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RESEARCH ARTICLE

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Selection of a suitable model for the prediction of soil water content in north of Iran

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Abstract

Multiple Linear Regression (MLR), Artificial Neural Network (ANN) and Rosetta model were employed to develop pedotransfers functions (PTFs) for soil moisture prediction using available soil properties for northern soils of Iran. The Rosetta model is based on ANN works in a hierarchical approach to predict water retention curves. For this purpose, 240 soil samples were selected from the south of Guilan province, Gilevan region, northern Iran. The data set was divided into two subsets for calibration and testing of the models. The general performance of PTFs was evaluated using coefficient of determination (R^2), root mean square error (RMSE) and mean biased error between the observed and predicted values. Results showed that ANN with two hidden layers, Tan-sigmoid and linear functions for hidden and output layers respectively, performed better than the others in predicting soil moisture. In the other hand, ANN can model non-linear functions and showed to perform better than MLR. After ANN, MLR had better accuracy than Rosetta. The developed PTFs resulted in more accurate estimation at matric potentials of 100, 300, 500, 1000, 1500 kPa. Whereas, Rosetta model resulted in slightly better estimation than derived PTFs at matric potentials of 33 kPa. This research can provide the scientific basis for the study of soil hydraulic properties and be helpful for the estimation of soil water retention in other places with similar conditions, too.

Additional keywords: multiple linear regression; neural networks; pedotransfer function; Rosetta; soil moisture curve.

Abbreviations used: ANN (artificial neural network); CEC (cation exchange capacity); FWC (field water capacity); MBE (mean bias error); MLP (multi-layer perceptron); MLR (multiple linear regressions); PTFs (pedotransfer functions); PWP (permanent wilting point); RMSE (root mean square error); SWR (soil water retention).

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Introduction

Soil hydrodynamic properties drive the flow of water in the soil-plant-atmosphere system, and hence control processes such as aquifer recharge or nutrient fluxes between soil and vegetation. Knowledge of soil hydrodynamics is important for modeling physical processes related to soil water content. Despite great advances in measurement methods, it is still difficult to determine soil hydraulic properties accurately, especially for undisturbed soils and in the dry range. However, the measurement of the soil hydraulic properties is time-consuming, labor-intensive and expensive (Merdun, 2010). If the area being evaluated is large enough to exhibit substantial spatial variability of soil water availability, it is costly and time consuming to perform adequate measurements to provide good estimates within the temporal and financial constraints of the project (Givi *et al.,* 2004).

Recently, an alternative, indirect estimation of soil hydraulic properties from widely available or more easily measured basic soil properties using pedotransfer functions (PTFs) has attracted considerable attention of researchers in a variety of fields such as soil scientists, hydrologists, and agricultural and environmental engineers (Minasny *et al.*, 2004; Huang *et al.,* 2010).PTFs are based on physical approaches or on empirical regression equations that link soil physical and/or chemical characteristics, easily measured, to hydrodynamic properties (Bouma, 1989; Hamblin, 1991) that just exist as a narrow relationship among these soil properties.

PTFs are classified in three main groups, *i.e.*, class PTFs (Baker & Ellison, 2008); point PTFs (Ghanbarian-Alavijeh & Millán, 2010); and parametric or function PTFs (Santra & Das, 2008). The classes PTFs are used to estimate an average value of soil hydraulic parameters for each class of soil texture. These PTFs are inexpensively developed; however, their accuracy is less than point and parametric PTFs (Abbasi *et al.*, 2011). Point PTFs functions estimate the water contents at fixed pressure heads, often including the water content at the field water capacity (FWC) and the permanent wilting point (PWP) or the water content at a given matric potential (Givi *et al.*, 2004). Function PTFs predict the parameters of a closed-form analytical equation or empirical parameters of water retention curve models, such as the model of Brooks & Corey (1964) or the van Genuchten equation (Van Genuchten, 1980).

At present, there are two common methods to develop PTFs for point and/or function estimations, which are the Multiple Linear Regression (MLR) method (Merdun *et al.*, 2006) and the Artificial Neural Network (ANN) method (Minasny *et al.*, 2004; Sarmadian & Mehrjardi, 2008). In recent years, the ANN method was used to improve the prediction accuracy of PTFs (Kumar *et al.,* 2010; Rezaei-Arshad *et al.,* 2013; Moghimi *et al.,* 2014; Mukhlisin & Abd Rahman, 2014; Rezaeianzadeh *et al.,* 2014).

An advantage of ANN, as compared to other methods, is that it does not require a priori models. The optimal, possibly nonlinear, relations which link the input data (bulk density, particle-size data, etc.) to output data (soil water retention, FWC, etc.) are obtained and implemented in an iterative calibration procedure (Schaap *et al.*, 2001). As a result, ANN method can typically extract the maximum amount of information from the data. For these reasons, the ANN method had a wide application (Merdun *et al.*, 2006; Yi *et al.,* 2013), and many scholars implicate that the general prediction of ANN is better than the MLR method (Moghimi *et al.,* 2014).

However, this method also has some significant disadvantages which must be taken into consideration (Minasny *et al.*, 2004). First of all, the interpretation of ANN is often difficult and subjective, because the fitting with the transfer function is a black-box approach. In addition, as it is usually the case in optimization, the sets of optimized weighting factors are not mathematically unique because the likelihood of convergence is at the local minimum. Consequently, different initial weight values may yield various results that deviate from the global minimum. Nevertheless, the ANN method showed good prediction function, and it would play a greater role in the prediction of soil hydraulic properties with the improvement of scientific technology.

Najafi & Givi (2006) used the ANN and PTF methods for prediction of soil bulk density. They pointed out that the ANNs are able to predict the soil bulk density better than the PTFs. Amini *et al.* (2005) estimated the cation exchange capacity (CEC) in the central part of Iran using soil organic matter and clay contents. They used the ANN and five experimental models that were on the basis of regression methods for their predictions. They showed that a neural network PTF with eight hidden neurons was able to predict CEC better than the regression PTFs. Also the ANN model significantly improved the accuracy of the prediction by up to 25%. They concluded that network models are in general more suitable for capturing the non-linearity of the relationship between variables. Jain & Kumar (2006) indicated that the ANN technique can be successfully employed for the purpose of calibration of infiltration equations. They had also found that the ANNs are capable of performing very well in situations of limited data availability. In contrast, Merdun (2010) pointed out that although the differences between regression and ANN models were not statistically significant, regression predicted point and parametric variables of soil hydraulic parameters better than ANN.

In order to make the PTFs as widely applicable as possible, Schaap *et al.* (2001) developed the Rosetta software by using a large number of soil hydraulic data and corresponding predictive soil properties. The Rosetta model based on ANNs works in a hierarchical approach which employs five different PTFs to predict water retention curves (Schaap *et al.*, 2001).Rosetta software is used widely by many scientists for the estimation of soil water retention (SWR), saturated hydraulic conductivity and unsaturated hydraulic conductivity parameters (Schaap *et al.*, 2001; Givi *et al.*, 2004; Minasny *et al.*, 2004; Stumpp *et al.*, 2009).

Although there are many studies on developing and using PTFs as listed above, there is no universal method for the prediction of soil hydraulic parameters. Moreover, the existing PTFs for the estimation of soil hydraulic properties in the literature were not always applicable in other regions with acceptable accuracy (Cornelis *et al.*, 2001; Wagner *et al.*, 2001; Nemes *et al.*, 2003). So, it is necessary to develop and evaluate the PTFs in different regions. Moreover, there are few studies comparing the performance of different methods simultaneously in the development of PTFs in the study area and its surrounding areas. Therefore, the objectives of this study were (1) to develop and validate the point PTFs using Multi-Layer Perceptron (MLP), MLR and function PTFs using the Rosetta software for the estimation of soil moisture in various matric potentials, and (2) to compare the predictive capabilities of the three methods using selected evaluation criteria in the Gilevan Region of Guilan Province, northern Iran.

Material and methods

Study area and data collection

Study area is located in south of Guilan province, Gilevan region, northern Iran (36° 54′ 10” to 36° 50′ 00” N, 49° 02′ 30” to 49° 16′ 08” E) (Fig. 1). The climate is aridic. The annual precipitation is 245.1 ± 3 mm, and the average temperature is17.4 ± 2°C.

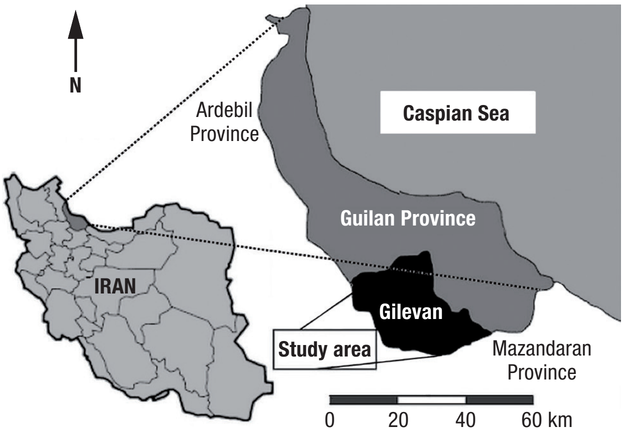

Figure 1. Location of study area in northern Iran.

Totally 240 samples were taken from 0–30 cm depth and air dried. Some clods were used to measure soil bulk density using clod method. Samples were passed through a 2mm sieve to determine particle-size distribution by the pipette method in combination with sieving method. The organic matter content was analyzed with the Walkly-Black method. Calcium carbonate was determined based on calcimetery method (Burt, 2004). Disturbed soil samples were used to measure soil water content at −10, −33, −100, −300 kPa matric potentials using pressure plate and at −500, −1000, and −1500 kPa using pressure membrane. The resulting curves were fitted to the Van Genuchten model using the RETC software package (Van Genuchten, 1980) that provides four parameters (θ*r*, θ*s,* α and n). The first step for using statistical methods is to study the normality of data. In order to know whether the data were normal, Kolmogorov-Smirnov test was used. The data sets were divided into two subsets, randomly. One subset that includes 80% of the total data was used for calibrating selected PTFs, and the other subset was used for testing the calibrated models includes 20% of total data.

Multiple linear regression method (MLR)

The most common method used in point PTFs is to employ MLR. Gupta & Larson (1979) used the MLR method to estimate the SWR characteristics according to the data, such as bulk density, organic matter and so on. This method also became one of the most popular methods. Therefore, based on this model, the following function was used to develop the PTFs in this study (Eq. [1]):

$$\theta_P = a_0 + a_1\left(sand\right) + a_2\left(silt\right) + a_3\left(clay\right) + a_4\left(OC\right) + a_5\left(BD\right) \quad [1]$$

where, θp is the soil water content at specific matric potentials; a_0 is the regression constant; a_1, a_2, a_3, a_4, a_5 are the regression coefficients; OC and BD represent the organic carbon and bulk density, respectively.

Artificial neural networks (ANN) model - MLP

Neural networks consist of a large class of different architectures. In many cases, the issue is approximating a static nonlinear, mapping *f*x with a neural network *fNN*x, where $x \in R^K$. The most useful neural network in function approximation is Multi-Layer Perceptron (MLP) network. A MLP consists of an input layer, several hidden layers, and an output layer. Node *i*, also called a neuron, in a MLP network is shown in Suppl. Fig. S1 [pdf online].

It includes a summer and a nonlinear activation function *g*. The inputs, x_k, $k = 1,\ldots,K$ to the neuron are multiplied by weights w_{ki} and summed up together with the constant bias term θ_i. The resulting *ni* is the input to the activation function *g*. The activation function was originally chosen to be a relay function, but for mathematical convenience a hyberbolic tangent (*tan h*) or a sigmoid function are most commonly used. Hyberbolic tangent is defined as:

$$\tan h\left(x\right) = \frac{1-e^{-x}}{1+e^{-x}} \quad [2]$$

The output of node *i* become:

$$y_i = g_i = g\left[\sum_{j=1}^{k} w_{ji}x_j + \theta_i\right] \quad [3]$$

Connecting several nodes in parallel and series, a MLP network is formed (Heikki, 2008). In MLP, the weighted sum of the inputs and bias term are passed to activation level through a transfer function to produce the output, and the units are arranged in a layered feed-forward topology called Feed Forward Neural Network (Venkatesan & Anitha, 2006).The three-layer neural network was used in this study: input, hidden and output layer. This type of network generally provides better performances in comparison to other types. The total number of nodes in the input and output layers coincides with the number of input and output variables in the data set. The ideal number of nodes in the hidden layer has to be found through trial-and-error method (Chang *et al.*, 2004). The number of neurons in the hidden layer is of great importance, as too many neurons may cause over-fitting problems (Huang & Foo, 2002). For this purpose, variables that were been finally selected in MLR for developing PTFs, were used as inputs in ANN. Also, we used 1-10 nodes, and the ideal node number selected based on the least RMSE value. Each node carries a weight. By changing these weights, the input–output relation can be simulated. Also, we used Tan-sigmoid (non-linear) and linear activation function for the hidden and output layers, respectively. For ANN modeling, the computer software MatLab and the Neural Network Toolbox were used (Demuth & Beale, 2004).

Rosetta method

To facilitate application of the PTFs, Schaap *et al.* (2001) developed "Rosetta", a computer program that implements some of the models published by Schaap & Leij (2000). Rosetta is able to estimate the Van Genuchten water retention parameters (Van Genuchten, 1980) and saturated hydraulic conductivity (Ks) (Mualem, 1976) based on pore-size model. The retention function is given by Eq. [4]:

$$\theta(h) = \theta r + \frac{\theta s - \theta r}{\left(1 + \left[\alpha h\right]^n\right)^{1-\frac{1}{n}}} \quad [4]$$

where θ(h) is the measured volumetric water content (cm^3/cm^3) at the suction h (cm, taken positive for increasing suctions). The parameters θs (cm^3/cm^3) and θr (cm^3/cm^3) are saturated and residual water contents respectively; $\alpha>0$ (in cm^{-1}) is related to the inverse of the air entry suction; and $n>1$ is a measure of the pore-size distribution (Van Genuchten, 1980). A hierarchical approach with limited or more extended sets of predictors was used to estimate the water retention parameters (θs, θr, α, n) and Ks (Schaap *et al.*, 2001).

Evaluation criteria

Accuracy of the MLR and Rosetta methods for derivation of PTFs was evaluated by using the coefficient of determination (R^2), root mean square error (RMSE) and mean biased error (MBE) between the measured and predicted values of a given hydraulic parameter. The R^2, RMSE and MBE are expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2} \quad [5]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad [6]$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right) \quad [7]$$

where y_i denotes the measured value, is the predicted value, is the average of the measured value, and n is the total number of observations. The MBE characterizes the mean difference between the calculated and measured data; hence, it is a criterion of systematic error in the model fitting. Negative and positive values of MBE indicate under and over estimation of PTFs for a given parameter respectively.

Results

In this paper, use of MLR, ANN and Rosetta models, for the prediction of soils water content, was described and compared. Descriptive statistics for soil properties are summarized in Table 1. The studied soils can be classified as clayey, clay loam, silty clay loam and sandy clay loam. In general, clay, silt and sand content were between 18% to 48%, 15% to 45.5%, and 14% to 57% respectively. Average bulk density was 1.42 g/cm^3 with values varying between 1.28 to 1.6 g/cm^3.

Correlation coefficients among the water content in each potential and soil physical and chemical properties were calculated and are reported in Table 2. From the values of correlation coefficients in Table 2, the soil bulk density (BD), clay and sand content have close relationships with the water content at 10 and 33 kPa at the significance level consistent with other scholars (Nemes & Rawls, 2006) and clay and sand content are only suitable for PTFs developing to predict the water content of 100, 300 and 500 kPa. The water content at 1000 and 1500 kPa were only controlled by clay con-

Table 1. Descriptive statistics of variables used for the development of PTFs.

	Variables[1]	Min	Max	Mean	CV[2]	Skewness	Kurtosis	Asymp. Sig.[3]
Training data (n=192)	Clay (%)	18	48	36.5	0.18	–0.63	–0.21	0.17
	Silt (%)	15	45.5	33.5	0.20	–0.67	0.9	0.32
	Sand (%)	14	57	29.95	0.33	1	0.9	0.24
	BD (g/cm^3)	1.29	1.6	1.44	0.04	–0.17	0.03	0.72
	OC (%)	0.2	1.6	1.57	0.40	0.61	–0.2	0.12
	CaCO3 (%)	4.1	12	7.39	0.25	0.98	0.45	0.35
Testing data (n=48)	Clay (%)	18.3	47.8	37	0.16	–0.31	–0.11	0.62
	Silt (%)	16	45	35	0.18	–0.36	0.46	0.56
	Sand (%)	15	55	28	0.31	0.45	0.51	0.41
	BD (g/cm^3)	1.28	1.6	1.38	0.03	–0.12	0.02	0.85
	OC (%)	0.22	1.5	1.4	0.32	0.25	–0.31	0.71
	$CaCO_3$ (%)	4.3	11	7.25	0.22	0.41	0.21	0.48

[1]BD: bulk density; OC: organic carbon. [2]CV: coefficient of variation, [3]Asymp. Sig.: Kolmogorov-Smirnov test index for normal distribution, that should be greater than 0.05.

Table 2. Correlation coefficients among the water content in each potential and soil properties from total measured data.

Water content (kPa)	Sand	Silt	Clay	BD	$CaCO_3$	OC
θ_{10}	–0.406**	0.113*	0.443**	–0.348**	0.002	0.0175
θ_{33}	–0.391**	0.125*	0.456**	–0.332**	0.008	0.0194
θ_{100}	–0.345**	0.128*	0.522**	–0.082	0.005	0.0161
θ_{300}	–0.342**	0.132*	0.551**	–0.012	0.004	0.0172
θ_{500}	–0.331**	0.143*	0.585**	–0.018	–0.003	0.0281
θ_{1000}	–0.151	0.143*	0.591**	0.0196	–0.006	0.0321
θ_{1500}	–0.102	0.173*	0.675**	0.0073	–0.008	0.0331

BD: bulk density; OC: organic carbon. **,*: correlations are significant at level of 0.01 and 0.05, respectively.

tent. The absolute effect of BD decreased with h_m in agreement with Nemes & Rawls (2006). The correlation coefficient of BD was negative for low h_m and positive for high h_m (*i.e.* 1000 and 1500 kPa). Dexter *et al.* (2008) found that BD decreased the SWR at low h_m and increased it at high h_m. Aina & Periaswamy (1985) also found a negative correlation between θ_{33} kPa and BD for western Nigerian soils. However, Hutson & Cass (1987) reported that BD had a non-significant effect on the SWR. Clay and silt increased the SWR for the major of h_m values due to their effects on water retention surfaces. But the effect of silt was not significant at 0.01. This is in agreement with Hutson & Cass (1987). Aina & Periaswamy (1985) found positive relations of θ_{33} kPa with silt and clay contents and of θ_{1500} kPa with clay content. Kern (1995) found that effects of silt content and BD on θ_{33} kPa and θ_{1500} kPa and effect of sand content on θ_{1500} kPa were not significant but that sand content significantly affected θ_{33} kPa. Nemes & Rawls (2006) reported that sand and silt contents decreased and clay content increased θ_{FC} and θ_{PWP}. Dexter *et al.* (2008) found a positive relation between θ_{PWP} and clay content. Decreasing effect of sand content on the SWR was obvious and had a descending trend fromθ_{10} to θ_{1500} kPa. Its effect on θ_{1000} and θ_{1500} kPa was not significant. The influence of $CaCO_3$ was minor and had no significant effect on SWR. It increased the SWR due to its impacts on aggregation and flocculation (by soluble Ca^{2+}). Rajkai & Varallyay (1992) found that $CaCO_3$ content was the second important independent variable entering PTFs for θ_{1500} kPa. Khodaverdiloo & Homaee (2004), however, observed that carbonates decrease the SWR at high h_m because the carbonates with clay size behave like silt in water retention. Effect of OC on the SWR was not significant. Increasing effect of organic matter on the SWR is dominant at low h_m. Gupta & Larson (1979) also reported that organic matter highly increases the SWR at low h_m. Bell & van Keulen (1995) found a positive and significant relation between θ_{PWP} and organic matter in four Mexican soils.

Based on the collected training data, the following PTFs using MLR method were developed and are listed in Table 3.The independent variables were selected at a 0.01 significance level for inclusion in the regression model. The values of adjusted coefficients of determination (R^2_{adj}) given in Table 3 indicate the range of the dependent variable that is explained by the

Table 3. The point PTFs derived from multiple linear regression (MLR) method (training data).

Point PTFs	R^2_{adj}	MSE
$\theta_{10} = 0.357clay - 0.169sand - 0.143BD + 26.945$	0.81**	$7.49 \cdot 10^{-4}$
$\theta_{33} = 0.384clay - 0.121sand - 0.127BD + 18.606$	0.79**	$7.48 \cdot 10^{-4}$
$\theta_{100} = 0.307clay - 0.152sand - 0.161$	0.72**	$5.53 \cdot 10^{-4}$
$\theta_{300} = 0.391clay - 0.171sand + 5.562$	0.81**	$2.49 \cdot 10^{-4}$
$\theta_{500} = 0.394clay - 0.103sand + 3.851$	0.77**	$1.96 \cdot 10^{-4}$
$\theta_{1000} = 0.412clay + 1.486$	0.87**	$1.52 \cdot 10^{-4}$
$\theta_{1500} = 0.428clay + 0.363$	0.87**	$1.43 \cdot 10^{-4}$

PTFs: pedotransfer functions. R^2_{adj}: adjusted coefficients of determination. MSE: mean square error. **correlations are significant at the level of 0.01

independent variables. These results show that at low pressure heads, the clay, sand and bulk density are appropriate predictors of water content. At high pressure heads (1000 and 1500 kPa), the clay content was a better predictor. These regression equations and their statistics are shown in Table 3. Table 3 showed that clay content is an important factor for predicting water content at all potential points. Also, the studied soils showed a high water content (saturation≅ 0.60 cm^3/cm^3 and wilting point ≅ 0.20 cm^3/cm^3).This feature can be related to high silt and clay particle size content (*e.g.,* Rawls *et al.*, 2003), which was always greater than 65% for all samples.

Clay type plays an important role in the retention properties of soils. So, soils in the humid tropics can have a much lower capacity to retain water than soils in the temperate regions with the same clay content but with a different type of clays (Christopher *et al.,* 2013). Soils in southern Guilan province are principally dominated by montmorillonite clay (Fig. 2) which is expanding type clay minerals and swell by absorbing substantial amounts of water in its interlayer space. Presence of 2:1 smectitic clays, especially, montmorillonite in these soils was also an important specific soil characteristic that contributed to increase the water retention and hygroscopic water content, *i.e.,* the water content in the driest part of the curve. Fig. 2 illustrates the X-ray difractogram of the clay fraction and shows presence of smectite clay minerals in studied soils.

Discussion

Comparison among different methods for prediction of soil water content from testing data is presented in Suppl. Figs. S2, S3 and S4 [pdfs online] and summarized in Table 4.

These figures and Table 4 imply that the general prediction was good for the three methods, but the ANN method had excellent performance and the prediction values were close to the measured values.

The RMSE values for the ANN were smaller than that for the derived point PTFs and Rosetta model in all matric potentials. MLR and Rosetta software hold the second and third places, respectively. The RMSE values for the derived point PTFs were smaller than that for the Rosetta model, except kPa that Rosetta model had better estimation than regression (Table 4). The R^2 values of ANN for all potentials were greater than regressions and regressions were greater than Rosetta, except kPa that Rosetta model had greater than regression. So, the accuracy of the ANN is better than that of the derived point PTFs and Rosetta model. This

Table 4. Comparison among different methods for prediction of soil water content from testing data.

		θ_{1500}	θ_{1000}	θ_{500}	θ_{300}	θ_{100}	θ_{33}	θ_{10}
ANN	RMSE	0.415	0.605	0.714	0.723	0.725	0.426	0.887
	MBE	–0.003	–0.013	–0.061	0.058	–0.025	–0.012	–0.009
	R^2	0.859	0.826	0.779	0.798	0.772	0.754	0.712
MLR	RMSE	0.880	1.162	1.505	1.174	1.530	0.947	1.826
	MBE	–1.157	–0.863	–0.386	–1.123	–0.872	–0.427	–0.867
	R^2	0.778	0.708	0.668	0.692	0.657	0.680	0.649
Rosetta	RMSE	1.656	1.484	1.572	1.837	1.568	0.864	2.22
	MBE	1.381	1.000	0.846	0.622	–0.455	0.522	0.958
	R^2	0.702	0.653	0.591	0.628	0.505	0.724	0.553

ANN: artificial neural network; MLR: multiple linear regression; RMSE: root mean square error; MBE: mean bias error.

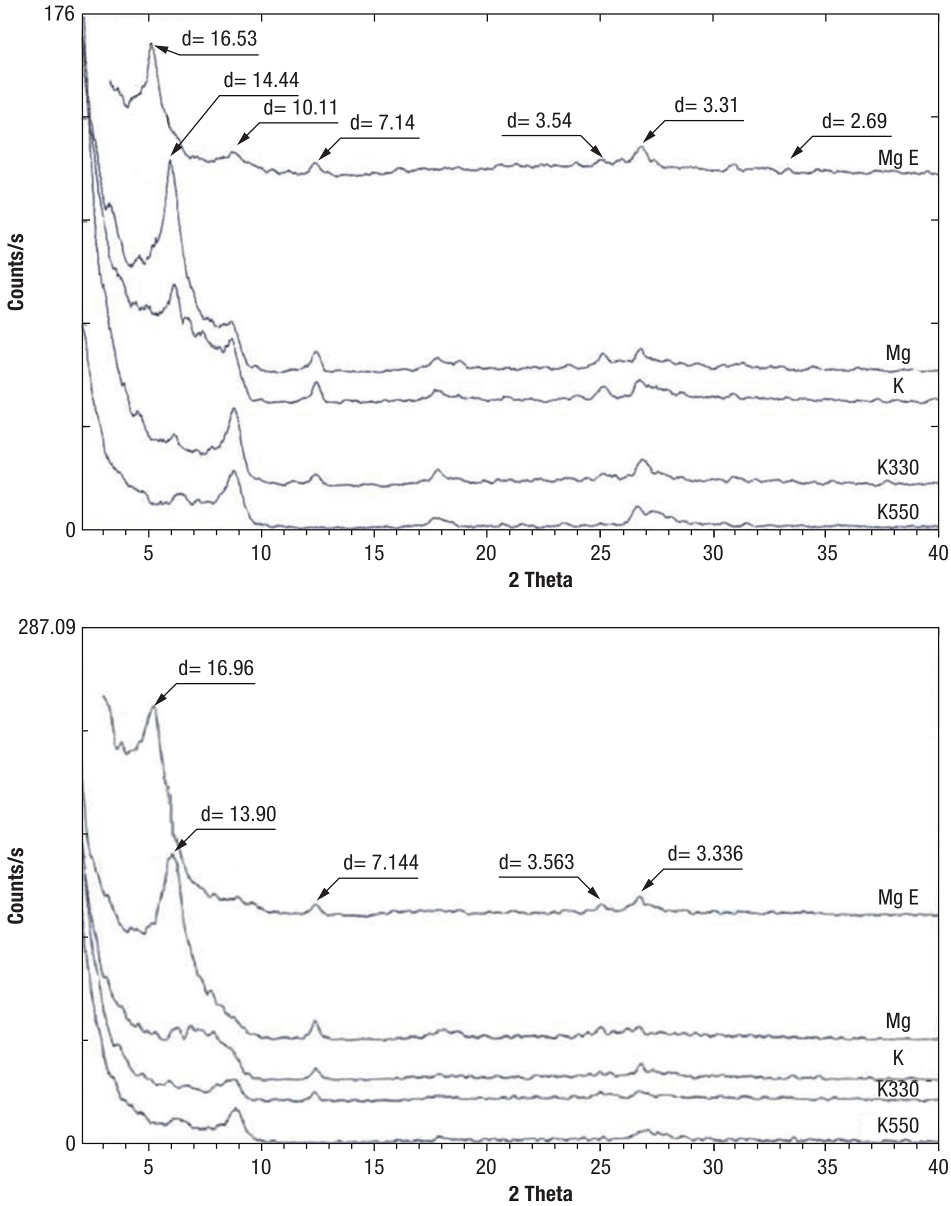

Figure 2. X-ray diffractogram of the clay fraction ("d" means interlayer spacing).

result is in line with the work done by Minasny *et al.* (2004) and Amini *et al.* (2005). But, with regard to evaluation criteria, our study is more accurate than other mentioned researches, because, selection of inputs and model designing (such as type of learning algorithm, the number of layers and neurons, etc,) is carried out more accurately.

The reason of this superior efficiency of ANNs models compared with the basic regression equations is probably because the PTFs that have derived from various areas have different efficiencies. On the other hand, according to the hypothesis of Schaap *et al.* (2001), for designing of a neural network we do not need a special equation. They also believe that by creating a suitable equation between input and output data we are able to achieve the best results. Also, due to the occurring of nonlinear equations between dependent variables and predicting variables, the neural network have the better efficiency compared with the basic regression equations. Yi *et al.* (2013) investigated the accuracy of ANN and analyzed the regression method using correlation coefficient and the RMSE. They reported that the neural network is able to predict the easily measurable soil parameters with more accuracy and less error. Similar results have been reported by Mukhlisin & Abd Rahman (2014) as well. They found that using ANN leads to less RMSE values than the MLR. They also reported that the neural network has not better efficiency than linear regression models in occasion of high stability of data. However, the high accuracy of data leads to more efficiency of neural network and also, shows the proper selection of testing and training data. Analysis of the ANN parameters suggested that more input variables were necessary to improve the prediction of soil parameters (Mermoud & Xu, 2006). The RMSE of the different neurons in hidden layer is plotted in Fig. 3. This figure illustrated that the best model obtained with 10, 5, 8, 4, 10, 9 and 7 neurons for 10, 33, 100, 300, 500, 1000 and 1500 kPa respectively.

The RMSE values of different ANN-PTFs and regression-PTFs were lower in the prediction of volumetric water content at PWP than the others. Likewise, based on MBE values, all these PTFs especially at PWP, showed slight underestimation of volumetric water content. But this underestimation of ANN model was very low and could be ignored. Also, in the evaluation study of Tomasella & Hodnett (2004), the general trend of lower RMSE values at permanent wilting point compared to field capacity conditions was observed for all the PTFs without any exception. Recently, Vereecken *et al*. (2010), also found that RMSE values at -1500 kPa are generally lower than at -33 kPa. The water content in the wet range of the retention curve is related more to the soil structural properties whereas in the dry range it depends more on the particle size distribution. Thus, the point PTFs were able to describe the water retention at different soil water pressure heads by incorporating different independent variables. The relationships between water retention parameters and basic soil properties are complex; consequently, the performance of point PTFs is better than that of Rosetta model. A similar comparison was made by Tomasella *et al*. (2003) both of whom reported similar differences between these two types of soil water prediction. The results of our investigation showed that in the reliability test, all the derived PTFs were associated with negative values of the MBE. Therefore, for the independent data set, the derived PTFs tend to underestimate the water retention curve (Table 4). As mentioned earlier, the range in clay content was not the major cause of its low predictive capability. Many authors, as Medina *et al.* (2002), indicated that clay type plays a vital role in the retention and transmission properties of a given soil. This is why soils in the humid tropics can have a much lower capacity to retain water than soils in the temperate regions with the same clay content but with a different type of

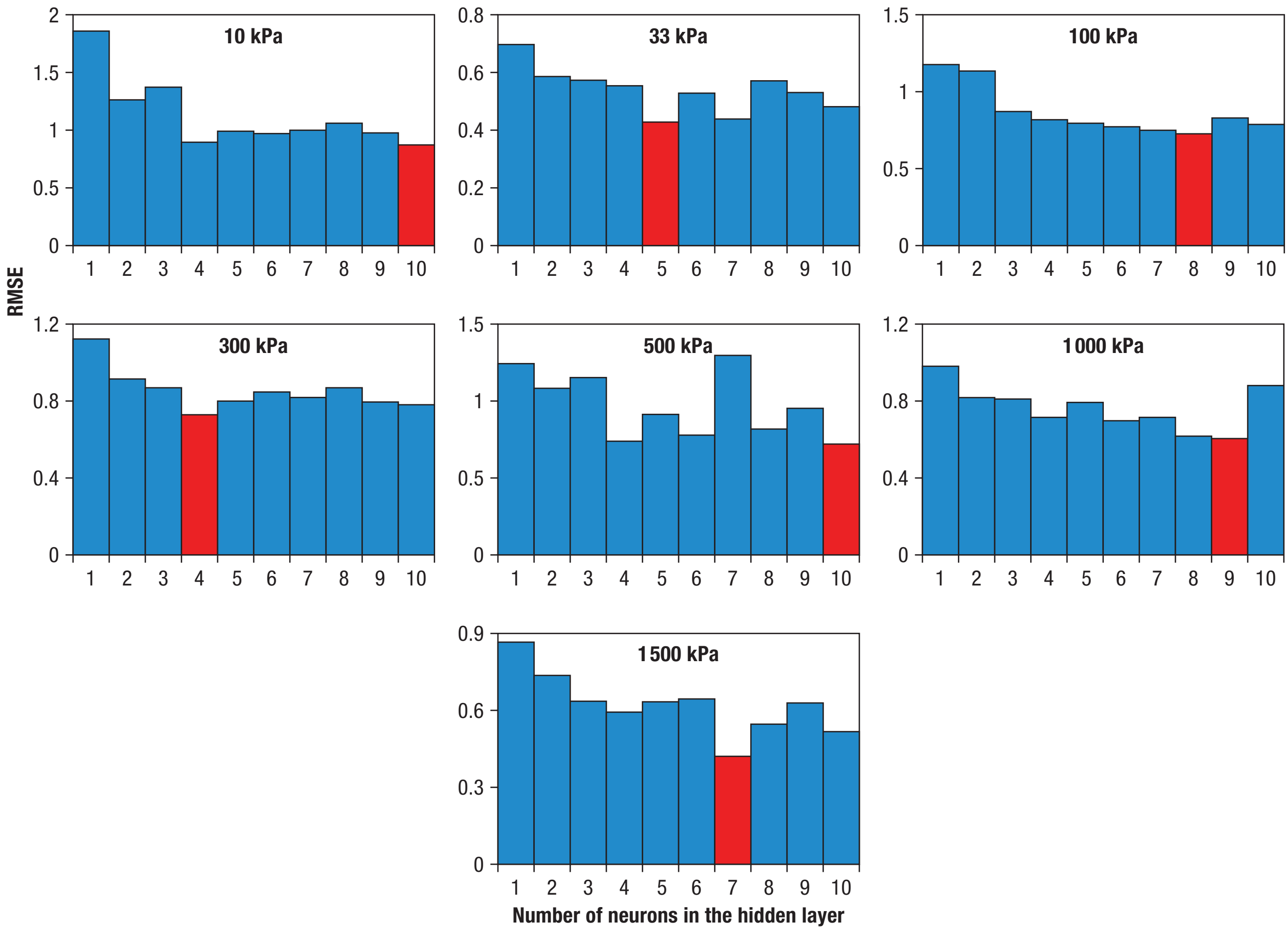

Figure 3. Relationship between root mean square error (RMSE) and number of hidden layer neurons in different matric potentials in artificial neural network (ANN) method. Red bars are number of neurons in hidden layer with the lowest RMSE.

clays (Christopher *et al*., 2013). Soils in southern Guilan province are principally dominated by montmorillonite clay (Fig. 3) which is expanding type clay minerals and swell by absorbing substantial amounts of water in its interlayer space. The prediction errors of these methods increased with increasing water content (high matric potentials) probably because at high matric potentials the water content is more related to the soil structure attributes. Because there was no predictor to adequately explain the soil structure effects on soil water content, and soil bulk density alone seems to be insufficient to represent these effects, the error prediction of the PTFs increased at high matric potentials. Comparison of these values with those obtained for the derived PTFs (Table 4) shows that all of the derived PTFs performed better than the Rosetta package. This may be related to the pedogenic differences between the data sets used to derive the Rosetta package and those for the reliability test. These low adjustments of Rosetta model, especially at–1500 kPa, could be related to the textural properties of these soils. Using a different particle size distribution, as does the Canadian Society of Soils Science (McKeague, 1978), a detailed silt particle-size distribution is obtained, where one can observe that exactly the fine silt content (5–2 µm) was between 57%and 84%. Thus, the hydrodynamic behavior of fine silt content, that could be similar to a clay particle size, would increase the water retention content near to PWP, and this would therefore justify the poor fits of Rosetta, because Rosetta predicts according to USDA textural distribution using three well-differentiated particle sizes (sand, silt and clay). The MBE values show that the Rosetta package overestimated water retention, especially at high pressure heads, except at 100 kPa pressure. This was also reported by Schaap *et al.* (2001).

With decreasing of matric potential (from 10 kPa to 1500 kPa), correlation coefficient increased in all three methods. In other words, the accuracy of prediction increased with increasing in soil suction. Because soils of study area had low content of organic matter and so, soil structure was very weak. On the other hand, the hydrodynamic behavior of fine silt content, that could be similar to a clay particle size, would increase the water retention content near to permanent wilting point. The content of fine silt of soils was between 57% and 84%.

In this study, multivariate linear regression and neural network model were employed to develop a pedotransfer function for predicting soil moisture using available soil properties. This neural network was consisted of three hidden layers, a sigmoid activation function in hidden and linear function in output layer. Results showed that artificial neural network gave the best model with Levenberg–Marquardt learning algorithm and tangent sigmoid (tansig) transfer function. Multi-Layer Perceptron architecture of different matric potentials according to number of inputs, number of neurons in the hidden layer and output parameter were as: 3-10-1, 3-5-1, 2-8-1, 2-4-1, 2-10-1, 1-9-1 and 1-7-1 for 10, 33, 100, 300, 500, 1000 and 1500 kPa, respectively. The ANN model was more suitable for capturing the non-linearity of the relationship between variables than multivariate regression and Rosetta, and can model non-linear functions and has been shown to perform better than linear regression. With regarding to the evaluation criteria, the results of this study revealed that the ANNs had superiority to the basic regression equations for prediction of mentioned soil parameter. This is a crucial result because, since ANN– PTFs formed from local data produce more accurate predictions than those built from data spread from a wider area, the concept of data conservation becomes a critical factor in ANN–PTFs construction (Baker & Ellison, 2008). However, due to difficulties of direct measurement of soil parameters, we recommend using of neuro-fuzzy models in the future studies for obtaining the logical equations of other soil parameters, especially soil hydraulic properties, in each area.

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