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THE USE OF AQUACROP MODEL FOR SOYBEAN IN VARIOUS WATER AVAILABILITY WITHIN A LYSIMETER SYSTEM

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***Abstract**. The AquaCrop model is widely used under various agro-ecological conditions to reduce farm water consumption. The study aimed to simulate, validate, and measure the performance of AquaCrop models for canopy cover, biomass and soybean crop yields cultivated within a lysimeter. This research was conducted in the experimental field of the Faculty of Agriculture, the University of Jember, Indonesia (8°09'45.1" S, 113°42'58.2" E, 101 m a.s.l). There are four treatments in 4 lysimeters, namely P1 (irrigation based on recommendation), P2 (irrigation 95-105% FC), P3 (irrigation 75-85% FC) and P4 (irrigation 55-65% FC). The AquaCrop model is calibrated using canopy cover (CC) and then validated to predict the biomass and soybean yield. The experiment revealed that the model simulates better CC, biomass, and soybean yields with full irrigation than deficit irrigation. The performance of the AquaCrop model for soybeans of the Deja 2 variety in predicting CC, biomass, and soybean yield is impressive and reasonable. For the CC we found R2 ranges from 0.956 to 0.995, RMSE 10.389% to 3,293%, NRMSE 0.154% to 0.051%, NSE 0.918 to 0.992, and d 0.980 to 0.998. For biomass the R2 is 0.842, RMSE 0.111 t ha-1, NRMSE 0.017%, NSE 0.712, and d 0.937. For soybeans production the R2 is 0.999, RMSE 0.045 t.ha-1, NRMSE 0.018%,, NSE 0.908 and d 0.970. This study demonstrated that based on WUE, 55-65% FC irrigation is the most efficient application.*
Keywords: *AquaCrop; biomass; canopy cover; model validation; soybean yield*

1. Introduction

Soybean legume (*Glycine max* (L.) Merril) is a potential source of vegetable protein. It plays an essential role as a food staple since it is widely consumed in Indonesia in fresh soybeans (edamame) or processed products (tempeh, tofu, and others). Indonesia's soybean production has been very volatile for four decades and shows a downward trend. In 2015 and 2019, national soybean production looked alarming since it declined by 37.33% in 2017 from the previous year (Badan Pusat Statistik, 2022; Kementerian Pertanian, 2020).

One of the causes of the decline in soybean production is due to the decline in harvest area and soybean productivity as a result of climate change. Climate change can result in excess water and unavailability of water or drought. Water requirements that Indonesian agriculture have for many years depended on rainfall (Molle & Larasati, 2020; Tukidin, 2010). However, the rainfall required for agricultural production is increasingly unreliable due to climate change which affects rainfall distribution (Rockström & Barron, 2007) and subsequently food production (Mibulo &

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Kiggundu, 2018).

The water-based growth model has undergone extensive development and application in a variety of agro-ecological settings (Adeboye *et al*., 2017). Crop simulation models such as APSIM (Wang *et al*., 2002), DSSAT (Abayechaw, 2021), and CropSyst (Morsy *et al*., 2018) have been widely used as a supporting tool in making decisions in the agricultural sector. However, such models can be applied only to calibrated fields and require many parameters (Mibulo & Kiggundu, 2018). The number of parameters required limits its application in Indonesia, where equipment and funds are a handicap in collecting meteorological data.

Food and Agricultural Organization (FAO) created the AquaCrop model, which seeks to forecast water results, demands, and productivity under predetermined conditions (Raes *et al*., 2009; Steduto *et al*., 2009). The AquaCrop model requires less data input than other models. Several parameters in the AquaCrop model have default values, although some of those parameters are not universal (Silva *et al*., 2018). As a result, it needs to be modified to account for regional conditions, cultivars, and plant management techniques. AquaCrop Model has been used by some previous researchers to create deficit irrigation schedules (Geerts *et al*., 2010), evaluate the productivity effects of crop and land management (Adeboye *et al*., 2019; Adeboye *et al*., 2021; Shrestha *et al*., 2013), determine the short- and long-term effects of climate change on crop production (Vanuytrecht *et al*., 2014), and create useful decision support tools for agricultural operations (Adeboye *et al*., 2021).

The AquaCrop model is applied in various parts of the world and has been confirmed to impact increasing and significantly reducing water consumption. While some studies focused on soybeans (Adeboye *et al*., 2017; Adeboye *et al*., 2021; Mohammad *et al*., 2018; Paredes *et al*., 2015; Silva *et al*., 2018), more research is needed to determine the influence of different water availability in tropical climates where soybeans are intensively produced. The AquaCrop model has not been proven in Indonesia, where soybeans are intensively cultivated under irrigation and rain-fed systems. It is expected that the Aquacrop model can be a feasible method for modeling various crop cultivars under various soil, climate and agricultural management conditions in the Indonesian region.

The study aimed to simulate, validate, and evaluate the performance of AquaCrop models for canopy cover, biomass and soybean crop yields cultivated within a lysimeter. The soybean variety of Deja 2 is the superior and most popular soybean variety in Indonesia that was released in 2017 (Indonesian Agency for Agricultural Research and Development, 2017).

2. Methods

2.1. Description of the Study Area

This study was carried out in the faculty of agriculture's experimental field at the university of Jember, Indonesia (8°09'45.1" S, 113°42'58.2" E, and 101 m a.s.l.). Meteorological data were collected from the AWS (Automatic Weather Station) located 10 meters from the lysimeter location (8°09'45.5" S, 113°42'58.2" E). The lysimeter (1.5m x 0.5m x 0.6m LWD) is filled with Inceptisol soil from the surface horizon. In Table 1, soil properties are shown.

Table 1. Soil characteristics in lysimeter

Parameters	Value
Sand (%)	46.7
Clay (%)	45.5
Silt (%)	7.8
Soil Texture	Sandy clay
BD (Mg m^{-3})	0.89
PD (Mg m^{-3})	2.43
Porosity (%)	63.37
OM (%)	1.07
FC (m^3 m^{-3})	0.426
PWP (m^3 m^{-3})	0.191
TAW (m^3 m^{-3})	0.235
pH (H_2O)	7.2
Total N (%)	0.15
P_2O_5 (ppm)	3.65
K_2O (cmol kg^{-1})	0.32

Remarks: *BD*: Bulk Density; *PD*: Particle Density; *OM:* Organic matter; *FC*: Field capacity; *PWP*: Permanent Wilting Point; *TAW*: Total available water

A lysimeter is a soil container of a specific volume and depth filled with disturbed or undisturbed soil, which is equipped with a connected device and used to collect percolation water on the other side of the lysimeter (Figure 1). This way, incoming and outgoing water in the lysimeter can be measured (Kidron & Kronenfeld, 2017; Kidron & Kronenfeld, 2020).

2.2. Experimental Design

The experiment used four irrigation treatments applied to four lysimeters namely 55-65%, 75-85%, 95-105% of field capacity and standard field irrigation commonly practiced by farmers in Jember (Table 2) using Low-Density Polyethylene (LDPE) mulch (Lubis *et al.*, 2017). Measurement of field capacity moisture content was carried out before planting to determine the initial soil field capacity. This value will later be used in determining the percentage of field capacity. Soybeans were planted on 13 December 2021, with planting distances in and between rows of 0.2 m and 0.3 m, respectively. In every single lysimeter, 14 plants grew (Figure 2). Two seeds per hole were planted at a depth of two centimeters, producing an equal population of 166,667 plants.ha^{-1}. Soybeans were grown following conventional agricultural management practices (weeding, pest control, and no change in fertilizing) with the application of rhizobium

(Budiastuti *et al.*, 2020) and rice husk ash (Perdanatika *et al.*, 2018) at early planting because the lysimeter soil has never been planted with legumes before. All treatments were covered with LDPE mulch. Irrigation was applied 26 days after planting (two weeks before the reproductive phase R1). Once a week, soil samples were taken at each lysimeter at depths of 0-10, 10-20, 20-30 and 30-35 cm to measure the moisture content and maintain the water content.

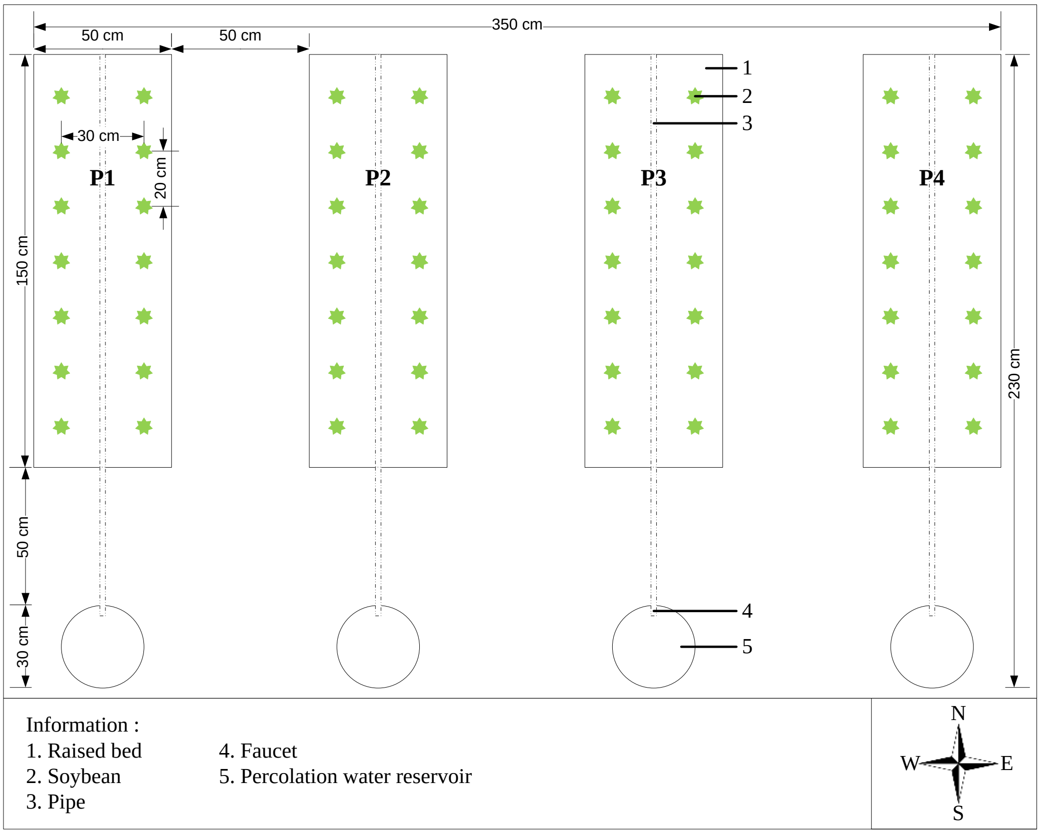

Figure 1. Lysimeter design and experimental plot

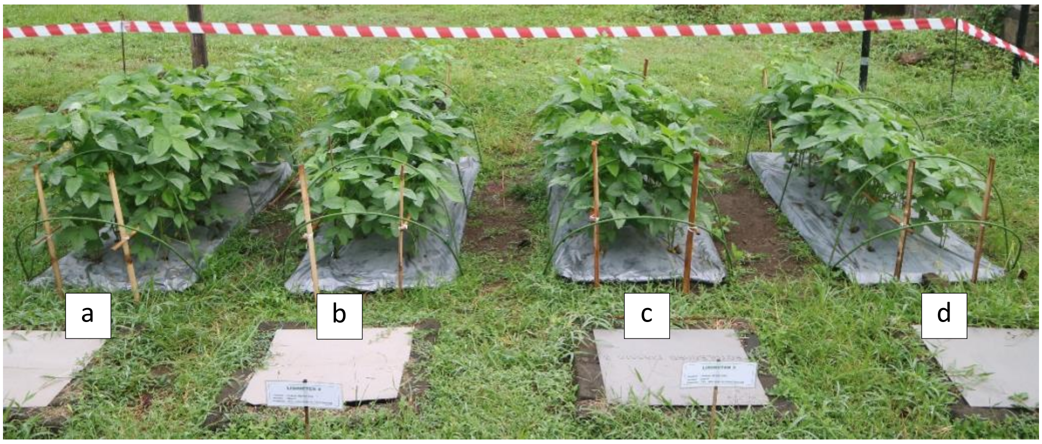

Figure 2. The experimental plot of soybean; treatments (a) P1, (b) P2, (c) P3, and (d) P4

Table 2. Experimental treatment

Treatment	Description
P1	Irrigation applied based on irrigation standards commonly practiced by farmers in Jember
P2	Irrigation to maintain 95-105% of field capacity
P3	Irrigation to maintain 75-85% of field capacity
P4	Irrigation to maintain 55-65% of field capacity

2.3. Model Input Data

The meteorological data needed are solar radiation, air temperature, relative humidity, wind speed, rainfall, and daily reference evapotranspiration (ETo) (Figure 3). Average atmospheric carbon dioxide concentrations are provided by AquaCrop and updated periodically, while ETo is determined during the growth season using the FAO Penman-Monteith method (Raes, 2017). The characteristics of plant data are presented in Table 3.

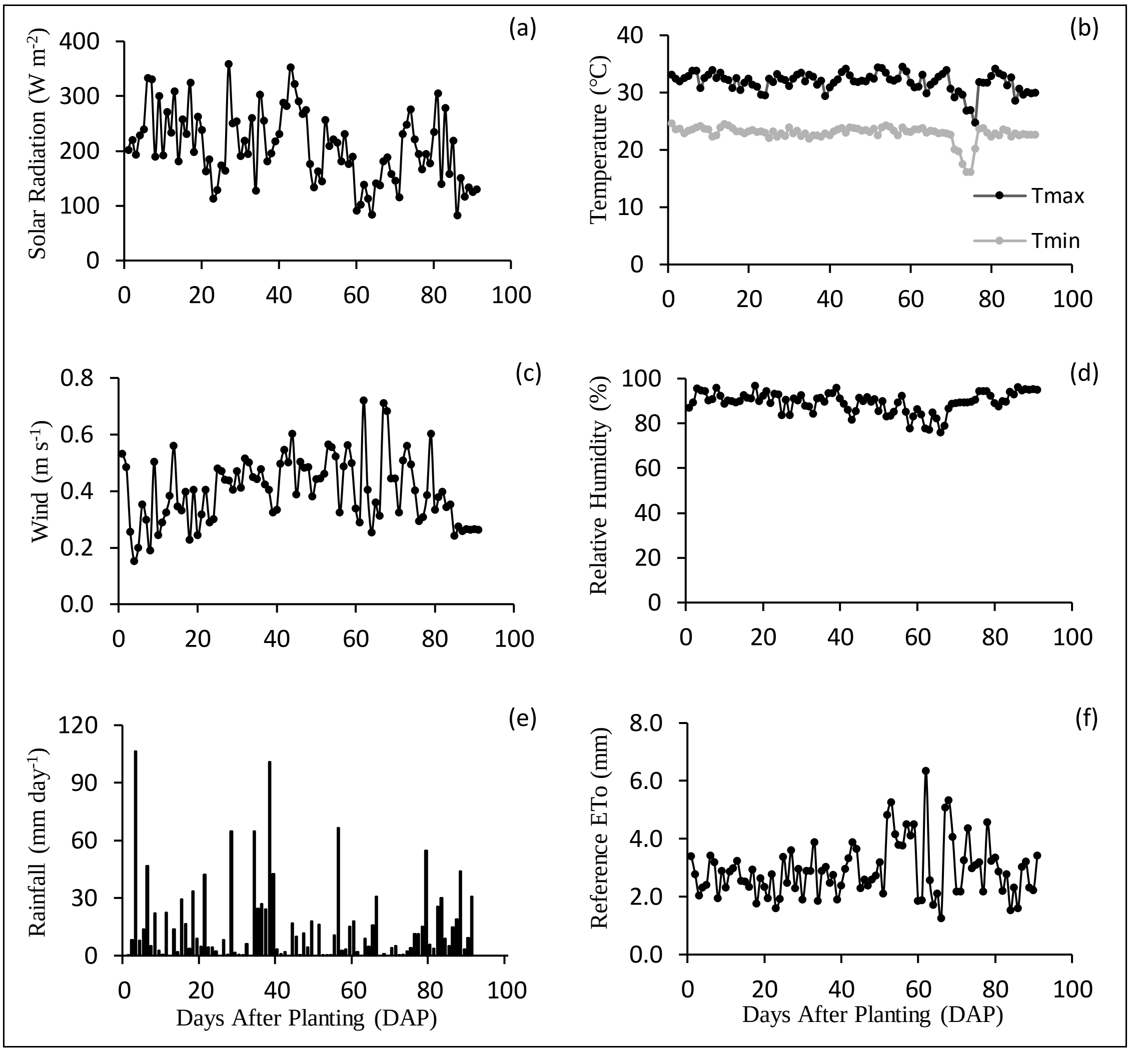

Figure 3. Daily (a) solar radiation, (b) temperature, (c) wind, (d) relative humidity, (e) rainfall, and (f) reference ETo for the 13 December 2021 to 13 March 2022 growing season

2.4. Model Description

The AquaCrop model requires climatic components (i.e., rainfall, relative humidity, wind speed, air temperature, solar radiation, and evapotranspiration), crops (phenology, canopy cover, biomass, and crop yields), land management (land fertility, irrigation, and land agronomic practices) as well as characteristics of the soil profile (Hsiao *et al*., 2009; Raes *et al*., 2009; Steduto *et al*., 2009).

Table 3. Selected crop parameters and values AquaCrop calibration for soybean

Parameters	Value	Unit
Upper temperature	30	°C
Cover per seedling	5	$cm^2.plant^{-1}$
Canopy growth coefficient (CGC)	14.3	$\%.d^{-1}$
Canopy decline coefficient (CDC)	15	$\%.d^{-1}$
Plant density	166,667	$plants.ha^{-1}$
Initial canopy cover CCo	0.83	%
Maximum canopy cover CCx	99	%
Time to maximum canopy cover	56	d
Time to flowering	40	d
Length of the flowering stage	32	d
Time to senescence	63	d
Time to maturity	91	d
Maximum rooting depth	0.6	m

2.5. Data Collection

Canopy values were obtained by taking images of three representative plants from each lysimeter using a Canon M3 camera (Canon Inc., 2015). The images were analyzed using the Digital Image Analysis (DIA) method with *ImageJ* software to obtain canopy cover values (Ferreira & Rasband, 2012; Mibulo & Kiggundu, 2018; Xiong *et al*., 2019). After harvest, biomass and soybean production were obtained from samples on each lysimeter plot. The final biomass and the collected soybean yield were dried and weighed using 0.01 g digital scales.

2.6. Calibration and Validation

The model was calibrated using the accumulated value of canopy cover for irrigation treatment based on irrigation standards commonly practiced by farmers in Jember under LDPE mulch (P1) (Mibulo & Kiggundu, 2018; Pawar *et al*., 2017). The remainder was used to validate the model.

2.7. Model Performance

Statistical indicators were used to assess the correlation between predicted and measured data, namely R^2, *RMSE*, *NRMSE*, *NSE* (Nash-Sutcliffe Efficiency), and *d* (Willmott's index of agreement), with Formula (1) - (5)

$$R^2 = \left[\frac{\sum(O_i-\bar{O})-(P_i-\bar{P})}{(O_i-\bar{O})\times\sum(P_i-\bar{P})}\right] \quad (1)$$

$$RMSE = \sqrt{\frac{\sum(P_i-O_i)}{n}} \quad (2)$$

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum(P_i-O_i)^2}{n}} \times 100 \quad (3)$$

$$NSE = 1 - \frac{\sum(P_i - O_i)^2}{\sum(O_i - \bar{O})^2} \quad (4)$$

$$d = 1 - \frac{\sum(P_i - O_i)^2}{\sum(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (5)$$

where: O_i = observed data; $\bar{O}$ = mean of observed data; P_i = simulated data; $\bar{P}$= average of simulated data; n = number of measurements taken; d = index of agreement.

The observed and forecasted data sets should coincide well when the R2 value is close to 1. R2 > 0,80 is advised for research of plant simulation (Ma *et al*., 2011). For plant simulation models, RMSE is regarded as "excellent" at 15% and "satisfactory" at 20%. (Adeboye *et al*., 2021)

A value of R^2 close to 1 indicates good agreement between the observed and predicted data sets. R^2 > 0,80 is advised for research of plant simulation (Ma *et al*., 2011). For plant simulation models, *RMSE* is regarded as "good" at 15% and "satisfactory" at 20% (Adeboye *et al*., 2021), while Hanson *et al*. (1999) recommend a maximum error of 15% for yield and biomass. *NRMSE* <10% considered as very good, 10-20% as good, 20-30% as fair and >30% as bad (Jamieson *et al*., 1991). *NSE* ranges from 0 to 1; a value close to 1 means the residual variance is much smaller than the observed data variance (Nash & Sutcliffe, 1970) and excellent model performance for plant modeling (Moriasi *et al*., 2007). Index *d* ranges from 0-1. One implies a perfect agreement among observed and predicted data, and 0 does not indicate an agreement (Krause *et al*., 2005). Index $d > 0.7$ is reasonable for calibration in agriculture (Saseendran *et al*., 2010).

2.8. Irrigation Efficiency

Crop evapotranspiration was determined using the groundwater balance approach (Ali, 2010). The effective daily rainfall is the rainfall interception water because this study uses a lysimeter and LDPE mulch. The contribution of groundwater is also ignored since it is a lysimeter system. Drainage under the root zone is considered negligible (Lovelli *et al*., 2007). Therefore, the actual evapotranspiration of plants is determined using Formula 6.

$$ETc = I + R - P \pm \Delta S \quad (6)$$

where: *ETc* = total actual soybean evapotranspiration (mm); *I* = irrigation (mm); *R* = rainfall (mm); *P* = percolation (mm); ΔS = change in the soil moisture content between measurements (mm).

Calibrated models were used to evaluate different irrigation schedules against soybean performance. Biomass water productivity (*WP* kg.m^{-3}) denotes the ratio between total soybean biomass and transpiration (Raes, 2017). Transpiration values were equal to evaporation values for the experiment which used LDPE mulch. *WP* was determined using Formula 7 (Raes, 2017).

$$WP = \frac{Total\ biomass\ produced\ (kg)}{Total\ water\ transpired\ (m^3)} \quad (7)$$

Water Use Efficiency (WUE kg.m^{-3}) or *ET* water productivity (WP_{ET}) states the ratio between the total yield of irrigation soybeans and the total irrigation water used (evapotranspiration water) (Raes, 2017). WUE was determined using Formula 8 (Raes, 2017).

$$WUE = \frac{Total\ irrigated\ soybean\ yield\ (kg)}{Total\ irrigation\ water\ applied\ (m^3)} \quad (8)$$

3. Results and Discussion

The Deja 2 variety is a new variety of soybeans released in 2017 with a potential yield of 2.75 tons ha^{-1} and an average yield of 2.38 tons ha^{-1} (Indonesian Agency for Agricultural Research and Development, 2017). Therefore, it is necessary to recognize the stages of growth of Deja 2 obtained in the field (Table 4).

Table 4. Number of days between stages as observed in the field

Stages	The average number of days (days)	Days After Planting (DAP)
Planting to VE (Emergence)	5	1-5
VE to VC (Unrolled unifoliolate leaves)	4	6-9
VC to V1 (First trifoliolate)	5	10-14
V1 to V2 (Second trifoliolate)	3	15-17
V2 to V3 (Third trifoliolate)	3	18-20
V3 to V4 (Fourth trifoliolate)	5	21-25
V4 to V5 (Fifth trifoliolate)	5	26-30
Beyond V5	9	31-39
R1 to R2 (Beginning flowering)	2	40-41
R2 to R3 (Full flowering)	7	42-48
R3 to R4 (Beginning pod)	4	49-52
R4 to R5 (Full pod)	5	53-57
R5 to R6 (Full seed)	5	58-62
R6 to R7 (Beginning maturity)	15	63-77
R7 to R8 (Full maturity)	14	78-91

3.1 AquaCrop Model Calibration

The AquaCrop model was calibrated utilizing actual canopy cover data for treatment of P1 to P4 compared to simulated output (Figure 4). Cover parameters such as initial cover, maximum cover, and decreasing cover are set manually during calibration (Pawar *et al*., 2017).

The observed model parameter values were the canopy cover (CC), biomass, and soybean yield compared to the simulation output to assess the model's performance. In the initial growth stage V1 to R7 (beginning of maturity), AquaCrop underestimates the CC, while in the R8 (full maturity) phase, AquaCrop overestimates the CC (Figure 4a). The calibration results show R^2 for all treatments close to the value of 1. This calibration indicates a strong correlation between measurable and simulated CC ($0.911 \leq R^2 \leq 0.969$). RMSE ranges from 7,348-11,596% and

NRMSE ranges from 0.115-0.179%. The NSE spans from 0.907-0.961, and the *d* spans 0.990-0.985. Figure 4a shows an overestimation tendency in the R8 phase in all treatments, so the Canopy Growth Coefficient (CGC) values and Canopy Decline Coefficient (CDC) need to be calibrated (Table 3).

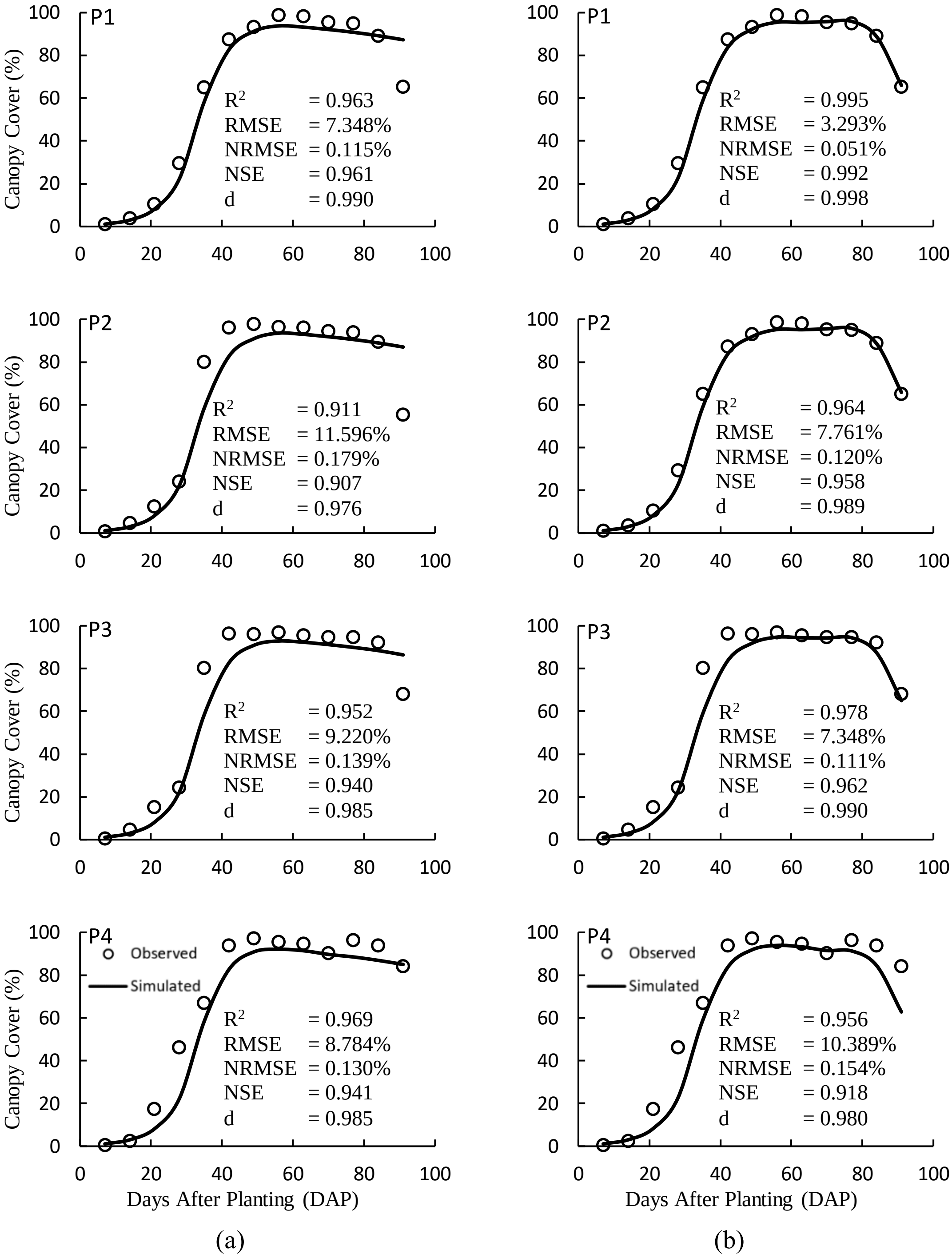

Figure 4. Simulated and observed CC for all treatments during (a) calibration and (b) validation

The CGC and CDC scores of 14.3%.d^{-1} and 15%.d^{-1} correspond to the actual CC (Figure 4b) in the R8 phase. The AquaCrop model shows good compatibility with the measured CC. The validation results showed a strong and significant correlation between measured and simulated CC

($0.956 \leq R^2 \leq 0.995$). RMSE and NRMSE values in the validation period were smaller than in the calibration period, and R^2, NSE, and *d* in the validation period were more significant than in the calibration period. The CC simulation and validation were satisfactory for entire treatments.

3.2 AquaCrop Model Validation

The model validates P1 to P4 and simulates cumulative yield and actual biomass, as presented in Table 5 and Figure 5. Table 6 presents the statistical test results for the validation period to evaluate the performance of the AquaCrop model.

Table 5. Observed and simulated values

Treatments	Biomass (t ha^{-1})			Grain yield (t ha^{-1})		
	Observed	Simulated	Deviation (%)	Observed	Simulated	Deviation (%)
P1	6.850	6.825	-0.365	2.737	2.730	-0.264
P2	6.689	6.804	1.721	2.716	2.722	0.204
P3	6.539	6.718	2.739	2.674	2.682	0.287
P4	6.288	6.229	-0.944	2.359	2.451	3.880

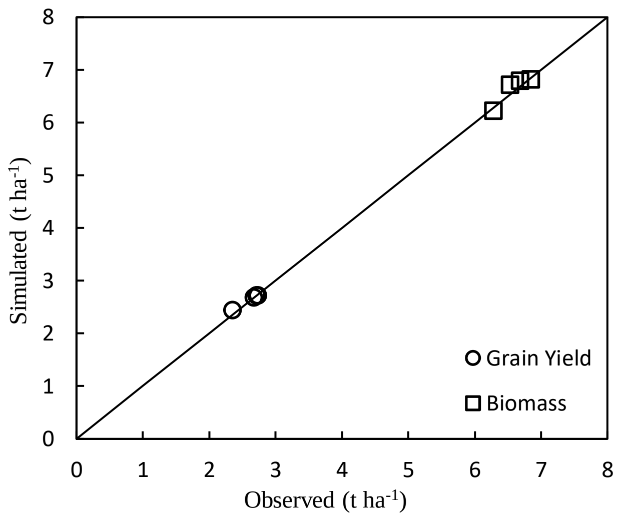

Figure 5. Simulated and observed final biomass and grain yield

Table 6. The AquaCrop model's performance in simulations of above-ground biomass and grain yield

Parameter	R^2	RMSE (t ha^{-1})	NRMSE (%)	NSE	d
Biomass	0.842	0.111	0.017	0.712	0.937
Grain Yield	0.999	0.046	0.018	0.908	0.970

A statistical analysis of the AquaCrop model's performance for all treatments revealed that soybean yields were more accurately simulated than biomass (Table 6). In the simulation study by Araya *et al*. (2010) on barley with various water deficits, NSE values for biomass simulation range between 0.53 to 1 and 0.5 to 0.95 compared to the obtained results, and RMSE values range from 0.36 t.ha^{-1} to 0.9 t.ha^{-1} and 0.07 t.ha^{-1} to 0.27 t.ha^{-1}, respectively. Moreover, Pawar *et al*. (2017) show the NSE value for biomass simulation and soybean yield obtained were at 0.96 and 0.93.

Adeboye *et al.* (2017) report that R^2 values for biomass simulations and soybean yields were 0.90 and 0.99. In the simulation of biomass and corn yields by Mibulo & Kiggundu (2018), the RMSE value for biomass simulation and the results obtained were equal to 1.52 t ha^{-1} and 0.11 t ha^{-1}, with NSE values of 0.69 and 0.87, respectively.

3.2 Effectiveness of Alternative Irrigation

WP and WUE were calculated to optimize the irrigation as presented in Table 7 for various irrigation treatments based on crop water needs (*ETc*) and actual results (Raes, 2017).

Table 7. WP and WUE for different irrigation treatments

Treatments	Irrigation applied (mm ha^{-1})	Water use/ ETc (mm ha^{-1})	Grain Yield (kg ha^{-1})	Variation in irrigation applied (%)	Variation in yield (%)	WP (kg m^{-3})	WUE (kg m^{-3})
Control, P1	325	356.8	2737.24	-	-	1.92	0.77
P2	400	453.6	2716.45	-27.15	0.76	1.47	0.60
P3	300	333.3	2674.33	6.58	2.30	1.96	0.80
P4	175	228.5	2359.45	35.96	13.80	2.75	1.03

The WP and WUE output is advantageous for optimizing the applied irrigation. Table 7 shows WP and WUE vary from P1 to P4, i.e., WP of 1.47 to 2.75 kg m^{-3} and WUE of 0.60 to 1.03 kg.m^{-3}. The result is similar to Pawar *et al.* (2017) using cabbage, demonstrating that WP and WUE increased along with the decrease in water use.

Table 7 shows that water use decreased by 35.96%, and soybean yield decreased by 13.80%. This result suggests that decreased water use causes a decline in yield. The P4 treatment reaches maximum WP and WUE and reduces water use by 35.96% compared to P1 but reduces soybean yield by 13.80%. Thus, P1 (recommended irrigation) is rated better compared to P2 (irrigation 95-105% FC), P3 (irrigation 75-85% FC), and P4 (irrigation 55-65% FC) in terms of soybean production, while P4 (55-65% FC irrigation) is ranked better compared to P1, P2, and P3 regarding WUE. Therefore, for soybean culture under mulch and water savings, it is recommended to apply irrigation based on 55-65% FC (P4) recommendation.

Research from Fu *et al.* (2019) shows that deficit treatments in maize and soybean crops are beneficial for increasing yield and WUE. However, it is important to recognize the critical growth stages of crop water requirements. Baghel *et al.* (2018) showed that water stress at the flowering stage severely decreased all of the above parameters in soybean. Jaybhay *et al.* (2019) reported that irrigation of soybean crop at flower initiation and seed filling stages helped to obtain optimal WUE. This study proves that the AquaCrop model moderately predicts soybean growth and yield using mulch in a tropical environment.

4. Conclusions

The AquaCrop model is calibrated using a CC value and validated to predict biomass and soybean yield. This model simulates better CC, biomass, and soybean yields in full irrigation than in deficit irrigation. AquaCrop model performance for soybean variety Deja 2 is acceptable in predicting CC, biomass, and soybean yield. Model calibration using local data (meteorological, crop, environmental, and management conditions) is essential to ensure optimal model performance in simulating parameters that can be used to formulate agricultural water management policies. Among the alternative irrigation, applications developed, the P4 (irrigation 55-65%) treatments under polyethylene (LDPE) mulch fit the best compared to other treatments in terms of WUE and water savings. These results challenge subsequent experiments on a larger area in the dry or rainy seasons under tropical conditions.

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