# Application of Neural Networks for Soil Moisture Estimation in Paddy Field with Limited Meteorological Data

Chusnul Arif[1,2)], Budi Indra Setiawan[2)], Masaru Mizoguchi[1)], Ryoichi Doi[1)]

## 1. Introduction

In paddy field, monitoring soil moisture is required for irrigation scheduling and water resource allocation, management and planning. Soil moisture variation affects the pattern of water balance components such as evapotranspiration, runoff and deep percolation in paddy field. At the same time, soil moisture level is predominately influenced by water input through precipitation and irrigation. However, those hydrological data are often limited because measurement in the field is costly, complicated, and time consuming. In addition, the detailed meteorological data required to determine crop evapotranspiration are not often available especially in developing countries such as Indonesia. Therefore, the method to estimate soil moisture is needed by considering limited meteorological data. The current study proposes Neural Networks (NN) model to estimate soil moisture in paddy field with limited meteorological data.

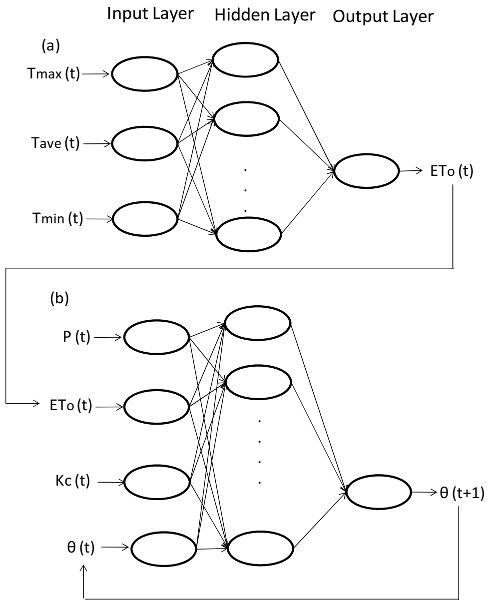
## 2. Materials and Methods

### 2.1 Field Experiment

The field experiment was conducted in the experimental paddy field in the Nusantara Organics SRI Center (NOSC), Sukabumi, West Java, Indonesia during two paddy cultivation periods. In both cultivation periods, the meteorological data consisting of air temperature and precipitation were measured every 30 minutes. For validation model, soil moisture was measured using 5-TE sensor (Decagon Devices, Inc, USA).

### 2.2 Development of Neural Networks (NN) models

Two kinds of NN model were developed integrating of three layers, i.e. input, hidden and output layers, respectively (Fig. 1). The first model was developed to estimate reference evapotranspiration (ETo) according to maximum, average and minimum values of air temperature. Commonly, minimum meteorological data are required to determine ETo from solar radiation and air temperature data using Hargreaves model. However, solar radiation data were often unavailable, thus we only used air temperature data for ETo estimation. For validation, the output of model was validated by comparing to ETo derived by the Hargreaves model. Then, estimated ETo and precipitation data were used to estimate soil moisture in the second model.




Tmax: maximum air temperature (°C), Tave: average air temperature (°C), Tmin: minimum air temperature (°C)

P: Precipitation (mm), Kc: Crop coefficient, θ : soil moisture (cm$^3$/cm$^3$), t : time (day)

Fig. 1 Neural networks model to estimate soil moisture in paddy field.

The observed data were divided into two data sets. The observed data from first paddy cultivation period were used for training process, while those from the second paddy cultivation period were used for validation process. Then, the developed NN model was evaluated by comparing observed and estimated values of soil

1) Dept. of Global Agricultural Sciences, the University of Tokyo
2) Dept. of Civil and Environmental Engineering, Bogor Agricultural University
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moisture using the indicator of coefficient of determination ($R^2$). The NN model was developed in Microsoft Excel with Visual Basic Application using back-propagation learning method, which is composed of two phases; first, propagation (forward and backward propagation), and second, weight update. All input parameters data were normalized between 0 and 1 by using fixed minimum and maximum values of each parameter.

## 3. Results and Discussion

### 3.1 Reference evapotranspiration estimation

Training process should be carried out firstly by the NN model to learn the pattern of observation data between input and output. In this process, a thousand iterations were performed to minimize the error of estimation.

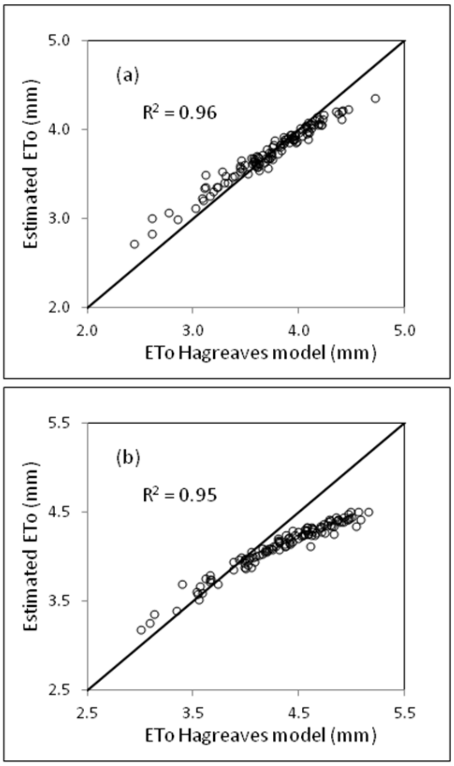


Fig. 4 Model evaluation of NN model for ETo estimation: a) training process, b) validation process.

As the result, the NN model estimated ETo with $R^2$ of 0.96 as shown in Fig. 2a. Then, the weights, results of training process, were used to estimate ETo using the second cultivation period data. Underestimation was occurred when ETo value was higher than 4.5 mm. However, with $R^2$ of 0.95, the estimated ETo showed good agreement to the Hargreaves model. Therefore, the NN model estimate ETo using the inputs of maximum, average and minimum values of air temperature.

### 3.2 Soil moisture estimation

The NN model estimated soil moisture with $R^2$ of 0.80 and 0.72 for both training and validation processes, respectively (Fig. 5). In both processes, tight linear correlations between observed and estimated values of soil moisture were observed, thus more than 72% of the changes in observed soil moisture were well described by the model. Therefore, the weights, representing relationship between the input and output model, could be used to estimate soil moisture in paddy field with limited meteorological data.

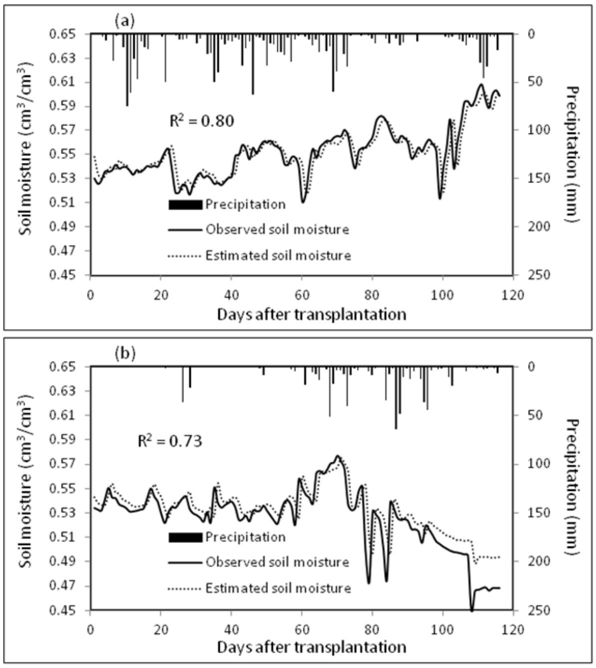


Fig. 5 Observed and estimated soil moisture during cultivation periods: a) first period, b) second period.

## 4. Conclusions

The NN model could be used to estimate reference evapotranspiration and soil moisture using limited meteorological data in a paddy field.