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Determination of irrigation depths using a numerical model of crop growth and quantitative weather forecast and evaluation of its effect through a field experiment for potato

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Abstract: A scheme for determining irrigation depth using a numerical model of crop response to irrigation and quantitative weather forecast was presented. To optimize each irrigation depth, a concept of virtual income, which is proportional to an increment in transpiration amount during an irrigation interval, is introduced. A field experiment was carried out to evaluate effectiveness of the presented scheme in terms of net income considering the price of water. Potato was grown in summer season of 2015 using a drip irrigation system in Arid Land Research Center, Tottori, Japan. Two treatments were conducted: automated irrigation and proposed scheme with two replicates for each. Results indicated that predicted water content agreed well with observation although some underestimation of water content due to overestimation of transpiration was observed. Proposed scheme could save water by 27 %, while yield was increased by 15 %, resulting in higher net income as compared to automated irrigation. Based on these results together with previous works, we can conclude that proposed scheme can at least realize similar net income to automated irrigation systems without high initial investment.

Key Words : irrigation, weather forecast, transpiration, net income

1. Introduction

Rapidly increasing population and intensified scarcity of water resources bring a new emphasis on efficient use of water in irrigation. Farmers are still widely relying on their intuition to determine an irrigation depth even in industrialized countries. Such conventional irrigation scheme may have caused yield reduction or waste water. To save irrigation water, a concept of deficit irrigation was introduced and many field studies has been carried out (Ati and Nafaou, 2012; Makau et al., 2014). In such studies, water use efficiency or water productivity which is generally defined as yield per unit amount of irrigated water have widely been used as target value to be maximized. However, for a farmer, net income, not water use efficiency, should be of primary concern. Therefore, we believe that net income should be the target value to be maximized.

Automated irrigation systems using sensors may be another alternative which have been developed to precisely meet crop water requirements and respond to drought stress quickly. Such systems require high initial investment to construct monitoring and controlling systems and have difficulty in adjusting irrigation depth to weather forecasts. For example, it is obviously wasteful to apply full irrigation when rain is forecast for the next day. Automated system may nevertheless do it whenever the currently monitored value reaches its threshold value. In these days, expensive monitoring using sensors can be altered by numerical simulation of water flow and crop growth. Nowadays, personal computers are getting affordable even for farmers in developing countries. Not only monitoring current status, a numerical model can predict upcoming conditions. We may optimize irrigation depths such that net income is maximized. Also, today, freely accessible quantitative weather forecasts, whose accuracy is improving, have been available on the web (e.g. accuweather.com). These technical as well as socio-economic progresses have enabled us to optimize irrigation depths using quantitative weather forecast as input data. Moreover, using a relationship between yield and transpiration (or evapotranspiration), numerical models can search irrigation depth such that net income is maximized. Hence, these optimizations will result in maximizing net income for farmers.

Several researchers have proposed to use weather fore-

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casts for irrigation scheduling. Venäläinen et al. (2005) evaluated accuracy of SWAP (van Dam et al., 1997) and AMBAV (Braden, 1995) models by inputting numerical weather forecast as atmospheric boundary conditions. Wang and Cai (2009) presented methods which combine the SWAP model and weather forecast. They suggested to apply water when predicted stress index (actual to potential transpiration ratio) becomes less than 0.85 and irrigation depth is determined to bring the root zone soil moisture to field capacity. They also presented an entire-season optimization scheme to maximize net income considering cost for water using genetic algorithm (GA). They evaluated potential advantage of their methods in terms of net income by performing numerical experiments. Lorite et al. (2015) presented a scheme which combines freely accessible weather forecast and AquaCrop model (Steduto et al., 2009) and evaluated the effect of uncertainty in weather forecast on simulated yield. Irrigation depth is determined so that soil moisture in the root zone returns to field capacity. AquaCrop is a water balance model which does not use Richards equation to simulate water flow and therefore soil water dynamics in root zone is not considered. Seidel et al. (2015) used HYDRUS model to minimize irrigation water applied. Delgoda et al. (2016) presented a scheme to determine irrigation depth using weather forecast to minimize both root zone soil moisture deficit and irrigation amount. They used a simple water balance model to calculate root zone soil moisture deficit. Fujimaki et al. (2014) presented a new scheme to optimize irrigation depths using weather forecast as input data for a numerical model which solves two-dimensional Richards' equation such that net income is maximized. They also presented results of preliminary two field experiments. The first experiment was carried out in Institute des Régions Arides (IRA) in Medenine, Tunisia, in 2011–2012. The soil was loamy sand and the crop was Barley (*Hordeum vulgar L. cv. Ardhaui*). The second one was carried out in Arid Land Research Center in Tottori, Japan, in 2013. The crop was Sweet Corn (*Zea mays*, *Amaenbou*86). These results still have not been satisfactory to evaluate the effectiveness of the new scheme and we need more experiments to evaluate the effectiveness of the new scheme under various combination of soil, climate and crops. This paper presents outline of the scheme and experimental results to evaluate the effectiveness of the scheme in terms of net income.

2. Outline of the scheme to determine irrigation depth

Outline of the scheme to determine irrigation depth (Fujimaki et al., 2014) is illustrated in Fig. 1. To obtain an initial condition of an irrigation day, numerical simulation is performed to estimate the current status using the previous weather data ([1] in Fig. 1). The records of climatic condition were downloaded from the website of Japan Meteorological Agency. The numerical simulation is performed by WASH_2D (Fujimaki et al., 2014), which solves governing equations, including Richards equation of water flow, for two-dimensional movement of water, solute and heat in soils with the finite difference method. The WASH_2D software is freely distributed with source code under the general public license from website of Arid Land Research Center, Tottori University (http://www.alrc.tottori-u.ac.jp/fujimaki/download/WASH_2D).

Then, quantitative weather forecast is downloaded as input data ([2] in Fig. 1). A software (WeatherForecastDownloader) has been developed to download the HTML file and parse the HTML for WeatherUnderground (http://www.wunderground.com) and Yahoo! Japan (http://weather.yahoo.co.jp/weather/jp/31/6910/31302.html) for consecutive days. Note that we may not obtain all the weather data usable for numerical simulation from these websites. Usually, quantitative weather forecasts provide values except for solar radiation. For example, WeatherUnderground provides cloud cover instead of solar radiation. In such case, empirically known relationship between cloud cover and the ratio of extraterrestrial radiation to solar radiation may be applied. Yahoo! Japan provides four qualitative descriptions, "clear", "cloudy", "rain", and "heavy rain". In this case, empirically determined average ratio of extraterrestrial radiation to solar radiation for each description (e.g. "clear" = 0.82, "cloudy" = 0.63, "rain" = 0.32) may be multiplied to extra-terrestrial short wave radiation.

Using the quantitative weather forecast, both evaporation rate, E (cm s^{-1}) and reference evapotranspiration rate, ET_{p} (cm s^{-1}) are calculated separately in WASH_2D. The E is calculated by a bulk transfer equation (van Bavel and Hillel, 1976). The E is used as boundary conditions for water flow in field soil. While, the ET_{p} is calculated by

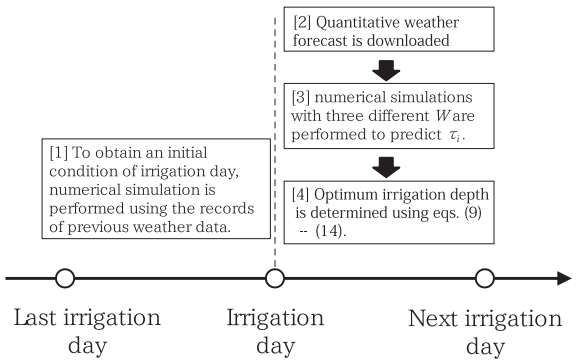


Fig. 1 Outline of the scheme to determine irrigation depth. Four steps described in this figure are repeated until last irrigation event.

the Penman-Monteith equation (Allen et al., 1998). The ET_p is used to estimate the transpiration rate, T_r (cm s^{-1}). The potential transpiration rate, T_p (cm s^{-1}) is calculated by multiplying with basal crop coefficient (K_c) at first.

$$T_p = ET_p K_c \tag{1}$$

A widely used macroscopic root water uptake model (Feddes and Raats, 2004) was used in predicting the water uptake rate, S (cm s^{-1}) next.

$$S = T_p \alpha_w \beta \tag{2}$$

where α_w and β are reduction coefficient and normalized root density distribution, respectively. The α_w is a function of matric and osmotic potential. This function is called as stress response function. WASH_2D uses so-called additive form stress response function:

$$\alpha_w = \frac{1}{1+\left(\frac{\psi}{\psi_{50}}+\frac{\psi_o}{\psi_{o50}}\right)^p} \tag{3}$$

where ψ_{50}, ψ_{o50} and p are fitting parameters (van Genuchten, 1987). The β, on the other hand, is described as

$$\beta = 0.75(b_{rt}+1){d_{rt}}^{-brt-1}(d_{rt}-z+z_{r0})^{brt} g_{rt}(1-x^2 {g_{rt}}^{-2}) \tag{4}$$

where x is horizontal distance from the center of the plant (cm), b_{rt} is a fitting parameter, and d_{rt} and g_{rt} are depth and width of the root zone (cm), z_{r0} is the depth below which root exists (cm). The z_{r0} was newly introduced because roots do not generally develop in very near surface layer except for plants grown under plastic mulch. Note that we added new parameter z_{r0} to one presented in Fujimaki et al. (2014) regarding to the two-dimensional root distribution. Finally, T_r is computed by integrating the S over the root zone.

$$T_r = {L_x}^{-1} \iint S dx dz \tag{5}$$

where L_x is the width of the calculated root zone. Based on the T_r values, we can estimate cumulative transpiration between irrigation intervals, τ_i, which dynamically responds to matric and osmotic potential in soil.

Although drip irrigation is a fully 3-dimensional flow problem, under certain conditions, the effects of individual emitters along the drip line can be neglected (e.g. Li et al., 2015). If emitter distance is narrow, the system can be approximated as line source. The numerical simulations with three different irrigation depths, W (cm) are performed to predict τ_i until next irrigation day ([3] in Fig. 1). The W is used as variable flux boundary conditions for water flow in field soil. The maximum W, W_{max} may be set at the cumulative reference ET between irrigation intervals ($= ET_p \times$ irrigation interval). The minimum W, W_{min} is set 0. The third value of W, W_{mid} is set between these values ($= (W_{max}+W_{min})/2$).

Based on the three pairs of W and τ_i, an economically optimum W is estimated ([4] in Fig. 1). To determine the optimum W, we introduce a 'virtual net income' during each irrigation interval. Although actual income is realized when crop is harvested and sold, we assume that a farmer can obtain virtual income, which is proportional to an increment of dry matter attained during an interval. Also, water must be priced high enough to give farmers incentive to save water. The virtual net income, I_n (\$ a^{-1}), during an interval is then defined as:

$$I_n = P_c \varepsilon \tau_i k_i - P_w W - C_{ot} \tag{6}$$

where P_c is the producer price of crop (\$ kg^{-1} DM), ε is crop water use efficiency, which is defined as the ratio of biomass produced to the rate of transpiration, k_i is income correction factor, which was introduced by Fujimaki et al. (2014) to correct the possible underestimation of the contribution of transpiration during the initial stage, P_w is the price of water (\$ kg^{-1}), and C_{ot} is the other costs (\$ ha^{-1}). In addition, response of τ_i to irrigation, W, was assumed to be empirically described as

$$\tau_i = \int T_r dt = a_t [1-\exp(b_t W)] + \tau_0 \tag{7}$$

where a_t and b_t are fitting parameters and τ_0 is the τ at $W = 0$. If yield is proportional to transpiration, relationship between W and τ_i may also be described with Eq. (7). Maximum net income is obtained at W at which derivative of Eq. (6) for W becomes zero.

$$\frac{dI_n}{dW} = -P_c \varepsilon k_i a_i b_i \exp(b_t W) - P_w = 0 \tag{8}$$

$$W = -\frac{1}{b_t} \ln\left(\frac{P_w}{P_c \varepsilon k_i a_i b_i}\right) \tag{9}$$

Therefore, if a_t and b_t are known, optimum W can be estimated. To obtain these two values, the τ_{max} and τ_{mid}, τ values at W_{max} and W_{mid}, respectively, are used.

$$\tau_{max} = a_t [1-\exp(b_t W_{max})] + \tau_0 \tag{10}$$

$$\tau_{mid} = a_t [1-\exp(b_t W_{mid})] + \tau_0 \tag{11}$$

Rearranging Eq. (10) gives

$$a_t = \frac{\tau_{max} - \tau_0}{[1 - \exp(b_t W_{max})]} \quad (12)$$

(10) − (11) gives

$$a_t = \frac{\tau_{max} - \tau_{mid}}{[\exp(b_t W_{mid}) - \exp(b_t W_{max})]} \quad (13)$$

Therefore,

$$\frac{\tau_{max} - \tau_{mid}}{[\exp(b_t W_{mid}) - \exp(b_t W_{max})]} - \frac{\tau_{max} - \tau_0}{[1 - \exp(b_t W_{max})]} = 0 \quad (14)$$

The value of b_t can be easily searched using the bisection method. Thus, by obtaining τ_i at three irrigation depths, W_{min}, W_{mid} and W_{max}, we may estimate the optimum irrigation depth by assuming that the response of transpiration during an interval to irrigation is described as an empirical equation with three unknown parameter values, unlike non-linear optimization which requires many repetitions. Since the optimization should be completed within a few hours practically, this simple estimation method developed by Fujimaki et al. (2014) is more suitable than the normal one-dimensional search algorithms such as the golden section method (Press et al., 1989). These steps describe above are repeated until the last irrigation event.

A protocol for crop growth is prepared in WASH_2D because of plant grows during cultivation period. Leaf area index (LAI), I, is expressed as a function of cumulative transpiration from germination, τ, since it may primarily depend on cumulative transpiration.

$$I = a_{LAI}[1 - \exp(b_{LAI}\tau)] \quad (15)$$

where a_{LAI} and b_{LAI} are fitting parameters. Since K_c depends mainly on LAI, K_c is also expressed as a function of τ:

$$K_c = a_{kc}[1 - \exp(b_{kc}\tau)] + c_{kc} \quad (16)$$

where a_{kc}, b_{kc} and c_{kc} are fitting parameters. Moreover, the depth of root zone, d_{rt}, is also expressed as function of τ:

$$d_{rt} = a_{drt}[1 - \exp(b_{drt}\tau)] + c_{drt} \quad (17)$$

where a_{drt}, b_{drt} and c_{drt} are fitting parameters. These functions are same form as Eq. (7) and they may express that the growth of leaves and root are nearly proportional to dry matter production at early stage of growth but the slopes gradually decrease and finally approach to near maximum value. K_c may be basically proportional to LAI and therefore it may be expressed as the same form.

3. Materials and Methods

3.1 Field experiment

Treatments

A field experiment was carried out in Arid Land Research Center in Tottori (35°32'09"N 134°12'39"E), Japan, in 2015. Two treatments were established: crop was irrigated with an automated irrigation system, treatment-A and proposed method with simulation was applied to the other treatment, treatment-S. Each treatment had two plots as replicates, each had a 15 m long and 16 m wide. To monitor water content, 12 TDR probes were inserted for each treatment and measurement was made at each hour. For automated irrigation, probes were installed at the depths of 5 and 15 cm below six plants. Regarding to treatment-S, TDR probes were installed 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 and plant. Evapotranspiration was measured for treatment-S with a weighing lysimeter whose diameter was 150 cm.

Irrigation

Irrigation was applied through a drip irrigation system whose lateral distance was 90 cm and emitter distance was 20 cm. Automated irrigation was set such that water was applied for one hour when average θ at the depth of 15 cm became less than 0.09 m^3 m^{-3}. Irrigation interval for treatment-S was set at two days. The records of climatic condition were downloaded from the website of Japan Meteorological Agency (http://www.data.jma.go.jp/obd/stats/etrn) and quantitative weather forecasts were downloaded from the website of Yahoo! JAPAN (http://www.yahoo.co.jp). Price of crop were set at 0.7 \$ kg^{-1} by referring producer price in the USA in 2011 (FAOSTAT, http://faostat.fao.org/). Price of water was set at 0.00025 \$ kg^{-1} based on that in Israel (Cornish et al., 2004). Liquid fertizer (N = 10 %, P_2O_5 = 4 %, K_2O = 8 %) and calcium chloride were mixed such that daily application rate became constant throughout growing season. Totally applied nitrogen was 3.8 g m^{-2} for each treatment. Since salinity of irrigation water was very low and current version of WASH_2D can simulate only one solute, "conceptual nutrient solute" assuming that all of solute in uptaken water by roots is also uptaken. Ionic diffusion coefficient of sodium chloride was used. Any adsorption, precipitation, nor chemical reaction were not considered. We did not consider the effect of uptake of nutrient on growth and assumed that growth depends simply on cumulative transpiration regardless of nutrient uptake.

Soil

Soil of the field was sand whose hydraulic properties are shown in Fig. 2. Solute transport parameters such as dispersivity (0.59 cm) and dependence of tortuousity factor for ionic diffusion on water content were also measured in laboratory (Fujimaki et al., 2012). Independently measured thermal properties such as dependence of thermal conductivity and albedo on water content and were also used. Thermal conductivity, k_{h} (W cm^{-1}K^{-1}), is given as a function of water content:

$$k_{\mathrm{h}} = a_{\mathrm{h}} + b_{\mathrm{h}} \left(\frac{\theta}{\theta_{\mathrm{sat}}} \right) - (a_{\mathrm{h}} - d_{\mathrm{h}}) \exp \left[-c_{\mathrm{h}} \left(\frac{\theta}{\theta_{\mathrm{sat}}} \right)^{e_{\mathrm{h}}} \right] \quad (18)$$

where θ_{sat} is saturated θ, a_{h}, b_{h}, c_{h}, d_{h}, and e_{h} are fitting parameters. We used values of 0.0061, 0.0032, 22.6, 0.0015, and 1.46, respectively. Albedo, α_{R}, is expressed as a function of average volumetric water content in top 1 cm, θ:

$$\alpha_{\mathrm{R}} = \frac{\alpha_{\max} - \alpha_{\min}}{1 + (a_{\mathrm{al}} \overline{\theta})^{b_{\mathrm{al}}}} + \alpha_{\min} \quad (19)$$

where $\alpha_{\max}$, $\alpha_{\min}$, a_{al}, and b_{al}, are fitting parameters. Values of 0.224, 0.159, 8 and 3, respectively, were used for the sand.

Plant

A cultivar of potato, May-Queen, was sown on April 14. Since stress response function of the plant has not been determined, tentatively set parameter values listed in Table 1 were used. These values are comparable for canola (Yanagawa and Fujimaki, 2013). As shown in Fig. 3, parameter values for crop coefficient function (Eq. (16)) were updated twice. First upward modification was made because we realized that with original parameter values, total transpiration would be only about 120 mm even without drought stress. Second downward modification was made because leaf area index measured on July 6 was only 0.59 and further increase was not expected. Parameters values for root distribution and LAI were chosen based on data obtained through growth measurement. Water use efficiency was set at 0.003. Unfortunately, disease of potato blight (*Phytophthora infestans*) was widespread in June particularly for treatment-A in spite of application of fungicide and yield was thus smaller than general for both treatments. Potato was harvested on July 21.

3.2 Numerical modeling

Width of the calculated region was 45 cm assuming symmetric system and depth of lower boundary was 50 cm. Horizontal space increment was constant at 1 cm while vertical increments were progressively increased from 0.25 cm at the top to 2.5 cm at the bottom. Time step was automatically regulated between 0.054 and 1.8 second.

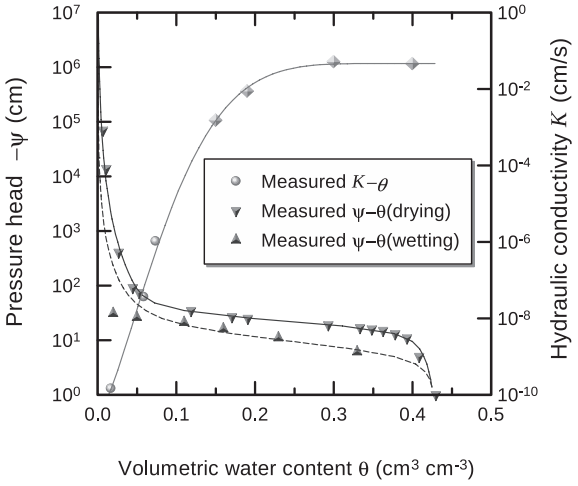


Fig. 2 Hydraulic properties of Tottori sand used in this study.

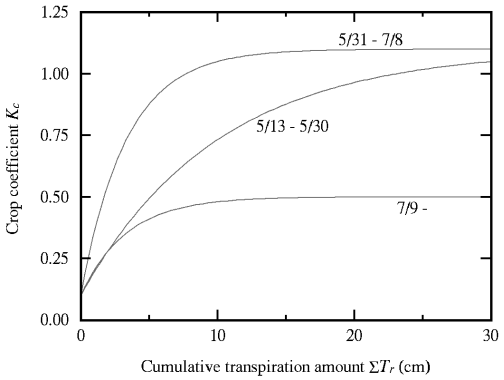


Fig. 3 Crop coefficient for transpiration as a function of cumulative transpiration. Parameter values for crop coefficient function were updated twice for representing plant growth well during field experiment.

Table 1 Parameter values of plant stress response and growth properties.

Parameter	Value	Equation number
ψ_{50} (cm)	−1000	Eq. (3)
ψ_{o50} (cm)	−3000	
p	3	
b_{rt}	1	Eq. (4)
d_{rt}	?	
g_{rt}	30	
z_{r0}	2	
a_{LAI}	1	Eq. (15)
b_{LAI}	−0.05	
a_{KC}	0.4	Eq. (16)
b_{KC}	−0.3	
c_{KC}	0.1	
a_{drt}	40	Eq. (17)
b_{drt}	−0.4	
c_{drt}	5	

Initial condition for water flow was constant pressure head at −40 cm while that for solute was constant at 0.1 g L^{-1}. Initial conditions for each two-days run were final water content (including hysteretic parameter values) and solute concentration of last run. Lower boundary condition for water flow was gravitational flow while that for solute transport was zero concentration gradient. Both right and left boundary were impeameable. Upper boundary condition was atmospheric and drip irrigation was applied to topmost and leftmost element as a source term.

4. Results and Discussion

Fig. 4 shows both measured and simulated LAI together with measured biomass data. For the twice measurements, the LAI was higher for the treatment S on June 9 despite the biomass was almost the same. This trend was observed until July 6. This relatively higher LAI might have led subsequent larger dry matter production, i. e., final dry matter production for the treatment S and the treatment A were 2.9 t ha^{-1} and 2.0 t ha^{-1}, respectively. However, both were smaller than normal potato cultivation which have been reported to vary between 3.5 and 6.0 t ha^{-1} (Battilani and Mannini, 1993). This poor growth may be due to late sowing date and potato blight. On the other hand, on June 8, we realized that simulated LAI was getting overestimated, because we did not consider this poor growth until then. This poor growth led the transpiration lower than that under normal growth. Hence, virtual net income during these periods was also overestimated. Then we adjusted cumulative transpiration value downward (from 3.1 to 1.3 cm) so that LAI dropped to near the actual one. Measured biomass on June 8 was 34 g m^{-2} (0.34 t ha^{-1}) and by dividing it with the water use efficiency of 0.003, estimated cumulative transpiration of 1.1 cm was obtained. Considering growth on June 9, cumulative transpiration was set at 1.3 cm. In simulations, we often assume ideal plant growth. However, it is important to adjust the parameter for growth depending on the cultivation processes and environment (including disease and pestilence). When poor growth is expected owing to poor pest or disease control, lower water use efficiency or lower crop coefficient which results in lower transpiration should be used. We adjusted crop coefficient to reflect damage by disease. Thus, we will be able to show more accurate virtual net income to farmers.

Fig. 5 shows the comparison between measured and simulated water contents for update run (using actual weather data) for a selected period. Legends x and z represent the horizontal distance from the drip tube and soil depth, respectively. The results show that the model underestimated water content at $(x, z) = (0, 15\ \text{cm})$. This might be due to an over-estimation of potential transpiration and root water uptake. On the other hand, the model could relatively accurately simulate the internal drainage which occurred after each irrigation for $(x, z) = (0, 45)$ and nearly bare condition for $(x, z) = (40, 5)$. In the (40, 5), daily change in water content was more significant par-

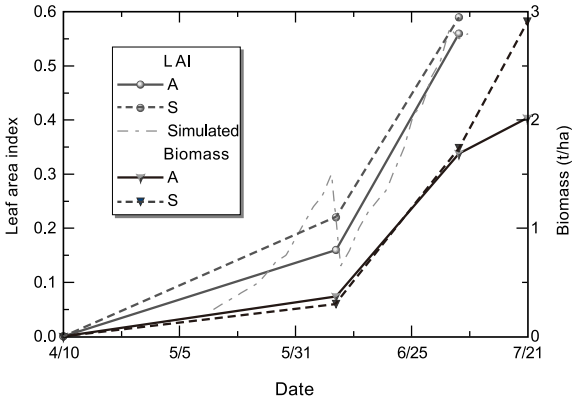


Fig. 4 Time evolution of leaf area index (LAI) and biomass. Solid and dashed lines with circles are measured LAI for treatment-A and treatment-S, respectively. Dot-and-dash line is simulated LAI. Solid and dashed lines with inverted triangles are measured biomass data for treatment-A and treatment-S, respectively.

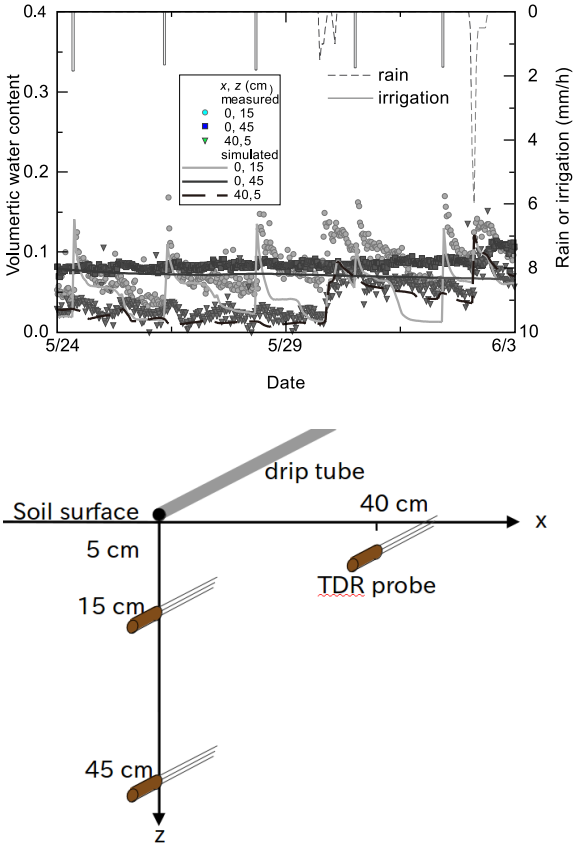


Fig. 5 a) Measured and simulated volumetric water contents for treatment-S. b) Location of TDR probes. Legends x and z represent the horizontal distance from the drip tube and soil depth, respectively. Filled circle, square, and inverted triangles are the measured water contents and solid and dashed lines are simulated ones at three locations.

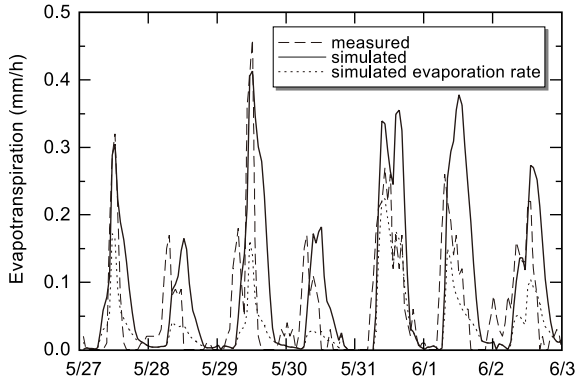


Fig. 6 Comparison of measured (dashed line) and simulated (solid line) evapotranspiration rate. Simulated evaporation rate (dot line) also shown for comparison.

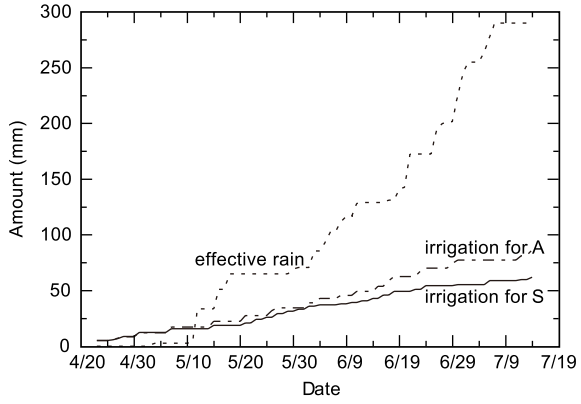


Fig. 7 Time evolution of cumulative rainfall and irrigation depths. Solid line and dot-and-dash line represent cumulative irrigation depths for treatment-S and treatment-A, respectively.

ticularly after May 29. This was due to rainfall events in those days as shown in Fig. 5. These results confirmed that the proposed scheme worked relatively well for irrigation scheduling in this field experiment. Therefore, numerical simulation of water flow and crop growth will provide relatively good prediction of crop water requirement.

In the proposed scheme, accurate estimation of evapotranspiration (ET) is important to optimizing irrigation depth. If simulated ET largely deviated from measured ones for daily scale, it means the first term of Eq. (6) is not accurately estimated. Fig. 6 compares measured and simulated ET for a selected period. Evaporation rate is average value across the soil surface. The simulation model tended to overestimate ET owing to unexpectedly slow growth of leaf area. We also have discrepancy in hourly pattern. Measured ET tends to more sharply rise in early morning and more steeply drop in early afternoon. One of these reasons would be underestimation in evaporation rate. Sharp drop in the afternoon might partly be due to the formation of dry sand layer. In the simulation, however, evaporation rate did not sharply decrease owing to larger leaf area than actual one. Evaporation rate tends to decrease as leaf area increases owing to shadowing and enhanced aerodynamic resistance (van Bavel and Hillel, 1976). Both mechanisms are incorporated into the numerical model and therefore an overestimation of leaf area leads to an underestimation of evaporation rate. Thus, in the simulation, evaporation rate persisted at low rates in the afternoon. Second reason might be a measurement error owing to thermal deformation of drip tube. Edge of the lysimeter was raised by about 3 cm above the ground and two drip tubes were on the lysimeter. In early morning when temperature was sharply increasing, the polyethylene drip tube might have become loosing and it might have eased downward tension and led underestimation of weight. Opposite mechanism might have occurred in the afternoon.

Fig. 7 shows the time evolution of rainfall and irrigation. Temporal change of cumulative irrigation depth for the proposed scheme was similar to that for the automated irrigation. This result is in agreement with the previous study (Fujimaki et al., 2014). These results suggested that the new scheme can alter automated irrigation system. Moreover, total amount of water applied was 86 mm for automated irrigation while proposed scheme applied 63 mm. These low total amounts were due to abundant water supply by rainfall. Still, potato might not have survived without irrigation under drought period such as from May 19 to May 28. The proposed scheme, treatment S, could save 27 % of irrigation water comparing with treatment A. However, saving irrigation water could not always be expected by using the proposed scheme. Fujimaki et al. (2014) reported that the proposed scheme gave 1.5 times more irrigation water compared with automated irrigation scheme in sweet corn cultivation. Because the simulation model did not consider the damage in the monitored plants as discussed above, ET was overestimated. Thus, saving irrigation water using the proposed scheme is largely affected by ET estimation.

Despite the treatment S received a 27 % lower irrigation water than treatment A, it attained higher yield by 15 %. As a result, the treatment S achieved higher net income than treatment A (1.28 times) as shown in Fig. 8. Income corresponds to first term of Eq. (6) but we applied actual fresh weight of tuber and producer price in Japan (0.7 \$ kg^{-1}). Although we set price of crop from producer price of potato in the US in the optimization, we used price in Japan since we obtained negative net income if we employed price in the US. Net income was calculated by subtracting cost for water and fertilizer from income. This result may demonstrate that not only saving cost for equipment required for automated irrigation, the proposed scheme can enhance net income compared with an automated irrigation scheme. This result could not always be obtained (Fujimaki et al., 2014), because the result

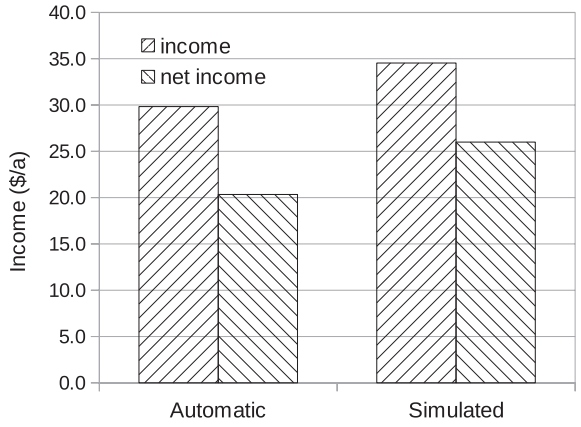


Fig. 8 Comparison between income and attained net income. 'Automatic' and 'Simulated' represent treatment-A and treatment-S, respectively.

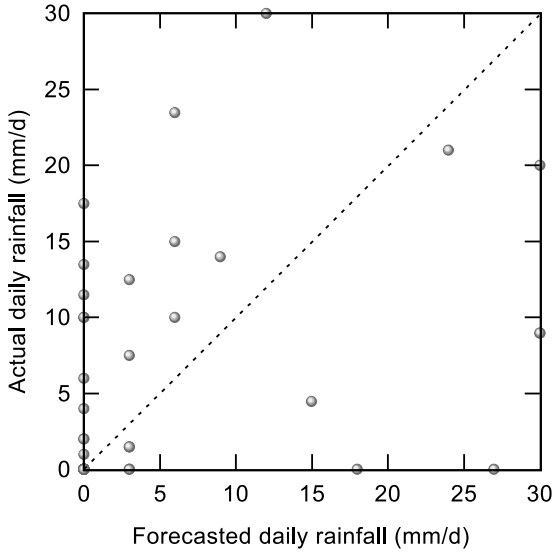


Fig. 9 Comparison between forecasted and actual daily rainfall. The dot line is the 1:1 line.

was sensitive to the crop growth. Even so, we could confirm that the new scheme can attain a similar net income to automated irrigation scheme. Fujimaki et al. (2014) compared net income by automated system and proposed scheme in two experiments. Regarding to an experiment using barley carried out in southern Tunisia, net income by proposed scheme was lower (0.86 times) than that by automated system. As for Corn in Tottori, opposite results (1.05 times) was obtained. Thus, summing up previous three experiments, proposed scheme outperformed for two in three trials.

Moreover, higher yield for treatment S might partly be attributed to lower nutrient loss due to lower deep percolation by considering forecast rain events. Simulated uptake of nutrients for treatment-A was lower than that for S by 39 %. Further evaluation of such a side effect of present scheme requires further intensive studies on nutrient balance in the future.

Finally, it might be worth reporting the accuracy of weather forecast. Root mean square error between forecasted and actual daily effective rainfall was 8.2 mm as shown in Fig. 9. In the analysis, we set effective rainfall as 30 mm. We had eight actual rain events when no rain was forecasted. The largest error occurred in July 5 when 84 mm was forecasted while actual rain was 9 mm. In addition to error in prediction due to insufficient modeling and inaccurate parameter values, advantage of optimization may be partly offset by inaccuracy in weather forecast. Still, we may expect that the accuracy will improve year by year.

5. Conclusion

We presented a scheme for determining irrigation depth using a numerical model of crop response to irrigation and quantitative weather forecast. A concept of virtual income is presented to optimize irrigation depth for each irrigation interval. A field experiment was carried out to compare net income attained by the presented scheme with that by the automated irrigation method. Results showed higher net income of presented scheme although the accuracy of simulation needs to be improved in terms of potential transpiration, particularly. These results were compared with our previous works reported by Fujimaki et al. (2014). Based on these results together with previous works, we concluded that proposed scheme can establish proper irrigation scheduling like automated irrigation systems without high initial investment.

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要　　旨

天気予報と土壌物理シミュレーションモデルを組み合わせ，純収入を最大化させる灌水量決定法を提示した．毎回の潅水量を最適化するため，次の灌漑までの蒸散量に比例する仮想収入の概念を導入した．砂丘圃場においてジャガイモを供試作物とした点滴灌漑による実験を行い，水分モニタリングに基づく自動灌漑区と，提示された方法に基づく灌漑区とで純収入を比較することにより，後者の効果を評価した．その結果，蒸散量の過大評価による水分の過小評価などの改善すべき課題が明らかとなったものの，提示された方法では 27 % 少ない潅水量で 15 % 多い収量が得られ，より高い純収入が得られた．これまでの圃場実験結果もふまえると，提示された方法は，少なくとも自動灌漑システムと同程度の純収入を与えうる，と言えよう．

キーワード：灌漑，天気予報，蒸散，純収入