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Optimizing Irrigation Depth Using a Plant Growth Model and Weather Forecast

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Abstract

Numerical models of crop response to irrigation and weather forecasts with internet access should be fully utilized in modern irrigation management. In this respect, we developed a new numerical scheme to optimize irrigation depth that maximizes net income. Net income was calculated as a function of cumulative transpiration over irrigation interval which depends on irrigation depth. To evaluate this scheme, we carried out a field experiment for groundnut (*Arachis hypogaea* L.) grown in a sandy field of the Arid Land Research Center, Tottori University, Japan. Two treatments were established to compare the net income of the proposed scheme with that of an automated irrigation system. Results showed that although the proposed scheme gave a larger amount of seasonal irrigation water 28%, it achieved 2.18 times of net income owing to 51% higher yield compared to results of the automated irrigation system. This suggests that the proposed scheme would be more economical tool than automated irrigation systems to optimize irrigation depths.

Keywords: automated irrigation, soil water content, drought, transpiration, net income, numerical simulation

1. Introduction

Irrigation is a vital factor for agriculture in both arid and semi-arid regions. Even in the humid and sub-humid regions, it is essential for rain-fed crops during drought periods when rainfall fails to provide sufficient moisture for stabilized crop production (Debaeke & Aboudrare, 2004). Approximately, 70% of global water resources are used for irrigation (WWAP, 2012). By 2050, the global population is forecasted to reach 9 billion (United Nations, 2007); therefore, the world needs to produce at least 50% more food (World Bank 2016). This gives the irrigation a great challenge in the coming decades to satisfy world's requirements from food, particularly in countries with limited water resources.

To manage irrigation more efficiently, both frequency and amount of watering must be determined carefully. With adopting computer and electronic technologies in agriculture, farmers may schedule irrigation water more efficiently. Mbabazi et al. (2017) used an average of the previous 5-day crop evapotranspiration to develop an irrigation scheduling for Avocado using technology of mobile irrigation applications. Yet irrigation scheduling is more efficient if methodologies of soil water sensors are used (Irrigation Association, 2011). Consequently, automated irrigation systems with sensors are widely used to meet crop water needs more precisely (Cancela et al., 2015; Osroosh et al., 2015). Liang et al. (2016) used data of soil water tension from wireless soil moisture sensors and the van Genuchten model (van Genuchten, 1980) to schedule irrigation water. Stirzaker et al. (2017) used electronic detectors for wetting front of infiltrated irrigation water through the soil profile to close a solenoid valve at a certain value to manage irrigation water. Those technologies, however, require high initial investment; therefore, the foundation of cheap technologies will encourage farmers to save irrigation water. For example, numerical simulation of water flow and crop growth can be utilized as a substitute for sensing drought stress.

Linking weather forecasts with irrigation scheduling may improve irrigation water management since availability of quantitative weather forecasts of acceptable accuracy with internet access. Lorite et al. (2015) used free accessible online weather forecasts to determine irrigation scheduling based on daily and weekly reference evapotranspiration. Delgoda et al. (2016) used weather forecasts and AquaCrop model (Steduto, Hsiao, Raes, & Fereres, 2009) to validate their framework that based on model predictive control to minimize both root zone soil moisture deficit and irrigation depth under water scarcity conditions. Combination of a multi-objective function and weather forecasts were used to give users a choice of optimal yield-irrigation combinations (Linker & Sylaios, 2016). This optimization was based on the end of seasonal yield and irrigation. Wang and Cai (2009) used a genetic algorithm (GA) to schedule irrigation water assuming perfect weather forecasts for either non-overlapping two weeks or the entire growing season.

Irrigation scheduling is generally targeted to improve water use efficiency; however, it is worth to consider net income as well. Concerning the economic benefits in relation to irrigation water, Yang et al. (2017) developed a flexible irrigation scheduling decision support system using fuzzy programming and interval optimization approaches. They used four multiple objective functions with different purposes (1) to maximize the gross economic profit; (2) to maximize the net economic profit; (3) to maximize the economic benefits per unit acreage of cultivated land; and (4) to maximize the economic benefits per unit cubic meter of irrigation water supply. Note that those functions were based on uncertain data of crop evapotranspiration; that would be a major constraint of that model. Moreover, Wang and Cai (2009) developed an optimization framework combined the SWAP model (Van Dam et al., 1997) and the GA to search for both irrigation dates and depths that maximize profits. They calculated net income for the entire season based on seasonal yield and seasonal fixed irrigation cost.

Water scarcity threatens the future of world food; therefore, governments typically set a price on water to motivate farmers to save irrigation water. Bozorg-Haddad et al. (2016) estimated farmer's response to the price of agricultural water. No effect on water use was found under low prices compared to non-priced water. Fujimaki et al. (2015) developed an optimization scheme to determine irrigation depths that maximize net income at fixed irrigation interval. That scheme was incorporated into a two-dimensional model of water, solute, and heat movement in soils (WASH_2D). To test that method, they carried out two preliminary field experiments in two different locations, soils and crops. The first experiment was carried out at the Institute des Régions Arides (IRA), Medenine, Tunisia, during 2011-2012. The measured crop was barley (*Hordeum vulgar* L. cv. Ardhaui) grown in loamy sand soil. The second experiment was carried out at the Arid Land Research Center, Tottori University, Japan, in 2013; the measured crop was sweet corn (*Zea mays*, cv. Amaenbou86) grown in sandy soil. Results of those experiments, however, are not satisfied to validate that scheme; it still needs more field experiments under different combinations of climate, soil, and crop to give users more confidence in its effectiveness. The objective of this paper, therefore, was to evaluate the optimization scheme to determine irrigation depth that maximizes net income using a major crop, groundnut. The specific goal was to replace capital-intensive automated irrigation methods with a low-cost scheme based on freely available weather data and numerical simulation.

2. Materials and Methods

2.1 The Process Model

A two-dimensional physically based model, WASH_2D was used. It can simulate water, solute, and heat movement in soils with the finite difference method. It includes a module for simulating root water uptake and crop growth. This software is freely distributed with source code under a general public license from the website of the Arid Land Research Center, Tottori University (http://www.alrc.tottori-u.ac.jp/fujimaki/download/WASH_2D). A detailed description of the model was informed by Fujimaki et al. (2015).

2.2 Numerical Scheme

2.2.1 Maximization of Net Income

Net income, I_n (\$ ha^{-1}) was calculated at each irrigation interval in proportion to the increment in dry matter attained during the irrigation interval (Fujimaki et al., 2015):

$$I_n = P_c \varepsilon \tau_i k_i - P_w W - C_{ot} \tag{1}$$

where, P_c is the producer's price of crop (\$ kg^{-1} DM), ε is transpiration productivity of the crop ((produced dry matter (kg ha^{-1}) divided by cumulative transpiration (kg ha^{-1})), τ_i is cumulative transpiration during the interval (kg ha^{-1}), k_i is the income correction factor, P_w is the price of water (\$ kg^{-1}), W is the irrigation depth (1 cm = 100 000 kg ha^{-1}), and C_{ot} is other costs (\$ ha^{-1}).

In Equation (1), the income correction factor was considered to avoid possible underestimation for the contribution of initial transpiration to the entire quantum of growth; because transpiration in the initial growth stage is smaller than that in later stages. Estimation of k_i was suggested in Fujimaki et al. (2015).

The transpiration rate, T_r (cm s^{-1}), was calculated by integrating the water uptake rate, S, over the root zone:

$$T_r = L_x^{-1} \int_0^{L_x} \int_0^{L_z} S\mathrm{d}x\mathrm{d}z \quad (2)$$

where, L_x and L_z are width and depth of root zone. A macroscopic root water uptake model (Feddes & Raats, 2004) was used to predict the water uptake rate, S (cm s^{-1}):

$$S = T_p \alpha_w \beta \quad (3)$$

where, T_p, α_w and β are potential transpiration (cm s^{-1}), reduction coefficient of root water uptake and normalized root density distribution, respectively. The T_p was calculated by multiplying reference evapotranspiration by basal crop coefficient, K_c, as follows:

$$T_p = E_p K_c \quad (4)$$

where, E_p is reference evapotranspiration (cm s^{-1}), calculated by the Penman-Monteith equation (Allen, Pereira, Raes, & Smith, 1998). Since the crop coefficient is largely affected by growth stage, it was expressed as a function of transpiration as follows:

$$K_c = a_{kc}\left[1 - \exp(b_{kc}\tau)\right] + c_{kc} \quad (5)$$

where, a_{kc}, b_{kc} and c_{kc} are fitting parameters. Estimated value of those parameters depends on each growth stage of the plant. Fujimaki et al. (2015) suggested their values by measuring cumulative transpiration rate via a weighing lysimeter.

The reduction of the water uptake rate, α is a function of drought and osmotic stresses; WASH_2D model uses so-called additive function as follows:

$$\alpha = \frac{1}{1 + \left(\frac{\psi}{\psi_{50}} + \frac{\psi_o}{\psi_{o50}}\right)^p} \quad (6)$$

where, ψ and ψ_o are the matric and osmotic heads, respectively, and ψ_{50}, ψ_{o50}, and p are fitting parameters (van Genuchten, 1987).

In this paper, the equation that describes the normalized root activity, β, is modified as follows:

$$\beta = 0.75(b_{rt} + 1)d_{rt}^{(-b_{rt}-1)}\left(d_{rt} - z + z_{r0}\right)^{b_{rt}} g_{rt}\left(1 - x^2 g_{rt}^{(-2)}\right) \quad (7)$$

where, b_{rt} is a fitting parameter; d_{rt} and g_{rt} are the depth and width of the root zone (cm), respectively; x is the horizontal distance; z is the soil depth; and z_{r0} is the depth below which roots exist (cm). In general, the roots of cultivated plants start from about 2.5 cm below the soil surface, therefore, we have added as a new parameter to make the model more realistic. The d_{rt} was also expressed as a function of transpiration as follows:

$$d_{rt} = a_{drt}\left[1 - \exp(b_{drt}\tau)\right] + c_{drt} \quad (8)$$

where, a_{drt}, b_{drt} and c_{drt} are fitting parameters. By expressing both K_c and d_{rt} as functions of cumulative transpiration as independent variables instead of days after sowing, WASH_2D may express plant growth more dynamically responding to drought or salinity stresses.

2.2.2 Optimization of Irrigation Depth

To minimize repetition of numerical prediction in non-linear optimization, we used the following scheme proposed by Fujimaki et al. (2015).

First, it is assumed that cumulative transpiration rate at each irrigation interval may be empirically described as:

$$\tau_i = \int T_r \mathrm{d}t = a_\tau\left[1 - \exp(b_\tau W)\right] + \tau_0 \quad (9)$$

where, a_τ and b_τ are fitting parameters and τ_0 is τ at W = 0. Note that even when W = 0, the plant can still uptake remained available water from the soil.

Second, maximum I_n is achieved when the derivative of Equation (1) for W becomes zero:

$$\frac{\mathrm{d}I_n}{\mathrm{d}W} = -P_c \varepsilon k_i a_\tau b_\tau \exp(b_\tau W) - P_w = 0 \quad (10)$$

$$W = -\frac{1}{b_\tau} \ln\left(\frac{P_w}{P_c \varepsilon k_i a_\tau b_\tau}\right) \quad (11)$$

The values of a_τ and b_τ must be known; therefore, two additional points of transpiration at maximum (W_{max}, τ_{max}) and intermediate (W_{mid}, τ_{mid}) irrigation depths should be assessed:

$$\tau_{max} = a_\tau\left[1 - \exp(b_\tau W_{max})\right] + \tau_0 \quad (12)$$

$$\tau_{mid} = a_\tau\left[1 - \exp(b_\tau W_{mid})\right] + \tau_0 \quad (13)$$

Rearranging Equation (12) gives,

$$a_\tau = \frac{\tau_{\max} - \tau_0}{1 - \exp(b_\tau W_{\max})} \tag{14}$$

and Equation (12)-Equation (13) gives,

$$a_\tau = \frac{\tau_{\max} - \tau_{\mathrm{mid}}}{\exp(b_\tau W_{\mathrm{mid}}) - \exp(b_\tau W_{\max})} \tag{15}$$

Then,

$$\frac{\tau_{\max} - \tau_{\mathrm{mid}}}{\exp(b_\tau W_{\mathrm{mid}}) - \exp(b_\tau W_{\max})} - \frac{\tau_{\max} - \tau_0}{1 - \exp(b_\tau W_{\max})} = 0 \tag{16}$$

The value of b_τ can be easily searched using the bisection numerical method. Finally, by predicting τ at three irrigation depths, zero, the upper limit, and an intermediate value, we can determine irrigation depth that maximizes the net income.

2.3 Optimization Procedure

The optimization procedure (Figure 1) consists of two major steps: (1) update run was done in the early morning of each irrigation day. It uses records of irrigation, weather and cumulative transpiration since the last irrigation day to estimate an initial condition of the soil moisture. Then, (2) optimization run was carried out using results of update run as initial condition and weather forecast data until the next irrigation day retrieved from the website of Yahoo! Japan (URL: http://weather.yahoo.co.jp/weather/jp/31/6910/31302.html) to determine irrigation depth. Weather data including solar radiation, air temperature, relative humidity, wind speed, and rainfall were collected from a weather station located at about 20 m away from the experimental field. This website provides all required parameters except solar radiation, but provides categorical estimates of cloud cover. Therefore, we used an empirical relationship between cloud cover and the ratio of extraterrestrial radiation to solar radiation. The estimated values of solar radiation in terms of the three classes of cloud cover were ("clear" = 0.82, "cloudy" = 0.63, and "rain" = 0.32).

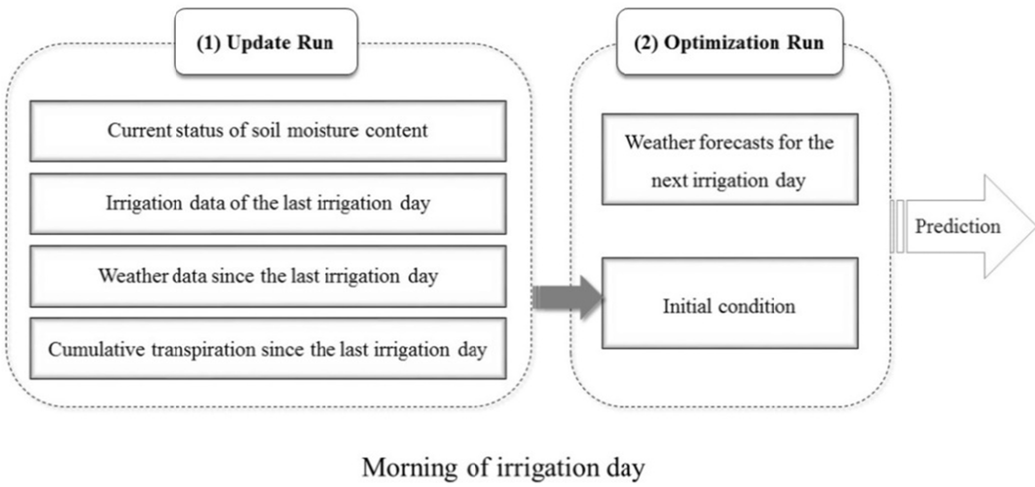

Figure 1. Numerical procedure of determination irrigation depth that maximizes net income

2.4 Field Experiment

A field experiment was carried out in a sandy field of the Arid Land Research center, Tottori, Japan (35°3209N 134°1239E), in 2017. Two treatments were established: (1) treatment A, an automated irrigation system based on a threshold value of soil water potential of 45 cm, and (2) treatment S, the proposed scheme. Each treatment had two plots as replicates. Each plot was 10 m long and 16 m wide.

The soil was sand with hydraulic properties as shown in Figure 2. In treatment A, three tensiometers were installed at the depth of 10 cm below three plants to automatically manage irrigation. In treatment S, the accuracy of numerical simulation was evaluated in terms of soil moisture using twelve time domain reflectometry probes (TDR-SK10 probes by Sankeirika, Japan and TDR 100 by Campbell Scientific, Ltd., USA). TDR probes were horizontally inserted at 6 locations ((x, z) = (0, 5), (0, 15), (0, 45), (15, 5), (15, 15), (45, 5)) with two replicates, where x is horizontal distance (cm) from drip tube.

Irrigation water was applied through a drip irrigation system with emitters spaced at 20 cm along laterals spaced at 90 cm. The discharge rate of emitters was 1 L h^{-1} and corresponding irrigation intensity was 5.55 mm h^{-1}. In treatment A, Irrigation water was applied for an hour when the average suction of the three tensiometers exceeded 45 cm. In the treatment S, the irrigation interval was fixed at two days and the optimized irrigation depth resulted from the simulation was manually applied. Transpiration productivity of the crop was set at 0.004. The water price was set at 0.0003 ($ kg^{-1}) which is similar to the level used in Israel (Cornish, Bosworth, & Perry, 2004). Liquid fertilizer (N = 12%, P_2O_5 = 5%, K_2O = 7%) and calcium chloride ($CaCl_2$) were applied at a constant daily rate throughout the growing season using a mixer. The total applied amount of N and $CaCl_2$ were 8.56 g m^{-2} and 12.96 g m^{-2}, respectively. The salinity of the irrigation water was as low as 0.1 dS m^{-1}.

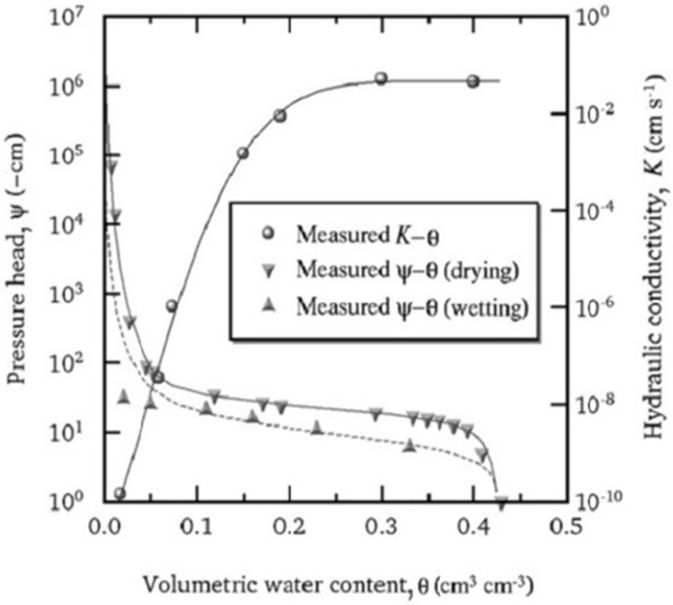

Figure 2. Hydraulic properties of the field soil

Groundnut (*Arachis hypogaea* L.) was planted in rows (laterals) at 20 cm spacing on 9 May. We independently determined parameter values of the stress response function for groundnut as listed in Table 1 using method described by Yanagawa and Fujimaki (2013).

Parameter values of the crop coefficients were updated four times throughout the growing season such that simulated evapotranspiration matched the measured values (Figure 3). Leaf area index (LAI) was calculated as the ratio of sampled leaf area to harvested ground area. Vegetative biomass was measured by separating leaves and stem of sampled plants and then dried at 70 °C until constant weight. The seasonal income was calculated by setting the price of seed crop at 5 $ kg^{-1} based on average marketable prices in Japan in 2017. Irrigation application was stopped on 5 September and the crop was harvested on 31 October.

Table 1. Parameter values of plant growth and stress response functions used in this numerical scheme

Parameter	Value	Remark
a_{kc}	1.2	
b_{kc}	-0.5	Equation (5)
c_{kc}	0.1	
ψ_{50} (cm)	-48	
ψ_{o50} (cm)	-3000	Equation (6)
P	4.7	
b_{rt}	1	
d_{rt}	?	Equation (7)
g_{rt}	30	
z_{ro}	2	
a_{drt}	43	
b_{drt}	-0.4	Equation (8)
c_{drt}	5	

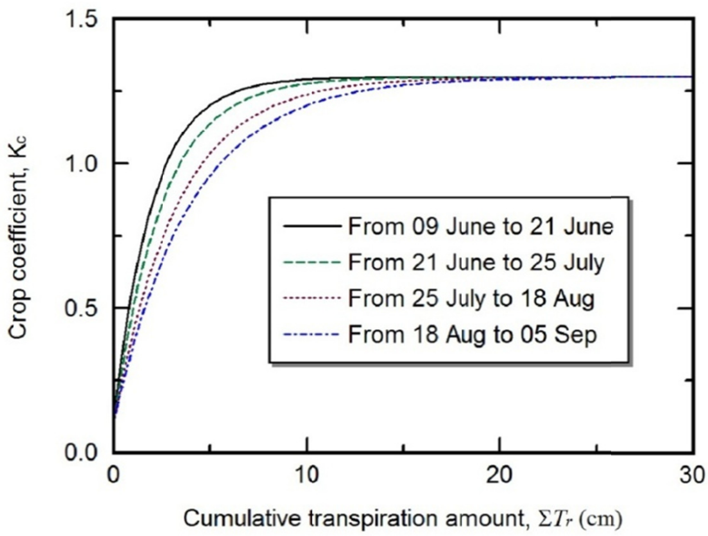

Figure 3. Crop coefficient in terms of cumulative transpiration updated for four time periods during the experimental crop development

3. Results and Discussion

3.1 Leaf Area Index and Biomass

Result of five measurements for either leaf area index or biomass was shown in Figure 4. Despite water applied to treatment S exceeded that of treatment A under the same application rate of nutrients, there was no large difference between leaf area indices or biomass till 75 days after planting (DAP) in both treatment A and S. During reproductive stages from R1 (31 DAP; beginning bloom; Boote, 1982) until R6 (74 DAP; full seed filling), both pegging and developing pods compete vegetative growth for carbohydrates and nutrients; that might be reduced growth of leaf area temporarily for the treatment S. Beyond the R6 stage till the maturity, both LAI and biomass of the treatment A were lagged behind compared to treatment S. Reduced water availability in the treatment A may have reduced both leaf area and biomass production. This result is in agreement with findings of (Haro, Dardanelli, Otegui, & Collino, 2008).

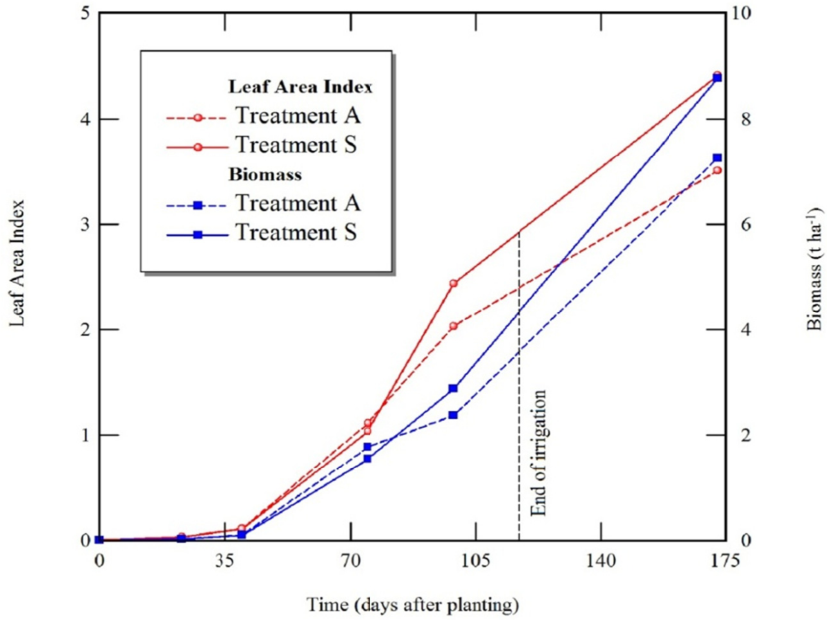

Figure 4. Measured leaf area index and biomass of groundnut (*Arachis hypogaea* L.) over time in two irrigation treatments

3.2 Soil Water Content

To evaluate the accuracy of the model on predicting soil water contents, we compared simulated water contents with measured ones (Figure 5). Both simulated and measured soil water contents were specified in two dimensions (x and z), where, x represents the horizontal distance from a lateral and z is the soil depth. We represented soil water contents for a period of one week under two different conditions: two irrigation events on 4 and 6 August; and rainfall events started from 7 August to 10 August. On 4 August, the model suggested 15.6 mm of irrigation depth for the next two days and this was the highest predicted value throughout the growing season. It was added twice, before and afternoon, due to water block. Consequently, at the point of x = 0 cm and z = 5 cm, the model underestimated the volumetric water content. This may be due to overestimation of potential transpiration and root water uptake, and hence crop coefficient function was corrected downward. Meanwhile, there were no remarkable changes in soil water status at the point (x = 40 cm and z = 5 cm) during irrigation events and the model could fairly simulate and respond to changes in volumetric water contents during rainfall events.

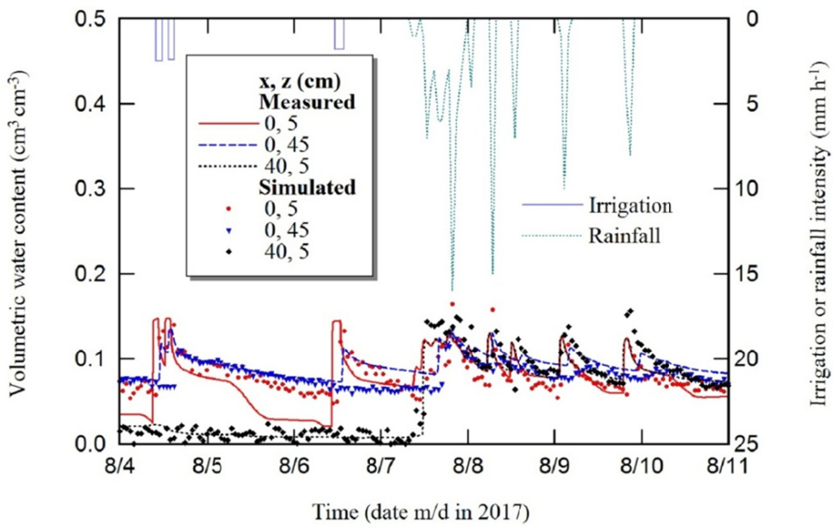

Figure 5. Comparison between measured and simulated volumetric soil water content at two dimensions (x = distance from nearest drip irrigation lateral, z = soil depth) in treatment S

3.3 Effectiveness of Integration of Weather Forecast With the Numerical Scheme

The integration of weather forecasts with the proposed scheme was effectively considered irrigation management. For example, the model suggested that no irrigation required on 10 August, as weather forecasts predicted 12 mm of rainfall in addition to water content stored in the soil were adequate to meet crop water needs. In contrast, 4.8 mm was applied through the automated irrigation system on 11 August just 5 h before rainfall (Figure 6).

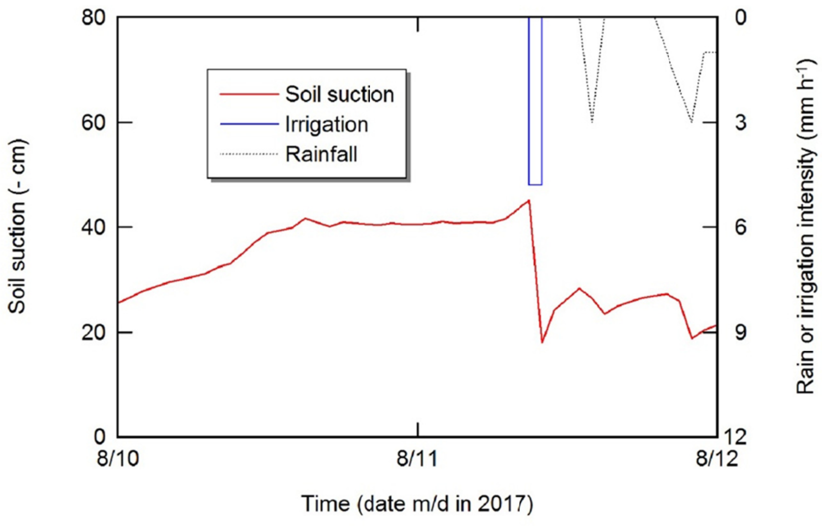

Figure 6. An example of improper application of water by the automated system. 4.8 mm was applied while presented scheme suggested not to irrigate in response to the forecast rain

3.4 Effectiveness of the Proposed Scheme on Net Income

As described in the previous section, the proposed scheme optimizes irrigation depth that gives maximal net income when three values of transpiration are predicted. An example of the optimization from a scheduled irrigation of 6 August is shown in Figure 7. An irrigation depth of 0.87 cm was derived at the maximum point of the net income curve. Note that predicted transpiration is lower at 0.87 cm than at 1.5 cm irrigation depth.

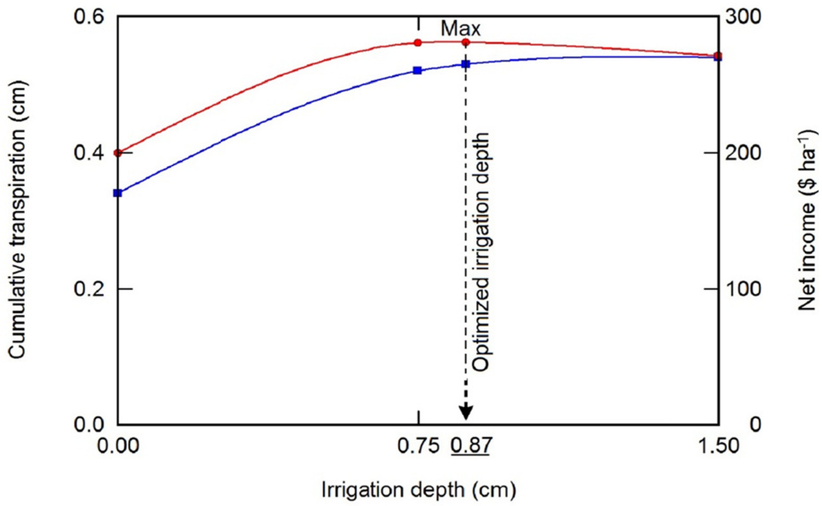

Figure 7. An example of how the irrigation depth is optimized on a scheduled irrigation day in the proposed scheme

Finally, the effect of the proposed scheme on total net income is shown in Figure 8. Although the treatment S gave the larger seasonal amount of irrigation water by 28%, it achieved 2.18 times of net income of treatment A. Seed yield of groundnut of treatment S was 51% larger than treatment A, and it could justify the cost of applied water. The reason for a lower yield in treatment A was probably due to smaller irrigation amount and trigger value of 45 cm might be too strict under current combination of prices for either crop or water. Difficulty in determining economically optimum trigger value without expensive field trials is another disadvantage of an automated irrigation system. During the harvest, we obtained a lot of pops (pods in full size with no kernels inside), that led yield decreased in both treatments A and S. This might be due to an inadequate amount of Ca applied to the crop in the early stages of reproductive stage.

3.5 Comparison Between Forecast and Actual Rainfall

Since accuracy in rainfall forecasts have a large effect on the performance of the proposed scheme, we compared between forecast and actual daily effective rainfall as shown in Figure 9. In the analysis, the daily effective rainfall was set as 20 mm, because additional rainfall larger than this value is lost due to deep percolation and cannot be used by crops. The RMSE was 4.63 mm. In comparison with Fujimaki et al. (2015), we found that accuracy of weather forecasts are getting improved that would improve efficiency of the proposed scheme to determine irrigation depth. Thus, it may be considered as an efficient and economical tool for irrigation water management.

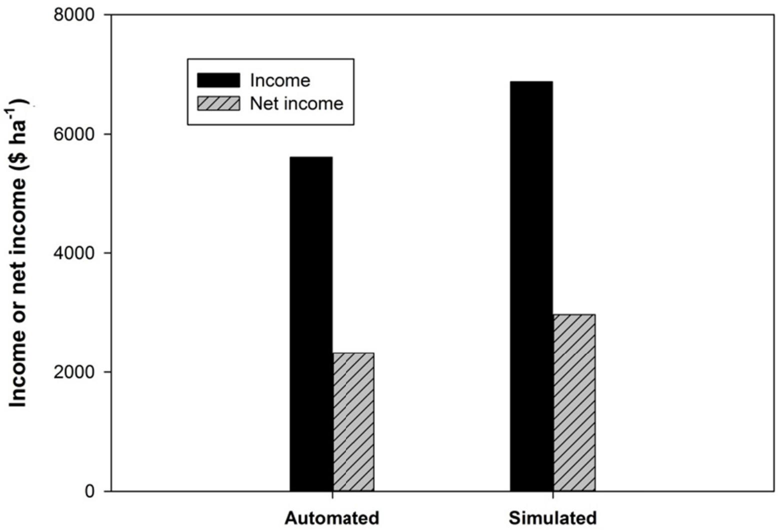

Figure 8. Total income and net income of the two irrigation treatments. (Treatment A: automated irrigation scheduling based on soil water suction monitoring; Treatment S: optimization of irrigation depth from the numerical scheme)

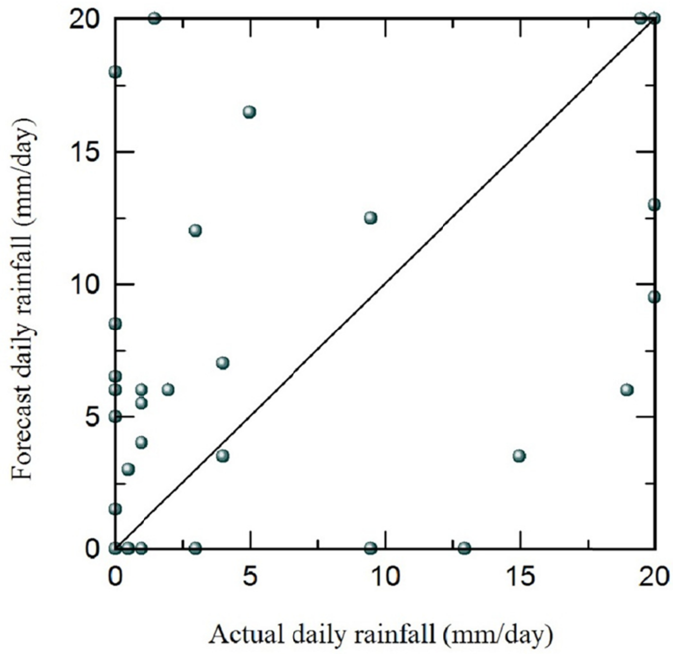

Figure 9. Comparison of forecast and actual daily effective rainfall for the entire growing season of the experimental period

4. Conclusion

In this paper, we evaluated the effectiveness of the proposed scheme on determination of optimum irrigation depth that maximizes net income using a major crop, groundnut (*Arachis hypogaea* L.). This scheme combined local weather forecasts and a plant growth model to predict cumulative transpiration in response to irrigation depth. It also considers water price which should be set at a high level that may give farmers incentive to save irrigation water. To check the benefits, the proposed scheme was compared with an automated irrigation method by carrying out a field experiment in a sand field. Although the proposed scheme required 28% more water than automated irrigation system, it could achieve 2.18 times of net income. This does not mean that proposed scheme wasted water as it gave a 51% higher seed yield compared to an automated irrigation treatment. This probably emphasizes that the proposed scheme is a useful tool to determine irrigation depths, enhance net income and save the initial investments required to construct an automated irrigation system.

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