



Article Calibration and Evaluation of the FAO AquaCrop Model for Canola (*Brassica napus*) under Varied Moistube Irrigation Regimes

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Abstract: The AquaCrop model was calibrated and validated for canola (*Brassica napus*) under Moistube irrigation (MTI) and various water regimes [(i) 100%, (ii) 75%, and (iii) 55% of crop water requirement (ET_c)] over two seasons, 2019 and 2020. The normalised root mean square (nRMSE), Model Efficiency (EF), R^2 , and the Willmot's index of agreement (d) statistics were used to evaluate the model's efficiency in simulating biomass (B), canopy cover (CC), yield (Y), and harvest index (HI). The calibration results indicated the model simulated with accuracy the CC (under 100% $ET_c R^2 = 0.99$, EF = 0.92, nRMSE = 6.4%, d = 0.98) and 75% $ET_c (R^2 = 0.99, EF = 0.92, nRMSE = 10.3\%, d = 0.98$). The model simulated CC well for validation for 100% $ET_c (R^2 = 0.97, EF = 0.93, nRMSE = 22.5\%,$ d = 0.98) and 75% $ET_c (R^2 = 0.84, EF = 0.45, nRMSE = 59.2\%, d = 0.86$) irrigation regimes. Final biomass simulations were reasonably good under 100% ET_c , 75% ET_c , and 55% ET_c irrigation regimes ($R^2 > 0.90$, d > 0.65). The study showed the usefulness of AquaCrop for assessing yield response of canola to full and deficit irrigation scenarios under MTI.

Keywords: biomass; crop modelling; water productivity; water regimes; yield

1. Introduction

The global agricultural water consumption utilises 70% of the world's freshwater. Water is a finite resource, and climate variability and change have exacerbated the natural resource's depletion. Burgeoning populations have also increased per capita water use, thus compounding the global freshwater water scarcity situation [1]. Modern agricultural practices in sub-Saharan Africa (SSA) are a dualistic exercise that meets the poor's food security needs and is also a primary economic driver [2]. As such, using advanced irrigation techniques will maximise water productivity (WP), and subsequently, increase yields. Climate variability and change threaten food security, and industrial crops are not spared. An increase in global temperatures will lead to high carbon concentrations and warmer temperature; this consequently impacts cool climate C3 (canola, flax, wheat, and soybean) industrial crops [3]. Expanding irrigation land under current irrigation technologies and strategies can accelerate water scarcity, i.e., an increase in demand will lead to water scarcity under the present climate change variability scenarios [4,5]. Henceforth, adopting efficient irrigation techniques and strategies can ameliorate the accelerated demand on the finite water resource [6].

Canola is a C3 crop of economic importance. The crop produces oilseed that is processed into oil products for human consumption [7], and it is also used for forage production and phytoremediation [8]. Canola is considered a "healthy" trade oil. It contains no cholesterol, thus reducing the risk of cardiovascular diseases [9]. This has subsequently increased



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). its demand, leading to expanded irrigated canola hectarage worldwide. Efficient irrigation technology is required for improved yield, water productivity (*WP*), and water use efficiency (WUE). Several researchers have investigated canola production under various drip irrigation technologies and deficit irrigation strategies. For example, Katuwal et al. [10] investigated and assessed the soil water extraction pattern and water use efficiency of spring canola under drip irrigation. Their study [10] revealed that deficit irrigated canola at the vegetative stage extracted the same amount of water as the fully irrigated canola. Safi et al. [11] investigated the effects of deficit irrigation (DI) on transplanted and directly sown spring canola and revealed that directly sown cultivars had low grain yield.

Hergert et al. [12] performed full and deficit drip irrigation trials on spring canola and revealed that deficit irrigation accelerated crop maturity. The study also showed a high WUE of 7.6 kg·ha⁻¹·mm⁻¹, thus proving that deficit irrigation is attractive for canola growth. Another study by Bañuelos et al. [8] investigated the vegetative production of canola under drip irrigation in central California, and the study argued that optimal yields were obtained by irrigating at 125% *ET_c*. Interestingly, the study by Bañuelos et al. [8] contradicted finding by Safi et al. [11] and Hergert et al. [12] despite employing nearsimilar DI strategies. Taylor et al. [13] also used drip irrigation to assess the effects of irrigation and nitrogen fertiliser on yield, oil content, nitrogen accumulation, and canola crop efficiency. The study revealed that the WUE for grain production and biomass were 7.5 and 23 kg·ha⁻¹·mm⁻¹, respectively. Other studies also performed different investigations on canola under different irrigation technologies and irrigation management processes [11,12,14–17].

Moistube irrigation (MTI) is a relatively new subsurface semi-permeable membrane irrigation technology [18]. Discharge is facilitated by a response to soil water potential and system pressure [18,19]. The matric potential effect can only be utilised for 44 h; thereafter, external pressure is required to drive the system [19,20]. MTI is a subsurface irrigation technology; hence, it minimises non-beneficial water such as deep percolation, run-off, and soil evaporation [19,21] and it has a reported high water use efficiency (WUE) compared to other technologies such as sprinkler and drip irrigation [19].

MTI has been used in China's arid regions and for legume production in some parts of SSA [22]. Kanda et al. [22] applied deficit irrigation techniques under MTI for cowpea production and the resultant WUE for grain production at 100% ET_c and 70% ET_c irrigation were 0.92 and 0.95 kg·m⁻³, respectively. The study by Kanda et al. [22] was a comparative study between MTI and subsurface drip irrigation (SDI), and MTI exhibited a high WUE (100% $ET_c = 0.95$ kg·m⁻³) as compared to SDI (100% $ET_c = 0.82$ kg·m⁻³). MTI presents an opportunity for canola production under various irrigation regimes. Despite the extensive research on irrigated canola, there is a gap in canola production under MTI. MTI can potentially offer realistic matric potential informed irrigation schedules for maximised irrigation water use.

Crop modelling is a cost-effective method for quantifying crop yields and crop WP [23]. Crop modelling tools are either carbon-driven, radiation use efficiency (RUE), or water-driven models [24]. Various studies have applied crop modelling techniques to canola production. For example, He et al. [25] used Agricultural Production Systems Simulator (APSIM), a radiation driven model to simulate canola phenology. The study revealed that APSIM accurately simulated canola phenology under different growing environments. However, the study also revealed that APSIM required extensive data for accurate canola phenology simulation during the vernalisation sensitivity; photoperiod sensitivity phases which subsequently influence grain yield formation. Robertson and Kirkegaard [26] used APSIM to simulate rainfed canola grain yields accurately. Qian et al. [27] carried out a comparative study to assess two C3 crops' simulation performance: canola and wheat under rained conditions. CROPGRO was used to simulate canola yields, whilst Crop Environment Resources Synthesis (CERES) was used to simulate wheat yields. The study results showed that both models successfully simulated yields with the $R^2 > 0.90$ and nRMSE range of 5–18.2%.

AquaCrop is a water-driven model that simulates yield, biomass production, and beneficial water use [28–30]. Water-driven models are an attractive option compared to their counterparts because of the ease of use. They facilitate easy normalisation of WP parameter under different climatic conditions (evaporative demand and atmospheric carbon dioxide). AquaCrop use has been applied to different crops such as cowpea [31], groundnuts [32], wheat [33–37], maize [38–40], and much recently on leafy vegetables [41]. Zeleke et al. [42] used AquaCrop to simulate canola yields under rainfed and irrigated conditions. The percentage relative difference (%D) between the observed and simulated yield was 2.2%. This signified AquaCrop's capability in simulating canola grain yield. This study investigated the capability of MTI for canola production under full and deficit irrigation scenarios. Identifying optimal DI strategies can potentially save water without imposing yield penalties on the canola grower. To extend the study's applicability beyond location-specific results, the experiment adopted AquaCrop modelling software [28]. The model has been used in numerous studies [31–34,37,38,40,41,43–47] to assess yield response to water stress; however, there is a need to calibrate and test the AquaCrop model for industrial crops such as canola under MTI. As mentioned prior, there is a gap in how canola performs under MTI water stress conditions. The study was premised on the hypothesis that AquaCrop cannot effectively simulate canola crop performance under varying MTI water regimes. The specific objectives for this study were to (i) calibrate AquaCrop for canola under MTI water stress conditions and (ii) evaluate its ability to simulate CC, biomass, yield, and evapotranspiration (ET) under local South African conditions.

2. Materials and Methods

2.1. Model Description

AquaCrop is a water-driven modelling software used to simulate plant growth processes such as canopy cover (*CC*), biomass accumulation, and yield [28]. The model simulates yield response to water, i.e., water productivity [41]. Water productivity (*WP**) is one of the crucial variables together with simulated transpiration (T_r), and reference evapotranspiration (*ET*₀) required to compute daily biomass (B) production (Equation (1)) [42]. For this study, canola biomass referred only to the above-ground component. AquaCrop's calculation scheme includes simulating the water stored in the root zone. The water stress coefficient is instrumental in determining the harvest index (*HI*). Once *B* is determined, the crop yield (*Y*) is then computed as per Equation (2):

$$WP^* = \frac{B}{\sum (Tr/ET_o)} \tag{1}$$

$$= B \times HI \tag{2}$$

where WP^* = water productivity (g·m⁻³), B = biomass (g·m⁻²), T_r = transpiration (mm), ET_o = reference evapotranspiration (mm), HI = harvest index, and Y = yield (kg·ha⁻¹).

Υ

AquaCrop simulates water use as a function of four stress factors, namely (1) canopy expansion, (2) stomatal closure, (3) early canopy senescence, and (4) aeration stress [41,46,48]. The model is relatively easy to use, as it requires few explicit parameters and largely intuitive input variables [29]. AquaCrop is underpinned by two sets of parameters: conservative parameters and non-conservative parameters. The former does not change with time management and are applicable on a large spatial variation scale, whereas the latter change with time, management, and location [41,49].

2.2. Experimental Design

Study Site and Description of the Field Experiment

The experiment was conducted at the Ukulinga farm at the University of KwaZulu-Natal in Pietermaritzburg, South Africa (29°39′44.8′′ S 30°24′18.2′′ E, altitude: 636 m). The experiment was run over two growing seasons, 2019 (July–September) and 2020 (September–November), in a tunnel, which was not temperature-controlled but was designed to exclude rainfall. The 2019 growing season was used to calibrate the AquaCrop model, and the 2020 season was used for model validation. The experiment was a split-plot design that consisted of three MTI regimes, namely 100%, 75% ET_c , and 55% crop water requirement (ET_c), under tunnel conditions measuring 30 m by 10 m. The ET_c was computed according to Equation (3):

$$ET_c = K_c \times ET_o \tag{3}$$

where $ET_c = \text{crop water requirement (mm \cdot day}^{-1})$, $K_c = \text{crop coefficient, and } ET_o = \text{evapo-transpiration (mm \cdot day}^{-1})$.

Each MTI regime comprised of four experimental plots measuring 2 m by 1 m. The MTI AquaCrop deficit irrigation schedules followed the procedure by Geerts et al. [50]. The varied irrigation scheduling is summarised in Table 1.

Irrigation Regime	100% ET _c			75% ET _c			55% ET _c		
	M 1	M 2	M 3	M 1	M 2	M 3	M 1	M 2	M 3
IF (days)	4.5	2.5	2.8	6.0	3.3	3.7	8.2	4.5	5.0
AT (h)	1.3	2.4	2.1	1.0	1.8	1.6	0.7	1.3	1.2

Table 1. Irrigation frequencies and application times.

M = Month, IF = Irrigation frequency, and AT = Application times.

The experiment was done under a tunnel to facilitate better control of water fluxes and exclude of rainfall. A 1-m buffer hydrologically separated each experimental plot; a 250-micron plastic sheeting was vertically inserted to a depth of 1 m in each buffer space. PR2/6 profile probe access tubes were installed in each plot for soil water measurement at depths of 10, 20, 30, 40, 60, and 100 cm. Soil water content (SWC) measurements were done weekly using a PR2/6 profile probe connected to an HH2 handheld moisture meter (Delta-T, Cambridge, UK). Kanda et al. [31] performed weekly SWC measurements for cowpea production under MTI and showed that there was minimal temporal and spatial SWC variability. The canola was nursed at the University of KwaZulu-Natal—Pietermaritzburg (UKZN—PMB) (29°37'34.0″ S 30°24'11.9″ E) Controlled Environment Facilities (CEF) for two months before transplanting to the Ukulinga farm. Soil water measurements commenced two weeks before transplanting. Each plot accommodated 18 plants resulting in 9 plants·m⁻². Heng et al. [40] adopted plant densities of 6–8 plants·m⁻² to prevent canola lodging.

2.3. Model Parameters and Input Data

The following data were collected during the July 2019–October 2019 and the October 2020–December 2020 growing season.

2.3.1. Weather Data

HOBO temperature and relative humidity (RH) sensors (Onset Computer Corporation, USA) were installed in the greenhouse for additional data collection (Figures 1 and 2 and Table 2). The ET_o for the local conditions (within), the greenhouse were calculated using the evapotranspiration (ET_o) calculator [51]. Some variables required for calculating ET_o were obtained from the automatic weather station (AWS) situated 100 m away from the greenhouse. The AWS uses the CS-500 Vaisala probe (Campbell Scientific, Logan, UT, USA) to measure temperature and relative humidity (converted into vapour pressure deficit), L1-200 pyranometer (Campbell Scientific, Logan, UT, USA) to measure solar radiation, and the Penman-Monteith equation to calculate reference evapotranspiration. The signal was transmitted wirelessly, and downloadable files are available from the South African Sugarcane Research Institute (SASRI) weather data portal.



Figure 1. Average maximum and minimum temperatures recorded in the greenhouse during the 2019 growing season.



Figure 2. Average maximum and minimum temperatures recorded in the greenhouse during the 2020 growing season.

Month	T _{max}	(°C)	T _{min}	(°C)	Solar Radiat	ion (MJ·m ^{−2})	ET _o (m	m·d ^{−1})
	S 1	S 2	S 1	S 2	S 1	S 2	S 1	S 2
1	33.0	44.3	9.2	13.5	20.12	37.15	7.4	9.6
2	36.0	48.1	10.0	12.7	24.66	41.69	8.0	9.7
3	39.6	49.0	9.2	12.6	30.96	43.70	8.7	9.7

Table 2. Summarised meteorological conditions for the respective growing seasons (S_i).

The weather data were used to create the climate file (.CLI) in AquaCrop consisting of ET_o (.ETO) and daily minimum and maximum temperature (.TMP). Solar radiation data were input into the ET_o calculator [51] for computing ET_o . There was no daily rainfall file (.PLU).

2.3.2. Canopy Cover (CC)

The leaf area index (LAI) was measured every two weeks using the LAI 2200 Canopy Analyser (Li-Cor, Lincoln, NE, USA). Since AquaCrop uses canopy cover (CC), Equation (4) was used to convert LAI to CC. Mabhaudhi et al. [46] argued that diffuse non-interceptance (DIFN) (Equation (5)), which is an output of the LAI 2200, can be used to compute CC. The DIFN utilises gap fractions to estimate the sections not "fully" obscured by the growing canopy [46,52]. The DIFN value ranges from 0 (no sky visible to the sensor) to 1 (no canopy obscuring the sun):

$$CC = 1 - DIFN$$
 (4)

$$DIFN = 2 \int_0^{\frac{\pi}{2}} \overline{cgf}(\theta) \sin\theta \cos\theta d\theta$$
(5)

where cgf = canopy gap fraction at zenith angle θ (averaged over azimuth angle and horizontal area) [52]. Since the seedlings were transplanted, the initial canopy cover (CC_o) was calculated by Equation (6). The computed CC_o was 4.5%:

$$CC_o = [\text{plant density (plants \cdot m^{-2})} \times \text{size of CC/seedling } (m^2 \cdot \text{plant}^{-1})] \times 100$$
 (6)

2.3.3. Soil Data

Soil samples were subjected to soil textural analyses using the hydrometer method. The experiment sampled five depths for textural analysis, and the resultant textural data were fed into the SPAW model (Saxton and Willey, 2005) to determine the saturated hydraulic conductivity (K_s) and the bulk density (BD) (Table 3). Other soil hydraulic parameters total porosity (θ_s) and residual soil water content (θ_r) were laboratory determined using the soil-water retention pressure method [53–55]. The soil data were used to create the soil file in AquaCrop (.SOL).

Depth (cm)	$ heta_s$ (cm ³ ·cm ⁻³)	$ heta_r$ (cm ³ ·cm ⁻³)	k_s (cm·d ⁻¹)	BD (g·cm ^{−3})
10	0.52	0.33	5.1	1.28
20	0.52	0.28	9.7	1.27
30	0.55	0.33	13.7	1.19
40	0.60	0.27	38.1	1.07
50	0.56	0.32	18.6	1.16

Table 3. Soil textural and soil hydraulic parameters.

Notes: θ_r = residual soil water content (SWC), θ_s = total porosity, k_s = saturated hydraulic conductivity, and BD = Bulk density.

2.4. Field and Water Management Practices

The experiment was done under greenhouse conditions; hence, no rainfed systems were considered. The canola was subjected to optimal and deficit irrigation (DI) regimes. The optimal conditions consisted of irrigating at 100% of the crop water requirements (100% ET_c), whereas the DI irrigation regimes consisted of 75% ET_c and 55% ET_c . The irrigation intervals were used to create the irrigation file (.IRR). The SWC data were one of the parameters used to create the observation file (.OBS). The .OBS file was used for calibration and validation, respectively. The experiment assumed zero fertility stress. Other field management practices considered were (i) no weeds, (ii) no mulch, and (iii) zero runoff.

2.4.1. Biomass (B)

The above-ground biomass (AGB) $(g \cdot m^{-2})$ was harvested three times during each growing season. To avoid border effects, the samples were collected from the middle row. The freshly collected leaves and stems were weighed and then oven-dried at 85 °C for four days until there was consistent mass. One of each irrigation regime's plot was dedicated to destructive sampling. The harvest index (HI) was calculated as per Equation (7):

$$I = Y/B \tag{7}$$

where HI = Harvest index (no units), Y = yield (g·m⁻²), and B = above ground biomass (g·m⁻²).

H.

Other crop parameters recorded were transplanting date, amount of irrigation water, agronomic practices, time to flowering, time to yield formation, time to senescence, and harvesting dates.

2.4.2. Actual Evapotranspiration (ET_a)

The water budget method (Equation (8)) [31,56] was used to compute actual evapotranspiration for canola over the growing seasons:

$$ET_a = P_r + I + C - D_r - SR \pm \Delta S \tag{8}$$

where ET_a = actual evapotranspiration (mm), P_r = rainfall/precipitation (mm), I = irrigation (mm), C = capillary rise (mm), SR = surface runoff (mm), D_r = drainage (mm), and ΔS = change in soil water storage (mm).

The experiments were carried out in a greenhouse; hence, rainfall was zero. MTI is a subsurface irrigation method; therefore, surface runoff assumed a zero value. The impermeable layer at Ukulinga farm lies at a depth of 60 cm; thus, it prevented drainage and capillary rise [31]. ET_a was converted from mm to m³·ha⁻¹ by multiplying Equation (8) by (10) [51].

2.4.3. Water Productivity (WP_{ET})

Water productivity (WP_{ET}) was computed by Equation (9) [33]:

$$WP_{ET} = \frac{Y}{ET_a} \tag{9}$$

where WP_{ET} = water productivity (kg·m⁻³).

2.5. Model Calibration

The calibration involved fine-tuning the non-conservative parameters for the canola crop. Table 4 presents summarised conservative and non-conservative values derived from the experiment. The parameters were adopted by Zeleke et al. [42] for calibrating and testing the FAO AquaCrop model for canola in Wagga Wagga, Australia. The study adopted the canola crop files calibrated by researchers from Lethbridge University Alberta, Canada [57]. The crop file was calibrated for warmer and drier climates in Swift Current, Saskatchewan, Canada.

The study destructively measured the seedling leaf area (4.50 cm²) of the canola shoots at 90% emergence. Other input parameters were minimum rooting depth at 90% emergence (5 cm) and maximum rooting depth at harvesting. The average maximum rooting depths were 15.69 cm, 16.24 cm, and 20.41 cm for the 100% ET_c , 75% ET_c , and 55% ET_c irrigation regimes, respectively. The reference harvest index (HI_o) was computed using Equation (2). Fine-tuning the HI_o resulted in adopting a value of 25% for good simulations.

The calibration involved adjusting the non-conservative parameters HI_o , initial canopy cover (CC_o), and canopy growth coefficient (CGC) until the simulated CC, B, and Y closely matched the observed data. The time to flowering was measured from the day of transplanting, and it was defined as the time when 50% of the plants had visible yellow flowering. Length of the flowering stage was the date after 50% flowering to the date when 50% of the plants had formed pods [31,58]. The maximum rooting depth was measured from the fully matured harvestable plants.

Parameter		Value		
Conservative				
Base temperature (°C)	Obtained from Zeleke et al. [42]		0	
Upper temperature (°C)	Obtained from Zeleke et al. [42]		30	
Canopy growth coefficient CGC ($\%$.day ⁻¹)	Derived from the model using time to reach CC_x and value of CC_x		8.9	
Canopy decline coefficient CDC ($\%$.day ⁻¹)	Derived from the model using time to reach senescence		5.2	
Canopy expansion	Derived from the model using time to reach CCx and value of CC_x		Very fast	
Soil water depletion factor for canopy expansion, upper limit	P _{upper}		0.10	
Soil water depletion factor for canopy expansion, lower limit	P _{lower}		0.45	
Shape factor for Water stress coefficient for canopy expansion	Obtained from Zeleke et al. [42]		3.5	
Soil water depletion factor for stomatal closure	P _{upper}		0.45	
Shape factor for Water stress coefficient for stomatal closure	Derived from the model		2.5	
Soil water depletion factor for early canopy senescence	P _{upper}		0.70	
Shape factor for water stress coefficient for canopy senescence	Derived from the model		5	
Normalised water productivity WP* $(g \cdot m^{-2})$	Calibrated from the regression of biomass accumulation and $\Sigma Tr/ET_o$		15.0	
Adjustment for yield formation (%)	Obtained from Zeleke et al. [42]		100	
Basal crop coefficient (maximum) ($K_{cb}(x)$)	Obtained from Zeleke et al. [42]		0.95	
Non-conservative		100% ET _c	75% ET _c	55% ET _c
Plant density (plants·m ⁻²)	Using intra- and inter-row spacing	9	9	9
Initial canopy cover CC_0 (%)	Derived from the model using initial seedling leaf area and plant density	1.25	1.25	1.25
Maximum canopy cover CC_x (%)	Consistent maximum cover read from observed canopy cover curve	93.1	91.1	74.4
Time to maximum canopy cover (d)	Time to reach peak canopy cover converted from LAI data using Equation (3)	72	72	72
Time to flowering (d)	Time taken to when 50% of the plants had formed flowers	32	38	44
Length of the flowering stage (d)	Date after 50% flowering to when 50% of the plants had formed pods	17	19	15
Time to senescence (d)	Time to when no new leaves are formed, and at least 10% of plants turned yellow	90	90	51
Maximum rooting depth (m)	Destructive measurement of a full-grown plant at harvesting	1.57	1.62	2.04
Minimum effective rooting depth (m)	Destructive measurement of the seedling root depth at 90% emergence	0.05	0.05	0.05
Reference harvest index HI_o (%)	Determined initially from optimum irrigation conditions and calibrated until simulated yield closely matched the observed yield	25	25	25

Table 4. Conservative and non-conservative parameters for canola.

2.6. Model Validation and Evaluation Statistics

The model was validated using an independent dataset from the 2020 growing season. The data consisted of optimum irrigation (100% ET_c) and two DI regimes of 75% ET_c and 55% ET_c . It was validated, similar to the calibration, for SWC, CC, final B, Y, and WP_{ET} .

Statistical analyses were employed to assess the model's ability to simulate canola crop growth and yield under MTI. The study applied the following criteria; normalised root mean square error (*nRMSE*), Wilmott's index of agreement (*d*), Model efficiency (*EF*), and the R^2 to assess the model's performance. The selected criteria are defined by Equations (10)–(13) [54,59]:

$$nRMSE = \frac{\sqrt{\left(\frac{1}{m}\sum_{i=1}^{m}(O_{i} - P_{i})^{2}\right)}}{O_{mean}}$$
(10)

$$d = 1 - \left[\frac{\sum_{i=1}^{m} (P_i - O_i)^2}{\sum_{i=1}^{m} (|(P_i - O_{mean})| + |(O_i - O_{mean})|)^2}\right]$$
(11)

$$EF = 1 - \left[\frac{\sum_{i=1}^{m} (O_i - P_i)^2}{\sum_{i=1}^{m} (O_i - O_{mean})^2}\right]$$
(12)

$$R^{2} = \left[\frac{\sum_{i=1}^{m}(O_{i}P_{i}) - \sum_{i=1}^{m}(O_{i})\sum_{i=1}^{m}(P_{i})}{\sqrt{\left[\left[\sum_{i=1}^{m}O_{i}^{2} - \sum_{i=1}^{m}(O_{i})^{2}\right]\left[\sum_{i=1}^{m}O_{i}^{2} - \right]\sum_{i=1}^{m}(O_{i})^{2}\right]}\right]^{2}$$
(13)

where O_i and P_i = observed and predicted value(s), respectively, O_i = mean observed data, and m = number of observations. The error index *nRMSE* showed the model's performance but did not clearly indicate the degree of over or under-estimation, hence using the *EF* statistical tool in the analysis. The *EF* statistic measured the residual variance vs. the measured data variance, and it ranges from $-\infty$ to 1. *EF* values between 0.0 and 1.0 are considered acceptable (Table 5); however, Yang et al. [60] asserted that there exists a positive and scattered correlation between *EF* and *d*. Thus, when estimating soil water content, a satisfactory agreement can be considered when *EF* is greater than or equal to -1 and when *d* is greater than or equal to 0.60. R^2 represents the goodness of fit between the observed and simulated values [31]. For R^2 , a range of 0.5–1.0 represents good collinearity between observed and simulated values [61].

Table 5. General performance rating for model evaluation statistics [61].

Performance Rating	d	EF
Very good	0.8 < d < 1.0	0.75 < EF < 1.00
Good	0.6 < d < 0.8	0.65 < EF < 0.75
Satisfactory	0.3 < d < 0.6	0.50 < EF < 0.65
Unsatisfactory	d < 0.2	$EF \leq 0.50$

Above ground biomass, yield, and *ET* differences were computed as percentage relative differences (%*D*) using Equation (14). Relative differences of $\pm 10\%$ were considered accurate, whilst differences of $\pm 20\%$ were deemed acceptable [29,32,45]:

$$\%D = [(P_i - O_i)/O_i] \times 100 \tag{14}$$

3. Results and Discussion

3.1. The Effects of Water Regimes on Growth, Yield, and Water Productivity of Canola

The leaf area index, represented by CC_x , was significantly high for the 100% ET_c treatment (Figure 3). CC_x under 100% ET_c was reached after approximately nine weeks after transplanting. Pavlista et al. [17] reached CC_x after 10 weeks of planting under optimal irrigation conditions. The 75% ET_c treatment recorded a 91% CC_x and 85.7% CC_x

for season 1 (S1) and season 2 (S2), respectively. The 55% ET_c treatment recorded a low 74% CC_x during S1 and CC_x of 86% for S2. The 55% ET_c S2 observation contradicted the norm since severe deficit irrigation is reported to yield a reduced canopy cover. The CC_x was reached at week eight and week seven after transplanting under 75% ET_c and 55% ET_c , respectively. Deficit irrigation allows early crop maturity and small canopy cover as a form of drought avoidance mechanism. Small canopy development occurs to minimise water losses through transpiration [31,62].



Figure 3. Variation in canopy cover for the 100% ET_c , 75% ET_c , and 55% ET_c irrigation regimes over two seasons (S_i).

Soil water content (SWC) varied across the irrigation regimes (Table 6). Soil water content between the 100% ET_c and 75% ET_c did not differ significantly (p > 0.05). There was no significant difference between the 75% ET_c and the 55% ET_c irrigation regime.

Table 6. Effects of irrigation regime on the soil water content.

Irrigation Regime	Mean Water Content (mm)
100% <i>ET</i> _c	413.6 (37.67) ^a
$75\% ET_c$	416.4 (39.35) ^{ab}
55% ET _c	363.1(62.89) ^c
LSD	55.5
CV (%)	12.3

Mean values in the same column, followed by the same superscript letter, do not significantly differ at 5% significance by LSD using Duncan's Multiple Test Range. Data in parenthesis are the standard deviations.

Under the 100% ET_c irrigation regimes, the recorded yields were 1.32 ton·ha⁻¹, whilst under 75% ET_c and 55% ET_c , the yield was 0.73 ton·ha⁻¹ and 0.56 ton·ha⁻¹, respectively, during S1. The recorded yields during S2 for the 100% ET_c , 75% ET_c , and the 55% ET_c irrigation regimes were 1.48 ton·ha⁻¹, 1.15 ton·ha⁻¹, and 0.75 ton·ha⁻¹, respectively (Table 7).

The recorded yields under $100\% ET_c$ were approximately consistent with Zeleke et al. [42], who obtained canola yields of about $1.75 \text{ ton} \cdot \text{ha}^{-1}$ using the Bln3343-Co0401 cultivar. Additionally, Zeleke et al. [63] recorded canola grain yields of $0.77-1.51 \text{ ton} \cdot \text{ha}^{-1}$ under stressed irrigation and final biomasses in the range of $4-10.47 \text{ ton} \cdot \text{ha}^{-1}$ for irrigated and stressed canola in Wagga Wagga, Australia. Pavlista et al. [17] recorded canola grain yields of $1.68 \text{ ton} \cdot \text{ha}^{-1}$ under fully irrigated canola in Nebraska, whilst Safi et al. [11] recorded a canola grain yield of $1.27 \text{ ton} \cdot \text{ha}^{-1}$. Majnooni-Heris et al. [16] also reported a canola yield range of $1.12-1.78 \text{ ton} \cdot \text{ha}^{-1}$ under full irrigation. Deficit irrigation imposed yield penalties

because limited irrigation water supply inhibits canopy growth. Small canopy size results in low biomass, which consequently affects pod formation and grain yield. Biomass accumulation was also influenced by deficit irrigation. Extreme deficit irrigation strategies are not suitable for canola crop growth and yield development. It is worth mentioning that the yields attained were under tunnel conditions and the referenced literature performed the experiments under field conditions. Thus, this study reveals that there is no significant effect in growing canola under tunnel conditions compared to field conditions under full and optimal irrigation.

Irrigation Regime	Seaso	n 1	Season 2		
	Yield (ton ha^{-1})	Biomass (ton∙ha ^{−1})	Yield (ton∙ha ⁻¹)	Biomass (ton∙ha ^{−1})	
100% ET _c	1.32	8.26	1.37	4.70	
75% ET _c	0.73	6.51	1.15	3.21	
55% ET _c	0.56	4.43	0.75	3.23	

Table 7. Summarised observed yields and biomass accumulation over two growing seasons.

3.2. Model Calibration

3.2.1. Soil Water Content

Since AquaCrop is a water-driven model, the model was firstly calibrated for soil water content (SWC). SWC simulations, if done accurately, will improve the accuracy of the simulated biomass and yield [31]. The model satisfactorily simulated the SWC under the 100% ET_c irrigation regime ($R^2 = 0.99$, nRMSE = 16.3%, and d = 0.44); thus, the model was successfully calibrated for SWC (Figure 4d). The EF was significantly low, considering that the model successfully simulated CC under the 100% ET_c regime. The low EF can potentially be attributed to inherent errors experienced during the calibration for CC. Under 100% ET_c, it is evident that the model over-estimated the SWC. This could be potentially attributed to discrepancies in initiating drainage under the continuous irrigation regime. Furthermore, MTI is a slow-release irrigation technology hence the delay in wetting the soil to field capacity. Zeleke et al. [42] attributed the same phenomenon to the lag in AquaCrop to initiate drainage. The model simulated the SWC under the 55% ET_c regime well ($R^2 = 0.98$, EF = 0.93, nRMSE = 4.5%, and d = 0.98) (Figure 4f). Despite having simulated the CC under the 75% ET_c irrigation regimes well, the model yielded average simulation statistics for SWC $(R^2 = 0.30, EF = 0, nRMSE = 15.1\%, and d = 0.53)$. Inherent modelling errors in simulating *CC* can be attributed to the poor \mathbb{R}^2 value under the 75% *ET*_c irrigation regime (Figure 4e).

3.2.2. Canopy Cover

The model successfully simulated the canopy cover for the 100% ET_c treatment ($R^2 = 0.99$, EF = 0.92, nRMSE = 6.4%, and d = 0.98) (Figure 4a). Under the 75% ET_c deficit irrigation regime (Figure 4b) the model performed well ($R^2 = 0.99$, EF = 0.92, nRMSE = 10.3%, and d = 0.98). The finding concurred with Zeleke et al. [42], who observed a nRMSE = 8.4–12.4%, EF = 0.72–0.82, and d = 0.90–0.97 during AquaCrop calibration for canola grown in Wagga Wagga, Australia. However, under the 55% ET_c irrigation regime, the model underestimated the CC; the evaluation statistics were: $R^2 = 0.50$, nRMSE = 66.3%, and d = 0.50). The R^2 and d-index were within the acceptable range; however, the EF was very low, and the nRMSE was significantly high. This resulted from the model capturing poor plant establishment and poor crop development after the transplanting exercise. Zeleke et al. [42] noted a poor CC whenever AquaCrop picked poor crop establishment and development. A careful calibration for C3 crops under extreme water deficit is required to produce a smooth and fitting CC curve. AquaCrop has simulation inaccuracies when predicting CC under water stress conditions [39,42].



Figure 4. Canopy cover (*CC*) for (**a**) 100% *ET*_c, (**b**) 75% *ET*_c, and (**c**) 55% *ET*_c and soil water content (SWC) for (**d**) 100% *ET*_c, (**e**) 75% *ET*_c, and (**f**) 55% *ET*_c irrigation regimes during calibration.

3.2.3. Biomass (B) and Yield (Y)

The model generally simulated the biomass well (Table 7). The model satisfactorily simulated the biomass accumulation for the 100% ET_c and 75% ET_c irrigation regimes ($R^2 > 0.90$, EF > 0.50, and d > 0.89). The *nRMSE* under 100 ET_c was 6.1%, and under 75% ET_c was 37.3%, signifying a high residual variance in estimating the biomass. The model simulated the biomass under the 55% ET_c irrigation regime well ($R^2 = 0.90$, EF = 0.30, *nRMSE* = 26.9%, and d = 0.75) (Figure 5). The *nRMSE* = 26.9% was seemingly high; however, Ahmadi et al. [39] asserted that an *nRMSE* < 30% could be acceptable for crop simulation models. Thus, AquaCrop was successfully calibrated for biomass accumulation. It is worth noting that under the 55% ET_c irrigation regime, the model under-estimated biomass by 25.50% (Figure 5c). This is a common phenomenon with AquaCrop under deficit irrigation scenarios [31]. On the contrary, Zeleke et al. [42] showed that AquaCrop over-estimated the canola biomass because of heat stress. This study, however, was carried out during the winter (cool) season. The model simulated biomass with deviations of -27.48%, -2.30%, and 20.31%. The deviations fell within the acceptable ranges; thus, further asserting that the model was successfully calibrated for biomass under MTI.

The model over-estimated yield simulations despite having simulated *CC* well. Yield simulations were in the over-estimation range of ± 34 –97% and an under-estimation under the 100% *ET_c* water regime, all of which are deemed unacceptable (Table 8). The inability of AquaCrop to simulate yield can be attributed to the low heat units available during the winter season in which the experiment was run. Spring canola cultivar is a cool-season crop that requires a substantial amount of heat units for optimal growth [17]. Hergert et al. [12] also attributed low grain yield for canola to frost.



Figure 5. Observed and simulated biomass (*B*) under (a) 100% *ET*_c, (b) 75% *ET*_c, and (c) 55% *ET*_c irrigation regimes.

	Yield (ton ha^{-1})			Biomass (ton ha ⁻¹)			
Irrigation Regime	Observed	Simulated	D (%)	Observed	Simulated	D (%)	
100% ET _c	1.32 (0.34)	0.87	34.17	8.26 (2.58)	4.01	51.45	
75% ET _c	0.73 (0.12)	1.44	-97.26	6.51 (2.32)	6.46	0.77	
55% ET _c	0.56 (0.12)	0.89	-58.9	4.43 (1.44)	3.35	20.31	

Note: Data in parenthesis are the standard deviations.

3.2.4. Water Productivity (WP_{ET})

The model successfully predicted the grain WP_{ET} under 100% ET_c and 75% ET_c irrigation regimes and, more interestingly, under 55% ET_c , since the yield was low. Under the 100% ET_c , the observed WP_{ET} was 0.42 kg·m⁻³, whilst the simulated WP_{ET} was 0.36 kg·m⁻³ (D = 14.29%). Under the 75% ET_c , the observed and simulated WP_{ET} were 0.48 and 0.49 kg·m⁻³, respectively, whilst under the 55% ET_c , the observed and simulated WP_{ET} was 0.26 kg·m⁻³. The WP_{ET} under the 55% ET_c represented an optimal calibration scenario, whilst under the 100% ET_c irrigation regime, the model under-estimated the WP_{ET} by 13% and over-estimated WP_{ET} by 2.1% under the 75% ET_c irrigation regime. The observed WP_{ET} under the 100% ET_c and 75% ET_c irrigation regimes slightly matched those reported by Kumar et al. [36] for potatoes (C3 crop) grown in saline soils. The reported WP_{ET} were in the range of 0.63–0.98 kg·m⁻³, although the model exhibited a low EF of 0.27.

3.3. Model Validation

Model validation was done after the calibration exercise. An independent dataset from the 2020 growing season was used to validate the model. Canola was transplanted on 27 October 2020 and harvested on 4 January 2021.

3.3.1. Soil Water Content

The model successfully simulated the SWC under the 100% ET_c irrigation regime ($R^2 = 0.90$, EF = 0.37, nRMSE = 8.7%, and d = 0.83) and 75% ET_c irrigation regime ($R^2 = 0.91$, EF = 0.17, nRMSE = 4.1%, and d = 0.79) (Figure 6d,e). The EF was relatively low, but it signified a generally good model performance for the crop models [60]. The model reasonably simulated the SWC under the 55% ET_c irrigation regime ($R^2 = 0.55$, EF = 0.05, nRMSE = 9.6%, and d = 0.63). The observation was attributed to the poor CC simulations' errors in which the model under-estimated the canopy growth (Figure 6c). The model successfully simulated SWC during the flowering and yield formation stages across all three irrigation regimes. The



evidence revealed the capability of AquaCrop to simulate soil water content with reasonable accuracy for canola grown under MTI.

Figure 6. Canopy cover (*CC*) for (**a**) 100% *ET*_c, (**b**) 75% *ET*_c, and (**c**) 55% *ET*_c and soil water content (SWC) for (**d**) 100% *ET*_c, (**e**) 75% *ET*_c, and (**f**) 55% *ET*_c irrigation regimes during validation.

3.3.2. Canopy Cover

The model successfully simulated the *CC* under the 100% *ET_c* ($R^2 = 0.97$, *EF* = 0.93, *nRMSE* = 22.5%, and *d* = 0.98) (Figure 6a). Under the 75% *ET_c*, the successfully simulated canopy growth during the early stages of plant growth ($R^2 = 0.84$, *EF* = 0.45, *nRMSE* = 59.2%, and *d* = 0.86); however, it under-estimated the canopy growth (Figure 6b). The model poorly simulated the *CC* under the 55% *ET_c* irrigation regime ($R^2 = 0.61$, *nRMSE* = 87.9%, and *d* = 0.40). This finding is consistent with literature that states that AquaCrop inaccurately simulates *CC* under water stress conditions for various crops such as sunflower (Todorovic et al. [30]), maize (Ahmadi et al. [39]), cotton (Farahani et al. [45]), canola (Zeleke et al. [42]), and cowpea (Kanda et al. [31]).

3.3.3. Biomass and Yield

The model simulated the yield with accuracy. The observed deviations (%*D*) were 7.43%, -25.22%, and 12.0% for the 100% *ET_c*, 75% *ET_c*, and 55% *ET_c* irrigation regimes, respectively (Table 9). The findings concur with Zeleke et al. [42], who found the D = -2.1-12% for spring canola cultivars grown in Wagga Wagga, Australia. The results obtained during validation were relatively accurate than those obtained during calibration.

Table 9. Observed and simulated yield and final biomass during validation.

		Yield (ton \cdot ha ⁻¹)		Biomass (ton ha ⁻¹)			
Irrigation Regime	Observed	Simulated	D (%)	Observed	Simulated	D (%)	
100% ET _c	1.48 (0.20)	1.37	7.43	4.70 (2.20)	7.26	-54.47	
75% ET _c	1.15 (0.29)	1.44	-25.22	3.21 (1.50)	6.46	-100	
55% ET _c	0.75 (0.10)	0.66	12	3.23 (1.50)	2.58	20.12	

The model over-estimated the final biomass under 100% ET_c and the 75% ET_c irrigation regimes giving $D \ge \pm 54.47\%$ deviations. The model reasonably simulated the biomass data under the 55% ET_c irrigation regime (D = 20.12%). The presented evidence demonstrates that AquaCrop can confidently simulate crop yields and biomass for canola under various MTI regimes with necessary adjustments.

3.3.4. Water Productivity (WP_{ET})

The simulated WP_{ET} across the three irrigation regimes matched those obtained during calibration; thus, AquaCrop was successfully calibrated and validated for simulating WP_{ET} . Under the 100% ET_c , the observed WP_{ET} was 0.42 kg·m⁻³, whilst the simulated was 0.36 kg·m⁻³ (D = 14.29%). Under the 75% ET_c , the observed and simulated WP_{ET} were 0.48 and 0.49 kg·m⁻³, respectively, whilst under the 55% ET_c , the observed and simulated WP_{ET} was 0.26 kg·m⁻³. The D values were within the good range ($D \le \pm 15\%$). WP_{ET} was high under the 75% ET_c , signifying that optimal yields and WP_{ET} can be achieved with optimal deficit irrigation management practices.

4. Conclusions and Recommendations

This study sought to calibrate and validate the FAO AquaCrop model for canola grown under MTI and local South Africa conditions. The study was premised on the hypothesis that AquaCrop cannot effectively simulate the yield response of canola under varying irrigation regimes. The study, thus, failed to reject the null hypothesis for the 100% ET_c and 75% ET_c and rejected the hypothesis for the 55% ET_c irrigation regime. The model was successfully calibrated and validated for soil water content, canopy cover, biomass accumulation, final biomass, yield, and water productivity under 100% ET_c and 75% ET_c irrigation regimes. AquaCrop poorly simulated the canopy cover and the SWC under the extreme deficit irrigation regime (55% ET_c). The poor simulation results can potentially be attributed to canola's sensitivity to extreme deficit irrigation scenarios. The study revealed that good deficit irrigation regimes could achieve optimum canola growth. The 75% ET_c irrigation regime had an optimal grain yield and relatively high water productivity (WP_{ET}) compared to the 100% ET_c irrigation regime. Thus, appropriate deficit management practices can produce high biomass and lower yield penalties. The study revealed the capability of the AquaCrop model to simulate canola response to various irrigation regimes. It is recommended that the study be done in open field conditions and assess the reliability of the reported results in this study. Additionally, the authors recommend the study be carried over several DI regimes and investigate the WP_{ET} and yield correlation. In addition, the field experiments will generate an independent dataset that will be used to further test AquaCrop.

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