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PREDICTION OF SOIL PENETRATION RESISTANCE WITH THREE DIFFERENT ARTIFICIAL NEURAL NETWORKING METHODS

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ABSTRACT

Soil compaction is one of the major problems of the agricultural sector affecting negatively the soil structure and impedes plant root growth. Soil penetration resistance should be measured from many points of the production land to determine the effects of plant growth problems. Collection of soil penetration values from huge lands is time-consuming, tiring, and tedious for researchers. Also, the number of measured points to what extent will be sufficient to evaluation on whole production area is not clear. To eliminate this ambiguity, soil penetration values of the unmeasured points should be estimated to evaluate the whole land. Artificial Neural Networks (ANN) are one of the most popular mathematical computing and modeling method used to estimate unknown data with the help of known data. In this study, we collected 1603 samples of geographical position and soil penetration value from 40 cm depth within the 20 ha field. From the 1603 values, 24% records were selected for testing and the remaining 76% records were used for training. Soil penetration values of the unmeasured points were estimated using Generalized Regression Neural Network (GRNN), Multi-Layer Perceptron (MLP) and Radial Bias Function (RBF) methods in MATLAB. In addition to mean squared error (MSE), root mean square error (RMSE) and mean absolute error (MAE) has been also used for evaluation of prediction accuracy on these methods. RBF results showed very good agreement between the predicted and the measured real values of soil resistance (MSE: 0.1608; RMSE: 0.3717; MAE: 0.3682).

Keywords: soil compaction, soil penetration resistance, artificial neural network, precision farming.

INTRODUCTION

Soil compaction is an important factor that negatively affects the physical, chemical and biological structure of the soil, restricts plant growth, reduces the water infiltration rate and thus reduces product yield and increases machine utilization costs. Soil penetration resistance data should be determined in order to investigate the negative effects of soil compaction and taking due precautions. Soil penetration resistance data are used to determine parameters such as the root growth and crop productivity (Colombi and Keller, 2019), water retention in soil (Bayat and Ebrahim Zadeh, 2018), effects of tillage systems (Tormena et al., 2017), characterization of soil properties (Reyes et al., 2014), thermal conductivity (Lines et al., 2017). Cone penetrometers are used for measuring soil penetration resistance because of their fast, economic and ease of use. Because the penetration resistance is highly affected by spatial variability, obtaining accurate data requires a huge amount of measurements to determine the relationship of soil penetration resistance with other parameters.

Precision farming provides a way to automate Site Specific Management (SSM) using information technology, thereby making SSM practical in commercial agriculture (Bongiovanni and Lowenberg-Deboer, 2004). The success of precision farming depends on more and high quality data to be collected from the field. In order to obtain quality data, it is necessary to implement methods, processes, repetitive measurement, iterative solutions, and specific techniques. Data collection activities are tedious and time-consuming in huge farmland. Therefore, since it is not easy to measure from each point of large production

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areas, it is necessary to estimate the unknown points by means of extrapolation and interpolation processes. Regression analysis, statistical methods and various extrapolation and interpolation methods are widely used in estimation problems. Nowadays, ANN is widely used in estimation applications due to high performance in linear or non-linear systems, and tolerance to missing and noisy data. Compared to multiple linear regressions (MLR), the ANN has a strong advantage to fit the nonlinear problem (Zhang et al., 2012).

ANNs are being widely used in agriculture science research such as approximating a nonlinear function relating corn yield to soil, weather, and management factors (Liu et al., 2001), classifying of the land cover data (Bocco et al., 2007), surface defection (Bennedsen et al., 2007), plant virus identification (Glezakos et al., 2010), prediction of the preliminary soil mapping units (Silveira et al., 2013), plant recognition (Sathiesh Kumar et al., 2016), estimation of fuel consumption (Borges et al., 2017), simulating of the the wetting pattern (Elnesr and Alazba, 2017), greenhouse climate control system (Manonmani et al., 2018), and yield prediction (Niedbala, 2019). Various investigators have made attempts to develop relationships to estimate soil penetration resistance by taking into account its soil properties such as type of the soil, particle size distribution, bulk density, and moisture content etc. (Bayat et al., 2008; Gunaydin et al., 2010; Holguin et al., 2011; Abrougui et al., 2014; Silva et al., 2016; Rizaldi et al., 2018; Pereira et al., 2018; Hosseini et al., 2018). Collecting soil penetration resistance data from huge production fields is usually much tedious and time-consuming task. The aim of this study was to estimate soil penetration resistance values of non-measured points were by using the real values of the measured points on the field. Three types of ANNs, GRNN, MLP, and RBF methods have been used to make estimates. The most suitable ANN model was tried to be determined by statistically comparing the three methods.

MATERIAL AND METHODS

Experimental site

The field study was conducted in agricultural research area of Akdeniz University. The experimental site is located approximately 20 km from Antalya between the coordinates of 30.84 E and 36.94 N. The soil type is clay-loam and consists of 42% sand, 25% silt, 34% clay. The organic matter content was 1.4%. Soil bulk density, water content and soil resistance values were determined as 1.31 g/cm^3, 7.6%, and 1.47 MPa at a depth between 0 and 20 cm, and 1.37 g/cm^3, 8.8%, 1.87 MPa at a depth between 20 and 40 cm, respectively.

Data collection

Penetration resistance data were collected from a 20 ha agricultural field shortly after wheat harvest. In this study, the horizontal penetrometer was used to collect penetration data. It was developed in our previous study (Topakci et al., 2010). The developed system was connected to a Massey Ferguson 3095D four-wheeled tractor (Figure 1). Soil penetration data were collected from 13 rows and the row spacing was 70 cm. Penetration resistance data were collected approximately at a depth of 40 cm. The depth of the hard pan is mostly ranged from 30 to 60 cm. In this study, the depth of 40 cm was used to get data on the hard pan level. The average operating speed was calculated as 2.1 km according to GPS data. The minimum and maximum operating speeds were determined as 1.80 km h^{-1} and 3.01 km h^{-1}, respectively. The time interval for the entire measurement was set to 1 second and 1603 data points were collected.

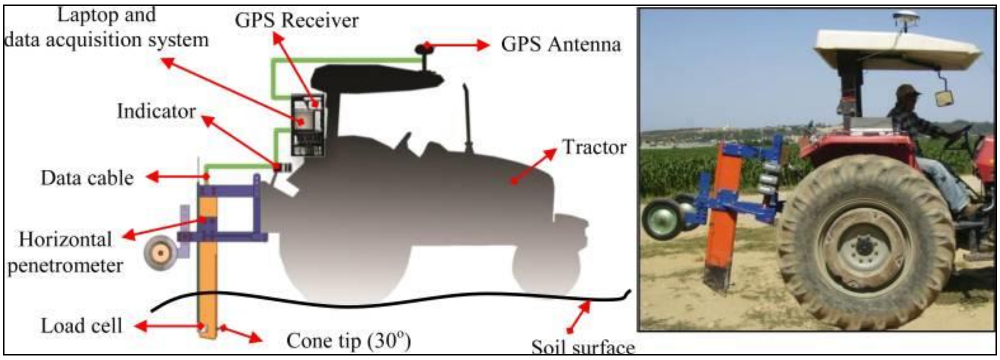

Figure 1. Horizontal Penetrometer (Topakci et al., 2010)

ANN models

ANN is a system that is based on the biological neural network which loosely models the neurons in a biological brain inspired by the human brain. The brain is made of approximately 100 billion neurons, which communicate with each other via electrochemical neurotransmitters. The neurons are connected to each other via as many as 1,000 trillion synapses. Each neuron has three part called cell body, dendrites, and axon to receive all incoming signals. If the sum of the incoming signals exceeds a certain threshold, a response is sent via the axon. An ANN has three types of neurons called input nodes, hidden nodes, and output nodes. There are many types of ANN models that operate in different ways to achieve different outcomes, solve problems, and make better decisions and predictions. In this study, three ANN models were used including GRNN, MLP, and RBF to compare their respective results in order to choose the best method for the estimation process. The dataset were divided into two parts, training data subset (76%) and testing data subset (24%) for ANNs. The developed ANN Models have 1 input layer, 2 hidden layers and 1 output layer. The ANN models were designed with 2 nodes in the input layer (Latitude and Longitude) and 1 node in output layer (soil penetration resistance). Customized codes written in the MATLAB and Neural Network Toolbox were used to estimate soil penetration resistance.

GRNN provides estimates of continuous variables and converges to the underlying (linear or nonlinear) regression surface (Specht, 1991). A GRNN consists of four layers called input layer, pattern layer, summation layer and output layer. The input layer is responsible for receiving the input vector X and distributing the data to the pattern layer. Each neuron in the pattern layer produces an output h and sends the result to the summation layer. The numerator and denominator neurons in the subsequent summation layer compute the weighted and simple arithmetic sums based on the values of h and wij learned in the supervised training (Palani et al., 2008). The neurons in the output layer then carry out the division of the sums computed by the neurons in the summation layer (Leung et al., 2000). The structure of the developed GRNN model in MATLAB is shown in Figure 2.

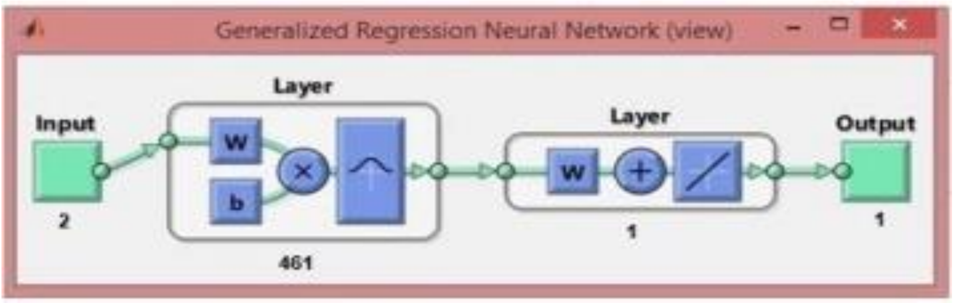

Figure 2. The structure of the developed GRNN model

MLP is the most widely used type of neural networks that the software offers (Vochozka et al., 2019). It has a structure containing various interconnected layers of neurons, starting from an input layer, hidden layers, and ending at an output layer. The number of hidden layers is variable, depending on the size and the characteristics of each problem. Each neuron is connected to the next neurons with the aid of artificial synapses and a weight coefficient is assigned to each synapse. The inputs for each neuron are multiplied by the weighting coefficient of the respective synapse, and then, they are summed; after that, the output from each neuron is generated by using an activation function, which usually is a sigmoid function, such as the hyperbolic tangent (Karkalos et al., 2019). The structure of the developed MLP model in MATLAB is shown in Figure 3.

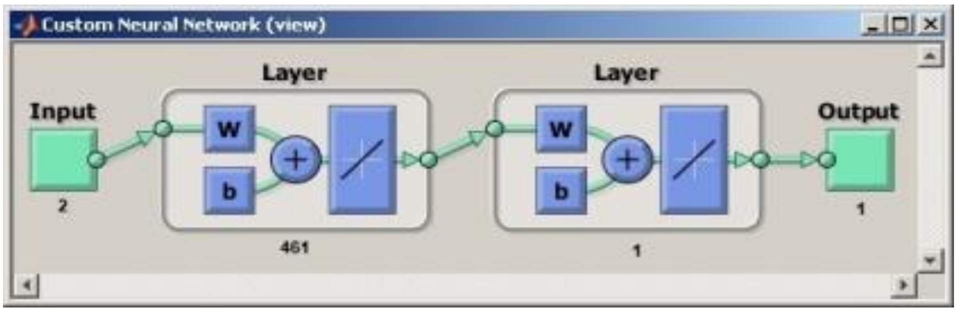

Figure 3. The structure of the developed MLP model

RBF networks represent an alternative architecture of neural networks, are mostly used for function approximation (Neruda and Neruda, 2002). An RBF network is a special class of feed forward neural network that is consists of three layers called the input layer, the hidden layer and the output layer. In the input layer, one neuron corresponds to each estimator variable. Hidden layer has a number of RBF non-linear activation neurons. Each neuron consists of a RBF centered on a point with the same dimensions as the predictor variables. The output layer produces the linear weighted summation of outputs from the hidden layer to form the network outputs. The structure of the developed RBF model in MATLAB is shown in Figure 4.

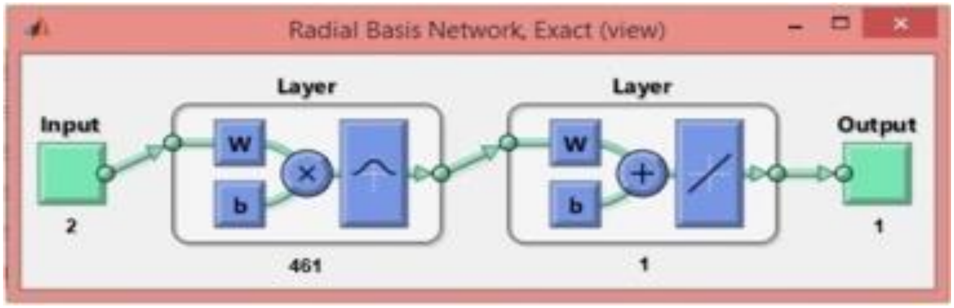

Figure 4. The structure of the developed RBF model

ANN models performance evaluation

Many different error measurements method have been proposed for model selection in literature. The performance of the ANN during its training and validation steps can be evaluated using diverse techniques, such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Sum of Squares of Error (SSE), Mean Error Ratio (MER), R2 correlation factor, Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC). In this study, the performance of developed ANN models was evaluated using MSE, RMSE, and MAE technique.

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

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

$$MAE = \frac{1}{T}\sum_{t=1}^{N} |Y_+ - O_T| \qquad (3)$$

where, Y_t is the expected exit, O_t is the obtained exit, T is the number of records, and N is the number of neurons in the pattern layer.

Sampling of ANN models used in the study

For this study, we transiently collected GPS data and soil penetration value on study field by the using horizontal penetrometer. The rate of data collection was 1 Hz. We collected 1603 GPS coordinate data and penetration value from 13 linear lines. First three and last three lines were used extrapolation process of estimating for GRNN, RBF, and MLP. Middle three lines were used interpolation process of estimating for GRNN, RBF, and MLP. In order to obtain the optimum amount of training data, three different types of training dataset are created: (1) extrapolation dataset (EXT 1); (2) interpolation dataset (INT 1); and (3) extrapolation dataset (EXT 2). The rest data is used for the validation of the corresponding models. Data collection map is given in Figure 5. Numbers of training and test datasets are given in Table 1.

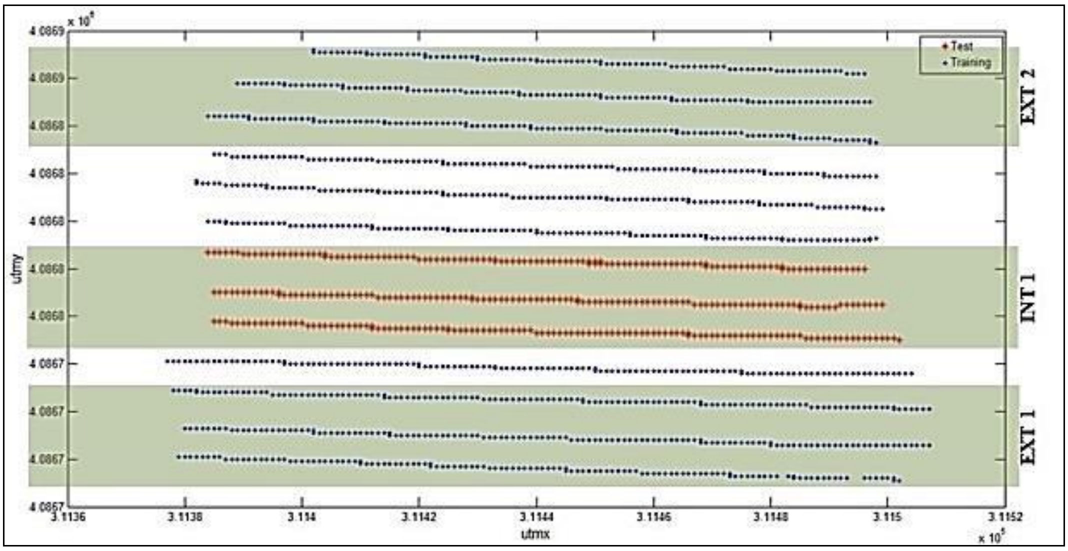

Figure 5. Data collection map

Table 1. Numbers of testing and training datasetse

	Test	Training
EXT 1	401	1202
INT 1	361	1242
EXT 2	340	1263

RESULTS AND DISCUSSION

In this study, three ANNs were used to estimate soil penetration resistance values at unknown points on the field by the using measured soil penetration resistance values at known points on the field. After that, the three methods were statistically compared between each other. For comparison process, we used the MSE, RMSE and MAE values. EXT 1 process results were given graphically in Figure 6. INT 1 process results were given graphically in Figure 7. EXT 2 process results were given graphically in Figure 8.

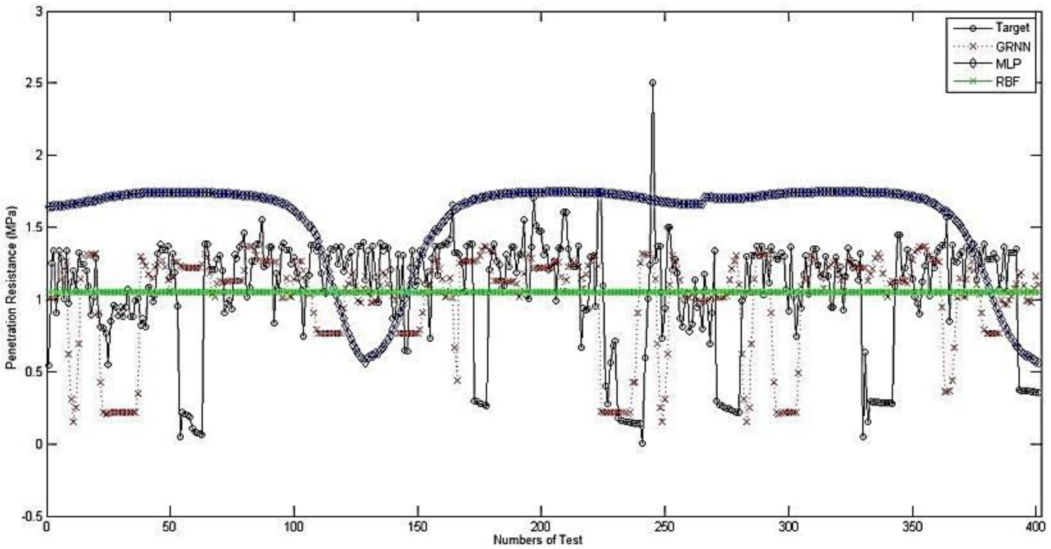

Figure 6. EXT 1 process results

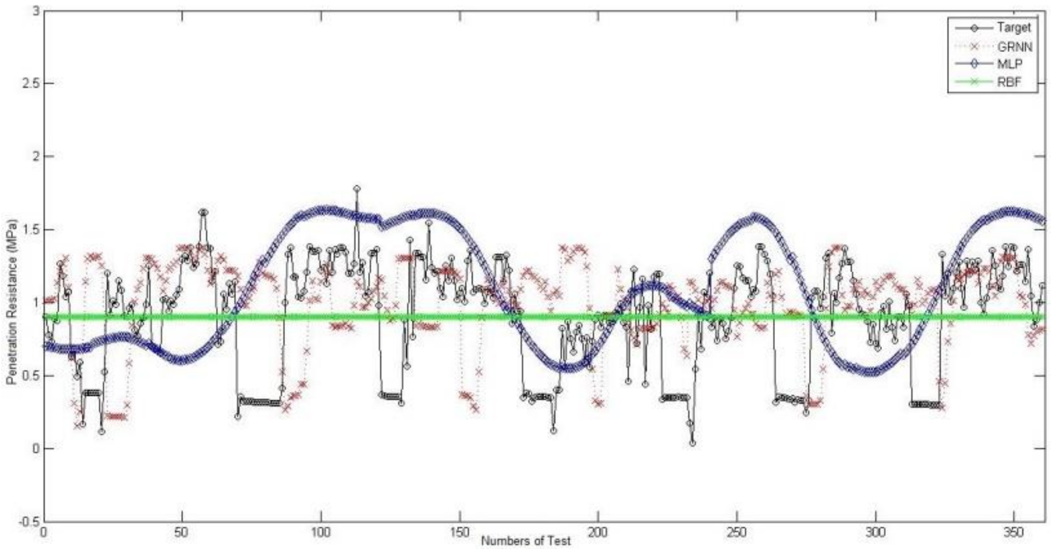

Figure 7. INT 1 process results

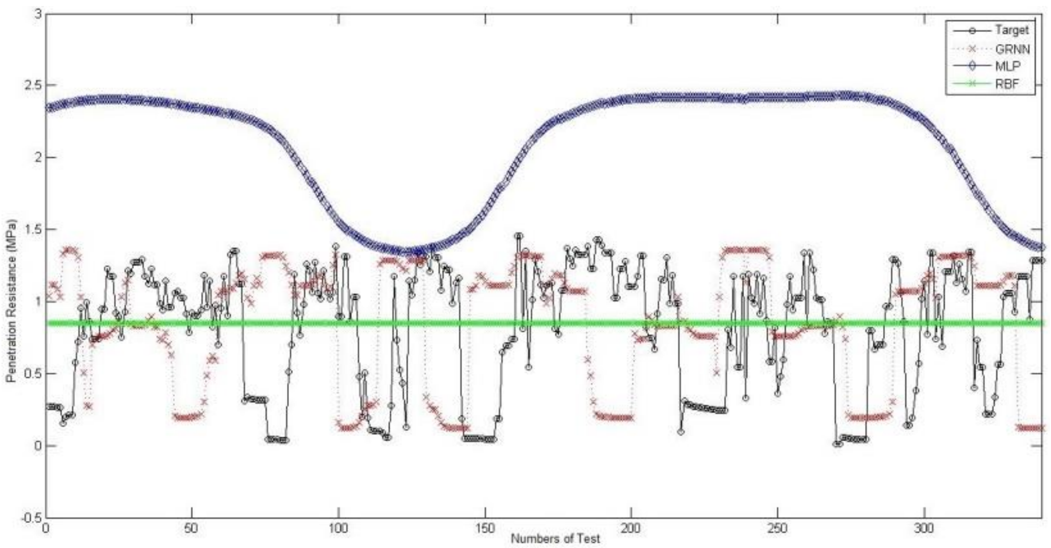

Figure 8. EXT 2 process results

The statistical results of extrapolation and interpolation process of the three methods were given in Table 2.

Table 2. Statistical results of extrapolation and interpolation process

		EXT 1	INT 1	EXT 2
GRNN (σ=1)	MSE	0.2506	0.2443	0.4092
	RMSE	0.5006	0.4943	0.6397
	MAE	0.372	0.4007	0.5136
MLP	MSE	**0.5454**	0.2504	1.9789
	RMSE	0.7385	**0.5004**	1.4067
	MAE	0.6111	0.4128	**1.2860**
RBF (σ=0.82)	MSE	**0.1608**	0.1382	0.1894
	RMSE	0.4010	**0.3717**	0.4352
	MAE	0.3104	0.3121	**0.3682**

As it can be seen in Table 2 and Figures 6, 7, and 8, when all three statistical methods are evaluated, it was observed that the RBF method gave a closer result to the actual values in soil penetration resistance value estimation than other methods (MSE: 0.1608; RMSE: 0.3717; MAE: 0.3682). As a result of the study, it was determined that MLP method gave the worst result in soil penetration resistance estimation process (MSE: 0.5454; RMSE: 0.5004; MAE: 1.2860). During the data collection process on study field, horizontal penetrometer was taken out from soil by the reason of some problems. As it can be seen in Figures 6, 7, and 8, analyze results were negatively affected by the soil penetration resistance values between 0 and 0.5 MPa. When this soil resistance values were removed from test dataset, MSE, RMSE and MAE values were move towards the 0.

In the literature, there is no study comparing all three methods in soil penetration resistance estimation at unknown points on the field by the using measured soil penetration resistance values at known points on the field. However, there have been studies comparing three methods on different subjects about soil science. Montana Moreno et al. (2011) offered a description and comparison of the main models of ANNs which have proved to be useful in time series forecasting, and also a standard procedure for the practical application of ANN in this type of task. MLP, RBF, GRNN, and Recurrent Neural Network (RNN) models were analyzed by the researchers. They reported that a comparative study establishes that the error made by the four neural network models analyzed was less than 10%. As a result, they said that the RBF, RNN and MLP models obtained the best results, whereas the GRNN networks obtained the worst results in time series forecasting. Faris et al. (2014) developed and compared MLP and RBF models for short-term predictions of surface ozone in order to have an early and accurate alert. They empirically demonstrated that the MLP neural network could lead to performance improvements over the RBF model, where the developed MLP network provided good estimation and prediction capabilities in training and testing cases. Kandirmaz et al. (2014) introduced an ANN using three ANN methods, GRNN, MLP, and RBF, which were applied to 34 stations approach for estimating monthly mean daily values of global sunshine duration for Turkey. They reported that the statistical indicators were shown that, GRNN and MLP models produced better results than the RBF model and could be used safely for the estimation of monthly mean sunshine duration.

However, there are not many studies on the mechanical properties of the soil especially soil penetration resistance. Krupp and Griffin (2006) developed a GRNN model for predicting soil composition from Cone Penetration Test

(CPT) data. Measured values of cone resistance and sleeve friction obtained from CPT soundings, together with grain size distribution results of soil samples retrieved from adjacent standard penetration test boreholes, were used to train and test the network. Researchers reported that the profiles of soil composition estimated by the GRNN generally compared very well with the actual grain-size distribution profiles, and overall the neural network had an 86% success rate at classifying soils as coarse grained or fine grained. Holguín et al. (2011) reported the elaboration of an ANN for the estimation of soil penetration resistance at different depths, considering as influential variables humidity, density, static load, and inflate pressure. They said that the ANN to predict penetrance resistance at 20-30 cm depth is the one with better performance. Bayat et al. (2008) used the ANN to simulate relationship between bulk density, gravimetric soil water content, and cone index. They reported that the ANN model predicted cone index from bulk density, gravimetric soil water content as predictors more accurately than the multiple linear regression and nonlinear regression models. They said that ANNs were powerful tools to simulate complex systems. Abrougui et al. (2012) determined the effect of soil bulk density, water content and the tillage technique on soil penetration resistance measured from the cone index.

They used Modular Feed Forward Networks which is a special class of MLP to predict soil penetration resistance. Santos et al. (2012) performed an analysis of the soil penetration resistance behavior measured from the cone index under different levels of bulk density and water content using statistical analyses, specifically regression analysis and ANN modeling. They reported that the regression analysis presented a determination coefficient of 0.92 and an RMSE of 0.951, and the ANN modeling presented a determination coefficient of 0.98 and an RMSE of 0.084. As a result, they said that the ANN modeling presented better results than the mathematical model obtained from regression analysis.

CONCLUSIONS

For researchers, data collection from huge fields is time-consuming and tedious application. Estimation process with the help of ANN saves time and costs on experimental execution. RBF modeling shows better prediction capability as compared to the other applied methods. Compared with the other two neural networks, RBF has a relatively simple and static structure. The results of the study show that using ANNs with better predictions is an important contribution to research and professional application of soil science.

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