Comparison of two different artificial neural network models for prediction of soil penetration resistance

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Abstract

A time-varying, nonlinear soil-plant system contains many unknown elements that can be quantified based on analytical methodologies. Artificial neural networks (ANNs) are a widely used mathematical computing, modeling, and predicting methods that estimate unknown values of variables from known values of others. This paper aims to simulate the relationship between soil moisture, bulk density, porosity ratio, depth, and penetration resistance and to estimate soil penetration resistance with the help of ANNs. For this aim, the generalized regression neural network (GRNN) and radial basis function (RBF) models were developed and compared for the estimation of soil penetration resistance values in MATLAB. A dataset of 153 samples was collected from experimental field. From the 153 data, 102 data (33%) were selected for training and the remaining 51 data (67%) were used for testing. The estimation process implemented 10 replications using randomly selected testing and training data. mean squared error (MSE), root mean square error (RMSE), and mean absolute error (MAE) were used to evaluate estimation accuracy on the developed ANN methods. Based on MSE, RMSE, MAE and standard deviation, statistical results showed that the GRNN modeling presented better results than the RBF model in predicting soil penetration resistance success.

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Introduction

Soil compaction is a significant component that has a detrimental impact on soil structure, inhibits plant development, lowers water penetration rate, diminishes crop production, and raises machine usage costs. It has strong dependence on soil type and such soil properties as soil moisture, bulk density, porosity ratio, depth, and also penetration resistance. Heavily compacted soils contain greater density. Soil penetrometer is used to measure and investigate the negative effects of this density. Soil penetration resistance data are used to calculate parameters such as root growth and crop productivity (Colombi *et al.,* 2019), water retention in soil (Bayat *et al.,* 2018), soil property characterization (Reyes *et al*., 2014), and thermal conductivity (Lines *et al*., 2017). Because soil penetration resistance is significantly impacted by geographical variability, acquiring correct data necessitates a large number of measurements in order to understand the connection of soil penetration resistance with other factors.

More and better-quality data from the field is required for successful soil-plant management. Methods, procedures, repetitive measurement, iterative solutions, and particular techniques must all be used to generate high-quality data. In agricultural research, regression analysis, statistical approaches, and different extrapolation and interpolation techniques are commonly utilized in estimating difficulties. Because of its great performance in linear and nonlinear systems, as well as its tolerance for missing and noisy data, Artificial neural network (ANN) is now commonly employed in estimate applications. When compared to other statistical analytic approaches, the ANN excels in fitting nonlinear situations (Zhang *et al*., 2012).

In agriculture science research, ANNs are commonly employed to approximate a nonlinear function such as data on predicting the firmness of Huanghua pears (Zhou and Li, 2007), surface blemishing (Bennedsen *et al*., 2007), prediction of solublesolids content of pineapple (Chia *et al*., 2012), preliminary soil mapping units prediction (Silveira *et al*., 2013), plant identification (Sathiesh Kumar *et al*., 2016), fuel consumption estimation (Borges *et al*., 2017), replicating the pattern of wetness (Elnesr and Alazba, 2017), temperature control system in a greenhouse (Manonmani *et al*., 2018), postharvest life of kiwifruit (Mohammadi Torkashvand *et al*., 2019) and yield prediction (Niedbala, 2019). Several researchers have attempted to construct correlations to predict soil penetration resistance based on soil parameters such as type, particle size distribution, bulk density, and moisture content, *etc*. (Abrougui *et al*., 2014; Silva *et al*., 2016; Rizaldi *et al*., 2018; Pereira *et al*., 2018; Hosseini *et al*., 2018; Jiang *et al*., 2020).

There have been studies in the literature comparing two methodologies on several soil science topics. Faris *et al*. (2014) built and evaluated Multilayer perceptron (MLP) and Radial basis function (RBF) models for short-term surface ozone forecasts. They empirically proved that the MLP neural network outperformed the RBF model in training and testing scenarios, with the constructed MLP network providing strong estimation and prediction skills. Kandirmaz *et al*. (2014) proposed an ANN that used three ANN approaches, Generalized regression neural network (GRNN), MLP, and RBF, to estimate monthly mean daily values of global sunlight duration for Turkey using a 34-station approach. According to the statistical indicators, the GRNN and MLP models gave better results than the RBF model and may be securely used to estimate monthly mean sunlight duration.

The aim of this study was to estimate soil penetration resistance by four basic soil properties: moisture (%), bulk density (g/cm^3), porosity ratio (%), and depth (cm), using GRNN and RBF methods in ANN, and compare these models in order to present the optimal one in estimating the soil penetration resistance. Soil penetration resistance is directly proportional to the mass density, porosity rate and depth, and inversely proportional to moisture (Lima *et al*., 2017; Siqueira *et al*., 2014). For this reason, these four parameters were used for both methods.

Materials and Methods

Experimental site and sampling pattern

The field study was conducted in a 12 da study area at the Batı Akdeniz Agricultural Research Institute (BATEM) Farm 36°56′ N, 30°52′ E, Antalya, Turkey. Data collection process from the experimental site was carried out at the beginning of July 2020, before sowing soybean as the second crop. The first crop was wheat. A conventional tillage method (Moldboard Plow+ Gobble Disc Harrow + Disc Harrow + Roller + Seed Drill) was used to prepare the soil. The soil characteristics of the experimental site are given in Table 1.

The study field was divided into 3 parcels. From each parcels, 51 undisturbed soil samples were taken from 0-10, 10-20 and 20-30 cm depths by stainless steel cylinders (2.50 cm radius and 4.50 cm height, 95 cm^3) for measuring moisture, bulk density and porosity. In this way, 153 undisturbed soil samples were taken from the whole study field. In order to optimize all data, the moisture, bulk density and porosity data of 3 adjacent points in each plot at depths of 0-10 cm, 10-20 cm and 20-30 cm were averaged. In this way, a total of 51 moisture, bulk density and porosity data were obtained for each depth from the whole study field. Soil penetration resistance was measured in situ by a cone penetrologger (Royal Eijkelkamp, Giesbeek, Netherlands) from the experimental site. Penetration resistance was used by taking the average of the data obtained in the range of 0-30 cm. Soil samples were taken from within the centre of 51 x 3 grids on the field (Figure 1). The area of each grid is about 78 m^2.

Artificial neural network models

The artificial neural network is a system that roughly simulates the neurons in a biological brain inspired by the human brain. The brain is made up of around 100 billion neurons that communicate with one another through electrochemical neurotransmitters. There are as many as 1,000 trillion synapses connecting the neurons. To accept all incoming impulses, each neuron has three parts: cell body, dendrites, and axon. A response is transmitted via the axon if the total of the incoming signals reaches a particular threshold. Input nodes, hidden nodes, and output nodes are the three types of neurons in an ANN. Artificial network models exist in a variety of shapes and sizes, and they may be used to achieve a variety of goals, solve issues, and make better judgments and predictions. Two ANN models, GRNN and RBF, were utilized in this study to evaluate their respective findings in order to determine the optimum strategy for the estimation process. For ANNs, the dataset was separated into two sections: training data subset (102 samples) and testing data subset (51 samples). The ANN models created contain one input layer, two hidden layers, and one output layer. The ANN models had four nodes in the input layer (soil moisture, bulk density, porosity ratio, and depth) and one node in the output layer (soil penetration resistance). To estimate soil penetration resistance, custom programs built in MATLAB and the Neural Network Toolbox were employed.

The underlying (linear or nonlinear) regression surface is converged to by GRNN, which produces continuous variable estimates (Specht, 1991). A GRNN is made up of four layers: the input layer, the pattern layer, the summation layer, and the output layer. The input layer is in charge of receiving the input vector X and passing it on to the pattern layer. Each pattern layer neuron generates an output h and transmits it to the summation layer. The weighted and basic arithmetic sums are computed by the numerator and denominator neurons in the next summation layer. (Palani *et al*., 2008). The sums generated by the neurons in the summation layer are then divided by the neurons in the output layer (Leung *et al*., 2000). The structure of the developed GRNN model in MATLAB is shown in Figure 2.

Table 1. The soil characteristics of the experimental site.

Properties	Value
pH (1:2.5)	7.5
Lime %	20.1
EC micromhos cm^{-1} (25°C)	195
Sand %	20
Clay %	35
Silt %	44
Organic matter %	1.8
P ppm	16
K ppm	265
Ca ppm	4570
Mg ppm	415

Figure 1. Grid soil sampling pattern.

RBFs are a type of neural network design that is commonly used for function approximation. (Yuguo *et al*., 2019). The input layer, hidden layer, and output layer make up an RBF network, which is a type of feed forward neural network with three layers. Each estimator variable is represented by one neuron in the input layer. A handful of RBF non-linear activation neurons are found in the hidden layer. Each neuron is made up of an RBF centred on a point of the same size as the estimator variables. To construct the network outputs, the output layer performs a linear weighted summation of the hidden layer's outputs. The structure of the developed RBF model in MATLAB is shown in Figure 3.

RBF emerged as a variant of ANN, have been successfully applied to a large diversity of applications including interpolation, chaotic time-series modeling, control engineering, image restoration, data fusion. However, there is no study using RBF to estimate soil penetration resistance. On the other hand, GRNN is one type of RBF, and its principal advantages are that it can quickly learn and rapidly converge to the optimal regression surface with large number of data sets. For the reasons mentioned above, these two models were preferred in the study. ANN designers can choose an approach to normalize their data. It would not be right to set a standard in this regard. The data used in the study are raw data taken directly from the field. Normalizing these data can be a significant problem and remove the relationship between actual and estimated values. For this reason, normalization procedures were not performed on the raw data.

Artificial neural network models accuracy indicators

In the literature, a variety of error measuring methods have been offered for model selection (Santos *et al*., 2012; Rizaldi *et al*., 2018; Jiang *et al*., 2020). Various methodologies may be used to evaluate the ANN's performance during the training and validation stages, including as mean squared error (MSE), root mean square error (RMSE), Mean absolute error (MAE), mean absolute percentage error, sum of squares of error, mean error ratio, R^2 correlation factor, Akaike information criteria, and Bayesian information criteria. The accuracy of created ANN models was assessed using MSE, RMSE, and MAE approaches in this work.

$$MSE = \sum_{t=1}^{N} \left(\frac{Y_t - O_t}{T}\right)^2 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{T}\left[\sum_{t=1}^{N} \left(\frac{Y_t - O_t}{Y_t}\right)^2\right]} \tag{2}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{N} |Y_t - O_t| \tag{3}$$

where Y_t is the expected exit, O_t – the obtained exit, T – the number of records, N – the number of neurons in the pattern layer. The MSE was used to measures the average squared difference between the estimated values and what is observed. The RMSE was used measure of the differences between estimated and the observed values. The MAE was used to measure average over the verification sample of the absolute values of the differences between estimate and the corresponding observation.

Results and Discussion

In this study, two different types of ANN models were used: GRNN and RBF have been used to predict the soil penetration resistance. ANN models were developed in MATLAB software. After statistical comparisons, the optimal model was determined for the estimation. In the study, moisture, bulk density, porosity and penetration resistance data were collected for 3 different depths. The average of the data collected from the study field for each depth is given in Table 2. The data collected in Figures 4-7 are shown graphically.

In GRNN and RBF models, the four numbers of input variables were used such as moisture, bulk density, porosity ratio, and depth in input layer, the output variable as soil penetration resistance was used in output layer. Out of 153 sets of experimental data, 102 (67%) were used for training and 51 (33%) were used for testing process. Training data were randomly determined and tested for each model in 10 replications. The estimation results of the measured and estimated soil penetration resistance values for each model were shown in Figures 8-12. It was seen that corresponding to GRNN model individual errors are the lowest than RBF model to predict the soil penetration resistance.

The optimal ANN model was selected on the results of statistical analysis. The statistical performance of developed GRNN and RBF models is shown in Table 2, which is based on the MSE, RMSE, MAE, and standard deviation (SD). It has been found that

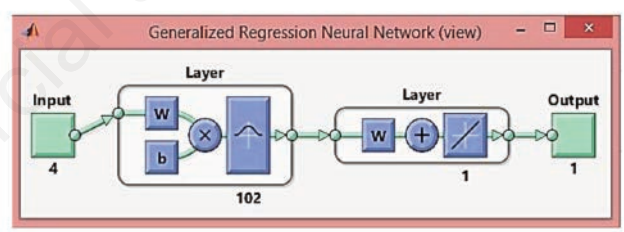

Figure 2. The structure of the developed generalized regression neural network model.

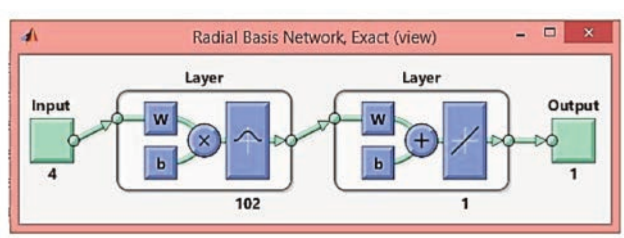

Figure 3. The structure of the developed radial basis function model.

Table 2. The average of the data collected from the study field for each depth.

Depth	0-10 cm	10-20 cm	20-30 cm
Moisture (%)	20.655	21.838	22.878
Bulk Density (g/cm^3)	1.203	1.307	1.360
Porosity (%)	39.559	39.175	40.998
Penetration Resistance (MPa)	1.003	1.203	1.698

the values of MSE of GRNN are between 0.0061 and 0.0097 after all replications. The values of RMSE of GRNN are between 0.0783 and 0.0983. The values of MAE of GRNN are between 0.0687 and 0.0854. On the other hand, the values of MSE of RBF are between 0.0213 and 1.6234. The values of RMSE of RBF are between 0.146 and 1.2741. The values of MAE of RBF are between 0.1161 and 0.8942. And also, the values of SD of GRNN for MSE, RMSE, and MAE were found 0.001084, 0.006142, and 0.005545 respectively. For RBF model, the values of SD of GRNN for MSE, RMSE, and MAE were found 0.484197, 0.336983, and 0.23718 respectively. The summary of the statistical results obtained at the end of the repetitions are given in Table 3.

In view of the Figures 8-12 and Table 4, it is mostly clear that the GRNN model is better than the RBF model, due to lowest MSE, RMSE, MAE and SD values, which is very close to unity and shows the accuracy of the model. As a result, it was found the GRNN model estimates the soil penetration resistance more accurately than the RBF model. In Figure 13, the MSE, RMSE, and MAE values were shown graphically at the end of 10 replications.

There haven't been many investigations on soil mechanical characteristics, particularly soil penetration resistance. Kurup and Griffin (2006) created a GRNN to forecast soil composition using CPT data. The network was trained and tested using measured values of cone resistance and sleeve friction received from CPT soundings, as well as grain size distribution data of soil samples collected from neighbouring standard penetration test boreholes.

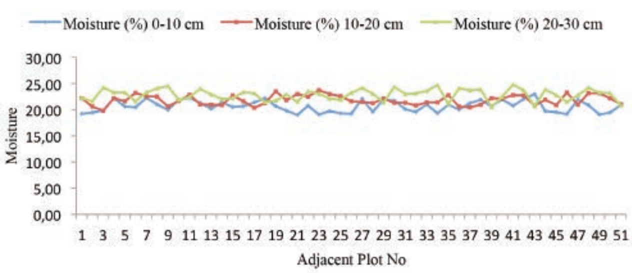

Figure 4. Graphical display of soil moisture data collected from the study area.

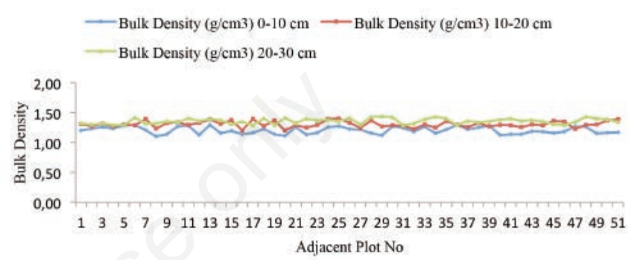

Figure 5. Graphical display of bulk density data collected from the study area.

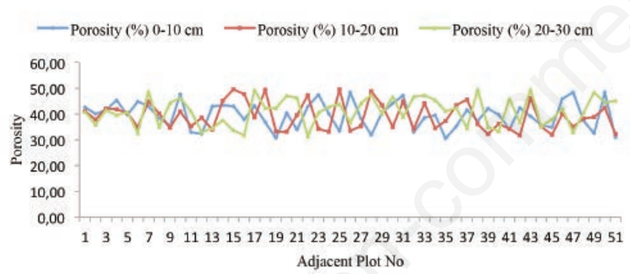

Figure 6. Graphical display of bulk density data collected from the study area.

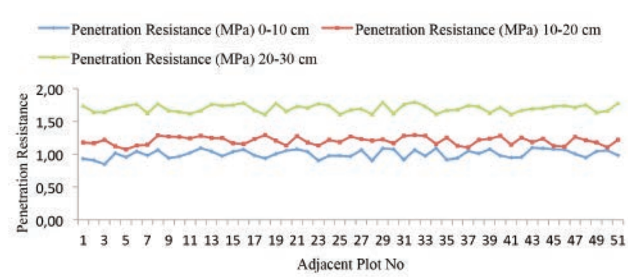

Figure 7. Graphical display of soil penetration resistance data collected from the study area.

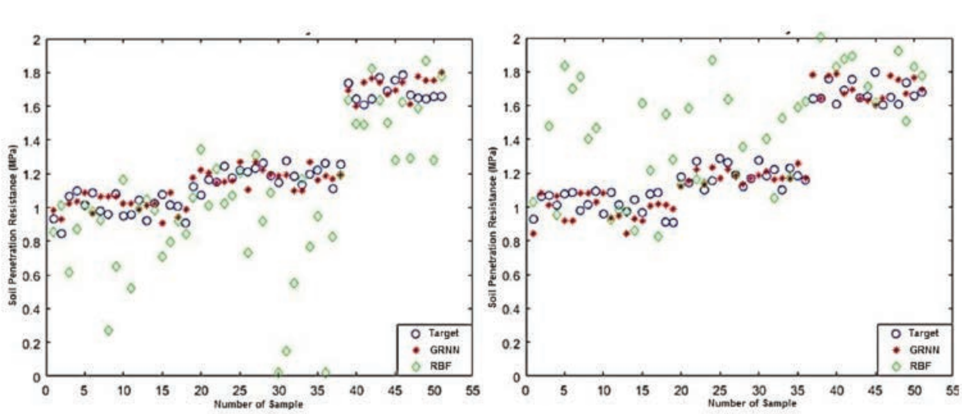

Figure 8. The estimation results of 1 and 2 replications.

According to the researchers, the GRNN-estimated soil composition profiles typically matched extremely well with the real grain-size distribution profiles and the neural network had an 86 percent success rate in identifying soils as coarse grained or fine grained. Holguin *et al*. (2011) described the development of an ANN for estimating soil penetration resistance at various depths, taking humidity, density, static load, and inflating pressure into account as relevant variables. They claimed that the ANN for predicting penetrance resistance at 20-30 cm depth performed the best.

The ANN was utilized by Bayat *et al*. (2008) to mimic the link between bulk density, gravimetric soil water content, and cone index. They found that the ANN model predicted cone index more

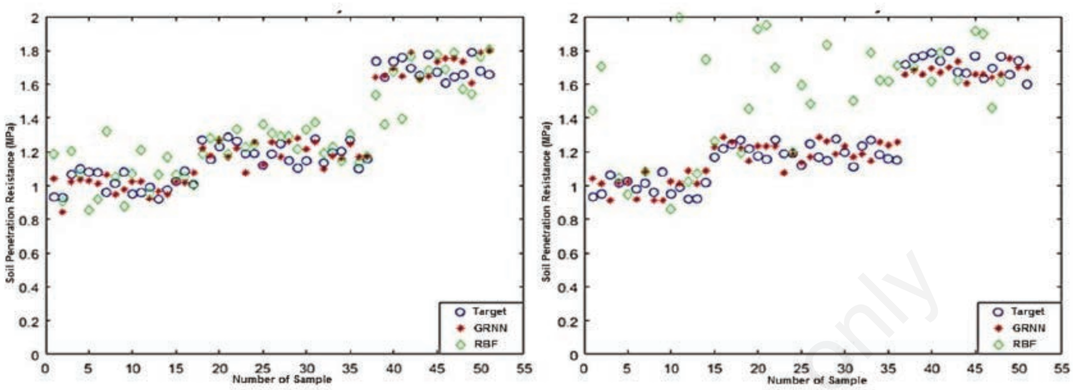

Figure 9. The estimation results of 3 and 4 replications.

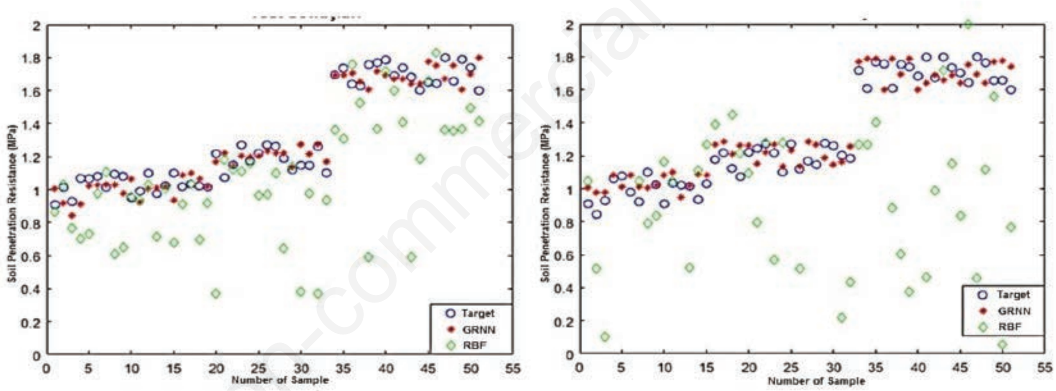

Figure 10. The estimation results of 5 and 6 replications.

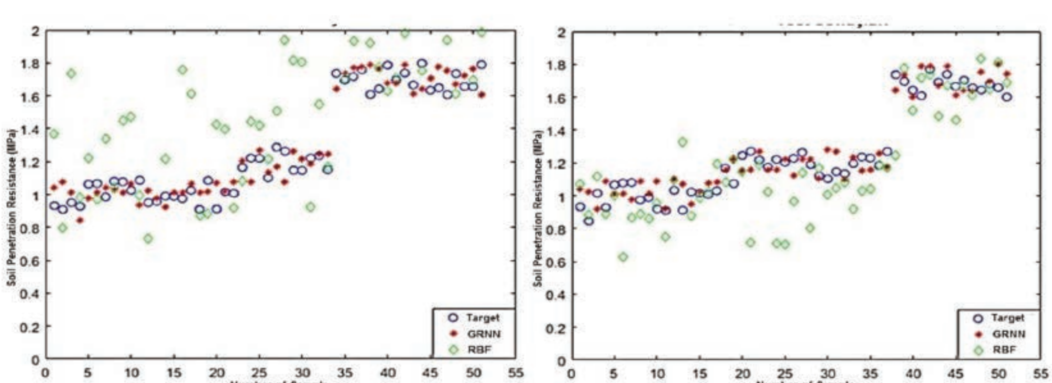

Figure 11. The estimation results of 7 and 8 replications.

correctly than the multiple linear regression and nonlinear regression models using bulk density and gravimetric soil water content as predictors. They claimed that ANNs were effective tools for simulating complicated systems. Abrougui *et al*. (2012) investigated the influence of soil bulk density, water content, and tillage technique on cone index-measured soil penetration resistance. To forecast soil penetration resistance, they employed Modular feed forward networks, a subclass of MLP. Santos *et al*. (2012) used statistical studies, namely regression analysis and ANN modeling, to examine the soil penetration resistance behaviour as evaluated by the cone index at various degrees of bulk density and water content. According to their findings, the regression analysis had a

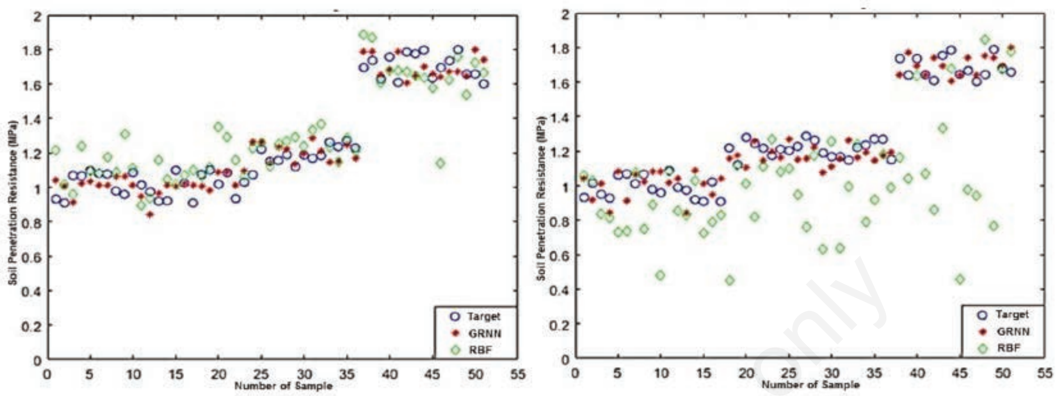

Figure 12. The estimation results of 9 and 10 replications.

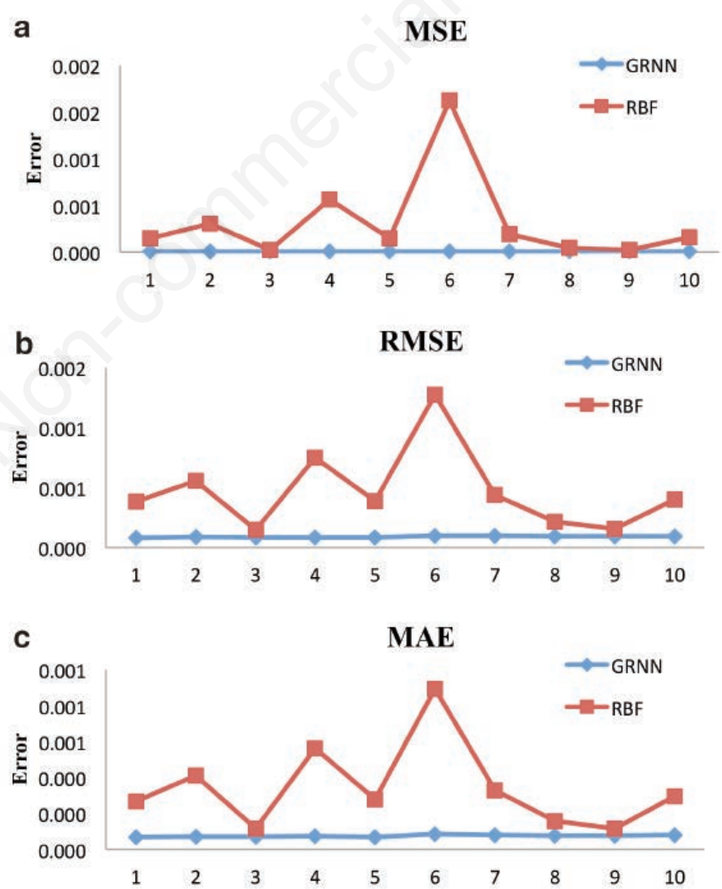

Figure 13. Graphical representation of mean squared error (MSE), root mean square error (RMSE), and mean absolute error (MAE) results.

Table 3. The summary of the statistical results obtained at the end of the repetitions.

	Minimum	Maximum	Average	SD	R^2
GRNN					
MSE	0.0061	0.0097	0.00782	0.001084	0.988
RMSE	0.0783	0.0983	0.08819	0.006142	0.995
MAE	0.0687	0.0854	0.07517	0.005545	0.995
RBF					
MSE	0.0213	1.6234	0.32323	0.484197	0.782
RMSE	0.1460	1.2741	0.47015	0.336983	0.795
MAE	0.1161	0.8942	0.34313	0.237180	0.799

GRNN, generalized regression neural network; RBF, radial basis function.

Table 4. The statistical performance of developed generalized regression neural network and radial basis function models.

Number of replication	GRNN MSE	GRNN RMSE	GRNN MAE	RBF MSE	RBF RMSE	RBF MAE
1	0.0061	0.0783	0.0687	0.1474	0,3839	0.2669
2	0.0076	0.0871	0.0711	0.3065	0,5537	0.4117
3	0.0068	0.0822	0.0704	0.0213	0,146	0.1161
4	0.0069	0.0829	0.0731	0.5616	0,7494	0.5631
5	0.0073	0.0852	0.0695	0.1507	0,3882	0.2778
6	0.0097	0.0983	0.0854	1.6234	1,2741	0.8942
7	0.0089	0.0944	0.0808	0.1919	0,4381	0.3307
8	0.0083	0.0912	0.076	0.0452	0,2127	0.1583
9	0.0082	0.0907	0.0774	0.024	0,155	0.1165
10	0.0084	0.0916	0.0793	0.1603	0,4004	0.296
SD	0.001084	0.006142	0.005545	0.484197	0.336983	0.23718

GRNN, generalized regression neural network; RBF, radial basis function; MSE, mean squared error; RMSE, root mean square error; MAE, mean absolute error.

determination coefficient of 0.92 and an RMSE of 0.951, whereas the ANN modeling had a determination coefficient of 0.98 and an RMSE of 0.084.

Recently, genetic algorithms (GA), particle swarm optimization (PSO), and multiple regression (MR) techniques have been used among optimization techniques for estimation of the soil penetration resistance. Hosseini *et al*. (2016) reported that PSO technique has a high accuracy in the estimation of penetration resistance (MSE=0.090, RMSE=0.301, and R2=0.937). Also, researchers reported that the PSO can estimate the soil mechanical resistance values more accurate than GA and MR model. On the other hand, the results in our study show that the both GRNN and RBF models predict more accurately than the PSO, GA and MR techniques for estimation of the soil penetration resistance.

As a consequence, they concluded that ANN modeling produced superior outcomes than the mathematical model derived through regression analysis.

Conclusions

GRNN modeling presented a lowest MSE of 0.0061, an RMSE of 0.0783 and an MAE of 0.0687, and the RBF modeling presented a lowest MSE of 0.0213, an RMSE of 0.146 and an MAE of 0.1161. The values of SD of GRNN presented 0.001084 for MSE, 0.006142 for RMSE and 0.005545 for MAE and the values of SD of RBF presented 0.484197 for MSE, 0.336983 for RMSE and 0.23718 for MAE. The GRNN modeling presented better results than the RBF modeling, due to lowest MSE, RMSE, MAE and SD values, which are very close to unity and show the accuracy of the model. GRNN generally performed better than RBF based on estimation. GRNN could provide not only a useful explorative tool to improve the relationships between soil parameters, but also a powerful technique to generate multivariable nonlinear mapping. The results of the study experiment show that using the ANNs for better predictions is an important method to researches and professional applications of soil science.

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