ESTIMATION OF SOIL PENETRATION RESISTANCE USING GENERALIZED REGRESSION NEURAL NETWORKING

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Abstract
Soil compaction is a major problem affecting negatively the soil physical, chemical and biological properties and impedes plant root growth. Soil penetration resistance values should be collected from many points of the production area to determine the effects of these problems on plant growth. Soil penetration value collection from large production areas is time-consuming and tedious application for researchers. Also, the number of measurement 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 area. Artificial neural networks are one of the most popular mathematical computing and modelling method used to estimate unknown data values with known data values. 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 educating and validating. Soil penetration values of the unmeasured points were estimated using Generalized Regression Neural Network (GRNN) method in Matlab. In addition to mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE) and R^2 has been also used for evaluation of prediction accuracy on GRNN method. The results showed very good agreement between the predicted and the measured real values of soil penetration resistance.

Key words: artificial neural networks, estimation, soil penetration resistance, GRNN.

INTRODUCTION

The tractors, tillage tools and the machine systems which are used in the agricultural production can cause field traffic. Especially today‘s machines such as powerful tractors, combine harvesters etc. which are becoming heavier because of their additional attached equipment, have become a reason for high level of soil compaction observed in agricultural fields. Another reason for soil compaction is tillage in non-suitable terms of the soil. In addition to these external effects, natural effects such as excessive rainfall and drought can also be a reason for high levels of soil compaction (PORTERFIELD ET AL., 1986; TEKIN ET AL., 2008).

Soil compaction can be defined as a function of the specific weight and humidity of the soil. During compaction, soil particles get closer each other and a diminishing of the entrapped air is seen. As a result; an increase is seen for soil bulk density and soil penetration resistance (CARRARA ET AL., 2007; RAPER, 2005). Soil compaction has also a negative effect on the physical, chemical and biological properties of the soil. This negative effect limits roots growth and the plants cannot complete their growth properly. Hence, less yield and economic losses are seen. In addition to this, the machines, which are operating on the compacted soil need extra energy (AL-ADAWI ET AL., 1996; ADAMCHUK ET AL., 2003). Therefore, the determination of the soil penetration resistance level is quite important for sustainable production, yield and conservation of the farmland. It also has a place in the precision farming approach, which promises that the field performance could be tracked, mapped and analyzed down to the square meter level so that farmers can know how well or poorly each part of a field is producing (TEKIN, 2010).

Agriculture sector plays major role directly or indirectly in improving economy of developing countries. Sustainable and competitive agricultural production can be made by using electronic and computer technology. Also, information, data or knowledge is one of the most importing factors for the precision agriculture technology. To make the right decisions in agriculture production, we should collect more data from large production areas. But, data collection process such as soil penetration data is time-consuming and tedious application for researchers. For this reason, researchers can use estimation techniques. In this context, the use of Artificial Neural Networks (ANN) can be considered an alternative approach for predicting soil penetration resistance. ANN have been employed to solve many problems in agriculture (ERZIN ET AL., 2010; KIM AND GILLEY, 2008). VARELLA ET AL. (2002) used ANN for the determination of land cover from digital images. KHAZAEI AND DANESHMANDI (2007) used ANN to model the drying kinetics of sesame seeds. They concluded that the ANN technique presented better results than traditional mathematical modeling. SARMADIAN ET AL. (2009) used ANN to model soil properties, and the results were better than the multivariate regression analysis, showing the effectiveness of the ANN technique. Recently, TRIGUI ET AL. (2011) used ANN model to predict sugar diffusivity as a function of date variety, temperature and diffusion period.

Artificial neural networks have been used to estimate parameters on different soil science struggles, like vegetation cover (KIMES ET AL., 1998; BUENDÍA ET AL., 2002; MENA AND MONTECINOS, 2006; BOCCO ET AL., 2007), soil hydrodynamics (MANETA AND SCHNABEL, 2003; RUBIO, 2005), soil erosion hydrodynamics (MAS ET AL., 2002), underground water contamination (REBOLLEDO ET AL., 2002; RODRÍGUEZ, 2009; GARCÍA ET AL., 2010), however there are few reports on variables related to mechanical properties of the soil. HALGUIN ET. ALL (2011) reported that the elaboration of an Artificial Neural Network for the estimation of soil penetration resistance at different depths, considering as influential variables humidity, density, static load, and inflate pressure. The best estimation results were obtained at a depth of 20-30 cm. BAYAT ET AL. (2007) were compared neural networks, linear and nonlinear regression techniques to model penetration resistance. The results further showed that ANN models performed better than nonlinear regression models. ABREQUIE ET AL. (2014) were evaluate in short-term the impact of different tillage systems in organic farming (traditional tillage to superficial tillage without reversal) on soil resistance to penetration. The results showed very good agreement between the predicted and the desired values of soil resistance (R^2 = 0.98). The objective of the present research is to estimate soil penetration resistance values for unmeasured points on farm land using generalized regression neural networking.

MATERIALS AND METHODS

Experiment field and soil

The field experiments using the system were carried out in agricultural research area of Akdeniz University. The experimental field is 20 ha in size. The research area 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 41% sand, 26% silt, 33% clay. Content of organic matter was 1.3%. Soil bulk density, water content and soil resistance values were determined as 1.32 g/cm^3, 7.5%, and 1.45 MPa at a depth between 0 and 20 cm, and 1.38 g/cm^3, 8.9%, 1.89 MPa at a depth between 20 and 40 cm, respectively.

Data collection

The horizontal penetrometer was used in this study. It was developed in our previous study (TOPAKCI ET AL., 2010). The designed system was connected to a Massey Ferguson 3095D four-wheeled tractor (Fig. 1). During the experiments, some small variations were seen in the tractor speed, even though care was taken to keep the tractor speed at a constant value to avoid any negative effect of speed changes on the penetration resistance. The experiments were carried out in a field shortly after a wheat harvest and measurement values of 40 cm operation depth and 15 m linear intervals were obtained. Much research indicates that the depth of the hard pan is mostly between 30 and 60 cm. The depth of 40 cm has been chosen as working depth to get data on the hard pan level of the field. The average speed of 2.39 km h^{-1} was calculated according to data from the GPS receiver. Forward speeds of 1.80 km h^{-1} and 2.96 km h^{-1} were determined as the minimum and maximum values, respectively. The time interval for the entire measurement was set to 1 second and 1816 data points were stored in the database.

Generalized Regression Neural Networks

In the literature, the fundamentals of the GRNN can be obtained from SPECHT (1991); NADARAYA (1964) KERNEL REGRESSION, TSOUKALAS AND UHRIG (1997), also SCHIOLER AND HARTMANN (1992). A diagrammatic of the GRNN is given in Fig. 2. A general regression neural network (GRNN) does not require an iterative training procedure. It can approximate any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Furthermore, it is consistent; that is, as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. The GRNN is used for estimation of continuous variables, as in standard regression techniques (NESIL ET AL., 2011).

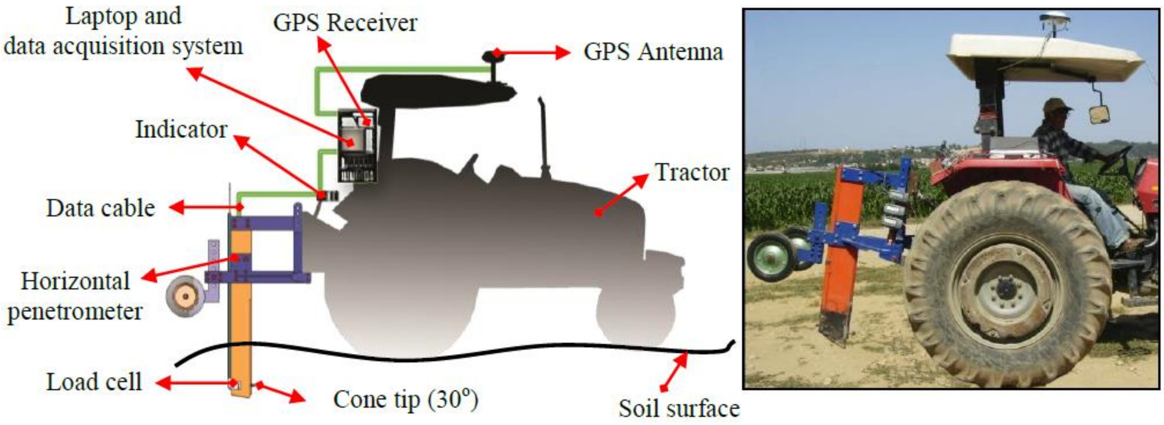

Fig. 1. – Horizontal penetrometer

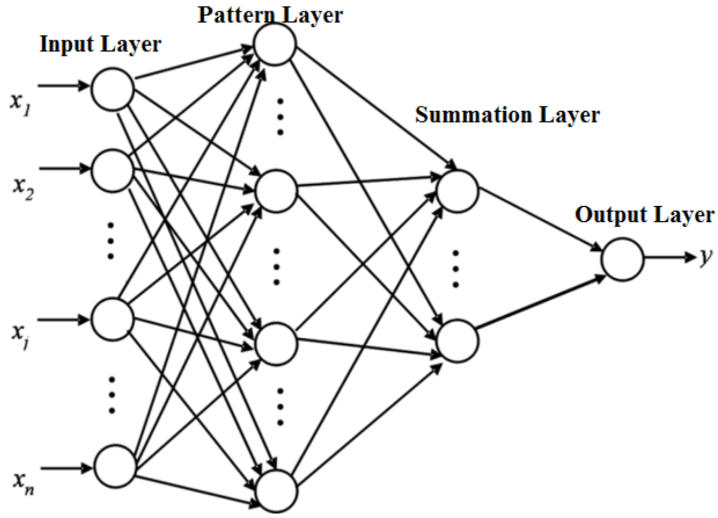

Fig. 2. – General structure of GRNN

A GRNN consists of four layers: input layer, pattern layer, summation layer and output layer. The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate un-weighted outputs of pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value Yi to an unknown input vector x as Equation 1 and 2 (JANG ET AL., 1997);

$$Y^i = \frac{\sum_{i=1}^{n} y_i . exp - D(x, x_i)}{\sum_{i=1}^{n} exp - D(x, x_i)} \tag{1}$$

$$D(x, x_i) = \sum_{k=1}^{m} \left(\frac{x_k - x_{ik}}{\sigma}\right)^2 \tag{2}$$

y_i is the weight connection between the i_{th} neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D is the Gaussian function, m is the number of elements of an input vector, x_k and x_{ik} are the j_{th} element of x and x_i, respectively, σ is the spread parameter, whose optimal value is determined experimentally.

GRNN performance evaluation

The performance of the artificial neural network during its training and validation steps, can be evaluated using diverse techniques, such as root mean squared error RMSE, sum of squares of error SSE, mean error ratio MER, mean square error MSE, R2 correlation factor (GOYAL AND GOYAL, 2011). We used MSE

(Equation 3), RMSE (Equation 4) and MAE (Equation 5) values for statistical analyze which were calculated as:

$$MSE = \sum_{t=1}^{N} \left(\frac{Y_t - O_t}{T}\right)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{T}\left[\sum_{t=1}^{N}\left(\frac{Y_t - O_t}{Y_t}\right)^2\right]} \tag{4}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{N} |Y_+ - O_T| \tag{5}$$

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.

GRNN development

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

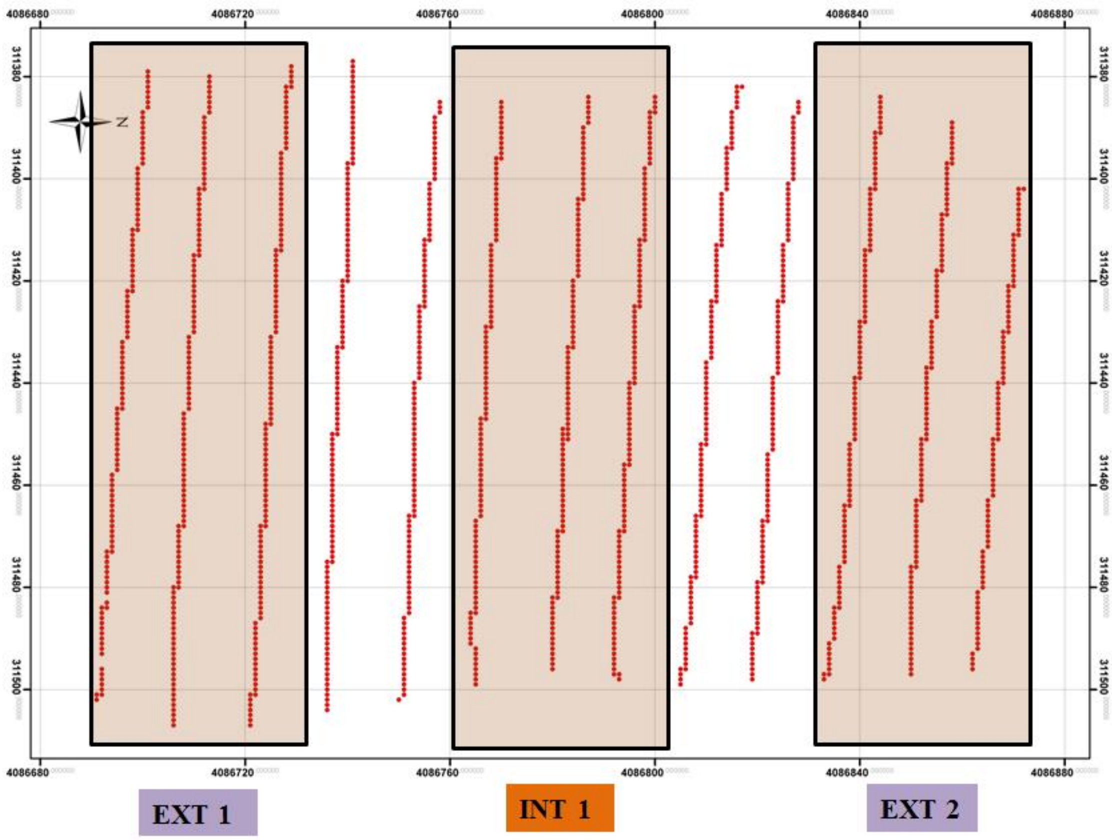

Fig. 3. – Data collection map

Tab. 1. – Numbers of training and test data sets

	Test	**Educating**
EXT 1	401	1202
INT 1	361	1242
EXT 2	340	1263

RESULTS AND DISCUSSION

In this study, we compared the real and the estimated soil penetration data using GRNN method. For comparison process, we used the RMSE and MSE values. EXT 1 process result is given graphically in Fig. 4. INT 1 process result is given graphically in Fig. 5. EXT 2 process result is given graphically in Fig. 6. The Error Analysis of Extrapolation and Interpolation Performances of the GRNN method are given in Tab. 2.

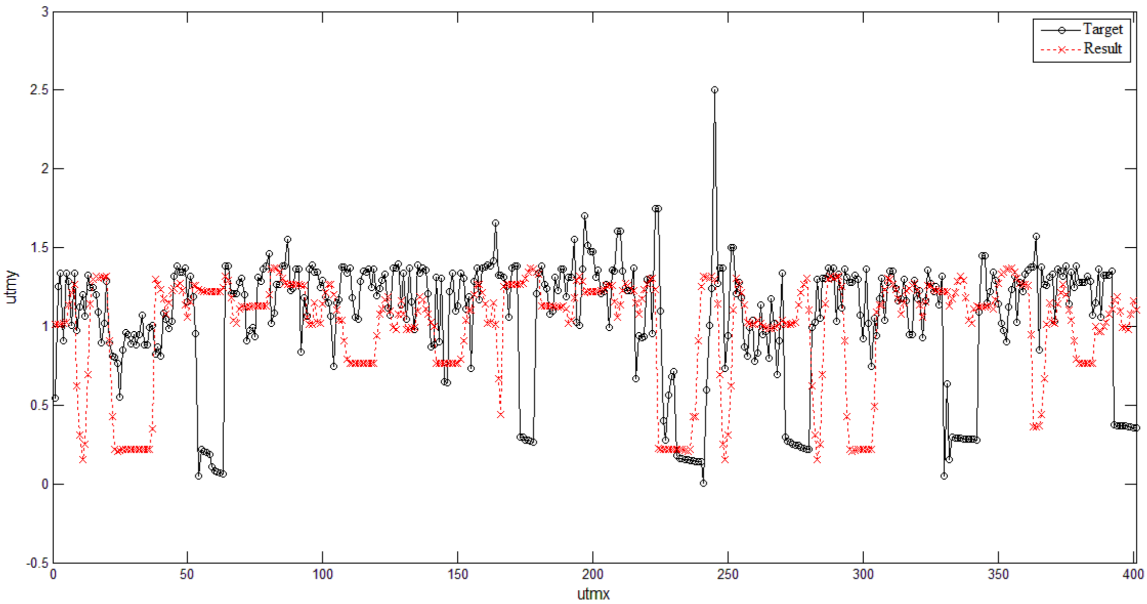

Fig. 4. – EXT 1 process result

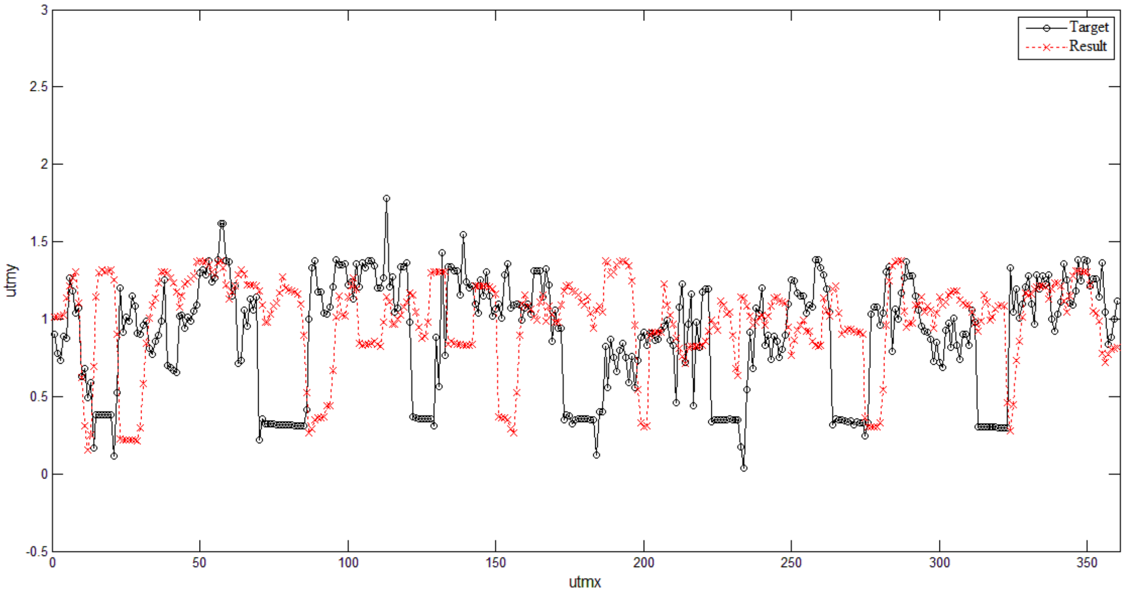

Fig. 5. – INT 1 process result

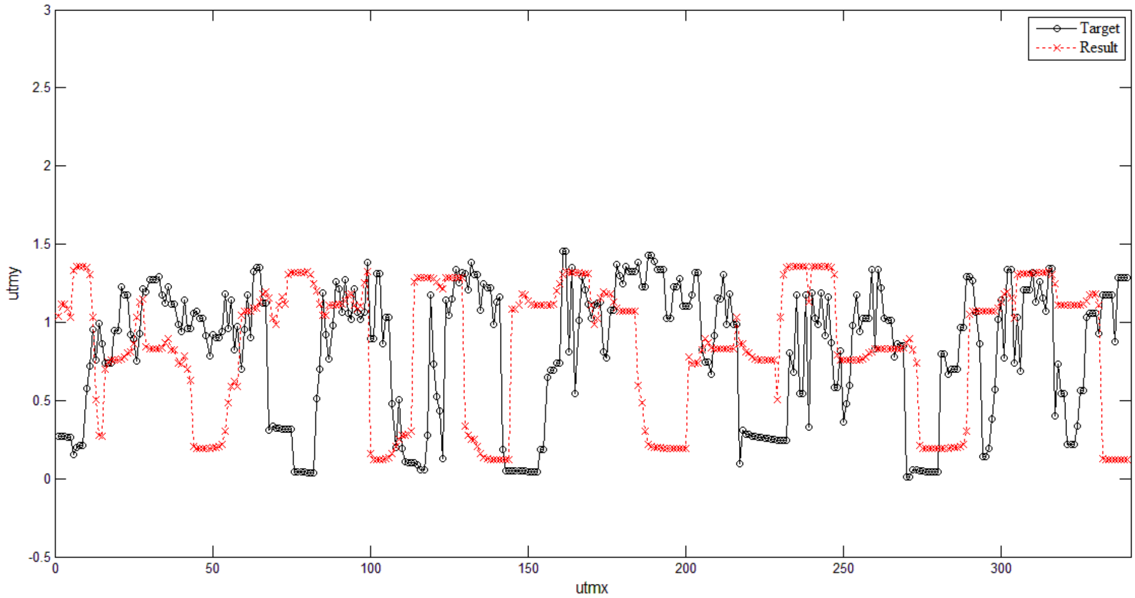

Fig. 6. – EXT 2 process result

Tab. 2. – The Error Analysis of Extrapolation and Interpolation Performances of the GRNN

σ = 1	**EXT 1**	**INT 1**	**EXT 2**
MSE	0.2443	0.2506	0.4092
RMSE	0.4943	0.5006	0.6397
MAE	0.4007	0.372	0.5136
R^2	0.847	0.905	0.831

As it can be seen in Tab. 2, and Fig. 4–6 generally GRNN method that used in this article are very successful for prediction of soil penetration resistance. 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 Fig. 4-6, analyze results were negatively affected by the soil penetration resistance values between 0 and 0.5 MPa. When this soil resistance values is removed from test dataset, MSE, RMSE and MAE values can be move towards the 0.

KRUPP AND GRIFFIN (2006), a general regression neural network (GRNN) was developed for predicting soil composition from CPT (Cone Penetration Test) 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 compare 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. CAI ET AL. (2015) were analyzed relationship between CPTU (Piezocone Penetration Test) parameters and soil types and strata, and was designed the structure of a general regression neural network (GRNN) for soil classification and soil strata identification. Researchers reported that the GRNN-based model was found to be correlating well for the 87% of the cases with the USCS classification system results. SANTOS ET AL. (2012) were to perform 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 (Artificial Neural Networking) modeling. 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. Researchers reported that the ANN modeling presented better results than the mathematical model obtained from regression analysis.

In this study, we compared real and predicted soil penetration resistance values by using regression analysis. The results of the regression analysis show that the predicted soil penetration resistance values was indeed positively correlated with real values (EXT1=0.847, INT1=0.905 and EXT2=0.831).

CONCLUSIONS

In this study, the possibility to use artificial neural networks on the prediction of soil penetrance resistance was explored. The results of the study show that using new artificial neural networks with better predictions is an important contribution to research and professional application of soil science. Soil penetration value collection from large production areas is time-consuming and tedious application for researchers. The option of using a prediction tool saves time and costs on experimental execution. In this paper, we used GRNN method for estimating soil penetration values. Compared with the other neural networks, GRNN has a relatively simple and static structure.

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