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Optimization of Pedotransfer Functions Using an Artificial Neural Network

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Abstract: Pedotransfer functions (PTFs) provide an alternative by estimating soil parameters from more readily available soil data. The two common methods used to develop PTFs are multiple-linear regression method and ANN. One of the advantages of neural networks compared to traditional regression PTFs is that they do not require a priori regression model, which relates input and output data and in general is difficult because these models are not known. 125 soil samples were collected from different horizons of 32 soil profiles located in the Gorgan Province, North of Iran. Measured soil variables included texture (determined by Bouyoucos hydrometer method), organic carbon (determined Using Walkely and Black rapid titration), water percentage at field capacity and wilting point (determined using a pressure plate apparatus), water saturation percentage (determined using gravimetry method), Bulk density (determined using clod) and Cation exchange capacity (determined Using Bower method). Then, multiple linear regression and neural network model (feed-forward back-propagation network) were employed to develop a pedotransfer function for predicting soil parameters using easily measurable characteristics of clay, sand, silt, SP, Bd and organic carbon. The performance of the multiple linear regression and neural network model was evaluated using a test data set. Results showed that artificial neural network with two neurons in hidden layer had better performance in predicting soil properties than multivariate regression. In conclusion, the result of this study showed that training is very important in increasing the model accuracy of one region.

Key words:: Pedotransfer functions, Artificial neural network, Multivariate regression, Soil properties

INTRODUCTION

The development of models simulating soil processes has increased rapidly in recent years. These models have been developed to improve the understanding of important soil processes and also to act as tools for evaluating agricultural and environmental problems. Consequently, simulation models are now regularly used in research and management (Minasny, and McBratney, 2002). Cation exchange capacity (CEC) FC and PWP are among the most important soil properties that are required in soil databases (Manrique *et al.,* 1991), and are used as inputs in soil and environmental models (Keller *et al.,* 2001 and Amini *et al.,* 2005).

Cation exchange capacity (CEC) is the amount of negative charge in soil that is available to bind positively charged ions (cations). Essential plant nutrients, K^+, Ca^{2+}, $Mg^{2+,}$ and NH^{4+} and detrimental elements, Na^+, H^+, and Al^{+3} are cations(). Cation exchange capacity is used as a measure of fertility, nutrient retention capacity, and the capacity to protect groundwater from cation contamination. Cation exchange capacity buffers fluctuations in nutrient availability and soil pH. Soil components known to contribute to CEC are clay and organic matter, and to a lesser extent, silt (Seybold *et al.,* 2005). Although CEC can be measured directly, its measurement is especially difficult and expensive in the Aridisols of Iran because of the large amounts of calcium carbonate (Carpena *et al.,* 1972) and gypsum (Fernando *et al.,* 1977).

Field capacity is defined as the maximum water content in a soil 2 or 3 days after being wetted and free drainage is negligible. Wilting point is defined as the soil water content where leaves of sunflower plants wilt continuously (Cavazza *et al.,* 2007).

Soil water contents at field capacity and wilting point are used to calculate the water depth that should be applied by irrigation (Givi *et al.,* 2004), and to determine water availability, which is a crucial factor in assessing the suitability of a land area for producing a given crop (Sys *et al.,* 1991).

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Several attempts have been made to estimate indirectly these properties from more easily measurable and more readily available soil properties such as particle-size distribution (sand, silt and clay content), organic matter or organic C content, bulk density, porosity, etc. Such relationships are referred to as pedo-transfer functions (PTFs) (Mermoud and Xu. 2006).

The two common methods used to develop PTFs are multiple-linear regression method and ANN. One of the advantages of neural networks compared to traditional regression PTFs is that they do not require a priori regression model, which relates input and output data and in general is difficult because these models are not known (Schaap and Leij, 1998, Mermoud and Xu. 2006).

A neural network is an attempt to build a mathematical model that supposedly works in an analogous way to human brain. A network consists of many elements or >neurons= that are connected by communication channels or >connectors=. These connectors carry numeric data arranged by a variety of means and organized into layers. The neural networks can perform a particular function when certain values are assigned to the connections or >weights= between elements. To describe a system, there is no assumed structure of the model, instead the networks are adjusted or >trained= so that a particular input leads to a specific target output (Minasny, and McBratney, 2002).

Tamari and Wösten (1996) gave a review on ANN and their application in predicting soil hydraulic properties. Most researchers have found that ANN performs better than multiple regressions. Amini *et al.,* (2005) tested several published PTFs and developed two neural network algorithms using multilayer perceptron and general regression neural networks based on a set of 170 soil samples for predicting of Cation exchange capacity in central Iran. They found that the neural network-based models provided more reliable predictions than the regression-based PTFs. Minasny and McBratney (2002) claimed that an advantage of using the neural network approach is that no relationships need to be assumed beforehand. Schaap *et al.,* (1998) used ANNs for predicting of some soil hydraulic properties. They also confirmed applicability of ANNs and concluded that accuracy of these models depend on number of inputs.

The objective of this paper is to evaluate the general applicability of artificial neural network and multivariate regression in estimating cation exchange capacity, FC and PWP in the soils of Iran.

MATERIALS AND METHODS

Data Collection and Soil Sample Analysis:

125 soil samples were collected from different horizons of 32 soil profiles located in the Gorgan Province, North of Iran.

Measured soil factors included texture (determined by Bouyoucos hydrometer method), Organic carbon (determined Using Walkely and Black rapid titration) and CEC (determined Using Rhoades, 1982 method). The clod method (Blake and Hartge, 1986) was used to determine bulk density. The moisture contents at field capacity and wilting point were determined with a pressure plate apparatus (Cassel and Nielsen, 1986) at _33 and _1500 kPa, respectively.

Methods to Fit Ptfs

Multivariate Regression:

The most common method used in estimation PTFs is to employ multiple linear regressions. For example: $Y = aX_1+bX_2+cX_3+....$

Where Y is depended variable, Xn is in depended variable and $a,b,$ Y. are coefficients.

Artificial Neural Network:

An artificial neural network is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Neurons having similar characteristics in an ANN are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is represented by what is known as a >connection strength= or >weight=. An ANN normally consists of three layers, an input layer, a hidden layer, and an output layer. In a feed forward network, the weighted connections feed activations only in the forward direction from an input layer to the output layer. On the other hand, in a recurrent network additional weighted connections are used to feed previous activations back into the network. The structure of a feed-forward ANN is shown in Fig. 1. In the Fig. 1, the circles represent neurons; the lines joining the neurons represent weights; the inputs are represented by X=s; Y represents the output; Vji and Wkj represent the weights between input and hidden and hidden and output layers, respectively. An important step in developing an ANN model is the training of its weight matrix. The weights are initialized randomly between a suitable range, and then updated using certain training mechanism (Jain. A and A. Kumar., 2006 and Minasny, and McBratney, 2002).

In this study, the training process was performed by the commercial package MATLAB, which includes a number of training algorithms including the back propagation training algorithm. This is a gradient descent algorithm that has been used successfully and extensively in training feed forward neural networks.

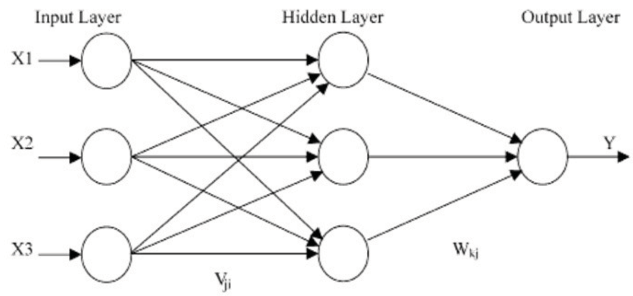

Fig. 1: Structure of feed-forward ANN.

Evaluation Criteria:

Accuracy of the regression equations for derivation of PTFs was evaluated using R^2 and RMSE between the measured and predicted values and expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(Z_s - Z_o)^2} \quad (1)$$

Z_s is observed value, Z_o is predicted value, n is number of samples.

RESULT AND DISCUSSION

Data summary of test and train are presented in Table.1 and 2. Data subdivided in two sets: 20% of the data for testing and the remaining 80% of the data were used for training.

Table 1: Statistics of the training and test data sets of cation exchange capacity

		OC	Clay	CEC
Training set	Min	11.6	0.03	6.5
	Max	75.4	8.8	39.6
	Mean	38.92	1.14	18.81
	Std	14.60	1.55	8.35
Test set	Min	16	0.04	6
	Max	60	6.33	43.4
	Mean	38.73	0.86	19.13
	Std	12.52	1.34	9.45

Table 2: Statistics of the training and test data sets of FC and PWP

		Clay	Silt	Sand	SP	OC	Bd	FC	PWP
Training set	Min	11.6	16.6	4	25.2	0.03	1.2	15.9	5.1
	Max	75.4	73	46.4	86.5	33	1.65	46.7	27.1
	Mean	39.97	43.52	16.40	51.06	1.09	1.45	30.71	15.79
	Std	15.41	11.71	9.23	12.75	3.49	0.09	6.32	5.20
Test set	Min	22	16	8	24	0.19	1.3	21.6	7.1
	Max	50	52	60	84	8.8	1.55	44.7	25.1
	Mean	33.80	32.98	32.31	54.21	2.68	1.43	32.93	16.71
	Std	7.75	8.70	13.36	14.08	2.54	0.07	7.01	5.78

Some soil parameters including: clay, silt, sand, water saturation percentage and bulk density were input data for prediction of FC and PWP. However, clay and organic carbon were considered as inputs for prediction of cation exchange capacity. Amini et al. 2005 stated that CEC has high correlation with these inputs.

The RMSE of the different neurons in hidden layer is plotted in Figure2, 3 and 4. These figures illustrated that the best model obtained with 2 neurons for all soil properties. Correlation coefficient and RMSE have been obtained 0.79 and 5.9 for cation exchange capacity, 0.79 and 5.6 for water percentage at field capacity and 0.75 and 4.2 for water percentage at permanent wilting point.

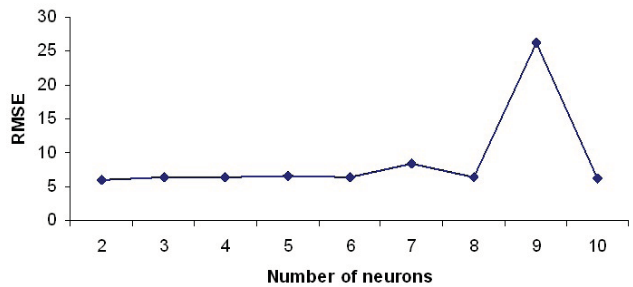

Fig. 2: RMSE value for 2-10 neurons (cation exchange capacity)

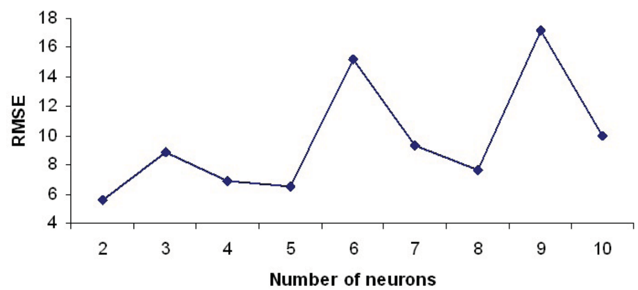

Fig. 3: RMSE value for 2-10 neurons (Field capacity)

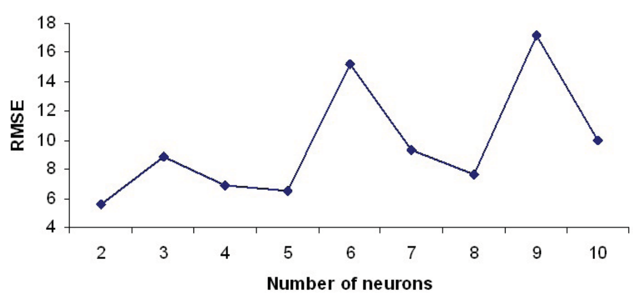

Fig. 3: RMSE value for 2-10 neurons (Permanent wilting point)

Multi regression was computed for three soil train data set by MINITAB software. These equations were expressed as:

$$CEC = 1.91 + 0.318Clay + 3.96OC \quad (2)$$
$$FC = -47.8 + 0.68Clay + 0.651Sill + 0.657Sand + 0.297SP + 0.184OC -1.96BD \quad (3)$$
$$PWP = -8.5 + 0.116Clay + 0.029Sill + 0.023Sand + 0.252SP + 0.14OC + 3.58BD \quad (3)$$

After determining of these equations, performance of multivariate regression was developed for test data set. Correlation coefficient and RMSE have been obtained 0.78 and 6.1 for cation exchange capacity, 0.75 and 5.8 for water percentage at field capacity and 0.66 and 4.3 for water percentage at permanent wilting point. Results showed that artificial neural network with two neurons in hidden layer had better performance in predicting all soil properties (CEC, FC and PWP) than multivariate regression which is in line with the work done by Amini *et al.,* 2005, Tamari and Wösten (1996), Minasny & McBratney (2002) and Schaap *et al.,* (1998). Amini *et al.,* (2005) found that the neural network-based models provided more reliable predictions than the regression-based PTFs. Schaap *et al.,* (1998) confirmed applicability of ANNs and concluded that accuracy of these models depend on number of inputs. Koekkoek and Booltink (1999) found that ANN performed slightly better, but the differences were not significant. The network models for three parameters were more suitable for capturing the non-linearity of the relationship between variables. One of the advantages of neural networks compared to traditional regression PTFs is that they do not require a priori regression model, which relates input and output data and in general is difficult because these models are not known (Schaap and Leij, 1998).

The scatter plots of the measured against predicted CEC, FC and PWP for the test data set are given in Figures 5, 6 and 7 for the ANN model, which we identified as being the best model for predicting soil parameters. As these figures showed that both ANN and regression predicted soil properties with relatively low accuracy (R2 = 0.63, 0.63 and 0.57 respectively). In practice, it is extremely difficult to saturate a soil with water because of air trapping (Hillel, 1998, Mermoud and Xu. 2006). Tamari *et al.,* (1996) poorly predicted K values at matric potentials of _10 and _25 kPa with both methods ANN and regression, and they suggested that soil samples should be classified based on their texture as coarse, medium and fine. Therefore, difficulty in measuring soil hydraulic properties in heterogeneous soils might cause this relatively poor prediction. Analysis of the ANN parameters suggested that more input variables were necessary to improve the prediction of unsaturated hydraulic conductivity (Tamari *et al.,* 1996, Mermoud and Xu. 2006). The differences between the field and laboratory determination of water retention data might be associated to the insufficient representation of large pores in the laboratory, sample disturbance and spatial variation, hysteresis, and scale effects related to the sample size (Field *et al.,* 1984; Shuh *et al.,* 1988, Mermoud and Xu. 2006). Pachepsky and Rawls (2003) found significant differences between the field and laboratory volumetric water contents for coarse-, intermediate-, and fine-textured soil horizons. Therefore, measurement errors might cause the poor prediction of the parameters.

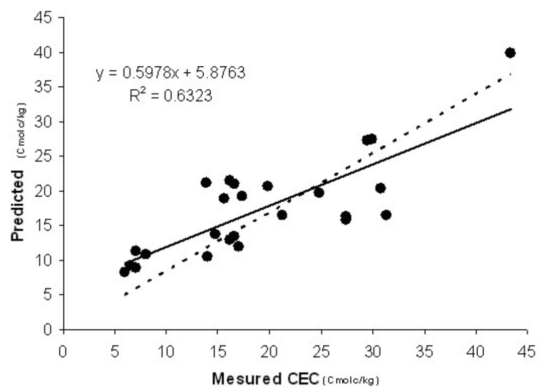

Fig. 5: The scatter plot of the measured versus predicted CEC

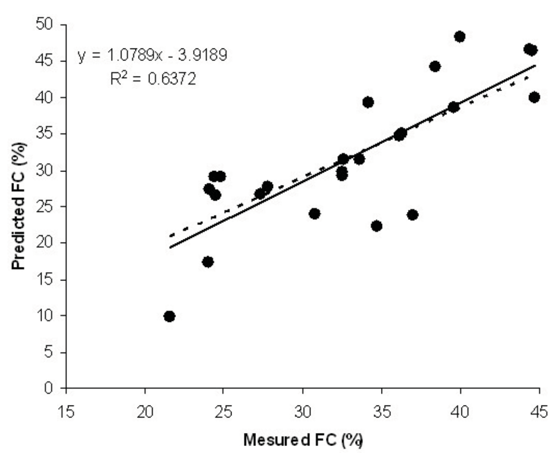

Fig. 6: The scatter plot of the measured versus predicted FC

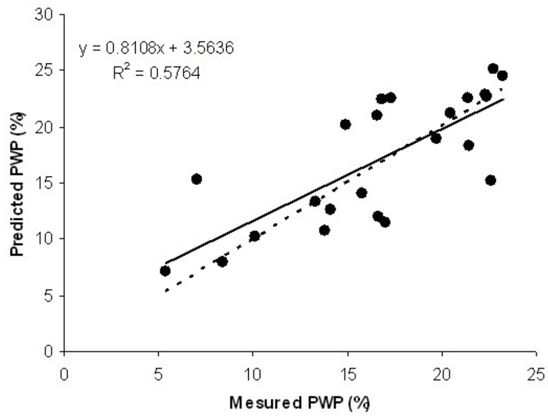

Fig. 7: The scatter plot of the measured versus predicted PWP.

Conclusion:

Multiple linear regression and neural network model (feed-forward back-propagation network) were employed to develop a pedotransfer function for predicting soil parameters included: cation exchange capacity, water percentage at field capacity and permanent wilting point by using available soil properties. The performance of the multiple linear regression and neural network model was evaluated using a test data set. Results showed that artificial neural network with two neurons in hidden layer had better performance in predicting soil properties than multivariate regression. The network models for three parameters were more suitable for capturing the non-linearity of the relationship between variables. ANN can model non-linear functions and have been shown to perform better than linear regression.

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