Asian Journal of Chemistry Vol. 21, No. 1 (2009), 239-247

Artificial Neural Network Based Modeling of Spatial Distribution of Phosphorus on the Tomato Area

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In this paper, an artificial neural network (ANN) based modeling has been presented. Simulation of spatial variability of available phosphorus levels for soils on the tomato crop area was done by using the model of ANN. The method is commonly successful in issues such as model selection and classification, function forecast, determination of optimum value and data classification. In this study, a program was developed in C++ programming language to analysis the data by means of ANN method. For this aim, topsoil (0-20 cm), subsoil (20-40 cm) and plant samples were taken from the tomato plots based on 20 meters period and the area was modeled with 5 meters period. The findings clearly showed that a great spatial variability occurred in available phosphorus for topsoil and subsoil. In order to observe the performance of ANN based phosphorus model, experimental data curves have been compared with the curves obtained after the ANN training. After comparing the experimental results with the recommended method, it is observed that it shows realistic results. The results obtained from the simulation show that the modeling which is formed for the available phosphorus change is applicable. Therefore the developed model could be an alternative method for the predictions of phosphorus in tomato crop areas since the created neural network model of phosphorus resembles the actual data.

Key Words: Artificial neural network, Phosphorus prediction, Tomato crop, Identification, Data mining, Simulation.

INTRODUCTION

Factors affecting crop yield and quality are site-specific[1]. Site-specific nutrient managements increase farmers' profitability and reduce the environmental impact of fertilizer applications[2]. Plant nutrients in the agricultural area should exist not only in sufficient levels, but also in balanced forms for sustainable soil fertility and crop quality. However, variability in soil properties causes uneven crop growth and decreases the effectiveness of uniformly applied fertilizer on a field scale[3]. For example, phosphorus

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accumulations or losses in agricultural systems are affected by many site-specific soil and management characteristics.

The economic benefits of phosphorus fertilization on crop production are well known. However, excessive soil phosphorus is a potential risk for environmental hazard. Crop uptake of fertilizer phosphorus per season varies between 5 and 25 % of the amount applied, although subsequent crops[4] take more up. Site-specific soil sampling methods and measurements can help in minimizing of the environmental impacts of phosphorus with avoiding excessive phosphorus fertilizer applications. Lauzon *et al.*[5] have revealed that in most cases, soil test variation maps based on 60 or 90 m grid soil samples did not result in an increased ability to predict the soil test level at a given location in the field. It was concluded that a grid spacing of 30 m or less would be required to adequately assess the spatial variation of soil test phosphorus. On the other hand, some methods such as electromagnetic induction (EMI) were used to easily measure soil variability for precision farming[6]. However, Webster[7] and Mallants *et al.*[8] emphasized that the problems for intensive soil samplings depending on spatial variability could be decreased by using package computer programs and jeoistatistical methods. Hence, the development of these information systems based on site-specific variability will help the managing of efficient use of phosphorus sources for intensive agricultural areas. In recent years, a lot of research[9-18] were carried about prediction of soil nonlinear specials.

Artificial neural networks (ANN) are the computer programs which are improved by the inspiration of brain physiology of human beings. ANN is generally successful in issues such as model selection and classification, function forecast, determination of optimum value and data classification. In this study, generally non-linear soil properties have been modeled by using ANN. The outputs of ANN model and the values of measurement have been compared with the simulation results; it has been figured out that ANN based modeling is a good alternative for other modeling methods.

EXPERIMENTAL

Artificial neural networks (ANN): Each neuron performs two functions as shown in Fig. 3. The first is to sum all the inputs from lower layer based on their weighing factors as given in eqn. 1. The second is to process this sum by a nonlinear sigmoid function as shown in eqn. 2. The input and output neurons may not contain nonlinear functions. The basic equations describing the dynamics of each neuron are;

$$net_j = \sum_i W_{ij} O_i \tag{1}$$

$$O_j = f\left(net_j + \theta_j\right) \tag{2}$$

where Wij weight between the jth neuron and the ith neuron in two adjacent layers, θj threshold of the jth neuron, Oi output of the ith neuron, Oj output of the jth neuron, f(.) sigmoid function.

A general structure of a multi-layer neural networks was shown (Fig. 1). Such a neural network contains three layers: input layer, hidden layer(s) and output layer. Each layer is composed of several neurons. The number of neurons in the input and output layers depends on the system dynamics and the desired accuracy. All the neurons in adjacent layers are interconnected. The strength of the interconnection was determined[19] by weighting vector of neural networks.

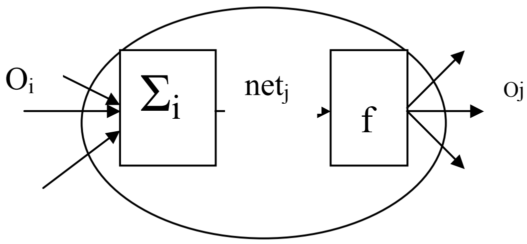


Fig. 1. A single neuron

Training of neural network: The most common method of neural networks training is back error propagation algorithm. The algorithm is based on the gradient search technique that minimization process is done by adjusting the weighting vector of the neural networks. Let the objective function (E) could be write as;

$$E = \frac{1}{2}\sum_{p}\sum_{j}\left(T_{pj} - O_{pj}\right)^2 \tag{3}$$

where Tpj is the target output of neuron j due to input pattern p. Opj is the neural networks output of the same neuron and for the same pattern. Minimizing eqn. 3 leads to a sequence of update of the weight vector. The weights of the interconnections between two adjacent layers could be updated based on the following formula.

$$W_{ij}(k+1) = W_{ij}(k) + \eta\frac{\delta E}{\delta W_{ij}(k)} + \alpha\Delta W_{ij}(k) \tag{4}$$

where k is the iteration number, η is the step size α is the momentum gain and ΔWij (k) is weight change based on the gradient of the cost function[19-21].

An artificial neural network (ANN) based modeling of a tomato crop area has been presented for simulation of spatial variability of available phosphorus levels. For this aim, topsoil (0-20 cm) and subsoil (20-40 cm) samples based on 20 × 20 m grids were taken from the plots under the tomato plants. The air-dried soils were screened to pass through a 2 mm mesh. Plant samples were also collected from the same plots together with soil samplings. In the soil samples, available phosphorus analysis was made by the method of Olsen *et al.*[22]. Determinations[23-26] were also made for saturation per cent, $CaCO_3$, pH, electrical conductivity[23] and organic matter contents for both topsoil and subsoil samples. Experimental data was subjected to the statistical analysis using StatMost package program[27]. In the experimental topsoils; saturation per cent was 46.45 %. Average value of $CaCO_3$ was 75.8 g kg^{-1}, pH was 8.01, organic matter content was 3.21 % and EC was 560 µmhos cm^{-1}. In the subsoils; saturation per cent was 43.52 %. Average value of $CaCO_3$ was 72.3 g kg^{-1}, pH was 8.03, organic matter content was 1.96 % and EC was 408 µmhos cm^{-1}.

By the reference of the experimentally obtained values, Supervized Learning method has been used for the modeling of mineral dispersion of soil area[28-31]. The increase in complexity directly prolongs the learning process and this could affect the performance of the structure in a negative way. In ANN applications, there is no rule to find the most suitable layer and the number of neurons. Generally the complexity of the system is uncluttered by the increase in the number of hidden layers and the hidden neurons. At the beginning of the study, the neural network with four layers, which are input layer, hidden layers and output layer, is chosen as having. By trial and error, it has found that the most suitable network structure for the system is composed of one input layer, two hidden layers and one output layer. The numbers of nodes for each layer are 2, 6, 6 and 1, respectively. For the chosen ANN structure, two hidden layers (5-5 neurons) have been used additionally to our input as east/north and output as P_2O_5. Fig. 2 shows ANN model used for the modeling of P_2O_5 change of soil. A packet program which can be used for the training of the systems with an input layer of 15 inputs and a output layer of maximum 10 outputs for the training of ANN by using the C++ Program Language has been prepared.

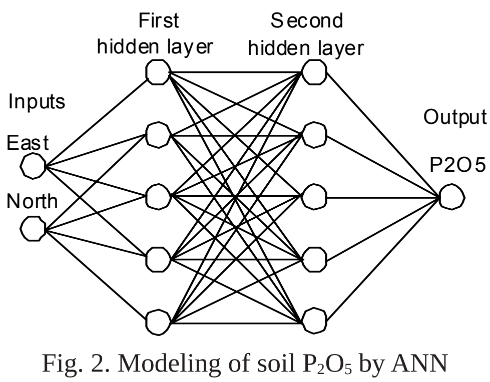


Fig. 2. Modeling of soil P_2O_5 by ANN

After the determination of the systems network structure, training of network begins with determining learning coefficient which will be used for the training, momentum coefficient and entering the numbers of data samples.

RESULTS AND DISCUSSION

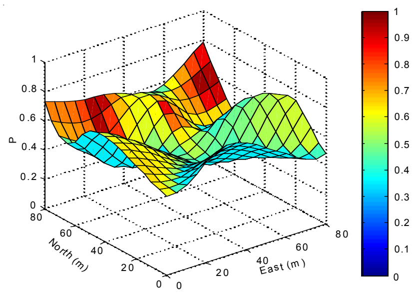
The coefficient of variance (CV), kurtosis and skewness values for site-specific phosphorus values of topsoils, subsoils and plants on the tomato area were presented Table-1.

TABLE-1
SPATIAL VARIABILITY OF SITE SPECIFIC P VALUES FOR TOPSOILS, SUBSOILS AND PLANTS ON THE TOMATO AREA

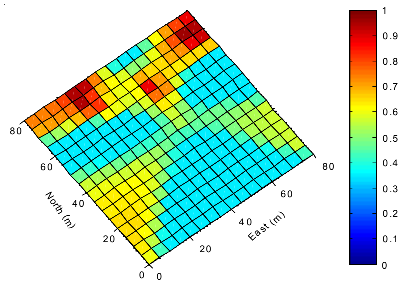
Parameters	Min.	Max.	Mean	CV (%)	Kurtosis	Skewness
Topsoil						
P, kg $P_2O_5.da^{-1}$	13.59	44.73	27.23	28.17	0.1124	0.4103
Subsoil						
P, kg $P_2O_5.da^{-1}$	6.26	16.79	11.78	20.96	-0.0539	-0.0027
Plant						
P, %	0.31	0.79	0.57	21.24	-0.4701	-0.1836

The maximum CV value of 28.17 % was obtained for topsoil phosphorus, while the CV value was 20.96 % for subsoil phosphorus. The available phosphorus contents of topsoil were varied from 13.59 to 44.73 kg P_2O_5 da^{-1} and average value was 27.23 kg P_2O_5 da^{-1}. For subsoil, the available phosphorus contents were varied from 6.26 to 16.79 kg P_2O_5 da^{-1} and average value was 11.78 kg P_2O_5 da^{-1}. The findings showed that phosphorus values were more variable in topsoils than in subsoils since the topsoils have been frequently mixed with plowing activities and applied phosphorus fertilizer[32]. Dikici and Gündogan[33] have also found a high coefficient of variation (CV 31 %) for Olsen's phosphorus values suggesting that there was a high phosphorus variability within cotton field. On the other hand, the coefficient of variance (CV), kurtosis and skewness values showed that variability occurred for site-specific phosphorus values of the tomato plants. The CV value of 21.24 % determined for phosphorus content of the plants. The values for phosphorus contents of tomato plants were varied from 0.31 to 0.79 % and average value was 0.57 %. Significant correlation, $r = 0.42$ and $p < 0.03$, was found between site specific plant phosphorus uptake and soil available phosphorus in the topsoil. It means that the plants have a higher spatial dependency of topsoil available phosphorus.

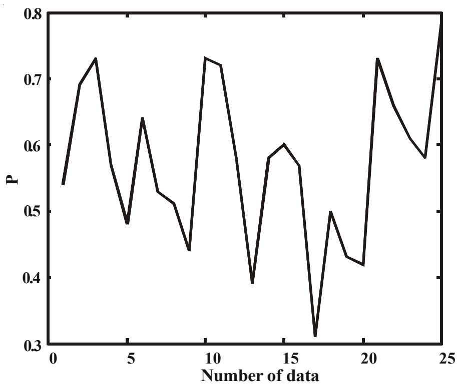
Fig. 3. shows that ANN model is applicable for expressing the phosphorus in the topsoil (a) three-dimensional maps of phosphorus and (b) contour maps of site-specific phosphorus levels for in topsoil c) the obtained curve of phosphorus in topsoil from calculated and simulated data.



(a) Three-dimensional map



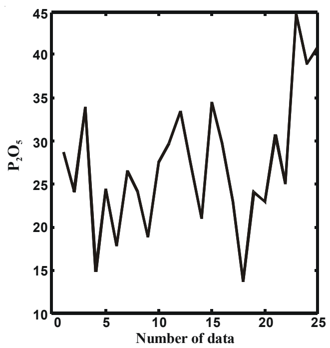
(b) Contour map



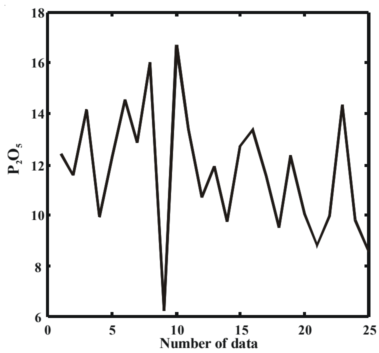
c) The obtained curve of calculated and simulated phosphorus data

Fig. 3. ANN model is applicable for expressing the phosphorus in topsoil

In order to see the performance of ANN based P_2O_5 model, experimental data curves have been compared with the curves obtained after the ANN training. The obtained curves have been shown in Fig. 4a and b show that the build up ANN model is applicable for expressing the P_2O_5 of the soil.



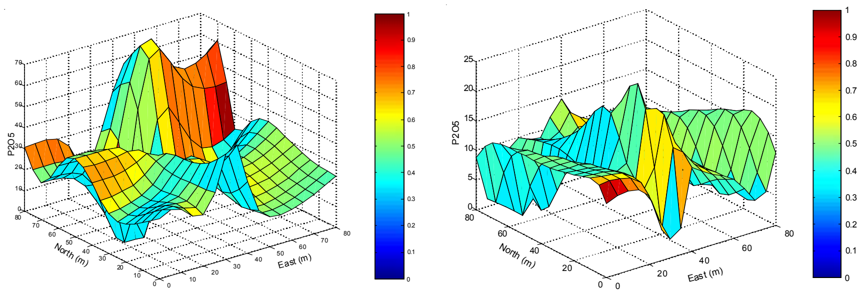
a) Topsoil



b) Subsoil

Fig. 4. The obtained curves of ANN model is applicable for expressing the P_2O_5 of the soil (a) Topsoil (b) Subsoil

Three-dimensional maps for topsoil and subsoil of the tomato area also indicated a great spatial variability of site specific available P_2O_5 as shown Fig. 5a and b. In general, experimental topsoil has a high and very high level of site-specific available phosphorus amounts, meaning that available phosphorus highly accumulated in topsoil. The results have revealed that uniform phosphorus fertilizer managements based on an average soil phosphorus levels will result in increasing unequal soil phosphorus distribution and unbalanced plant phosphorus consumption.

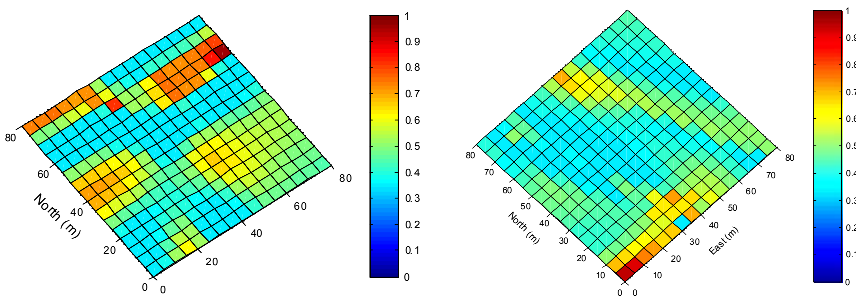


a) Topsoil b) Subsoil

Fig. 5. Three-dimensional maps of available P_2O_5 in the soil, kg da^{-1}

The contour maps for topsoil and subsoil of the tomato area also indicated a great spatial variability of site specific available P_2O_5 as shown Fig. 6a and b.

The findings clearly showed that the site specific phosphorus level in the tomato soil was important factor for maximum phosphorus utilization by the tomato plants. Thus, fertilization programme based on site-specific phosphorus demands of the plants will increase phosphorus use efficiency of the plants with proper phosphorus rates.



(a) Topsoil (b) Subsoil

Fig. 6. Contour maps of site specific P_2O_5 levels for topsoil and subsoil, kg da^{-1}

For the determination of selected soil properties change of the simulated area, a measurement method based on the measurement of minerals of soil has been used. After the calculation of selected soil properties 0-80 m with 20 m periods to the North and to the East 0-80 m (20 m rise by threes), the obtained values have been shown in Table-2.

TABLE-2
COMPARING OF SIMULATED AND MEASURED VALUES FOR SITE SPECIFIC SOIL P_2O_5 (kg da^{-1}) LEVELS AND PLANT PHOSPHORUS CONTENTS (%)

East (m)	North (m)	Simulated topsoil P_2O_5	Measured topsoil P_2O_5	Simulated subsoil P_2O_5	Measured subsoil P_2O_5	Simulated plant P	Measured plant P
0	0	28.709692	28.710001	12.435506	12.435402	0.539998	0.540000
0	20	24.070064	4.070000	11.588206	11.588440	0.689991	0.690000
0	40	33.979104	33.980000	4.169242	14.169184	0.729986	0.730000
0	60	14.729519	14.730000	9.924180	9.924407	0.570004	0.570000
0	80	24.530177	24.530001	12.325563	12.325795	0.480006	0.480000
20	0	17.820139	17.820000	14.517877	14.517933	0.639965	0.640000
20	20	26.540084	6.540001	12.854826	12.853901	0.530029	0.530000
20	40	24.120779	24.120000	16.022445	16.022538	0.510009	0.510000
20	60	18.828237	18.830000	6.237489	6.237629	0.439995	0.440000
20	80	27.519676	27.519999	16.730277	16.730000	0.730000	0.730000
40	0	29.649849	29.649999	13.402797	13.401936	0.720021	0.720000
40	20	33.459265	33.460001	10.691941	10.691656	0.579992	0.580000
40	40	27.630365	27.630000	11.917022	11.917261	0.389999	0.390000
40	60	21.039585	21.040000	9.695712	9.695230	0.579997	0.580000
40	80	34.519568	34.520000	12.703676	12.704437	0.600002	0.600000
60	0	29.749341	29.749999	13.370838	13.372043	0.570008	0.570000
60	20	22.949063	22.949999	11.558233	11.558547	0.309992	0.310000
60	40	13.590268	13.590000	9.505576	9.505908	0.500005	0.500000
60	60	24.060146	24.059999	2.335134	12.335760	0.430002	0.430000
60	80	22.949477	22.949999	10.035177	10.034015	0.420004	0.420000
80	0	30.720066	30.719999	8.808298	8.808410	0.729999	0.730000
80	20	24.960018	24.960000	9.974921	9.974228	0.660000	0.660000
80	40	44.727267	44.730000	14.369021	14.368470	0.610003	0.610000
80	60	38.893899	38.889999	9.785264	9.784908	0.579999	0.580000
80	80	40.888874	40.889999	8.519010	8.519446	0.790000	0.790000

*Available phosphorus; high = 9-15 kg P_2O_5 da^{-1} and very high = 15 kg P_2O_5 da^{-1}

Conclusion

With the help of this developed NN model, it is intended to determine the P_2O_5 of selected soil area properly. In order to see the performance of ANN based P_2O_5 model, experimental data curves have been compared with the curves obtained after the ANN training. After comparing the experimental results with the recommended method, it is concluded that it shows very realistic results. The results obtained from the simulation show that the modeling which is formed for the P_2O_5 change is applicable. Simulations results show very good agreement with measured results.

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(*Received*: 10 December 2007; *Accepted*: 20 August 2008) AJC-6762