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Effect of deficit irrigation on the growth and yield of peanuts (*Arachis hypogaea* (L.) Merr.) compared to AquaCrop model simulation

Febery Hery Suandana[1], Cahyoadi Bowo[2]*, and Sigit Soeparjono[1]

[1]Department of Agronomy, Faculty of Agriculture, Universitas Jember
Jl. Kalimantan 37, Jember, East Java, Indonesia 68121
[2]Department of Soil Science, Faculty of Agriculture, Universitas Jember
Jl. Kalimantan 37, Jember, East Java, Indonesia 68121
*Corresponding author: cahyoadi.bowo.faperta@unej.ac.id

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Abstract

The availability of irrigation water during the growing season reflects on the potential yield at the end of the peanuts' growing season. Monitoring water availability is essential to optimize production. This study aimed to identify the effect of irrigation water on peanuts (*Arachis hypogaea* (L.) Merr.) under various irrigation conditions between actual and simulated AquaCrop. The research was conducted in the experimental field utilizing four irrigation treatments which were 60%, 80%, 100% of field capacity (FC), and standard irrigation. The correlation results between the actual and simulated ones showed that the R2 value was 0.974–0.990 for the canopy cover parameter, 0.026–0.534 for ETc, and 0.542-0.554 for production. Comparison between actual and simulated AquaCrop showed Root Mean Square Error (RMSE) values of 5.08–9.74 for canopy cover parameters, 1.11–3.12 for ETc, and 0.82–1.09 for production. Welch test statistical analysis indicated values of 2.31–5.52 for plant biomass and 0.04–3.98 for dry pod yields. The AquaCrop simulation accurately predicted canopy cover at 80% irrigation treatment compared to 60%, 100%, and standard irrigation treatments. Parameter of ETc in AquaCrop simulations showed inaccurate predictions for biomass production and pod dry weight when compared with actual results on all irrigation treatments.

INTRODUCTION

Water is crucial in agricultural land management for plant growth and development. As the primary water resource, rainfall is essential to agriculture systems (Adeboye et al., 2020; Harahap, Purba and Rauf, 2021; Lyons et al., 2021). It is necessary to provide reliable weather data to build resiliency for weather forecasting abilities. The risk of reduced agricultural productivity will increase along with the unpredictable weather changes in the region (Nsabagwa et al., 2019; Lyons et al., 2021).

Peanut (*Arachis hypogaea* (L.) Merr.) has long been cultivated in Indonesia and grown commonly on dry land. Crop production indicates plant growth that reflects on previous crop management (Rahmianna et al., 2012; Nomura et al., 2022). Meteorological data, such as rainfall, temperature, wind speed and direction, and humidity, directly and indirectly, affect the regional economic growth. Varying factors implicate peanut productivity for each region and production area (Rahmianna et al., 2012; Nsabagwa et al., 2019; Mujiyo et al., 2022). Thus, understanding this meteorological information is very important as a supporting tool in formulating irrigation decisions.

AquaCrop is a valuable software used for examining the effects of irrigation at present or in the future. The AquaCrop model simulation is created in a complex process to produce information related to recommendations for appropriate cropping patterns

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based on actual environmental conditions (Allen et al., 2006; Pirmoradian and Davatgar, 2019; Chibarabada et al., 2020).

AquaCrop model simulation requires relatively few input parameters and is easy to obtain and applicable to various plants. AquaCrop can help optimize the use of nitrogen fertilizers and irrigation for soybeans (Adeboye et al., 2020; Han et al., 2020). AquaCrop has also been used to simulate cotton growth and productivity under deficit irrigation conditions and has presented good results. AquaCrop is a tool to improve grapevine irrigation management (Er-Raki et al., 2020; Aziz et al., 2022).

The AquaCrop model simulation gets ahead to simulate biomass, canopy cover, and wheat yield in winter under different irrigation treatments. AquaCrop can facilitate water management planning under various levels of availability. Through remote sensing, the AquaCrop model simulation can also be advantageous on a broader scale in the regional scope (Butler et al., 2017; Xing et al., 2017; Han et al., 2020). AquaCrop provides facilities that bridge the gap between research and practice in the field (Kelly and Foster, 2021). Different soil types will have other characteristics, so that the treatment will be further. The increasing organic C and total N content will affect changes in other soil chemical and physical properties (Kelly and Foster, 2021; Iskandar et al., 2022; Latorre and Pe, 2022).

Plant evapotranspiration is the sum of water evaporation in plants through the stomata and the soil surface by the way of soil pores due to meteorological effects. Evapotranspiration reflects a large amount of water that plants and soil evaporate. Reference evapotranspiration is the evaporation of a surface in a water-saturated state (Gebremedhin et al., 2022; Jiang et al., 2022; Liu, 2022).

Temperature is the main factor in the evapotranspiration process (Jiang et al., 2022), while vegetation is the second factor in most areas of the world. According to Nomura et al. (2022), canopy cover represents the amount of plant tissue available for photosynthesis and transpiration. Soil moisture affects the rate of evaporation and transpiration in each growing phase and each irrigation (Lyons et al., 2021).

Information about the growth and productivity of peanuts in various conditions of soil water availability has not been widely available to date. The use of lysimeters and simulations with AquaCrop in verifying peanut growth and productivity is not widely known. This study aimed to evaluate irrigation model simulations using AquaCrop software as a reference for crop water needs and irrigation management.

MATERIALS AND METHODS

Time and Location

The study was conducted in the experimental field of the Faculty of Agriculture, the University of Jember, (8009’45.1” S, 113042’58.3” E), with an altitude of ±103 m above sea level (a.s.l.). This study was divided into two steps: the preparation was conducted from July to October 2021 and the planting was from November 2021 to February 2022.

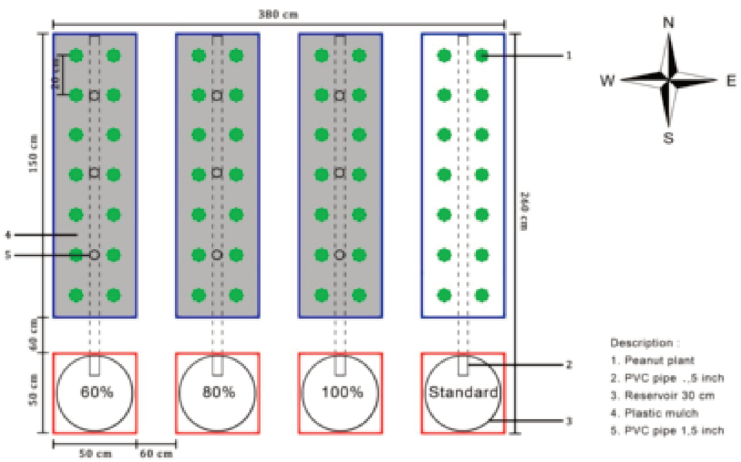

Figure 1. Experimental design layout

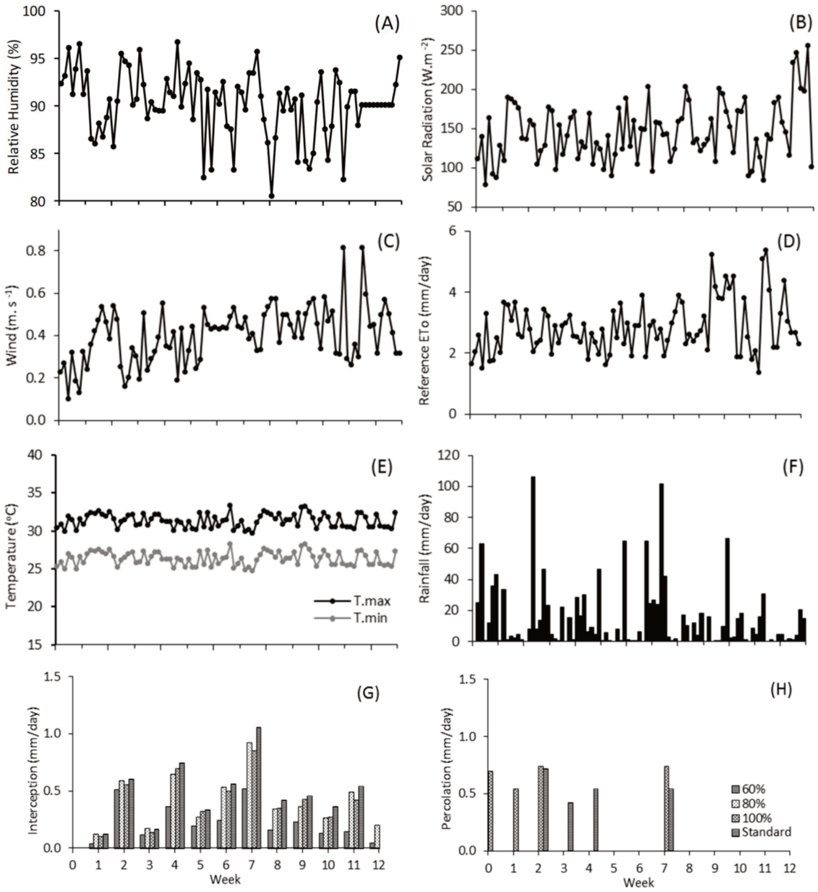

Figure 2. Meteorological data collected from AWS during the growing season

Experimental Design

This experiment used four lysimeters with 150 × 50 x 50 cm dimensions transverse from North to South (Figure 1). Each lysimeter contained 14 plants of groundnut Takar-2 variety. Each lysimeter acquired different irrigation treatments, namely 60% (±5%), 80% (±5%), 100% (±5%) of field capacity, and standard field irrigation, which farmers in Jember typically apply (Table 1). Irrigation treatment was also included in the AquaCrop model simulation to examine the differences between the actual and prediction results. The experimental parameters were canopy cover, crop evapotranspiration ETc, and the production between simulation and actual ETo.

Meteorological data

Daily rainfall during the planting period was collected using the Automatic Weather Station (AWS) on experimental land at the research site (Figure 2).

Soil Data

Data from the soil chemical and physical properties analysis are essential because it relates to the applied treatment. The soil used in the lysimeter was from the upper horizon of ±30 cm depth of Inceptisols. The soil chemical and physical properties can be referred to in Table 2.

Table 1. Irrigation treatment during the growing season.

Treatment Label	Irrigation
60%	60% FC
80%	80% FC
100%	100% FC
Standard irrigation	Standard irrigation

Remarks: Irrigation applied 14 days after planting.

Table 2. Soil Chemical and physical characteristics

Chemical	Value	Physics	Value
pH (H_2O)	7.2	Bulk Density (g/cm3)	0.82
Organic C (%)	1.87	Soil Texture	Sandy Loam
Total N (%)	0.30	Field Capacity (100%)	45.62
P_2O_5 (ppm)	19.74	Particle Density	2.42
K_2O (me/100 g)	0.45	Porosity (%)	63.38

Remarks: Results of soil chemical and physical analysis.

Canopy Cover

The canopy cover is an area or proportion of soil covered by a healthy plant crown, including leaves, branches, and stems, and is generally expressed in cm^2 or %. As the plant ages, the canopy cover increases (Walters and Sinnett, 2021). A digital camera with a distance of 1 meter from the canopy was used for the imaging process. The images were taken perpendicular to the canopy and processed using ImageJ software to determine the actual canopy cover. The capturing distance and position were valid until the next interval.

Determination of canopy cover in the AquaCrop was done by inputting meteorological data, the peanut plants, and the applied irrigation during the planting period. The Root Mean Square Error (RMSE) assessed dissimilarity between actual and simulated canopy cover.

Reference Evapotranspiration (ETo) and Crop Evapotranspiration (ETc)

Reference evapotranspiration (ETo) is the evaporation of a surface in a saturated state, while plant evapotranspiration (ETc) is the evaporation of plants under optimal growth conditions. Meteorological conditions, moisture content, and soil temperature strongly affect the plant transpiration. The Penman-Monteith method is used to calculate the ETo value, while ETc is calculated through the water balance on the lysimeter. Equation 1 and 2 shows calculations of the average daily ETo, ETc (Gebremedhin et al., 2022; Kuwagata et al., 2022; Nikolaou et al., 2022).

$$ETo = \frac{0.408\Delta\,(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma\,(1 + 0.34 u_2)} \qquad \text{...................(1)}$$

$$ETc = \left[\frac{(I + P - D + \sum_{i=1}^{n} (\theta 1 - \theta 2) \Delta Si)}{\Delta t}\right] \qquad \text{...................(2)}$$

Where R_n is the net radiation at the reference surface ($MJ.m^{-2}.day^{-1}$), G is the soil temperature ($MJ.m^{-2}.day^{-1}$), T is the daily average temperature, U_2 is the wind speed, e_s is the saturated vapor pressure, e_a is the actual vapor pressure of $e_s - e_a$ is the saturated vapor pressure deficit, Δ is the slope of the vapor pressure curve, and γ is the psychometric constant. The ETc equations *I, P,* and *D* which are irrigation, rainfall, and percolation, respectively in mm, *n* is the number of layers, *S* is the thickness of each soil layer in mm, and $\vartheta 1$ and $\vartheta 2$ are the soil water content using the volumetric method at the time of measurement. The first and second measurements are in $m^3.m^{-3}$ units. Δt is the same time, and *t* is the time interval between two consecutive measurements in days (Liu, 2022).

Biomass and Dry Yield

The actual biomass measurement was calculated at harvest by separating the pods and stems, and then weighed to estimate the wet weight and dried under sunlight for one week until dry to determine the plant's dry weight. The amount of irrigation provided got significant attention since it showed that water applied and evapotranspiration determined groundwater availability, created drought stress, and affected crop yields (Puértolas et al., 2020).

Unlike the case with actual biomass measurements, simulated biomass can be determined by entering climate data, types of plants planted, and irrigation given according to each treatment during the planting period, and later running the simulation.

Statistical Analyses

The RMSE analysis determines the model's accuracy: the smaller the RMSE value, the more accurate the prediction results. The RMSE and R^2 equation is in equation (3) and (4).

$$RMSE = \sqrt{\frac{\sum(P_i - O_i)}{n}} \qquad \text{....................................(3)}$$

$$R^2 = \left[\frac{\sum(O_i - \bar{O}) - (P_i - \bar{P})}{(O_i - \bar{O}) \times \sum(P_i - \bar{P})}\right] \qquad \text{....................................(4)}$$

with P_i, O_i, n, $\bar{O}$, and P are the simulation data, the observed data, the number of measurements made, the observed data, and the average of simulation data, respectively. It shows the dissimilarity of the plant canopy cover between the actual and the simulation data.

The Welch's test calculates the average equality of two data groups under various data variances (Brown and Knowles, 2021). The Welch test was used to test the equality of the population mean from different data groups (Karagöz, 2016). The data groups in question were the actual and simulated data groups on plant biomass and dry pod yields. The variance between biomass parameters and the pod's dry weight between the actual and the prediction is calculated in Equation (5).

$$t_w = \frac{\bar{y}1 - \bar{y}2}{\sqrt{S1^2/n1 + S2^2/n2}} \qquad \text{...................(5)}$$

RESULTS AND DISCUSSION

Canopy Cover

The irrigation treatment affected both simulated and actual canopy cover, as depicted in Figure 3. The simulated canopy cover in 60% of irrigation was below the prediction compared to the actual canopy cover at 0–6 weeks but higher than the actual at 7–12 weeks. The simulated canopy cover at 80% of FC was likely similar to the actual one at 0–7 weeks, even higher after 8–12 weeks. Meanwhile, the simulated canopy cover at 100% and the standard irrigation were lower than the actual one for most of the planting age.

The canopy cover dynamics were susceptible to water content and soil moisture (Lyons et al., 2021). Atmospheric conditions influenced transpiration as a significant physiological phenomenon in plants (Kuwagata et al., 2022). The highest RMSE value was in standard irrigation, which was 9.74, while the lowest RMSE value was in 80% FC, which was 5.08. AquaCrop accurately predicted canopy cover at 80% FC but was low at 100% FC.

The coefficient of determination (R2) expresed the relationship between the actual and simulated values. The category of value was very good if > 0.91, was quite good if 0.81 – 0.90, was good if 0.66 – 0.80 and was not good if 0.50 – 0.65 (Man et al., 2019). The highest R2 value of 0.990 was found in 80% FC, while the lowest R2 value of 0.974 was at 60% FC. This result showed that AquaCrop was very good in predicting the canopy cover if the applied irrigation was sufficient (80% FC), but decreased as the irrigation was less (60% FC) or excess (100% FC) and standard irrigation.

These results were also similar to related studies (Giménez et al., 2017; Chibarabada et al., 2020),

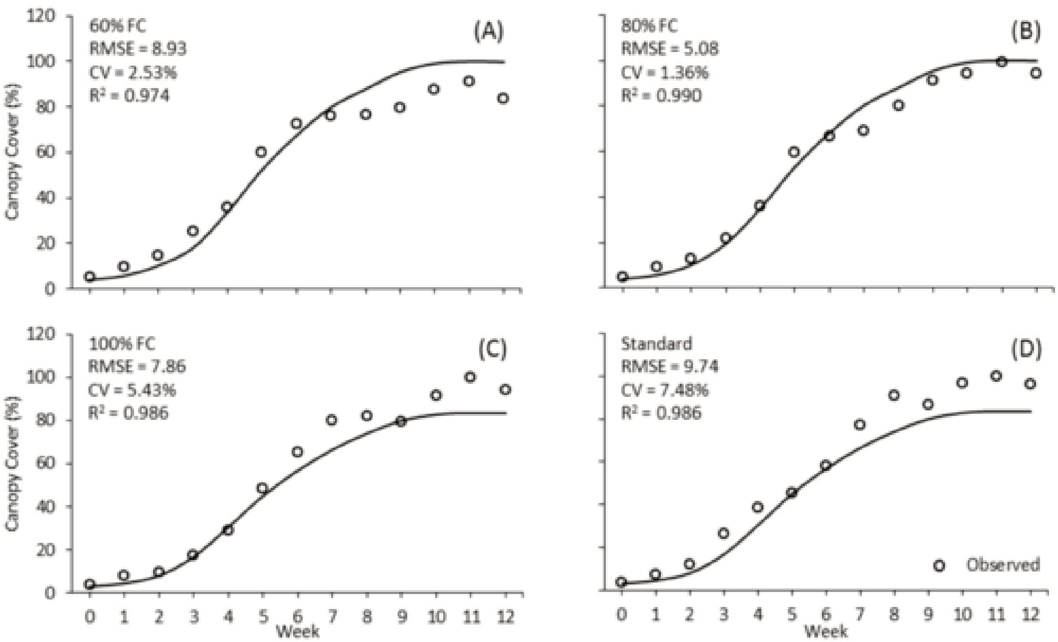

Figure 3. Observed and predicted canopy cover for all irrigation treatments.

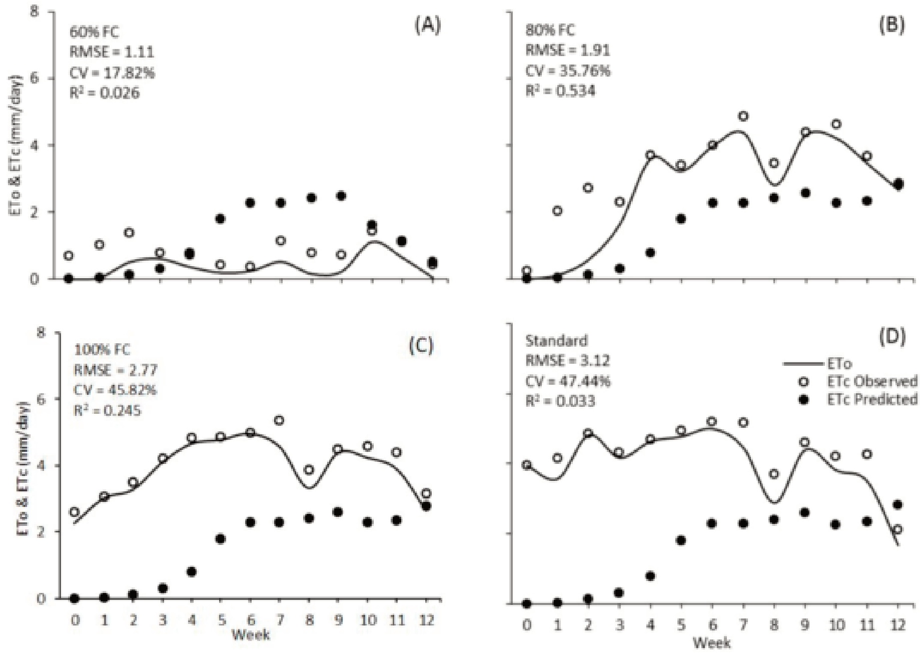

Figure 4. Observed ETo and ETc for all treatments during growing season.

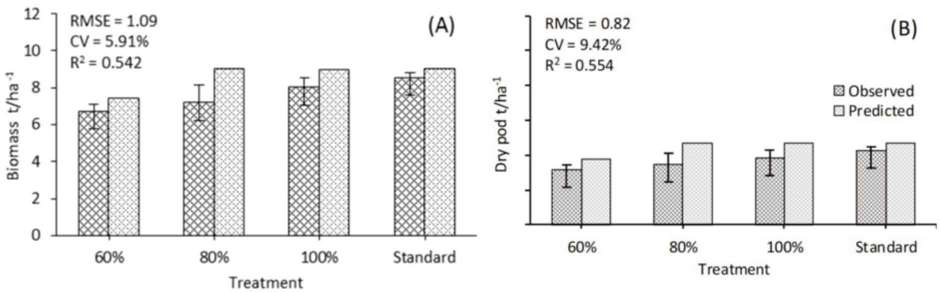

Figure 5. Biomass and dry pod between observation and prediction (N=14 samples) (A) Plant biomass; (B) Dry pod.

which showed that AquaCrop could predict the growth of the canopy of peanut plants (*Arachis hypogaea* (L.) Merr.) well on deficit irrigation and full irrigation in the South African region. AquaCrop also showed promising results in predicting the growth of soybean canopy in drought stress by giving almost the exact yield as the actual ones.

Reference Evapotranspiration (ETo) and Crop Evapotranspiration (ETc)

Figure 4 demonstrates that each treatment of Eto and ETc were different and permanently changed along with plant growth. Also, the irrigation treatment affected ETc and ETo, both simulated and actual. The simulated ETc on 60% irrigation treatment was lower than the actual ETc at 0–3 weeks but higher at 5–10 weeks. The simulated ETc on irrigation treatment was 80% and 100%, and the standard irrigation was lower than the actual ETc throughout the planting age.

The highest R2 value was in 80% of FC, which was 0.534. At the same time, the lowest R2 value was at 60% FC, namely 0.026, with the lowest RMSE value being 1.11 while the highest one was 3.12. The smaller the RMSE value, the more accurate the prediction result will be (Man et al., 2019). This result showed that the simulations could accurately predict the actual ETc compared to the other three irrigation treatments at 60%.

Peanut evapotranspiration during the growth phase experienced an inconsistent increase and decrease, while other studies carried out by Silva et al. (2018); Souza et al. (2020) showed different results, where evapotranspiration experienced a consistent increase along with plant growth. The difference in average air temperatures, as well as different amounts and conditions of vegetation, was the source of the inconsistency. This statement was supported by Gebremedhin et al. (2022); Jiang et al.

(2022), which conveyed that temperature was the main factor in the evapotranspiration process, while vegetation was the second factor in most regions of the world. In addition to temperature and vegetation, soil moisture also affected evapotranspiration. This statement corresponded to the result of Lyons et al. (2021) and Kuwagata et al. (2022), which conveyed that the rate of evaporation and transpiration in each growth phase and irrigation treatment could be different because it was affected by soil moisture.

Biomass and Dry Yield

Figure 5A presents the results of the actual and simulated biomass calculations. Figure 5A shows that the irrigation treatment given affected plant biomass. The higher the irrigation given, the higher the plant biomass produced.

The 60% FC irrigation treatment presented the lowest biomass compared to other treatments. In comparison, the 100% FC irrigation treatment and standard irrigation, which the farmers in Jember generally apply, showed the highest actual and simulated biomass. The actual and simulated biomass at 60% FC was 6.76 and 7.43 tons/ha; at 100% FC, it was 8.08 and 9 tons/hectare, while in standard irrigation, it was 8.57 and 9.03 tons/hectare, respectively. Figure 5A also shows that the actual biomass was lower than the simulated biomass; this explained that the AquaCrop simulation presented a prediction that was (over-predicted) compared to the real (Butler et al., 2017).

The prediction that was too high was the most evident in the irrigation treatment of 80% of the field capacity with the difference between the actual and the simulated values of 1.79 tons/hectare. On the other hand, almost the exact prediction shown in the standard irrigation treatment was under the difference between the actual and the simulated being only 0.46 ton/hectare. This result showed that the standard irrigation treatment used by farmers in Jember, the AquaCrop simulation, could predict the actual biomass, which was inclined to be more accurate when compared to other treatments, 60% FC to 100% FC.

Figure 5B compares dry pod yield in each lysimeter, both actual and simulation. Figure 5B shows that the irrigation treatment also affected the pods' dry yield. Sufficient irrigation provided a higher dry pod product (Wasko et al., 2022). The 60% FC irrigation treatment gave the lowest dry yield of pods compared to other treatments. The 100% FC and standard irrigation treatments gave the highest pod dry gains compared to actual and simulated treatments.

The actual and simulated pod dry yields at 60% FC were 3.17 and 3.76 tonnes.ha^{-1}, at 80% FC was 3.48 and 4.69 tonnes.ha^{-1} and 100% FC were 3.86 and 4. 68 tonnes.ha^{-1}, while the standard irrigation was 4.24 and 4.69 tonnes.ha^{-1}. The actual dry pod yield which tended to be lower than the simulated pod dry yield explained that the AquaCrop simulation provided too high (over predicted) predictions compared to the actual results. The most significant over-predicted was obtained in 80% FC with a difference of 1.21 tonnes.ha^{-1}. Meanwhile, the higher prediction accuracy was shown in standard irrigation, with a difference of 0.45 tonnes.ha^{-1}.

The results of the Welch tests in Table 3 show that in the treatment plant biomass of 60%, 80%, 100%, and standard irrigation, the actual plant biomass differed from the average simulated plant biomass. Meanwhile, the dry yield of 60% and 100% of treatment pods and standard irrigation did not differ from the average dry yield of simulated pods. This experiment showed a difference between the actual and the

Table 3. Welch tests of biomass and dry yield between observation and prediction.

Observation Variable	Treatment	P – Value > < α (0.05)	Interpretation
Biomass	60% FC	5.52 >	Different
	80% FC	3.74 >	Different
	100% FC	2.31 >	Different
	Standard	3.83 >	Different
Dry Yield	60% FC	0.04 <	No different
	80% FC	3.98 >	Different
	100% FC	0.09 >	Different
	Standard	0.04 <	No different

Remarks: Welch test's result for the variation of two sample groups with different populations.

AquaCrop simulation, while the dry pod yield was not different.

The simulated biomass was higher than the actual biomass in 60% irrigation. This difference was in contrast to the research conducted by other researchers (Paredes et al., 2015; Chibarabada et al., 2020), which showed that in 60% irrigation, the simulated biomass presented the same results as actual biomass.

Furthermore, further experiments (Pirmoradian and Davatgar, 2019; Kelly and Foster, 2021) showed that simulated biomass was too high or too low from actual biomass, indicating that AquaCrop exceeded predictions in conducting simulations. Nonetheless, the dry yield of simulated and actual pods on irrigation of 60% gave the same results as the study conducted by (Khov et al., 2017; Chibarabada et al., 2020), although in this case, the dry yield of simulated pods tended to be higher than the dry yield of actual pods.

CONCLUSIONS

The simulation of the AquaCrop model was entirely accurate in predicting the canopy cover of peanut plants if sufficient irrigation was provided (80% FC). However, the accuracy would decrease if the irrigation was less (60% FC) or excess (100% FC and standard irrigation). Meanwhile, on the parameters of ETc and production (biomass and dry weight of pods), the AquaCrop simulation showed inaccurate predictions compared to the actual output in all irrigation treatments. The high rainfall during the rainy season was challenging in this research. We recommend the following experiment during the dry season to compare this study's results.

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