CALIBRATION OF THE AQUACROP MODEL TO SIMULATE SUGAR BEET PRODUCTION AND WATER PRODUCTIVITY UNDER DIFFERENT TREATMENTS

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ABSTRACT. *The AquaCrop model, calibrated for 2002 and validated for 2003, is used to simulate sugar beet root dry yield, dry biomass, water productivity based on irrigation (WP_i), and water productivity based on total water input (WP_{i+p}) in an experimental field of the Karaj Sugar Beet Seed Institute (Karaj, Iran). Three irrigation treatments including full irrigation, 75% deficit irrigation, and 50% deficit irrigation were carried out in the main plots. The results of statistical comparison between the model output and observed data in the calibration (2002) and validation (2003) years showed that the AquaCrop model reliably simulated sugar beet yield and the biomass under different genotypes and irrigation levels. AquaCrop did a better job of simulating dry biomass than root dry yield. The findings show that by decreasing water input, including irrigation and precipitation, WP_i, and WP_{i+p} will increase. In total, statistical indicators and scatter plots indicated that the AquaCrop model had enough fitness to predict yield, biomass, and water productivity for the future.*

Keywords. *AquaCrop, Yield; Biomass, WP_i, WP_{i+p}.*

Different experiments and methods are required to increase the efficient use of water in agricultural fields, particularly in the arid and semi-arid regions of the world. Sugar beets are industrial crops that play an important role in sucrose production in Iran. Sucrose is a sweet and stable product that can be used in many foods, drinks, and drugs (Cooke and Scott, 1993). However, experiments related to water scarcity conditions, such as deficit irrigation over different cultivars, are applicable in terms of optimizing the net irrigation water requirements for sugar beet production.

AquaCrop is a water productivity model that was recently developed by the Food and Agriculture Organization (FAO) to simulate yield and biomass by considering the responses of these parameters to water. On the other hand, the AquaCrop model, with minimal input parameters, has a good performance under water-limiting conditions with a good balance between simplicity, accuracy, and robustness (Raes et al., 2009b; Steduto et al., 2009). AquaCrop was designed to estimate the yields of major herbaceous crops, even when the crops face water stress. The model has been tested under different irrigation treatments for various crops in different regions of the globe, e.g., teff (Araya et al., 2010); rice (Amiri et al., 2015); barely (Tavakoli et al., 2015); potato, and sunflower (García-Vila and Fereres, 2012; Yuan et al., 2013); wheat (Andarzian et al., 2011; Shrestha et al., 2013); cotton (Farahani et al., 2009; Hussein et al., 2011; García-Vila and Fereres, 2012; Heidariniya et al., 2012) ; maize (Abedinpour et al., 2012; Ahmadi et al., 2015); and soybean (Giménez et al., 2017). Water productivity was also determined in order to optimize the irrigation management of different crop models, such as SWAP (Amiri, 2017) and ORYZA2000 (Amiri and Rezaei, 2010; Amiri et al., 2011). However, studies have indicated a research gap in terms of the simulation of yield, biomass, and water productivity of sugar beet genotypes under water scarcity conditions.

Therefore, this study aims to evaluate the capability of the AquaCrop model to simulate yield and biomass for three different genotypes under three irrigation levels.

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Furthermore, water productivity per unit of water applied, including water productivity based on irrigation (WP_i), and water productivity based on irrigation and precipitation (WP_{i+p}), will be computed for different genotypes.

Material and Methods

Field Experiment and Treatments

The study area was located in an experimental field of the Karaj Sugar Beet Seed Institute, Iran (35°50′21.6″N, 50°52′22″E). This area has a cold semi-arid climate with a temperate summer and semi-cold winter. The data was selected from two experiments that took place in 2002 and 2003, and analyses were conducted in the form of randomized complete block designs with four replications. Three sugar beet genotypes, 7112 (V1), BP-Mashhad (V2), and Rasoul (V3), were sown on 18 May 2002 and 11 May 2003 and harvested on 10 November 2002 and 3 November 2003, respectively. Furrow irrigation was employed, and the cultivated area was approximately 1800 m^2 for each of the two experimental years. The irrigation depth and intervals for all treatments were the same as those for the control treatments until the plant emergence and establishment stage. After this growth stage, three irrigation treatments were implemented during which soil moisture reached 60%, 47%, and 37% of field capacity (FC) that were assigned to the treatments involving full irrigation or without water stress (I1), 75% deficit irrigation or mild water stress (I2), and 50% deficit irrigation or severe water stress (I3), respectively. Finally, in order to simulate the yield and biomass of sugar beet genotypes under different irrigation levels, AquaCrop version 4.0 (Raes et al., 2012b) was calibrated for 2002 and validated for 2003.

Aquacrop Model

AquaCrop is a water-driven model designed to yield responses in relation to the water supply and agronomic practices by using soil-water budgeting relations (Raes et al., 2009b). The model algorithms and structural detail are described by Raes et al. (2009b), whereas the specifications of the model, including conceptual framework, underlying principles, and distinctive components, are discussed by Steduto et al. (2009). An empirical production function developed by Doorenbos and Kassam in 1979, is shown in equation 1. It is a basic equation for the prediction of yield in response to water (Raes et al., 2009a):

$$\left(1-\frac{Y}{Y_x}\right)=k_y\left(1-\frac{ET}{ET_x}\right) \tag{1}$$

where Y_x and Y are the maximum and actual yield, respectively; ET_x and ET are the maximum and actual evapotranspiration, respectively; and k_y is the proportionality factor between the relative yield decrease and relative reduction in evapotranspiration (fig. 1).

Based on a modification of the Ritchie's approach and distinctive feature of daily water balance, the AquaCrop model is able to separate evapotranspiration into soil evaporation and crop transpiration and this distinguishes

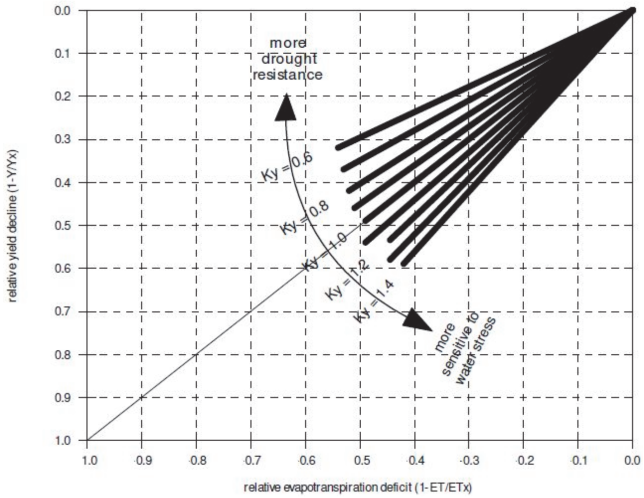


Figure 1. Relationship between relative yield decrease (1-Y/Ym) and relative evapotranspiration deficit (1-ET/ETc) for the total growing period for various yield response factor (Ky).

AquaCrop from other crop simulation models. However, a point of weakness of the model is its inability to consider the effects of diseases and pests; neglecting these effects may lead to an overestimation of yield (Raes et al., 2009a). The core of the AquaCrop growth engine was established based on the conservative behavior of water productivity, which is the ratio of biomass to cumulated water transpired over the time period in which the biomass is produced (Steduto et al., 2009).

Input Data in Aquacrop Model

The model is dependent on data related to the weather (temperature, rainfall, ETo, and CO_2), crop, soil, and field management (irrigation dosage and fertilizer) used to describe the crop development environment. Meanwhile, input data related to the crop is determined from model defaults, experimental measured data, and calibrated parameters. The Leaf Area Index (LAI) was measured for each single treatment and replication during different phonological intervals on observation dates that include 5 August, 14 September, 13 October, and 10 November. The percentange of canopy cover in each phonological interval (observation date) was estimated via the following equation by Andrieu et al. (1997).

$$f=\left(0.986+\left(-0.725*exp\left(-LAI\right)\right)\right)^2 \tag{2}$$

where f is the percentage of canopy cover and LAI is the Leaf Area Index. The mean values of four replications derived from the estimated canopy cover as well as values from other similar field experiments in the study area and the AquaCrop default values were considered for the calibration of the canopy cover. The crop parameters and the measured physical soil characteristics for the study area are shown in tables 1 and 2.

Climatic data, such as minimum and maximum temperatures and precipitation on a daily basis, were collected from the Karaj meteorology station, which is approximately 8 km from the experimental field. Among various calculation methods for finding the reference evapotranspi-

Table 1. Main crop parameters in the calibration of the AquaCrop model for sugar beets.

Crop parameters	7221-I-79 I1	7221-I-79 I2	7221-I-79 I3	BP-Mashhad I1	BP-Mashhad I2	BP-Mashhad I3	Rasoul I1	Rasoul I2	Rasoul I3	Remarks[a]
Base temperature, °C	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	D
Upper temperature, °C	30.0	30.0	30.0	30.0	30.0	30.0	30.0	30.0	30.0	D
Canopy growth coefficient (CGC),% day^{-1}	10.6	10.0	10.0	10.9	10.9	10.7	9.9	9.8	9.8	C
Maximum canopy cover (CCx),%	97	94	94	96	95	90	93	92	93	C
Canopy decline (CDC),%day^{-1}	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	C
Minimum effective rooting depth, m	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	D
Maximum effective rooting depth, m	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	D
Sowing to emergence, days	10	10	10	10	10	10	10	10	10	M
Sowing to maximum canopy, days	99	104	104	96	96	97	105	105	106	C
Sowing to start senescence, days	150	150	150	154	150	135	157	140	138	C
Sowing to maturity (length of crop cycle), days	177	177	177	177	177	177	177	177	177	M
Water Productivity normalized, gram m^{-2}	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	17.0	D
Reference harvest index (HI0),%	70	70	70	70	70	70	70	70	70	D

[a] C – calibrated, D – default, M – measured.

Table 2. Physical characteristics of silty clay soil in the experimental fields.

Soil Texture	Depth (cm)	Permanent Wilting Point (PWP) (vol%)	Field Capacity (FC) (vol%)	Saturation Point (SAT) (vol%)	Total Available Water (TAW) (mm/m)	Saturated Hydraulic Conductivity (Ksat) (mm/day)
Silty clay	0-30	14.0	28.0	48.0	140	133.6
(2002)	30-60	14.0	28.0	48.0	140	145.0
Silty clay	0-30	14.0	28.0	50.0	140	132.1
(2003)	30-60	14.0	28.0	49.0	140	150.7

ration (ETo), the Penman-Monteith method (PM) is commonly recognized as a standard method of comparison. The values of ETo calculated using Hargreaves-Samani (HS) were compared to those obtained using the PM method via regression on a daily basis in order to evaluate the performance of this temperature-based method (HS).

Model Prediction Accuracy

The model prediction accuracy is evaluated based on the most important statistical indicators, including the absolute root mean square error (RMSE) (eq. 3); root mean square error normalized (RMSEn) (eq. 4); the index of agreement (d) (eq. 5), as calculated by Willmott (1982); and MBE (mean bias error) (eq. 6). These indicators represented agreement between the observed and simulated root dry yield and dry biomass.

$$RMSE = \left[\frac{\sum_{i=1}^{n} (Pi - Oi)^2}{n} \right]^{1/2} \tag{3}$$

$$RMSEn = 100 \frac{RMSE}{\bar{O}} \tag{4}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Pi - Oi)^2}{\sum_{i=1}^{n} \left(\left| Pi - \bar{O} \right| + \left| Oi - \bar{O} \right| \right)^2} \tag{5}$$

$$MBE = \frac{1}{n} \left[\sum_{i=1}^{n} (Pi - Oi) \right] \tag{6}$$

where Pi and Oi are the simulated and observed value, respectively; $\bar{O}$ is the average value of observed data, and n is the number of observations. RMSE is a useful index for crop modelling (Jacovides and Kontoyiannis, 1995) and fluctuates between 0 and positive infinity. When residual estimation errors decrease, the RMSE values are close to zero. Moreover, the RMSEn is a percentage index for describing relative differences between predictions and observations. When the values of RMSEn are smaller than 10%, the accuracy of model is excellent; when they are between 10% and 20%, the accuracy is good; accuracy is fair if the values are between 20% and 30%, and accuracy is poor if the values are larger than 30% (Raes et al., 2012a).

The index of agreement (d) is a descriptor, and its values range from 0 to 1. The model simulated the appointed parameter better as d approaches 1 (Stricevic et al., 2011). Further, the MBE reveals the long-term performance of the model. A positive value of the MBE shows the average amount of overestimation in the estimated values, whereas a negative value indicates underestimation (Iqbal et al., 2014). The "goodness-of-fit" between the observed and simulated yield and biomass was evaluated using t-tests and determination coefficient (R^2) analysis (Amiri and Rezaei, 2010). The squared value of the Pearson correlation coefficient (R^2), which ranges from 0 to 1 (Raes et al., 2012a), is commonly acceptable in watershed scales if its value is greater than 0.5 (Vara Prasad et al., 2005). However, if the p-value from the t-test is greater than 0.05, there is not any significant difference between the observed and simulated value (Amiri and Rezaei, 2010).

Water Productivity

Water productivity is defined based on crop production (root dry matter or grain yield) and the amount of water in the form of evapotranspiration, irrigation, and precipitation, all of which will be used by a crop during its growing period. The following equations were applied to estimate water productivity based on irrigation (WP_i), and water productivity based on irrigation and precipitation (WP_{i+p}).

$$WP_i = \frac{y}{i \times 10}, \tag{7}$$

$$WP_{i+p} = \frac{y}{(i+p)\times 10}, \tag{8}$$

where y is root dry matter (kg ha^{-1}), i is irrigation (mm), and p is precipitation (mm).

Results

Rerference Evapotranspiration (ETo)

The regression model between the daily ETo calculated via Penman-Monteith and Hargeaves-Samani from the first day of January 2002 to the last day of December 2003 is shown in figure 2. The daily regression model had a high value of R^2, showing that the HS model had enough validity to be used in the calibration and validation years. Moreover, under arid and semi-arid climatic conditions, such as the study area, the HS method is one of the most suitable ETo estimation methods (Lang et al., 2017; Raziei and Pereira, 2013; Tabari, 2010).

Calibration Set

The calibration results for the yield and biomass under different treatments in 2002 are described in table 3. Due to the water stress, the values of observed and simulated yield and biomass reduced under treatments with deficit irrigation. The minimum prediction errors between the observed and simulated root dry yield within different genotypes with designated irrigation treatments were assigned in ascending order to treatments V3I1, V1I1, and V2I1, while the maximum prediction errors were assigned to treatments V1I3, V3I3, and V2I3. It can be interpreted that the yield model prediction accuracy is weakened by increasing water stress. Furthermore, the minimum prediction errors between observed and simulated dry biomass within different genotypes with designated irrigation treatments were assigned in ascending order to treatments V3I2, V2I2, andV1I1, while the maximum prediction errors were assigned to treatments V2I1, V1I2, and V3I3. AquaCrop simulated the yield with a smaller average of errors for V1 genotypes, whereas it simulated the biomass with a smaller average of errors for the V2 genotypes.

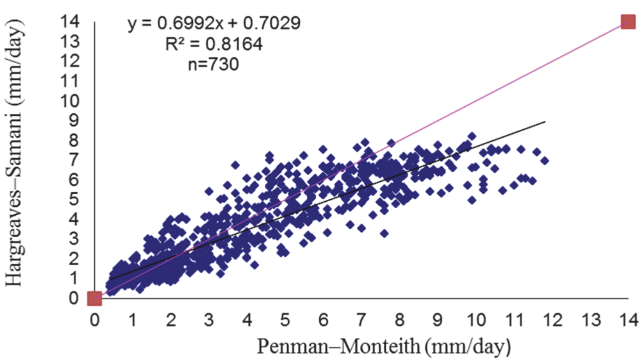


Figure 2. Regression model between the daily ETo calculated via Penman-Monteith and Hargeaves-Samani. The pink line represents a 1:1 relationship.

The results of the statistical comparison between the simulated and observed yield and biomass for nine treatments in the calibration year (2002) are shown in table 4. The RMSEn values are smaller than 10%, showing excellent model performance in the simulation of both yield and biomass, but more accuracy in the case of the dry biomass. The index of agreement (d) shows that model simulates biomass better than it does yield in the calibration year. However, the positive value of the MBE for yield represents a model overestimation in the calibration year, whereas the model underestimates the biomass.

The correlation coefficients (R^2), with values of 0.58 for yield and 0.86 for biomass, show that the observed and simulated values have significant correlations. In addition, the t-test results ($p > 0.05$) show that there is no significant difference between the observed and simulated yield and biomass. The scatter plots for the simulated and observed yield and biomass in the calibration year are shown in figures 3a and 3b.

Validation Set

Validation results for the yield and biomass under different treatments in 2003 are described in table 5. Due to the water stress, the values of observed and simulated yield and biomass reduced under treatments with deficit irrigation. The minimum prediction errors between the observed and simulated root dry yield within different genotypes with designated irrigation treatments were assigned in ascending order to treatments V2I1, V1I1, and

Table 3. Calibration results for the root dry yield and biomass of sugar beet under different irrigation levels in 2002.

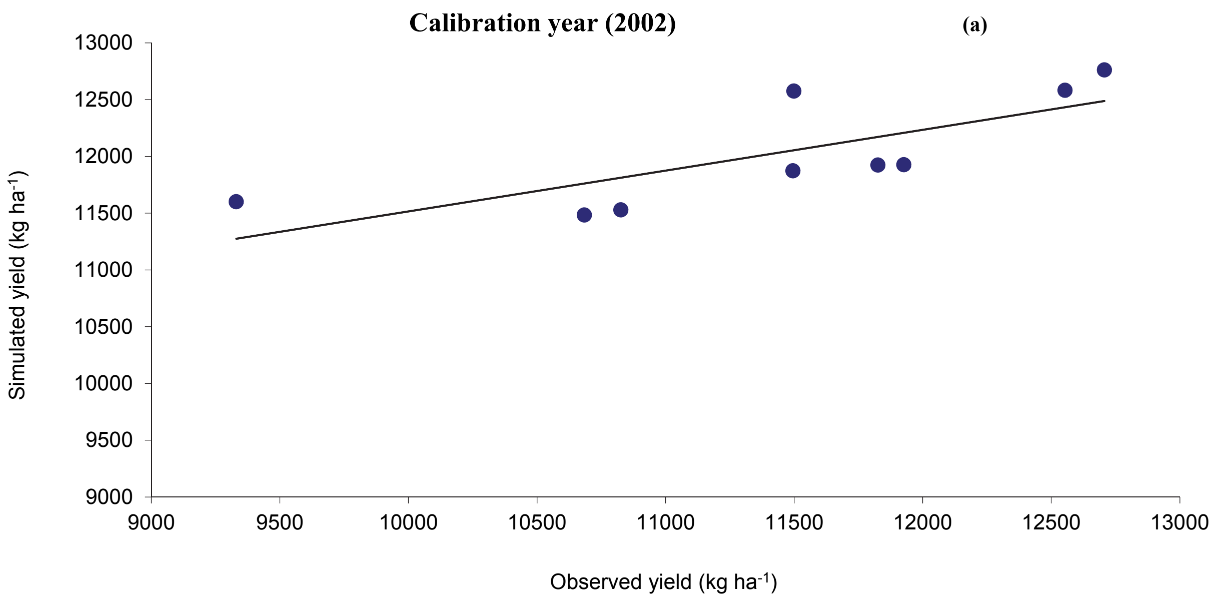
Genotypes	Irrigation Level (mm)	Yield (kg ha^{-1}) Obs	Yield (kg ha^{-1}) Sim	Pe (±%)	Biomass (kg ha^{-1}) Obs	Biomass (kg ha^{-1}) Sim	Pe (±%)
7221-I-79 (V1)							
Without water stress (I1)	1150	12553	12582	0.2	17554	17516	-0.2
Mild water stress (I2)	942	11826	11923	0.8	17457	16216	-7.1
Severe water stress (I3)	738	11496	11872	3.3	15407	15151	-1.7
BP-Mashhad (V2)							
Without water stress (I1)	1150	12707	12761	0.4	18552	17782	-4.2
Mild water stress (I2)	942	11499	12575	9.4	17063	17030	-0.2
Severe water stress (I3)	738	9331	11600	24.3	14287	14634	2.4
Rasoul (V3)							
Without water stress (I1)	1150	11926	11926	0.0	16597	16670	0.4
Mild water stress (I2)	942	10826	11528	6.5	15604	15602	0.0
Severe water stress (I3)	738	10684	11483	7.5	13417	14779	10.1

Table 4. Evaluation results for the AquaCrop simulations in terms of root dry yield (kg ha^{-1}) and dry biomass (kg ha^{-1}) for the calibration sets.

Year	Variable	Xobs (SD)	Xsim (SD)	RMSE	RMSEn	d	MBE	R^2	t-test
2002	Yield	11428 (979)	12028 (462)	919	8.8	0.652	600	0.58	0.068
	Biomass	16216 (1572)	16153 (1108)	682	4.2	0.933	-62	0.86	0.464

V3I1, while the maximum prediction errors were assigned to treatments V1I3, V3I3, and V2I3. It can be interpreted that yield model prediction accuracy is weakened by increasing water stress, and these findings are in agreement with those obtained by Razzaghi et al. (2017). Moreover, the validation results for the biomass showed that, among different genotypes with designated irrigation treatments, the minimum prediction errors between observed and simulated dry biomass were assigned in ascending order to treatments V2I2, V1I2, and V3I2, while the maximum prediction errors were assigned to treatments V2I3, V1I1, and V3I3. Similarly to the calibration year, AquaCrop simulated yield with a smaller average of errors for the V1 genotypes, whereas it simulated the biomass with a smaller average of errors for the V2 genotypes.

The results of the statistical comparison between the simulated and observed yield and biomass for nine treatments in the validation year (2003) are shown in table 6. The RMSEn values are between 10% and 20%, demonstrated that model has good performance in the simulation of the yield and biomass, but simulates the dry biomass more accurately. The index of agreement (d)



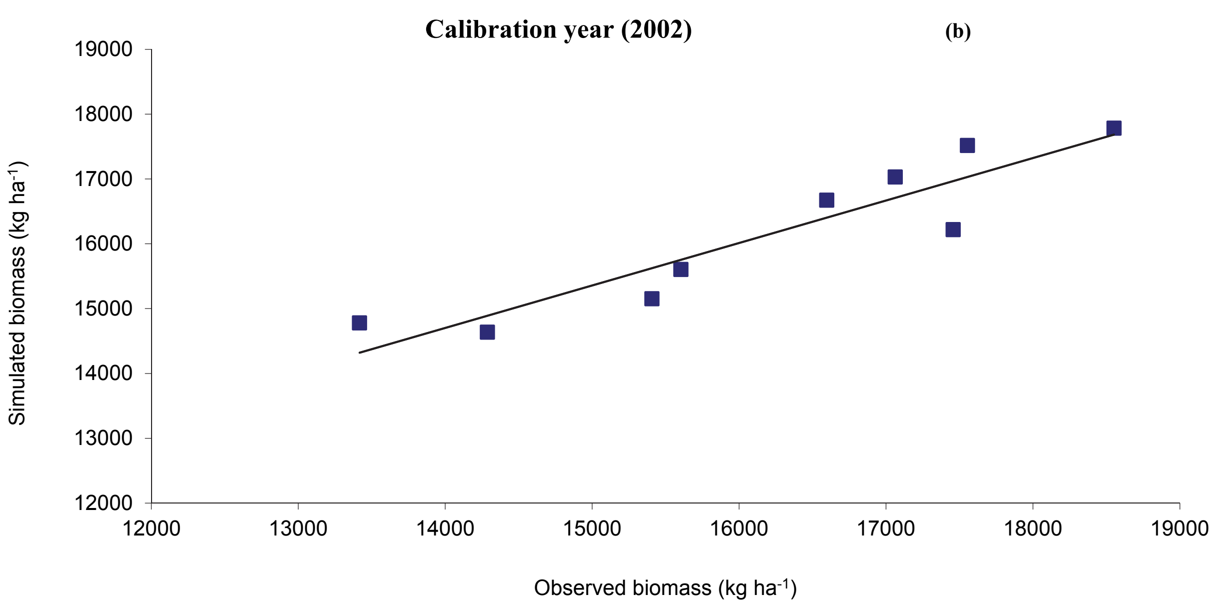


Figure 3. Scatter plots for simulated and observed (a) yield and (b) biomass in the calibration year (2002).

Table 5. Validation results for the root dry yield and biomass of sugar beet under different irrigation levels in 2003.

Genotypes	Irrigation Level (mm)	Yield (kg ha^{-1}) Obs	Yield (kg ha^{-1}) Sim	Pe (±%)	Biomass (kg ha^{-1}) Obs	Biomass (kg ha^{-1}) Sim	Pe (±%)
7221-I-79 (V1)							
Without water stress (I1)	1099	14289	13648	-4.5	16800	19348	15.2
Mild water stress (I2)	922	12323	13195	7.1	16084	16666	3.6
Severe water stress (I3)	682	10134	11064	9.2	15300	13958	-8.8
BP-Mashhad (V2)							
Without water stress (I1)	1099	13558	13826	2.0	18602	19601	5.4
Mild water stress (I2)	922	12011	13955	16.2	17891	17517	-2.1
Severe water stress (I3)	682	7867	11240	42.9	12011	13728	14.3
Rasoul (V3)							
Without water stress (I1)	1099	11987	12979	8.3	15059	18425	22.4
Mild water stress (I2)	922	10107	12688	25.5	13234	16156	22.1
Severe water stress (I3)	682	7831	10823	38.2	10781	13440	24.7

Table 6. Evaluation results for the AquaCrop simulations in terms of root dry yield (kg ha^{-1}) and dry biomass (kg ha^{-1}) for the validation sets.

Year	Variable	Xobs (SD)	Xsim (SD)	RMSE	RMSEn	d	MBE	R^2	t-test
2003	Yield	11123 (2170)	12602 (1169)	1940	17.4	0.724	1479	0.79	0.055
	Biomass	15085 (2486)	16538 (2263)	2099	13.9	0.812	1453	0.64	0.120

shows that model simulates biomass better than it simulates yield in the validation year. Further, the positive MBE values for yield and biomass represent model overestimation in the validation year. The correlation coefficients (R^2), with values of 0.79 for yield and 0.64 for biomass, show significant correlation between observed and simulated values. In addition, the t-test results ($p > 0.05$) show that there is no significant difference between the observed and simulated yield and biomass. The scatter plots for the simulated and observed yield and biomass in the validation year are shown in figures 4a and 4b. All in all, the results from the observed and simulated data for both the calibration and validation years show that water stress reduces yield, which is in agreement with the results of Shawquat et al. (2016).

WATER PRODUCTIVITY

The values of water productivity per unit of water applied (WP_i and WP_{i+p}) under different irrigation levels for the observed and simulated sets in two consecutive years are shown in table 7. The results show that, by enhancing water stress, the values of WP_i and WP_{i+p} will be increased for both the observed and simulated sets of the calibration year. However, with the exception of V2I3 for observed set, WP_i and WP_{i+p} will be also increased by enhancements in water stress in the validation year. The results of this study are in agreement with those obtained by Amiri and Rezaei (2010) and Amiri et al. (2011), which declared that irrigation water productivity increases in treatments with less water input. The average values of water productivity within all treatments showed that model overestimated WP_i and WP_{i+p} in the calibration and validation years, which is in line with the results for the yield simulated by the model shown in tables 4 and 6. The treatment V1I3 had the maximum values of WP_i and WP_{i+p} for the observed and simulated sets in the calibration year. On the other hand, V1I3 had the maximum values of WP_i and WP_{i+p} for the observed set in the validation year, whereas V2I3 had the maximum values of WP_i and WP_{i+p} for the simulated set. Moreover, among all treatments for the two years, V3I1 had the minimum values for the observed and simulated sets.

A comparison between the trends in the observed and simulated WP_i under different treatments in 2002 and 2003 is shown in figure 5. The values of the simulated WP_i were larger than the observed values for most treatments with the exception of V1I1 in 2003. Although the averages of the observed WP_i were the same in both years, the averages of the simulated WP_i in 2003 were larger than the corresponding values in 2002 (table 7 and fig. 5). A comparison between the trends in the observed and simulated WP_{i+p} under different treatments in 2002 and 2003 are shown in figure 6. The values of the simulated WP_i were larger than the observed values for most treatments, with the exception of V1I1 in 2003. The results in table 7 and figure 6 show that average values of the observed WP_{i+p} in 2002 were larger than they were in 2003, while the averages of the simulated WP_{i+p} in 2003 were larger than the corresponding values in 2002.

CONCLUSION

The regression between the Penman-Monteith (PM) and Hargreaves-Samani (HS) methods showed that HS was valid enough to be applied to the AquaCrop model, particularly in the case when fewer climatic variables are used, as in climate change studies. Therefore, temperature-based methods such as HS for ETo calculation in climate change studies decrease the uncertainties in AquaCrop outputs.

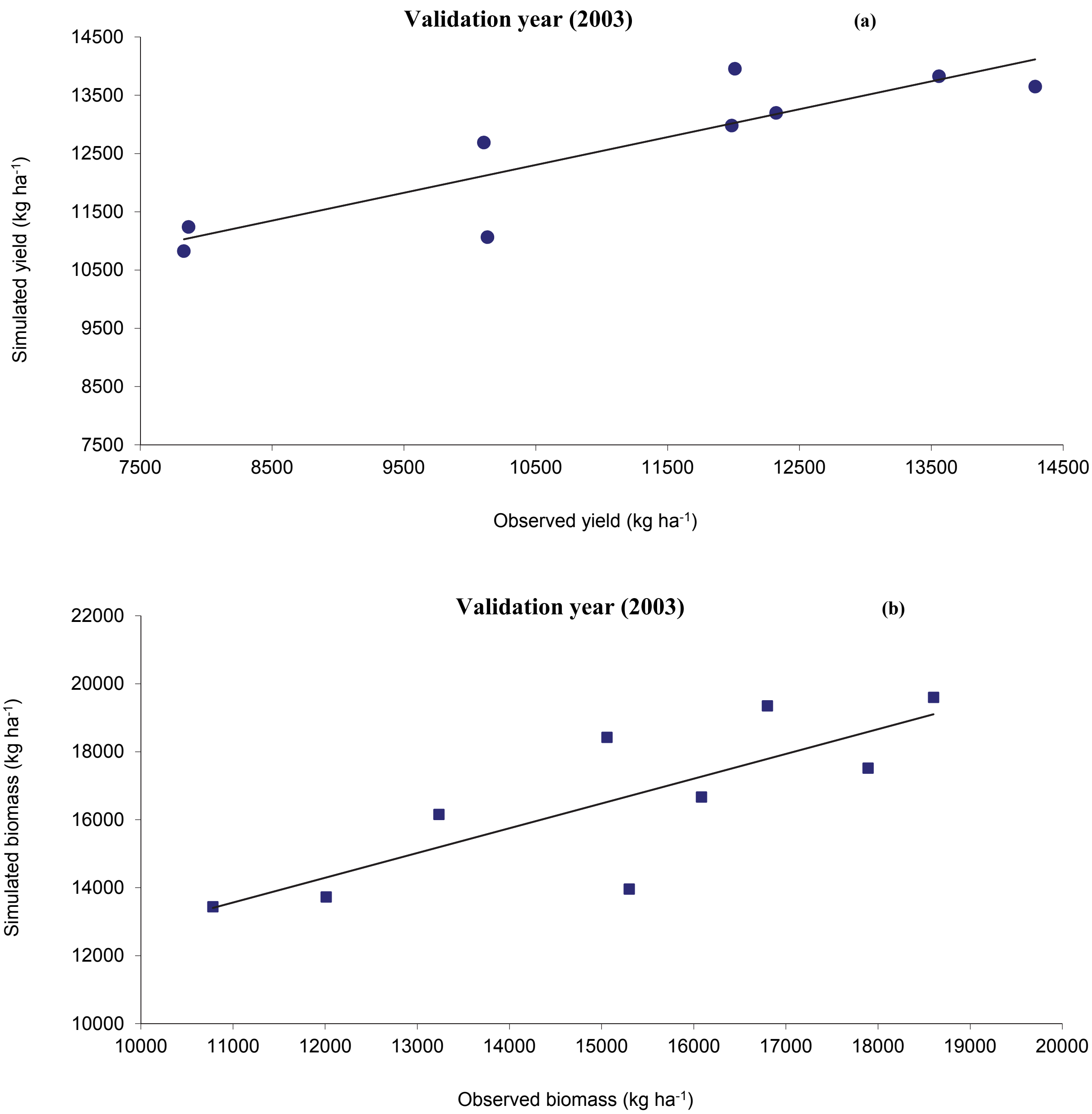


Figure 4. Scatter plots for simulated and observed (a) yield and (b) biomass in the validation year (2003).

In terms of the prediction errors between the observed and simulated yield, the results indicated that, for all three genotypes, when water stress was increased, the prediction errors also increased, while the biomass did not necessarily follow that trend. AquaCrop keeps track of the incoming and outgoing water fluxes in the crop root zone. On the other hand, in the AquaCrop model, the soil-water balance is a critical component in terms of simulating the root yield. Therefore, it can be proposed that for tuber crops such as sugar beet, AquaCrop is more sensitive to water stress in the simulation the root compared to the top, which may lead to a better simulation of dry biomass than root dry yield. In the current study, the values of RMSEn showed that the AquaCrop model predicts dry biomass better than root dry yield and these findings were in agreement with those obtained by Bitri and Grazhdani (2015). Moreover, under each irrigation level, the yield and biomass of the sugar beets changed based on the genotype with different prediction errors. Therefore, statistical indicators should be implementd over all treatments to eveulate the total perormance of the AquaCrop model in the simulation of sugar beet yield and biomass. In total, the statistical indicators and scatter plots showed that the AquaCrop model had enough fitness for the simulation of root dry yield, dry biomass, and water productivity per unit of water applied.

Table 7. Water productivity per unit of water applied (WP_i and WP_{i+p}) under different irrigation levels and sugar beet genotypes in the years 2002 and 2003.

Treatments	2002 WP_i (Obs) (kg m^{-3})[a]	2002 WP_i (Sim) (kg m^{-3})	2002 WP_{i+p} (Obs) (kg m^{-3})	2002 WP_{i+p} (Sim) (kg m^{-3})	2003 WP_i (Obs) (kg m^{-3})	2003 WP_i (Sim) (kg m^{-3})	2003 WP_{i+p} (Obs) (kg m^{-3})	2003 WP_{i+p} (Sim) (kg m^{-3})
V1I1	1.09	1.09	1.08	1.08	1.30	1.24	1.26	1.20
V1I2	1.26	1.27	1.24	1.25	1.34	1.43	1.28	1.37
V1I3	**1.56**[b]	**1.61**[b]	**1.54**[b]	**1.59**[b]	**1.49**[b]	1.62	**1.41**[b]	1.54
V2I1	1.10	1.11	1.10	1.10	1.23	1.26	1.19	1.22
V2I2	1.22	1.33	1.21	1.32	1.30	1.51	1.25	1.45
V2I3	1.26	1.57	1.25	1.55	1.15	**1.65**[b]	1.09	**1.56**[b]
V3I1	**1.04**	**1.04**	**1.03**	**1.03**	**1.09**	**1.18**	**1.05**	**1.14**
V3I2	1.15	1.22	1.14	1.21	1.10	1.38	1.05	1.32
V3I3	1.45	1.56	1.43	1.53	1.15	1.59	1.09	1.50
Average	1.24	1.31	1.22	1.30	1.24	1.43	1.19	1.37
Min	1.04	1.04	1.03	1.03	1.09	1.18	1.05	1.14
Max	1.56	1.61	1.54	1.59	1.49	1.65	1.41	1.56

[a] The **bold** values represent the minimum and maximum values of the observed and simulated water productivity.
[b] Better values in 2002 and 2003.

The results showed that by decreasing the irrigation levels and precipitation rates, the values of water productivity based on irrigation (WP_i) and total water input (WP_{i+p}) increase. In fact, treatments with maximum water productivity can be considered as an optimum cultivar in the case when irrigation management and saving water in the agricultural sectors are important, finally leading to better irrigation scheduling. For example, in case of water-limiting conditions and under severe water stress, the 7221-I-79 genotype is recommended for cultivation; while under mild water stress, 7221-I-79 and BP-Mashhad should be considered to be the genotypes that will lead to more sugar beet production in the future. In total, AquaCrop is a valuable tool with which to simulate the yield, biomass, and water productivity of sugar beet genotypes in order to develop irrigation water management in water-limiting conditions. The calibrated AquaCrop model can be applied for simulation of yield and biomass under projected climate change in the future studies.

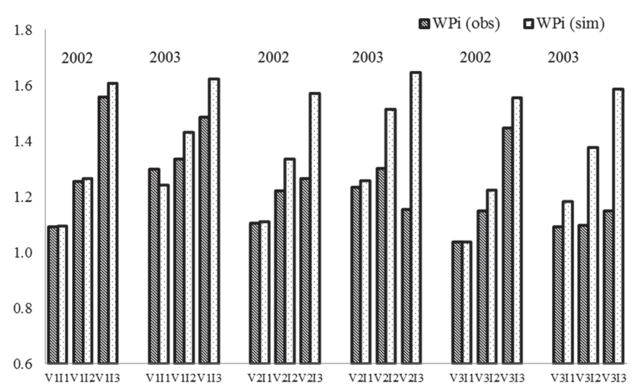


Figure 5. Comparison between the trends in observed and simulated WP_i under different treatments in 2002 and 2003.

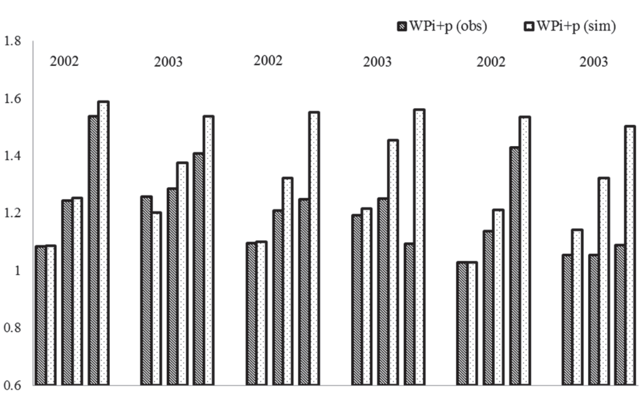


Figure 6. Comparison between the trends in the observed and simulated WP_{i+p} under different treatments in 2002 and 2003.

Disclosure Statement

The authors declare no conflict of interest.

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References

Abedinpour, M., Sarangi, A., Rajput, T. B., Singh, M., Pathak, H., & Ahmad, T. (2012). Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. *Agric. Water Manag., 110*, 55-66. https://doi.org/10.1016/j.agwat.2012.04.001

Ahmadi, S. H., Mosallaeepour, E., Kamgar-Haghighi, A. A., & Sepaskhah, A. R. (2015). Modeling maize yield and soil water content with aquacrop under full and deficit irrigation managements. *Water Resour. Manag., 29*(8), 2837-2853. https://doi.org/10.1007/s11269-015-0973-3

Amiri, E. (2017). Evaluation of water schemes for maize under arid area in iran using the SWAP model. *Commun. Soil Sci. Plant Anal., 48*(16), 1963-1976. https://doi.org/10.1080/00103624.2017.1408817

Amiri, E., & Rezaei, M. (2010). Evaluation of water-nitrogen schemes for rice in Iran, using ORYZA2000 model. *Commun. Soil Sci. Plant Anal., 41*(20), 2459-2477. https://doi.org/10.1080/00103624.2010.511377

Amiri, E., Ahmadzadeh Araji, H., Wayayok, A., & Rezaei, M. (2015). Simulation of rice yield under water and salinity stress in rasht area using aquacrop model. *Jurnal Teknologi, 76*(15).

Amiri, E., Razavipour, T., Farid, A., & Bannayan, M. (2011). *Effects of crop density and irrigation management on water productivity of rice production in northern Iran: Field and modeling approach* (Vol. 42). https://doi.org/10.1080/00103624.2011.596238

Andarzian, B., Bannayan, M., Steduto, P., Mazraeh, H., Barati, M. E., Barati, M. A., & Rahnama, A. (2011). Validation and testing of the AquaCrop model under full and deficit irrigated wheat production in Iran. *Agric. Water Manag., 100*(1), 1-8. https://doi.org/10.1016/j.agwat.2011.08.023

Andrieu, B., Allirand, J. M., & Jaggard, K. (1997). Ground cover and leaf area index of maize and sugar beet crops. *Agronomie, 17*(6-7), 315-321. https://doi.org/10.1051/agro:19970602

Araya, A., Keesstra, S. D., & Stroosnijder, L. (2010). Simulating yield response to water of Teff (Eragrostis tef) with FAO's aquacrop model. *Field Crops Res., 116*(1), 196-204. https://doi.org/10.1016/j.fcr.2009.12.010

Bitri, M., & Grazhdani, S. (2015). Validation of Aqua Crop model in the simulation of sugar beet production under different water regimes in southeastern Albania. *Parameters, 4*(6).

Cooke, D. A., & Scott, R. K. (1993). *The sugar beet crop: Science into practice.* Chapman & Hall. https://doi.org/10.1007/978-94-009-0373-9

Farahani, H. J., Izzi, G., & Oweis, T. Y. (2009). Parameterization and evaluation of the AquaCrop model for full and deficit irrigated cotton. *Agron. J., 101*(3), 469-476. https://doi.org/10.2134/agronj2008.0182s

Garcia-Vila, M., & Fereres, E. (2012). Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. *Eur. J. Agron., 36*(1), 21-31. https://doi.org/10.1016/j.eja.2011.08.003

Gimenez, L., Paredes, P., & Pereira, L. S. (2017). Water use and yield of soybean under various irrigation regimes and severe water stress. Application of AquaCrop and SIMDualKc models. *Water, 9*(6), 393. https://doi.org/10.3390/w9060393

Heidariniya, M., Naseri, A. A., Boroumandnasab, S., Moshkabadi, B. S., & Nasrolahi, A. H. (2012). Evalution of AquaCrop model application in irrigation management of cotton. World Rural Obs., 4, 55-59.

Hussein, F., Janat, M., & Yakoub, A. (2011). Simulating cotton yield response to deficit irrigation with the FAO AquaCrop model. *Spanish J. Agric. Res., 9*(4), 1319-1330. https://doi.org/10.5424/sjar/20110904-358-10

Iqbal, M. A., Shen, Y., Stricevic, R., Pei, H., Sun, H., Amiri, E., . . . del Rio, S. (2014). Evaluation of the FAO AquaCrop model for winter wheat on the North China Plain under deficit irrigation from field experiment to regional yield simulation. *Agric. Water Manag., 135*, 61-72. https://doi.org/10.1016/j.agwat.2013.12.012

Jacovides, C. P., & Kontoyiannis, H. (1995). Statistical procedures for the evaluation of evapotranspiration computing models. *Agric. Water Manag., 27*(3-4), 365-371. doi:http://dx.doi.org/10.1016/0378-3774(95)01152-9

Lang, D., Zheng, J., Shi, J., Liao, F., Ma, X., Wang, W., . . . Zhang, M. (2017). A comparative study of potential evapotranspiration estimation by eight methods with FAO Penman-Monteith Method in Southwestern China. *Water, 9*(10), 734. https://doi.org/10.3390/w9100734

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2009a). AquaCrop-The FAO crop model to simulate yield response to water. Rome, Italy: Land and Water Division, FAO.

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2009b). AquaCrop The FAO crop model to simulate yield response to water: II. Main algorithms and software description. *Agron. J., 101*(3), 438-447.

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2012a). Land and water division. Rome, Italy: FAO.

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2012b). Reference Manual AquaCrop 4.0. Rome, Italy: FAO. Retrieved from http://www.fao.org/nr/water/aquacrop.html

Raziei, T., & Pereira, L. S. (2013). Estimation of ET o with Hargreaves-Samani and FAO-PM temperature methods for a wide range of climates in Iran. *Agric. Water Manag., 121*, 1-18. https://doi.org/10.1016/j.agwat.2012.12.019

Razzaghi, F., Zhou, Z., Andersen, M. N., & Plauborg, F. (2017). Simulation of potato yield in temperate condition by the AquaCrop model. *Agric. Water Manag., 191*, 113-123. https://doi.org/10.1016/j.agwat.2017.06.008

Shawquat, M., Karim, M., Haque, M., Islam, M. M., Karim, A. J., & Mian, M. (2016). *Influence of salt and water stress on growth and yield of soybean genotypes* (Vol. 39).

Shrestha, N., Raes, D., Vanuytrecht, E., & Sah, S. K. (2013). Cereal yield stabilization in Terai (Nepal) by water and soil fertility management modeling. *Agric. Water Manag., 122*, 53-62. https://doi.org/10.1016/j.agwat.2013.03.003

Steduto, P., Raes, D., Hsiao, T. C., Fereres, E., Heng, L. K., Howell, T. A., . . . Izzi, G. (2009). Concepts and applications of AquaCrop: The FAO crop water productivity model. In *Crop modeling and decision support* (pp. 175-191). Springer. https://doi.org/10.1007/978-3-642-01132-0_19

Stricevic, R., Cosic, M., Djurovic, N., Pejic, B., & Maksimovic, L. (2011). Assessment of the FAO AquaCrop model in the simulation of rainfed and supplementally irrigated maize, sugar beet and sunflower. *Agric. Water Manag., 98*(10), 1615-1621. https://doi.org/10.1016/j.agwat.2011.05.011

Tabari, H. (2010). Evaluation of reference crop evapotranspiration equations in various climates. *Water Resour. Manag., 24*(10), 2311-2337. https://doi.org/10.1007/s11269-009-9553-8

Tavakoli, A. R., Moghadam, M. M., & Sepaskhah, A. R. (2015). Evaluation of the AquaCrop model for barley production under deficit irrigation and rainfed condition in Iran. *Agric. Water Manag., 161*, 136-146. https://doi.org/10.1016/j.agwat.2015.07.020

Vara Prasad, P. V., Allen Jr., L. H., & Boote, K. J. (2005). Crop responses to elevated carbon dioxide and interaction with temperature: Grain legumes. *J. Crop Improvement, 13*(1-2), 113-155. https://doi.org/10.1300/J411v13n01_07

Willmott, C. J. (1982). Some comments on the evaluation of model performance. *Bull. American Meteorological Soc., 63*(11), 1309-1313. https://doi.org/10.1175/1520-0477(1982)063<1309:SCOTEO>2.0.CO;2

Yuan, M., Zhang, L., Gou, F., Su, Z., Spiertz, J. H., & Van Der Werf, W. (2013). Assessment of crop growth and water productivity for five C 3 species in semi-arid Inner Mongolia. *Agric. Water Manag., 122*, 28-38. https://doi.org/10.1016/j.agwat.2013.02.006