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Simulating Cotton Growth and Productivity Using AquaCrop Model under Deficit Irrigation in a Semi-Arid Climate

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Abstract: AquaCrop is a water-driven model that simulates the effect of environment and management on crop production under deficit irrigation. The model was calibrated and validated using three databases and four irrigation treatments (i.e., 100%ET, 80%ET, 70%ET, and 50%ET). Model performance was evaluated by simulating canopy cover (CC), biomass accumulation, and water productivity (WP). Statistics of root mean square error (*RMSE*) and Willmott's index of agreement (*d*) showed that model predictions are suitable for non-stressed and moderate stressed conditions. The results showed that the simulated biomass and yield were consistent with the measured values with a coefficient of determination (R^2) of 0.976 and 0.950, respectively. *RMSE* and d-index values for canopy cover (CC) were 2.67% to 4.47% and 0.991% to 0.998% and for biomass were 0.088 to 0.666 ton/ha and 0.991 to 0.999 ton/ha, respectively. Prediction of simulated and measured biomass and final yield was acceptable with deviation <10%. The overall value of R^2 for WP in terms of yield was 0.943. Treatment with 80% ET consumed 20% less water than the treatment with 100%ET and resulted in high WP in terms of yield (0.6 kg/m^3) and biomass (1.74 kg/m^3), respectively. The deviations were in the range of −2% to 11% in yield and −2% to 4% in biomass. It was concluded that AquaCrop is a useful tool in predicting the productivity of cotton under different irrigation scenarios.

Keywords: AquaCrop model; canopy and biomass simulation; stressed irrigation; water use efficiencies; water production function

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1. Introduction

The agriculture sector is integral to Pakistan's economy. This sector contributes over 21% of GDP, absorbing 45% of the country's total labor [1]. Cotton is one of the commercial cash crops of Punjab and Sindh in Pakistan [2]. The evaporative demand is high in semi-arid and arid areas of Indus Basin because of changing climatic conditions and rainfall patterns, which results in limiting agricultural productivity in the entire basin, except for the areas which receives plenty of water for agriculture. AquaCrop simulates in rainfed, deficit and full irrigation water regimes and predicts the achievable yields of the major crops. With the help of water driven function, AquaCrop calculates and converts the transpiration loss into biomass by using crop specific parameters [3,4]. AquCrop simulation using default cotton conservative parameters exhibited the best results [5]. Water productivity (WP) is a key element of agricultural water management in agricultural irrigated regions, and AquaCrop is a suitable tool to assess the water response to crop water productivity [6]. The maximum WP for wheat cultivar was found to be 1.54 kg/m^3 that was acquired from 60% deficit irrigation [7,8]. Water being a precious commodity, could be saved by adapting water-saving techniques, which is only possible with proper assessment of water response to crop production [9]. Previous studies have demonstrated that AquaCrop accurately simulates the aboveground biomass and canopy cover of the crops under regular and deficit irrigation regimes [10–13]. As the world population increases, less water will be available for irrigation purposes in response t natural losses due to deep percolation, evaporation, and conveyance in furrow irrigation systems [14]. Drip irrigation uses less water than surface irrigation; thus, the irrigation water productivity is larger for drip systems in cotton production areas [15]. Rising water shortages [16,17] correlates the burden on agricultural productivity and sustainable increase in food demand [18]. AquaCrop model of the United Nations is simple, user friendly, and is practical for ultimate users such as extension workers, water managers, and professionals of irrigation organizations for planning purposes [19]. To evaluate how agricultural productivity will be affected by future shifts in water availability due to climate change, water production functions can be linked with crop models [8]. All other crop models are complicated, demanding advanced skills of calibration and operation as well as need a large number of parameters [20]. AquaCrop calibration is least demanding as compared to other crop models and has a limited number of key parameters to be adjusted. The model was originated from the yield response to water data and evolved to normalized water productivity. It was used to simulate crop productivity in multiple scenarios. The model was already parameterized for *Gossypiumhirsutum* for full irrigation (100% ET) and stressed (40%, 60%, and 80% of full 100% ET) irrigation levels for the Mediterranean environment of northern Syria [19]. Several climatic and agricultural procedure settings determined the optimal level of irrigation water applied for cotton production in southern Spain [19]. The AquaCrop model needs input data related to climate, soil, crop, irrigation, and initial soil water conditions [20]. Jin et al. [21] suggested that the AquaCrop model successfully predicted the canopy cover, biomass, and grain yield of winter wheat with high accuracy under different planting dates and irrigation environments. By drawing the water production function, the user can estimate the best water deficit level to obtain maximum yield. Keeping in view the water scarcity in the Pothwar area of Punjab, Pakistan, the AquaCrop model is planned to calibrate and revalidate for enhancing water productivity in the area. Thus, the main objective of the current study is to calibrate and validate the AquaCrop model (version 3.1) for full (100% ET) and stress or deficit (80%ET, 70% ET, and 50%ET) irrigation treatments for the semi-arid subtropical climate of Chakwal, Pakistan to find out the best optimal deficit irrigation level for cotton crop. The main features of the study model are to simulate canopy cover and biomass simulation and to draw water production functions.

2. Materials and Methods

2.1. Research Area

The experiments were conducted at Barani Agricultural Research Institute, Chakwal, Punjab laying at 32°55′ N, 72°43′ E with 575 m altitude. The climate in the region is mainly semi-arid subtropical, with annual average rainfall is 350–500 mm. High-intensity rain showers are received during monsoon periods (July to September); the annual average rainfall for the period 1999–2017 was recorded as 235 mm.

2.2. Weather and Soil Data

The weather data for the last 18 years (1999–2017) were collected from the nearby weather observatory of Soil and Water Conservation Research Institute (SAWCRI), Chakwal. This data was comprised of daily precipitation, daily maximum, and minimum air temperatures (Figure 1). FAO driven ETo calculator (http://www.fao.org/nr/water/eto.html (accessed on 10 November 2021)) [22] was used to calculate daily reference evapotranspiration (ETo). The calculator estimated the ETo from meteorological data of maximum, minimum temperature, solar radiation, wind speed and air humidity using FAO Penman-Monteith equation. Total rainfall of 291, 227, and 217 mm was received during the growing periods of 2015, 2016, and 2017, respectively (Figure 1). Normally, the driest month of the year was May, with an average humidity of around 30% (1999–2017). Soil characteristics of the experimental site were assessed by digging a pit (Figure 2) down to a depth of 1.2 m. The soil samples were collected from varying depths and analyzed in the laboratory, as given in Table 1. These soils were suitable for very distinct crops [23].

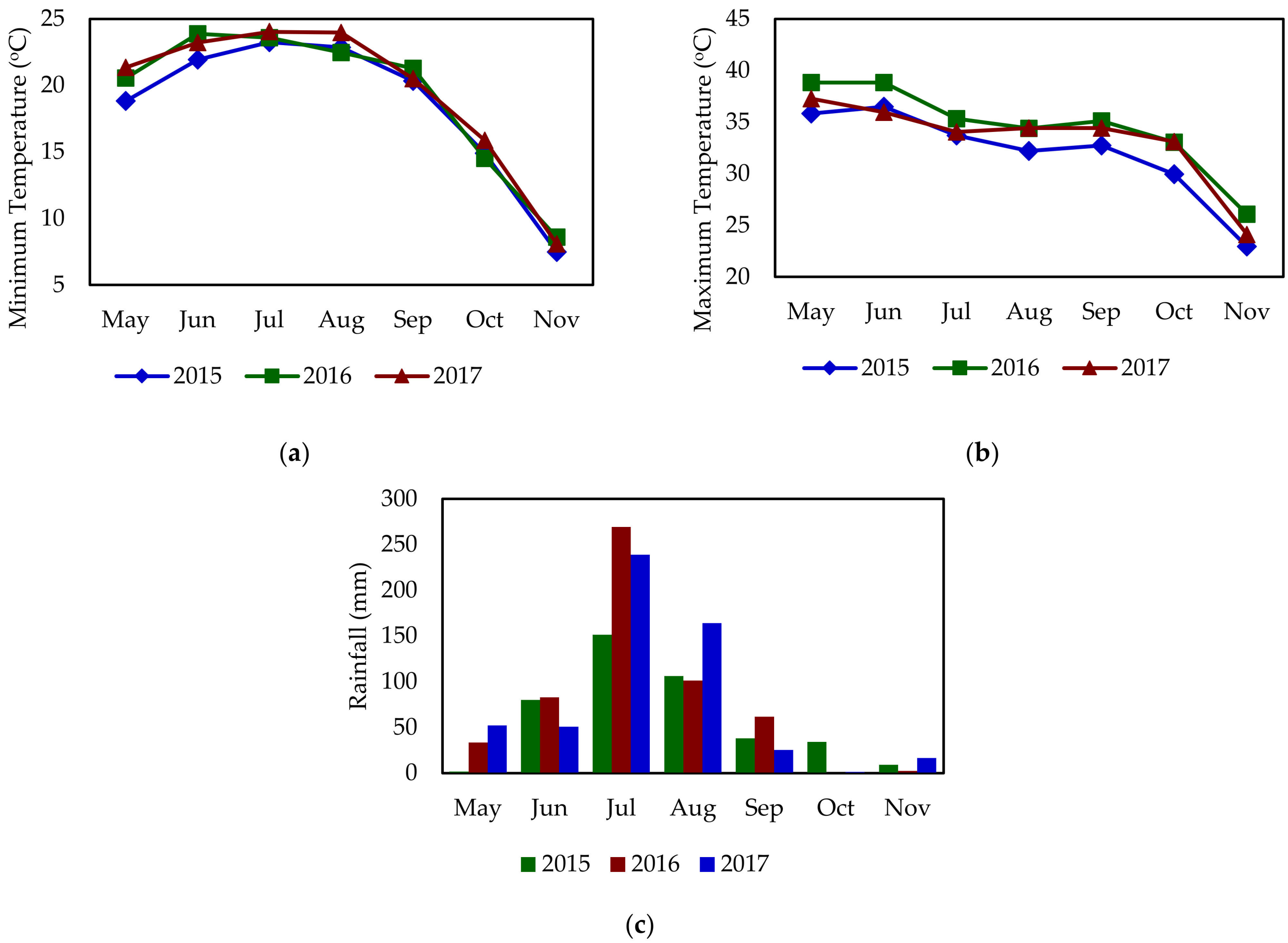


Figure 1. Monthly growing season weather data of (**a**) minimum temperature, (**b**) maximum temperature, and (**c**) rainfall (mm) (2015, 2016, and 2017).

The soil water contents were measured with the help of a neutron moisture meter monitored with 7 days interval. Installed access tubes of poly vinyl chloride (PVC) in the field down to the depth of 1.3 m. The neutron probe was calibrated gravimetrically and developed the following two equations from calibration curves.

$$\theta v = 0.596\ n - 0.122 \text{ For top-soil surface layer } (R^2 = 0.97)$$

$$\theta v = 0.331\ n - 0.124 \text{ For subsurface soil layers } (R^2 = 0.98)$$

where θv = volumetric soil moisture content; n = count ratio, (observed counts/standard counts). Two calibration curves are required because the soil of the experimental area was sandy clay loam, the upper and deeper layer monitor the loss of neutron in surface and sub surface soil layers.

(**a**) (**b**)

Figure 2. (**a**) Soil pit to study soil properties from different depths of soil and (**b**) measurement of different depths.

Table 1. Soil characteristics of experimental field.

Depth	Texture	Bulk Density	K_{sat}	Organic Carbon	Clay	Silt	Nitrogen	FC	pH in Water
(m)	-	(g/cm^3)	(mm/day)	(%)	(%)	(%)	(%)	m^3 m^{-3}	-
0–0.3	Sandy loam	1.52	0.75	0.45	6	16	0.04	0.10	9.1
0.3–0.6	Sandy loam	1.7	0.6	0.35	14	8	0.02	0.13	9.1
0.6–0.9	Sandy loam	1.6	0.8	0.2	6	20	0.02	0.15	8.9
0.9–1.2	Sandy loam	1.39	0.83	0.02	8	22	0.02	0.18	8.9

K_{sat}: saturated hydraulic conductivity; FC: field capacity.

2.3. Field Management and Crop Data

The cotton (*Gossypiumhirsutum*) variety Desi was sown on 15 May 2015, 21 May 2016, and 15 May 2017, respectively, by keeping plant spacing of 0.7 × 0.45 m. The experimental plots were laid out in randomized complete block design (RCBD) with three replications (Figure 3). Four moisture levels of 100%ET, 80% ET, 70% ET, and 50% ET were maintained. The plot size was kept as 12 × 13 m (156 m^2). The control treatment was kept at full water requirement of the plant (100% irrigation) throughout the growing season. Recommended doses of fertilizers were applied, i.e., nitrogen (114 kg/ha) in the form of urea (split doses giving a basal dose of 28 kg/ha at seed bed preparation while remaining quantity fertigated at alternative irrigations). Phosphorus was applied as basal dressing in the form of Tri super phosphate (TSP, 46% P_2O_5) at the rate of 125 kg/ha and potassium 62 kg/ha.

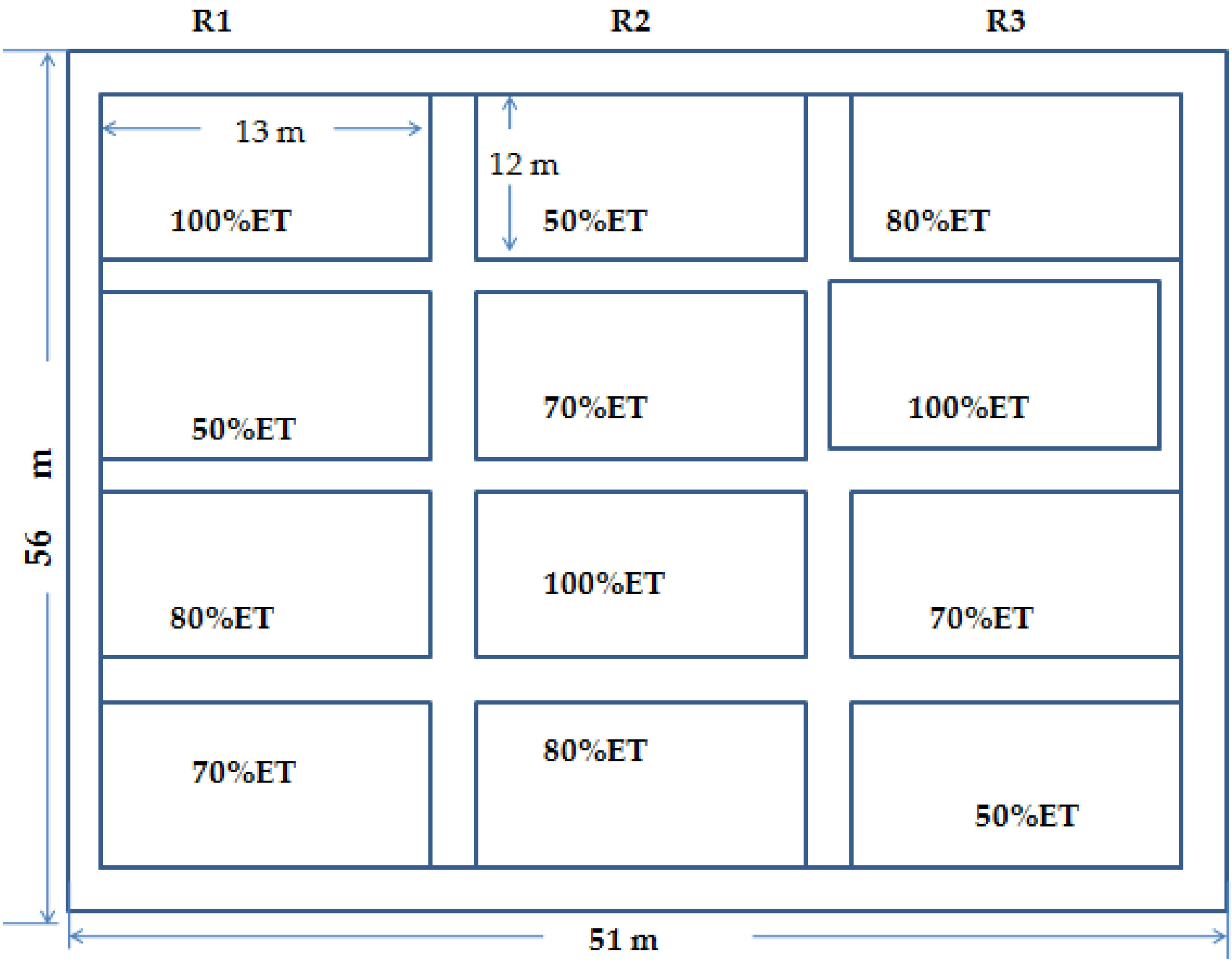


Figure 3. The experimental layout of the study with four subsurface irrigation treatments.

Data regarding canopy cover and aboveground biomass were recorded throughout the cropping season. Canopy cover was determined using ImageJ (Version 1.71) software. ImageJ measures canopy cover by digital images of the crop [24]. Cotton canopy images were acquired with the help of a Sony DKC-IDI digital camera with a spatial resolution of 786 × 561 pixels on a clear sunny day, when the sun was on peak (12:00–01:00 P.M) (Figure 4). With 10 days interval from the date after sowing (DAS). Only the two central rows of each plot were picturized. The final yield was taken at harvest. Statistical analysis was performed by using COSTAT software (www.softwaresea.com/Windows/download-CoStat-10243679.htm accessed on 15 May 2018) [25]. Treatment means of canopy cover, biomass, and yield were compared using DMR at a 5% significance level.

Three plants of cotton were randomly selected from each plot with an interval of 20 DAS and oven-dried at 105 °C for 24 h to obtain the aboveground biomass. The final yield of cotton was calculated from three samples of 2 m^2 selected randomly and harvested from each plot once the cotton reached maturity.

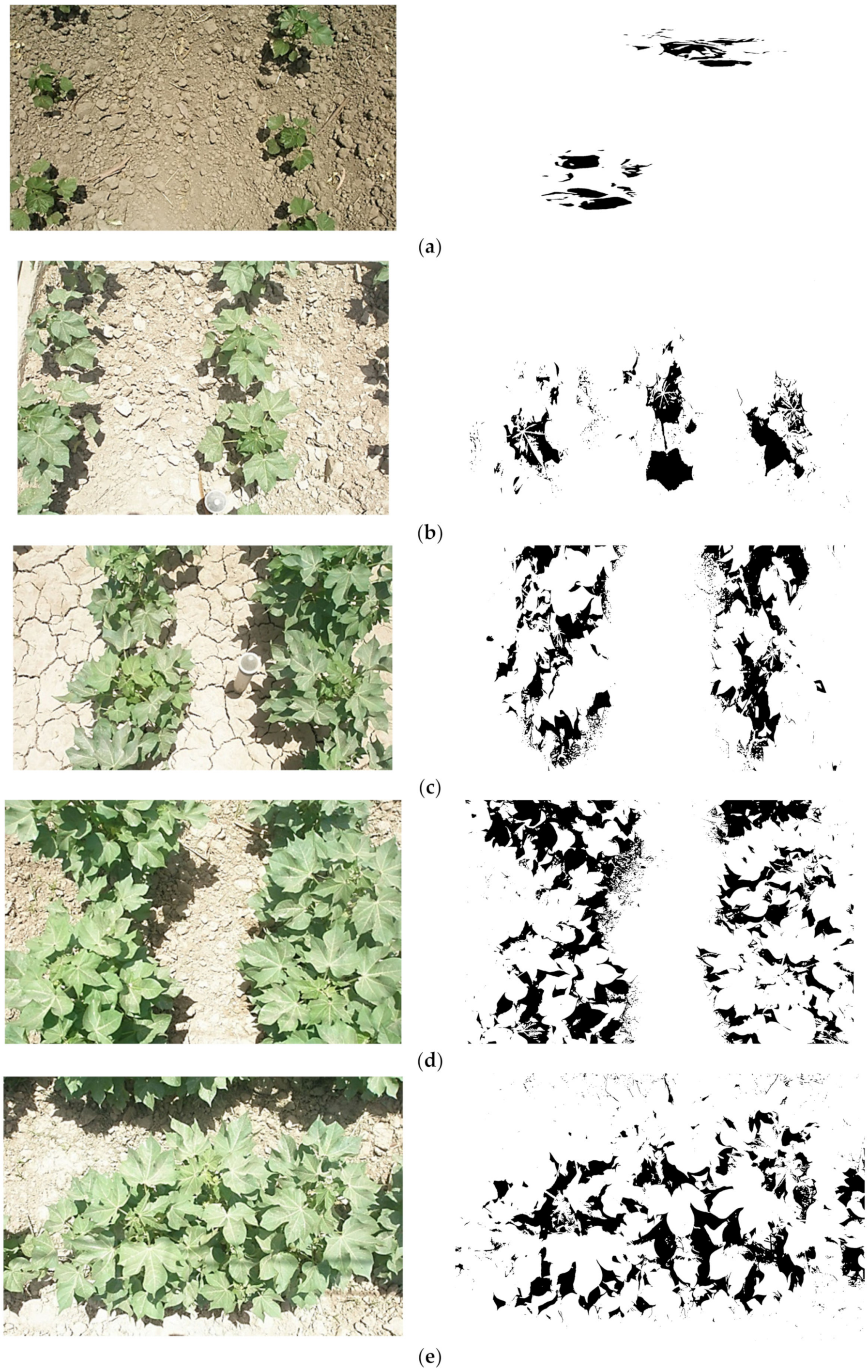


Figure 4. Digital images of cotton plants. (**a**) Image of 20 DAS, (**b**) image of 40 DAS, (**c**) image of 50 DAS, (**d**) image of 60 DAS, and (**e**) image of 70 DAS.

2.4. Calibration of AquaCrop Model

AquaCrop was calibrated by using data of 2015, initially comparing the performance of 100%ET (full irrigation) for canopy cover (%) and biomass (ton/ha). The variables required for model calibration were explained specifically by the authors of [26,27] (Table 2) for each day of the simulation period.

Table 2. Main phenologic growth stages in days after sowing (DAS) and seasonal water applied for different treatments.

Agronomic Details	Growing Seasons		
	2015	**2016**	**2017**
Plant population (plants/ha)	29,240	27,240	27,533
Date of sowing (DAS)	15-May	21-May	15-May
Emergence (DAS)	7	9	8
Flowering (DAS)	55	57	60
Senescence (DAS)	121	133	135
Maturity (DAS)	160	175	165
Maximum rooting depth (cm)	102	104	102
Amount of irrigation water applied (m^3/ha)			
100%ET	5500	5070	5340
80%ET	4400	4230	4270
70%ET	3850	3810	3740
50%ET	2750	2970	2670

2.5. Model Evaluation

To evaluate the performance of AquaCrop, a straight line R^2 value was calculated by plotting regression between the measured and simulated values of canopy cover (%), biomass (ton/ha), and yield (ton/ha), and correlation coefficients were determined. The subsequent statistics explicitly considered checking model goodness of fit: *RMSE* (root mean square error) and index of agreement (*d*) statistics [28]. The overall deviation in simulated and observed values are measured with the help of *RMSE* [29]. Index of agreement (*d*) is a measure of relative error in model estimates; it represents the degree to which simulated and observed values show similar deviations from the measured means [30]. When the value of *RMSE* approaches 0 and the value of *d* approaches 1, then the model shows perfect agreement.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Oi - Si)^2} \quad (1)$$

where Oi = observed value; Si = simulated value; and N = no. of observations.

$$d = 1 - \frac{\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n}(|Pi'| + |Oi'|)^2} \quad (2)$$

where d = Willmott's index of agreement, $P''= Pi - P$; Pi = measured value; P = mean of measured value; $O'= Oi - O$; Oi = simulated value; and O = mean of simulated value.

3. Results

3.1. Model Calibration

AquaCrop was calibrated using the data set of 2015 (Table 2). The calibrated results revealed that the model was able to simulate canopy cover (CC) at different stages of crop growth (Figure 5). The values of *RMSE* were low and were considered suitable for model calibration.

The model showed an underestimation of the CC in the 100%ET irrigation treatment. The simulated maximum CC (%) was somewhat lower than the measured values (4% deviation). It could be possible due to the differentiation in initial moisture content between the simulated and measured values in deficit irrigation treatments. Strong agreement existed between measured and simulated canopy cover (Figure 5) for all the treatments. *RMSE* ranged from 2.670% to 4.082% and values of d-index from 0.996 to 0.998, respectively. Moreover, the results of low d-index value and high *RMSE* value in 70%ET. The values of the d-index clearly showed that the model predicted canopy cover very well in all irrigation treatments. The assessment of the model showed that the canopy cover of cotton simulated very well.

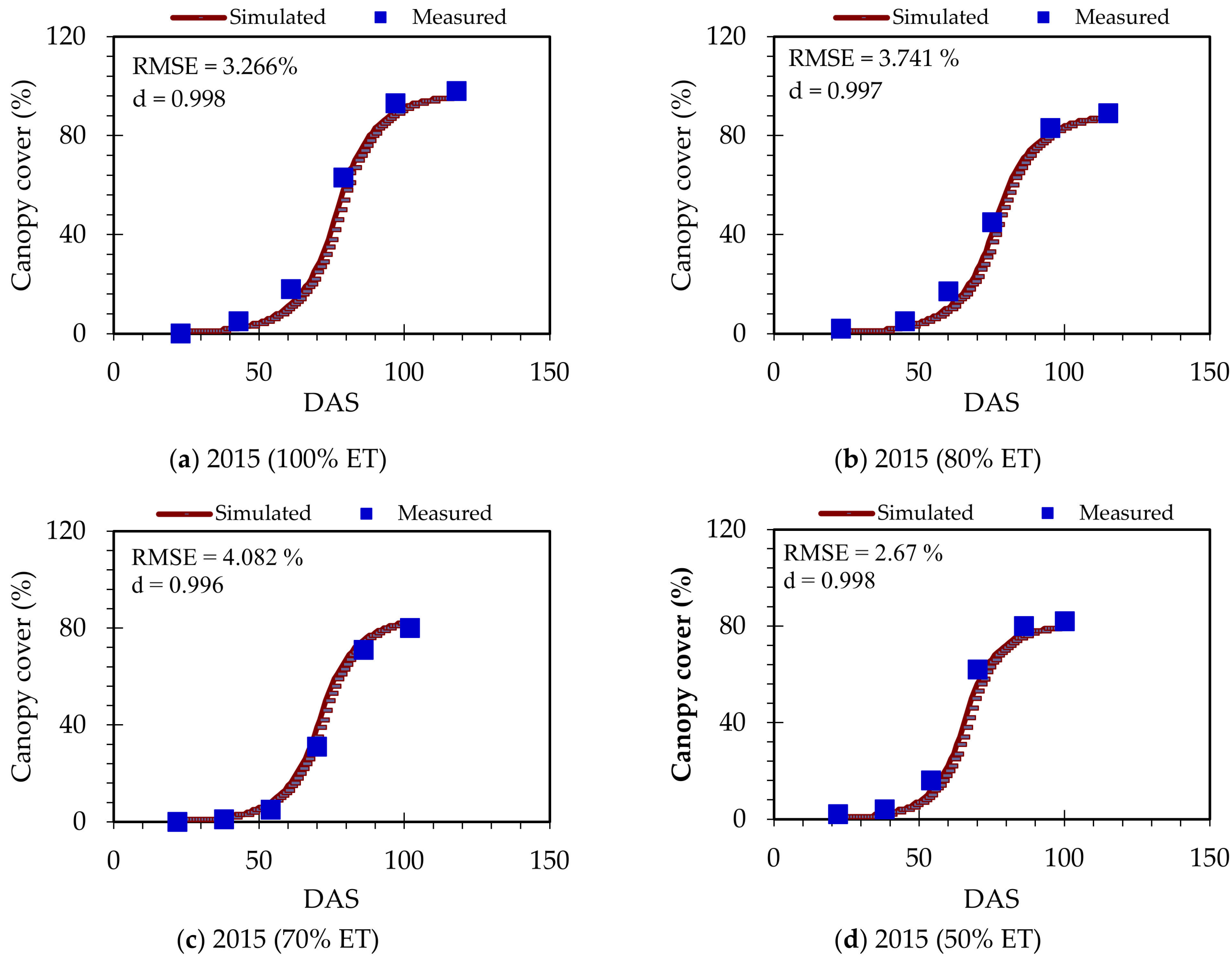


Figure 5. Measured and simulated canopy cover under various irrigation treatments; (**a**) 100% ET, (**b**) 80% ET, (**c**) 70% ET, and (**d**) 50% ET.

Figure 6 and Table 3 shows that AquaCrop simulated the aboveground biomass accurately for all irrigation treatments. Generally, there is a suitable fit between simulated and observed values of biomass by low *RMSE* and high d-index value (Figure 6). AquaCrop reasonably simulated the aboveground biomass for deficit treatments 80%ET and 70%ET (Table 3), as reflected by the statistical parameters. The highest value of *RMSE* was recorded in 50%ET treatment; the model showed an overestimation of biomass with a 4% deviation (Table 3). This treatment was observed to experience more water stress, an onset that began during the vegetative growth stage. As water stress increases, model robustness decreases. In the calibration process, canopy cover was underestimated, and biomass overestimated in 50%ET treatment. The overall model overestimates the biomass except for 80% ET treatment with 0 deviations (Table 3). The observed values of biomass were 9.837, 9.750, 8.785, and 7.201 ton/ha, while simulated values were 10.002, 9.729, 8.830, and 7.328 ton/ha for 100%ET, 80%ET, 70%ET, and 50% ET treatments, respectively (Table 3, Figure 7).

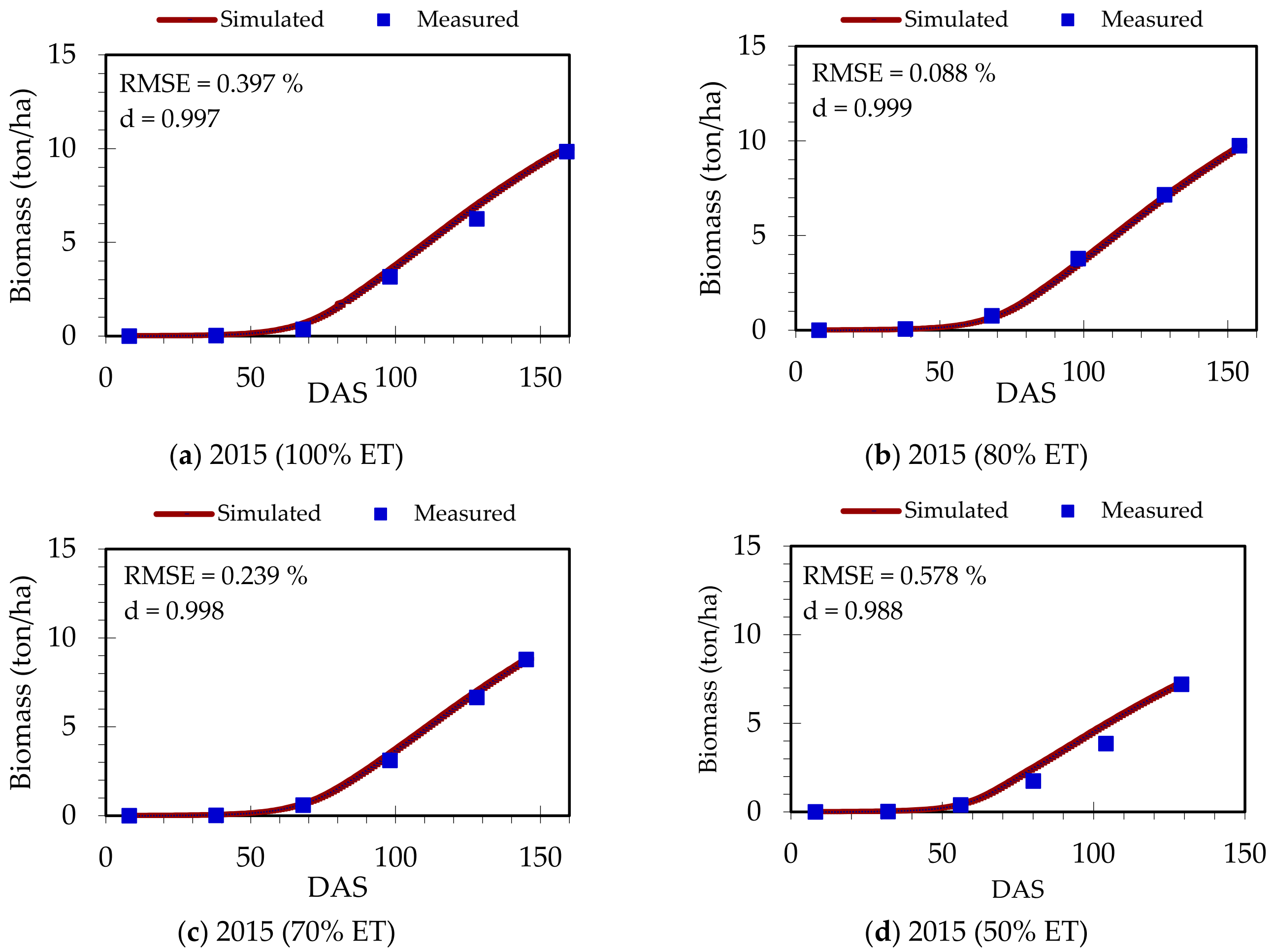


Figure 6. Measured and simulated biomass ton/ha under various irrigation treatments (**a**) 100% ET, (**b**) 80% ET, (**c**) 70% ET, and (**d**) 50% ET for the year 2015.

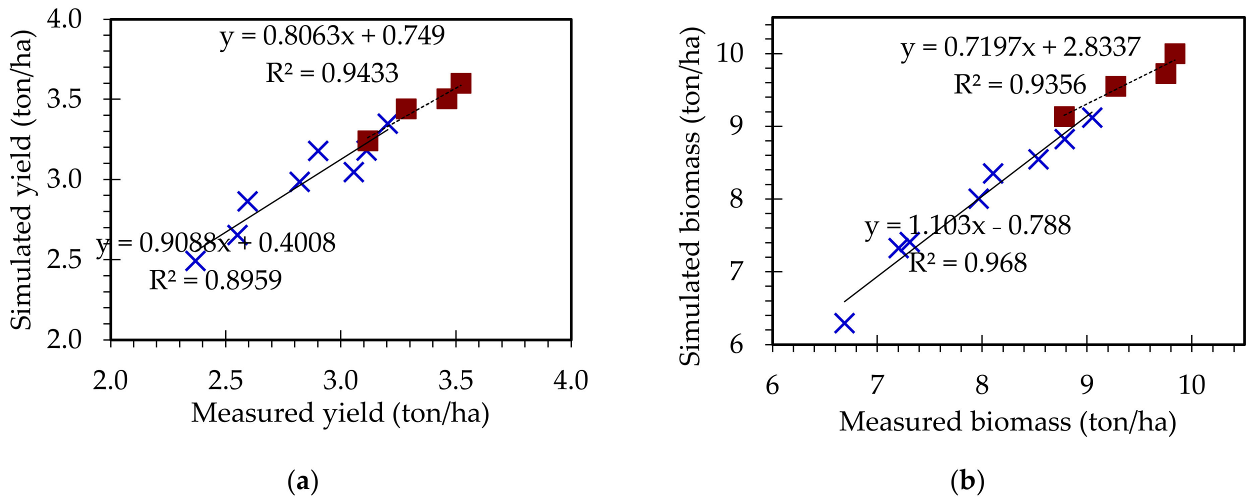


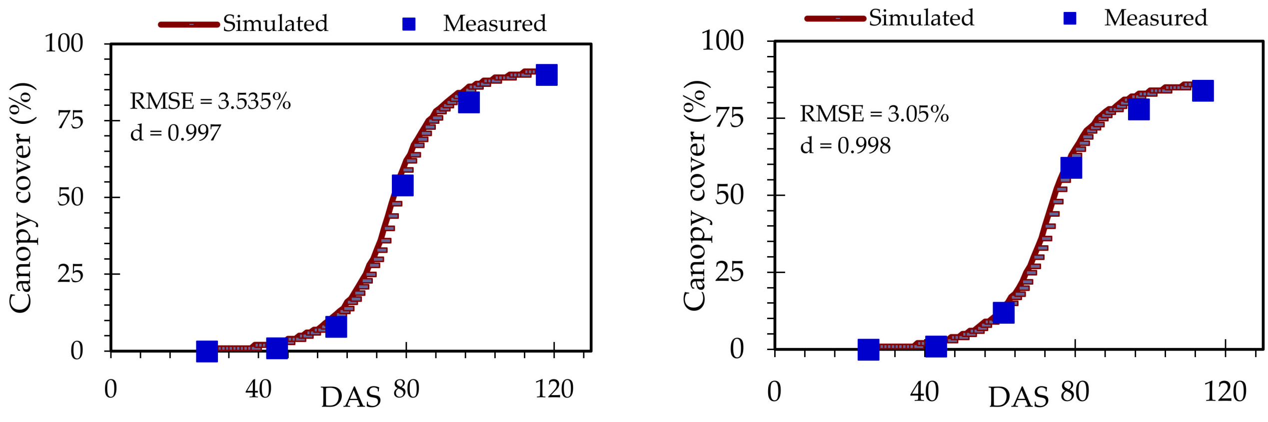
Figure 7. Relationship between measured and simulated (**a**) lint yield and (**b**) biomass for the calibration (square) and validation databases (cross).

Table 3. Calibration results of biomass and lint yield for all four irrigation treatments for the year 2015.

Treatments	Variables	Measured	Simulated	Deviation (%)
100%ET	Biomass (ton/ha)	9.837	10.002	2
	Yield (ton/ha)	3.521	3.6	2
80%ET	Biomass (ton/ha)	9.75	9.729	0
	Yield (ton/ha)	3.46	3.503	1
70%ET	Biomass (ton/ha)	8.785	8.83	1
	Yield (ton/ha)	3.11	3.179	2
50%ET	Biomass (ton/ha)	7.201	7.328	2
	Yield (ton/ha)	2.55	2.654	4

3.2. Model Validation

The calibrated parameters were used to validate AquaCrop for the years 2016 and 2017.The model favorably simulated the canopy cover development in 2016 and 2017 for all irrigation treatments. However, 50%ET in 2016 showed an overestimation of canopy cover (Figure 8d) with *RMSE* 4.472% and d-index value 0.992, but in 2017, 50%ET showed underestimation of canopy cover (Figure 8h) with *RMSE* 3.342%. The validation results of biomass are shown in Figure 9; accurate predictions of biomass were achieved for the years 2016 and 2017. The model over predicts the biomass, except for 50%ETwith *RMSE* = 0.335 to 0.179 % and d-index 0.995 to 0.998 for 2016 and 2017, respectively (Figure 9d,h). The results showed that performance of model was preferable (*RMSE* = 0.204% to 0.410%, d-index = 0.995 to 0.999) in 2017 as compared to 2016 (*RMSE* = 0.666% to 0.335%, d-index = 0.996 to 0.991) as depicted in Figure 9. AquaCrop predicted well aboveground biomass in 80%ET as compared to 100%ET in 2016 (Figure 9a,b) with *RMSE* = 0.413% and d-index = 0.996. Deficit irrigation treatments provided a suitable prediction of aboveground biomass for both years. *RMSE* values in 2017 were lower than all years because the model under predicted canopy cover in 2017.



(**a**) 2016 (100% ET) (**b**) 2016 (80% ET)

Figure 8. *Cont.*

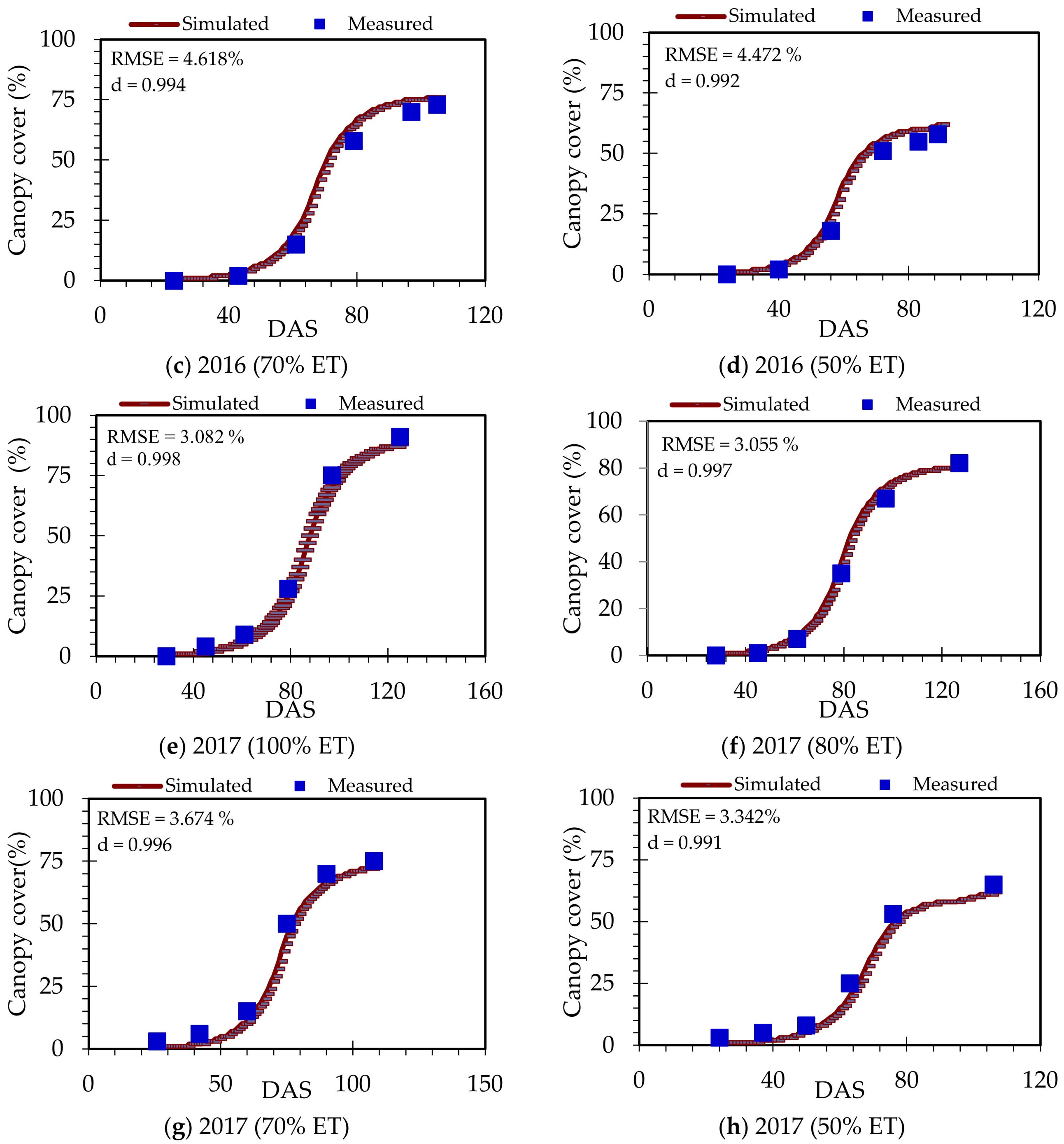


Figure 8. Validating results showing the comparison between measured and simulated values of canopy cover for the years 2016 (**a**–**d**) and 2017 (**e**–**h**).

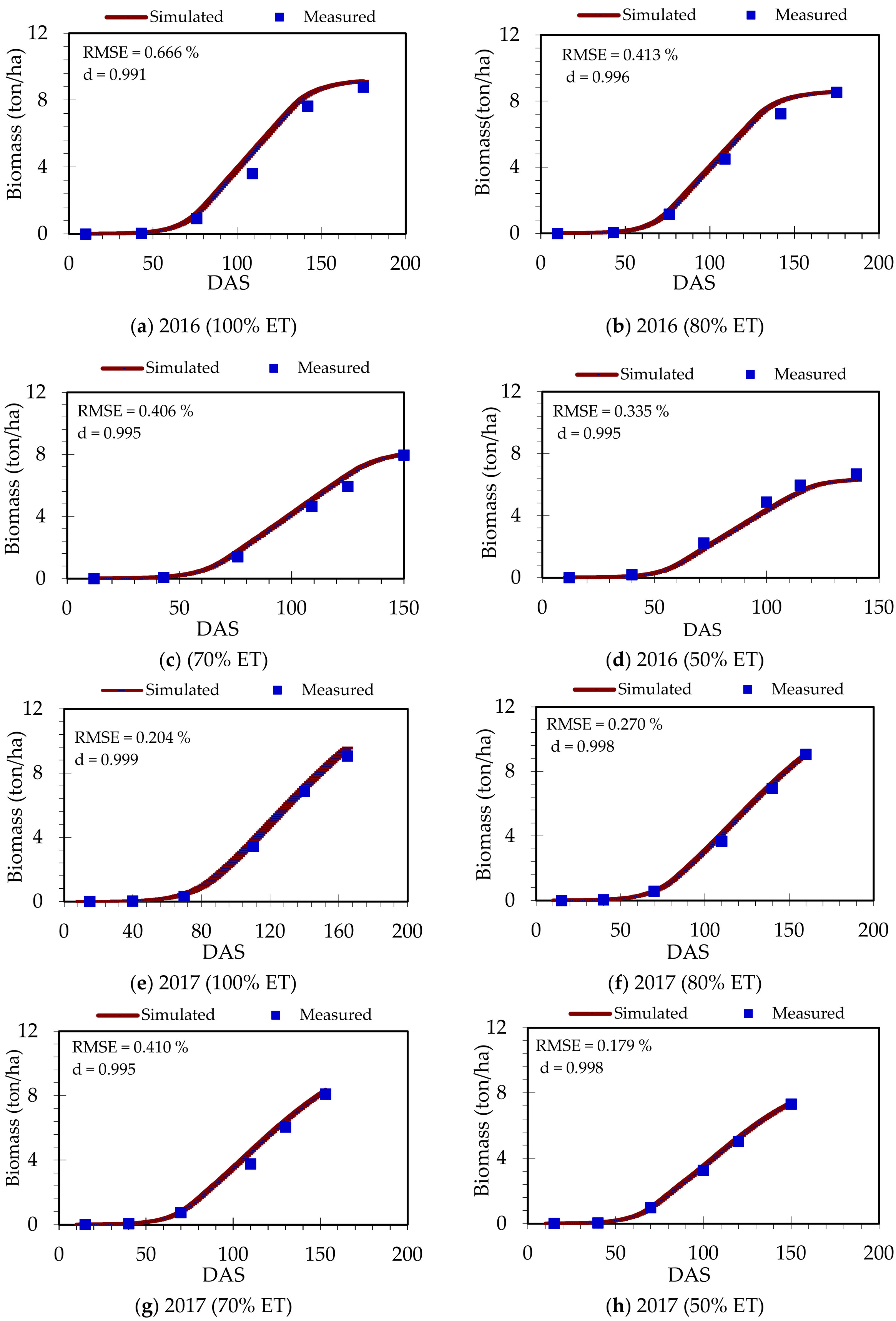


Figure 9. Validating results showing the comparison between measured and simulated values of biomass for the year 2016 (**a**–**d**) and for the year 2017 (**e**–**h**).

For 2017 the observed values of biomass ranged from 7.308 to 9.271 ton/ha, while simulation values ranged from 7.413 to 9.556 ton/ha (Table 4). The deviations ranged from −6% to 4% between simulated and observed values for the cropping seasons of 2016 and 2017. An overall R^2 value of 0.968 (validation database) was observed for the analysis of simulated and observed biomass for both years 2016 and 2017, Figure 7b, biomass was predicted with higher R^2 value.

Table 4. Validation results of biomass and lint yield for all four irrigation treatments for the year 2016 and 2017.

Treatments	Variables	2016			2017		
		Measured	Simulated	Deviation (%)	Measured	Simulated	Deviation (%)
100% ET	Biomass (ton/ha)	8.78	9.136	4	9.271	9.556	3
	Yield (ton/ha)	3.116	3.24	4	3.282	3.441	5
80% ET	Biomass (ton/ha)	8.534	8.551	0	9.046	9.126	1
	Yield (ton/ha)	3.055	3.046	0	3.203	3.347	4
70% ET	Biomass (ton/ha)	7.963	8.007	1	8.102	8.358	3
	Yield (ton/ha)	2.82	2.985	6	2.900	3.177	10
50% ET	Biomass (ton/ha)	6.685	6.298	−6	7.308	7.413	1
	Yield (ton/ha)	2.367	2.493	5	2.593	2.863	10

Lint yield measured for the year 2016 and 2017 were ranged from 2.367 to 3.116 ton/ha and 2.593 to 3.282 ton/ha, while simulated values were ranged from 2.493 to 3.24 ton/ha and 2.863 to 3.441 ton/ha, respectively, among treatments (Table 4). The difference in yield between 100%ET and 80%ET was small (no significant difference in yield) in 2015, 2016, and 2017 (Tables 3 and 4). However, there was a significant difference in yield in 70%ET and 50%ET treatments. The model accuracy for yield prediction is shown in Figure 7a. The R^2 value for yield was 0.895 between measured and simulated values using validation data bases, which verify that the model presents high accuracy in predicting yield.

3.3. Water Productivity

The differences in the yield water productivity (YiWP) and biomass water productivity (BiWP) between measured and simulated values are shown in Table 5. Yield water productivity (YiWP) and biomass water productivity (BiWP) decreased with the increase in stress of water except 80%ET during all three years Figure 7a,b. In the present study, YiWP ranged from 0.43 to 0.63 kg/m^3 reaching its maximum value of 0.63 kg/m^3 in 2016 in 100% and 80% ET. Similarly, the value of BWP ranged from 1.44 to 1.79 kg/m^3 reaching its maximum value of 1.79 kg/m^3 in 2015 in 100% ET treatment. AquaCrop consistently overestimates the water use efficiencies, and due to water stress the deviations increased. The deviations were in the range of −2% to 11% in YiWP and −2% to 4% in BWP. The deviations were higher in YiWP as compared to BiWP; this is because the model also showed maximum deviation in the simulation of yield (Table 4). Maximum deviation was observed in YiWP of 50%ET treatment (10%, 9%, and 11% in 2015, 2016, and 2017, respectively). However, YiWP and BiWP were better in 80%ET both for calibration and validation databases (Table 5), indicating a potential for water saving. No significant difference was found in yield and biomass from 80%ET; thus, this treatment could be the best alternative to100%ET. The overall prediction of biomass water use efficiency in 2016 is better than that of 2015 and

2017. The linear regression between simulated and observed yield water productivity has the R^2 value of 0.943 (Figure 10), suggesting that model prediction is fair.

Table 5. Comparison between measured and simulated water use efficiencies of three cropping seasons (2015, 2016, and 2017).

Treatments	Yield Water Productivity (YiWP) (kg/m^3)			Biomass Water Productivity (BiWP) (kg/m^3)		
	Measured	Simulated	Deviation (%)	Measured	Simulated	Deviation (%)
2015						
100%ET	0.57	0.59	4	1.79	1.8	1
80%ET	0.58	0.59	2	1.78	1.83	3
70%ET	0.51	0.55	8	1.72	1.78	4
50%ET	0.46	0.51	10	1.58	1.65	5
2016						
100%ET	0.63	0.65	3	1.75	1.79	2
80%ET	0.63	0.63	0	1.75	1.77	1
70%ET	0.53	0.58	9	1.67	1.72	3
50%ET	0.50	0.54	9	1.53	1.59	4
2017						
100%ET	0.58	0.57	−2	1.68	1.7	1
80%ET	0.59	0.6	3	1.69	1.65	−2
70%ET	0.50	0.53	6	1.57	1.63	4
50%ET	0.43	0.48	11	1.44	1.5	4

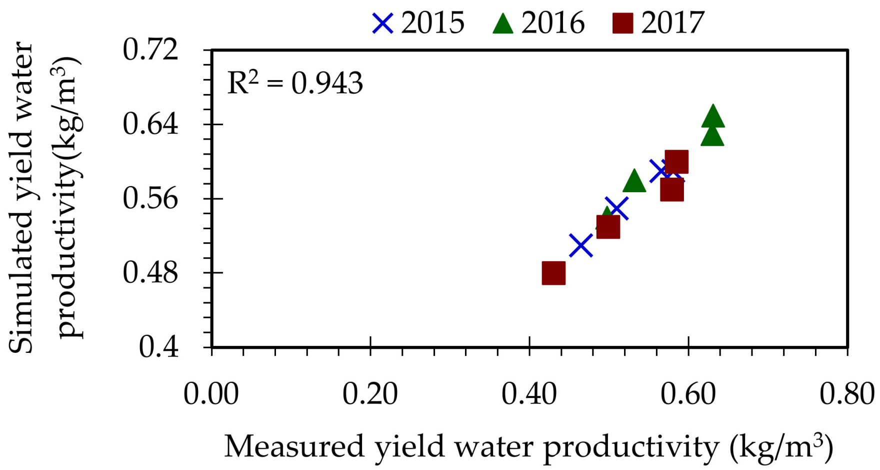


Figure 10. Comparison between measured and simulated yield water productivity for three cropping seasons (2015, 2016, and 2017) under different water treatments.

4. Discussion

AquaCrop uses conservative parameters such as canopy cover, biomass, harvest index for simulation purposes. In the present study, AquaCrop simulated the canopy cover development and biomass accumulation of cotton for four irrigation treatments (100%ET, 80%ET, 70%ET, and 50% ET) and three databases (2015, 2016, and 2017). AquaCrop successfully predicted the canopy cover, biomass, and cotton lint yield. Suitable relationships were obtained among simulated canopy cover, biomass, yield, and water productivities (YiWP and BiWP) across three years under four treatments (Figures 5–11, Tables 3–5). These results are in concurrence with that of the works of [11,31].

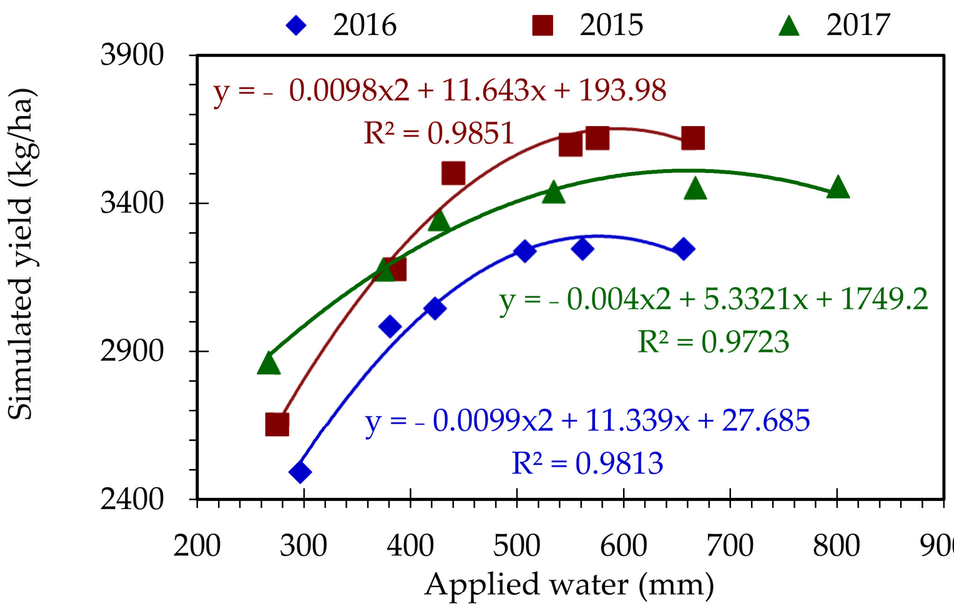


Figure 11. Simulated cotton yield water functions obtained by varying the seasonal applied irrigation water.

The model successfully predicted the lint yield of cotton with small deviations of 1% to 2%. Coefficient of variation R^2 value of 0.943 and 0.935 (using calibration data set) were observed for the analysis of simulated and measured yield and biomass, respectively, indicating that model predicted yield and biomass very perfectly. However, there was a tendency to overestimate biomass in 2015. Figure 7a shows the accuracy of the model in predicting lint yield. A strong correlation was observed between the simulated and the measured values for the calibrated database (R^2 = 0.943 and R^2 = 0.935 for lint yield and biomass, respectively). The reduction in cotton yield mainly occurs when stress occurs in the reproductive stage of the crop. The most severely stressed treatment, 70% ET, and 50%ET in 2016, showed maximum deviation (10%) in yield between simulated and observed values. Simulated yield within 5% deviation shows the accuracy of AquaCrop in predicting yields, while the deviation values of 10% indicate that model accuracy declines in conditions of stressed water conditions. The same situations were reported by [32].

All irrigation treatments validated well the biomass (ton/ha) and canopy cover (%). The different climatic conditions in 2016 and 2017 lowered the yield; the reason might be the lower water productivity. AquaCrop provided suitable and adequate results of the biomass and canopy cover. The measured and simulated canopy cover used for validation AquaCrop model is shown in Figure 8 for the years 2016 and 2017, respectively. In general, simulation of canopy cover for the year 2017 showed the strongest agreement between simulated and observed values of canopy cover with lower *RMSE* (3.055% to 3.674%) and higher d-index values (0.991 to 0.998). The canopy cover simulation results were performed better in treatment of 80%ET (*RMSE* = 3.05%, d-index = 0.998 to 0.997) as compared to 100%ET (*RMSE* = 3.535% to 3.082%, d-index= 0.997 to 0.998) for both year 2016 and 2017 (Figure 8). It was concluded that to simulate canopy cover, biomass, and yield of cotton, AquaCrop model can be used. This research, as reported by the work of [12], suggested that climatic conditions, variety of crop, and irrigation practices can influence the performance of the AquaCrop model. The results showed that performance of model was better (*RMSE* = 0.204% to 0.410%, d-index = 0.995 to 0.999) in 2017 as compared to 2016 (*RMSE* = 0.666% to 0.335%, d-index = 0.996 to 0.991) which also depicted in Figure 9. AquaCrop predicted well aboveground biomass in 80%ET as compared to 100%ET in 2016 (Figure 9a,b) with *RMSE* = 0.413% and d-index = 0.996. The overview of some researchers is that AquaCrop model overestimates and underestimates the biomass and canopy cover, respectively, in the middle of the crop growth stage [33,34]. Similar results were obtained in the present study for all irrigation treatments. This could be possible due to the reason that AquaCrop clarifies the process of canopy cover decrease at crop senescence [35]. Biomass and yield water productivity decreases by the increase in transpiration amount in all four treatments. In the present study, the values of biomass water productivities were ranged from 1.44 to 1.79 kg/m^3 in all growing seasons, and yield water productivity ranged from 0.43 to 0.63 kg/m^3. These results are in agreement with the results reported in [36].

The model simulated canopy cover and biomass under different weather conditions with varying performance degrees. The year 2015 was the driest year, giving the lowest agreement between simulated and measured data. Severe water stress was observed during the early growth period of cotton in 2015 because the temperature was higher, and rainfall was less. Katerji et al. [37] reported that the level of plant water stress affected the model performance.

For quantification of the economic benefit of irrigations on average yield, it was required to calculate the estimated increase in yield as a function of increasing amounts of water delivered by the irrigation system. AquaCrop was run by changing the applied water values including water application at 150%ET, 120%ET, 100%ET, 80%ET, 70%ET, and 50%ET to verify the effect of increased and decreased irrigation water on the yield of cotton and keeping all the factors and data set constants. The simulated yield of cotton varied by changing applied water in three years (2015, 2016, and 2017). The plot showed that at a certain level, as depicted in Figure 11, yield decreased by increasing water applied for cotton.

There is a parabolic shape pattern achieved for water applied and simulated yield, which showed that cotton yield will be affected if water application increases from a certain safe level (Figure 11). The curve starts from a high slope, demonstrating that the production function is using water efficiently at low levels of irrigation. As the application of water level increases by 20%, the slope decreases. The slope of the parabolic line goes to zero as the water function attains maximum yield. AquaCrop works well for deficit irrigation, and if we increase water beyond 100%, then it will not change yield until and unless all crop parameters should be measured at that irrigation. Yield became stagnant after 100% ET, though we increased the amount of applied water (mm), 120%ET, and 150%ET, the last two points in three curves in Figure 8. The water production functions are curved lines, which change among climate scenarios. Using the quadratic formula, the best fit was observed; yield deficit and square of the available water deficit were varied proportionately. The regression lines fit very well with $R^2 \geq 0.97$ for the three functions. So, it indicated that AquaCrop worked well in water limiting conditions rather than in saturation. It predicts the impact of water stress on yield. In 2015 and 2017, yield versus water simulations, 80%ET showed better results, and there were no significant differences in yield in 100%ET and 80%ET treatments, but in 2016 there was a significant difference in yield in both treatments (100%ET and 80%ET). AquaCrop is stable and useful for different crops and environmental conditions. This study was conducted on cotton crops; however, other crops can also be studied.

5. Conclusions

Canopy cover, above ground biomass, lint yield and water productivity terms of grain yield and biomass of cotton were calibrated and validated by using AquaCrop model under four irrigation treatments. From the results of the present study, it was concluded that AquaCrop demonstrated its capability in simulating canopy cover, grain, and biomass yield to the reasonably suitable accuracy (d = 0.997 and 0.998, $RMSE$ = 0.397% and 3.266%, for canopy cover and biomass, respectively). *RMSE* and d-index statistics were used for canopy cover (CC) for validation database were 2.67% to 4.47% and 0.991% to 0.998%, and for biomass were 0.088% to 0.666% and 0.991% to 0.999% for 2016 and 2017, respectively. Yield and biomass water productivity was found maximum in 80%ET, and there was no significant difference of yield in 100%ET and 80%ET, which indicated that the regions with a low delta of water will have yield loss. Model accuracy correlated (R^2 = 0.95 and

0.97) between final measured and simulated yield and biomass, respectively. Thus, it is concluded that this model can be used as a decision-making tool for effective irrigation management practices.

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