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ORIGINAL PAPER

Smart irrigation for management of processing tomato: a machine learning approach

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Abstract

Implementation of the Internet of Things (IoT) is revolutionizing agricultural techniques in modern precision irrigation systems. This research was conducted in an open field trial on processing tomato to evaluate the application of machine learning (ML)-based decision support systems (DSS) for predictive optimization of deficit irrigation strategies. A smart irrigation system (SIS) was adopted to investigate the effect of different management strategies under water deficit conditions. Four irrigation treatments using drip irrigation were tested: Full irrigation (FI) - (100% of ETc), Deficit irrigation (DI_1) - (80% of ETc), Regulated Deficit irrigation (RDI) - (60-80-60% of ETc) and Deficit irrigation (DI_2) - (60% of ETc). The trial was monitored via an ML-based SIS connected to a network of soil moisture and temperature sensors. This study aims to: (i) assess how processing tomato responds to controlled deficit irrigation using an ML-based DSS; (ii) examine the correlation between various water productivity indices (WP, TYWP, MYWP, and IWP) and tomato yields and quality; (iii) investigate the impact of temperature and thermal stress on tomato performances under different irrigation regimes. Results show significant effects of deficit irrigation on growth and yield parameters ($p \leq 0.001$). Both RDI and DI_1 achieved high water productivity, with no significant differences compared to FI. In the 2022 growing season, deficit irrigation, particularly DI_1, resulted in higher WP values, saving 32.66% of water and improving fruit quality. The study emphasizes the potential of deficit irrigation for achieving high yields and quality in processing tomatoes. However, the ML-based DSS, while effective in water management, requires enhanced sensitivity to crop susceptibility to heat and water stresses.

Introduction

Global water scarcity poses a significant risk to agriculture and the security of world food systems, but for some countries it is already an emergency (FAO 2016). Altered precipitation patterns driven by climate change are making extreme weather events with extreme periods of drought and flooding increasingly frequent and severe (IPCC 2014; IPCC 2021), outlining future scenarios of water shortage for many countries. To address these challenges, a more sustainable and rational water management approach in agriculture must be prioritized. In this context, numerous policy actions have been put in place worldwide, including the announcement of the Sustainable Development Goals (SDGs) agenda by the United Nations (UN Water 2023). Among the various strategies to be implemented for freshwater management, identifying innovative, sustainable solutions in the agricultural sector is paramount, given the magnitude of the challenge. Available scientific literature indicates that adopting measures to reduce water consumption will be the main strategy to combat drought and water scarcity, as opposed to increasing supply (Ingrao et al. 2023; Hasan et al., 2023). On average, agriculture is responsible for about 70% of global freshwater withdrawals, with approximately 70% of this water being lost to the environment due to inefficient irrigation systems and unsustainable water management practices(FAO SOLAW, 2021). The Mediterranean area is particularly vulnerable to water scarcity due to the

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high water demand, limited natural resources and increasing drought frequency (European Commission, 2007). As reported by the Global Drought Observatory in 2022, the northern Mediterranean experienced a severe drought, and extreme heat waves led to a significant reduction in crop yields. In this framework, agriculture is facing a great challenge because many horticultural crops grown in the Mediterranean region, such as tomato, need a high volume of irrigation throughout the growth period (Patanè et al. 2011; Giuliani et al. 2016). The tomato is classified as a high-water demand crop, (Shahin, S. M. 2024; Chand et al., 2020) with water requirements ranging between 400 and 600 mm depending on climatic conditions (FAO n.d.). Irrigation is crucial for tomato cultivation in key producing countries like Italy, the US and China, not only because of the gap between rainfall and evapotranspiration (ET), but also because it is a critical determinant of yield and product quality (Du et al. 2018; Lu et al. 2019). Tomato (*Solanum lycopersicum* L.) is one of the most cultivated vegetable crops worldwide (Panno et al. 2021), with global production exceeding 186 million tons over 4.9 million ha (FAO, 2020). In this context, optimizing water uses and maximizing crop yields through efficient management strategies, such as the conservative irrigation, is crucial (Pereira et al. 2012; Lu et al. 2019; Wang et al. 2023). Deficit irrigation strategies are practical solutions to increase water productivity (Lovelli et al. 2017). Deficit irrigation allows competitive yields while reducing water application to match crop needs (Valcárcel et al. 2020). Several methods of deficit irrigation have been studied including conventional or classic deficit irrigation (CDI), regulated deficit irrigation (RDI), and partial root zone drying (PRD) (Khapte et al. 2019). Most of the studies focused on the effects of DI on Water Use Efficiency (WUE) and on tomato fruit quality (Patanè and Cosentino 2010; Bai et al. 2023). A meta-analysis of 25 studies covering over 560 experimental groups and 145 control groups highlights a wide variability of tomato yields and quality (Lu et al. 2019). This variability is attributed to factors such as crop genotype, agronomic management, and pedoclimatic conditions. This suggests that DI outcomes are influenced by the ability to control environmental and crop-specific variables (Geerts and Raes 2009; Patanè and Cosentino 2010; Sillo et al. 2022). Based on the literature reviewed in this paper, deficit irrigation strategies clearly show promise for reducing irrigation water consumption while sustaining yields. However, further optimization is needed studying the effects of water on crop biophysical variables (i.e. Leaf Area Index (LAI), chlorophyll content, Photosynthetically Active Radiation (PAR) Absorption). Modern technologies applied to agriculture can play an important role in ensuring the sustainability of irrigation and in meeting crop water needs throughout the growing cycle. The application of innovative technologies such as artificial intelligence, machine learning and remote sensing can be extremely relevant in deficit irrigation management. The use of machine learning for the management of irrigation systems is becoming increasingly popular as highlighted in recent literature(Benos et al. 2021; Rozenstein et al. 2023). Decision Support systems (DSS) are powerful management tools for optimizing irrigation water usage and can help farmers make decisions (Navarro-Hellín et al. 2016; Bonfante et al. 2019). Several studies have shown that implementing sensor-activated deficit irrigation scheduling in the soil-plant-atmosphere system significantly enhances WP with positive results in terms of water savings (Cáceres et al. 2021; Abioye et al. 2022). State-of-the-art research emphasizes the need for accurate monitoring of crop water requirements and crop evapotranspiration (ETc), using different tools and technologies (Pereira et al. 2020; Alexandris et al. 2021). Enhanced precision in ETc can contribute to improve irrigation management and optimize the efficiency of water use throughout the entire crop growth cycle(Rozenstein et al. 2023). However, applying DI to water-stress-sensitive crops like tomatoes remains complex and risky, with potential yield reductions under excessive stress (Lu et al. 2019). Given these challenges, a three-year field trial was conducted to evaluate the effects of DI techniques on the yield, fruit quality, and water productivity WP of processing tomatoes in a Mediterranean environment. The main objectives of this study include: the evaluation of processing tomato response to deficit irrigation driven by a ML-based DSS; the analysis of the interaction between water use, yields and quality of processing tomato; the investigation of the effects of temperature and thermal stress on yields and fruit quality of processing tomato under different irrigation regimes.

Materials and methods

Area of the study and experimental design

Processing tomato (var. Durpeel F1) was grown from May to August for the 2021, 2022 and 2023 seasons. Tomato was cultivated on a total area of 240 m^2, in continuous double rows with 33.5 cm space between plants, 50 cm between rows, 1.10–1.20 m between double rows, with a final plant density of 32 plants/m^2. Transplanting was carried out on 22 May 2021, 27 May 2022 and 26 May 2023. Standard agricultural practices were implemented consistently throughout all three seasons. Fertilization was carried out in two phases: the first at transplanting consisting of 100 kg/ha diammonium phosphate ((NH4)3PO4; Phosagro®:NP 18–46%), 180 kg/ha ammonium nitrate (NH_4NO3; YaraTera™ N 34%) and 480 kg/ha potassium sulphate (K_2SO_4; Kalisop®

K 50%); the second at post-transplant stage consisting of 87 kg/ha of urea (CO(NH2)2 YaraVera™, N: 46%). Soil sampling was conducted prior to transplanting in April of the first year (2021) to determine the main physicochemical properties of the soil. Samples were taken following standard procedures at depths of 15 cm and 30 cm. Parameters assessed included gravel content (%), soil texture, bulk density (kg/m³), pH, and organic matter content (%) (Table 1).

Meteorological data

Meteorological data were obtained using an automatic weather station (μMETOS NB-IoT is a LPWAN weather station by Pessl) installed on the field. Daily average, maximum and minimum temperatures (°C), minimum, maximum and average relative humidity (%), solar radiation (MJ m^{-2}), wind speed ($m\ s^{-1}$), rainfall (mm), and daily reference evapotranspiration (ETo, mm day^{-1}) were calculated using the FAO Penman- Monteith approach. All meteorological data were continuously monitored during the three-year trial period.

Irrigation treatments

Irrigation was carried out using a drip system (dripping hose: Toro AquaTraxx® drip tape with 0.57 l/h low flow emitters spaced at 10 cm distance - p/n RA5080467). Four irrigation treatments were defined based on the percentage of reduction of ETc reintegration as follows: full irrigation (FI 100%), deficit irrigation (DI_1-80%), regulated deficit irrigation (RDI-60-80-60%) and deficit irrigation (DI_2-60%). FI consistently restored 100% of the tomato ETc throughout the growing cycle. DI_1 and DI_2 maintained constant regimes with restoration levels of 80% and 60% of the ETc, respectively. RDI adopted a variable regime, ensuring restoration of 60%, 80%, and 60% of the ETc during PS1 correspondent from formation of lateral sprouts to flower emergency (from BBCH2 to BBCH5), PS2 correspondent to flowering (BBCH6) and PS3 correspondent from fruit setting to beginning of ripening of fruits (from BBCH7 and BBCH8) phenological stages, respectively (Table 2). The irrigation ended about 10 days before the start of the assumed harvest.

The model used for irrigation scheduling is a commercial product, that integrates IoT, artificial intelligence, and machine learning. It is designed for predictive irrigation optimization, registering and analyzing data from various sources such as IoT sensors and weather forecast services to develop a machine learning-based soil water balance model. The system maintains data accessibility and provides irrigation advice to users through a web-based graphical user interface. The modeling aims to predict soil water potential for a specific soil with a specific crop; it incorporates parameters such as soil water potential, crop evapotranspiration, rainfall, irrigation, and meteorological data collected on that soil cultivated with the considered crop. In addition, web-based weather forecast services are used to provide future weather data. The acquisition of weather forecast data, for the area of interest, is obtained from web-based weather services. Forecasts must cover at least the next 5 days, divided into time slots of usually 3 h each. Then, optimization algorithms infer on the trained model to measure the effectiveness of many proposed irrigation schedules and select the most appropriate one. This integrated approach utilizes advanced technologies to provide real-time information and optimize irrigation management practices for efficient water usage in agriculture. Irrigation recommendations aim to maintain the soil water potential below the field capacity (10 Kpa), a threshold consistent with the results of previous studies. An example of the monitoring of a specific period of the experiment is shown in Fig. 1. For more details on the structure of the model used, see the next Chap. (2.4).

The daily reference evapotranspiration (ET0) was calculated according to FAO Penman-Monteith's equation (Cai et al., 2007) using hourly data recorded by the weather station installed in the field. The daily ETc was calculated according to a two-step approach (ETc = ET0 x Kc) where the crop coefficients (Kc) were detected in an environment similar to our experimental site (Rinaldi et al., 2011; Di Lena 2017): ranging between 0.6 and 0.7 from transplanting to crop establishment; between 0.7 and 0.9 from crop establishment to the beginning of flowering; between 1.0 and 1.15 from beginning of flowering to the beginning of fruit set; between 1.0 and 0.6 from the beginning of fruit set to full maturity. The seasonal tomato water consumption or ET, under the

Table 1 Main soil chemical and physical properties of the experimental site

	Unit of measurement	Value
pH		7
EC	mS/cm at 25 °C	0.21
Salt	‰	0.30
Total N [Kjeldahl method]	N g/Kg	1.50
Avaible P [Olsen method]	P_2O5 mg/Kg	36.00
Exchangeable K [BaCl2 method]	K_2O mg/Kg	478.00
Organic Matter [Walkley-Black method]	%	2.61
C/N		10.10
C.S.C [BaCl2 method]	meq/100 g	23.00
Sand [USDA method]	%	23.20
Clay [USDA method]	%	41.00
Sint [USDA method]	%	35.80
Field capacity (-0,03 Mpa)	% d.w	11.30
Wilting point (-1.5 Mpa)	% d.w	24.00
Bulk density	Kg/m³	1270.00

Table 2 Number irrigations and volume applied for each phenological stage and irrigation treatments

Year	Ph. stage	Irrigations ($n°$)	Irrigation regimes (m^3)			
			FI	DI_1	RDI	DI_2
2021						
	PS_1	2	241.4	192.91	144.08	144.08
	PS_2	8	1571	1257.2	1257.2	942.9
	PS_3	9	2197	1758.12	1507.92	1318.59
	Total	**18**	**4009.41**	**3208.23**	**2908.20**	**2405.57**
	ET (mm)		**537.41**	**457.20**	**427.36**	**376.990**
2022						
	PS_1	6	1325	1060	955	795
	PS_2	7	1484	1187.2	1187	890.4
	PS_3	15	3411	2728	2046.6	2046.6
	Total	**28**	**6220.00**	**4975.20**	**4188.60**	**3732.00**
	ET (mm)		**659.72**	**535.32**	**456.00**	**410.92**
2023						
	PS_1	3	815.43	652.35	489.24	489.24
	PS_2	4	1165.43	932.35	877.98	699.24
	PS_3	6	1766.36	1413.10	1413.10	1059.78
	Total	**13**	**3747.22**	**2997.80**	**2780.32**	**2248.26**
	ET (mm)		**629.19**	**554.25**	**532.50**	**479.30**

PS1, time corresponding to BCCH2 and BCCH5 phenological stage; PS2, time corresponding to BCCH6 phenological stage; PS3,; time corresponding to BCCH7 and BCCH8 phenological stage; FI, full irrigation (restoration of 100%); DI1, "first" deficit irrigation (restoration of 80%); RDI, Regulated deficit irrigation (restoration of 60% during growing (PS1), 80% during flowering (PS2), 60% during ripening fruit (PS3)); DI2, "second" deficit irrigation (restoration of 60%)

Fig. 1 Environmental and soil parameters monitored during the growing: datalogger with soil water sensors at two different depths (15 cm and 30 cm) Soil water potential - SWP1 (blue), Soil Water potential - SWP2 (red), air temperature (yellow), pluviometer (teal), water stress threshold (green)

different irrigation treatments, was calculated using the soil water balance equation as reported by Patanè et al. (2011):

$$ET = \mathrm{I} + \mathrm{P} + \mathrm{Cr} - \mathrm{R} \pm \Delta C \quad (1)$$

Where ET is the water consumption (mm), P is the precipitation (mm), I is the total water applied by means of irrigation (mm), R is runoff losses (mm), Cr is the drainage (mm) below the root zone, and ΔC is the difference between soil water content at transplanting and soil water content at harvest (mm). Runoff losses were considered to be zero, as the rain never exceeded the soil infiltration rate (Perry 2007). Drainage from the root zone was considered negligible. Soil water content at transplanting and at harvest was measured using data recorded at the same stages by the capacitive soil sensor.

Machine learning-based smart irrigation systems (ML-based SIS)

The commercial ML-Based Smart Irrigation System (SIS) used in the experiment is a cloud-based solution integrating Internet of Things (IoT) technologies and web services. It leverages artificial intelligence algorithms to process data from IoT sensors, which gather soil and environmental information. The system also connects to online services for weather forecasting. The Decision Support System (DSS) infrastructure consists of several components, including machine learning (ML), automated irrigation control, a back end for data storage, and a graphical user interface (GUI). The hardware setup includes a weather station, specifically the µMETOS NB-IoT by Pessl, which operates using LPWAN technology, and a data logger connected to tensiometers (WATERMARK Soil Moisture Sensors). These tensiometers are installed at various depths to monitor soil water potential, a crucial metric for understanding soil water dynamics. The DSS framework was developed using a combination of Java and Python programming languages.

In detail, the system employs a two-layer logical structure: Soil Water Balance Prediction Using Machine Learning and Irrigation Optimization using genetic algorithm. The first layer focuses on modeling the soil water balance using machine learning to predict the soil water potential for the next five days. This model operates on a time step of three hours. The predictive model consists of a set of random forests, a machine learning algorithm developed by Breiman (2001). During training, it builds multiple decision trees based on an input dataset that include historical soil water potentials, historical and forecast crop evapotranspiration, rainfall data, irrigation events, and meteorological data. An example of decision tree diagram is provided below (Fig. 2). Since the machine learning model consists of a set of random forests, its replicability depends on the replicability of the random forests themselves.

The second layer (Irrigation Optimization using genetic algorithm) is responsible for generating irrigation recommendations using the predictions from the first layer. The optimization process is performed via a genetic algorithm, a heuristic search method inspired by natural selection principles.

Genetic algorithms simulate evolution by introducing random variations and selecting the best-fitting solutions over successive generations. In this context, the algorithm aims to optimize the irrigation schedule, determining the timing and water volume (expressed in cubic meters per hectare). The fitness of each solution is evaluated by

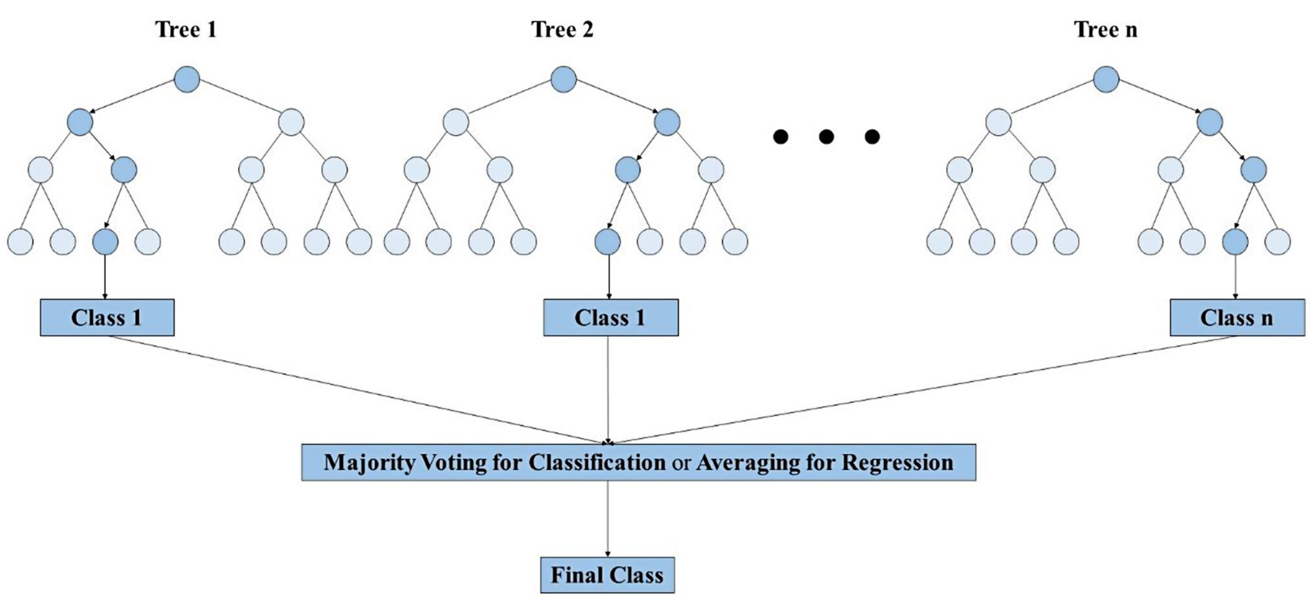

Fig. 2 Schematization of random forest models

predicting its impact on the soil's water balance and calculating three distinct loss functions. These functions assess how much each proposed solution deviates from the optimal condition for the crop. The three loss functions are:

- **amount(s)**: This function monitors the total water applied, ensuring the delivery of the precise amount needed, avoiding both excess and shortage.

2. **overstress(s)**: This function assesses whether irrigation effectively prevents water deficits that could stress the plants, aiming to avoid water-related stress conditions.

- **optimal distance(s)**: This function evaluates how effectively the proposed irrigation brings the soil to its field capacity, which is the optimal water content level for plant growth.

The genetic algorithm is designed to minimize these loss functions aiming to find a solution that balances water application, prevents plant water stress, and maintains optimal soil conditions for plant growth. In summary, the genetic algorithm evolves solutions through three phases: crossover, which generates new solutions by averaging the irrigation timing and volume; mutation, which randomly alters parameters with a 30% probability; and fitness evaluation, which calculates the aforementioned loss functions using the predictive model. Selection is performed through a tournament process, where one-third of the population is evaluated based on the loss functions, and better-performing solutions have a higher probability of being selected. The algorithm terminates when the predicted soil water potential approaches the field capacity threshold after an irrigation event. The final solution is chosen using a metric called "Optimal Distance", with the solution having the minimum value selected as the optimal irrigation recommendation. The flowchart of this genetic algorithm is shown in Fig. 3.

Growth and yield measurements

During the phenological phases of leaf development and flower emergence (PS1: corresponding to BBCH 2 to BBCH 5), flowering (PS2: corresponding to BBCH6), fruit development and ripening (PS3: corresponding to BBCH7 and parts of BBCH8) and harvesting (H: corresponding to BBCH9), for each plot the following parameters were measured: fresh total biomass (g), stems and roots length (cm). During the harvest phase, nine representative selected plants for each plot, were used for yield determination and quality parameters assessment. Samples (stems + leaves + roots) were dried in an oven at 70 °C until constant weight, for dry biomass determination (g). Total fruit yield (Mg ha^{-1} fresh weight - FW) was determined, and marketable yield (Mg ha^{-1} FW) was measured considering red and disease-free fresh fruits. Ripened fruits of the first and second trusses (approximately 2 Kg per plot) were sampled at harvest for

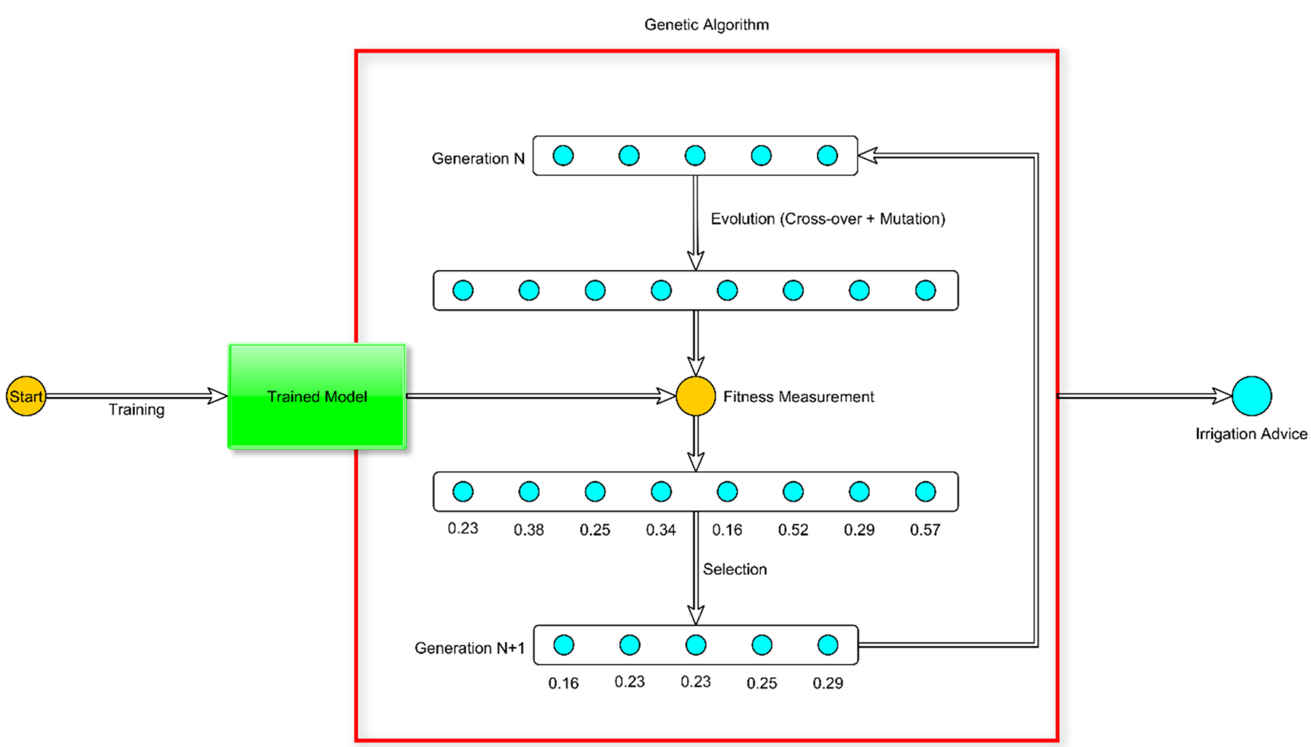

Fig. 3 ML-DSS genetic algorithm flowchart

laboratory analyses. Tomatoes were washed, dried and analyzed for single fresh fruit: fresh and dry weight (g), length and diameter (mm), total soluble solids (TSS, °Brix), pH and water content (%). All analyses were carried out in triplicate. The parameters of water productivity with regard to biomass (WP, kg m^{-3}), total fruit yield (TYWP, kg m^{-3}) and marketable yield (MYWP, kg m^{-3}) were calculated respectively from the ratio of dry matter at harvest (DW, kg ha^{-1}), total fresh yield (FW, Kg ha^{-1}) and marketable yield (FW, Kg ha^{-1}) with the total water consumption (expressed as ET, m^{-3} ha^{-1}). (Patanè et al. 2011). Irrigation Water Productivity (IWP, kg total yield m^{-1}), calculated as the ratio between total fruit yield (kg) and total irrigation input for each irrigation treatment. Harvest Index (HI) was computed as the total fruit yield (kg) divided by total dry biomass (Mukherjee et al. 2023).

Magnitude of heat stres

A heat stress index was used to assess the heat stress of tomatoes during growing seasons. For the determination of the index, later called crop heat stress index (CHSI), reference was made to studies by Teixera et al. (2013) and Challinor et al. 2005 concerning the parameterization of high temperature stress on different crops. The basic principles behind the choice of this index are that: i) processing tomato is particularly sensitive to high temperatures (Khan et al. 2024; Alsamir et al. 2021) (ii) Optimum temperatures (T. Opt. ° C) and maximum critical temperatures (T Cri. Max. °C) are known for each phenological phase of the tomato (Velazquez et al., 2022; Geisenberg and Stewart 1986) iii) the impact of maximum heat stress on the crop occurs when the daily maximum temperature exceeds the critical temperature threshold (TCri, max °).

The formula adopted is as follows:

Daily CHSI = T. max (°C) – T. Opt (°C) / TCri, max (°C) – T. Opt (°C).

A positive value (CHSI > 0) indicates that the daily maximum temperature (T. Max) has exceeded the optimal temperature (T. Opt.), suggesting the onset of thermal stress. If the maximum daily temperature Tmax exceeds the critical temperature Tcrit, the CHSI value will be greater than 1 (CHSI > 1), indicating high and harmful stress. Conversely, a zero value indicates that the maximum temperature is equal to or lower than the optimal temperature, signaling the absence of thermal stress.

Data analysis

Data of dry biomass, yield and quality traits were analyzed by a 1-way analysis of variance (ANOVA) using STATISTICA Software version 10 (STATsoft.). The analysis of variance was conducted by a group within each year, considering water treatment as fixed factor. Differences between means were valued for significance using Newman-Keuls test. The correlation analysis was used to study the relationship between the season irrigation volumes, climate parameters and yield quantity and quality parameters. Moreover, all data were subjected to a Principal Component Analysis (PCA). A PCA model was calculated considering, for each irrigation treatment, the average values of replicates recorded for tomato yield parameters, fruit quality and agro-climatic parameters during the crop cycles. A factor-loading showed correlations between the principal components (PC1 and PC2) and the original parameters. The graphical representation of the PCA results is a scatterplot of the correspondent score plot. In this way, it was also possible to observe the distribution of various irrigation regimes across the four quadrants of the principal components through the implementation of a score plot.

Results and discussion

Meteorological data

Climographs for the three experimental years are shown in Fig. 4, while the average temperatures for each PS (maximum, minimum and average) for different tomato crop cycles are reported in Table 3.

Meteorological data were representative of a typically Mediterranean environment. There were differences in the amounts and distribution of rainfall, especially during the phenological phase PS1. In 2021, 52.40 mm of rainfall was recorded during PS1, while in 2022 and in 2023, only 1.60 mm and 19.54 mm were recorded (Table 3).

In the last year of the experiment, about 100 mm of rainfall was recorded approximately 10 days before transplanting. This variability in rainfall between years and phenological phases adds an important environmental dimension to the study's results and will be analysed in detail later. The cumulative ET0 and cumulative ETc were 386.70 mm and 353.8 mm in 2021, 436.89 mm and 393.70 mm in 2022, 380.87 mm and 342.30 mm in 2023.

Tomato yield, biomass and fruits quality

Table 4 reports the effects of different irrigation regimes on the tomato yield in the three experimental years.

The analysis of variance (ANOVA) reveals that dry biomass, stems height, root length and yield parameters are significantly influenced by different deficit irrigation treatments ($p \leq 0.001$).

Fig. 4 Meteorological graphs of the three years (2021, at the top, 2022, in the middle, and 2023, at the bottom) and irrigation volumes related to Full Irrigation treatment (FI)

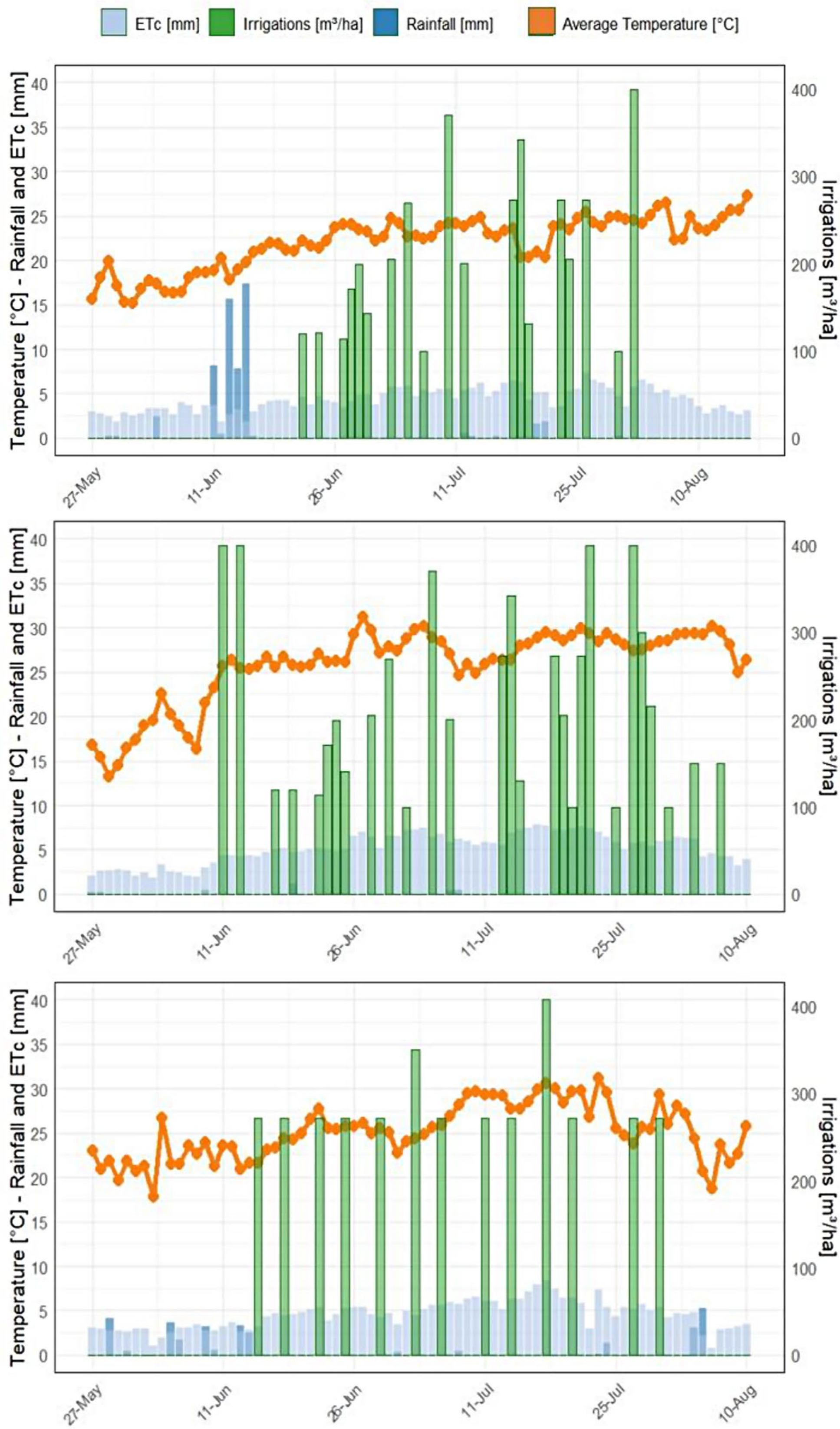

Table 3 Climatic parameters for the main phenological stages in the three years of experiment

	T	PS1	PS2	PS3	H	Tot./ Avg.
Year 2021						
Daily avg temperature (°C)	16.82	19.00	23.24	23.61	24.70	21.47
Max. daily temperature (°C)	17.40	21.47	25.55	26.36	28.32	23.82
Min. Daily temperature (°C)	14.87	16.00	21.17	19.45	21.50	18.59
Rainfall [mm]	0.00	52.40	0.00	4.60	0.00	57.00
Daily ETC [mm]	2.82	3.26	4.83	5.42	3.86	4.03
Year 2022						
Daily avg temperature (°C)	16.10	22.37	28.14	28.18	28.04	24.56
Max. daily temperature (°C)	22.10	33.83	39,21	36.57	36.88	33.71
Min. Daily temperature (°C)	11.00	16.60	17.18	30.71	14.87	18.07
Rainfall [mm]	0.40	1.60	0.80	0.00	0.00	2.80
Daily ETC [mm]	2.39	3.68	6.42	6.48	4.06	4.60
Year 2023						
Daily avg temperature (°C)	22.00	23.00	25.70	27.97	22.20	24.17
Max. daily temperature (°C)	28.61	35.05	35.70	38.76	30.42	33.70
Min. Daily temperature (°C)	12.69	15.13	19.22	18.91	17.22	16.63
Rainfall [mm]	0.00	19.54	0.82	4.50	5.25	30.11
Daily ETC [mm]	3.03	3.41	5.12	5.82	2.60	3.99

T, transplanting; PS1, time corresponding to BCCH2 and BCCH5 phenological stage; PS2, time corresponding to BCCH6 phenological stage; PS3 time corresponding from BCCH7 to BCCH8 phenological stage, H: harvest corresponding into BCCH9 phenological stage

Table 4 Values of dry biomass, stem height, root length, total yields and marketable yields for irrigation treatment and experimental year

Year	Irrigation treatment	Dry biomass (Mg ha^{-1})	Stems height (cm)	Root length (cm)	Total yield (Mg ha $^{-1}$)	Marketable yield (Mg ha $^{-1}$)
2021	FI (100%)	2.52 ^{a}	82.44 ^{a}	30.33	49.30 ^{a}	40.08 ^{a}
	DI_1 (80%)	1.91 ^{b}	72.33 ^{b}	27.89	32.05 ^{b}	23.24 ^{b}
	RDI (60-80-60%)	1.56 ^{b}	75.78 ^{ab}	28.00	27.95 ^{b}	19.95 ^{b}
	DI_2 (60%)	1.14 ^{c}	60.44 ^{d}	29.78	10.75 ^{c}	8.50 ^{c}
	Significance	***	***	ns	***	***
2022	FI (100%)	1.64 ^{a}	78.88^{a}	32.44 ^{a}	28.09 ^{a}	20.52^{a}
	DI_1 (80%)	1.35 ^{ab}	71.11^{b}	23.89 ^{b}	26.23 ^{a}	18.71^{a}
	RDI (60-80-60%)	1.04 ^{b}	66.33 ^{b}	24.44 ^{b}	19.67 ^{b}	13.17^{b}
	DI_2 (60%)	0.69 ^{c}	60.33^{c}	20.67 ^{c}	10.90 ^{c}	7.25^{c}
	Significance	***	***	***	***	***
2023	FI (100%)	2.20 ^{a}	71.72 ^{a}	26.38 ^{a}	50.10 ^{a}	46.41 ^{a}
	DI_1 (80%)	1.93 ^{b}	63.12 ^{b}	23.22 ^{b}	37.38 ^{b}	33.88 ^{b}
	RDI (60-80-60%)	1.47 ^{c}	47.97 ^{b}	17.63 ^{b}	25.98 ^{c}	23.32 ^{c}
	DI_2 (60%)	1.00 ^{d}	32.62 ^{c}	12.02 ^{c}	17.67 d	15.86 d
	Significance	***	***	***	***	***

FI, full irrigation; DI1, deficit irrigation; RDI, regulated deficit irrigation; DI2, deficit irrigation. *$P<0.05$; **$P<0.01$; ***$P<0.001$; ns, not significant). Means followed by the same letters in the same column are not significantly

Total biomass (Mg ha^{-1} DW) exhibits variable average values across irrigation treatments, ranging from 1.14 to 2.52 Mg ha^{-1} in 2021, 0.69 to 1.64 Mg ha^{-1} in 2022, and 1.00 to 2.20 Mg ha^{-1} in 2023. The maximum and minimum values are observed in FI and DI_2, respectively. In the initial two years, no significant differences between DI_1 and RDI are observed. However, in 2023, a significant decrease in biomass production is evident by reduced water supply. Overall, FI positively impacts biomass compared to irrigation deficits, confirming that water supply promotes plant growth. Plant height was significantly ($p<0.001$) reduced by the soil water deficit ranging from 77.68 cm (±2.70) to 68.85 cm (±2.36), 63.36 cm (±6.67) and 51.13 cm (±7.47) respectively under FI, DI_1, RDI and DI_2. Root length is not significantly affected by irrigation in the first year but shows differences in the second and third years. In all experimental years, FI treatment leads to longer roots. Deficit irrigation treatments (DI_1, RDI, and DI_2) enhance root length in DI_2 (29.78 ± 6.88 cm) and RDI (24.44 ± 1.01 cm) in 2021 and 2022, with no such positive effect observed in 2023. Regarding this, similar studies conducted on tomatoes recorded a significant decrease in growth variables such as plant height and similar increase (Nangare et al. 2016), even if there is still an open debate in the available scientific literature on the effect of deficit irrigation on roots development. This could be because the significance of the effect of deficit irrigation on the length of the roots also depends on other multiple stresses such as heat (Sillo et al. 2022) pathogens, physical characteristics of the soil or nutrient status (Whitmore and Whalley 2009). Total fruit yield was higher in 2023 (50.10 Mg ha^{-1}) than in 2021 and 2022 (49.30 Mg ha^{-1} and 28.09 Mg ha^{-1}, respectively). Throughout all three years, the highest total yield is recorded under full irrigation (FI), while the lowest is under DI_2 (10.75, 10.90, and 17.67 Mg ha^{-1} in 2021, 2022, and 2023, respectively). In 2022, there is a drastic decrease in yields, with significantly reduced variability between irrigation treatments compared to other years. Both total yield (Mg ha-1 FW) and marketable yield (Mg ha-1 FW) are significantly influenced by the irrigation treatment. In 2021 and 2023, total fruit yield correlates more closely with irrigation volumes ($r=0.95$) than in the total three years. Water stress leads to a significant reduction in total fruit yield in 2021 and 2023, while the Δ yield losses in 2022 are less significant than in other years (Table 5).

Compared to similar studies, the yield losses between irrigation treatments is notably greater (Patanè and Cosentino 2010; Lovelli et al. 2017). Marketable yield was negatively affected by the very early water shortage in DI_2, decreasing by 78.19%, 61.17% and 64.73% in the first, second- and thrd-year espect to the mean yield of the full irrigation treatments. The main reduction may be attributable to the decrease in fruit weight and the number of marketable fruits per plant (Lovelli et al. 2017). It is important to note that a significant positive correlation was observed between the fresh fruit weight (g *per fruit*) and the marketable yield ($r=0.85$), as well as between the number of commercial fruits per plant and the volumes of irrigation ($r=0.60$). These results agree with the finding of (Marouelli and Silva 2007; Mukherjee et al. 2023) who observed that the number of marketable fruits per plant was reduced as soil water decreased. Total fruit production was directly related to the total dry biomass for each year ($r>0.98$) and over the three total years ($r>0.68$) highlighting the ability of the crop to regulate the proportion of biomass of the fruits in relation to the total accumulated biomass. Total dry biomass positively influenced the fresh and dry fruit weight ($r=0.63$ in average). DI on fruit quality did not generally show significance on fruit yield and weight (Table 6).

The greatest fruit yields (> 77 g FW) were obtained from plants of FI and DI_2. As expected, fruit size was significantly ($p\leq0.01$) lower (< 66 g FW) in plants where an early cut-off of irrigation was applied, in all the years. On average, the highest size fresh fruit was observed in DI_1 in 2021 only. In general, the fruit weight, for the three years, was affected by the irrigation volumes ($0.79<r<0.98$). Similar effects of severe water stress upon fruit weight are reported in other studies (Patanè and Cosentino 2010; Lovelli et al. 2017; El Chami et al. 2023). Dry fruit weight significantly increased ($p\leq0.05$) in deficit irrigation treatments. Additionally, the size of the fruits, in terms of length and diameter, may be influenced by water stress and temperature, as.

reported in previous studies (Al-Selwey et al. 2021.)

Other research has indicated that a reduction in irrigation water can lead to higher total soluble solids (TSS or Brix°) contents; however this study often found this trend to be non-significant. 2023 stood out with a significant increase ($p\leq0.001$) (Lovelli et al. 2017). Moderate water stress throughout the entire growing season improved fruit quality in terms of TSS in 2021 (with DI_1 and DI_2 showing progressively higher levels than RDI) and in 2022 (with DI_1 and DI_2 showing progressively higher levels than F), similarly to the trend observed in 2023. From an economic standpoint, the positive influence of °Brix on the quality of deficit irrigation treatments aligns with findings by(Whitmore and Whalley 2009. Notably, we didn't observe a clear effect of water stress on fruit pH over the three experimental years, consistently with other study (Lovelli et al. 2017). The pH ranged from 4.77 to 5.00 in 2021, 4.86 to 5.03 in 2022, and 4.82 to 5.14 in 2023, with the lowest values observed in the RDI treatment. As noted in (Patanè and Cosentino 2010; the pH tended to decrease with deficit irrigation, while Brix increased, although not significantly.

Total dry biomass and marketable yield vs. seasonal evapotranspiration (ET)

Evapotranspiration (ET), or the total amount of water consumed, in the first year ranged from 240.55 mm to 400.94 mm while in the second and third experimental years, ET values were quite similar (Table 2), ranging between 376.99 mm and 629.19 mm. The ratio of total dry

Table 5 Yield losses (%) and irrigation water saving of the deficit irrigation treatments compared to FI Kgt/m³ in the three years of experiment

Deficit Irrigation treatments	Yield losses (Δ%)			Irrigation water saving (%)		
	2021	**2022**	**2023**	**2021**	**2022**	**2023**
DI_1 (80%)	34.99	6.66	25.38	20.00	20.00	20.00
RDI (60-80%-60%)	43.31	29.97	48.14	27.45	32.66	25.81
DI_2 (60%)	78.19	61.17	64.73	40.00	40.00	40.00

Table 6 Average dry and fresh weight of fruits, fruit length and diameter, soluble solids and pH in the different irrigation regimes

Year	Irrigation treatments	Fruit fresh weight (g)	Fruit dry weight (g)	Fruit length (mm)	Fruit diameter (mm)	TSS (°Brix)	pH
2021	**FI (100%)**	82.78 ^{a}	2.07^{a}	77.89	43.53^{a}	5.99	5.00^{a}
	DI$_1$(80%)	85.01 ^{a}	2.46^{c}	76.27	45.08^{ab}	5.76	4.91^{a}
	RDI (60-80-60%)	76.85 ^{b}	2.36^{b}	76.16	42.24^{a}	5.63	4.77^{b}
	DI$_2$(60%)	63.20^{c}	2.49^{c}	73.60	39.93^{ac}	6.09	4.83^{a}
	Significance	**	*	ns	*	ns	*
2022	**FI (100%)**	82.26^{a}	2.07^{a}	84.33	44.39	5.21	4.98
	DI$_1$(80%)	77.01^{b}	2.45^{c}	75.74	40.79	5.40	5.03
	RDI (60-80-60%)	68.78^{c}	2.36^{b}	77.69	39.72	5.11	4.86
	DI$_2$(60%)	66.02^{c}	2.48^{c}	76.88	40.58	5.41	4.92
	Significance	**	*	ns	ns	ns	ns
2023	**FI (100%)**	87.17^{a}	2.26^{a}	98.79^{a}	47.98^{a}	5.75^{a}	5.00^{a}
	DI$_1$(80%)	83.26^{a}	2.24^{a}	78.44^{a}	41.25^{ab}	5.54^{a}	5.14^{a}
	RDI (60-80-60%)	75.47^{b}	2.42^{b}	79.57^{b}	39.58^{b}	5.23 ^{ab}	4.82^{b}
	DI$_2$(60%)	69.69^{c}	2.29^{a}	76.19^{b}	40.45^{a}	5.55^{a}	4.94 ^{ab}
	Significance	**	*	***	***	***	*

FW, fresh weight; DW, dry weight; FI, full irrigation; DI$_1$, "first" deficit irrigation; RDI, regulated deficit irrigation
; DI$_2$, "second" deficit irrigation. *$P<0.05$; **$P<0.01$; ***$P<0.001$; ns, not significant. Means followed by the same letters in the same column and within each year are not significantly different according to the NK test

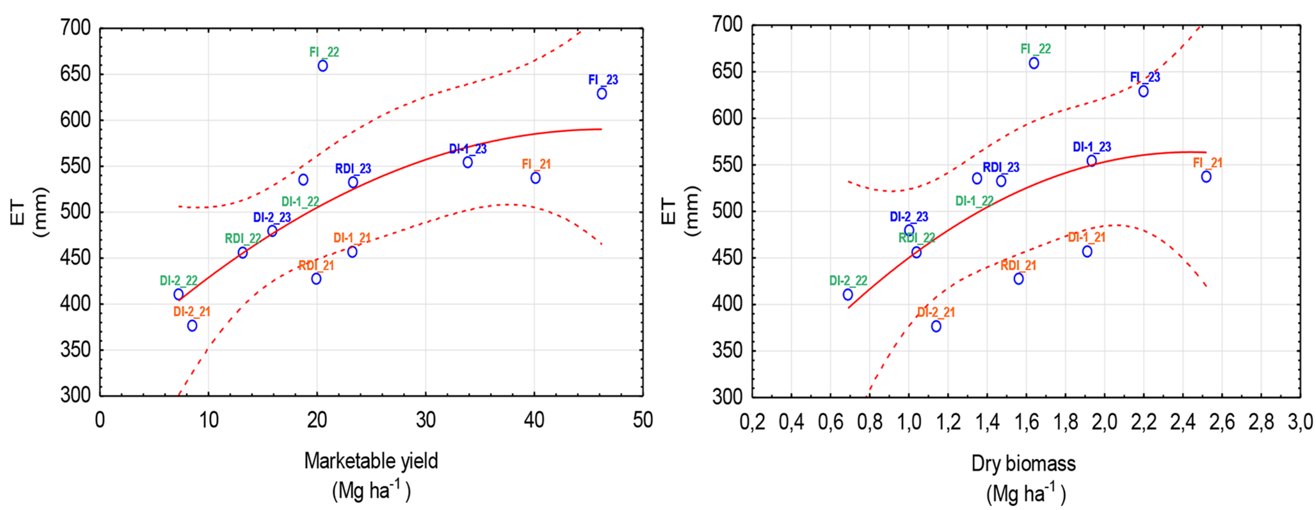

Fig. 5 Relationship between seasonal evapotranspiration (ET) and marketable yield (left); relationship between seasonal evapotranspiration (ET) and) total dry biomass (right)

biomass to marketable yield, compared to seasonal evapotranspiration, was analyzed using the data collected over the three years. The graphs in Fig. 5 provide an overview of crop response during the three experimental years in terms of yields and biomass production.

Data analysis shows a sudden increase in total epigeous dry biomass with the increase in ET from 450 mm to about 550 mm. The biomass accumulation trend in relation to seasonal evapotranspiration shows a more exponential trend in 2022 and 2023 compared to 2021. Regarding About commercial production, a comparable trend to dry biomass observed in 2022, while in 2021 and 2023 the commercial yields constantly grow above the ET values of 350 mm. Differences in trends could be attributed to annual climatic variations that affect the crop's growth and its response to water.

Water productivity

Water productivity that was computed based on total dry biomass (WP) and TYWP (calculated on total fresh yield), were influenced differently by DI (Table 7).

Overall, the results show that the irrigation regime can significantly affect WP and crop yield. In this sense, the FI treatment shows the best performances. In fact, FI treatment has consistently shown higher WP values for all three years, ranging between 2.05 Kg m^{-3} and 3.89 Kg m^{-3}. This suggests that a complete water supply improves biomass production and thus, a more efficient use of water. This process allows plants to maximize the production of dry biomass in relation to the water used. On the other hand, our results show that certain irrigation deficit regimes can have different impacts depending on the year. In 2021 and 2023 the DI_1 treatment showed higher WP values (3.37 kg m^{-3} and 2.88 kg m^{-3}) out of other deficit irrigation treatments unlike the 2022, where RDI showed higher values (1.85 kg m^{-3}). This suggests that a relative irrigation strategy, with variations during key growth phases, can positively affect the efficiency of water use under certain conditions. However, this is not entirely true if other indices are taken into consideration. In fact, contrary to previous evidence, in 2022 deficit irrigation treatments (DI and RDI) showed significantly greater results of WP in relation to total and marketable production (TYWP, MYWP) and irrigation (IWP). This result highlights how deficit irrigation strategies can support production and rationalize water consumptions in those years characterized by water scarcity and significant temperature peaks. Regarding TYWP in the 2021 and 2023, the highest values were observed in the full irrigation treatment (18.49 kg m^{-3} and 16.05 kg m^{-3}, respectively) while in 2022, both the DI_1 and RDI treatments showed higher performances than the other irrigation treatments with values of 8.81 kg m^{-3} and 7.75 kg m^{-3}, respectively.

Table 7 Water productivity (WP), total yield water productivity (TYWP), marketable yield water productivity (MYWP) and irrigation water productivity (IWP) values

Year	I.T	WP (kg, DW m^{-3})	TYWP (kg, FW m^{-3})	MYWP (kg, FW m^{-3})	IWP (kg, FW m^{-3})
All years	FI (100%)	3.04	14.06	11.83	10.05
	DI_1 (80%)	2.62	11.64	9.23	9.24
	RDI (60-80-60%)	2.42	10.26	7.81	7.88
	DI_2 (60%)	1.71	6.38	5.11	5.08
2021	FI (100%)	3.89	18.49	15.03	12.29
	DI_1 (80%)	3.37	12.53	9.09	9.98
	RDI (60-80-60%)	3.11	13.19	9.42	9.6
	DI_2 (60%)	2.09	6.95	5.49	4.46
2022	FI (100%)	2.05	7.66	5.59	4.51
	DI_1 (80%)	1.60	8.81	6.29	5.27
	RDI (60-80-60%)	1,85	7.75	5.19	4.69
	DI_2 (60%)	1.32	4.77	3.17	2.92
2023	FI (100%)	3.18	16.05	14.87	13.37
	DI_1 (80%)	2.88	13.59	12.32	12.47
	RDI (60-80-60%)	2.28	9.83	8.83	9.35
	DI_2 (60%)	1.72	7.43	6.67	7.86

FW, fresh weight; DW, dry weight; FI, full irrigation; DI_1, "first" deficit irrigation; RDI, regulated deficit irrigation

; DI_2, "second" deficit irrigation

However, in the third year, TYWP values exhibited a proportionally negative trend with irrigation conditions. For MYWP values, in the first and third years, the highest values were recorded in FI (15.03 Kg m^{-3} and 14.87 Kg m^{-3}, respectively). In the first year, the RDI treatment reached higher results than DI_1 and DI_2 (9.42 Kg m^{-3}, 9.09 Kg m^{-3}, and 5.49 Kg m^{-3}, respectively), although still lower compared to FI. In the third year, MYWP values exhibited a proportionally negative trend with deficit irrigation conditions. Giuliani et al. (2016) featuring four irrigation methods, revealed similar outcomes. The study suggests that tailoring water provision to the plant's phenological phases allows better results, considering the varying susceptibility to water stress of crops throughout the growing cycle.

Effect of heat stress on tomato growth and yield

The variations observed in all measured parameters across experimental years suggest that the decrease in yield is influenced not only by irrigation deficit but also by other factors. In particular, the climatic conditions during the growing season have a decisive influence on the yield and quality of the fruits (Patanè and Cosentino 2010). This relationship has been emphasized in numerous studies(Patanè and Cosentino 2010; Nangare et al. 2016; Valcárcel et al. 2020) which attribute differences in yields between years to climatic factors, particularly temperature. The optimal range for average daily temperatures for tomato growth lies between 21 °C and 24 °C, depending on the specific developmental phase of the plant (C. Geisenberg and K. Stewart 1986). For example, a temperature of 22 °C for vegetative development, below 25 °C during flowering and 22–26 °C for fruit growth have been recommended as optimal (Shamshiri et al. 2018). Table 8 provides a summary of the optimal and maximum cardinal temperature values for growth stages, as extracted from the literature (Shamshiri et al. 2018; Adams et al. 2001).

High temperatures act as a limiting factor for tomato growth, impacting the physiological and biochemical development of the plant and, consequently, leading to a significant reduction in fruit yields (Alsamir et al. 2021). Research indicates that daily temperatures exceeding 25 ºC have a notable adverse effect on both the number and size of fruits per plant in tomato (Harel et al. 2014). The reproductive stage of the plant is generally more vulnerable to high temperatures than the vegetative stage (Al-Selwey et al. 2021). Moreover, temperatures exceeding 35 °C have been reported to induce floral abortion, resulting in an 80% loss of flowers in tomato plants and a subsequent decrease in fruit set. Among the three years, 2022 was the most severe one in terms of thermal stress, with a frequency of 9 days where temperatures exceeded the optimal growth and fruit

Table 8 Optimum and maximum critical temperature for tomato growth at different reference phenological stages

Growth stage	Optimum temperature (°C)	Maximum critical temperature (°C)
Vegetation	22.00	35.00
Flowering	21.00	30.00
Fruit setting	20–25	27.00
Fruiting	15–25	35.00

* Velazquez et al., 2022; Geisenberg and Stewart 1986

formation temperatures for tomatoes by 14 °C (ranging from 20 °C to 25 °C) during the day (Sillo et al. 2022). In this year, average maximum temperatures during the flowering period were 34.99 °C, close to the maximum cardinal temperature for tomato (35 °C) (Table 3). This extreme heat is further reflected in the analysis of daily trends in the Crop Heat Stress Index (Fig. 6), which shows that while the critical threshold of 1 was never exceeded during the first experimental year, both the second and third years, particularly 2022, experienced prolonged periods of heat stress above this threshold, especially during the flowering stage.

The significant Total yield decrease in 2022 (Table 4) can be primarily attributed to the adverse effects of temperature during the critical flowering period (PS2). Throughout the three experimental years, the trend of average daily temperatures exerted a predominant influence on the daily reference evapotranspiration ($r = 0.83$). The rise in temperatures and the extent of ET0 had a detrimental effect on all parametric water use efficiency (WP, r=-0.73; TYWP, r= -0.60; MYWP, r= -0.60, and IWP r=-0.67). This underscores the importance, especially in arid environments, of adopting those practices aiming at maintaining an efficient use of irrigation water. The observed temperature trends had a notable impact on both dry biomass and plant height, aligning with prior research that underscores the influence of high temperatures on these morpho-physiological parameters (Sillo et al. 2022). A study by Nangare et al. (2016) reported a significant reduction in growth variables, including plant height and Leaf Area Index (LAI), when subjected to a controlled deficit irrigation level of 0.6 ETc.

The findings of the present study indicate that the growth parameters of tomato, specifically dry biomass and plant height, have a considerable influence on the number of fruits. The reduced growth is associated with a lower formation of inflorescences, contributing to the observed negative impact on fruit yield.

Similarly, root length was negatively correlated, although not significant, with the increase in the average seasonal temperature (r= -0.50). The study of the relationship between climatic parameters and fruit quality parameters, in all the three experimental years, showed a significant decrease

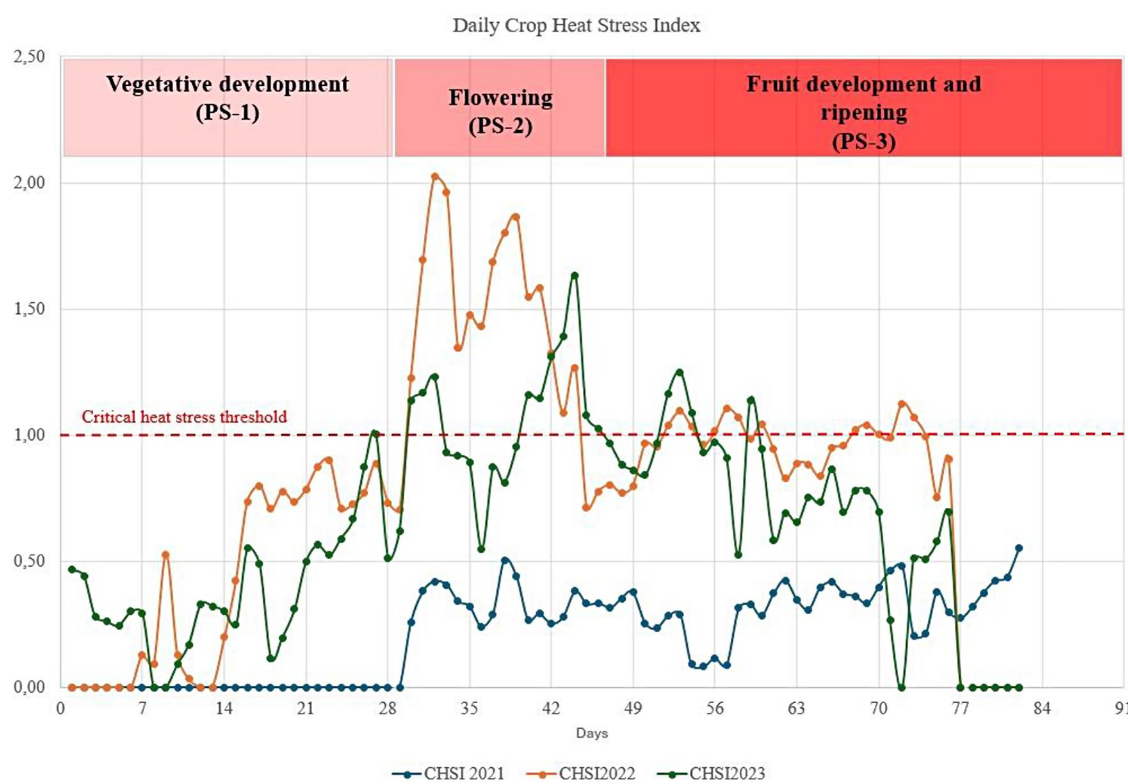

Fig. 6 Daily trends of the Crop Heat Stress Index recorded during the experimental years 2021, 2022, and 2023. CHSI values above threshold of 1 indicate that the daily maximum temperature (°C) is exceeding the maximum critical temperature for the crop

Table 9 Factor loadings, eigenvalues and percentages of total variance for the two principal component derived parameters measured each year

Measurements	PC1	PC2
ET0 daily	-0.65	-0.72
T. avg daily	-0.50	-0.74
T. max daily in PS3 stage	-0.57	-0.76
ET	0.42	-0.83
Water irrigation (m^{-3})	-0.06	-0.84
Dry Biomass	0.83	-0.07
WUE	0.96	0.18
TYWUE	0.98	-0.01
MYWUE	0.95	-0.05
IWP	0.90	0.05
Fruits per plant	0.72	-0.61
Marketable yield	0.90	-0.32
Total yield	0.93	-0.34
Eigenvalue	8.81	4.78
Total variance (%)	35.24	19.12

of TSS (°Brix) as a function of daily average temperature ($r = -0.79$) and daily ET0 (r= -0.77). This result is reported in similar studies (Patanè and Cosentino 2010; Alsamir et al. 2021) showing how the high temperature altered the production of compounds, such as carbohydrates, polyamine and proline.

Results of principal component analysis

To comprehensively explore the interactions between environmental conditions recorded and the resulting fruit yield and quality, we employed a PCA. The initial multivariate data analysis considered various parameters, including total climatic variables, irrigation volumes, yield, and the water productivity indexes per treatments where irrigation was considered as categorical factor. Table 9 reports that the first principal component (PC1) possesses a higher eigenvalue (8.81) than the second principal component (PC2) (4.78), indicating that PC1 explains a larger proportion of the variability within the considered dataset.

Collectively, the two principal components elucidate approximately 53.36% of the total variance. Specifically, climatic variables such as daily ET0 and temperatures exhibit negative loads on both PC1 (-0.65) and PC2 (-0.72). Furthermore, irrigation demonstrates a negative load (-0.84) on the second component (PC2). In this context, climatic variations associated with PC2 may have negative effects on irrigation volumes, suggesting a potential reduction in irrigation volumes in response to specific climatic conditions. The orientation of irrigation treatments in the scatterplot (Fig. 7) is influenced by their loads on the main components, illustrating their responses to distinct climatic variations. Notably, treatments {FI_2021}, {DI-1_2022}, {RDI_2022}, {DI-2_2023}, and {RDI_2023} exhibit positive loads on PC1, indicating a positive response to climatic variations represented by PC1. Similarly, treatments {DI-2_2021}, {DI-2_2022}, and {DI-2_2023} show a positive response to climatic variations represented in PC2. Conversely, treatments {FI_2022}, {DI-1_2021}, {DI-2_2021}, {DI-1_2023}, and {DI-2_2022} manifest a negative response to climatic variations on PC1, while {DI-1_2022} and {DI-2_2022} exhibit negative responses to climatic variations

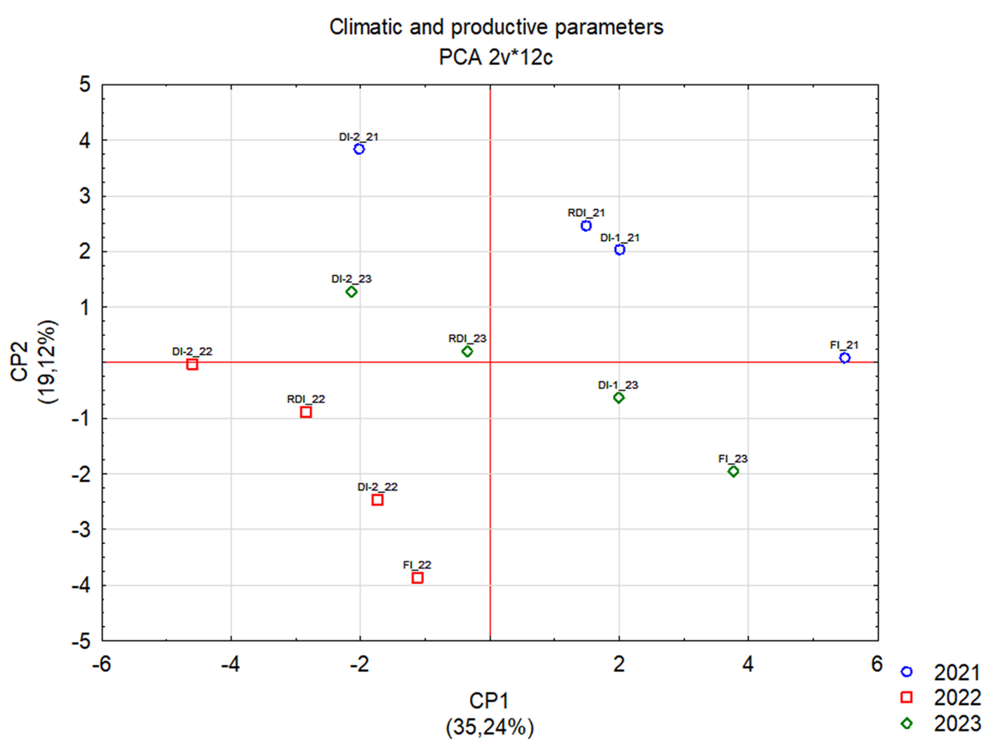

Fig. 7 Scatterplot of PCA on some yield parameters (dry biomass, total yield and marketable yield, number red fruit per plant, WP, TYWP, MYWP, WP and agro-climatic parameters (ET and irrigation volumes, daily ET0 and daily temperature and daily maximum Temperature in PS3)

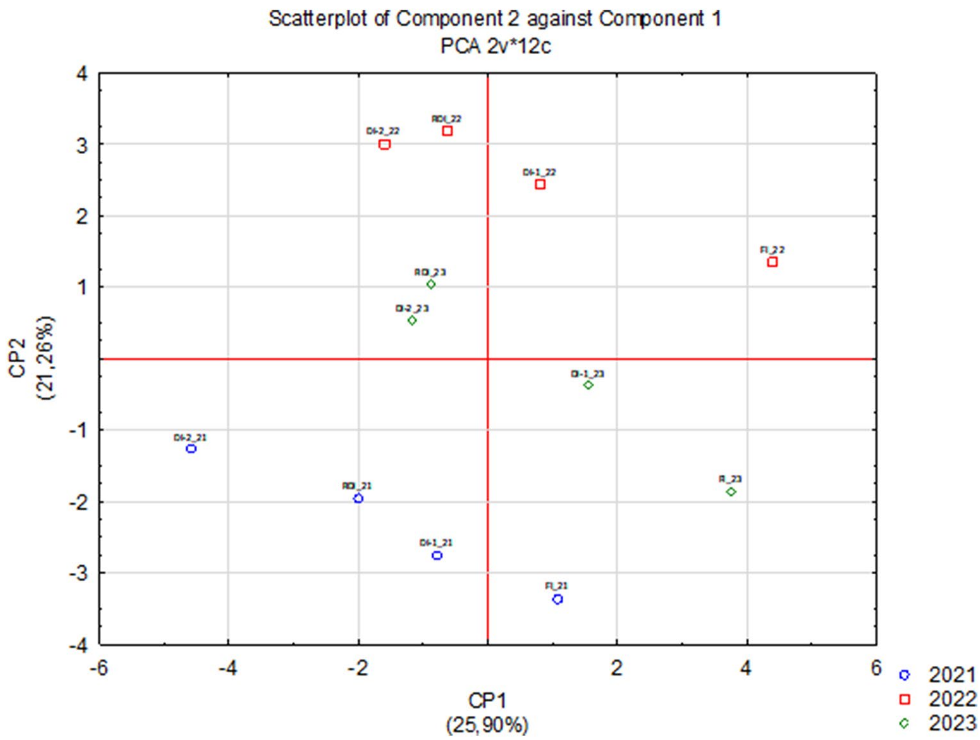

Fig. 8 Scatterplot of PCA on fruit quality parameters (TSS° Brix, pH, fruit fresh and dry weight, fruit length and diameter) and agro climatic parameters (daily ET0, daily temperature and daily maximum Temperature in PS3, ET and irrigation volume)

Table 10 Factor loadings, eigenvalues and percentages of total variance for the two principal component derived parameters measured each year

Measurements	PC1	PC2
ET	0.95	-0.03
Water irrigation (m-3)	0.69	0.35
T. avg daily	0.45	0.83
T. max daily in PS3 stage	0.43	0.88
ET0 daily	0.32	0.90
Fresh fruit weight (g per fruit)	0.76	-0.52
Size Dry fruit weight (g per fruit)	-0.71	0.28
Water (%)	0.82	-0.48
Lenght (mm)	0.72	-0.15
Diameter (mm)	0.65	-0.57
TSS (°Brix)	-0.28	-0.82
pH	0.66	-0.01
Eigenvalue	6.21	5.10
Total variance (%)	25.90	21.26

on PC2. In more specific terms, this confirms that different irrigation treatments have divergent reactions to climate changes. For instance, it may be possible that a treatment displaying a positive response to PC1 may be more suitable for climatic conditions represented by PC1, whereas a treatment with a negative response to PC2 may not perform optimally in conditions represented by PC2. This diversity of responses confirms the necessity of adapting irrigation practices to specific climatic conditions, offering valuable insights for the more effective management of tomato under diverse environmental conditions.

PCA on the qualitative variables allowed us to separate the three experimental years, as shown in Fig. 8. When analyzing the response of irrigation, especially concerning quality, to climate, analyzing the loads of individual variables on the principal components (PC1 and PC2) provides valuable insights.

In Table 10, PC1 has a much higher eigenvalue than PC2 (6.21 and 5.10, respectively), explaining a total of about 47.16% of the variance. Examining the loads of qualitative, climatic, and irrigation variables on PC1 and PC2 reveals distinct patterns.

The weight, length, and diameter of the fruit, as well as pH, are positively associated with PC1. On the other hand, PC2 is positively associated with pH and Brix. The findings of PCA on quality indicate that increased water intake and specific irrigation approaches positively affect tomato growth and quality. However, certain irrigation deficits, especially in 2022, show negative associations with specific principal components, which negatively impact certain qualitative and productive aspects. Despite these instances, positive loads on the second component of RDI suggest a potential improvement in fruit quality through this treatment. Reducing water supply during specific growth phases might contribute to better sensory quality in the fruit.

Conclusions

Irrigation is essential for supporting agricultural production, yet there is an increasing need to optimize water use. Both growth variables and yield parameters are significantly affected by deficit irrigation treatments. Fruit yields and dry biomass are highest under full irrigation conditions. The effect of deficit irrigation on improving WP was studied. The study of irrigation efficiency parameters shows similar WP among Regulated Deficit Irrigation, Deficit Irrigation and Full irrigation. However, significant positive outcomes were observed with the implementation of deficit irrigation in 2022, a year characterized by severe thermal stress. Specifically, water use efficiency indices (WP, TYWP, MYWP, and IWP) were higher under deficit irrigation (DI_1) compared to all other irrigation methods, resulting in approximately 33% of water savings and improved fruit quality. A strong positive relation was found between water use optimization and fruit quality. Conversely, yields were strictly dependent on evapotranspiration and thermal parameters. Our study emphasize the importance of irrigation management and the consideration of thermal stresses to optimize yields and quality of tomatoes. The effect of temperatures and the growing frequency of heat waves on plant's growth and yields requires adopting practices to optimize water use and evapotranspiration. In conclusion, the ML-based DSS proved to be effective in determining amount of water volumes, but it should consider with greater sensitivity the susceptibility of the crop to thermal and water stress. This will better adapt irrigation practices to specific environmental conditions, thus improving the overall effectiveness of water management with a view to maximizing production and preserving crop quality. Moreover, the performance of deficit irrigation treatments during extremely dry years highlights the importance of adapting irrigation strategies to specific environmental conditions, emphasizing the potential benefits of deficit irrigation in years characterized by water stress and high temperatures. Further research and validation of these results under different environmental conditions would help refine irrigation management practices and promote sustainable water use in agriculture. Effectively implementing deficit irrigation strategies can achieve a favorable balance between processing tomato yield and fruit quality. This approach has led to significant water savings and improved water productivity, which is particularly crucial in environments where escalating water scarcity and rising costs pose substantial challenges for producers.

Author contributions AM, DR and FB conducted the research; AM, DR, IIMD and LV wrote the main manuscript text; FB and ADM supervised the research, the writing process, and revised the paper. AM, DR, IIMD and LV carried out the revision process following reviewer comment's.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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