http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (16): 3650-3654, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.3650.3654

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

Qiaoli Wang, Jianhui Lin, Yanfeng Xu
School of Technology, Beijing Forestry University, Beijing 100083, China

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 (θ_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 θ_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 θ_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 (θ_v), pdeotransfer 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) (Jalabert *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 leaded 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 (θ_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

Corresponding Author: Jianhui Lin, School of Technology, Beijing Forestry University, Beijing 100083, China

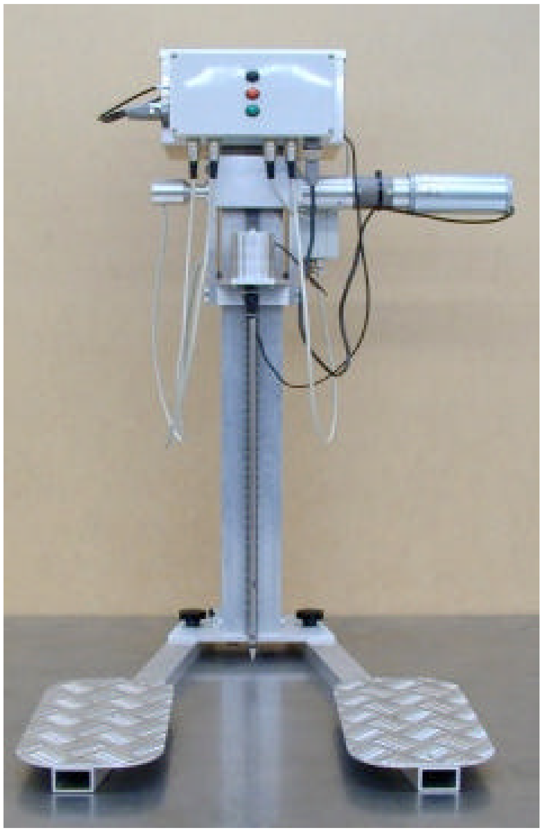

Fig. 1: Dual-sensor penetrometer

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_b's nonlinear dependence on PR and θ_v. 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, θ_v and measure depth (d) simultaneously. The maximum PR it could measure was 1000 N, θ_v was 0.6 V and d was 700 mm. Specially, θ_v was counted in voltage. When θ_v 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 (ASAE, 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 θ_g, 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 θ_g, three kinds of samples with different theoretical D_b 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 θ_v 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, θ_v and d acted as inputs of BP neural networks and D_b as output. Each parameter had different rang of value. The value of PR could change from 0 to 1000 N, θ_v from 0 to 0.6 V, d from 0 to 700 cm and D_b 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:

$$x_s = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where, x_s is the normalized value and x is the original value; x_{min} and x_{max} is the upper and lower limit of variables. In order to assess the performance of D_b-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); (3) 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 θ_v 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 Db 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.

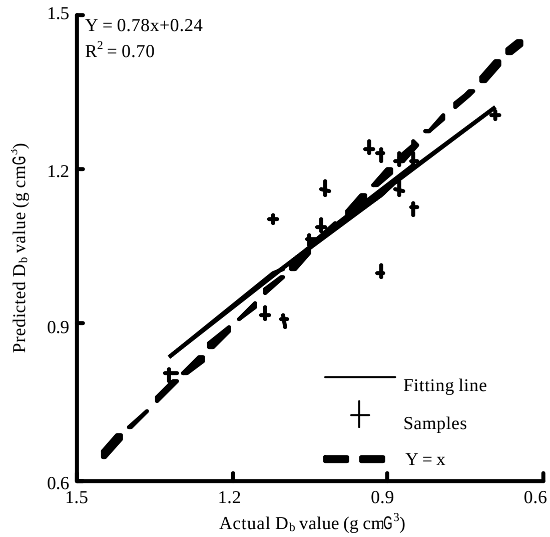

Fig. 2: Prediction results of M1

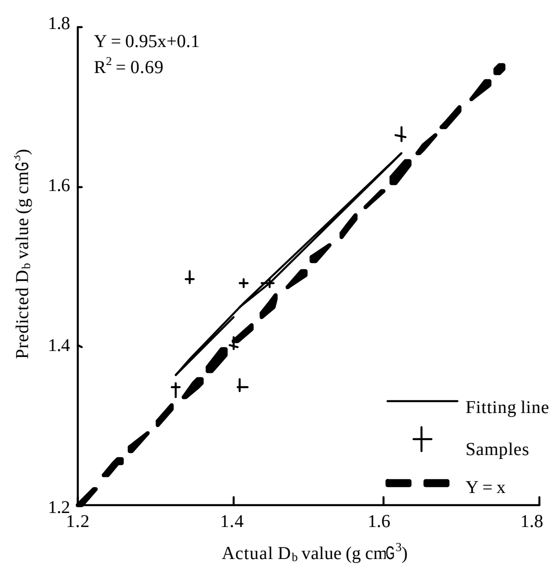

Fig. 3: Prediction results of M2

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.

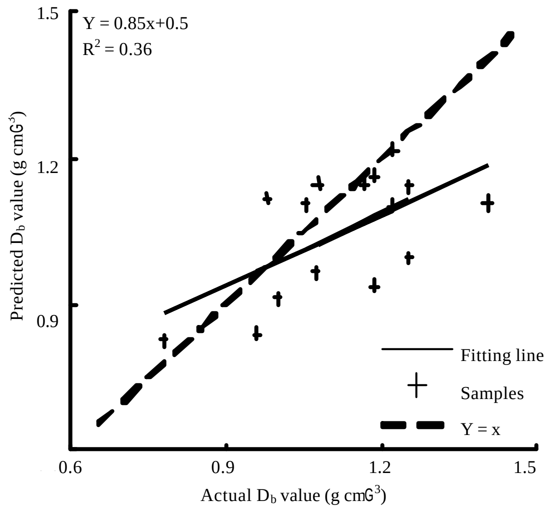

Fig. 4: Prediction results of M3

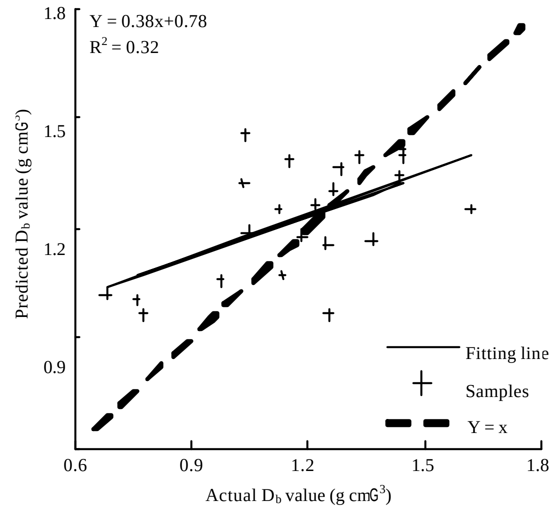

Fig. 6: Prediction results of M5

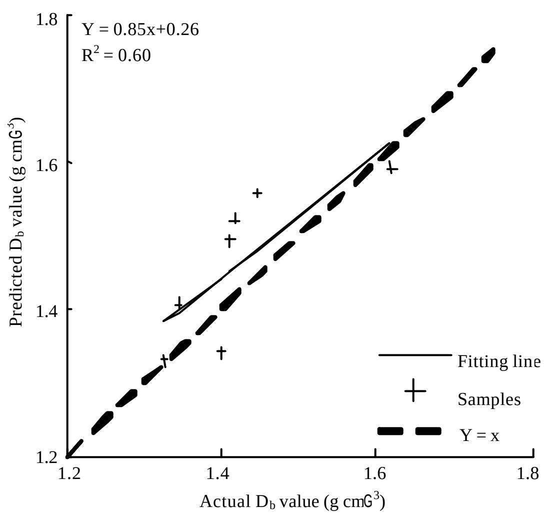

Fig. 5: Prediction results of M4

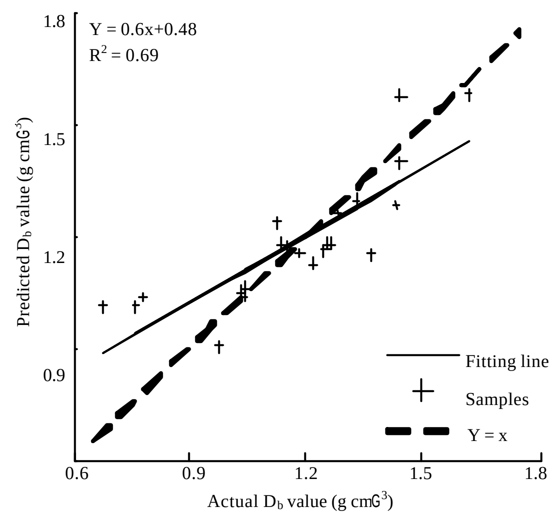

Fig. 7: Prediction results of M6

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 θ_v 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}.

The comparison of M1, M2, M5 and M6 supported soil texture's important role in D_b 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 D_b of different soils.

CONCLUSION

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

ACKNOWLEDGMENTS

This study was supported by the Fundamental Research Funds for the Central Universities (No. TD2013-3) and NSFC project (No.11202031). We also wish to thank DFG-NSFC (No. GZ888) for promoting this Sino-German Cooperation Group Research.

REFERENCES

ASAE, 2009. ASAE/ASABE S313.3: Soil Cone Penetrometer. ASAE, St. Joseph, Mich.

Adams, W.A., 1973. The effect of organic matter on the bulk and true densities of some uncultivated podzolic soils. J. Soil Sci., 24: 10-17.

Alexander, E.B., 1980. Bulk densities of California soils in relation to other soil properties. Soil Sci. Soc. Am. J., 44: 689-692.

Arrouays, D., W. Deslais and V. Badeau, 2001. The carbon content of topsoil and its geographical distribution in France. Soil Use Manage., 17: 7-11.

Brahim, N., M. Bernoux and T. Gallali, 2012. Pedotransfer functions to estimate soil bulk density for Northern Africa: Tunisia case. J. Arid Environ., 81: 77-83.

Cai, X., Y. Sun, P. Schulze-Lammers, W. Buescher and C. Maack *et al*., 2013. Shaft friction of an ASABE standard soil cone penetrometer. Trans. ASABE, 56: 839-846.

Ghehi, G.N., A. Nemes, A. Verdoodt, E. Van Ranst, W.M. Cornelis and P. Boeckx, 2012. Nonparametric techniques for predicting soil bulk density of tropical rainforest Topsoils in Rwanda. Soil Sci. Soc. Am. J., 76: 1172-1183.

Hernanz, J.L., H. Peixoto, C. Cerisola and V. Sanchez-Giron, 2000. An empirical model to predict soil bulk density profiles in field conditions using penetration resistance, moisture content and soil depth. J. Terra Mech., 37: 167-184.

Hollis, J.M., J. Hannam and P.H. Bellamy, 2011. Empirically-derived pedotransfer functions for predicting bulk density in European soils. Eur. J. Soil Sci., 63: 96-109.

Jalabert, S.S.M., M.P. Martin, J.P. Renaud, L. Boulonne, C. Jolivet, L. Montanarella and D. Arrouays, 2010. Estimating forest soil bulk density using boosted regression modelling. Soil Use Manage., 26: 516-218.

Jones, R.J.A., R. Hiederer, E. Rusco and L. Montanarella, 2005. Estimating organic carbon in the soils of Europe for policy support. Eur. J. Soil Sci., 56: 655-671.

Quraishi, M.Z. and A.M. Mouazen, 2013. Development of a methodology for in situ assessment of topsoil dry bulk density. Soil Tillage Res., 126: 229-237.

Santos, F.L., V.A.M. Jesus and D.S.M. Valente, 2012. Modeling of soil penetration resistance using statistical analyses and artificial neural networks. Acta Scientiarum Agron., 34: 219-224.

Topp, G.C., G. St-Amour and B.A. Compton, 1996. Measuring cone resistance and water content with a TDR-penetrometer combination. Proceedings of the 3rd Eastern Canada Soil Structure Workshop, Volume 3, August 21-22, 1996, Merrickville, Ontario, Canada, pp: 1-6.

Vaz, C.M.P. and J.W. Hopmans, 2001. Simultaneous measurement of soil penetration resistance and water content with a combined penetrometer-TDR moisture probe. Soil Sci. Soc. Am. J., 65: 4-12.

Vereecken, H., J. Maes, J. Feyen and P. Davis, 1989. Estimating the soil moisture retention characteristic form texture, bulk density and carbon content. Soil Sci., 148: 389-403.

Zhang, X.Y., L.W. Shao, H.Y. Sun, S.Y. Chen and Y.Z. Wang, 2012. Incorporation of soil bulk density in simulating root distribution of winter wheat and maize in two contrasting soils. Soil Sci. Soc. Am. J., 76: 638-647.