

Article

Modeling Sugar Beet Responses to Irrigation with AquaCrop for Optimizing Water Allocation

Margarita Garcia-Vila ^{1,*} , Rodrigo Morillo-Velarde ² and Elias Fereres ^{1,3}¹ Agronomy Department, University of Cordoba, 14007 Córdoba, Spain; ag1fecae@uco.es² Research Association for Sugar Beet Crop Improvement, 47012 Valladolid, Spain; rmorillovelarde@icloud.com³ Institute for Sustainable Agriculture, CSIC, 14004 Córdoba, Spain

* Correspondence: g82gavim@uco.es; Tel.: +34-957-499-231

Received: 31 July 2019; Accepted: 10 September 2019; Published: 14 September 2019



Abstract: Process-based crop models such as AquaCrop are useful for a variety of applications but must be accurately calibrated and validated. Sugar beet is an important crop that is grown in regions under water scarcity. The discrepancies and uncertainty in past published calibrations, together with important modifications in the program, deemed it necessary to conduct a study aimed at the calibration of AquaCrop (version 6.1) using the results of a single deficit irrigation experiment. The model was validated with additional data from eight farms differing in location, years, varieties, sowing dates, and irrigation. The overall performance of AquaCrop for simulating canopy cover, biomass, and final yield was accurate (RMSE = 11.39%, 2.10 t ha⁻¹, and 0.85 t ha⁻¹, respectively). Once the model was properly calibrated and validated, a scenario analysis was carried out to assess the crop response in terms of yield and water productivity to different irrigation water allocations in the two main production areas of sugar beet in Spain (spring and autumn sowing). The results highlighted the potential of the model by showing the important impact of irrigation water allocation and sowing time on sugar beet production and its irrigation water productivity.

Keywords: modelling; AquaCrop; calibration; sugar beet; irrigation water allocation; water productivity

1. Introduction

Sugar beet (*Beta vulgaris*), together with sugarcane (*Saccharum officinarum*), are the main sources of commercial sucrose worldwide. Even though the sugar beet cropped area has been decreasing over recent decades, total production remains stable due to increasing yields [1]. The highest average fresh root yield has been recorded in Spain (90 t ha⁻¹), despite it not being ranked among the world's 10 largest producing countries, which have yields ranging from 39 t ha⁻¹ to 88 t ha⁻¹ [1]. This is the result of a significant effort made over recent decades to increase crop productivity through the adoption of optimum farming practices, together with plant breeding efforts, to introduce new, adapted varieties, which was led by the Spanish Research Association for Sugar Beet Crop Improvement (AIMCRA, in its Spanish acronym). Although only about one-fourth of the world's area devoted to sugar beet is irrigated, the fraction of irrigated area varies greatly from region-to-region, between 20% and 100% of the sugar beet area [2]. Because of the different environments where both crops are grown, sugar beet consumes from 500 to 800 mm of water [2], while the annual evapotranspiration of sugarcane ranges between 800 and 2000 mm [3]. This lower water consumption of sugar beet makes it suitable for water-limited environments (e.g., the Mediterranean region of limited rainfall concentrated in the winter and a rainless summer), where governments are fostering sugar beet production as an

alternative to sugarcane. Thus, one would expect an increase of the sugar beet area in those countries in the coming years.

Sugar beet is sensitive to water deficits, particularly in the early growing stages [2,4], and there is a positive linear relationship between water use and root production [2,5]. Water stress is the major cause of sugar beet yield loss in many regions, even in areas where the crop is not normally irrigated or is supplementary irrigated [6]. Furthermore, yield losses due to water stress are expected to increase in the future, which becomes a serious new problem in many areas, such as North-East France and Belgium [7]. Under this scenario, optimum water usage, irrespective of its source (irrigation or rainfall), becomes a key target for sugar beet producers.

The response of crop to water availability is complex, but their characterization through field experiments have been conducted for many years [8]. However, the empiricism, time consumption, and the amount of resources needed limit their implementation for designing optimum irrigation management. Given these constraints, crop simulation models are a promising alternative used to simulate the crop response to different water supply scenarios. There are several examples of crop models used to simulate the sugar beet production under different environments and management practices. Simple models such as the one presented by Reference [9] or Reference [5] (PLANTGRO), both based on the approach in Reference [10], have been proposed. Under the production function approach, a crop response factor relates the normalized yield to its potential value against the normalized evapotranspiration or transpiration to their potential values. These models have limited capacity to predict yield response to water since they do not include the water stress effects on the different crop eco-physiological processes. To overcome these limitations, more complex process-based models have also been adapted to simulate sugar beet production, such as Broom's Barn crop growth model [6,11], CSM-CERES-Beet model, or DSSAT [12], STICS [13,14], Greenlab [14,15], LNAS [14], and PILOTE [14,16]. In addition, the AquaCrop model [17], in an attempt to develop a simple, versatile, and robust water-driven model, has been calibrated and validated for sugar beet [18–22]. This model can simulate the yield response to water more accurately with a relatively small number of parameters than other models, which makes it more attractive for simulations under water-limited conditions or for irrigation scheduling. For these reasons, AquaCrop has been implemented to assess the sugar beet production under different scenarios [23,24]. Nevertheless, as for any model application, AquaCrop must be accurately calibrated and validated. In the case of sugar beet, earlier calibration and validation efforts in AquaCrop have yielded uncertain results [18–22]. One reason may be that important modifications in the quantification of soil water stress have been introduced in the new model versions (v6.0 and v6.1), which makes it necessary to carry out a new calibration and validation process.

Once the model is properly parameterized, it can be used for multiple purposes, both at the plot scale (e.g., irrigation scheduling, as in Reference [25]) or farm scale (e.g., optimization of the irrigation and cropping patterns, as in Reference [26]) and at basin (e.g., integrated assessment modelling, as in Reference [27]) or regional level (e.g., crops responses to climate change [23]). Ultimately, AquaCrop can be a useful tool for supporting decision-making at different levels, especially in terms of irrigation water management for a crop such as sugar beet, which is facing water scarcity challenges in most of the production areas. In this regard, the application of the model for better irrigation water allocation, an issue faced by water authorities, would be relevant in a water scarce environment. A proper irrigation water allocation must enhance the irrigation water productivity, taking into account the availability of a scarce resource, as water, and ensuring the farmers' profitability.

Thus, the objectives of this work were first to calibrate and validate the AquaCrop model (version 6.1) for sugar beet grown under different levels of irrigation. Additionally, a scenario analysis was carried out to assess the crop response in terms of yield and water productivity to different irrigation water allocations in the two main production areas of sugar beet in Spain (spring and autumn sowing).

2. Materials and Methods

2.1. Calibration and Validation of AquaCrop for Sugar Beet

2.1.1. Datasets

A field experiment was performed in 2012 at the experimental station of the Research Association for Sugar Beet Crop Improvement (AIMCRA, in its Spanish acronym), Valladolid, Central Spain (41°39' N, 4°41' W, 690 m a.s.l.) to calibrate the model. The climate in the area is typically Mediterranean with an annual average precipitation of around 400 mm, and about 1200 mm average annual reference evapotranspiration (ET_o). The soil of the experimental area is a Gleyic Cambisol of 1.2 m depth with uniform clay loam texture. Sugar beet was planted on 21 February, 2012, at a final density of 14.5 plants m⁻² (row spaced 0.5 m apart), and the selected cultivar was *Amalia* KWS.

The experimental design was a randomized complete block with 144 m² plots with four irrigation treatments replicated four times. The four treatments were: control (100% ET_c), two sustained deficit irrigation treatments (70% and 55% of the control), and a rainfed treatment. In order to enable proper crop germination and establishment, all the treatments were fully irrigated to cover the crop needs until June 1st. The irrigation system used was a sprinkler that adapted the nozzle orifice size to the irrigation treatment (3.6–4.4 mm). In order to avoid nutritional stresses, 220 Kg N ha⁻¹, 100 Kg P₂O₅ ha⁻¹, 100 kg K₂O ha⁻¹, and 50 Kg MgO ha⁻¹ were applied in all treatments. Pests and diseases were carefully controlled, and no weeds were allowed to develop in the field.

Green canopy cover was monitored weekly at 5 points per replication by taking zenithal photographs above the canopy with a digital camera. Images were analyzed using the Green Crop Tracker v.1.0 software, developed by Agriculture and AgriFood Canada [28]. Biomass (leaves and roots) sampling (one row of 1.4 m long per plot) was performed monthly in every treatment, and oven dried (at 70 °C) to assess the time course of biomass. Final yield was determined by harvesting 7 m² per replicate plot in every treatment and drying the roots at 70 °C.

To validate the model, eight commercial farms from part of the AIMCRA trials were selected. AIMCRA technicians collect detailed data on the soil, crop, and irrigation management, as well as the final fresh yield. The conditions in the selected farms cover the variability found in the main sugar beet production areas in Spain, i.e., weather and soil variability (different years and locations), different varieties, sowing dates, plant density, and irrigation. A summary of the information on the selected farms is provided in Table 1. Another important aspect taken into account during the farms selection was that yield had not been limited by nutritional stresses pests and/or diseases. Dry yield was estimated considering a dry matter content of 20%, the average value obtained in the calibration experiment.

Table 1. Experimental data sets and farmers' fields measurements used for the calibration and validation of AquaCrop for sugar beet. n is the number of irrigation treatments.

Data Sets	Location	Year	n	Cultivar	Sowing Date	Plant Density (Plants m ⁻²)	Soil Texture
<i>Calibration</i>							
AIMCRA	Valladolid (Valladolid)	2012	4	Amalia KWS	21 February	14.5	Clay loam
<i>Validation</i>							
FARM1	Villabañez (Valladolid)	2012	1	Amalia KWS	9 March	10.5	Silty clay
FARM2	Pozáldez (Valladolid)	2012	1	Ludwina KWS	1 March	10.6	Clay
FARM3	Herrera de Pisuerga (Palencia)	2012	1	Ludwina KWS	16 March	10.4	Loam clay
FARM4	Donhierro (Segovia)	2012	1	Geraldina	28 February	10.8	Loam
FARM5	Villamarciel (Valladolid)	2013	1	Amalia KWS	25 April	9.6	Loamy sand
FARM6	Lebrija (Sevilla)	2014	1	Brahms	28 October	11.1	Clay
FARM7	Lebrija (Sevilla)	2014	1	Sanlúcar	16 October	10.5	Clay
FARM8	Lebrija (Sevilla)	2014	1	Portal	24 October	10.9	Clay

2.1.2. Calibration and Validation Procedures

AquaCrop v6.1 has been used in this study and its algorithms, calculation procedures, and parameters are described in detail in the model reference manual [29], while a brief description of the

concepts and basic development can be found in Reference [17] and Reference [30]. The calibration process was performed by adjusting the conservative parameters [31] comparing the simulated with the observed values of green canopy cover (CC), dry biomass (B), and dry yield at harvest (Y), in that order, as recommended by Reference [31]. This approach is in line with the calculation scheme of AquaCrop, which estimates crop yield in four steps operating on a daily basis: (1) calculation of CC, (2) calculation of transpiration (T) proportional to CC, (3) conversion of T into B through a normalized water productivity (WP *) factor, and (4) calculation of Y as the product of B and the harvest index (HI). The crop water stress parameters were adjusted after satisfactory results for the control treatment were achieved. The global sensitivity analysis performed by Reference [32] was taken into account during the calibration process. The validation procedure was carried out by comparing the simulated with the observed values only of Y, since there was no data on CC or B.

The input climate data required by AquaCrop (minimum and maximum air temperature, rainfall, and ETo calculated by the FAO Penman-Monteith equation) were obtained from a weather station located at the experimental station, in the case of the calibration, and from weather stations nearby for the validation. Input data on plant density, phenology, and development were obtained from the experimental results. The soil hydraulic properties, i.e., soil water content at permanent wilting point, field capacity, and saturation, and hydraulic conductivity at saturation, were estimated from the soil texture using pedo-transfer functions [33]. The initial soil water content was considered at field capacity due to the pre-sowing irrigation carried out in all cases.

AquaCrop performance was evaluated by linear regression between the observed and simulated values of CC, B, and Y, and the slope, intercept, and coefficient of determination (r^2) were determined. The goodness of fit was also assessed by the following two statistics: root mean square error (RMSE, Equation (1)) and the index of agreement (d) of Reference [34] (Equation (2)).

$$RMSE = \sqrt{1/n \sum_{i=1}^n (O_i - S_i)^2} \quad (1)$$

$$d = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (2)$$

where O_i and S_i are the observed and simulated values, respectively, and n is the number of observations. The model fit improves as RMSE, an indicator of the absolute model uncertainty, approaches zero while d , which is a stable and bounded index, approaches unity.

2.2. Simulating the Crop Response to Different Irrigation Water Allocations

Once AquaCrop was calibrated and validated for sugar beet, the model was used to optimize the irrigation schedules and to simulate yield and irrigation water productivity (WP) under different irrigation water allocation (IWA) scenarios in the two main production areas of Spain: Central-North area, where the sowing is carried out in spring, and the Southern area of autumn sowing. The two locations selected for the simulations were Valladolid and Sevilla, which are both locations representative of the production areas. The calibrated crop parameter values were used for the simulations, and AquaCrop was run in the growing degree day mode, which uses a base temperature and an upper or optimum temperature (the temperature above which crop development no longer increases with an increase in air temperature [29]).

The sowing dates used in the simulations (2 April and 6 November for North and South area, respectively) were the average sowing dates obtained from the AIMCRA database. The input soil parameters were those of the AIMCRA experiment for the North area, while a clay soil was used to represent the South area. The initial soil water content was considered at field capacity, which was consistent with the rainfall patterns and the pre-sowing irrigation practices in the study areas. The

simulated irrigation method was sprinkler with an application efficiency of 80%, which is the average value obtained by AIMCRA in previous irrigation performance assessments.

To account for climate variability in the crop response to irrigation, a synthetic 30 years series of climate data for each study area was generated using the stochastic weather generator CLIMAGEN [35], based on SIMMETEO [36]. The climate data series were generated on the basis of the statistical characteristics of the observed weather at Valladolid and Sevilla locations. Using these climate data series, AquaCrop was run to simulate and analyze various IWA scenarios in both production areas, focusing on the potential yield and related irrigation WP (defined as the ratio of the dry root yield to the gross applied irrigation water). The current IWA for sugarbeet in each area (reference scenario), of 600 mm and 400 mm for the North and South area, respectively, was analyzed. Two alternative scenarios were also assessed: an increase of 100 mm in the irrigation water supply (i.e., 700 mm and 500 mm for the North and South area, respectively), and a 25% reduction in IWA under water scarcity (i.e., 450 mm and 300 mm for the North and South area, respectively). Under these three scenarios, AquaCrop was used to generate an optimum irrigation schedule to achieve maximum yield (potential yield). The irrigation strategy followed avoided water stress in the early growing stages (most sensitive period), while it allowed moderate water deficits toward the end of the season [2]. The simulated yield and irrigation WP gaps between the reference scenario and the two alternative IWA scenarios were analyzed.

3. Results

3.1. Calibration and Validation of AquaCrop for Sugar Beet

The calibration of the crop parameters involved in the simulation of the time course of CC was carried out first. Figure 1 presents a comparison between observed and simulated CC for the four irrigation treatments of the AIMCRA experiment. A very good matching of simulated CC against measured CC was found for all treatments, with the exception of the rainfed treatment (Figure 1d). It appears that, despite the improvements introduced in AquaCrop v6.0 and v6.1 to account for the effects of a light rain on the level of soil water stress of deep rooted crops [29], the model was not able to stop the early senescence despite a rainfall event (11 mm) which occurred on day 156 after sowing and slowed down the canopy senescence in the field (Figure 1d). The rainfall event was insufficient to reduce the simulated water depletion in the top soil up to the threshold for triggering early senescence. Nevertheless, a proper fit of water stress response parameters for early senescence can be observed by analyzing the simulated senescence process in the 70% Control and 55% Control treatments. The calibrated values of the crop parameters for sugar beet can be found in Table 2. The overall performance of AquaCrop for simulating CC is shown in Table 3, with an RMSE of 11.39% and d value of 0.999.

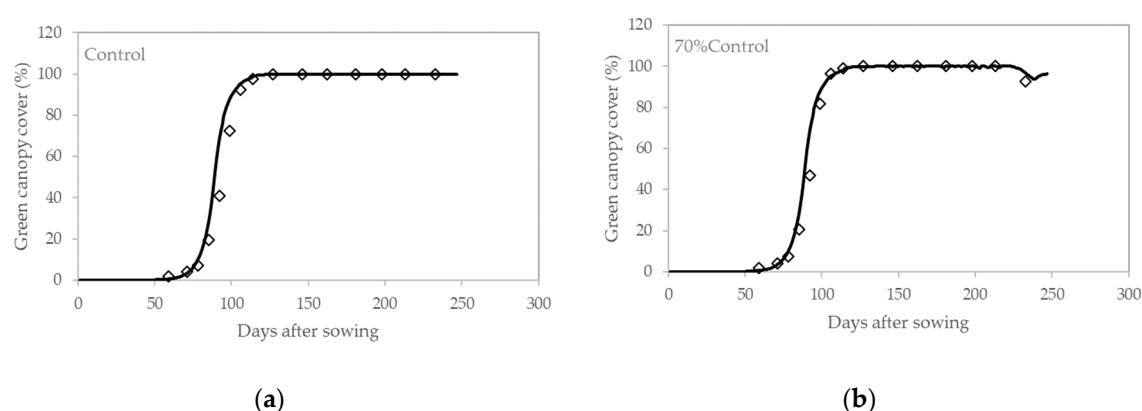


Figure 1. Cont.

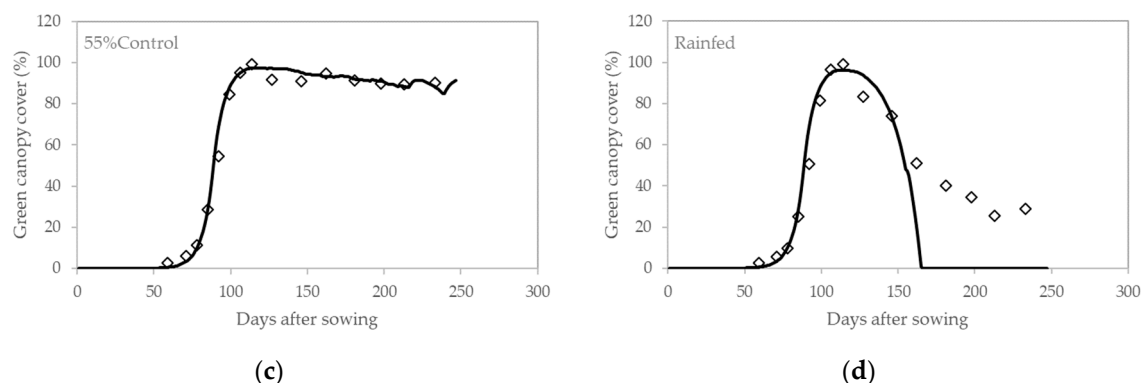


Figure 1. Observed and simulated seasonal course of green canopy cover for the irrigation treatments of the AIMCRA experiment used for model calibration: (a) control, (b) 70% control, (c) 55% control, and (d) rainfed.

Table 2. Calibrated values for selected AquaCrop crop parameters for sugar beet. The AquaCrop default values for sugar beet and the values calibrated in selected previous studies are shown. Information about the calibration process (model version, location, observed yield range, and evaluated variables) is presented. CC, B, and Y are green canopy cover, biomass, and yield, respectively.

	Calibration	Default	Stricevic et al., (2011) [18]	Alishiri et al., (2014) [19]	Van Straaten (2017) [20]	Malik et al., (2017) [21]
AquaCrop version	6.1	4.0	4.0	4.0	5.0	-
Location	Spain	Italy	Serbia	Iran	Morocco	Pakistan
Observed dry yield range (t ha ⁻¹)	4.8–25.8	-	8.5–19.8	4.0–12.0	10.0–25.0	7.3–15.0
Evaluated variables	CC, B, Y	-	Y	CC, B, Y	Y	CC, B, Y
Crop parameters						
<i>Threshold air temperatures</i>						
Base temperature, T _{base} (°C)	3	5	5	5	5	5
Upper temperature, T _{upper} (°C)	25	30	30	30	30	30
<i>Crop transpiration</i>						
Kc _{TX}	1.15	1.10	1.10	1.10	1.15	1.10
<i>Production</i>						
Normalized water productivity, WP* (g m ⁻²)	18.0	17.0	17.0	18.0	18.0	16.7–18.6
Reference harvest index, H _{lo} (%)	75	70	70	60	70	68–73
<i>Water stress response</i>						
Top soil thickness (cm) ¹	20	10	10	10	10	10
Canopy expansion p _{upper}	0.20	0.20	0.20	0.25	0.20	0.10–0.20
Canopy expansion p _{lower}	0.60	0.60	0.60	0.70	0.60	0.45–0.55
Canopy expansion shape factor	3.0	3.0	3.0	4.0	3.0	0.5–3.2
Stomatal closure p _{upper}	0.65	0.65	0.65	0.65	0.57	0.45–0.65
Stomatal closure shape factor	3.0	3.0	3.0	2.5	2.5	2.5–2.8
Canopy senescence p _{upper}	0.75	0.75	0.75	0.75	0.75	0.45–0.55
Canopy senescence shape factor	3.0	3.0	3.0	2.5	2.5	1.2–3.0
H _{lo} adjustment-Before yield formation (+)	None	None	None	None	None	None
H _{lo} adjustment-During yield formation (+)	6	4	4	4	4	4
H _{lo} adjustment-During yield formation (-)	None	None	None	None	1	None

¹ Top soil thickness considered for the estimation of soil water depletion (Program settings: Crop parameters). -: Information is not available.

Table 3. Statistics (root mean square error–RMSE- and index of agreement–*d*-) for the comparisons between observed and simulated values of green canopy cover (CC), total dry biomass (B), and root dry yield (Y) for the calibration and validation of the AquaCrop model. Slope, intercept, and *r*² are for the linear regression of observed against simulated values. *n* is the number of observed data used in the calibration and validation process.

Variable	n	Observations Range	Simulations Range	RMSE	<i>d</i>	Slope	Intercept	<i>r</i> ²
Calibration								
CC (%)	60	2–100	0–100	11.39	0.999	1.038	−2.748	0.924
B (t ha ⁻¹)	18	1.56–34.0	4.50–30.21	2.10	0.983	0.857	2.172	0.957
Y (t ha ⁻¹)	4	4.83–25.80	3.49–25.18	0.85	0.999	1.056	−1.256	0.994
Validation								
Y (t ha ⁻¹)	8	16.18–27.00	16.26–27.63	1.17	0.998	0.945	1.278	0.908

The satisfactory performance in the simulation of CC led to a reasonable fit in biomass accumulation for all treatments, as indicated by the high value of *d* and moderate RMSE (Table 3). Figure 2 depicts

the comparison between observed and simulated seasonal course of biomass accumulation for all the treatments of the AIMCRA experiment. A slight tendency to over-predict (in all treatments) and under-predict (in control and rainfed treatments) at the beginning and end of the season, respectively, can be observed (also see slope and intercept in Table 3). These results are more than satisfactory when taking into account the uncertainty in the measurement errors in biomass sampling, which indicates a proper adjustment of the crop parameters related to transpiration, as well as the normalized water productivity (WP^*) (Table 2).

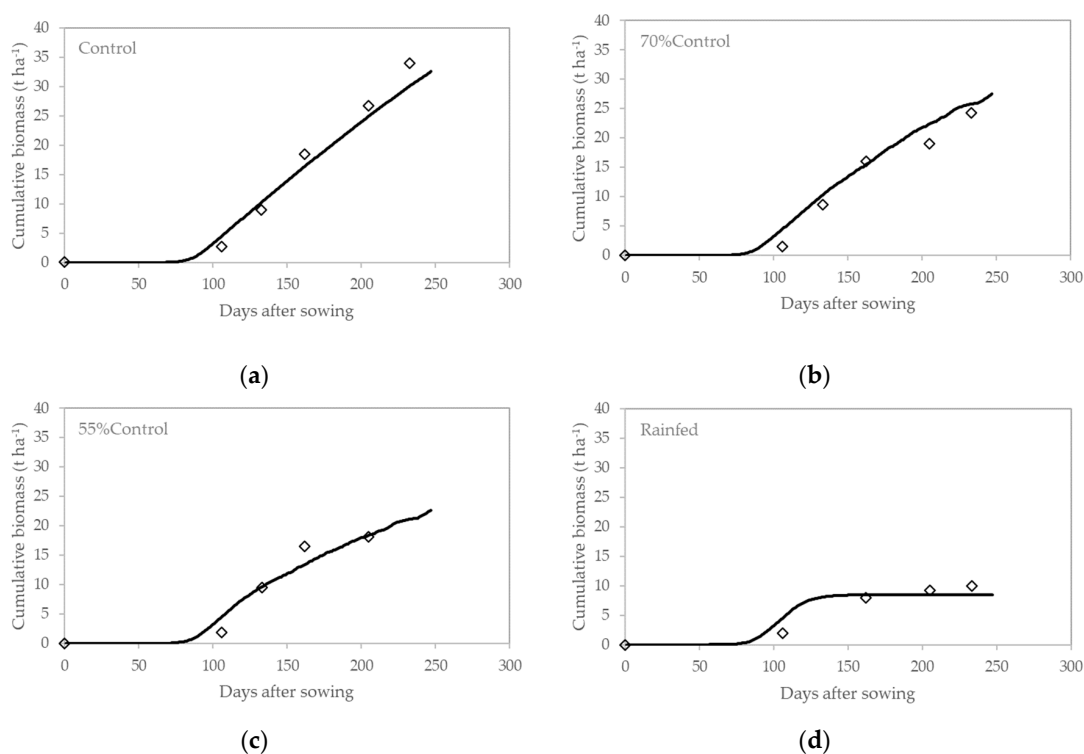


Figure 2. Observed and simulated seasonal course of biomass accumulation in dry terms for the irrigation treatments of the AIMCRA experiment used for model calibration: (a) control, (b) 70% control, (c) 55% control, and (d) rainfed.

Figure 3 presents the comparison between observed and simulated dry root yield at harvest using the calibrated and the default crop parameters. The calibration improved yield prediction relative to the use of the default parameters, where simulated yields were below the observed yields, particularly near the maximum (Figure 3). After calibration, the simulation of yield was good for all treatments (deviation of less than 5%), with the exception of the rainfed treatment (deviation of 28%). The under-prediction of yield in this treatment must be mostly related to the differences between observed and simulated CC and biomass at the end of the season (Figures 1d and 2d). The premature canopy senescence stopped the build-up of the simulated harvest index (HI), which reached a value of only 41%. The simulation of HI under terminal drought conditions, where accelerated canopy senescence has a major impact, is particularly difficult [17]. Nevertheless, the overall yield predictions in the range of 4.8 to 25.8 t ha⁻¹ are good, as shown in Table 3 (RMSE = 0.85 t ha⁻¹, $d = 0.999$). It is also important to highlight how well the model simulates the positive impact of water stress on the HI during yield formation, as observed in the 70% control and 55% control treatments (Figure 3).

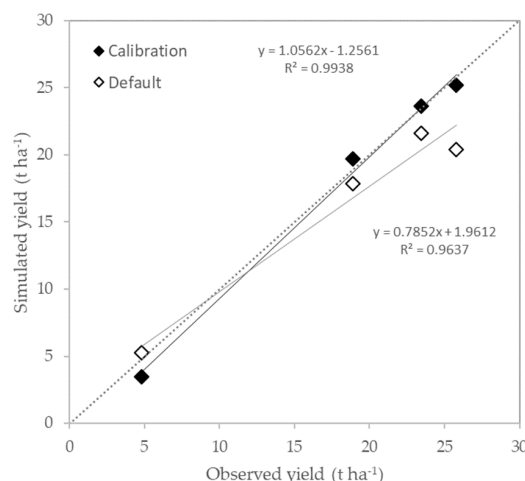


Figure 3. Simulated versus observed dry root yield at harvest for the AIMCRA experiment used for model calibration with the calibrated and default crop parameters.

Validation of the model was performed with the calibrated crop parameters using the dataset from commercial farms described above. The agreement between observed and simulated dry root yield at harvest is presented in Figure 4 for a large spectrum of production levels (from 16 to 27 t ha⁻¹). This comparison shows that all simulated yields have a deviation of less than 10%, without an apparent trend for over-prediction or under-prediction (Slope = 0.945, Intercept = 1.278, and $r^2 = 0.908$, Table 3). Thus, there was a very good fit, with a high value of d and moderate RMSE (Table 3).

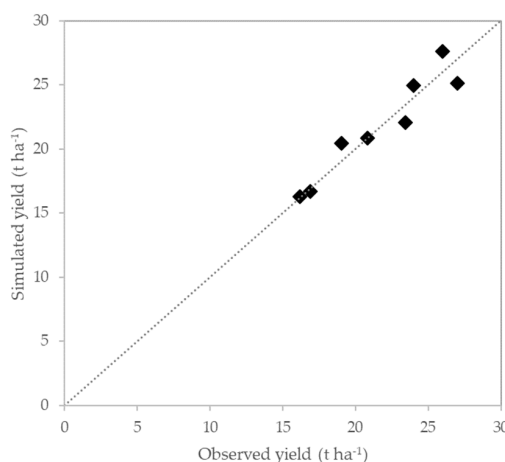


Figure 4. Simulated versus observed dry root yield at harvest for the FARM1-8 datasets used for the model validation.

3.2. Crop Response to Different Irrigation Water Allocations

The calibrated and validated AquaCrop model for sugar beet was used to simulate the crop response to different IWA under optimum irrigation schedules in the two main production areas of Spain with climatic datasets of 30 years generated by CLIMAGEN software. Figure 5 depicts the range of cumulative rainfall and ETo values just for the growing cycle of sugar beet in Valladolid (North area) and in Sevilla (South area) for the 30 simulated seasons. The North area presents much higher ETo (around 1030 mm) and lower rainfall (around 200 mm) than the South area (around 630 and 500 mm of ETo and rainfall, respectively) ($p < 0.05$, Tukey test), although a higher inter-annual variability is observed in the South, particularly in rainfall. Note that there are different sowing times, with spring and autumn for North and South areas, respectively. This is reflected in the current irrigation water allocation of 600 mm in the North versus 400 mm in the South.

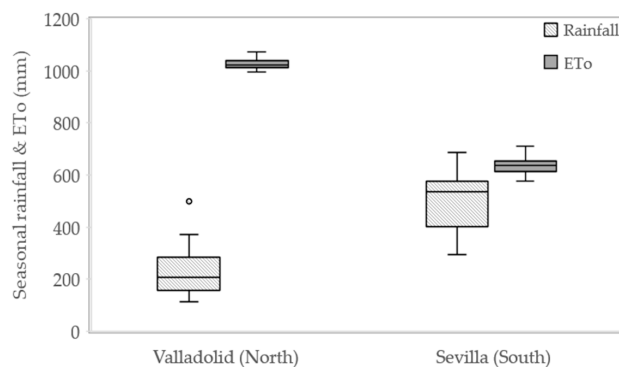


Figure 5. Cumulative rainfall and reference evapotranspiration (ETo) for the sugar beet growing cycle in Valladolid (North productive area) and Sevilla (South productive area), and for the 30 simulated seasons. The box represents 50% of the data, where the box's upper boundary represents the upper quartile (Q3) of the data, the lower boundary represents the lower quartile (Q1) and the line inside the box represents the median (Q2). The whiskers show the largest and smallest values. The circle denotes outlier values.

The potential dry root yields under the different irrigation water allocation scenarios for the 30 simulated seasons in the two productive areas were simulated with AquaCrop and are presented in Figure 6. The average potential yield for the reference IWA scenario is higher in the South, with an average of 24 versus 22 t ha⁻¹ in the North. Yields similar to those in the South were achieved in the North under the IWA scenario of 700 mm (Figure 6a). As a consequence, the irrigation WP is considerably higher in the South than the North area (Figure 7), with average values of 6.1 Kg m⁻³ and 3.7 Kg m⁻³ under the IWA reference scenario, respectively. Similarly, evapotranspiration WP (defined as the ratio of the dry root yield to the water consumed–ET–) followed the same pattern, with average values of 4.1 Kg m⁻³ and 2.7 Kg m⁻³ for the North and South areas, respectively. As might be expected, the increase in IWA led to a downward trend in irrigation WP in both areas ($p < 0.05$, Tukey test) (Figure 7). Regarding the year-to-year variability, the highest variability in yield occurred in the North under a 25% reduction in IWA (Figure 6), where a greater dependency on seasonal rainfall under this deficit IWA scenario increased the inter-annual variability. On the contrary, the maximum variability in irrigation WP was found in the South for the highest IWA (Figure 7). For this location, in this scenario, an increase in IWA did not enhance yields in up to 33% of the years, due to the rainfall patterns, which explained the high variability observed.

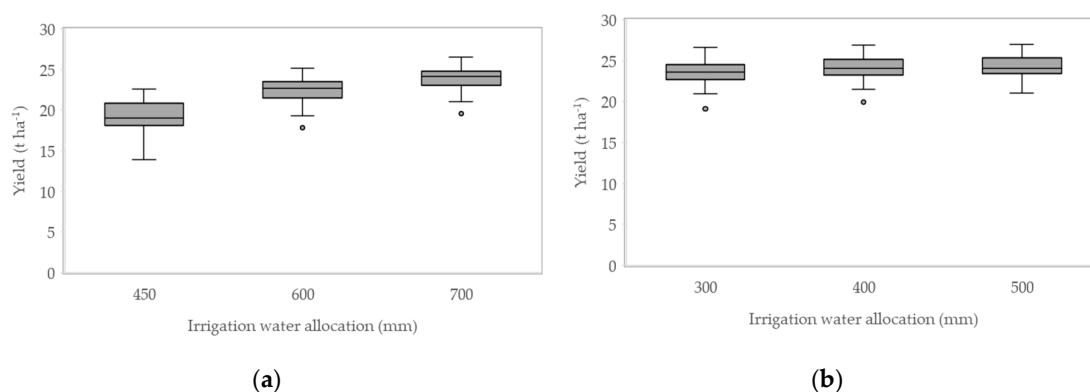


Figure 6. Potential dry root yield at harvest under three different irrigation water allocation scenarios for the 30 simulated seasons in the two main productive areas: (a) North (Valladolid), and (b) South (Sevilla). The box represents 50% of the data, where the box's upper boundary represents the upper quartile (Q3) of the data, the lower boundary represents the lower quartile (Q1), and the line inside the box represents the median (Q2). The whiskers show the largest and smallest values. The circles denote outlier values.

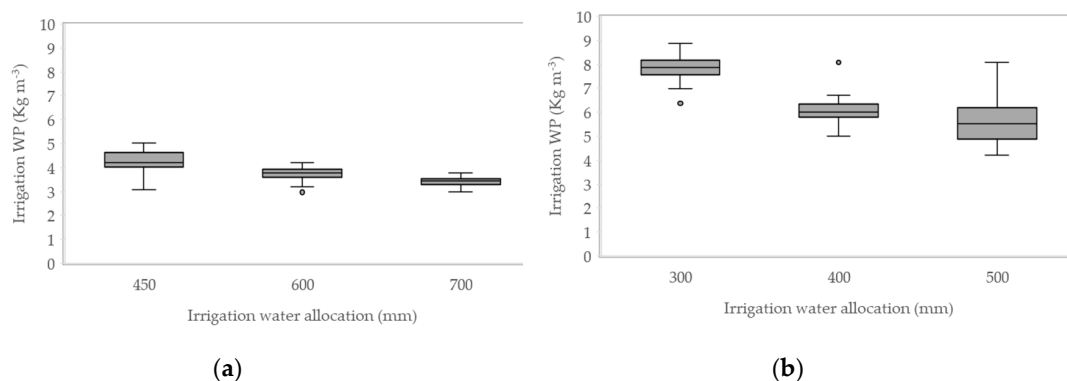


Figure 7. Simulated irrigation water productivity (WP) under three different irrigation water allocation scenarios for the 30 simulated seasons in the two main productive areas: (a) North (Valladolid), and (b) South (Sevilla). The box represents 50% of the data, where the box's upper boundary represents the upper quartile (Q3) of the data, the lower boundary represents the lower quartile (Q1), and the line inside the box represents the median (Q2). The whiskers show the largest and smallest values. The circles denote outlier values.

3.3. Yield and Water Productivity Gaps

The average yield and irrigation WP gaps for each scenario are presented in Figures 8 and 9, respectively. In the South, the potential yields were not affected by increasing the IWA in 100 mm, unlike the Northern area where the yields rose almost 1.5 t ha^{-1} (Figure 8). A similar situation was observed under a 25% reduction in IWA, with a yield gap of around 3 t ha^{-1} in the North in comparison with only 0.5 t ha^{-1} in the South. The greater seasonal rainfall in the South leads to negligible yield gaps (Figure 8). In the case of the irrigation WP gaps (Figure 9), the pattern is the opposite of that observed in the yield gaps. The highest irrigation WP gaps were simulated in the South, with an average increase of 1.8 Kg m^{-3} by increasing the IWA in 100 mm.

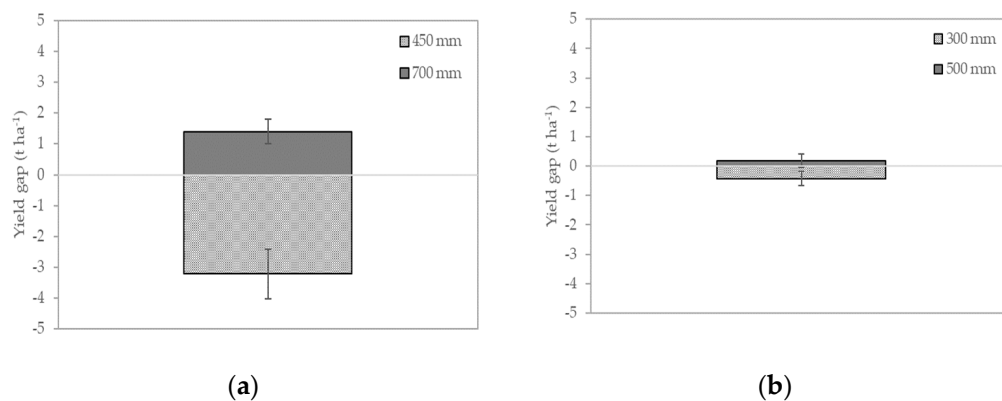


Figure 8. Average potential dry root yield gap of the different irrigation water allocation scenarios with respect to the normal irrigation water allocation (reference scenario) for the 30 simulated seasons in the two main productive areas: (a) North (Valladolid), and (b) South (Sevilla). Vertical bars represent the standard deviation.

The detailed year-to-year simulated yields comparison in the three IWA scenarios is presented in Figure 10. In the North, yields under low IWA were always less than the reference yields and quite variable (Figure 10a). By contrast, in the South, there was very little impact of a reduced IWA given that the inter-annual rainfall variability is corrected with optimal irrigation (Figure 10b).

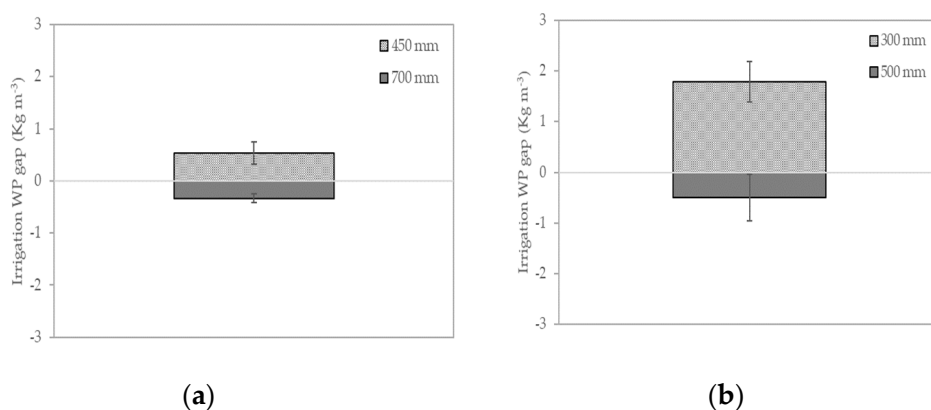


Figure 9. Average simulated irrigation water productivity (WP) gap of the different irrigation water allocation scenarios with respect to the normal irrigation water allocation (reference scenario) for the 30 simulated seasons in the two main productive areas: (a) North (Valladolid), and (b) South (Sevilla). Vertical bars represent the standard deviation.

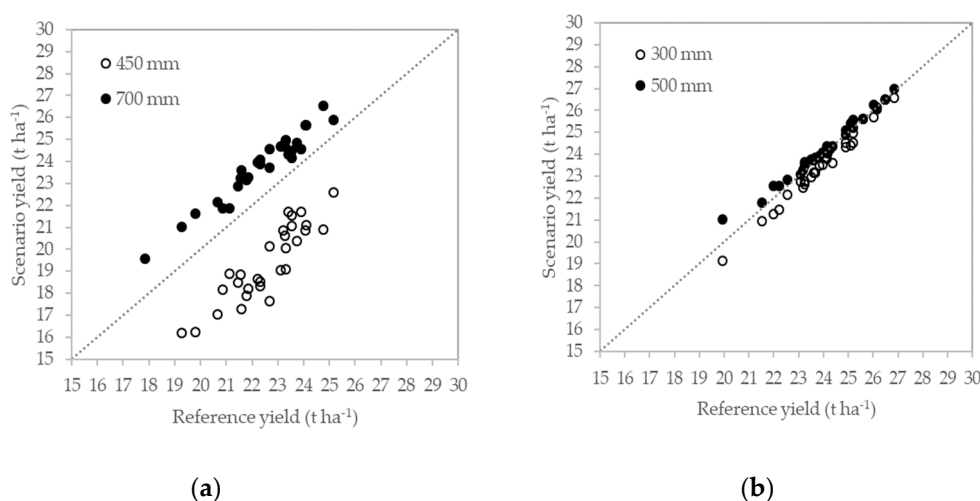


Figure 10. Comparison of potential dry root yield at harvest under different irrigation water allocation scenarios (scenario yield) with potential dry root yield at harvest under the normal irrigation water allocation (reference yield) for the 30 simulated seasons in the two main productive areas: (a) North (Valladolid), and (b) South (Sevilla).

4. Discussion

In the view of the calibration and validation results (Figures 1–4), AquaCrop effectively reproduced (Table 3) the main features of yield responses of sugar beet to water deficits. It is important to acknowledge that AquaCrop is focused mainly to simulate water-limited yields. Calibration was carried out with the results of a single deficit irrigation experiment, while the model validation was carried out with data from eight farms differing in location, years, varieties, sowing dates, and irrigation (Table 1), with an observed yield range between 16 to 27 t ha⁻¹ (Figure 4). This high variability in environmental conditions and management provides robustness to the simulated results. No previous studies of calibration/parameterization and validation of AquaCrop for sugar beet have covered this broad range of production levels (Table 2). Only Reference [20] used a comparable yield range (by introducing differences in sowing dates and irrigation) from experimental fields located in the Tadra irrigation scheme (Morocco), but neither B or CC were experimentally assessed, and agreement statistics were not reported. These shortcomings make it difficult to evaluate the goodness of the adjustment they proposed for the crop parameters (Table 2). The same applies to Reference [18], where only the model performance to predict yield is assessed. In the case of Reference [19], the calibration

process (based on irrigation and fertilization experiments) was performed using only a full irrigation treatment (the deficit irrigation treatments were included only in the validation process). This hampers the proper adjustment of the crop water stress parameters. The calibration process in Reference [21] is more unsuitable, since the crop parameters values changed for the different treatments.

Based on the calibration performed here, a set of conservative parameters was adjusted, as reported in Table 2. These crop parameters values do not differ greatly from those in the default crop file for sugar beet within the AquaCrop model database (Table 2). However, there were significant changes in some key crop parameters, such as the normalized WP (WP *), which was increased from 17 g m^{-2} in the default file to 18 g m^{-2} (Table 2), which has an important impact on yield simulation (Figure 3). The new WP * value was already proposed by References [19] and [20] (Table 2). By contrast, Reference [18] considerably under-predicted the yield in the irrigated treatments using the default WP * value of 17 g m^{-2} (Table 2). Another important change was the modification of the base and upper temperature (Table 2) for better simulation of the crop development and the impact of low temperatures on stomatal conductance [29]. Our proposed changes are in line with those recommended by Reference [37] for the base temperature and by References [38] and [39] for the upper temperature. Although the default crop water stress parameters (Table 2) satisfactorily simulated the crop response under deficit irrigation (Figure 1b–d, Figures 2b–d and 3), a small change in the parameter that adjust H_{lo} for water stress during yield formation (Table 2) allowed the correct simulation of the increase in HI due to the water stress suffered during the leaf expansion, as observed by Reference [40]. Furthermore, the validation of the default crop water stress parameters was crucial, since important modifications in the determination of soil water stress were performed in versions 6.0 and 6.1 of AquaCrop [29] in comparison with previous versions. In the 6.1 version, the water depletion in the top soil is compared against whole root zone depletion in order to determine which part of the soil profile controls the water stress. Therefore, the proper definition of the top soil thickness for each crop (Table 2) is also a relevant task for the calibration of the new model versions.

Using these calibrated parameters, AquaCrop accurately simulated the evolution of CC (Figure 1) and biomass (Figure 2), as well as the final root yield (Figure 3). Nevertheless, despite the improvements introduced for better accounting of water stress in the new model versions (v6.0 and 6.1), AquaCrop was not able to simulate the effect of a light rainfall on the water stress reductions (Figure 1d), likely because, in the field, the rainfall triggers new root growth in the surface layers that facilitates rapid extraction of the infiltrated soil water, which quickly reduces water stress, as shown in grain sorghum [41]. The model could not simulate such an adaptive response and this resulted in under-prediction of the final yield for the rainfed treatment (Figure 3). Note that AquaCrop predictions were less accurate for the most deficit irrigated treatments in Reference [19]. This has been observed in other works for different crops, such as in maize [42] and in dry beans [43]. There seems to be a need for improving the AquaCrop simulations under severe water stress. Nevertheless, in view of the good results obtained in the extensive validation test performed in this study with a wide range of production levels (Table 3), it can be concluded that AquaCrop reproduced quite well the main features of sugar beet production as a function of the water supply. Overall, the model performance may be considered satisfactory, particularly when compared with the performance of more complex models such as STICS in Reference [13], but not in Reference [14], or CSM-CERES-Beet [12], even when water stress conditions were not simulated, as in the latter. Therefore, the calibrated crop parameters for sugar beet can be used with confidence in AquaCrop under different environmental conditions and management and for a wide range of current varieties. However, while commercial varieties seem to have similar yield responses to water stress [44,45], the existence of lines with greater drought tolerance [44] could result in new commercial varieties (recent breeding priority) that may require a re-calibration of the crop water stress parameters in the future.

Once AquaCrop has been properly calibrated and validated, it is possible to use it for the simulation of some features that require excessive time and resources in field experimentation. An illustration of this potential is presented here, by simulating the potential yield and the irrigation

WP as a function of IWA in the two main production areas in Spain. The results highlighted that sowing time, associated with location and IWA, significantly impact sugar beet production and its irrigation WP in a given environment. The average potential yield and irrigation WP were higher in the South (autumn sowing) than in the North (spring sowing), with an irrigation water saving of 33%, which is a significant amount for a water-limited environment (Figures 6 and 7). These results can be attributed to the higher evaporative demand and the lower rainfall in spring sowing in the North, which causes a higher irrigation demand (Figure 5). On the other hand, the longer period in autumn sowings during which assimilates are translocated and accumulated in the roots leads to higher root yields. The benefits of autumn sowing have been reported by Reference [46] in a three-year experiment in another Mediterranean environment. Furthermore, the values of irrigation WP reported in Reference [46] for the autumn and spring sowings (5.6 and 4.1 g m^{-3} , respectively) are quite similar to those obtained in this case (6.1 and 3.7 g m^{-3} , respectively). In fact, even the evapotranspiration WP values were nearly identical (2.8 g m^{-3} with respect to 2.7 g m^{-3} simulated in this study). This confers a great reliability on the model performance and in the analysis we have carried out. In view of the results, in environments with low-risk of winter frost and with common summer drought, autumn sowings should be encouraged, both for their high yields and higher irrigation WP. Early plantings of sugar beet in Northern environments have also become a breeding priority, by selecting sugar beet lines with frost resistance [47] and bolting resistance [48].

Water authorities in many parts of the world have proposed to optimize water use through a proper IWA for each crop. AquaCrop can be a useful tool to carry out this undertaking, as has been demonstrated in this study. In the North, the curvilinear relationship between yield and AIW [8,49] was evident in the results ($p < 0.05$, Tukey test) (Figure 6a), increasing the yields almost 1.5 t ha^{-1} by increasing the IWA in 100 mm or with a yield decrease of around 3 t ha^{-1} under a 25% reduction in IWA (Figure 8a). This inversely impacts the irrigation WP (Figures 7a and 9a). The tradeoff between yield and irrigation WP must be taken into account by the water authorities and policymakers in their decisions not to compromise the profitability of the sugar beet production. On the contrary, in the South, an increase or reduction in IWA did not have a significant impact on the yields ($p < 0.05$, Tukey test) (Figures 6b and 8b) due to greater influence of the seasonal rainfall on yields. In this case, however, a high increase in irrigation WP was simulated under a 25% reduction in IWA (Figures 7b and 9b), which could lead to a significant improvement in the water use efficiency without having a significant yield penalty. In the South, under water scarcity situations, restrictions in IWA could be applied to sugar beet without having significant negative impacts when compared with the impact on summer crops or on sugar beet in the Northern area.

Author Contributions: Data curation, formal analysis, investigation, methodology, software, validation and writing – original draft, M.G.-V.; Funding acquisition and writing – review & editing, R.M.-V. and E.F.; Supervision, M.G.-V., R.M.-V. and E.F.

Funding: AIMCRA and the H2020 SHui project (Project number: 773903) funded this research.

Acknowledgments: We thank S. Blanco, J.A. Centeno, and C. Ruz for help with this work.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. FAOSTAT Database. Available online: <http://www.fao.org/faostat/en/#home> (accessed on 15 July 2019).
2. Rinaldi, M.; Horemans, S. Sugar beet. In *Crop Yield Response to Water*; Steduto, P., Hsiao, T.C., Fereres, E., Raes, D., Eds.; FAO: Rome, Italy, 2012; pp. 202–208.
3. Singels, A.; van der Laan, M. Sugarcane. In *Crop Yield Response to Water*; Steduto, P., Hsiao, T.C., Fereres, E., Raes, D., Eds.; FAO: Rome, Italy, 2012; pp. 174–180.
4. Sadeghian, S.Y.; Yavari, N. Effect of Water-Deficit Stress on Germination and Early Seedling Growth in Sugar Beet. *J. Agron. Crop Sci.* **2004**, *190*, 138–144. [CrossRef]
5. Davidoff, D.; Hanks, R.J. Sugar beet production as influenced by limited irrigation. *Irrig. Sci.* **1989**, *10*, 1–17. [CrossRef]

6. Pidgeon, J.D.; Werker, A.R.; Jaggard, K.W.; Richter, G.M.; Lister, D.H.; Jones, P.D. Climatic impact on the productivity of sugar beet in Europe, 1961–1995. *Agric. For. Meteorol.* **2001**, *109*, 27–37. [\[CrossRef\]](#)
7. Jones, P.D.; Lister, D.H.; Jaggard, K.W.; Pidgeon, J.D. Future climate impact on the productivity of sugar beet (*Beta vulgaris* L.) in Europe. *Clim. Chang.* **2003**, *58*, 93–108.
8. Fereres, E.; Soriano, M.A. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* **2007**, *58*, 147–159. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Werker, A.R.; Jaggard, K.W. Dependence of sugar beet yield on light interception and evapotranspiration. *Agric. For. Meteorol.* **1998**, *89*, 229–240. [\[CrossRef\]](#)
10. Doorenbos, J.; Kassam, A.H. *Yield Response to Water*; FAO Irrigation and Drainage Paper No. 33; FAO: Rome, Italy, 1979.
11. Qi, A.; Kenter, C.; Hoffmann, C.; Jaggard, K.W. The Broom's Barn sugar beet growth model and its adaptation to soils with varied available water content. *Eur. J. Agron.* **2005**, *23*, 108–122. [\[CrossRef\]](#)
12. Anar, M.J.; Lina, Z.; Hoogenboom, G.; Sheliab, V.; Batchelor, W.D.; Tebohe, J.M.; Ostlie, M.; Schatze, B.G.; Khanf, M. Modeling growth, development and yield of Sugarbeet using DSSAT. *Agr. Syst.* **2019**, *169*, 58–70. [\[CrossRef\]](#)
13. Beaudoin, N.; Launay, M.; Saubouac, E.; Ponsardina, G.; Marya, B. Evaluation of the soil crop model STICS over 8 years against the “on farm” database of Bruyeres catchment. *Eur. J. Agron.* **2008**, *29*, 46–57. [\[CrossRef\]](#)
14. Baey, C.; Didier, A.; Lemaire, S.; Maupas, F.; Cournède, P.-H. Parametrization of five classical plant growth models applied to sugar beet and comparison of their predictive capacity on root yield and total biomass. *Ecol. Model.* **2014**, *290*, 11–20. [\[CrossRef\]](#)
15. Lemaire, S.; Maupas, F.; Cournède, P.-H.; de Reffye, P. A morphogenetic crop model for sugar-beet (*Beta vulgaris* L.). In Proceedings of the International Symposium on Crop Modeling and Decision Support: ISCMDS 2008, Nanjing, China, 19–22 April 2008.
16. Taky, A. Maîtrise des Excès d'eau Hivernaux et de L'Irrigation et de Leurs Conséquences sur la Productivité de la Betterave Sucrière dans le Périmètre Irrigué du Gharb (Maroc). Analyse Expérimentale et Modélisation. Ph.D. Thesis, AgroParisTech, Paris, France, 2008.
17. Steduto, P.; Hsiao, T.C.; Raes, D.; Fereres, E. Aquacrop—The FAO Crop Model to Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agron. J.* **2009**, *101*, 426–437. [\[CrossRef\]](#)
18. Stricevic, R.; Cosic, M.; Djurovic, N.; Pejic, B.; Maksimovic, L. Assessment of the FAO AquaCrop model in the simulation of rainfed and supplementally irrigated maize, sugar beet and sunflower. *Agric. Water Manag.* **2011**, *98*, 1615–1621. [\[CrossRef\]](#)
19. Alishiri, R.; Paknejad, F.; Aghayari, F. Simulation of sugar beet growth under different water regimes and nitrogen levels by AquaCrop. *Int. J. Biosci.* **2014**, *4*, 1–9.
20. van Straaten, J.W. Regional Modelling of Water Stress. Irrigation Water Requirement Meets Water Availability in the Oum er Rbia Basin. Master's Thesis, Utrecht University, Utrecht, The Netherlands, 2017.
21. Malik, A.; Shakir, A.S.; Ajmal, M.; Khan, M.J.; Khan, T.A. Assessment of AquaCrop Model in Simulating Sugar Beet Canopy Cover, Biomass and Root Yield under Different Irrigation and Field Management Practices in Semi-Arid Regions of Pakistan. *Water Resour. Manag.* **2017**, *31*, 4275–4292. [\[CrossRef\]](#)
22. Araj, H.A.; Wayayok, A.; Khayamim, S.; Teh, C.B.S.; Abdullah, A.F.; Amiri, E.; Bavani, A.M. Calibration of AquaCrop model to simulate sugar beet production and water productivity under different treatments. *Appl. Eng. Agric.* **2019**, *35*, 211–219. [\[CrossRef\]](#)
23. Vanuytrecht, E.; Raes, D.; Willems, P. Regional and global climate projections increase mid-century yield variability and crop productivity in Belgium. *Reg. Environ. Chang.* **2016**, *16*, 659–672. [\[CrossRef\]](#)
24. Gobin, A.; Kersebaum, K.C.; Eitzinger, J.; Trnka, M.; Hlavinka, P.; Takác, J.; Kroes, J.; Ventrella, D.; Dalla Marta, A.; Deelstra, J.; et al. Variability in the water footprint of arable crop production across European regions. *Water* **2017**, *9*, 93. [\[CrossRef\]](#)
25. Geerts, S.; Raes, D.; Garcia, M. Using AquaCrop to derive deficit irrigation schedules. *Agric. Water Manag.* **2010**, *98*, 213–216. [\[CrossRef\]](#)
26. Garcia-Vila, M.; Fereres, E. Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. *Eur. J. Agron.* **2012**, *36*, 21–31. [\[CrossRef\]](#)
27. Carmona, G.; Varela-Ortega, C.; Bromley, J. Supporting decision making under uncertainty: Development of a participatory integrated model for water management in the middle Guadiana river basin. *Environ. Model. Softw.* **2013**, *50*, 144–157. [\[CrossRef\]](#)

28. Liu, J.; Pattey, E. Retrieval of leaf area index from top-of-canopy digital photography over agricultural crops. *Agric. For. Meteorol.* **2010**, *150*, 1485–1490. [CrossRef]
29. Raes, D.; Steduto, P.; Hsiao, T.C.; Fereres, E. Chapter 3. Calculation procedures. In *AquaCrop Version 6.0—6.1. Reference Manual*; Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., Eds.; FAO: Rome, Italy, 2018; pp. 1–141.
30. Raes, D.; Steduto, P.; Hsiao, T.C.; Fereres, E. AquaCrop—The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agron. J.* **2009**, *101*, 438–447. [CrossRef]
31. Hsiao, T.C.; Fereres, E.; Steduto, P.; Raes, D. AquaCrop parameterization, calibration, and validation guide. In *Crop Yield Response to Water*; Steduto, P., Fereres, E., Raes, D., Eds.; FAO: Rome, Italy, 2012; pp. 70–87.
32. Vanuytrecht, E.; Raes, D.; Willems, P. Global sensitivity analysis of yield output from the water productivity model. *Environ. Model. Softw.* **2014**, *51*, 323–332. [CrossRef]
33. Saxton, K.E.; Rawls, W.J. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Sci. Soc. Am. J.* **2006**, *70*, 1569–1578. [CrossRef]
34. Willmott, C.J. Some comments on the evaluation of model performance. *Bull. Meteorol. Soc.* **1982**, *63*, 1309–1313. [CrossRef]
35. CLIMAGEN. Available online: <http://www.uco.es/fitotecnia/contents/index.html> (accessed on 15 July 2019).
36. Geng, S.; Auburn, J.S.; Brandstetter, E.; Li, B. *A Program to Simulate Meteorological Variables: Documentation for SIMMETEO*; Agronomy Progress Rep. 204; Dep. of Agronomy and Range Science, Univ. of California: Davis, CA, USA, 1988.
37. Milford, G.F.J.; Pocock, T.O.; Riley, I. An analysis of leaf growth in sugar beet. I. Leaf appearance and expansion in relation to temperature under controlled conditions. *Ann. Appl. Biol.* **1985**, *106*, 163–172. [CrossRef]
38. Terry, N. Developmental Physiology of Sugar Beet: I. The influence of light and temperature on growth. *J. Exp. Bot.* **1968**, *19*, 795–811. [CrossRef]
39. Radke, J.K.; Bauer, R.E. Growth of Sugar Beets as Affected by Root Temperatures. Part I: Greenhouse Studies. *Agron. J.* **1969**, *61*, 860–863. [CrossRef]
40. Werker, A.R.; Jaggard, K.W.; Allison, M.F. Modelling partitioning between structure and storage in sugar beet: Effects of drought and soil nitrogen. *Plant Soil* **1999**, *207*, 97–106. [CrossRef]
41. Fereres, E. Short and Long-Term Effects of Irrigation on the Fertility and Productivity of Soils. In Proceedings of the 17th Colloquium of the International Potash Institute, Bern, Switzerland, 2–6 May 1983; pp. 283–304.
42. Hsiao, T.C.; Heng, L.; Steduto, P.; Rojas-Lara, B.; Raes, D.; Fereres, E. AquaCrop—The FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. *Agron. J.* **2009**, *101*, 448–459. [CrossRef]
43. Espadafor, M.; Couto, L.; Resende, M.; Henderson, D.W.; García-Vila, M.; Fereres, E. Simulation of the responses of dry beans (*Phaseolus vulgaris* L.) to irrigation. *Trans. ASABE* **2017**, *60*, 1983–1994. [CrossRef]
44. Ober, E.S.; Luterbacher, M.C. Genotypic variation for drought tolerance in *Beta vulgaris*. *Ann. Bot.* **2002**, *89*, 917–924. [CrossRef]
45. Hoffmann, C.M.; Huijbregts, T.; Van Swaaij, N.; Jansen, R. Impact of different environments in Europe on yield and quality of sugar beet genotypes. *Eur. J. Agron.* **2009**, *30*, 17–26. [CrossRef]
46. Rinaldi, M.; Vonella, A.V. The response of autumn and spring sown sugar beet (*Beta vulgaris* L.) to irrigation in southern Italy: Water and radiation use efficiency. *Field Crops Res.* **2006**, *95*, 103–114. [CrossRef]
47. Reinsdorf, E.; Koch, H.J.; Märlander, B. Phenotype related differences in frost tolerance of winter sugar beet (*Beta vulgaris* L.). *Field Crops Res.* **2013**, *151*, 27–34. [CrossRef]
48. Hoffmann, C.M.; Kluge-Severin, S. Growth analysis of autumn and spring sown sugar beet. *Eur. J. Agron.* **2011**, *34*, 1–9. [CrossRef]
49. Stewart, J.I.; Hagan, R.M. Functions to predict effects of crop water deficits. *J. Irrig. Drain. Div.* **1973**, *99*, 421–439.

