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NEURAL NETWORK MAPPING TO OBTAIN 2D DISTRIBUTED FIELD INFORMATION

—— Application to Spatially Varied Infiltration Data ——

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Introduction

In agricultural engineering, we usually deal with spatially distributed data in agricultural fields. The relation between spatial coordinate (x, y) and spatially distributed parameter obtained in the filed is recognized by a type of non linear mapping. Neural network model is getting popular as a non linear regression tool. The application of neural network modeling has been receiving increased attention in many engineering fields[1)-4)]. It is suggested that the neural network model can be applied to many types of non-linear maps, if the pertinent variables were adjusted properly. Spatial distribution of infiltration data can be recognized as a kind of non-linear mapping between infiltration data and spatial coordinate. It is very profitable to obtain contour map of agricultural field parameter from limited discreate data[5)-7)]. In this study, neural network model was applied to spatially dependent final infiltration rate. The results showed that neural network modeling can be used to describe the spatial variability of infiltration data. It was also shown that the neural network model can easily be used for spatial interpolation and the contour map was clearly obtained.

Water Infiltration Data

The water infiltration data were collected using double ring infiltration tests conducted in a Yolo Loam soil near U. C. Davis campus to investigate the spatial variability of water infiltration data. The cumulative infiltration was represented by integral of Hortion's equation : $Q=A_0(1-e^{-Ct})+A_1t$ in all cases tested, where Q(mm) is cumulative infiltration ; t is time (h) ; A_0, C, and A_1 are empirical coefficients. Sixty-three infiltration tests were conducted over a period of 21 days. Each infiltration datum was collected for a period of 24 hours. Unfortunately, five of 63 data sets were not used, resulting in 58 good data sets which were used in this analysis. Sakai et. al.[8] and Upadhyaya et. al.[9] have described the double ring infiltration test procedure in more detail. Sakai et. al.[10] found that neither the coefficient A_0 nor C was spatially dependent. However, the final infiltration rate A_1 was found to be spatially variable. In this study, therefore the spatially dependant final infiltration rate A_1 was analyzed using neural network model. Spatial distribution of the data are shown in Figure 1.

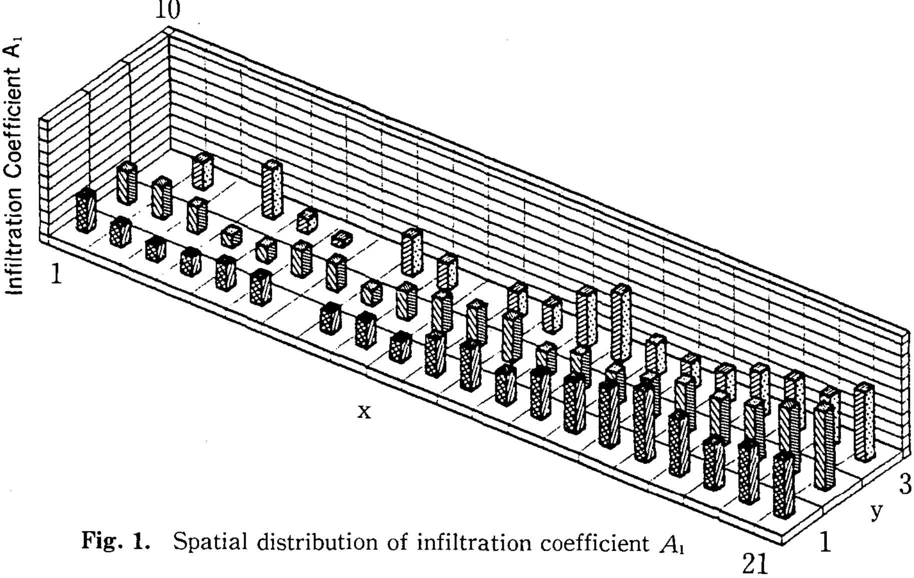

Fig. 1. Spatial distribution of infiltration coefficient A_1

Neural Network Model

1. Neuron model

A neuron model consists of multilayered network as shown in Figure 2. The

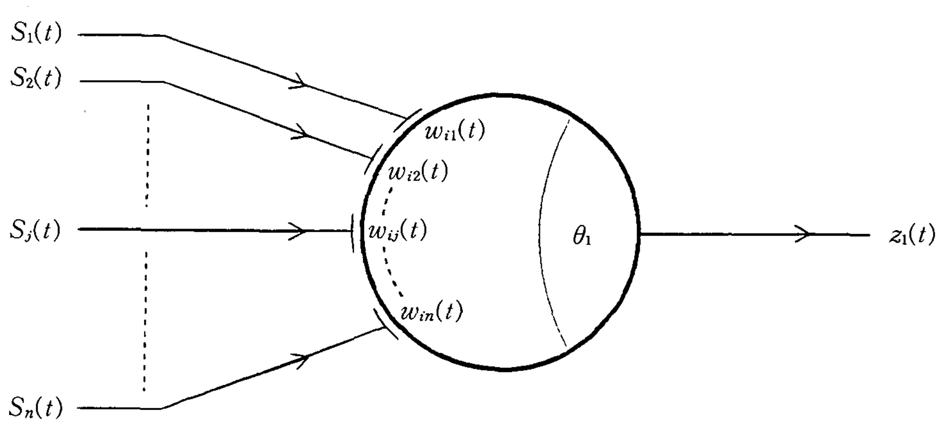

Fig. 2. Neuron model

potential $u_l(t)$ of the neuron is given by the weighted summation of all former neuron units and offset. The output of a neuron z_l is a sigmoid function of its potential u_l.

$$u_l(t)=\sum w_{ij}(t)S_j(t)+\theta_i$$
$$z_i(t)=f(\{u_i(t)\}$$
$$f(x)=1/\{1+\exp(-x)\}$$

2. Network structure

The field was divided into five blocks and neural network model was constructed for all the blocks. The neural network has three layers such as input layer, hidden layer and output layer (Figure 3.). The x and y coordinate data were normalized to the values from 0 to 1. The hidden layer has 7 neurons while the outer layer has one. This is a feed forward structure in one direction from the input layer to the output layer. Potential S_k and output O_k of unit k on the

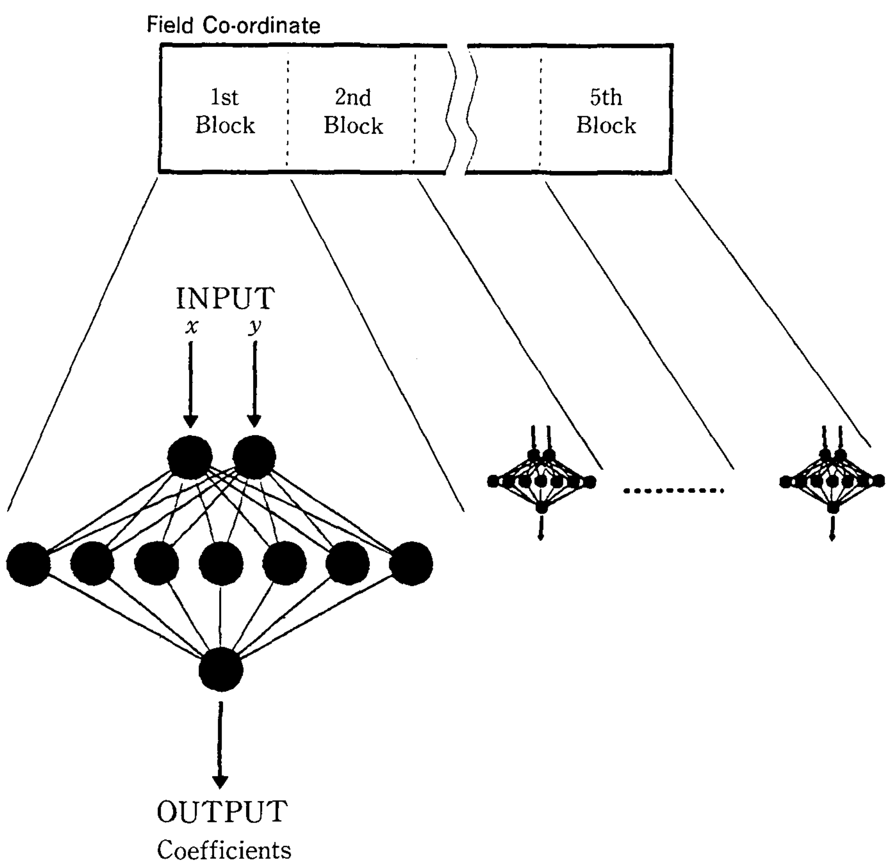

Fig. 3. A three-layer neural network model

output layer are expressed as follows ;

$$S_k = \sum V_{kj} H_j + \gamma_k$$
$$O_k = f(S_k)$$

where, V_{kj} : a weight value
H_j : output of unit i on the hidden layer
γ_k : offset of unit k on the output layer
Potential U_j and output H_j of unit j on the output layer are expressed as follows ;

$$U_j = \sum W_{ji} I_i + \theta_j$$
$$H_j = f(U_j)$$

where, W_{ji} : a weight value
I_j : output of unit i on the hidden layer
θ_j : offset of unit k on the output layer

3. Learning procedure

The back propagation method was applied to adjust the weight and offset of all units in this neural network model. The total error function E to be minimized was defined as follows :

$$E = \frac{1}{2} \sum_k (T_k - O_k)^2$$

Based on the steepest decent method, all weights and offsets were changed on each learning step as shown in the following equations :

$$V_{kj}(t+1) = V_{kj}(t) + \alpha \delta_k H$$
$$\gamma_k(t+1) = \gamma_k(t) + \beta \delta_k$$

$$W_{ji}(t+1) = W_{ji}(t+1) = W_{ji}(t) + \alpha \sigma_j I_i$$
$$\theta_j(t+1) = \theta_j(t) + \beta \sigma_j$$

where,

$$\delta_k = (T_k - O_k) O_k (1 - O_k)$$
$$\sigma_j = \sum \delta_k V_{kj} H_j (1 - H_j)$$

Regression and Interpolation on a 2D Space

Using the back propagation method, connection weights and offsets of all units on the network were adjusted. Predicted and experimental data of A_1 are presented in Figure 4. The determined coefficient for the model was 0.913. It can be concluded that the predicted value by developed neural network model fits very well to the experimental data. Using the neural network model, it is easy to conduct the interpolation for spatially distributed A_1. Contour map technique is shown in Figure 5. At every boundary, some discontinuity was observed. To eliminate this discontinuity, a neural network model must be constructed for the hole data (undivided). Clearly the neural network modeling can be a strong tool for creating non linear mapping of spatially distributed agricultural data.

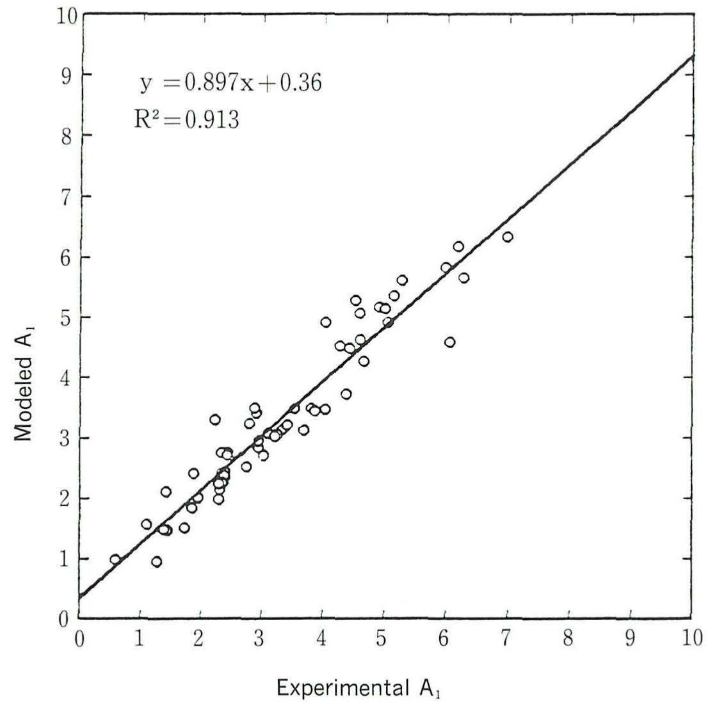

Fig. 4. Variation of experimentally obtained coefficient A_1 with coefficient A_1 predicted by the neural network model

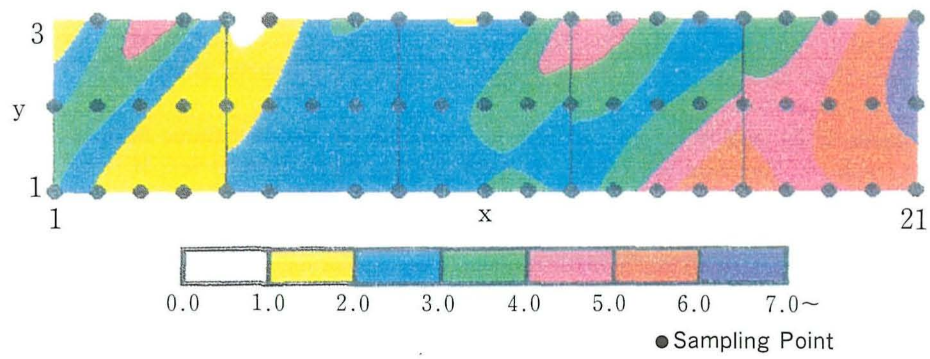

Fig. 5. Contour map for A_1 illustrated by the neural network model

Conclusion

Neural network modeling was applied to spatially distributed water infiltration data. The constructed neural network model has three layers-input, hidden and output layers. The input layer has two neurons corresponding to x and y coordinate. The hidden layer has seven neurons and the outer layer has a single neuron.

The back propagation method was applied to adjust the weights and offsets of all units on the model. Predicted data showed good agreements with their experimental data with a very high coefficient of 0.913. Using the neural network model, it is easy to conduct the interpolation and illustrate the contour map for spatially distributed A_1. The neural network modeling is a strong tool for creating non linear mapping of spatially distributed agricultural data.

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