

Soil Moisture and Crop Evapotranspiration Forecast for Winter Wheat Based on Weather Information in North China Plain

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Abstract—Soil moisture and crop evapotranspiration (ET_c) forecast based on weather information is a basis for realizing precise irrigation, which could be an innovative technique for water-saving strategy in irrigated district. Combined with long-term experimental data in People's Victory Canal irrigated district, we put forward a systematic soil moisture forecast method for winter wheat using related weather information. In this study, hourly soil moisture was automatically monitored by a soil moisture monitoring system. Weather information for the following two weeks was automatically acquired. Combined with ET_c , soil moisture forecast can be used to predict irrigation time and amount which differs among growth stages of winter wheat. In particular, irrigation time can be decided by monitoring soil moisture when reaching to lower limit of soil moisture for winter wheat, and the irrigation amount can be determined by calculating soil water storage needed to meet planned wetting layer according to crop growth monitoring. Parameters in soil moisture and crop evapotranspiration forecast models were determined using Levenberg–Marquardt regression. Validation test suggests that the models we developed are reliable. We conclude that the models can serve as a useful tool for future irrigation forecast.

Keywords—irrigation forecast; prediction model; crop water requirement; precipitation

I. INTRODUCTION

Soil moisture forecast is a dynamic process based on weather forecast information updated hourly by China Meteorological Administration [1]. Through estimating crop evapotranspiration (ET_c) by prediction model, and measuring current soil moisture by soil moisture monitoring system, when and how much water should be irrigated for crops can be predicted [2]. In particular, future soil moisture simulation is mainly dependent upon weather forecast information and current soil moisture monitoring. To precisely forecast irrigation, best-fitted prediction model is needed to estimate ET_c . Nowadays, it has been widely used for ET_c prediction models established on water balance equation [3]. The core technique for when and how much water need to be irrigated is based on accurate soil moisture monitoring and precise weather forecast [4]. Therefore, the accuracy of irrigation prediction largely depends on how to acquire precise weather data for the following days. It is equally important that we

should accurately estimate ET_c by coupling reference evapotranspiration (ET_0) with crop coefficient (K_c) for irrigation forecast [5]. The estimate of ET_0 is usually based on measurable and accessible climatic factors such as air temperature, solar radiation, and precipitation etc. [6]. Given that air temperature in weather forecast is a quantified figure that can be directly used and accumulated, model for accumulated air temperature simulation can be used to calculate ET_c . As a result, choosing an optimal model for ET_c and soil moisture forecast can be applied to improve the accuracy of irrigation forecast when parameters needed are of high accuracy [7]. The feasibility of a model usually needs to be validated through field experiments. In this study, we hypothesized that soil moisture forecast model developed based on weather forecast information was suitable and reliable for forecasting the irrigation time and amount in the People's Victory Canal irrigated district, North China Plain.

II. WATER BALANCE EQUATION

Soil moisture forecast is basically established on soil moisture monitoring system and crop evapotranspiration (ET_c) estimated by weather forecast information [8]. That is, a forecast of an increase or decline of soil water content in the root zone, which changes with crop growth stages, can be estimated by subtracting predicted ET_c from the current ET_c , then we got the how much water should be consumed for the following days. Thus, it provides a possibility for forecasting irrigation time and amount for a given date. Water balance equation, which is used to calculate current ET_c , is established to a depth equal to planned wetting layer [3]:

$$W_i = W_0 + W_{ri} + P_{ei} + I_i - ET_{ci} - G_i - R_i$$

where W_0 and W_i are soil water storage (mm) in planned wetting layer at the initial (0) and current time (i); W_{ri} is increased soil water storage (mm) due to increasing planned wetting layer with crop growth proceeding; I_i is irrigation amount (mm); P_{ei} is effective precipitation (mm); ET_{ci} is future crop evapotranspiration (mm) to be predicted by an empirical model; R_i is surface runoff (mm); G_i is ground water recharge (mm).

The runoff is negligible due to less precipitation in the People's Victory Canal irrigated district during the entire growth period of winter wheat [9]. Thus R_i is assumed to be 0. In the mean time, the ground table is below 5m, therefore the upward movement is also neglected, i.e., G_i is assumed to be 0. Thus, the equation can be simplified as:

$$W_i = W_0 + W_{ri} + P_{ei} + I_i - ET_{ci}$$

Initial soil water content (W_0), current soil water content in planned wetting layer (W_i), and increased soil water storage due to the planned wetting layer deepening with crop growth (W_r) can be obtained by field observation. Soil water storage (mm) in the planned wetting layer is a product of volumetric water content ($\text{cm}^3 \cdot \text{cm}^{-3}$) and soil depth (cm) [9]. Irrigation amount (I_i) is measured using a flow meter at the recharge end of a water pipe system.

III. PREDICTION MODELS

ET_c can be calculated from meteorological data and crop coefficients (K_c). ET_c is considered as a combined effect of the climate factors and crop growth on crop water requirements, which is illustrated by ET_0 and K_c .

A. Prediction Model for Crop Evapotranspiration

Calculation of ET_{ci} can be achieved by multiplying reference evapotranspiration (ET_{0i}) with crop coefficient (K_{ci}) at a certain growth stage [3], and it can be expressed as:

$$ET_{ci} = K_{ci} \cdot ET_{0i}$$

If soil water is deficit, the calculation should introduce a correction factor (K_{si}):

$$ET_{ci} = K_{si} \cdot K_{ci} \cdot ET_{0i}$$

When K_{si} equals 1.0, the simulation of ET_{ci} is considered under non-water stress condition [2].

B. Prediction Model for Reference Evapotranspiration

Estimate of ET_0 is a basis for soil moisture and ET_c forecast. Because Harg model explicitly accounts for solar radiation and temperature [11], ET_0 simulated by Harg model can be expressed as:

$$ET_0 = 0.0023 \cdot \frac{1}{\lambda} \cdot (T_{\max} - T_{\min})^{0.5} \left(\frac{T_{\max} + T_{\min}}{2} + 17.8 \right) R_a$$

where R_a is solar radiation ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$); λ is latent heat of vaporization with a value of $2.45 \text{ MJ} \cdot \text{kg}^{-1}$ [12]; T_{\max} and T_{\min} are maximum and minimum air temperature ($^{\circ}\text{C}$), respectively.

Comparing the results of ET_0 calculated by Harg model to that by Penman-Monteith (PM) model using a long term

(1951–2002) ten-day meteorological data from Xinxiang city, North China Plain, the two calculation methods showed good consistency in ET_0 simulation, with a mean deviation of 3.5 mm, and mean relatively deviation of 10% (Figure 1). Our results are consistent with the findings of Liu and Luo (2010) [13], who conducted a similar evaluation in North China Plain. The correlation coefficient (r^2) between the two ET_0 results reached 0.81, showing a significant correlation between Harg and PM methods ($P < 0.05$).

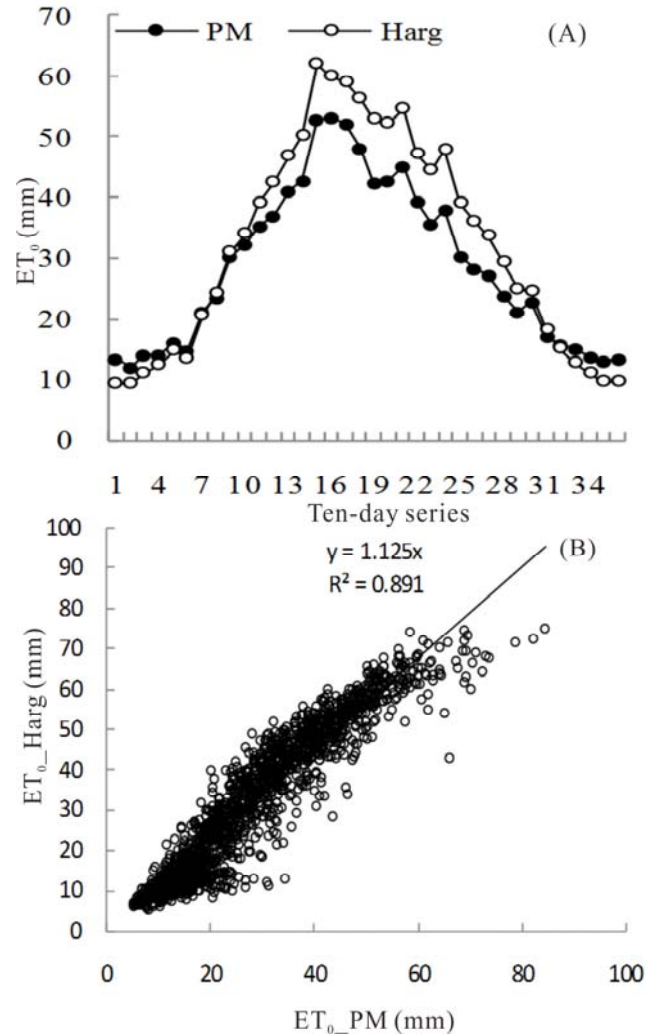


FIGURE 1. (A) ET_0 CALCULATED USING HARG MODEL AT TEN-DAY SERIES, AND (B) THE CORRELATION ANALYSIS BETWEEN ET_0 CALCULATED BY HARG AND BY PM MODELS.

In order to improve the accuracy of the predicted ET_0 values, some corrections for parameters like K , n , and T_{off} need to be iterated in Harg model using Levenberg-Marquardt regression:

$$ET_0(HG) = K \frac{1}{\lambda} (T_{\max} - T_{\min})^n \left(\frac{T_{\max} + T_{\min}}{2} + T_{off} \right) R_a$$

where K is a constant to be fitted for determining the slope; n is an empirical exponential coefficient to be fitted. T_{off} is an

empirical temperature value calibrated to offset biases in “ $T_{max}-T_{min}$ ” at different latitudes. To calibrate the Harg model, parameters were iterated into Levenberg–Marquardt Algorithm using Statistical Analysis Software (SPSS 19.0, SPSS Institute Inc., USA). After the iteration, the best fitted values for the parameters are 0.008 (K), 0.796 (n), and 29.506 (T_{off}) ($r^2=0.907$, $P<0.01$), respectively. The parameters estimated in this study are similar to the results of Tang et al. (2016) [12], who concluded some key parameters for the model using Harg formula in the Huang–Huai–Hai Plain.

C. Determination of Crop Coefficient (K_{ci})

For a given cultivar of winter wheat, K_{ci} is mainly controlled by crop growth stages, and is also linked with crop canopy development [3]. Our study showed that there existed a significant linear relationship between leaf area index (LAI) and K_{ci} :

$$K_{ci} = a \cdot LAI + b$$

where a and b are the slope and interception for the equation. By iterating field observed data into Levenberg–Marquardt regression, it was suggested that 0.14 (a), and 0.3918 (b) be the best fittest parameters ($r^2 = 0.928$, $P<0.01$).

Except the indigenous genetic traits, cumulative relative growth degree days ($RGDD$, $^{\circ}C \cdot d$) during the growing season is a major factor determining crop growth and development [14]. Since $RGDD$ is a product of accumulated air temperature ($^{\circ}C$) and elapsed time (d) for fulfilling a life cycle of crops, the requirement of crops to $RGDD$ is always stable and unchangeable. Namely, $RGDD$ must be adequate to meet the crop demand. Our study showed that there existed a good correlation between $RGDD$ and LAI , and the regression between $RGDD$ and LAI was fitted to j -th order ($j=0, \dots, 5$) Logistic curve, where the fifth-order Logistic curve had the best goodness of fit (**Figure 2**):

$$LAI = \frac{b \cdot LAI_{max}}{1 + \exp\left(\sum_{j=0}^5 a_j RGDD^j\right)}$$

where LAI_{max} is the largest LAI value during the entire growth stage; $RGDD$ is the relative cumulative growth degree days (that is, the ratio of phase cumulative $RGDD$ to the whole $RGDD$); j is the j -th power of the Logistic curve; a_j ($j=0, \dots, 5$) and b are empirical coefficients to be fitted. After regression by fifth-order, it was suggested that 24.84 (a_0), -161.4 (a_1), 374 (a_2), -392.6 (a_3), 169.2 (a_4), -11.46 (a_5), and 1.169 (b) be the best fitted parameters ($r^2=0.977$, $P<0.01$). Our results are in good agreement with the findings of Wang et al., (2011) [15], who conducted a similar simulation between LAI and $RGDD$, but we obtained a higher fitness for the model due to a higher order curve than that of Wang et al. (2011) [15].

When integrate the two models into one, a model for predicting crop coefficient (K_{ci}) based on $RGDD$ can be established. It is necessary that, when to predict K_{ci} using the

integrated model, we should consider the freezing period when a very low temperature might occur in the wintering period of winter wheat, and correct the K_{ci} to be 0.4 rather than a value predicted by the model [13]. While before and after the wintering period, the predicted K_{ci} values can be acceptable for calculating ET_c .

D. Determination of Calibration Coefficient for Soil Moisture (K_{si})

If observed soil water content is significantly lower than the critical value that triggers crop wilting, ET_c will be markedly constrained [3]. Otherwise, soil water content will normally not be a constraint to depressing ET_c . Thus, the K_{si} can be expressed as:

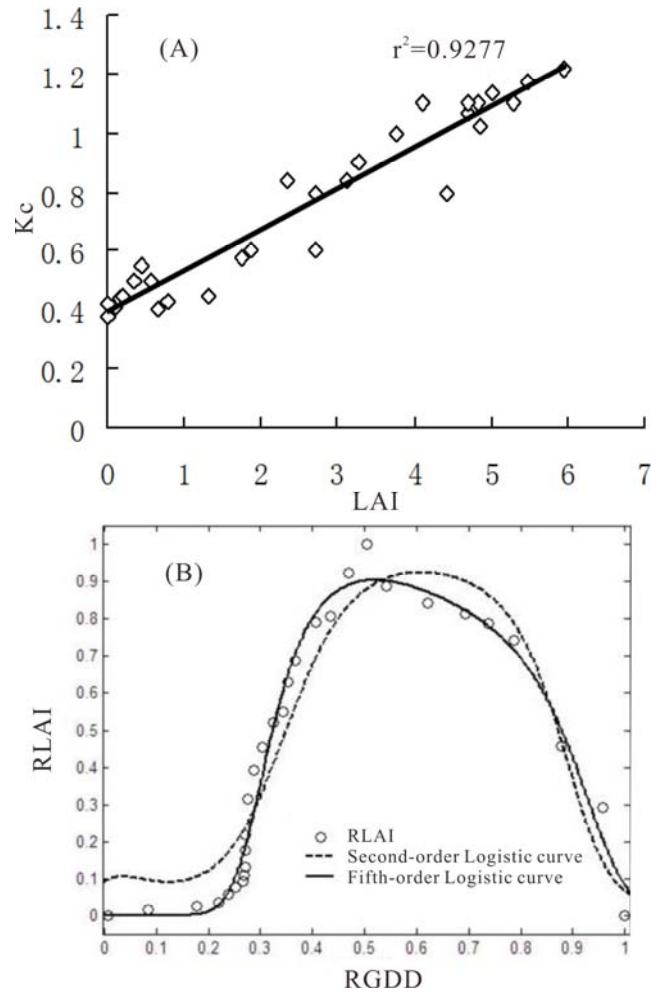


FIGURE II. (A) RELATIONSHIP BETWEEN CROP COEFFICIENT (K_c) AND LEAF AREA INDEX (LAI), AND (B) RELATIONSHIP BETWEEN CUMULATIVE RELATIVE GROWTH DEGREE DAYS ($RGDD$, $^{\circ}C \cdot d$) AND RELATIVE LEAF AREA INDEX ($RLAI$).

$$K_{si} = \left(\frac{\theta_i - \theta_{up}}{\theta_j - \theta_{up}} \right)^d \quad (\theta_i < \theta_j)$$

where d is an empirical coefficient obtained from field observation, and it changes with crop growth stages and soil water status. θ_i is mean soil water content during a given growth phase; θ_{up} is the wilting point; θ_j is the critical soil water content. According to the ranges of K_{ci} changing with crop growth stages, four growth stages were classified as follow: sowing to wintering stage, wintering to turning-green stage, turning-green to tasseling stage, and tasseling to maturity. After iteration using Levenberg-Marquardt Algorithm, it was suggested that the corresponding θ_j values be 23.07, 22.52, 20.20, and 22.68 for the four growth phases of winter wheat, and the corresponding d values be 0.8156, 0.9563, 0.7584, and 0.8753, respectively. Our results are consistent with the findings of Wang et al. (2010) [16], who established a simulation model based on plant height and leaf area index for winter wheat in the North China Plain. According to Wen et al. (2015) [17], those models can be integrated into one model for predicting ET_c so that they can help local farmers and district governors determine irrigation time and amount.

E. Validation of the Model for Forecasting Soil Moisture

The ten-day soil water content can be predicted by the established ET_c model (Figure 3). Also, the predicted soil moisture values can be updated hourly according to the weather forecast information and observed soil water content. Compared the predicted and observed soil water content during the winter wheat growing season in 2012 and 2013, they basically showed good consistency, with a mean deviation of 2.45%. This indicated that the established soil moisture forecast model is reliable, and can serve as a useful tool for irrigation forecast in People's Victory Canal irrigated district, Xinxiang city, North China Plain.

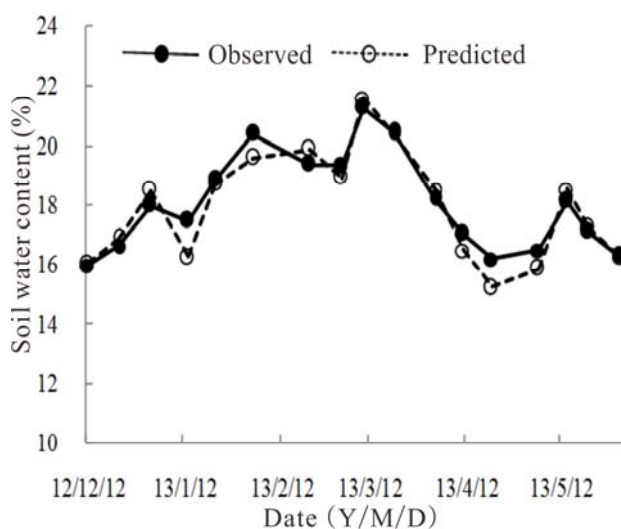


FIGURE III. PREDICTED SOIL WATER CONTENT IN COMPARISON TO OBSERVED SOIL WATER CONTENT USING THE SOIL MOISTURE FORECAST MODEL.

IV. CONCLUSIONS

The model for predicting daily ET_c based on weather forecast information has proven to be reasonable and reliable

in the present study. On the basis of the model, a prediction model for simulating soil moisture has been established, and can be adopted to forecast daily soil moisture dynamics in the following two weeks in winter wheat growing season. Our study showed that there existed a very good agreement between the observed and predicted values of soil moisture, as well as ET_c , indicating a good model performance. Taking lower limit of soil moisture and planned wetting layer into account, the models can serve as a strong support for establishing a irrigation forecast model for People's Victory Canal irrigated district, North China Plain, in the near future.

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