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ORIGINAL ARTICLES

Assessment Intelligence Artificial Neural Networks For Simulation Soil Hydralulic Properties

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ABSTRACT

This research attempt to using artificial neural networks (ANNs) for estimation of soil hydraulic properties. Simulation of soil hydraulic properties is a suitable method for saving time and cost spent for direct measurement. This research comprises regression pedotransfer functions (RegPTFs) and artificial neural networks (ANNs) for estimation of available water capacity (AWC) and saturated hydraulic conductivity (K_s). First AWC and Ks data of 221 soil samples from clay soils (clay>40%) of Guilan Province were collected and %silt, %clay, %sand, bulk density and %organic carbon values were determined. The data were spilt randomly into a calibration data subset (187 samples) and validation data subset (34 samples). Regression pedotransfer functions was performed by stepwise method and for establishing ANNs we used Marquardt-levenburg training algorithm and 3-layer perceptron structure with 6 neuron in one hidden layer. Regression functions for K_s was Ks= -3.288 + 15.168BD - 0.198%C + 0.531%OC included with easily available parameters: bulk density (BD), %clay (C) and %organic carbon (OC) with R^2=0.972 and AWC%= -17.830 + 0.974%C with R^2=0.885 for available water capacity. For determination of best ANNs model, we used three input pattern: SSC (sand, silt and clay), CBDOC (clay, bulk density and organic carbon) and SSCBDOC (sand, silt, clay, bulk density and organic carbon). Result showed that artificial neural networks with CBDOC input pattern with R^2= 0.98 and R^2= 0.91 for Ks and AWC respectively, had most accurate prediction. With comparison of ANN with CBDOC input pattern and regression pedotransfer functions, we found that ANNs with CBDOC input pattern had higher R^2 and Lower RMSR (root mean square of residual) and hence ANNs could estimate saturated hydraulic conductivity and available water capacity more accurately.

Key words: Simulation, Hydraulic proprties, artificial neural networks, soil.

Introduction

Soil hydraulic properties determination is essential to hydrological practices, solute transport models and runoff measurement, but direct measurement of hydraulic properties is time consuming and costly and so are called "Costly measured properties". However several researches have been done for indirect estimation of hydraulic properties from surrogate data such as texture, organic matter and bulk density. regression pedotransfer functions and Artificial neural are methods that can be used for simulation of soil hydraulic properties such as saturated hydraulic conductivity and available water capacity.

Regression Pedotransfer Functions:

Bouma (1989) expressed relationship between soil hydraulic properties and surrogate data such as particle size distribution, organic matter and bulk density and named it regression pedotransfer functions. Using regression pedotransfer function is not restricted to soil hydraulic properties estimation and used for simulation of soil chemical and biological properties. Gupta and Larson (1979), represent regression models for estimation of soil moisture at different matrices potential from sand, silt, clay, bulk density and organic carbon content. They showed that regression coefficient was higher than 0.94 at all of matrices potential. Regression pedotransfer functions with stepwise method can be used for permanent wilting point prediction accurately (Bell and Van keulen, 1995). Wosten and Van Genukhten (1986), Rawls *et al*. (1991) and Rawls *et al*. (1998) showed that regression models are suitable methods for simulation hydraulic conductivity and water retention curve properties.

Artificial Neural Networks:

Artificial neural networks are intelligent modeling methods and can be used for costly measured soil properties estimation. They have the capability of learning complex relationship between multiple input and

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output variables (Nemes *et al*., 2002). Artificial neural network is an attempt to build numerical techniques that are supposedly analogous to biological human neural system. Artificial neural network that were used in this research consist of an input, hidden and output layer, all containing simple autonomous processing elements (neuron, nodes, units) which are connected by adaptable communication paths called connectors (Minasney *et al*., 2004). Each connector is parameterized with a numeric value (weights) which indicated the strength of the connection between the connected neurons and ability to pass signals (Kralish *et al*., 2003). The number of neurons in input and output layers correspond to the number of input and output variables of the model. The number of hidden neurons can be varied freely but the optimal number depends on uncertainty and complexity of the modeling problem (Nemes *et al*., 2002). All input neurons $j = 1...J$ with the input variables $x_1...x_J$, are linked to all hidden layer neurons $k = 1...K$ by means of numeric adaptable connectors "weights" (W_{jk}). The input values is multiplied by weights and summed at the hidden neurons (Eq 1). The hidden neurons consist of weighted input and bias (W_{j0}). A bias is simply a weight with constant input of 1 that serves as a constant added to the weights and these are calculated from a set of data through training process. (Minasney & McBartney, 2002; Norgaard, 2002).

$$S_k = \sum_{j=0}^{J} (w_{jk} x_j) + w_{j0} \tag{1}$$

The result, S_k is used as a input for a So called activation function such as sigmoid functions yielding the hidden neuron output H_k (Eq 2).

$$H_k = \frac{1}{1 + e^{-S_k}} \tag{2}$$

Then H_k are multiplied by the weights of W_{kl} (Eq 3) and in a same way as H_k , model outputs, Y_l are calculated (Eq 4).

$$Z_l = \sum_{k=0}^{k} (W_{kl} \times H_k) \tag{3}$$

$$Y_l = \frac{1}{1 + e^{z_l}} \tag{4}$$

Artificial neural networks can be used for simulation saturated hydraulic conductivity (Tamari *et al*., 1998; Schapp and leij, 1998; Minasney *et al*., 2004), Water retention curve properties (Pachepskey *et al*., 1996; Schapp and leij, 1998) and another soil properties such as soil loss and runoff (Liznar and Nearing, 2003; Rosa *et al*., 1999) , soil particle size distribution (Nemes *et al*., 2002), soil dielectric constant (Person *et al*, .2002) and nitrate-nitrogen in drainage water (Sharma *et al*., 2003).

Material and Methods

The data for this study were taken from all the related research and experiment conducted in Guilan province research Institutes such as Rice Research Institute, Tea Research center and etc. which consist of 221 entries of field measured saturated hydraulic conductivity (using double ring) and laboratory measured available water capacity (pressure plate), sand, silt, clay, organic carbon and bulk density. All of samples have clay content > 40% and divided into clay soil according to texture classification. The data were spilt randomly into a calibration data subset (187 samples) and validation data subset (34 samples). Moreover, data subset used for determining the performance of two modeling method; artificial neural networks (ANNs) and Regression pedotransfer functions (RegPTFs).

Estimation of hydraulic conductivity and available water capacity using RegPTFs were initially carried out using SPSS 11.5 for windows with stepwise method.

For establishing ANNs, We used Neural Works Plus Software with marquardt-levenburgtraining algorithm and 3-layer perceptron structure with 6 neuron in hidden layer. The number of neurons in the input and output layers corresponded to the number of Input and output variables. The number of hidden layers and its neuron is

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determined by try and error method and assumed equal to 1 and 6 respectively. Activation function was defined as a sigmoid tangent function. For determination of the best ANNs, we used three input pattern: SSC (Sand, silt and clay), CBDOC (clay, bulk density and organic carbon) and SSCBDOC (Sand, silt, clay, bulk density and organic carbon). Saturated hydraulic conductivity and AWC assumed as output parameters.

Corresponding 3 patterns above, 3 ANNs with 3-6-2, 3-6-2 and 5-6-2 Structure were established.

The performance of the PTFs estimating the Saturated hydraulic conductivity and AWC, were assessed using three criteria: regression coefficient (R^2), root mean square of error (RMSR) and relative improvement (RI).

R2 is expressed as equation 5 where Y_i denote the measured value, $\hat{Y}$ is the estimated value, $\overline{Y}$ is the average of the measured value Y , and n is the total number of observation.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}_i\right)^2} \tag{5}$$

The root mean square of error indicated mean accuracy of prediction which represents the expected magnitude of error (eq 6). (Minasny and MCbartney, 2002; Schaap and leij, 1998).

$$RMSR = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{6}$$

And the another crition was relative improvement (RI) and related to performance improvement from one model (a) to another (b) (Eq 6). (Minasny and MCbartney, 2002; Schaap and leij, 1998).

$$RI = \frac{RMSR_a - RMSR_b}{RMSR_a} \tag{7}$$

R^2 and $RMSR$ were calculated for calibration and validation data subset and assumed that the best model is the model with highest R^2 and the lowest $RMSR$.

Results and Discussion

For saturated hydraulic conductivity estimation using RegPTF, Bulk density, %Clay and %OC entered in regression equationEquation regression coefficient for these variables were -0.198, 15.168 and 0.531 respectively and were statistically significant ($P<0.01$) with $R^2 = 0.97$ (Eq 8).

$$Ks = -3.288 + 15.168\ BD - 0.198\ \%C + 0.531\%\ OC \tag{8}$$

Where Ks is the soil saturated hydraulic conductivity, BD, C and OC are Bulk density, %Clay and %Organic carbon respectively. In other hand RegPTF for available water capacity, consist of only %clay with R2= 0.974 and was significant statistically (P < 0.01), (Eq8).

$$\%AWC = -17.830 + 0.974\%C \tag{9}$$

Where *AWC* is available water capacityand C is clay content. The prediction of K_s and AWC for 34 samples from Independent data subset using Equations 7 and 8, resulted in R^2 of 0.85 and 0.77 (fig 1) and RMSR values 0.39 and 1.5 respectively. RMSR values for Calibration data subset (187 samples) were 0.167 and 1.34 for AWC and Ks respectively. Our postulate was the best model has the lowest RMSR and the highest R^2. Descriptive statistics for saturated hydraulic conductivity (Ks) using three ANN models and regressions pedotransfer functions are summarized in Table 1. The R2 and RMSR of ANN prediction for saturated hydraulic conductivity ranged between 0.90-0.92 and 0.160-0.309 for calibration data set. In the other hand R2 and RMSR ranged between 0.84-0.91 and 0.226-0.394 respectively for testing data set. Comparison of three ANN models showed that ANN with CBDOC input pattern had highest R2 and the lowest RMSR in testing and calibration data set so ANN with CBDOC pattern performed best prediction within another ANN models.

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Table 1: R2 and RMSR values for estimation available water capacity (PWP-FC) using three ANNs and RegPTFs functions in calibration and testing data subset.

Model	R^2_{cal}	R^2_{test}	$RMSR_{cal}$	$RMSR_{test}$
SSC_{ANN}	0.90	0.84	0.309	0.394
$CBDOC_{ANN}$	0.97	0.91	0.160	0.226
$SSCBDOC_{ANN}$	0.92	0.89	0.164	0.252
Reg PTFs	0.97	0.89	0.167	0.390

Table 2: R2 and RMSR values for estimation available water capacity (PWP-FC) using three ANNs and RegPTFs functions in calibration and testing data subset.

Model	R^2_{cal}	R^2_{test}	$RMSR_{cal}$	$RMSR_{test}$
SSC_{ANN}	0.81	0.73	1.61	1.66
$CBDOC_{ANN}$	0.91	0.82	1.06	1.40
$SSCBDOC_{ANN}$	0.72	0.68	2.17	2.10
Reg PTFs	0.85	0.73	1.34	1.50

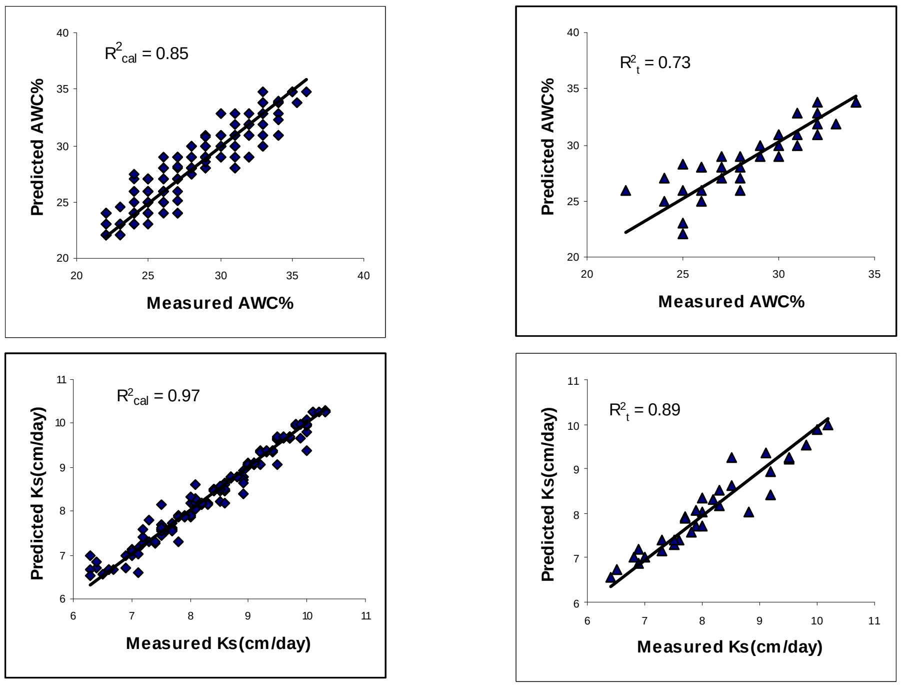


Fig. 1: Graphs for calibration and test data subset for Ks estimation using ANNs, cal and t subscripts indicated calibration and test.

In comparison of ANN using CBDOC input pattern with regression pedotransfer functions, There is no considerable difference between R^2 and RMSR in calibration data set but there is high difference between R^2 and RMSR in testing data set indicated the higher performance of ANN than regression in saturated hydraulic conductivity. Similar results were reported by Pachepskey *et al* (1996). The R^2 values of both three ANN models and regression pedotransfer functions were significant based on the analysis of variance (ANOVA test) ($P>0.01$). Generally, Both ANN and regression models could predict Ks accurately but ANN performed slightly better. However analysis of the ANN parameters suggested that more input variable and accurate data set were necessary to improve the prediction of hydraulic conductivity. (Tamari *et al*, 1999; Merdun *et al*, 2005). R^2 and RMSR used in three ANN models and regression pedotransfer functions prediction of AWC are tabulated in table2. R^2 and RMSR varied from 0.72 -0.91 and from 1.06-2.17 for calibration data set and varied from 0.68-0.82 and 1.40-2.10 for testing data subset respectively. Even thought both regression and ANN perform reliable prediction of AWC, but ANN produce promising results in calibration and testing data subset. In comparison of three ANN models, we found that ANN using clay, Bulk density and organic carbon as input pattern resulted in more accurate prediction. R^2 values were significantly in the base of ANOVA test ($P>0.01$). Using more input variable such as soil structure, and water content can improve estimation performance of available water capacity, saturated hydraulic conductivity or another soil hydraulic properties. (Schaap *et al*, 1998; Schaap and Leij, 1998; Merdun *et al*, 2005). Recent research stated using large data set produced more relevant prediction although some literature indicated using small set of promising data set. (Mayr and Jarvis, 1999; Nemes *et al*, 2002).

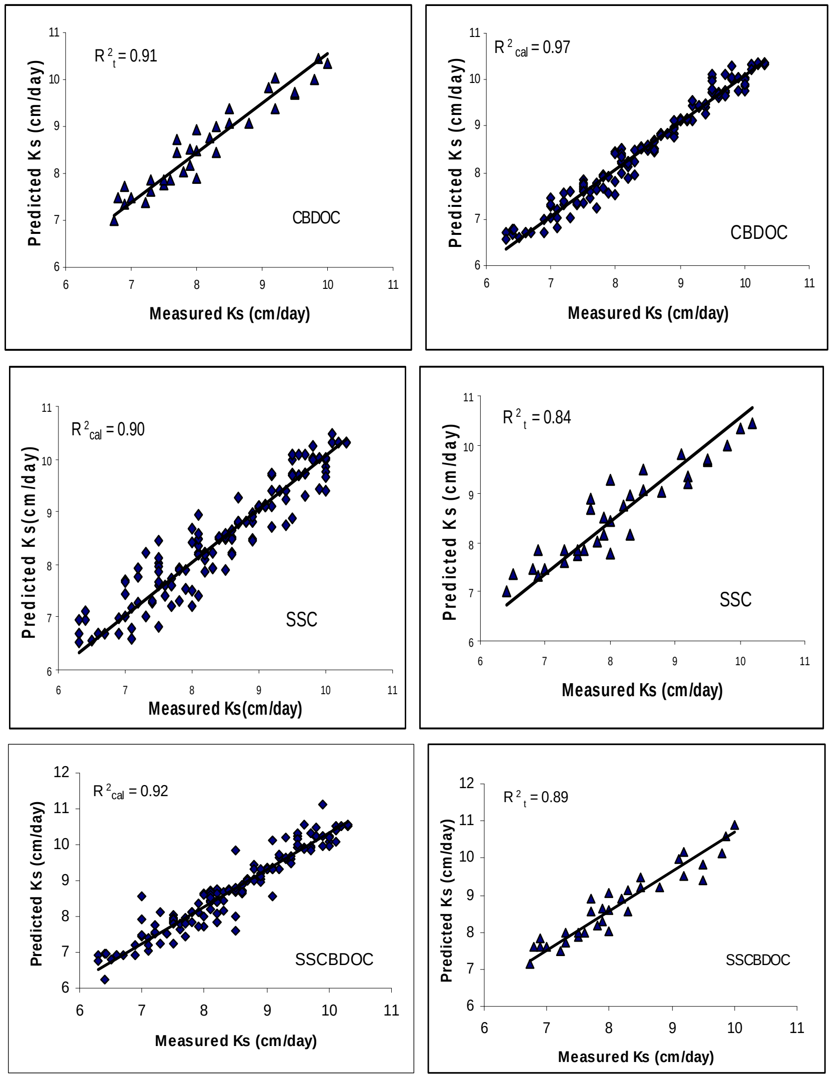
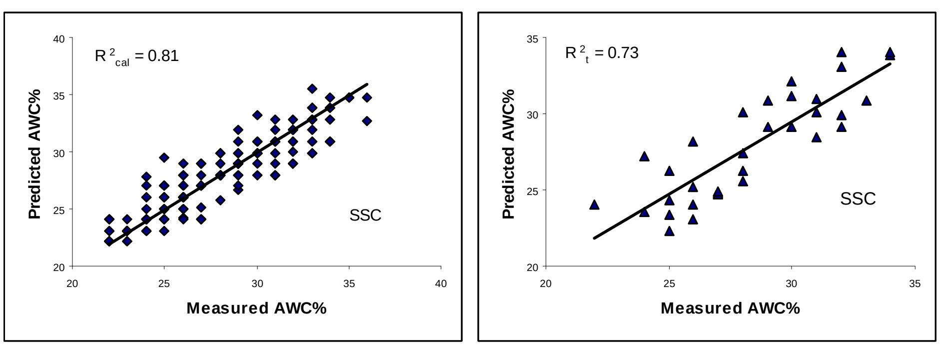


Fig. 2: Graphs for calibration and test data subset for Ks estimation using ANNs, cal and t subscripts indicated calibration and test.



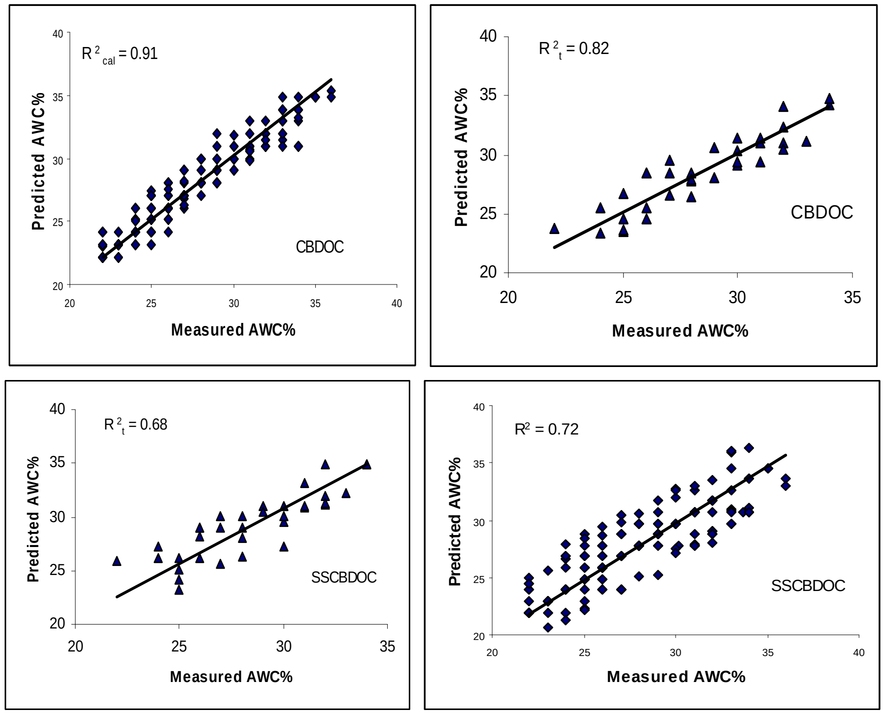


Fig. 3: Graphs for calibration and test data subset for AWC estimation using ANNs, cal and t subscripts indicated calibration and test.

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