



Implementing the dual crop coefficient approach in interactive software: 2. Model testing

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ABSTRACT

This paper is the second of a two-part series, with the first part describing the SIMDualKc model, an irrigation scheduling simulation tool that employs the dual crop coefficient approach for calculating daily crop *ET* and then performs a water balance for a cropped soil. The model was applied, calibrated and validated for rainfed and basin irrigated maize (Coruche, Portugal), rainfed and surface irrigated wheat (Aleppo, Syria), and furrow irrigated cotton (Fergana, Central Asia). Results show good agreement between available soil water content observed in the field and that predicted by the model. Results indicate that the calibrated model does not tend to over- or underestimate available soil water over the course of a season, and that the model, prior to calibration, and using standard values for many parameters, also performed relatively well. After calibration, the average growing season maximum estimation errors were 10 mm for maize, 8 mm for winter wheat and 9 mm for cotton, i.e., respectively 3.6, 2.9 and 5.0% of total available water. Results indicate that the separation between evaporation and transpiration and the water balance calculation procedures are accurate enough for use in operational water management. The indicators used for assessing model performance show the model to accurately simulate the water balance of several crops subjected to a variety of irrigation management practices and various climate conditions. In addition, the model was applied to alternative irrigation management scenarios and related results are discussed aiming at assessing the model's ability to support the development of alternative active water management strategies.

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1. Introduction

Most irrigation simulation models that compute crop evapotranspiration (ET_c) use time averaged crop coefficients (K_c), which provide satisfactory results for various time step calculations, including for daily ET_c estimation, with appropriate accuracy for most applications. However, for high frequency irrigation and for partial cover crops, as well as when frequent rainfall events occur, the adoption of the dual K_c approach may produce more accurate ET_c estimates (Allen et al., 2005a). Partitioning the K_c into the soil evaporation component (K_e) and the basal crop ET component (K_{cb}) makes it possible to better assess the impacts of soil wetting by rain or irrigation, as well as the impacts of keeping part of the soil dry or using mulches for controlling soil evaporation (E). The SIMDualKc model, described in the companion paper (Rosa et al., 2012), was developed to compute crop ET using many recent refinements

and extensions to the dual K_c approach (Allen et al., 1998, 2005b, 2007; Allen and Pereira, 2009) and to perform soil water balance simulations for irrigation scheduling.

The SIMDualKc model was applied to various data sets representing field experiments with maize, winter wheat, and cotton with the purpose of testing its accuracy and flexibility in describing local conditions and cultural practices. The model was calibrated and validated for those crops where different irrigation methods and water management approaches were used by comparing the observed and the simulated soil water content. This paper presents the application of the SIMDualKc model for those crops using standard and calibrated crop and soil evaporation parameters and analyzing the respective performance. The application of the model to alternative management scenarios is also presented and results are discussed aiming at analyzing the model ability to support the development of alternative water management strategies.

2. Materials and methods

The SIMDualKc model (Rosa et al., 2012) uses the dual crop coefficient approach (Allen et al., 1998, 2005b) to calculate crop

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evapotranspiration (ET_c), with separate consideration of the soil evaporation and crop transpiration components. It allows for more precise analysis of how water from precipitation and irrigation is used by the crop. The actual crop evapotranspiration, which differs from ET_c when water stress occurs, is defined as:

$$ET_a = (K_s K_{cb} + K_e) ET_o \quad (1)$$

where ET_a is the actual crop evapotranspiration [mm d^{-1}], K_{cb} the basal crop coefficient [], K_s the water stress coefficient [], K_e the soil evaporation coefficient [] and ET_o the reference crop evapotranspiration [mm d^{-1}]. A complete description of the model is presented in the companion paper by Rosa et al. (2012).

The model was evaluated by comparing observed and simulated available soil water values, over time, for several field experiments involving maize, wheat, and cotton. The simulations were performed using soil, crop, irrigation, and weather data collected during complete crop seasons. Other information needed for running the model that was not collected in the field was estimated or taken from standard tables; this was the case for the basal crop coefficients (K_{cb}), depletion fraction for non-stress (p), total evaporable water (TEW), readily evaporable water (REW), thickness of the evaporation soil layer (Z_e) (Allen et al., 1998, 2007) and, in some cases, the parameter values used to estimate deep percolation and groundwater contribution in the presence of a shallow water table (Liu et al., 2006). All of the standard parameters are designed to be transferred for use in different climates, but they may need to be calibrated according to specific cropping conditions and soil characteristics.

Data from several field experiments were used: (1) at Sorraia irrigation district, Coruche, Portugal, with maize cropped under full and deficit surface irrigation, and rainfed conditions (Fernando, 1993); (2) at Aleppo, Syria, for wheat under rainfed conditions and surface supplemental irrigation (Oweis et al., 2003); and (3) in Fergana Valley, Uzbekistan, for cotton cropped under various furrow irrigation management practices (Cholpankulov et al., 2008).

Soil data collected at the experimental sites included basic soil hydraulic properties and soil water content measured at different depths within effective rooting zones throughout the crop seasons. Crop data included observed crop growth stage dates, crop cover parameters, crop height and root depths from planting to harvesting. Meteorological data from the nearest weather station were used to input precipitation and reference evapotranspiration, which was computed using the FAO Penman–Monteith method (Allen et al., 1998). The capillary rise from a shallow water table was estimated using the parametric equations from Liu et al. (2006) in Coruche (Portugal) and Fergana Valley (Central Asia). For this latter case study, parametric equations of Liu et al. (2006) were also used to estimate deep percolation fluxes caused by the application of large irrigation depths.

The calibration procedure consisted of adjusting the non-observed (i.e., standard) parameters (K_{cb} , p , TEW , REW , initial soil water content, capillary rise and deep percolation parameters) to minimize differences between observed and simulated available soil water values relative to the entire root depth profile (Popova and Pereira, 2011). A first set of soil parameters was estimated according to Rosa et al. (2012). Then a trial and error procedure was initiated for selecting values for K_{cb} and p , starting with the standard tabled values. When K_{cb} and p values were in an acceptable range, trial and error was then applied to the soil parameters and again for crop parameters, until differences between observed and simulated values were approximately minimized and stabilized. The validation of the model consisted of using the calibrated values to simulate other local field experiments. When the results for validation were not appropriate, the process of calibration was repeated as noted. For Coruche, experimental data on rainfed maize were used for calibration and data from the deficit and full

irrigation experiments were used for validation. At Aleppo, data from a rainfed wheat experiment were taken for calibration, and supplemental irrigation data were used for validation. For cotton in Fergana, the model was first calibrated for 2001 observations and validated with 2003 data. For all cases, the model was also applied using standard parameters proposed by Allen et al. (1998, 2007) to assess how well the daily time step model performed using general crop coefficients and soil parameters based on soil texture.

Both qualitative and statistical means were used to assess the goodness of fit of SIMDualKc model predictions to observations. The qualitative strategy consisted of graphically presenting soil water content values observed in the field versus those simulated by the model. This strategy provided a good perspective on trends and/or biases in modeling and when they occurred. The second assessment strategy used linear regression forced through the origin between observed and predicted soil water content data. Generally, the observed soil water data were collected on a daily to weekly interval, depending on the time during the growing season and proximity to irrigation events. A regression coefficient (b) is close to 1.0 when the covariance was close to the variance of the observed values, indicating that predicted and observed values were statistically similar; a coefficient of determination (R^2) close to 1.0 indicated that most of the total variance of the observed values was explained by the model. Additionally, a set of indicators describing residual estimation errors was used, as employed in previous studies and applications (Green and Stephenson, 1986; Loague and Green, 1991; Liu et al., 1998; Legates and McCabe, 1999; Cholpankulov et al., 2008; Moriasi et al., 2007; Popova and Pereira, 2011).

The goodness of fit was assessed through the indicators listed below, where O_i and P_i ($i = 1, 2, \dots, n$) represent pairs of observed and predicted values for a given variable, and \bar{O} and \bar{P} are the respective mean values:

- The coefficients of regression and determination relating observed and simulated data, b and R^2 respectively, are defined as:

$$b = \frac{\sum_{i=1}^n O_i P_i}{\sum_{i=1}^n O_i^2} \quad (2)$$

$$R^2 = \left\{ \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^n (O_i - \bar{O})^2 \right]^{0.5} \left[\sum_{i=1}^n (P_i - \bar{P})^2 \right]^{0.5}} \right\}^2 \quad (3)$$

- The root mean square error, $RMSE$, which characterizes the variance of the estimation error:

$$RMSE = \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{n} \right]^{0.5} \quad (4)$$

- The average absolute error, AAE , which expresses the mean size of estimation error:

$$AAE = \frac{1}{n} \sum_{i=1}^n |O_i - P_i| \quad (5)$$

- The average relative error, ARE [%], that expresses the size of error in relative terms:

$$ARE = \frac{100}{n} \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right| \quad (6)$$

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