

Article

Simulating Water Use and Yield for Full and Deficit Flood-Irrigated Cotton in Arizona, USA

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Abstract

Improved irrigation guidelines are needed to maximize crop water use efficiency. Combining field data with simulation models can provide information for better irrigation management. The objective of the present study was to evaluate the effects of two flood irrigation treatments on fiber yield (FY) and quality during the 2023 and 2024 growing seasons in Maricopa, Arizona, USA. Two irrigation treatments, denoted as F100% and F80%, were arranged in a randomized complete block design with three replicates. Then, AquaCrop was used to simulate cotton yield (Y_{Tot}), water use (ET_{obs}), and total soil water content (WC_{Tot}) for the two irrigation treatments. Six statistical metrics, including the coefficient of determination (R^2), the normalized root-mean-square error (NRMSE), the mean absolute error (MAE), simulation error (S_e), the index of agreement (D_{index}), and the Nash–Sutcliffe efficiency coefficient (NSE), were employed to assess model performance. The results of the field trial demonstrated that reducing the irrigation rate to 80% of ET_c negatively impacted cotton FY and ET water productivity (ETWP); the FY declined by 45.2% ($ETWP = 0.097 \text{ kg} \cdot \text{ha}^{-1}$) in 2023 and by 38.1% ($ETWP = 0.133 \text{ kg} \cdot \text{ha}^{-1}$) in 2024. Conversely, F100% produced a more uniform and stronger fiber than F80%, with the uniformity index (UI) and fiber strength (STR) measuring 81.7% and 29.5 g tex^{-1} in 2023 and 82.2% and 30.0 g tex^{-1} in 2024, indicating that UI and STR were well correlated with soil water during both growing seasons. AquaCrop showed an excellent performance in simulating cotton CC during the two growing seasons. The R^2 , NRMSE, D_{index} , and NSE were between 0.97 and 0.99, 8.45% and 14.36%, 0.98 and 0.99, and 0.96 and 0.98, respectively. Moreover, the AquaCrop model accurately simulated Y_{Tot} during these seasons, with R^2 , NRMSE, D_{index} , and NSE for pooled yield data of 0.93, 8.05%, 0.95, and 0.78, respectively. The model consistently overestimated Y_{Tot} , ET_{obs} , and WC_{Tot} , but within an acceptable S_e ($S_e < 15\%$) during both growing seasons, except for WC_{Tot} under the 80% treatment in 2023 ($S_e = 26.4\%$). Consequently, AquaCrop can be considered an effective tool for irrigation management and yield prediction in arid climates such as Arizona.



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Keywords: AquaCrop; arid climate; cotton (*Gossypium hirsutum* L.); water use; total soil water content

1. Introduction

Cotton (*Gossypium hirsutum* L.) represents a crucial economic crop cultivated primarily in subtropical and dry tropical regions [1] across more than 90 countries worldwide [2]. It serves as a common fiber crop, providing essential raw materials for the textiles industry [3]. In the USA, the third-largest cotton producer globally, about 40% of cotton is grown under irrigated conditions. It is considered a major summer crop within the Arizona low desert, contributing notably to economic revenue and employment within the agricultural sector. The Arizona cultivated area was estimated to be 44,515 ha in 2024, with an annual production value approximating \$32 million for both Pima and upland cotton [4]. Cotton is commonly cultivated on raised beds with flood irrigation [5], mainly due to the existing infrastructure for conveying irrigation water from the Colorado River to farmers through irrigation canals.

Like many arid regions around the world, agroecosystems in Arizona are vulnerable to water stress. Water limitations in Arizona are due to the ongoing drought in the Colorado River basin, depletion of groundwater storage and reservoir water supplies, and increased distribution of water for industrial and municipal needs [6–10]. Reduced water allocations are now mandated for most of the water districts in Arizona due to the severe drought in the southwestern U.S., which imposes substantial challenges for cotton producers in the state. Moreover, climate change, which is projected to substantially impact cotton production in central Arizona [11], accelerates the risk of water scarcity [12].

To date, many irrigation strategies and technologies have been proposed to enhance irrigation management and promote the efficient use of water resources [13,14]. The application of deficit irrigation strategies at certain crop growth stages with low sensitivity to water stress can improve on-farm management practices by reducing irrigation water use, decreasing evaporation losses, minimizing energy consumption, and increasing economic returns from investment in irrigation water supplies [15–17]. Crop growth simulation models such as CWUModel, HYDRUS (2D/3D), SALTMED, DSSAT, SWAP/WOFOST, APSIM, CropSyst, DAISY, and HERMES [18–22], the ORYZA 2000 model [23], and the STIRPAT model [24] have been demonstrated as powerful tools to provide a scientific irrigation scheduling for agricultural water [14]. These models can help to simulate crop growth under various conditions for optimizing irrigation. Moreover, crop models can assess the impact of water stress on crop yields. However, the majority of these models require highly detailed, accurate input data and advanced modeling skills for their calibration and simulation [25]. AquaCrop, a water-driven model, was developed by the Food and Agriculture Organization (FAO) to simulate crop growth as a function of weather and irrigation. In comparison with most other models, it has a relatively limited number of input parameters, achieving a balance between output accuracy and simplicity.

Many studies have evaluated AquaCrop in simulating crop development and yield for many crops such as wheat [26,27], maize [28], soybean [29], rice [15,30,31], sunflower [32], pea [33], and potato [34]. Meanwhile, several studies have evaluated the model's performance for cotton. For instance, Farahani et al. [35] parameterized and assessed the model for cotton under full and deficit irrigation with a drip system in north Syria. García-Vila et al. [36] simulated cotton yield response to irrigation water with a drip system in southern Spain. They then obtained optimum applied irrigation using an economic optimization procedure. Voloudakis et al. [37] evaluated the performance of AquaCrop in predicting

cotton yield response to climate change in seven areas of Greece under drip irrigation conditions. Tsakmakis et al. [38] evaluated AquaCrop simulations of cotton growth under deficit irrigation with sprinkler and drip-line systems. Thorp [39] compared three computer simulation models for cotton irrigation scheduling, including AquaCrop-OSPy, under an overhead lateral-move sprinkler irrigation system with advanced geospatial technologies for site-specific irrigation applications within the georeferenced plot boundaries at Maricopa, Arizona. Considering that none of the previous studies have assessed the model under full and deficit flood irrigation or even under arid climate conditions in Arizona, the aims of the current study were as follows: (1) evaluate the effect of two flood irrigation treatments on fiber yield and quality and (2) simulate cotton yield, water use, and total soil water content under full and deficit flood irrigation for two growing seasons in central Arizona, USA.

2. Materials and Methods

2.1. Area of the Study

The field experiments were conducted during the 2023 and 2024 cotton-growing seasons at the Maricopa Agricultural Center (MAC), the University of Arizona, USA (33.07° N lat; 111.97° W long; 362 m a.s.l.), as shown in Figure 1. The experimental site has arid climate conditions: a hot summer, with daily observed maximum, minimum, and average air temperatures exceeding 46 °C, 32 °C, and 37 °C, respectively, during the growing season in July [40]. Two irrigation treatments based on furrow flood irrigation (F), denoted as F100% and F80%, respectively, were randomly distributed in a randomized complete block design (RCBD) with three replicates (R). Cotton was planted on April 13 and April 23 in 2023 and 2024, respectively. At the beginning of November, cotton was machine-harvested using a four-row mobile cotton picker, which collects the cotton harvest data quickly, easily, and accurately with one-button operation (<https://www.system-scale.com/products/agriculture-scales>, Last accessed on 4 April 2025). Yield samples were collected from each plot, bagged, and weighed separately. Then, a 150 g yield sample from each plot was bagged and transferred to the Maricopa ginning facility to separate cottonseed, fiber, and trash. After ginning, 10 g of cotton fiber was collected from each plot and sent to Cotton Incorporated (Cary, NC, USA) for fiber quality analysis. Four evaluation indices, including micronaire (MIC, unitless), uniformity index (UI, mm mm⁻¹), upper half mean length (UHML, mm), and fiber strength (STR, HVI g tex⁻¹), were used to assess fiber quality.

The general systematic framework adopted for the current study is summarized in Figure 2.

2.2. Soil Water and Irrigation Monitoring

Over the two growing seasons, soil water and irrigation were monitored weekly using a calibrated neutron probe (503 ELITE Hydroprobe), a subsurface measurement device designed to measure soil moisture and aid in irrigation scheduling (<https://www.instron.com/products/503-elite-hydroprobe>, Last accessed on 25 March 2025). In May 2023 and 2024, a 2.10 m-long, 51 mm diameter galvanized steel access tube was installed in the middle of each plot, sufficient to disclose any deep percolation (Figure 3).

During the installation of the access tubes, soil samples were collected from each plot (0.0–1.8 m below the soil surface, every 0.3 m) for soil chemical and physical properties as summarized in Table 1.



Figure 1. Geographic location of the study area.

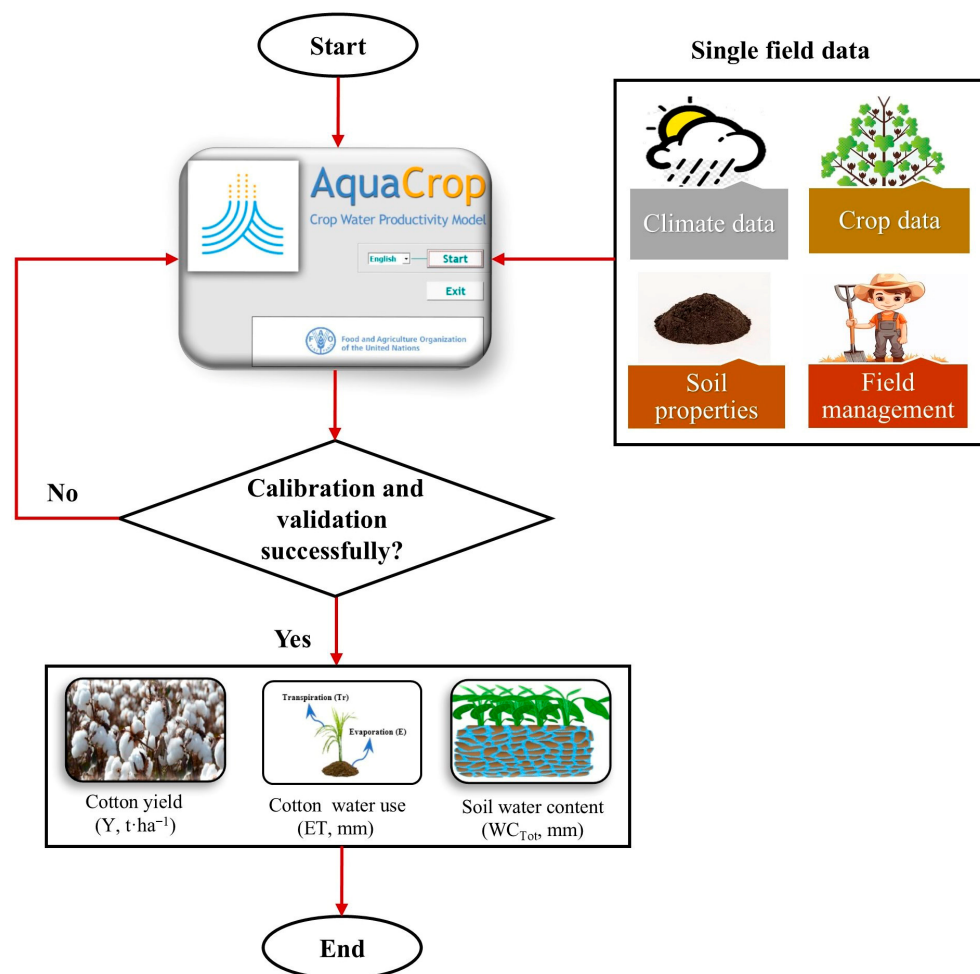


Figure 2. General systematic framework adopted for the current study.

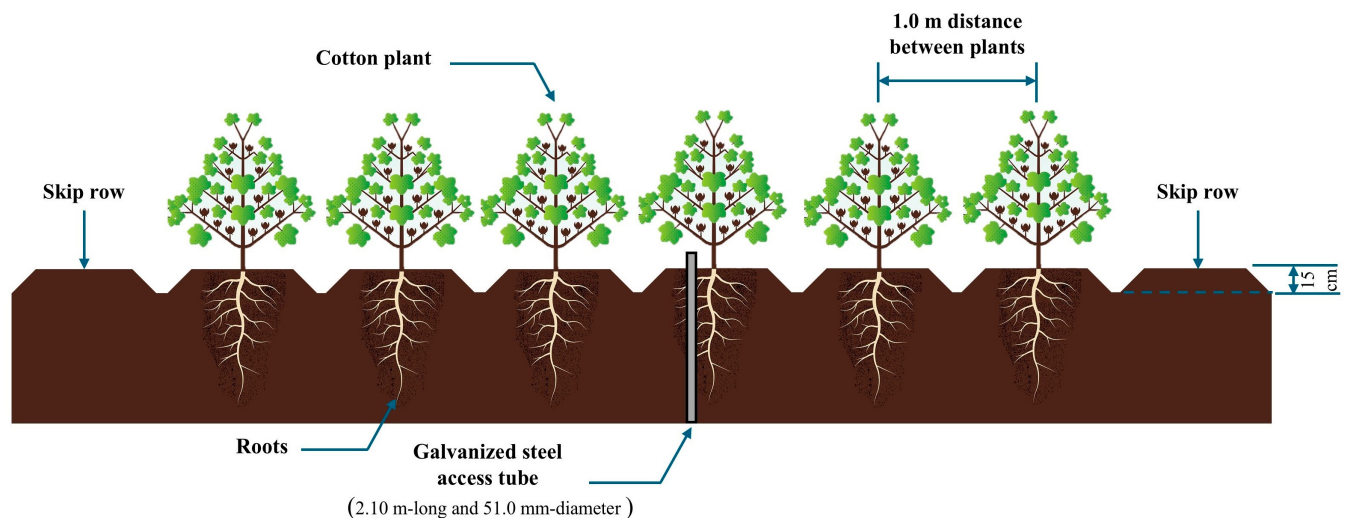


Figure 3. Experimental plot set up.

Table 1. Soil properties of the experimental field.

Profile Depth, m	Soil pH	Soluble Salts, mmho/cm	OC, %	FC, %	PWP, %	Soil Texture			
						S, %	Si, %	C, %	Texture Class
0.0–0.3	8.3	0.14	0.31	28.80	14.00	53	17	30	Sandy clay loam
0.3–0.6	8.5	0.17	0.20	29.90	14.60	51	17	32	Sandy clay loam
0.6–0.9	8.3	0.44	0.43	33.20	16.80	39	23	38	Clay loam
0.9–1.2	8.1	0.61	0.66	34.60	18.00	35	23	42	Clay
1.2–1.5	8.1	0.56	0.09	32.10	16.00	43	21	36	Clay loam
1.5–1.8	8.1	0.39	0.05	26.90	13.10	55	17	28	Sandy clay loam

Notes—OC: organic carbon, FC: field capacity, PWP: permanent wilting point, S: sand, Si: silt, and C: clay.

The neutron probe data were collected for each 0.3 m layer of the soil profile to a depth of 1.8 m. For F100% (full irrigation), cotton was flood-irrigated when the average fraction (p) of total available soil water (TAW) reached 65%, refilling the soil root zone to the field capacity (FC). For the deficit irrigation treatment (F80%), irrigation occurred on the same day as F100%, but the duration of irrigation application was reduced to 80% of F100%. This approach maintains comparable phenological timing and avoids confounding differences in irrigation frequency across treatments. It also reflects on-farm practice, where growers commonly reduce application depth (or set time) rather than running entirely independent schedules for each management unit. The last irrigation application was by mid- and late August, with 17 and 14 total irrigation events in 2023 and 2024, respectively.

2.3. Cotton Water Use

At the beginning of the cotton season, crop evapotranspiration (ET_c) was estimated for the first 4–5 weeks of crop establishment using the FAO56 dual crop coefficient procedures that separate K_c into soil evaporation and plant transpiration (basal) coefficients [41]:

$$ET_{c,i} = ET_{o,i} (K_{cb,i} + K_{e,i}) \quad (1)$$

where $ET_{c,i}$ is crop evapotranspiration on day i (mm), $K_{cb,i}$ and $K_{e,i}$ are the basal crop coefficient and soil evaporation coefficient on day i , respectively (unitless), and $ET_{o,i}$ is the grass reference crop evapotranspiration calculated using the FAO56 standardized Penman-Monteith equation on day i (mm).

The daily meteorological data, such as maximum, minimum, mean air temperature, and effective precipitation ($T_{\max}$, $T_{\min}$, T_{ave} , and P_r , respectively), were collected from the Arizona Meteorological Network (AZMET, Maricopa, AZ, <https://cals.arizona.edu/AZMET/06.htm>, Last accessed on 25 May 2025), about 20 m from the experimental field. ET_o was computed using the Penman-Monteith equation [41], as follows (Figure 4):

$$ET_o = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)} \quad (2)$$

where ET_o is the reference evapotranspiration (mm day^{-1}), R_n is the net radiation at the crop surface ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$), G is the soil heat flux density ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$), T is the mean daily air temperature at 2 m height ($^{\circ}\text{C}$), u_2 is the wind speed at 2 m height ($\text{m} \cdot \text{s}^{-1}$), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), $e_s - e_a$ is the saturation vapor pressure deficit (kPa), Δ is the slope vapor pressure curve ($\text{kPa} \cdot ^{\circ}\text{C}^{-1}$), and γ is the psychrometric constant ($\text{kPa} \cdot ^{\circ}\text{C}^{-1}$).

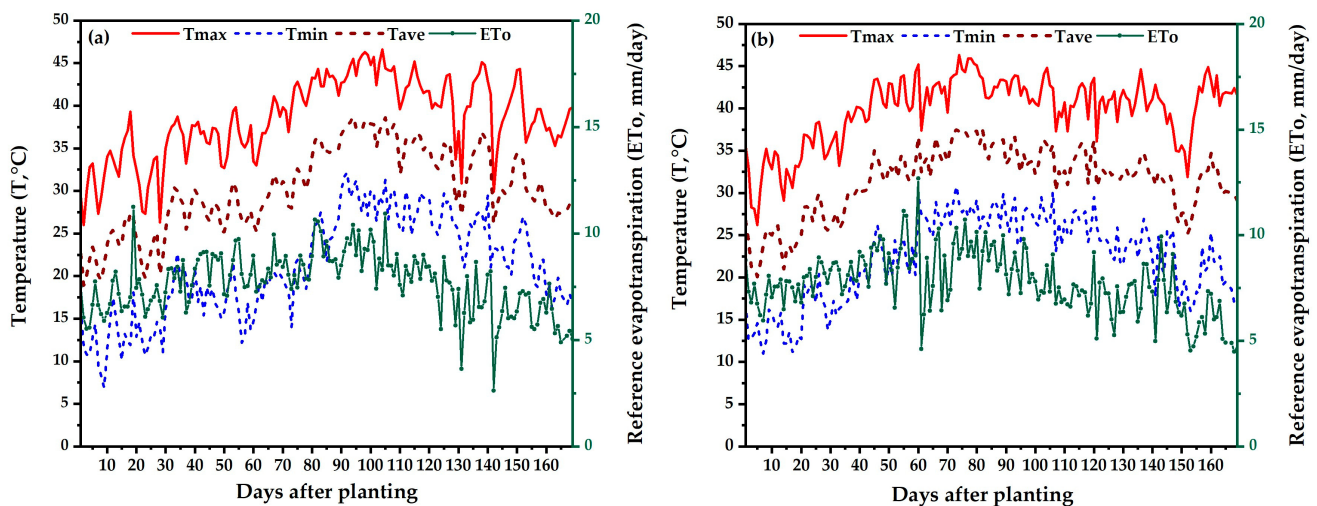


Figure 4. Daily maximum, minimum, average temperature, and reference evapotranspiration patterns ($T_{\max}$, $T_{\min}$, T_{ave} , ET_o) during the cotton growing seasons of 2023 (a) and 2024 (b).

In May 2023 and 2024, observed cotton evapotranspiration (ET_{obs}) was estimated using the soil water balance method, as follows [41]:

$$ET_{\text{obs}} = I + P_r - Cr - Dp + R_{\text{off}} + \Delta\text{SWS} \quad (3)$$

where I , P_r , Cr , DP_i , and R_{off} are irrigation, precipitation, capillary rise, deep percolation, and runoff, respectively. ΔSWS is the average change in soil water storage (all units in mm).

P_r was collected from the AZMET weather station, 20 m from the experimental field. The CR was assumed as zero because of the deep groundwater table in Pinal County (<https://www.azwater.gov/hydrology/depth-water-data>, Last accessed on 25 May 2024). The DP was assumed to be zero because the measured soil water storage within the root zone did not exceed FC storage during the growing seasons. R_{off} was negligible because of basin bunds (blocked furrows) and controlled irrigation during the two seasons. ΔSWS was determined weekly using a calibrated neutron probe (503 ELITE Hydroprobe).

ET water productivity ($ETWP$, kg m^3) was estimated as follows:

$$ETWP = \frac{FY}{W_{ET}} \quad (4)$$

where FY is cotton fiber yield (kg ha^{-1}) and W_{ET} is the water evapotranspired in $\text{m}^3 \text{ha}^{-1}$ during the growing season.

2.4. AquaCrop: Theory and Description

The AquaCrop model follows the Doorenbos and Kassam concept of “yield response to water” that was presented in FAO Irrigation and Drainage Paper No. 33 [42].

$$\left(1 - \frac{Y_{act}}{Y_{max}}\right) = k_y \left(1 - \frac{ET_{act}}{ET_{max}}\right) \quad (5)$$

where Y_{act} and Y_{max} are the actual and maximum yield, and ET_{act} and ET_{max} are the actual and maximum evapotranspiration, respectively. K_y is a factor that represents the proportion between the relative reductions in both yield and evapotranspiration.

The final crop yield (Y , $\text{t} \cdot \text{ha}^{-1}$) in AquaCrop is determined as follows [43]:

$$Y = B * HI_o * F_{HI} \quad (6)$$

where B and HI_o are the cumulative dry biomass ($\text{t} \cdot \text{ha}^{-1}$) and reference harvest index, respectively. F_{HI} is the adjustment factor of the reference harvest index due to stress.

AquaCrop can execute the simulations in two modes: (1) calendar days (CDay) and (2) growing degree-days (GDDay). In the current study, the GDDay mode was used to execute simulations, where canopy development was adjusted to the temperature regime of distinctive years.

2.5. Model Calibration and Validation

The AquaCrop model was calibrated using the 2023 experimental data, while the validation was conducted using the 2024 data. The default values of the non-conservative cotton parameters were used initially and then adjusted during the model calibration process (Table 2).

For crop response to stress parameters, the sensitivity to water stress was considered by setting the lower and upper thresholds of canopy expansion ($p_{exp, lower}$ and $p_{exp, upper}$), the upper threshold of stomatal closure ($p_{sto, upper}$), and early canopy senescence ($p_{sen, upper}$). Similarly, sensitivity to temperature stress was considered by setting the base (T_{base}) and upper temperature (T_{upper}), and then the calibration was performed. The thresholds of response to water and temperature stresses are shown in Table 2.

Before model calibration, crop development parameters from day 1 after planting to: emergence, maximum canopy cover (CC_x), flowering, senescence, maturity, and duration of flowering were estimated based on field observations (Table 2).

Cotton canopy cover curves, including the initial and maximum canopy cover (CC_o and CC_x), were estimated following the approach of Elshikha et al. [44]. Normalized water productivity (WP^*) and H_o were calibrated until a good match between the observed and simulated Y was achieved.

The trial-and-error approach was used to minimize the differences between the simulated and observed data, whereas a specific input parameter was selected as a reference variable. Then, only those parameters that most affected the reference variable were adjusted. Finally, these steps were frequently repeated until the closest match between simulated and observed data was found.

Table 2. AquaCrop-calibrated cotton parameters.

Crop Parameter	Default Value	Calibrated Value		Unit
		F100%	F80%	
Initial canopy cover (CC ₀)	0.72	0.54	0.54	
Maximum canopy cover (CC _x)	98.0	84.0	78.0	%
Minimum rooting length (Z _x)	0.30	0.30	0.30	m
Maximum rooting length (Z _n)	2.00	1.60	1.70	m
Day 1 after sowing to:				
Emergence	12	59	68	GDDay
Maximum canopy cover (CC _x),	1156	1169	1056	GDDay
Flowering	502	719	654	GDDay
Canopy senescence	1601	1948	1724	GDDay
Maturity	1956	2162	1991	GDDay
Duration of flowering	709	905	798	GDDay
Maximum standard crop transpiration coefficient (K _{C_{Tr,x}})	1.10	1.10	1.10	Unitless
Normalized water productivity (WP*)	15.0	15.0	15.0	g·m ^{−2}
Reference harvest index (HI ₀)	35.0	33.0	31.0	%
Response to water stress				
Lower threshold of canopy expansion (p _{exp, lower})	0.70	0.70	0.60	Unitless
Upper threshold of canopy expansion (p _{exp, upper})	0.20	0.20	0.25	Unitless
Upper threshold of stomatal closure (p _{sto, upper})	0.75	0.75	0.65	Unitless
Upper threshold of early canopy senescence (p _{sen, upper})	0.75	0.75	0.65	Unitless
Threshold temperatures for crop development				
Base temperature (T _{base})	12	12.7	12.7	°C
Upper temperature (T _{upper})	35	30.0	30.0	°C

Notes: F100%: flood 100%; F80%: flood 80%. The upper threshold for leaf expansion (p_{exp, upper}) is the fraction (p) of total available soil water (TAW) that can be depleted before leaf expansion starts to be limited, while the lower threshold for leaf expansion (p_{exp, lower}) is the p of TAW at which leaf expansion is fully stopped. Between the upper and lower thresholds, the model reduces expansion. The upper threshold for stomatal inhibition (p_{sto, upper}) is the p of TAW at which the crop first starts to close its stomata in response to soil water depletion. The upper threshold of early senescence (p_{sen, upper}) is the p of TAW that can be depleted before canopy senescence is triggered.

2.6. Evaluation Metrics

Six statistical metrics, namely, the coefficient of determination (R²), the normalized root-mean-squared error (NRMSE), the mean absolute error (MAE), simulation error (S_e), the index of agreement (D_{index}), and the Nash–Sutcliffe efficiency coefficient (NSE) were used to assess AquaCrop performance.

$$R^2 = \left[\frac{\sum_{i=1}^n (Obs_i - Obs^-) (Sim_i - Sim^-)}{\sqrt{\sum_{i=1}^n (Obs_i - Obs^-)^2} \sqrt{\sum_{i=1}^n (Sim_i - Sim^-)^2}} \right]^2 \quad (7)$$

$$NRMSE = \frac{100}{Obs^-} \sqrt{\frac{\sum_{i=1}^n (Sim_i - Obs_i)^2}{n}} \quad (8)$$

$$MAE = \frac{\sum_{i=1}^n |Sim_i - Obs_i|}{n} \quad (9)$$

$$S_e = \frac{Sim_i - Obs_i}{Obs_i} \times 100\% \quad (10)$$

$$D_{index} = 1 - \frac{\sum_{i=1}^n (Obs_i - Sim_i)^2}{\sum_{i=1}^n (|Sim_i - Obs^-| + |Obs_i - Obs^-|)^2} \quad (11)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (Obs_i - Sim_i)^2}{\sum_{i=1}^n (Sim_i - Sim^-)^2} \quad (12)$$

where Obs_i is the observed value, Sim_i is the simulated value, and n is the number of values. Obs^- and Sim^- are the means of observed and simulated values, respectively. The R^2 close to 1.0 indicates a good match between the simulated and observed datasets. The $NRMSE$ value ranges between 0 and ∞ . The simulation is excellent if the estimation results of $NRMSE < 10\%$ and good if the result ranges between 10 and 20%. A result from 20 to 30% indicates fair performance, while $NRMSE > 30\%$ indicates poor performance [45]. The MAE reflects the difference between the mean absolute value of the Sim and the Obs value. The lower the MAE value, the greater the simulation accuracy. The S_e between ± 15 is acceptable [46]. The R^2 values reflect the strength of the simulated datasets. The D_{index} values vary between 0.0 and 1.0. The $D_{index} = 1.0$ reflects perfect agreement among the simulated and observed datasets.

3. Results and Discussion

3.1. Results of the In-Field Experiments

3.1.1. Yield-Water Relation

The results, including the fiber yield (FY, $\text{kg} \cdot \text{ha}^{-1}$), ET_{obs} (mm), and $ETWP$ ($\text{kg} \cdot \text{m}^{-3}$) during 2023 and 2024, are listed in Table 3. Cotton yields responded consistently to irrigation treatments during the two growing seasons, whereas the highest fiber yields were recorded under the F100% ($1694 \text{ kg} \cdot \text{ha}^{-1}$ and $1456 \text{ kg} \cdot \text{ha}^{-1}$). However, decreasing the irrigation rate to 80% of ET_c negatively affected cotton yield, and the FY declined by 45.2% ($798 \text{ kg} \cdot \text{ha}^{-1}$) and 38.1% ($1049 \text{ kg} \cdot \text{ha}^{-1}$) during 2023 and 2024, respectively (Table 3). A continuous water supply enhances the water absorption capacity of cotton roots, mitigates periodic stress, alleviates soil water stress caused by drought, and reduces yield losses due to root degradation [47]. In contrast, water stress reduces plant growth and development due to reduced turgor pressure [48], crucial for cell elongation. Moreover, it decreases node production [49,50]. Both vegetative and reproductive growth are inhibited under water stress, resulting in fewer fruiting sites and thus, accelerating maturation and lowering yields [51]. The yield reductions for water-stressed cotton were in the same range of 7.23–49.4%, as reported under moderate water stress by Cetin et al. [52] and Hu et al. [53]. Moreover, the results aligned with previous studies, which reported that plots receiving more irrigation water had higher yields than those under medium and low irrigation amounts [53–55].

Compared to F100%, there was a notable reduction in ET_{obs} of 14.3% and 14.0% under the F80% treatments during 2023 and 2024, respectively. This resulted from soil evaporation (E_s) reduction due to the drying soil surface, accompanied by a decrease in transpiration (T). As a C3 crop, cotton exposed to water stress tends to close its stomata to preserve the inner moisture content, reducing ET_{obs} .

Despite the elevated temperatures during 2024 compared to 2023, the cotton yields increased by 3.66% (F100%) and 10.7% (F80%), while ET_{obs} decreased by 4.09% and 3.80% for the F100% and F80% treatments, respectively. Subsequently, the highest $ETWP$ value was recorded during the same season ($0.184 \text{ kg} \cdot \text{ha}^{-1}$ under F100% in 2024). This was likely due to the notable cotton vegetative growth during 2023. Because the available sprayer during 2023 exceeded the plot dimensions (4–8 rows, 4.06–8.13 m), challenges were found in applying growth regulators to inhibit vegetative growth. The resulting larger cotton plants typically had more fruiting sites; however, the excessive vegetative growth likely

limited light permeation to lower branches and reduced boll retention. More energy and resources are put into growing vegetative parts instead of reproductive parts [56,57]. In addition, excess vegetative growth leads to floral buds or bolls shedding from lower nodes and thus lower cotton yields [58–60]. Meanwhile, inadequate growth regulators in 2023 led to lower water productivity under the two irrigation treatments, whereas ETWP was $0.152 \text{ kg} \cdot \text{m}^{-3}$ under F100% and $0.097 \text{ kg} \cdot \text{m}^{-3}$ under F80% in 2023 (Table 3). As cotton plants develop more leaves and branches, their transpiration rate increases, leading to higher water consumption and lower water productivity.

Table 3. Average cotton water use, fiber yield, water productivity, and fiber quality indices during 2023–2024.

Growing Season	Treatment	ET _{obs}	FY, kg ha ^{−1}	ETWP, kg·m ^{−3}	Fiber Quality Indices			
					MIC	UHML, mm	UI, %	STR, g tex ^{−1}
2023	F100%	960	1456	0.152	4.97	28.45	81.73	29.51
	F80%	823	798	0.097	4.36	27.43	80.55	27.88
2024	F100%	921	1694	0.184	3.72	28.96	82.20	30.10
	F80%	792	1049	0.133	3.31	28.91	81.90	30.00

Notes: Mean values for the two irrigation treatments are presented. F100%: flood 100%; F80%: flood 80%. ET_{obs}: Observed evapotranspiration (water use). FY and ETWP refer to fiber yield and ET water productivity, respectively. MIC: Micronaire (unitless), UHML: upper half mean length, UI: uniformity index, STR: fiber strength. A micronaire reading below 3.0 is considered very fine, and 5.0 and above is considered coarse; 3.5 to 4.9 is most desirable for upland cotton varieties.

3.1.2. Fiber Quality

Table 3 presents the effect of irrigation treatments on fiber quality indices, including micronaire (MIC, unitless), upper half mean length (UHML, mm), uniformity index (UI, mm mm^{−1}), and fiber strength (STR, g tex^{−1}) during the two growing seasons. The MIC decreased as irrigation decreased during 2023 (4.97 for F100% and 4.36 for F80%) and 2024 (3.72 for F100% and 3.31 for F80%). Previous studies reported conflicting responses of MIC to water stress, demonstrating that the MIC value may decrease [61], increase [62], or be unaffected [63] by irrigation increases. Our results are in agreement with Snowden et al. [64] who observed an increase in MIC with the increase in irrigation level. Moreover, our findings highlighted that MIC responses vary based on the growing environment [65], whereas a longer cotton season (2023) resulted in higher MIC values (F100% = 4.97 and F80% = 4.36). These findings are consistent with those obtained by Dağdelen et al. [66] and Pettigrew [67].

F100% improved UHML during 2023 and 2024, as compared to F80% (Table 3). This might be a result of the increased irrigation amount, which assists in preserving a higher amount of soil moisture [68], thus mitigating water stress [69]. Cotton fiber is foremost cellulose; thus, a reduction in carbon assimilation will rebate fiber growth [70]. Moreover, the plant water level affects fiber elongation as cell expansion is mainly driven by turgor [70,71]. Our results agreed with Balkcom et al. [72], Darawsheh [73], Ertek and Kanber [74], and Lascano et al. [75].

Similarly, F100% produced a more uniform and stronger fiber than F80% (Table 3), indicating UI and STR were well correlated with soil water during the two growing seasons. Similar findings were reported by Johnson et al. [76]; Pettigrew [67]; Yilmaz et al. [77].

3.2. Calibrated Cotton Parameters

The calibrated cotton parameters were notably changed under the two irrigation treatments, as listed in Table 2. Based on our field observations, the cotton growing cycle was not consistent with the default AquaCrop parameters. This was mainly because of the difference in climate and water conditions where the default cotton file was developed. Therefore, the growing cycle was adjusted from 1956 GDDay to 2162 GDDay and 1991 GDDay under F100% and F80%, respectively. Also, other growth stages were calibrated based on field observations for flood treatments, as summarized in Table 2. The CC_x were 84% and 78% under the F100% and F80%, respectively. These values reached nearly the middle of the flowering stage. The maximum rooting length (Z_n) changed from 1.60 m to 1.70 m, while the minimum rooting length (Z_x) was unchanged (0.30 m) under the F100% and F80%, respectively. These results aligned with Elsadek [78] and Elsadek et al. [15], who reported that under water deficit conditions, plants tend to extend their roots to obtain more water and nutrients. The base and upper-temperature thresholds for Arizona cotton are 12.7 °C and 30 °C, respectively [79]. Thus, the default T_{Base} was increased by 0.7 °C while the default T_{upper} was decreased by 5.0 °C during the calibration process. The Ks values varied between 0.20 and 0.75, reflecting a moderate tolerance to moderate sensitivity to water stress under the two irrigation treatments. The WP* value was set as 15 g·m⁻², which was in the recommended range of 15–20 g·m⁻² for C3 crops, including cotton [80]. A similar value of 15 g·m⁻² was obtained by García-Vila et al. [36], Masasi et al. [81], and Tsakmakis et al. [38], who assessed AquaCrop simulations for full and deficit irrigated cotton. The calibrated HI₀ varied slightly under the two flood treatments (F100% = 33.0% and F80% = 31.0%), which might be a result of the randomized in-field variations. These were consistent with Farahani et al. [35] and Masasi et al. [81], who reported HI₀ values of 30 and 35 for cotton under full and deficit irrigation conditions.

3.3. Model Performance

3.3.1. Canopy Cover

Statistical metrics for simulating cotton canopy cover (CC, %) under the two irrigation treatments during 2023 and 2024 are summarized in Table 4. AquaCrop showed an excellent performance in simulating cotton CC during the two growing seasons. The R², NRMSE, D_{index}, and NSE were between 0.97 and 0.99, 8.45% and 14.36%, 0.98 and 0.99, 0.96 and 0.98, respectively (Table 4).

Table 4. Statistical criteria for simulating cotton canopy cover (CC, %) by AquaCrop during 2023–2024.

Statistical Metrics	Canopy Cover (CC, %)				Evaluation
	Calibration (2023)		Validation (2024)		
	F100%	F80%	F100%	F80%	
R ²	0.98	0.97	0.99	0.98	Strong fit
NRMSE	12.46%	14.36%	8.45%	10.96%	Excellent
D _{index}	0.99	0.98	0.99	0.99	Perfect agreement
NSE	0.97	0.96	0.98	0.97	Acceptable

Note: The R², NRMSE, D_{index}, and NSE refer to the coefficient of determination, the normalized root-mean-squared, the index of agreement, and the Nash–Sutcliffe efficiency coefficient, respectively.

For the 2023–2024 growing seasons, vegetative growth was hampered by deficit irrigation under F80% treatments, as evidenced by reductions in CC when compared with the full irrigation treatments (Figures 5 and 6). In addition to water stress, cotton was more vulnerable to heat stress under deficit irrigation treatments (F80%), resulting in a negative effect on the cotton leaf area and lowering CC. Similar observations were reported for field crops, including cotton, under deficit irrigation and arid climate conditions, e.g., Elsadek et al. [15]; Elsadek [16]; Guo et al. [82]; Meng et al. [83]; Wei et al. [84]; Yang et al. [85].

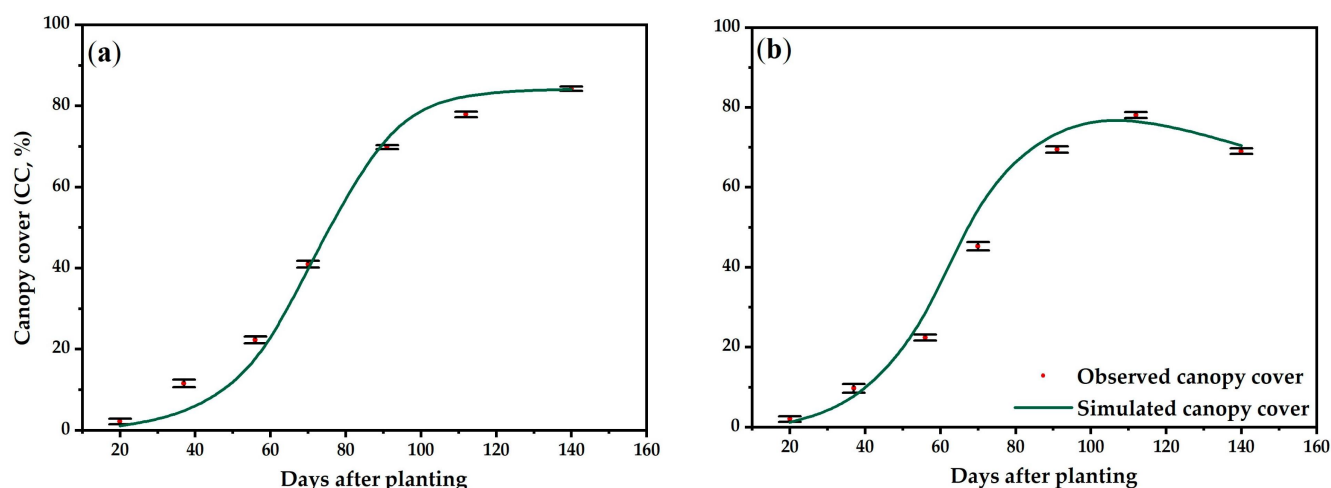


Figure 5. Observed and simulated cotton canopy cover (CC, %) for the 2023 cotton growing season. Flood 100%, 2023 (a) and 80%, 2023 (b). Average values are presented. The error bar indicates standard deviation (SD) among the three replicates.

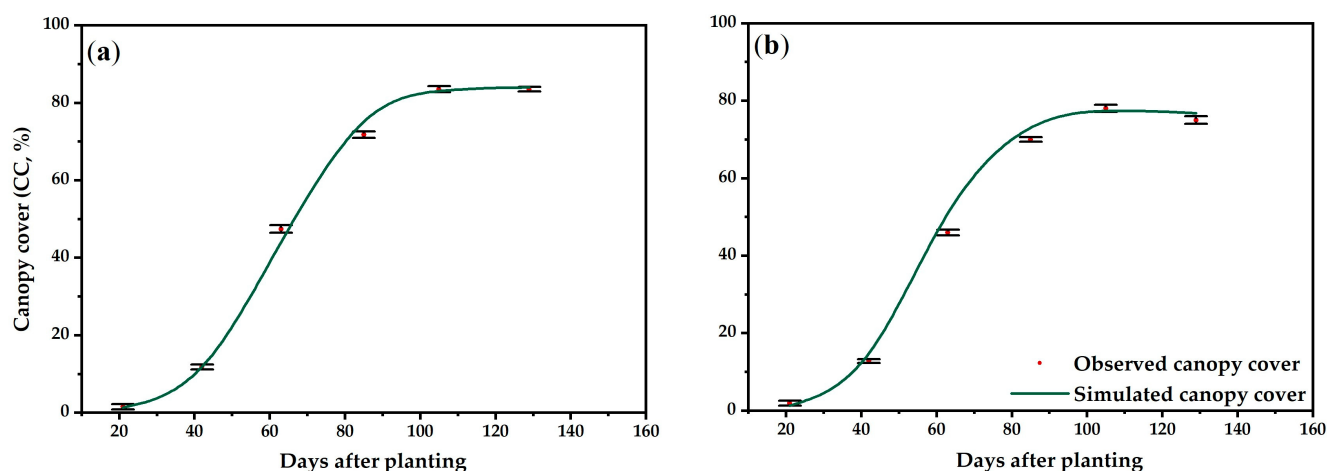


Figure 6. Observed and simulated cotton canopy cover (CC, %) for the 2024 cotton growing season. Flood 100%, 2024 (a) and 80%, 2024 (b). Average values are presented. The error bars indicate standard deviation (SD) among the three replicates.

3.3.2. Cotton Yield

The correlation and regression equation between observed and simulated total cotton yields [fiber, cottonseed, and trash] (Y_{Tot} , $t \cdot ha^{-1}$) for the 2023 and 2024 pooled data are shown in Figure 7. Overall, the evaluation metrics indicated an excellent performance of AquaCrop in simulating cotton yields during the two growing seasons. The R^2 , NRMSE, D_{index} , and NSE for pooled yield data were 0.93, 8.05%, 0.95, and 0.78, respectively. The model simulated cotton yields with MAE 0.05–0.41 $t \cdot ha^{-1}$ and S_e 1.61–14.6%, indicating a general tendency to overestimate cotton yields under the two irrigation treatments during 2023 and 2024 (Table 5).

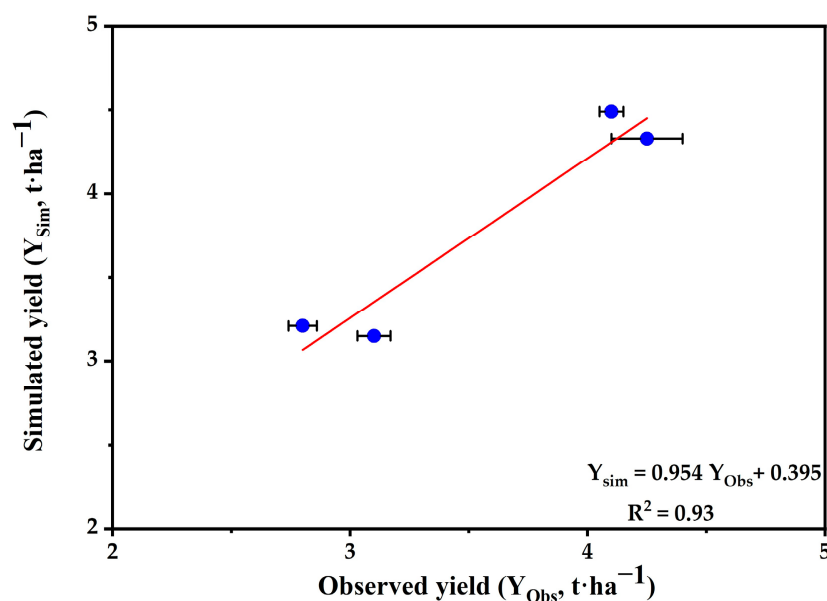


Figure 7. The correlation (R^2) and regression equation between observed (Obs) and simulated (Sim) total cotton yields (Y , $t \cdot ha^{-1}$) for the 2023 and 2024 pooled data on average. $R^2 > 0.5$ indicates a good correlation between Obs and Sim values. The error bars indicate standard deviation (SD) among the three replicates.

Table 5. Statistical criteria and regression equation between observed and simulated total cotton yields (Y_{Tot} , $t \cdot ha^{-1}$) by AquaCrop during 2023–2024.

Total Cotton Yields (Y_{Tot} , $t \cdot ha^{-1}$)	Observed (Obs)	Simulated (Sim)	Evaluation
	3.56	3.79	
R^2	0.93		Strong fit
NRMSE	8.05%		Excellent
D_{index}	0.95		Perfect agreement
NSE	0.78		Acceptable
Regression equation	$Y_{Sim} = 0.954 \cdot Y_{Obs} + 0.395$		

Note: The R^2 , NRMSE, D_{index} , and NSE refer to the coefficient of determination, the normalized root-mean-squared, the index of agreement, and the Nash–Sutcliffe efficiency coefficient, respectively.

Based on our analysis, the highest deviations were recorded during 2023, whereas S_e was 14.6% close to the maximum limit (15%) recommended by Brisson et al. [46] for the crop simulation models. This was due to excess vegetative growth in 2023, resulting in lower cotton yields [58–60] and thus increased simulation errors, especially for the F80% treatment. Our statistical results aligned with many peer-reviewed studies that simulated cotton yields under full and deficit irrigation using AquaCrop (e.g., Farahani et al. [35], García-Vila et al. [36], Masasi et al. [81], and Tsakmakis et al. [38]).

3.3.3. Water Use

For the 2023 and 2024 seasons, observed and simulated cotton evapotranspiration are shown in Figures 8 and 9. AquaCrop simulated ET_{obs} acceptably under the two irrigation treatments during the two growing seasons, whereas NRMSE ranged between 21.52 and 25.01 (Table 6) with R^2 values between 0.61 and 0.72 (Figures 8 and 9) under the two irrigation treatments during the growing seasons. Yet, there was a general tendency for AquaCrop to overestimate the ET_{obs} under F100% and F80% consistently. MAE values were 23.58–50.08 mm, with acceptable S_e between 2.87% and 6.07%, reflecting a good match between ET_{obs} and ET_{Sim} under two irrigation treatments in 2023 and 2024. This

overestimation might be a result of errors in estimating the adjusted basal crop coefficients ($K_{c_{Tr,x}}$) by the model. The $K_{c_{Tr,x}}$ is extremely correlated to the canopy cover curve, thus less influenced by water stress and leading to overestimation of plant transpiration. Similarly, E_s is underestimated because it is also dependent on the canopy cover curve. However, the cumulative ET during the growing season could be simulated quite well, as the overestimated T is compensated by the underestimation of E_s . Therefore, it is recommended to revise the ET partition in AquaCrop using the proposed approaches in FAO56 [86].

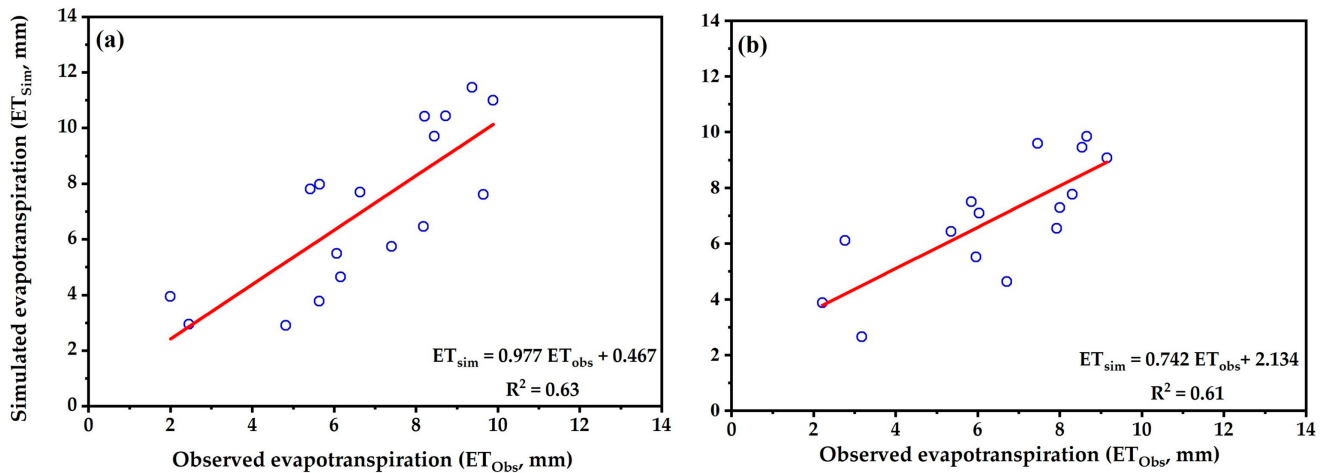


Figure 8. Observed and simulated cotton evapotranspiration (ET, mm) for the 2023 cotton growing season. Flood 100%, 2023 (a) and 80%, 2023 (b). $R^2 > 0.5$ indicates a good correlation between observed (Obs) and simulated (Sim) cotton evapotranspiration.

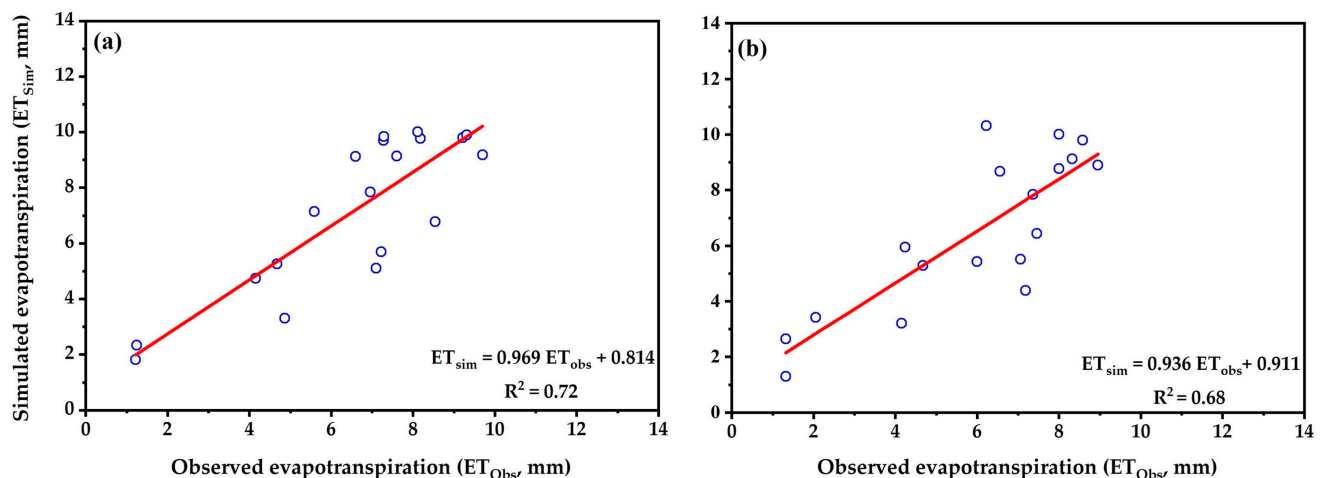


Figure 9. Observed and simulated cotton evapotranspiration (ET, mm) for the 2024 cotton growing season. Flood 100%, 2024 (a) and 80%, 2024 (b). $R^2 > 0.5$ indicates a good correlation between observed (Obs) and simulated (Sim) cotton evapotranspiration.

Compared with 2024, the highest simulation errors of 5.22% under F100% and 6.07% under F80% might be a result of the extensive vegetation growth, which was not considered by AquaCrop. Under extensive vegetation growth, cotton plants develop more leaves and branches, and their transpiration rate increases, leading to higher water consumption. Similar ET simulation errors were reported by Farahani et al. [35] for cotton (2.1% to 10.2%), Heng et al. [87], and Raja et al. [88] for maize (0.9% to 8.4%).

Table 6. Statistical indicators in simulating total yield (Y_{Tot} , $t \cdot ha^{-1}$), water use (ET_{obs} , mm), and total water content (WC_{Tot} , mm) during 2023 and 2024.

Statistical Metrics		Total Yield (Y_{Tot} , $t \cdot ha^{-1}$)		Water Use (ET_{obs} , mm)		Total Water Content (WC_{Tot} , mm)	
		F100%	F80%	F100%	F80%	F100%	F80%
Calibration Season (2023)	Obs.	4.10	2.80	960.02	822.89	407.53	390.18
	Sim.	4.49	3.21	1010.10	872.8	456.83	493.91
	NRMSE	9.51	14.64	24.49	21.61	13.03	27.92
	MAE	0.39	0.41	50.08	49.91	49.29	103.09
	S_e , %	9.51	14.64	5.22	6.07	12.10	26.38
Validation Season (2024)	Obs.	4.25	3.10	920.72	791.62	448.16	435.13
	Sim.	4.33	3.15	947.10	815.6	474.91	498.36
	NRMSE	1.88	1.61	21.52	25.01	7.25	17.18
	MAE	0.08	0.05	26.38	23.58	26.75	63.23
	S_e , %	1.88	1.61	2.87	2.98	5.97	14.53

Notes: Mean values for the two irrigation regimes are presented. F100%: flood 100%; F80%: flood 80%. Obs, Sim, NRMSE, and S_e refer to the observed value, simulated value, normalized root-mean-squared error, and simulation error, respectively. NRMSE < 10% is excellent, 10–20% is good, 20–30% is acceptable, and NRMSE > 30% is poor. The lower the MAE value, the greater the simulation accuracy. The S_e between ± 15 is acceptable.

3.3.4. Total Soil Water Content

AquaCrop performed well in simulating total water content (WC_{Tot} , mm) in the soil profile of 1.70 m during the two growing seasons, except for the F80% in 2023, in which the model performance was poor (Table 6 and Figures 10 and 11). The average NRMSE ranged between 7.25 and 27.92 under the two irrigation treatments during 2023–2024 (Table 6).

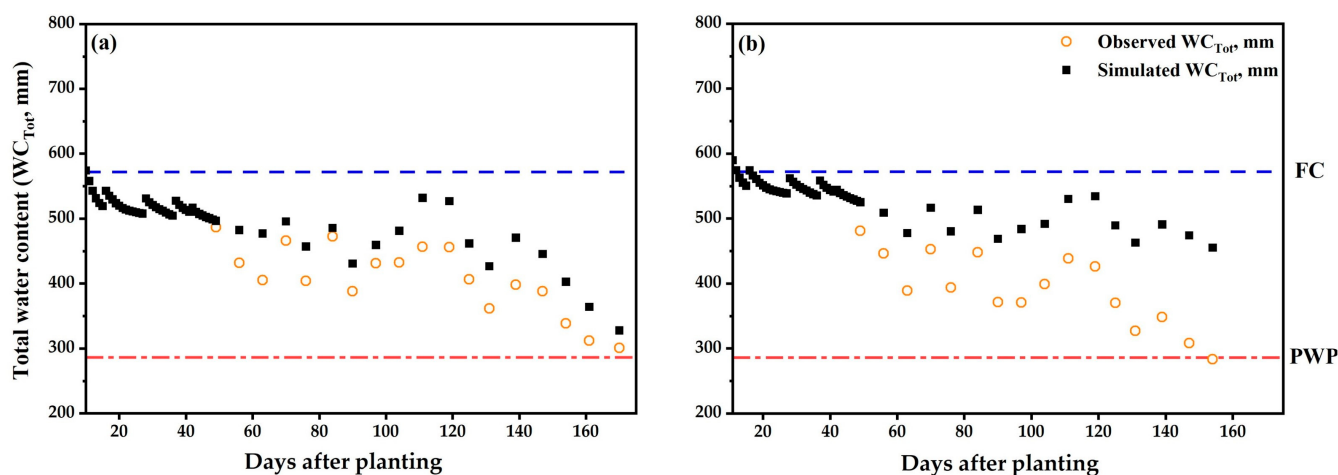


Figure 10. Observed and simulated total water content (WC_{Tot} , mm) in the soil profile of 1.70 m during the 2023 cotton growing season. Flood 100%, 2023 (a) and 80%, 2023 (b). FC and PWP refer to field capacity and permanent wilting point, respectively.

For the two growing seasons, the model consistently simulated the trend of soil wetting and drying cycles due to irrigation events, yet the simulated values deviated from the observed values. The model showed a general tendency to overestimate WC_{Tot} , whereas MAE ranged between 26.75 mm and 103.09 mm in 2023 and 2024. The S_e on average were between 5.97% and 26.38% during the two growing seasons. The deviation exceeded 15%, as recommended by Brisson et al. [46] for crop simulation models, reflecting a poor match between the observed and simulated WC_{Tot} under the F80% treatment in 2023 (Table 6).

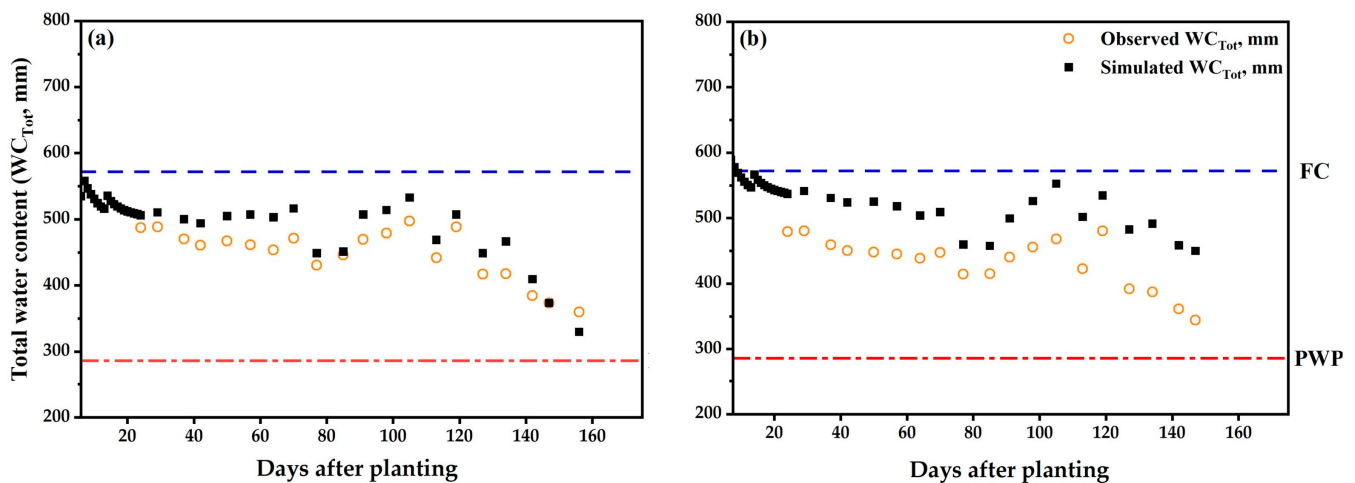


Figure 11. Observed and simulated total water content (WC_{Tot}, mm) in the soil profile of 1.70 m during the 2024 cotton growing season. Flood 100%, 2024 (a); and 80%, 2024 (b). FC and PWP refer to field capacity and permanent wilting point, respectively.

The highest simulation errors during 2023 might be a result of the extensive vegetation growth, which was not considered by AquaCrop. Under extensive vegetation growth, cotton plants develop more leaves and branches, and their transpiration rate increases, leading to higher water consumption and lower WC_{Tot}. Another potential reason is the overestimated transpiration due to the errors in estimating adjusted basal crop coefficients, accompanied by the underestimation of soil evaporation. Additionally, the inexact simulation of root expansion, whereas the model simulates root development as an empirical formula in time and maximum effective rooting depth. Therefore, it is recommended to add some parameters to the estimation of root distribution in AquaCrop, like root density or specific root depth [89]. Similar overestimations of WC_{Tot} were reported for different crops, such as cotton [35,89,90], Maize [86], and soybeans [91] using the AquaCrop model.

3.4. Recommendations and Outlooks

While the study provides valuable insights into cotton water use and yield under full irrigation and a moderate deficit level that farmers in the region could realistically adopt, future studies on a broader range of irrigation levels would facilitate a more comprehensive assessment of cotton response to water scarcity. Moreover, future studies addressing the effectiveness of adopting deficit irrigation strategies with different irrigation systems are recommended. Factors such as irrigation system costs, labor requirements, energy use, and potential market price fluctuations can influence the profitability and practical adoption of deficit irrigation strategies. Thus, incorporating such economic analyses in future studies would provide a more comprehensive evaluation, enabling growers and policymakers to make informed decisions that balance water conservation goals with economic sustainability.

On the other hand, AquaCrop consistently overestimated yields, water use, and WC_{Tot}, with some discrepancies under the 80% treatment. This might be due to the extensive vegetative growth, which was not considered by the AquaCrop model. Moreover, the overestimated transpiration was due to the errors in estimating adjusted basal crop coefficients, accompanied by the underestimation of soil evaporation. Therefore, it is recommended to revise the ET partition in AquaCrop using the proposed approaches in FAO56. Additionally, there was an inexact simulation of root expansion, where the model simulates root development as an empirical formula with time and maximum effective

rooting depth. Therefore, adding some parameters to the estimation of root distribution in AquaCrop, like root density or specific root depth, could improve the model's accuracy.

4. Conclusions

This study was conducted to evaluate the effect of two flood irrigation treatments on fiber yield and quality under arid climate conditions in Maricopa, Pinal County, Arizona, USA. Then, the feasibility of AquaCrop in simulating cotton yield, water use, and total soil water content (WC_{Tot}) was assessed under full and deficit flood irrigation during the 2023 and 2024 growing seasons. Results demonstrate that decreasing the irrigation rate to 80% of cotton evapotranspiration (ET_c) negatively affected cotton fiber yield and ET water productivity (ETWP). Moreover, the inhibited vegetative growth under water stress resulted in fewer fruiting sites, thus accelerating maturation and lowering yields. Therefore, maintaining a 100% ET_c water supply under flood irrigation is recommended to enhance the water absorption of cotton roots, mitigate periodic stress, alleviate soil water stress caused by drought, reduce yield losses, and thus increase ETWP. Meanwhile, AquaCrop consistently overestimated yields, water use, and WC_{Tot} , with acceptable model performance overall, except for WC_{Tot} under the 80% treatment in 2023. This was possibly due to model limitations in accounting for vegetative growth, root expansion, and soil evaporation. Considering the model's limitations and its overall performance, our results highlighted the potential of using AquaCrop for irrigation management and climate impact projections under arid climate conditions, particularly in Arizona.

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