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CALIBRATION OF THE CROPWAT MODEL FOR THE STUDY OF SOYBEAN PRODUCTION SYSTEMS

Lidiane D. Gomes[1], Danilton L. Flumignan[2*],
Éder Comunello[2], Rodrigo A. Garcia[2]

[2*]Corresponding author. Embrapa Agropecuária Oeste/Dourados - MS, Brasil.
E-mail: danilton.flumignan@embrapa.br | ORCID ID: https://orcid.org/0000-0002-2959-2164

KEYWORDS

Evapotranspiration, *Glycine max,* modeling.

ABSTRACT

CROPWAT is a model that uses water balance to study the water factor and productivity in production systems. In this sense, this study aimed to calibrate the CROPWAT for modeling rainfed and irrigated soybean production systems. Climate and soil data from a soybean-producing region in the south of Mato Grosso do Sul, Brazil, were used to implementing simulations in nine agricultural years, and crop shortfalls were calculated and compared with reference data. Statistical indices were applied to evaluate the performance of the model in its calibration. For validation, two field trials with 12 cultivars were implemented under irrigation and rainfed and the mean productivity in each water management was compared with the CROPWAT estimate by Student's t-test. Accuracy (r) was 0.976 ("very strong"), precision (r^2) was equivalent to 95.3%, and the indices of agreement (d) and performance (c) were considered excellent (0.95 and 0.93, respectively) in the calibration. Validation demonstrated that the hypothesis that CROPWAT correctly estimated soybean productivity under irrigated and rainfed systems cannot be rejected at 1 or 5% significance levels.

INTRODUCTION

Agriculture is among the main economic activities in Brazil and soybean cultivation is very relevant in this sector given its cultivated area (41 million ha in the 2021/2022 agricultural year), production (mean of 124 million tons in the 2017/2018 to 2021/2022 agricultural years), and productivity levels (mean of 3,307.6 kg ha^{-1} in the 2017/2018 to 2021/2022 agricultural years), according to data obtained from CONAB (2022). Its relevance considering the economic aspect is also easily perceived, as the soybean production chain is the leader in gross production value with R$ 419 billion in the 2020/2021 agricultural year (CNA, 2022).

Soybean experiences very different production environments, as it is a crop widely cultivated in Brazil. Therefore, the crop water requirement and the precipitation available to meet it are widely variable between these environments, a fact that justifies studies related to the subject.

Simulation models are important tools for studying water in the soil-plant-atmosphere system, as well as for verifying its effects and/or of other factors on the production responses of crops. The models vary in terms of their complexity and predictive performance (Battisti et al., 2017) and have even been used to investigate the risks of agriculture associated with climate change and propose adaptation alternatives (Challinor et al., 2018).

According to Silva et al. (2021a), CSM-CROPGRO-Soybean is among the main models used to study soybean, but it is quite demanding regarding the need for parameterization and input data (Cuadra et al., 2021; Silva et al., 2021b). The Food and Agriculture Organization (FAO) provides the Crop Water and Irrigation Requirements (CROPWAT) model, which has robustness and simplicity as its main characteristics. It implements a water balance model capable of simulating plant water stress conditions and assessing its effect on productivity reduction. This model is widely used to define crop water

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[1] Universidade Federal da Grande Dourados/Dourados - MS, Brasil.
[2] Embrapa Agropecuária Oeste/Dourados - MS, Brasil.

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requirements and the water depth to be applied via irrigation in crops around the world (Surendran et al., 2015; Akinbile et al., 2020; Gabr, 2021; Khaydar et al., 2021). However, this model should not be used without prior calibration, even considering the crop under local conditions (Vozhehova et al., 2018).

This study aimed to calibrate the CROPWAT for modeling soybean production systems and verify its performance in predicting irrigated and rainfed soybean productivity.

MATERIAL AND METHODS

CROPWAT model calibration

The study considered the municipality of Dourados, MS, as representative of a traditional soybean production area in Brazil. According to IBGE (2021), the state of Mato Grosso do Sul is the fifth in planted area, with 3.1 million ha and, in the state, Dourados is in the center of the main producing region, and four municipalities with the largest planted area in the state are found within a radius of 200 km from Dourados. Only these municipalities (Maracaju, Ponta Porã, Sidrolândia, and Dourados, in this order) account for 975 thousand hectares of area planted with soybean.

This region has a humid mesothermal climate and can be classified as Cwa, according to Fietz et al. (2017). According to these authors, the regional climate is characterized by a hot and rainy summer and a moderately dry winter, demonstrating great variance in the amount and distribution of rainfall. This irregularity in precipitations often causes reductions in crop productivity even in areas where the best management practices are adopted.

According to historical data from the Agrometeorological Station located at Embrapa Western Agriculture (accessible at http://clima.cpao.embrapa.br/), the mean annual precipitation is 1,413 mm, with December being the rainiest month (178 mm) and July the driest (46 mm). The mean annual temperature is 23 °C, with January being the hottest month (26 °C) and July the coldest (18 °C). According to Flumignan et al. (2015), the atmospheric evaporative demand, represented by the reference evapotranspiration (ET_0), has an annual mean value of 4.2 mm day^{-1}, with 80% of days with demand varying between 2 and 6.3 mm day^{-1} when excluding the 10% of days with the lowest demand and the 10% with the highest demand. November and December have the highest mean demand (5.3 mm day^{-1}), unlike June, which has the lowest mean demand (2.4 mm day^{-1}).

The soil is classified as a deep, very clayey-textured dystroferric Red Latosol (Oxisol), with a low water holding capacity (WHC), around 83 mm for the first meter of depth due to the high aluminum oxide content (Amaral et al., 2000). These data originate from several samples collected in the region by Embrapa Western Agriculture and constitute a representative mean value.

Actual productivity reductions (shortfalls) were compared with those simulated in the software for each of the nine agricultural years evaluated between 2001/02 and 2011/12 to calibrate the model. The 2003/04 and 2004/05 agricultural years were not considered due to the Asian soybean rust disease epidemic in Mato Grosso do Sul, as well as in Brazil (Godoy et al., 2016). The productivity reduction in these seasons could have been strongly influenced by the effect of the disease and it could conflict with the result of the model, which, in turn, investigates only the relationships between productivity and water deficit.

The actual crop shortfall in each agricultural year was based on the mean local productivity for the municipality published by IBGE, and the potential productivity considered at the studied region (Equation 1).

$$SA = 100 - \frac{P_A \times 100}{P_P} \tag{1}$$

In which:

SA is the actual crop shortfall (%);

P_A is the actual productivity (kg ha^{-1}), and

P_P is the potential productivity (kg ha^{-1}), which was considered in this study equal to 5,400 kg ha^{-1}, equivalent to 90 bags ha^{-1}.

The value of 5,400 kg ha^{-1}, which was accepted as potential soybean productivity in the region, represents an approximate level of mean productivity of the best plots cultivated without significant water restriction in the region and which adopt an optimized technological level.

Data on climate, crop, and soil were required in the parameterization of the model to simulate the crop shortfall of each agricultural year. A historical series of daily climatological data of ET_0 and total precipitation (Pt) was used in the period from 2001 to 2012, obtained from the database of the Agrometeorological Station at Embrapa Western Agriculture, located in Dourados, MS, Brazil.

Parameters related to soybean were inserted in the next step. The sowing dates varied according to the Agricultural Climate Risk Zoning recommendations in the region (Table 1), considering the rainfall dynamics in each agricultural year, as the only water input into the system was precipitation for model calibration, that is, there was no irrigation, as rainfed soybean represents almost all areas in the region.

TABLE 1. Simulated dates of each agricultural year for soybean sowing (dates refer to the 1st or 16th days of each month).

Agricultural year	**Sowing**
2001/02	Oct. 1st
2002/03	Oct. 16th
2005/06	Oct. 1st
2006/07	Oct. 1st
2007/08	Oct. 16th
2008/09	Oct. 1st
2009/10	Nov. 1st
2010/11	Oct. 1st
2011/12	Oct. 16th

Figure 1 shows the crop parameters, calibrated at each soybean phenological stage. The length of all stages and the initial and late season crop coefficients (K_c) were experimentally defined by Rezende (2019). The mid-season stage K_c was based on the FAO Irrigation and Drainage Paper 56 (Allen et al., 1998). The production response factor (K_y = 1.28) was obtained through the modeling used by Rezende (2019), considering the K_c values of each stage used in the present study (initial K_c = 0.5; mid-season K_c = 1.15; late season K_c = 0.3).

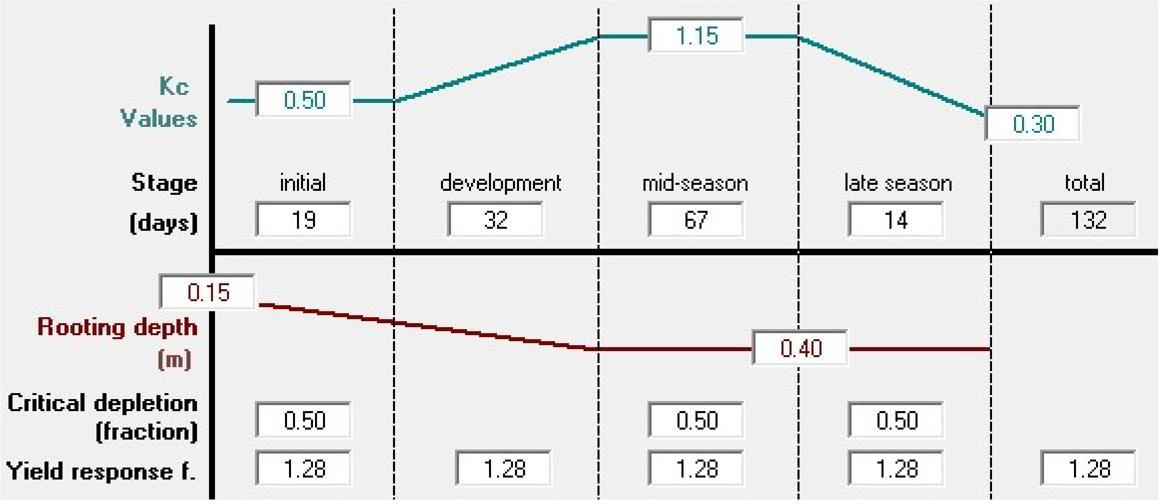

FIGURE 1. Crop parameters calibrated for soybean simulation.

Studying soybean in Dourados, Salton and Tomazi (2014) determined that the effective rooting system depth of soybean, with fully developed plants, was 0.4 m. Araújo et al. (2011) estimated soybean productivity in the region of Ponta Grossa, Paraná, and assumed that this effective rooting depth was 0.15 m at the beginning of the cycle (Stage 1), 0.30 m at growth (Stage 2), and 0.40 m from the intermediate stage to the end of the cycle (Stages 3 and 4). Based on these studies, we assigned 0.15 m at the initial stage and 0.40 m at the mid- and late season.

The critical soil water depletion factor (f) considered the recommendation of Allen et al. (1998) and was defined with a value of 0.5, that is, restrictions on evapotranspiration rates would only be imposed when less than 50% of WHC remained in the soil. Flumignan et al. (2015) also used f value of 0.5 in studies on the need for supplementary irrigation for soybean in Mato Grosso do Sul.

General information about the dystroferric Red Latosol (Oxisol), inserted in the model parameterization, came from the database of soil samples from Embrapa Western Agriculture (Amaral et al., 2000) and are representative of the soils of the study region (Table 2).

TABLE 2. Calibrated soil parameters for the simulations.

Attribute	**Value**
Water-holding capacity (mm m^{-1})	83
Maximum rain infiltration rate (mm day^{-1})	19
Maximum rooting depth (cm)	300
Initial soil moisture depletion (%)*	0
Initial available soil moisture (mm m^{-1}) *	83

*Values defined considering that soil moisture was at an optimal level when starting the simulations.

Data entry was completed in the model, which determined the water requirements and effective water use by calculating the ten-day water balance, that is, by the difference between crop evapotranspiration (ET_c) and effective precipitation (P_{eff}) that occurred over periods of ten days.

ET_c expresses the amount of water that returns to the atmosphere through the surface of a crop in the form of vapor and was calculated by CROPWAT through [eq. (2)].

$$ET_c = ET_0 \times K_c \times K_s \tag{2}$$

Where:

ET_c is the crop evapotranspiration (mm day^{-1});

ET_0 is the reference evapotranspiration (mm day^{-1});

K_c is the crop coefficient (dimensionless), and

K_s is the water stress coefficient, calculated according to Allen et al. (1998) (dimensionless).

Effective precipitation was considered as the difference between total precipitation and losses by surface runoff and deep percolation. The model has five options for calculating effective precipitation. The USDA soil conservation method, calculated by eqs (3) and (4), was used in this study. It was elaborated through water balances relating the input of precipitation with the outputs (surface runoff, percolation, and water retained in the root zone) for several crops (Sampaio et al., 2000).

$$P_{eff} = \frac{P_t \times 125 - 0.6 \times P_t}{125} \text{ for } P_t \leq \frac{250}{3} \text{ mm} \tag{3}$$

$$P_{eff} = \frac{125}{3} + 0.1 \times P_t \text{ for } P_t > \frac{250}{3} \text{ mm} \tag{4}$$

In which:

P_{eff} is the effective precipitation (mm), and

P_t is the total precipitation (mm).

Finally, the model showed the yield reduction due to water stress, that is, the shortfall index, as a percentage of the maximum production achievable in the area under ideal conditions. Thus, the crop shortfall estimated by the model was numerically equal to the first term of [eq. (5)], as described by Doorenbos & Kassam (1979).

$$\left(1 - \frac{Y_a}{Y_m}\right) = K_y \left(1 - \frac{ET_a}{ET_m}\right) \tag{5}$$

Where:

$\left(1 - \frac{Y_a}{Y_m}\right)$ is the productivity shortfall index (decimal; ranging from 0 for full production to 1 for total production shortfall);

Y_a is the actual productivity (kg ha^{-1});

Y_m is the maximum productivity in case of the crop water demand is fully met (kg ha^{-1});

K_y is the yield response factor (dimensionless), $\left(1 - \frac{ET_a}{ET_m}\right)$ is the shortfall rate in meeting the water requirement (decimal; ranging from 0 for total water requirement meeting and 1 for total water deficiency);

ET_a is the actual total evapotranspiration of the soybean cycle (mm cycle^{-1}), and

ET_m is the maximum total evapotranspiration of the soybean cycle (mm cycle^{-1}), considering the crop without experiencing water deficit.

Statistical indices used to compare observed data with simulated data were implemented as provided by Wallach et al. (2006), and are described below: bias (Equation 6), mean squared error (MSE) (Equation 7), root mean squared error (RMSE) (Equation 8), mean absolute error (MAE) (Equation 9), relative root mean squared error (RRMSE) (Equation 10), relative mean absolute error (RMAE) (Equation 11), modeling efficiency (EF) (Equation 12), correlation coefficient (r) (Equation 13), coefficient of determination (r^2) (Equation 14), Willmott index of agreement (d) (Equation 15), and performance index (c) (Camargo & Sentelhas, 1997) (Equation 16).

$$\mathrm{Bias} = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i) \tag{6}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{8}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |(Y_i - \hat{Y}_i)| \tag{9}$$

$$\mathrm{RRMSE} = \frac{\mathrm{RMSE}}{\bar{Y}} \tag{10}$$

$$\mathrm{RMAE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|Y_i - \hat{Y}_i|}{|Y_i|} \tag{11}$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \tag{12}$$

$$r = \frac{\sum_{i=1}^{N}[(Y_i - \bar{Y})(\hat{Y}_i - \tilde{Y})]}{\sqrt{\sum_{i=1}^{N}[(Y_i - \bar{Y})^2]\sum_{i=1}^{N}[(\hat{Y}_i - \tilde{Y})^2]}} \tag{13}$$

$$r^2 = \left(\frac{\sum_{i=1}^{N}[(Y_i - \bar{Y})(\hat{Y}_i - \tilde{Y})]}{\sqrt{\sum_{i=1}^{N}[(Y_i - \bar{Y})^2]\sum_{i=1}^{N}[(\hat{Y}_i - \tilde{Y})^2]}}\right)^2 \tag{14}$$

$$d = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(|\hat{Y}_i - \bar{Y}| + |Y_i - \bar{Y}|)^2} \tag{15}$$

$$c = r \times d \tag{16}$$

Where:

N is the number of observations;

Y_i is the measured value;

$\hat{Y}_i$ is the calculated value;

$\bar{Y}$ is the mean of measured values, and

$\tilde{Y}$ is the mean of calculated values.

The c performance index was interpreted and distributed according to the classes provided in Table 3.

TABLE 3. Interpretation of the performance index of the model estimate compared to the observed values, according to Camargo & Sentelhas (1997).

Performance index "c"	Class
> 0.85	Excellent
0.76-0.85	Very good
0.66-0.75	Good
0.61-0.65	Average
0.51-0.60	Bearable
0.41-0.50	Bad
≤ 0.40	Terrible

Performance evaluation for validation

The model performance in predicting soybean productivity under irrigated and non-irrigated conditions was evaluated after its calibration. For this purpose, two field trials (irrigated and rainfed) were implemented in the 2021/2022 agricultural year in the experimental area of Embrapa Western Agriculture, in Dourados, MS, Brazil (22°16′51″ S, 54°48′40″ W, and 395 m altitude).

A total of 12 commercial cultivars recommended for cultivation in the center-south and southwest region of Mato Grosso do Sul, the edaphoclimatic region REC 204, were sown on 09/22/2021 (irrigated) and 09/24/2021 (rainfed). The following cultivars were sown: BRASMAX 64I61RSF IPRO, BRASMAX 65I65RSF IPRO, DONMARIO 64I63RSF IPRO, DONMARIO 66I68RSF IPRO, EMBRAPA BRS 388RR, EMBRAPA BRS 543RR, EMBRAPA BRS 544RR, EMBRAPA BRS 1001 IPRO, EMBRAPA BRS 1003 IPRO e EMBRAPA BRS 1061 IPRO, MONSOY 6210 IPRO, and MONSOY 6410 IPRO.

The experimental design was completely randomized, with each of the 12 cultivars grown under two water management systems (irrigated and rainfed). Each water management area had four replications of each cultivar, totaling 48 plots in each area (Figure 2). Each plot had 8 rows of 12 m in length, with an inter-row spacing of 0.5 m and 11 plants m^{-1}. The entire experimental area (1.8 ha) was located within the same contour line, under a center pivot, but only the irrigated management area received water application. The area of the irrigated and rainfed plots had a total size equal to 0.3 ha each, while the remaining 1.2 ha composed the border.

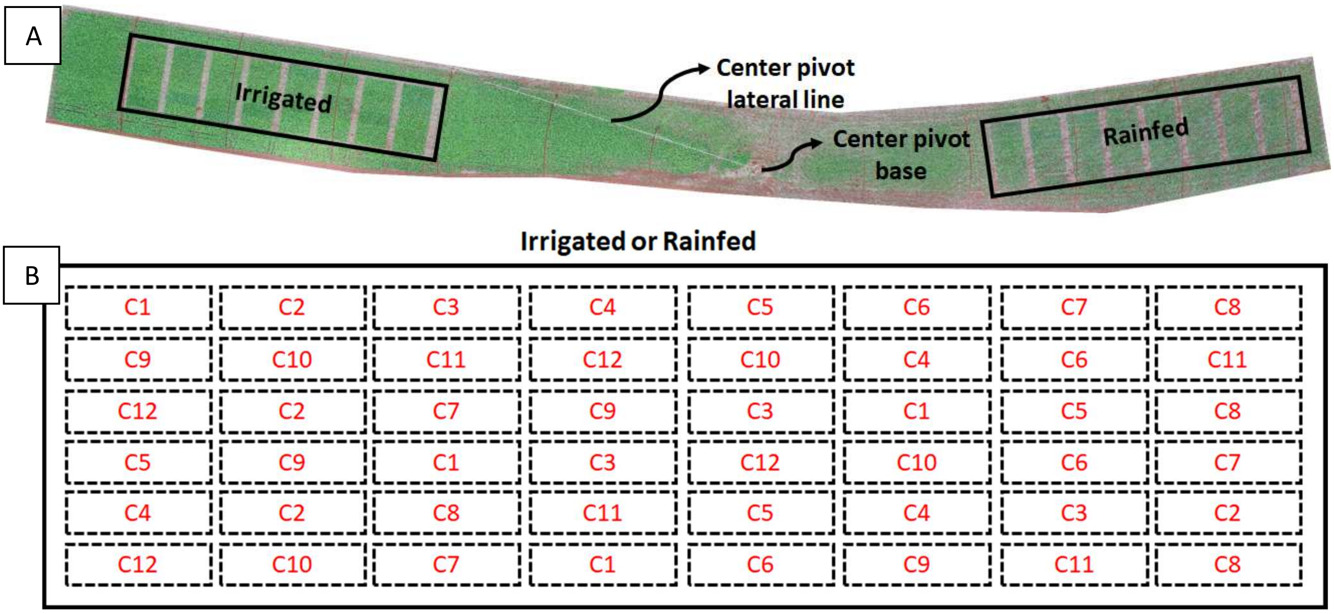

FIGURE 2. Aerial image of the experimental areas obtained through drone flyover (A) and sketches (B) of the randomization of soybean cultivars in irrigated and non-irrigated areas (rainfed).

The agronomical practices were similar to what is practiced in the region aiming that the crop could express its productive potential. Management was standardized by crop rather than variable depending on water management and cultivars. The predecessor crop in the experimental area was forage radish, which was desiccated with glyphosate and rolled before soybean sowing. Sowing fertilization was carried out with the application of 350 kg ha^{-1} of 04-18-18 fertilizer, and topdressing fertilization was not carried out. Weed control was performed with post-emergence application of glyphosate, while pests were controlled with insecticides based on thiamethoxam, lambda-cyhalothrin, imidacloprid, and bifenthrin, and diseases with fungicides based on trifloxystrobin, prothioconazole, mancozeb, fluxapyroxad, and pyraclostrobin.

An irrigation management strategy with a controlled water deficit was used for the area of irrigated plots. The management consisted of letting the soil water storage, within the layer considered useful, be lowered to 15% of the WHC, when the time for irrigation was configured. The net applied depth was fixed and equal to 8 mm at Stages I and II (initial and development; Figure 1) and 16 mm at Stage III (mid-season). Irrigation was suspended at Stage IV (late season).

Irrigation was managed via climate, following the same CROPWAT protocol, using the same parameters, but with the daily water balance being simulated in a spreadsheet set up for this purpose. Precipitation and ET$_0$ data was obtained in real-time at the Agrometeorological Station of Embrapa Western Agriculture, located less than 1,000 m away from the experimental area. Therefore, the irrigated treatment received 21 mm of net water depth on the sowing day and another 152 mm throughout the cycle, totaling 173 mm of irrigation water during the experimental period, which took place in a year of unprecedented and severe drought in the region.

The five central meters of the four central rows of each plot were harvested at the end of the experiment. The mass and moisture of grains were evaluated and then the productivity was calculated in kg ha^{-1}, with moisture corrected to 13%. These data were compared with the productivity estimate given by the CROPWAT model (using the spreadsheet) for its validation. For this, the data obtained in the irrigated and rainfed experimental areas were evaluated for their normality and then the means of each water management were compared with the CROPWAT estimates by Student's t-test at the 1 and 5% probability levels. The null hypothesis (H$_0$) assumed that the productivity estimate provided by CROPWAT was equal to that measured in the field, confirming the model's validity. The alternative hypothesis (H$_1$) assumed that the CROPWAT model was different from reality, producing underestimation or overestimation.

RESULTS AND DISCUSSION

Calibration

The ET$_m$ variation demonstrated a much smaller range than the effective precipitation, indicating that the soybean demand for water does not vary greatly, differently from the precipitation. The latter, related to its variable behavior between years, motivates the occurrence of different levels of water deficiency, responsible for reducing the ET$_a$ rates and, consequently, culminating in different levels of productivity shortfall (Table 4).

TABLE 4. Results of simulations of the CROPWAT calibration step and the actual soybean shortfall rate for the agricultural years in Dourados, MS, Brazil, according to IBGE data.

Agricultural year	ET$_a$	ET$_m$	P$_t$	P$_{eff}$	PE (%)	WD	SA (%)	SC (%)
2001/02	357.6	626.6	723.1	531.6	73.5	269	50	55
2002/03	426.9	659.6	1014.7	568.7	56	232.7	47.8	45.2
2005/06	331.5	621.7	792.4	497.7	62.8	290.2	57.8	59.7
2006/07	371.3	599.4	752.2	618.1	82.2	228.1	47.8	48.7
2007/08	383.5	600.5	751.8	503.3	66.9	217	50	46.3
2008/09	280.8	649.5	454.8	281.3	61.9	368.7	64.4	72.7
2009/10	436.9	607.6	947.8	492.7	52	170.7	42.2	35.9
2010/11	443.9	586.5	802.2	601.7	75	142.6	38.9	31.1
2011/12	307.7	637.5	544.8	398.5	73.1	329.8	63.3	66.2
Mean	371.1	621.0	753.8	499.3	67	249.9	51.4	51.2

ET$_a$ (mm cycle^{-1}): actual crop evapotranspiration under natural conditions of water availability; ET$_m$ (mm cycle^{-1}): crop evapotranspiration without water restriction; P$_t$ (mm cycle^{-1}): total precipitation; P$_{eff}$ (mm cycle^{-1}): effective precipitation; PE: precipitation efficiency, which indicates how much P$_t$ was actually stored and made available for use by the crop in the form of P$_{eff}$; WD (mm cycle^{-1}): water deficit, which indicates how much the soil-plant system stopped evapotranspiring (ET$_m$ − ET$_a$); SA: actual soybean shortfall index for the agricultural years in Dourados, MS, Brazil, according to IBGE data; SC: shortfall index calculated by CROPWAT.

The results shown in Table 4 demonstrate that soybean cultivation in the southern region of Mato Grosso do Sul experiences, on average, effective precipitation in the order of 499.3 mm cycle^{-1}, resulting from an efficiency over total precipitation of 67%, showing that 1/3 of the precipitation that occurs during the cycle is not used by the crop. The rainfall available for soybean cultivation is not enough to fully meet the crop water requirements (621 mm cycle^{-1}), meeting only 59.8% of the required amount (371.1 mm cycle^{-1}). This fact implies a mean water deficit per cycle of 249.9 mm, which can be totally or partially supplied in productive systems that have irrigation. In addition, good agricultural practices that aim at better use of rainwater, such as deepening the root system or reducing soil evaporation, can contribute especially in rainfed production systems. The mean crop shortfall rate is 51.4% in response to the water deficit that is systematically experienced by soybean plantations in the region, showing that just over half of the crop productive capacity is lost due to the water factor.

The 2008/09 agricultural year culminated in the highest water deficit (368.7 mm cycle^{-1}) due to the combined effect of a high crop evapotranspiration demand (649.5 mm cycle^{-1}) and low rainfall (281. 3 mm cycle^{-1}). Consequently, ET$_a$ was 57% lower than ET$_m$, resulting in the highest percentage of productivity loss of the entire studied period, both by evaluating SA (64.4%) and SC (72.7%).

On the other hand, the crop required the lowest evapotranspiration in the historical series in the 2010/11 agricultural year (586.5 mm cycle^{-1}) and the effective rainfall was above average (601.7 mm cycle^{-1}). This precipitation, which was 75% efficient, resulted in the lowest water deficit in the historical series (142.6 mm cycle^{-1}), and, consequently, in the lowest productivity shortfall (SA of 38.9% and SC of 31.1%). It shows that losses still occur due to water deficit even in years when the climate is considered favorable and management is appropriate, as observed by Battisti et al. (2018) in other soybean-producing regions of Brazil.

Similarly, Flumignan et al. (2015) and Gava et al. (2018) corroborated the perception of the need for supplementary irrigation as a strategy to overcome the problem related to the water deficit to produce soybean in Mato Grosso do Sul.

Table 4 shows that CROPWAT could estimate the percentage of crop shortfall, as the mean value obtained from SC was equal to 51.2%, while SA reached 51.4%. However, Figure 3 shows that the crop shortfalls calculated by CROPWAT were more distant in some years, especially in extreme years, although close to the actual shortfalls. It was the case for the 2008/09, 2009/10, and 2010/11 agricultural years. Even so, the trends have always been similar, denoting the years of high and low shortfalls.

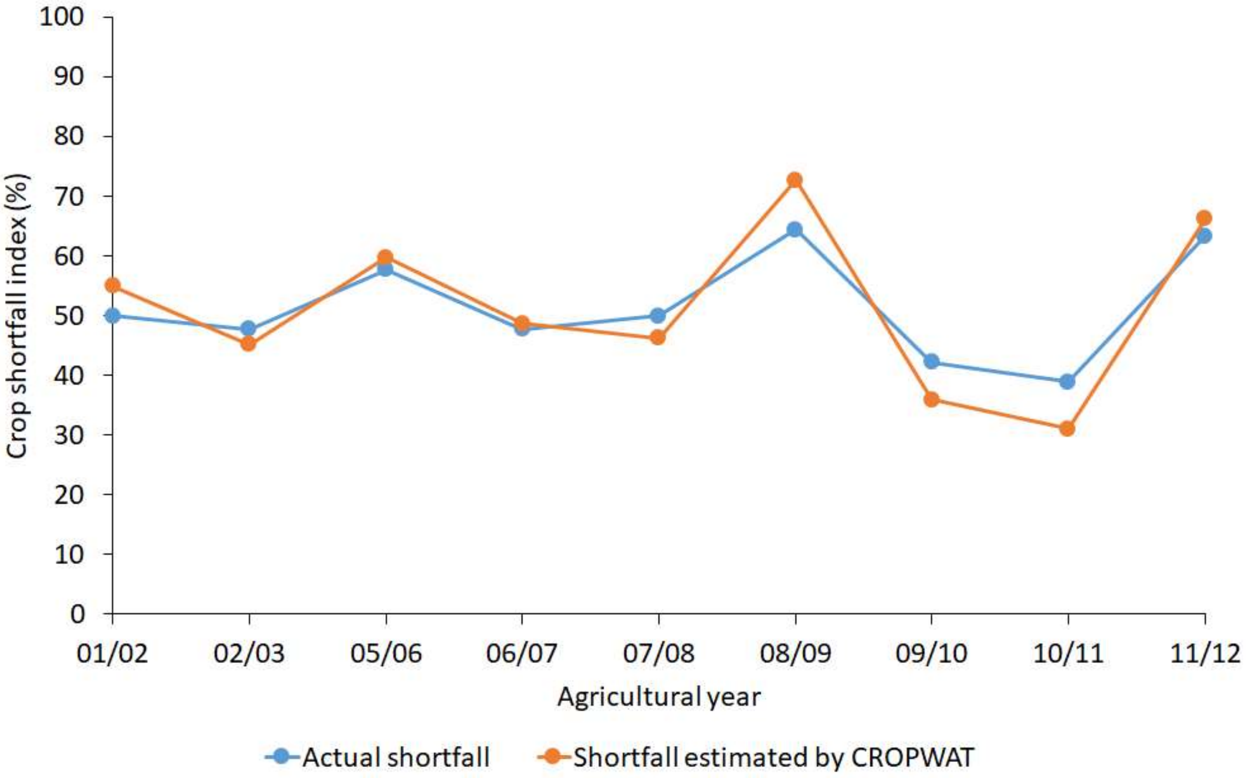

FIGURE 3. Actual and CROPWAT crop shortfall index for Dourados, MS, Brazil, for soybean crops evaluated in the period from 2001/02 to 2011/12.

In general, the statistical indices used to compare the quality between the CROPWAT model and the observed data showed excellent performance (Table 5). The bias of only 0.158%, an index that measures the difference between the mean of the actual shortfall and the mean of the calculated shortfall of the evaluated agricultural years, was small and its positive result indicates that the model underestimates the observed values by 0.158%.

TABLE 5. Results of the statistical indices used to evaluate the performance of the CROPWAT model in its calibration.

Index	Result
Bias (%)	0.158
MSE (%²)	25.21
RMSE (%)	5.02
MAE (%)	4.37
RRMSE (%)	9.78
RMAE (%)	8.51
EF (%)	96.2
r (dimensionless)	0.976
r^2 (dimensionless)	0.953
d (dimensionless)	0.95
c (dimensionless)	0.93

According to Wallach et al. (2006), the bias alone is not enough to evaluate the model, as a value close to 0 can be a consequence of very small errors or large errors that cancel each other out. Two classic measures eliminate the bias compensation problem, the first and most used is the MSE (mean squared error), which presented a value of 25.21% in this study. It is usually convenient to work with RMSE (root mean squared error) because this index has the same unit as Y (analyzed value), facilitating its understanding. An RMSE value of 5.02% was observed in this evaluation. The second measure, which avoids compensation between under- or overestimation of results, is MAE (mean absolute error), which has the same unit as Y (analyzed value). The value found in this study was 4.37%. The results demonstrate that the modeling embedded in CROPWAT presented a maximum error of 5.02% regardless of the indicator used.

The index RRMSE (relative root mean squared error) provides the relationship between RMSE and the mean of the actual shortfall values. In this case, RRMSE represented 9.78% of the mean SA. RMAE (relative mean absolute error) resulted in 8.51%, that is, the mean absolute error represents 8.51% of the mean of the actual shortfall values.

The modeling efficiency, indicated by EF, was 96.2%; the correlation between the observed and estimated values, measured by the r coefficient, which indicates the model accuracy, was classified as very strong, with a value of 0.976, demonstrating that, when the measured productivity increased or decreased, the simulated one followed this trend. The model precision, expressed by the coefficient of determination (r^2), was equivalent to 95.3%. The index of agreement (d) and the performance index (c) were considered excellent (0.95 and 0.93, respectively), evidencing the high agreement between the values estimated by the model and the actual shortfall values.

Performance analysis for validation

Productivity under irrigated management among the 12 evaluated soybean cultivars varied between 2,428.6 and 3,563.6 kg ha^{-1}, with a mean of 3,014.6 kg ha^{-1}. The CROPWAT model estimated an expected productivity value for this management of 3,045.6 kg ha^{-1}, an overestimate of 31 kg ha^{-1}, equivalent to 1% (Table 6). The productivity of the 12 cultivars in the rainfed management ranged from a minimum of 1,159.2 kg ha^{-1} to a maximum of 2,334.2 kg ha^{-1}, with a mean of 1,580.4 kg ha^{-1}. In this management, CROPWAT underestimated productivity by 284.4 kg ha^{-1}, equivalent to 18%.

TABLE 6. Productivity statistics of 12 soybean cultivars irrigated by a center pivot (using a strategy with controlled water deficit) and rainfed in the 2021/2022 agricultural year, in Dourados, MS, Brazil.

Cultivar	Irrigated		Rainfed	
	Mean (kg ha^{-1})	CV (%)	Mean (kg ha^{-1})	CV (%)
BRASMAX 64I61RSF IPRO	2,428.6	12.8	1,692.1	12.9
BRASMAX 65I65RSF IPRO	2,736.1	7.2	1,593.2	17.8
DONMARIO 64I63RSF IPRO	3,285.8	5.8	2,002.5	9.6
DONMARIO 66I68RSF IPRO	2,918.3	12.7	1,596.5	8.3
EMBRAPA BRS 388RR	3,058.8	4.3	1,559	19.3
EMBRAPA BRS 543RR	3,563.6	6.5	2,334.2	20.5
EMBRAPA BRS 544RR	2,952.8	12.2	1,592.2	10
EMBRAPA BRS 1001 IPRO	2,979.7	13	1,306.6	12.1
EMBRAPA BRS 1003 IPRO	2,944.2	11.8	1,159.2	23.2
EMBRAPA BRS 1061 IPRO	3,217.1	12.9	1,177.7	10.1
MONSOY 6210 IPRO	2,997.6	10.9	1,568.4	15.3
MONSOY 6410 IPRO	3,092.8	11.2	1,383.3	23.2
Overall mean	3,014.6	10.1	1,580.4	15.2
CROPWAT estimate	3,045.6 **	-	1,296 *	-

According to Student's t-test, the estimated value (CROPWAT) is contained in the confidence interval of the sample (overall mean) with 99% (*) or 95% (**) probability.

The differences observed between the productivity estimated by the CROPWAT model and the overall mean of the 12 cultivars in each water management demonstrated that the H_0 hypothesis cannot be denied, that is, it cannot be denied that the productivity estimate was equal to that measured in the field, thus resulting in the consideration that the model is valid. The test significance at a 5% probability in the irrigated management demonstrates that the estimate provided by CROPWAT was closer to the measurements obtained in the field compared to rainfed, which could already be predicted due to the decrease in the predictive capacity of the model in the case of productivity extremes, whether high or low, as shown in Figure 3.

CONCLUSIONS

CROPWAT was satisfactorily calibrated for modeling soybean production systems, demonstrating predictive capacity with very strong accuracy, high precision, and excellent indices of agreement and performance. Its application in production planning can serve to obtain improvements in the production process, as well as better management of water resources in the case of irrigated agriculture.

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