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Full Length Research Paper

Estimation of infiltration rate and deep percolation water using feed-forward neural networks in Gorgan Province

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The two common methods used to develop PTFs are multiple-linear regression method and Artificial Neural Network. 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. So at present research, we compare performance of feed-forward back-propagation network to predict soil properties. Soil samples were collected from different horizons profiles located in the Gorgan Province, North of Iran. Measured soil variables included texture, organic carbon, water saturation percentage Bulk density, Infiltration rate and deep percolation. Then, multiple linear regression and neural network model were employed to develop a pedotransfer function for predicting soil parameters using easily measurable characteristics of clay, silt, SP, Bd and organic carbon. The performance of the multiple linear regression and neural network model was evaluated using a test data set by R^2, RMSE and RSE. Results showed that artificial neural network with two and five neurons in hidden layer had better performance in predicting soil hydraulic properties than multivariate regression. In conclusion, the result of this study showed that both ANN and regression predicted soil properties with relatively high accuracy that showed that strong relationship between input and output data and also high accuracy in determining of data.

Keywords: Infiltration rate, Deep percolation, Pedotransfer function

INTRODUCTION

Infiltration is water entry into the soil, generally by downward flow through all or part of the soil surface. Percolation is the downward flow of water through saturated or nearly saturated layers of the soil profile, generally due to gravity (i.e., where suction gradients are negligible (Daniel, 2003). 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. However, models usually require a large number of parameters to describe the transport coefficient, content of substances in the soil, or other physical and chemical properties. Thus, collecting soil property data has become an urgent need to feed the very hungry, almost insatiable, environmental (simulation) management models. As soil properties can be highly variable spatially and temporally,

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measuring these properties is both time consuming and expensive. As a result, the most difficult and expensive step towards the process of environmental modeling is the collection of data (Minasny and McBratney, 2004). The term pedotransfer function (PTF) was coined by Bouma (1989) as translating data we have into what we need (Bouma, 1989). The most readily available data come from soil survey, but survey data usually only contain basic soil properties such as field morphology, texture, structure and pH. Pedotransfer functions allow basic information from soil surveys to be translated into other more laborious and expensively determined soil properties. Pedotransfer functions can be defined as predictive functions of certain soil properties from other easily, routinely, or cheaply-measured properties (Minasny and McBratney, 2002). A new method for developing of PTFs is artificial neural network. Artificial neural networks (ANNs) are nonparametric statistical tools that can be viewed as universal approximates. ANNs specialize in identifying non-linear relationships given extremely large datasets and have a relatively simple mathematical architecture that makes them computationally efficient. This computational efficiency offers significant advantages for predictions using real time sensors or large data sets that would be unwieldy with other estimation methods. ANNs were developed as large parallel-distributed information processing systems that attempt to model the learning procedure of the human brain (Rumelhart and McClelland, 1988). Their architecture consists of layers of nodes with weighted arcs connecting the nodes within the different layers. The information passing structure, the number of layers, the number of nodes and the algorithms selected for adjusting the internal weights create alternative types of ANNs (Besawa et al., 2006). Many of soil scientists in the world try to predict some soil properties from easily parameters. 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 (Tamari et al., 1996). 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 (Amini et al., 2005). Minasny and McBratney (2002) claimed that an advantage of using the neural network approach is that no relationships need to be assumed beforehand (Minasny and McBratney, 2002). 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 (Schaap et al., 1998).

The objective of this paper is to evaluate the general applicability of artificial neural network and multivariate regression in estimating Infiltration rate and deep percolation in the soils of Iran.

MATERIALS AND METHODS

Data collection and soil sample analysis

Soil samples were collected from different horizons soil profiles located in the Gorgan Province, North of Iran. Measured soil factors included texture, Organic carbon, Infiltration rate and deep percolation. The clod method (Blake and Hartge, 1986) was used to determine bulk density (Sparks et al., 1996).

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,* …. are coefficients.

Feedforward neural networks

Artificial Neural Networks (ANNs) are universal estimators of multivariate non-linear mappings that are capable of learning and generalizing from examples (training data). The key to successfully training an Artificial Neural Network is choosing the right network architecture and training algorithm. A feedforward artificial neural network is used in this study to approximate the relation between hydraulic onductivity/Transmissivity values of the region in question and bthe resulting hydraulic conductivity values. Feedforward networks are a subclass of layered networks in which there no intra-layer connections are and whose main feature is that connections are allowed from node ‘i’ only to nodes in layer iC1. Feedforward neural networks are among the most common neural networks in use (Mehrotra et al., 1997). They were chosen for use in this study because they are simple, easily trained, and can be readily inverted. The feedforward process from which the name was derived involves presenting an input pattern to input layer neurons that pass the input values into the first hidden layer. Each of the hidden layer nodes (neurons) computes a weighted sum of the inputs, passes the sum through the transfer (activation) function, and presents the results to the next layer until the output layer is reached. Determining the architecture of a neural network involves determining the number of layers in the network as well as the number of nodes (neurons) in each layer

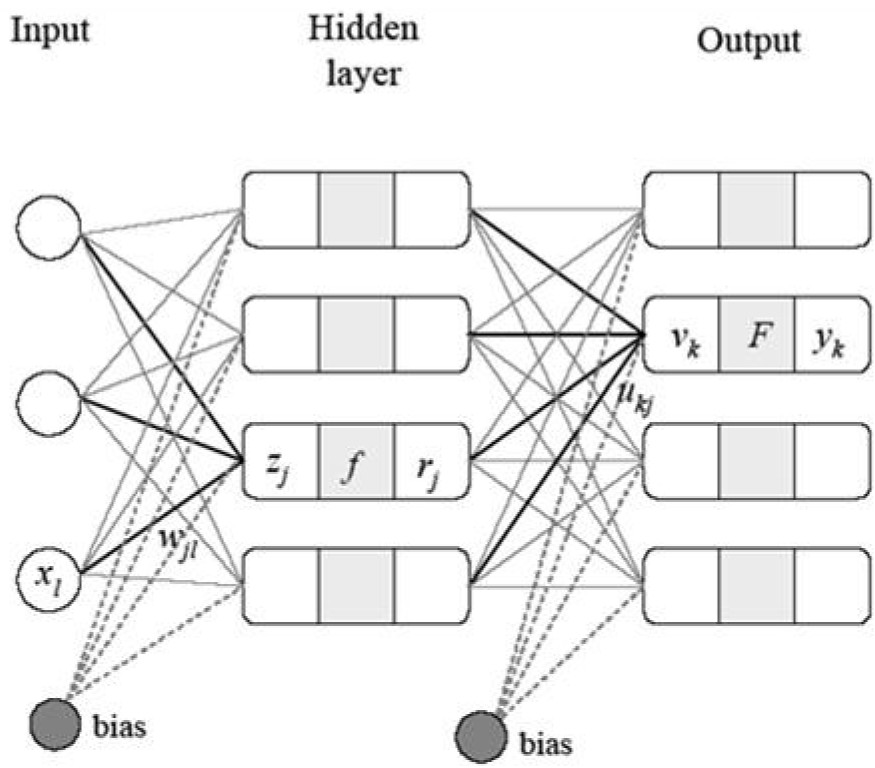

Figure 1. Structure of feed-forward ANN

(Luis and Abdalla, 2006). 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. (Figure 1)

Evaluation criteria

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

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

$$RSE = \frac{\sqrt{\frac{1}{n}\sum_{k=1}^{n}(z_s - z_o)^2}}{z_{ave}} \quad (2)$$

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 Data subdivided in two sets: 20% of the data for testing and the remaining 80% of the data were used for training.

Some soil parameters including: clay, silt, Bulk density, water saturation percentage and organic carbon were input data for prediction of Infiltration rate and Deep percolation. Firs step was to evaluate accuracy of artificial neural network for predicting known data. So we modeled the artificial neural network for predicting of training data. Results presented in Figure 2 and 3. These figures revealed that high accuracy of PTFs and neurons that used in modeling of artificial neural network.

After confirming of performances of artificial neural network, different neurons were examined for achieving the best neuron for predicting of soil properties. In this stage we used RMSE and RSE criteria for determine the best model. Results showed that for infiltration rate five neurons and for deep percolation two neurons had the lowest RMSE. Results plotted in the Figure 4 and 5.

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

I = 12.7 - 0.188 Clay - 0.053 silt - 10.3 BD + 0.187 SP - 0.199 OC (3)

P = 37.3 - 0.289 Clay - 0.176 silt - 17.4 BD + 0.130 SP - 0.488 OC (4)

After determining of these equations, performance of multivariate regression was developed for test data set. Correlation coefficient has been obtained 0.94 for

Table 1. Statistics of the training and test data sets of Infiltration Rate and Deep percolation

		Clay	Silt	BD	SP	OC	I	P
Training set	Min	15.00	19.00	1.30	38.30	0.34	0.25	0.09
	Max	54.00	73.00	1.65	84.00	8.80	6.50	8.70
	Mean	34.30	43.11	1.48	51.99	2.05	1.51	2.55
	Std	10.92	12.37	0.09	12.40	1.89	1.89	2.87
Test set	Min	26.00	30.00	1.30	60.00	1.22	0.40	0.40
	Max	47.00	46.00	1.55	72.60	10.25	4.70	5.50
	Mean	33.60	36.14	1.39	67.80	5.26	1.75	3.11
	Std	7.82	5.46	0.08	4.31	3.38	1.58	2.01

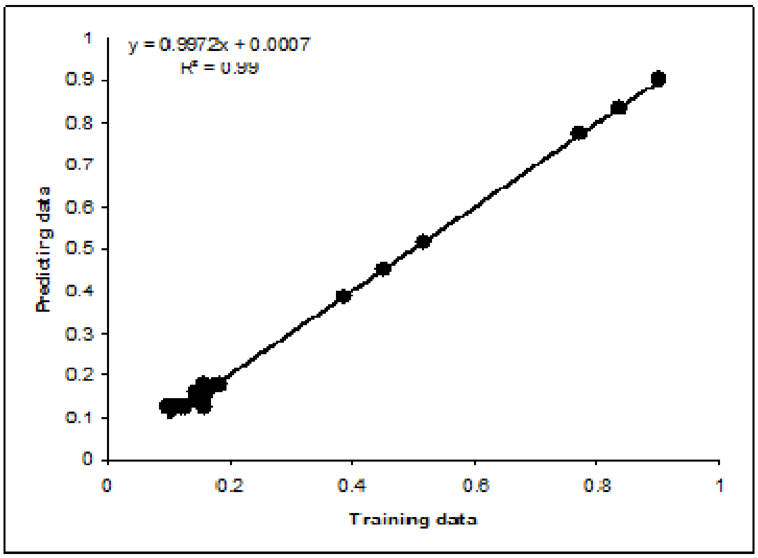

Figure 2. The scatter plot of the measured versus predicted Infiltration rate for training data

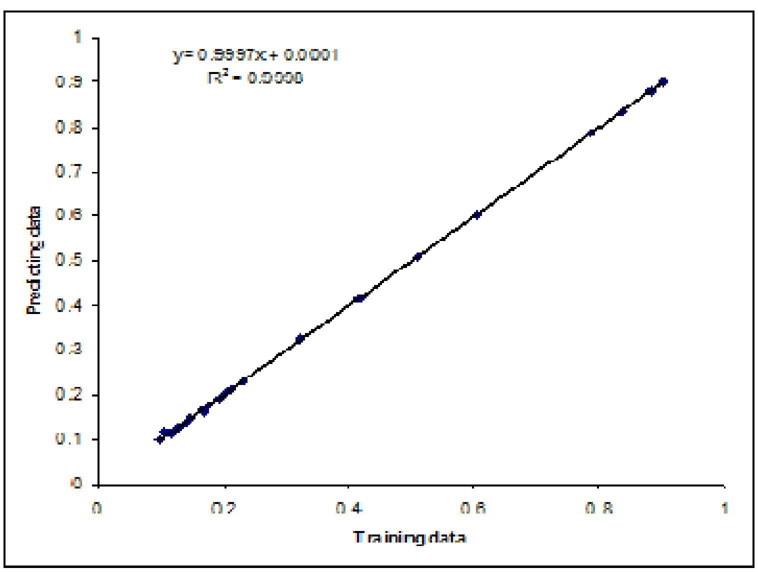

Figure 3. The scatter plot of the measured versus predicted Deep percolation for training data

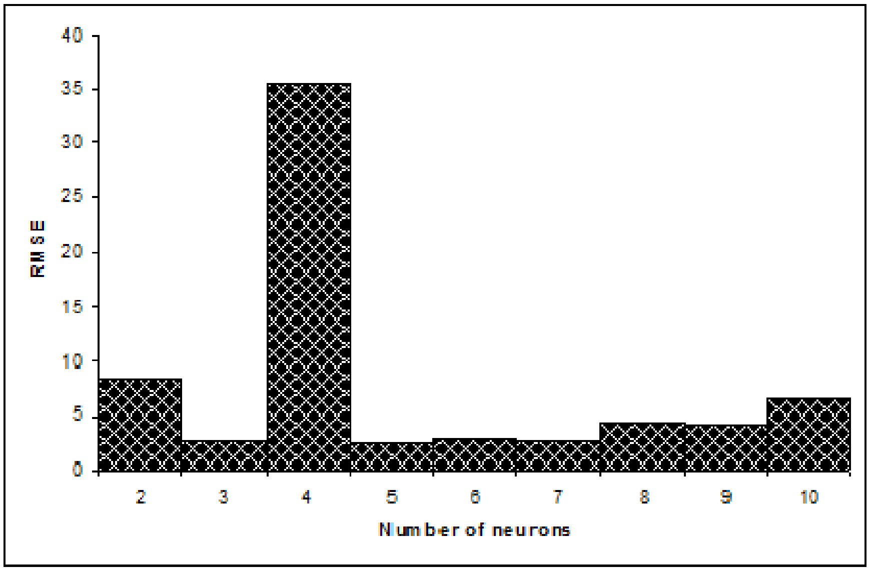

Figure 4. RMSE value for 2-10 neurons (Infiltration rate)

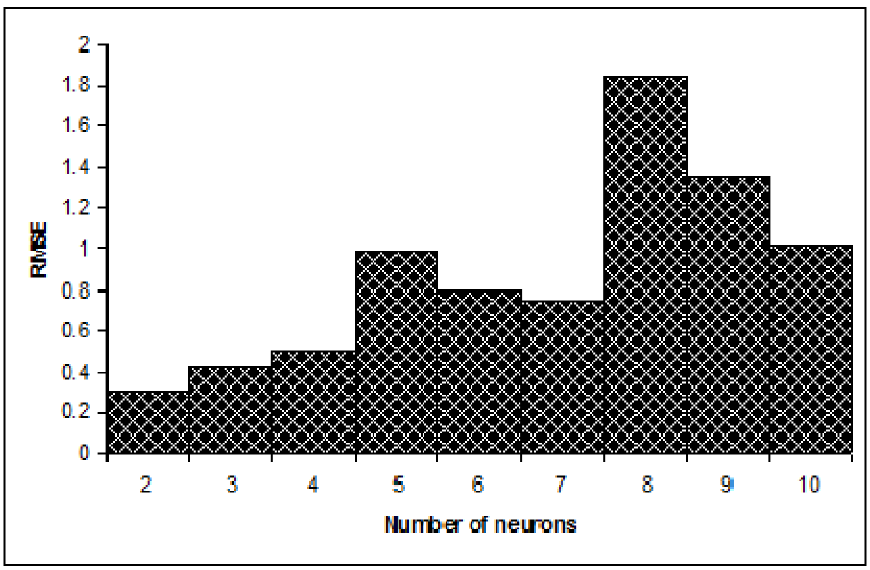

Figure 5. RMSE value for 2-10 neurons (Deep percolation)

infiltration rate and 0.95 for deep percolation. With comparison between artificial neural network and multivariate regression showed that applicability of artificial neural network. Results showed that artificial neural network with two and five neurons in hidden layer had better performance in predicting all soil properties (infiltration rate and deep percolation) than multivariate regression which is in line with the work done by Amini et al. 2005, Tamari and Wösten (1996), Minasny and 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 two parameters were more suitable for capturing the non-linearity of the relationship between variables (Koekkok and Booltink, 1999). 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,

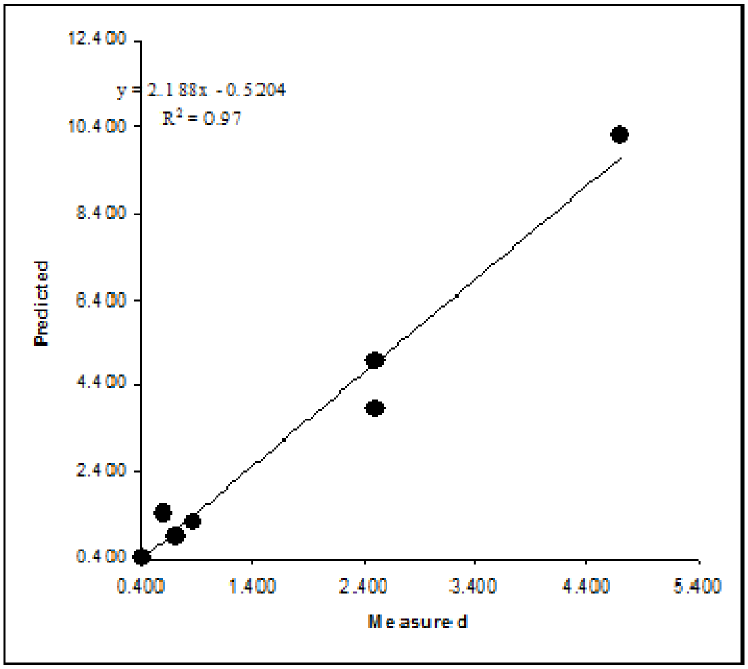

Figure 6. The scatter plot of the measured versus predicted infiltration rate

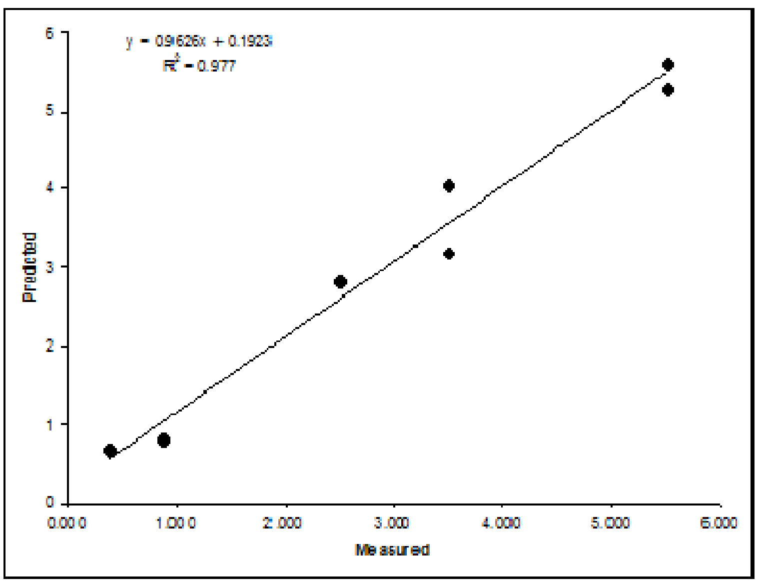

Figure 7. The scatter plot of the measured versus predicted deep percolation

1998). The scatter plots of the measured against predicted infiltration rate and deep percolation for the test data set are given in Figures 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 high accuracy that showed that strong relationship between input and output data and also high accuracy in determining of data.

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: infiltration rate and deep percolation 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 and five neurons in hidden layer had better performance in predicting soil properties than multivariate regression. The network models for two 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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