Computers and Electronics in Agriculture 150 (2018) 387–393

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

A new scheme to optimize irrigation depth using a numerical model of crop response to irrigation and quantitative weather forecasts

Hassan M. Abd El Baki[a], Haruyuki Fujimaki[a,*], Ieyasu Tokumoto[b], Tadaomi Saito[a]

[a] Tottori University, 4-101 Koyamacho-minami, Tottori 680-0001, Japan
[b] Saga University, 1 Honjo-machi, Saga 840-8502, Japan

ARTICLE INFO

Keywords:
Automated irrigation
Simulation
Transpiration
Drought
Net income

ABSTRACT

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, we developed a numerical scheme to determine optimal irrigation depth on scheduled irrigation days based on a concept of virtual net income as a function of cumulative transpiration over each irrigation interval; this scheme combines a numerical model of crop response to irrigation and quantitative weather forecasts. To evaluate benefits, we compared crop growth and net income of this proposed scheme to those of an automated irrigation method using soil water sensors. Sweet potato (*Ipomoea batatas* (L.), cv. Kintoki) was grown in 2016 in a sandy field of the Arid Land Research Center, Tottori University, Japan under either a non-optimized automated irrigation or the proposed scheme. 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.

1. Introduction

The determination of how much water to apply during irrigation is one of the most crucial topics of agricultural water management. Most farmers rely on intuition to determine water amount (referred to hereafter as irrigation depth; McCown et al., 2012). Most tend to believe that high yields are achieved by applying more water. By adding water beyond optimal levels, they may waste water or even reduce yield. To improve water management, the idea of deficit irrigation was developed, and it may be an efficient method of reducing irrigation water use. Many studies have been conducted with the aim of either reducing applied water or testing crop response under different deficit-irrigation management strategies (Makau et al., 2014; Gheysari et al., 2016; Lopez et al., 2017). Deficit irrigation has been widely used to maximize water use efficiency or water productivity as the primary objective. However, it would be net income (or profit), not water use efficiency or water productivity, farmers are willing to maximize.

Automated irrigation systems using sensors are another strategy used to quickly respond to drought stress (Dursun and Ozden, 2011; Nikolidakis et al., 2015). However, such systems require high initial investment in the sensor system and are not designed to adjust irrigation intervals to weather forecasts. The numerical simulation of water flow and crop growth can be utilized to predict crop water stress rather than monitoring soil water content with sensors (Gu et al., 2017). And now quantitative weather forecasts of acceptable accuracy are readily available to farmers with internet access.

Integration of weather forecasts into irrigation scheduling has become more viable in recent years. Lorite et al. (2015) used free accessible online weather forecasts to determine irrigation scheduling based on daily and weekly reference evapotranspiration. Venäläinen et al. (2005) evaluated the accuracy of SWAP (van Dam, 1997) and AMBAV (Braden, 1995) models by inputting numerical weather forecast as atmospheric boundary conditions. Delgoda et al. (2016) used weather forecasts in a theoretical framework based on model predictive control model to minimize soil water depletion in the root zone and determine irrigation depth under conditions of water deficit. Ballesteros et al. (2016) developed FORETo software to forecast reference evapotranspiration and thereby improve irrigation scheduling. Furthermore, decision support systems have been used to improve irrigation scheduling. Linker and Sylaios (2016) presented a hybrid formulation to minimize the number of decisions used in a multi-objective function of yield–irrigation combinations. Yang et al. (2017) used multiple objective functions to develop a flexible irrigation scheduling decision support system using fuzzy programming and interval optimization

* Corresponding author.
E-mail address: fujimaki@alrc.tottori-u.ac.jp (H. Fujimaki).

https://doi.org/10.1016/j.compag.2018.05.016
Received 8 February 2018; Received in revised form 31 March 2018; Accepted 13 May 2018
0168-1699/

approaches. This approach based on uncertain data of crop evapotranspiration; that would be a major constraint of this model.

Concerning water use efficiency and farmer's benefits, Wang and Cai (2009) used a theoretical approach by applying various modelling methods and using various types of weather forecasts in the SWAP model. They used a genetic algorithm to optimize the irrigation scheduling that maximizes seasonal net income. However, this approach had some limitations as they assumed (1) irrigation had to be applied if the stress index was below 0.5, regardless of weather forecasts; (2) a synthetic weather forecast; and (3) simplified water–yield relationships.

To motivate farmers to save water, governments typically set a price on water. Bozorg-Haddad et al. (2016) estimated farmer's response to the price of agricultural water. They found that low water prices have no effect on water use compared to non-priced water. Raising water prices gives farmers an incentive to save irrigation water. Assuming that water is appropriately priced, Fujimaki et al. (2015) presented a new scheme to optimize irrigation depths in which net income is maximized based on present-day weather forecasts. This scheme was incorporated into their WASH_2D model, which predicts the two-dimensional movement of water, solutes, and heat. They carried out two preliminary field experiments in two different locations. The first experiment was carried out at the Institute des Régions Arides (IRA), Medenine, Tunisia, during 2011–2012; the crop was barley (*Hordeum vulgar* L. cv. Ardhaui) grown in loamy sand soil. The second experiment was carried out at the Arid Land Research Center, Tottori University, Japan, in 2013; the crop was sweet corn (*Zea mays*, cv. Amaenbou86) grown in sandy soil. The experiments were limited to clearly ascertaining that the new scheme is beneficial and worth promoting. The applicability of this optimization procedure requires more extensive validation under various combinations of climate, soil, and crop to give users more confidence in its reliability. The purpose of this study, therefore, was to evaluate the Fujimaki scheme with respect to net income using a major crop, sweet potato. The specific goal was to replace capital-intensive automated irrigation methods with a low-cost scheme based solely on weather data and numerical simulation.

2. Scheme description

2.1. Maximization of net income

Fujimaki et al. (2015) 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. Net income can be calculated in proportion to the increment in dry matter attained during the interval from

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

where P_c is the producer's price of crop (\$ kg^{-1} DM), ε is transpiration productivity of the crop (produced dry matter (kg ha^{-1}) divided by cumulative transpiration (kg ha^{-1})), τ_i is cumulative transpiration during the interval 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 (\$ ha^{-1}).

Transpiration in the initial growth stage is smaller than that in later stages; therefore, we used the income correction factor to avoid underestimating the contribution of initial transpiration to the entire quantum of growth. It was described by Fujimaki et al. (2015) as;

$$k_i = \frac{\bar{k}_c}{k_c} = \frac{\int k_c d\tau}{\tau_f k_c} = \frac{(a_{kc} + c_{kc})\tau_f - \frac{a_{kc}}{b_{kc}}[\exp(b_{kc}\tau_f - 1)]}{\tau_f K_c} \tag{2}$$

where $\bar{k}_c$ is average values of crop coefficient, k_c over expected period of growth; τ_f is the expected transpiration at final period; a_{kc}, b_{kc} and c_{kc} are fitting parameters.

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

$$T_r = L_x^{-1} \int_0^{L_x} \int_0^{L_z} S \mathrm{d}x \mathrm{d}z \tag{3}$$

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

$$S = T_p \beta \alpha_w, \tag{4}$$

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 condition, WASH_2D can calculate both evaporation and transpiration rates separately. The evaporation rate was calculated with a bulk transfer equation (van Bavel and Hillel, 1976) while the T_p was calculated by multiplying reference evapotranspiration by basal crop coefficient, k_c as follows:

$$T_p = E_p k_c, \tag{5}$$

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

$$K_c = a_{kc}[1 - \exp(b_{kc}\tau)] + c_{kc} - d_{kc}\tau^{e_{kc}} \tag{6}$$

where d_{kc} and e_{kc} are fitting parameters. The last term $d_{kc}\tau^{e_{kc}}$ of Eq. (6) expresses decline in latest stage of growing season. The reduction of the water uptake rate, α is a function of drought and osmotic stresses; WASH 2D model uses the so-called additive function as follows:

$$\alpha = \frac{1}{1 + \left(\frac{\psi}{\psi_{50}} + \frac{\psi_o}{\psi_{o50}}\right)^p} \tag{7}$$

where ψ_{50}, ψ_{o50} and p are fitting parameters (van Genuchten, 1987). In this paper, we modified the equation that describes the root activity, β:

$$\beta = 0.75(b_{rt} + 1) d_{rt}^{-b_{rt}-1}(d_{rt} - z + z_{r0})^{b_{rt}} g_{rt}(1 - x^2 g_{rt}^{-2}) \tag{8}$$

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

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

$$d_{rt} = a_{drt}[1 - \exp(b_{drt}\tau)] + c_{drt}, \tag{9}$$

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

2.2. Determination of optimum irrigation depth

To minimize repetition of numerical prediction in non-linear optimization, Fujimaki et al. (2015) proposed the following scheme: First, the relationship between transpiration and irrigation depth is described as

$$\tau_i = \int T_r \mathrm{d}t = a_t[1 - \exp(b_t W)] + \tau_0 \tag{10}$$

where T_r is the transpiration rate (cm s^{-1}), a_t and b_t are fitting parameters and τ_0 is τ at W = 0. 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. (1)