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ORIGINAL ARTICLE

Calibration and evaluation of the FAO AquaCrop model for canola (*Brassica napus*) under full and deficit irrigation in a semi-arid region

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Abstract

Field experiments were conducted in the cropping years 2012 and 2013 with four irrigation treatments, I_1, I_2, I_3, and I_4, respectively, corresponding to full irrigation, 20, 35, and 50% less than the crop water requirement in a semi-arid region of Iran. Data were used for calibration (2012) and validation (2013) of biomass (B), grain yield (GY), soil water content (SWC), canopy cover (CC), and evapotranspiration (ET) of canola by the AquaCrop model. Model coefficients were calibrated for *I*1 treatment in 2012, and the calibrated parameters were used for other treatments in both years. Based on the results, the NRMSE value for SWC ranged from 10 to 20%. Simulated and measured SWC for the four water treatments showed that AquaCrop has good accuracy. Overall, the results of the model in simulating SWC for both years were satisfactory. AquaCrop provided overestimation in the calibration phase of ET and underestimation in the ET validation phase. The results also showed that AquaCrop is overestimated in the simulation and prediction of CC and is less satisfactory under water stress. The model evaluation showed that AquaCrop can simulate B and GY with high accuracy. In general, AquaCrop was identified as a good tool for studying irrigation management, crop B and GY, CC, SWC, and other factors affecting the canola growth in the studied fields and climate.

Keywords AquaCrop model · Biomass · Canola · Crop simulation · Grain yield · Semi-arid area

Introduction

Canola is one of the crops whose cultivation is increasing due to oilseeds and food consumption (Reddy and Redi, 2003). In addition to its high yield potential, canola has a high percentage of seed oil (40 to 45%) when compared with other oilseeds. Currently, canola is the focus of plans for increasing oilseeds production in Iran. The nutritional value of this crop along with its adaptation to different climate conditions has caused this plant to be cultivated in most parts of Iran (Zomorodian et al. 2010). Although the production of this product is of considerable importance in the food industry, the conditions of Iran's water resources have led to the application of scenarios to reduce the irrigation water for various crops, including canola (Mousavizadeh et al. 2016). On the other hand, limited research budgets and time-consuming field experiments to investigate the crop response to different irrigation scenarios have resulted in envisaging simulation models for this purpose (Raes et al. 2009; Geerts and Raes 2009).

Simulation models represent mutual relationship between the components of a system by mathematical equations (Wallach et al. 2019). Models are classified into four groups based on the relationships in the simulation process: 1. mathematical models, 2. experimental models, 3. static models, and 4. dynamic models. In the dynamic models, the temporal variations of variables have been considered. That is while static models do not have the ability to predict the

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state of the system in future periods. The experimental models, unlike mathematical models that are completely based on cause-and-effect relationships between variables, have been developed based on regression relationships. Therefore, the experimental models cannot be generalized to different conditions and will provide appropriate results only under the same conditions by calibrating constant coefficients of equations (Overman and Scholtz 2002). Crop models are recognized as a valuable tool for the integrated simulation of processes affecting crop growth (Wallach et al. 2019). These models have been used in many research fields, including predicting the production of agricultural crops under different environmental and managerial conditions (Ahmadi et al. 2015; Sandhu and Irmak 2019) as well as scheduling and optimizing water and fertilizer consumption (Fang et al. 2017a, 2017b; Liu et al. 2017). It is known that crop models are considered as a comprehensive tool for estimating the crop yield, a comprehensive combination of values under physiological conditions (Azam-Ali et al. 2001; Steduto et al. 2009) and for evaluating crop management options (Mabhaudhi et al. 2014). Crop models that can accurately estimate various crop growth parameters, soil water dynamics, plant water use, and expected yield under different levels of irrigation can provide essential assistance to the successful implementation of limited and complete irrigation management practices (Sandhu and Irmak 2019).

Given that previous simulation models had a lot of complexity in addition to many input parameters, extensive efforts have been made by FAO to develop a model with high accuracy, simplicity and capability. Eventually, this effort led to AquaCrop, which is an engineering model (Nyakudya and Stroosnijder 2014). The AquaCrop model, whose algorithm has been developed based on the amount of water consumed by the plant (transpiration), is one of the most widely used and simplest models for simulating the crop growth (Raes et al. 2009; Steduto et al. 2009). AquaCrop is a comprehensive model, meaning that it can be used for a wide range of crops including fodder, vegetables, grains, fruits, oils and tubers. AquaCrop improves farm management strategies including planting time, plant density and chemical fertilizers and simulates water use performance and efficiency. The applications of this model include evaluation of rainfed crop production in the long term, effect of low fertilization, actual water productivity (WP) on the farm, analysis of future climate scenarios, deficit irrigation scheduling and supplementary irrigation among others. There are many models that estimate the crop water requirement based on the plant, soil and climate systems. The AquaCrop model simulates the economic yield (Y) and biomass (B) of different crops (Raes et al. 2009). Compared with other simulation models, AquaCrop requires fewer parameters and input data (including climate data, plant, farm and irrigation management, soil and groundwater characteristics) to simulate the crop response to water (Mousavizadeh et al. 2016). This model can be used for most major crop and plant products worldwide. It also focuses on the plant's response to water (Steduto et al. 2009). In fact, simulating crop growth with limited and unlimited irrigation is one of the main applications of this model (Mousavizadeh et al. 2016).

So far, extensive research has been conducted in relation to AquaCrop model for different crops in different countries. AquaCrop has been applied in different parts of the world to determine the crop response to water stress (Azam-Ali et al. 2001; Steduto et al. 2009; Singels et al. 2010; Sandhu and Irmak 2019), develop low irrigation scheduling (Geerts et al. 2010; Andarzian et al. 2011; Ahmadi et al. 2015), improve on-farm irrigation management (García-Vila et al. 2009; Heng et al. 2009; García-Vila and Fereres 2012), assess increasing crop production potential and farm management (Zinyengere et al. 2011; Abraha et al. 2012; Mhizha et al. 2014), assess the impact of climate change on crop production (Raes et al. 2009), and develop decision support tools to carry out farm operations (Cusicanqui et al. 2013).

So far, limited research has been done on canola using the AquaCrop model. There is still a lack of valuable information about the model performance in canola plant simulation under different irrigation managements in arid and semi-arid regions (Mousavizadeh et al. 2016). The studies conducted by Zeleke et al. (2011), Arvaneh and Abbasi (2014) and Mousavizadeh et al. (2016) are among the limited studies performed on this canola using this model. Arvaneh and Abbasi (2014) used field data collected to calibrate AquaCrop. After calibration, the research simulated canola Y and soil water content (SWC) change using this model, showing that the obtained results were in acceptable agreement with the field results. Zeleke et al. (2011), after evaluating AquaCrop in Australia, reported that the model shows overestimated SWC values at the depths of 0 to 100 cm in most of the time during the growing season. But it can well simulate the SWC variation trend at these depths. They also reported satisfactory results from canopy cover (CC) simulation, B and Y of the crop. They stated that AquaCrop's prediction in severe water stress conditions was less satisfactory (Zeleke et al. 2011), which has been mentioned as one of the shortcomings of the model in accurate simulation in severe water stress conditions (Mousavizadeh et al. 2016). Mousavizadeh et al. (2016) also calibrated and validated AquaCrop for canola and reported that this model has an acceptable ability to simulate Y and SWC values of canola. In general, AquaCrop is a useful and reliable tool for simulating CC and evapotranspiration (ET) on a daily scale and simulating high-precision B and Y of grains at the end of the crop growth period (Mousavizadeh et al. 2016).

The above results show the need for proper AquaCrop calibration and validation for specific areas to improve the model performance in estimating the crop Y, water consumption, crop growth parameters and evaluating limited irrigation practices to develop effective management strategies (Sandhu and Irmak 2019). The purpose of this study is to calibrate and then evaluate the AquaCrop model in the simulation of SWC, ET, CC, B and Y spring canola (RGS003 variety) under different water stress conditions in the arid and semi-arid regions of Iran (Karkaj, Tabriz). Further evaluation of the AquaCrop model using measured field transpiration and evaporation data to determine the accuracy of plant ET partitioning by the model is necessary to better simulate soil water and ET, which is very important for estimating irrigation requirement during crop growth period, B and Y (Sandhu and Irmak 2019). It should be noted that in the present study, drainage lysimeter and microlysimeter were used in the field to accurately measure transpiration and evaporation.

Methods and materials

Study area and soil description

Field experiment in 0.5 m wide furrows in 5 m long plots, including 8 rows of spring canola (*Brassica Napus* L.) with a density of 80 plants per square meter in a land area of 400 square meters in the Faculty of Agriculture of the University of Tabriz (Iran), located in the Karkaj region, was implemented during 2012 and 2013. The longitude and latitude of the region and its height above sea level are 46° 37′ E, 37° 03′ N and 1567.3 m, respectively. In both experimental years, canola was planted in early May and harvested in early August. Canola seeds were placed at a depth of one centimeter from the soil surface. To facilitate germination, the seeds were covered with aerated sand (Majnooni-heris et al. 2014). Soil samples were taken from different depths of the field soil to determine the physical properties of the soil using sampling cylinders and auger. The field capacity (FC) limit and permanent wilting point were measured using a pressure plate device. Other soil physical parameters are presented in Table 1.

Experimental design and treatments

In both cropping years, field experiments including four irrigation treatments I_1, I_2, I_3 and I_4 are, respectively, equal to full irrigation (without water stress), 20, 35 and 50% less than the canola water requirement in four replications in a complete random block design. Figure 1 shows images of different stages of canola growth in a study field. Irrigation restrictions were applied after the plant was fully established in the field. In both years, the first four irrigations were considered the same for all treatments.

Field-based drainage lysimeter was used to measure the plant ET. Furthermore, the rate of evaporation from the soil surface was calculated using a microlysimeter installed between the plant cultivation rows. For the required climatic information, the daily data of the meteorological station of the Faculty of Agriculture of Tabriz University were used. The reference ET was also calculated based on the FAO Penman–Monteith method using the ET_o Calculator program (Allen et al. 1998). The irrigation schedule of the design for different irrigation treatments in both years is according to Fig. 2.

Irrigation method and determining irrigation depth

The irrigation method used in this study was closed-end furrow irrigation in which water was supplied to the roots using furrows created in the field. The first sufficient irrigation in both years was done after planting with the aim of wetting the farm soil with water. In order to fully establish the plant, water restriction was started from the fifth irrigation. Irrigation water values increased by increasing the leaf area index (LAI) of canola. The last irrigation in the first (2012) and second (2013) experimental years was 95 and 94 days after planting, respectively (Fig. 2). The PR2 device was used to measure SWC at different depths. This device is used in two models PR2/4 (with 4 sensors) and PR2/6 (with 6 sensors) to measure the water content in the vertical section of the soil (Khorsand et al. 2019). In this study, the PR2/6 device was used, which was calibrated with weight-water content data. The pipes of this device were placed in the middle of different plots. Before each irrigation, SWC was read using PR2 at the depths of 10, 20, 30, 40, 50, 60 and

Table 1 Physical properties of the experimental soil

Soil depth(cm)	Particle size distribution (%)			Texture class	FC(cm^3 cm^{-3})	PWP(cm^3 cm^{-3})	SAT(cm^3 cm^{-3})	BD(g cm^{-3})
	Clay	Silt	Sand					
0–30	12.2	24.2	63.6	Sandy Loam	0.280	0.120	0.410	1.58
30–60	12.5	24.8	62.7	Sandy Loam	0.282	0.123	0.412	1.56

Clay (< 0.002 mm), silt (0.002 – 0.05 mm), sand (0.05 – 2 mm) (USDA classification). FC: field capacity; PWP: permanent wilting point; SAT: Saturation; BD: bulk density

Fig. 1 View of the research farm; preparation **A** vegetative **B** flowering **C** and maturation **D** stages

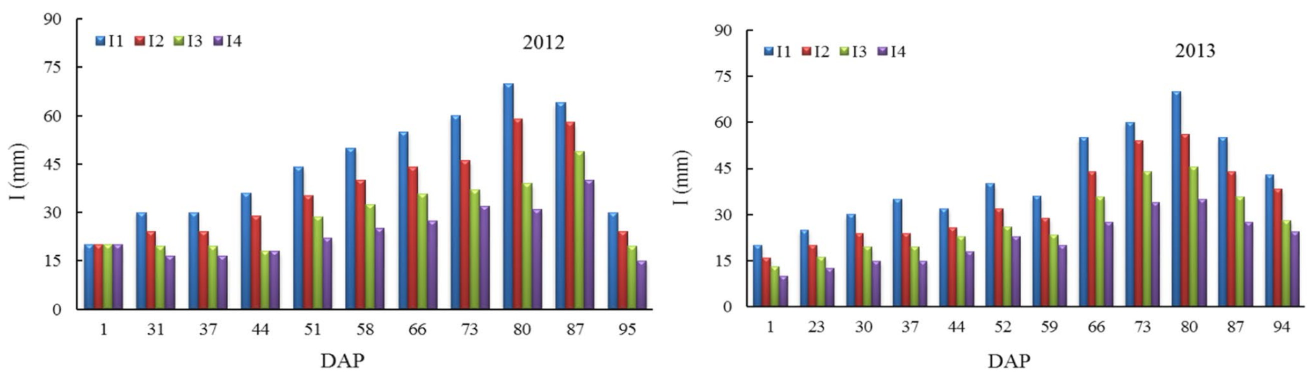

Fig. 2 Irrigation depth values *I* in the days after planting (DAP) in the first and second crop year

100 cm. In each irrigation, the amount of soil water shortage and subsequently the water required for the treatments that received full irrigation water was determined by the following equation:

$$d = \sum_{i=1}^{n} \left(\theta_{fi} - \theta_i\right)\Delta z \tag{1}$$

where n is the number of layers to the depth of root development, i denotes the number of each layer, d represents the depth of irrigation water (cm), θ_{fi} and θ_i, respectively, represents the FC and the available water in the soil before irrigation ($cm^3\ cm^{-3}$) in layer i and Δz denotes the thickness of the layer (cm). The required volume of water for each treatment was delivered using a counter meter during irrigation. The irrigation period of canola in the present study was seven days.

AquaCrop description

The AquaCrop model is one of the crop models developed by FAO with a focus on water use productivity. It is also used as an analytical tool to study the effect of different agricultural management scenarios (Steduto et al. 2009). AquaCrop, while simulating the daily water balance which is the basis of B and WP simulations, separates ET into evaporation from the soil surface (E) and transpiration from the plant surface (Tr). This feature distinguishes AquaCrop from other crop growth models (Abedinpour et al. 2012). In AquaCrop, water is recognized as a determinant of crop productivity. Therefore, the daily Tr of the plant and the normalized productivity factor is converted to B (Raes et al. 2009). This model is able to simulate the Y obtained from plant products under different managements and environmental conditions using several plant parameters and a small number of input variables (Vanuytrecht et al. 2014b). Harvestable Y is a function of B and the harvest index, thereby differentiating the effect of environmental stresses on B and the harvest index (Ahmadi et al. 2015).

In AquaCrop, an accurate CC estimation plays an important role in the modeling process and, ultimately, the accuracy of the model performance. In this model, the CC development is expressed by the CC growth curve (Steduto et al. 2009). To measure the leaf area of canola, a mobile leaf area measuring device was used several times during the growing season. The AquaCrop model does not use LAI directly but uses CC. Therefore, the following experimental equation was used to convert LAI to CC in AquaCrop (Garcia-Villa et al., 2009):

$$CC = \frac{\left(1 - e^{-0.77(LAI)}\right)}{\left(1 + e^{-0.77(LAI)}\right)} \tag{2}$$

Calibration, validation and assessment of AquaCrop

Calibration is the estimation of model parameters in a way that the difference between the measured values and its computational values estimated by the model is minimized (Singh 2004). In this study, calibration was done manually and by applying ± 10% of the default value in the AquaCrop model for each of the parameters, calibration was done. The model evaluation is to prove the efficiency of the model for future use. The purpose of calibration is to adjust the parameters and inputs of the model with least uncertainty (Khorsand et al. 2014a). The efficiency of a model is evaluated through calibration and evaluation of the model for the set goals (Osmani et al. 2013). In the present study, the model parameters were calibrated using 2012 data and validated using 2013 data. First, the calibrated parameters were adjusted for SWC and Y of canola seed and then for ET, CC and B (Mousavizadeh et al. 2016). The calibration process was performed focusing on the treatment I_1 and then the treatments I_2, I_3 and I_4 until the best compatible parameters were achieved. Then, the calibrated model was used for validation without changing the calibrated parameters (Ahmadi et al. 2015). Table 2 presents the calibrated parameters of the AquaCrop model in two groups of conservative and non-conservative parameters for spring canola.

Conservative parameters depend on the type of plant and factors such as time and place. The amount of these parameters is affected by management conditions (Raes et al. 2009). In other words, these parameters are essentially the same sensitive parameters in the model that need to be calibrated (Mousavizadeh et al. 2016). But in different environmental and managerial conditions, the sensitivity of each of these parameters and the effect of the changes of each on the output of the model vary.

Given that no measurement alone can show how a model has performed the simulation effectively, a combination of statistical indicators is used to evaluate the model (Gauch et al. 2003; Iqbal et al. 2014). To evaluate and measure the validity of AquaCrop, the indicators of normalized root mean square error (NRMSE), relative error (RE), index of agreement (d), root mean square error (RMSE) and coefficient of determination (R^2) were used.

$$NRMES = \frac{1}{\overline{O}} \times \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \times 100 \tag{3}$$

$$RE = \sum_{i=1}^{n}\left(\frac{O_i - S_i}{O_i}\right) \times 100 \tag{4}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|S_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \tag{6}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \overline{O})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2(S_i - \overline{S})^2}}\right]^2 \tag{7}$$

In these equations, n is the number of measurements, O_i and S_i measured and predicted values, and $\overline{O}$ and $\overline{S}$ mean measured and predicted values.

The NRMSE index measures the relative difference between observational and simulated data and shows the percentage of the simulation error. The excellent NRMSE value for modeling is less than 10%. NRMSE lying in the ranges of 10 to 20% and 20 to 30%, respectively, indicates the good and moderate condition of the model in forecasts while in the ranges more than 30% it indicates uncertainty of the model (Raes et al. 2012). A positive value of RE indicates an underestimation of the model, and a negative value indicates an overestimation of the model (Singh et al. 2008). The d index is widely used to evaluate the performance of models.

Table 2 List of parameters of AquaCrop model for spring canola in the in the Karkag of Tabriz

Parameters	Values	Units
1) Conservative		
Base temperature	5	°C
Upper temperature	40	°C
Canopy size seedling	5.0	cm^2 $plant^{-1}$
Canopy growth coefficient, CGC	7.3	% day^{-1}
Canopy decline coefficient, CDC	8.4	% day^{-1}
Soil water depletion threshold for canopy expansion, P_{upper}	0.2	–
Soil water depletion threshold for canopy expansion, P_{lower}	0.55	–
Shape factor for water stress coefficient for canopy expansion	3.5	–
Soil water depletion threshold for stomatal control, P_{upper}	0.65	–
Shape factor for water stress coefficient for stomatal control	5.0	–
Soil water depletion threshold for canopy senescence, P_{upper}	0.7	–
Shape factor for water stress coefficient for canopy senescence	3.0	–
Soil water depletion factor for pollination (p–pol), P_{upper}	0.85	–
Normalized water productivity, WP*	15.3	g m^{-2}
Crop Transpiration, $Kc_{Tr,x}$	1.0	–
2*) Non-conservative*		
Plant density	800,000	plants ha^{-1}
Initial canopy cover, CC_o	4.0	%
Maximum canopy cover, CC_x	87	%
Time from sowing to emergence	10	day
To maximum canopy cover	87	day
Time from sowing to flowering	79	day
Time from sowing to start senescence	89	day
Time from sowing to maturity	114	day
Length of the flowering stage	15	day
Duration of flowering	21	day
Maximum effective rooting depth	79	cm
Minimum effective rooting depth	30	cm
Reference harvest index, HI_o	17	%

This indicator shows the degree of agreement between the observed and measured data. This index is non-dimensional, and its variation range is between zero and one. The closer the value of this index is to one, the higher the compliance rate with the value of one indicating the best fitness (Willmott 1982). The RMSE index indicates the absolute uncertainty of the model. If this index is lower and closer to zero, it shows the better estimation of the model. R^2 is the measure of dispersion between the predicted and measured values and varies between zero and one (Moriasi et al. 2007).

Results and discussion

Soil water content (SWC)

The simulated and measured SWC values can be only observed for the I_1 treatment during the dynamic calibration and validation steps in Figs. 3 and 4. The values of statistical indices for water treatments in the calibration and evaluation steps of the model are presented in Table 3 and 4, respectively. According to these tables, the NRMSE index was calculated for SWC for both years (calibration and validation), which was in the range of 10 to 20%. The SWC simulated and measured in the root development area (depths of 0–10, 10–20, 20–30 and 30–40 cm) for four water treatments showed that the AquaCrop model has an acceptable capability (appropriate accuracy) in the prediction of SWC.

Zeleke et al. (2011) confirmed that AquaCrop reliably simulates the amount and trend of SWC for canola, but tends to overestimate during the harvest season. Arvaneh and Abbasi (2014) also examined changes in the water content. The results were such that the measured values of SWC varied from 32 to 39% during the growing season of canola. AquaCrop simulated changes in SWC from 32 to 37%, which was in good agreement with the measured values. The small difference between the measurement and simulation values

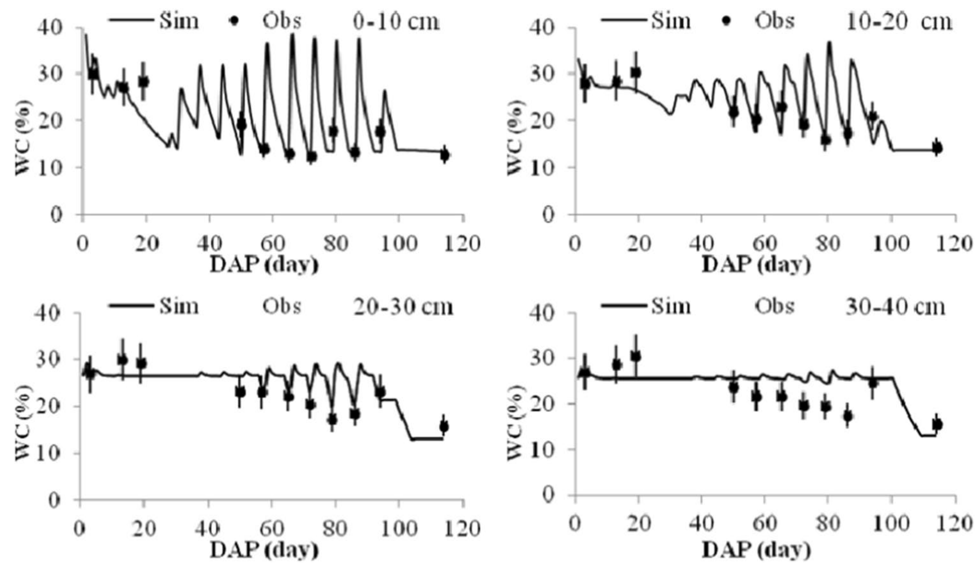

Fig. 3 The observed and simulated volumetric SWC profiles in *I*1 treatment (full irrigation) for year 2012 (calibration)

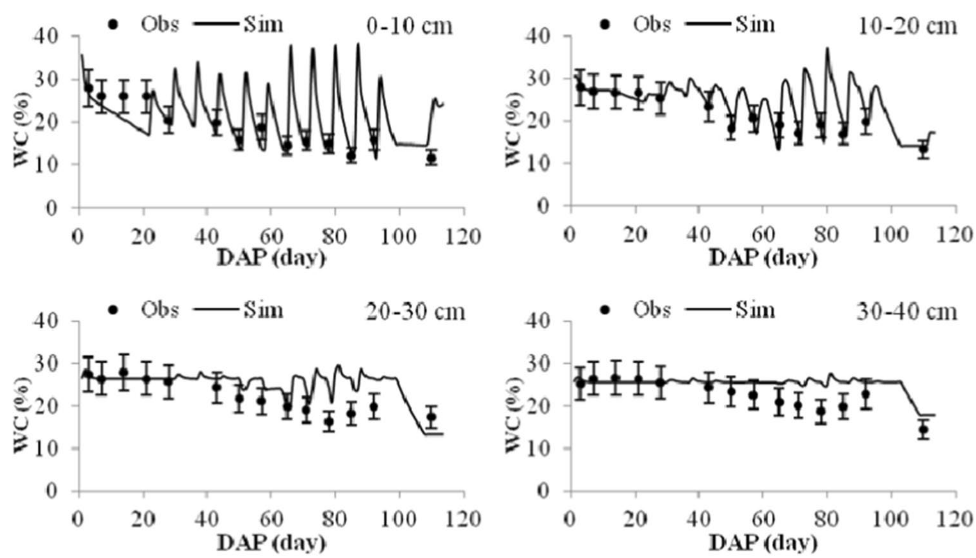

Fig. 4 The observed and simulated volumetric SWC profiles in *I*1 treatment (full irrigation) for year 2013 (validation)

at the beginning of the crop season may have been due to an error in measuring the initial SWC studied.

Other studies have reported the desirable performance of the AquaCrop model in SWC simulations for a variety of crops, including wheat (Andarzian et al. 2011; Zhang et al. 2013; Khorsand et al. 2014b), maize (Hsiao et al. 2009; Ahmadi et al. 2015), cotton (Farahani et al. 2009; Hussein et al. 2011), and teff (Araya et al. 2010b). In a study by Andarzian et al. (2011) for wheat, SWC was estimated with excellent accuracy (NRMSE less than 10%). The results obtained by Khorsand et al. (2014b) showed that AquaCrop predicts SWC with relatively good accuracy. They also calculated NRMSE statistics for wheat varieties in the range of 10 to 20%. According to Hussein et al. (2011), the model prediction of SWC in soil profiles was close to the general trend of measurements.

According to Table 3, the NRMSE value increased from treatment I_1 to I_4. Therefore, the model performed better in the SWC simulation in stress-free treatment (I_1) than in other treatments. $NRMSE_{max}$ also occurred in the treatment I_4 (severe water stress) whose values in the calibration and validation stages were 18.13 and 16.72%, respectively. AquaCrop does the simulation well when water is available to plants. But by increasing the water stress, the model results become less satisfactory (Mousavizadeh et al. 2016).

In this study, the RE values in the calibration and evaluation steps of the model were negative for the treatments I_1 and I_2 and positive for the treatments I_3 and I_4. This index showed that the model tends to overestimate SWC in the treatments I_1 and I_2 and tends to underestimate in the treatments I_3 and I_4. Farahani et al. (2009) reported for cotton that AquaCrop simulates the total water content of the soil

Table 3 The statistical results for SWC, ET, CC, B and GY for year 2012 (calibration procedure)

Statistical indicators/ Treatment	Soil Water Content (SWC)				Average	Standard deviation
	I_1	I_2	I_3	I_4		
NRMSE (%)	15.40	16.89	16.98	18.13	16.85	0.97
RE (%)	−0.61	−1.80	5.49	1.73	1.20	2.78
d	0.80	0.70	0.87	0.88	0.81	0.07
R^2	0.63	0.59	0.70	0.69	0.65	0.04
Statistical indicators/ Treatment	**Total Evapotranspiration (ET)**				**Average**	**Standard deviation**
	*I*1 (full irrigation)					
NRMSE (%)	28.59				–	–
RE (%)	−3.11				–	–
d	0.87				–	–
R^2	0.60				–	–
Statistical indicators/ Treatment	**Canopy Cover (CC)**				**Average**	**Standard deviation**
	I_1	I_2	I_3	I_4		
NRMSE (%)	6.53	10.76	9.91	11.41	9.65	1.88
RE (%)	−4.39	−12.40	−5.10	−5.15	−6.76	3.27
d	0.98	0.97	0.96	0.89	0.95	0.04
R^2	0.97	0.87	0.84	0.64	0.83	0.12
Statistical indicators/ Treatment	**Biomass (B)**				**Average**	**Standard deviation**
	I_1	I_2	I_3	I_4		
RMSE (t ha^{-1})	1.16	0.91	0.67	0.80	0.89	0.18
RE (%)	−1.12	−1.17	−1.14	−1.75	−1.29	0.26
d	0.96	0.98	0.98	0.95	0.97	0.01
R^2	0.90	0.89	0.89	0.76	0.86	0.06
Statistical indicators/ Treatment	**Final Grain Yield (GY)**				**Average**	**Standard deviation**
	I_1	I_2	I_3	I_4		
Observed (t ha^{-1})	1.84	1.69	1.37	0.98	1.47	0.33
Simulated (t ha^{-1})	1.68	1.66	1.35	1.04	1.43	0.26
RE (%)	8.73	1.21	1.19	−6.13	1.25	5.25
NRMSE (%)	5.90				–	–
d	0.98				–	–
R^2	0.93				–	–

profile in an acceptable way. However, there is a constant tendency to overestimate the total SWC, especially in deficit irrigation treatment. They also said that this model tends to overestimate in the surface layer of soil and tends to underestimate in deeper layers. Araya et al. (2010b) for teff confirmed an estimate of less than the SWC of the simulated using AquaCrop under high stress conditions. In general, however, there was a perfect compliance between the simulation and measurement datasets.

According to the results (Table 3 and 4), the dispersion of measurement and prediction values relative to each other is relatively high, as shown by the R^2 index. Overall, this model predicted SWC to be lower than the actual values, which is confirmed by the equation coefficient of fitness line below one in both the calibration and validation stages. In fact, the SWC underestimation of this study for canola is consistent with the results of other studies conducted for various crops, including maize (Biazin and Stroosnijder 2012; Mebane et al. 2013) and wheat (Mkhabela and Bullock 2012; Khorsand et al. 2014b; Iqbal et al. 2014). In contrast, other studies for canola (Zeleke et al. 2011), maize (Hsiao et al. 2009; Paredes et al., 2014; Ahmadi et al. 2015), and cotton (Farahani et al. 2009) have shown that the AquaCrop model predicts SWC more than the observable values. These discrepancies may have a variety of causes that can lead to underestimation or overestimation of SWC (Farahani et al.

Table 4 The statistical results for SWC, ET, CC, B and GY for year 2013 (validation procedure)

Statistical indicators/ Treatment	Soil Water Content (SWC)				Average
	I_1	I_2	I_3	I_4	
NRMSE (%)	15.99	14.88	16.54	16.72	16.03
RE (%)	−7.80	−0.88	3.43	2.37	−0.72
d	0.68	0.76	0.82	0.82	0.77
R^2	0.50	0.59	0.58	0.58	0.56
Statistical indicators/ Treatment	Total Evapotranspiration (ET)				Average
	I_1 (full irrigation)				Average
NRMSE (%)	27.43				–
RE (%)	5.13				–
d	0.89				–
R^2	0.68				–
Statistical indicators/ Treatment	Canopy Cover (CC)				Average
	I_1	I_2	I_3	I_4	
NRMSE (%)	11.18	11.41	8.94	9.12	10.16
RE (%)	−23.42	−26.58	−17.02	−3.76	−17.69
d	0.96	0.95	0.94	0.89	0.94
R^2	0.83	0.81	0.78	0.59	0.75
Statistical indicators/ Treatment	Biomass (B)				Average
	I_1	I_2	I_3	I_4	
RMSE (t ha^{-1})	1.61	1.15	0.26	0.35	0.84
RE (%)	0.07	−0.03	−0.09	−0.04	−0.02
d	0.92	0.95	0.99	0.98	0.96
R^2	0.89	0.93	0.98	0.94	0.94
Statistical indicators/ Treatment	Final Grain Yield (GY)				Average
	I_1	I_2	I_3	I_4	
Observed (t ha^{-1})	1.79	1.59	1.25	1.13	1.44
Simulated (t ha^{-1})	1.70	1.68	1.37	1.03	1.45
RE (%)	4.87	−5.45	−10.10	8.95	−0.43
NRMSE (%)	7.05				–
d	0.96				–
R^2	0.86				–

2009; Zeleke et al. 2011; Khorsand et al. 2014b; Ahmadi et al. 2015) or accurate estimation of SWC (Araya et al. 2010b; Andarzian et al. 2011), which are explained below.

One reason is that soil is heterogeneous throughout the field. Therefore, the model cannot consider soil variability in the SWC simulation. Another reason for the components of the soil–water balance of the model is that it starts drainage at SWC or above the FC and probably begins to penetrate deep into the water content below FC (Zeleke et al. 2011; Ahmadi et al. 2015). Khorsand et al. (2014b) attributed the possible reasons for the underestimation of the model to the type of equation governing the water balance in which some factors affecting the movement of water such as preferential currents and the phenomenon of hysteresis are not considered. According to Paredes et al. (2014), the variability of soil structure, the presence of large pores and soil crusts can increase the drainage through the preferential flow. Depending on the formation, soil crusts can be biological (microorganisms) or physical (raindrops). Moreover, Paredes et al. (2014) attributed another important reason to the choice of unregulated plant coefficient (K_c). Finally, they said that AquaCrop could not be used for irrigation scheduling purposes. Selecting an accurate K_c can have a significant effect on the accurate modeling of SWC, E and Tr (Ahmadi et al. 2015).

According to Figs. 3 and 4, the simulated SWC values at a depth of 30–40 cm were predicted with less accuracy (almost linearly) by the model. One of the reasons for this is the reduction of water absorption by the roots at this depth. It should also be noted that this factor can be considered as AquaCrop's weakness in estimating SWC at lower depths. Accurate information about the root distribution, main root length and longitudinal root density in the model leads to accurate SWC prediction because it also directly affects Tr simulation (Ahmadi et al. 2015). Overall, the results of the AquaCrop model in the SWC simulation for both years of 2012 and 2013 were satisfactory. The calibrated parameters in SWC were acceptable because statistical indicators were good in evaluating the results (Table 4).

Evapotranspiration (ET)

As mentioned earlier, AquaCrop is capable of separating E and Tr. In this section, the cumulative ET, Tr and E results simulated by the model with the measured values for the control treatment (I_1) in the days after planting (DAP) of canola (106 days for 2012 and 112 days for 2013) are shown in Fig. 5. Two points can be found according to Fig. 5.

First, AquaCrop simulates Tr better and more accurately than E. Second, the cumulative ET simulated by the model was higher than the values measured at the beginning of the canola growth period. At the end of the crop growth period, however, the simulated and measured ET values came so close to each other that this result is seen to be consistent with the results obtained by Mousavizadeh et al. (2016) for canola.

The values of NRMSE, RE, d and R^2 statistics for ET in the calibration and validation steps for I_1 treatment are reported in Table 3 and 4. According to Table 3 and 4, NRMSE was obtained in the stages of calibration and evaluation of ET at 28.59% and 27.43%, respectively, which showed that the model has a moderate status in the ET simulation and estimation. Furthermore, the negative and positive values of the RE index were obtained, respectively, in the calibration and evaluation steps of Canola ET, which showed that AquaCrop is overestimated in the calibration step and underestimated in the validation stage. The ET value of canola in 2012 and 2013 was 489.0 and 500.98 mm, respectively, which were estimated at 504.20 and 475.30 mm by the model, respectively. Canola is less resistant than other cereal crops (including wheat and barley) to water shortages. The amount of water consumed by the canola crop from planting to harvest can vary from 160 to 180 mm (in low rainfall) and 400 to 500 mm in optimal conditions (Zeleke et al. 2011).

In a study conducted by Zeleke et al. (2011), the canola potential ET during growth period was 356.0 mm; while the

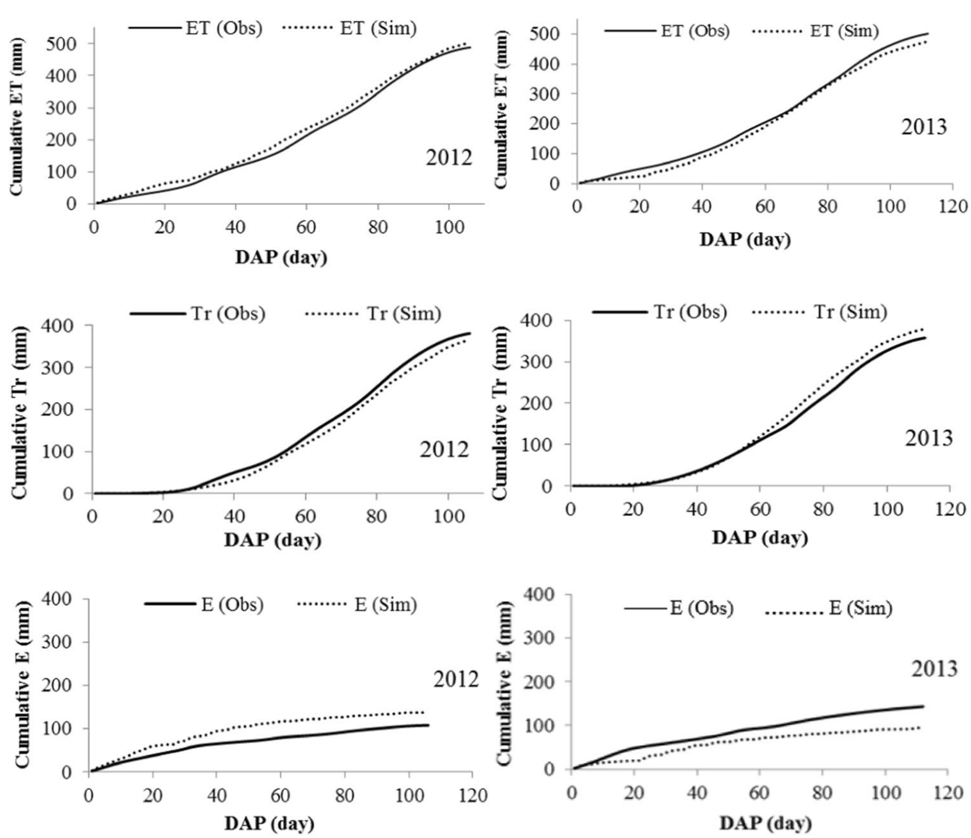

Fig. 5 Cumulative ET, Tr and E observed and simulated by model in $I1$ treatment for years of 2012 and 2013

actual ET was 330.0 mm. In AquaCrop, the actual ET was divided into 82.0 mm E and 248.0 mm Tr. Under real conditions, salinity, temperature, water, fertility, pest and wetland stresses may reduce ET relative to potential conditions. The actual Tr of canola was 100% of the potential Tr during the season, indicating that the difference between the actual ET and the potential ET resulted from the differences in E. This result means that the plant's water requirement has been met and the plant has not been under stress (Zeleke et al. 2011). In the study conducted by Arvaneh and Abbasi (2014) at the beginning of the growing season of canola, due to the empty soil surface of CC, the value of E was higher than Tr, and in the middle and end of the growing season, the value of Tr was higher than the value of E. Their research, which was conducted in a four-hectare and a one-hectare field, found that the ET value of canola by AquaCrop during the growing season was 308.8 and 259.4 mm, respectively, for the fields. These values were less than the total water consumed by canola during the growing season. Therefore, the results showed that the model has underestimation (Arvaneh and Abbasi 2014). Mousavizadeh et al. (2016) simulated ET of canola by AquaCrop slightly higher than the measured values, but the results were satisfactory. The results of the present study in the calibration step of ET of canola in terms of RE index were consistent with the results obtained by Mousavizadeh et al. (2016).

The results of various studies reviewed for ET simulation by AquaCrop are as follows: The results obtained by Heng et al. (2009) showed that AquaCrop is able to simulate the plant ET with moderate accuracy in semi-arid regions. But in hot and dry areas, the model has poor performance. Katerji et al. (2013) concluded that the ET model simulates the plant less than the measured values. When deficit irrigation is high, the underestimation of ET by the model is high. In general, according to them, the quality of ET simulation by AquaCrop is poor. But Garcia-Vila et al. (2009) found a better correlation between the measured and simulated ET values for treatments with low ET values. Paredes et al. (2014) in their study stated that AquaCrop is more accurate in predicting the seasonal plant ET without overestimation and underestimation. They also cited the SWC overestimation trend (discussed in the previous section) as the result of an incorrect division of Tr (model tendency to overestimation) and E (model tendency to underestimation) by AquaCrop. Sandhu and Irmak (2019) observed in the model evaluation step the underestimation trend of plant ET by AquaCrop (except rainfed treatments), which was consistent with the results of the present study in the model evaluation step. Sandhu and Irmak (2019) also attributed the inaccuracy in the ET simulation to the SWC simulation, which in many cases was not simulated with sufficient accuracy by the model. Calibration coefficients such as Kc_{Tr} (plant transpiration coefficient) and K_e (soil surface evaporation coefficient) are effective in accurate ET simulation (Mousavizadeh et al. 2016). According to Pereira et al. (2015), calibrated parameters such as $Kc_{Tr,x}$ (crop transpiration) and CC_x parameters (CC coefficient of maximum plant density under optimal conditions) are changed internally by AquaCrop. This fact indicates a problem with the use of AquaCrop because the user has no control over the parameter and calibration processes (Mousavizadeh et al. 2016).

Canopy cover (CC)

CC is a very important parameter mainly because it shows how the crops grow and develop during their growth period as well as the periods when the plants are subjected to stress (Mousavizadeh et al. 2016). CC simulation and forecasting by AquaCrop were performed at 24, 44, 56, 63, 71, 77 and 85 days for calibration and at 38, 42, 50, 57, 64, 75 and 83 days for evaluation in four water treatments. Figures 6 and 7 present comparison of the CC measurements and simulations. Meantime, the values of statistical indicators for CC in the calibration and evaluation steps are reported in Table 3 and 4.

According to Table 3 and 4, the range of NRMSE in the calibration and evaluation steps of CC was obtained between 6 and 12 (%) and 8 to 12 (%), respectively. RE statistical values for CC in the calibration and evaluation process were negative for all four water treatments. Therefore, the negative values of this statistic showed that the model is overestimated in simulating and predicting the CC parameter of canola. The reasons for the underestimation and overestimation of the AquaCrop model are fully discussed in the sections B and GY.

According to Figs. 6 and 7, it can be found that the AquaCrop model at the beginning and end of the canola growth period could not accurately adapt to the measured CC parameter. The results obtained by Zeleke et al. (2011) in the validation phase for canola showed that CC started with a slight non-compliance from planting to flowering (early growth period), which is consistent with the validation results of the present study. CC has a greater effect on B than on other simulated parameters. In AquaCrop, as the crop approaches maturity (end of the growing season), CC is in a declining phase due to the aging of the plant's leaves. Therefore, CC is less satisfactory at the end of the plant growing season (Abedinpour et al. 2012; Mousavizadeh et al. 2016). In the study conducted by Xiangxiang et al. (2013), CC simulations for full irrigation (without stress) were well adapted to the field data at all winter wheat growth stages. The results of studies on cotton and canola plants also showed that the model in CC simulation under water stress is less satisfactory (Farahani et al. 2009; Zeleke et al. 2011; Mousavizadeh et al. 2016), which is consistent with the results of the present study.

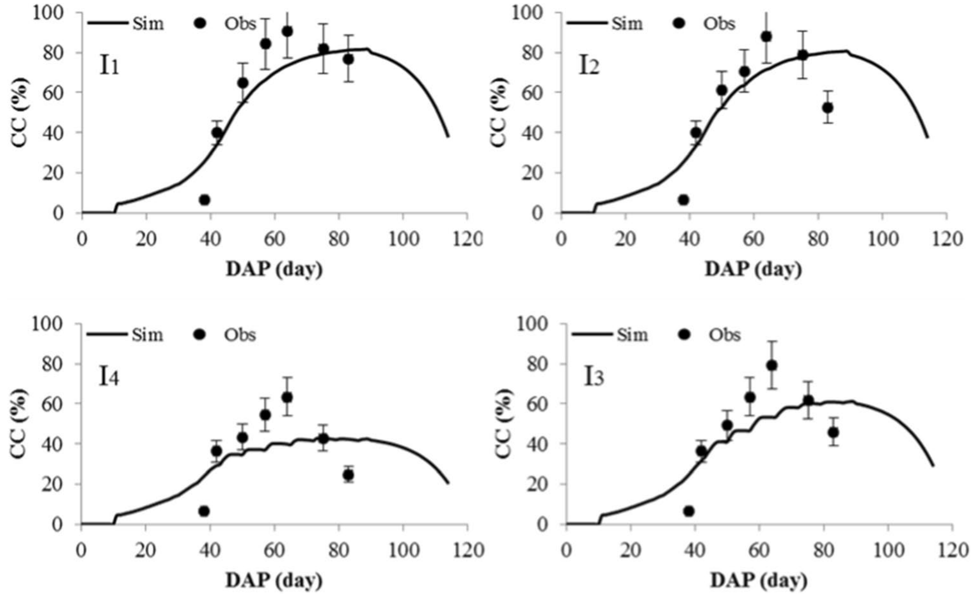

Fig. 6 The observed and simulated CC in total treatments for year 2012 (calibration)

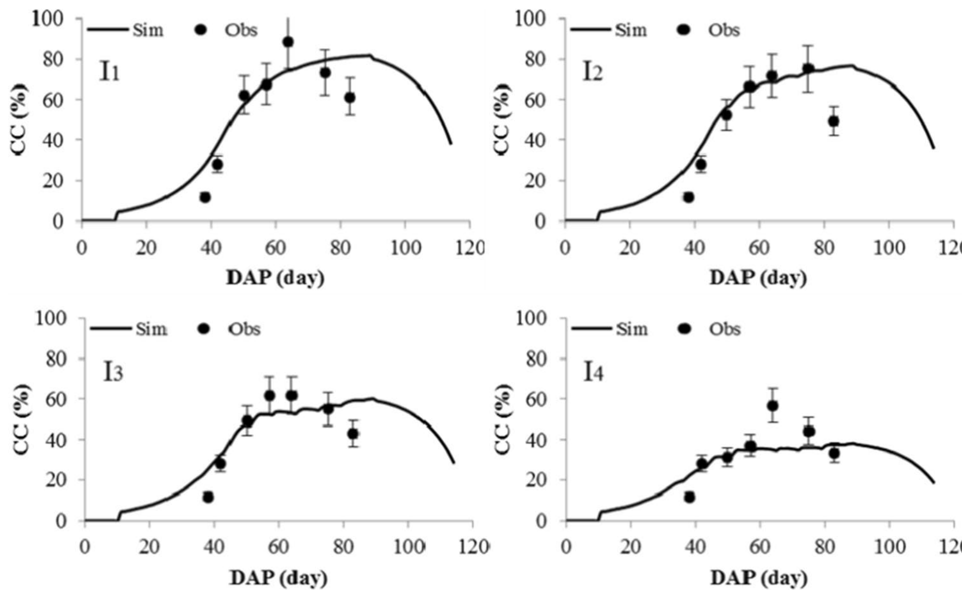

Fig. 7 The observed and simulated CC in total treatments for year 2013 (validation)

The results of research conducted to simulate CC in different plants in terms of statistical indicators are as follows. Zeleke et al. (2011) obtained RMSE values for Hyola50 (calibration) and Skipton (evaluation) varieties of canola at 8.4 and 9.8%, respectively. Mabhaudhi et al. (2014) calculated the values of RMSE, d and R^2 indices for the Taro plant at 2.38%, 0.92 and 0.79, respectively. Kim and Kaluarachchi (2015) used the AquaCrop model for the simulation and the remote sensing (RS) to predict CC under normal conditions for three plants. They obtained the efficiency coefficients for maize, barley and alfalfa in the calibration step (AquaCrop) at 0.94, 0.85 and 0.99, respectively, and in the evaluation step (RS) at 0.88, 0.92 and 0.80, respectively. Sandhu and Irmak (2019) for maize also obtained a smaller NRMSE error value in 2009 and 2010 equal to 15.6% (excluding minor differences in 2010) for the daily CC simulation. As CC is affected by both water stress and severe temperature stress, AquaCrop should be well calibrated for all stresses that may affect the simulation results (Andarzian et al. 2011; Mousavizadeh et al. 2016).

Biomass (B)

The B and GY performance are the main economic members of crops and that is why plant development models are targeted for acceptable simulations (Ahmadi et al. 2015).

By simulating the water conditions that affect crop growth, the B results can be further discussed (Mousavizadeh et al. 2016). In the present study, the simulation and dynamic prediction of B by the AquaCrop model at 24, 43, 47, 50, 52, 56, 63, 71, 77, 85, 92 and 100 days after irrigation for calibration and at 38, 42, 50, 57, 64, 71, 79 and 100 days after irrigation were validated in four water treatments. The values of calibration and validation statistical indices for B are presented in Table 3 and 4. Moreover, the dynamic results B for all four irrigation treatments on different days after canola planting are shown in Figs. 8 and 9.

According to Table 3 and 4, the RMSE range in the dynamic calibration B was obtained between 0.6 and 1.2 (t ha^{-1}). The value of this statistic for the treatments I_2, I_3 and I_4 showed that the model has moderate accuracy. Meantime, the RMSE range in dynamic evaluation B was obtained between 0.2 and 1.7 (t ha^{-1}). The value of this statistic for the two treatments I_3 and I_4 showed that the model has good accuracy, but for the two treatments I_1 and I_2 the RMSE value was calculated to be more than one (t ha^{-1}). Moreover, $RMSE_{Max}$ for treatment I_1 is obtained at 1.16 and 1.61 (t ha^{-1}) and $RMSE_{Min}$ for treatment I_3 at 0.67 and 0.26 (t ha^{-1})

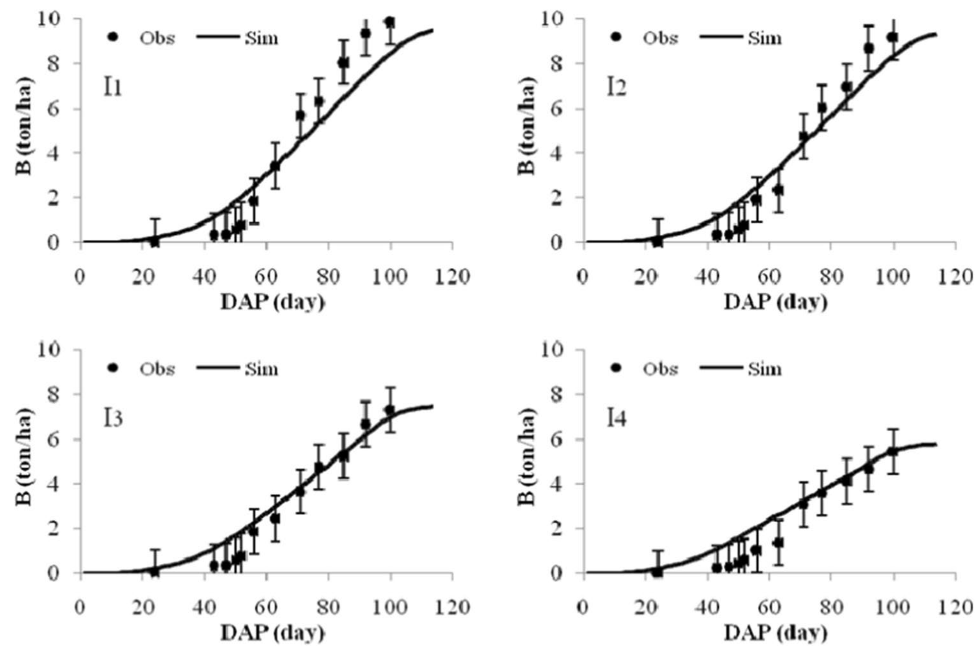

Fig. 8 The observed and simulated B in total treatments for year 2012 (calibration)

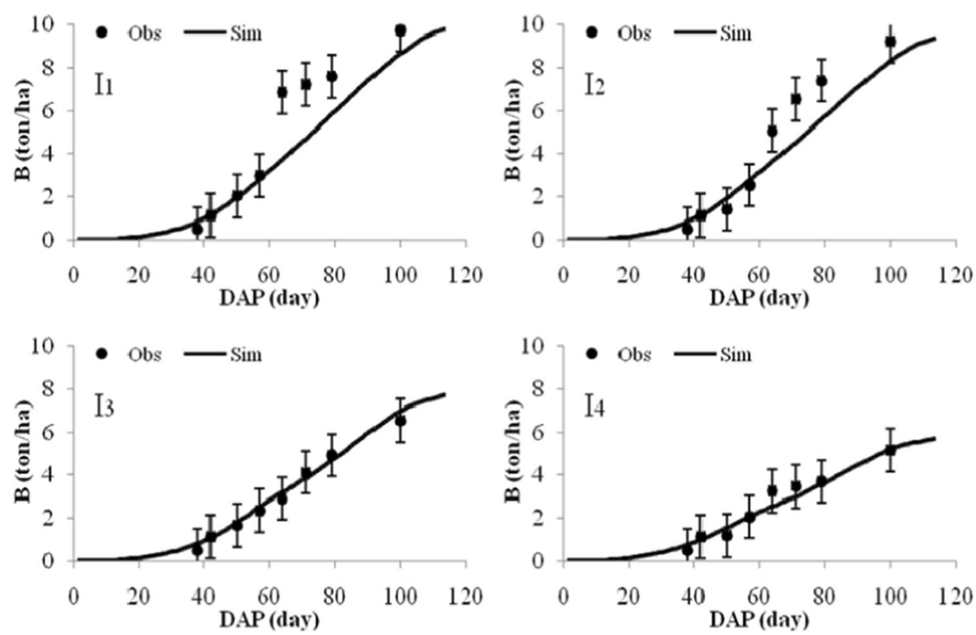

Fig. 9 The observed and simulated B in total treatments for year 2013 (validation)

by the model in the calibration and validation steps, respectively. Zeleke et al. (2011) tested the AquaCrop model for dynamic B study of two canola varieties (Hyola50 variety for calibration and Skipton variety for validation). Based on the results, the percentage of deviation from canola B in the calibration and evaluation steps was calculated to be 1.2 and − 9.7%, respectively. Furthermore, the RMSE of calibration and evaluation of 2.10 and 2.58 (t ha^{-1}) was obtained, respectively. The RMSE values obtained by Zeleke et al.'s (2011) were doubled the mean RMSE values of the present study. They also obtained the index *d* during calibration and validation steps for B at 0.97 and 0.95, respectively. This is consistent with the results of the present study where the mean index *d* values of 0.97 and 0.96 were obtained during the calibration and validation steps, respectively. In the study conducted by Mousavizadeh et al. (2016) in Shiraz (Iran) on canola with five irrigation treatments, RMSE values of 0.92 and 0.84 (t ha^{-1}) were obtained in the calibration and evaluation steps, respectively, which are also consistent with the results of this study.

In the present study, the RE index showed that the model in the prediction B provides the simulation with values higher than those measured in the calibration phase. Moreover, this index tends to overestimate in the evaluation step (except for treatment I_1) and tends from negative values of the calibration step to almost zero in the evaluation step (Table 3 and 4). In general, according to the values of statistical indicators (Table 3 and 4), the results provided by AquaCrop have been improved for the second year, which can be attributed to the high accuracy of the calibration method (applying ± 10% changes to the calibrated parameters) for the first year and also an increase in the accuracy of field measurements in the second year. Differences in tendency to overestimate and underestimate of B in AquaCrop model depend on various factors such as stresses (water, temperature, salinity and pests), irrigation system and management, environmental conditions (soil types, fertilizers, soil water characteristics and available water in soil), the quality of field measurement data and ultimately the accuracy of the calibration method (Heng et al. 2009; Abedinpour et al. 2012; Paredes et al., 2014; Ahmadi et al. 2015; Amiri et al. 2018).

Mousavizadeh et al. (2016) in a study on canola at the validation level showed that AquaCrop could not accurately simulate B during the growth season. This model needs to be modified and improved for the accurate simulation of GY. The comments of this study are inconsistent with the results of the present study for canola because the results of the model were appropriate for the second year (validation) in this study. Ahmadi et al. (2015) concluded that AquaCrop in the calibration phase estimates B more than the measured values. Meanwhile, the model in the validation stage at the beginning and end of the crop growth season for deficit irrigation treatments has tendency to overestimate and underestimate, respectively. The results obtained by Ahmadi et al. (2015) for maize are consistent with the results of the present study by the AquaCrop model.

In several studies, the B of different plants such as wheat, maize, barley and teff was examined by the AquaCrop model, which is discussed below.

Andarzian et al. (2011) reported the statistical parameters NRMSE and index *d* at 4.4% and 0.97, respectively, to predict the B of wheat. Another study was conducted on the South China Plateau to investigate the performance of the AquaCrop model on wheat crop in rainfed conditions, and perennial field test data were used to calibrate and validate the model in B and GY simulations. According to the results, the RMSE statistical range of 0.16 to 0.38 (t ha^{-1}) was considered for the B simulation and 0.5 to 1.44 (t ha^{-1}) for GY. In general, the performance of the model for simulating Y was more accurate than for B, and the model was able to simulate the GY of wheat in rainfed conditions (Zhang et al. 2013). Iqbal et al. (2014) presented investigations on wheat in northern China for B and Y for the years 1999–2000 and 2000–2001 to show that there is a relatively good consistency between the measured and simulated values. They also stated that major deviations were observed under severe stress conditions. Their overall results showed that AquaCrop is a valid model and can be used to optimize Y and B with a confident accuracy and precision of the model (Iqbal et al. 2014). Abedinpour et al. (2012) examined maize with different treatments of full and deficit irrigation by the model. According to the results, the harvesting estimation error was between 1.7 and 3.6%. Araya et al. (2010a, 2010b) reported the error range of − 0.13 to 15.1% and − 2.8 to 8.5% for B of barley and teff by AquaCrop, respectively.

In a study by Mabhaudhi et al. (2014) on the Taro plant in South Africa concluded that the model simulations for crop B and Y are very satisfactory. Despite the obvious challenges of the model in CC simulation in rainfed conditions, the model was able to successfully simulate the final B and Y. According to researchers, the AquaCrop model is not accurate enough in simulating the aging stage of the plant and has caused premature aging under water stress (Zeleke et al. 2011; Ahmadi et al. 2015). Because of the weakness of the model, Ahmadi et al. (2015) suggested that the future versions of AquaCrop require modifications and revisions in the crop growth development equations. Zeleke et al. (2011) also emphasized the importance of accurate modification of crop growth parameters to increase the efficiency of the crop model. It should be noted that in the present study, this model was sufficiently accurate in deficit irrigation treatments, especially in the B evaluation step.

Final grain yield (GY)

Figure 10 presents a comparison of the calculated and predicted GY values provided by the model during the calibration and validation steps. The quantitative values of model evaluation and validity measurement parameters in the GY prediction of canola are also reported in Table 3 and 4. Based on the results, the model simulated the crop GY with appropriate accuracy.

The NRMSE values for both years were less than 10%, showing that the GY modeling is ideal according to this statistic. The values of this statistic for GY in the calibration and evaluation steps were 5.90 and 7.05%, respectively. In the research conducted by Mousavizadeh et al. (2016), the NRMSE values for the GY of canola in calibration and validation steps were 13.12 and 10.01%, respectively, which has a good status (NRMSE between 10 to 20%) in the simulation. However, this study showed a lower step in terms of NRMSE statistical accuracy than the results presented in this study. Meantime, according to the values of R^2 and Fig. 10, it is observed that the observed and simulated values for both years have a good correlation. The *d* index is close to one, which indicates the consistency of the *Y* reduction trend with the irrigation water amount in the model with the real *Y*.

According to the results, RE_{max} and RE_{min} values are associated with the I_1 and I_4 treatments in the calibration step and the I_4 and I_3 treatments in the validation stage, respectively. A positive RE indicates that the model estimates GY less than the actual value and a negative RE value indicates that the model overestimated the parameters. The positive and negative mean values of RE statistics were obtained in the two stages of calibration and evaluation, which showed that the model has a slight tendency to underestimate and overestimate in these stages. Therefore, it can be concluded that the model in the GY prediction provides the simulation less than the values measured in the calibration step and predicts more than the values measured in the evaluation step. Therefore, this issue can be attributed to other parameters affecting the plant that do not exist in the model, such as the combined effect of fertilizer and water stress. Furthermore, the accuracy of measurements per year can also be effective (Amiri et al. 2018).

In general, the model showed underestimation in the calibration step of canola GY and overestimation in the evaluation step because the mean values of RE index in these stages were 1.25 and − 0.43, respectively. The results of research conducted on canola and wheat showed that AquaCrop simulates the GY of the crops for deficit and over-irrigation treatments as overestimate and underestimate, respectively (Zeleke et al. 2011; Xiangxiang et al. 2013). Ahmadi et al. (2015) also reported that the model structure can be modified to improve B and GY simulations at different stages of severe water stress.

There are numerous studies showing that the AquaCrop model has an acceptable performance in simulating the final GY of canola (Zeleke et al. 2011; Arvaneh and Abbasi 2014; Mousavizadeh et al. 2016; Amiri et al. 2018), wheat (Andarzian et al. 2011; Mkhabela and Bullock 2012; Zhang et al. 2013; Khorsand et al. 2014b; Iqbal et al. 2014), maize (Heng et al. 2009; Abedinpour et al. 2012; Ahmadi et al. 2015) and cotton (Garcia-Vila et al., 2009; Farahani et al. 2009; Hussein et al. 2011). Zeleke et al. (2011) examined the AquaCrop model for the evaluation of the canola GY in the semi-arid region of Australia under environmental stress. According to the obtained results, the percentage of deviation from the GY of the crop in the calibration and validation steps was 4.7 and − 2.1%, respectively. They concluded that the model is able to satisfactorily simulate GY. It was also less satisfactory in GY simulations under conditions of severe water stress (especially when stress occurred in the post-flowering stage). Arvaneh and Abbasi (2014) conducted a study on canola (Hyola401) in two farms: A (four hectares) and B (one hectare) in Iran. They showed that the model simulations were very satisfactory for GY. The GY value measured in field A was

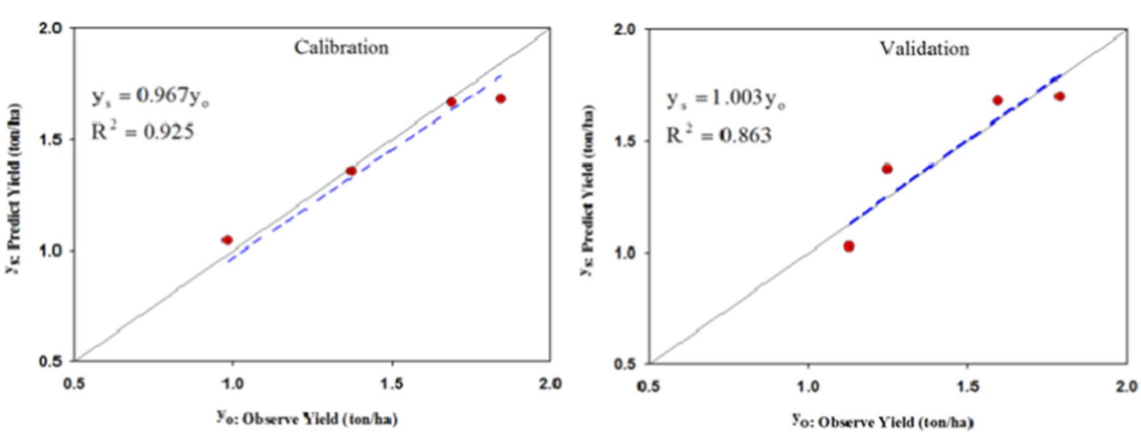

Fig. 10 Graphical test of the simulated versus observed GY of canola

1.90 (t ha^{-1}) and the model presented the GY value of 1.84 (t ha^{-1}) through simulation (calibration step). Also, in field B, the measured GY value was 1.65 (t ha^{-1}) and AquaCrop estimated the GY value at 1.51 (t ha^{-1}) (evaluation step). The main reason for low GY of canola in farm B compared to farm A was the 20-day delay in the date of planting canola (Arvaneh and Abbasi 2014). The measured GY value in this study for non-stress treatment (I_1) was 1.84 (t ha^{-1}), which is very close to the GY value (field A) measured by Arvaneh and Abbasi (2014).

Hsiao et al. (2009) calibrated and evaluated the AquaCrop model for maize. According to the results of the validation step, the error range of the prediction for maize GY was 1% to 24%. In the studies conducted by Heng et al. (2009) for calibration and validation of AquaCrop for maize in three regions with completely different conditions, it was found that the model satisfactorily simulates the growth of B and GY under conditions of without water stress and with moderate water stress. However, the model for the treatments of severe water stress, especially when water stress occurs during the critical stage of crop growth, cannot simulate these parameters satisfactorily. Araya et al. (2010a, 2010b) obtained the GY error range of barley and teff at − 5.6 to 14.6% and − 22.5 to 8.5%, respectively. Khorsand et al. (2014b) examined the GY of wheat subjected to salinity and water stresses by this model. According to the obtained results, the NRMSE value of GY prediction for Roshan and Quds varieties in the calibration step was 3.84 and 6.65%, respectively, and in the evaluation step, 4.65 and 4.55% respectively. Apart from that, the results of a study conducted by Mkhabela and Bullock (2012) on wheat in Western Canada showed that the model simulations for GY were very satisfactory. In other studies including Amiri et al. (2018), Andarzian et al. (2011) and Heng et al. (2009), the model predicted the GY of wheat subjected to water stress, the GY of wheat subjected to full irrigation and deficit irrigation, and GY of maize subjected to full irrigation and deficit irrigation with a relative error of less than 10%, which is consistent with the results of the present study.

AquaCrop is in general a water-based model, and the performance of GY and B simulation depends on accurate simulation of soil water dynamics (Ahmadi et al. 2015). According to Ahmadi et al. (2015), it is better to consider some calibration information about the root growth distribution pattern in soil in future versions of AquaCrop. The root information and data of each plant variety help to accurately simulate the Tr and GY rates of the plant (Vanuytrecht et al. 2014a; Ahmadi et al. 2015).

Conclusions

In this study, the calibration and evaluation of the AquaCrop model during two cropping years (2012 and 2013) were tested in the climate conditions of Iran (semi-arid region) subjected to full irrigation and deficit irrigation conditions on the canola growth. The simulated and measured soil water content in canola root development area for irrigation treatments showed that the model has an acceptable capability. According to the results, AquaCrop shows overestimation in the evapotranspiration calibration phase and underestimation in the evapotranspiration validation phase. More attention should be paid to evapotranspiration; because it has a great impact on the canopy cover, biomass and final yield. The results also showed that the model provides overestimation in the simulation and prediction of canola canopy cover and is less satisfactory subjected to water stresses. Evaluation of AquaCrop model showed that this model is able to simulate biomass and grain yield with high accuracy. The value of normalized simulation and prediction error for grain yield by the model was less than 10%.

AquaCrop can be used with reliable accuracy under mild water stress to determine the lowest sensitivity stages and stress thresholds of crop growth period, which is a useful and efficient tool for designing and evaluating low irrigation strategies. Overall, despite simplicity, the AquaCrop model was a good tool for studying irrigation management, biomass and crop yield, canopy cover, soil water content and other factors affecting canola growth in the fields and climate under study. It is suggested to examine the efficiency of the model in future studies for other crops (including canola), different soils and under other climate conditions.

Author contributions AK and AMH performed the experiments and drafted the manuscript. HD conceived and designed the experiments, supervised the work, interpreted the data and wrote the paper. HA and VR contributed to analysis or interpretation of data for the work. All authors read and approved the final manuscript.

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Data availability The datasets generated during and/or analyzing for the current study are available from the corresponding author on reasonable request.

Code availability For this publication, we did not used any code.

Declarations

Conflict of interest The authors declare they have no conflict of interest.

Consent to participate The authors declare they have consent to participate.

Consent for publication The authors declare they have consent to publication.

Ethical approval
Hereby, I / Hossein Dehghanisanij consciously assure that for the manuscript Calibration and Evaluation of the FAO AquaCrop Model for Canola (*Brassica napus*) under full and deficit irrigation in a semi-arid region the following is fulfilled:
1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by
using quotation marks and giving proper reference.
7) All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.
I agree with the above statements and declare that this submission follows the policies of Solid State Ionics.

References

Abedinpour M, Sarangi A, Rajput TBS, Singh M, Pathak H, Ahmad T (2012) Performance evaluation of AquaCrop model for maize crop in a semi-arid environment. Agric Water Manage 110:55–66

Abraha B, Delbecque N, Raes D, Tsegay A, Todorovic M, Heng L, Vanuytrecht E, Geerts S, Garcia-Vila M, Deckers S (2012) Sowing strategies for barley based on modelled yield response to water with AquaCrop. Exp Agr 48:252–271

Ahmadi S, Mosallaeepour E, Kamgar-Haghighi A, Sepaskhah A (2015) Modeling maize yield and soil water content with AquaCrop under full and deficit irrigation managements. Water Resour Manag 29(8):2837–2853

Allen RG, Pereira LS, Raes D, Smith M (1998) Crop Evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome 300(9):D05109

Amiri E, Khorsand A, Daneshian J, Yousefi M (2018) Predicting biomass and grain yield in canola under different water regimes and fertilizers using AquaCrop model. JISE 41(1):57–72

Andarzian B, Bannayan M, Steduto P, Mazraeh H, Barati ME, Barati MA, Rahnama A (2011) Validation and testing of the AquaCrop model under full and deficit irrigated wheat production in Iran. Agric Water Manage 100(1):1–8

Araya A, Habtu S, Hadgu KM, Kebede A, Dejene T (2010a) Test of AquaCrop model in simulating biomass and yield of water deficient and irrigated barley (Hordeum vulgare). Agric Water Manage 97(11):1838–1846

Araya A, Keesstra SD, Stroosnijder L (2010b) Simulating yield response to water of Teff (Eragrostis tef) with FAO's AquaCrop model. FIELD CROP RES 116(1–2):196–204

Arvaneh H, Abbasi F (2014) Calibration and validation of the AquaCrop model for canola in the field. Iranian J Water Res 8(14):9–17 ((**In Persian**))

Azam-Ali SN, Sesay A, Karikari S, Massawe FJ, Aguilar-Manjarrez J, Bannayan M, Hampson KJ (2001) Assessing the potential of an underutilized crop – a casestudy using Bambara groundnut. Exp Agr 37:433–472

Biazin B, Stroosnijder L (2012) To tie or not to tie ridges for water conservation in Rift Valley drylands of Ethiopia. SOIL TILL RES 124:83–94

Cusicanqui J, Dillen K, Garcia M, Geerts S, Raes D, Mathijs E (2013) Economic assessment at farm level of the implementation of deficit irrigation for quinoa production in the Southern Bolivian Altiplano. SJAR 11:894–907

Fang Q, Ma L, Ahuja L, Trout T, Malone R, Zhang H, Guo D, Yu Q (2017a) Long-term simulation of growth stagebased irrigation scheduling in maize under various water constraints in Colorado, USA. FASE 4(2):172

Fang QX, Ma L, Trout TJ, Comas LH, DeJonge KC, Ahuja LR (2017b) Modeling N concentration and uptake for maize hybrid under growth stage based deficit irrigations. FASE 60(6):2067–2081

Farahani H, Izzi G, Oweis TY (2009) Parameterization and evaluation of AquaCrop for full and deficit irrigated cotton. Agron 101:469–476

García-Vila M, Fereres E (2012) Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. Agron 36:21–31

García-Vila M, Fereres E, Mateos L, Orgaz F, Steduto P (2009) Deficit irrigation optimization of cotton with AquaCrop. Agron 101:477–487

Gauch H, Hwang JTG, Fick GW (2003) Model evaluation by comparison of model-based predictions and measured values. Agron 95:1442–1446

Geerts S, Raes D (2009) Deficit irrigation as on-farm strategy to maximize crop water productivity in dry areas. Agric Water Manage 96:1275–1284

Geerts S, Raes D, Garcia M (2010) Using AquaCrop to derive deficit irrigation schedules. Agric Water Manage 98:213–216

Heng LK, Evett SR, Howell TA, Hsiao TC (2009) Calibration and testing of Food and Agriculture Organization AquaCrop model for maize in several locations. Agron 101(3):488–498

Hsiao TC, Heng L, Steduto P, Rojas-Lara B, Raes D, Fereres E (2009) AquaCrop—the FAO crop model to simulate yield response to water: III. Parameterization Test Maize Agron 101(3):448–459

Hussein F, Janat M, Yakoub A (2011) Simulating cotton yield response to deficit irrigation with the FAO AquaCrop model. Spanish SJAR 9:1319–1330

Iqbal M, Shen Y, Stricevic R, Pei H, Sun H, Amiri E, Penas A, delRio 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 Manage 135:61–72

Katerji N, Campi P, Mastrorilli M (2013) Productivity, evapotranspiration, and water use efficiency of corn and tomato crops simulated by AquaCrop under contrasting water stress conditions in the Mediterranean region. Agric Water Manage 130:14–26

Khorsand A, Rezaverdinejad V, Shahidi A (2014a) Performance evaluation of AquaCrop model to predict yield production of wheat, soil water and solute transport under water and salinity stresses. Water Irrig Manage 4(1):89–104 ((**In Persian**))

Khorsand A, Rezaverdinejad V, Shahidi A (2014b) Comparison of Food and Agriculture Organization AquaCrop and SWAP agro-hydrological models to simulate water and salt transport during growing season of winter wheat. IJB 4:223–233

Khorsand A, Rezaverdinejad V, Asgarzadeh H, Majnooni-Heris A, Rahimi A, Besharat S (2019) Irrigation scheduling of maize based on plant and soil indices with surface drip irrigation subjected to different irrigation regimes. Agric Water Manage 224:105740. https://doi.org/10.1016/j.agwat.2019.105740

Kim D, Kaluarachchi J (2015) Validating FAO AquaCrop using Landsat images and regional crop information. Agric Water Manage 149:143–155

Liu C, Qi Z, Gu Z, Gui D, Zeng F (2017) Optimizing irrigation rates for cotton production in an extremely arid area using RZWQM2 simulated water stress. Trans ASABE 60(6):2041–2052

Mabhaudhi T, Modi AT, Beletse YG (2014) Parameterisation and evaluation of the food and agriculture organization Aquacrop model for a South African taro (*Colocasia esculenta* L. Schott) landrace. AGR FOREST METEOROL 192:132–139

Majnooni-Heris A, Nazemi AH, Ashraf-Sadraddini A (2014) Effects of deficit irrigation on the yield, yield components, water and irrigation water use efficiency of spring canola. JBES 5:44–53

Mebane VJ, Day RL, Hamlett JL, Watson JE, Roth GW (2013) Validating the FAO AquaCrop model for rain-fed maize in Pennsylvania. Agron 105:419–427

Mhizha., Geerts S, Vanuytrecht E, Makarau A, Raes D (2014) Use of the FAO AquaCrop model in developing sowing guidelines for rainfed maize in Zimbabwe. Water SA 40 (in press). Available on website: http://www.wrc.org.

Mkhabela MS, Bullock PR (2012) Performance of the food and agriculture organization AquaCrop model for wheat grain yield and soil moisture simulation in Western Canada. Agric Water Manage 110:16–24

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50(3):885–900

Mousavizadeh SF, Honar T, Ahmadi SH (2016) Assessment of the AquaCrop model for simulating canola under different irrigation management in a semiarid area. INT J PLANT PROD 10(4):1735–6814

Nyakudya IW, Stroosnijder L (2014) Effect of rooting depth, plant density and planting date on maize (*Zea mays* L.) yield and water use efficiency in semi-arid Zimbabwe: modelling with AquaCrop. Agric Water Manage 146:280–296

Osmani H, Motamed Vaziri B, Moeini A (2013) Simulation of discharge, calibration and validation of SWAT model, case study: Tehran Latyan dam upstream. J Watershed Eng Manage 5(2):134–143 ((**in Persian**))

Overman AR, Scholtz RV III (2002) Mathematical models of crop and growth yield. CRC Press

Paredes P, de Melo-Abreu JP, Alves I, Pereira LS (2014) Assessing the performance of the FAO AquaCrop model to estimate maize yields and water use under full and deficit irrigation with focus on model parameterization. Agric Water Manage 144(81):97

Pereira LS, Paredes P, Rodrigues GC, Neves M (2015) Modeling barley water use and evapotranspiration partitioning in two contrasting rainfall years. Assessing SIMDualKc and AquaCrop models. Agric Water Manage 159:239–254

Raes D, Steduto P, Hsiao TC, Fereres E (2009) AquaCrop-the FAO crop model to simulate yield response to water II. Main Algorithms Softw Descr Agron 101:438–447

Raes D, Steduto P, Hsiao TC, Fereres E (2012) Reference Manual AquaCrop (Version 4.0). AquaCrop Website http://www.fao.org/nr/water/aquacrop.html Refsgaard, J.C., van der Sluijs, J.P.

Reddy TY, Reddi GHS (2003) Principles of agronomy.Kalyani Publishers. Ludhiana: 48–77.

Sandhu R, Irmak S (2019) Performance of AquaCrop model in simulating maize growth, yield, and evapotranspiration under Rainfed, limited and full irrigation. Agric Water Manage 223:105687

Singels A, Crosby CT, Green GC, Van Heerden PS, Durand W, De Jager JM, Steyn JM, Inman-Bamber NG, Schulze RE, Van Rensburg LD, Annandale JG (2010) Modelling crop growth and water relations in South Africa: past achieve-ments and lessons for the future. South Africa Plant Soil 27:49–65

Singh R (2004) Simulations on direct and cyclic use of saline waters for sustaining cotton–wheat in a semi-arid area of north-west India. Agric Water Manage 66(2):153–162

Singh AK, Tripathy R, Chopra UK (2008) Evaluation of CERES-Wheat and CropSyst models for water–nitrogen interactions in wheat crop. Agric Water Manage 95(7):776–786

Steduto P, Hsiao TC, Raes D, Fereres E (2009) AquaCrop the food and agriculture organization model to simulate yield response to water. Agron 101:426–437

Vanuytrecht E, Raes D, Willems P (2014a) Global sensitivity analysis of yield output from the water productivity model. ENVIRON MODELL SOFTW 51:323–332

Vanuytrecht E, Raes D, Steduto P, Hsiao TC, Fereres E, Heng LK, Vila MG, Moreno PM (2014b) AquaCrop: FAO's crop water productivity and yield response model. ENVIRON MODELL SOFTW 62:351–360

Wallach D, Makowski D, Jones JW, Brun F (2019) Working with Dynamic Crop Models, Chapter 6: Uncertainty and Sensitivity Analysis.

Willmott CJ (1982) Some comments on the evaluation of model performance. Bull Am Meteorol Soc 63:1309–1313

Xiangxiang W, Quanjiu W, Jun F, Qiuping F (2013) Evaluation of the AquaCrop model for simulating the impact of water deficits and different irrigation regimes on the biomass and yield of winter wheat grown on China's Loess Plateau. Agric Water Manage 129:95–104

Zeleke KT, Luckett D, Cowley R (2011) Calibration and testing of the food and agriculture organization AquaCrop model for canola. Agron 103:1610–1618

Zhang W, Liu W, Xue Q, Chen J, Han X (2013) Evaluation of the AquaCrop model for simulating yield response of winter wheat to water on the southern Loess Plateau of China. WATER SCI TECHNOL 68(4):821–828

Zinyengere N, Mhizha T, Mashonjowa E, Chipindu B, Geerts S, Raes D (2011) Using seasonal climate forecasts to improve maize production decision support in Zimbabwe. AGR FOREST METEOROL 151(12):1792–1799

Zomorodian A, Kavoosi Z, Momenzadeh L (2010) Determination of EMC isotherms and appropriate mathematical models for canola. FOOD BIOPROD PROCESS 89(4):407–413