Predicting iron and zinc content of soils in an apple orchard using artificial neural network

M. Rustu Karaman*, Ismail Iseri, Fatih Er and Tekin Susam

Department of Soil Science and Plant Nutrition, Agricultural Faculty, Gaziosmanpasa University, Tokat, Turkey.

Accepted 7 June, 2012

Evaluation of neural network based simulation models for the prediction of site specific soil properties of the large agricultural areas will provide important technological benefits for the efficient use of land resources and Agricultural Decision Making System. In this study, an artificial intelligence model was investigated for simulation of site specific iron (Fe) and zinc (Zn) levels in the soils of apple orchard by using a feedforward multilayered Artificial Neural Network (ANN). The measurements of Fe and Zn were made for the topsoil (0-25 cm) and subsoil samples (25-50 cm) collected from forty five different coordinates within intervals of 20 x 10 m based on a grid sampling system in the east and north directions. The measured coordinate values were reflected to the input layer of the developed two input one output feedforward multilayer of the ANN model. Respectively, the measured Fe and Zn values were reflected to its output layer, and then the training stage was started. In the training, back propagation algorithms were used to get the most suitable NN structure for the prediction. As a result of varied trainings, the ANN having two hidden layers and ten neurons produced the best estimation values for site specific Fe and Zn estimations. The most suitable prediction values ($R^2$ = 0.98 and $R^2$ = 0.97, $P<0.01$) were obtained from the ANN with 10.10.1 structure for site specific Fe and Zn levels in the topsoil. When the simulated values obtained from the ANN model were compared with the measured values, it was observed that successful results were achieved based on varied training values. Hence, the ANN based model should be calibrated for varied training conditions depending on different soil conditions to get more reliable results.

Key words: Artificial neural network, neural structures, iron, zinc, apple orchard.

INTRODUCTION

Proper soil management systems based on spatial variability of fields have to be developed and popularized in order to make healthy agricultural production that provides the protection of natural resources and considers the quality of the environment. Thus, many studies were carried out to predict the degree of site specific variability of agricultural soil properties (Keller et al., 2001; Park and Vleek, 2002; Tan et al., 2004; Sarmadian et al., 2009). However, heavy metal pollution has a special concern for many agricultural areas, but it is generally non-feasible to site specific sampling and monitoring of these chemicals due to economical limitations and other impossibilities.

It has been emphasized that these problems could be decreased by using the computer based geostatistical programs. Recently, fast developments in the computer based modeling studies have made the average and general studies in agricultural areas superficial which provided important chances for detailed spatial variability studies and site specific management applications. However, these models developed for one region may not give adequate estimates for a different region (Wagner et al., 2001). Artificial Neural Network (ANN) models can be used to overcome the non-linearity problem. The ANNs are the form of artificial intelligence based on the biological background for solving complex problems (Haykin, 1994; Samarasinghe, 2007; Huang, 2009). The computer based simulation models of ANNs are rapid, cost effective having greater prediction reliability and fast information processing and adaptation (Xu and Wu, 2002; Parvizi et al., 2010). One of

*Corresponding author. E-mail: rkaraman@gop.edu.tr.
the known neural network models are the multi-layer neural networks (Rumelhart and McClelland, 1986). Within this framework, it is possible to see the application possibilities of these models for agricultural and natural science studies. For example, a multi-layer ANN model was developed to predict the removal efficiency of Cd ions from aqueous solution (Arora and Srivastava, 2010). Amini et al. (2005) found that the neural network-based models provided more reliable predictions than the regression-based predictions. Many studies were also carried out using ANNs to estimate the spatial variability of some soil properties (Bayat et al., 2007; Sarmadian et al., 2009; Keshavarzia and Sarmadian, 2010; Parvizi et al., 2010).

Using the computer based ANN models for simulation of the spatial distributions of chemical soil properties such as iron (Fe) and zinc (Zn) has potential to get valuable advantage, because these immobile metals are greatly variable depending on non-linear site specific soil parameters such as calcium carbonate levels, clay contents etc. The bioavailability of these heavy metals has also great importance for the plant nutrition together with human beings and environment (Mengel and Kirkby, 2001). Thus, information on spatial distributions of heavy metals such as iron (Fe) and zinc (Zn) are important for refining farm managements for optimal plant growth and environmental aspect. Evaluation of the ANN based models could improve the decision support for field management practices in a more healthy and moderate way. In this study, an artificial intelligence model was investigated for prediction of site specific Fe and Zn levels on the soils of apple orchard by using a feedforward multilayered Artificial Neural Network (ANN) with proper training.

**MATERIALS AND METHODS**

**Site description and data selection**

The soil samples were obtained from an apple orchard area in Konya city (Turkey), located on a flat plain. The region is located between latitudes of 36°41′ and 39°16′ N and between longitudes of 31°14′ and 34°26′ E which has the area about 38.257 km². The average elevation of this land is 1.016 m with average annual precipitation about 326 mm, dominantly on May. Annual average temperature is 11.5°C, and average humidity is 60%. 60% of all area of Konya is covered by agricultural plantation, and apple orchard is valuable for this area. The soil samples were collected by hand auger from 0-25 (topsoil) and 25-50 cm (subsoil) depths at forty-five intersections of the grid system with intervals of 20 m in the east to west and 10 m in the north to south directions. The collected soil samples were air dried and ground to pass through a 2 mm sieve, and analyzed for DTPA-extractable Fe and Zn by flame AAS (Lindsay and Norvell, 1978). In the experimental topslois, saturation percent was 67.10%. It had also the following chemical properties: calcium carbonate content = 34.9%, pH (1:2.5) = 6.81, organic matter content = 1.90%, available soil phosphorus = 18.85 kg da⁻¹ and EC = 407 µmhos cm⁻¹. In the subsoils, saturation percent was 66.00%. It had also the following chemical properties: calcium carbonate content = 46.9%, pH (1:2.5) = 7.25, organic matter content = 1.43%, available soil phosphorus = 12.81 kg P₂O₅ da⁻¹ and EC = 427 µmhos cm⁻¹. A sample from the two data sets used for this study can be seen in Table 1. For both of the data sets (topsoil-subsoil), 63% of the total data was used in the training of the artificial neural network model, and the remaining 27% was used in the testing process (Jamshid and Ersoy, 1992; Dumuth and Beale, 2000). In a similar study, 20 soil samples were used for application of back-propagation artificial neural network in speciation of cadmium (Wang et al., 2010). In other study, the model has been established by training a back-propagation neural network with 58 samples and tested with other 14 samples (Liu et al., 2005). According to findings of Lake et al. (2009) and Amini et al. (2005) increasing the number of inputs will decrease the accuracy of the estimations (Keshavarzi and Sarmadian, 2010).

**Training of artificial neural networks**

In the application of ANN model for the present study, a multi-layered feedforward artificial neural network was developed. Two data sets containing the Fe and Zn values for topsoil and subsoil samples were estimated for the application of ANN model. In the study, measured coordinate values were reflected to the input layer of the developed two input and one output feedforward multilayer of ANN model. Hence, measured iron and zinc values were reflected to its output layer, and then the training stage was started. In the input layer of the developed artificial neural network, the coordinate values (east and north) were located, whereas the iron and zinc values were located as output layer (Dursun and Karaman, 2009). The used neural network model for Fe and Zn simulation outputs can be seen in Figure 1. Two different feedforward neural network models having two hidden layers with similar structures were used for the estimation of Fe and Zn values. In the training of the ANN, back-propagation algorithms were used, and input values of the output nodes are calculated by using the following equation:

$$I_{O_n} = \sum_{j=1}^{h} w_{jn} H_{O_j} \cdot \ n = 1,\ldots,m$$ (1)
In this equation; \( IO_n \) is the input value of the neurons at the output layer. These obtained values are passed through the efficiency function of the output layer, and \( O_n = f(IO_n) \) network output values are calculated. Each hidden neuron cell forms a hidden neuron output of \( HO_j \) by using a sigmoid activation function. It is calculated as below:

\[
HO_j = f(H_j) = \frac{1}{1 + \exp(-H_j + \theta_j)} \cdot f(H_j)
\]

In this equation; the output value of the \( j \)th is hidden neuron. \( \theta_j \) is the start value expressed as the bias constant, and it is connected to each neuron in the every layer. \( HO_j \) will be the input of the next layer (Dumuth and Beale, 2000; Elmas, 2003; Dursun and Karaman, 2008). In the training of the network, back-propagation algorithm (Matlab name is "trainrp") was used (Riedmiller and Braun, 1993; Gilat, 2004). The application was started by using an ANN model with a hidden layer. Each neural network model used for the Fe and Zn estimation were trained starting from 1000 steps up to 6000 steps with increments of 1000 steps. The same trainings were repeated up to obtain the best network structure. Back-propagation algorithm was used to minimize the obtained error by iterations and thus by weight updates. All formulas used for this study were copy pasted from general concepts (Dumuth and Beale, 2000; Elmas, 2003).

**Performance criteria**

The performance of the ANN model was determined by using the coefficient of determination \( (R^2) \) between predicted and measured data. The coefficient of determination is a measure that allows us to determine how certain one can be in making predictions from a certain model/graph (Colin et al., 1997). In a similar study, the coefficient of determination \( (R^2) \) was also properly used as performance criteria of ANN based prediction of soil parameters (Keshavarzia and Sarmadian, 2010).

**RESULTS AND DISCUSSION**

The 1000-6000 step trainings and the obtained test results with the real values \( (R^2 \) values) for the ANNs (in the structures of 5-5-1, 10-10-1, 15-15-1, 20-20-1) used the structures of 5-5-1, 10-10-1, 15-15-1, 20-20-1) used in the estimation of Fe and Zn distributions for topsoil and subsoil were presented in Figures 2 and 3, respectively. As a result of the trainings, while the optimal structures of 10-10-1, 10-10-1 were obtained for topsoil, the optimal structures of 5-5-1, 20-20-1 were obtained for subsoil. Thus, the best results for the estimation of Fe and Zn values for topsoil were obtained from the ANN model with 10-10-1 structure which contain two hidden layers and 10 neurons at each hidden layer \( (R^2 = 0.98, P<0.01 \) and \( R^2 = 0.97, P<0.01 \) for Fe and Zn values, respectively). For the subsoil Fe estimation, the best results were obtained from the ANN with 5-5-1 structure \( (R^2 = 0.83, P<0.01) \), whereas the best results for the subsoil Zn estimation were obtained from the ANN with 20-20-1 structure \( (R^2 = 0.96, P<0.01) \). In Figures 4 and 5, the comparison (by using test data) of the measured and simulated values for Fe and Zn levels obtained by using the ANN model were presented. As it is seen from the Figures 4 and 5, the values estimated by the ANN model are very close to the measured values which mean that the ANN model adequately simulated Fe and Zn levels for each soil layer. In the similar studies; site specific properties of soils were also successfully predicted using the model of ANN (Bayat et al., 2008; Sarmadian et al., 2009; Parviz et al., 2010).

When the test results of the application were examined, it can be seen from Table 2 that the best \( R^2 \) values have been obtained from models having different number of neurons. For example, whereas the most suitable Fe estimation value for topsoil was obtained from the ANN model with 10-10-1 structure, the most suitable Fe estimation value was obtained from the ANN with 5-5-1 structure Similarly the most suitable Zn value for the topsoil was obtained from the ANN model with 10-10-1 structure, whereas the most suitable value for the subsoil was obtained from the ANN model with 20-20-1 structure. The results indicated that the structures used for the ANN model depended on the selected training data and the initial values of the network such as weights, training and
Figure 2. $R^2$ values for the ANN used in estimation of topsoil Fe and Zn levels.

Table 2. $R^2$ values (P<0.01) obtained for varied ANN structures having varied hidden layer neurons.

<table>
<thead>
<tr>
<th>R² value</th>
<th>ANN structure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5-5-1</td>
</tr>
<tr>
<td>Topsoil Fe</td>
<td>0.83</td>
</tr>
<tr>
<td>Topsoil Zn</td>
<td>0.94</td>
</tr>
<tr>
<td>Subsoil Fe</td>
<td>0.83</td>
</tr>
<tr>
<td>Subsoil Zn</td>
<td>0.66</td>
</tr>
</tbody>
</table>

momentum coefficients.

Conclusion

The ANN model showed a good performance on prediction Fe and Zn levels of soils in an apple orchard. When the simulated values obtained from the ANN model were compared with the measured values, it has been observed that successful results were achieved based on varied training values. Another interesting point was that each network model used for training has produced the best results at different training values (1000-6000). This indicated that once the learning was completed, the
Figure 3. $R^2$ values for the ANN used in estimation of subsoil Fe and Zn levels.

Figure 4. Measured and ANN-simulated Fe and Zn levels for topsoil.
Figure 4. Contd.

Figure 5. Measured and ANN-simulated Fe and Zn levels for subsoil.
training has to be stopped, otherwise the overtraining of the ANN models will not result in the obtaining of good results. Hence, the ANN based model should be calibrated for varied training conditions depending on different soil conditions to get more reliable results.

REFERENCES


