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ORIGINAL ARTICLE

Simulating maize water productivity at deficit irrigated field in north west Ethiopia

Daniel G. Eshete[1] · **Berhanu G. Sinshaw**[1] · **Habtamu D. Gizaw**[1] · **Baye A. Zerihun**[2]

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Abstract

Irrigation agriculture in Ethiopia can be improved by applying appropriate irrigation levels. Since water scarcity is the major problem in Ethiopia, and farmers apply water without knowledge of the amount of water to be applied, appropriate irrigation levels for maize crops should be investigated in the central Gondar zone, Ethiopia. This paper aims to investigate the effect of deficit levels of irrigation on crop parameters and evaluate the AquaCrop model for its predictability potential of water productivity. The experiment has four levels of water application (Full Irrigation (100%), 75%, 50%, and 25% of crop evapotranspiration) at 10 days of irrigation interval using Randomized Complete Block Design with three replications. Data collected in two experiments in the different seasons were soil moisture, canopy cover, biomass, and final yield. As high R^2 (0.93) and Nash–Sutcliffe Efficiency (NSE) (0.91) values indicated, the model performed well in simulating canopy cover, above-ground biomass, and yield in all treatments except 25% full irrigation (FI) with prolonged water deficit. Grain yield measured from experiment 2 was within the range of 4.6 t/ha to 7.4 t/ha. Even though a high yield was found from FI, the measured water use efficiency was better in 75% FI treatment, indicating a potential for water-saving by this treatment than FI. Higher grain yield was observed for maize sown in January at experiment 1. This was attributed to the rainfall impact on the experiment since it was spring season in Ethiopia at which some rainfall in the region is pronounced. In addition, AquaCrop thoroughly underestimated the seasonal evapotranspiration values and the deviations were commonly bigger as stress levels increased. Therefore, AquaCrop can be used in the simulation of crop parameters, prediction of irrigated outputs, and assessing the impact of irrigation scheduling.

Keywords AquaCrop · Deficit irrigation · Ethiopia · Water use efficiency · Maize

Introduction

Globally, it is a known fact that agricultural water productivity needs to be increased to satisfy the increasing demand for food, which will double by 2050 (Sarangi 2012). Using water resources sustainably and effectively is currently the main challenge. Different methods and approaches should be identified and developed to enhance the water use efficiency for meeting the demand of the rapidly growing population, as water is becoming a scarce resource (Kadam et al. 2017). In recent times, rapid population growth, land-use change, and change in precipitation patterns caused by climate change have affected the quantity and quality of water resources in irrigated agriculture (Greaves and Wang 2016). For better crop growth and productivity, soils must have better soil moisture, lesser salinity, and more fine particles (Hu et al. 2020). Since the number of water resources allocated to agriculture is declining and the population is rising, crop water productivity should be improved (Kijne et al. 2003). And also, the quality of the surface water is deteriorated by the impact of rapid industrialization and urbanization (Khan et al. 2020). Deficit irrigation that focuses on agricultural water productivity improvement tied with a simulation model to investigate multiple alternatives has a significant role to make water resources sustainable (Greaves and Wang 2016). Furthermore, it is necessary to evaluate the potential impact of water deficit on crop water productivity. Consequently, quantification of crop water needs and evaluation

✉ Daniel G. Eshete
geletawdaniel@gmail.com

[1] Department of Hydraulic and Water Resource Engineering, Insititute of Technology, University of Gondar, P.O. Box 196, Gondar, Ethiopia

[2] Amhara Region Agricultural Research Institute, Gondar Agricultural Research Center, Gondar, Ethiopia

of crop water productivity are crucial steps for the efficient establishment of systems that enable scarce water resources to be distributed for the inclusive advantage of the country's economy (Li et al. 2016). Although smallholder farmers dominate, Ethiopia is among the major maize producers in sub-Saharan African countries. Maize is mainly cultivated in three regions of the country namely: Oromia, Amhara, and the South Nation, Nationalities, and Peoples (Gebreselassie et al. 2015). In the central Gondar zone, maize is one of the most vital and highly demanded crops cultivated by furrow irrigation with the highest average grain yield per hectare.

AquaCrop models are one of the crop growth simulation models that are important for evaluating the effects of water shortage on crop water productivity and yield (Mehraban 2013). The two mainly water-driven models used for simulation are CropSyst (Stockle et al. 2003) and AquaCrop (Steduto et al. 2009). The FAO-AquaCrop model keeps a good balance between the robustness and the accuracy of the output and crop water productivity model that is used for many crops (Vanuytrecht et al. 2014).

The AquaCrop model can simulate the potential yields of the major herbaceous crops when the crops are subjected to water stress (Steduto et al. 2009). The model has been used and tested for many crops in different parts of the world for example maize was tested in California, USA (Hsiao et al. 2009), Zaragoza, Spain (Heng et al. 2009), Kenya (Ngetich et al. 2012), South Ethiopia (Gebreselassie et al. 2015), and also AquaCrop was tested for barley in Ethiopia (Abrha et al. 2012). But the model is not tested yet for the Maize crop in the Central Gondar zone, Ethiopia. Although food production systems in a sustainable way are necessary to feed the populations in Ethiopia, the systems require efficient water use yet agricultural water use faces competition from non-agricultural sectors. Different irrigation water-saving technologies have been developed and used worldwide. However, Ethiopia is still a country of smallholder agriculture (Gebreselassie 2006).

In the central Gondar zone, where water shortage is the main problem, irrigation scheduling that improves water use efficiency and provides high yield is inevitable. Thus, there is a need to select appropriate irrigation levels and accurately predict yields (biomass and grain harvest) of crops like maize to reduce farmers' labor costs and input costs to ensure that the input loss is minimal in the event of a crop disaster. Even though many studies (Abrha et al. 2012; Gebreselassie et al. 2015) are undertaken, none of them are linked to irrigation water application level in central Gondar and still, there is a gap in evaluating crop productivity using deficit irrigation. Therefore, this study aims to evaluate the effect of different deficit irrigation levels on crop yield and to simulate the maize yield, biomass, and water productivity using the FAO AquaCrop model in the study area. This study will provide new insights into deficit irrigation water application without compromising crop needs. Through this research, the community will realize the importance of saving irrigation water to irrigate extra fields. Moreover, the analysis presented will convey important information for future research that will discover the various relationships between irrigation water deficit and yield gap analysis. This paper will also contribute to adding the state of knowledge to the existing literature.

Description of the study area

The experiment was conducted in the central Gondar zone of the Amhara regional state. The study was performed at the Shinta experimental field of the University of Gondar which is located 180 km far from Bahir Dar town for two cropping seasons. The first experiment was conducted from January to June 2020 and the second experiment was conducted from November 2020 to March 2021. There was a substantial difference in rainfall between the two seasons. Experiment 1 was approaching the rainy season and it received a significant amount of rainfall with a total of 40 mm. However, during experiment 2 the rainfall amount was minimum and it was about 12 mm. The study area is found between the latitude of 12° 25′00″ N and 12° 40′00″ N and between the longitude of 37° 20′00″ E and 37°35′00″ E (Fig. 1). Based on the rainfall, the climate of the area can be categorized into two major seasons; the dry season (winter) which covers the period from October to May and the wet season (summer) extends from June to September, with slight rainfall during autumn and spring. The average long-term rainfall in the study area is 1160 mm per annum. The long-term annual mean maximum, mean, and mean minimum temperatures are 24.5, 19.08, and 13.35 °C, respectively. The study area is located in the foothills of the Semen (Northern) mountain chains at an average elevation of 2200 m above sea level, and the landscape opens to a valley and distant views of Lake Tana, the source of the Blue Nile (Tegegne et al. 2017).

Materials and methods

Climate data

Daily values of minimum and maximum air temperatures, rainfall, and ETo are the data required by AquaCrop. The weather data were collected from Gondar-Azezo meteorological station situated nearby the experimental site. The CO_2 concentration at Mauna Loa Observatory, Hawaii, was used. The long-term statistical values of the weather parameters are shown in Table 1. To calculate daily reference evapotranspiration (ETo), the standard procedure was used by following the FAO Penman–Monteith equation.

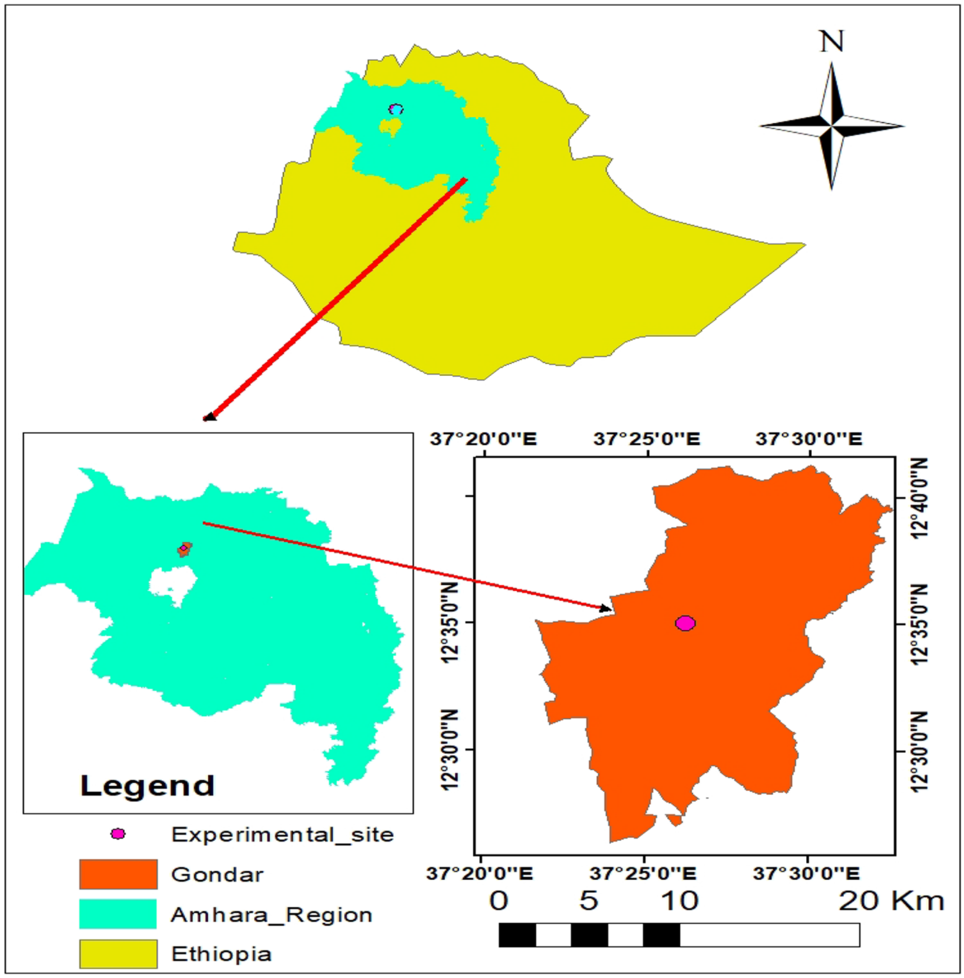

Fig. 1 Location map of the study area

Table 1 Long-term climate data obtained from Gondar meteorological station

Month	Tmin (°C)	Tmax (°C)	Humidity (%)	wind speed(m/s)	SSH	Radiation (MJ/M^2/day)	Eto (mm/day)
January	11.9	28.6	42	1.3	8.7	19.5	4.11
February	13.7	30.1	38	1.6	9.1	21.6	4.95
March	15.0	30.5	38	1.5	7.1	19.9	4.94
April	15.6	30.3	40	1.5	7.6	21.2	5.18
May	15.2	28.6	56	1.6	6.5	19.3	4.63
June	14.4	26.6	71	1.5	4.6	16.2	3.68
July	13.1	23.4	80	1.3	3.9	15.2	3.11
August	13.8	23.8	81	1.2	4.7	16.6	3.25
September	13.3	25.6	73	1.3	5.4	17.4	3.58
October	11.2	26.7	66	1.4	7.5	19.5	3.98
November	12.6	27.2	54	1.2	8.3	19.2	3.86
December	12.5	27.5	50	1.3	7.3	17.1	3.68
Average	12.68	27.34	57.42	1.39	6.73	18.56	4.08

Table 2 Physical and chemical properties of the soil at the experimental site

Soil depth	EC (ds/m)	PH	% Sand	%Silt	%Clay	Texture	Organic matter%	Organic carbon%	FC (%)	PWP (%)
60 cm	0.155	6.7	28.7	27.6	43.65	Clay	2.02	1.17	32.27	20.79

Table 3 Detail of treatments used

Treatment	Specification	Symbol
T1	100% of irrigation water requirement	Full irrigation
T2	75% of irrigation water requirement	75%FI
T3	50% of irrigation water requirement	50%FI
T4	25% of Irrigation water requirement	25%FI

Table 4 Total number of treatment combinations over cropping stages

Treatment	Cropping growing stage/level of water application in %			
	1	2	3	4
T_1	100	100	100	100
T_2	100	75	75	75
T_3	100	50	50	50
T_4	100	25	25	25

Soil data

Soil samples were collected from average root depth to characterize the soil in terms of physical characteristics such as texture, PH, organic matter, electric conductivity, field capacity, and permanent wilting point. The above-mentioned soil parameters were analyzed at the soil laboratory of Amhara design and supervision enterprise. From the laboratory result, the soil texture in the study area was classified as clay soil having an organic matter of 2.02% and organic carbon of 1.17%. The average volumetric water content at 0.6 m depth was 32.27% at field capacity and 20.79% at the permanent wilting point stages. Table 2 shows the important soil physical characteristics of the experimental site.

Experimental design and treatments

The experiment was conducted by exposing maize crops to water deficit at different growing stages. During the experiment, four treatments were used. i.e. 100%, 75%, 50%, and 25% of ETC to that of total crop water requirement during the total growing stage based on literature (Tables 3 and 4). To illustrate the impact of water deficit on canopy cover, yield, biomass, and WUE, this study was conducted as a randomized complete block design (RCBD), and three replications to form a total of twelve experimental plots. The plot was prepared across the general slope of the field to have similar soil settings within the blocks. The size of each experimental plot is 4*3 m. The space between plots and replication is 1 m by 1 m, respectively. Maize was planted at 40 cm intervals between plants and the row spacing was 80 cm (Gebreselassie et al. 2015). The maize crop was selected for its good adaptability and usability in the area.

Crop parameter and measurement

From field observation, sowing date, seedling canopy size, days to emergence, days to maximum CC, days to flowering, days to senescence, and days to maturity were recorded. Duration of flowering and maximum effective rooting depth data was also collected. A small tape meter was used to measure leaf length and width. To assess crop development, leaf area index, total aboveground biomass, and final yield were monitored. During experiment 1, due to COVID-19, our laboratory was closed and unable to use the oven-dry for biomass measurement. Therefore, only canopy cover data were collected at 10 days intervals from sowing to harvest regularly. However, for experiment two, the data were collected in a two-week interval for crop parameters and biomass measurement. Before cutting the plants at the ground level, the growth stage was recorded. The base and upper temperatures were taken as 10 °C and 30 °C respectively. Root observation was done in the field at the time of maximum canopy cover and maturity from all plots. The total leaf area (cm^2) for maize leaves was calculated using a relationship based on Kang et al. (2003) as cited in (Gebreselassie et al. 2015).

$$A = 0.759 \sum_{i=1}^{m} L_i * W_i, \tag{1}$$

The leaf area index was obtained by the ratio of total leaf area of the crop per unit of ground area

$$\mathrm{LAI} = \frac{\text{Measured leaf area per plant}\left(\mathrm{cm}^2\right)}{100*100} * \frac{\text{number of plants}}{\mathrm{m}^2}, \tag{2}$$

Aqua crop simulates transpiration based on canopy cover (CC) of the crop, but in an experiment, LAI is measured not canopy cover. Consequently, canopy cover was estimated from the leaf area index based on Hsiao et al. (2009) and Heng et al (2009).

$$CC = 1.005 * \lceil 1.\exp(-0.6LAI) \rceil^{1.2}, \quad (3)$$

where CC (%) is canopy cover and LAI is leaf area index. An empirical relation between CC and LAI of maize was estimated by regression. The above-ground biomass samples were collected by cutting the crop at the ground level, oven-dried for two days, and weighed on a digital weighing scale. The final yield samples were also harvested, dried to 12% moisture content in the drier, and weighed on the electronic balance.

Agronomic practices and water application

The farmland was prepared by plowing to 30 cm depth with "Maresha" which was pulled by a pair of oxen. Maize was sown manually in mid-January 2020 and the harvest time was at the beginning of June of the same year for experiment 1 (Table 5). The planting and harvesting dates for experiment 2 were in mid -November 2020 and the end of March 2021, respectively. Water was applied by using the overhead irrigation method. Seeds were sown at a rate of 54 kg/ ha in rows spaced 0.8 m apart. Diammonium Phosphate (DAP) fertilizer was applied all at once during sowing which is 12 kg/ha whereas 10 kg/ ha urea was applied half-close at sowing and the second half at the tillering stage after weeding. During experiment 1, manual weeding was carried out three times at 4, 8, and 12 weeks after sowing. During experiment 2, however, weeding was carried out at 2, 7 and 12 weeks after sowing. This is attributed to the minimum rainfall contribution for weed development during experiment 2. In both experiments, pests were not experienced. After calculating the total irrigation water requirement, different water application levels to induce water deficit were quantified. Irrigation water was controlled to avoid the flow of water into other plots. Since the furrows are close-ended all water flowing into each furrow was infiltrated over the entire length as a result there was assumed no runoff. Since the furrows are short and the cut-off time is short, no significant deep percolation was expected.

Table 5 Time frame of main phenological growth stages in days after planting (DAP)

No.	Particulars	Experiment 1	Experiment 2
1	Plant density (plants/ m^2)	8	8
2	Number of plots	12	12
3	Seed rate	54 kg/ha	54 kg/ha
4	Date of sowing	18/01/2020	02/11/2020
5	Emergency (DAP)	7	6
6	Maturity (DAP)	141 days	151

Table 6 Amount of irrigation water applied for different treatments for the two experiments (mm)

	Experiment 1	Experiment 2
Total irrigation water applied (mm)		
FI	651.9	748.3
75% FI	505.2	578.8
50% FI	354.6	426.4
25% FI	220.1	259.2

Crop water requirements and irrigation scheduling

The daily crop water requirement of maize was calculated by multiplying the reference evapotranspiration value with the maize crop coefficients (0.3, 0.5, 1.2, and 0.5) at the initial, develop, midseason, and late development stages, respectively according to values based on Allen et al (1998). The Optimal or no stress irrigation was calculated using the FAO CROPWAT model to calculate the amount of irrigation required to refill the soil moisture deficit with a 10-day irrigation water application interval. Calculation of water and irrigation requirements was done using inputs of climate data, crop data, soil data, and rainfall data (Table 6). Reference evapotranspiration value was calculated from maximum temperature, minimum temperature, relative humidity, sunshine hour, and wind speed based on the FAO Penman–Monteith equation (Allen et al. 1998).

AquaCrop model description

FAO AquaCrop uses a water balance approach to simulate the soil water condition in the plant root zone by partitioning evapotranspiration to actual crop transpiration and soil evaporation using the soil water condition and the plant canopy cover information (Li et al. 2016). It requires a relatively low number of parameters; input data which requires only explicit and mostly intuitive parameters and variables; it is simple without compromising accuracy, and robustness; its applicability to be used in diverse agricultural systems that exist worldwide (Raes et al. 2018). The conservative crop parameters that do not adjust include soil water extraction pattern; canopy growth as a percentage of canopy cover; WP* for biomass; crop coefficient for full canopy transpiration; canopy expansion water stress response coefficients, stomatal closure, and early canopy senescence. Among the user-specific parameters, plant density, time to emergence, time to senescence, time to maturity, flowering period, yield formation, and rooting depth were included. The crop yield response to water was calculated using the following equation (Doorenbos and Kassam 1979).

Table 7 Phonological observation of Maize crop (BH 140) from the experimental field

Growth Parameter	Days
Sowing to emergence	8
Sowing to flowering	70
sowing to maximum root depth	108
Sowing to maximum canopy cover	75
Sowing to the start of senescence	115
Sowing to harvesting	151

$$\left(\frac{Y_x - Y}{Y_x}\right) = K_y\left(\frac{\mathrm{ET}_x - \mathrm{ET}}{\mathrm{ET}_x}\right), \tag{4}$$

where Y_x is the maximum yield and Y is the actual yield, ET_x the maximum actual evapotranspiration and ET are actual evapotranspiration, and K_y is the proportionality factor between the relative yield loss and relative reduction in crop water consumption. AquaCrop evolves from Doorenbos and Kassam's (1979) approach by separating (i) the evapotranspiration (ET) into soil evaporation (E) and crop transpiration (T_r) and (ii) the final grain yield (Y) into final biomass (B) and harvest index and these changes led to the following equation for the AquaCrop model.

$$B = \mathrm{WP} * \sum T_r, \tag{5}$$

$$Y = \mathrm{B} * \mathrm{HI}, \tag{6}$$

where T_r is the crop transpiration (mm) and WP $*$ is the normalized water productivity parameter (kg of biomass per m^2 and per mm of cumulated water transpired over the time in which the biomass is produced), Y is the grain yield kg/m^2, and HI is the harvest index.

Irrigation water use efficiency (WUE) is a key term in evaluating deficit irrigation (Molden et al. 2003). WP is defined as the ratio of the mass of grain yield (kg/ha) to the volume of water consumed by the crop (ET, mm).

$$W_P = \frac{Y_a}{\mathrm{ET}_a}, \tag{7}$$

ET_a refers to soil evaporation and transpiration from the plant during the crop growth period. In this study, the two processes are generally combined under the term evapotranspiration.

$$\mathrm{ET} = I + P \pm \Delta\mathrm{SW} - \mathrm{DP} - Q, \tag{8}$$

where I is the amount of irrigation water applied (mm), P is the precipitation (mm), ΔSW is the change in soil water content (mm), DP is the amount of deep percolation(mm), and Q is the amount of runoff (mm). The amount of deep percolation and runoff in this study is not considered.

Calibration and validation of the AquaCrop model

To assess the performance and applicability of the AquaCrop model under different crop water deficit levels, comparing the simulated crop parameters and water productivity of maize against field measurements were undertaken. The canopy cover and the final yield data were collected from experiment 1 which was conducted from mid-January to June 2020. These data were used for calibration of the model since more data were collected during this season. Initially, the calibration procedure was started by comparing observed and simulated CC values under full irrigation and simulated and observed grain yield comparison was done for calibration. Lastly, the calibration was conducted by comparing the simulated and observed values for grain yield for the deficit treatments. During the simulation, there were no conditions for nutrient and salinity stress. The calibration was done by varying crop growth parameters, observed phonological stages, and conservative parameters adapted from Hsiao et al.'s (2009) document. Once the input dataset is entered and files are created, the model was run using an iterative process by adjusting the model parameters until the simulated and measured data from the field was best matched. The final values of the adjusted parameters at which the model simulated outputs had the highest correlation with the field-measured data were adopted as input data for the model. By considering the calibrated crop parameters and observed data, validations were executed. The canopy cover, biomass, and yield data collected from the second experiment were used for the validation of the model (Table 7).

Assessment of AquaCrop performance

To evaluate the goodness of fit between simulated AquaCrop results and measured canopy cover, biomass, yield, ETc, and WUE, four statistical variables were used: the coefficient of determination (R^2), the Root Mean Squared Error (RMSE) (Chai and Draxle 2014), the Nash–Sutcliffe model efficiency (Nash and Sutcliffe 1970), and Willmott's Index of Agreement (d) and it were computed using the following equation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (S_i - M_i)^2}, \tag{9}$$

Table 8 AquaCrop default and calibrated values for the main parameters used in the simulation

Parameters	Default	Calibrated	Unit or meaning
Base temperature	8	10	°C
Cut off temperature	30	30	°C
Time from sowing to anthesis (GDD)	800	774	Growing degree days
Time from sowing to maturity (GDD)	1700	1607	Growing degree days
Reference harvest index (%)	70	68	common for good conditions
Crop water productivity(gm^{-2}) to the year 2020	33.7	32	Biomass per square meter
Initial canopy cover	0.49	0.4	%
Canopy cover per seedling at 90% emergence	6.5	5	cm^2
Maximum canopy cover %	96	90	–
Maximum root depth (m)	2.3	0.6	–
Canopy growth coefficient CGC(%/day)	16.3	10.4	Increased in CC relative to existing CC per GDD
Canopy decline coefficient CDC (%/day)	11.7	8.1	Decreased in CC relative to
Crop coefficient for transpiration at CC = 100%	1.03	1.15	Full canopy transpiration relative to ETo
Leaf growth threshold p—upper	0.4	0.25	As a fraction of TAW, above this leaf growth is inhibited
Leaf growth threshold p—lower	0.72	0.6	Leaf growth stops completely
Leaf growth stress coefficient curve shape	2.9	3	Moderately convex curve
The upper threshold for canopy senescence	0.69	0.7	Above this senescence begins

Table 9 Statistical indices of AquaCrop simulated result for the calibration of canopy cover

Statistics	Treatment			
	FI	75% FI	50%FI	25%FI
Variable			Canopy cover	
R^2	0.98	0.97	0.94	0.88
RMSE (%)	7.3	9.6	12.7	15.8
NSE	0.93	0.91	0.85	0.63
D	0.97	0.98	0.91	0.9

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}\left(S_{\mathrm{i}} - M_{\mathrm{i}}\right)^2}{\sum_{i=1}^{N}\left(M_{\mathrm{i}} - M_{\mathrm{av}}\right)^2}, \tag{10}$$

$$d = 1 - \frac{\sum_{i=1}^{n}\left(M_{\mathrm{i}} - S_{\mathrm{i}}\right)^2}{\sum_{i=1}^{n}\left(\left|M_{\mathrm{i}} - M_{\mathrm{av}}\right| + \left|S_{\mathrm{i}} - M_{\mathrm{av}}\right|\right)^2}, \tag{11}$$

where M_{i} and S_{i} are the measured and simulated values respectively, n represents the number of observations, and M_{av} is the mean of n measured values. The RMSE is the measure of the overall mean deviation between measured and simulated values (Greaves and Wang 2016). It is a systematic indicator of the existence of absolute uncertainty (Heng et al. 2009). Since RMSE has the same unit as that of the variable being simulated, when the value is closer to zero, the model simulation performance is better. The NSE expresses how much the overall deviation between observed and simulated values departs from the overall deviation between observed values and their mean value. The values of the Nash Sutcliffe efficiency range between 1 and $-\infty$, when values are closer to 1, the better model simulation efficiency. The index of agreement, d, indicates the relative error in model estimates. It is a dimensionless quantity that ranges from 0 to 1, where 0 describes complete disagreement and 1 indicates perfect model agreement.

Results

Calibration

The model is calibrated using the measured crop parameters for all treatments. In Table 8, the main parameters that were used to calibrate the AquaCrop model for simulating maize growth and water productivity for the area are presented together with the default values contained in the AquaCrop files.

Canopy cover value

The main calibration parameters for canopy cover were the canopy growth coefficient (CGC), the canopy decline coefficient (CDC), the water stress at upper and lower, the

Table 10 Measured values compared with simulated values of grain yield for experiment 1

Yield			
Treatment	Measured (t/ha)	Simulated (t/ha)	Deviation (%)
FI	8.1	8.7	7.4
75% FI	7.9	8.3	5.1
50% FI	5.6	5.4	− 3.5
25% FI	4.6	4.2	− 8.7

Table 11 Statistical indices of AquaCrop simulated result for the calibration dataset for yield

Statistics	Treatment			
	FI	75% FI	50%FI	25%FI
Variable yield				
R^2	0.97	0.97	0.95	0.85
RMSE(t/ha)	1.8	2.5	3.2	4.1
NSE	0.96	0.93	0.53	0.35
D	0.98	0.99	0.88	0.85

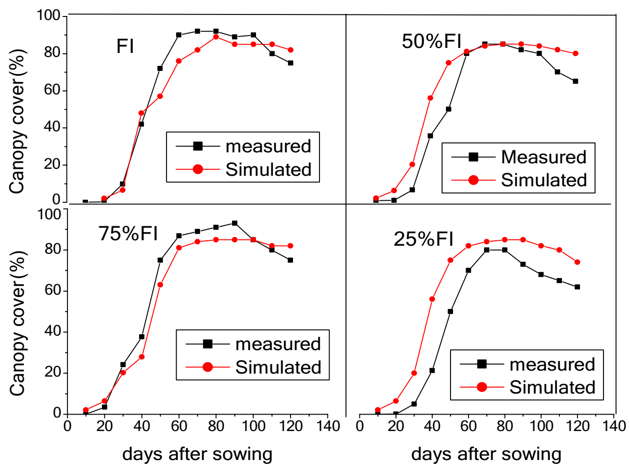

Fig. 2 Simulated and measured canopy cover for the different irrigation treatments used for AquaCrop calibration

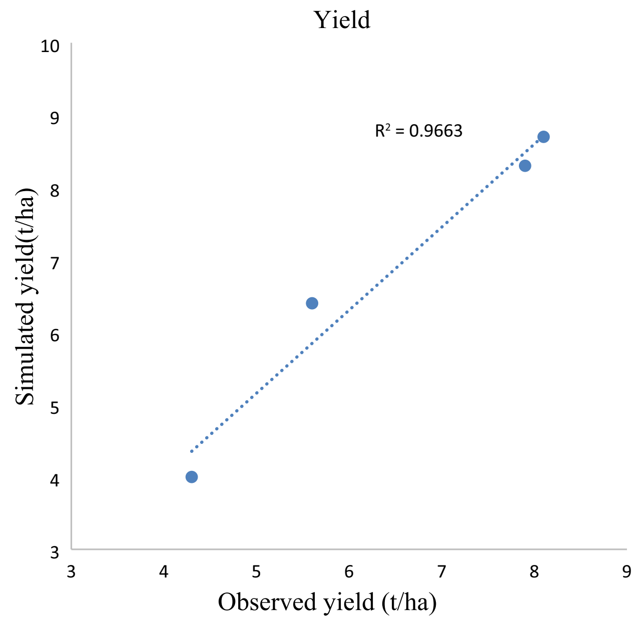

Fig. 3 Relation between measured and simulated values for grain yield for the calibration dataset

shape factors affecting leaf expansion, and early senescence. Even though the model was inclined to undervalue canopy cover during early vegetative growth for FI and 75%FI, generally, the model was able to predict the seasonal trend of canopy cover in a good manner. The outcomes revealed that the AquaCrop model can accurately simulate canopy cover, particularly in optimum irrigations. Furthermore, the model overestimates the canopy cover at 25% FI and it does not capture the measured field data. The accuracy of the calibrated model in simulating canopy cover development was assessed by statistical values which are indicated in Table 9.

For the FI and 75% FI treatments, high NSE values of 0.93 and 0.91 were obtained, while the moderate NSE values of 0.85 and 0.63 for deficit treatments 50% FI and 25% FI were obtained, respectively. This statistical value revealed that the model capability declined in a situation where the stress level is increased. However, the high value of d for all irrigation treatments revealed that the model performed well in simulating canopy cover in several water application treatments. For the calibration dataset, a strong 1:1 correlation between simulated and measured values was observed with an overall $R^2 = 0.93$.

Grain yield

From the first experiment, the final measured grain yield varied from 4.6 to 8.1 t/ha among the treatments, while the simulated yield values lie from 4.2 and 8.7 t/ha. The deviations ranged between 3.5 and 8.7% for measured and simulated values during this cropping season (Table 10). Figure 2 shows the robustness of the AquaCrop model in predicting the final grain yield of maize during the calibration period. The maximum R^2 (0.96) value indicates there was a strong 1:1 correlation between simulated and measured values for the calibrated dataset. The values for NSE, d, and R^2 are close to 1 which indicates the

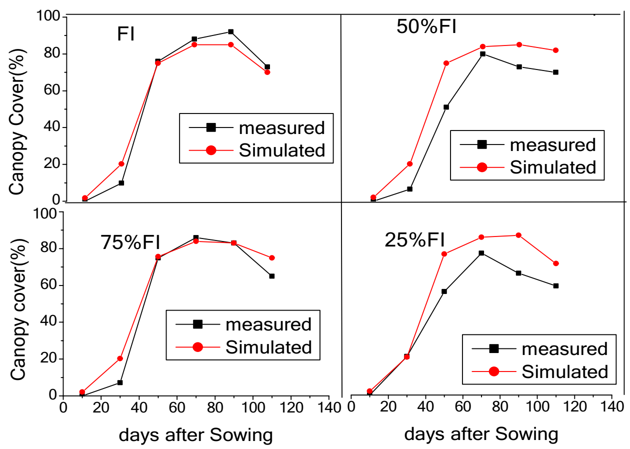

Fig. 4 Simulated and measured canopy cover for the different irrigation treatments used for AquaCrop Validation in experiment 2

Table 12 Statistical indices of AquaCrop simulated result for the validation dataset for canopy cover

Statistics	Treatment			
	FI	75% FI	50%FI	25%FI
Variable			Canopy cover	
R^2	0.99	0.97	0.96	0.86
RMSE (%)	5.5	6.7	12.3	13.1
NSE	0.96	0.91	0.79	0.71
D	0.98	0.99	0.88	0.85

simulated grain yield agreed well with the observed grain yield (Table 11) (Fig. 3).

Validation

Canopy cover

The measured and simulated canopy cover from experiment 2 used to validate the model for simulation of maize grown in different water application treatments are given in Fig. 4. The validation result showed that the model was able to optimally simulate the canopy development over the entire season for the FI and 75% FI treatments. However, AquaCrop slightly overestimates the canopy development during the first few weeks, during early vegetative growth for these treatments. Similarly, this mismatch during the early stage was more obvious in deficit treatments with 50% FI owing to the water stress incurred. Besides, the maximum canopy cover in the 25% FI was overestimated after the initial stage. The goodness of fit between measured and simulated CC is reflected in the statistical parameters shown in Table 11. The high values of NSE and d for the FI and 75% FI revealed the overall good agreement between the simulated and measured CC values used for validating the model. The 50% FI gets a high d value of 0.88 but a moderate efficiency value of 0.79. The more severely stressed 25% FI had an efficiency value of 0.71, indicating that the model performance is fair in severely stressed moisture conditions (Table 12).

Table 13 Statistical indices of AquaCrop simulated result for the validation dataset for Biomass

Statistics	Treatment			
	FI	75% FI	50%FI	25%FI
Variable			Biomass	
R^2	0.98	0.98	0.96	0.91
RMSE(t/ha)	1.2	1.75	4.2	5.1
NSE	0.99	0.97	0.65	0.51
D	0.99	0.97	0.9	0.85

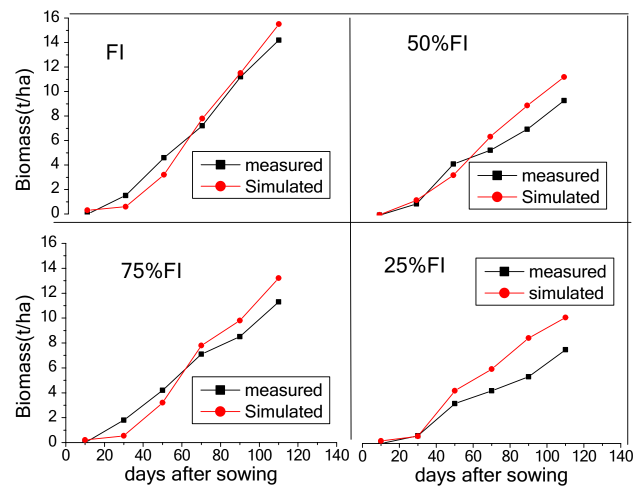

Fig. 5 Simulated and measured biomass for the different treatments used for validation

Above ground biomass

Seasonal measured biomass accumulated was compared with seasonal simulated biomass value to validate calibrated crop parameters for field-grown maize during November 2020–March 2021 experimental season (Fig. 4). It can be observed that except for the 25% FI, there is generally a good fit between the datasets. Although the deviation is high for 25% FI treatment, the model tended to over-predict the seasonal biomass for all treatments. Table 13 presents the values of the simulated seasonal biomass compared to field observations. The higher deviation for 25%FI has been attributed to the crop experiencing more water stress during this growing period. Furthermore, it can be observed that the model tries to simulate well the initial stage of more deficit irrigation treatment.

Grain yield

Grain yield measured from experiment 2 was within the range of 3.2–7.4 t/ha. The observed and simulated yield result is displayed in Table 14, and their relationship is presented in Fig. 5. The model underestimates the grain yield values for severely stressed treatments 50% FI and 25% FI and resulted in higher negative deviation values of − 7.9 and − 19.3% respectively.

This value shows that model accuracy decreases in the situation of severely stressed water environments. However, there was a low deviation for full irrigation treatment. Moreover, a high value of grain yield (7.4 t/ha) was found from FI and 7.2 t/ha from 75% FI. Whereas the minimum yield of maize (4.2 t/ha) was obtained from 25%FI which is exposed to the deficit for the whole growing season except during the initial stage. Generally, full irrigation cannot significantly improve the grain yield when compared to 75% deficit irrigation treatment. In the Araya et al. (2010) study, the above-ground biomass and grain yield NSE values during simulations were observed to vary from 0.53 to 1 and 0.5 to 0.95, respectively for barley crops. The RMSE values ranged from 0.36 to 0.9 t/ha and 0.07 to 0.27 t/ha for biomass and yield. In line with Gebreselassie (2015), the maize crop (BH-140) in this study area has shown a positive response to a mild water stress environment (Fig. 6).

Table 14 Observed and simulated final yield

Treatment	Measured yield (t/ha)	Simulated (t/ha)	Deviation (%)
FI	7.4	7.8	5.13
75% FI	7.2	7.5	6.9
50% FI	6.3	5.8	− 7.9
25% FI	4.6	3.4	− 19.3

Crop evapotranspiration and water use efficiency

For optimum irrigation application, the determination of water use efficiency is one of the most necessary steps. The AquaCrop model was assessed for its capability to simulate seasonal crop evapotranspiration and similarly the WUE under different irrigation scenarios. The simulated and the measured seasonal evapotranspiration values using the Penman–Monteith method for experiment 2 are presented in Table 15.

Like the observations of Greaves and Wang (2016), AquaCrop steadily underestimates the seasonal ET values of maize and the disparity is bigger as the soil water deficit becomes severe. The deviations ranged from 11.2 to 15.8% for the different treatments. Due to some mismatch between simulated and observed ETc values, the deviation between actual and simulated WUE of grain yield was large for most treatments. The result indicated no consensus of the deviations in WUE values being a function of the level of plant

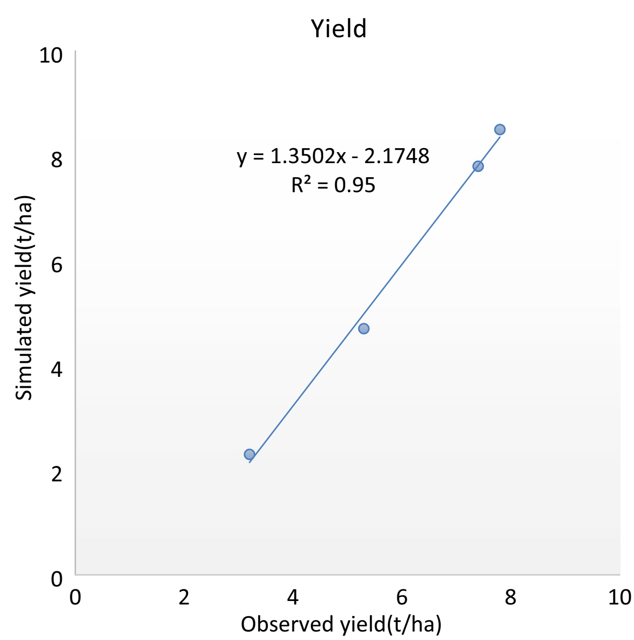

Fig. 6 Relationship between observed and simulated yield from the experiment

Table 15 The observed and simulated value of ET_c and WUE

Seasonal ETc WUE						
Treatment	Measured (m^3)	Simulated (m^3)	Deviation %	Measured (kg/m^3)	Simulated (kg/m^3)	Deviation%
FI	6619	5950	− 11.24	1.12	1.22	8.9
75% FI	5082.8	4550	− 11.71	1.53	1.61	5.1
50% FI	3546.5	3120	− 13.66	1.45	1.59	9.6
25% FI	2200	1900	− 15.78	1.47	1.69	14.9

water stress. However, measured WUE was seemingly better in the 75% FI, indicating a potential for water-saving given yields for this treatment were comparable to those obtained in the FI Mehraban (2013) gets the same result for wheat and in severe stresses, the model shows WUE lower than measured amounts, and in optimum irrigation treatments, WUE is a few higher than measured amounts.

Discussions

The FAO AquaCrop model's important feature is the use of conservative parameters which are nearly constant and do not vary with time and management practices, and are used for different environmental conditions and climate situations as stated in Steduto et al. (2009). Based on Heng et al. 2009, in this study proposed conservative parameters for maize were tested using an iterative process. Although there was a mismatch in model prediction and observed values for crop growth parameters in severely stressed treatment (25% FI), as unaffected values in Table 7 demonstrate, the parameters worked fine to simulate crop growth. The objective of the calibration process was to test for values that can work satisfactorily under all treatments and values were sustained for use in predicting crop growth and water productivity as they were good in non-stressed and moderately stressed conditions. This was confirmed by statistical indicators of NSE, RMSE and d observed during the calibration (Tables 9 and 11). The validation process revealed the water stress level affects the performance of the AquaCrop model. In the validation, both the CC and biomass were underestimated by the model except for the severely stressed condition (25% FI), where the values were underestimated. From Fig. 4, contrasting to other deficit treatments, for the more severely stressed condition of 25% FI the model underestimated the biomass through the entire growing season, which shows the model was not able to capture the temporary break from moisture stress by irrigation water application. Additionally, there was a high deviation noticed between observed and simulated values under stressed water deficit treatment. This condition for maize and barley crop also was reported by Greaves and Wang (2016) and Araya et al. (2010), respectively. Similarly, Heng et al. (2009), noticed that inclination of the AquaCrop simulation model to overestimate maize biomass under stressed conditions can be related to the actual stomatal conductance being less than the simulated one. In the validation work using experiment 2 the simulated grain yields were reduced by 4.3% for 75% FI, 33% for 50% FI, and 54% for 25% FI regarding the yield simulated at full irrigation treatment. However, the measured yield reduction was 2.7%, 17.5%, and 59.8% for 75% FI, 50% FI, and 25% FI, respectively from the FI. Higher grain yield was observed for maize sown in January at experiment 1. This was attributed to the rainfall impact on the experiment since it was spring season in Ethiopia at which some rainfall in the region is pronounced. And also, during this growing period, the higher growing degree days would have an impact on canopy cover and biomass accumulation as revealed by Farahani et al. (2009) which contributes to yield increment. So that the planting date during the two experiments would have valuable effects.

The seasonal ETc and WUE simulation capability of the model was also tested for different irrigation treatments. Like the finding of Greaves and Wang (2016), Table 15 depicted AquaCrop thoroughly underestimating the seasonal ET and the deviations commonly bigger as stress levels increased. The reduction range was 11.2–15.8% between simulated ETc compared to observed values which are higher than the values reported by Heng et al. (2009) during the validation of the model for maize, but less than the range of 6.5–22% for maize grown in varying levels of irrigation deficit observed by Greaves and Wang (2016). The soil spatial variability would contribute to the divergence between observed and simulated values. The model assumption of uniform distribution of water during simulations will certainly lead to significant differences in the results of soil moisture content. Although the simulated WUE values are similar to Heng et al. (2009) study, the significant mismatch between simulated and observed ETc values leads to a higher deviation between actual and simulated WUE (Table 15). Katerji et al. (2013), cited in Greaves and Wang, 2016) stress that AquaCrop's performance is unsatisfactory in cases of severe moisture stress specifically for predicting WUE. If the model is correctly calibrated, it can be reliable to make predictions of agronomic variables.

Conclusions

The AquaCrop model was calibrated and validated for its ability to simulate green canopy cover, biomass, grain yield, crop evapotranspiration (ETc), and water use efficiency (WUE) for full and deficit-irrigated maize in central Gondar, Ethiopia. Statistical values of root mean square error, Nash Suite Clif efficiency, and index of agreement showed that AquaCrop was able to simulate CC and biomass with a high degree of accuracy; however, model performance becomes lessened as crops experience more water deficit. During CC calibration, for the FI and 75% FI, high NSE values of 0.93 and 0.91 were obtained, while the moderate NSE values of 0.85 and 0.63 for deficit treatment 50% FI and 25% FI were obtained, respectively. During validation of above-ground biomass, a higher deviation for 25% FI has been attributed to the crop experiencing more water stress in this treatment. Even though there was no significant difference with 75% FI, a high yield was found from FI which is 7.4 t/ha. However measured WUE was better in the 75% FI, indicating a potential for water-saving given yields for this treatment than obtained in the FI. The simplicity of AquaCrop input data, which are readily available, has made it user-friendly (Heng et al. 2009). The model can help for office task assessment of the impact of different irrigation scheduling methods. Using the validated model, the possible impact of a developed irrigation scheduling on the crop and its environment can be analyzed without going to the field. These results suggest that FAO AquaCrop can be used in the prediction of irrigated outputs, and hence, has greater potential to guide irrigation management practices toward increasing food production. However, there is a need to test the model with rain-fed agriculture and fertilizer management practices to explore its performance under such conditions. From the result of the experiment continuously applying only 25% of crop irrigation water, requirement leads to yield reduction. Similarly, 50% of water applications cause yield reduction. This shows that the water deficit for a long time below 50% makes a significant yield reduction. Gebresellassie et al. (2015) have got the same result. AquaCrop can be recommended for applications under different agro-climatic conditions in the central part of Ethiopia. To evaluate the water use efficiency of irrigated agriculture only, it is advisable to have a rain shade at the experiment field to reduce the addition of rainfall.

Author contributions DGE collects data and undertakes write-up activities. BGS is engaging in model running and editing manuscripts. HDG contributes to data collection and proposal development. BAZ participates in purchasing equipment and facilitating field works.

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Availability of data and materials Data and materials will be available upon request.

Declarations

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

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