The first report of machine learning

LEI, ZHENG-YAN
Department of Bio-industrial Mechatronics Engineering
National Chung Hsing University
Taichung 402, Taiwan
jm21611294@gmail.com

***Abstract*—In this work, the infrared thermal image monitoring system was proposed for estimating the plant water stress. Nowadays, most of plant water stress monitoring is primarily dependent on the farmer experience which is not a precise and rapid method. Besides, the soil moisture sensors are a good solution for estimating the water stress. However, the sensing spatial area of the soil moisture sensor is limited for estimating the plant water stress. In this work, an infrared thermal image monitoring system was proposed and developed for estimating the plant water stress. The developed system was used for collecting the plants and environmental information in the experimental net house. The correlation between the measured leaf temperature, environmental information and stomatal conductance were analyzed. According to the results of experiment, the plant leaf temperature which encountered water stress would be 2-4 ºC higher than others. Besides, the stomatal conductance of the plant which experienced water stress was lower than well irrigation. The results show the infrared thermal sensor could be used as a sensor for monitoring the plant growing environment.**

Keywords—Stomatal conductance, Leaf temperature, Machine learning, Smart agriculture

I. Introduction

Recently, the environment of plant growth was changed with abnormal weather, climate change, fresh water security, agricultural or industrial pollution and so on. Not only animals but also plants would be affected by the rising temperature. So, lots of research teams are doing plant related research including plant physiology, growth environmental control, or genetic modification for improving the ability of growing and building an optimum growth condition. The agriculture development likes precision agriculture and smart agriculture would also promote by the new technology. With the advance of Internet of Thing (IoT), it would get the ability for big data analytics from intelligent monitoring at production environment to food traceability in order to increase agricultural production value and yield. Moreover, many countries invest lots of human power, expenditure, and equipment for building up the professional human, agricultural abilities and knowledge so as to improving agriculture.

The operation of plant physiology would be affected by the level of stomatal opening. The ability of plant physiology would be different due to the density of stoma. Otherwise, the conditions could be regulated by plant hormone for adapting the environmental change. For example, the abscisic acid plays a role in changing leaf size, stomatal size and root development. It also initiates leaf senescence by transcriptional regulation when plant under severe conditions. However, the plant physiology was affected not only by hormone regulation but also by environmental factors, such as light, ambient temperature, humidity, soil moisture, wind speed and so on. The severe conditions would make the partial closure of stomata for water saving. Simultaneously, the ability of gas exchange through stomata would be poor and the leaf temperature would be increased due to the lower heat abstraction. Otherwise, the crop water stress index could be used for measuring growing environment conditions. Furthermore, the amount of gas exchange could be obtained by measuring stomatal conductance and vapor pressure deficit for evaluating the plant physiology. In addition, the deposition of dust would also block the stomata, which would reduce the stomatal conductance and affect plant physiology.

The leaf temperature could be utilized by many research teams for rapidly and precise measurement about plant canopy temperature. The heat of leaf would be dissipated through the stomata and keep the temperature under optimum growing state when plant has sufficient water content for conducting photosynthesis and other physiological actions. On the contrary, the opening degree of stomata would be closed gradually for maintaining water state when plant under severe environment. However, the closure stomata would make leaf temperature increase, so infrared thermal image sensor could be used for observing plant situation. Otherwise, the measurement of leaf temperature combines with other indexes such as crop water stress index, vapor pressure deficit, rate of photosynthesis, and stomatal conductance would make the correlation result more precise. Besides, the target of observation is not limited to low plants because the unmanned aerial vehicle (UAV) combined with the infrared thermal image sensor. And it also could be used for observing tea leaf blight disease. The temperature of the region infected by the disease would be higher than healthy region. Thus, using infrared thermal image sensor could rapidly observe the growing condition and disease for improving the environment.

In order to achieve a more accurate analysis, many research teams use artificial neural network to obtain correlations that affect plant growth. Machine learning is an approach to put artificial intelligent (AI) into practice, which is applied in different kinds of science field. In agriculture, machine learning is introduced for effective yield prediction, crop or poultry physical detection, and so on. Those applications are included in smart agricultural management, and are able to benefit farmer constructively. Although machining learning is suitable for agriculture, there are some preliminary works to fulfill this technique. In this work, we demonstrate several steps to process collected data, including grouping data, training, and evaluating prediction results.

The prediction trend of the data is essentially needed for building a smart agricultural monitoring system and this development will be effective on agricultural products cultivating.

In this work, the infrared thermal image sensor was applied for observing leaf temperature, the porometer was utilized for measuring stomatal conductance, the environmental sensors for measuring the environmental factors, and raspberry pi embedded board for recording the collected information. This system can be employed for the long-term monitoring leaf temperature and estimating the water stress. The growing environment of cucumber were separated in well water and water stress respectively. It is possible to initially establish the optimal environmental model after machine learning to find out the correlation between leaf temperature, stomatal conductance and environmental factors.

II. The Papers Excepted to Read

A. *Plant physiology*

In the first paper [1], the objectives of this study were hence to detect water status in sesame under greenhouse conditions using Crop Water Stress (CWSI) and stomatal conductance (Ig) Indices. And using thermal infrared and visible cameras to obtain the thermal and visible images. One hundred and fifty pots were randomly assigned to three equal groups which were irrigated at soil water potential of −0.1 MPa (well-watered, WW), −1.0 MPa (moderate-water stressed, MWS), and −1.5 MPa (severe-water stressed, SWS). The soil-water potential based on depletion of ASW was determined by a soil moisture release curve which is the relationship between soil water content and water potential. The ASW and V_{irrig} were determined using Eqs. (1) and (2), respectively.

$$ASW = (\theta_{FC} - \theta_{PWP}) \times \rho_b \times V_{pot} \quad (1)$$

$$V_{irrig} = ASW \times P \quad (2)$$

where θ_{FC} and θ_{PWP} are the percentage of gravimetric soil water content at field capacity and permanent wilting point, respectively and ρ_b is soil bulk density (g cm^{-3}).

The result of this paper show that leaf temperature of moderate-water stressed and severe-water stressed plants was higher than well-watered plants by 1.9 and 2.6 ºC, respectively (Fig. 1). And stomatal conductance of moderate-water stressed and severe-water stressed was lower than well-watered plants.

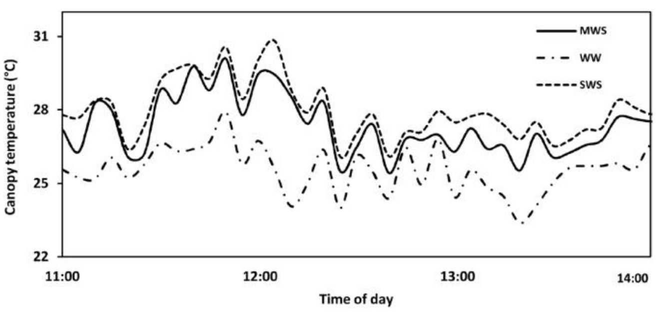

Fig. 1. Time variation in canopy temperature of sesame under three irrigation regimes (WW, MWS, and SWS) during 11:00 to 14:00 h.

The objective of the second paper [2] was to examine the effects of dust deposits on cotton leaves and to estimate their impact on crop development and yield. And the experiment was set up having two treatments and one control. The treatments were respectively having additional dust and having clean dust. In all the treatments, stomatal conductance, leaf temperature, biomass and yield were measured. A high-resolution thermal camera was used to measure canopy temperature (Fig. 2). All images were acquired between 12:00 and 14:00. And stomatal conductance was measured at the same time when infrared images were taken using a portable porometer. Measurements were taken on the abaxial side on three randomly-selected, fully-developed, sunlit leaves per plot.

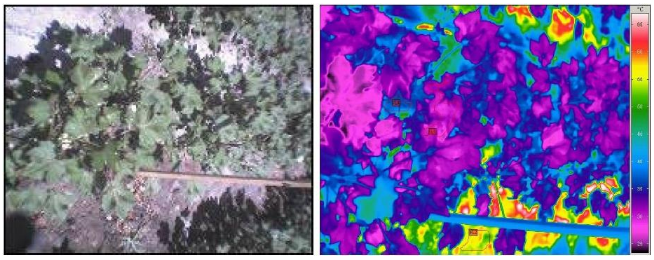

Fig. 2. Digital image and the corresponding infrared image of a cotton row.

The results show a 28% reduction in yield and 30% reduction in stomatal conductance of the dust treatment compared to the control treatment. This indicates blocking of the stomata on the top of the leaf surface. In addition, the canopy temperature of the dust-applied leaves was always higher than the control and treatment.

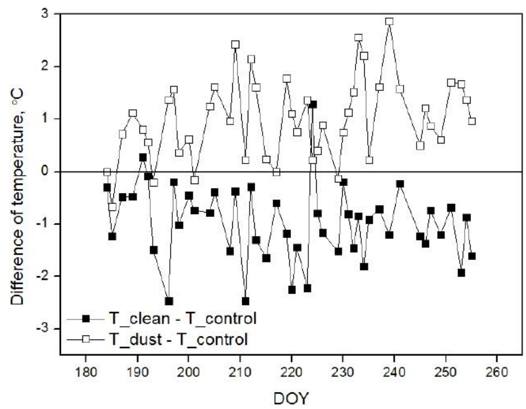

Fig. 3. Canopy temperature difference between the treatment and control throughout the growing season.

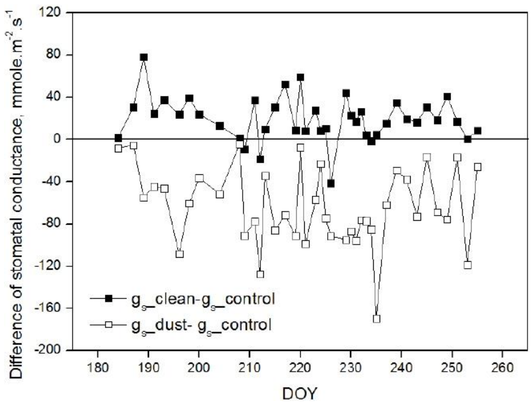

Fig. 4. Difference of stomatal conductance between treatment and control.

B. Machine learning in applied in agriculture

In the third paper was conducted in order to determine energy consumption, model and analyze the input–output, energy efficiencies and greenhouse gas emissions for watermelon production using artificial neural networks [3]. Data used in this study were collected from 120 watermelon producers. In this study, Levenberg–Marquardt learning Algorithm was used for training artificial neural networks based on data collected from watermelon producers. One prediction model was energy equivalent. The inputs of energy equivalent prediction model were chemicals, human labor, machinery, diesel fuel, chemical fertilizers, farmyard manure, biocides, electricity and seed, and the output was watermelon yield. The other prediction model was greenhouse gas emission. The inputs of greenhouse gas emission prediction model were machinery, diesel fuel, chemical fertilizer, biocides and electricity.

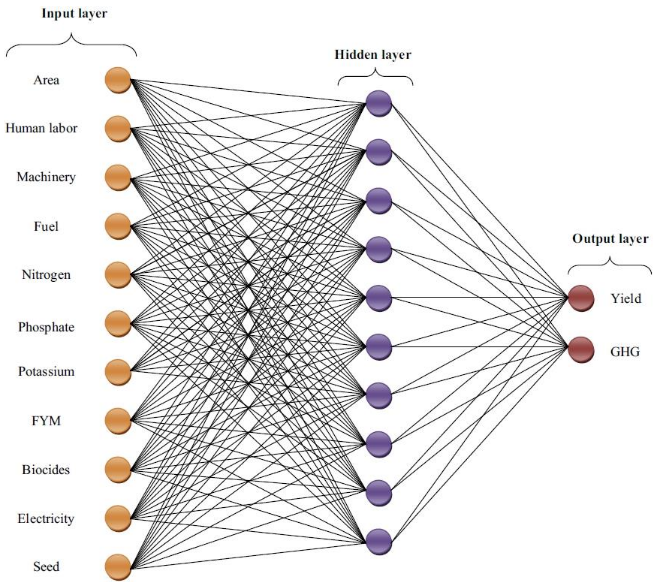

Fig. 5. The artificial neural networks model with 11-10-2 structure.

The results show that the artificial neural networks model with 11–10–2 structure was the best one for predicting the watermelon yield and greenhouse gas emissions (Fig. 5). In the best topology, the coefficient of determination was calculated as 0.969 and 0.995 for yield and greenhouse gas emissions of watermelon production, respectively. Accordingly, the best topology had the highest R^2 and the lowest values of RMSE and MAPE for watermelon yield and greenhouse gas emissions in both training and testing which indicate the artificial neural networks predicted watermelon yield by this model tends to follow the corresponding actual ones quite closely (TABLE I.). Furthermore, the results of sensitivity analysis revealed that the seed and human labor had the highest sensitivity in modeling of watermelon yield and greenhouse gas emissions, respectively.

TABLE I. THE RESULT OF DIFFERENT ARRANGEMENTS OF MODELS.

Items	R2		RMSE		MAPE	
	Train	*Test*	*Train*	*Test*	*Train*	*Test*
Yield	0.969	0.952	0.142	0.111	0.005	0.004
GHG	0.995	0.997	0.059	0.025	0.004	0.001

The forth paper was using artificial neural networks and the empirical methods for estimating the reference evapotranspiration with daily meteorological data [4]. These datasets consisted of daily meteorological measurements from a station covering a period of five years. Those datasets were used for training and testing the artificial neural network. The algorithm that was used is of the multi-layer feed forward artificial neural networks and of the backpropagation for optimization. The architecture that was finally chosen has the 4-6-1 structure (Fig. 6), with 4 neurons (temperature, relative humidity, wind speed and solar radiation) in the input layer, 6 neurons in the hidden layer and 1 neuron in the output layer which corresponds to the reference evapotranspiration, using a sigmoid transfer function.

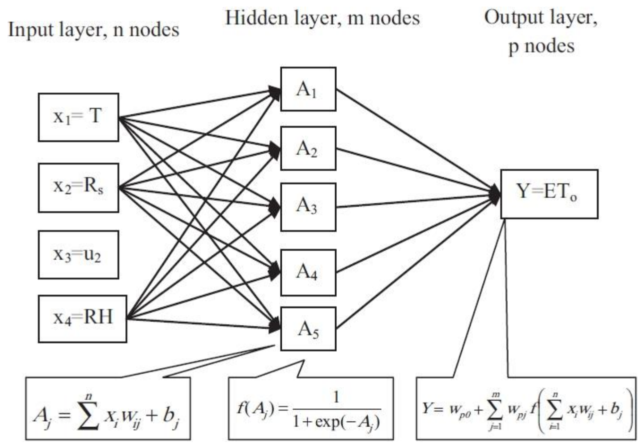

Fig. 6. Typical architecture of artificial neural networks.

The result show that the artificial neural networks model with 4-6-1 had less error in predicting evapotranspiration by daily reference compare with 3-6-1 and 2-6-1 prediction models (TABLE II).

TABLE II. THE ERROR RESULT OF DIFFERENT ANN MODELS.

	ANN(4-6-1)	ANN(3-6-1)	ANN(2-6-1)
RMSE	0.961	0.971	0.936

The fifth paper [5] indicated that weather conditions have a direct effect on crop yield. And suggested that artificial neural networks could be demonstrated to be powerful tool for modeling and prediction, in order to increase their effectiveness. Crop prediction methodology need various sensing parameter of soil and atmosphere such as pH, nitrogen, potassium, copper, iron, rainfall, temperature, humidity and so on. Through artificial neural networks to predict crop yield.

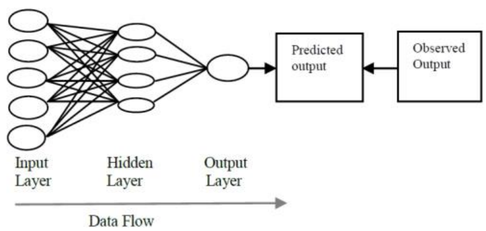

Fig. 7. Layer and connection of a feed-forward back-propagating ANN.

In the sixth paper [6] presented a comprehensive literature survey on the artificial neural networks in agriculture. The agriculture is facing some challenges such as abnormal weather conditions, improper soil treatment, disease and pest infestation. The field of artificial intelligence with its rigorous learning capabilities have become a key technique for solving different agriculture related problems. In this paper, one hundred important contributions such as crop, pest, soil and irrigation, product monitoring, disease, weed and yield management where artificial intelligent techniques employed to face the agricultural challenges.

The seventh paper [7] discussed about the techniques like IOT, wireless communications, machine learning and artificial intelligence applied in agriculture. Automation of farming has proved to enhance the gain from soil and has strengthened the soil fertility. In this paper, it supplied a brief overview about the current implementation of automation in agriculture. As AI stimulated, many new logics and method were invented and discovered which makes the process of problem- solving more simple such as Fuzzy logic, Artificial neural networks, Neuro-fuzzy logic and Expert systems. And the architecture of artificial neural network consists of three layers including input layer, hidden (middle) layer and output layer (Fig. 8).

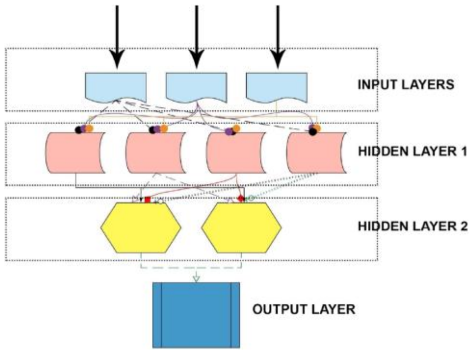

Fig. 8. Layer and connection of a feed-forward back-propagating ANN.

REFERENCES

[1] A. Khorsandi, A. Hemmat, S. A. Mireei, R. Amirfattahi, and P. Ehsanzadeh, "Plant temperature-based indices using infrared thermography for detecting water status in sesame under greenhouse conditions," Agricultural Water Management, vol. 204, pp. 222–233, 2018.

[2] S. Zia-Khan, W. Spreer, Y. Pengnian, X. Zhao, H. Othmanli, X. He, and J. Müller, "Effect of dust deposition on stomatal conductance and leaf temperature of cotton in northwest China," Water, vol. 7, pp. 116–131, 2015.

[3] A. Nabavi-Pelesaraei, R. Abdi, and S. Rafiee, "Neural network modeling of energy use and greenhouse gas emissions of watermelon production systems," Journal of the Saudi Society of Agricultural Sciences, vol. 15, pp. 38–47, 2016.

[4] V. Z. Antonopoulos, and A. V. Antonopoulos, "Daily reference evapotranspiration estimates by artificial neural networks technique and empirical equations using limited input climate variables," Computers and Electronics in Agriculture, vol. 132, pp. 86–96, 2017.

[5] S. S. Dahikar, and S. V. Rode, "Agricultural crop yield prediction using artificial neural network approach," International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, vol. 2, pp. 683–686, 2014.

[6] G. Bannerjee, U. Sarkar, S. Das, and I. Ghosh, "Artificial Intelligence in Agriculture: A Literature Survey," International Journal of Scientific Research in Computer Science Applications and Management Studies, vol. 7, pp. 1–6, 2018.

[7] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," Artificial Intelligence in Agriculture, vol. 2, pp. 1–12, 2019.