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Research Paper

Modelling the response of tomato on deficit irrigation under greenhouse conditions

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ABSTRACT

To optimize crops irrigation strategy is crucial to improve the production sustainability in a climate change scenario characterized by an ever-increasing water shortage. Crops simulation models, combined with experimental data, can be useful tools. AquaCrop, a crop water productivity model, has been widely used to reach this aim in open field condition but it has been limited adopted under greenhouse conditions. This study aims to calibrate and validate AquaCrop model through a greenhouse tomato cultivation using a split plot experimental design. Crop irrigation management was the main treatment [full irrigation (FI) at 100 % crop evapotranspiration (ET_c) vs. deficit irrigation (DI) at 75 % of FI] and fertilization [no fertilization, mineral fertilization, organic fertilization with compost, and organic fertilization with sieved (< 2 mm) compost] the subplots. Fresh yield, above-ground biomass, water productivity, and net irrigation requirements were simulated. The validated model also permitted to evaluate the impacts of changing temperature outside the greenhouse on fruits yield, biomass, and water productivity using 30 years of historical weather data. The results showed that the model accurately estimated crop parameters, although it tended to overestimate soil water content. On average, DI reduced fruit yield by 14.1 % compared to FI. Over the last 30 years, the validated model permitted to calculate an average fruits yield reduction due to DI of 12.6 %. Our findings suggest that models like AquaCrop can assist in optimizing greenhouse agriculture by predicting crop performance under different conditions. Our study also highlights that external temperature and AquaCrop can be used to estimate tomato yields in the greenhouse by providing decision support tools for end-users (farmers, farmer associations, and policymakers) seeking sustainable and efficient greenhouse farming practices in a changing climate.

1. Introduction

Ensuring food production is one of the major challenges that agriculture faces in the context of climate change, with increasing temperatures, reduced available water resources, and simultaneous global population growth (Hanjra and Qureshi, 2010; Wheeler and von Braun, 2013). Globally, irrigated lands represent 20 % of cultivated land but account for 40 % of production (Molden et al., 2010; FAO, 2014). This highlights that irrigation is a fundamental agronomic technique for achieving high yields (Ahmad et al., 2021) and ensuring food security in the coming decades. However, considering that the agricultural sector alone accounts for approximately 70 % of total freshwater withdrawals (McDermid et al., 2023), significant efforts are required to reduce the volumes of water used, especially in water-stressed conditions. Therefore, better water resource management is necessary to avoid a reduction in irrigable areas. The adoption of those strategies that help reduce irrigation volumes without compromising yield (Nangare et al., 2016), thereby increasing water use efficiency (WUE) is crucial (Khapte et al., 2019).

There are two main approaches to increase WUE, which can also be adopted simultaneously. The first involves using drought-resistant cultivars, although their genetic selection has been challenging and their

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Table 1
Soil physico-chemical characteristics (dry weight basis) at the beginning of the experiment.

Parameters	Value
Field capacity	34.0 %
Permanent wilting point	13.5 %
Bulk density	1.45 Mg m^{-3}
Organic carbon	0.74 %
Total Kjeldhal nitrogen	0.09 %
NO_3^-	98.4 mg kg^{-1}
PO_4^{3-}	1.6 mg kg^{-1}
K^+	2589.4 mg kg^{-1}

Table 2
Chemical composition of compost (dry weight basis) used for organic fertilization.

Element	Content
Total N	1.99 %
Total C	22.41 %
P	6373 mg kg^{-1}
K	26,549 mg kg^{-1}
Cd	0.74 mg kg^{-1}
Cr	36.96 mg kg^{-1}
Cu	104.64 mg kg^{-1}
Pb	37.37 mg kg^{-1}
Zn	247.55 mg kg^{-1}

widespread use is limited. The second approach involves adopting more efficient irrigation techniques, such as drip irrigation systems, which reduce surface runoff and evaporation losses (Khapte et al., 2019), as well as implementing deficit irrigation (DI) practices (Patanè et al., 2011; Douh et al., 2021; Kiyan et al., 2022).

DI is a water-saving strategy that involves the application of a reduced irrigation volume compared to those necessary to satisfy the crop's maximum evapotranspiration (ET_c). This practice significantly reduces irrigation volumes, but increased WUE is achieved only if the yield reduction is limited. Therefore, it is crucial to determine the appropriate level of stress to apply and understand the crop's behavior at different growth stages (Zhang et al., 2017; Khapte et al., 2019; Mukherjee et al., 2023). In addition to the timing and stage at which stress is imposed, the intensity of stress also influences WUE. Wang et al. (2011) found that applying 1/3 or 2/3 of FI amount at the flowering and fruit development stage and no water stress in other growth stages appears to be the suitable irrigation scheduling with a compromise between higher yield and better quality. Similarly, Jiang et al. (2019) confirmed an acceptable balance between high WUE and yield supplying 2/3 of FI at flowering and fruit development.

Crop productivity is influenced not only by water but also by nutrient availability (Wang and Xing, 2017). However, excessive use of synthetic fertilizers has resulted in negative impacts, such as a progressive decrease in soil organic matter, greenhouse gas emissions, increased soil acidity, deterioration of soil physical properties leading to reduced water retention capacity, increased runoff, and erosion (Chandini et al., 2019).

Field experiments are being implemented to understand the impacts of different agronomic practices on the yield and water productivity of crops. However, this is always labor-intensive and costly and produces variable results due to variations in agrometeorological factors. For this reason, greenhouse experiments offer an alternative way since growing conditions are under control. On the other hand, crop growth models are good options for predicting crop responses to various weather conditions and field management practices. One example is AquaCrop which is a water-driven model developed by Food and Agriculture Organization (FAO). After it was initially released, many developments have been made in this software and applications have been extended to various crops and geographical regions including crops that have been grown in greenhouse conditions (Sabzian et al., 2021; Cheng et al., 2022). However, to our knowledge only few studies have been conducted under greenhouse conditions to calibrate and validate this model. Khafajeh et al. (2020) reported that cucumber grown in greenhouse hydroponics, AquaCrop model can estimate evapotranspiration with the least error, also estimating the crop yield and biomass product. In view of this, the model can be used for irrigation planning if properly optimized and applied. Cheng et al. (2022) in a greenhouse cherry tomato experiment designed to evaluate different irrigation levels and N fertilizer rates reported that AquaCrop model adequately simulated the above-ground biomass and final fruit yield. However, they also observed that the model severely overestimated soil water content (SWC), especially under full irrigation, and largely underestimated the ET.

Taking into account the above-reported considerations, the objectives of this study were to: 1) parametrize and evaluate the AquaCrop model for tomato (*Lycopersicum esculentum* L., one of the most water demanding crop) under greenhouse conditions; 2) simulate the fresh yield, above-ground biomass, water productivity, and net irrigation requirements (NIR) of tomato under greenhouse conditions in a climate change scenario.

2. Materials and methods

2.1. Experimental site

The experiment was conducted on tomato from June to September 2022 in a polyethylene greenhouse tunnel at the "L. Toniolo" experimental farm of the University of Padova, located in North-Eastern (45°21′00″ N, 11°57′02″ E; 7 m a.s.l.) Italy. The tunnel was 50 m long and 8 m wide, central height 4.5 m and ceiling height of 2.3 m. It was covered with high-density transparent polyethylene diffuser film to exclude rainwater and shaded at 50 % rate. The side and front openings were equipped with an insect net. Considering tunnel characteristics and small volume, a determinate tomato genotype (HEINZ 1281 F1 - Furia Seed) was chosen.

The climate of the area is subhumid with an average annual temperature of 13.5 °C. The average annual precipitation (1994–2021) is 830 mm, but reference evapotranspiration (ET_0) usually exceeds precipitation from April to September by an average of about 260 mm (Berti et al., 2014).

The soil is Fluvi-Calcaric Cambisol (CMcf) with a silty-loam texture (IUSS Working Group WRB, 2015). The main soil physico-chemical characteristics are summarized in Table 1.

2.2. Experimental design and data collection

The adopted experimental design was a split plot with two replicates. Crop irrigation management was the main treatment [full irrigation (FI) at 100 % crop evapotranspiration (ET_c) vs. DI at 75 % of FI] and fertilization [no fertilization, mineral fertilization, organic fertilization with compost, and organic fertilization with sieved (< 2 mm) compost] in subplots.

Tomato was transplanted on June 14th, 2022 with a planting density of 2.5 plants m^{-2} and harvested on September 27th, 2022. Before transplanting the soil was tilled two times (15 days and 1 day before transplanting) with rotary tiller. The fertilization was carried out between the two tillage events supplying 150 kg N ha^{-1}, 100 kg P_2O_5 ha^{-1} and 200 kg K_2O ha^{-1}. The chemical composition of compost used for organic fertilization is presented in Table 2. The tomato agronomic management like weeds, disease, and pest control followed the typical local practices except for irrigation and fertilization.

The crop irrigation was carried out by using a drip irrigation system (Irritec IT, in line emitters, 2 L h^{-1}, spaced 0.3 m) installed the day before transplanting. Just after transplanting, an irrigation to replenish the soil field capacity was performed to overcome the transplanting stress. After this, during the growing season, the irrigation was managed

Table 3
Input parameters in simulating the response of tomato using AquaCrop.

Parameter	*Default value	Value	Unit	Remarks
Crop phenology				
Base temperature (T_{base})	7	7	°C	Default value
Upper temperature (T_{upper})	28	2 8	°C	Default value
Soil surface covered by an individual seedling	5.0 to 20 (transplant)	15.0	cm^2 $plant^{-1}$	Measured value
Number of plants per hectare	15,000 – 80,000	25,333	plants ha^{-1}	Estimated value
**Transplant to recovery	40 – 80	5	day	Measured value
**Canopy growth coefficient (CGC)	0.0075	Very fast expansion (20.7) - deficit Very fast expansion (21) - full	% day^{-1}	Calibrated value
Maximum canopy cover (%)	Fairly to almost entirely covered	Well covered (80) - deficit Almost entirely covered (90) - full	%	Measured value
**Time from transplant to start senescence	Recovery + 1300 – 1600	73	day	Measured value
**Canopy decline coefficient (CDC)	0.004	Slow decline (9.7)	% day^{-1}	Calibrated value
**Time from transplant to maturity	Recovery + 1500 – 2000	106	day	Measured value
**Time from transplant to flowering	Recovery + 250 – 400	(35) calibration (21) validation	day	Measured value
**Length of the flowering stage	600 – 900	44	day	Measured value
Crop determinacy linked with flowering	No	No	–	Default value
Minimum effective rooting depth (Z_n)	0.30	0.30	m	Default value
Maximum effective rooting depth (Z_x)	Up to 2.00	Shallow-medium rooted crop (0.60)	m	Measured value
Shape factor describing root zone expansion	1.5	1.5	–	Default value
Crop transpiration				
Crop coefficient when canopy is complete but prior to senescence	1.10	1.10	–	Default value
Decline of crop coefficient as a result of ageing, nitrogen deficiency, etc.	0.15	0.15	% day^{-1}	Default value
Effect of canopy cover on reducing soil evaporation in late season stage	60	60	%	Default value
Biomass production and yield formation				
Water productivity normalized for ET_0 and CO_2	18.0	18.0	g m^{-2}	Default value
Water productivity normalized for ET_0 and CO_2 during yield formation (as percent WP* before yield formation)	100	100	%	Default value
Reference harvest index (HI)	55 – 65	60	%	Estimated value
Possible increase (%) of HI due to water stress before flowering	None	Small - deficit None - full	–	Estimated value
Excess of potential fruits	Large	Small (50)	%	Estimated value
Coefficient describing positive impact of restricted vegetative growth during yield formation on HI	None	None - deficit Small - full	–	Default value Estimated value
Coefficient describing negative impact of stomatal closure during yield formation on HI	Strong	Small - deficit None - full	–	Estimated value
Allowable maximum increase (%) of specified HI	15	15	%	Default value
Soil water stress				
Soil water depletion threshold for canopy expansion - Upper threshold	0.15	0.10 - deficit 0.30 - full		Estimated value
Soil water depletion threshold for canopy expansion - Lower threshold	0.55	0.47 - deficit 0.65 - full		Estimated value
Shape factor for Water stress coefficient for canopy expansion	3.0	3.0		Default value
Soil water depletion threshold for stomatal control - Upper threshold	0.50	0.50		Default value
Shape factor for Water stress coefficient for stomatal control	3.0	3.0		Default value
Soil water depletion threshold for canopy senescence - Upper threshold	0.70	0.70		Default value
Shape factor for Water stress coefficient for canopy senescence	3.0	3.0		Default value
Soil water depletion threshold for failure of pollination - Upper threshold	0.92	0.92		Default value
Vol% at anaerobiotic point (with reference to saturation)	5.0	5.0		Default value

*Source: Raes et al. (2022); ** values in growing degree days unit.

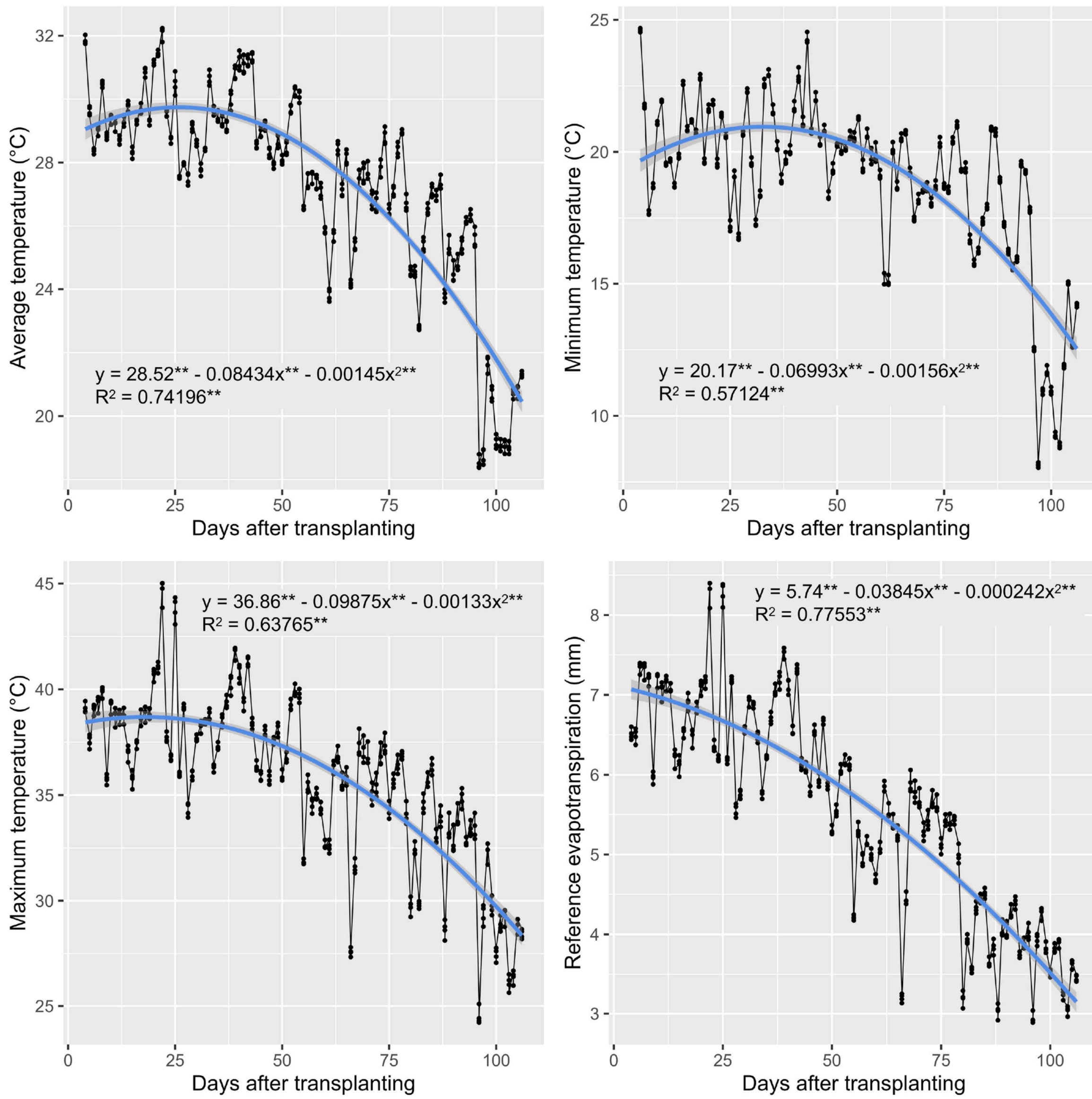

Fig. 1. Average (based on the 24 h readings), minimum, and maximum temperature and reference evapotranspiration during the 2022 growing cycle.

to replace the soil field capacity in the 0–60 cm profile in the FI treatment whereas the DI treatment was supplied with 75 % of the water volume distributed in FI.

The soil moisture content was measured and monitored using Teros 10 (METER Group, Inc., Pullman, WA, USA) volumetric water content sensors. The sensors were installed at 20, 40, and 60 cm depths in one replicate for each treatment for a total of eight measurement points (2 irrigation levels x 4 fertilization types) to measure the soil moisture at the effective root zone (ERZ) depth of tomato crop. Each of the main plots was equipped with a flowmeter to detect the cumulative water volume applied during the whole growing season. The soil water content (SWC) in the ERZ at every 20 cm depth was calculated using Eq. (1) (Adeboye et al., 2017; Morales-Santos et al., 2023):

$$\mathrm{SWC} = \sum_{i=1}^{n} \theta_i \times z_i \tag{1}$$

Where SWC is the total soil water content in the ERZ (mm), θ_i is the water content for soil layer i (m^3 m^{-3}), z is the soil depth for layer i (mm), and n is the number of soil layers within the root zone.

On the other hand, the cumulative growing season actual evapotranspiration (ET_a) was estimated using a simplified soil water balance formula, Eq. (2) (Lhomme and Katerji, 1991; Cheng et al., 2022):

$$ET_a = \pm \Delta W + I \tag{2}$$

Where $\pm$ ΔW is the difference in soil water storage in the 0–60 cm soil profile (mm) at the beginning and at the end of the experiment and I is the total irrigation amount supplied during the growing cycle (mm).

From June 28th to September 6th, on a weekly basis, the main morphological (plant height and stem diameter) and phenological (flowering date) parameters were monitored in three plants per plot. In the same three plants, at the harvest time (September 28th), the fruit yield and the plant above-ground dry biomass (65 °C) were also determined.

2.3. Model description and input parameters

The AquaCrop version 7.0 was used for the simulations. The model simulates daily biomass production and final crop yield. It considers factors such as water supply, consumption, and agronomic management, incorporating current concepts of plant physiology, soil water, and salt budgeting (Vanuytrecht et al., 2014; Raes et al., 2022). The AquaCrop requires several input parameters including climate, crop, management,

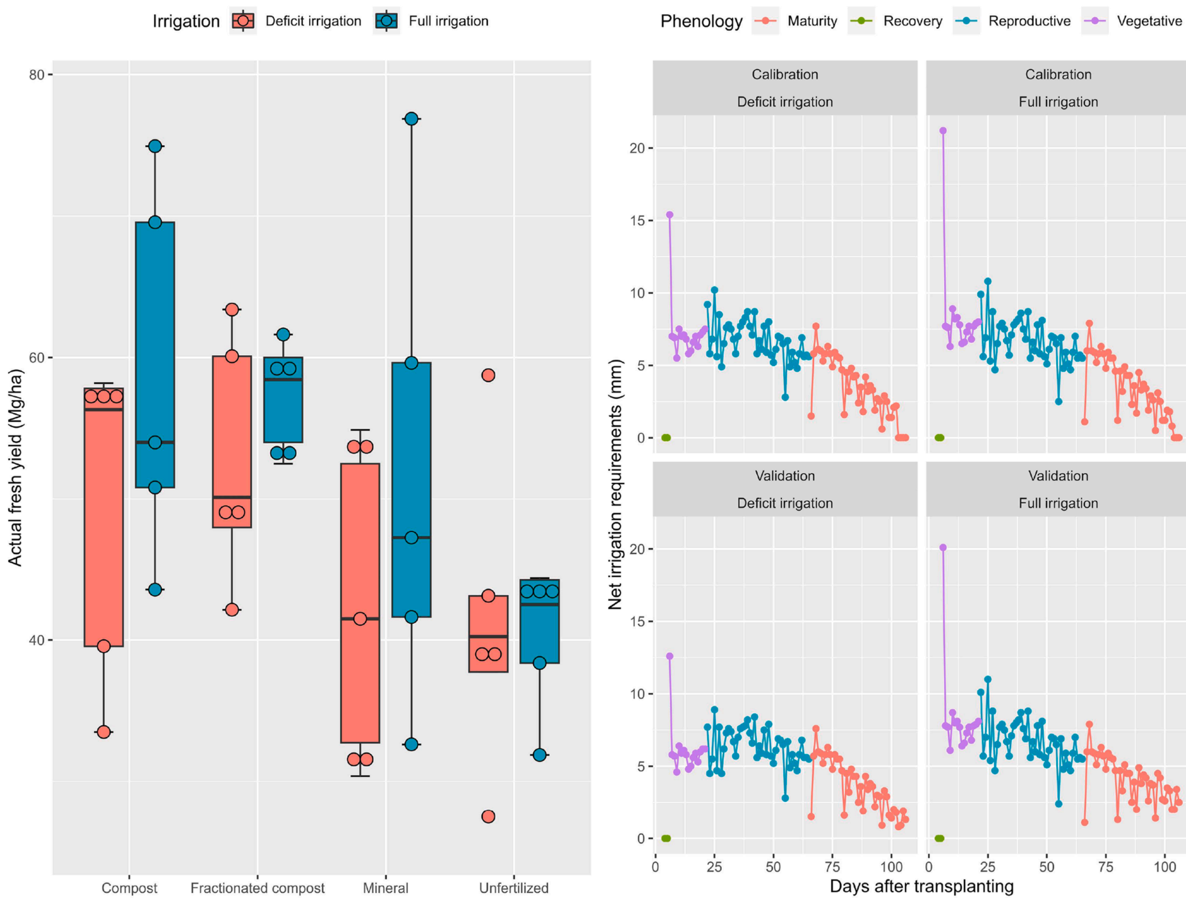

Fig. 2. Observed yield in the mineral and unfertilized treatments used for calibration and compost and fractionated compost used for validation, and simulated net irrigation requirements (NIR) for the 2022 growing cycle.

Table 4
Performance evaluation of AquaCrop model in simulating yield and soil water content using several statistical indices such as root mean square error (RMSE), normalized root mean square error (NRMSE), and Nash-Sutcliffe model efficiency (NS).

	Yield		Soil water content	
	Full	*Deficit*	*Full*	*Deficit*
RMSE	4.87 (5.21)	0.35 (3.97)	1.28 (1.03)	1.27 (1.11)
NRMSE	10.59 (9.00)	0.83 (8.19)	0.78 (0.61)	0.78 (0.67)
NS	−0.48 (−135.34)	−0.14 (−98.85)	−2.19 (−0.68)	−3.05 (−0.58)

values inside parenthesis are for validation.

and soil data.

The basic climate inputs in AquaCrop include precipitation (mm), solar radiation (MJ m^{-2} day^{-1}), minimum and maximum air temperature (°C), relative humidity (%), and wind speed (m s^{-1}) to calculate the daily ET_0 based on the FAO Penman-Monteith method (Allen et al., 1998). However, since this study was conducted in the greenhouse, the ET_0 was calculated using the Hargreaves equation (Eq. (3)) calibrated specifically for the Veneto region (Berti et al., 2014).

$$ET_{0,Har} = H_A \times R_e(T + 17.8) \times \Delta T^{H_E} \quad (3)$$

Where H_A and H_E are the empirical parameters (standard values: H_A = 0.0020 and H_E = 0.5), R_e is the water equivalent of the terrestrial radiation (mm d^{-1}), T is the mean temperature ($(T_{max} + T_{min})/2$ °C) and ΔT is the difference between maximum and minimum temperature.

The meteorological data were recorded outside and inside the greenhouse. Specifically, the outside meteorological data such as solar radiation, air temperature, air humidity, rain, and wind speed were obtained from the Veneto Regional Agency for Environmental Protection (ARPAV) agrometeorological station (www.arpav.it) located 200 m away from the greenhouse. The long-term meteorological data (1993–2022) were also obtained from this station. Inside the greenhouse, air temperature was recorded in four points distributed along the longitudinal transect with sensors positioned 1 m above the soil level.

A climate file was then created consisting of minimum and maximum temperature, ET_0, rainfall, and CO_2 files. The precipitation was zero since the tomato was grown in greenhouse conditions while ET_0 was directly imported after it was calculated using Eq. (3). AquaCrop considers by default a CO_2 concentration of 369.41 ppm by volume as the reference. It is the average atmospheric CO_2 concentration measured at Mauna Loa Observatory in Hawaii since 1958 and is valid for simulations using historical climatic data (Raes et al., 2022).

The crop input file was created based on model defaults, and calibrated parameters from Raes et al. (2022) and the experimental results of this study (Table 3). The cultivar-specific and non-conservative crop parameters were adjusted since they vary with the selected cultivar and might be affected by field management, conditions in the soil profile, or the climate.

For the management, an irrigation file was created considering 50 % readily available water (RAW) to determine the net irrigation requirements (NIR) of tomato across the growing cycles.

A soil profile file was created using the soil characteristics of the sites (Table 1) to simulate the retention of water in the ERZ and soil water movement (Raes et al., 2022). In addition, the initial SWC was also included in the model by specifying the measurements from the sensors at particular depths.

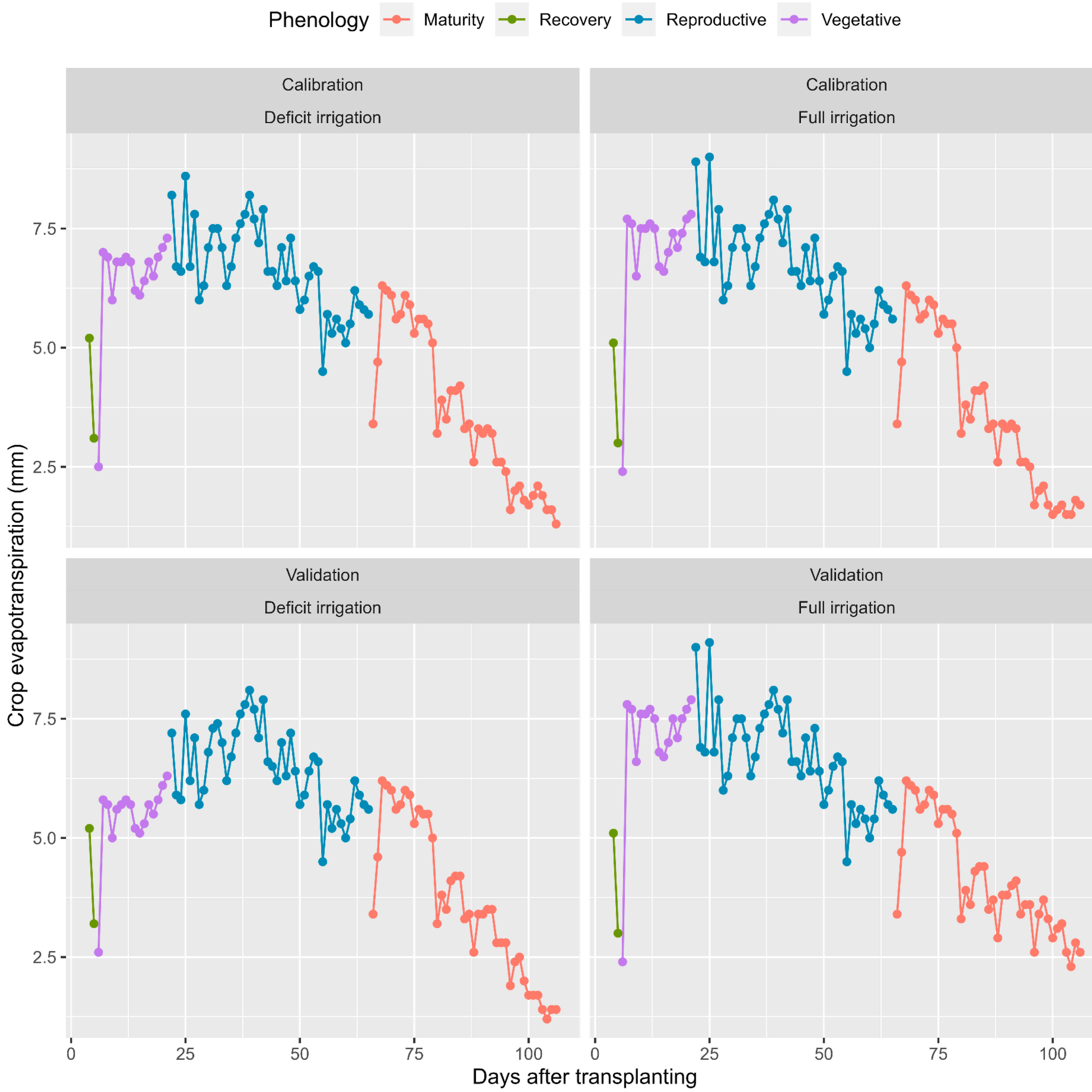

Fig. 3. Crop evapotranspiration (ET_c) for the 2022 growing cycle.

2.4. *Model application, calibration, and validation*

Experimental data from unfertilized and mineral fertilization treatments were used for the calibration while fertilization treatments involving compost and fractionated compost were used for validation. Phenology plays a critical role in accurately simulating crop development during the calibration process. The start of flowering differs between the fertilization treatments, thus, phenology was refined during both calibration and validation process by specifying the actual flowering date in the model. Several important parameters such as canopy development, flowering and yield formation, root deepening, and soil water stress were adjusted by trial and error method within the range of value provided by the user manual (Raes et al., 2022) and the fine-tuning procedure given by Vanuytrecht et al. (2014). Some default parameters provided by the manual were adopted directly, especially the ones that are conservative and generally applicable for tomato crop.

The calibrated and validated model was further evaluated using the 30-year past historical data in Legnaro, Italy. Statistical indices were used to evaluate the performance of the AquaCrop model. The most recommended ones that are scientifically sound and deemed relevant for the calibration and validation are root-mean-square error (RMSE) (Eq. (4)), normalized root mean square error (NRMSE) (Eq. (5)) as the error index, and Nash-Sutcliffe model efficiency (NS) (Eq. (6)) as the dimensionless index.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{4}$$

$$\text{NRMSE} = \frac{RMSE}{\overline{O}} \times 100 \tag{5}$$

$$\text{NS} = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{6}$$

Where: O_i is the measured data, $\overline{O}$ is the mean of measured data, S_i is the simulated data, $\overline{S}$ is the average of simulated data, and n is the number of observations.

For RMSE and NRMSE, values close to 0 indicate perfect model performance. Furthermore, the NRMSE values were classified as: <10 % - excellent, 10–20 % - good, 20–30 % - fair, and >30 % - poor (Jamieson et al., 1991). On the other hand, NS values close to 1 indicate perfect

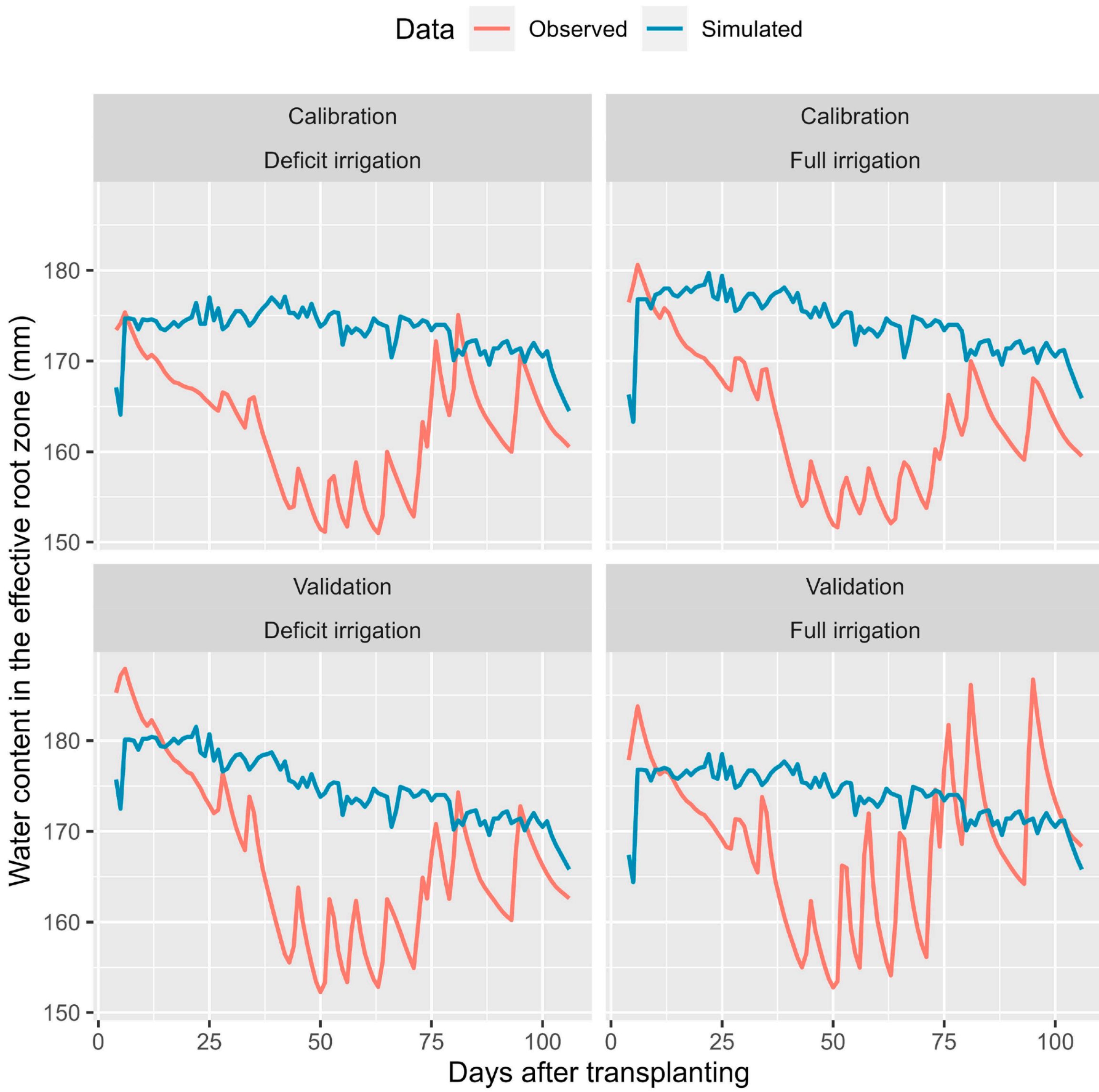

Fig. 4. Observed and simulated soil water content (SWC) in the effective root zone of tomato (0.6 m) for the 2022 growing cycle.

model performance while negative values of NS implies that the mean of the observed data would be a better predictor than the model (Lyle et al., 2013).

3. Results and discussion

3.1. Dynamics of meteorological variables

The average, minimum, and maximum temperatures and ET_0 inside the greenhouse during the 2022 growing cycle showed high variability and a significant decreasing trend ($R^2 = 0.571–0.776$) with about 10 °C and 3.0 mm difference from the start to end of the growing cycle (Fig. 1). The AquaCrop model uses temperature data to calculate the growing degree days which determine crop development and phenology including adjustment in crop transpiration during cold periods, while the ET_0 is used as a measure of the evaporative demand of the atmosphere (Raes et al., 2022). A recent review by Alsamir et al. (2021) discussed the detrimental effects of high temperatures on the reproductive physiology of tomato. In this study, though the average and maximum temperatures reached up to 32 °C and 45 °C respectively, this did not occur during the peak of the reproductive stage which is the most critical phenological phase of tomato. Furthermore, there was no detected temperature stress during the simulations.

3.2. Yield, NIR, and crop evapotranspiration

Tomato fresh yield in FI and DI treatments, on average of mineral and unfertilized treatments, was 45.94 and 41.94 Mg ha^{-1}, respectively, having a percentage reduction of 8.7 % (Fig. 2). On the other hand, it was relatively higher on the average of compost and fractionated compost with a value of 57.94 and 48.51 Mg ha^{-1} under FI and DI, respectively, having a percentage reduction of 16.3 %. In open field conditions, similar tomato yield reduction was observed by Lahoz et al. (2016) (−16.4 %) applying DI at 75 % ET_c and by Patanè et al. (2020) (−15.8 %) applying DI at 50 % of ET_c. Whereas no effect on tomato marketable yield was detected by Patanè et al. (2011) with a DI equal to 50 % of ET_c level. Under greenhouse conditions, applying a DI of 75 % ET_c during the whole growing season, a tomato yield reduction of 15 % was found by Al-Harbi et al. (2015) and of 3 % by Wu et al. (2022). Statistical analysis showed that the differences in fresh yield between fertilization ($F = 3.53, p < 0.05$) were significant but not in irrigation ($F = 2.14, p = 0.15$) treatments indicating less detrimental effects of DI on the yield of tomato. No significant interaction was detected statistically between fertilization and irrigation treatments ($F = 0.51$, $p = 0.68$).

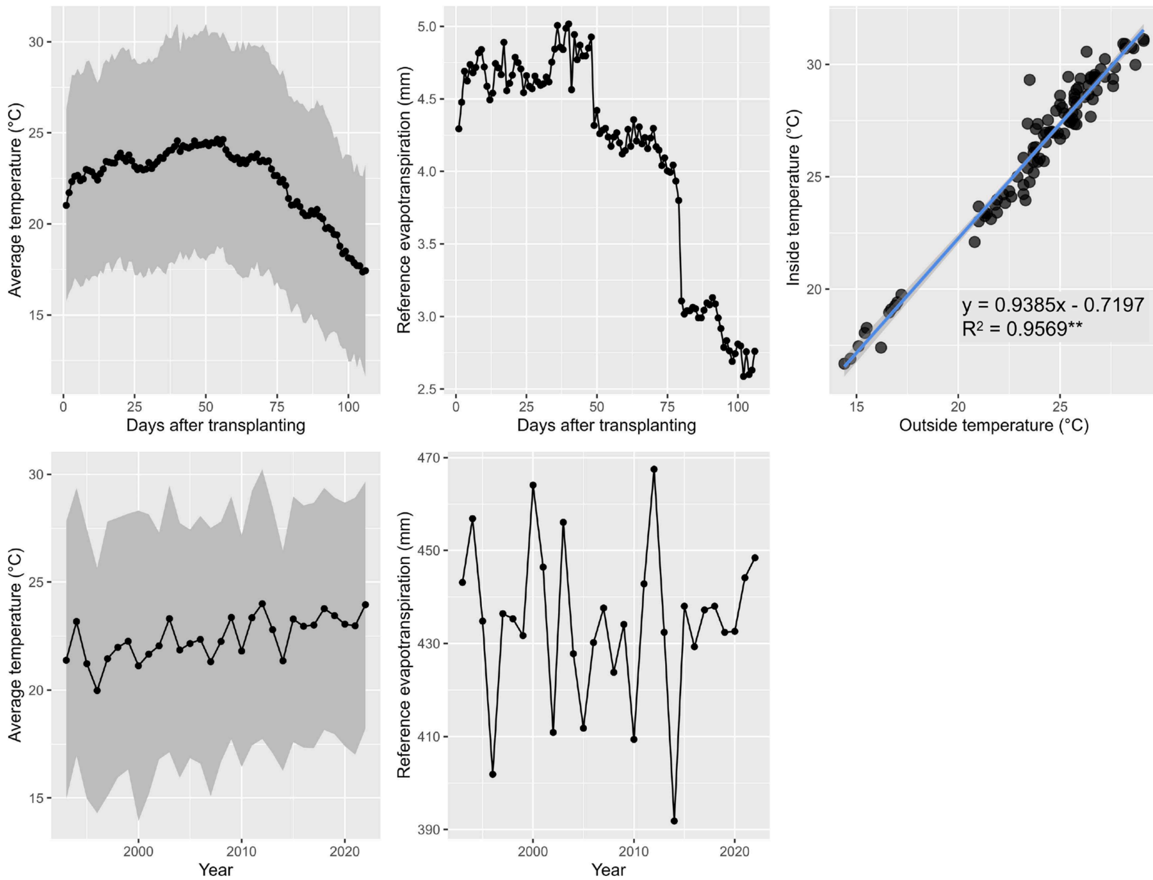

Fig. 5. Correlation between inside and outside temperature in the greenhouse, and reference evapotranspiration (ET_0) and average temperature during tomato growing season from 1993 to 2022. The grey shaded areas in the average temperature represent the minimum and maximum temperature.

AquaCrop simulated well the tomato yield with a value of 49.85 and 42.11 Mg ha^{-1} for FI and DI treatments during the calibration, and 50.60 and 42.92 Mg ha^{-1} during the validation. The results of the evaluation of the model using several statistical indices are presented in Table 4. The NRMSE values in FI were 10.59 and 9.00 whereas, 0.83 and 8.90 in DI indicating good to excellent performance of the model. The obtained results agree with previous findings reported under greenhouse conditions for tomato by Cheng et al. (2022), lettuce by Sabzian et al. (2021), and for cucumber by Khafajeh et al. (2020).

The NIR is the seasonal amount of irrigation water needed to keep the water content in the soil profile above the specified threshold of depletion to avoid yield loss (Raes et al., 2022). The results showed that the trend of NIR across the growing cycle was decreasing. Higher NIR was observed at the beginning of the vegetative phase of both irrigation treatments though it is more obvious in FI treatment (Fig. 2). Furthermore, there is no statistical evidence that NIR differs between FI and DI ($F = 2.62$, $p = 0.11$). Calibration of the model resulted in 540 and 527 mm NIR for FI and DI treatments whereas, validation resulted in 541 and 476 mm. These NIRs are higher than the actual irrigation water supplied during the 2022 growing cycle (FI = 320 mm; DI = 240 mm).

The same trend was observed for ET_c in FI and DI both for calibration and validation. It increased at the beginning of the vegetative stage until the second half of the reproductive stage then decreased until maturity (Fig. 3). There was also no statistical evidence that ET_c differs between FI and DI ($F = 3.35$, $p = 0.07$). The simulated ET_c was 546 and 534 mm for FI and DI during the calibration whereas, it was 548 and 490 mm during the validation.

3.3. *Soil water content*

In general, the observed SWC in the tomato ERZ of 0.6 m is fluctuating. The SWC decreased from the start to the early stage of maturity and suddenly increased towards the end of the growing cycle with about 17 and 12 mm difference in FI and DI treatment during the calibration. It was a little bit higher during validation with about 20 and 23 mm difference. Statistical analysis showed that the SWC of FI was not significantly different than DI ($F = 1.52$, $p = 0.22$) while the observed and simulated SWC were significantly different ($F = 407.30$, $p < 0.01$). Although an overestimation of SWC was observed for both irrigation treatments, the AquaCrop model simulated well the SWC of the tomato (Fig. 4). This is further supported by the results of the evaluation of the model with NRMSE values of 0.78 and 0.61 for FI and 0.78 and 0.67 for DI indicating excellent performance (Table 4). In a greenhouse experiment on cherry tomato, Cheng et al. (2022) also observed an overestimation of SWC, especially under FI treatment.

3.4. *Impacts of changing temperature and 30 years simulation*

Irrigation requirements of crops grown in a greenhouse or screenhouse, where ET of a reference crop outdoors may not be relevant, are much less documented (Hadad et al., 2020). During the 2022 growing cycle, there was a high correlation ($R^2 = 0.96$) between the inside and outside temperatures in the greenhouse (Fig. 5) with about a 2.5 °C increase on the inside. Our observation agrees with Chaves et al. (2021) that reported a very good correlation between temperatures inside and outside the greenhouse. In contrast, Hadad et al. (2020) reported a low correlation in sweet peppers grown in the greenhouse and screenhouse ($R^2 = 0.003$ to 0.35). Based on the correlation observed in 2022, we

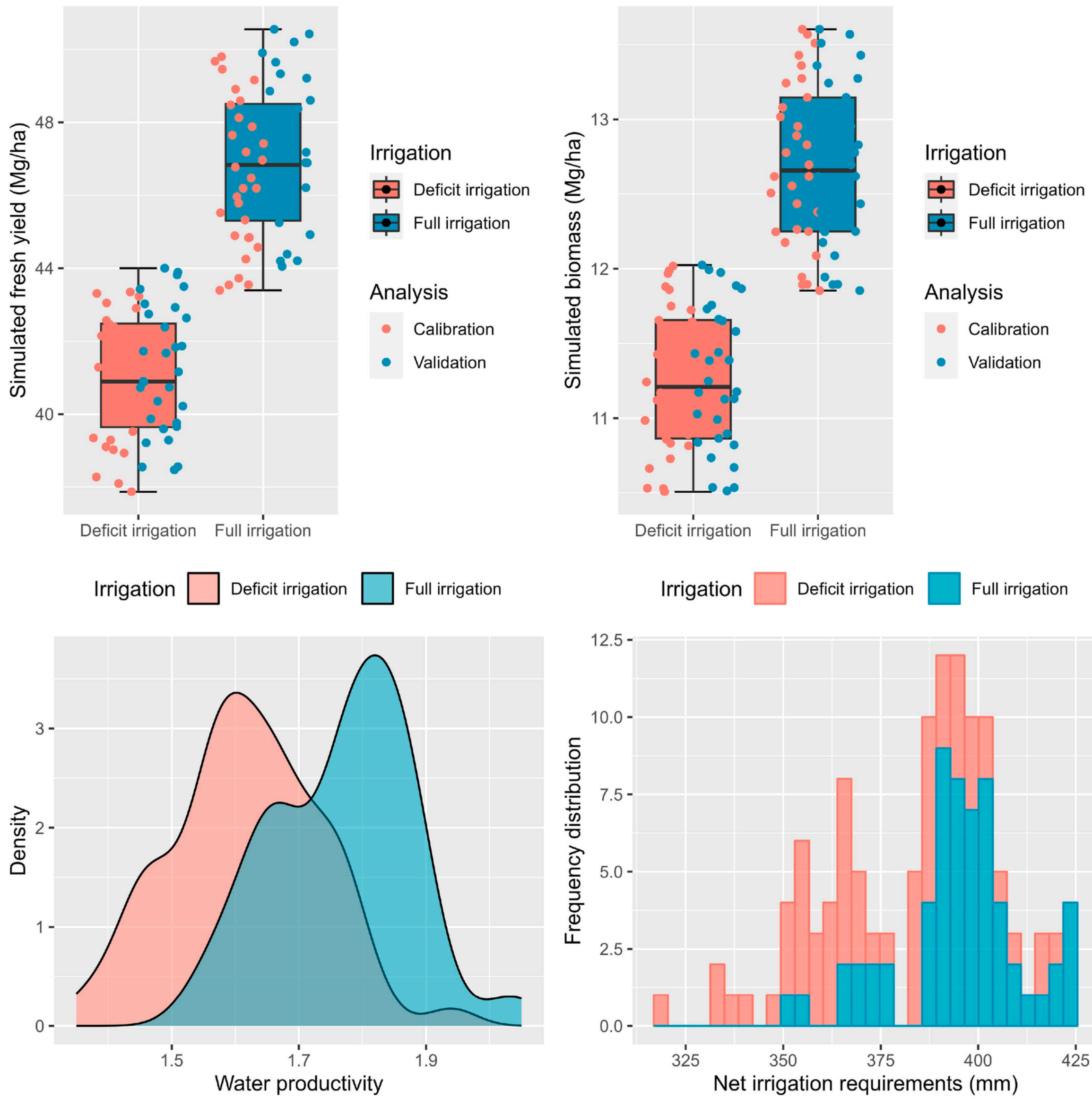

Fig. 6. Simulated yield, biomass, water productivity, and net irrigation requirements (NIR) for the 30-year period (1993–2022).

simulated the potential impacts of changing temperature on the yield, biomass, and water productivity of tomato in a greenhouse condition using 30-year (1993–2022) outside weather historical data. In addition, the NIR of tomato was also run in AquaCrop to have an overview of the seasonal irrigation amounts that covered the crop's needs over the years.

In the last 30 years, during the growing season, ET_0 ranges from 392 mm to 468 mm with an average of 434 mm whereas, and temperature ranges from 20 °C to 23 °C with an average of 22 °C (Fig. 5). An increasing linear trend over the 30-year period was observed in simulated fresh yield and dry above-ground biomass for both irrigation treatments, with a magnitude higher in FI than DI. Though fluctuating, this was also observed for water productivity, while no particular pattern was observed in NIR over the years. The 30-year average fresh fruit yield and biomass in FI was 46.9 and 12.7 Mg ha^{-1}, respectively while it was 41.0 and 11.3 Mg ha^{-1} in DI (Fig. 6). The fruit yield reduction using the DI was of 12.6 % compared with FI, which agree with the result (−16.7 %) previously reported by Nardella et al. (2012). Taking only the year 2022, simulation results showed that the average yield values of the calibrated and validated models were similar to the observed yield in the 2022 growing cycle both for FI and DI. This indicated that the external temperature could be a potential substitute for estimating ET_0 to predict the yield of tomato grown in a polyethylene greenhouse tunnel condition. However, the use of either the locally-calibrated ET_0 estimation method or the Hargreaves equation is recommended because of their simplicity and reliability (Fernández et al., 2010). The estimated average ET_c for FI and DI in the 30 years period was 402 mm and 387 mm, respectively. In a three years study, supplying water at 65 % and 87 % of tomato ET_c, under greenhouse conditions, an average cumulative ET_c during growing season of 265 and 337 mm, respectively, was observed by Gong et al. (2020). Under greenhouse conditions and plastic mulching, an ET_c of 280 and 230 mm supplying water at 100 % and 75 % of tomato ET_c, respectively, was reported by Wu et al. (2022). The 30-year average water productivity, expressed as kg of dry fruit biomass produced for each m^3 of ET_c, was 1.77 and 1.62 kg m^{-3} for FI and DI, respectively, similar with values already obtained by Cheng et al. (2022). Finally, the 30 years average NIR was 395 mm for FI and 374 for DI. For the year 2022, the simulated NIR was 407 and 385 for FI and DI, respectively which were higher than the actual irrigation water applied during the 2022 growing cycle.

4. Conclusions

Agriculture is more and more affected by climatic variability and adaptation strategies are urgently needed. The future water demands of tomato, as well as other crops, are expected to change over time. For this reason, efficient irrigation approaches adapted to changing climate and environmental conditions can support yields and water resource use. To reach this aim, models can effectively support agriculture by providing tools to optimize the production process and guide future decisions. The AquaCrop model well simulated the above-ground biomass and fresh commercial yield of tomato managed with different fertilization sources and irrigation volumes under greenhouse conditions. The model also well estimated the actual evapotranspiration (ET_a) with a low error highlighting that Hargreaves equation can be used under greenhouse conditions. External temperature and AquaCrop can be used to estimate tomato yields in the greenhouse by providing decision support tools for end-users (farmers, farmer associations, and policymakers).

CRediT authorship contribution statement

Silvia Locatelli: Investigation, Data curation, Writing – original draft, Writing – review & editing. **Wilfredo Barrera:** Formal analysis, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Leonardo Verdi:** Formal analysis, Methodology, Writing – review & editing. **Carlo Nicoletto:** Conceptualization, Supervision, Writing – review & editing. **Anna Dalla Marta:** Data curation, Methodology, Writing – review & editing, Supervision. **Carmelo Maucieri:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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