Research article

Prediction of soils penetration strength using artificial neural networks

Estimación de la resistencia a la penetración de suelo usando redes neuronales artificiales

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Abstract

Artificial Neural Networks simulate the learning process of biological neurons, and they have been successfully used in the computation of parameters on several engineering problems where a strong nonlinear relation among the variables exists. In soil science, estimation of some properties involves variables that are complicated to estimate using mathematical models, so the solution for the problems fall into the field of Artificial Intelligence. The present paper reports 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.

Key words: Artificial intelligence, artificial neural networks, soils, soil compaction, soil penetration strength.

Resumen

Las redes neuronales artificiales, simuladoras del proceso de aprendizaje de las neuronas biológicas, han sido utilizadas con éxito en el cálculo de parámetros en diversos problemas de ingeniería, donde las variables involucradas tienen una alta relación no lineal entre sí y la modelación no permite representar el problema mediante una función matemática de fácil deducción. En la ciencia del suelo, la predicción de algunas propiedades involucra diversas variables que hacen de su estimación por medio de modelos matemáticos un proceso complejo, trasladando la solución del problema al campo de la inteligencia artificial. En el presente artículo se reporta la elaboración de redes neuronales artificiales para la estimación de la resistencia a la penetración a diferentes profundidades de un suelo; se consideran como variables influyentes el contenido de humedad, la densidad, la carga estática, y la presión de inflado. Los resultados muestran una mejor estimación para profundidades entre 20 cm y 30 cm.

Palabras clave: Compactación del suelo, inteligencia artificial, redes neuronales artificiales, resistencia a la penetración, suelo.

Introduction

Soil compression consists on the reduction of its volume by applying a heavy load. It is called consolidation when it happens on saturated soils and water is excluded, and it is compaction when it occurs on dry soils and air is excluded (Bradford and Gupta, 1986; Pinzón and Amézquita, 1991). Compaction causes changes on water content and gas exchange between soil and atmosphere, and it prevents root growth (Horn *et al.*, 1995; Colmer, 2003; Foloni *et al.*, 2003) (Picture 1) and in the upper layer causes physical and pedogenetic changes (Pinzón and Amézquita, 1991).

It is considered that compaction by transit is associated with a serious damage on soil structure, due porosity loss leading to mechanical impedance generated by such load (Gerster and Bacigaluppo, 2004). As an alternative to reduce impedance, mechanical decompaction has been suggested, however the results of such experience have been contradictory (Balbuena, 2009). In some studies it has been suggested to use the mechanical resistance to penetration as an indicator to determine the degree of physical impedances in the soil, because above certain value, it shows a reduction in crop yield (Díaz-Zorita, 2004). In consequence, mechanical resistance to penetration could be a sensitive indicator to study the effects of mechanical decompaction and, soil preparation sequence for a crop, related to yield (Gerster *et al.*, 2010).

The wide use of mechanical resistance to soil penetration as a method to identify and characterize densified layers due to tillage, have shown that its results correlate with root growth and crop productivity (Ehlers *et al.*, 1983), horizons water content (Cerana *et al.*, 2005), and soil moisture and bulk density as indicators of soil quality (Díaz *et al.*, 2010). Nonetheless, some variables involve in soil characterization under penetrance resistance remain unexplored, and not all the variables can be resolved on a single mathematical mo–del able to show a complex relationship among them. A cause of this scientific ignorance is the high no-lineal relation and the dynamic of the variables on the estimation of parameters related to science problems (Valdés, 2010).

Artificial intelligence is a research area which unifies a series of techniques for computer use aiming to develop its capacity to perform learning and autocorrecting functions, by using algorithms or computational programming codes to resolve diverse problems, in a similar way as a human being could think. The main paradigms for artificial intelligence are: Artificial Neural Networks, Evolutive Algorithms, and Diffuse Logic (Trujillo and Gómez, 2007; Ponce-Cruz, 2010).

In modeling, artificial neural networks are black box models, develop to resolve problems in which the different components have a complex relation, the variables or relation rules are not easy to get, knowledge is scare but there is a series of data experience (López and Caicedo, 2006). These networks are a simulation of a biological neural network, therefore, from a functional point of view, they are processors of information with a channel for information entrance and an exit channel, with a high capacity to communicate and connect among them, which union is known

Figure 1. Negative effects of soil compaction on the limitation of root development zones
Source: Taken from Alliaume and Hill, 2008.

as synapsis (Trujillo and Gómez, 2007; Ponce-Cruz 2010).

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 no reports on variables related to mechanical properties of the soil. The state of art shows that, it is of interest to estimate penetrance resistance from an artificial neural network. This document presents a first approximation to estimate such parameters using different artificial neural networks, which have been done with that aim.

Materials and methods

Database

A database done by Váldes (2010) was used, it covers the available information on mechanical resistance to penetration on diverse soils (Pérez, 1997; Gómez and Torres, 1997; Vidal, 1997; Bonilla, 1998; Viveros and Jaramillo, 2003), located on different thermal floors and climatic conditions. The database is used for teaching, training and validation on computational programs for artificial neural networks; it consists of 192 records which form the vectors of complete information from the database matrix array for the variables involved. The mechanical resistance experiment is based on the cone index standard methodology using impact penetrometer (Saravia, 1997; Rangeon *et al.*, 2008), which measures the hit depth and number of hits that will be translated in pressure units (KPa).

Database variables are: water content (H) in %, soil mass in humid state (MSH) in g, soil mass in dry state (MSS) in g, bulk density (Da) in g/cm^3, static load applied to the soil (Ce) in KN, wheels inflate pressure (Prin) in psi, porosity (pores) in %, void ratio (Rel_Vacios) in %, and cone index for penetrance resistance measured at depths of 0 - 0 cm (IC-H_0), 10-20 cm (IC-H_{10}), 20-30 cm (IC-H_{20}), and 30-40 cm (IC-H_{30}) in KPa.

Artificial neural networks development

In the Mathematics department of the Universidad Nacional de Tucumán, it was constructed a computer program with the algorithm for an artificial neural network used in the estimation of cone index for penetrance resistance of soil. Information gathered on a general database was arranged to form six subsets with 192 information vectors for the first three sets and 64 vectors for the other ones. This in turn, forms six new specific databases which associate penetrance resistance values on the mentioned depths (IC-H_{10}, IC-H_{20}, y IC-H_{30}) as information of interest for its estimation. As programming language to write the artificial neural network algorithm it was used Matlab®; the neural network was created using the neural network tool box of the mentioned program (The Math Works Inc., 2000) and the information vectors were read by files on an Excel® sheet (The Math Works Inc., 2002). Artificial neural network typography belongs to a multilayer network (‘feedforward’) and the learning method was backpropagation, a data division technique of cross validation (K-Fold Cross Validation) with k=3, which is used to teach – train – validate. Se utilizó una técnica de división de datos para enseñanza-entrenamiento-validación denominada validación cruzada (K-Fold Cross Validation) con k = 3.

Artificial neural network architecture

According to the theorem of Kolmogorov (Kurkova, 1992; Haykin, 1999) any continuous increasing function in **n** variables can be analyzed using only lineal sums and a continuous no-lineal function that increases in a variable; this demonstrates that the group of neural networks in three layers (entrance, hidden and exit) is dense in the space of all the continuous functions in **n** variables and, therefore, a multilayer with a unique hidden layer can approximate any continuous function till the desired level on an interval, being these ones the universal function takers.

Feedforward typology with backpropagation learning, defined by Rumelhart *et al.* (1986) corresponds to a parallel computational type structure where little calculation units called neurons, are massively interconnected with the anterior layer from which they receive information, and with the posterior layer to which they transmit it. Such kind of networks consist of a first layer of entrance with selected variables –called entrance or perceiving neurons-, which influences the problem results; this is connected to one or more hidden layers, where calculations are performed; and finally, the transformed information reaches an exit layer, from where the results of the exit variables are obtained –called exit neurons-, those exit variables interpret the problem behavior according to the entrance variables. In the estimation using trained neural networks the exit variable corresponds to the estimated variable. Their hidden layers have an activation function which limits the exit to a short range, and from this exit layer all the estimated values can be produced. The exit from the layer is represented as:

$$Y_{Nx1} = f\left(W_{NxM}X_{M,1} + b_{N,1}\right) \qquad \textbf{(1)}$$

where, Y is a vector containing the exit from each one of the N neurons on a given layer, W is the matrix with the synaptic weights (importance) for each one of the M exits for all the N neurons, X is the vector with the entrances, b is the vector containing the biases, and f is the activation function. For the constructed artificial neural network, the no-lineal activation function is a sigmoidal function expressed as:

$$f(Z) = \frac{1}{1+e^{-Z}} \qquad \textbf{(2)}$$

being Z the expression contained between the equation **1** parentheses.

For network typology, the choice on the number of neurons of the hidden layer depends on factors like problem nature or data quality and size; a small number of data largely simplifies the network and does not have enough capacity to learn, and large amount of data causes overlearning, meaning a good adjustment with low power to predict new data (Tam and Kiang, 1992; Brockett *et al.*, 1997).

In multilayer networks, practice has suggested that hidden layers should have a neuron number in a 10:1 ratio to entrance layer neurons, with acceptable results for the training and validation processes in the artificial neural network, using as indicator the calculated error value. This relation is determined with preliminary tests which start with a low neuron number that increment gradually until a maximum number. The optimal amount of neurons in the hidden layer is the one that gives the lowest possible error (Buendía *et al.*, 2002). The minimal neuron number (N_{hidden}), is given as a value between the neuron number in the entrance layer (N_{entrance}) and the exit layer (N_{exit}) (Fritz, 1999; Kimes *et al.*, 1998):

$$N_{hidden} = Rounding\left(\sqrt{N_{entrance} * N_{exit}}\right) \qquad \textbf{(3)}$$

For the case of this study, Váldes (2010) performed training tests in one of the conformed networks; he used a hidden layer with 5 to 80 neurons, and repeated the procedure for 50, 60, 80 and 100 generations. He found that the best results are achieved for 100 generations and before 50 neurons you get the lowest error. When that number of neurons is increased there are no better approximations with a continuous increasing error. The present work chose a hidden layer with 40 neurons.

Artificial neural network learning and training

Backpropagation learning technique consists in using an optimization based on derivatives, in which error is derived not only in function of the exit layer weight, but also in function of the entrance layer weight, by using the chain rule (Hinton, 1989). This rule minimizes the training error of the neural network –the difference between the calculated values for a training using a determinate weight set, and the original values. The error and the corrections made to the weights are moved from the exit layer back to the entrance layer, from which comes the name backpropagation. As training method it was chosen the conjugated gradient or descending gradient method, corresponding to the scale conjugate gradient (SCG).

SCG has been defined by Moller (1993) and replace the lineal search for a step scaling, which depends on the success reducing the error and its good performance of its square approximation. This is motivated to accelerate the typical low convergence associated with the descendent gradient method while the information requirement, like evaluation, storage and inversion of the Hessian matrix, for the association are admitted, as it is required by the Newton method. SCG is considered as the fastest method from other existing ones (Moghassem *et al.*, 2010).

Artificial neural network 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, R^2 correlation factor (Goyal and Goyal, 2011). For the training process this study used MSE, during validation it was used RMSE and MRE (the last one was used as a final error report, which were calculated as:

$$MSE = \sum_{t=1}^{N} \left(\frac{Y_t - O_t}{T}\right)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{T}\left[\sum_{t=1}^{N} \left(\frac{Y_t - O_t}{Y_t}\right)^2\right]} \quad (5)$$

$$MER = \frac{1}{T}\left[\sum_{t=1}^{N} \left(\frac{Abs\,[Y_t - O_t]}{Y_t}\right)\right] \quad (6)$$

where, *Yt* is the expected exit, *Ot* is the obtained exit, *T* is the number of records on the database, and *N* is the number of neurons in the hidden layer.

Random division of the database

The decision technique ´K-Fold Cross Validation´ with k=3 divides each specific database of the same length on three groups of information vectors randomly chosen, using alternatively two groups as educational set for the network (learning and training) and a third one as validation (Refaeilzadeh *et al.*, 2008). The technique uses a Bayesian statistical regulation, and eliminates the biases on selection, it also gives a better idea on the validation errors and the existence of outliers that

Table 1. Relation between the entrance and exit variables (neurons) for the constructed and trained artificial neural networks to estimate soil resistance to mechanical penetrance.

RNA	Entrance	Exit
RNA_1	H, MSH, MSS, Da, Ce, Prin, IC-H_0	IC-H_{10}
RNA_2	H, MSH, MSS, Da, Ce, Prin, IC-H_0, IC-H_{10}	IC-H_{20}
RNA_3	H, MSH, MSS, Da, Ce, Prin, IC-H_0, IC-H_{10}, IC-H_{20}	IC-H_{30}
RNA_4	H, MSH, MSS, Da, Ce, Prin, Poros, Rel_Vacios, IC-H_0	IC-H_{10}
RNA_5	H, MSH, MSS, Da, Ce, Prin, Poros, Rel_Vacios, IC-H_0, IC-H_{10}	IC-H_{20}
RNA_6	H, MSH, MSS, Da, Ce, Prin, Poros, Rel_Vacios, IC-H_0, IC-H_{10}, IC-H_{20}	IC-H_{30}

RNA: Artificial Neural Network.

Table 2. Specific characteristics of the artificial neural network constructed and trained to estimate penetrance resistance in soil, for 20-30 cm depth.

Concept	Characteristic
Type:	Multilayer Perceptron
Architecture:	3 layers: entrance layer, a hidden layer, exit layer.
Training algorithm :	Bayesian Regulation Backpropagation
Entrance layer (neurons):	8 neurons: H, MSH, MSS, Da, Ce, Prin, IC-H_0, IC-H_{10}
Hidden layer neurons):	40 neurons
Exit layer (neurons):	1 neuron: IC-H_{20}
Error:	Learning phase: 10.7389%
	Training phase: 13.4008%
	Validation phase: 11.9886%

are masked due to data division and other effects (Varmuza and Filzmoser, 2009).

Artificial neural network development

For this study, six artificial neural networks were done and trained. They had a multilayer typology with an entrance layer, a hidden layer of 40 neurons, and an exit layer with one neuron corresponding to the value of mechanical resistance to penetration on a reference depth (IC-H_{10}, IC-H_{20}, and IC-H_{30}). The entrance and exit variables (neurons) in each artificial neural network made and trained are displayed on Table 1.

Results and discussion

The six artificial neural networks to estimate soil penetrance resistance at different depths (Table 1) were constructed and trained according to the procedure mentioned above. As a performance indicator of the artificial networks, the computational behavior of the data in the training and validation phases was analyzed together with the reported error for each validation phase.

The best data performance on the validation phase was presented in the RNA_2 network, which estimates penetrance resistance at 20-30 cm depth (IC-H_{20}), its specific characteristics are depicted in Table 2. In Figure 2 it is shown the performance result on the validation phase for the RNA_1, RNA_3, RNA_4 and RNA6. As it can be observed when comparing to the data of the same phase on RNA_2 (Figure 3a), the networks approximation to a correlation line (R^2=1) is highly dispersed. With the aim to help a better understanding of the estimated results of a trained neural network, the performance indicator is shown as a graphic.

For the network with best performance, RNA_2, it is included in Figure 3a the comparative between the real data vs. estimated data on the computational training and valida-

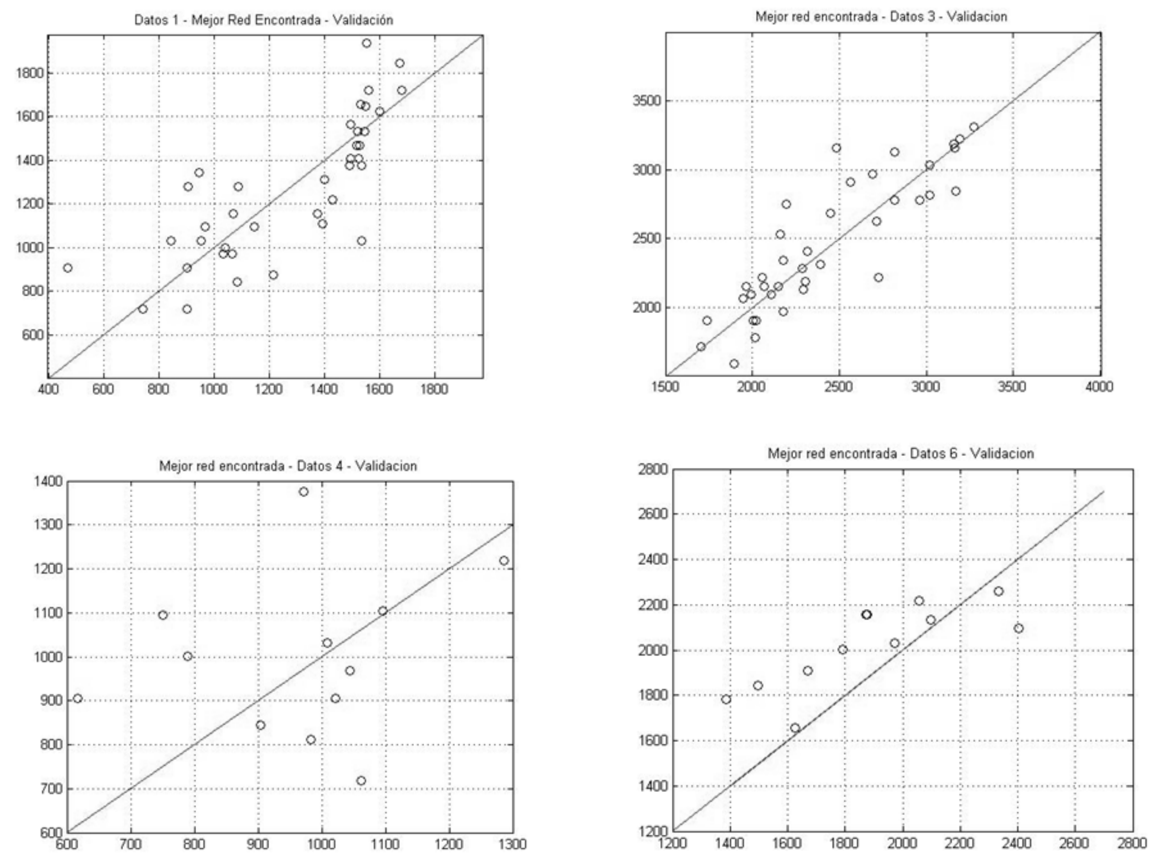

Figure 2. Validation results for three artificial neural networks RNA_1, RNA_3, RNA_4 y RNA_6, respectively.

tion phases. Data out of a performance pattern are observed, however they are not erroneous data on the original experiment, and cannot be identified to be excluded from the databases, to allow a process replication and error reduction. It is important to name that in the training database used it is possible to eliminate the records with such kind of data, which is done by using other specific techniques in the computational tool but, including them on the constructed algorithm (Valdés and González 2011).

To analyze the relation type (lineal or no-lineal) between variables, the network with best performance (RNA_2) was computationally trained and validated by using a function for lineal activation expressed as:

$$f(Z) = Z \qquad \textbf{(7)}$$

being Z the expression that appears between the equation parentheses (**1**). The training and validation phase using a function for lineal activation, is shown non Figure 3b; where it is exposed a similar behavior when the activation function is lineal, therefore from this specific estimation case, it could be concluded that variables relationship is based on a lineal dependence and such prediction is not affected if the variables relationship is no-lineal.

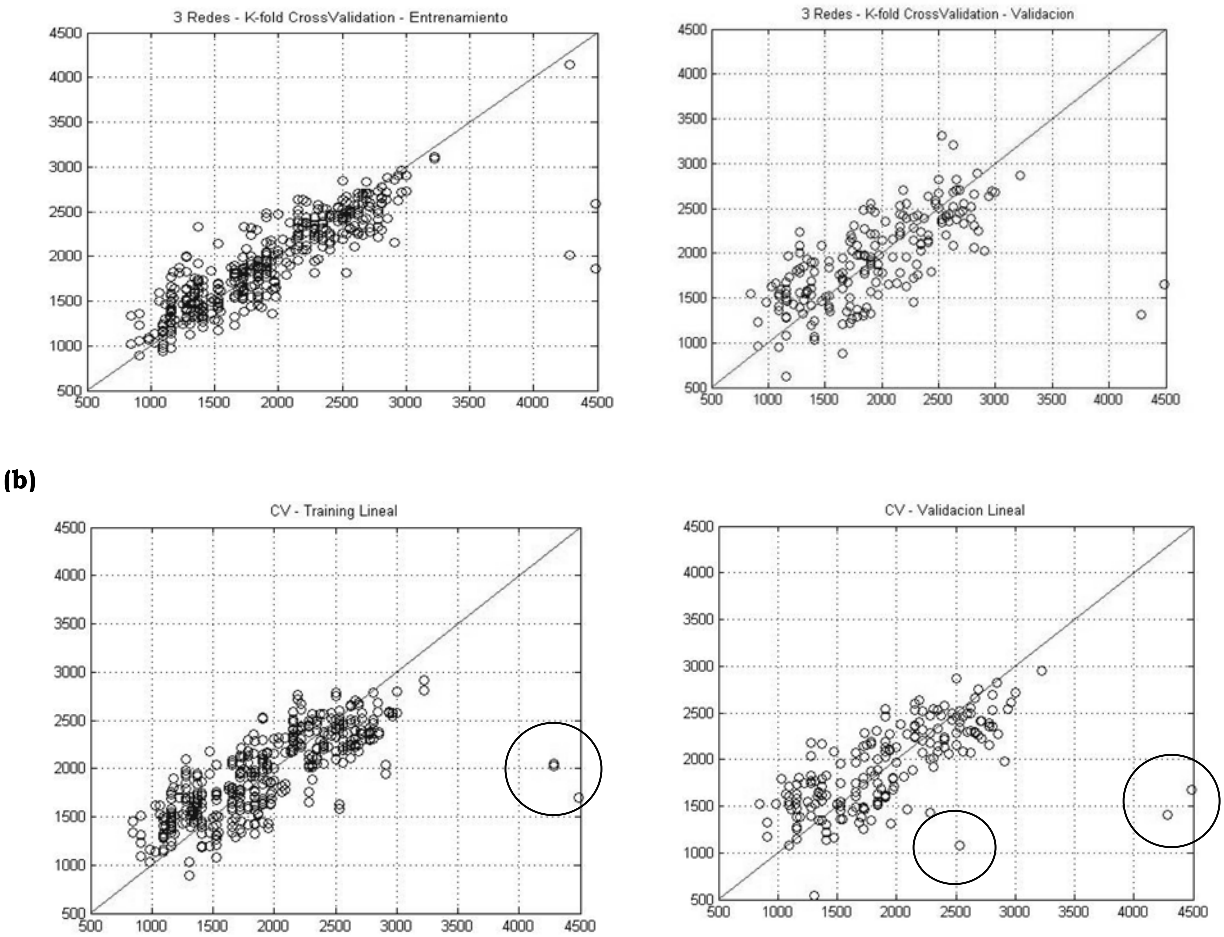

Figure 3. Behavior of the artificial neural network with best performance, RNA_2: **(a)** Interrelation of the entrance variables with no-lineal activation function for the training and validation phases, respectively; **(b)** Interrelation of the entrance variables with lineal activation function for the training and validation phases, respectively. In circles are the values that were identified to follow a different behavior pattern.

Conclusions

- The possibility to use artificial neural networks on the prediction of penetrance resistance at different soil depths was explored. The artificial neural networks with feedforward typology, backpropagation learning and multilayer architecture were constructed and evaluated using as performance indicators the relative error in the validation phase. According to this indicator, the artificial neural network to predict penetrance resistance at 20 – 30 cm depth is the one with better performance.
- Despite of the error obtained in the prediction, is important to notice that the best estimation for one of the greater depths (20 – 30 cm), in which the values of penetrance resistance at lesser depths (0 – 0 cm and 10 – 20 cm) was added as an entrance variable, suggests that the experiment should be done at lesser depths, reliving time and costs.
- The results of the present study show that using new artificial neural networks with better predictions, is an important contribution to research and professional application of soil science, because of: (1) Mechanical penetrance resistance, obtained with the standard cone index method, is used as a reliable indicator to correlate yield and soil; however, it should be done extensively on tilling areas and at four different depths. The option of using a prediction tool saves time and costs on experimental execution. (2) Rooting depth is defined as the thickness of the best zone for root development (Alliaume and Hill, 2008), it is classified into three groups: superficial (0 - 15 cm), media (15 cm - 30 cm), and deep (> 30 cm). It is important that the tool can report reliable predictions on resistance to mechanical penetrance at greater depths, since it allows knowing the soil conditions for a suitable development on those species of high economic importance which require more than 30 cm for rooting.
- It is suggested that the new artificial neural networks, take into account, additionally, as entrance variables, soil type, thermic floor location, tilling type, climate conditions, among others. Although some of these are qualitative variables, when treated as class variables they can be recognized by the artificial neural network and be associated to a behavior pattern.

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