Estimation of Evapotranspiration Rate Using Neural Network with Plant Motion

Tsuyoshi OKAYAMA*,†, Yang YANG**, Peter P. LING* and Haruhiko MURASE**

* Department of Food, Agricultural, and Biological Engineering, Wooster, Ohio 44691, USA
** Wye Research and Education Center, University of Maryland, Queenstown, Maryland 21658, USA
*** Graduate School of Life and Environmental Science, Osaka Prefecture University, Sakai, Osaka 599-8531, Japan

(Received January 21, 2008)

Two neural network (NN) models were developed to estimate evapotranspiration (ET) rate of New Guinea Impatiens (Impatiens New Guinea Hibrid). Inputs of one NN model were canopy temperature, environmental factors (air temperature, relative humidity, radiation), and the plant motion (optional). The plant motion was calculated using the top projected canopy area. The mechanistic model was used in order to provide a baseline with which to compare performances of the NN models. In non-drought stress condition, root mean square error (RMSE) between estimated and measured ET rate of the NN model with the plant motion (NNP), the NN model without plant motion (NN), and the mechanistic model were 21.80%, 22.04%, and 29.94%, respectively. In drought stress condition, RMSE of the NNP, the NN, and the mechanistic model were 39.02%, 49.81%, and 72.09%, respectively. The plant motion could contribute the better performance when the plants were in drought stress condition. The NN model could estimate the ET rate without parameters used in the mechanistic model.

Keywords : drought stress, modeling, New Guinea Impatiens, non-contact sensing, top projected canopy area

INTRODUCTION

The maintenance of adequate water supply to plants is crucial to obtain maximum productivity. This is because physical activities and membrane transport process highly depend on water condition of a plant. Precise control of water delivery to greenhouse crop optimizes production quality, while minimizing inputs to the system. Over-watering crop is not only inefficient in terms of water usage, it also leads to higher expenses in pumping energy, heat energy to dry the environment, and disease and pest treatment for damp conditions. Thus, effective water use is a priority for greenhouse growers. Accurate water management in controlled environment crop production is accomplished if plant’s water status is detected precisely.

Experienced growers judge a plant’s water status by touching or visual observation. They probe soil or weigh pots to have an idea of how much water is in the soil. Visually, light soil surface color, dull leaf color, or slight wilting of the canopy are used as indicators that watering is needed. To automate the irrigation decision process, objective sensing methods and decision algorithms are needed. Evapotranspiration (ET) calculations, such as the Penman-Monteith models

Corresponding author: Tsuyoshi Okayama, fax: +81-72-254-2126, e-mail: okayama@bics.envi.osaka-f.ac.jp

†Present address : Nisshoku Corporation, Sakai, Osaka 599-8530, Japan
(Monteith and Unsworth, 1990), and the model proposed by Kacira et al. (2002a) estimated plant water use with climate measurements and physical and empirical characteristics of evapotranspiration of agricultural crops. A summary of evapotranspiration models used in greenhouse applications was given by Prenger et al. (2002). These mechanistic models could show good performance, however they work when plants is well watered. And they also have some parameters too difficult to measure. For example, the stomatal resistance changes with varying physiological and environmental conditions. The nature of the stomatal response is highly dependent on plant species, making it difficult to measure (Hatfield et al., 1985; Jalali-Farahani et al., 1994). And also precise leaf area index (LAI) is difficult to measure non-destructively.

In recent years neural network (NN) models, mimicking the work of biological brains, have shown to be effective as an exciting alternative to deal with complex systems. With their high learning ability, they have the capability of identifying and modeling the complex nonlinear relationship between the input and the output of a system (Rumelhart et al., 1986; Hunt et al., 1992). Numerous researchers have proven the applicability of NN models to problems in the agricultural field. One of advantages of using NN models is that any kind of information can be inputs and outputs of the NN model as long as they can be converted into numbers.

Some reports said that plant motion can be an indicator of drought stress of plants (Seginer et al., 1992; Murase et al., 1997). Kacira et al. (2002b) suggested that top projected canopy area (TPCA) could be used for estimating drought stress of plants. Therefore, the plant motion calculated based on the TPCA was used as one of the inputs of the NN model.

The objectives of this study were to develop NN models for estimating evapotranspiration rate without parameters which are difficult to measure such as, stomata resistance, and aerodynamic resistance, and to compare the performance of the NN model with the plant motion, of the NN model without the plant motion, and the mechanistic model. New Guinea Impatiens was used as a model plant in this study.

MATERIALS AND METHODS

Experimental setup

In this study, four experiments were conducted in a walk-in growth chamber in the Department of Food, Agricultural and Biological Engineering at The Ohio State University, Wooster, Ohio. The air temperature was controlled by a Honeywell temperature controller (UCD 3300, Honeywell, Fort Washington, PA). The relative humidity level was controlled by a steam humidifier (AutoFlo, Model WSU-14, EWC Controls Inc., Englishtown, NJ). The lighting system included eight 400W high pressure sodium and seven 400W metal halide lamps mounted. A detailed description of the chamber is reported by Kacira and Ling (2001).

Air temperature was measured using a type-K thermocouple, radiation level was measured using a LI-COR sensor (PY 8017, LI-COR, Inc., Lincoln, NE), and the relative humidity was measured using a relative humidity sensor (H3V-200, Rotronic Instrument Corp., Huntington, NY).

New Guinea Impatiens was used as a model plant in this study. Paradise Red on Pink variety was used in experiments 1, 3, and 4. Pure Beauty variety was used in experiment 2. Table 1 shows the measured environmental conditions during the experiments.

Plant motion

Kacira (2002b) suggested that the top projected canopy area (TPCA) could be used for an indicator of drought stress of plants. The image acquisition system consisted of a monochrome CCD camera (Pulnix TM-200, Pulnix America Inc., USA) and a 630 × 480 × 8 resolution frame grabber board (Matrox Meteor II Standard, Matrox Electronic Systems Ltd., Dorval, Quebec, Canada) installed in a personal computer. The camera was mounted perpendicular to the horizontal plane at a height of 1.0 m above the plant. After thresholding the original gray-level image, a binary image,
ET ESTIMATION USING NN MODEL

Table 1  Measured environmental conditions during the experiments.

<table>
<thead>
<tr>
<th>Air Temperature (°C)</th>
<th>RH (%)</th>
<th>Radiation (W m⁻²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp. 1</td>
<td>27.0±0.1</td>
<td>34.7±1.3</td>
</tr>
<tr>
<td>Exp. 2</td>
<td>28.6±0.2</td>
<td>36.3±2.8</td>
</tr>
<tr>
<td>Exp. 3</td>
<td>26.9±1.0</td>
<td>29.3±9.0</td>
</tr>
<tr>
<td>Exp. 4</td>
<td>27.7±0.2</td>
<td>47.0±4.2</td>
</tr>
</tbody>
</table>

g(x, y), was obtained. The TPCA was calculated by the number of pixels in the image (X), thus the definition of the TPCA was:

\[
TPCA = \sum_{i,j} g(x_i, y_j)
\]

\[
g(x_i, y_j) = \begin{cases} 
1 & \text{if pixel lies within object } X \\
0 & \text{otherwise} 
\end{cases}
\]  

(1)

Usually TPCA of a well-watered plant is gradually increasing. However, if the plant is under drought stress, TPCA decreases (Fig. 1). This result indicates TPCA represents water status of a plant. Therefore, the plant motion was employed as one of inputs of the NN model. The equation of the plant motion was:

\[
\text{The plant motion} = \frac{TPCA_{t+n}}{TPCA_i}
\]  

(2)

\(TPCA = \) top projected canopy area at time \(i \) (pixel)
\(TPCA_{t+n} = \) top projected canopy area at time \(i+n \) (pixel): \(n=2 \) in this study.

Mechanistic model of ET rate

Kacira et al. (2002a) used a modified Penman-Monteith model (the 2LAI term was added to the original formulation) to calculate ET rate (g m⁻² hr⁻¹) in growth chamber studies. This mechanistic model was used in order to provide a baseline with which to compare performances of NN models.

\[
ET\ rate = \left[\frac{2LAIpC_pVPD_s + \delta Q_{hadi}}{\delta + \gamma \left( 0.81 + \frac{r_{e}}{r_{ns}} \right)}\right] \times \frac{1}{\lambda}
\]  

(3)

(A list of symbols is provided at the end of this article.)

Fig. 1  Typical TPCA change of plants without irrigation.
Neural network model of ET rate

Neural Network Toolbox of Matlab by Mathworks Inc. (Demuth and Beale, 1998) was used throughout this study. The NN models have one hidden layer. A hyperbolic tangent sigmoid transfer function was used between the input and the hidden layer and linear transfer function was used between the hidden and the output layer. The number of units in the hidden layer was defined by trial-and-error method. The training, validation and testing data are very important to obtain a well-generalized network without overtraining. One common method of preventing overtraining is early stopping method. The method stops training process when the validation error increases for a pre-defined number of iterations (Demuth and Beale, 1998). The training set was used to train the network and the validation set was used for early stopping method. And test data set was used to evaluate the performance of a model. The data in three experiments was used as training and validation data. The data in the remaining experiment was used as the test set. Two NN models were developed. Inputs of one NN model were canopy temperature, environmental factors (air temperature, relative humidity, radiation), and the plant motion, and inputs of the other NN model were canopy temperature and environmental factors. Figure 2 shows schematic of the NN model. Four types of data sets for training, validation, and testing were investigated.

RESULTS AND DISCUSSION

Relationship between ET rate and the plant motion

Table 2 summarizes the equation of trend lines and $R^2$ values between the ET rate and the plant motion in each experiment. Experiment 2 had the highest $R^2$ value. This result indicates that the plant motion of Pure Beauty variety used in the experiment 2 is more affected by the ET rate than one of Pradice Red on Pink variety. And the relative humidity influenced the $R^2$ value. Experiment 4 had the highest relative humidity and also had a lowest $R^2$ value. Comparison between the performance of NN model with the plant motion and without the plant motion.

Figures 3 and 4 showed the results of case 3 and 4, respectively. The mechanistic model could not estimate the ET rate when plants were in the drought stress condition. Because the assumption in the mechanistic model is that the plants have always enough water for transpiration. Therefore, the results were divided into two groups, one was when plants were in non-drought stress condition, and the other was in drought stress condition. Condition of plants was classified based on the threshold value which was defined as the subtraction from the mean value to 1.96 times the standard deviation of the ET rate of control plants (well-watered plants).

Table 3 shows the results when plants were in non-drought stress condition, and Table 4 shows the results when plants were in drought stress condition. When plants were in non-drought...
ET ESTIMATION USING NN MODEL

Table 2  Relationship between the ET rate and the plant motion.

<table>
<thead>
<tr>
<th>Regression formula</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp. 1 The plant motion = 2E-05 ET rate + 0.9965</td>
<td>0.122</td>
</tr>
<tr>
<td>Exp. 2 The plant motion = 2E-05 ET rate + 0.9971</td>
<td>0.4131</td>
</tr>
<tr>
<td>Exp. 3 The plant motion = 4E-05 ET rate + 0.9965</td>
<td>0.2113</td>
</tr>
<tr>
<td>Exp. 4 The plant motion = 3E-05 ET rate + 0.9968</td>
<td>0.0668</td>
</tr>
</tbody>
</table>

![Graph showing ET rate versus time with different models and drought stress threshold.]

Fig. 3  Evapotranspiration rate of measured, the NN model with the plant motion, the NN model without the plant motion, and the mechanistic model in case 3.

![Graph showing ET rate versus time with different models and drought stress threshold.]

Fig. 4  Evapotranspiration rate of measured, the NN model with the plant motion, the NN model without the plant motion, and the mechanistic model in case 4.

stress condition, both of the NN models show better performance than one of the mechanistic model in case 3 and 4. However, the RMSE of the mechanistic model was better than one of the NN models in case 2. This was because the training data set of case 2 included only information of the Paradise Red on Pink variety. Therefore, the NN models could not estimated ET rate of the Paradise Beauty used in Exp. 2. There was not much difference of the performance between the NN model with the plant motion and the NN model without the plant motion.

When the plants were in drought stress condition, the RMSE of all models were higher than when the plants were in non-drought stress condition. This could be because the ET rate became unstable when the plants were in drought stress condition. The NN models showed much better


Table 3  Comparison root mean square errors between measured ET rate and estimated ET rate by the NN model with the plant motion, the NN model without the plant motion, and the mechanistic model, when plants were in non-under drought stress condition.

<table>
<thead>
<tr>
<th>Case</th>
<th>Training and validation set</th>
<th>Test set</th>
<th>The NN model with the plant motion (%)</th>
<th>The NN model without the plant motion (%)</th>
<th>The mechanistic model (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Exp. 2, 3, and 4</td>
<td>Exp. 1</td>
<td>22.01</td>
<td>18.46</td>
<td>20.52</td>
</tr>
<tr>
<td>2</td>
<td>Exp. 1, 3, and 4</td>
<td>Exp. 2</td>
<td>28.69</td>
<td>38.95</td>
<td>18.00</td>
</tr>
<tr>
<td>3</td>
<td>Exp. 1, 2, and 4</td>
<td>Exp. 3</td>
<td>14.98</td>
<td>12.64</td>
<td>39.96</td>
</tr>
<tr>
<td>4</td>
<td>Exp. 1, 2, and 3</td>
<td>Exp. 4</td>
<td>21.52</td>
<td>18.09</td>
<td>41.28</td>
</tr>
</tbody>
</table>

Average                                      21.80                                  22.04                                     29.94

Table 4  Comparison root mean square errors between measured ET rate and estimated ET rate by the NN model with the plant motion, the NN model without the plant motion, and the mechanistic model, when plants were in drought stress condition.

<table>
<thead>
<tr>
<th>Case</th>
<th>Training and validation set</th>
<th>Test set</th>
<th>The NN model with the plant motion (%)</th>
<th>The NN model without the plant motion (%)</th>
<th>The mechanistic model (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Exp. 2, 3, and 4</td>
<td>Exp. 1</td>
<td>72.20</td>
<td>98.75</td>
<td>51.72</td>
</tr>
<tr>
<td>2</td>
<td>Exp. 1, 3, and 4</td>
<td>Exp. 2</td>
<td>26.34</td>
<td>25.60</td>
<td>63.96</td>
</tr>
<tr>
<td>3</td>
<td>Exp. 1, 2, and 4</td>
<td>Exp. 3</td>
<td>21.30</td>
<td>33.97</td>
<td>72.17</td>
</tr>
<tr>
<td>4</td>
<td>Exp. 1, 2, and 3</td>
<td>Exp. 4</td>
<td>36.23</td>
<td>40.90</td>
<td>100.52</td>
</tr>
</tbody>
</table>

Average                                      39.02                                  49.81                                     72.09

Performance than the mechanistic model. The NN model with the plant motion shows smaller RMSE than the NN model without the plant motion. This was because the relation between ET rate and the plant motion becomes clearer when the plants are in drought stress condition. Therefore, the plant motion could contribute the better performance when the plants were in drought stress condition.

CONCLUSION

In this study the NN model for estimating evapotranspiration rate were developed. The NN model could eliminate the need to consider parameters which are difficult to measure such as, stomata resistance, and aerodynamic resistance. The inputs of the NN model were canopy temperature, air temperature, relative humidity, and radiation, and the plant motion. They can be measured easily by non-destructive method and real-time. In three cases out of four cases, the NN model showed better estimation than the mechanistic model. The effectiveness of using the plant motion as one of the inputs of the NN model was depends on the relative humidity. Because the higher humidity plants were in, the less clear relations there were. Normal plant canopy movement has a number of contributors including diurnal, air-movement-induced, and water-stress-induced movements. For using the plant motion for the water stress detection, it is important to decouple the stress-related plant motion from the other and to determine it quantitatively. In this study, the environmental condition was extremely more stable than the one of commercial greenhouses. For practical use of NN models, it is necessary to apply the NN models for the data in greenhouses, and to investigate how many data is required to obtain a NN model having good and stable performance.
ET ESTIMATION USING NN MODEL

List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_v$</td>
<td>Specific heat of the air at constant pressure</td>
<td>J kg⁻¹ °C⁻¹</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf area index</td>
<td>m² m⁻²</td>
</tr>
<tr>
<td>$Q_{\text{rad}}$</td>
<td>Radiation</td>
<td>W m⁻²</td>
</tr>
<tr>
<td>$r_a$</td>
<td>Air resistance for heat diffusion</td>
<td>m s⁻¹</td>
</tr>
<tr>
<td>$r_e$</td>
<td>Resistance to water vapor transfer at leaf level</td>
<td>m s⁻¹</td>
</tr>
<tr>
<td>$\nu_{\text{PD}}$</td>
<td>Vapor pressure deficit of air</td>
<td>kPa</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Thermodynamic psychrometric constant</td>
<td>Pa °C⁻¹</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Slope of saturated vapor pressure-temperature curve</td>
<td>Pa °C⁻¹</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Latent heat of vaporization of water</td>
<td>J kg⁻¹</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Density of the air</td>
<td>kg m⁻³</td>
</tr>
</tbody>
</table>

REFERENCES


