ASSOCIATION INTELLIGENCE ARTIFICIAL NEURAL NETWORKS FOR SIMULATION SOIL HYDRAULIC PROPERTIES

1Forough Allahyaripour and 2Meysam Doai

1Damavand branch, Islamic Azad University, Damavand, Iran.
2Master of science, Department of Soil Science, Faculty of Agriculture, Gilan University, Gilan, Iran.

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 (Ks). 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 split 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 Ks was $K_s = -3.288 + 15.168BD - 0.198%C + 0.531%OC$ 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 properties, 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
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 ($W_{jk}$). 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).

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

(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).

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

(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).

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

(3)

$$Y_l = \frac{1}{1+e^{-Z_l}}$$

(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 splilt 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-levenburtraining 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
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).

$R^2$ is expressed as equation 5 where $Y_i$ denote the measured value, $\hat{Y}$ is the estimated value, $\bar{Y}$ is the average of the measured value $Y$, and $n$ is the total number of observation.

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

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

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

And the another crition was relative improvement ($RI$) and related to performance improvement from one model (a) to another (b) (Eq 6). Minasny and Mcbratney, 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 $R^2 = 0.974$ and was significant statistically ($P < 0.01$), (Eq8).

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

Where $AWC$ is available water capacity and 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 $K_s$ respectively. Our postulate was the best model has the lowest RMSR and the highest $R^2$. Descriptive statistics for saturated hydraulic conductivity ($K_s$) 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.
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.

<table>
<thead>
<tr>
<th>Model</th>
<th>R² cal</th>
<th>R² test</th>
<th>RMSR cal</th>
<th>RMSR test</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSCANN</td>
<td>0.90</td>
<td>0.84</td>
<td>0.309</td>
<td>0.394</td>
</tr>
<tr>
<td>CBDOCANN</td>
<td>0.97</td>
<td>0.91</td>
<td>0.100</td>
<td>0.226</td>
</tr>
<tr>
<td>SSCBDOCANN</td>
<td>0.92</td>
<td>0.89</td>
<td>0.164</td>
<td>0.252</td>
</tr>
<tr>
<td>Reg PTFs</td>
<td>0.97</td>
<td>0.89</td>
<td>0.167</td>
<td>0.390</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th>Model</th>
<th>R² cal</th>
<th>R² test</th>
<th>RMSR cal</th>
<th>RMSR test</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSCANN</td>
<td>0.81</td>
<td>0.73</td>
<td>1.61</td>
<td>1.66</td>
</tr>
<tr>
<td>CBDOCANN</td>
<td>0.91</td>
<td>0.82</td>
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<td>1.40</td>
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<tr>
<td>SSCBDOCANN</td>
<td>0.72</td>
<td>0.68</td>
<td>2.17</td>
<td>2.10</td>
</tr>
<tr>
<td>Reg PTFs</td>
<td>0.85</td>
<td>0.73</td>
<td>1.34</td>
<td>1.50</td>
</tr>
</tbody>
</table>

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 R² and RMSR in calibration data set but there is high difference between R² 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 R² 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). R² and RMSR used in three ANN models and regression pedotransfer functions prediction of AWC are tabulated in table2. R² 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 $K_s$ 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.

References


