New Scheme to Optimize Irrigation Depths Using a Numerical Model of Crop Response to Irrigation and Quantitative Weather Forecast

(作物の灌漑への応答の数値モデルと数値天気予報を利用した灌漑水量の新しい最適化法)

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2018

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A thesis

submitted to the United Graduate School of Agricultural Sciences, Tottori University,

in the partial fulfillment of the requirements for the degree of Doctor of Philosophy

The United Graduate School of Agricultural Sciences

Tottori University, Japan.

2018

I dedicated this thesis to my parents, my sisters, and my uncle

for their never-ending fount of moral support

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WUE	water use efficiency
ISM	irrigation scheduling methods
ET	evapotranspiration (mm d^{-1} or mm h^{-1})
DI	deficit irrigation
CWP	crop water production
ET_o or E_p	reference evapotranspiration (mm h^{-1})
P_c	producer's price of crop (\$ kg^{-1} DM),
ε	transpiration productivity of the crop
τ_i	cumulative transpiration at an irrigation interval (cm)
k_i	income correction factor
P_w	water price (\$ kg^{-1})
W	irrigation depth (mm)
C_{ot}	other costs
k_c	crop coefficient
$\bar{k}_c$	average crop coefficient over expected period of growth
τ_f	expected transpiration at final period
a_{kc}, b_{kc}, c_{kc}, d_{kc}, e_{kc}	fitting parameters for crop coefficient equation
T_r	transpiration rate (cm s^{-1})
S	water uptake rate (cm s^{-1})
T_p	potential transpiration (cm s^{-1})
α_w	reduction coefficient of water uptake
β	normalized root density distribution

ψ_{50}, ψ_{050}, p	fitting parameters for reduction coefficient equation
b_{rt}	fitting parameter for normalized root density distribution equation
d_{rt}	depth of the root zone (cm)
g_{rt}	width of the root zone (cm)
x	horizontal distance between lateral and plant (cm)
z	soil depth (cm)
z_{r0}	depth below which roots exist (cm)
a_{drt}, b_{drt}, c_{drt}	fitting parameters for depth of the root zone
I or LAI	leaf area index
a_{LAI} , b_{LAI}	fitting parameters of leaf area index equation
a_{t}, b_{t}	fitting parameters of water depth optimization
W_{max}	maximum irrigation depth
W_{mid}	50% of maximum irrigation depth
τ_{max}	transpiration at maximum irrigation depth
τ_{mid}	transpiration at 50% of maximum irrigation depth
θ or VWC	volumetric water content
t	time (s)
q_{l}	liquid water flux (cm s^{-1})
q_{v}	water vapor flux (cm s^{-1})
K	hydraulic conductivity (cm s^{-1})
ψ_{m}	matric potential (cm)
a	air-filled porosity
τ	tortuosity for gas transport
D_{va}	water vapor diffusion coefficient in free air (g cm^{-2} s^{-1})

ρ_{w}	density of water (0.997 g cm^{-3} at 25°C)
ψ	water potential (cm)
η	enhancement factor of thermal water vapor movement
ρ_{vsat}	saturated water vapor density (g cm^{-3})
T_{s}	soil temperature (K)
R_{v}	gas constant for water vapor (4697 cm K^{-1})
h_r	relative humidity
h_{rs}	relative humidity at the soil surface
c	concentration of the solute (mg cm^{-3})
q_{s}	solute flux density (mg cm^{-2} s^{-1})
S_{c}	sink term
s	crystal content
c_{max}	saturated concentration (mg cm^{-3})
D	dispersion coefficient (cm^{2} s^{-1})
D_{iw}	ionic diffusion coefficient
τ_s	tortuosity factor for ionic diffusion
λ_L	longitudinal dispersivity (cm)
λ_T	transversal dispersivity (cm)
k_{su}	passive uptake ratio
C_{hs}	heat capacity of soil (J cm^{-3}K^{-1})
q_h	sensible heat flux (W cm^{-2})
L	latent heat of water (J g^{-1})
C_{hw}	heat capacity of water (4.18 cm^{-3} K^{-1})
k_h	thermal conductivity of soil (W cm^{-1} K^{-1})

E	evaporation rate (J g^{-1})
ρ_{vss}	saturated vapor concentration at the soil surface (g cm^{-3})
ρ_{vsa}	saturated vapor concentration at reference height (g cm^{-3})
h_{ra}	relative humidity at reference height
r_a	aerodynamic resistance (s cm^{-1})
r_{sc}	resistance due to salt crust (s cm^{-1})
K	plant-specific parameter
u_2	wind speed at height of 2 m
R_a	short-wave radiation flux (W cm^{-2})
R_l	long-wave radiation flux (W cm^{-2})
α_r	albedo
T_a	temperature at the reference height (K)
T_w	temperature of infiltrating water or soil surface (K)
q_{v0}	vapor flux at the soil surface (cm s^{-1})
q_{l0}	liquid flux at the soil surface (cm s^{-1})
a_{Rs}	plant-specific parameter
h_{50}, h_{050}, and p	fitting parameters of reduction coefficient equation
x_r	sensor output at reference temperature (K)
α_T	temperature coefficient
T	temperature (K)
T_{ref}	reference temperature (K)
σ_b	bulk electrical conductivity (dS m^{-1})
σ_w	electrical conductivity of soil solution (dS m^{-1})
ω	unit-conversion factor (10.2 cm kg J^{-1})

ν	number of ions per molecule
M	molecular mass of NaCl, 58.5 (g mol^{-1})
R	universal gas constant (8.31 J mol^{-1} K^{-1})
τ_r	relative transpiration (cm s^{-1})
T_{cal}	calculated transpiration rate (cm s^{-1})
RMSE	root main square error
RWU	root water uptake
QWF	quantitative weather forecast
AIS	automated irrigation system
DAP	days after planting
PWF	perfect weather forecast
AWF	actual weather forecast

Acknowledgements

After four years spent at Tottori University, I have learned one thing – I could never have done any of this, particularly the research and writing that went into this dissertation, without the support and encouragement of a lot of people.

First and foremost I want to thank my supervisor professor Dr. Haruyuki Fujimaki. I owe to him so much. He has taught me new techniques related to soil water science and has been a never-ending fount of moral support. I appreciate all his contributions of time, ideas, and for allowing me to participate in international conferences for making my Ph.D. experience productive and potential.

I would also like to thank the rest of my thesis committee for their support, professor Dr. Tsugiyuki Masunaga, Shimane University, and Assoc. professor Dr. Saito Tadaomi, Tottroi University, provided me with invaluable advice and comments on my research study.

I extend my thanks and appreciation to Dr. Ieyasu Tokumoto, Saga University for his concrete advice and comments on both my research and my future research career plans.

I would also like to express my thanks to my research group in the Arid Land Research Center, Tottori University, Prof. Dr. Mitsuhiro Inoue, emeritus professor, for including me in his experiments work, that thing gives me a lot experience; the thank is also extended to Assoc. professor Dr. Amrakh Mamedov, Dr. I. Sakaguchi, Dr. A. Suetsugu, Mr. M. Shibata, Ms. Y. Fuji, Mr. K. Magara, Mr. T. Matsubara, and Mr. M. Atarashi for their assistant in my experiments work.

Special thanks to Ms. Masako Tamura which played a potential role for processing my application forms to get MNOBUSHO scholarship, Ms. Yuak Kikagawa helped me and facilitated everything to me; I am really appreciated to them.

I would particularly like to thank technician and affairs staff of Arid Land Research Cenetr, for processing my documents and providing me with all equipments or tools what I needed in my experiment work.

This work was supported with a grant from Japan Ministry of Education, Culture, Sports, Science and Technology (MNOBUSHO). This vital support is also greatly acknowledged.

I would like to dedicate this work to my parents and my sisters. Without their unending support and love from childhood to now, I never would have made it through this process or any of the tough times in my life. Thank you.

Finally, All the praise is due to Allah for providing me the will and the strength.

Chapter 1

Introduction

Irrigated agriculture plays a vital role in the future of world food security. Especially in developing countries, water is a scarce resource due to both unequal geographical distribution and unequal consumption of water in the world (UN-Water, 2007). People in developed countries generally use about 10 times more water daily than those in developing countries; reported by "Aral Sea trickles back to life" (http://silkroadintelligencer.com/2010/07/27/aral-seatrickles-back-to-life/, Retrieved on May 15, 2018). Generally, it takes around 2,000 - 3,000 liters of water to produce enough food to satisfy one person's daily dietary need (UN-Water, 2007). In the future, even more water will be needed to produce food because the global population is forecasted to reach 9 billion by 2050 (United Nations, 2007); and there will be an additional 3.5 billion people with most of the growth in those countries that already live under conditions of severe water scarcity.

Water scarcity is the lack of sufficient available fresh water resources to meet water demand. According to the Falkenmark Water Stress Indicator, a region is said to face "water stress" when annual water supplies drop below 1,700 m^3 $head^{-1}$ yr^{-1}. At levels between 1,700 and 1,000 m^3 $head^{-1}$ yr^{-1}, periodic or limited water shortages can be expected (http://www.wateracademy.org/article.php3? id_article=27, Retrieved on May 15, 2018). When water supplies drop below 1,000 m^3 $head^{-1}$ yr^{-1}, the country faces "water scarcity" (http://www.financingwaterforall.org/fileadmin/wwc/Library/Publications_and_reports/CamdessusSummary.pdf, Retrieved on May 15, 2018). The United Nations' FAO states that by 2025, 1.9 billion people will live in regions with absolute water scarcity, and two-thirds of the world population could be under stress conditions.

The effects of climate change also need to be considered along with other evolving factors that affect agricultural production, such as changes in farming practices and technology (EPA, 2017). The World Bank 2016 states that the world needs to produce at least 50% more food by 2050, but climate change could cut crop yields by more than 25%. Moreover, potential impacts of climate change may alter precipitation and evapotranspiration patterns, hence affecting renewable water resources. It will further reduce the availability of reliable and high quality water, impacting on productivity, costs, incomes and reputation. (Morrison et al., 2009).

It will likely increase water demand for agriculture, primarily for irrigation, due to prolonged dry periods and severe drought. Some research estimates an over 40 percent increase in irrigated land by 2080 (Fischer et al., 2007). In addition, different climate models project different worldwide changes in net irrigation requirements, with estimated increases ranging from 1 to 3% by the 2020s and 2% to 7% by the 2070s (Parry et al., 2007). If climate change results in greater water scarcity relative to demand, adaptation may include technical changes that improve water-use efficiency (WUE) and demand management (e.g., through metering and pricing).

Development of new action plans may have an effective role to reduce the hazard of water shortage, climate change and food insecurity. One of those plans would be optimizing irrigation amounts at the farm level. In coming sections, common methods used to determine irrigation depths in relation to maximize net incomes, considering free internet weather forecast and water pricing are presented.

1.1. The contribution of irrigation in global agricultural production

Irrigation is vital for agricultural production in both arid and semi-arid regions. Even in the humid and sub-humid regions, it ensures growth of rain-fed crops during drought spells when rainfall fails to provide sufficient moisture for stabilized crop production; this practice has been called supplemental irrigation (Cabelguenne et al., 1995; Debaeke and Aboudrare, 2004). It not only contributes to increase crop production but may also reduce variation in production through improved control of the crop environment. Rosegrant (1992) examined the effect of supplemental irrigation in diversion irrigation systems in the Philippines. These systems divert a portion of water from a natural water resource mixed with or without intermediate storage to be used for watering crops. He used an irrigation system simulation model to analyze the impact of irrigation on the variability in area, yield, production, and farm income. Irrigation more than doubled crop-year rice production and income.

Some have estimated that as little as 15% to 20% of the worldwide total cultivated area is irrigated, producing nearly 40% of food and agricultural products on agricultural land. For example, irrigated crop production in Egypt achieved tangible progress, particularly during the past two decades, hence reflecting the success of extension of irrigated land and increase of yields per unit area of land (Lebdi, 2016). This emphasizes that irrigation is an important factor for the future of world agriculture.

Irrigated agriculture will face a number of difficulties in the future. One of the major concerns is the generally poor efficiency with which water resources have been used for irrigation. It is relatively estimated that 40% or more of the water diverted for irrigation is wasted at the farm level through either deep percolation or surface runoff. Moreover, most of farmers are widely relying on their intuition to apply irrigation. They may over irrigate their crops leading to increases in the total maximum daily loads of nitrates, and salinity in natural water (Chapman, 1992). In contrast, many farmers sometimes receive water allocations below crop water requirements, and have to irrigate their land with levels below full crop water needs. And they may have to switch to poor quality water sources such as saline groundwater or drainage, which may cause salinity hazard afterwards. In both situations, farmers may reduce crop yields that eventually reduce their net income. Therefore, the concept of irrigation scheduling has been existed to address those issues.

1.2. The contribution of irrigation scheduling in irrigation management

Optimal irrigation management at field level needs a good knowledge of the duration of the irrigation interval and irrigation depth; this concept has been called irrigation scheduling. Where irrigation is vital for crops to complete or partial substitution of their water requirements, adequate methods of irrigation scheduling are necessary to improve WUE. This is especially important in the context of increasing competition between the environment and the various end users of water resources (Jones, 2004).

There are many irrigation scheduling methods (ISM). It can generally be divided into three categories, soil water based measurements (Dane and Topp, 2002; Hansen et al., 1980; Smith and Mullins, 2001), meteorologically calculated crop demands (Allen et al., 1998) and plant based measurements of water stress (Jones, 2004). Stevens (2007) investigated the use of ISM in South Africa. They found that only 18% of South African farmers used ISM, while the rest makes use of subjective scheduling based on intuition, local knowledge and experience.

Initially, irrigation scheduling was developed to avoid plant drought stress. The amount of water that should be applied at each irrigation event depends primarily on the soil and the amount of water it can retain for plant use (Evans et al., 1996). Irrigation application causes some water is stored in the soil and taken up by crops; while, the other parties lost by evaporation, deep percolation, runoff, or seepage. The amount of water lost through these processes is affected by irrigation system design and irrigation management. To improve irrigation application, lots of techniques to observe crop water requirements were developed. Sensors to continuously monitor either soil moisture or plant water status have been proposed as tools for irrigation scheduling (e.g. Campbell and Campbell, 1982; Jones, 1990;

Goldhamer, 2003; Jones, 2004; Intrigliolo and Castel, 2004). Yet, common practice is a calendar-based or time-based schedule which uses farmers' knowledge of crop requirements and historical weather conditions (Migliaccio et al., 2010).

In general, the most accurate method to estimate crop water use and to develop crop coefficient functions is weighing lysimeters (Howell et al., 1991). Weighing lysimeters determine evapotranspiration (ET) directly by measuring changes in mass of a soil container with plants positioned on a scale or other weighing device. Crop growth within the lysimeter container should represent the field conditions where data will be collected, and the crop surrounding the lysimeter should be similar to that inside the lysimeter (Allen et al., 1991). The lysimeter should be situated within a field that is as level as possible and away from any obstructions that potentially alter radiation and wind patterns. Therefore, the accuracy of lysimeter regarding to ET measurements varies depending on area and mass of the lysimeter as well as the type of scale system used (Howell et al., 1991). On the other hand, the Penman-Monteith energy balance equation (Allen et al., 1998) has become more popular as a method to estimate reference evapotranspiration as it estimates the flux of energy and moisture between atmosphere, soil and plant. As it is an energy conservation equation, it is universally accepted. It is thought to be the most reliable because these methods are based on physical principles and consider all the climatic factors, which affect reference evapotranspiration (Lee et al., 2004).

1.3. The contribution of deficit irrigation in irrigation management

Under conditions of scarce water supply and drought, deficit irrigation (DI) has been proposed to achieve higher water productivity (yield per unit of water used in ET, Kijne et al., 2003) than maximize yields per unit of water for a given crop. DI is the opposite term of full irrigation. It is defined as the application of water below the maximum crop water requirements (English, 1990). It was found that DI increases water productivity, relative to its value under full irrigation, as resulted from many experiments with different crops (Zwart and Bastiaansen, 2004). DI can be sustainable and viable for saving irrigation if the depleted available water taken up by plants is replenished and accumulated salts are removed by seasonal rainfall.

This approach particularly requires precise knowledge of crop response to water as drought tolerance varies considerably by species, cultivar and stage of growth (Kirda and Kanber, 1999). When water deficit occurs during a specific crop development period, the yield response can vary depending on crop sensitivity at that growth stage. Therefore, timing the water deficit appropriately is another factor for scheduling irrigation. Kang et al. (2000) have shown that regulated deficit irrigation at certain periods during maize growth saved water while maintaining yield. On the other hand, Kirda et al. (1999) found that soybean yield decreases disproportionately where evapotranspiration deficiency takes place during flowering and pod development rather than during vegetative growth.

In order to ensure successful deficit irrigation, it is necessary to consider the water retention capacity of the soil. In sandy soils plants may quickly experience water stress under deficit irrigation, whereas plants in deep soils of fine texture may have appropriate time to adjust to low soil water matric potential, and may remain unaffected by low soil water content (Hillel et al., 1972; Libardi et al., 1980). The crop water production (CWP) functions should also be considered to identify the level of the reduction in yield by water deficits. Generally, the CWP functions permit an analysis of the total dry matter production or commercial matter production of the crops for transpiration, evapotranspiration or quantity of water applied by irrigation. Knowing these relationships is necessary to assess irrigation strategies (Stewart et al., 1977; Doorenbos and Kassam, 1979; Mantovani et al., 1995; Stewart and Nielsen, 1990).

The close link between biomass production and water use makes it difficult to use DI when the objective is the production of total biomass. Therefore, it would be worth to show the following example. Fig. 1 illustrates the generalized relationship between yield and irrigation water for an annual crop. According to Fig. 1, small amounts of irrigation increase crop ET, more or less linearly till a point where the relationship becomes curvilinear as part of the water applied is not used in ET and is lost. At the point (IM, Fig. 1), yield reaches its peak where additional amounts of irrigation do not cause any increment. Note that the position of (IM, Fig. 1) is not easily defined under either conditions of water shortage or cheap price of water (Fereres et al., 1993). Therefore, there are several reasons for increased water productivity under deficit irrigation. The negative effect of drought stress during specific phenological stages on biomass partitioning between reproductive and vegetative biomass (Fereres and Soriano, 2007; Hsiao et al., 2007; Reynolds and Tuberosa, 2008) is avoided, which stabilizes or increases the number or the individual mass of reproductive organs (Karam et al., 2009). Water loss through evaporation is also reduced, thereby, water productivity for the net assimilation of biomass is increased as drought stress is mitigated or crops become more hardened. This effect is thought to be rather limited given the conservative behavior of biomass growth in response to transpiration (de Wit, 1958; Steduto et al., 2007).

DI also entails number of constraints. The use of DI requires following conditions: Crop response to drought stress should be studied carefully (Hsiao, 1973). Determining optimal timing of irrigation is particularly difficult for crops using CWP functions in which maximal WP is found within a small optimum range of ET; irrigators should have unrestricted access to irrigation water during sensitive growth stages. This is not always the case in large block designs (Zhang, 2003) or during periods of water shortage; a minimum quantity of irrigation water should always be available for application (Kang et al., 2002;

Fereres and Soriano, 2007; Geerts et al., 2008). This is not always possible in extremely dry regions where irrigation water is scarce (Enfors and Gordon, 2008).

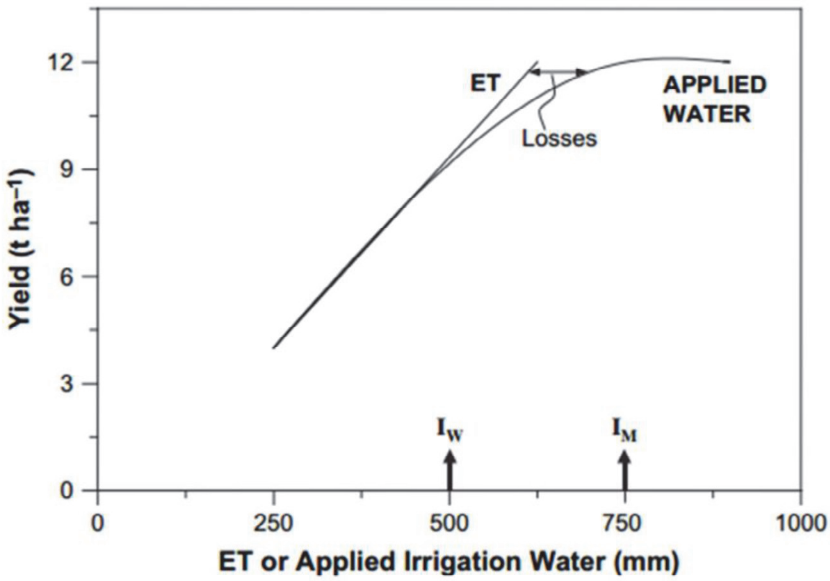

Fig. 1.1. Generalized relationships between applied irrigation water, ET, and crop grain yield (Fereres and Soiano, 2007). (I_W indicates the point beyond which water productivity starts to decrease, and IM indicates the point beyond which yield does not increase any further with additional water application.)

1.4. Modern technologies for on-farm irrigation management

Nowadays, new technologies being developed are helping farmers to make decisions in irrigation scheduling. Either automated irrigation systems or computer programs using climate-crop-soil data to predict time and amount of next irrigation events are practical services many farmers would like. In this section, the role of either automated irrigation systems or computer models in terms of irrigation water management is presented.

1.4.1. Automated irrigation systems

Automated irrigation systems have been given considerable attention during the past decades. Those systems have been developed to meet crop water needs more precisely (Hibbs et al., 1992; Hornbuckle et al., 2009). It uses valves to turn irrigation ON and OFF. Those valves may be easily automated by using controllers and solenoids. To manage irrigation water more efficiently, farmers should not use timers or make irrigation decisions based on the visual appearance of the plants (Nemali et al., 2007). Instead, environmental measurements such as evapotranspiration, soil suction or water content should be used to schedule irrigation water which secures plant water needs. Nemali and van Iersel (2006) developed an automated irrigation system that can maintain substrate water content at specific set-points. They used dielectric moisture sensors to measure water content which interfaced with a data logger and solenoid valves. Abraham et al. (2000) developed and tested two automated drip irrigation systems for Okra (Abelmoschus esculentus): one based on soil electrical conductivity and the other based on leaf–air temperature differential.

Recent advances in sensing of soil water, soil and suction and weather parameters can make the commercial use of these technologies possible to automate irrigation management. Tensiometers and granular matrix sensors were the first sensing types used for automatic irrigation control (Muñoz-Carpena and Dukes, 2008). However, capacitance soil moisture sensors are more useful to automate irrigation as they require less maintenance and provide data that are easier to interpret than tensiometers. In general, soil water sensors provide an estimate of the water content and control irrigation using either bypass or on demand operations. Bypass control measures soil water content and either allows or bypasses an irrigation event based on a set-point. On demand control allows irrigation events to occur at set low water content and terminates irrigation at set high water content. Soil water sensors are installed in the plant root zone and are used to schedule irrigation based on a predetermined threshold value (Dobbs et al., 2013). For the ET based scheduling, controllers use weather data (e.g., relative humidity, temperature, rainfall, wind speed and solar radiation) and plant characteristics to schedule irrigation. There are three major types of ET based controllers which are varied in their technique to receive weather data: historical based, signal based, and stand-alone ET controllers (Davis and Dukes, 2010; Dukes, 2012; Rutland and Dukes, 2014).

It has been proved that those technologies have usefulness to schedule irrigation. Nemali and van Iersel (2006) found that those irrigation systems were able to maintain water content for a long period within an acceptable range of the set-point despite large variations in environmental conditions and plant size. In addition, farmers using automation system are able to reduce runoff from over watering saturated soils, avoid irrigating at the wrong time of day, which will improve crop production by ensuring adequate water and nutrients when needed (Kansara et al., 2015). The limitation of those systems is that a basic knowledge of programming and wiring dataloggers is required. Moreover, installation of ET controllers and soil water sensors are not always a viable option. This is due to costs and technical skills required for installation and maintenance. Soil water sensors itself may not provide accurate estimates of field water conditions because of spatial and temporal variability of soil characteristics. Also, use of ET based controllers is limited by the availability of accurate crop coefficients required to calculate crop ET values (Migliaccio et al., 2010).

1.4.2. Computer models

Computer models are important to simulate on-farm irrigation water demands, which are based on climate–soil–plant systems (Keller, 1987; Smith, 1991; Prajamwong, 1994). In this section, a review of models which is more closed to this study (e.g., crop models based irrigation, evapotranspiration partitioning models, and soil water balance models) is presented.

1.4.2.1. Crop models based irrigation

Crop models which are based on different irrigation strategies and specific edaphoclimatic conditions can be used to predict crop yields (Pereira et al., 2002). Hanks (1974) developed a model to predict plant yield and total dry matter, as a function of water use. He assumed: (1) the ratio of actual to potential dry matter yield is directly related to the ratio of actual to potential transpiration; and (2) surface evaporation decreases with the square root of time after (irrigation or rain) as well as with the stage of growth. He found that the shape of the relative yield-water use curve was sensitive to the evaporation and transpiration assumptions, but insensitive to the function used to describe the influence of soil water status on transpiration. Furthermore, a study has been accomplished to predict crop production as related to plant water stress (Hanks and Rasmussen, 1982).

One of the early examples of computer models used to crop water management is FAO CROPWAT in FAO Irrigation and Drainage Paper No. 46 (Smith, 1992). Another one which widely used is the AquaCrop (Steduto et al., 2009). A number of studies have shown that AquaCrop is an effective tool to predict both total biomass and final yield in response to various irrigation strategies for several crops, including cotton (Farahani et al., 2009), maize (Katerji et al., 2013; Paredes et al., 2014), wheat (Andarzian et al., 2011), and potato (García-Vila and Fereres, 2012). However, those crop-based simulation models were found to employ very simple calculation methods of water and solute movement in soil and they do not allow water flux influence by time nor do they allow upward flow (Nimah and Hanks, 1973). Therefore, those are unsuitable for the detailed predictions required for soil water flow under drip irrigation and soil salinity management (Acock et al., 1983; Baker et al., 1983).

1.4.2.2. Evapotranspiration partitioning models

Accurate estimation of ET is essential to determine water management practices, design irrigation systems, and calculate crop yield (Allen et al., 1998). The partitioning ET is also fundamental for yield estimation and developing precise irrigation scheduling (Steduto et al., 2012; Ding et al., 2013; Paredes et al., 2014). Plant transpiration is strongly linked to crop production since it occurs simultaneously with photosynthesis (Pieruschka et al., 2010), while, evaporation from soil surface does not contribute to crop production, and should be reduced by management practices (Allen, 2000; Zhao et al., 2010). There is no easy way to distinguish between the two (Er-Raki et al., 2010); in addition, direct measurement of them is difficult, costly and not available in many regions (Allen et al., 1998; Monteith and Unsworth, 2008; Shuttleworth, 2007).

Computer models could alleviate the difficulty in ET partitioning and are commonly categorized into mechanistic and empirical approaches models. For examples: (a) the FAO dual-Kc model (Allen et al., 1998) is an analytical model using an empirical approach. It was preferred due to its simplicity for fewer input data and robustness for separately predicting soil evaporation and plant transpiration (Allen, 2000; Er-Raki et al., 2010). It has been widely used in scheduling irrigation and improving agricultural production (Allen, 2000; Liu and Luo, 2010; Zhao and Ji, 2010). However, it cannot calculate daily actual value of basal crop coefficient, although daily actual value is likely important to calculate the dynamics of transpiration. (b) The HYDRUS-1D (Šimůnek et al., 2008) is a numerical model based on mechanistic approach, solves the Richards equations for water flow and convection dispersion equation for heat and solute movement in soils. The water flow equation includes a sink term to account for root water uptake of plants. Evaporation is computed as a water flux turn off the soil system as described by Neuman et al. (1975); while, transpiration is estimated as a function of root water uptake. In addition to HYDRUS-1D, a 2D/3D version (Šimůnek et al., 2011) was released, allowing modeling of spatial dynamics in ET partitioning studies.

1.4.2.3. Soil water flow models

Dynamic simulation models are very useful to assess the effect of water management measures such as irrigation and regional water supply plans, on the components of the water balance of agricultural areas. Since Buckingham (1907) introduced the energy concept to describe the condition of water and Richards (1931) formulated the partial differential equation for water flow in unsaturated soil, a quantitative analysis was developed (Feddes et al., 1988). As a result, soil water flow models for the simulation of runoff, infiltration, soil water storage, evapotranspiration, capillary rise and percolation are used within irrigation practices (e.g. Singh et al., 1999).

Most of those models including HYDRUS model (presented in section 4.2.2) simulate root water uptake with a volumetric sink term, which is added to the continuity equation for soil-water flow. The sink term in these models requires detailed information about the root system as functions of, e.g., root density, root distribution, root length (Belmans et al., 1983). Ragab et al. (1990) carried out a simulation study of the soil water balance under oat (Arena saliva L.) to test the effectiveness of the model in predicting the soil water balance components and to determine whether the plant water uptake rate can be simulated by applying a rather simple approach. Integration of a soil water flow model, dated water production function with cumulative function of water sensitivity index, and a nonlinear search method was used to investigate the irrigation scheduling of winter wheat (Shang and Mao, 2006).

1.5. The contribution of weather forecast in irrigation management

One step to estimate how much water will be needed for irrigation in the future is to quantify how climate will affect irrigation water requirements (DÖLL, 2002). Therefore, continuous development of crop simulation models and numerical weather prediction models presents an opportunity to combine these models into a single crop and weather forecasting system (Challinor et al., 2003). Indeed, the use of weather forecast in irrigation scheduling was already proposed over 40 years ago (Rochester and Busch, 1972). Since then, the use of seasonal forecasts has been assessed by several researchers (Hansen et al., 2006; Mishra et al., 2008; Hansen et al., 2009; Varshneya et al., 2010). All over the world, public and private institutions provide online weather forecast and in most cases these are freely accessible to all. These weather forecast services are based on complex numerical models (e.g., Unden et al. 2002; Seity et al. 2011; Navascués et al. 2013; Perera et al. 2014). Those models incorporate the physics and chemistry of the atmosphere, as well as modulation by land surface and oceans.

Owing to availability of freely public weather forecasts, many schemes have been developed for irrigation water management. Those public weather forecast contain enough parameters for reference evapotranspiration (ETo) forecasting which were confirmed by several researchers (Cai et al., 2007; Guo et al., 2011; Luo et al., 2014). Based on the methodology and the input data, the ETo forecasting procedures can be divided into direct and indirect methods (Perera et al., 2014). In direct methods, current and historical data is used for medium- or long-term ETo forecasting either using time series methods or artificial neural networks. While, in indirect methods, numerical weather forecast data are utilized to forecast daily ETo, and several studies reported that numerical weather prediction models might be more accurate than historical models (Arca et al., 2003; Ishaket al., 2010).

The use of short-term weather forecasts should be considered to ensure more efficient use of rainfall during the growing season. Gowing and Ejieji (2001) presented an approach to predict short-term supplemental irrigation schedules for potatoes using short-term weather forecasts for optimal irrigation decisions. Following this study, many studies of using short-term weather forecasts were carried out. Cai et al. (2007) estimated ET0 with the FAO Penman–Monteith equation using daily weather forecast messages. Luo et al. (2014) proposed a method for short-term 7-day-ahead ET0 forecasting using the Hargreaves-Samani model and temperature forecasts. Lorite et al. (2015) developed a user-friendly procedure for ETo estimation based on the use of free public weather forecast. Giusti and MarsiliLibelli

(2015) used weather forecast and fuzzy rules for irrigation control, based on approximate fuzzy models of the complex physical model. Thus, short-term weather forecasts offer the possibility for the future real-time irrigation decision management.

The development of decision support systems has been the focus of numerous studies. It helps growers irrigate their crops more efficiently and achieve high yield by avoiding over-irrigation (Mohan and Arumugam, 1997; Bergez et al., 2001; Shani et al., 2004; Rinaldi and He, 2014). If weather forecasts and growth models are available, constrained non-linear optimization can be used to compute an optimal irrigation schedule (Linker and Ioslovich, 2016; Linker et al., 2015).

Still, rainfall prediction is one of weather forecast challenges. Venäläinen et al. (2005) found that errors in seasonal rainfall forecasts can have a major effect on predicted irrigation demands. Dealing with this uncertainty, advances in climate modeling have resulted in increased ability of rainfall prediction in many parts of the world with different ranges from a few days to a few months, by using dynamical forecasts or statistical methods (Njau, 2010). To remove the uncertainty in weather forecasts, Saleem et al. (2013) used actual rainfall data as weather forecasts. In this context, Delgoda et al. (2016) designed a model predictive control to accommodate uncertainty in weather forecasts by matching this assumption to the real field application. If ET0 is accurately forecasted, it can solve the problem associated with the lack of meteorological variables and eliminate or reduce the size of automated weather networks that are currently used to provide near-real time ETo data for irrigation scheduling. This will reduce costs and provide ETo data in a more timely fashion (Duce et al., 2000). Farmers also could significantly benefit from forecasts. The question of how ‘reliable’ farmers find forecasts has been studied primarily via structured interviews and focus groups (e.g. Changnon, 2004; Artikov et al., 2006; Crane et al., 2010; Mehta et al., 2013). Artikov et al. (2006) find that ‘attitude’ is among the strongest determinants of farmers’ likelihood to use weather forecasts.

1.6. Water price and farmers' behavior

Water scarcity due to large water demand for irrigation is already a critical issue in many countries; therefore, governments began to set a price on water to motivate farmers to save irrigation water. Water pricing is believed to be the most effective economic tool to promote better water allocation and water conservation (Tsur and Dinar, 1997); as it target: (a) to recover the cost of providing water delivery service; (b) to provide an incentive for efficient use of scarce water resources; and (c) to achieve equity, fairness and income redistribution (Boland and Whittington 2000; Perry, 2001). Farmers' demand from water is not only affected by the price of water, but also is affected by their income, precipitation, evaporation, crop structure, and water conservation technologies adopted (Pei et al., 2003).

Theoretically, pricing of irrigation water refers to any charges paid by farmers to get access to irrigation water (Tiwari and Dinar, 2002). The methods which employed in charging water fees to the users are known as water pricing practices. Basically, it can be divided into three categories: non-volumetric water pricing, volumetric water pricing and differential water pricing (Johansson, 2000).

1.6.1. Non-volumetric water pricing

It is known as area-based water pricing, in which water fees are charged per unit irrigated area (Johansson et al., 2002). It is usually calculated by dividing both the operation and maintenance costs by the total irrigated area. This method is preferred as it includes the simple calculation of water fees, simplicity and low implementation cost (Easter and Liu, 2005). However, in this method, the marginal cost of using one more unit of water is zero. Thus, water charges do not affect users' water consumption and may cause over-utilization of water resources (Mamitimin et al., 2015). This method is commonly implemented in many countries such as Pakistan (Hussain et al., 2005), India (Singh, 2007), Palestine (Abu-Madi, 2009) and Japan (Fujimoto and Tomosho, 2004).

1.6.2. Volumetric water pricing

In this regime, water fee is charged per volume of water used by the user (Easter, 1986). This method has a great impact on water saving. However, high implementation cost is the main weaknesses, as it requires the installation of special equipment to measure the volume and strict management of canal/pipeline. Moreover, the implementing of this method is more complicated compared to the non-volumetric water pricing method (Johansson et al., 2002; Easter and Liu, 2005). High water pricing is also a sensitive issue in developing countries where the farmers rely on irrigation water for ensuring their basic living conditions (Tsur et al., 2004). Many studies have found that increasing water pricing resulted in a significant decline in farmers' income (Berbel and Gómez-Limón, 2000; Latinopoulos, 2008; Speelman et al., 2009); but when water prices increase, farmers basically can change their traditional flood irrigation to water saving irrigation such as furrow irrigation, sprinkler irrigation and drip irrigation in order to mitigate the impact of increased water charges on their profit by reducing water use (Molle et al., 2008). This method is implemented in some parts of Spain and several states of the U.S.A. (Molle, 2009).

1.6.3. Differential water pricing

It considers charging a low water price within a prefixed volume of water consumption and a significantly higher water price when the prefixed volume is exceeded (Tsur, 2005). It can be used, when farmers' affordability is the main concern. This method is implemented in several countries such as: Jordan (Molle et al., 2008), Israel (Just et al., 1999) and Botswana (Dinar and Subramanian, 1997).

1.7. The effect of water saving on farmers' net income

Net income is a measure of the profitability of a venture after accounting for all costs and taxes (Farris et al., 2010). It is also known as net return (Álvarez et al., 2004), net gain (Xu et al., 2005), net revenue (Wichelns, 2014) or net profit (Cai and Wang, 2009). Farmers believe that maximization of net income can be achieved by maximizing the average productivity of water. This is not the appropriate criterion. Rather, farmers must seek to equate the incremental gains of water and other inputs with their incremental costs (Wichelns, 2014). In conditions when water supplies are scarce, relative to available land, farmers will choose the strategy that maximizes net income to their limited water supplies. In order to achieve this strategy, the deficit irrigation method should be adopted (Stegman et al., 1980).

Many researchers have concluded that deficit irrigation can increase net farm income (English, 1990; Martin et al., 1989; Fardad and Golkar, 2002; Zhang et al., 2002). The potential returns of deficit irrigation derive from three factors: increased irrigation efficiency, reduced cost of irrigation, and the opportunity cost of water (English et al., 1990). Ali et al. (2007) conducted a field experiment to study the effect of water deficit on the net return of wheat. They found that under land-limiting condition excluding the opportunity cost of irrigation water, the optimum water application strategy will be that maximizes net return per unit of land. Zhang et al. (2002) studied the benefit of deficit irrigation on irrigation scheduling for maximal profit in different rainfall years, dry, normal and wet years by design its own program. They calculated the net income per unit area which is the subtraction between total outputs per unit area and total inputs per unit area. Total outputs were calculated by considering price of grain yield, price of straw yield and the ratio of straw yield to grain yield multiply by the total grain yield. Total inputs were calculated by considering water fee and irrigation energy cost multiply by total water applied plus other costs. On the other hand, Fujimaki et al. (2015) used cumulative transpiration rate during each irrigation interval instead of total yield. This allows users to have estimation for real-time net income. Feinerman and Yaron (1983) presented linear programing models to calculate the net profit for the determination of an optimal mix of crops in the short run under conditions of irrigation with saline water by excluding water cost. On the other hand, Sepaskhah and Akbari (2005) used a curvilinear revenue function to represent the gross income.

1.8. Objectives of the study

The main objective of this study was to propose new scheme to optimize irrigation depth which gives maximal net income at each irrigation interval to replace capital-intensive automated irrigation method with a low-cost scheme based solely on weather data and numerical simulation. The specific goals were (a) to check the accuracy of WASH 2D to simulate water flow in soil; and (b) to evaluate the effectiveness of new scheme as compared with automated irrigation method.

1.9. Outline of the thesis

The thesis presents a new scheme which is developed to determine irrigation depths using a numerical model of crop response to irrigation and quantitative weather forecast. The introductory chapter 1 presents current and future situation of water resources in the world, and how researchers could address and evaluate those conditions. This evaluation includes (a) the impact of the irrigation on food production, (b) the usefulness of combining weather forecast in irrigation management, and (c) the role of irrigation scheduling, deficit irrigation, computer models and water pricing for improving irrigation management.

Chapter 2 describes the methodology of how the proposed numerical scheme is incorporated in the numerical model, WASH 2D, and how users could implement this scheme.

In chapter 3, 4 and 5, three experiments were carried out in the sandy field of the Arid Land Research Center to evaluate benefits of the proposed numerical scheme compared to an automated irrigation method. In chapter 3, the crop was potato (Solanum tuberosum L.), cultivated in 2015. In chapter 4, the crop was sweet potato (Ipomoea batatas L., cv. Kintoki), cultivated in 2016. In chapter 5, the crop was groundnut (Arachis hypogaea L.), cultivated in 2017.

Chapter 6 demonstrates an example to estimate parameter values of stress response function for groundnuts. These values are required as input data for WASH 2D model to simulate plant growth during growing season.

In chapter 7, general discussion was made out to show both benefits and limitations of the proposed scheme. Appropriate solutions and recommendations were also provided in this context.

Finally, chapter 8 generally concludes results obtained from physical implementation of the proposed scheme through three field experiments and its advantages compared to an automated irrigation method.

Chapter 2

Methodology

2.1. Description of new numerical scheme

This scheme has been developed based on the following two major steps:

2.1.1. Maximization of net income

Net income is considered to be the most important target that farmers are looking for. Most of them tend to believe that, net income can be increased whenever yield is increased. To do so, they intuit to add more water to plants. Consequently, problems of wasting water, leaching of nutrients or waterlogging may have occurred. In this study, effectiveness of a scheme to optimize irrigation depth presented by Fujimaki et al. (2015) was investigated. I have tried to research on this conundrum by addressing a relationship of dependence of net income on irrigation depth. In general, net income is calculated as total gross returns minus total cost for crop production, where the later consists of variable and fixed costs. In this study, the concept which was presented by Fujimaki et al. (2015) was employed. They proposed that net income, I_{n} (\$ ha^{-1}), may be calculated for each irrigation interval even though income is not realized until the crop is harvested and sold. Hence, they calculated I_{n} based on the increment in dry matter attained during the interval. Net income is calculated as total gross income minus total cost for crop production, where the later consists of variable and fixed costs as follows:

$$I_{\mathrm{n}} = P_{\mathrm{c}} \varepsilon \tau_{\mathrm{i}} k_{\mathrm{i}} - P_{\mathrm{w}} W - C_{\mathrm{ot}} \tag{2.1}$$

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 between two irrigation events (1 mm = 10,000 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 mm = 10,000 kg ha^{-1}), and C_{ot} is other costs (e.g., labors, fertilizers, etc.) ($ ha^{-1}). In Eq. (2.1), water is assumed to be set at high price to give farmers incentive to save irrigation. To calculate I_n more accurately, the k_i was used to avoid underestimating the contribution of initial transpiration to the entire quantum of growth. This is because transpiration in the initial growth stage is smaller than that in later stages; therefore, the k_i was calculated as:

$$k_{\mathrm{i}} = \frac{\overline{k}_{\mathrm{c}}}{k_{\mathrm{c}}} = \frac{\int k_{\mathrm{c}} \mathrm{d}\tau}{\tau_{\mathrm{f}} k_{\mathrm{c}}} = \frac{(a_{\mathrm{kc}} + c_{\mathrm{kc}})\tau_{\mathrm{f}} - \frac{a_{\mathrm{kc}}}{b_{\mathrm{kc}}}[\exp(b_{\mathrm{kc}}\tau_{\mathrm{f}} - 1)]}{\tau_{\mathrm{f}} k_{\mathrm{c}}} \tag{2.2}$$

where $\overline{k}_{\mathrm{c}}$ is average values of crop coefficient, k_{c} over expected period of growth, τ_{f} is the expected transpiration at final period, and a_{kc}, b_{kc} and c_{kc} are fitting parameters.

Transpiration dynamically responds to soil water matric and osmotic potentials. Therefore, a sophisticated model of crop responses to irrigation is required. Physical numerical models such as HYDRUS (Šimůnek et al., 2006), the SWAP model (Van Dam et al., 1997), the RZWQM (Ahuja et al., 2000), and WASH 2D (Fujimaki et al., 2015) can be used for estimating actual transpiration. In this study, transpiration rate, T_r (cm s^{-1}), was calculated by integrating the water uptake rate, S, over the root zone:

$$T_{\mathrm{r}} = {g_{\mathrm{rt}}}^{-1} \int_0^{g_{\mathrm{rt}}} \int_0^{d_{\mathrm{rt}}} S \mathrm{d}x\mathrm{d}z \tag{2.3}$$

Where g_{rt} and d_{rt} are the width and depth of the root zone (cm), respectively. A macroscopic root water uptake model (Feddes and Raats, 2004) was used to predict the water uptake rate, S (cm s^{-1}):

$$S = T_{\mathrm{p}} \beta \alpha_{\mathrm{w}} \tag{2.4}$$

where T_p, α_w and β are potential transpiration (cm s^{-1}), reduction coefficient and normalized root density distribution, respectively.

By using quantitative weather forecast or actual meteorological data for atmospheric boundary, T_p can be calculated by multiplying reference evapotranspiration and basal crop coefficient, k_c:

$$T_p = E_p k_c \tag{2.5}$$

where E_p is reference evapotranspiration (cm s^{-1}), calculated by the FAO Penman Monteith equation (Allen et al., 1998). Since the crop coefficient is largely affected by growth stage, it is expressed as a function of cumulative transpiration as:

$$k_c = a_{kc}[1 - \exp(b_{kc}\tau)] + c_{kc} - d_{kc}\tau^{e_{kc}} \tag{2.6}$$

where d_{kc} and e_{kc} are fitting parameters. The last term $d_{kc}\tau^{e_{kc}}$ of Eq. (2.6) was developed to express decline of k_c in latest stage of growing season. The reduction of the water uptake rate, α is a function of drought and osmotic stresses. So-called additive function (van Genuchten, 1987) was used in WASH 2D as follows:

$$\alpha = \frac{1}{1 + \left(\frac{\psi}{\psi_{50}} + \frac{\psi_o}{\psi_{o50}}\right)^p} \tag{2.7}$$

where ψ_{50}, ψ_{050} and p are fitting parameters. In this study, the equation that describes the root activity, β, was modified from its original function in Fujimaki et al. (2015) as:

$$\beta = 0.75(b_{rt} + 1)d_{rt}{}^{-b_{rt}-1}(d_{rt} - z + z_{r0})^{b_{rt}} g_{rt}(1 - x^2 g_{rt}{}^{-2}), \tag{2.8}$$

where b_{rt} is a fitting parameter; x is the horizontal distance between lateral and plant (cm); z is the soil depth (cm); and z_{r0} is the depth below which roots exist (cm). In general, roots of cultivated plants start from about 2.5 cm below the soil surface, therefore, a new parameter, z_{r0} was added to make the model more realistic.

The d_{rt} was also expressed as a function of cumulative transpiration:

$$d_{\mathrm{rt}} = a_{\mathrm{drt}}[1 - \exp(b_{\mathrm{drt}}\tau)] + c_{\mathrm{drt}} \tag{2.9}$$

where a_{drt}, b_{drt} and c_{drt} are fitting parameters. The parameter which primarily depends on cumulative transpiration is the leaf area index, I, was described as:

$$I = a_{\mathrm{LAI}}[1 - \exp(b_{\mathrm{LAI}}\tau)] \tag{2.10}$$

where a_{LAI} and b_{LAI} are fitting parameters. By expressing the parameters K_{c}, d_{rt} and I as functions of cumulative transpiration as independent variable instead of days after sowing, WASH 2D model may express plant growth more dynamically responding to drought or salinity stresses.

2.1.2. Determination of optimum irrigation depth

To minimize repetition of numerical prediction in non-linear optimization which requires heavy computation and long time to be completed, Fujimaki et al. (2015) proposed the following scheme. First, as Heermann et al. (1990) and Fereres and Soriano (2006) found a fair correlation between the yield and the irrigation depth called as generalized relationship, the relationship between transpiration and irrigation depth can be described as

$$\tau_{\mathrm{i}} = \int T_{\mathrm{r}}\,\mathrm{dt} = a_{\mathrm{t}}[1 - \exp(b_{\mathrm{t}}W)] + \tau_0 \tag{2.11}$$

where T_{r} is the transpiration rate (cm s^{-1}), a_{t} and b_{t} are fitting parameters and τ_0 is τ under no irrigation conditions.

This empirical function was chosen due its simplicity and fair fitness. Other empirical functions which convex upward and have constant asymptote may be used. Note that even when W = 0, the plant can still uptake available water from the soil and τ_0 tends to be large after rain.

Second, maximum I_{n} is obtained when the derivative of Eq. (2.1) with regard to W becomes zero:

$$\frac{\mathrm{d}I_{\mathrm{n}}}{\mathrm{d}W} = -P_{\mathrm{c}}\varepsilon k_{\mathrm{i}} a_{\mathrm{t}} b_{\mathrm{t}} \exp(b_{\mathrm{t}}W) - P_{\mathrm{w}} = 0 \tag{2.12}$$

$$W = \frac{1}{b_{\mathrm{t}}} \ln\left(-\frac{P_{\mathrm{w}}}{P_{\mathrm{c}}\varepsilon k_{\mathrm{i}} a_{\mathrm{t}} b_{\mathrm{t}}}\right) \tag{2.13}$$

In order to determine the optimum irrigation depth, the values of a_{t} and b_{t} must be known. Those values can be obtained by assessing transpiration at maximum (W_{max}, τ_{max}) and intermediate (W_{mid}, τ_{mid}) irrigation depths:

$$\tau_{\mathrm{max}} = a_{\mathrm{t}}[1 - \exp(b_{\mathrm{t}}W_{\mathrm{max}})] + \tau_0 \tag{2.14}$$

$$\tau_{\mathrm{mid}} = a_{\mathrm{t}}[1 - \exp(b_{\mathrm{t}}W_{\mathrm{mid}})] + \tau_0 \tag{2.15}$$

Rearranging Eq. (2.14) gives

$$a_{\mathrm{t}} = \frac{\tau_{\mathrm{max}} - \tau_0}{1 - \exp(b_{\mathrm{t}}W_{\mathrm{max}})} \tag{2.16}$$

and Eq. (2.14) – Eq. (2.15) gives

$$a_{\mathrm{t}} = \frac{\tau_{\mathrm{max}} - \tau_{\mathrm{mid}}}{\left(\exp(b_{\mathrm{t}}W_{\mathrm{mid}}) - \exp(b_{\mathrm{t}}W_{\mathrm{max}})\right)} \tag{2.17}$$

Therefore,

$$\frac{\tau_{\mathrm{max}} - \tau_{\mathrm{mid}}}{\left(\exp(b_{\mathrm{t}}W_{\mathrm{mid}}) - \exp(b_{\mathrm{t}}W_{\mathrm{max}})\right)} - \frac{\tau_{\mathrm{max}} - \tau_0}{\left(1 - \exp(b_{\mathrm{t}}W_{\mathrm{max}})\right)} = 0 \tag{2.18}$$

The value of b_{t} can be quickly estimated using the bisection method. The user interface of WASH 2D asks users to set upper limit value of irrigation depth. Thus, by obtaining τ from the numerical prediction at three irrigation depths, zero, the upper limit, and an intermediate value, the optimum irrigation depth can be determined.

Although drip irrigation is a three 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 distances are narrow, the system can be approximated as line source. The numerical simulations with three different irrigation depths are performed to predict τ_i until next irrigation day. Irrigation depth is used as variable flux boundary conditions for water flow in field soil. The maximum irrigation depth may be set at the cumulative reference ET between irrigation intervals (= $ET_p \times$ "irrigation\ interval"), while the minimum irrigation depth should be set at zero.

2.2. Description of numerical model

The algorithm described above and a user interface for inputting parameter values have been incorporated into a numerical model, WASH 2D, which solves equations governing the two-dimensional movement of water, solutes, and heat in soils by the finite difference method. 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).

2.2.1. Governing equation of water flow

The two-dimensional water balance equation of the combined liquid and gaseous phases is given by

$$\frac{\partial \theta}{\partial t} = -\left[\frac{\partial q_{lx}}{\partial x} + \frac{\partial q_{lz}}{\partial z}\right] - \left[\frac{\partial q_{vx}}{\partial x} + \frac{\partial q_{vz}}{\partial z}\right] - S \tag{2.19}$$

where θ is volumetric water content, t is time (s), q_l is the liquid water flux (cm s^{-1}), q_v is the water vapor flux (cm s^{-1}), x is horizontal distance, z is depth (cm), and S is a sink term that refers to plant water uptake. Both subscripts of x and z refer to direction of liquid and vapor fluxes. The q_l is described using Darcy's law:

$$q_{lx} = -K\frac{\partial \psi_m}{\partial x} \tag{2.20a}$$

$$q_{\mathrm{lz}} = -K\left(\frac{\partial \psi_{\mathrm{m}}}{\partial \mathrm{z}} - 1\right) \tag{2.20b}$$

where K is the hydraulic conductivity (cm s^{-1}) and ψ_{m} is the matric potential (cm).

Water vapor flux is divided into two terms due to water potential and thermal gradient. To consider the effect of "Liquid Island", thermal gradient should be multiplied by mechanical enhancement factor η (Phillip and de Vries, 1957).

$$q_{\mathrm{vx}} = -a\tau\rho_{\mathrm{w}}{}^{-1}h_{\mathrm{r}}D_{\mathrm{va}}\left(\frac{\rho_{\mathrm{vsat}}}{R_{\mathrm{v}}T_{\mathrm{s}}}\frac{\partial \psi}{\partial \mathrm{x}} + \eta\frac{\partial \rho_{\mathrm{vsat}}}{\partial T_{s}}\frac{\partial T_{\mathrm{s}}}{\partial \mathrm{x}}\right) \tag{2.21a}$$

$$q_{\mathrm{vz}} = -a\tau\rho_{w}^{-1}h_{\mathrm{r}}D_{\mathrm{va}}\left(\frac{\rho_{\mathrm{vsat}}}{R_{\mathrm{v}}T_{\mathrm{s}}}\frac{\partial \psi}{\partial \mathrm{z}} + \eta\frac{\partial \rho_{\mathrm{vsat}}}{\partial T_{\mathrm{s}}}\frac{\partial T_{\mathrm{s}}}{\partial \mathrm{z}}\right) \tag{2.21b}$$

where a is the air-filled porosity, τ is the tortuosity for gas transport, D_{va} is the water vapor diffusion coefficient in free air (g cm^{-2} s^{-1}), and ρ_{w} is the density of water (0.997 g cm^{-3} at 25°C), h_{r} is the relative humidity, ψ is the water potential (cm), η is the enhancement factor for thermal water vapor movement, ρ_{vsat} is the saturated water vapor density (g cm^{-3}), T_{s} is soil temperature (K), and R_{v} is the gas constant for water vapor (4697 cm K^{-1}). By assuming thermodynamic equilibrium between the liquid and gaseous phases, the relative humidity in a soil, h_{r} or at the soil surface, h_{rs} can be calculated using (Philip and de Vries, 1957):

$$h_{\mathrm{r}} = \exp\left(\frac{\psi_{\mathrm{w}}}{R_{\mathrm{v}}T_{\mathrm{s}}}\right) \tag{2.22}$$

2.2.2. Governing equation of solute movement

The two-dimensional solute balance is given by

$$\frac{\partial(\theta \mathrm{c})}{\partial \mathrm{t}} = -\left(\frac{\partial q_{\mathrm{sx}}}{\partial \mathrm{x}} + \frac{\partial q_{\mathrm{sz}}}{\partial \mathrm{z}}\right) - S_{\mathrm{c}} \qquad s = 0 \cap c < c_{\max} \tag{2.23}$$

where c is the concentration of the solute (mg cm^{-3}), q_{s} is solute flux density (mg cm^{-2} s^{-1}), S_{c} is the sink term, s is crystal content (the mass of crystal per unit volume, in unit of mg cm^{-}

^{3}), $c_{\max}$ is the saturated concentration (mg cm^{-3}). By assuming that precipitation and dissolution occur instantaneously, s can be calculated as

$$\frac{\partial s}{\partial \mathrm{t}} = -\left(\frac{\partial q_{\mathrm{sx}}}{\partial \mathrm{x}} + \frac{\partial q_{\mathrm{sz}}}{\partial \mathrm{z}}\right) - S_{\mathrm{c}} - c_{\max}\frac{\partial \theta}{\partial \mathrm{t}} \qquad s > 0 \cap c = c_{\max} \tag{2.24}$$

$$\frac{\partial c}{\partial t} = 0$$

The solute fluxes are calculated by the convection-dispersion equation as:

$$q_{\mathrm{sx}} = -\theta D_{\mathrm{xx}}\frac{\partial \mathrm{c}}{\partial \mathrm{x}} - \theta D_{\mathrm{xz}}\frac{\partial c}{\partial \mathrm{z}} + q_{\mathrm{lx}}c \tag{2.25a}$$

$$q_{\mathrm{sz}} = -\theta D_{\mathrm{zz}}\frac{\partial c}{\partial \mathrm{z}} - \theta D_{\mathrm{zx}}\frac{\partial c}{\partial \mathrm{x}} + q_{\mathrm{lz}}c \tag{2.25b}$$

where D is the dispersion coefficient (cm^{2} s^{-1}) and the first and the second subscripts of D refer to direction of flux and concentration gradient, respectively. The D of each direction is given by:

$$\theta D_{\mathrm{xx}} = \theta D_{\mathrm{iw}}\tau_{\mathrm{s}} + \frac{\lambda_{\mathrm{L}} {q_{\mathrm{lx}}}^{2} + \lambda_{\mathrm{T}} {q_{\mathrm{lz}}}^{2}}{(q_{\mathrm{l}})} \tag{2.26a}$$

$$\theta D_{\mathrm{zz}} = \theta D_{\mathrm{iw}}\tau_{\mathrm{s}} + \frac{\lambda_{\mathrm{L}} {q_{\mathrm{lz}}}^{2} + \lambda_{\mathrm{T}} {q_{\mathrm{lx}}}^{2}}{(q_{\mathrm{l}})} \tag{2.26b}$$

$$\theta D_{\mathrm{xz}} = \theta D_{\mathrm{zx}} = \frac{(\lambda_{\mathrm{L}} - \lambda_{\mathrm{T}}) q_{\mathrm{lx}} q_{\mathrm{lz}}}{(q_{\mathrm{l}})} \tag{2.26c}$$

Where D_{iw} is the ionic diffusion coefficient, and τ_{s} is the tortuosity factor for ionic diffusion, λ_{L} is longitudinal dispersivity (cm) and λ_{T} is transversal dispersivity (cm).

The sink term S_{c} is calculated by

$$S_{\mathrm{c}} = k_{\mathrm{su}} c S \tag{2.27}$$

where k_{su} is the passive uptake ratio. Note that current version of WASH_2D can simulate only one solute.

2.2.3. Governing equation of heat movement

Heat conservation in the soil can be described as

$$C_{\mathrm{hs}}\frac{\partial T_{\mathrm{s}}}{\partial \mathrm{t}}=-\left(\frac{\partial q_{\mathrm{hx}}}{\partial \mathrm{x}}+\frac{\partial q_{\mathrm{hz}}}{\partial \mathrm{z}}\right)-L\rho_{\mathrm{w}}\left(\frac{\partial q_{\mathrm{vx}}}{\partial \mathrm{x}}+\frac{\partial q_{\mathrm{vz}}}{\partial \mathrm{z}}\right) \tag{2.28}$$

where C_{hs} is the heat capacity of soil (J cm^{-3} K^{-1}), q_{h} is the sensible heat flux (W cm^{-2}), L is the latent heat of water (J g^{-1}).

Heat flux for in directions of x and z is given by

$$q_{\mathrm{hx}}=-k_{\mathrm{h}}\frac{\partial T_{\mathrm{s}}}{\partial \mathrm{x}}+C_{\mathrm{hw}}T_{\mathrm{s}}q_{\mathrm{lx}} \tag{2.29}$$

$$q_{\mathrm{hz}}=-k_{\mathrm{h}}\frac{\partial T_{\mathrm{s}}}{\partial \mathrm{z}}+C_{\mathrm{hw}}T_{\mathrm{s}}q_{\mathrm{lz}} \tag{2.30}$$

where C_{hw} is the heat capacity of water (4.18 cm^{-3} K^{-1}) and k_{h} is the thermal conductivity of soil (W cm^{-1} K^{-1}).

2.2.4. Governing equation of evaporation rate

Evaporation rate, E, is calculated by a bulk transfer equation as:

$$E=\frac{\rho_{\mathrm{vss}}h_{\mathrm{rs}}-\rho_{\mathrm{vsa}}h_{\mathrm{ra}}}{r_{\mathrm{a}}+r_{\mathrm{sc}}} \tag{2.31}$$

where ρ_{vss} is the saturated vapor concentration at the soil surface (g cm^{-3}), ρ_{vsa} is the saturated vapor concentration at reference height (g cm^{-3}), h_{ra} is the relative humidity at reference height, r_{a} is the aerodynamic resistance (s cm^{-1}) and r_{sc} is the resistance due to salt crust (s cm^{-1}). For uniform bare field, the r_{a0} of bare soil surface, is calculated from wind velocity at the height of 2 m, u_2 (cm s^{-1}) (van Bavel and Hillel, 1976).

$$r_{a0} = \frac{\ln(\frac{200}{z_m})^2}{\kappa^2 u_2} \tag{2.32}$$

where z_m is the surface roughness (cm) and k is the Karman constant (0.4). The increment in aerodynamic resistance due to plant cover is can be expressed as a function of leaf area index.

$$r_a = r_{a0}(1 + a_{ra} I) \tag{2.33}$$

where a_{ra} is a plant-specific parameter.

2.2.5. Heat flux at the soil surface

Heat flux at the soil surface, q_{h0} is given by the heat balance equation considering convective heat transfer by rainfall and irrigation.

$$q_{h0} = (1 - \alpha_r) R_a + R_l - L q_{v0} - C_{ha} \frac{T_{s0} - T_a}{r_a} + C_{hw} T_w q_{l0} \tag{2.34}$$

where R_a is the short-wave radiation flux (W cm^{-2}), R_l is the long-wave radiation flux (W cm^{-2}), α_r is the albedo, T_a is temperature at the reference height (K), T_w is the temperature of infiltrating water or soil surface. q_{v0} and q_{l0} are vapor and liquid flux at the soil surface (cm s^{-1}), respectively. The flux of shortwave radiation which arrives at the soil surface is decreased by vegetation cover; therefore, the shortwave flux is expressed as a function of leaf area index as

$$R_s = R_{sc} \exp(-a_{Rs} I) \tag{2.35}$$

where R_{sc} is R_s at canopy and a_{Rs} is a plant-specific parameter. Campbell (1985) presented a typical value of a_{Rs} as 0.82.

2.3. Optimization procedure

2.3.1. Theoretical optimization procedure

The routine calculation procedure (Fig. 2.1) begins with (1) acquiring recent weather records in the early morning of each irrigation day to (2) perform a numerical simulation to estimate and current condition. Then, after (3) obtaining quantitative weather forecast data until the next scheduled irrigation, (4) three simulations are run to determine the optimum irrigation depth to be applied using the result of (2) as initial condition. The irrigation is then performed. On the next irrigation day, (6) the current status is estimated by (5) simulation using the actual records of irrigation depth and weather since the last irrigation. Then (7) the weather forecast until the next scheduled irrigation is used to (8) perform the irrigation depth optimization for that irrigation day. This cycle continues until the final irrigation.

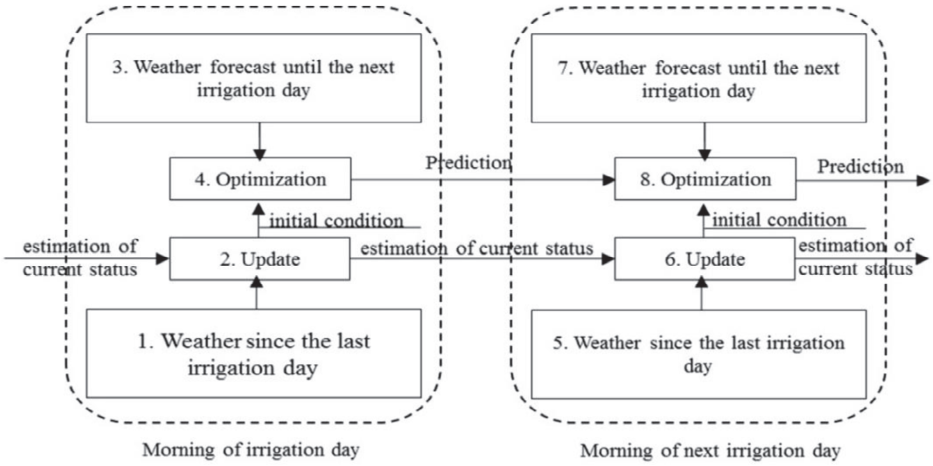

Fig. 2.1. Optimization procedure for determining irrigation depth on scheduled irrigation days using the proposed scheme.

In this study, 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. A utility program (WeatherForecastDownloader) was developed by professor Haruyuki Fujimaki, Tottori University, Japan to download the HTML file of 2 days of quantitative weather forecasts from the website of Yahoo! Japan (

URL:http://weather.yahoo.co.jp/weather/jp/31/6910/31302.html, confirmed on February 7, 2018). These weather forecasts provide quantitative values for all required parameters except solar radiation, but provide classes of cloud such as “rain”, “cloudy” or “clear”. Therefore, an empirical relationship between such descriptions and the ratio of extraterrestrial radiation to solar radiation was used. The representative values of solar radiation corresponding to the different classes of cloud cover were (“clear” = 0.82, “cloudy” = 0.63, and “rain” = 0.32).

2.3.2. Implementation of the optimization procedure using WASH 2D model

This section presents a set of steps to perform the simulation procedure for optimizing irrigation depths.

Step 1: run the WASH 2D software, and then the user interface will be shown (Fig. 2.2). In this step, (1) the user may select “prediction” to perform “update run” (estimation of initial condition) or may select “optimization of irrigation amount” to perform “optimization run”;

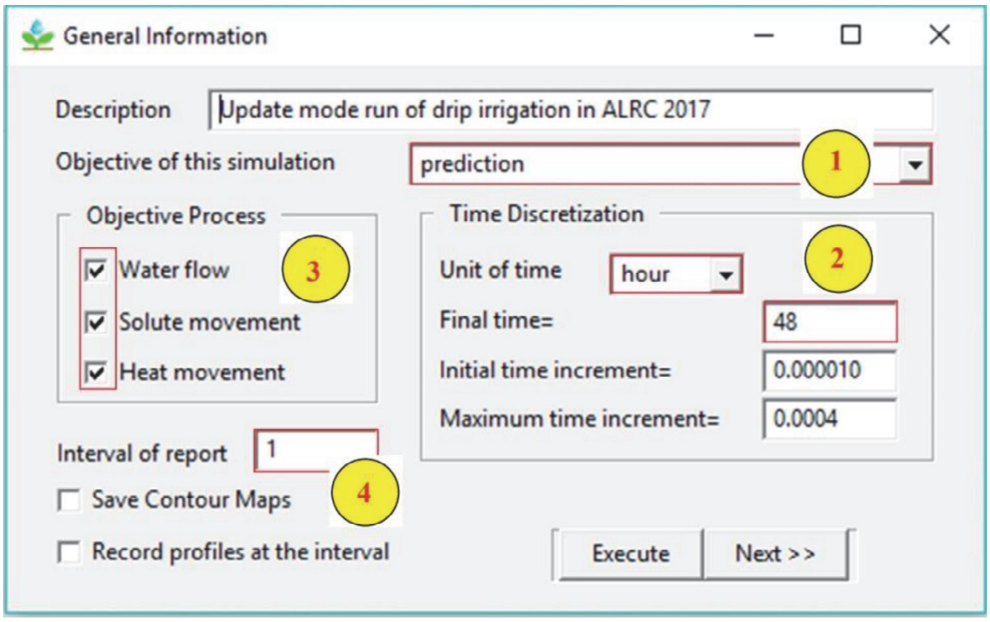

Fig. 2.2. Step 1: general information required to start a new simulation.

(2) in time discretization tap, the user is able to set the unit of time and the length of irrigation interval (final time); (3) the user may check each box to solve the governing equations mentioned in section 2.2; and (4) the user may set the simulation interval (e.g., 1 hour).

Step 2: in water flow module (Fig. 2.3),

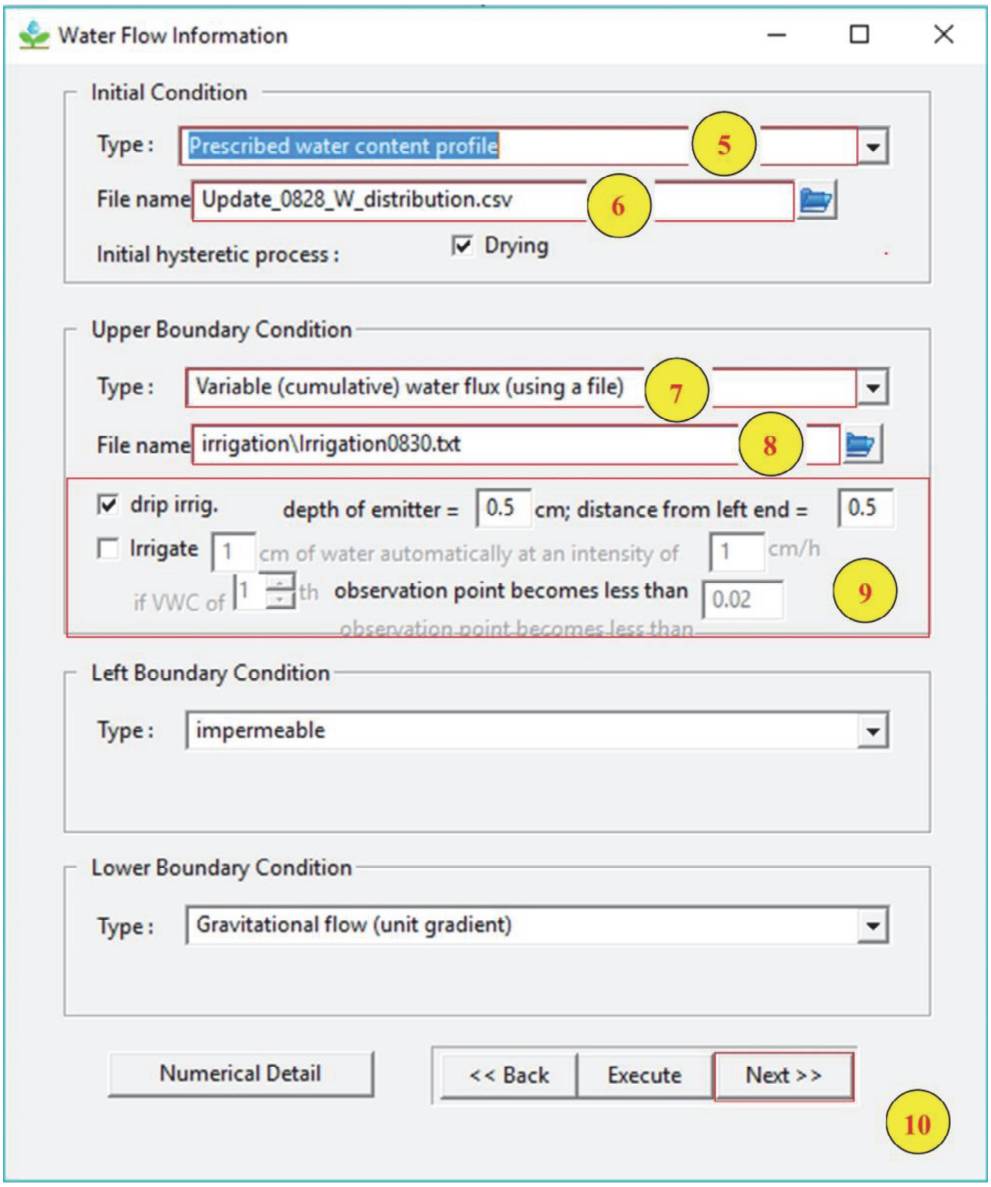

Fig. 2.3. Step 2: interface of water flow module in WASH 2D.

(5) the user may select the type of initial condition as "uniform water content" or "uniform pressure head" in case of first irrigation; (6) the user should select "prescribe water content

profile” if the updated file of water content distribution from the previous irrigation is existed; (7) the user should select “atmospheric boundary condition” from type of upper boundary condition if there is no irrigation occurred in the last simulation interval; otherwise, (8) he or she should select “variable (cumulative) water flux (using a file)” if irrigation is performed in the last irrigation time; (9) the user should put required information of drip irrigation system if this system is used; and (10) click to the next step.

Step 3: As shown in Fig. 4, (11) the user should select “variable condition (using a file)” to insert (13) a file of weather condition recorded since the last irrigation in case of update run or a weather forecast file of the next irrigation interval in case of optimization run; (12) the user should set both expected irrigation start time and irrigation date; and then, (14) click next.

Step 4: regarding to Fig. 2.5, (15) the user may select “uniform” in case of first irrigation simulation or select “input from a file (concentration)” to insert the updated file of solute distribution (16) resulted from the last update run; (17) the user may select “constant (including zero)” in case of the fertilizer is added (18); and then (19) click next.

Step 5: (20) the user should insert parameter values of plant properties (Fig. 2.6), manually or using an input file of crop properties. Note that those parameter values have been estimated for several crops by the team of Fujimaki’s lab, Arid Land Research Center, Tottori University, Japan. Before clicking the next step (21), cumulative transpiration resulted from the simulation should be inserted in unit of cm.

Step 6: it is required only in the optimization run (Fig. 2.7). The user should set the required information (22); and then (23) click next to start (24) whether update run by excluding step 6 or start optimization run as shown in Fig. 2.8.

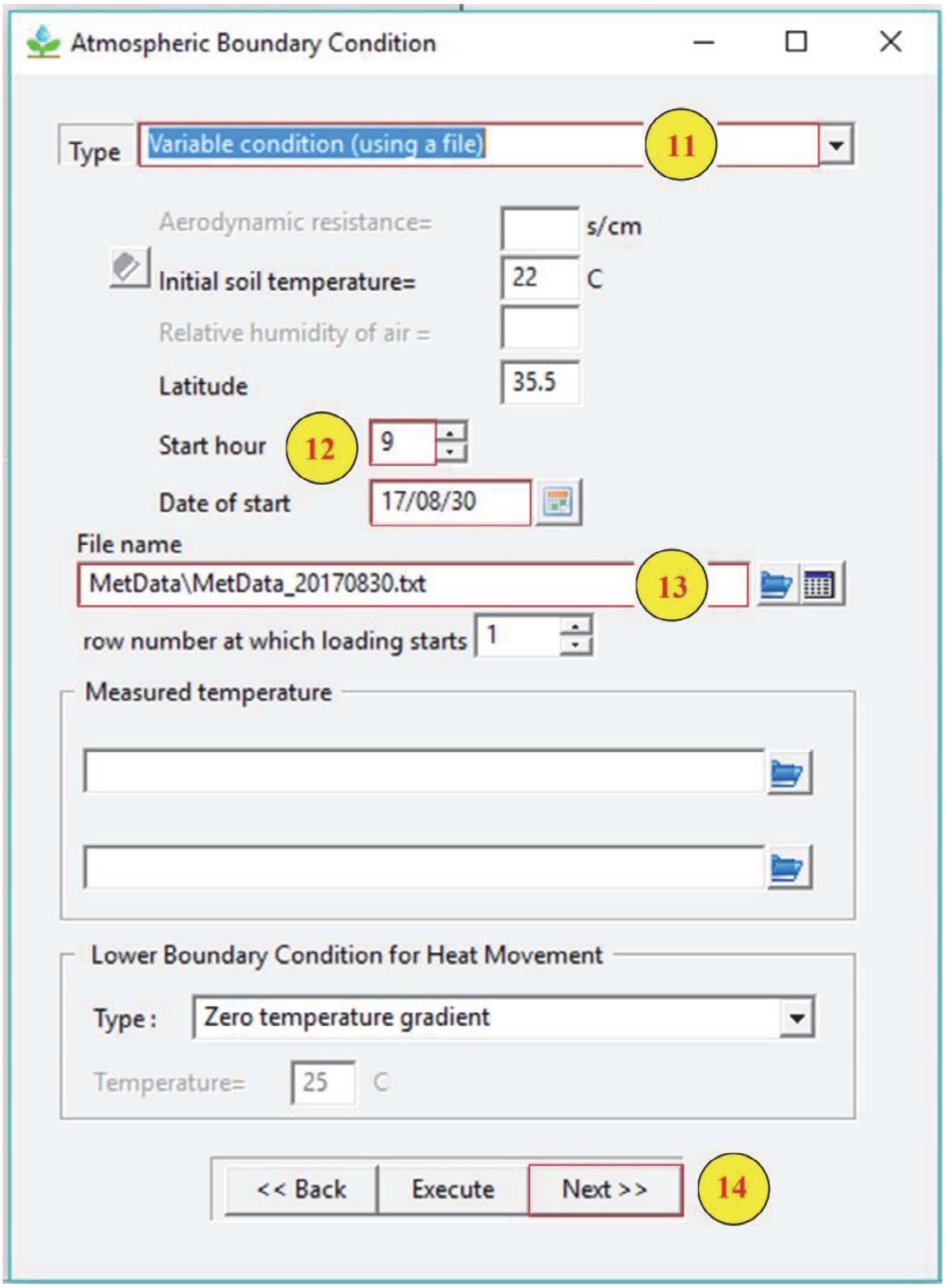

Fig. 2.4. Step 3: interface of atmospheric boundary condition module in WASH 2D.

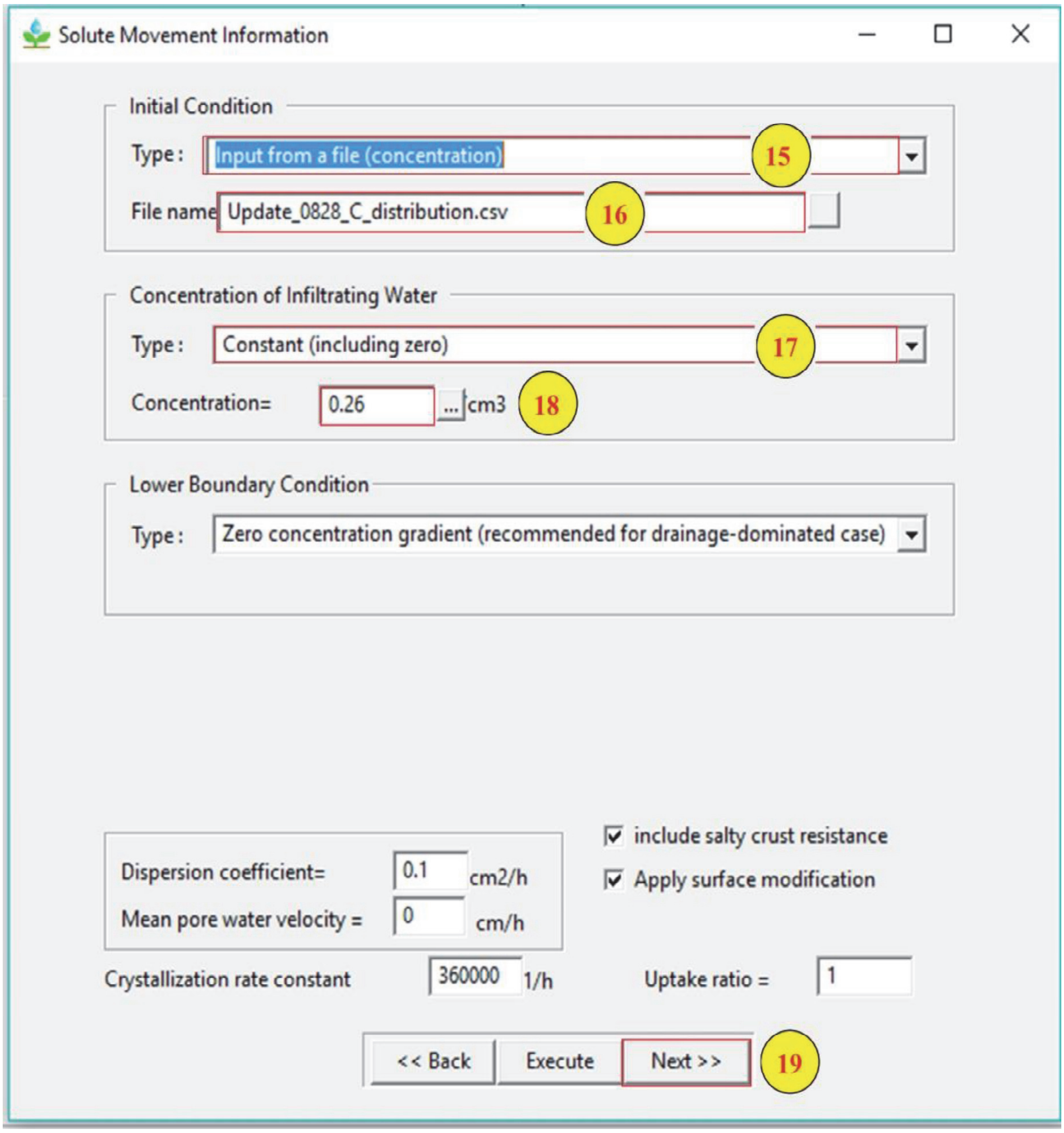

Fig. 2.5. Step 4: interface of solute movement module in WASH 2D.

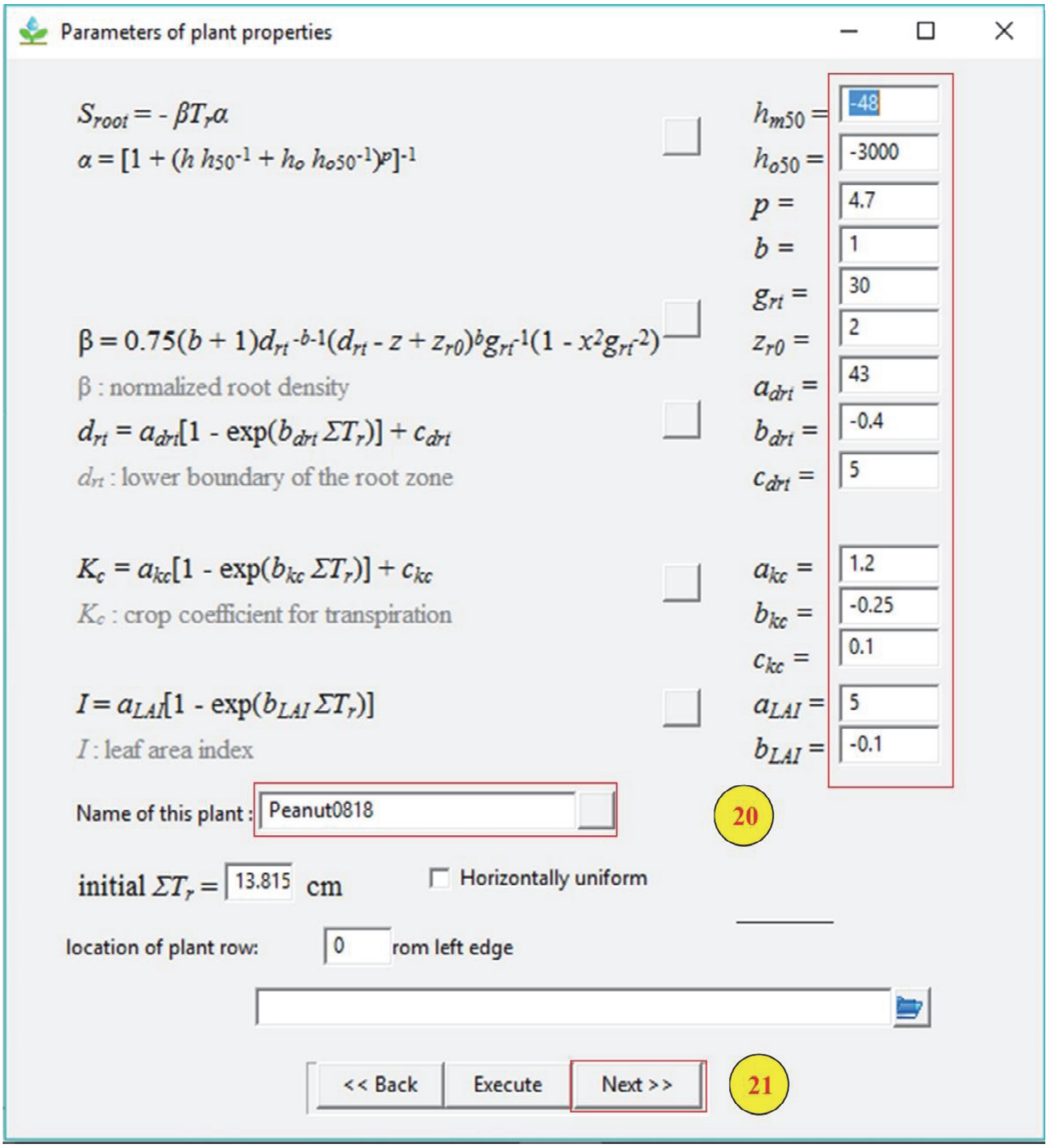

Fig. 2.6. Step 5: interface of root water uptake module in WASH 2D.

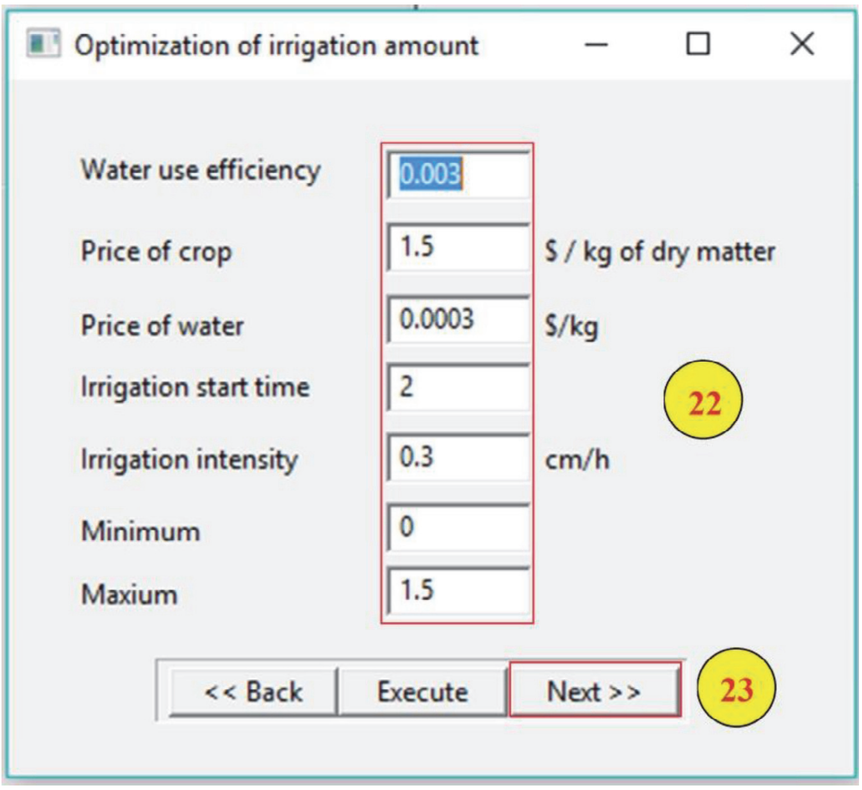

Fig. 2.7. Step 6: required information to optimize irrigation depth.

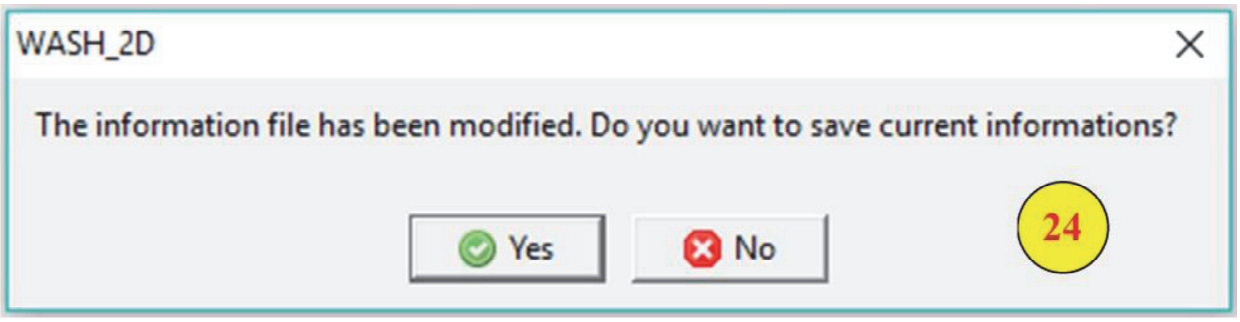

Fig. 2.8. WASH 2D message to save and start performing a new simulation.

By performing this procedure, (25) user may get recommended values of irrigation depth and net income (Fig. 2.9) if plant needs to be irrigated

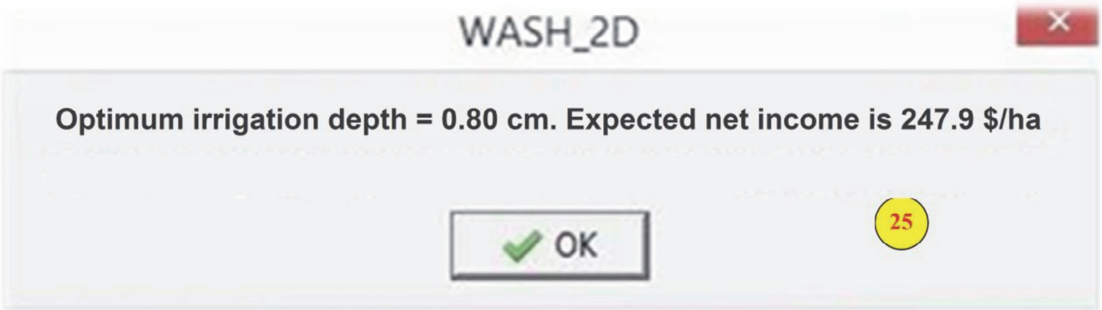

Fig. 2.9. A result of recommended values of optimal irrigation depth and net income at an irrigation interval.

or (26) no-irrigation is required (Fig. 2.10) if the soil water is readily enough to plants.

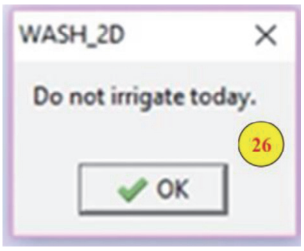

Fig. 2.10. WASH 2D message in case of no-irrigation is required.

Chapter 3

A validation study of the proposed scheme for potato (*Solanum tuberosum* L.)

Summary

A scheme to determine 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 32%, while yield was increased by 15%, resulting in higher net income as compared to automated irrigation. Based on these results together with previous works, the proposed scheme can at least realize similar net income to automated irrigation systems without high initial investment.

3.1. Introduction

Potato (*Solanum tuberosum* L.) is one of the most important vegetables in the world, rates fourth among the world's agricultural products in production volume, after wheat, rice and corn (Fabeiro et al., 2001). World Potato Research Center projected that world demand form potatoes will exceed those three crops by 2020. It is a temperate crop, which grows well and gives a higher yield in humid climates. It is widely cultivated in Japan under either irrigated or non-irrigated conditions.

Drip irrigation is an efficient method of applying water and nutrients to plants; and it highly recommended for vegetables production. Determination of both irrigation frequency and irrigation amount is one of the most important factors in drip irrigation management. Therefore, automation systems are widely adopted with this irrigation method. Several researchers stated that drip irrigation is an effective method for high potato yields (Kang et al., 2004; Onder et al., 2005; Hou et al., 2010). Tensiometers are common devices to measure soil matric potential, are widely used for drip irrigation scheduling (Wilson et al., 2001; Kang et al., 2004). Soil water is considered to be a major limiting factor for potatoes production. Many studies showed that potatoes are relatively sensitive to drought stress (Opena and Porter, 1999; Porter et al., 1999; Fabeiro et al., 2001) because it possess a sparse root system and nearly 85% of the root length is concentrated in the upper 30 cm of soil profile (Opena and Porter, 1999). Wang et al. (2007) suggested range values for soil matric potential between −15 kPa and −45 kPa for growing potatoes in Loam soil.

As discussed in Chapter 1, Fujimaki et al. (2014) presented a new scheme to optimize irrigation depths using freely internet weather forecast. 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*, Amaenbou86). These results still have not been satisfactory to evaluate the effectiveness of the proposed scheme. In this chapter, a field experiment was carried out for potatoes to evaluate the effectiveness of this scheme in terms of net income and irrigation amount, compared with an automated irrigation method.

3.2. Materials and Methods

3.2.1. 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, twelve 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.

3.2.2. 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 an hour when average θ at the depth of 15 cm became less than 0.09 cm^3 cm^{-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 fertilizer (N = 10%, P2O5 = 4%, K2O = 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 simulates only one solute, "conceptual nutrient solute" assuming that all of solutes in soil water are taken up by roots. Ionic diffusion coefficient of sodium chloride was used. Any adsorption, precipitation, or chemical reactions were not considered. The effect of nutrients uptake on growth was not considered and assumed that growth depends simply on cumulative transpiration regardless of nutrients uptake.

3.2.3. Soil

Soil of the field was sand whose hydraulic properties are shown in Fig. 3.1. Solute transport parameters such as dispersivity (0.59 cm) and dependence of tortuosity 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:

$$k_{\mathrm{h}} = a_{\mathrm{h}} + b_{\mathrm{h}}\left(\frac{\theta}{\theta_{\mathrm{sat}}}\right) - (a_{\mathrm{h}} - d_{\mathrm{h}})\exp\left[-c_{\mathrm{h}}\left(\frac{\theta}{\theta_{\mathrm{sat}}}\right)^{e_{\mathrm{h}}}\right] \tag{3.1}$$

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

$$\alpha_{\mathrm{R}} = \frac{\alpha_{\max} - \alpha_{\min}}{1 + \left(a_{\mathrm{al}}\bar{\theta}\right)^{b_{\mathrm{al}}}} + \alpha_{\min} \tag{3.2}$$

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

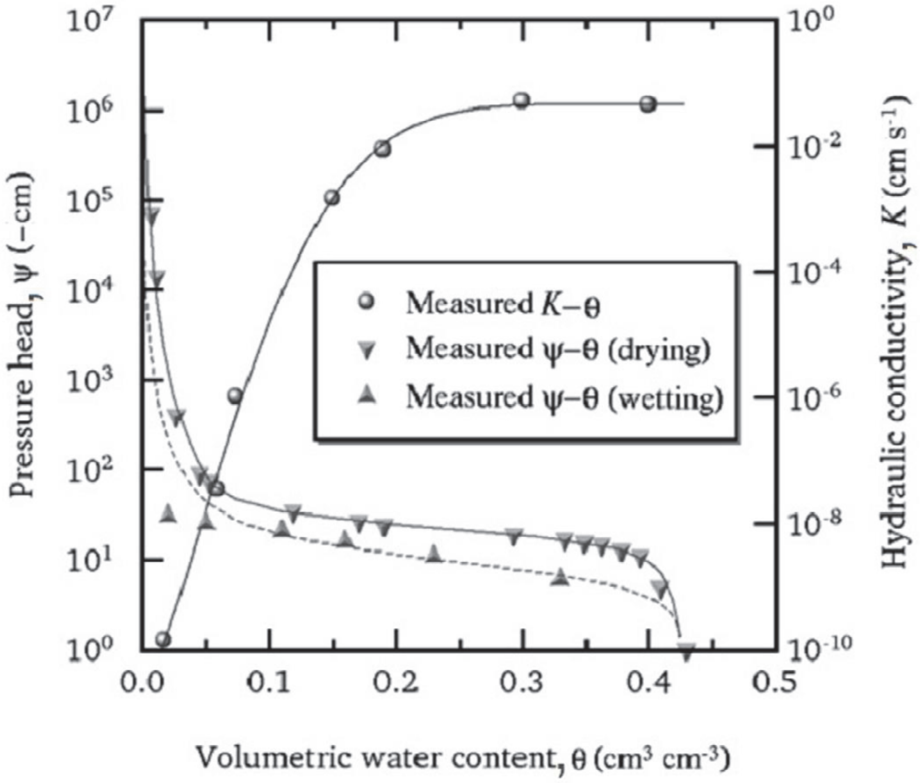

Fig. 3.1. Hydraulic properties of Tottori

3.2.4. 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 3.1 were used. These values are comparable for canola (Yanagawa and Fujimaki, 2013). As shown in Fig. 3.2, parameter values for crop coefficient function 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 21 July.

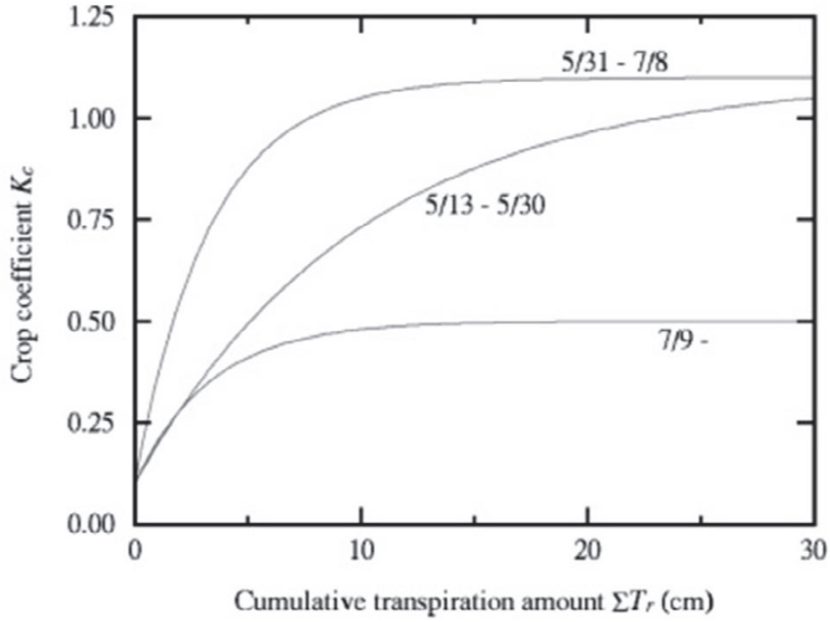

Fig. 3.2. Crop coefficient for transpiration as a function of cumulative transpiration.

3.2.5. 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. Initial condition for water flow was constant pressure head at - 40 cm while that for solute was constant at 0.1 g l^{-1}. The Initial conditions for each two days runs 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 impermeable. Upper boundary condition was atmospheric and drip irrigation was applied to topmost and leftmost element as a source term.

Table 1.1. Parameter values of plant stress response and growth properties. Equation numbers are quoted from chapter 2.

Parameter	Value	Remark
a_{kc}	0.4	
b_{kc}	-0.3	Eqs. (5) and (6)
c_{kc}	0.1	
ψ_{50} (cm)	-1000	
ψ_{o50} (cm)	-3000	Eq. (7)
P	3.0	
b_{rt}	1	
d_{rt}	?	Eq. (8)
g_{rt}	30	
z_{ro}	2	
a_{drt}	40	
b_{drt}	-0.4	Eq. (9)
c_{drt}	5	
a_{LAI}	1	
b_{LAI}	-0.05	Eq. (10)

3.3. Results and Discussion

Both measured and simulated LAI were compared each other, together with measured biomass data as shown in Fig. 3.3. For the twice measurements, the LAI was higher for the treatment S on 9 June 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 and 2.0 t ha^{-1}, respectively. However, both of them were smaller than normal potato growth which has 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 8 June, the simulated LAI was getting overestimated, because this poor growth was not considered 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, cumulative transpiration value was adjusted downward (from 3.1 to 1.3 cm) so that LAI dropped to near the actual one. Measured biomass on 8 June was 34 g m^{-2} and by dividing it with the water use efficiency of 0.003, estimated cumulative transpiration of 1.1 cm was obtained. Considering growth on 9 June, cumulative transpiration was set at 1.3 cm. In simulations, ideal plant growth is often assumed. 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. Crop coefficient was adjusted to reflect damage by disease. Thus, estimation of virtual net income became be more accurate to farmers.

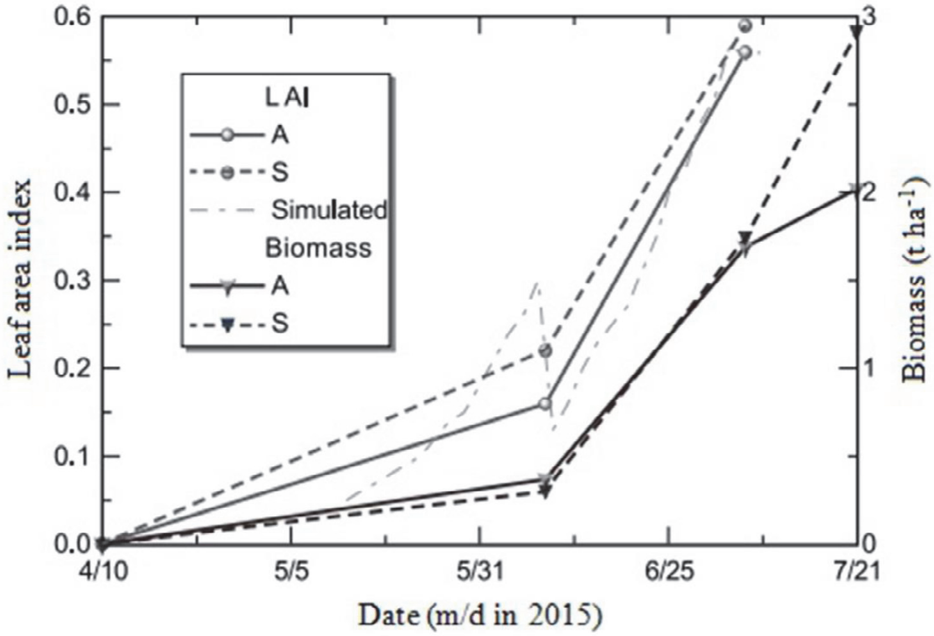

Fig. 3.3. Time evolution of leaf area index (LAI) and biomass. Solid and dashed lines with circles are measured LAI for treatments A and S, respectively. Dot and dash line is simulated LAI. Solid and dashed lines with inverted triangles are measured biomass data for treatments A and S, respectively.

To check the model accuracy in terms of soil water content simulation, measured and simulated water contents for update run (using actual weather data) for a selected period were compared as shown in Fig. 3.4. Legend x represents the horizontal distance from the drip tube (cm); while Legend z represents the soil depth (cm) as shown in Fig. 3.5. The model underestimated water content at (x, z) = (0, 15). 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).

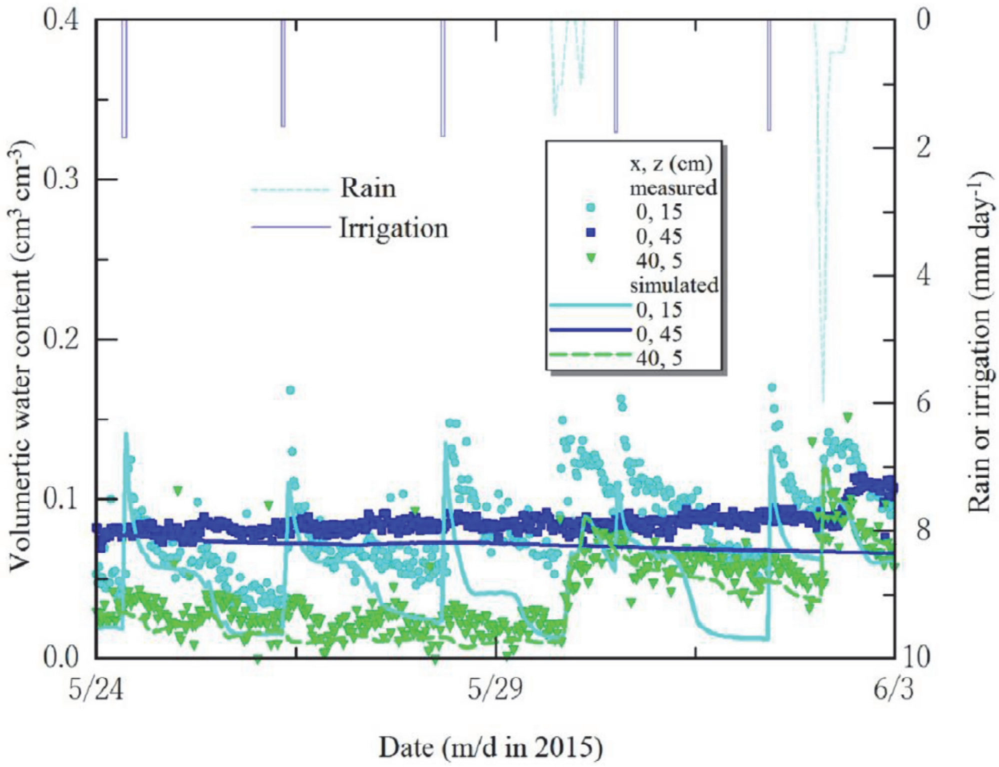

Fig. 3.4. Measured and simulated volumetric water contents for treatment S.

In the (40, 5), daily changes in water content were more significant particularly after 29 May. This was due to rainfall events in those days. 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 is important for optimizing irrigation depth. If simulated ET largely deviated from measured ones for daily scale, it means the first term of Eq. (2.6) is not accurately estimated. Comparison between measured and simulated ET for a selected period were shown in Fig. 3.6.

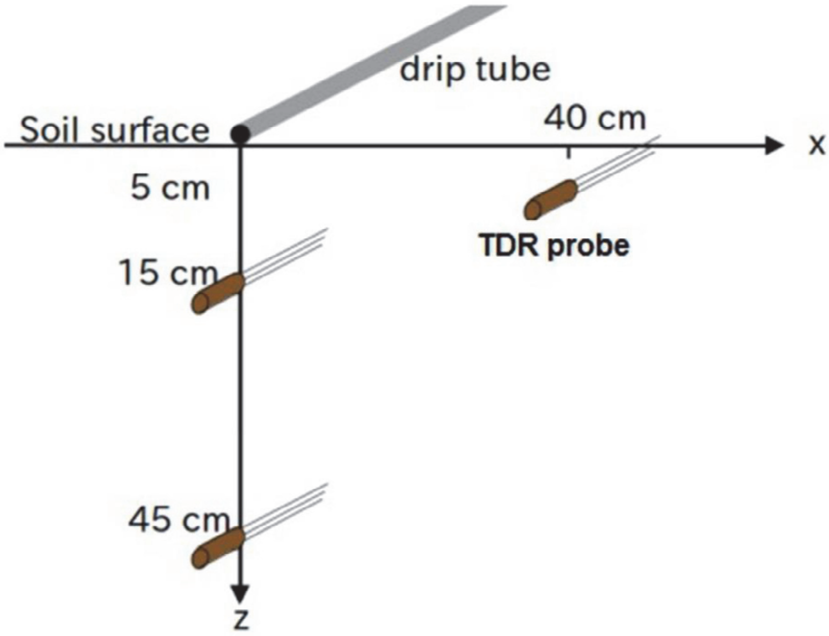

Fig. 3.5. Location of TDR probes. Legends x and z represent the horizontal distance from the drip tube and soil depth, respectively. Filled circle, square, and inverted triangles are the measured water contents and solid and dashed lines are simulated ones at three locations.

Evaporation rate was in average value across the soil surface. The simulation model tended to overestimate ET owing to unexpectedly slow growth of leaf area. Discrepancy in hourly pattern was occurred. 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.

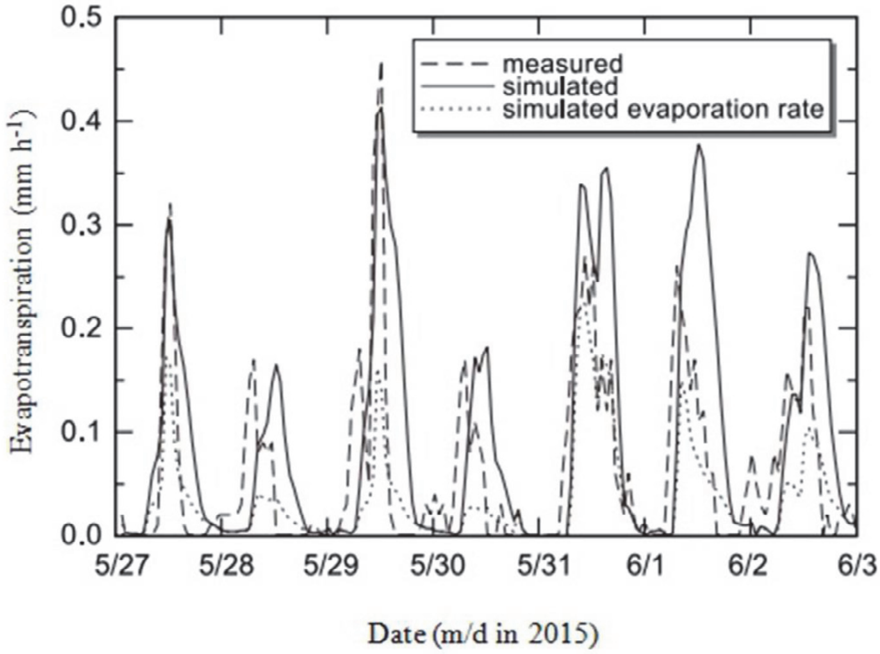

Fig. 3.6. Comparison of measured (dashed line) and simulated (solid line) evapotranspiration rate. Simulated evaporationrate (dot line) is also shown for comparison.

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.

Time evolution of rainfall and irrigation is show in Fig. 3.7. 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 73 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 19 May to 28 May. The proposed scheme, treatment S, could save 9 % 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 32% 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. 3.8. 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 price of crop was set based on producer price of potato in the US in the optimization, producer price in Japan we used since negative value of net income was obtained.

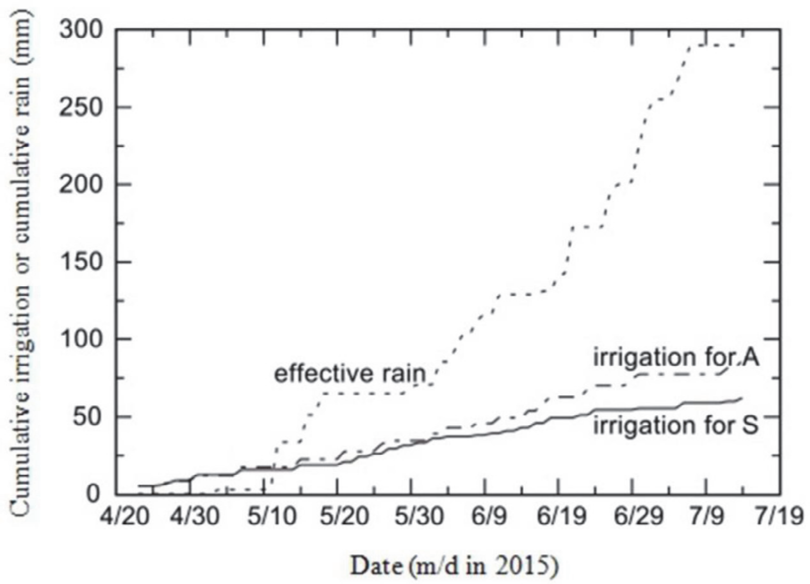

Fig. 3.7. Time evolution of cumulative rainfall and irrigation depths. Solid line and dot-and-dash line represent cumulative irrigation depths for treatment S and treatment A, respectively.

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 was sensitive to the crop growth. Even so, the new scheme was confirmed that 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.

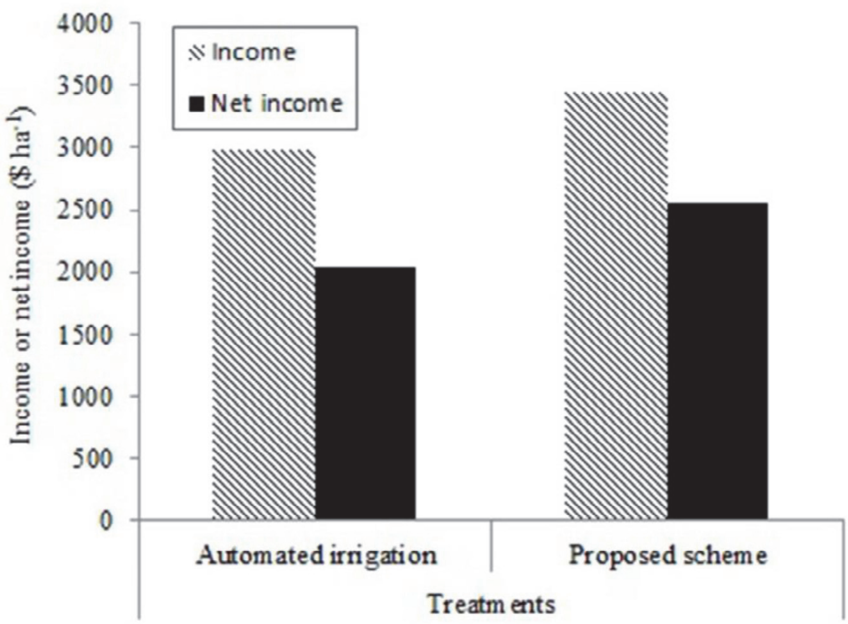

Fig. 3.8. Comparison between income and attained net income. ‘Automated irrigation’ and ‘Proposed scheme’ represent treatment A and treatment S, respectively.

Moreover, higher yield for treatment S might partly be attributed to lower nutrients loss due to lower deep percolation by considering forecast rain events. Simulated uptake of nutrients for treatment A was lower than that for treatment 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. Forecasted daily rainfall events were underestimated, as the root mean square error between forecasted and actual daily effective rainfall was 8.2 mm as shown in Fig. 3.9. In the analysis, effective rainfall was set at 30 mm. Ratio of actual and forecasted daily rainfall occurrence over growing season were 41% and 31%, respectively. . The largest error occurred in 5 July 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.

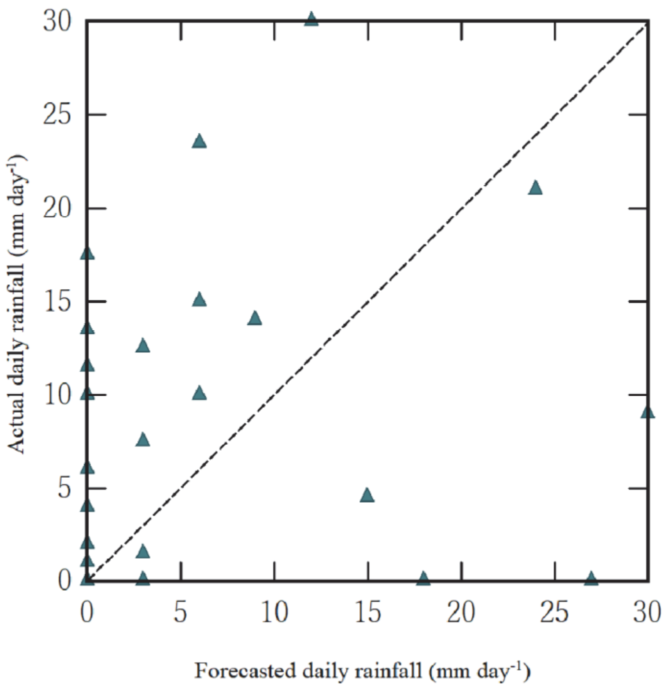

Fig. 3.9. Comparison between forecasted and actual daily rainfall.

3.4. Conclusion

The proposed scheme to determine irrigation depths for potato crop using a numerical model of crop response to irrigation and quantitative weather forecast was examined. The 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, the proposed scheme may establish proper irrigation scheduling like automated irrigation systems without high initial investment.

Chapter 4

A validation study of the proposed scheme for sweet potato (*Ipomoea batatas* L.)

Summary

Irrigation management can be improved by utilizing advances in numerical models of water flow in soils that can consider future rainfall by utilizing data from weather forecasts. Toward this end, the proposed scheme to determine optimal irrigation depth on scheduled irrigation days based on a concept of virtual net income was examined for sweet potato (*Ipomoea batatas* (L.), cv. Kintoki). To evaluate benefits, both crop growth and net income of this proposed scheme were compared to those of an automated irrigation method. Under the proposed scheme, 18% less water was applied; yield increased by 19%, and net income was increased by 25% compared with the results of the automated irrigation system. In addition, soil water content simulated by the proposed scheme was in fair agreement with observed values. Thus, it was shown that the proposed scheme may enhance net income and be a viable alternative for determining irrigation depths.

4.1. Introduction

Sweet potato (*Ipomoea batatas* L.) is an important vegetable crop. It is known by its resistance to dry weather, achieving higher production and higher profit compared other vegetables. Rather than tubers, the stems and leaves can be used for livestock feeding. It is considered to be a drought tolerant crop. Yield of sweet potato irrigated at 20% of total available water in soil found to be equivalent to those irrigated at soil water levels of 40, 60, and 80 % (Hernandez and Barry, 1966; Jones, 1961). Watanabe (1979) reported that when soil water content was high, sweet potato had superior vegetative growth and little tuber development. In this study, a field experiment was conducted for sweet potato. The main objectives were (1) to evaluate the benefits of this scheme in terms of net income, and (2) to check the accuracy of WASH 2D model to simulated soil water content.

4.2. Material and Methods

4.2.1. Treatments

To validate the scheme described in chapter 2, a field experiment was carried out at the Arid Land Research Center, Tottori, Japan, in 2016. Two treatments were established: (1) treatment A, automated irrigation based on either soil moisture or suction status monitoring, and (2) treatment S, the proposed numerical scheme. Two plots were established as replicates for each treatment. Each plot was 15 m long and 16 m wide. A weighing lysimeter with a diameter of 150 cm was used to measure evapotranspiration in treatment S. Volumetric soil water content was measured by time domain reflectometer (TDR-SK10 probes by Sankeirika, Japan and TDR 100 by Campbell Scientific, Ltd., USA). Twelve probes were installed in each treatment. In treatment A, (1) TDR probes were installed at depths of 5 cm and 15 cm below six plants; and (2) three tensiometers were installed at a depth of 20 cm from 5 August until the end of the experiment.

4.2.2. Irrigation

Irrigation water was applied by means of a drip irrigation system with lateral pipes and emitters spaced at 90 cm and 20 cm, respectively. The discharge rate of the emitters was 1 L h^{-1}. In treatment A, from planting until 5 August water was applied for 1 h with irrigation intensity 5.5 mm when the average volumetric soil water content at 15 cm was below 0.09. After 5 August, water was applied when the average suction of the three tensiometers exceeded 70 cm. Those threshold values were set referring to preliminary experiments. In treatment S, the irrigation interval was set at 2 days. In the morning of each irrigation day, the routine procedure (section 3.1, chapter 2) was performed using last irrigation data, updated files of water and solute distribution obtained from the last update run, cumulative transpiration and quantitative weather forecast as input files. The resulted irrigation depth at each irrigation day was implemented manually to the treatment S. The water price was set at 0.0003 (\$ kg^{-1}) which is similar to the level used in Israel (Cornish et al., 2004). Transpiration productivity was set at 0.003. Liquid fertilizer (N = 12%, P_2O_5 = 5%, K_2O = 7%) was applied through fertigation throughout the growing season. To evaluate the effect of irrigation on gross net income between the two treatments, it was applied such that daily application rate was constant and the same. In total, 89 kg ha^{-1} of N was applied in both treatments. The salinity of the irrigation water was a low 0.1 dS m^{-1}. The E_p and rainfall throughout the growing season are shown in Fig. 4.1.

4.2.3. Soil

The soil was Tottori sand whose properties have been reported in Chapter 3.

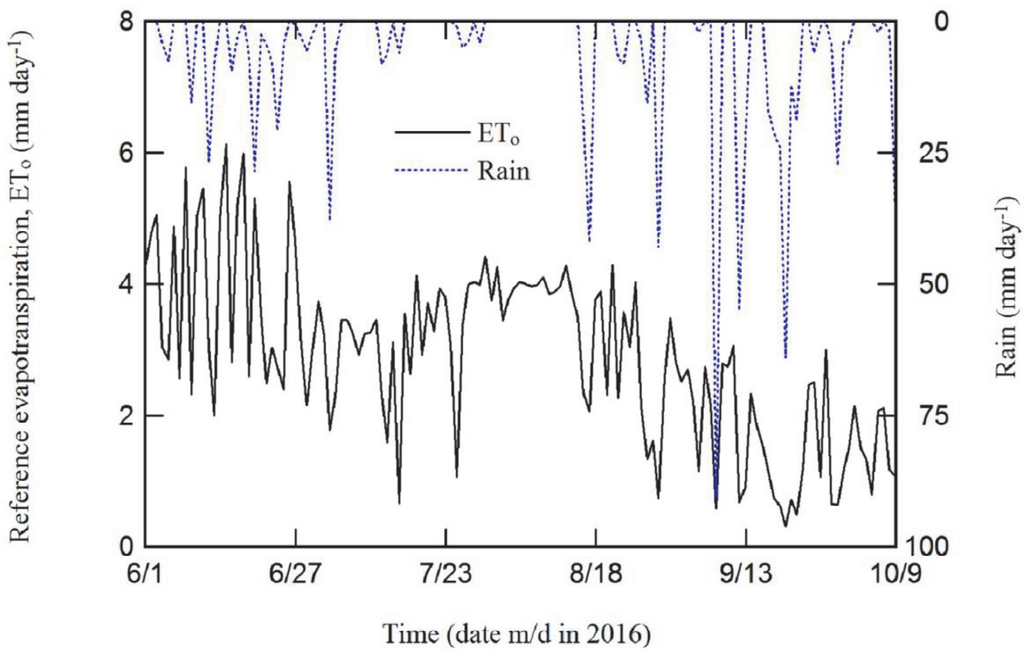

Fig. 4.1. Fluctuation of E_p and rainfall during the growing season. E_p was calculated by the penman Montieth equation.

4.2.4. Plant

Sweet potato (*Ipomoea batatas* (L.), cv. Kintoki) cuttings were transplanted on 1 June at a spacing of 40 cm along the laterals (rows). Parameter values of the stress response function were not measured, but adopted values comparable to those given by Yanagawa and Fujimaki (2013) as listed in Table 1. Parameter values of the crop coefficients were initially set referring values by Allen et al. (1998) assuming that average reference ET during initial, development, and middle stages are 2, 3, 4 mm/d, respectively. Those parameter values were then updated twice throughout the growing season such that simulated evapotranspiration matched the measured values (Fig. 4.2). Since the plant leaves did not shrivel and irrigation was not carried out during the latest stage of the plant growth, decline in basal crop coefficient which expressed by last term $d_{\mathrm{kc}}\tau^{e_{\mathrm{kc}}}$ (Eq. 2.6) was not included. Biomass was measured by separating leaves stem and tubers of sampled plants, and then dried at 70°c until constant weight.

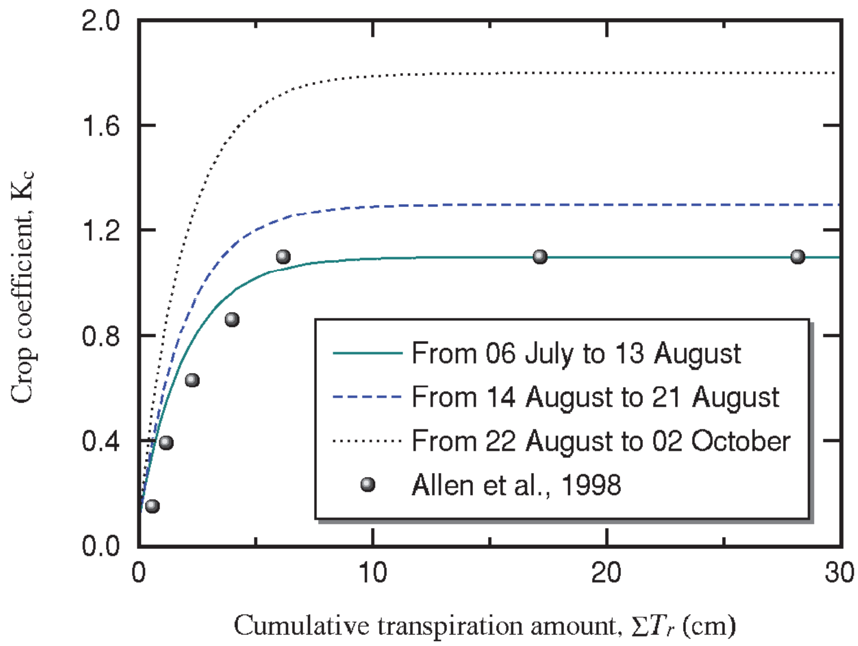

Fig. 4.2. Crop coefficient as a function of cumulative transpiration for three periods during the experimental crop development.

Tubers of sweet potato were harvested on 20 October. The price of the crop was set at 1.5 (\$ kg^{-1} DM) by referring to prices received by producers in the USA in 2011 (FAOSTAT, http://faostat.fao.org/).

Table 4.1. Parameter values for plant stress response and growth properties used in the numerical modeling in this study (Equation numbers are regarding to chapter 2).

Parameter	Value	Remark
a_{kc}	1	
b_{kc}	–0.5	Eq. (2) and Eq. (6)
c_{kc}	0.1	
d_{kc}	0	
ψ_{50} (cm)	–300.0	
ψ_{050} (cm)	–3000.0	Eq. (7)
p	3	
b_{rt}	1	
d_{rt}	?	Eq. (8)
g_{rt}	30	
z_{r0}	2	
a_{drt}	40	
b_{drt}	–0.4	Eq. (9)
c_{drt}	5	

4.3. Results and Discussion

4.3.1. Leaf area index and biomass

To evaluate the effect of the proposed scheme on the growth of sweet potato, values at four measurements of leaf area and biomass are shown in Fig. 4.3. Whereas the leaf area index (LAI) of treatment A peaked at 93 days after planting (DAP), that of treatment S continued to increase and was consistently higher than that of treatment A. Consequently, treatment S achieved a higher biomass than treatment A, especially in the late stage of crop growth (from 94 to 141 DAP). Hence, treatment S increased plant growth compared to treatment A. This may likely be due to excess irrigation which pronounced leaching of nutrients beyond the plant root zone. Fig. 4.4 shows simulated nutrients uptake and leaching assuming that nutrients included in water uptake are also fully taken up, and it implies that nutrients uptake by plants grown in treatment S were greater than that in treatment A.

4.3.2. Soil water content

To check the performance of the proposed scheme with respect to the soil water regime, measured and simulated water contents in treatment S were compared (Fig. 4.5). The positions of the soil volumetric water content measurements were specified in two dimensions (x and z), where x represents the horizontal distance from a lateral and z is the depth in the soil. At two locations: (x = 0 cm and z = 5 cm) and (x = 0 cm and z = 45 cm) the model could simulate volumetric water content well with a root mean square error (RMSE) of 0.024 and 0.006, respectively. At the other position (x= 45 cm and z = 5 cm), between plant canopies where the soil was nearly bare, the model could simulate water content with fair accuracy (RMSE = 0.013). Note that simulations of volumetric water content were carried out independent of the measurements.

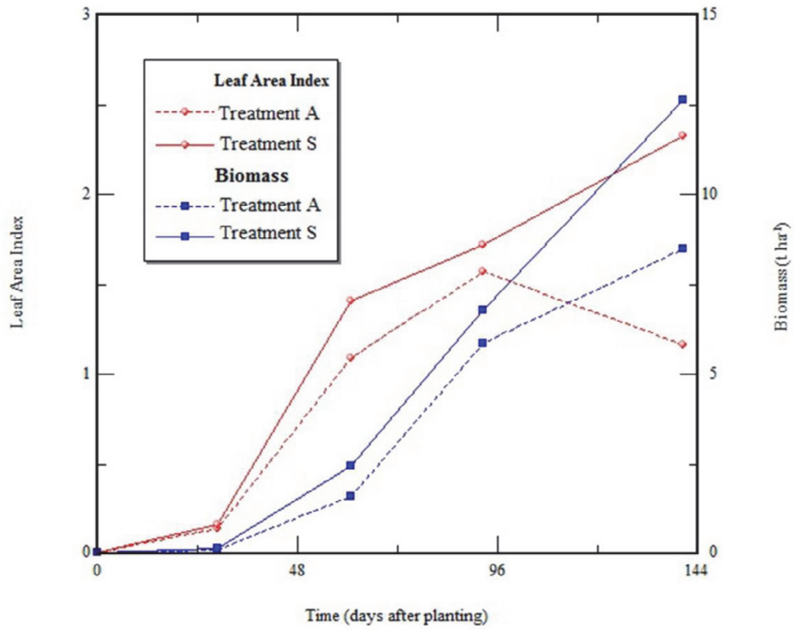

Fig. 4.3. Leaf area index and biomass of sweet potato crop over time in two irrigation treatments (Treatment A: automated irrigation scheduling based on soil moisture and suction monitoring; Treatment S: optimization of irrigation depth derived from the numerical scheme).

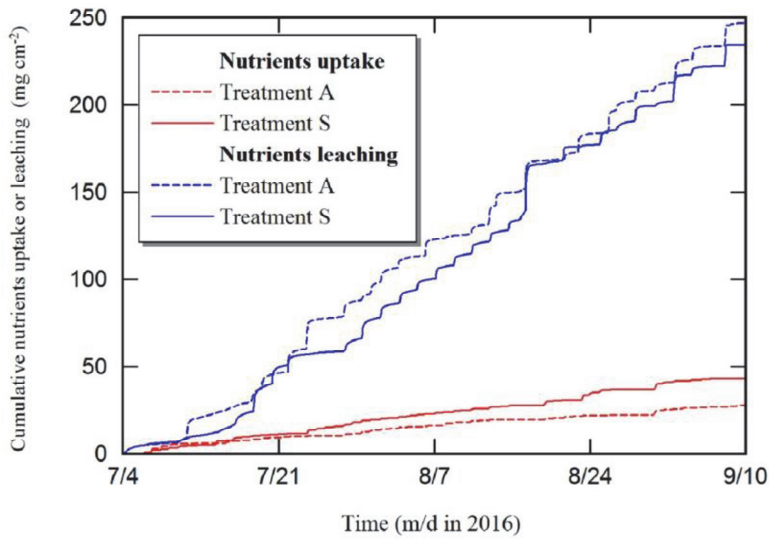

Fig. 4.4. Simulation of the fate of nutrients throughout the growing season for both treatments A and S.

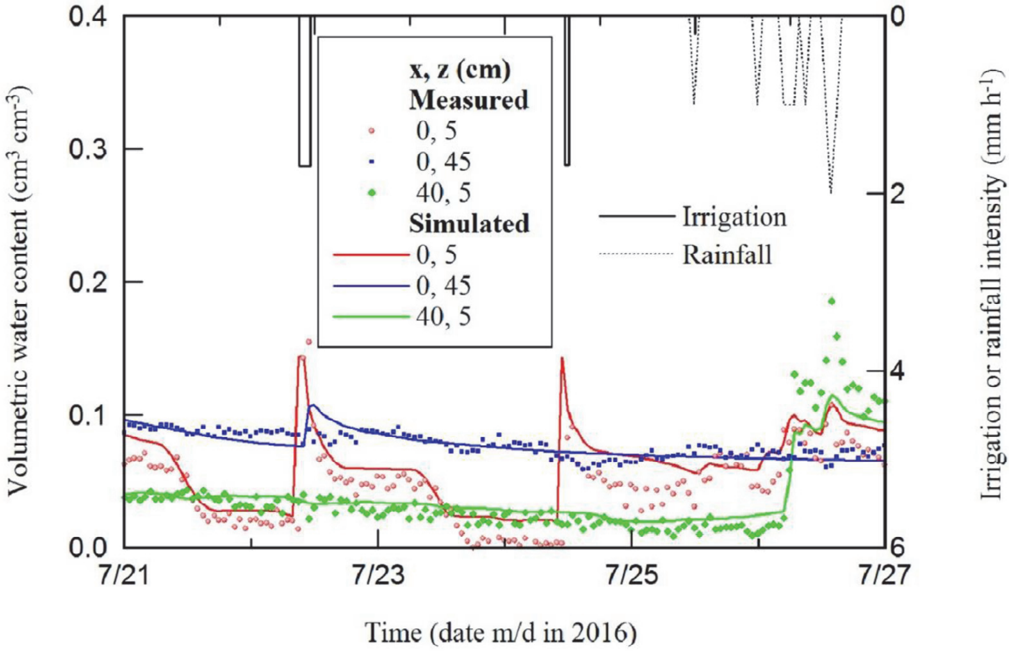

Fig. 4.5. Comparison of measured and simulated volumetric soil water content at three positions (x = distance from nearest drip irrigation lateral, z = soil depth) in treatment S.

4.3.3. Evapotranspiration

Simulated and measured evapotranspiration (ET) of treatment S were also compared (Fig. 4.6). The model tended to underestimate ET values. This might have occurred for two reasons. First, five plants were growing in the study area of the lysimeter. In our growth survey of 20 October, one of those plants had an extremely large leaf area that raised the average LAI from 2.33 in the area surrounding the lysimeter to 2.79. Secondly, the soil surface of the lysimeter was about 5 cm above the surrounding area, which might have led the plants to transpire more due to greater exposure to wind. Due to those specific reasons, the model had to use high basal crop coefficient in the last update from 21 August to 02 October.

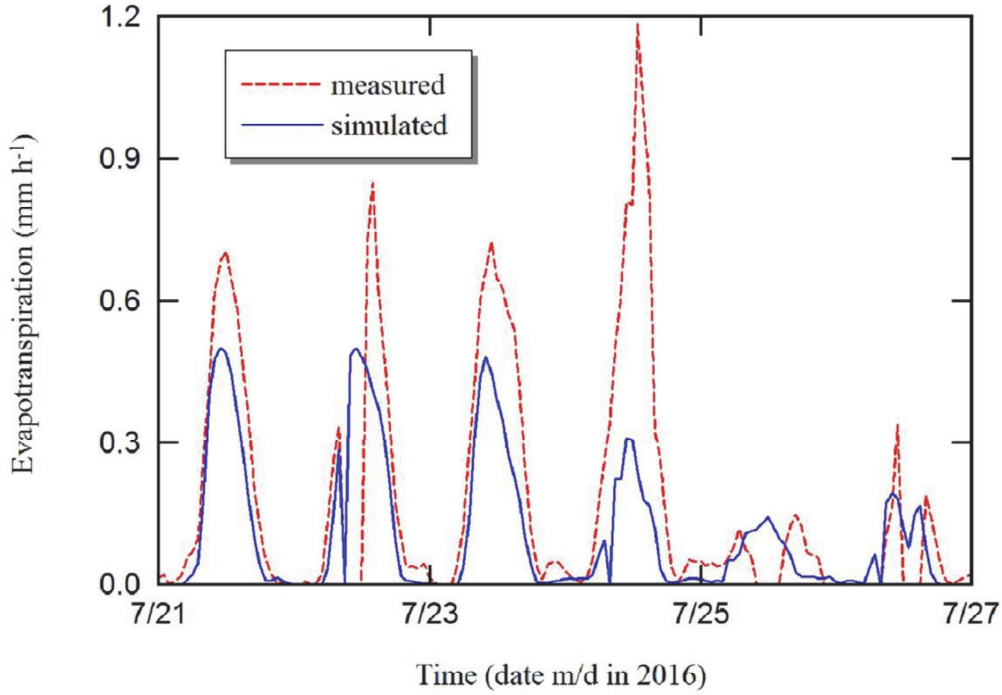

Fig. 4.6. Comparison of measured and simulated evapotranspiration in treatment S (Evapotranspiration was measured by a weighing lysimeter and was simulated using the WASH_2D model).

4.3.4. Effectiveness of the proposed scheme on net income

As described in chapter 2, the proposed scheme determined irrigation depths based on the maximization of net income. An example of the optimization from a scheduled irrigation of 4 September (Fig. 4.7) shows how irrigation depth is determined based on three predicted values of transpiration at three irrigation depths. An irrigation depth of 1.39 cm was derived at the maximum point of the net income curve. Note that predicted transpiration is lower at 1.39 cm than at 2.5 cm irrigation depth. The effect of the proposed scheme on net income is shown in Fig. 4.8. Treatment S reduced the amount of irrigation water applied by 18% and increased tuber yield by 19% compared to treatment A. As a consequence, treatment S achieved 125% higher net income than that of treatment A.

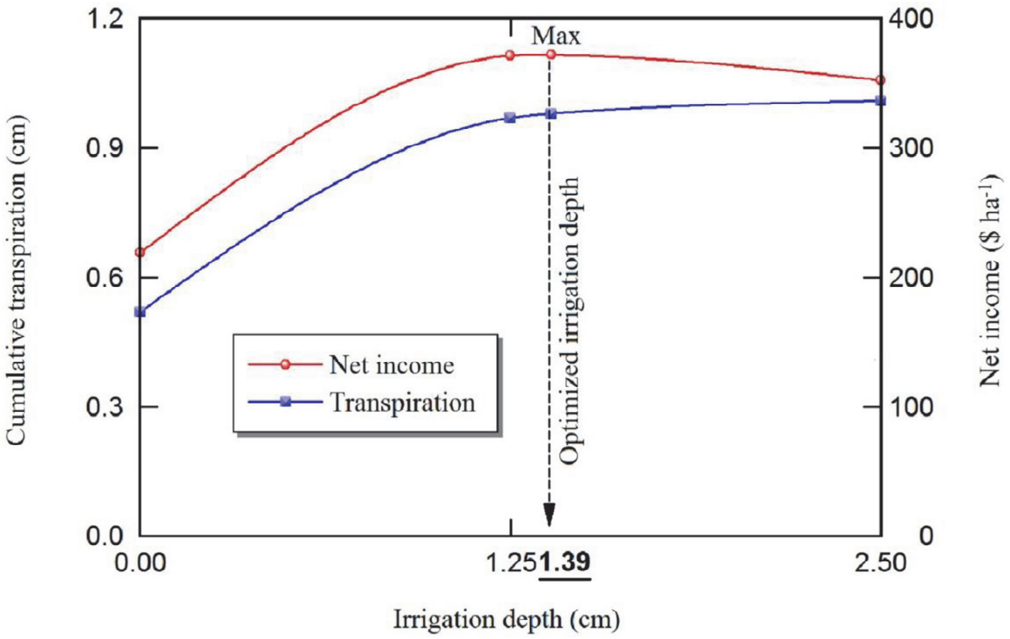

Fig. 4.7. An example of how the irrigation depth is optimized on a scheduled irrigation day in the proposed scheme. Those values were resulted from the simulation on 4 September.

One reason that treatment A applied water less effectively is that it disregarded forecast weather. An example of the effect of this is that on 12 July the proposed scheme suggested "no irrigation" for the next two days in response to forecast rainfall on 12 July, whereas the automated irrigation system applied 2.14 mm of irrigation on 13 July in response to soil moisture falling below the threshold for irrigation, just 5 h before the rain event. In addition, the trigger value of 0.09 might have been too high and might have led to apply water in that day. Difficulty in determining economically optimum trigger value without expensive field trials is another disadvantage of an automated irrigation system.

4.3.5. Comparison between forecast and actual rainfall

The accurate prediction of rainfall amount has a large effect on the performance of the proposed scheme. A comparison between forecast and actual daily effective rainfall is shown in Fig. 4.9. In the analysis, daily effective rainfall was set as 20 mm. Forecasted daily rainfall events were overestimated as the RMSE was 10.4 mm. Ratio of actual and forecasted daily rainfall occurrence over growing season were 29% and 33%, respectively. The largest error occurred on 22 September when 79.5 mm was forecast and the actual rain was only 7.5 mm. In the present study, even under the given uncertainty of weather forecasts, the proposed scheme was effective in determining optimum irrigation depths and increasing net income.

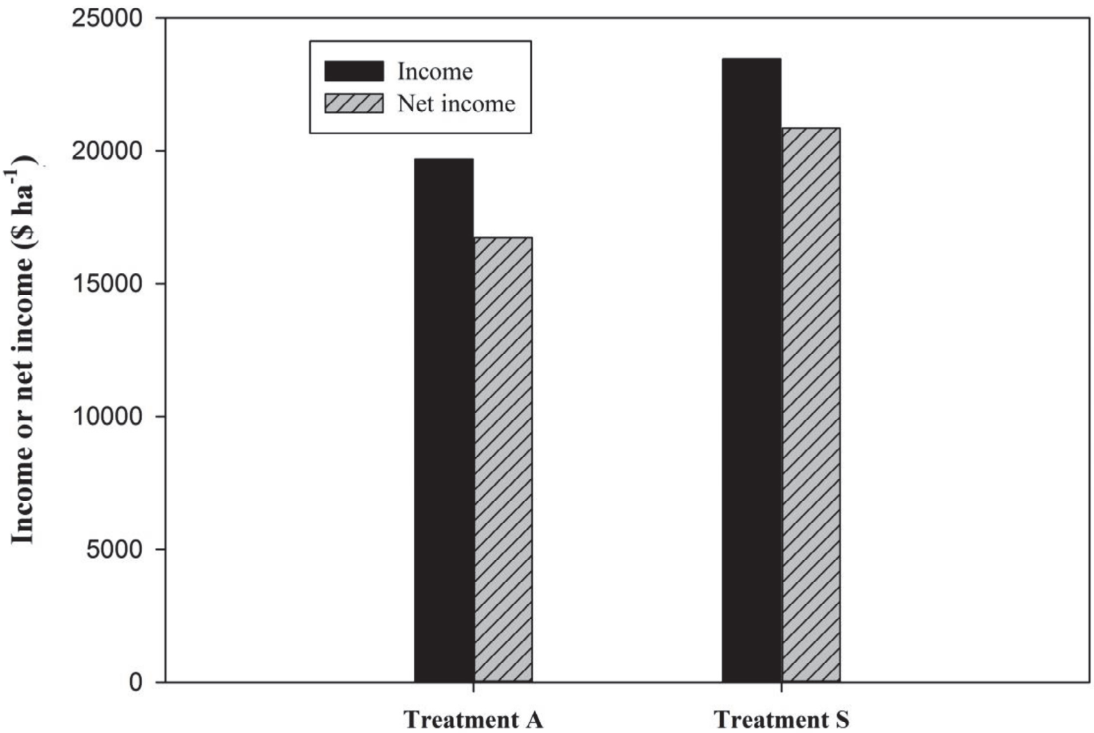

Fig. 4.8. Total income and net income from two irrigation treatments. Treatment A: automated irrigation scheduling based on soil moisture and suction monitoring; Treatment S: optimization of irrigation depth from the numerical scheme.

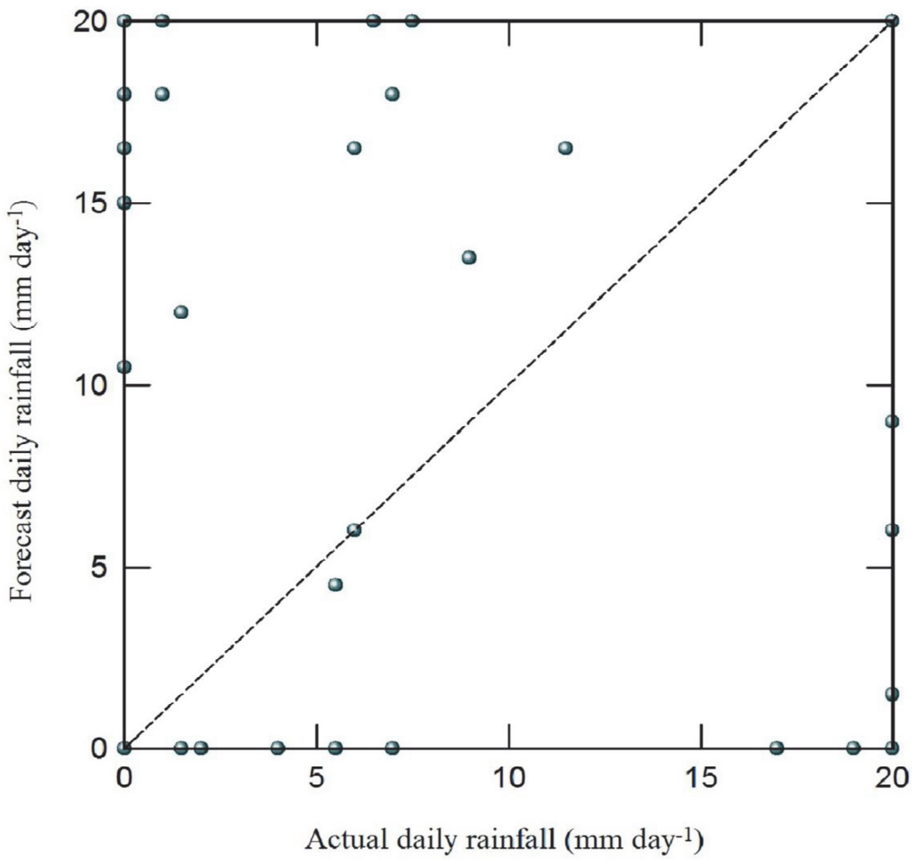

Fig. 4.9. Comparison of forecast and actual daily effective rainfall for the entire growing season of the experimental period.

4.4. Conclusion

The numerical simulation-based scheme was examined to determine irrigation depths for sweet potato cultivated in a sandy field. Compared to a non-optimized automated irrigation method, the proposed scheme, which incorporates weather forecast data, resulted in the application of 18% less irrigation water, increased yield by 19%, and increased net income by 25%. In addition, the proposed scheme simulated soil water content at each observed depth with a fair level of accuracy. This scheme imposes moderate drought stress which is being recently accepted among irrigation scientists and also being disseminated through extension services. Unlike conventional deficit irrigation, the target was not maximizing water productivity but net income which may be accepted by farmers who use priced water or can increase irrigated lands by saving water. This scheme would be less applicable for the clayed soil because of longer irrigation intervals and associated uncertainty of weather forecast. Even so, our results show that the scheme has potential to deliver greater benefits if accuracy of weather forecast is improved.

Chapter 5

A validation study of the proposed scheme for groundnuts (*Arachis hypogaea* L.)

Summary

Numerical models of crop response to irrigation and weather forecasts with internet access should be fully utilized in modern irrigation management. In this respect, the proposed scheme was evaluated to determine irrigation depths for groundnut (*Arachis hypogaea* L.). Two treatments were carried out 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.

5.1. Introduction

Groundnut or peanut (*Arachis hypogaea* L.) is one of the most important legume and oil seed crops in the world; provides a major source of vegetable protein (Onemli, 2012). It is best cultivated in sandy soils whose well drainage and neutral pH. It is more sensitive to various abiotic constraints such as high temperature, drought stress and nutrients deficiency, especially in the growth stages of reproductive development, flowering, and early pod development. The yield production of groundnut depends on proper management of fertilizer, selection of variety and other management practices (Lourduraj, 1999). Therefore, the highest productivity of 3500 kg ha^{-1} is achieved in the United States of America. While, the lowest productivity is less than 800 kg ha^{-1}, achieved in Africa (Prasad et al., 2010). Thus, optimization of irrigation amount is one key for optimizing groundnut production. The objective of this study, 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.

5.2. Materials and Methods

A field experiment was carried out in a sandy field of the Arid Land Research center, Tottori, Japan, 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 Tottori sand whose properties have been reported in chapter 3. 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 and laterals spacing at 20 cm and 90 cm, respectively. The discharge rate of an emitter 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}. On 9 May, groundnut (*Arachis hypogaea* L.) was planted in rows (laterals) at 20 cm spacing. Parameter values of the stress response function were independently determined as listed in Table 5.1 following the 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 (Fig. 5.1). 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.

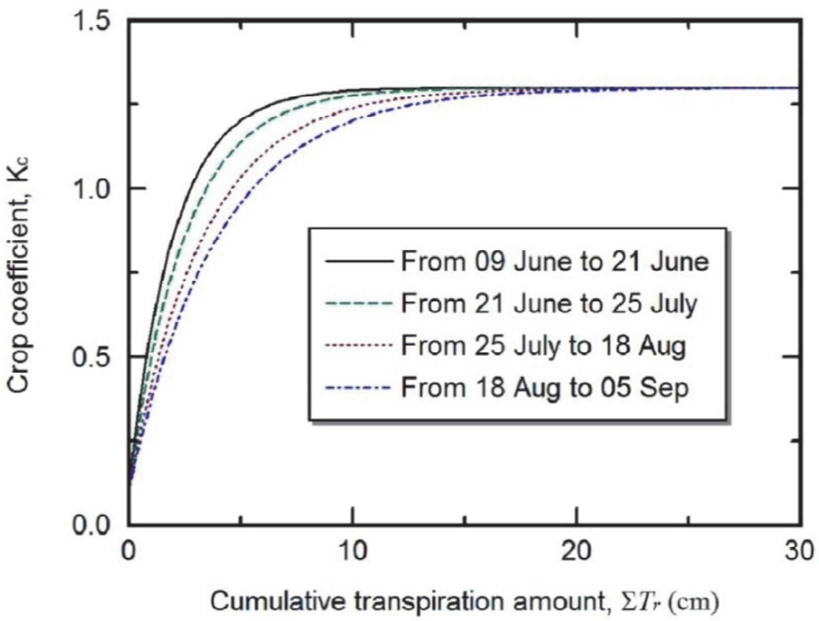

Fig. 5.1. Crop coefficient in terms of cumulative transpiration updated for four time periods during the experimental crop development.

Table 5.1. Parameter values of plant growth and stress response functions used in this numerical scheme. Equation numbering are regarding to chapter 2.

Parameter	Value	Remark
a_{kc}	1.2	
b_{kc}	-0.5	Eqs. (2) and (6)
c_{kc}	0.1	
ψ_{50} (cm)	-48	
ψ_{o50} (cm)	-3000	Eq. (7)
P	4.7	
b_{rt}	1	
d_{rt}	?	Eq. (8)
g_{rt}	30	
z_{ro}	2	
a_{drt}	43	
b_{drt}	-0.4	Eq. (9)
c_{drt}	5	

5.3. Results and Discussion

5.3.1. Leaf area index and biomass

Result of five measurements for either leaf area index or biomass was shown in Fig. 5.2. 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 et al., 2008).

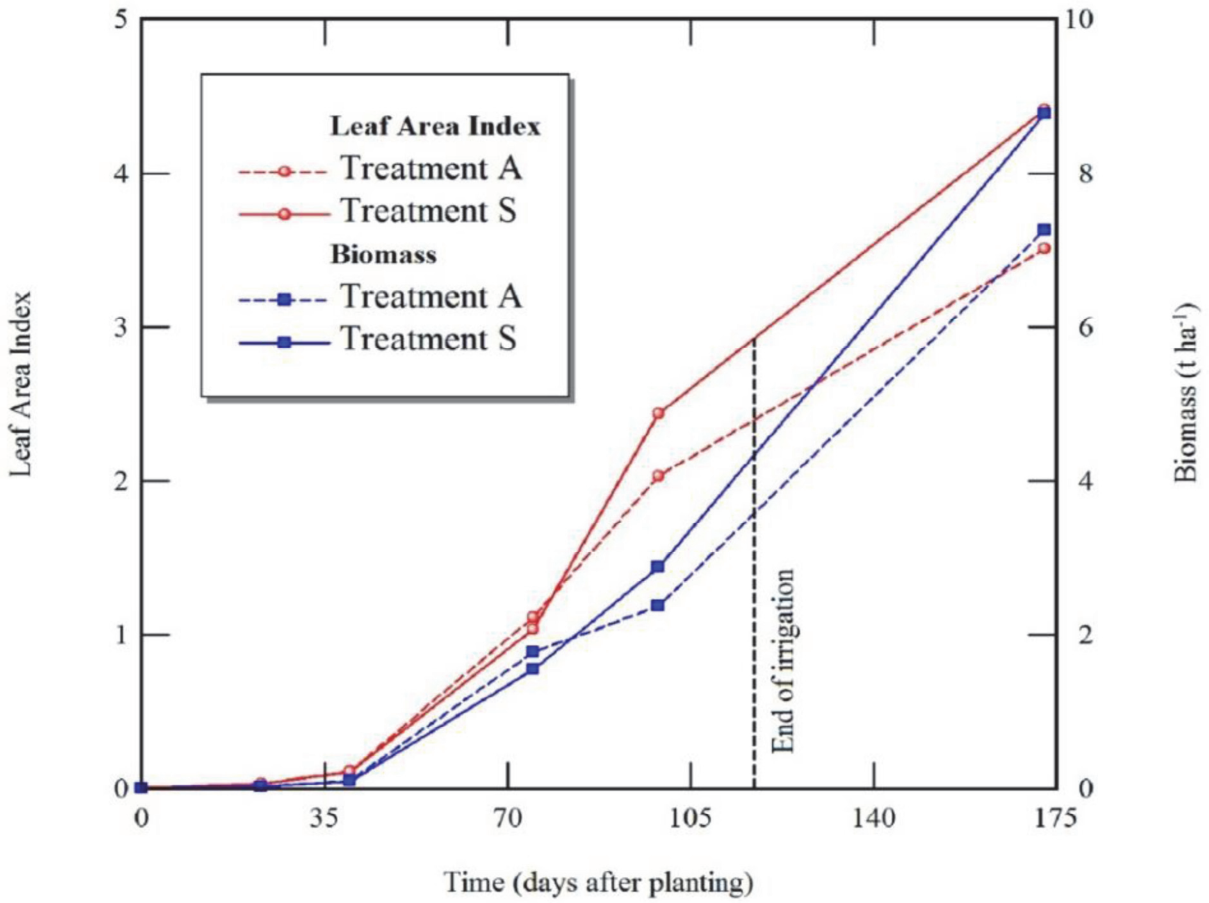

Fig. 5.2. Measured leaf area index and biomass of groundnut (*Arachis hypogaea* L.) over time in two irrigation treatments.

5.3.2. Soil water content

To evaluate the accuracy of the model on predicting soil water contents, simulated water contents were compared with measured ones (Fig. 5.3). 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. Soil water contents for a period of one week under two different conditions were represented: 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.

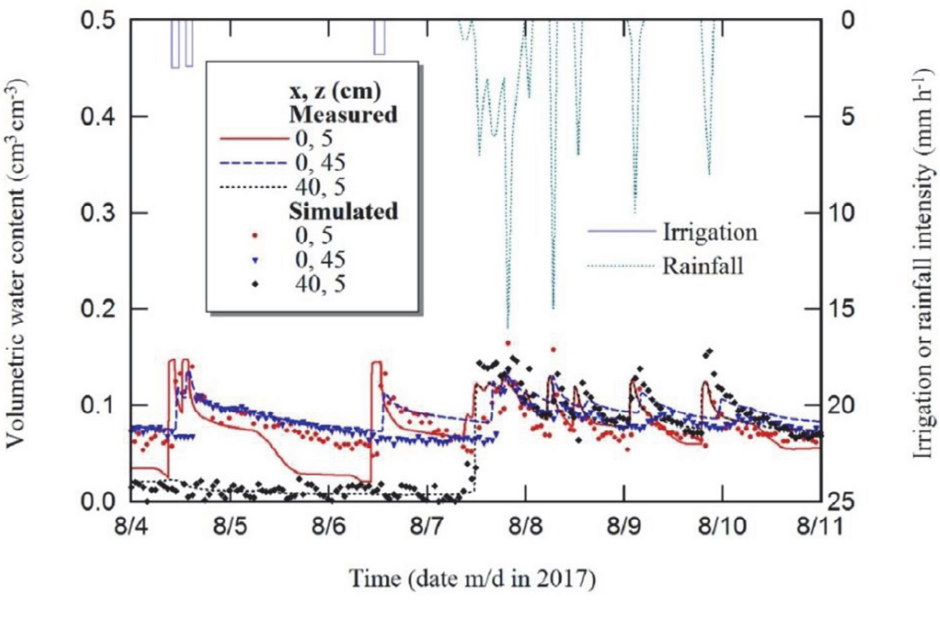

Fig. 5.3. Comparison between measured and simulated volumetric soil water content at two dimensions (x = distance from nearest drip irrigation lateral, z = soil depth) in treatment S.

5.3.3. 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 (Fig. 5.4).

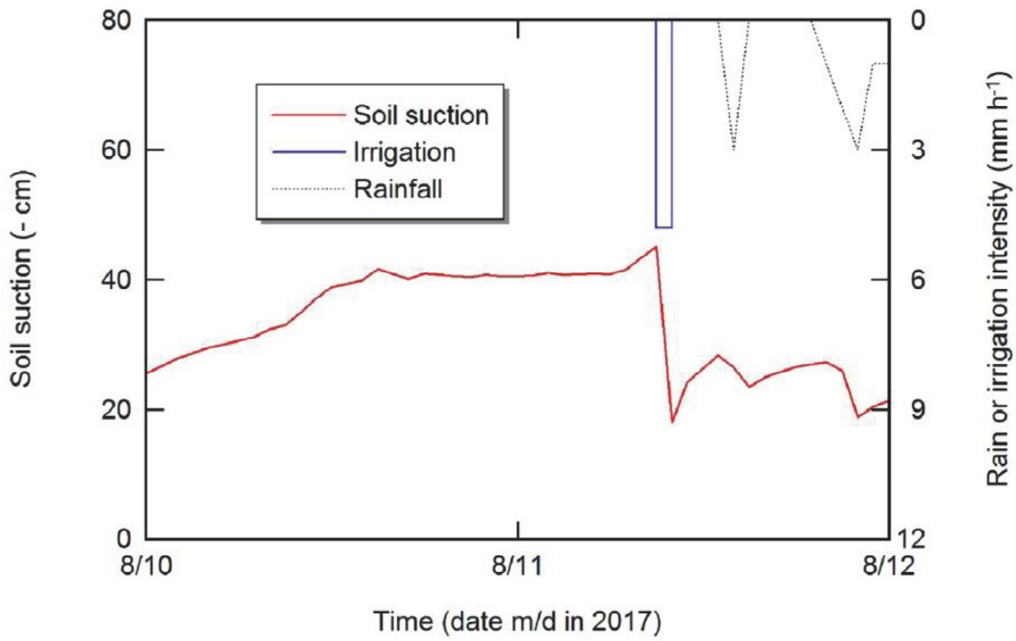

Fig. 5.4. An example of improper application of water by the automated system. 4.8 mm was applied while presented scheme suggested not irrigating in response to the forecast rain

5.3.4. 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 Fig. 5.5. 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.

Finally, the effect of the proposed scheme on total net income is shown in Fig. 5.6. 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.

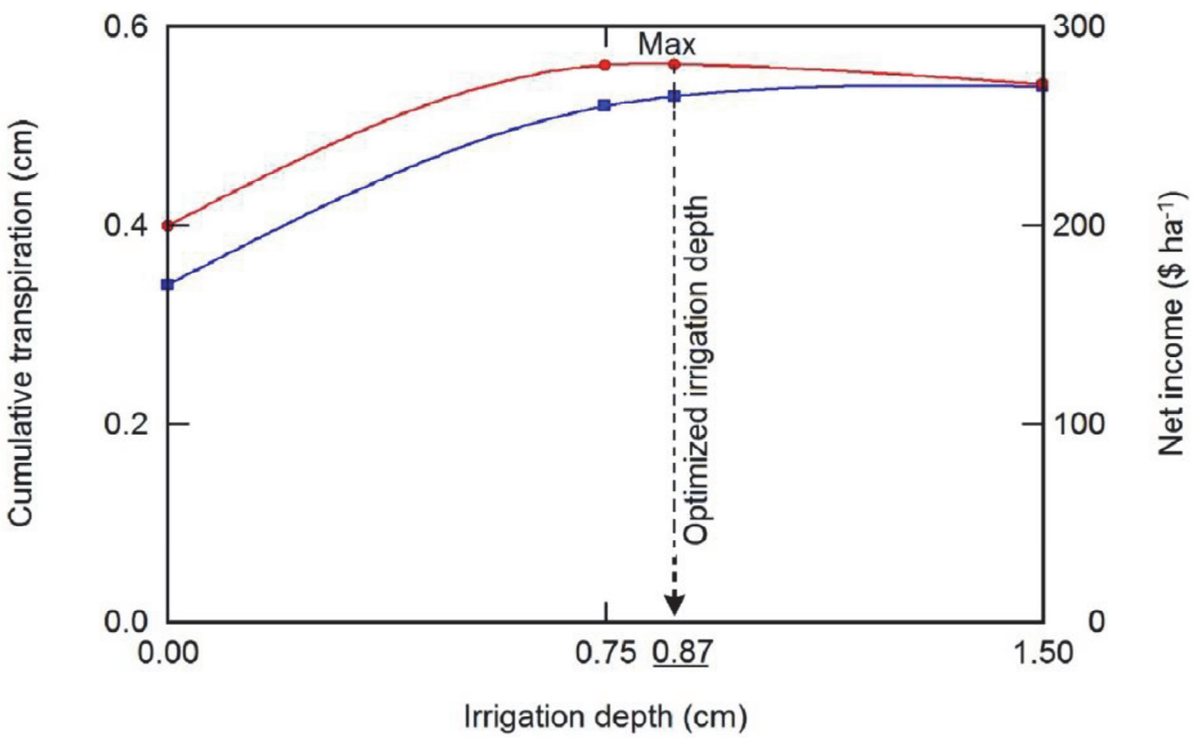

Fig. 5.5. An example of how the irrigation depth is optimized on a scheduled irrigation day in the proposed scheme

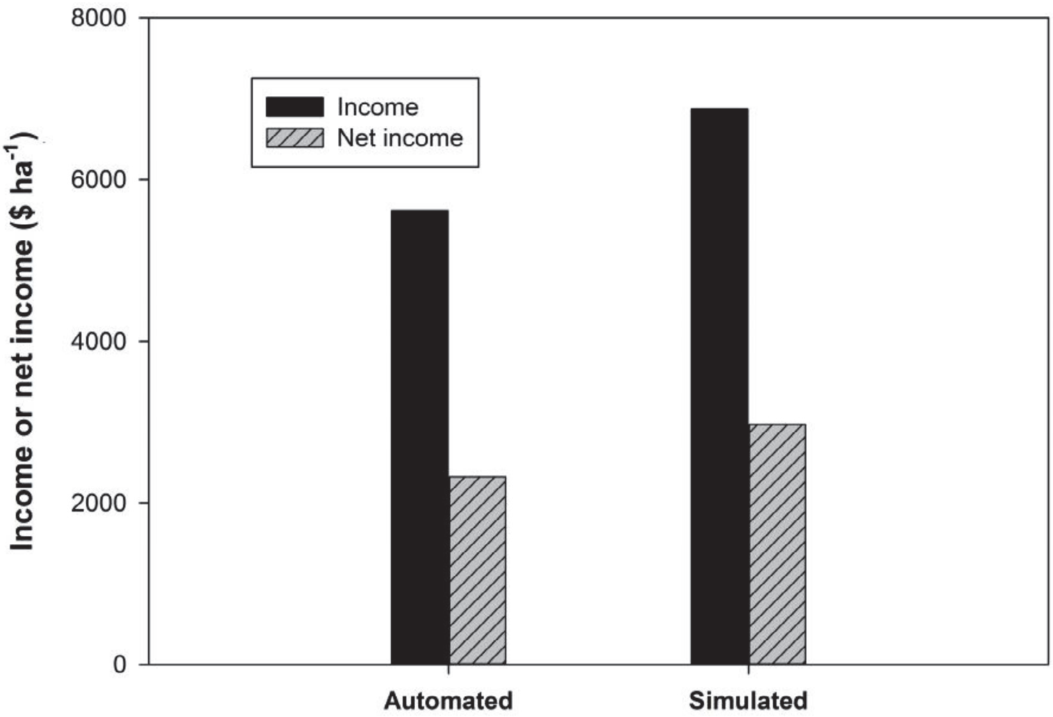

Fig. 5.6. Total income and net income of the two irrigation treatments. (Treatment A: automated irrigation scheduling based on soil water suction monitoring; Treatment S: optimization of irrigation depth from the numerical scheme)

5.3.5. Comparison between forecasted and actual rainfall

Since accuracy in rainfall forecasts have a large effect on the performance of the proposed scheme, comparison between forecasted and actual daily effective rainfall were demonstrated as shown in Fig. 5.7. 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. Forecasted daily rainfall events were overestimated in which the RMSE was 4.63 mm. Ratio of actual and forecasted daily rainfall occurrence over growing season were almost same 29%. In comparison with the previous studies, accuracy of weather forecasts are getting improved that would improve efficiency of the proposed scheme to determine irrigation depths. Thus, it may be considered as an efficient and economical tool for irrigation water management.

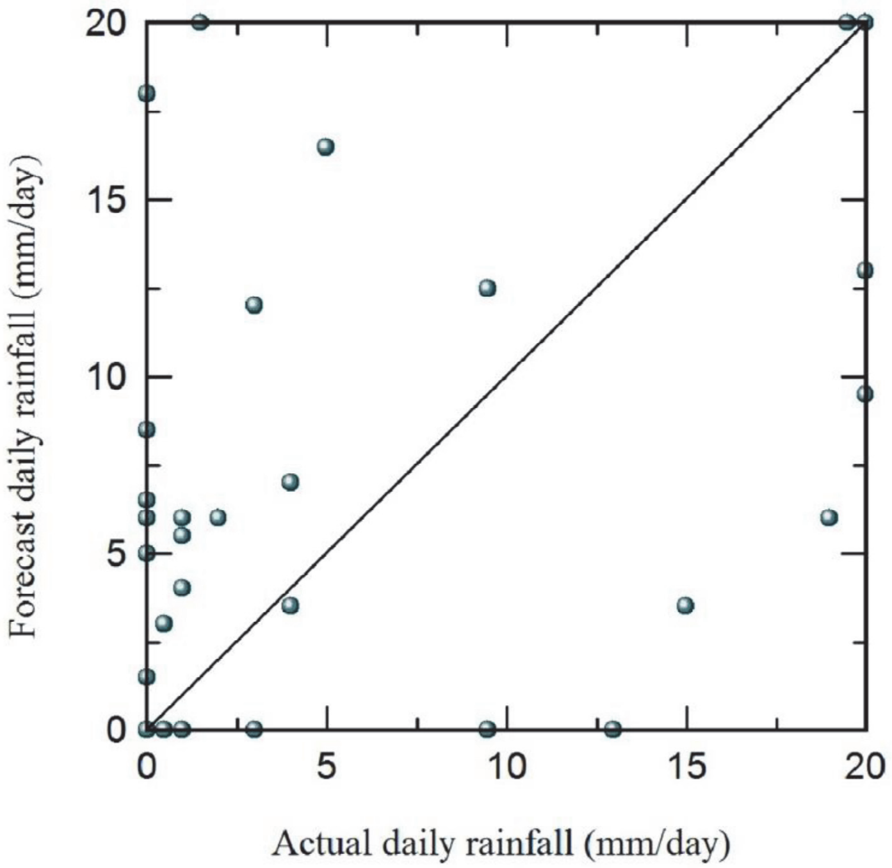

Fig. 5.7. Comparison of forecast and actual daily effective rainfall for the entire growing season of the experimental period.

5.4. Conclusion

In this study, the effectiveness of the proposed scheme was evaluated to determine optimal irrigation depths for groundnut (*Arachis hypogaea* L.). A field experiment was carried out in a sandy soil to compare benefits of the proposed scheme with an automated irrigation. 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.

Chapter 6

Determination of parameter values of stress response function for groundnut (*Arachis hypogaea L.*)

Summary

Groundnut (*Arachis hypogaea* L.) is an important source of oil (51 percent), protein (28 percent) and minerals (2.5 percent). In this study, the tolerance of groundnut to drought and salinity stresses was evaluated in terms of parameter values in a macroscopic root water uptake model. An experiment was conducted using five columns with single plant. Two columns were set for drought and salinity stresses, while the other three were used to provide potential transpiration. To monitor soil water content and electrical conductivity, two 5TE probes were inserted into each of the columns whose stress conditions. Weight of each column was manually measured every day to provide daily transpiration. Water uptake at each depth and time was calculated by substituting linearly interpolated matric and osmotic potentials into the stress response function. Resulted showed that groundnut is more sensitive to drought stress while it is more tolerant to salinity stress compared to canola and Jatropha. Matric potential was more determining factor for groundnut growth than osmotic potential in terms of root water uptake. These parameter values are needed as input data for WASH 2D model.

6.1. Introduction

Practical usage of crop models in agriculture has shown satisfactory results for crops grown under favorable conditions (Boote et al., 1997). However, if the crop encounters stress conditions during its growth period, crop models may perform inadequately (Sau et al., 1999; Calmon et al., 1999). Therefore, ability of estimating parameter values of root water uptake may improve the ability of crop models to predict plant stress conditions. Macroscopic root water uptake models using stress response functions are widely employed in user-friendly hydraulic simulation models of the soil-atmosphere-plant system such as HYDRUS (Šimůnek et al., 2006; Twarakawi et al., 2010), SWAP (Van Dam et al., 1997) and WASH_2D as described in Chapter 2.

Groundnut encounters several biotic and abiotic stresses. Drought, high temperature and salinity are the major abiotic constraints (Collino et al., 2000; Singh et al., 2007). It is most sensitive to drought stress during vegetative, flowering and yield formation periods which may cause delay in flowering and harvest, and reduce growth and yield. It has a well-developed tap root with many laterals which may extend to a depth of 1.5 m, but the only top 0.6 m of soil layer is the most effective part. It was estimated that the rate of crop water uptake starts to reduce when 50% of the total available soil water is depleted under an evapotranspiration rate of 5 to 6 mm/day (FAO, 2018). Therefore, water uptake by the plant should be considered carefully, as in sandy soils plants may undergo water stress quickly, whereas plants in deep soils of fine texture may have ample time to adjust to low soil water matric pressure, and may remain unaffected by low soil water content.

Salinity is also an important constraint factor to be considered; as it reduces the ability of plants to take up water, and quickly decreases germination and seedling growth, dry matter production (Nautiyal et al., 1989; Singh et al., 1989; Janila et al., 1999), and causing yield losses (Hunshal et al., 1991). Saline and sodic soils limit groundnut cultivation as it is grouped under sensitive crop to soil salinity (Singh and Abrol, 1985). It can be grown with water having electrical conductivity up to 3.0 dS m^{-1} (Gupta and Yadav, 1986). Within a short time of salinity, a significant decrease in growth rate will be occurred, but the decrease may be the same for species that have quite different reputations for salt tolerance. (Munns, 2002). Many studies considered the salinity effect on the yield and water uptake of peanut. For example, Shalhevet et al. (1969) found that the yield of peanuts grown in artificially salinized plots was reduced to 20% at soil salinity (ECe) of 3.8 dS m^{-1} and by 50% at ECe of 4.7 dS m^{-1}. As soil salinity increases, reduction in water uptake occurs and subsequent reduction in growth rate.

The purpose of this study was (1) to determine the tolerance of groundnuts to drought and salinity stresses in terms of root water uptake model parameters; and (2) To compare parameter values of this crop with those of another oilseed crop, Canola (Yanagawa and Fujimaki, 2013) and Jatropha (Fujimaki and Kikuchi, 2010). This chapter presents an example of how to determine crop parameters used in crop growth module in WASH 2D model.

6.2. Materials and methods

6.2.1. Column experiment

Five columns with height and inner diameter of 15 cm and 20 cm, respectively, were placed above ground in a glass house in Arid Land Research Center, Tottori University, Japan. Columns (Wanger pots) were made of a material of high impact polystyrene, having a white color to minimize the temperature fluctuation due to either solar radiation or temperature effect due to the posture on ground. Two columns (A and B) were used to evaluate the tolerance of groundnut for both drought and salinity stresses. Two dielectric moisture probes (5TE, Meter, Inc. Pullman, WA) were inserted horizontally at each of the two pots as the center rods were located at depths of 5 and 15 cm, respectively as shown in Fig. 6.1. These probes were used to provide data of water content, bulk electrical conductivity (σ_b) and temperature in the soil every hour. The other three columns (C, D, and E) were used to provide potential transpiration.

Air-dried soil, Tottori sand (sand 99.7%, silt 0.3%) with hydraulic properties shown in Chapter 3, was packed into the five columns at a target bulk density of 1.45. Two seeds of groundnut (*Arachis hypogaea* L.) were sown at each pot on 1 September 2016 and thinned to one plant after ten days. The stressed period was started after healthy plants had grown with tap water (EC = 0.15 dS m^{-1}) mixed with 500 fold-diluted fertilizer (N-P-K = 12-5-7, Hyponex Japan, Osaka, Japan).

A white-colored, 1 cm –thick styrene foam was used to cover the soil surface of each column to prevent soil evaporation. Thus, the daily transpiration was calculated by measuring the weight of each column every morning. To obtain potential transpiration, water was applied every day to maintain volumetric water content (VWC) at 0.25; and it was calculated by multiplying the mean value of potential transpiration rate of the columns: C, D, and E by a correction factor representing the differences in growth among the columns.

The drought stress period started on 22 September 2016 after setting the initial VWC at 0.35. The salinity stress treatment started just after the drought stress period using two different concentrations of NaCl solution. First, NaCl solution of 3000 ppm was applied on 3 October 2016 until the average VWC in column reached 0.30. Since no reduction in transpiration was observed until 14 October 2016, NaCl solution of 5000 ppm was applied on 15 October 2016. The experiment was terminated when the relative transpiration (ratio of actual to potential transpiration) becomes less than 50%.

6.2.2. Root distribution

At the end of experiment, the columns (A and B) were dismantled to obtain root length density distribution. Roots were extracted from soil sample at each 5 cm layer by wet-sieving with a 2 mm screen; and were air-dried using a 0.8 mm screen. Then, the air-dry roots were scanned with a flatbed scanner with 300 dpi. Total length of roots in an image was determined with the intersection method (Newman, 1966). Malfunction of sensor response occurred at column B during the stress period.

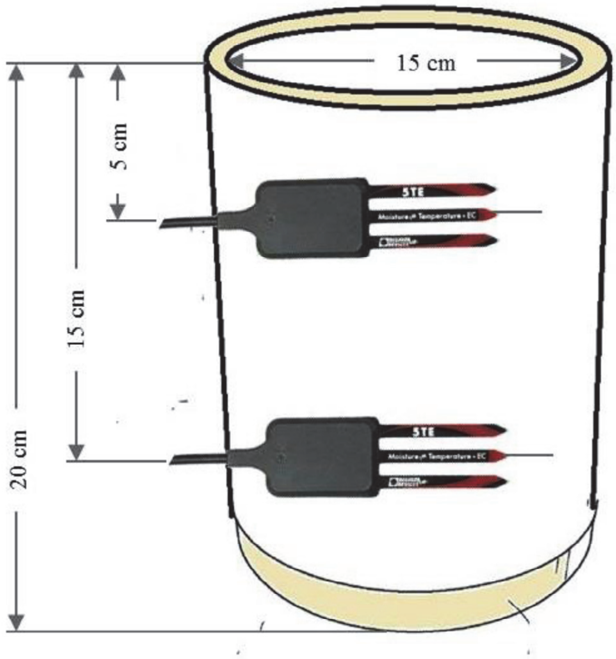

Fig. 6.1. Schematic of the design of the experiment. Two 5TE sensors for each of column (A and B) were located at 5 and 15 cm to measure soil water content and EC.

Thus, the parameter values for salinity stress were determined based on the results of the columns A only.

6.2.3. 5TE calibration

To obtain accurate soil water content data using a dielectric moisture probe, 5TE, a set of calibration steps were carried out. First, the sensor output, x was corrected to eliminate the effect of temperature. Since the relationship was found to be linear, the sensor output at reference temperature, x_r was calculated by:

$$x_r = x - \alpha_T(T - T_{ref}) \tag{6.1}$$

where α_T, T and T_{ref} are temperature coefficient, temperature (K) and reference temperature, respectively. The temperature coefficient was also found to have a linear relationship with sensor output (Fig. 6.2), as follows:

$$\alpha_T = 0.001x + 0.0005 \quad (6.2)$$

Second, the 5TE sensor was calibrated with different NaCl solutions and VWC, θ (Fig. 6.3), resulting the following equation:

$$\theta = 0.91x - 0.042\sigma_b - 0.014 \quad (6.3)$$

where σ_b is the bulk electrical conductivity.

Water content at each depth was estimated by interpolating or extrapolating measured values at the two depths. Matric head, *h*, at each depth was estimated using retention curve of the soil considering its hysteresis using a simple method of Kool and Parker (1987).

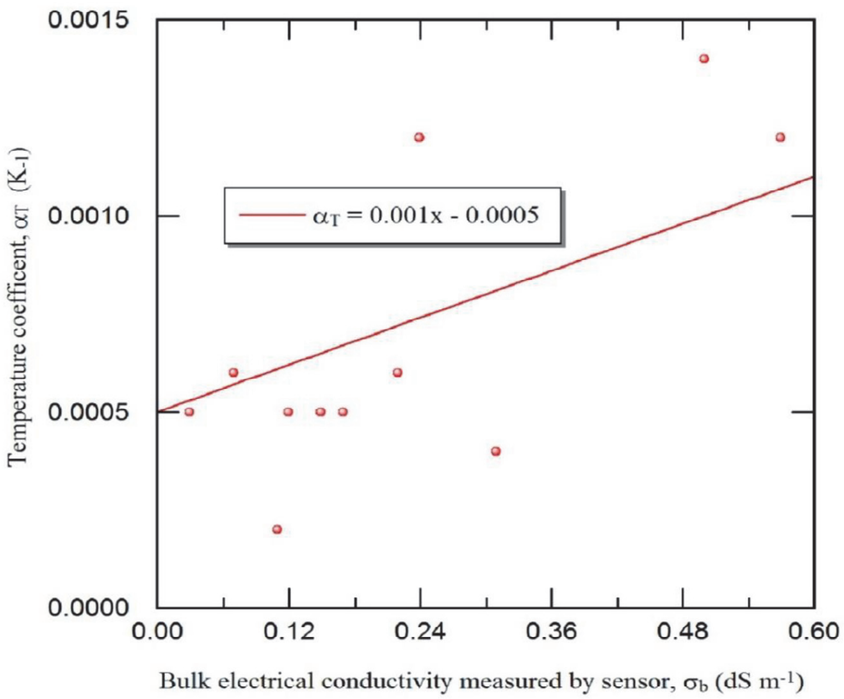

Fig. 6.2. Dependence of temperature coefficient on bulk electrical conductivity measured by sensor.

To calculate the EC of soil solution, σ_w from σ_b, the dependence of $\sigma_b$on θ measured with 5TE sensor is shown in Fig. 6.4:

$$\frac{\sigma_b}{\sigma_w} = 1.03\theta^{1.53} \tag{6.4}$$

Since σ_w is affected by temperature fluctuations, it was normalized to the reference temperature using the following equation (Noborio, 2003):

$$\sigma_{w25} = \sigma_b \frac{1 + \frac{(298 - T_s)}{49.7} + \frac{(298 - T_s)^2}{3728}}{1.03\theta^{1.53}} \tag{6.5}$$

where T_s is the soil temperature (K).

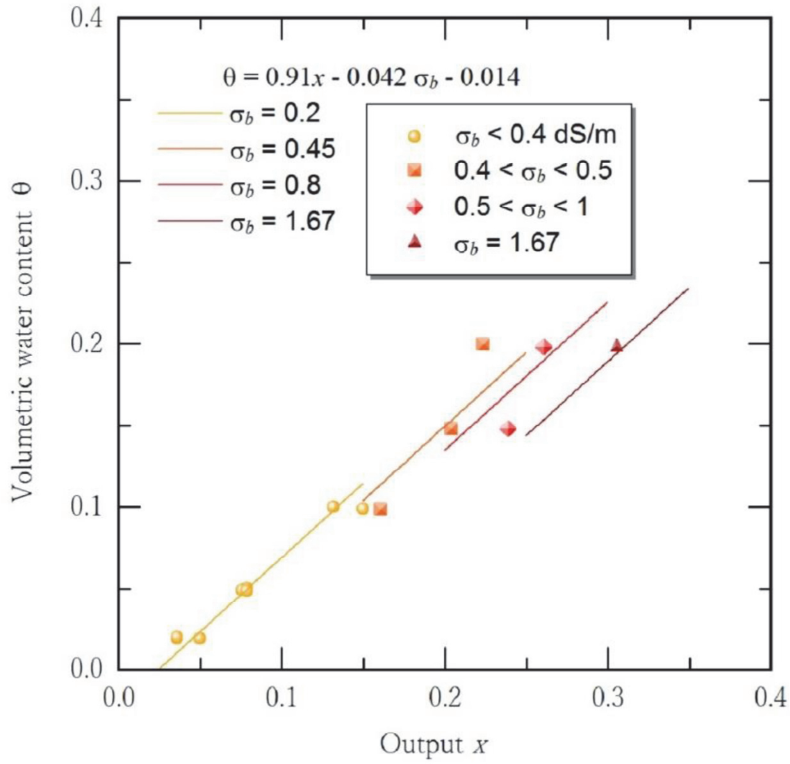

Fig. 6.3. Calibration function of 5TE sensor for Tottori sand soil.

The concentration of NaCl, c (mg cm^{-3}) was calculated from the σ_w using the following calibration function (Fujimaki et al., 2008).

$$c = 0.465{\sigma_{w25}}^{1.08} \tag{6.6}$$

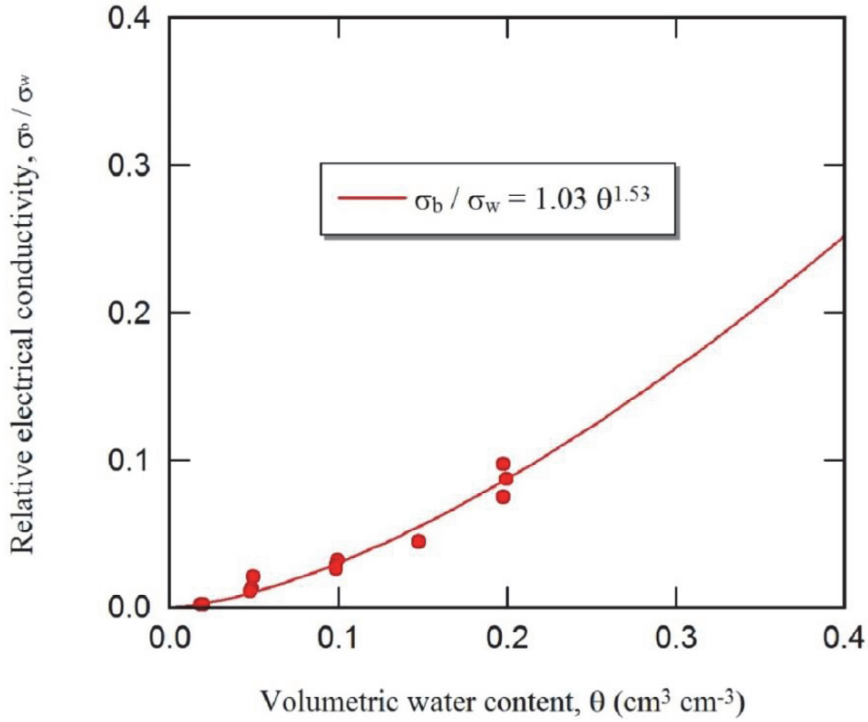

Fig. 6.4. Dependence of relative electrical conductivity of the soil on volumetric water content for Tottori sand.

The osmotic potential, h_0 of the soil solution can be estimated according to (Campbell, 1985) as follows:

$$h_0 = \omega v \frac{c}{M} x R T_s \tag{6.7}$$

where ω is a unit-conversion factor (10.2 cm kg J^{-1}); v is the number of ions per molecule; M is the molecular mass of NaCl, 58.5 (g mol^{-1}); x is the osmotic coefficient which assumed to be unity; and R is the universal gas constant (8.31 J mol^{-1} K^{-1}).

6.2.4. Determination of parameter values of stress response function

Parameter values in the response function, h_{50}, h_{050}, and p were estimated by inverse analysis with Levenberg-Marquardt's maximum neighborhood method (Marquardt, 1963). At given combination of those parameters, transpiration rate at each hour time was calculated as shown in chapter 2). The Potential transpiration rate, T_p was estimated assuming that Tp is proportional to short wave radiation, Ra (W m^{-2}) (Fujimaki and Kikuchi, 2010):

$$T_p = \tau_p \frac{R_a}{\int_{0:00}^{24:00} R_a \mathrm{dt}} \quad (6.8)$$

where τ_p is the potential daily transpiration (cm). The relative transpiration was estimated as follows:

$$\tau_r = \frac{\tau}{\tau_p} \quad (6.9)$$

where τ is the actual daily transpiration.

The daily transpiration was calculated by integration of hourly calculated transpiration rates, T_{cal} (cm s^{-1}):

$$\tau_{cal}(\vec{B}) = \int_{0:00}^{24:00} T_{cal}(\vec{B})\, \mathrm{dt} \quad (6.10)$$

where $\vec{B}$ is the vector of the optimized parameter.

Root mean square error (RMSE) was used as an objective function to minimize the difference between actual and calculated daily transpiration as follows:

$$RMSE(\vec{B}) = \left\{ \frac{1}{N} \sum_{\tau=1}^{N} \left[\tau_{cal}(\vec{B}) - \tau \right]^2 \right\}^{0.5} \quad (6.11)$$

6.3. Results and Discussion

Results of drought stress are shown for columns A and B, while results of salinity stress was examined for column A only due to a sensor malfunction column B. Changes in volumetric water content during drought stress period are illustrated in Fig. 6.5. In the beginning, the plant started to take up water from the top layer of the soil, and when water becomes limited at this layer, it attempted to take up water from the bottom layer, so the VWC at 15 cm started to decrease after 27 September. Regarding to Fig. 6.6, irrigation with NaCl solution, 3000 ppm was applied on 3 October; therefore, VWC at depths of 5 and 15 started to decrease when no irrigation was performed until 12 October. As a result, EC started to increase at both depths. As NaCl solution was applied from the top, the EC at 15 cm increased compared to its value at 5 cm.

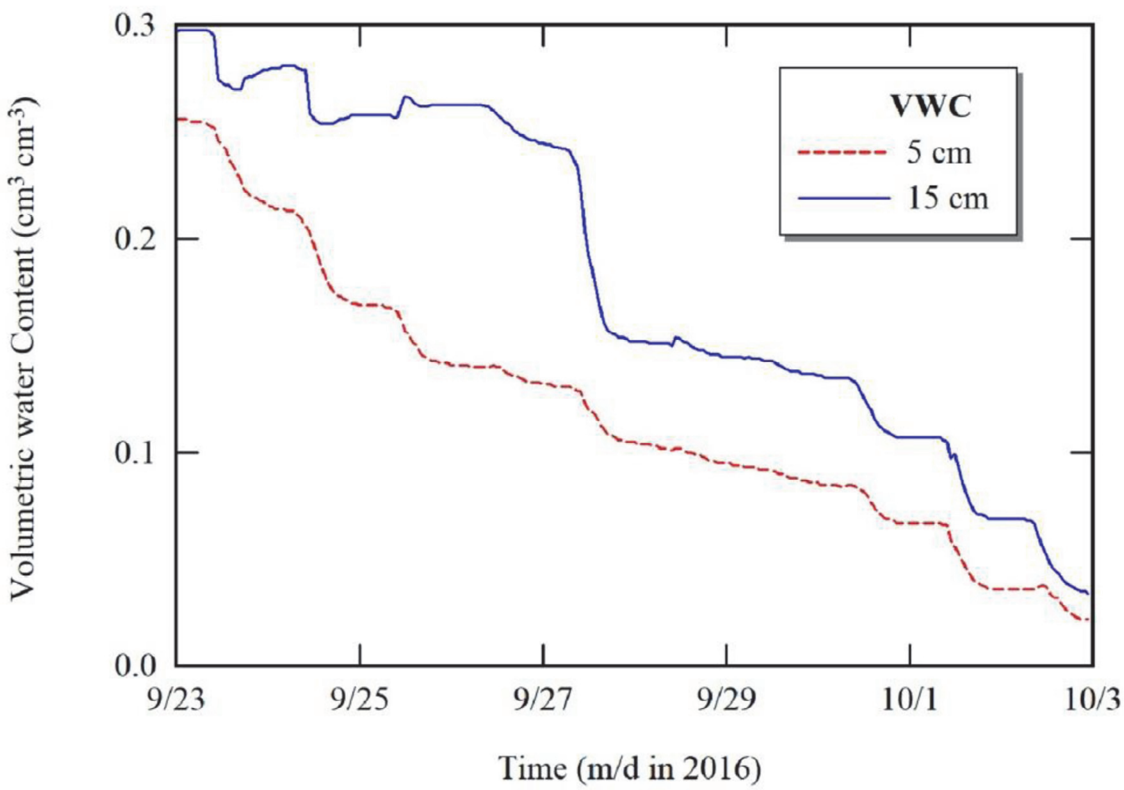

Fig. 6.5. Example of soil water content changes at two soil depths: 5 and 15 cm of column A during drought period.

The time evolution of potential and relative transpiration of columns A and B, and average daily transpiration of columns C, D and E are shown in Fig. 6.7.

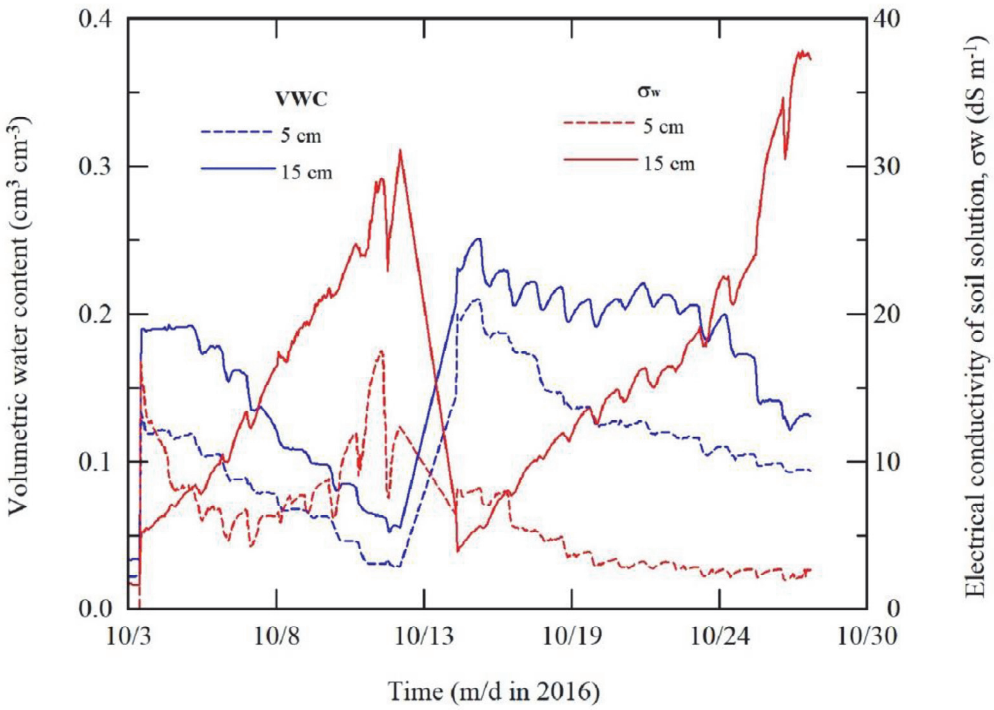

Fig. 6.6. Evolution of soil moisture and electrical conductivity of soil solution at 5 and 15cm depth for column A. NaCl solution of 3000 ppm was applied from 3 October and NaCl solution of 5000 ppm was applied from 15 October.

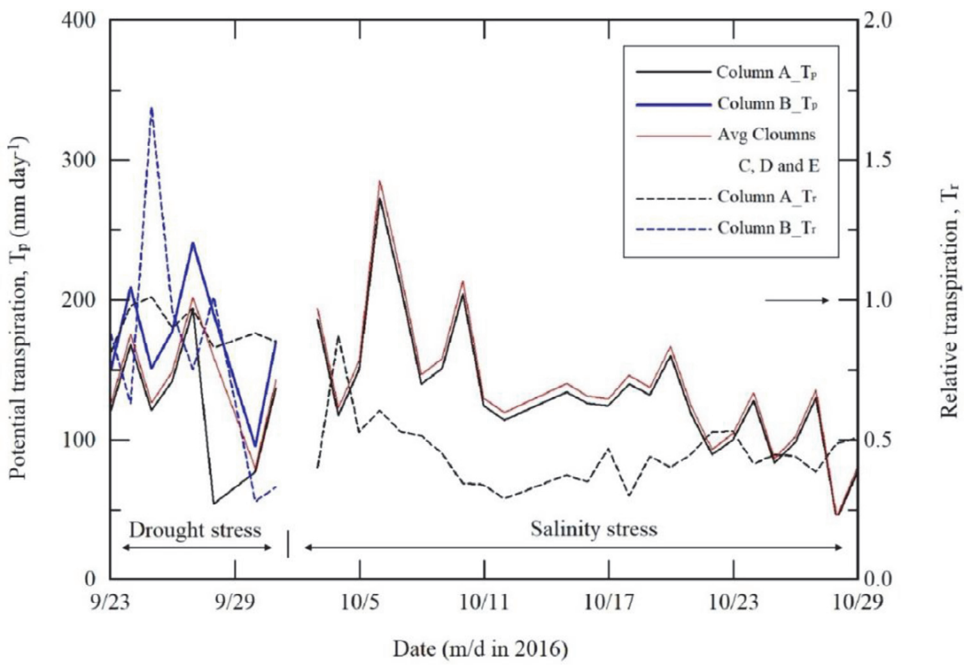

Fig. 6.7. Time evolution of daily potential transpiration and ratio of actual to potential transpiration.

During drought stress period, relative transpiration in column A decreased after 1 October, when the average VWC value was 0.09. In salinity stress period, relative transpiration decreased after 9 October when the average VWC value was the same as it value in drought stress period, 0.09. After 9 October, no irrigation was performed until 15 October which might have exposed the plant to salinity stress under limited water condition. As a result, the plant could not be recovered when NaCl solution of 5000 ppm was applied. Therefore, the plant was exposed to sever salinity stress although the averaged VWC was 0.2.

Parameter values of salinity stress response function were optimized after the drought stress period. Therefore, the highest value EC of soil solution was evaluated properly. According to Shalhevet et al. (1969), groundnut is moderately sensitive to salinity stress, can tolerate 3.4 dS m^{-1}. The results were agreed with their finding as shown in Fig. 6.8. Osmotic head was high at the depth of 5 cm, while matric head was around -40, throughout the root zone. Lower osmotic head at high root density at around 5 cm depth, reduced root water uptake, and resulted in decreasing the ratio of actual to potential transpiration after 15 October.

Measured and calculated ratio of actual to potential daily transpiration for column A is shown in Fig. 6.19. Large discrepancy in the ratio occurred for cloudy days, where solar radiation was small. When potential transpiration values were high, the error may have occurred due to individual difference in growth. Calculated values of relative transpiration, T_r around the dotted 1: 1 line, shows good fit, especially when the plant was under sever salinity stress. Stress response function for groundnuts was compared with that for canola (Yanagawa and Fujimaki 2013) and Jatropha (Fujimaki and Kikuchi, 2010) as shown in Fig. 6.10.

Drought stress response function is drawn by setting osmotic head to zero, while salinity stress response functions is drawn by setting matric head to zero.

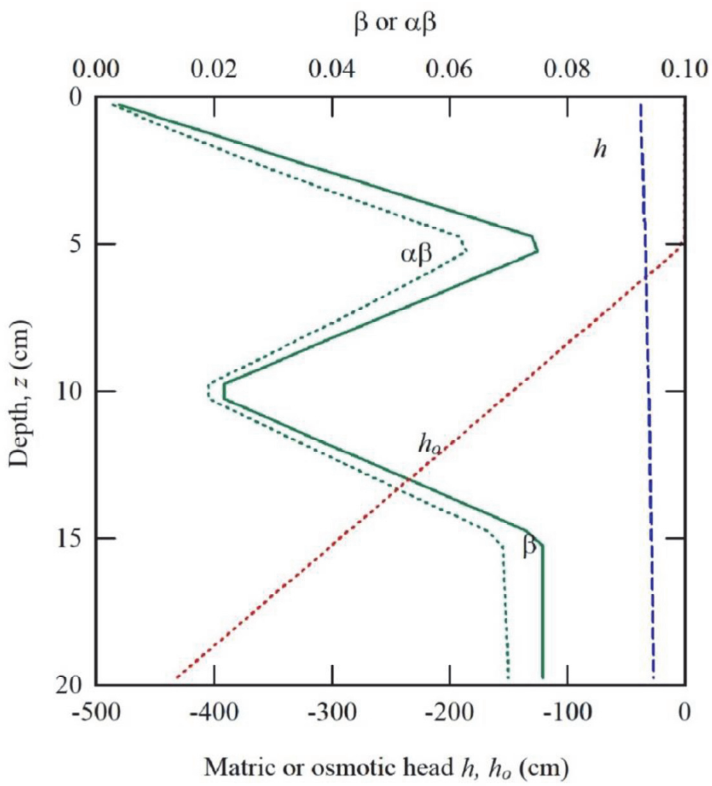

Fig. **6.8.** Root activity (β) and reduced root activity (αβ) along soil profile in column, A, on 29 October.

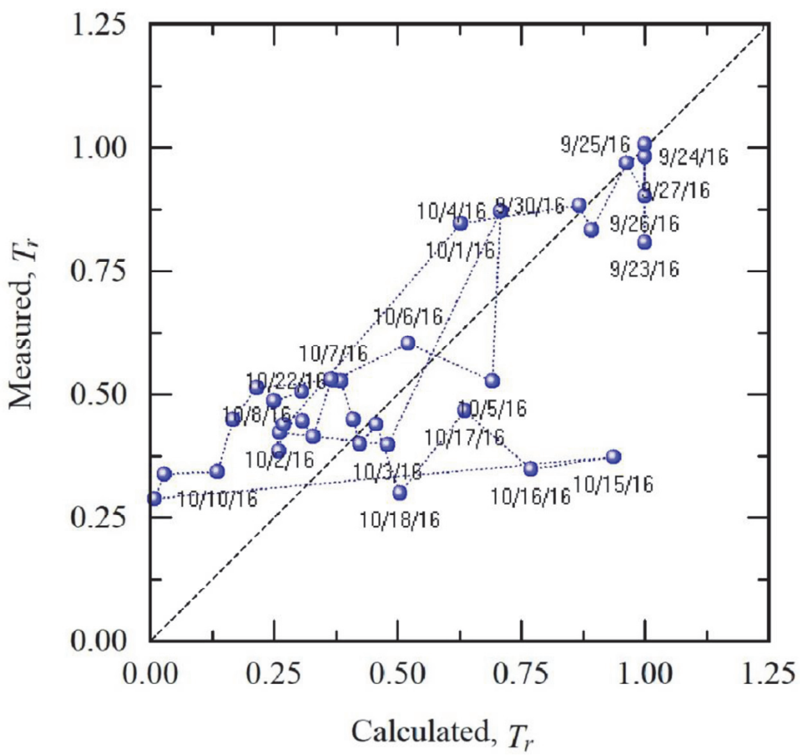

Fig. 6.9. Comparison of measured and calculated relative transpiration in column A.

Estimated parameter values of stress response function shows that groundnut is more sensitive to drought stress, while it is more tolerant to salinity stress compared to canola and Jatropha. Thus, matric potential was found to be determining factor for root water uptake than osmotic potential. Higher absolute value of h_{o50} is common among various plants (Feddes and Raats, 2004). This is mainly because there would be large difference in macroscopic matric potential measurable with soil moisture sensor and matric potential at just beside the roots. In case of sand, this effect would be larger than fine textured soil. Another reason would be that the plasma membrane of the root cells is not an ideal semi-permeable membrane, and some ions may intrude into the cells, reducing the difference between the inner and outer osmotic potentials. Estimated parameter values of drought and salinity stresses are shown in Table 6.1.

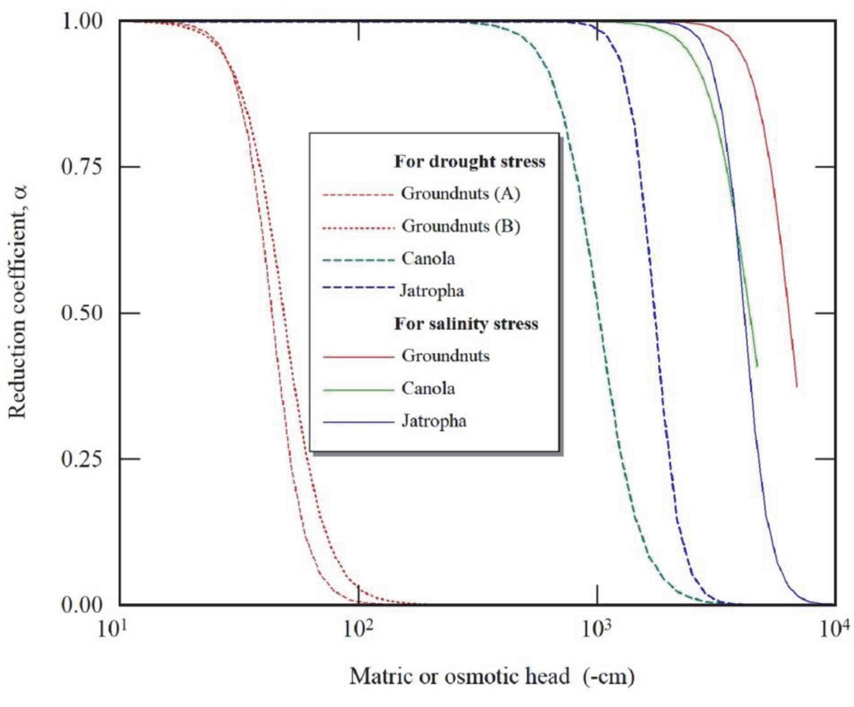

Fig. 10. Drought and salinity stress response functions for groundnuts, canola and Jatropha.

Results showed that groundnuts can be grown with saline irrigation water. According to Rhoades et al. (1999), EC of soil solution (dS m^{-1}) at 25°C can be converted to osmotic potential (MPa) using the following equation:

$$h_0 \approx 0.04\sigma_{\mathrm{w}} \tag{6.12}$$

Table 6.1. Parameter values of stress response function.

	Drought stress		Salinity stress	Average	Standard deviation
	A	B	A		
h_{50}	-43	-49		-46	3.72
h_{o50}			-6412		
p	6.203	4.873	6.203	5.538	0.94

Regarding to this study, the value of h_{o50} was found to be equal to -6412 cm. This value can be converted to 16 dS m^{-1} of EC of soil solution. According to FAO data on irrigation water quality (Ayers and Westcot, 1985), EC of soil solution is approximately 3.2 times more concentrated than the applied irrigation water. The 16 dS m^{-1} EC of soil solution might be resulted by irrigation with 5 dS m^{-1}. If the relative transpiration is proportional to relative yield (ratio of actual to potential yield), the resulted 5 dS m^{-1} is higher than the one which reported by with Ayers and Westcot (1985).

6.4. Conclusion

Parameter values of drought and salinity stress response functions for groundnut were estimated by conducting column experiment. These parameters, h_{50}, h_{o50} and p, were inversely determined by minimizing the sum of square difference measured and calculated daily transpiration rates. Water uptake at each depth and time was calculated by substituting linearly interpolated osmotic potential into the stress response function. Results showed that groundnut is more tolerant to salinity stress than canola and Jatropha. Resulted matric potential was more critical than osmotic potential to root water uptake. Frequent irrigation would be essential for growing groundnut in arid and semi-arid regions.

Chapter 7

General Discussion

7.1. The effect of the proposed scheme on plant growth

Knowledge of the effect of evapotranspiration and soil water management on plant growth is important for agronornic and economic evaluation of irrigation system. In this study, I concentrated on the two basic factors: leaf area index and biomass to evaluate the plant growth during each growing season. Those are most dominant factors having a close relationship to the transpiration rate. Many hydrologists, engineers, and economists are using growth models relating yield to evapotranspiration (or water applied, water used, etc.) (Packer et al., 1969; Yaron, 1971). Since water use includes evaporation directly from the soil, transpiration, and drainage, it was necessary to devise a procedure to separate the components of evapotranspiration into evaporation (E) which was calculated with Eq. 2.31 and transpiration (T) that was calculated with Eq. 2.5. It was assumed that the only process influencing plant growth directly is transpiration. Evaporation and drainage have an indirect influence on the amount of water available and thus transpiration. de Wit (1958) proposed an equation to relate dry matter yield to transpiration. In another work under field conditions, Hanks et al. (1969) stated that potential yield is occurred when actual transpiration is equal to potential transpiration. In the proposed scheme, transpiration is used to calculate total dry matter produced during each irrigation interval, and thus easily calculate net income assuming priced water Eq. 2.1.

In this study, accurate prediction of T will allow users to determine irrigation depth gives the maximal net income. In the FAO irrigation and drainage paper no. 56, T is separated from ET and is plotted in correspondence to leaf area per unit surface of soil below it. Indeed, leaf area actively affects the surface heat and vapor transfer. This made it the most dominant factor that affecting T. In this study, LAI was calculated as a function of T (Eq. (2.10)). LAI also affects aerodynamic properties which cause the crop evapotranspiration to differ from the reference crop evapotranspiration under the same climatic conditions. Therefore, aerodynamic resistance in this study was calculated as a function of LAI.

To check the benefits of the proposed scheme, I compared it to an automated irrigation system using soil water sensors or tensiometers. Automated irrigation system was selected, as it enables farmers to apply water more efficiently than fixed schedule or intuition. On the other hand, it has several defects: (1) simple type of this system which was applied in this study does not consider rainfall if it occurs directly after irrigation. As a result, water will be lost through deep percolation; (2) it requires high investment and regular maintenance; and (3) to know the optimum trigger value of soil suction or soil water content, field experiments are required. Therefore, the proposed scheme was developed to treat all those defects by considering weather forecast and using free software.

In this study, the plant growth was affected by two major variables: amount of irrigation and nutrients uptake. During three years research, the proposed scheme effectively increased both LAI and biomass for potato, sweet potato and groundnut. In both experiments of potato and sweet potato, AIS applied more water compared to the proposed scheme. This may drive to leach nutrients out of root zone, and hence reduced nutrients taken up by plants. On the other hand, in the groundnut experiment, AIS applied less water compared to the proposed scheme. This may be due to a higher trigger value of soil suction set to operate AIS. As a result, the plant was imposed to severer drought stress, which may be the reason to reduce both LAI and biomass of AIS compared to the proposed scheme. Proposed scheme does not consider the effect of nutrient although cumulative nutrient uptake may affect parameters such as a_{kc}, a_{LAI}, or transpiration efficiency and this effect should be incorporated in near future.

7.2. Validation of WASH 2D model in terms of soil water content and ET

The VWC of soil was measured using a time domain reflectometer (TDR-SK10 probes by Sankeirika, Japan and TDR 100 by Campbell Scientific, Ltd., USA). Twelve probes were installed in each treatment as shown in Fig. 7.1.

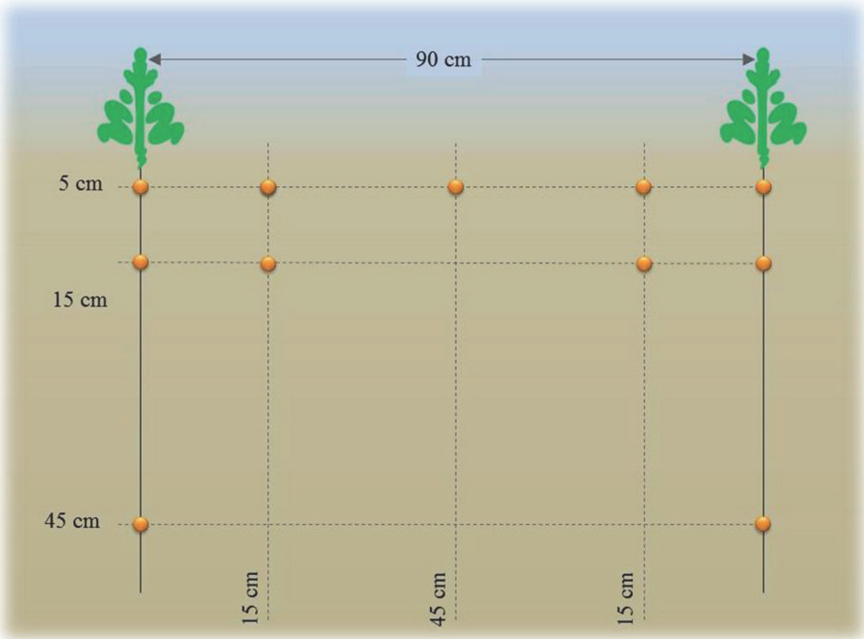

Fig. 7.1. Distribution of TDR probes in soil profile under the proposed scheme treatment

VWC was measured at each point (x and z) where x refers to the horizontal distance from the drip tube, and z refers to the soil depth. We selected only three locations to compare between measured and simulated values of VWC. Indeed, simulation of VWC highly depended on estimated parameter values of root water uptake. In the location (x = 0 cm and z = 5 cm), the model well simulated VWC for potato and sweet potato experiments while the model underestimated VWC values in groundnut experiment. This may be due to overestimation of potential transpiration and root water uptake. The other two locations were (x = 0 cm and z = 45 cm) which represented VWC at the lower layer under the drip tube; and (x = 45 cm and z = 5 cm) which represented the nearly bare soil condition. Data of the latter location was chosen to check the ability of the model to simulate rainfall events. In these two locations, the model accurately simulated VWC under the three experiments of potato, sweet potato and groundnut.

ET was measured using a weighing lysimeter with a diameter of 150 cm. The measured values of ET were compared to the simulated ones. Throughout the three experiments, the model tended to underestimate ET values. This might have occurred due to a technical problem. The soil surface of the lysimeter was about 5 cm above the surrounding area, which might have led the plants to transpire more due to greater exposure to wind. I tried to fill soil round the lysimeter to unite the level between inside and outside the lysimeter, but it does not fit completely as it requires more soil to include at least half of the field.

To predict T, the basal crop coefficient values at each growth stage should be accurately determined. In this study, the weighing lysimeter was used to correct the relationship between the cumulative transpiration and basal crop coefficient, not to observe hourly transpiration rate. Farmers cannot use lysimeter in their field. We presented Eq. 2.6 to represent the relationship between cumulative transpiration and basal crop coefficient. Indeed, this function differs from crop to crop and thereby field experiments to determine parameter values of this function must be carried out for major crops. However, I advise users to use recommended parameter values (Eq. 2.6) as listed in table 7.1. These values were derived from fitting the calculated values of basal crop coefficient to cumulative transpiration rate, the FAO irrigation and drainage paper no. 56 as shown in Fig. 7.2.

7.3. The effect of the proposed scheme on yield, amount of irrigation and net income

Although the proposed scheme applies a bit reduction in cumulative transpiration rate in order to maximize net income at an optimum irrigation depth, it could achieve higher yield for potato, sweet potato and groundnuts by 15%, 19% and 51%, respectively compared to AIS. Water price was assumed at a high level to give farmers incentive to save water.

Table 7.1: Recommended parameter values (Eq. (6), chapter 2) to estimate basal crop coefficient.

Crop	Parameter values of Eq. (6), chapter 2				
	a_{kc}	b_{kc}	c_{kc}	d_{kc}	e_{kc}
Potato	1.16	-0.27	0.1	1.82E-06	3.86
Sweet potato	1.18	-0.25	0.1	1.69E-06	3.6
Groundnut	1.23	-0.2	0.1	2.08E-06	3.94

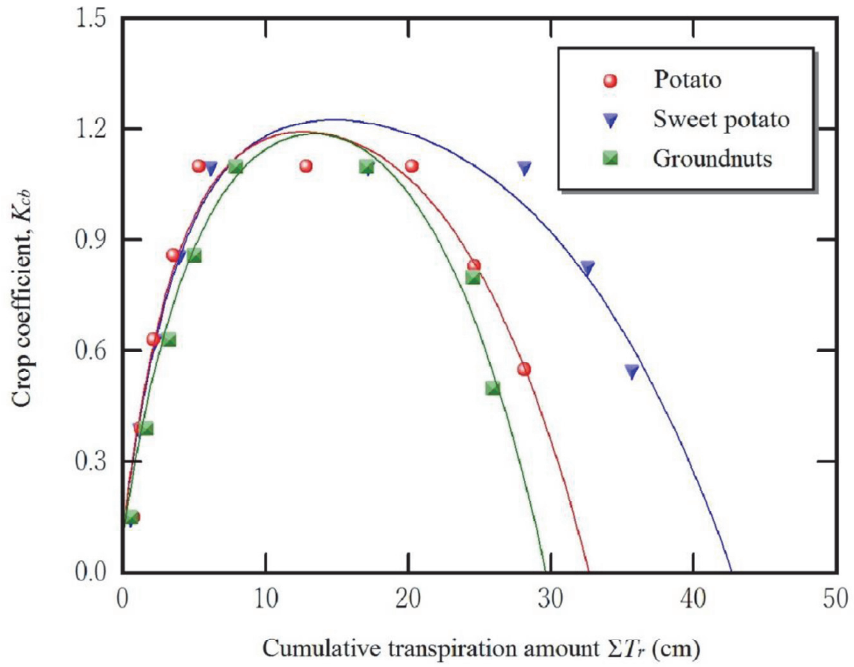

Fig. 7.2. Basal crop coefficient as a function of cumulative transpiration rate estimated from the FAO irrigation and drainage paper no. 56.

Applied amount of irrigation may largely affect the farmer's net income. As I mentioned above, results showed that the proposed scheme could save irrigation water by 27% and 18% for potato and sweet potato experiments, respectively while it resulted in application larger amount of water about of 28% compared to AIS for groundnuts. As a result, the proposed scheme increased the net income for potato, sweet potato and groundnuts by

1.28, 1.25 and 2.18 times, respectively compared to AIS. In groundnuts experiment, larger amount of yield could cover the cost for water and achieved higher net income. As shown in Fig. 7.3, the efficiency of AIS is highly affected by settings of trigger value of soil suction or soil water content as I previously discussed.

7.4. The importance of integrating weather forecast in irrigation management

The proposed scheme was designed to consider quantitative weather forecast (QWF) to determine irrigation depth. Nowadays, farmers can download QWF from internet for free. Public QWFs provide enough parameters such as air temperature, solar radiation, relative humidity, wind speed which are used to predict potential transpiration as well as rainfall (or probability of rain). The use of seasonal QWF has been assessed by several researchers (Hansen et al., 2006; Mishra et al., 2008; Hansen et al., 2009; Varshneya et al., 2010), but few studies such as Cai et al. (2007), Gowing and Ejieji (2001) have focused on short-term QWF. Integration of short-term QWF with the proposed scheme has a good impact on saving water as discussed in chapters 4 and 5. It also has advantage by considering near future rainfall in comparison with AIS. Indeed, inaccuracy of rainfall forecasts can have a major effect on predicted irrigation demands (Venäläinen et al., 2005). Therefore, short-term QWF (2 days in case of this study) is preferable to avoid errors in rainfall forecasts and this scheme would be more suitable for sandy soil with small irrigation interval. Indeed, QWF is getting improved year by year as results showed. RMSE values between forecasted and actual daily effective rainfall were 8.2, 10.4 and 4.6 mm in 2015, 2016 and 2017, respectively. This scheme would be less applicable for the clayed soil because of longer irrigation intervals and associated uncertainty of QWF.

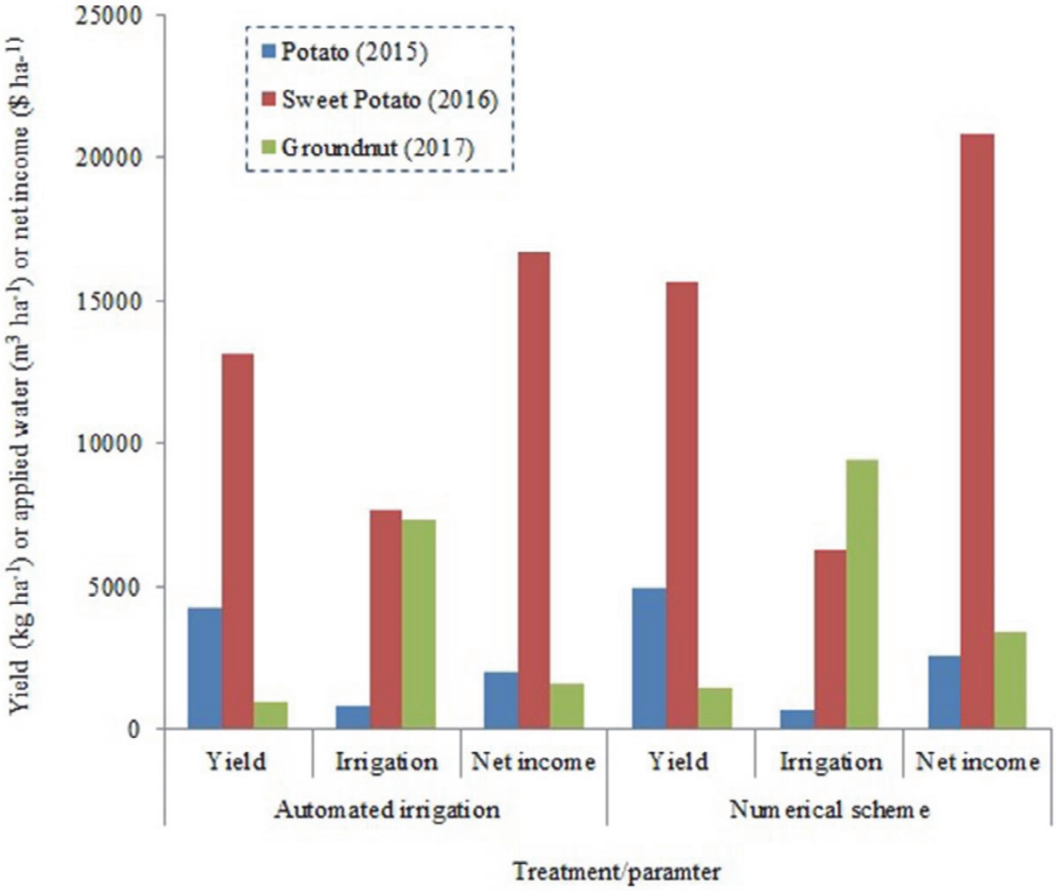

Fig. 7.3. Results of yield, applied water and net income for AIS and the proposed scheme.

7.5. Determination of appropriate water price

Water pricing is believed to be the most effective economic tool to promote more efficient water allocation and water conservation (Tsur and Dinar, 1997). As presented in Chapter 1, there are three major water pricing practices: non-volumetric, volumetric and differential water pricing. In this study, the volumetric water pricing approach was assumed. Water price was set at 0.00025 ($\$ \ kg^{-1}$) for potato crop in 2015; while it was set at 0.0003 ($\$ \ kg^{-1}$) for both sweet potato and groundnuts in 2016 and 2017, respectively. To select appropriate water price to realize net income, two suggestions were derived from analysis of Eq. 2.12 before conducting sweet potato experiment in 2016 as shown in Fig. 7.4. In this analysis, water price was set at 0.0001 ($\$ \ kg^{-1}$) and 0.00005 ($\$ \ kg^{-1}$) in 23 March and 10

April in 2016, respectively. Crop price was set at 0.05 (\$ kg^{-1}) and net income coefficient, k_i was set equals to unity. The values of a_t and b_t were estimated as shown in Fig. 7.5. Suggestion 1: To achieve net income, Eq. (7.1) must be greater than zero.

$$I_n = P_c \varepsilon \tau_i k_i - P_w W - C_{ot} > 0 \tag{7.1}$$

If transpiration rate during an interval, τ_i is given by

$$\tau_i = \varepsilon_\tau W \tag{7.2}$$

By merging Eq. (7.2) with Eq. (7.1),

$$I_n = P_c \varepsilon \varepsilon_\tau W k_i - P_w W - C_{ot} > 0 \tag{7.3}$$

Therefore, the recommended water price is given by

$$P_w < P_c \varepsilon \varepsilon_\tau k_i - \left(\frac{C_{ot}}{W}\right) \tag{7.4}$$

The value of ε_τ may be taken around one.

Suggestion 2: When irrigation is applied,

$$W = \frac{1}{b_t} \ln\left(-\frac{P_w}{P_c \varepsilon k_i a_t b_t}\right) > 0 \tag{7.5}$$

Therefore,

$$-\frac{P_w}{P_c \varepsilon k_i a_t b_t} > 1 \tag{7.6}$$

Then the recommended range of water price is given by

$$P_w < -P_c \varepsilon k_i a_t b_t \tag{7.7}$$

Otherwise, water is not applied. According to Fig. 7.4, on 23 March when the plant was under favorable conditions of soil water, the irrigation was not suggested under water pricing of 0.0001 (\$ kg^{-1}). At the same day, when the water price was halved, a 1.5 cm of irrigation depth was suggested, resulting in very small net income. On 10 April, when the plant was under drought stress and water price was 0.0001 (\$ kg^{-1}), a 4 cm of irrigation depth was suggested, resulting in higher net income.

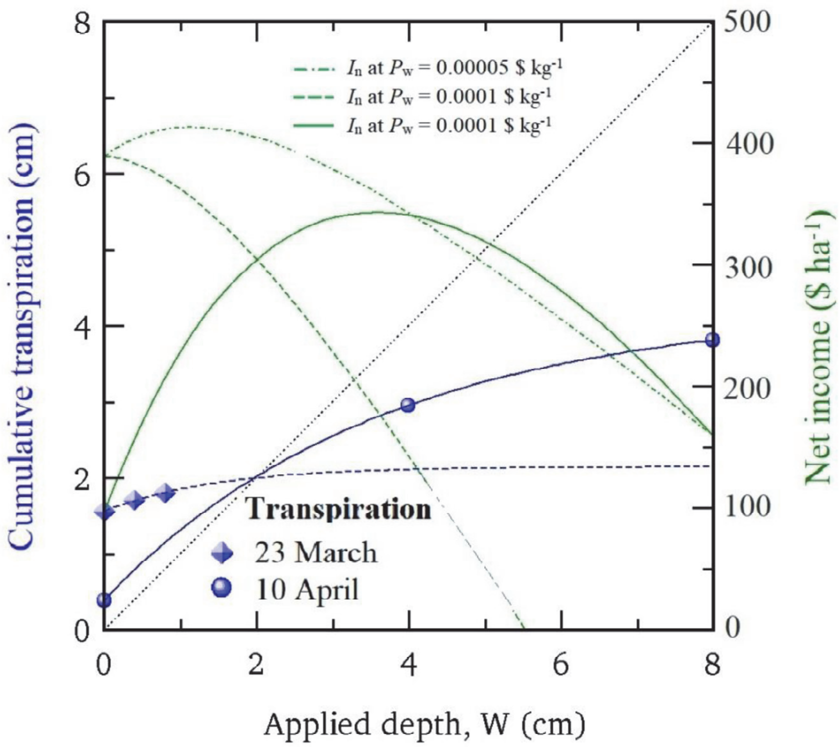

Fig. 7.4. Cumulative transpiration rate as a function of irrigation depth

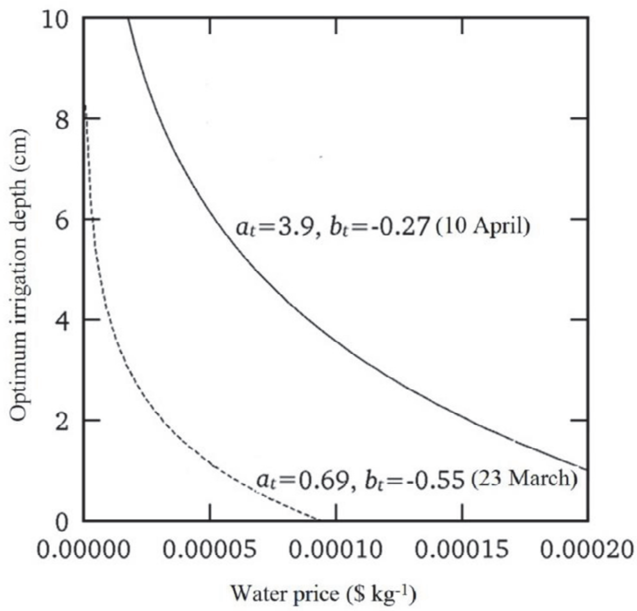

Fig. 7.5. Optimum irrigation depth as a function of water price.

7.6. Comparison between perfect and imperfect weather forecast

Accuracy in weather forecast plays an important role to improve the ability of the proposed scheme to optimize irrigation depths. In this respect, a numerical experiment was performed for 15 irrigation events during sweet potato experiment in 2016. Actual weather records were used as weather forecast data representing the perfectly accurate condition, while actual weather forecast data was used, representing the imperfect condition. Irrigation depths resulted from optimization runs using actual weather forecast (AWF) generally overestimated compared to perfect weather forecast (PWF) as shown in Fig. 7.6. The RMSE was 0.29 cm. For example, on 23 August, irrigation was not recommended using PWF while 0.51 cm was recommended using AWF. This is because on 22 August, 7 mm of rain occurred, while rain was not forecasted. On the other hand, on 6 September, a 0.57 mm was suggested for irrigation using PWF while irrigation was not suggested using AWF. This is because on 6 September, 1 mm of actual rain occurred while forecasted rain was 4 mm. In addition, 13.9 mm and 6.9 mm were recommended for irrigation on 4 September using AWF and PWF, respectively.

In general, there were not significant differences between PWF and AWF on both yield and net income according to results of the numerical experiment. Results of 15 simulation runs showed that a 1 cm of irrigation depth could give cumulative transpiration with 1 cm and 0.99 cm using PWF and AWF, respectively. It also achieved net income with 420.2 \$ ha^{-1} and 417 \$ ha^{-1} using PWF and AWF, respectively. These results indicate that the advantage of the proposed scheme to optimize irrigation depth and thus maximize net income is not fully offset by error in weather forecast and may be improved if the quality of weather forecast is improved.

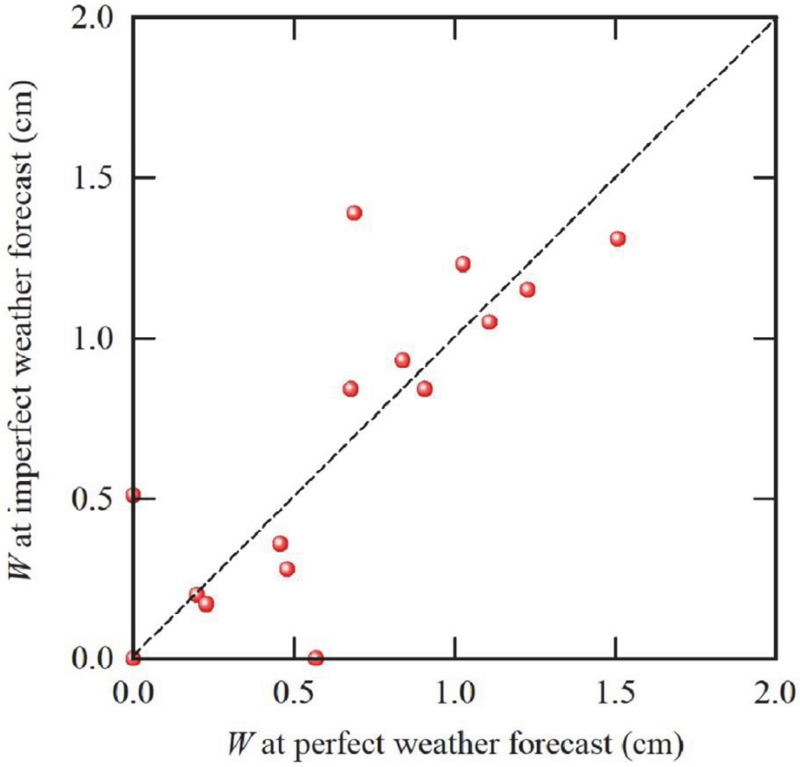

Fig. 7.6. Comparison between irrigation depths recommended by proposed scheme using either PWF or AWF.

Chapter 8

General conclusions

Water scarcity in arid and semi-arid regions is a major concern for agricultural production around the world. With advances in computer technology and theory in soil physics, numerical modelling has been used to predict soil water flow in soil and crop growth. This may help in decision-making through simplified representations of the real situation, allowing simulation under various scenarios and estimating its impact on crop production. As weather is dramatically changed, affecting crop water requirements, it is worth to incorporate weather forecasts with free internet access into simulation. This will improve irrigation management, considering future rainfall.

In this study, a new numerical scheme to optimize irrigation depths at each irrigation interval was developed. This scheme was incorporated in a numerical model of crop response to irrigation, considering freely accessible weather forecasts. This scheme optimizes irrigation depth assuming that net income can be estimated and maximized at each irrigation interval. This assumption has been introduced because farmers prefer to maximize their net income rather than water productivity. As farmers are widely waste much water in irrigation, water price has been introduced in this scheme to give them incentive to save water. Net income was calculated as a function of cumulative transpiration at each irrigation interval. This scheme used to predict transpiration responding to available water in soils. A numerical model, WASH 2D was used to simulate water and solute transport in soil to solve water flow under drip irrigation. The finite difference method was used to approximate the governing equation of water, solute and heat movement in soil. In the realm of soil physics, irrigation and plant science, it has long been known and widely accepted that plants respond to soil matric potential rather than to soil water content. Thus, those governing equations include a sink term that represents root water uptake which is a function of matric and osmotic potential.

To examine this scheme, three field experiments: potato (2015), sweet potato (2016) and groundnuts (2017) were carried out in the Arid Land Research Center, Japan. Two treatments were compared, automated irrigation system (AIS) and the proposed numerical scheme. I tried to evaluate the net income of the proposed scheme in comparison with AIS. As the soil was sand, irrigation interval was set at two days for the treatment of the proposed scheme.

Results showed that proposed scheme effectively increased both LAI and biomass for potato, sweet potato and groundnut, resulting in higher yield by 15%, 19% and 51%, respectively compared to AIS. In both experiments of potato and sweet potato, the proposed scheme required less water by 27% and 18%, respectively compared to AIS while it resulted in application larger amount of water about by 28% for groundnut compared to AIS. This may be due to a higher trigger suction set to operate AIS. As a result, the plant was under severer drought stress, which may be the reason to reduce both LAI and biomass of AIS compared to the proposed scheme. The proposed scheme increased the net income for potato, sweet potato and groundnuts by 1.28, 1.25 and 2.18 times, respectively, compared to AIS. In groundnuts experiment, larger amount of yield could cover the cost for water and achieve higher net income. The model could simulate soil water content in acceptable error. The accuracy of VWC simulation depends on the accuracy in predicting parameter values of root water uptake. Therefore, an example to determine parameters for root water uptake in case of groundnut was discussed in chapter 6.

The proposed scheme effectively considered future rainfall events that could improve irrigation management compared to AIS. In the present study, even under given uncertainty of weather forecasts, the proposed scheme was effective in determining irrigation depths and increasing net income. This scheme imposes moderate drought stress, being recently accepted among irrigation scientists and also being disseminated through extension services. This scheme would be less applicable for the clayed soil because of longer irrigation intervals and associated uncertainty of weather forecast.

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Summary in English

With increasing scarcity and growing competition for water, irrigation managers should adopt new approaches for irrigation scheduling to sustain crop production, and thereby maximize net income. About two thirds of irrigated farms are located in developing countries which are the main source of food production. With advances in computer technology and theory in soil physics, the use of numerical models can be an important tool to simulate crop water behavior under different conditions of water supply. It can also simulate water flow in the root zone and crop growth and is useful tool for extrapolating findings from field studies to conditions not tested yet, allowing projection for irrigation scheduling.

In this study, new numerical scheme was verified through three field experiments to determine irrigation depths which maximize net incomes at each irrigation interval. Quantitative weather forecasts which are freely available on the internet were used as inputs data. This scheme was incorporated in a numerical model, WASH 2D, which simulates two-dimensional water, solute, heat movement in soil with finite difference method. Net income was calculated as a function of cumulative transpiration over the irrigation interval. By predicting transpiration rates, the irrigation depths can be optimized to maximize net income. Parameter values of stress response function for both drought and salinity stresses were considered. Water pricing is also considered in this scheme to give farmers incentive to save water.

To evaluate the economic benefits of this scheme, three field experiments were carried out in the sand field of Arid Land Research Center, Tottori University, Japan. This scheme was compared with automated irrigation system (AIS) as it efficiently meets plant requirements by setting appropriate trigger value of soil water content or soil suction. On the

other hand, the AIM requires high initial investment and fails to adjust irrigation interval to weather forecasts, especially the traditional methods. The objective of this study was to verify the new scheme to optimize irrigation depth which gives maximal net income.

In chapter one, I showed general introductory for status of water resources in the world. Rapid growth of the world population will require more water and food in the future. Agriculture sector uses more than 70% of all water withdrawals; therefore, the importance of irrigation for food production should be addressed carefully. To do so, researchers adopted both irrigation scheduling and deficit irrigation practices which have been showed good results in irrigation management. Due to climate change which will affect the agriculture production, the merging weather forecasts in agriculture should be adopted. Nowadays, modern technologies in agriculture are widely developed. Those technologies include devices and software. Extensive practical use of models in agriculture water management has shown satisfactory results for crop production, and simulating water flow in soils. This eventually will lead to maximize net profits of farmers.

In chapter two, I presented the governing equations, sub-models and methodology of how the proposed numerical scheme is incorporated in the numerical model, WASH 2D. I started by addressing equations of how to determine irrigation depth and thereby, maximize net income. Assumptions like as water pricing or relation between dry matter and cumulative transpiration rate were also presented. In this study, WASH 2D model was used to combine the proposed scheme. Details of this model were also presented. I also showed how to perform the routine optimizing procedure. The implementation of this scheme using WASH 2D model was also explained through a set of steps. .

In chapter three, an experiment for potato (*Solanum tuberosum* L.) which was carried out in 2015 to evaluate effectiveness of this scheme was reported. Results showed that proposed scheme achieved higher yield and net income by 15% and 28%, compared to AIS. It required less water about of 27% compared to AIS.

In chapter four, an experiment for sweet potato (*Ipomoea batatas* (L.), cv. Kintoki) which was carried out in 2016 to evaluate effectiveness of this scheme. Results showed that proposed scheme achieved higher yield and net income by 19% and 25%, compared to AIS. It also required less water about of 18%, compared to AIS.

In chapter five, an experiment for groundnut (*Arachis hypogaea* L.) which was carried out in 2017 to evaluate effectiveness of this scheme was reported. Results showed that proposed scheme achieved higher yield about of 19% and net income 2.18 times, compared to AIS. It required more water about of 28%, compared to AIS. Larger amount of resulted yield could cover the cost due to water price and achieve higher net income.

In chapter six, an example for determining parameter values of stress response function was shown. The groundnut was found to be moderately tolerant to salinity stress.

In chapter seven, general discussion was made to show benefits and drawbacks of the proposed scheme. The appropriate solutions were also presented.

In general, the proposed scheme effectively considered future rainfall events that could improve irrigation management compared to AIS. This scheme would be less applicable for the clayed soil because of longer irrigation intervals and associated uncertainty of weather forecast. Even under given uncertainty of weather forecasts, the proposed scheme was effective in determining optimum irrigation depths and increasing net income.

Summary in Japanese

乾燥地および半乾燥地における水不足は、世界中で農業生産への深刻な懸念を呼びおこしている。コンピューター技術と土壌物理理論の発達により、土壌水分移動と作物成長の予測に数値モデルが使われてきた。現実を簡略化したモデルにより、様々なシナリオが作物生産に与える影響の予測を可能ならしめている。天気は劇的に変化し、作物の水要求量に影響するため、無料でアクセスできる天気予報をシミレーションに組み込むことは有用である。今後の雨を考慮することは灌漑管理を改善するであろう。

本研究では、無料でアクセスできる数値天気予報を考慮しながら毎回の灌漑において灌水量を最適化する新しい方法の有効性を３つの圃場実験により検証した。この方法は作物の灌漑への応答の数値モデルの一つである WASH_2D に既に組み入れられている。灌漑水量は次の予定灌水日までの純収入が推定できると仮定して最適化される。この仮定は、農民が水生産性よりもむしろ純収入の最大化を望むためである。水がしばしば浪費されている灌漑において節水を促すため、水への課金が導入されてきている。純収入は各間断期間における積算蒸散量の関数として計算される。点滴灌漑条件下での水移動を解析するため、２次元の水分移動数値解析モデル WASH_2D を用いた。

WASH_2D では差分法により水、熱、溶質移動の基礎式を近似している。土壌物理学や灌漑学、作物学の領域において、植物は土壌水分そのものよりもマトリックポテンシャルに応答することが広く受け入れられている。従って、基礎式には

マトリックおよび浸透ポテンシャルの関数である吸水を表すためのシンク項が含まれている。

この方法の有効性を検証するため、ジャガイモ(2015年)、サツマイモ(2016年)、ラッカセイ(2017年)を供試作物とする３つの圃場実験を鳥取大学乾燥地研究センターにおいて行った。水分もしくはサクションの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。土壌が砂であったため、間断日数は２日に固定した。

実験の結果、 いずれの作物でも提示された方法に基づく灌漑区では葉面積と乾物生産量が自動灌漑区を上回り、その結果、収量は ジャガイモで 15%、サツマイモで 19%、ラッカセイで 51%高くなった。ジャガイモでは 27%、サツマイモでは 19%灌水量が自動灌漑区に比べ少なかったのに対し、ラッカセイでは 28%灌水量が多かった。これはラッカセイにおける灌水基準サクションが高く、自動灌漑区の作物がより厳しい乾燥ストレス条件下にあったためと思われる。提示された方法では、純収入がジャガイモで自動灌漑区の 1.28 倍、サツマイモで 1.25 倍、ラッカセイで 2.18 倍であった。ラッカセイの場合、収量の増加による収入増が灌水量の増加に伴う水の費用の増加を上回った。また、数値モデルにより推定された土壌水分は概ね測定値と一致していた。土壌水分の推定値の精度は根の吸水速度に依存するため、根の吸水に関するパラメータの決定方法の一例を６章で示した。

提示された方法は、将来の降雨を効果的に考慮し、自動灌漑に比べ灌漑管理を改善した。本研究においては、降水量の予測がさほど正確でないにしても、提示された方法は灌漑水量を決定し、純収入を増やすことが明らかとなった。提示され

た方法は、軽度の乾燥ストレスを与えるものであるが、それは現在、不足灌漑として灌漑の研究者に広く受け入れられ、改良普及活動により普及している。本方法は間断日数の長い粘土質土壌においては、数日後以上の期間の天気予報の精度が未だ低いため適用は難しいと思われる。

List of publications

Abd El Baki, H. M., Fujimaki, H., Tokumoto, I. and Saito, T. 2017. 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 .Journal of the Japanese Society of Soil Physics 136:15–24. (Chapter 3)

Abd El Baki, H. M., Fujimaki, H., Tokumoto, I. and Saito, T. 2018. A new scheme to optimize irrigation depth using a numerical model of crop response to irrigation and quantitative weather forecasts. Computers and Electronics in Agriculture 150: 387–393. (Chapter 4)

Abd El Baki, H. M., Fujimaki, H., Tokumoto, I. and Saito, T. 2018. Optimizing Irrigation Depth Using a Plant Growth Model and Weather Forecast. Journal of Agricultural Science 10(7):55–66. (Chapter 5)