Performance assessment of the FAO AquaCrop model for soil water, soil evaporation, biomass and yield of soybeans in North China Plain

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Abstract:

Four years of soybean experimental data observed at Daxing, North China Plain, were used to assess the ability of the AquaCrop model to predict soybean final biomass and yield. The model was parameterized and calibrated using field data on leaf area index (LAI), available soil water, soil evaporation, biomass and final yield data. The model was assessed using calibrated and default parameters. Data on LAI was used to derive the fraction of ground cover and to calibrate the green canopy cover (CC) curve. An accurate calibration of the CC curve was performed, with low root mean square errors ($RMSE < 7.3\%$). Results relative to soil water balance simulations show a high variability of the predictions, thus a bias of the estimation, with R^2 ranging 0.22 – 0.86 and low Nash-Sutcliffe efficiency EF, ranging between -0.47 and 0.82. The estimation errors were relatively high, with RMSE not exceeding 22.9 mm. AquaCrop was compared with the soil water balance model SIMDualKc, that has shown better performance with $R^2 \geq 0.83$, EF generally greater than 0.75 and RMSE smaller than 12.5 mm. The soil evaporation (E_s) simulations were compared with the observations performed using microlysimeters; results for Aquacrop have shown a clear trend for under-estimation of E_s , with “goodness-of-fit” results worse than for SIMDualKc (Wei et al., 2015). In general, AquaCrop has shown serious limitations to estimate crop transpiration or soil

evaporation, which is likely due to abandoning the FAO dual K_c approach. However, the model performed well relative to biomass and yield predictions, with a yield RMSE of 302 kg ha⁻¹. Overall, results show the adequacy of AquaCrop for estimating soybean biomass and yield when the model is appropriately parameterized. However, AquaCrop is not appropriate to support irrigation scheduling.

Keywords: *Crop coefficients curve, Dual crop coefficient approach, Partitioning crop evapotranspiration, Plant transpiration, Soil water balance, SIMDualKc model*

1. Introduction

Soybeans are a main summer crop in North China Plain, where they are cropped during the rainy season, thus only requiring supplemental irrigation to fulfil the crop water requirement. The prediction of the soybean yield and of the yield response to water is mandatory for developing strategies for irrigation management and to support related farmers' decision-making under limited water availability conditions.

To assess the impacts of different irrigation scheduling strategies on yield various modelling approaches may be used such as coupling a soil water balance model with water yield functions describing the relationships between crop evapotranspiration or crop transpiration with yield. A successful approach applied to soybeans is described by Wei et al. (2015) that adopted the SIMDualKc soil water balance model (Rosa et al., 2012) coupled with the Stewart's water-yield model (Stewart et al., 1977). The SIMDualKc model applies the FAO dual crop coefficient approach for computing and partitioning the daily crop evapotranspiration (ET_c , mm) into crop transpiration (T_c , mm) and soil evaporation (E_s , mm). SIMDualKc performs a daily soil water balance for the entire root zone and a daily water balance of the soil evaporation layer adopting the two stages Ritchie's evaporation approach (Ritchie, 1972; Allen et al., 1998; Allen and Pereira, 2009). Deep percolation (DP, mm) and capillary rise (CR, mm) are computed using the parametric equations proposed by Liu et al.

(2006), and runoff (RO) is estimated using the curve number (CN) approach (Allen et al., 2007). SIMDualKc allows computing the daily ET_c and T_c deficits (ET_d and T_d) defined respectively as the difference between the standard ET_c and the actual ET ($ET_{c\ act}$) and as the difference between T_c and actual transpiration (T_a). Those values may be used with the Stewart's water-yield model (Stewart et al., 1977), thus adopting a simple, linear crop-water production function that relates seasonal ET_d or T_d with the relative yield loss (RYL) through an appropriate water-yield factor, K_y , as reported by Paredes et al. (2014a) for maize.

A more complex modelling approach is used in the FAO crop yield model AquaCrop (Raes et al., 2012; Steduto et al., 2012), that simulates crop biomass and yield in response to water and other abiotic stresses (temperature, fertilization, salinity, CO_2). AquaCrop uses an empirical approach to estimate T_c and E_s depending upon the canopy cover curve, which is different from the FAO dual K_c approach described in FAO56 (Allen et al., 1998) and bases upon a K_c curve that does not relate with the common FAO K_c curve adopted in FAO24 and FAO 56 (Doorenbos and Pruitt, 1977; Allen et al., 1998). AquaCrop performs a daily soil water balance and estimates RO using also the CN method. Differently from SIMDualKc, it uses a semi-empiric DP estimation procedure that requires the knowledge of the saturated hydraulic conductivity, K_{sat} , throughout the soil profile (Raes et al., 2006).

The AquaCrop model was already applied to several annual field crops but only a few applications analysed the model behaviour relative to the soil water and evapotranspiration, e.g., Farahani et al. (2009) for cotton, Katerji et al. (2013) for tomato, and Paredes et al. (2014b) for maize. However, assessments of ET partitioning in AquaCrop are limited (Pereira et al., 2015b) and there are no assessments of the model's ability to predict soil evaporation.

Considering the above discussions on the possible appropriateness and limitations of the AquaCrop model, as well as the previous results obtained when using the SIMDualKc and Stewart's modelling approaches described by Wei et al. (2015), the objectives of the present

study are: 1) assessing the performance of AquaCrop for soybean yield estimation when using calibrated and default parameters; 2) to test the AquaCrop ability to partitioning crop ET in comparison with the FAO dual Kc approach; 3) to assess the ability of AquaCrop to simulate soil evaporation comparing with observations performed with microlysimeters along four soybean seasons; and 4) to compare the AquaCrop approaches used for soil water balance and soil evaporation estimation with the ones used by the soil water balance SIMDualKc. The same data used by Wei et al. (2015) are used in this study.

2. Material and methods

2.1 Experimental site characterisation and observations

Soybean (*Glycine max* L.) experiments were performed at the Irrigation Experiment Station of the China Institute of Water Resources and Hydropower Research (IWHR) located at Daxing (39°37' N, 116°26'E, and 40.1 m altitude). The soybean variety Zhonghuang No. 13 was sown using conventional tillage with a plant density of 15 plants m⁻² and an inter-row spacing of 0.4 m. This variety is a high-yielding semi-determinate cultivar that belongs to the maturity group II and takes an average of 96 days to reach full maturity (Wang et al., 2013). The experiments were performed from 2008 to 2011, with sowing by mid-June and harvesting by early October. Further information is provided by Wei et al. (2015).

The climate in the experimental site is sub-humid of monsoon type, with cold and dry winter and hot and humid summer, which is classified as Dwa according to the Köppen classification (Kottek et al., 2006). Climatic data used in the study were collected from an automatic meteorological station installed inside the experimental station. Daily data used included precipitation, maximum and minimum air temperature, relative humidity, global and net radiation, and wind speed at 2 m height. The climatic data sets were checked for quality assessment as recommended by Allen et al. (1998). The reference ET (ET_o) was computed

with the FAO Penman-Monteith method (Allen et al., 1998). Table 1 presents the climatic characterization of the four crop seasons for the period 2008 to 2011. Detailed information on weather data relative to the four years of observations is provided by Wei et al. (2015). Climatic data (Table 1) suggest that differences among years were small except relative to precipitation, which was higher in 2009 and 2011.

The soils in the experimental field are silty soils formed by deposits of the loess formations. By 2007, four undisturbed soil samples of 250 cm³ for each soil layer to a depth of 1 m were collected in various plots to determine the soil water retention curve and the hydraulic conductivity curve in laboratory. The ku-pf apparatus (Umwelt-Geräte-Technik, Müncheberg, Germany) was used. Averaged values of basic soil hydraulic properties are presented in Table 2. The K_{sat} values are in the range of those proposed by Rawls et al. (1998) and Raes et al. (2012) for silt loam soils, however they higher than those formerly observed in the region (Pereira et al., 2003). Capillary rise from the groundwater was not considered because the average groundwater table was deep, near 18 m, in all four years of observations.

The irrigation schedules were set using two soil water thresholds, of 75% and 60% of θ_{FC} , respectively treatment T1 and T2. Thus, irrigation was performed whenever the soil water content reached those thresholds. Treatments were performed with three replications in plots of 30 m² each. Since the crop develops during the monsoon rainy season, lower irrigation thresholds could not be selected. In 2009 and 2011, due to abundant rainfall, no distinction could be made between treatments thus, resulting in a total of six data sets.

Field observations included:

(a) The dates of each crop growth stage (Table 3).

(b) The leaf area index (LAI, cm² cm⁻²), that was measured along the crop season at several locations using a ceptometer (AccuPAR LP-80, Decagon Devices) and a leaf area scanner (F915900 model, Cannon).

(c) The root depth (Z_r , m), observed in randomly distributed plants; by full soil cover, Z_r reached 1.0 m depth, hence in agreement with data reported by Yan (2007).

(d) The soil water content, that was monitored with a previously calibrated TDR system (TRIME®-T3/IPH, IMKO GmbH). Measurements were performed at each 0.10 m until the maximum depth of 1.0 m, with three replications, every 5 days. When precipitation or an irrigation event occurred, the soil water content was measured in the following day. For simulation purposes, the soil water content was converted into available soil water, which is the depth of water stored in the soil above the wilting point (ASW, mm).

(e) Soil evaporation, that was measured using two microlysimeters in each plot; the microlysimeters were made of PVC with an internal diameter of 0.10 m and a depth of 0.17 m. Weighing was performed every day around sunset, when energy available for evaporation and transpiration was reduced.

(f) The final crop biomass and yield, that were determined by harvesting plant samples in each plot, with a total of 3 samples per treatment. The samples were placed in refrigerated containers until they were weighed in the lab to obtain the fresh weight and, later, oven dried at $65 \pm 5^\circ\text{C}$ to obtain the dry weight.

Further description of the experiments and further observed data, namely relative to root depths and irrigation schedules, are presented by Wei et al. (2015).

2.2. Modelling approaches. ET partitioning and yield prediction

The Aquacrop model (Steduto et al., 2012; Raes et al., 2012) is basically a crop yield model that computes biomass and yield considering the actual transpiration (T_a , mm). It separately computes T_a and E_s using a daily time step. The daily actual crop ET ($ET_{c \text{ act}}$, mm day⁻¹) is obtained as the sum of T_a and E_s , which are respectively computed as

$$T_a = K_s CC^* K_{c,Tr \times} ET_o \quad (1)$$

and

$$E_s = K_r (1 - CC^*) K_{ex} ET_o \quad (2)$$

where ET_o is reference evapotranspiration (mm day^{-1}), $K_{c,Tr x}$ is the maximum standard crop transpiration coefficient (non-dimensional), or maximum basal crop coefficient when $CC = 100\%$; CC^* is the actual green crop canopy cover (%) adjusted for micro-advective effects; K_s (0 - 1) is the water stress coefficient; K_{ex} is the soil evaporation coefficient for fully wet and non-shaded soil surface (non-dimensional); and K_r (0 - 1) is the evaporation reduction coefficient (Raes et al., 2012). Thus, the computation of both ET components is mainly tied to the simulated crop canopy cover (internally adjusted for micro-advective effects), CC^* . This is an approach very different from FAO56 (Allen et al., 1998), thus from the approach used with SIMDualKc (Rosa et al., 2012) despite this model estimates K_{cb} with a density coefficient K_d that is a function of the fraction of ground covered or shaded by the crop (f_c , non-dimensional) and of the crop height (h , m) as described by Allen and Pereira (2009).

The soil evaporation coefficient is computed in AquaCrop using a deep modification of the Ritchie's two stages approach, including a skin layer modification (Raes et al., 2012). Stage I is determined by the available energy at the soil surface, thus not limited by the evaporable water available in the surface soil layer; E_s is then at its potential rate and it is assumed that water evaporates from a thin soil surface layer with 0.04 m depth that directly contacts with the atmosphere (Raes et al., 2012). When water is evaporated from this thin surface layer, an upwards flux from the soil layer underneath occurs and evaporation is in stage II. At this stage, evaporation is limited by the soil water availability and the soil hydraulic properties determining the transfer of water from the underneath soil layer to the evaporative surface layer. The soil water content in the underneath soil layer progressively decreases resulting in a decrease of the evaporation rate with time. AquaCrop uses a mechanistic approach to describe the falling evaporation rate during Stage II which makes that K_r is computed as a function of

time and, among other factors, of the amount of water extracted by the crop roots from the upper soil layer and of the decline of the unsaturated hydraulic conductivity with the decrease of the soil water content. An exponential equation is used to relate the evaporation reduction coefficient K_r with the relative water content of the surface soil layer, which depends of a decline factor (f_K) and of the relative water content of the soil layer (W_{rel}) through which water moves to the evaporative surface layer. The default value $f_K = 4$ is provided in the model manual, as well as of the thickness of the surface layer (0.15 m including the skin layer). However, according to Raes et al. (2012), when W_{rel} drops below a threshold of 0.4, the thickness is expanded to a depth set by default as 0.3 m. The approach is reasonable but has not been proved in practice or mentioned in any model users' publication. There is no reference to the need for calibration of the required parameters or relative to their calibration by the users.

SIMDualKc, contrastingly, computes K_e with the Ritchie's model and by performing a daily soil water balance of the evaporable layer (Allen et al., 2005; Rosa et al., 2012). In SIMDualKc, the evaporable layer is characterized by its thickness (Z_e , m), that is assumed to vary 0.10 to 0.15 m, the total evaporable water (TEW, mm), which is the maximum depth of water that can be evaporated from that soil layer after it has been fully wetted, and the readily evaporable water (REW, mm), which is the depth of water that can be evaporated without water availability restrictions, i.e., during stage I of soil drying. Furthermore, the evaporation coefficient K_e is maximum when the soil is wet but is limited by the energy available at the soil surface, thus its value cannot exceed the difference $K_{c\ max} - K_{cb}$, between the maximum daily K_c and the basal crop coefficient at the same day. As the topsoil dries and less water is available for evaporation, a reduction in E_s occurs in proportion to the amount of water remaining in the surface soil layer, which is used to define the evaporation reduction

coefficient (K_r , non-dimensional) as described by Allen et al. (1998; 2005). Due to adopting different approaches, K_r is obviously different in both models.

According to Raes et al. (2012), the model estimates the CC evolution along time in three distinct phases: a) the first phase begins at the crop emergence and ends when half of the maximum CC (CC_x) is attained; b) the second phase follows the previous one until CC_x is reached; and c) the third phase begins when senescence starts and ends at harvest. An exponential function of time is used in the 1st and 2nd phases, beginning with the canopy cover when 90% emergence has occurred (CC_o) and using a growth rate defined by the canopy growth coefficient (CGC). The third and last phase refers to the decline of green canopy cover and its shape is defined by the canopy decline coefficient (CDC). Therefore, to parameterize the CC curves it is necessary to use the four referred parameters CC_o , CC_x , CGC and CDC. In contrast, instead of simulating CC, SIMDualKc adopts the observed f_c fraction of soil cover by vegetation as defined FAO56 (Allen et al., 1998). In addition to the referred adjustment of K_{cb} values through a density coefficient, f_c is also used to limit K_e ($K_e \leq f_{ew} K_{c\ max}$) where the fraction of soil wetted and exposed to solar radiation (f_{ew} , non-dimensional), from where soil evaporation originates, is depending on f_c (Allen et al., 1998; 2005). The approaches used in AquaCrop and with the dual K_c methodology used in SIMDualKc are therefore different.

AquaCrop estimates the above ground dry biomass (B , t ha⁻¹) by multiplying the water transpired by the crop along the season (T_a) by the adjusted biomass (water) productivity (BWP^* , g m⁻²). BWP^* represents the above ground biomass produced per unit of land area considering both the cumulative transpiration, after adjustment for atmospheric CO₂ concentration and ET_o (Raes et al., 2012). The actual yield (Y_a , t ha⁻¹) is predicted by the model using the reference harvest index (HI_o , %) and B . The HI_o is adjusted when water stress occurs by a factor integrating five water stress factors relative to the inhibition of leaf growth, inhibition of stomata, reduction in green canopy duration due to senescence, reduction in

biomass due to pre-anthesis stress, and pollination failure (Raes et al., 2012). Relative to yield estimation differences between AquaCrop and the Stewart's model are enormous because the latter uses just an empirical relation between the relative yield loss and the season ET deficit while AquaCrop uses a deterministic approach as briefly described above.

Further descriptions of the AquaCrop model and auxiliary equations are provided by Raes et al. (2012).

2.3. Model parameterization, calibration and validation

The AquaCrop model uses a large number of parameters relative to crop characteristics and effects of crop management on the crop growth. Some of those parameters, named conservative parameters, are expected to change little with time, with management condition or with the location. They are identified, described and tabled by Raes et al. (2012). These tabled values were used to start the simulations and were adjusted using field observations. Because CC determines the partition of ET into crop transpiration and soil evaporation (Eqs. 1 and 2), the parameterization firstly focused on the CC curve, i.e., the parameters CC_o , CC_x , CGC and CDC. The CC measured values were derived from the observed leaf area index (LAI) and crop height using the approach proposed by Allen and Pereira (2009), previously used with SIMDualKc (Wei et al., 2015). CC_o was obtained from plant density after emergence, CC_x was the maximum CC observed for no water stress conditions, and a trial and error procedure was used for CGC and CDC. The trial and error procedure was initiated using parameter values tabled by Raes et al. (2012) and ended when the simulated CC curve fitted the observed CC values as described by Paredes et al. (2014b) in a previous application to maize. Subsequently, a trial and error procedure focused on adjusting the $K_{c,Tr\ x}$ by comparing simulated and observed field data of available soil water. In this application, the initial value for $K_{c,Tr\ x}$ was 1.10 as proposed by Raes et al. (2012). The model was calibrated with the data

of Treatment 1 in 2008 and was tested with the remaining data collected in the crop seasons of 2008 to 2011.

To simulate soil evaporation, a value for the readily evaporable water (REW, mm), was obtained from soil textural and hydraulic properties of the soil as defined by Allen et al. (1998). To estimate runoff, the curve number (CN) method is used by the model; the CN values were obtained from tabled values proposed by Allen et al. (2007) for soils with medium texture whose previous crop was a cereal. REW and CN were not obtained through the trial and error procedure because they were available from the previous calibration of the model SIMDualKc (Wei et al., 2015).

The reference harvest index HI_o was obtained from yield data observations performed in all seasons, without occurring water stress; it resulted the average value $HI_o = 0.38$. The retained HI_o value is within the range of HI_o values, 0.30 to 0.43, reported by Donatelli et al. (1997) and is only slightly lower than values reported by Cui and Yu (2005) with $HI_o = 0.41$.

The BWP^* was obtained using a trial and error procedure aimed at minimizing differences between predicted and observed above ground dry biomass. BWP^* was set at 17 g m^{-2} , which is slightly higher than the tabled value proposed by Raes et al. (2012) for soybean [15 g m^{-2}], and the range of values proposed by Steduto et al. (2012) [$12 \text{ to } 16 \text{ g m}^{-2}$]; however it is within the range of values proposed by the same authors for C3 plants.

The “goodness-of-fit” relative to both the calibration and validation processes was assessed using a set of indicators described previously (Wei et al., 2015). A linear regression forced through the origin was performed to compare observed and simulated (predicted) values, O_i and P_i , whose means are respectively $\bar{O}$ and $\bar{P}$; the regression coefficient (b) and the determination coefficient (R^2) were then assumed as main statistical indicators. To analyse the residual estimation errors a set of indicators were also used, mainly the root mean square error

(RMSE) to express the variance of errors (Bowermann et al., 2005), and the average relative error (ARE) to indicate the average size of the estimated errors. These indicators are computed from the pairs of observed and predicted values O_i and P_i ($i = 1, 2, \dots, n$) as

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

and

$$ARE = \frac{100}{n} \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right| \quad (4)$$

These indicators were calculated at each iteration of the trial and error procedure to support finding the calibrated parameters that lead to minimize the estimation errors.

In addition, an indicator of the quality of modelling was used, the Nash and Sutcliffe (1970) modelling efficiency (EF, non-dimensional), that is a normalized statistic which corresponds to the ratio between the residual variance and the observations variance

$$EF = 1.0 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (5)$$

The target value for EF is 1.0, while a null or negative value indicates that the mean of observations is as good or better predictor than the model.

3. Results and discussion

3.1. AquaCrop model parameterization, calibration and validation

As previously referred, model calibration was performed using data of 2008-T1 by minimizing the differences between observed and simulated canopy cover (CC, %), available soil water (ASW, mm), soil evaporation (E_s , mm), biomass (B , kg ha⁻¹) and yield (Y_a , kg ha⁻¹). Due to

the interdependence of the calibrated model parameters, the main focus was the accuracy of B and Y_a predictions. The parameterization of the CC curve was first performed.

Table 4 presents the default value (Raes et al., 2012) of the main model parameters used to initiate the model application, as well as the calibrated values of the previously referred parameters CC_o , CC_x , CGC, CDC, $K_{c,Tr\ x}$, BWP*, and HI_o .

As previously discussed considering Eqs. 1 and 2, an accurate parameterization of the CC curve is of major importance for appropriate computation of T_a and E_s and, subsequently, estimating biomass and yield. Specific CGC and CDC were obtained for each year (Table 4). Differences among years relate with the observed differences in CGDD required by the crop to reach the crop development and mid-season stages (Table 3). Selected results of the fitted and the default CC curves are presented in Fig. 1. Relative to the calibrated CC curves, results show that the model tends to over-estimate CC during the initial and crop development stages and to slight under-estimate CC during the mid-season in 2008 and 2009 (e.g. Fig. 1a) but to over-estimate in 2010 and 2011 (e.g. Fig. 1b). This may relate with the fact that AquaCrop internally adjusted the calibrated CC_x (Table 4) to 97.9% for both treatments in 2008 and 2011, to 90.8% in 2009, to 93.9% and 95.2% respectively for T1 and T2 in 2010. Raes et al. (2012) explains internal model adjustments as due to stress, but it was not observed or computed by the model in the present study. If default parameters (CC_x , CGC and CDC in Table 4) are used there is a clear trend for under-estimation of the observed CC values mainly during the initial, crop development and mid stage periods.

The “goodness-of-fit” indicators relative to the CC curves when using default and calibrated parameters are presented in Table 5. After accurate calibration of the CC curve parameters (CC_o , CC_x , CGC and CDC) results do not show any clear trend to over or under-estimation, with b ranging from 0.96 to 1.04 (Table 5). The determination coefficients are high ($R^2 > 0.91$), indicating that the CC model is able to explain the variance of observed CC values. EF

values are also high (≥ 0.91), showing that the variance of residuals was much smaller than the measured data variance. Consequently, the estimation errors are low, with RMSE ranging 4.3 to 7.4% (of canopy cover) and ARE not exceeding 10.2%. If default parameters (CC_x , CGC and CDC in Table 4) are used there is a clear trend for under-estimation of the observed CC values, with b ranging 0.73 to 0.86. Estimation errors are high, with ARE exceeding 26.7%, thus definitely non negligible. The model efficiency values are low, including a negative value, -0.71, in 2011, thus when b is the smallest and errors are the highest. The less good results obtained when using default parameters relate with the natural variability of crop growth (Table 3), which relates with the variability of climatic conditions (Table 1) despite these were generally small except for rainfall.

Results discussed above indicate that the use of default values may lead to large inaccuracies in the computations that use the CC curves. Therefore, there is a need for an appropriate revision of the CC default values by the model developers. Meanwhile, it is advisable that at least a couple of CC curves should be locally calibrated and related results used as default parameters.

3.2. Simulation of the available soil water

Selected results relative to comparing the observed and simulated ASW after appropriate model calibration are presented in Fig. 2. Also included the values simulated with the default parameters listed in Table 4. ASW were observed and simulated for the maximum root depth. The target upper limit of ASW is the the total available soil water (TAW, mm) that corresponds to the ASW stored at field capacity in the root zone, and the target lower limit for ASW without water stress is the readily available water, $RAW = p \text{ TAW}$, where p is the depletion fraction for no stress (Allen et al., 1998). In this application, p was previously calibrated with SIMDualKc (Wei et al., 2015). Results in Fig. 2 show that ASW generally varied between RAW and TAW, thus evidencing that only negligible water stress may have

occurred. This is due to the fact that irrigation treatments T1 and T2 were designed for depletion fractions smaller than p .

Fig. 2 shows that the model tends to under-estimate ASW during most of the mid-season and end season and to over-estimate ASW during crop development and part of the mid-season. This behavior is particularly evident for 2010 and 2011 (Fig. 2c and d). Results indicate a bias in the estimation of the ASW along the season. Bias in the soil water simulation by AquaCrop were identified in studies relative to barley (Pereira et al., 2015b), cotton (Farahani et al., 2009) and maize (Paredes et al., 2014b). The analysis by Pereira et al. (2015b) suggests that the referred biased estimation of ASW is likely due to AquaCrop abandoning the FAO K_c and K_{cb} curve, changing the procedures to compute K_e , and thus abandoning the FAO dual K_c approach to make T_a and E_s to depend too much from the CC curve. This is analyzed in (Section 3.3) through comparing the K_{cb} and K_e curves relative to AquaCrop and to SIMDualKc when using the FAO dual K_c approach. Results became worse when using default parameters in 2008, but not those for 2009, 2010 and 2011. One cannot find a reason for that when knowing that the CC curves simulated with default parameters show much larger errors than those using calibrated values (Table 5). This is probably due to internal adjustments of the model not open to the users.

Results of the “goodness-of-fit” indicators relative to the ASW simulations when using default and calibrated parameters are presented in Table 6 together with results obtained by Wei et al. (2015) when using SIMDualKc. After AquaCrop calibration, the determination coefficients vary in a wide range, indicating that the variability of the ASW observations is not well captured by the model. Errors are generally relatively small but RMSE may reach 24 mm and ARE can attain 14.1%. The regression coefficients are around 1.0 but these b values mask the over-estimation of ASW in the first half of the season and the under-estimation in the second half. The worse results are for 2011 when EF takes a negative value, thus

indicating that the residuals variance was larger than the measured data variance; on the contrary, the other data sets had positive EF indicating that the residuals variance was lower than the measured data variance. Differently, the “goodness-of-fit” indicators relative to SIMDualKc are overall better than those reported for AquaCrop, particularly with quite good results for 2010 and 2011 when AquaCrop results are worse (Fig. 2 and Table 6). Thus, the poor simulation results relative to these data sets are not due to some peculiar data combination but to some insufficiency in modelling, likely due to abandoning the FAO well proven approaches and to internal model adjustments that change the parameter values.

When using default parameters, some indicators are worse and other are better than using calibrated parameters (Table 6). This fact is tied with problems of calibration because, as discussed by Pereira et al. (2015b), the calibrated parameters such as $K_{c,Tr\ x}$, or the CC_x parameters, are internally changed by the model. This fact identifies a difficulty in the use of the model because the user has no control on the parameterization and/or calibration processes. Thus, overall, the indicators of “goodness-of-fit” of the AquaCrop model using calibrated or default parameters failed the limits for R^2 and EF, respectively 0.80 and 0.70, proposed by Ma et al. (2011) for agricultural models.

3.3. ET partitioning and evaporation and transpiration crop coefficients

Fig. 3 presents examples of the daily variation of the crop coefficients under standard conditions (K_{cb} and $K_{c,Tr}$), adjusted to water stress ($K_{cb\ act}$ and $K_{c,Tr\ act}$) as well as the evaporation coefficient (K_e) relative to the same data sets of Fig. 2 estimated with AquaCrop and SIMDualKc. The pictures relative to AquaCrop include the crop coefficient and evaporation curves computed with calibrated and default parameters aiming at explaining the simulation results in Fig. 2. Rainfall and irrigation are represented in the pictures relative to the K_{cb} and K_e curves computed with SIMDualKc.

Fig. 3 clearly shows the differences in K_{cb} curves by SIMDualKc, following the linear shaped crop coefficients curve assumed in FAO56 (Allen et al., 1998); in contrast with those derived with AquaCrop, where the $K_{c,Tr}$ curves consist of curvilinear shaped curves proportional to the CC curve (e.g., Fig. 1). Thus, Fig. 3 clearly show that AquaCrop nearly abandoned the FAO “ $K_c - ET_o$ ” approach despite, as discussed by Pereira et al. (2015a), its simplicity, accuracy and common application.

In AquaCrop, the crop coefficients curves are built using a daily modified $K_{c,Tr}$ that depends upon the CC adjusted for micro-advection and of the $K_{c,Tr\ x}$, that is the $K_{c,Tr}$ value when $CC = 100\%$. The model internally adjusts $K_{c,Tr\ x}$ when the actual $CC < 100\%$ and, as previously discussed, the model internally adjusts CC_x without apparent reason. In SIMDualKc, differently, the K_{cb} curves are built taking into consideration the K_{cb} values for the initial ($K_{cb\ ini}$), mid ($K_{cb\ mid}$) and end ($K_{cb\ end}$) stages, with $K_{cb\ mid}$ and $K_{cb\ end}$ adjusted for climate (Allen et al., 1998, 2005) and for crop density using the observed fraction of ground cover and plant height (Allen and Pereira, 2009; Rosa et al., 2012). The referred different approaches are the cause for the different crop coefficient curves represented in Fig. 3.

The calibrated $K_{c,Tr\ x}$ was 1.12 (Table 4), that is higher than $K_{cb\ mid} = 1.05$ obtained by Wei et al. (2015) when calibrating SIMDualKc for the same observation data sets. The difference is explained by the fact that $K_{cb\ mid}$ refers to the entire mid season while $K_{c,Tr\ x}$ is the maximum value of $K_{c,Tr}$ for $CC = 100\%$. In Fig. 3 $K_{cb\ mid} < 1.05$ because it is adjusted to climate and to crop density. AquaCrop did not compute any stress resulting that the $K_{c,Tr}$ and $K_{c,Tr\ act}$ curves are coincident. Differently, SIMDualKc adjusted K_{cb} for any occasion when a stress occurred, in the present application for only short periods (Fig. 3b, d and f). Results show that $K_{c,Tr}$ during the mid-season was higher than K_{cb} due to the higher $K_{c,Tr\ x}$ adopted. The calibration could have selected a smaller $K_{c,Tr\ x}$ but this would lead to poor results for biomass and yield predictions since the various model parameters are interlinked. In addition,

as discussed by Pereira et al. (2015b) the procedure relative to the internal adjustment of $K_{c,Trx}$ for every crop having $CC < 100\%$, should be revised since it makes this calibration a difficult task with insufficient control by the user.

The soil evaporation coefficient K_e (Fig. 3) is highest during the initial stage, keeps high but decreasing during the crop development stage, and becomes small during the mid season, when the soil is well covered by the crop, increasing again but few during the late season. This behavior is common to both models and all crop seasons. Numerous peaks are shown as responses to soil wettings by precipitation. However, there are differences between the K_e values computed with both models. During the initial and crop development stages, K_e from AquaCrop are higher than K_e from SIMDualKc (Fig. 3). By the mid- and late-season, when the maximum f_c or CC is attained, AquaCrop computes generally lower K_e values and less K_e peaks than SIMDualKc, thus showing a poor reaction to the precipitation or irrigation events occurring then. The referred differences in K_e results along the crop season are very likely due to the differences in modeling approaches used, as discussed in Section 2.2, included differences in calibration parameters, more exigent in case of SIMDualKc, as previously discussed for a barley application (Pereira et al., 2015b).

When using default parameters the $K_{c,Tr}$ and K_e values change relative to those computed when calibrated values were used. This is expected since base parameters used in computations are different; the $K_{c,Tr}$ curve is shifted down and to the right (Fig. 3a, c, e, g) similarly to the shift of the CC curve (Fig. 1). The K_e peaks are about the same during the initial stage but are increased when the $K_{c,Tr}$ curves obtained with default values are below those computed with calibrated parameters. However, this behavior does not justify the upward or downward shifts of the ASW simulation with default parameters in Figs 2 a, c, e, and g or in “goodness-of-fit” indicators in Table 6.

Figure 3a and b shows that $K_{c,Tr}$ values are very different of the K_{cb} values resulting in $T_a = K_{c,Tr} ET_o$ much smaller than $T_c = K_{cb} ET_o$ during the initial and first part of the crop development stages, when K_e from AquaCrop were larger than for SIMDualKc. It resulted $(K_e + K_{c,Tr})$ likely smaller than $(K_{cb} + K_e)$ during this period, thus less water use by then, which may explain the corresponding over-estimation of ASW (Fig. 2). For the last part of the crop development and the mid-season $K_{c,Tr}$ is larger than K_{cb} while K_e is reduced. Thus $(K_e + K_{c,Tr})$ become larger than $(K_{cb} + K_e)$ and the over-estimation of ASW turns into an underestimation. During the late-season, $(K_e + K_{c,Tr})$ keep larger than $(K_{cb} + K_e)$. Therefore, there is a trend for $ET_{c\ act} = (K_e + K_{c,Tr}) ET_o$ to be initially under-estimated, thus leading to a small soil water depletion and, therefore, to an over-estimation of ASW during the first half of the crop season. $ET_{c\ act}$ becomes progressively higher and likely over-estimated in the second half of the crop season when, due to increased water depletion, ASW becomes under-estimated. This behavior is apparent for all cases in Fig. 2 but over- and under-estimations vary in intensity, which is not explained with results in Fig. 3. Moreover, the behavior of the model when using default parameters, which produce $K_{c,Tr}$ curves with much smaller values, is not explainable. It may depend upon internal adjustments unknown for the user. In our condition of model users, we just consider necessary a deep change in procedures and a better control of the parameterization by the users. Otherwise, the soil water computations should be used only for BWP* calibration aiming at biomass and yield predictions.

3.4. Soil evaporation testing

The AquaCrop model was tested for soil evaporation computed with Eq. 2 compared with microlysimeter observations of soil evaporation (Fig. 4). E_s simulations show that the model tends to under-estimate microlysimeter observation data, especially during the mid- and late-season. This type of behaviour was expected because microlysimeter evaporation is higher than soil evaporation since the latter is affected by water uptake by roots active in the

evaporative soil layer while those roots do not exist in the microlysimeters. A similar behaviour was observed by Wei et al. (2015) when using SIMDualKc but under-estimations were smaller (Fig. 4). Relative to other crops, under-estimations of lysimeter observations were reported by Klocke et al. (1990, 1996), Jara et al. (1998) and, for maize in the same experimental area, by Zhao et al. (2013). In addition to under-estimations, a large variability of E_s measured values is commonly reported.

The larger under-estimations by AquaCrop relative to SIMDualKc may be explained by different approaches relative to E_s computations, mainly referring to the reduction coefficient K_r (previously discussed in Section 2.2) since the K_e values computed by both models do not show large differences as analysed before (Section 3.3). The limitations of E_s estimation by AquaCrop were discussed by Pereira et al. (2015b) for a barley application under contrasting wetness and dryness conditions.

Table 7 presents the results of the “goodness-of-fit” indicators of the E_s estimations when using both models. Results show that, after calibration, AquaCrop presents a clear tendency for under-estimation of E_s , with lower values of b for 2010 and 2011, which are the seasons when most observations were performed during mid and late seasons (Fig. 4d and e). These seasons were those where worse results were obtained for simulating ASW as reported in Section 3.2. This may indicate that when E_s is largely underestimated, particularly in those seasons, the simulation of ASW is also under-estimated (see Figs. 2e and g). In these years, R^2 varied in a wide range, thus reflecting a bias in the estimation, particularly during the second half of the crop season. Consequently, errors are high, both RMSE and ARE; however, RMSE are smaller in 2010 and 2011 relative to 2008 and 2009, which likely depend from the size of observations, which was larger in the later years because they largely refer to the periods when the canopy cover was low and E_s were large (Figs 4a, b and c). As expected,

the EF values are smaller for 2010 and 2011 because the referred under-estimation of E_s leads to larger residual's variance.

Less expected are the results when default values were used with AquaCrop. For 2008 and 2009 results on R^2 , RMSE, ARE and EF are similar to those relative to using calibrated parameters but b values indicate a tendency for over-estimation of E_s . In contrast, for 2010 and 2011, larger RMSE and smaller ARE values were obtained, as well as an important over-estimation with $b = 1.41$ for 2011. Low EF values resulted, with a negative value for 2011. The contrast between results for 2011 when using calibrated or default values is enormous in terms of b values, RMSE and EF values. This explains why simulations of ASW in 2011 were also contrasting, with worse results when using calibrated parameters (Table 6). This behaviour is therefore associating the ASW simulation with the E_s estimation, thus indicating that better ASW simulation results are obtained when E_s values are high during the mid- and late-season since a worse ASW under-estimation occurs during these crop stages. This identifies a problem in the computation of E_s , as already discussed by Pereira et al. (2015b), that may relate to the already discussed mechanistic approach used for computing the reduction coefficient K_r (Section 2.2). Thus, it is advisable that model developers revise the E_s estimation procedures.

When using the SIMDualKc model, results presented by Wei et al. (2015) show a slight tendency for under-estimation, particularly during 2010 (Table 7). As previously pointed out, under-estimation is likely due the fact that most of E_s observations were performed during mid and late seasons when microlysimeters are expected to evaporate more than the surrounding soil where, in addition to evaporation, water is also extracted by crop roots. The RMSE and ARE values are smaller than those by AquaCrop (Table 7) while R^2 and EF values are consistently higher. These good results evidence the goodness of the FAO dual Kc approach relative to the E_s estimation.

Table 8 presents the results of comparing AquaCrop and SIMDualKc simulated E_s and $E_s/ET_{c\ act}$ for the various crop stages and all seasons and treatments. During the initial stage, the ratios $E_s/ET_{c\ act}$ computed with AquaCrop are consistently higher than those obtained with SIMDualKc, however with small differences in terms of the E_s amount (Fig. 3), which is even smaller in case of AquaCrop for the 2008-T1 and 2009 experiments. This behaviour results from an underestimation of the transpiration during that period because T_a is computed from CC (Eq. 1), which is extremely small during the initial crop stage. It results, therefore, a very large proportion of E_s relative to $ET_{c\ act}$, ranging 91 to 97% while that percentage varies 72 to 85% with SIMDualKc. These results indicate that T_a are under-estimated by AquaCrop during the initial crop stage.

During the crop development stage, the E_s values simulated with AquaCrop were smaller than those obtained with SIMDualKc in the last part of this crop stage (Fig. 3), with the ratios $E_s/ET_{c\ act}$ consistently smaller (Table 8). This may be due to an overestimation of T_a during that same period as discussed in the precedent Section. During mid-season the same trend is observed but with a very low E_s and $E_s/ET_{c\ act}$ values computed with AquaCrop, also consistently smaller than for SIMDualKc (Table 8 and Fig. 4). These differences are coherent relative to results in Fig. 3, previously discussed. The tendency of AquaCrop for under estimating E_s was maintained during the late-season (Fig. 4), excepting for the crop season of 2009, which is also likely related to the same insufficiencies in describing the $K_{c,Tr}$ curve discussed in Section 3.3. Consequently, for all crop seasons, the total evaporation depths and the ratios $E_s/ET_{c\ act}$ are consistently smaller when computed with AquaCrop (Table 8). The difference was higher for the T2-2010 data set, with AquaCrop computing almost half of the E_s computed by SIMDualKc. Therefore, it is likely that E_s computations when the canopy cover is complete or is near completion are too much depending on CC and little on the soil evaporative characteristics, i.e., the respective parameterization, referred before, is insufficient

relative to that proposed by Allen et al. (1998; 2005) and adopted in SIMDualKc (Rosa et al., 2012). Conclusions reported by Farahani et al. (2009), Katerji et al. (2013), and Paredes et al. (2014b), as well as the analysis by Pereira et al. (2015b), show that the procedures for estimation of E_s in AquaCrop are questionable and should be improved.

3.5. Soybean biomass and yield predictions

The observed final harvested biomass (B) and yield (Y_a) used to test the AquaCrop predictions are presented in Table 9. The highest yield was obtained with the treatment T1 in 2010 (4230 kg ha^{-1}) while the lowest refers to 2011 (3222 kg ha^{-1}). Differences in yield may be partially explained by differences in climatic conditions along the crop seasons. Since radiation and temperature averages along those referred crop seasons are very similar (Table 1), differences in Y_a may relate to the diurnal and nocturnal temperatures as discussed by Tao et al. (2008) relative to the Hebei province or as reported by Puteh et al. (2013) for Malaysia, namely referring to high temperature stress during the reproductive growth stage. Differences in crop management may also have contributed to differences in yield.

AquaCrop predictions of both biomass and yield when using only default parameters show a clear trend for under-estimation, with deviations higher than 27% and 20% of the observed final biomass and yield, respectively (Table 9). In contrast, when the model was appropriately calibrated the deviations between observed and predicted biomass were much small, generally smaller than 9%. Relative to the final yield, deviations were below 8.6% except for two cases, when they were of 11.8 and 12.9%. Results may be considered excellent for 2008 and 2009 and reasonably good for 2010 and 2011. It may be noticed that these results relate with the quality of soil water simulations, not good for 2010 and 2011 (Fig. 2 and Table 6). The worse B and Y_a results may have been influenced by the difficulties in achieving a good partition of $ET_{c \text{ act}}$, with poor estimation of E_s and T_a , the latter contributing to the estimation of B and Y_a . Nevertheless, if good B and Y_a estimations could be achieved this is due to the satisfactory

calibration of BWP*, which highly influences biomass and yield estimation. One may hypothesize that if a better estimation of E_s and T_a could be achieved also better estimations of the final biomass and yield would have been attained.

The biomass RMSE is 1056 kg ha^{-1} , which represent less than 12% of the observed final biomass while for the final yield it was quite low, 302 kg ha^{-1} , thus representing 8% of the averaged observed yield. Results fall within the category of “very good modelling results” as proposed by Hanson et al. (1999) since the deviations were lower than 15% of the observed values except for one prediction of B. Despite the low accuracy of the ASW simulations, indicative of poor E_s and T_a estimation, yield predictions could be very good due to an appropriate BWP* calibration. If default parameters are used then B and Y_a estimations have much larger errors, probably not acceptable for most applications.

Similar yield predictions, with $\text{RMSE} = 381 \text{ kg ha}^{-1}$, were obtained by Wei et al. (2015) with the same data sets but using the Stewarts’ model combined with the SIMDualKc model, however with a larger over-prediction. Using the CROPGRO-soybean model, Calviño et al. (2003) reported $\text{RMSE} = 512 \text{ kg ha}^{-1}$, i.e., approximately 18% of the average observed Y_a , while Liu et al. (2013) found RMSE representing 15 to 22% of the average Y_a in Northeast China. Stöckle et al. (2003) applied the CropSyst model and reported RMSE corresponding to 14% of the average Y_a . Mohanty et al. (2012) when using the APSIM model reported an under-estimation of only 100 kg ha^{-1} , i.e., less than 6% of Y_a . Overall, results of the present study fall within the reported soybean applications, thus indicating that AquaCrop may be further used for yield predictions when appropriately calibrated.

4. Conclusions

The AquaCrop model was parameterized using four years of field observations of a soybean crop in the North China Plain. The model was tested using default and calibrated parameters and compared with the soil water balance model SIMDualKc (Wei et al., 2015), that was

calibrated and validated with the same data sets on weather, soil and crop data. In addition, microlysimeters data on soil evaporation were used to test the soil evaporation component of the model.

Results have shown that an appropriate parameterization of the CC curve contributed to better simulating the available soil water and soil evaporation, as well as to improve biomass and yield predictions. The AquaCrop model has shown, however, a lower accuracy for simulating the soil water content along the crop seasons. This reveals a model insufficiency since using calibrated instead of default parameters lead to small differences in performance, which was sometimes in favour of default parameters. Results have shown a bias in the estimation of ASW, with a tendency for over-estimation during the first half of the season and under-estimation during the other half. This resulted from the K_c curve used in AquaCrop, as well as the mechanistic approach used for soil evaporation. The insufficiencies in simulating the latter were demonstrated by the consistent under-estimation of the E_s micro-lysimeter data.

When comparing AquaCrop with SIMDualKc results show the higher accuracy of the latter for simulating ASW and E_s , which was demonstrated by the “goodness-of-fit” results achieved. Since SIMDualKc uses the FAO56 dual K_c approach, its good results, namely referring to partitioning crop evapotranspiration, are due to the accuracy of that approach, following good results reported by several researchers as recently revised by Kool et al. (2014) and Pereira et al. (2015a). In contrast, the abandon of the FAO56 dual K_c approach by the FAO AquaCrop model was not properly tested through specific and focused studies, thus resulting in poor ET partition and soil water simulations. Therefore, in agreement with other studies (Katerji et al., 2013; Pereira et al., 2015b), we conclude that AquaCrop is not suitable to be used for irrigation scheduling purposes prior to its improvement. Very likely, as also

referred by those authors, since AquaCrop abandoned the dual K_c approach it should also abandon the “ $K_c - ET_o$ ” methodology and assume a fully mechanistic approach.

Good final biomass and yield estimations were achieved, particularly due to the satisfactory calibration of BWP*. However, one may hypothesize that if a better estimation of E_s and T_a could be achieved also better estimations of the final biomass and yield would have been attained. However, the use of AquaCrop default parameters for yield predictions is questionable since results show a clear tendency for under-estimation. Thus, in the absence of field data the model should be used with caution. In this perspective, priority should be given to improve model predictions with limited parameterization or using default parameters.

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731 **List of symbols and abbreviations**

732		
733	ARE	Average relative error (%)
734	ASW	Available soil water (mm)
735	B	Above ground dry biomass (t ha^{-1})
736	b	Regression coefficient (non-dimensional)
737	BWP*	Biomass (water) productivity adjusted for ET_o and CO_2 (g m^{-2})
738	CC	Green canopy cover (%)
739	CC*	Actual crop canopy cover adjusted for micro-advective effects (%)
740	CC_o	Canopy cover at 90% of emergence (cm^2 per plant)
741	CC_x	Maximum green canopy cover (%)
742	CDC	Canopy decline coefficient ($\% \text{ GDD}^{-1}$ or $\% \text{ day}^{-1}$)
743	CGC	Canopy growth coefficient ($\% \text{ GDD}^{-1}$ or $\% \text{ day}^{-1}$)
744	CGDD	Cumulative growing degree days ($^{\circ}\text{C}$)
745	CN	Curve number (non-dimensional)
746	CR	Capillary rise from shallow water table (mm)
747	DP	Deep percolation (mm)
748	EF	Modelling efficiency (non-dimensional)
749	E_s	Soil evaporation (mm)
750	ET	crop evapotranspiration (mm)
751	ET_c	Standard (non-stressed) crop evapotranspiration (mm)
752	$\text{ET}_{c \text{ act}}$	Adjusted or actual crop evapotranspiration (mm)
753	ET_d	Crop evapotranspiration deficit (mm)
754	ET_o	Reference evapotranspiration (mm)
755	f_c	Fraction of soil cover by vegetation (non-dimensional)
756	f_{ew}	Fraction of soil wetted and exposed to solar radiation (non-dimensional)
757	f_k	Decline factor (non-dimensional)
758	GDD	Growing degree days ($^{\circ}\text{C}$)
759	HI_o	Reference harvest index (%)
760	K_c	Crop coefficient (non-dimensional)
761	$K_{c \text{ max}}$	Maximum value of crop coefficient (following rain or irrigation) (non-dimensional)
762	K_{cb}	Basal crop coefficient (non-dimensional)
763	$K_{cb \text{ act}}$	Actual or adjusted basal crop coefficient (non-dimensional)
764	$K_{cb \text{ end}}$	Basal crop coefficient at end of the late season growth stage (non-dimensional)
765	$K_{cb \text{ ini}}$	Basal crop coefficient during the initial growth stage (non-dimensional)
766	$K_{cb \text{ mid}}$	Basal crop coefficient during the mid-season growth stage (non-dimensional)
767	$K_{c \text{ max}}$	Maximum value of the crop coefficient (K_c) following rain or an irrigation event (non-
768		dimensional)
769	$K_{c, \text{Tr}}$	Crop transpiration coefficient (non-dimensional)
770	$K_{c, \text{Tr act}}$	Actual crop transpiration coefficient (non-dimensional)
771	$K_{c, \text{Tr x}}$	Maximum standard crop transpiration coefficient (non-dimensional)
772	K_{ex}	Soil evaporation coefficient for fully wet and non-shaded soil surface (non-
773		dimensional)
774	K_d	Density coefficient (non-dimensional)
775	K_r	Evaporation reduction coefficient (non-dimensional)

776	K_s	Water stress coefficient (non-dimensional)
777	K_{sat}	Saturated hydraulic conductivity (cm d^{-1})
778	K_y	Yield response factor (non-dimensional)
779	LAI	Leaf area index ($\text{cm}^2 \text{cm}^{-2}$)
780	R^2	Determination coefficient (non-dimensional)
781	RAW	Readily available soil water (mm)
782	REW	Readily evaporable soil water (mm)
783	RMSE	Root mean square error (same units as observations)
784	RO	Runoff (mm)
785	RYL	Relative yield losses (%)
786	T_a	Actual transpiration (mm)
787	TAW	Total (plant) available soil water (mm)
788	T_c	Crop transpiration (mm)
789	T_d	transpiration deficit (mm)
790	TEW	Total evaporable water (mm)
791	W_{rel}	Relative soil water content (%)
792	Y_a	Actual yield (t ha^{-1})
793	Z_e	Evaporable layer thickness (m)
794	Z_r	Root depth (m)
795	θ_{FC}	Volumetric water content at field capacity ($\text{m}^3 \text{m}^{-3}$)
796	θ_{sat}	Volumetric water content at saturation ($\text{m}^3 \text{m}^{-3}$)
797	θ_{WP}	Volumetric water content at wilting point ($\text{m}^3 \text{m}^{-3}$)
798		
799		

Table 1. Average monthly weather data relative to the soybean season, years 2008-2011.

	Year	Jun	Jul	Aug	Sep	Oct
Max. air temperature, °C	2008	27.7	31.5	30.3	25.9	20.2
	2009	31.5	31.4	29.8	25.7	21.2
	2010	29.3	32.7	30.7	25.5	18.5
	2011	32.0	31.6	30.4	25.2	19.5
Min. air temperature, °C	2008	17.4	21.7	20.3	14.0	6.0
	2009	17.5	21.1	20.2	14.2	6.3
	2010	18.2	23.2	20.1	14.0	6.1
	2011	18.8	22.1	20.6	12.3	6.0
Min. Relative Humidity, %	2008	63	64	66	64	54
	2009	44	64	69	65	47
	2010	59	63	63	62	57
	2011	48	66	70	57	60
Solar radiation, MJ m ⁻² d ⁻¹	2008	21.4	21.5	19.8	15.9	11.4
	2009	22.5	21.5	19.4	14.9	12.1
	2010	22.3	19.4	19.0	15.2	11.2
	2011	22.7	20.9	20.1	16.0	11.4
ET _o , mm	2008	118	132	113	72	42
	2009	147	140	113	70	52
	2010	132	135	115	72	43
	2011	146	137	119	81	40
Precipitation, mm	2008	103	66	64	123	42
	2009	81	206	104	21	6
	2010	87	42	141	69	32
	2011	72	210	72	33	10

Table 2. Average soil hydraulic properties of Daxing experimental fields

Layer	Depth (m)	θ _{sat} (cm ³ cm ⁻³)	θ _{FC} (cm ³ cm ⁻³)	θ _{WP} (cm ³ cm ⁻³)	K _{sat} (cm d ⁻¹)
1	0.00-0.10	0.46	0.32	0.09	97.1
2	0.10-0.20	0.46	0.34	0.13	91.5
3	0.20-0.40	0.47	0.35	0.10	98.5
4	0.40-0.60	0.45	0.33	0.11	88.0
5	0.60-1.00	0.44	0.31	0.16	37.1

θ_{FC}, θ_{WP} and θ_{Sat} represent the soil water content at field capacity, wilting point and saturation respectively; K_{sat} is the saturated hydraulic conductivity.

Table 3. Soybean crop growth stages dates and cumulative growing degree days (CGDD) for all experimental years.

Crop growth stages		Soybean			
		2008	2009	2010	2011
Initial	Dates	24-06 to 13-07	14-06 to 09-07	25-06 to 18-07	22-06 to 07-07
	CGDD (°C)	372	463	468	302
Crop development	Dates	14-07 to 07-08	10-07 to 31-07	19-07 to 20-08	08-07 to 07-08
	CGDD (°C)	910	948	1163	969
Mid-season	Dates	08-08 to 16-09	01-08 to 09-09	21-08 to 19-09	08-08 to 13-09
	CGDD (°C)	1642	1690	1713	1676
Late Season	Dates	17-09 to 09-10	10-09 to 02-10	20-09 to 08-10	14-09 to 02-10
	CGDD (°C)	1898	2027	1922	1872

Table 4. Conservative and calibrated crop parameters of AquaCrop model

Description	Units or symbol meaning	Value				
Conservative parameters		Default*				
Base temperature	°C	5				
Cut-off temperature	°C	30				
Canopy cover at 90% emergence (CC ₉₀)	cm ² per plant	5.00				
Soil water depletion threshold for canopy expansion	Upper threshold	0.15				
Soil water depletion threshold for canopy expansion	Lower threshold	0.65				
Shape factor for water stress coefficient for canopy expansion	Curve shape moderately convex curve	3.0				
Soil water depletion threshold for stomatal control	Fraction of TAW at which stomata start to close	0.50				
Shape factor for water stress coefficient for stomatal control	Highly convex curve	3.0				
Soil water depletion threshold for failure of pollination	Fraction of TAW at which pollination starts to fail	0.85				
Calibrated parameters		Default*	Calibrated			
Crop coefficient for transpiration at CC=100%	Basal crop coefficient (K _{c,Tr x})	1.10	1.12			
BWP*	Biomass (water) productivity adjusted for ET ₀ and CO ₂ (g m ⁻²)	15	17			
HI ₀	Reference harvest index (%)	0.40	0.38			
Canopy cover curve parameters		Default*	2008	2009	2010	2011
Maximum green canopy cover, CC _x ,	%	99	98	98	98	98
Canopy growth coefficient, CGC	% GDD ⁻¹	0.45	0.71	0.62	0.72	0.74
Canopy decline coefficient, CDC	% GDD ⁻¹	1.50	1.04	0.870	1.04	1.50

* default parameters are tabled by Raes et al. (2012)

Note: GDD represents growing degree days; Conservative parameters are those that are expected to change little with time, with management condition or with the location

Table 5. “Goodness-of-fit” indicators relative to the canopy cover curve using default and calibrated parameters

	Year and treatment	Number of observations	b	R ²	RMSE (%)	ARE (%)	EF
Using default parameters	2008, T1	13	0.81	0.93	20.0	31.5	0.49
	2008, T2	13	0.80	0.93	20.3	31.8	0.48
	2009	14	0.85	0.92	18.4	26.7	0.38
	2010, T1	12	0.76	0.81	25.2	36.1	0.23
	2010, T2	11	0.86	0.91	16.4	26.7	0.72
	2011	11	0.73	0.74	30.1	37.6	-0.71
Using calibrated parameters	2008, T1	13	1.01	0.94	7.4	10.2	0.93
	2008, T2	13	1.01	0.94	7.2	9.9	0.94
	2009	14	0.97	0.95	5.7	9.0	0.94
	2010, T1	12	0.96	0.99	5.3	9.4	0.97
	2010, T2	11	1.04	0.99	4.3	7.2	0.99
	2011	11	1.00	0.99	5.4	7.9	0.95

Table 6. “Goodness-of-fit” indicators relative to simulations of ASW (mm) with AquaCrop when using default and calibrated parameters and to SIMDualKc model (Wei et al., 2015)

		Year and treatment	Number of pairs	b	R ²	RMSE (mm)	ARE (%)	EF
AquaCrop	Using default parameters	2008, T1	18	1.10	0.69	20.4	12.0	0.28
		2008, T2	18	1.16	0.35	26.8	17.5	-1.11
		2009	21	0.99	0.83	11.4	5.9	0.79
		2010, T1	33	0.99	0.92	6.4	3.7	0.90
		2010, T2	33	1.06	0.81	11.6	7.0	0.56
		2011	32	1.06	0.70	19.9	10.2	-0.12
	Using calibrated parameters	2008, T1	18	1.01	0.85	11.4	6.0	0.78
		2008, T2	18	0.99	0.85	10.6	6.8	0.67
		2009	21	0.98	0.86	10.7	6.1	0.82
		2010, T1	33	0.94	0.82	12.3	6.5	0.64
		2010, T2	33	0.95	0.22	15.6	10.0	0.19
		2011	32	1.01	0.58	22.9	14.1	-0.47
SIMDualKc (Wei et al., 2015)		2008, T1	18	0.99	0.93	10.7	6.0	0.80
		2008, T2	18	0.98	0.84	12.5	8.4	0.54
		2009	21	0.97	0.95	7.8	3.5	0.90
		2010, T1	33	1.00	0.84	9.2	5.5	0.79
		2010, T2	33	1.02	0.83	8.6	5.1	0.76
		2011	32	1.03	0.86	9.3	4.8	0.76

Table 7. Indicators of “goodness-of-fit” relative to simulating soil evaporation with AquaCrop and SIMDualKc models.

		Year and treatment	Number of observations	b	R ²	RMSE (mm d ⁻¹)	ARE (%)	EF
AquaCrop	Using default parameters	2008, T1	65	0.96	0.72	0.66	59.7	0.61
		2008, T2	54	1.08	0.84	0.48	68.2	0.72
		2009	82	1.04	0.72	0.76	78.8	0.65
		2010, T1	47	1.16	0.71	0.55	57.1	0.18
		2011	42	1.42	0.77	0.69	68.2	-0.17
	Using calibrated parameters	2008, T1	65	0.88	0.73	0.68	71.9	0.59
2008, T2		54	0.98	0.81	0.52	72.7	0.68	
2009		82	0.89	0.76	0.66	56.0	0.74	
2010, T1		47	0.84	0.65	0.50	66.3	0.31	
2011		42	0.66	0.73	0.45	80.4	0.50	
SIMDualKc (Wei et al., 2014)		2008, T1	65	0.97	0.85	0.52	57.7	0.76
		2008, T2	54	0.99	0.89	0.48	60.1	0.73
		2009	82	0.96	0.79	0.65	56.4	0.74
		2010, T1	47	0.90	0.86	0.38	60.5	0.62
		2011	42	0.95	0.84	0.24	39.5	0.85

Table 8. Soil evaporation and evaporation ratio ($E_s/ET_{c \text{ act}}$) simulated when using AquaCrop (Aqua) and SIMDualKc (SIM) models after calibration, for each development stage and for the entire season

Year/treatment		Crop stage									
		Initial		Crop development		Mid-season		Late season		Entire season	
		Aqua	SIM*	Aqua	SIM*	Aqua	SIM*	Aqua	SIM*	Aqua	SIM*
2008, T1	E_s (mm)	62	66	33	36	1	7	5	6	101	115
	$E_s/ET_{c \text{ act}}$ (%)	97	85	36	40	1	6	15	19	31	36
2008, T2	E_s (mm)	61	57	31	30	1	7	5	7	98	101
	$E_s/ET_{c \text{ act}}$ (%)	97	83	35	34	1	5	14	20	30	32
2009	E_s (mm)	72	73	33	38	7	10	6	1	118	122
	$E_s/ET_{c \text{ act}}$ (%)	91	80	37	43	5	7	14	4	33	35
2010, T1	E_s (mm)	45	44	30	32	2	2	3	7	80	85
	$E_s/ET_{c \text{ act}}$ (%)	92	72	24	28	3	3	9	24	27	30
2010, T2	E_s (mm)	46	46	14	23	1	3	3	7	64	79
	$E_s/ET_{c \text{ act}}$ (%)	91	72	12	22	1	4	9	24	21	28
2011	E_s (mm)	47	43	51	52	1	9	2	2	101	106
	$E_s/ET_{c \text{ act}}$ (%)	97	80	40	43	1	7	5	7	29	32

*Adapted from Wei et al. (2015)

Table 9. Deviations between predicted and observed soybean final biomass and yield (kg ha^{-1}), when using default and calibrated parameters, compared with Stewart's and SIMDualKc combination

	Year	Observed* (kg ha ⁻¹)	AquaCrop						Stewart's model with T data from SIMDualKc		
			Default parameters			Calibrated					
			Predicted		Deviation	Predicted	Deviation		Predicted	Deviation	
			(kg ha ⁻¹)	(kg ha ⁻¹)	(kg ha ⁻¹)	(kg ha ⁻¹)	%	(kg ha ⁻¹)	(kg ha ⁻¹)	%	
Dry final above ground biomass, B	2008-T1	9631 (± 690)	6532	-3099	32.2	9742	111	1.2			
	2008-T2	8948 (± 906)	6509	-2439	27.3	9722	774	8.6			
	2009	9118 (± 651)	6387	-2731	30.0	9425	307	3.4			
	2010-T1	11840 (± 617)	6530	-5310	44.8	9731	-2109	17.8			
	2010-T2	10965 (± 598)	6949	-4016	36.6	10143	-822	7.5			
	2011	10757(± 510)	6536	-4221	39.2	9830	-927	8.6			
Dry final yield, Y	2008-T1	3778 (± 272)	2613	-1165	30.8	3703	-75	2.0	4046	267	7.1
	2008-T2	3549 (± 358)	2607	-942	26.5	3698	149	4.2	4009	461	13.0
	2009	3454 (± 246)	2192	-1262	36.5	3522	68	2.0	3689	234	6.8
	2010-T1	4230 (± 222)	2556	-1674	39.6	3731	-499	11.8	4443	214	5.1
	2010-T2	3578 (± 196)	2819	-759	21.2	3884	306	8.6	4260	682	19.1
	2011	3222 (± 151)	2550	-672	20.9	3637	415	12.9	3374	152	4.7

* dried at $65 \pm 5^\circ\text{C}$; Standard deviation between brackets

Fig. 1. Best and worse simulated canopy cover (CC) curves when using default parameters (---) and after calibration (—) compared with observed values (●): (a) T1 in 2008, and (b) T2 in 2010.

Fig. 2. Observed (•) and simulated (—) daily available soil water (ASW) with AquaCrop, on the left, compared with SIMDualKc, on the right (data from Wei et al., 2015): (a, b) T1 in 2008, calibration; (c, d) 2009, (e, f) T2 in 2010, and (g, h) 2011 (error bars refer to the standard deviation of ASW observations). Also included the simulation with AquaCrop when using default parameters (---)

Fig. 3. Seasonal variation of the soil evaporation coefficient (K_e) and crop coefficients (K_{cb} or K_{cTr}) relative to: (a, b) T1 in 2008, calibration; (c, d) 2009, (e, f) T2 in 2010, and (g, h) 2011. For simpler visualization, rainfall and irrigation are represented only in the pictures on the right.

Fig. 4. Daily soil evaporation (E_s) dynamics along soybeans seasons when using the AquaCrop after adequate calibration (—) and SIMDualKc (----) compared with microlysimeters observations ($\circ$) for: (a) T1 in 2008, calibration, (b) T2 in 2008; (c) 2009, (d) T1 in 2010, and (e) 2011 (SIMDualKc data from Wei et al., 2015)