Prediction of Soil Bulk Density Based on BP Neural Network Using Dual-sensor Penetrometer Data

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Abstract: Although, soil bulk density ($D_b$) plays a significant role in modern agriculture, its obtaining is still a pressing question because of high cost and heavy work. The development of mathematical modeling techniques makes indirect $D_b$ acquisition possible. This paper developed $D_b$-predicted Pedotransfer functions (PTFs) involving penetration resistance (PR) and soil volumetric water content ($\theta_v$), using BP neural network. Totally 6 models (M1, M2, ..., M6) were established. All were based on laboratory data acquired by a dual-sensor penetrometer. M1 and M2 predicted clay’s and silt-loam’s $D_b$ from PR and $\theta_v$. They proved the feasibility of using BP to build $D_b$-predicted PTFs. Adding the measure depth (d) of dual-sensor penetrometer as another input, M3 (clay) and M4 (silt-loam) demonstrated d’s irrelevance in $D_b$-prediction. Then M5 used PR and $\theta_v$ to predict $D_b$ for two kinds of soils in the same way. And M6 added soil texture to M5 after quantifying soil texture. M6 presented better result than M5’s. It also pointed a way for finding universal methods to get different soils’ $D_b$.

Key words: Soil bulk density ($D_b$), penetration resistance, volumetric soil water content ($\theta_v$), pedotransfer function, BP neural network, prediction

INTRODUCTION

Easy access to real-time soil environment information is at the request of modern agriculture. The measurement technique of soil parameters, such as moisture content, nutrient content, soil compaction and so on, has been focused at the study of agricultural engineering (Arrouays et al., 2001). Bulk density ($D_b$) is an important parameter characterizing soil compaction. It relates with soil quality and crop growth closely and is one of the crucial variables in the study of soil characteristics models (Zhang et al., 2012). However, the cylinder core sampling, has shortcomings (e.g., heavy work, time-consuming) (Jalibert et al., 2010). Another tool, gamma-ray tomography, has potential risk of radiation exposure (Hernanz et al., 2000). Hence, more and more indirect methods to get $D_b$ were studied over the past decade.

Pedotransfer functions (PTFs) have been used to predict $D_b$ (Brahim et al., 2012; Hollis et al., 2011). PTFs are models that use known/easily accessible variables to predict unknown/uneasily accessible variables. It had been applied to predict soil hydraulic parameters (Vereecken et al., 1989), carbon content (Jones et al., 2005), penetration resistance (Santos et al., 2012).

The most commonly-used variables to predict $D_b$ included soil organic content (Adams, 1973; Alexander, 1980), soil water content (Hernanz et al., 2000), soil texture (Ghehi et al., 2012), penetration resistance (Quraishi and Mouazen, 2013) and so on. The published models of $D_b$-predict PTFs were established using multiple regression analysis (Ghehi et al., 2012) or artificial neural networks. Furthermore, the PTFs using artificial neural network presented better prediction performance under the same conditions. However, most established $D_b$-predict PTFs depended on too many input variables and different variables were measured by different instruments. All of these led to problems, such as complex calculation, high cost of data-acquisition and time-consuming.

With the intention to measure penetration resistance (PR) and volumetric soil water content ($\theta_v$) simultaneously, various soil water content sensors have been combined with the conventional penetrometers (Topp et al., 1996; Vaz and Hopmans, 2001). However, no study has been reported to build PTFs by these advanced techniques. Thus, the major objective of this paper was to build PTFs based on BP neural network using dual-sensor penetrometer data.

MATERIALS AND METHODS

Model of BP neural network: With nonlinear differentiable functions as activation functions, BP neural network model is an error back propagation network. It
revises connection weights through a gradient descent algorithm. Because single hidden layer BP neural networks are competent to map arbitrary nonlinear continuous functions in closed intervals, it was selected to explore \( D_i \)'s nonlinear dependence on \( PR \) and \( \theta_c \). In the selected BP neural network, each node had no coupling with others within the same layer and it was connected to all nodes in the previous and next layers.

**Dual-sensor penetrometer:** The dual-sensor penetrometer (Fig.1) could measure \( PR \), \( \theta_c \), and measure depth (d) simultaneously. The maximum \( PR \) it could measure was 1000 N, \( \theta_c \) was 0.6 V and d was 700 mm. Specially, \( \theta_c \) was counted in voltage. When \( \theta \) changed, the measured voltage would change along with it. The penetration speed of the tool was fixed at 30 mm sec\(^{-1}\) according to the ASABE Standards (ASABE, 2009).

**Soil sample and experimental method:** Two groups of soil samples (clay and silt-loam) were prepared. The clay is made of 14% sand, 13% silt and 73% clay; while the silt-loam is made of 11% sand, 71% silt and 18% clay. After 24 h over-drying at 105 and passing through a 2 mm sieve, these soil samples were remoistened with different levels of \( \theta_t \), in an interval of 5% ranging from dry to saturation. After remoistened and fully stirred, the samples were sealed in a container for 48 h to make sure the internal moisture migration could reach equilibrium. Then the samples were made into soil column with the assistance of a special container, 700 mm length and 150 mm in diameter. For each level of \( \theta_t \), three kinds of samples with different theoretical \( D_i \) were packed. The actual d (penetrating depth) ranged from 0 and 650 mm. Each sample was measured five times to guarantee the data reliability. Using the dual-sensor penetrometer, soil columns' PR and \( \theta_c \) at different d were gotten. Following this step, the soil columns were sampled with cutting ring, too. It was done along container’s sidewall vertically, with an interval of 100 mm in depth.

**RESULTS AND DISCUSSION**

**Data preprocessing:** The \( PR \), \( \theta_c \) and d acted as inputs of BP neural networks and \( D_i \) as output. Each parameter had different rang of value. The value of \( PR \) could change from 0 to 1000 N, \( \theta_c \) from 0 to 0.6 V, d from 0 to 700 cm and \( D_i \) from 0 to 1.8 g cm\(^{-3}\). The values of different parameters differed greatly from each other. Before establishing models, the inputs and output were normalized to dimensionless values in (0, 1). This processing was to balance effects of different variables’ fluctuation on output and to simplify calculation. The normalization Eq. was defined as:

\[
x_i = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

where, \( x_i \) is the normalized value and \( x \) is the original value; \( x_{\text{max}} \) and \( x_{\text{min}} \) is the upper and lower limit of variables. In order to assess the performance of \( D_i \)-predicted BP neural networks, a part of experimental data must be picked out to test the established models. For clay, 15 data out of 75 formed the test set, while 7 out of 39 for silt-loam.

**Establishment and evaluation**

**Establishment of BP neural networks:** BP neural networks with single hidden layer were adopted in the study. Still, the node number of the hidden layer should be determined. Since there's no universal algorithm for determining node numbers, the node number for each network was gotten through a comparison method. The specific means is: (1) Established BP neural networks with different nodes separately for clay and silt-loam; (2)
Trained the networks and got their Root Mean Square Error (RMSE) and determination coefficient ($R^2$). With the criteria of minimum simulation RMSE and maximum simulation $R^2$, chose the best node numbers for further study.

**Evaluation of BP neural networks:** Before generalization, the established BP neural networks should be evaluated whether their performance met the need. It consisted of assessments of both network simulation and network prediction. The former was based on training sets and the later on test sets. Simulation assessment meant the comparison between the network output values and actual values of $D_b$ corresponding to the training set. Similarly, prediction assessment meant the comparison between the network output values and actual values of $D_b$ corresponding to the test set. The RMSE and $R^2$ were calculated to evaluate networks’ performance. And paired sample t-test on prediction was also conducted.

**Prediction of $D_b$ based on clay:** In each data, PR and $\theta$, acted as inputs and $D_b$ acted as output. On MATLAB 2008a, the clay BP neural networks with 5, 10, 15, 20, 25, 30, 35 nodes separately in single hidden layer were established. For each network’s simulation, RMSE and $R^2$ were calculated.

At the beginning, the RMSE of network simulation decreased and the $R^2$ increased gradually with the increase of node number. But when it was more than 25, the simulation RMSE and $R^2$ changed in an opposite direction, getting worse. It’s likely because the computational complexity and the number of iterations to the same error increased as well when the node number increased. Seen from the index value, the clay BP neural network with 25 nodes in the hidden layer (M1) had the best simulation result (RMSE = 0.1196 g cm$^{-3}$, $R^2 = 0.72$). The prediction result (RMSE = 0.1164 g cm$^{-3}$) of M1 were presented in Fig. 2.

Further, paired sample t-test between the predicted and actual clay $D_b$ was conducted using SPSS. The $t$ value was 1.306 and the significance (p) was 0.213. This convinced us of the fact that there’s no significant difference between the predicted and actual values of clay $D_b$. On the other hand, the prediction $R^2$ reached 0.70. It could be concluded that the predicted values of clay $D_b$ based on M1 could well simulate the actual values of clay $D_b$.

**Prediction of $D_b$ based on silt-loam:** As for clay, the silt-loam BP neural networks with 5, 10, 15, 20, 25, 30, 35 nodes separately were established. For each network, the simulation RMSE and $R^2$ was calculated.

Compared with clay, silt-loam models presented smaller fluctuations of simulation indexes. The simulation RMSE and $R^2$ of 15 nodes, 20 nodes and 25 nodes were almost the same. To weaken soil texture’s effect on network structure, the 25 nodes model (M2) was chosen for silt-loam (RMSE = 0.1286 g cm$^{-3}$, $R^2 = 0.79$). Its prediction result (RMSE = 0.1446 g cm$^{-3}$) were presented in Fig. 3.

The $t$ is -1.436 and $p$ is 0.201. The prediction $R^2$ reached 0.69, which meant the predicted values of silt-loam $D_b$ from M2 could well represent the actual ones.
Fig. 4: Prediction results of M3

Fig. 5: Prediction results of M4

Fig. 6: Prediction results of M5

Fig. 7: Prediction results of M6

**Influence of measure depth (d):** To confirm whether $D_b$ prediction would be affected by $d$ or not, $d$ was added into M1 and M2 as third input, to form M3 and M4. Figure 4 and 5 are the prediction results of M3 and M4. M3 showed a drop of prediction $R^2$ to 0.36 after the introduction of $d$. And the calculated RMSE rose up to 0.2504 g cm$^{-3}$. Performance of M4 went worse, too. (RMSE = 0.1622 g cm$^{-3}$, $R^2 = 0.60$). This proved $d$ was an irrelevant factor for $D_b$ prediction using BP model. It was consistent with the conclusion of Cai et al. (2013).

**Influence of soil texture:** According to the results of M1 and M2, the prediction accuracies of different soil types differed slightly. For further investigation of soil texture’s influence, two groups of data were processing together. After mixed, 114 data was divided into 92 and 22 randomly. As with clay or silt-loam alone, M5 used PR and $\theta$ to predict $D_b$ for two soils in a universal way. Figure 6 is the result. Compared with M1 and M2, the RMSE increased (to 0.1942 g cm$^{-3}$) and the $R^2$ dropped (to 0.32), an apparent deterioration of performance. It confirmed soil texture’s crucial role.

Given that the difference of silt and clay percentages between two soils was obvious, percentages of silt and clay could be indicators that characterized soil texture. M6 introduced soil texture into M5 (Fig. 7). The RMSE dropped to 0.1281 g cm$^{-3}$. 

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The comparison of M1, M2, M5 and M6 supported soil texture’s important role in Ds prediction using BP models. If soil’s composition percentages could be gotten, the prediction accuracy could be improved efficiently. Compared with M1 and M2, M6 weakened prediction’s dependence on soil texture. It’s important for finding universal methods to get Ds of different soils.

CONCLUSION

Although studies have shown Ds relates with PR, θ, and soil texture, the relevant models have problems in application. This thesis built Ds-predicted models using BP algorithm. It was concluded as following: (1) It’s demonstrated BP neural network could effectively predict Ds from PR and θ, acquired by dual-sensor penetrometer. (2) No improvement was made assuming d was an independent factor in Ds prediction. (3) When soil texture was considered, the result supported soil texture’s significance in Ds prediction. However, it’s difficult to acquire soil texture quickly in field condition by existing technique.

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