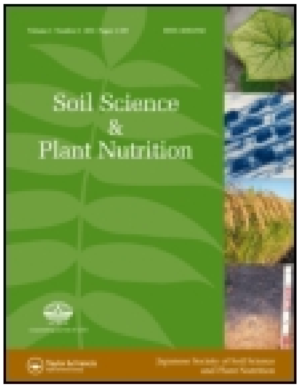

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Soil shear strength prediction using intelligent systems: artificial neural networks and an adaptive neuro-fuzzy inference system

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ORIGINAL ARTICLE

Soil shear strength prediction using intelligent systems: artificial neural networks and an adaptive neuro-fuzzy inference system

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Abstract

Surface soil shear strength can be a useful dynamic index for soil erodibility and thus a measure of soil resistance to water erosion. In this study, we evaluated the predictive capabilities of artificial neural networks (ANNs) and an adaptive neuro-fuzzy inference system (ANFIS) in estimating soil shear strength from measured particle size distribution (clay and fine sand), calcium carbonate equivalent (CCE), soil organic matter (SOM), and normalized difference vegetation index (NDVI). The results showed that the ANN model was more feasible in predicting the soil shear strength than the ANFIS model. The root mean square error (RMSE), mean estimation error (MEE), and correlation coefficient (R) between the measured soil shear strength and the estimated values using the ANN model were 0.05, 0.01, and 0.86, respectively. In ANFIS analysis, the RMSE was 0.08 and a lower correlation coefficient of 0.60 was obtained in comparison with the ANN model. Furthermore, the ANN and ANFIS models were more accurate in predicting the soil shear strength than was the conventional regression model. Results indicate that the ANN model might be superior in determining the relationships between index properties and soil shear strength.

Key words: ANFIS, ANNs, regression, soft computing, surface soil shear strength.

INTRODUCTION

Soil erosion is a major global environmental threat to the sustainability and productive capacity of soils, which causes great economic losses (Zhang 1999; Silva *et al.* 2010). It can also adversely affect the quality of surface and groundwater by adding transported sediments, nutrients, and pesticides, and also by increased turbidity (Zehetner *et al.* 2008; Cheng *et al.* 2010). Soil erodibility is usually defined as the ease of soil detachment by splash during rainfall and/or surface flow (Renard *et al.* 1997). During rainfall, raindrop compaction and soil suspension movement by water result in high shear stress, leading to an intensive local deformation in soil erosion (Ghadiri and Payan 1986; Rose *et al.* 1990). As a concomitant process the soil surface transfers into a layer, ranging from 1 to 10 mm, resulting in higher bulk density, lower porosity, and lower hydraulic conductivity (Moore 1981) and an increase in soil shear strength (Bradford *et al.* 1992). Critical shear strength has been also proposed as a key parameter for rill formation; hence, the condition at which rill flow becomes erosive would be controlled by surface soil shear strength (Brunori *et al.* 1989; Zimbone *et al.* 1996). Consequently, shear strength of surface soil can be proposed as a measure of soil resistance to water erosion (Zhang *et al.* 2001).

Determination of the shear strength of soils in a direct way has been a priority issue for engineers and soil scientists for a long time (Goktepe *et al.* 2008). Many techniques including cone penetrometer, shear vane, torsional shear boxes, direct shear box, and Zhang's method have been developed to directly measure soil shear strength (Rauws and Govers 1988; Zhang *et al.* 2001). However, most of these techniques are rather complicated, time-consuming, and/or difficult to apply on a large scale. Alternatively, soil shear strength can be estimated using routinely available data by the use of

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pedotransfer functions (PTFs) (Bouma 1989) and soil property prediction functions (Lagacherie and McBratney 2006).

Soft computing techniques such as artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) have attracted greater interest recently for use in the prediction of soil properties (Minasny *et al.* 2004; Azamathulla *et al.* 2009; Kalkan *et al.* 2009; Huang *et al.* 2010; Dai *et al.* 2011). These methods, in comparison to the traditional regression soil property prediction functions and PTFs, do not require a priori regression models to relate input and output data (Schaap and Leij 1998).

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).

Treatment of data non-linearities using ANN and ANFIS approaches has recently been found to be useful in soil analysis (Tayfur 2002; Minasny *et al.* 2004; Uno *et al.* 2005; Anagu *et al.* 2009; Azamathulla *et al.* 2009; Khalilmoghadam *et al.* 2009; Kisi *et al.* 2009; Huang *et al.* 2010; Silva *et al.* 2010). However, these techniques (particularly ANFIS) have rarely been used to predict soil mechanical properties. Therefore, this study was conducted to investigate the efficacy of ANFIS and ANN techniques in developing prediction functions using soil and vegetation properties for estimating surface soil shear strength. Comparison of the predictive capabilities of ANNs and ANFIS with traditional regression prediction functions was also part of the goal.

MATERIALS AND METHODS

Study area

The study area was a part of the Bazoft watershed (31° 37′ to 32° 39′ N and 49° 34′ to 50° 32′ E) in the northern part of the Karun River basin in central Iran (Fig. 1). The major river in the watershed is AbBazoft, which is joined by the Karun River at the outlet of the watershed. The elevation ranges from 880 m at the southern end of the watershed to 4300 m on Zardkuh Mountain. The long-term average rainfall and temperature in the region are around 800 mm and 10°C, respectively. The slope class of 40–70% is the major class of slope in this watershed, which covers about 46% of the study area. The dominant slope shape in the watershed is also convex. Approximately 56% of the watershed is covered by pastures and the rest is covered by forest and bare lands. *Quercus* spp. and *Astragalus* spp. are the dominant vegetations covering the forests and pastures, respectively.

Old terrace deposits (Qt1) are the dominant geological units, having moderate weathering and erosion sensibility with some marl enrichment with gypsiferous rock and sandstone (mp1) (Iranian Geological Organization 2006). The soils include Calcic Argixerolls, Typic Calcixerepts, Typic Xerorthents, Typic Cryorthents, and Typic Haploxerolls in the watershed (Soil Survey Staff 2006). Soil depth is less than 5 cm in the steep areas and as deep as 150 cm in the lowlands. The soil textural classes are mainly silt loam, loam, silty clay loam, clay

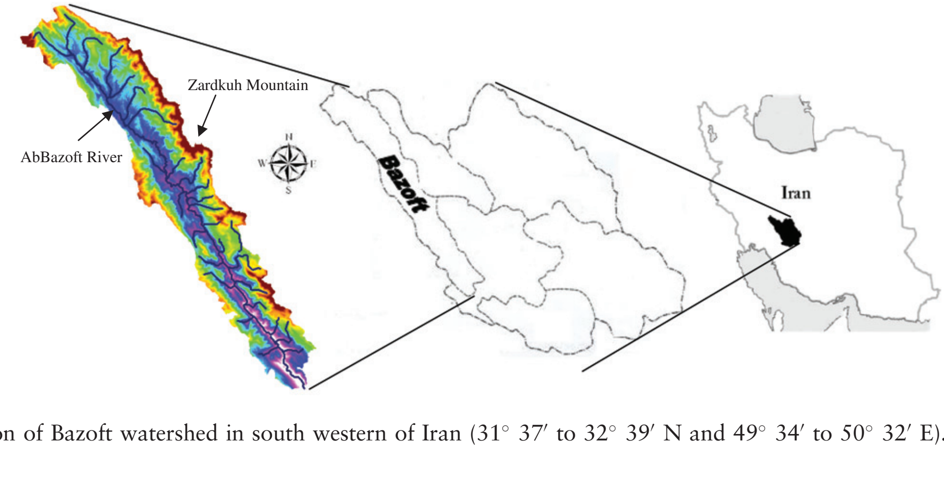

Figure 1 Location of Bazoft watershed in south western of Iran (31° 37′ to 32° 39′ N and 49° 34′ to 50° 32′ E).

loam, and silty clay. Furthermore, mountains, hills, plateau and upper traces, alluvial plains, and gravelly colluvial fans are the dominant physiographic units in the study area.

Soil sampling design and analysis

A supervised random sampling method was designed in different land unit tracts defined using geology, topography, and land use maps in the environment of ILWIS 3.4 software to collect soil samples (ITC, University of Twente, Netherlands). A total of 165 soil samples were collected from the top 5 cm of soil surface to produce a measurement of diversity of soil properties within each land unit tract. Furthermore, the positions of the sampling points were identified by GPS (model: 76CSx, Garmin Inc., Olathe, Kansas, USA). Soil organic matter (SOM) content was determined by the Walkley-Black method (Nelson and Sommers 1986). Percentages of clay and fine sand particles in each soil sample were measured using the procedure described by Gee and Bauder (1986). Calcium carbonate equivalent (CCE) content was measured by the back-titration method (Nelson 1982). For quantifying the vegetation in each representative point, the normalized difference vegetation index (NDVI) was derived using an IRS-1D satellite image from April 2008 at a spatial resolution of 24 m by 24 m (Indian Space Applications Centre, Ahmedabad, India). The NDVI can be calculated as the ratio of the red and near infrared (NIR) bands of a sensor system:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

NDVI values range from −1 to +1. Healthy vegetation covers are represented by high NDVI values between 0.05 and 1, while non-vegetated surfaces yield negative values of NDVI (Khalilmoghadam *et al.* 2009; Lillesand and Keifer 1994).

Measurement of soil shear strength

A shear vane (model: BS1377-9, Controls Group Com., Italy) was used to measure surface soil shear strength (SSSS) in saturation condition. For this purpose, the shear vane device was first pushed into the soil surface until the blades were covered (about 8 mm depth); a clockwise rotation rate was then applied to ensure that failure developed within 5 to 10 s. The maximum stress value was recorded on a dial at the top of the shear vane driver. A non-return pointer assisted in readings. The shear strength in each representative point was measured in triplicate.

Descriptive statistics

Descriptive statistics of measured soil properties and NDVI index including mean, minimum, maximum, standard deviation (SD), variance, and skewness were determined using SPSS statistical software (IBM Com., Chicago, USA). All the data [i.e., Clay, fine sand (FS), SOM, CCE, NDVI, and SSSS] were normalized within the range of 0.1–0.9 using Eq. 2 and then were used for soil shear strength prediction by multiple-linear regression (MLR), ANN, and ANFIS techniques.

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

Multiple-linear regression (MLR)

In regression analysis, the relationship between one or more independent and dependent variables is modeled by linear equations to find the appropriate equation for this relationship. In the current study MLR, a popular technique used in many disciplines to predict a particular variable of interest using independent variables (Mishra *et al.* 2010), was used in the regression analysis. The global regression model used in the data set was as follows:

$$Y = \beta + aX_1 + bX_2 + cX_3 + dX_4 + eX_5 \tag{3}$$

where Y is the dependent variable, β is a constant representing the value of Y when all the independent variables are zero, X is theindependent variable, and a, b, c, d, and e are regression coefficients. The SAS statistical software was used for the MLR modeling (Cary, NC., USA).

Artificial neural networks (ANNs)

For neural network analysis, the multilayer perceptron (MLP) with back-propagation (BP) learning algorithm, the most commonly used neural network structures in ecological modeling and soil science (Dawson and Wilby 2001), were used. Two main processes are performed in a BP algorithm, forward pass and backward pass. In the forward pass, an output pattern is presented to the network and its effects propagate through the network layer by layer. In the MLP, the output of the network, surface soil shear strength (SSSS), is calculated as follows (Juang *et al.* 1999):

$$SSSS = f_2\left\{B_0 + \sum_{k=1}^{n}\left[w_k f_1\left(B_{Hk} + \sum_{i=1}^{m}[w_{ik}P_i]\right)\right]\right\} \tag{4}$$

where $SSSS$ is in (kPa); 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 of the hidden layer ($k = 1, \ldots, n$); w_{ik} is the weight of connection between input variable i ($i = 1, \ldots, m$) and neuron k of the hidden layer; P_i is the input variable i; $f_1(h_k)$ is the transfer function of each neuron 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 in this study were sigmoid functions defined by:

$$f_N(\lambda) = \frac{1}{1 + e^{-\lambda}} \quad \text{For } N = 1{,}2 \tag{5}$$

In neural network analysis, the data set is automatically and randomly divided by the software into three subsets of training, testing, and validation. In the current study, the training set of 99 samples was obtained out of a total of 165 and the remaining 66 soil samples were used equally in two parts as the testing and validation sets. The number of neurons and epochs were determined by a trial and error procedure. Seven hidden neurons and an epoch set number of 3000 were generated as the satisfactory result (evaluated by the network performance). Neural network analyses were performed using MatLab 7.6, Neural Networks Toolbox (Mathworks, Inc., Natick, MA, USA).

Adaptive neuro-fuzzy inference system (ANFIS)

The architecture of an ANFIS model with two input variables is shown in Fig. 2. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first-order Sugeno model can be considered (Takagi and Sugeno 1985):

$$\text{Rule 1: IF } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ THEN } (f_1 = p_1 x + q_1 y + r_1), \tag{6}$$

$$\text{Rule 2: IF } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ THEN } (f_2 = p_2 x + q_2 y + r_2), \tag{7}$$

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rules, and p_i, q_i, and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is also shown in Fig. 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

In the first layer of ANFIS, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{Ai}(x), \quad i = 1{,}2, \tag{8}$$

$$O_i^1 = \mu_{Bi-2}(y), \quad i = 3{,}4, \tag{9}$$

where μ is an obtained weight according to the related fuzzy membership function, $\mu_{Ai}(x)$, and $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{Ai}(x)$ is given by:

$$\mu_{Ai}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}} \tag{10}$$

where a_i, b_i, and c_i are the parameters of the membership function, governing the bell-shaped functions accordingly.

In the second layer, the nodes are fixed nodes to perform as a simple multiplier. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad i = 1{,}2, \tag{11}$$

which are the so-called firing strengths of the rules.

In the third layer, the nodes are also fixed nodes to play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1{,}2, \tag{12}$$

which are the so-called normalized firing strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of

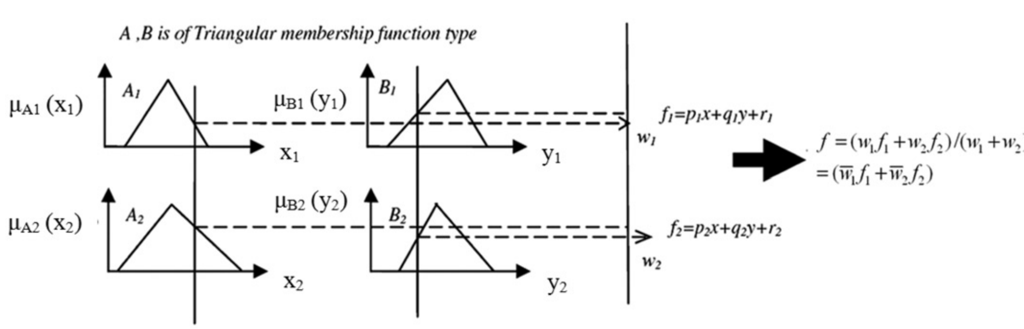

Figure 2 The reasoning scheme of an ANFIS model (Sobhani *et al.* 2010).

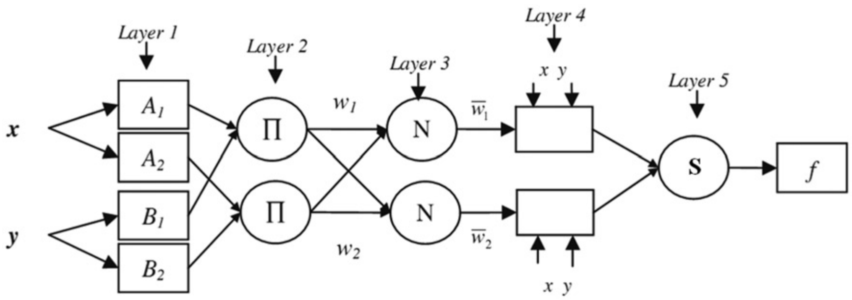

Figure 3 A basic adaptive neuro-fuzzy inference system (ANFIS) network architecture (Sobhani *et al.* 2010).

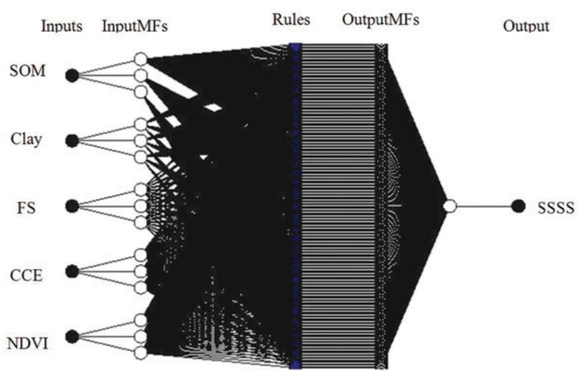

Figure 4 The schematic of adaptive neuro-fuzzy inference system (ANFIS) architecture based on Sugeno fuzzy model developed in the current study. SOM, soil organic matter content; Clay, clay content; FS, fine sand content; CCE, calcium carbonate equivalent content; NDVI, normalized difference vegetation index; SSSS, surface soil shear strength; and MFs, membership functions.

the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1,2, \tag{13}$$

In the fifth layer, there is only one single fixed node labeled with *S*. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{14}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first and the fourth layers. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first-order polynomial. These parameters are the so-called consequent parameters (Ceylan *et al.* 2010).

In this study, a command genfis1 (generate fuzzy inference system) with different numbers and types of membership functions (including gbellmf, gaussmf, gauss2mf, psigmf, dsigmf, pimf, trapmf, and trimf) and epochs were tried until the best training performance with minimum squared error was obtained. The genfis1 is a command in the MatLab software which generates a Sugeno-type fuzzy inference system (FIS) structure used as initial conditions (initialization of the membership function parameters) for the ANFIS training. It also generates a single-output Sugeno-type FIS using a grid partition on the data.

A hybrid learning algorithm was also employed as an optimization method for the learning procedure of the ANFIS model in each trial. It applies a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. Finally, the generalized bell-shape fuzzy membership function (i.e., gbellmf) with 3 numbers of membership functions was conducted for the adaptive system analysis. Fig. 4 shows the schematic architecture of the ANFIS model used in the current study.

Evaluation criteria

The root mean square error (RMSE), mean estimation error (MEE), and correlation coefficient (R) between the measured and the estimated SSSS values were used to evaluate the performance of different models. The RMSE and MEE statistics are denoted as below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[P(x_i) - M(x_i)]^2} \tag{15}$$

$$MEE = \frac{1}{n}\sum_{i=1}^{n}[P(x_i) - M(x_i)] \tag{16}$$

where $P(x_i)$ denotes the predicted value, $M(x_i)$ is measured value, and n is the total number of observations. The R shows the degree to which two variables are linearly related.

RESULTS AND DISCUSSION

Soil characteristics and vegetation index

Table 1 shows mean, minimum, maximum, standard deviation (SD), variance, and skewness of soil properties and NDVI index used to develop the soil shear strength prediction models. There was little variability in the sample distributions of the variables used in this study to develop the SSSS prediction models, indicating that their values were all normally distributed. Based on the particle size distribution, the dominant soil textures in the studied sites were silt loam, loam, silty clay loam, and clay loam. The wide range of CCE content may be due to different parent material in the study area. In marls, because of enrichment with carbonates, calcium carbonate ($CaCO_3$) has a larger value than in other geological units.

In various studies, the soil particle size distributions, $CaCO_3$, and organic matter contents have been reported as the most common soil properties affecting the SSSS. Mosaddeghi *et al.* (2006), for instance, reported that the $CaCO_3$ equivalent content is an important factor affecting the strength of the soil in arid regions. Horn *et al.* (2005) indicated that the changes in shear strength values for arable soils depended on the shape and size distribution of the sand particles. They also added that the same is true for soils with higher amounts of $CaCO_3$, which are less susceptible to soil compaction due to stronger aggregates and more rigid pore systems.

The mean value of NDVI in the studied sites was 0.13. The NDVI is a greenness index that is related to the proportion of photo-synthetically absorbed radiation and reflects the chlorophyll activity in plants. Within a remote sensing pixel, an increase in NDVI value signifies an increase in green vegetation. The effective roles of vegetation in improving the soil shear strength and thus on the stability of slopes can be discussed through root reinforcement, soil moisture depletion, buttressing and arching, and surcharge (Fan and Su 2008). This index can be also considered as an indirect indicator of amount of biomass added to the soil surface, which may be related to SOM content and surface soil shear strength. Gray and Sotir (1996) reported that the most conspicuous source by which vegetation enhances the shear strength and slope stability is via root reinforcement. Fan and Su (2008) found that the residual shear strength of root-reinforced soils is much higher than that of root-free soils. Leonard and Richard (2004) indicated that the presence of a network of roots, which helps in constituting large soil aggregates, has a great influence on the critical shear stress of soil.

Table 1 Summary statistics of soil properties and vegetation index used in modeling of soil shear strength

Parameter	Mean	Minimum	Maximum	SD	Variance	Skewness
Clay (%)	31.61	8.0	81.60	9.17	84.01	0.73
FS (%)	4.12	0.18	16.02	3.33	11.12	1.27
SOM (%)	2.58	0.22	6.33	1.30	1.69	0.48
CCE (%)	24.93	0.25	80.65	21.17	448.26	0.62
NDVI	0.13	−0.31	0.47	0.08	0.01	−0.61
SSSS (kPa)	6.38	3.34	9.70	1.20	1.43	0.14

Clay, clay content; FS, fine sand content; SOM, soil organic matter content; CCE, calcium carbonate equivalent content; NDVI, normalized difference vegetation index; SSSS, surface soil shear strength; SD, standard deviation.

A wide range of SSSS was encountered for the studied sites. Overgrazing, untimely grazing, shrub burning and tillage, land degradation, and soil erosion have severely affected the soil properties of the study area and thus the soil shear strength. Lower SSSS might be related to soil aggregates disruption (due to tillage), or organic carbon and root network reduction (due to untimely grazing, overgrazing, and shrub burning). Franti *et al.* (1999) reported that the presence of a network of roots on no-tilled soil probably contributed to more soil resistance. Furthermore, land degradation may have a positive effect on soil strength in the study area. As tillage disrupts soil aggregates (Filho *et al.* 2002), erosion removes fine particles from steep areas and hence, soil shear strength in steep areas may be increased by topsoil loss and stone concentration. In addition, crust formation in low lands may increase soil shear strength. Merz and Bryan (1993) measured shear strength values between 1.8 and 13.5 kPa in a sampled similar soils and similar manner. Rauws and Govers (1988) reported soil shear strength values ranging from 2 to 9 kPa on the silt loam soil. Large values of shear strength (>50 kPa) have been reported by Krishnamurthy (1983) for compacted clay samples.

Regression model

The results on prediction of SSSS using the MLR model are presented in Table 2. The MEE and RMSE values for the proposed MLR model were 0.01 and 0.07, respectively. The obtained correlation coefficient (R) value between the measured and the predicted SSSS values was also 0.41. According to the evaluation indices, it appears that the conventional regression models were to some extent poor in predicting the SSSS. The worse performance of MLR approach in estimating the SSSS can be also seen in Fig. 5, where the measured and the predicted values are more scattered. Therefore, these results suggest that conventional regression techniques (i.e., MLR) may fail to be reliable for predicting the SSSS in the studied site.

A reason for this finding may be related to the scarce available data for developing a reasonable MLR model. Another reason for the low accuracy of the MLR approach in estimating the measured SSSS values might be associated with the sample distribution, spatial variation, and study area scale effects. Furthermore, the major conceptual limitation of all regression techniques, that one can only ascertain relationships, but never be sure about the underlying causal mechanism, should be considered (Yilmaz and Yuksek 2009). Sobhani *et al.* (2010) also reported that the regression models may have low accuracy and prediction capability.

Table 2 Goodness-of-fit of the proposed MLR, ANN, and ANFIS models for soil shear strength prediction

Model Type	*R*	MEE	RMSE
MLR	0.41	0.01	0.07
ANN	0.86	0.01	0.05
ANFIS	0.60	0.02	0.08

MLR, multiple-linear regression; ANN, artificial neural network; ANFIS, adaptive neuro-fuzzy inference system; *R*, correlation coefficient; MEE, mean estimation error; and RMSE, root mean square error.

ANN model

Neural networks can be used as a direct substitute for auto correlation, multivariable regression, linear regression, trigonometry, and other statistical analysis and techniques (Yilmaz and Yuksek 2009). Table 2 shows the evaluation criteria of the constructed ANN model in the current study. Normalized predicted data versus normalized measured data for the testing data set of the ANN

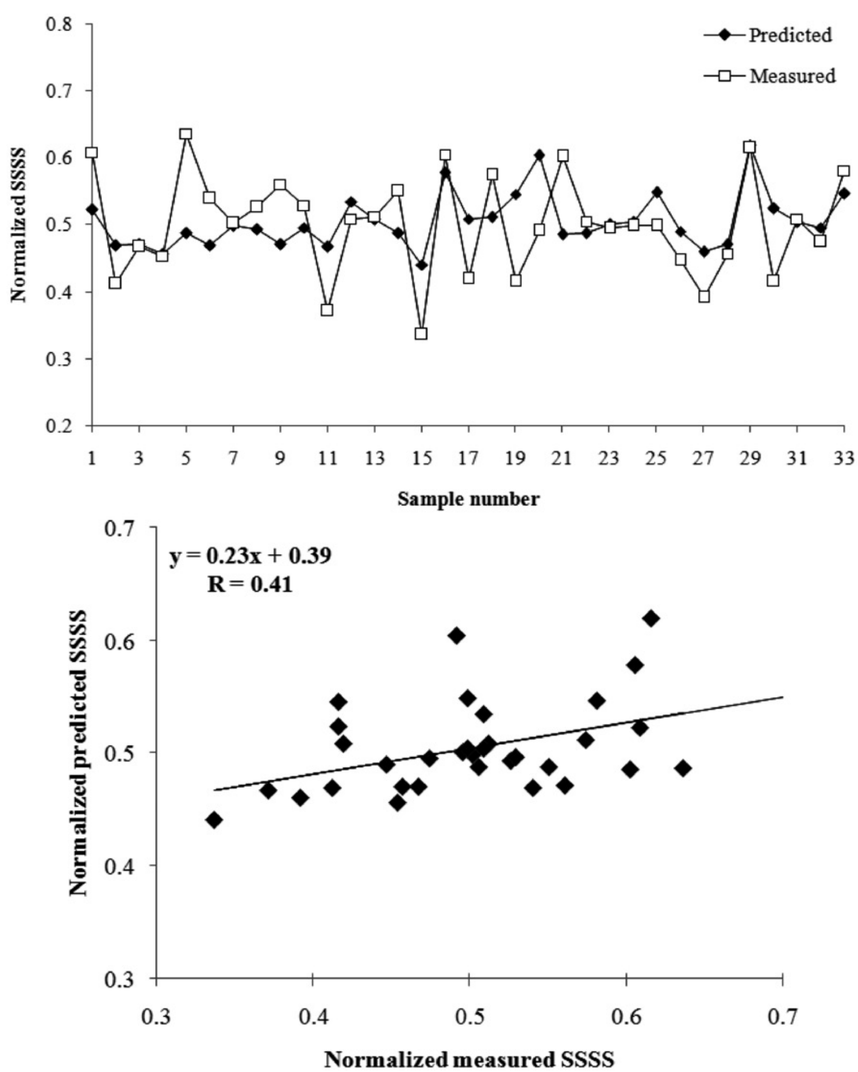

Figure 5 Comparison of the normalized predicted and the measured surface soil shear strength (SSSS) values for the testing data set of the multiple-linear regression (MLR) model.

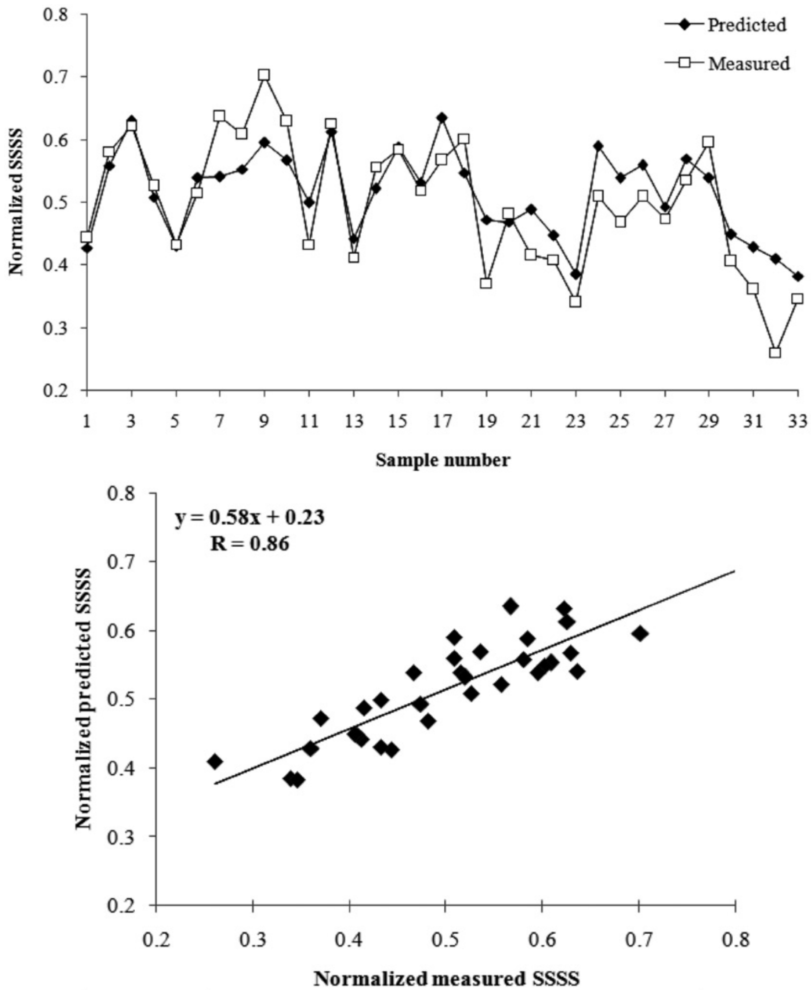

Figure 6 Comparison of the normalized predicted and the measured surface soil shear strength (SSSS) values for the testing data set of the artificial neural network (ANN) model.

model are also plotted in Fig. 6. The *R*, RMSE, and MEE values in SSSS prediction using ANN technique were 0.86, 0.05, and 0.01, respectively. These indices reveal the significance of a combination of soil properties with the vegetation index together in estimation of soil shear strength using ANNs. Therefore, it appears that there is a greater possibility of estimating soil shear strength using ANNs than MLR in the study area. The higher accuracy of the ANN model in predicting the measured SSSS values in comparison with the MLR model can be also seen in Fig. 6, where the measured and the predicted values using the ANN model are more in agreement than those for the MLR model.

Khalilmoghadam *et al.* (2009) investigated the potential use of three different neural network structures (i.e., generalized feed-forward, MLP, and modular feed-forward networks) for estimating the surface soil shear strength and reported that use of the MLP neural network resulted in higher correlation coefficients as compared with the generalized feed-forward and modular neural network. Kalkan *et al.* (2009) indicated that ANN models can be developed as useful tools for predicting the unconfined compressive strength of compacted granular soils. Anagu *et al.* (2009) concluded that ANN is a versatile tool for the estimation of heavy metal sorption from basic soil properties. Dai *et al.* (2011) found that ANNs are useful for investigating and understanding the relationship between crop yield and soil moisture and salinity at different crop growth stages.

ANFIS model

The ANFIS estimation results associated with the measured SSSS values are shown in Fig. 7. The *R*, MEE, and RMSE values for the proposed ANFIS model are also presented in Table 2. The evaluation criteria and scatter plot displaying the relationships between the predicted and the measured SSSS values showed that the

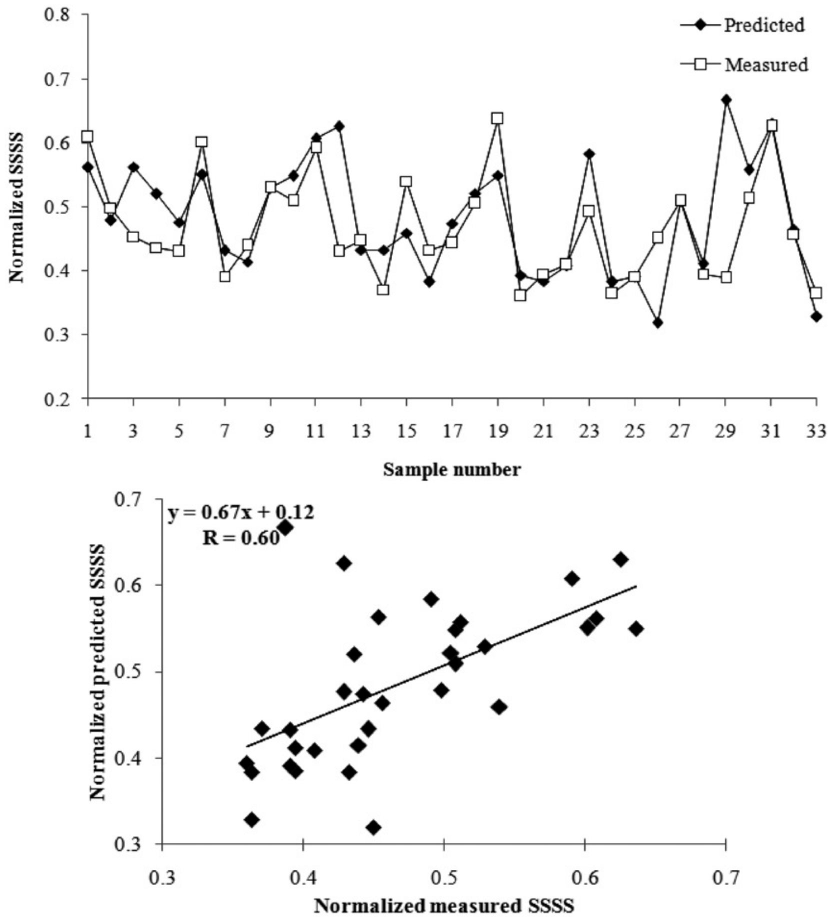

Figure 7 Comparison of the normalized predicted and the measured surface soil shear strength (SSSS) values for the testing data set of the adaptive neuro-fuzzy inference system (ANFIS) model.

constructed ANFIS model seems to have an acceptable prediction capability, especially when compared with the regression model results. The RMSE value for the ANFIS model was 0.08 and a higher correlation coefficient of 0.60 was obtained in comparison with the regression model.

In other studies, Azamathulla *et al.* (2009) reported that an ANFIS-based approach could accurately predict the bed-load of moderately sized rivers. Sobhani *et al.* (2010) indicated that all of their proposed ANFIS models had acceptable performance for prediction of the compressive strength of no-slump concrete. Kisi *et al.* (2009) reported that neuro-fuzzy models can be employed successfully in monthly suspended sediment estimation. Mashrei *et al.* (2010) concluded that ANFIS can serve as reliable and simple predictive tool for the prediction of moment capacity of ferrocement members. Cevik and Ozturk (2009) found that their proposed neuro-fuzzy model could predict accurately the shear strength of reinforced concrete beams. Yilmaz and Yuksek (2009) concluded the ANFIS model had a high performance in predicting the strength and elasticity modulus of gypsum.

Comparison of the MLR, ANN, and ANFIS approaches

Comparing the obtained results from the proposed MLR, ANN, and AFIS models indicated that ANN and AFIS techniques were more feasible in predicting the soil shear strength than the linear regression technique. This might be due to the large amount of data required for developing a sustainable regression model, while the neural network and ANFIS models could recognize the relationships with less data for distributed and parallel computing natures. A second reason why the linear models (i.e., the MLR model) might be unreliable to predict SSSS in the study area is the effect of the predictors on the dependent variable, which may not be linear in nature. In other words, the ANN and ANFIS models could probably predict SSSS with a better performance owing to their greater flexibility and capability to model nonlinear relationships. Therefore, in the case of data sets with a limited number of observations which regression models fail to capture reliably, advanced soft computing approaches like ANN and ANFIS may be preferred.

On the other hand, the proposed ANN model in the current study was more effective in SSSS estimation than the ANFIS model when the evaluation criteria were compared. The RMSE and R values for the ANN model were 0.05 and 0.86, respectively, while they were 0.08 and 0.60 for the AFIS model (see Table 2). Neural networks, in fact, can extract patterns and detect 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. In addition, the flexibility and capability of ANNs to model nonlinear relationships should be noted (Kisi *et al.* 2009).

Our findings agree well with those of other authors: Goktepe *et al.* (2008), for instance, concluded that ANN-based models were more successful in estimating the shear strength of plastic clays with reference to multiple regression-based models. Kaul *et al.* (2005) compared the effectiveness of utilization of regression and ANN models in predicting corn (*Zea mays*) and soybean (*Glycine max*) yields and reported that ANN models consistently gave more precise yield predictions than regression models. Kalkan *et al.* (2009) concluded that the intelligent systems (i.e., ANNs and ANFIS) are reliable and useful simple prediction tools for the unconfined compressive strength of compacted soils. Mashrei *et al.* (2010) indicated that predictions of the moment capacity of ferrocement members by ANFIS and ANN models were much better than those of empirical methods. They also added that the ANN model was more useful than the ANFIS model since the ANN training and testing results were closely in agreement with the experimental results.

Conclusion

The results of the current study revealed that deployment of artificial intelligent systems (i.e., neural network and neuro-fuzzy approaches) made more reasonable and accurate predictions of soil shear strength compared to those of the conventional multiple-linear regression model. The ANFIS model had a weaker estimation of soil shear strength compared to the ANN model. This indicates that the ANFIS approach may not always be a better choice for predicting this property of soil. Nevertheless, it should be pointed out that although the predictive accuracy of the ANFIS technique was slightly lower compared to that of ANNs in this study, its advantages (such as more flexibility in incorporating real-world systems and relating a large amount of input and output data at once, therefore saving time and energy) should motivate soil scientists to evaluate the potential use of this approach for other soil properties. Finally, it can be concluded that in large-scale areas, with a relatively high heterogeneity and nonlinear relationships, there is a need for a more suitable tool for developing soil shear strength prediction functions. This could be achieved by using soft computing intelligent methods rather than the commonly used conventional regression methods.

REFERENCES

Anagu I, Ingwersena J, Utermann J, Streck T 2009: Estimation of heavy metal sorption in German soils using artificial neural networks. *Geoderma*, **152**, 104–112.

Azamathulla HM, Chang CK, Ghani AA, Ariffin J, Zakaria NA, Abu Hasan Z 2009: An ANFIS-based approach for predicting the bed load for moderately sized rivers. *J. Hydro-environ. Res.*, **3**, 35–44.

Bouma J 1989: Using soil survey data for quantitative land evaluation. *Adv. Soil Sci.*, **9**, 177–213.

Bradford JM, Truman CC, Huang C 1992: Comparison of three measures of resistance of soil surface seals to raindrop splash. *Soil Technol.*, **5**, 47–56.

Brunori F, Penzo MC, Torri D 1989: Soil shear strength: its measurement and soil detachability. *Catena*, **16**, 59–71.

Cevik A, Ozturk S 2009: Neuro-fuzzy model for shear strength of reinforced concrete beams without web reinforcement. *Civ. Eng. Environ. Syst.*, **26**, 263–277.

Ceylan M, Arslan MH, Ceylan R, Kaltakci MY, Ozbay Y 2010: A new application area of ANN and ANFIS: determination of earthquake load reduction factor of prefabricated industrial buildings. *Civ. Eng. Environ. Syst.*, **27**, 53–69.

Cheng S, Fang H, Zhu T, Zheng J, Yang X, Zhang X, Yu G 2010: Effects of soil erosion and deposition on soil organic carbon dynamics at a sloping field in Black Soil region, Northeast China. *Soil Sci. Plant Nutr.*, **56**, 521–529.

Dawson CW, Wilby RL 2001: Hydrological modeling using artificial neural networks. *Prog. Phys. Geogr.*, **25**, 80–108.

Dai X, Huo Z, Wang H 2011: Simulation for response of crop yield to soil moisture and salinity with artificial neural network. *Field Crops Res.*, **121**, 441–449.

Fan CC, Su CF 2008: Role of roots in the shear strength of root-reinforced soils with high moisture content. *Ecol. Eng.*, **33**, 157–166.

Filho CC, Lourenco A, Guimaraes MDF, Fonseca ICB 2002: Aggregate stability under different soil management systems in a red Latosol in the state of Parana, Brazil. *Soil Till. Res.*, **65**, 45–51.

Franti TG, Laflen JM, Watson DA 1999: Predicting soil detachment from high discharge concentrated flow. *Trans. ASAE.*, **42**, 329–335.

Gee GW, Bauder JW 1986: Particle size analysis. *In* Methods of Soil Analysis: Part 1: Agronomy Handbook No 9, Ed. Klute A, pp. 383–411. American Society of Agronomy and Soil Science Society of America, Madison, WI.

Ghadiri H, Payne D 1986: The risk of leaving the soil surface unprotected against falling rain. *Soil Till. Res.*, **8**, 119–130.

Goktepe AB, Altun S, Altintas G, Tan O 2008: Shear strength estimation of plastic clays with statistical and neural approaches. *Build. Environ.*, **43**, 849–860.

Gray DH, Sotir RB 1996: Biotechnical and Soil Bioengineering Slope Stabilization: A Practical Guide for Erosion Control. John Wiley and Sons, New York.

Horn R, Fleige H, Richter FH *et al.* 2005: SIDASS project, Part 5: Prediction of mechanical strength of arable soils and its effects on physical properties at various map scales. *Soil Till. Res.*, **82**, 47–56.

Huang Y, Lan Y, Thomson SJ, Fang A, Hoffmann WC, Lacey RE 2010: Development of soft computing and applications in agricultural and biological engineering. *Comput. Electron. Agric.*, **71**, 107–127.

Iranian Geological Organization 2006: *Geological Survey of Iran*. Shahrekord, Iran.

Jang JSR, Sun CT 1995: Neuro-fuzzy modeling and control. *Proc. IEEE.*, **83**, 378–406.

Juang CH, Chen CJ, Tien YM 1999: Appraising CPT-based liquefaction resistance evaluation methods-artificial neural network approach. *Can. J. Geotech.*, **36**, 443–454.

Kalkan E, Akbulut S, Tortum A, Celik S 2009: Prediction of the unconfined compressive strength of compacted granular soils by using inference systems. *Environ Geol.*, **58**, 1429–1440.

Kaul M, Hill R, Walthall C 2005: Artificial neural networks for corn and soybean yield prediction. *Agric. Sys.*, **85**, 1–18.

Khalilmoghadam B, Afyuni M, Abbaspour KC, Jalalian A, Dehghani AA, Schulin R 2009: Estimation of surface shear strength in Zagros region of Iran - A comparison of artificial neural networks and multiple-linear regression models. *Geoderma*, **153**, 29–36.

Kisi O, Haktanir T, Ardiclioglu M, Ozturk O, Yalcin E, Uludag S 2009: Adaptive neuro-fuzzy computing technique for suspended sediment estimation. *Adv. Eng. Softw.*, **40**, 438–444.

Krishnamurthy M 1983: Incipient motion of cohesive soils. *In* Proceedings of the Conference on Frontiers in Hydraulic Engineering, Ed. Shen HT, pp. 96–101. American Society of Civil Engineers, New York.

Lagacherie P, McBratney AB 2006: Spatial soil information systems and spatial soil inference systems: perspectives for digital soil mapping. *Dev. Soil Sci.*, **31**, 3–22.

Leonard J, Richard G 2004: Estimation of runoff critical shear stress for soil erosion from soil shear strength. *Catena*, **57**, 233–249.

Lillesand TM, Keifer W 1994: *Remote Sensing and Image Interpretation*. John Wiley & Sons, New York.

Mashrei MA, Abdulrazzaq N, Abdalla TY, Rahman MS 2010: Neural networks model and adaptive neuro-fuzzy inference system for predicting the moment capacity of ferrocement members. *Eng. Struct.*, **32**, 1723–1734.

Merz W, Bryan R 1993: Critical conditions for rill initiation on sandy loam brunisols: laboratory and field experiments in southern Ontario, Canada. *Geoderma*, **57**, 357–385.

Minasny B, Hopmans JW, Harter T, Eching SO, Tuli A, Denton MA 2004: Neural networks prediction of soil hydraulic functions for alluvial soils using multistep outflow data. *Soil Sci. Soc. Am. J.*, **68**, 417–429.

Mishra U, Lal R, Liu D, VanMeirvenne M 2010: Predicting the spatial variation of the soil organic carbon pool at a regional scale. *Soil Sci. Soc. Am. J.*, **74**, 906–914.

Moore ID 1981: Effect of surface sealing on infiltration. *Trans. ASAE.*, **24**, 1546–1552.

Mosaddeghi MR, Hajabbasi MA, Khademi H 2006: Tensile strength of sand, palygorskite, and calcium carbonate mixtures and interpretation with the effective stress theory. *Geoderma*, **134**, 160–170.

Nelson RE 1982: Carbonate and gypsum. *In* Methods of Soil Analysis: Part I: Agronomy Handbook No 9, Ed. Page AL, pp. 181–197. American Society of Agronomy and Soil Science Society of America, Madison, WI.

Nelson DW, Sommers LP 1986: Total carbon, organic carbon and organic matter. *In* Methods of Soil Analysis: Part 2: Agronomy Handbook No 9, Ed. Page AL, pp. 539–579. American Society of Agronomy and Soil Science Society of America, Madison, WI.

Rauws G, Govers G 1988: Hydraulic and soil mechanical aspects of rill generation on agricultural soils. *Eur. J. Soil Sci.*, **39**, 111–124.

Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC 1997: *Predicting Soil Erosion by Water: a Guide to Conservation Planning With the Revised Universal Soil Loss Equation (RUSLE)*. Agriculture Handbook, Vol. 703, 404 pp. U.S. Department of Agriculture, Washington, DC.

Rose CW, Hairsine PB, Proffitt APB, Misra RK 1990: Interpreting the role of soil strength in soil erosion process. *Catena*, **17**, 153–165.

Schaap MG, Leij FJ 1998: Using neural networks to predict soil water retention and soil hydraulic conductivity. *Soil Till. Res.*, **47**, 37–42.

Silva RB, Iori P, Armesto C, Bendini HN 2010: Assessing rainfall erosivity with artificial neural networks for the Ribeira Valley, Brazil. *Int. J. Agron.*, 1–7.

Sobhani J, Najimi M, Pourkhorshidi AR, Parhizkar T 2010: Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models. *Cons. Build. Mat.*, **24**, 709–718.

Soil Survey Staff 2006: *Keys to Soil Taxonomy*. U.S. Department of Agriculture, Natural Resources Conservation Service, Washington, DC.

Takagi T, Sugeno M 1985: Fuzzy identification of systems and its applications to modeling and control. *IEEE Trans Syst. Man. Cybernet.*, **15**, 116–132.

Tay JH, Zhang X 1999: Neural fuzzy modeling of anaerobic biological waste water treatment systems. *ASCE: J. Environ. Eng.*, **125**, 1149–1159.

Tayfur G 2002: Artificial neural networks for sheet sediment transport. *Hydrol. Sci. J.*, **47**, 879–892.

Uno Y, Prasher SO, Lacroix R, Goel PK, Karimi Y, Viau A, Patel RM 2005: Artificial neural networks to predict corn yield from compact airborne spectrographic imager data. *Comput. Electron. Agric.*, **47**, 149–161.

Yilmaz I, Yuksek G 2009: Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. *Int. J. Rock Mech. Min. Sci.*, **46**, 803–810.

Zehetner F, Vemuri NL, Huh CA, Kao SJ, Hsu SC, Huang JC, Chen ZS 2008: Soil and phosphorus redistribution along a steep tea plantation in the Feitsui reservoir catchment of northern Taiwan. *Soil Sci. Plant Nutr.*, **54**, 618–626.

Zhang B, Zhao QG, Horn R, Baumgart T 2001: Shear strength of surface soil as affected by soil bulk density and soil water content. *Soil Till. Res.*, **59**, 97–106.

Zhang J 1999: Soil erosion in Guizhou province of China: a case study in Bijie Prefecture. *Soil Use Manage.*, **15**, 68–70.

Zimbone SM, Vickers A, Morgan RPC, Vella P 1996: Field investigation of different techniques for measuring surface soil shear strength. *Soil Technol.*, **9**, 101–111.