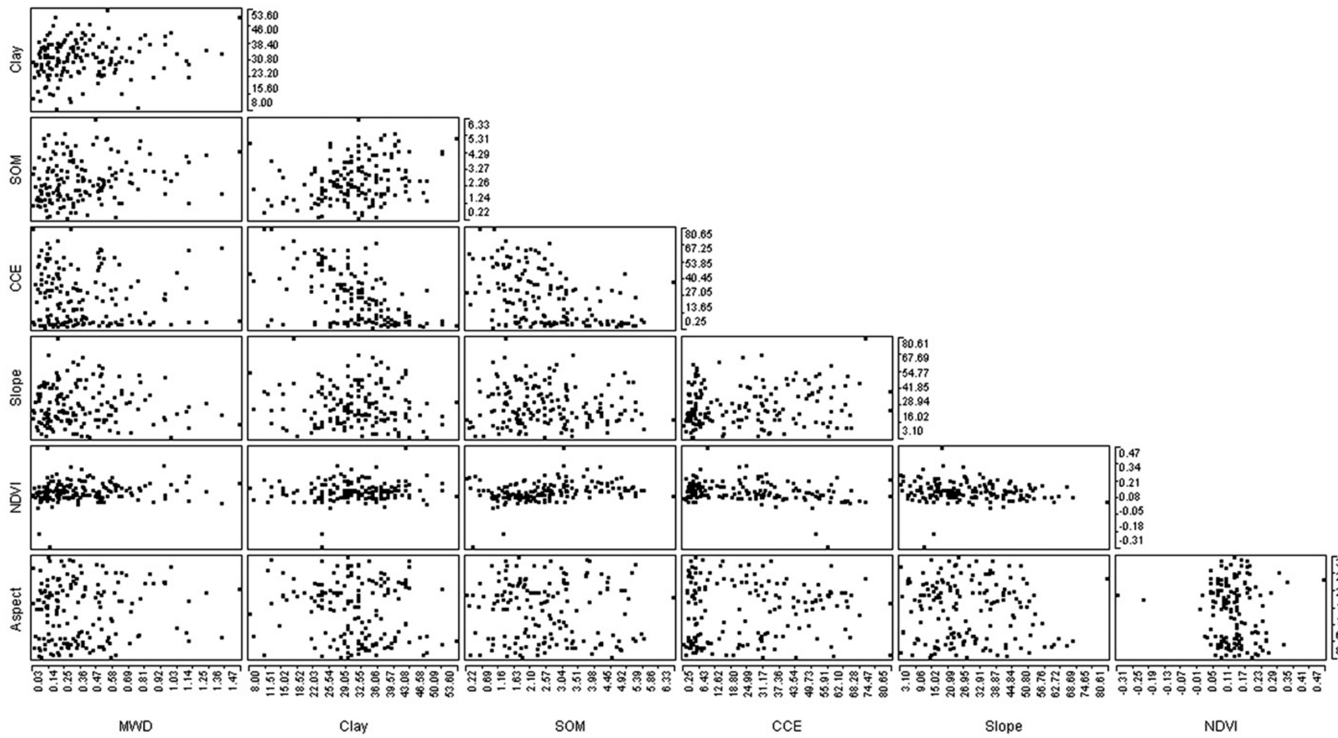

Fig. 1. Scatter plot matrices displaying the relationships between the analyzed variables; mean weight diameter (MWD), clay content (Clay), soil organic matter content (SOM), calcium carbonate equivalent content (CCE), slope (Slope), and normalized difference vegetation index (NDVI).

13.03, 8.11% and 0.77, respectively, whereas they were 70.01, 15.13, 10.37%, and 0.53 for the constructed ANN model using TVA data (Figs. 3 and 4; Tables 3 and 4). It appears that ANN technique may have an acceptable performance for the prediction of MWD in the studied sites, especially, when a combination of soil properties, topographic and vegetation attributes together are used as input variables.

3.2.4. ANFIS model

The obtained evaluation criteria and correlation coefficient values showed that ANFIS may be a suitable tool for the prediction MWD, especially, when its accuracy is compared with that of conventional regression techniques. The MEF, AEP, and RMSE values for the developed ANFIS model using SP data set were 77.15, 11.43%, and 8.21, respectively (Table 3). Constructed ANFIS model using TVA data set had the lowest *R* among the proposed ANFIS models similar to the obtained results for other approaches (Figs. 2, 3, and 4). Furthermore, the model efficiency factor for this model was considerably lower than the other developed ANFIS models (Tables 3, 4, and 5). Adding slope and NDVI to soil properties (i.e. STV data set) increased the MEF in comparison with SP data set; however, the increases were not noticeable (Table 5). The coefficient of correlation between the measured and predicted MWD values for the proposed ANFIS using STV data set was 0.73 while it was 0.70 for SP data set (Figs. 2 and 4). These results suggest a greater influence of soil

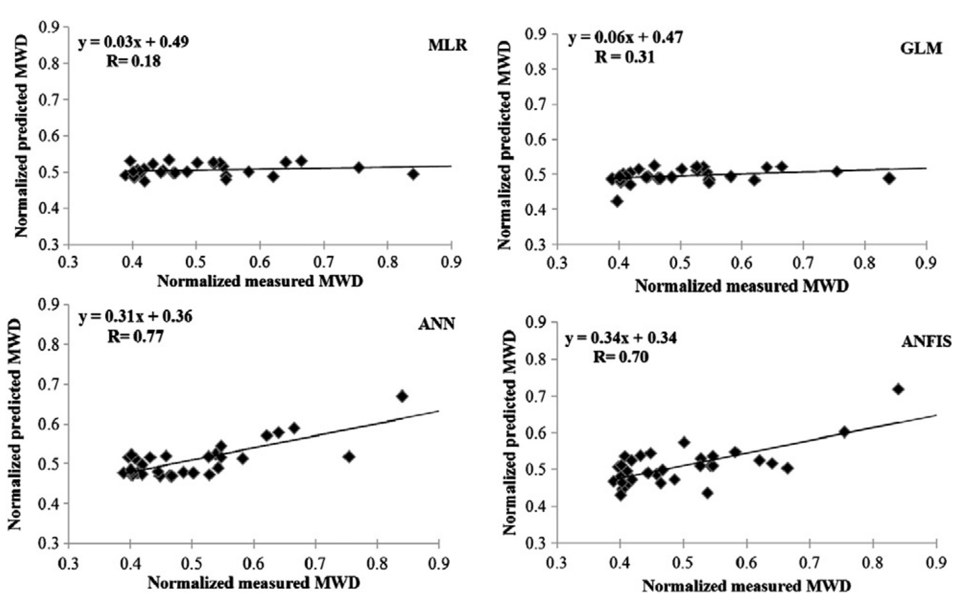

Fig. 2. Relationships between the normalized predicted and measured MWD values for the test sample sets of constructed MLR, GLM, ANN, and ANFIS models using soil data.

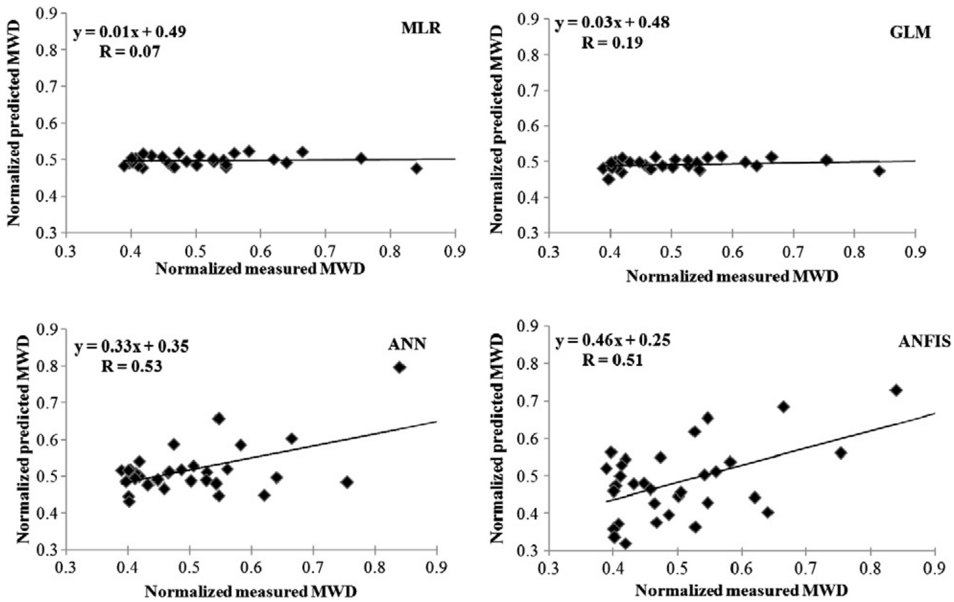

Fig. 3. Relationships between the normalized predicted and measured MWD values for the test sample sets of constructed MLR, GLM, ANN, and ANFIS models using topographic and vegetation data.

properties than topographic and vegetation attributes as inputs of the models in MWD prediction by neuro-fuzzy approach.

In other studies, Turan et al. (2011) used ANNs for modeling of adsorption of Cu (II) from industrial leachate by pumice and concluded that by the use of ANNs removal of Cu (II) from aqueous leachate effectively improved up to about 98%. Huading et al. (2007) found that a combination of GIS and neural networks was useful for assessing wind erosion hazard in Inner Mongolia, China. Bocco et al. (2010) evaluated the potential use of linear models and neural networks in estimating solar radiation and obtained better estimation results using neural networks. Gago et al. (2010) concluded that ANNs are useful alternatives to the traditional statistical methodology for analyzing plant data. Azamathulla et al. (2009) reported that an ANFIS-based approach could accurately predict the bed-load of moderately-sized rivers. Mashrei et al. (2010) indicated that ANN model was more useful than ANFIS model for prediction the moment capacity of ferrocement members since the ANN training and testing results were closely in agreement with the experimental results. Cevik and Ozturk (2009) found that their proposed neuro-fuzzy model could accurately predict the shear strength of reinforced concrete beams.

3.3. Comparisons and discussions

The comparison of the four methods (i.e. MLR, GLM, ANN, and ANFIS) demonstrates that ANFIS and ANN methods provide more accurate predictions of MWD than MLR and GLM methods. However, the statistical parameters of the results obtained from the studied models show that ANN technique is more feasible than ANFIS technique, particularly, when a combination of soil properties, topographic and vegetation attributes together (i.e. STV data set) is used to build the models. This might be due to the larger amount of data that are required for

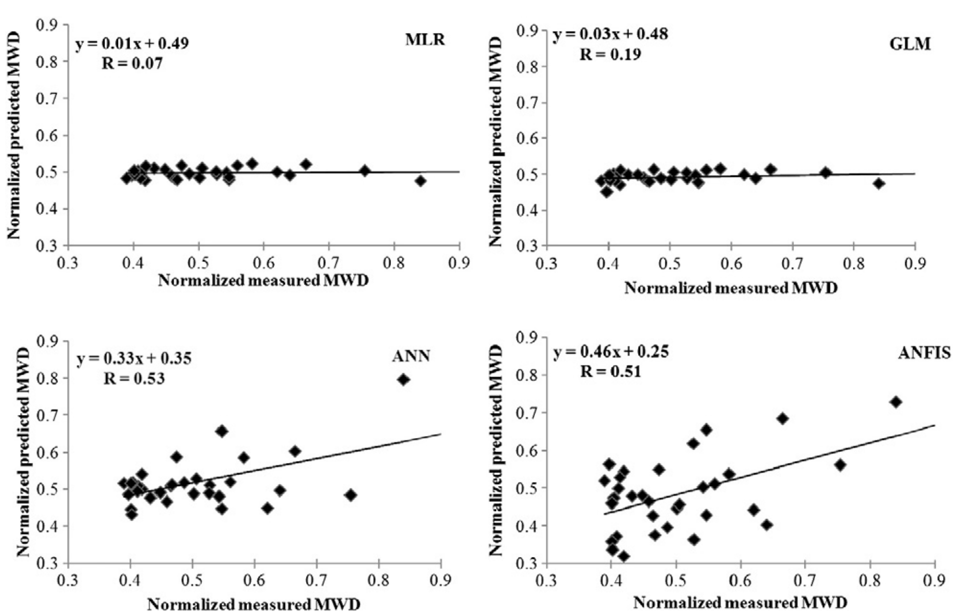

Fig. 4. Relationships between the normalized predicted and measured MWD values for the test sample sets of constructed MLR, GLM, ANN, and ANFIS models using combined soil, topographic, and vegetation data.

Table 3
Comparison of performances of the proposed models for the MWD prediction using soil data.

Model type	Evaluation criterion		
	MEF	AEP	RMSE (%)
MLR	60.76	16.70	8.21
GLM	62.98	15.93	10.45
ANN	77.68	13.03	8.11
ANFIS	77.15	11.43	8.21

MEF: model efficiency factor, AEP: absolute error percentage, RMSE: root mean square error, MLR: multiple linear regression, GLM: generalized linear model, ANN: artificial neural network, and ANFIS: adaptive neuro-fuzzy inference system.

developing a sustainable regression model comparing to intelligent systems. Furthermore, only the linear effects of the predictors on the dependent variable can be extracted by linear models while in many cases the effects may not be linear in the nature. Meanwhile, neural networks and neuro-fuzzy models are suitable for modeling nonlinear relationships and their major advantage is that these methods can be developed without knowing the exact form of analytical function on which the model should be built. Nevertheless, the physical effects of the variables in ANN and ANFIS models cannot be interpreted via the parameters of the model unlike the regression model which is one of the main disadvantages of these intelligence models over regression model. The physical meaning of the relationship can be only shown by using regression model at hand.

The comparison of performance of the constructed models using different input data sets to predict MWD also demonstrates that use of a combination of soil properties, topographic and vegetation attributes together (i.e. STV data set) as input data set might give more accurate prediction results. This is evident from a lower RMSE and AEP and a higher R and MEF values (see Tables 3, 4, and 5 and Figs. 2, 3, and 4).

On the other hand, the proposed ANN models were, in general, more feasible than the ANFIS models in predicting MWD when the evaluation criteria are compared. However, the predictive capability of the constructed ANN model using soil properties alone was not higher than that of the ANFIS model (see Tables 3, 4, and 5). As it can be seen in Fig. 1, the existing patterns and trends among the input variables and the output (MWD) are relatively complex and intricate. It appears that, the ANN model was more capable in extracting the existing patterns among the input variables and the output. Neural networks, in fact, can extract the patterns and detect the trends that are too complex to be noticed by either humans or other computer techniques because of their remarkable ability to derive a general solution from complicated or imprecise data (Yilmaz and Kaynar, 2011). These artificial networks have the capability of learning from examples and are capable to solve intricate, nonlinear problems and problems which are very tedious to solve by conventional methods. In addition, when a data stream is analyzed using a neural network, it is possible to detect the important predictive patterns that are not previously apparent to a non-expert (Yilmaz and Kaynar, 2011). Finally, all these indicate that ANFIS approach may not always be a better choice for predicting soil aggregate stability.

Table 4
Comparison of performances of the proposed models for the MWD prediction using topographic and vegetation data.

Model type	Evaluation criterion		
	MEF	AEP	RMSE (%)
MLR	60.44	16.20	10.37
GLM	61.43	15.74	10.62
ANN	70.01	15.13	10.37
ANFIS	63.23	17.67	10.37

MEF: model efficiency factor, AEP: absolute error percentage, RMSE: root mean square error, MLR: multiple linear regression, GLM: generalized linear model, ANN: artificial neural network, and ANFIS: adaptive neuro-fuzzy inference system.

Table 5
Comparison of performances of the proposed models for the MWD prediction using combined soil, topographic, and vegetation data.

Model type	Evaluation criterion		
	MEF	AEP	RMSE (%)
MLR	62.15	16.01	10.52
GLM	64.23	15.30	10.22
ANN	89.10	10.04	6.26
ANFIS	81.16	13.93	7.43

MEF: model efficiency factor, AEP: absolute error percentage, RMSE: root mean square error, MLR: multiple linear regression, GLM: generalized linear model, ANN: artificial neural network, and ANFIS: adaptive neuro-fuzzy inference system.

4. Conclusion

The pixel-scale soil aggregate stability predicted using the developed models demonstrates the usefulness of incorporating topographic and vegetation information along with the soil properties as predictors. However, it is essential question to ask which developed model here is preferable for the prediction of MWD according to the obtained results. The answer of this question depends on how much error, works and efforts, and expenses for the MWD prediction would be acceptable. For instance, if a relatively less work and experiments are considered and as well as a high error rate would be acceptable then the constructed ANN model with topographic and vegetation data would be preferable, because the model can be constructed simply since the topographic and vegetation data can be easily extracted from a digital elevation model map and a satellite photo. On the other hand, if the researcher looks for a prediction which has smallest error rate and highest efficiency then the constructed ANN model with a combination of soil, topographic and vegetation attributes together as input data set can be used.

Nevertheless, the physical effects of the variables in ANN model cannot be interpreted via the parameters of the model unlike the regression model which is one of the main disadvantages of ANN model over regression model. The physical meaning of the relationship can be only shown by using regression model at hand. Thus, if it is needed to explain the physical effects of the variables on MWD prediction then the MLR model with a combination of soil data, topographic and vegetation attributes together as input data set can be used. It is also concluded that the ANN and ANFIS models showed greater potential in predicting soil aggregate stability from soil and site characteristics, whereas traditional regression methods (i.e. the MLR and GLM models) did not perform well.

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