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Comparing Neural Networks, Linear and Nonlinear Regression Techniques to Model Penetration Resistance

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Abstract: Penetration resistance (PR) is an important property of soils, and can be expressed as cone index (CI). Because of high variability, there are no accurate and representative PR data in most cases. Variable PR is considerably affected by gravimetric soil water content (GWC) and bulk density (BD). In this study, artificial neural networks (ANNs) were used to simulate relationship between BD, GWC, and CI. A data set of 381 samples was collected from 2 study sites, Hamadan and Maragheh. Pedotransfer functions (PTFs) were developed using ANNs and linear and nonlinear regression models to predict CI for the combined data set and each data set separately. For the combined and Hamadan data sets, ANNs produced a greater correlation coefficient (R = 0.85) and lower root mean square error (RMSE) compared with the linear regression model (R = 0.70). For the Maragheh data set, however, the regression model yielded better results. Introducing TP and relative saturation (θ_V/TP) into the models improved the prediction of CI. The results further showed that ANN models performed better than nonlinear regression models. Therefore, ANNs were recognized as powerful tools to predict CI by BD, GWC, TP, and θ_V/TP as the independent variables under the very diverse conditions of the soils and treatments employed.

Key Words: Artificial neural networks, bulk density, cone index, regression models, water content

Abbreviations: PR, penetration resistance; CI, cone index; PTFs, pedotransfer functions; GWC, gravimetric water content; BD, bulk density; ANNs, artificial neural networks; TP, total porosity; R, correlation coefficient; RMSE, root mean square error; θ_V/TP, relative saturation; R^2, coefficient of determination; SWCC, soil water characteristic curve; R_i, relative improvement.

Introduction

Penetration resistance (PR), expressed as cone index (CI), is an important property of soils. It correlates with several soil properties such as vehicle trafficability (Dexter and Zoebisch, 2002), resistance to root penetration (Taylor and Ratliff, 1969), seedling emergency, and soil compaction by farm machinery (Vaz et al., 2001).

Because of the high spatial variability of PR, it is difficult to obtain data with an adequate accuracy (Vaz et al., 2001). This necessitates the use of pedotransfer functions (PTFs) to estimate CI using readily available soil data such as compaction, porosity, texture, structure, organic matter, and soil water content (Grunwald et al., 2001b; To and Kay, 2005). Researchers have demonstrated close relationships between CI and BD (Pidgeon and Soane, 1977; Henderson et al., 1988), and also between CI and soil gravimetric water content (GWC) (Faure and da Mata, 1994).

Water content has a considerable influence on soil strength and PR, yet no theoretical function has been proposed to define their relationship (Lapen et al., 2004). The relationship between water content and PR varies with texture and relative compaction (To and Kay, 2005). They reported that the relative saturation exerted a minor impact on CI. Generally, at a given bulk density, CI decreases with an increase in GWC (Laboski et al., 1998),

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and the bulk density effect on CI becomes greater as GWC decreases. A similar finding has been reported by Mulqueen et al. (1977). Grunwald et al. (2001b), on the other hand, concluded that BD is the most effective parameter in predicting CI, followed by GWC. Clay and silt contents and soil depth had minor effects on CI. A close relationship between CI and soil texture has also been reported by Kurup et al. (1994) and Puppala et al. (1995). Puppala et al. (1995) obtained greater values of CI in coarse-textured than in fine-textured soils. They concluded that, at the same texture and GWC, cementing agents such as carbonate, silica, and hydrous iron oxide would increase CI. Grunwald et al. (2001a) reported a highly significant correlation between GWC and soil texture. This implies that the texture effect on CI could be taken into account indirectly by including GWC as a predictor parameter.

Many different models (e.g., polynomial, exponential, power, and linear) have been used to test the relationship between BD, GWC, and CI (Vaz et al., 2001). Upadhyaya et al. (1982) suggested a power exponential equation for predicting CI as a function of BD and GWC for a silt loam soil. They also suggested additional experimental work for its validation.

Busscher (1990) examined 10 different functions to evaluate their accuracy in predicting PR from GWC for sieved soils with textures ranging from sand to sandy loam. The function $PR = a\varphi^{b}BD^{c}$ produced the largest coefficient of determination (R^2), where φ is the soil matric suction (MPa), and *a, b*, and *c* are constants.

da Silva and Kay (1997) applied the function $PR = a\theta_v{}^{b}BD^{c}$ to predict PR in undisturbed samples with clay contents ranging from 6% to 37%. They showed that this model produced good results for the examined soils.

Grunwald et al. (2001b) developed regression functions to express the relationship between CI, GWC, BD, soil texture, and depth. For their data set (n = 296), obtained R^2 ranged from 0.35 to 0.48. By arranging the data into 5 groups based on CI, R^2 values were much improved (from 0.62 to 0.98). The regression models showed the greatest sensitivity to BD and GWC among the variables.

To and Kay (2005) proposed the model $PR = ah^{b} - ch$ to predict PR; *h* is the soil matric suction, and *a, b*, and *c* are constants to be determined by PTFs using clay content, organic matter content, and BD as predictors. They obtained $R^2 = 0.47$ for 192 undisturbed samples of Canadian soils with all 12 textural classes. The accuracy of the model, however, may increase when applied to more homogeneous soil textures. Using this model, however, required a soil water characteristic curve (SWCC), which limits the applicability of the model.

Dexter et al. (2007) proposed the model $PR = a + b(1/S) + c\sigma'$, where *S* is the slope of SWCC [d*GWC* / *d*(*ln*h)] at its inflection point (Dexter, 2004a, 2004b, 2004c), and σ' is the effective stress generated by internal stresses. They found $R^2 = 0.375$ and concluded that the low value of R^2 might be because of the high spatial variability of PR. Another function was introduced by Whalley et al. (2007): $\log PR = a \log \sigma_w + BD + c$, where σ_w is the effective stress as a function of soil water potential. They claimed that the predictors of their model are easy to measure and do not vary with the soil type.

Measurement of soil matric suction or effective stress in the last 2 models (To and Kay, 2005; Dexter et al., 2007) is expensive and time consuming and they usually are not available in soil databases. Thus, finding models to predict CI with the least cost and using the available data such as BD and GWC would be valuable. Because of a complex relationship between CI, BD, and GWC (Vaz et al., 2001), it is expected that ANNs can simulate the behavior of such a complex system (Pachepsky et al., 1996). ANNs have not been applied to predict CI yet, although the proposed linear or nonlinear models have been fairly successful (low R^2) to estimate this parameter. Measured total porosity (TP) and relative saturation (θ_v/TP) may also correlate with CI (Grunwald et al., 2001b). They are often available in soil databases and have been overlooked as parameter predictors in regression models.

Our objectives in this study were: a) to develop PTFs by using ANNs to predict CI by BD and GWC; b) to examine the contribution of TP and θ_v/TP besides BD and GWC to predict CI, and c) to compare the performance of ANNs with proposed nonlinear regression models.

Materials and Methods

In order to provide wide ranges of BD, GWC, TP, and CI, 2 study sites were selected, Hamadan (west of Iran) and Maragheh (northwest of Iran), and the data were combined to form a combined data set (n = 381).

Hamadan Agricultural Research Station is located 5 km from the city of Hamadan, Iran. The soil is classified as coarse loamy, mixed, mesic Calcixerolic Xerochrepts. A split-plot field experiment with completely randomized arrangement of treatments was used in 3 replications to study tillage and wheel traffic effects on the soil physical properties. Sand, silt, and clay contents were 65%, 24%, and 11%, respectively. Combinations of 2 tillage methods: moldboard plows (MP) and chisel plow (CP), and 3 tractor types: John Deer (3708 kg), Romania (3450 kg) and Massey Ferguson (2800 kg), were the treatments. The inflation pressure of the front and rear tires was fixed at 228 and 105 kPa, respectively, for all 3 tractors. Soil samples were taken 1 week after planting wheat in the autumn and at the end of growth season (early summer) 3 days after the last irrigation. The samples were collected from both traffic and non-traffic zones (as sub-plots) and from 4 soil layers: 0-7.5, 7.5-15, 15-22.5, and 22.5-30 cm.

Core samples were taken using cylinders (5.1 cm diameter and 7.5 cm height) to measure bulk density (BD) and total porosity (TP). A Rimik cone penetrometer (model CP20) was used to measure in situ the cone index (CI) at 2.5 cm intervals. The cone angle and base diameter were 30° and 12.8 mm, respectively. Disturbed samples were also taken for soil water content measurements. This data set contained 312 data records.

The second site was Maragheh Dry Farming Research Institute (in cooperation with ICARDA) located in Maragheh, East Azerbaijan. The soil moisture and temperature regime are xeric and mesic, respectively. It is classified as Inceptisols with soil texture varying from clay loam to silty clay loam. Average sand, silt, and clay contents of the soil were 25%, 40%, and 35%, respectively.

The statistical design of the experiment was split plot with 3 replications. Three crop rotations including: a) wheat–wheat, b) pea–wheat, and c) fallow–wheat were taken as the main plots, and 3 tillage methods: a) moldboard plow followed by disk (MT), b) reduced tillage consisting chisel plow followed by sweep (RT), and c) no tillage with the residues left on the soil surface (NT) as sub-plots. This study was carried out to evaluate the tillage and crop rotation effects on soil physical properties. Soil samples were taken early in the growing season after tillage operations and 88 items of data were recorded. The total data set from both sites making the combined data set comprised 381 records. Before analysis, all data were normalized to have zero mean and unit variance; then the results were converted to the original scale.

Before analysis, 19 items of noisy data were omitted from the Hamedan data set and the remaining 293 records were combined with 88 records of the Maragheh site to form the combined data set. From the 381 combined records, 250 samples were randomly selected for modeling and the remaining 131 records were used for validation. The corresponding numbers for the Hamadan data set were 170 and 123 and for the Maragheh data set were 58 and 30, respectively. Testing groups of BD and GWC in each case (combined, Hamadan, and Maragheh) were introduced into ANNs models and the second group was used for validation. Accuracy of the developed PTFs was evaluated using 2 indices, namely Pearson correlation coefficient (R) (Dexter et al., 2007), root mean square error (RMSE), and relative improvement (R_i):

$$R_i = \left(\frac{RMSE_2 - RMSE_1}{RMSE_1}\right) \times 100 \quad (1)$$

where $RMSE_1$ is the higher root mean square error and $RMSE_2$ is the lower root mean square error (Zhang et al., 1992). These indices were computed using differences between estimated and measured CI values according to Pachepsky and Rawls (1999). Similar data analyses were performed by stepwise adding total porosity (TP) and relative saturation (θ_v/TP) to the input variables. Resulting PTFs were evaluated using previously mentioned indices. Besides the ANN model, multiple linear regression and nonlinear models of Upadhyaya et al. (1982) and da Silva and Kay (1997) were also applied to predict CI.

Results

The measured variables (CI, TP, GWC, and BD) have wide ranges (Table 1) and thus developed PTFs would have high generality to predict CI (To and Kay, 2005).

Correlations between CI and BD (Table 2) were positive and highly significant for the combined and Hamadan data sets, but not significant for the Maragheh data set.

Table 2 shows a highly significant negative correlation ($P < 0.01$) between CI and GWC for both the Hamadan

Table 1. Statistical results of soil properties for the 3 data sets.

Data set	Variable	Minimum	Maximum	Mean	Standard deviation
combined	TP$ (%)	36.38	63.36	46.12	5.41
	GWC (%)	1.2	30.16	19.64	6.54
(n = 381)	BD (Mg m^{-3})	0.97	1.79	1.44	0.16
	CI (kPa)	34.6	1585	439.3	359.9
Hamadan	TP (%)	36.38	49.87	43.41	2.45
	GWC (%)	19.21	25.61	22.48	2.1
(n = 293)	BD (Mg m^{-3})	1.25	1.79	1.52	0.09
	CI (kPa)	147.78	1585	572.3	332.52
Maragheh	TP (%)	40.78	63.36	53.54	4.23
	GWC (%)	1.2	30.16	11.86	8.09
(n = 88)	BD (Mg m^{-3})	0.97	1.57	1.23	0.11
	CI (kPa)	34.6	109.8	75.18	20.4

$BD, bulk density (Mg m^{-3}); CI, cone index (kPa); GWC, gravimetric water content (%); TP, total porosity (%). For Hamadan site sand, silt and clay contents were 65%, 24%, and 11%, respectively. For Maragheh site sand, silt and clay contents of the soil were 25%, 40%, and 35%, respectively.

Table 2. Pearson correlation coefficient (r) between CI and soil physical properties for the 3 data sets.

Data set	Variable	TP$	GWC	BD	CI
combined	TP	1	-0.516 **	-0.935	-0.662 **
(n = 381)	GWC		1	0.463 **	0.293 **
	BD			1	0.719 **
	CI				1
Hamadan	TP	1	0.355 **	-0.676	-0.507 **
(n = 293)	GWC		1	-0.557	-0.633 **
	BD			1	0.610 **
	CI				1
Maragheh	TP	1	0.169	-1.0 **	-0.036
(n = 88)	GWC		1	-0.169	-0.493 **
	BD			1	0.036
	CI				1

$BD, bulk density (Mg m^{-3}); CI, cone index (kPa); GWC, gravimetric water content (%); TP, total porosity (%) *. Significant at $P < 0.05$ (2 tailed); **. Significant at $P < 0.01$ (2 tailed).

and Maragheh data sets. However, unexpectedly it was positive for the combined data set. This ambiguity will be discussed below. Correlations between CI and TP, as expected, were significantly ($P < 0.01$) negative for the combined and Hamadan data sets.

ANNs were used and PTFs were developed to predict CI by stepwise entering BD, GWC, and TP as predictors into the models. Multiple linear regression was also performed on the combined, Hamadan, and Maragheh data sets. Table 3 shows R and RMSE values for ANNs and for the linear regression models as criteria for evaluation of their predicting accuracy. For the combined and Hamadan data sets, ANNs produced greater R, lower RMSE, and improved prediction up to 19.9%, compared

Table 3. Root mean squared error (RMSE), correlation coefficient (R), and relative improvement (R_i) of CI prediction from BD, GWC, TP, and θ_v/TP as independent variables using ANNs and linear regression.

Data set	Variables	Linear regression		ANNs		
		RMSE$	R	RMSE (kPa)	R	R_i
Combined	BD and GWC	250.13	0.721	208.55	0.805	19.94
	BD, GWC, and TP	250.35	0.721	201.79	0.818	24.06
Hamadan	BD and GWC	236.49	0.705	219.77	0.751	7.62
	BD, GWC, and TP	232.44	0.719	199.94	0.791	16.25
	BD, GWC, and θ_v/TP	231.63	0.721	202.27	0.8	14.52
Maragheh	BD, GWC, and TP	17.89	0.495	30.5	0.363	70.48

$RMSE is in kPa

to the regression model. For the Maragheh data set, however, the regression model produced better predictions.

Figure 1 shows that, for the combined data set, ANNs predicted reasonable values for CI over the whole range of the input variables. In some cases, linear regression predicted negative CI values, which are physically meaningless.

Introducing TP as a predictor besides BD and GWC had no significant contribution to improve estimation of CI by linear regression models (Figure 1a and c, Table 3). Prediction of CI was improved by the ANN model for the

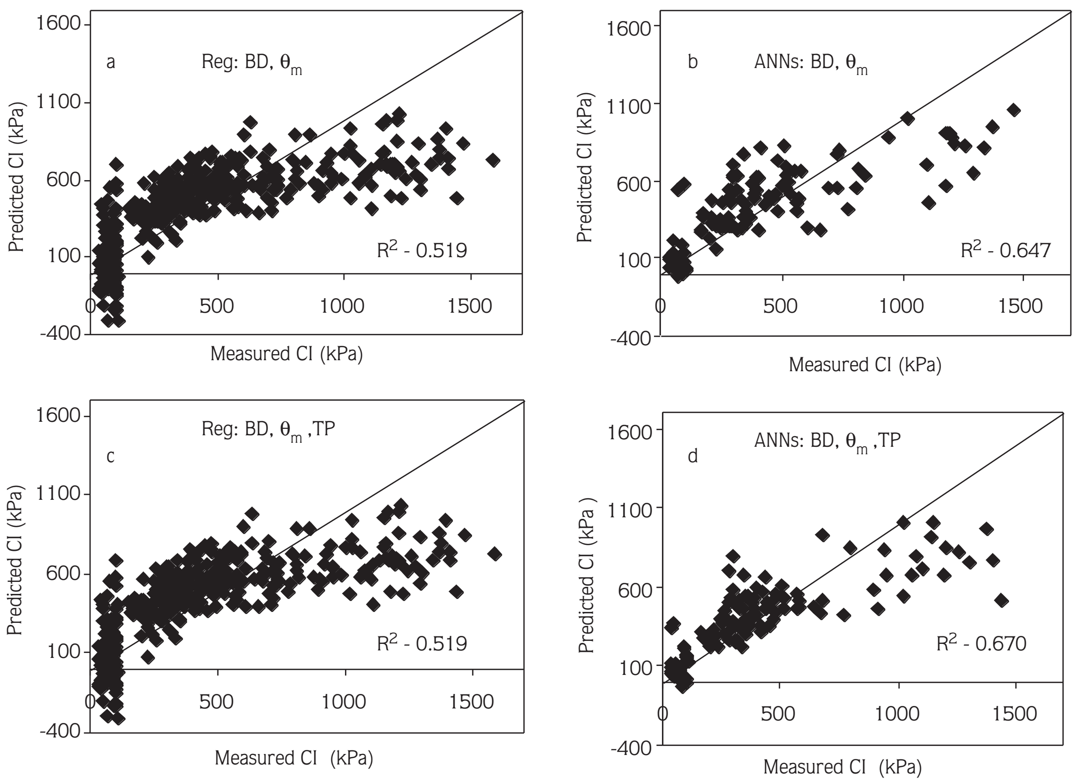

Figure 1. Comparisons of predicted and measured CI for the combined data set by linear regression (a and c) and ANNs (b and d) using either BD and GWC or BD, GWC, and TP as independent variables.

combined and Hamadan data sets (Figures 1 and 2). For the Maragheh data, the regression model predicted CI with a greater R (0.495) compared to ANNs (0.363, Table 3). The linear regression model also yielded a lower RMSE.

Relative saturation (θ_v/TP)

The contribution of relative saturation (θ_v/TP) in the ANNs and regression models in predicting CI is depicted in Table 3 and Figure 3a and 3b. The θ_v/TP increased R from 0.705 to 0.721 and decreased RMSE up to 2.1% for the regression model (Table 3). For ANNs, entering θ_v/TP produced an even greater improvement in CI prediction. It raised the R from 0.751 to 0.800 and decreased the RMSE by 8.7%.

Sensitivity analysis

In order to assess the relative importance of the variables in PTFs developed by ANNs, sensitivity analysis was performed. Figure 4a shows that for the combined data set BD had the greatest influence on CI; GWC and TP had a lesser contribution to the prediction of CI. For the Hamadan data set, θ_v/TP was the most important predictor for CI and BD was the second.

Model of Upadhyaya et al. (1982) and da Silva and Kay (1997)

For Hamadan data, 170 records used in the ANN model development were also applied to the nonlinear regression models given by Upadhyaya et al. (1982)

$$\left(PR = a\,\frac{BD^n}{\rho_s}\,e^{-b\theta_v}\right)$$

and da Silva and Kay (1997) ($PR = a\theta_v^{\,b}\ BD^c$), and coefficients were calculated. Using those coefficients, for the remaining 123 data records CI was predicted and compared with the measured ones. The statistical results are shown in Table 4. ANNs yielded relatively closer

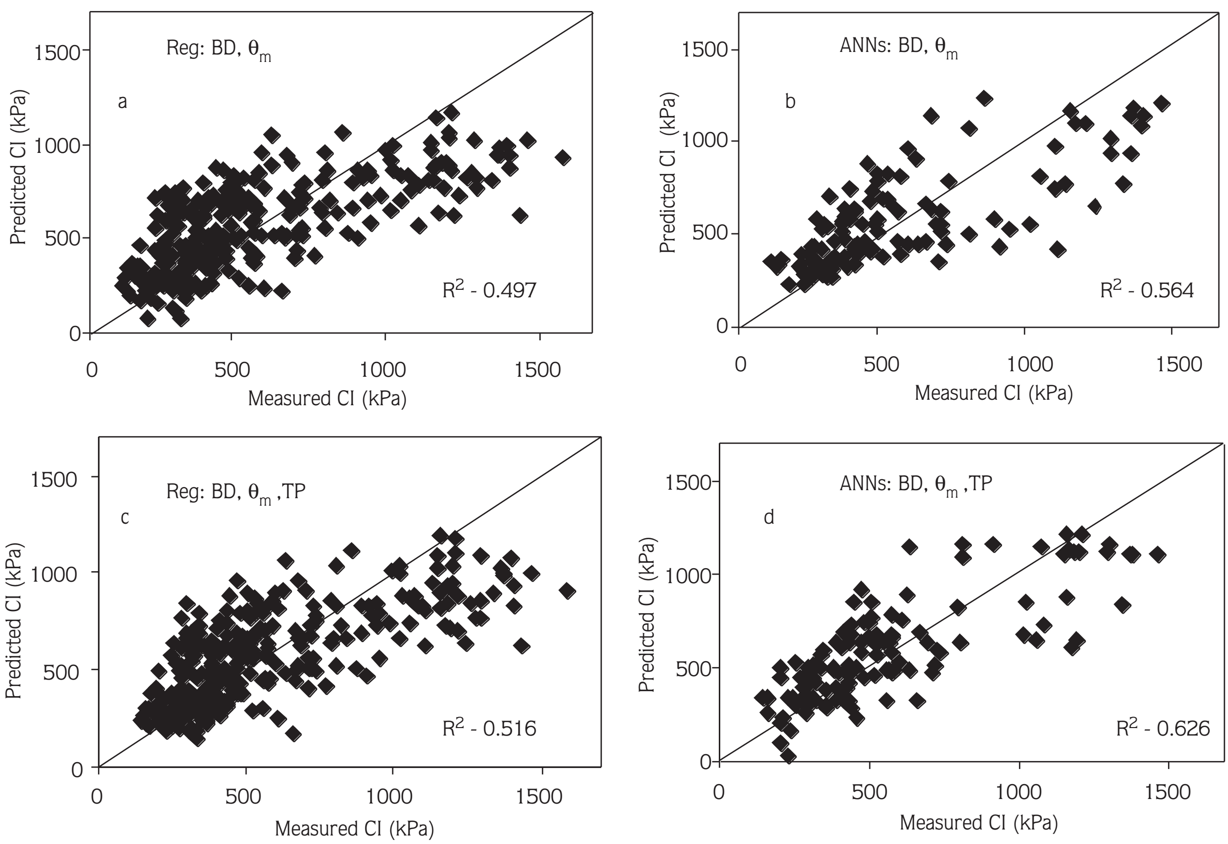

Figure 2. Comparisons of the predicted and measured CI for the Hamadan data set by linear regression (a and c) and ANNs (b and d) using either BD and GWC or BD, GWC, and TP as independent variables.

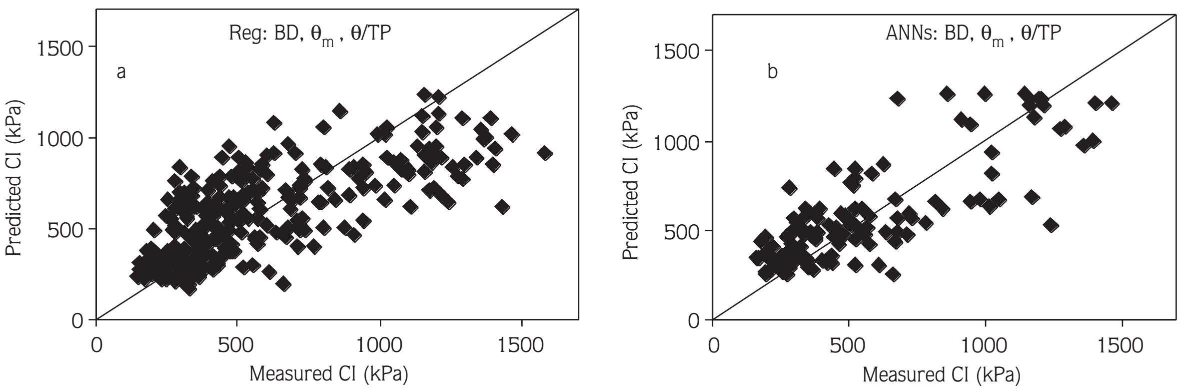

Figure 3. Comparison of predicted and measured values of CI for the Hamadan data set by including BD, GWC, and θ_v/TP as predictors using a) linear regression and b) ANNs.

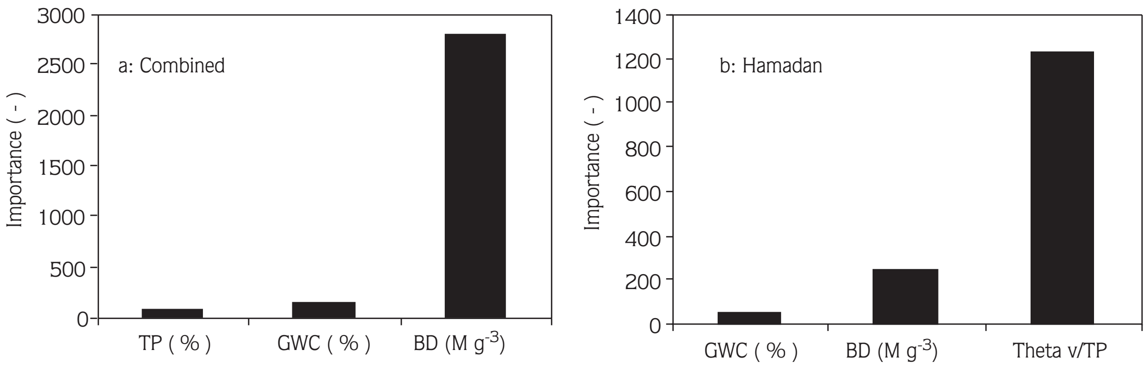

Figure 4. Sensitivity analysis of PTFs developed by ANNs using BD, GWC, and TP for a) combined and b) Hamadan data sets.

Table 4. Root mean square error (RMSE) and correlation coefficient (R) calculated between measured and predicted values of CI using Hamadan data.

Method	RMSE (kPa)	R
ANNs	219.77	0.751
Upadhyaya et al. (1982)	248.87	0.686
da Silva and Kay (1997)	248.38	0.69

estimates of CI compared with both nonlinear models. ANNs improved the RMSE by 13% compared to the model described by da Silva and Kay (1997).

Discussion

Differences in Pearson correlation coefficient between CI and BD for various data sets (Table 2) indicate that the nature of the relation between CI and BD is highly dependent on soil type and management. This finding, however, needs further investigation. The correlation coefficient between CI and GWC for the combined data set unexpectedly appeared positive (Table 2). We are well aware that this seems impossible, but the explanation may be that the Hamadan data set has a quite narrow range of GWC (19.2% to 25.6%) with a wider range of CI (147.8 to 1585.0 kPa) (Table 1). For the Maragheh data set, the reverse occurred: a narrow range of CI (34.6-109.8 kPa) associated with a wide range of GWC (1.2%-30.2%). This led to an unexpected positive correlation between GWC and CI when the 2 data sets were combined. The management effect would be another factor affecting CI. Considerable evidence confirms the dependence of the CI-GWC relationship on soil type, structure (To and Kay, 2005), and management (Lapen et al., 2004). The interaction between soil properties (texture, structure, BD etc.) and treatments (tillage, tractor, depth, wheel traffic, rotation, and sampling time) may also contribute to this apparent discrepancy. Another reason may be the effect of cementing agents that were not measured in this study. At this stage we are not in a position to interpret this particular result on physical grounds. A data set of different soil types and classes would be necessary for deeper investigation. This ambiguity, however, should not overshadow our major finding: the ability of ANNs to predict CI from BD, TP, and GWC more accurately and realistically under very diverse conditions of soils and treatments compared to regression models. The latter model obviously failed to simulate the complex nature of the relations among the 4 variables. The regression model, however, did not predict negative values of CI for the Hamadan data set (Figure 2). This might be because of homogeneity of the soil texture, BD, and management in this data set (Grunwald et al., 2001b). As pointed out by To and Kay (2005), arranging a large data set into several groups of narrow range may result in PTFs that can predict CI with a greater accuracy. The narrower ranges of soil properties in the Hamadan data set led to a more satisfactory prediction of CI (smaller RMSE, Table 3).

Improving CI estimation by ANNs for the combined and Hamadan data sets, excluding the Maragheh data set (Table 3), may be related to the method of TP measurement. At the Hamadan site, TP was measured directly by saturating and then oven drying the core samples. At the Maragheh site, it was calculated by $TP = 1 - BD / PD$ and assuming PD = 2.65 g cm^{-3}. Even though the improvement obtained by including TP in the ANNs may not be noticeable, its direct measurement is not difficult and expensive; moreover, it is usually available in most databases.

Although ANNs did not improve CI prediction compared with the regression model for the Maragheh site (Table 3), using the new algorithm of ANNs may enhance their performance. Merdun et al. (2006) concluded that new versions of ANNs improved SWCC prediction.

Relative saturation (θ_v/TP) as an additional independent variable improved CI's prediction. Soil internal effective stress as an influential parameter on CI (Whalley et al., 2005a; Dexter et al., 2007) varies with θ_v/TP (Vepraskas, 1984), which would justify its contribution to better prediction of CI with the ANN model. Whalley et al. (2007), however, reported no relation between CI and θ_v/TP. They used effective stress in their model and therefore indirectly have taken θ_v/TP into account and entering it into their model did not produce further improvement.

Sensitivity analysis shows that θ_v/TP has a greater effect on predicting CI (Figure 4b). This result was in contrast to those reported by others (Whalley et al., 2007). Grunwald et al. (2001a, 2001b) have also reported similar findings and found BD as the most influential variable for CI prediction (Figure 4a). Topp et al. (2003), on the other hand, reported GWC as a dominant variable in predicting CI.

Accuracy of ANNs was compared with nonlinear regression models. Although da Silva and Kay (1997) reported good performance of their model for many soils, our results showed that ANNs performed better. It seems that the application of the model of da Silva and Kay (1997) to other soils needs further investigation.

Conclusions

The ANN model predicted CI from BD, GWC, and θ_v/TP as predictors more accurately than the multiple linear regression and nonlinear regression models of Upadhyaya et al. (1982) and da Silva and Kay (1997).

The PTF$_S$ that were developed by ANNs in this study need to be validated on other soil textural classes. Using TP with the ANN model improved the CI prediction. Since TP is available in the most soil databases, its use as a predictor would be a great advantage in estimation of CI. ANNs are powerful tools to simulate complex systems. The major finding was the ability of ANNs to predict CI from BD, TP, and GWC more accurately and realistically under very diverse conditions of soils and treatments compared to regression models. Prediction of CI by ANNs may be improved using other soil properties as input.

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