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AquaCrop model to optimize water supply for a sustainable processing tomato cultivation in the Mediterranean area: A multi-objective approach

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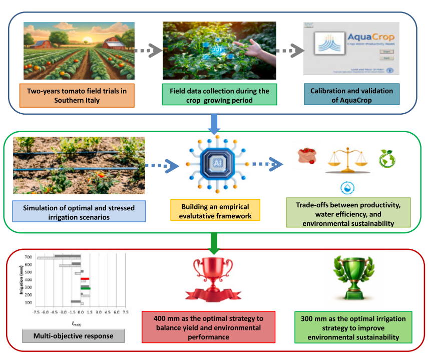
HIGHLIGHTS

- The framework balances crop yield, water efficiency, and economic returns.
- Optimal ranges of irrigation depth for various objectives were identified.
- Defined optimal irrigation at 400 mm for maximizing key performance indices.
- Seasonal irrigation of 300 mm improves water savings without compromising yield.
- Multi-objective analysis identifies optimal irrigation range for sustainable cropping.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Efficient irrigation management must consider multiple aspects of cropping systems, such as productivity, water use efficiency, and economic viability. Crop simulation models like AquaCrop are essential tools for analyzing crop responses under different irrigation scenarios. Organizing the model's outputs into standardized parameters allows for a multi-objective evaluation, which can be consolidated into a single index for optimizing irrigation strategies.
OBJECTIVE: This study aims to formalize the response of processing tomato cropping systems in Southern Italy to various irrigation regimes and develop a framework to identify optimal irrigation volumes for production, water use efficiency, and economic returns.
METHODS: AquaCrop was used to assess the effects of different seasonal water supplies on dry yield, water use efficiency, and irrigation water use efficiency. Sustainability was evaluated via the blue water footprint and drainage, while economic sustainability was measured through net income and irrigation economic efficiency. A multi-objective evaluation framework was built, developed to consolidate performance indices into a single multi-aggregated index (I_{mobj}). The AquaCrop model was calibrated and validated using field data, with high accuracy in simulating canopy cover, biomass, and dry yield ($NRMSE < 30$ %, $r > 0.90$, and $d > 0.97$). Polynomial regression was used to model the relationships between irrigation volumes and cropping system

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variables. Each variable was assigned a truth value (TW_i), derived from regression coefficients, statistical significance, and model fit. These values were normalized using a sigmoid function and consolidated into the I_{mobj} index, providing an overall measure of irrigation performance.

RESULTS AND CONCLUSIONS: AquaCrop accurately simulated canopy cover, biomass, and dry yield. Multi-objective analysis showed yield and profitability were most sensitive to irrigation changes, followed by drainage, blue water footprint, and water use efficiency. The 500 mm irrigation regime yielded the highest productivity and profitability but negatively impacted water use efficiency and environmental sustainability. Irrigation volumes above 500 mm worsened all water-related variables, while volumes of 400 mm reduced profitability but improved the sustainability. The I_{mobj} index identified that irrigation between 300 mm and 400 mm provided the best trade-off across all evaluated variables.

SIGNIFICANCE: This study highlights the value of integrating crop productivity, economic viability, and sustainability into irrigation management. The proposed framework, combined with AquaCrop, offers a holistic tool for optimizing irrigation strategies in agriculture. It emphasizes the need for balanced irrigation that not only maximizes yield but also enhances resource efficiency and environmental sustainability.

1. Introduction

The world faces an unprecedented confluence of challenges in agriculture, where the sustainable cultivation of crops stood as a linchpin in ensuring global food security (UN, 2015). Among the numerous complexities confronted by modern agriculture, the efficient utilization of water resources emerged as a paramount concern. Water, the lifeblood of agriculture, was increasingly becoming a scarce and contested resource due to burgeoning global population growth, rapid urbanization, and climate change-induced alterations in precipitation patterns (Kang et al., 2017).

In the Mediterranean environment, water was a limiting factor for crop yield, necessitating a careful evaluation of the method, timing, and volume of water supplied to rationalize and preserve this resource, maximize crop yield and ensure a suitable income for farmers (Rinaldi et al., 2011).

In Mediterranean countries, agriculture consumed about 80 % of water resources, and it was estimated that the agricultural area in several countries would increase by 15 % within a few years (Crovella et al., 2022).

Among these countries, Italy had one of the highest levels of water withdrawals for agriculture, accounting for almost 50 % of total water consumption (ISTAT, 2019) and was the leading producer of processing tomatoes in Europe, with 51 % of the entire European harvest in 2021 (European Commission, 2021).

Among horticultural crops, processing tomato cultivation represented one of the most intensive uses of agricultural land in terms of water use and chemical input (Rinaldi et al., 2007).

Achieving adequate fruit yield levels for tomato fruits and maximizing net income for farmers required improvements in water management to prevent water waste (Rinaldi et al., 2011).

In Mediterranean countries, agriculture consumes approximately 80 % of available water resources, with projections estimating a 15 % increase in agricultural areas in the near future (Crovella et al., 2022). Italy stands out among these countries for having one of the highest levels of water withdrawals for agricultural purposes, accounting for nearly 50 % of total water consumption (ISTAT, 2019). As the leading producer of processing tomatoes in Europe, Italy contributed 51 % of the total European harvest in 2021 (European Commission, 2021).

Processing tomato cultivation is notably water-intensive, involving significant chemical inputs (Rinaldi et al., 2007) and to achieve sufficient fruit yields and maximize farmer income, substantial improvements in water management practices are essential to prevent wastage (Rinaldi et al., 2011).

Traditional irrigation practices that rely on fixed schedules or volumes often result in inefficiencies such as nitrogen leaching, excessive drainage and reduced water use efficiency, all of which can adversely impact farmer profitability. To tackle these inefficiencies, comprehensive, long-term studies are needed to evaluate various irrigation strategies and optimize water management. However, conducting extensive field trials to test all possible combinations of irrigation schedules and crop responses is often impractical due to time, cost, and logistical complexities. In this context, growth simulation models emerge as powerful tools for predicting for predicting how different water management strategies interact with varying pedo-climatic conditions, thus facilitating more informed agricultural decision-making. A lot variety of crop models have been developed to describe plant growth and yield; Todorovic et al. (2009) classified these models into three main categories based on their driving factors: carbon-driven models such as WOFOST (Van Diepen et al., 1989) CROPGRO, and DSSAT (Jones et al., 2003), solar radiation-driven models including CERES (Ritchie et al., 1988), EPIC (Jones et al., 1991), STICS (Brisson et al., 2003) and APSIM (Keating et al., 2003) and water-driven models like AquaCrop (Raes et al., 2009a), and CropSyst (Holzworth et al., 2014; Stöckle et al., 2003).

Among the models tested or adapted for the Mediterranean region are DSSAT, WOFOST, EPIC, CropSyst and STICS. The choice of model largely depends on the specific phenomenon being studied and the conditions of the study area.

In Mediterranean latitudes, solar radiation is not typically a limiting factor for crop production, as the intercepted photosynthetically active radiation (*IPAR*) is usually sufficient for achieving high yields. Therefore, the adoption of non-radiation-driven models like AquaCrop can be beneficial in evaluating water use efficiency (Buesa et al., 2020).

AquaCrop, developed by the Food and Agriculture Organization (FAO) (Hsiao et al., 2009; Raes et al., 2009a; Steduto et al., 2009), is specifically designed to predict crop yield, water requirements, and water productivity (*WP*, Doorenbos and Kassam, 1979) under various irrigation regimes (Kanda et al., 2018). Its applications span various environmental conditions and management practices, including rainfed, deficit irrigation, supplemental irrigation, full water supply, and on-farm water management strategies, all aimed at improving water use efficiency in agriculture (Heng et al., 2009).

Since its introduction in 2009, AquaCrop has been evaluated and calibrated across a wide range of crops and strategies tailored for arid and semi-arid conditions, as well as other case studies on water scarcity (Bird et al., 2016; Katerji et al., 2013).

AquaCrop uses the crop *WP* values (Arumugagounder et al., 2022), normalized for climatic conditions, including atmospheric evaporative demand and CO_2 concentration to drive the crop growth. This conservative approach allows for the extrapolation of water-driven models to diverse locations and future climate scenarios, where CO_2 concentrations are expected to rise (Steduto et al., 2007). It is simple to use, requiring only a small number of intuitive input parameters (Abi Saab et al., 2015; Ahmadi et al., 2015; Dhouib et al., 2022; Garcia-Vila and Fereres, 2012; Heng et al., 2009; Steduto et al., 2009; Raes et al., 2009b; Vanuytrecht et al., 2014), and is publicly available, featuring a user-friendly interface (Hunink and Droogers, 2011). These features make AquaCrop applicable not only to researchers aiming to enhance water use efficiency (*WUE*) but also to farmers, agricultural consultants and water managers (Farahani et al., 2009).

The model's effectiveness in simulating the crop response under water scarcity has been highlighted by numerous studies (Iqbal et al., 2014; Jin et al., 2014; (Raes et al., 2009a) Steduto et al., 2009; Xiangxiang et al., 2013), particularly in Mediterranean hilly areas characterized by rainfed agriculture (Dhouib et al., 2022). In addition, this model has become a valuable decision-making tool for developing crop management strategies at the farm level (Sam-Amoah et al., 2013).

Regarding tomato crop, several studies (Garofalo and Rinaldi, 2015; Katerji et al., 2013; Linker et al., 2016; Rinaldi et al., 2011; Soddu et al., 2013) have successfully assessed the suitability of AquaCrop to simulate tomato growth and optimize daily irrigation schedules to achieve optimal yields with limited water resources.

However, AquaCrop's applications focussed on specific aspects of water resource utilization, including *WUE* (Katerji et al., 2013), growth and yield (Hendy et al., 2019), economic returns (Rinaldi et al., 2011) and water footprint (Sidhu et al., 2021).

In contrast to AquaCrop, other models can be more complex, requiring highly detailed input data about crop growth that may not be readily available in many locations. Additionally, these models often necessitate advanced skills for calibration and operation (Heng et al., 2009).

Despite its many advantages, AquaCrop has some limitations, as noted by the FAO's Land and Water Division (https://www.fao.org/aquacrop/en/). It is designed to predict crop yields at the single field-scale (point simulations), thus not accounting for spatial heterogeneity in crop development, transpiration, soil characteristics, or management practices; it assumes uniform field conditions. AquaCrop also consider only vertical water fluxes for rainfall, irrigation, capillary rise, evaporation, transpiration and deep percolation.

The AquaCrop model is available through a compiled software package (Raes et al., 2023) and the user-friendly interface means that users cannot write or program the model code for specific case studies (Foster et al., 2017).

Furthermore, AquaCrop has limitations, which concerning the fertilization regimes, adopting a semi-quantitative method to evaluate fertilizer stress. The effect of soil nutrients on crop growth is expressed as a percentage reduction in biomass and crop coefficient relative to full irrigation and fertilization (Akumaga et al., 2017; Van Gaelen et al., 2015). The model may not accurately simulate plant responses to fertilization based on nutrient demand and soil nutrient content, leading to potentially inaccurate assessments of fertilizer stress (Adeboye et al., 2021; Rahimikhoob et al., 2021).

Additionally, AquaCrop lacks a soil temperature module which can significantly affect outcomes in scenarios involving film mulching (Cheng et al., 2022).

Again, other models such as CropSyst, APSIM, DSSAT, STICS, and WOFOST offer more integrated functionalities that include detailed representations of radiation use efficiency, carbon balance, and nutrient dynamics. Anyway, these models provide a more comprehensive view of crop growth under varying conditions but may also require more complex input data and greater user expertise.

The guidance on water resource management that can be derived when using a crop simulation model for individual issues of the cropping system may vary depending on the aspect that is emphasized over another. For instance, maximizing crop productivity and its profitability may rely on intensive irrigation schedules. Conversely, maximizing *WP* and reducing drainage water loss may endorse reduced water supply. Clearly, it becomes evident that the optimization of water resources must consider all the various aspects of the system directly related to irrigation practices. Nevertheless, crop simulation models can serve as a cornerstone for more complex, multi-objective evaluations that address competing objectives like maximizing productivity, enhancing water efficiency, and minimizing environmental impact simultaneously.

This integration allows for evaluating how different irrigation regimes affect yield and their implications for water sustainability, profitability, and water savings. AquaCrop, like other crop simulation models, can thus facilitate broader analyses that extend beyond traditional crop yield assessments, equipping decision-makers with tools to balance competing objectives in water-scarce environments. This enables farmers and policymakers to make informed decisions that align short-term productivity with long-term sustainability goals.

However, such a proposed multi-objective analysis can pose two challenges for investigations. The first issue is that the response of variables under exploration, as affected by irrigation, has to be comparable to each other, irrespective of their scale and data nature (e.g. comparing productivity expressed in kg ha^{-1} with drainage expressed in mm). The second challenge involves aggregating this information into a single, easily readable, and interpretable benchmark that could be tailored to the needs of the end user and serves as the basis for optimizing water resources.

The multi-layered data structure or complex data aggregation processes of the multi-objective approaches could vary depending on the method of aggregating available information, potentially affecting the replicability of the methodology and/or the expertise required to adapt such an approach to different contexts and users (Garofalo et al., 2020; Ren et al., 2019; Wang et al., 2019).

To address these complexities and make meaningful progress, this paper proposed a hierarchical framework designed to simplify the process of optimizing irrigation strategies. The framework began with the calibration and validation of the AquaCrop model using field data, ensuring that the model's predictions were accurate and reliable. Building upon this foundation, various irrigation scenarios were constructed to explore a broad spectrum of irrigation options. This approach allowed for the development of an empirical model, based on second-order polynomial regressions between irrigation volumes and water-related parameters (such as yield, *WUE*, water drainage, profitability). The aggregation of parameters related to these polynomials involved algebraically summing the values of the regressor coefficients with the values (ranging from 0 to 1) assigned to significance level and R^2 based on their meaning. This process then enabled the weighting and comparison of the effects that different irrigation management practices had simultaneously on the individual variables analyzed. It provided a qualitative-quantitative assessment regardless of the different nature and scale of the parameters involved.

Subsequently, the framework aggregated these metrics into a single multi-aggregated index. This index served as a comprehensive measure for comparing and assessing various options in terms of seasonal irrigation volumes, while also considering the sometimes-conflicting results that different irrigation strategies might produce on individual aspects of the cropping system. This approach thus allowed rapid screening and selection of irrigation management practices aimed at optimizing the productive, environmental, and economic performance of the investigated system.

2. Materials and methods

2.1. Characteristics of the cultivation area

In the Capitanata plain, located in the Apulia region, southern Italy (41.4611° N, 15.5494° E), processing tomato cultivation uses an area of approximately 17,800 ha (ISTAT, 2023), which represents 22 % of the total Italian acreage dedicated to this crop. The production from this area accounts for more than 23 % of the national production (ISTAT, 2023).

2.1.1. Experimental site

The field experiments were carried out for two years (2021,2022) in farms associated to Futuragri association group, in the Capitanata irrigation consortium (Southern Italy; lat. 41° 26′ 39.7" N; long. 15° 41′ 20.9″ E, alt. 37 m a.s.l.).

The climate in Capitanata is "accentuated thermo-Mediterranean"

(Emberger et al., 1962) with temperatures below 0 °C in the winter and above 40 °C in the summer. The average maximum annual temperature for the area is 28 °C while the average minimum temperature is 14 °C. Annual rainfall (average 550 mm) is mostly concentrated during the winter months and class “A pan” evaporation exceeds 10 mm day^{-1} in summer.

Meteorological data of maximum and minimum temperature (°C; *Tmax* and *Tmin),* relative air humidity (%; *RH*), rainfall (mm) and solar radiation (MJ m^{-2}) at daily scale during the experimental years (2021 and 2022) were collected at the nearby (about 15 Km from field) Amendola Foggia meteorological station (of the Italian Air Force's meteorological network). Some of these variables (rainfall and solar radiation) were also monitored in the experimental plots or provided by the nearby meteorological station of CREA-Cereal and Industrial Crop Research Centre (about 17 Km from field).

Daily reference evapotranspiration (ET_{0i}; mm) in the experimental field was estimated by the FAO Penman-Monteith equation as described in Allen et al. (1998), using the daily data of solar radiation, *Tmax, Tmin* and *RH* from the meteorological stations.

The soil of the experimental site was classified as a silty loam according to USDA Soil Taxonomy, with the following composition: 29.4 % sand, 48.8 % silt, 21.8 % clay (hydrometer method; Gee and Bauder, 1986) and 1.5 % organic matter (Walkley-Black method; Nelson and Summers, 1982).

The soil texture, organic matter and bulk density were carried out by three replicates through the experimental plot at the following depths: 0.00–0.15 m and 0.15–0.30 m. Such soil samples were taken in May 2021, before that the experiment was set up. The soil texture and bulk density of the two layers were similar, so a unique soil layer was considered (0.00–0.30 m).

By soil texture data, bulk density and organic matter, the soil hydraulic properties were estimated implementing the pedotransfer functions HYPRES (Wösten et al., 1999). The soil layer from 0.00 to 0.30 m deep was characterized as follows: volumetric water content at field capacity (*FC*) 0.33 m^3 m^{-3}; volumetric water content at permanent wilting point (*WilP*) 0.14 m^3 m^{-3}; total available water content 57 mm, bulk density 1.10 kg m^{-3}, saturated hydraulic conductivity (*Ksat*) 25.4 mm h^{-1}.

The soil water content (%) was monitored by the gravimetric method. Therefore, soil samples were taken at beginning and during the crop cycle every two weeks. Samples were taken from each plot and replicates at a depth of 0.00–0.10, 0.10–0.20 and 0.20–0.30 m. The volumetric water content (*SWC*, m^3 m^{-3}) was determined multiplying the water content (%) by the bulk density.

2.1.2. Field experiment

Field trials were carried out on a processing tomato crop (*cv.* Taylor); it was transplanted on June 5, 2021, and May 13, 2022, in 750 m^2 plots using a double-row pattern with distances of 0.30 m between plants on the row and 1.85 m between rows. Plant density was 3.6 plants per square meter. Fertilizer applications were considered optimal for all field.

The experimental design was a completely randomized block with three replications. Crop development and phenological phases were monitored during the entire crop cycle.

Destructive plant tissue samples were collected at 2-week interval from the time of transplanting to the time of final harvest. The length of crop cycle assured about 7/8 sampling per treatment in each year, to guarantee sufficient data to drive AquaCrop simulation model. Six representative plants per treatment were harvested, placed in paper bags and take directly to the laboratory for subsequent determinations. Plants were partitioned into roots, stem, leaves and fruits. Fresh leaves were used for leaf area measurements and roots were cleaned and washed free of soil particles. Fresh leaves, roots, stems and fruits were dried in a ventilated oven at 65 °C until a constant weight was achieved and then weighed. At harvest time, larger samples were used, namely 2.5 m^2 per treatment were collected.

The *LAI* (m^2 m^{-2}) was measured with direct and destructive method by LICOR-3100C leaf area meter (Li-COR Biosciences) at each sampling time by harvesting vegetation leaves. The LAI values were then converted into canopy cover (*CC*) using Beer's law (Beer, 1852):

$$CC = 1 - e^{(-ek \times LAI_d + Cf)} \tag{1}$$

Where *ek* is the light extinction coefficient (0.75; Rinaldi et al., 2011), LAI_d is the green leaf area and Cf is the clumping factor, calculated as:

$$Cf = 0.75 + (0.25) \times \left(1 - e^{(-0.35 \times LAI_d)}\right) \tag{2}$$

In the study area, processing tomato is irrigated with seasonal water volumes ranging from 4000 to 6000 m^3 ha^{-1} (Giuliani et al., 2005; Rana et al., 2000).

In both years, the full-water treatment followed the farmer practice (*FARM*). The Farmers in the study area tend to irrigate tomato crops every day or with close irrigation shifts and often they provide more water than is necessary for plant development. Hence, in the *FARM* treatment (2021 and 2022) the dates and volumes of irrigation events were decided by the farmers. Then, to obtain the stressed treatments *RED-20* (2021), and *RED-40* (2022), the dates and duration of irrigation events were left the same of the *FARM* and the volumes of each day were reduced by 20 and 40 % compared to the volumes of the *FARM* treatment. More severe reductions of irrigation water volumes, with respect to *FARM,* were not implemented during the experimental years because in the Mediterranean environment, the tomato water demand is very high, and stressing the crop beyond a certain threshold could have seriously compromised productivity. Not to mention the economic return, which would not be feasible for the farmers.

Irrigation was supplied by self-compensating drip lines; drippers with different flow rates were used to obtain the different irrigation depths in the *FARM* and *RED* treatments. Uniform water distribution was ensured by using high-quality drippers designed for consistent flow despite varying pressures. The discharge rates were 1.6 L h^{-1} for the *FARM* treatment, and 1.3 L h^{-1} and 1.1 L h^{-1} for the *RED-20* and *RED-40* treatments, respectively. Monitoring with water meters at each irrigation event, ensured that any discrepancies were promptly addressed.

In the experimental plots, irrigation volumes were monitored using water meters, with readings taken every week (Table 1).

2.2. The AquaCrop model

AquaCrop simulates, at a daily time step, the vertical water fluxes across the soil–plant–atmosphere continuum (Dhouib et al., 2022) or rather the water exchange between the soil and the roots.

It formalizes soil water dynamics, canopy development, phenology, plant growth, and yield formation. It considers both potential growth and growth modulated by thermal and water stresses. These stress factors are affected by climate, including its thermal regime, rainfall, evaporative demand, and carbon dioxide concentration (Muroyiwa et al., 2022). Irrigation management in AquaCrop impacts on the soil water balance, crop development and yield (Raes et al., 2009a).

Table 1
Processing tomato water management reported as irrigation events and seasonal water supply (sum of irrigations and rainfalls) for well-watered (*Farm*) and deficit irrigation treatments (*Red-20* and *Red-40*), in the 2021 and 2022 experimental years.

Year	Treatment	Irrigation events	Seasonal supply
		n°	mm
2021	*Farm*	75	546
	Red − 20	75	438
2022	*Farm*	72	752
	Red − 40	72	452

Water is added to the soil reservoir by rainfall and irrigation. When the rainfall intensity is too high, part of the precipitation might be lost by surface runoff and only a fraction will infiltrate. The infiltrated water cannot always be retained in the root zone. When the root zone is too wet, part of the soil water percolates out of the root zone and is lost as deep percolation. Water can also be transported upward to the root zone by capillary rise. Processes such as soil evaporation and crop transpiration remove water from the reservoir.

Concerning the water consumed by the cropping system, daily crop transpiration (Tr_i, mm day^{-1}) is calculated through ET_{0i} and driven by the canopy cover adjusted for micro advection (CC^*) as follows:

$$Tr_i = K_s \times CC^* \times K_c \times ET_0 \tag{3}$$

where K_S is the soil water stress coefficient and crop coefficient (K_c).

The aboveground biomass (TDM, t ha^{-1}) is calculated through the water productivity normalized for ET_{0i} (WP^*, g m^{-2}) and) Tr_i (Wellens et al., 2022):

$$TDM = WP^* \times \sum_{i=1}^{n} \frac{Tr_i}{ET_{0i}} \tag{4}$$

Finally, dry yield (Y, t ha^{-1}) is estimated from TDM at maturity and harvest index (HI, %) as follows:

$$Y = HI \times TDM \tag{5}$$

Soil water stress affects the development of the canopy cover, the expansion of the root zone, results in stomata closure, in a reduction of crop transpiration rate, and in failure of pollination, alters the harvest index, and even triggers early canopy senescence. Soil water stress affects the above processes when the soil water stored in the root zone drops below a threshold level. The thresholds are expressed as root zone depletion, i.e., a fraction of the total available water.

2.2.1. Model parameterization and input

The application of the AquaCrop model requires few and intuitive inputs related to the climate, crop, crop management and soil properties.

2.2.1.1. Climatic Data inputs. AquaCrop requires minimum and maximum air temperature, ET_0 and rainfall. ET_0 can be directly put into the model or calculated by it according to the FAO-56 methodology (Allen et al., 1998) providing the coordinates of meteorological station (altitude and latitude) and daily measurements of global radiation, air humidity, wind speed, temperature. Additionally, mean annual atmospheric CO_2 concentration should be provided because it affects canopy expansion and crop water productivity.

Temperature data are used to calculate growing degree day (GDD or so-called heat units) which can be used to track plant development through the crop cycle, from transplant to maturity, and for adjusting biomass production during damaging cold periods (Raes et al., 2009a).

The climate data, we provided as inputs to the model, were the daily data of $Tmax$, $Tmin$, solar radiation and RH to calculate ET_0 and reported in section 2.1.1.

The CO_2 file was built with the yearly atmospheric CO_2 concentration of Mauna Loa Observatory records in Hawaii provided by the model (Steduto et al., 2009).

2.2.1.2. Soil Data inputs. The creation of the soil file in AquaCrop required soil texture class and soil hydraulic parameters: *Ksat*, volumetric water content at saturation (θsat), *FC* and *WilP*. It is possible to use indicative values provided by AquaCrop for various soil textural classes or import values determined experimentally or derived from soil texture with the help of pedo-transfer functions. Different horizons can be set and for each one it is necessary to indicate its own physical characteristics.

Moreover, the soil water content at the beginning of the crop cycle was also given as an input.

The soil data that have been used as model inputs are reported section 2.1.1.

2.2.1.3. Crop data inputs. Crop parameters necessary as input are divided in conservative and non-conservative and are provide as default values in the model for major agriculture crops. The first ones do not change with location, management, cultivars, and time and are relatively stable (Canopy growth - *CGC* and canopy decline - *CDC* coefficients; full canopy *Kc*; biomass *WP* and soil water depletion thresholds).

In contrast, the non-conservative parameters that are user-specific parameters, varied significantly with the year, site and variety depending on crop and field management, soil type, and climate (sowing date and density, length of crop cycle and phenological stages, maximum canopy cover, etc.). Non-conservative parameters were determined by the experiment, based on field observations of crop development and phenology. They are calibrated with data of the crop grown under favourable and nonlimiting conditions but remain applicable for stress conditions via their modulation by stress response function.

The crop calibrated parameters derived from crop sampling reported in section 2.1.2.

2.2.1.4. Management data inputs. Field management inputs regard:

a) data on soil fertility levels and agronomic practices that affect the soil water balance (e.g. mulching, tillage);
b) data on irrigation management.

In the absence of inputs related to *a)*, soil fertility is considered unlimited and field surface practices do not affect soil evaporation or surface run-off.

For the *b)* case, it is necessary to choose whether the crop is rainfed or irrigated. For irrigated crops, the irrigation method and the percentage of the wetted soil surface by the irrigation must be defined. Afterwards the user can select:

i) net irrigation water requirement (i.e. the amount of water required to avoid crop water stress is estimated in a way to keep the root zone depletion above the specified threshold value given as default, but which can be adjusted by the user);
ii) irrigation schedule, where date calendar, depth and water quality must be specified for each irrigation event;
iii) generation of an irrigation schedule by specifying a time (i.e. irrigations at fixed interval or when an allowable depletion in either water amount - mm or fraction of *RAW*) and depth criterion (i.e. a fixed depth - mm or a return to *FC* can be set).

In the present study soil fertility was non-limiting and weed under management, they were not limiting factors for soil evaporation. Regards to irrigation inputs, drip irrigation with 30 % of the soil surface wetted has been set and an irrigation schedule by specifying date and depth of each irrigation event has been provided according to the experimental irrigation management reported in section 2.1.2.

2.2.2. Model calibration and validation

To instruct AquaCrop in simulating processing tomato growth and development in a Mediterranean environment, the parameters and coefficients implemented in the crop algorithms were modified through two phases, namely, the calibration phase and then the validation phase.

Firstly, calibration process focussed on the *CC* development; a good simulation of this affects transpiration and in turn final crop's biomass and yield.

The calibrated parameters for good estimation of *CC* were: initial canopy cover -CC_0 (used to derive the corresponding plant density and the canopy size of the seedling, if not directly put as inputs); maximum canopy cover (CC_x), *CGC*, *CDC* and the values of cumulative growing degree days (*CGDD*) in each development stages (from transplant to full plant recovery, from transplant to maximum *CC*, from transplant to start senescence and from transplant to maturity).

Secondly, the calibration continued by modifying the parameters which determines yield and biomass formation (time of flowering or to start yield formation and to reach the maximum rooting depth; the maximum and minimum effective rooting depth). Some of these parameters (e.g., maximum effective rooting depth) are influenced by conditions in the soil profile, such as initial soil water content, the characteristics of soil horizons, and surface runoff. As a result, adjusting these parameters automatically adjusts the evaporation-related factors. Lastly, the *HI* was fine-tuned based on the efficient simulation of the biomass.

The effects of water stress on canopy expansion, stomatal conductance, and early canopy senescence are described in AquaCrop by the stress coefficients (*Ks*). These coefficients were calibrated to account for the impact of water stress on leaf expansion, stomatal closure, and anticipated senescence by selecting a sensitivity class. The upper and lower soil water depletion thresholds (*p*), which modulate the magnitude of these impacts, were also defined, thereby influencing the water stress-related conservative parameters.

The calibration process adapted AquaCrop outcome to the data obtained from the 2021 growing season under on the well-watered treatment, free of any water stress (*FARM* treatment).

The calibration of crop non-conservative parameters followed a trial-and-error approach, as recommended by developers and performed by other authors (Abedinpour et al., 2012; Amiri et al., 2024; César Augusto Terán-Chaves et al., 2022; Hsiao et al., 2009; Kanda et al., 2021; Mubvuma et al., 2021; Raes et al., 2012; Oiganji et al., 2016; Paredes et al., 2014; Raes et al., 2012; Sandhu and Irmak, 2019; Wellens et al., 2022; Zeleke et al., 2011). Initially, simulations used estimated or guessed parameter values, which were iteratively adjusted based on comparisons with measured experimental data. This process was repeated until simulated results closely matched experimental data (Hsiao et al., 2023). The conservative crop parameters were chosen within physically realistic ranges, guided by our understanding of crop growth and response to water deficits. Through iterative adjustments and comparisons across treatments and years, a set of valid parameter values was established.

Irrigation management replicated the events and the amount of water applied by the farmer (*FARM*) in 2021 (Table 1). These data were used as input to run the AquaCrop model in the calibration mode.

The validation phase, on the other hand, is crucial to test the robustness of the model after calibration and was carried out with datasets different from those used for calibration (*FARM* treatment 2021) but using the same crop file. The validation phase occurred by comparing the response of AquaCrop with what was observed in the *FARM* treatments of 2022 and *RED* treatments in both experimental years (2021 and 2022).

Irrigation events of *FARM* treatment of 2022, of *RED-20* treatment of 2021 and of *RED-30* treatment of 2022 were used for validation step, accordingly.

2.2.3. Model evaluation

During the calibration and validation processes, same evaluative statistical indices were used to verify the model performance and simulations accuracy, evaluating the consistency between the simulated and observable values.to The statistical indices used were the normalized root mean square error (*NRMSE*), Pearson correlation coefficient (*r*) and index of agreement (*d*) defined in the following equations:

$$NRMSE = \frac{1}{\overline{M}}\sqrt{\sum_{i=1}^{n}\frac{(S_i - M_i)^2}{n}} \times 100 \tag{6}$$

$$r = \frac{n(\sum M_i{*}S_i) - (\sum M_i){*}(\sum MS_i)}{\sqrt{\left[n\sum {M_i}^2 - (\sum M_i)^2\right]{*}\left[n\sum {S_i}^2 - (\sum S_i)^2\right]}} \tag{7}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sqrt{\sum_{i=1}^{n}(|S_i - \overline{M}| + |M_i - \overline{M}|)^2}}\right]^2 \tag{8}$$

where n is the number of observations, S and M are the simulated and measured values, respectively. $\overline{S}$ and $\overline{M}$ are the means of simulated and measured values, respectively.

NRMSE (%) is the relative difference between the model simulated and measured results, the simulation quality is excellent when the *NRMSE* is $<$10 %, good if it is between 10 and 20 %, acceptable if it is between 20 and 30 %, and poor if $>$30 % (Jamieson et al., 1991).

r is a statistical measure of the strength of the relationship between the relative movements of observed and simulated variables (Blyth, 1994). A correlation of -1.0 shows a perfect correlation but negative, (inverse relationship between the variables), while a correlation with 1.0 value shows a perfect correlation in positive (direct relationship between the variables). A correlation with 0.0 value shows no relationship between the movement of your two variables.

d is the index of agreement of Willmott (1982) to measure the degree to which the measured data are approached by the simulated data. It ranges between 0 and 1, with 0 indicating no agreement and 1 indicating a perfect agreement between the simulated and measured data (Saad et al., 2014).

2.3. Irrigation management scenarios

To achieve a wide range of responses of the cropping system under different irrigation options and growing seasons, artificial scenarios were performed using meteorological data of the years 2016, 2019 (datasets of 2016 and 2019 were rebuilt from Corbari and Mancini, 2023, Corbari et al., 2020, 2021), 2020 and 2021 (datasets recorded from nearby meteorological station, reported in the section 2.1.1).

The processing tomato was 'in-silico' exposed to various water supply treatments selecting the drip irrigation option, subjecting it to optimal water supply conditions until significant reductions in seasonal irrigation volumes were reached. The optimal irrigation strategy (*OPT*) was based on a time criterion, triggering irrigation when 20 % of the total available water was depleted the root zone. Building from this baseline, water deficit strategies were set by reducing the water supply at each irrigation event of *OPT* (thus, the date of each water supply was kept constant) at steps of 10 % (ranging from *OPT-10* to *OPT* − *90*). Additionally, two irrigation strategies that provided a surplus (10 %, *OPT* + *10*; 20 %, *OPT* + *20*) of water for each irrigation event of *OPT* were also investigated (Fig. S1, supplementary materials).

This approach ensured the simulation of irrigation scenarios that were more controllable, compared to setting water return thresholds based on total available water (*TAW*) depletion. The latter would have resulted in longer irrigation intervals but with significantly larger irrigation volumes, which would not have been suitable for this study. Such volumes could have caused excessive drainage and would not have aligned with the volumes typically distributed by farmers using common drip irrigation systems.

It is important to highlight that one of the key elements of the framework presented in the paper is the response curves for various parameters (e.g., yield, drainage, etc.) against seasonal irrigation volumes. To derive reliable data from the empirical model, it is crucial to explore an adequate number of irrigation scenarios. The purpose of these scenarios is to parameterize the empirical model's relationship between the response variables (yield, economic return, environmental burdens and water efficiencies) and seasonal irrigation volumes.

Therefore, the irrigation scenarios presented, while not necessarily mirroring field irrigation management, serve the purpose of understanding the model's response across a range of conditions. This approach ensures the model captures a comprehensive spectrum of irrigation responses, which is crucial for robust empirical model development and application.

2.4. Irrigation impact assessment

The impact of irrigation management was evaluated based on AquaCrop output parameters, either as-is or derived accordingly (Fig. S1, supplementary materials). The performance of the crop following changes in seasonal irrigation volume was assessed by means of *Y*. To assess the water use efficiency, irrigation water use efficiency (*IrrUE*; kg mm^{-1}) was used, which is the ratio between the dry yield and seasonal amount of irrigation water, and *WP* (kg mm^{-1}, the ratio between the dry yield and crop evapotranspiration). Environmental sustainability of irrigation management was assessed through the blue footprint (*Blue_FP*; mm kg^{-1}), i.e., the ratio between irrigation water and dry yield, and through the water lost with drainage (mm).

To measure economic sustainability, this study examined the net income (*NetInc*; Euro ha^{-1}) calculated as:

$$NetInc = G_i - (SdlCost + FertCost + IrrCost) \tag{9}$$

where G_i is the income from fresh yield (Euro ha^{-1}), as:

$$G_i = S_p * (Y/cv) \tag{10}$$

S_p is the selling price of processing tomato (145 Euro t^{-1}; ISMEA, 2023), *Y* is the dry yield, *cv* is a coefficient to convert dry weight of tomato fruits to fresh weight (0.07), *SdlCost* is the cost of seedlings (20 cents per 360,000 plants per hectare), *FertCost* the cost of fertilizer (calculated as 380 kg of ammonium nitrate at 26 %, priced at 1.6 Euro per kg) and *IrrCost* is the irrigation cost (Euro mm^{-1}).

For the latter, three thresholds of seasonal water supply were applied, as entailed by the local irrigation consortium (Capitanata irrigation consortium).

Specifically: *i)* if the seasonal irrigation (formalized by AquaCrop) did not exceed 200 mm, then the irrigation cost was 1.2 Euro per mm; *ii)* if the seasonal irrigation water exceeded 200 mm but below the threshold of 400 mm, then the irrigation cost was 1.8 Euro per mm for the share exceeding 200 mm; and finally; *iii)* if the seasonal water was above the 400 mm threshold, then the cost increased to 2.4 Euro per mm for the share exceeding 400 mm.

Additionally, the irrigation economic efficiency (*IrrEcEff;* kg Euro^{-1}), defined as the ratio between the yield and irrigation cost, was investigated.

To assess the extent to which a dependent variable (performance, efficiencies, and profitability) was shaped on an independent variable (seasonal irrigation volumes), a regression analysis was performed. A second-order polynomial regression was applied for this study; that is, the effect of input variable (water supply) was directly accounted for by linear terms as a first-order approximation but also include the effects of second order nonlinearities associated with each evaluated variable.

Although regression analysis can be useful to predict a response based on the values of the explanatory variables (for example, determining the increase in tomato productivity or drainage with increasing irrigation water amount), it does not allow for an assessment of the weight that the independent variable has on the dependent variable; nor it can provide comparisons among variables, because of differences in the magnitudes and variability of explanatory variables, and because the variables are usually measured with different units.

The dependent variables can be made uniform by subtracting the average and dividing by the standard deviation of the values of the original variables, resulting in standardized variables with an average of zero and a variance of one. When performing regression analysis on these standardized variables, it yields standardized coefficients.

$$Y_p = \beta_0 + (\beta_i * X^2) + (\beta_{ii} * X) \tag{11}$$

where βs are regression coefficients, Y_p is the standardized dependent variable and *X* is the independent variable (in this case, seasonal irrigation).

Eq. (11) allows for the quantification of the impact of irrigation on the behaviour of the variables examined within the cropping system. Using standardized regression coefficients, it is feasible to numerically compare the magnitude of this impact, irrespective of the nature or scale of the dependent variables. This approach enables the evaluation of how irrigation influences agricultural system variables, without concern for units of measurement or relationship between them. A higher value (negative or positive) of βi or βii indicates a greater impact of irrigation on the examined variable, while a higher β_0 value suggests a significant impact even in the absence of irrigation. Anyway, combining these three parameters into a single index not only provides a clearer and more easily interpretable but also allows for the ranking of the irrigation effect on the various examined variables (performance, water efficiencies and profitability).

To achieve a single index for each analyzed parameter, several stages were sequentially followed.

Firstly, the significance (α; *p*-value) of each regressor was checked; α represents the probability that variations in the standardized examined variable are related to the variation in the independent variable (seasonal irrigation volume) or that this variable is not influenced by irrigation management. Depending on the value of α, a weight factor for each regressor (WR_f) was calculated as:

$$WR_f = \begin{cases} 1 \text{ if } \alpha < 0.001; \\ 0.66 \text{ if } 0.01 > \alpha > 0.001; \\ 0.33 \text{ if } 0.05 > \alpha > 0.01; \\ 0 \text{ if } \alpha > 0.05 \end{cases} \tag{12}$$

Besides α, within the evaluative framework delineated herein, the inclusion of R-squared (R^2) was implemented. R^2 serves as a metric signifying the goodness of fit of the polynomial model (Eq. 11).

A weight was also assigned to R^2 as follows:

$$WR_{R2} = \begin{cases} 1 \text{ if } R^2 > 0.75; \\ 0.5 \text{ if } 0.75 > R^2 > 0.5; \\ 0.25 \text{ if } 0.5 > R^2 > 0.25; \\ 0 \text{ if } R^2 < 0.25 \end{cases} \tag{13}$$

where WR_{R2} is the weighted value of R^2.

Finally, the standardized score for each analyzed variable (StV_i) within the tomato cropping system was afterward calculated as:

$$StV_i = \left(WR_{fi} * [\beta_i]\right) + \left(WR_{fii} * [\beta_{ii}]\right) + \left(WR_{f0} * [\beta_0]\right) + \left(WR_{R2} * [R^2]\right) \tag{14}$$

The value of StV_i, calculated through Eq. 14 could exceed unity (1). This could make the interpretation of StV_i less straightforward. Furthermore, to quantify the extent or influence of the variable being analyzed in relation to water supply, StV_i was normalized within the range of 0 to 1, calculating WV_i through a sigmoid function, as follows:

$$WV_i = \frac{1}{(1 + EXP(-k * (StV_i - b)))} \tag{15}$$

where *k* and *b* are dimensionless coefficients. In this context, *b* is equal to:

$$b = \frac{\sum_{i=1}^{n} \frac{StV_{i,i}}{obs}}{2} \quad (16)$$

Here, *obs* represents the quantity of computed StV_i, while k is a variable spanning from 0 to 10, that allows to tune the StV_i's score to irrigation during the WV_i calculation. Smaller values of k correspond to a higher weighting when StV_i is lower than b, whereas higher values of k correspond to a higher weighting when StV_i is higher than b (value of 5 indicates an average weight).

WV_i allowed to compare the effect of irrigation on individual analyzed parameters. Evidently, same impact of such index for the variables under study provided conflicting indications: for example, a high value of WV_i had a completely opposite meaning for both performance and drainage.

A significant increase in yield with increasing irrigation volumes was considered "positive", whereas an increase in drainage was considered "negative"; so that for those variables that negatively affect the performance of cropping system as whole (i.e. drainage and *Blue_FP*), WV_i assumed negative values, positive values for the remaining evaluative parameters.

Furthermore, WV_i quantified the impact of irrigation on individual parameters of the tomato cropping system, but it did not facilitate comparisons among different irrigation scenarios.

To achieve an evaluation index modulated on seasonal irrigation volumes and normalized for the effective impact of the water supply on the analyzed parameter, the truth value (TW_i) of the normalized index was calculated as follows:

$$TW_i = \beta_0 + \left(\beta_i {}^*X^2\right) + \left(\beta_{ii} {}^*X\right)^* \pm WV_i \quad (17)$$

where WV_i could assume positive (yield, *IrrUE*, *WP*, *NetInc*, *IrrEcEff*) or negative (drainage, *Blue_FP*) values depending on positive or negative effect of irrigation on the analyzed parameter.

To transition from a score to a synthetic judgment, TW_i was mapped onto categories of "Very strong," "Strong," "Moderate," "Poor," and "Not significant" depending on whether the TW_i value exceeded 0.8, fell between 0.8 and 0.6, between 0.6 and 0.4, between 0.4 and 0.2, or was below 0.2, respectively.

Finally, the multi-objective index (I_{mobj}) computed for every irrigation scenario was determined as the sum of TW_i is estimated for each parameter *intra-scenario*:

$$I_{mobj} = \sum_{i=1}^{n} TW_i \quad (18)$$

3. Results

3.1. Meteorological data during the growing seasons

The detailed weather conditions during the two growing seasons 2021 and 2022 are shown in Fig. 1.

The meteorological data during the growing seasons were used to run AquaCrop model.

During the 2021 growing season, rainfall was very low, with a total amount of 66 mm. In 2022, rainfall was higher than in 2021, with a total of 153 mm, although most of this amount was distributed in a few rainfall events.

3.2. Model calibration and validation

Table S2 in supplementary material presents the default crop file parameters alongside the calibrated values obtained to achieve the best fit between observed data and AquaCrop simulations, for processing tomato during the 2021 growing season, under the FARM treatment.

A good agreement between observed and simulated data was reflected not only in the closeness of the field-measured values and those predicted by the model (Fig. 2) but also in the statistical indices (Table 2).

Specifically, statistical analysis of model accuracy metrics demonstrated that AquaCrop effectively replicated the beavhiour of *CC* throughout the growing season, evidenced by a high $r = 0.98$, a d index closes to 1 and a low *NRMSE*.

For *TDM* and *Y*, d and r values were consistently approached 1, indicating a strong agreement and linear relationship between observed and simulated data. Specifically, the high r values suggest that the model accurately followed the trends in biomass accumulation and yield across different growth stages, while d values close to 1 demonstrate that AquaCrop effectively captured both the trends and the magnitude of observed variations.

However, the *NRMSE* value ranged between 20 % and 29 %, particularly for *TDM* and *Y*, which can be attributed to the significant variability observed during field measurements, especially during the yield formation phase. This variability was particularly pronounced even among plants within the same plot, due to differences in the appearance and growth timing of the fruits. This variability is reflected in the high standard deviations recorded during field data collection, making it challenging for the model to perfectly replicate each individual observation averaged across each sampling (in terms of date and sampling replicates).

Nonetheless, despite this field variability, AquaCrop consistently simulated growth curves and developmental metrics that fell within the observed mean values and their standard deviations. The model's performance remained acceptable, with *NRMSE* values indicating a reasonable approximation given the inherent complexity of the tomato cropping system.

For *SWC,* AquaCrop achieved excellent results, with *NRMSE* values below 10 %, and satisfactory r and d values, confirming the model's strong predictive accuracy for soil water dynamics after calibration.

The validation step involved comparing AquaCrop's performance with the observed data under the *FARM* treatments of 2022 and the *RED* treatments across both experimental years (Table 3). The model's

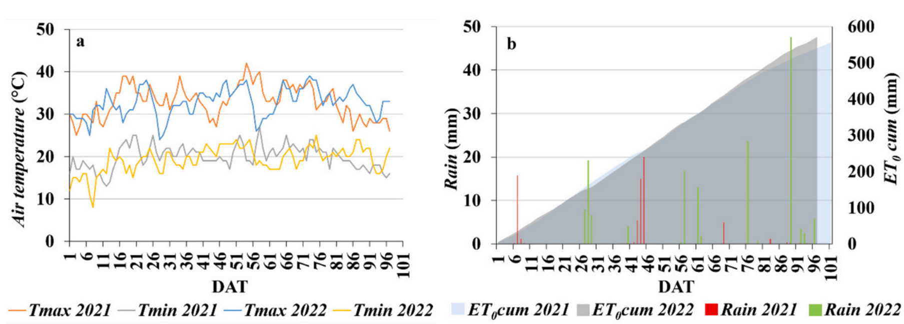

Fig. 1. Variations in *a)* daily maximum and minimum air temperatures (*Tmax* and *Tmin*; *b)* cumulative reference evapotranspiration (ET_0cum) and rainfall (*Rain*) during the processing tomato growing seasons of 2021 and 2022. Data were recorded by weather stations near the experimental field.

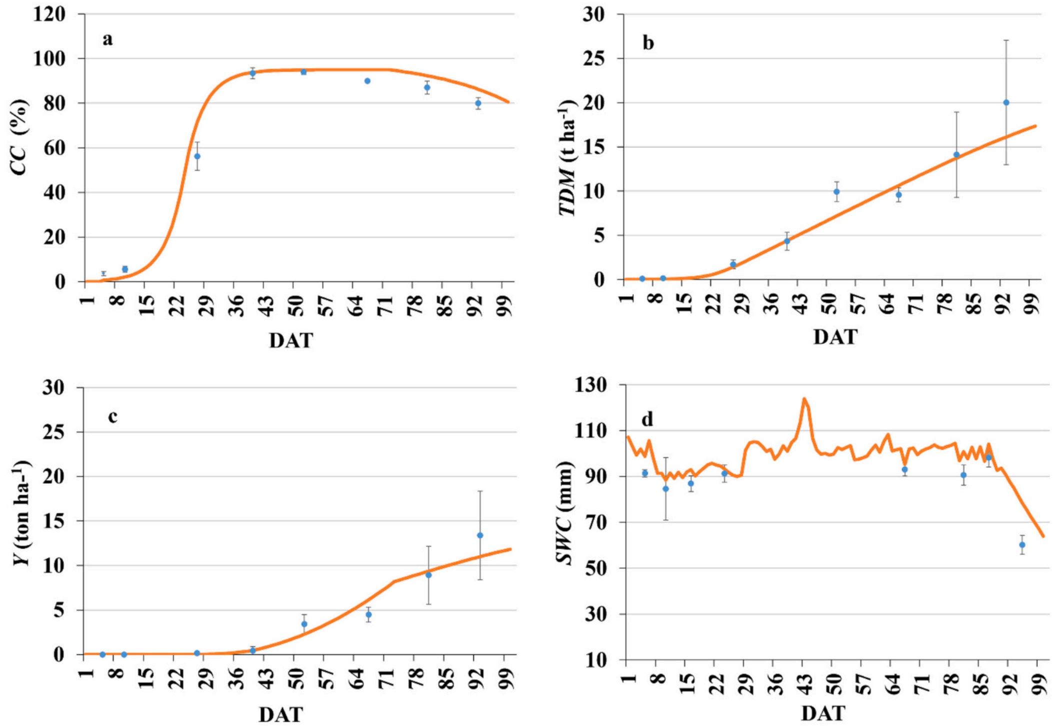

Fig. 2. Calibration phase: comparison between AquaCrop simulated values (continuous line) and observed experimental values (dots) of *a)* canopy cover (*CC*), *b)* total dry biomass (*TDM*), *c)* dry yield (Y) and *d)* soil water content (SWC) during 2021 growing season, under *FARM* water regime. The bars indicate the standard deviation for the observed values. DAT indicates the number of days after transplanting.

Table 2
Statistical indices of comparison of simulated vs. observed values of canopy cover (*CC*), total dry biomass *(TDM*), dry yield *(Y*) and soil water content (*SWC*) of tomato in the calibration phase, during 2021 growing season, under FARM water regime.

Parameter	Unit	Observation	Observed mean	Simulated mean	Diff. %	*NRMSE*[a]	*r*[b]	*d*[c]
CC	*%*	8	63.7	67.1	5.3	10.3	0.98	0.99
TDM	$t\ ha^{-1}$	8	7.5	6.7	10.7	23.2	0.96	0.98
Y	$t\ ha^{-1}$	8	3.8	3.7	2.6	29.0	0.95	0.98
SWC	*mm*	8	87.0	94.0	8.0	9.8	0.84	0.80

[a] Normalized root mean square error.
[b] Correlation coefficient.
[c] Index of agreement of Willmott.

Table 3
Statistical indices of comparison of simulated vs. observed values of canopy cover (*CC*), total dry biomass (*TDM*), dry yield (*Y*) and soil water content (*SWC*) of tomato in the validation phase during 2021 and 2022 growing season, under *FARM* and deficit water regime (*RED-20* and *RED-40).*

Year	Treatment	Parameter	Unit	Observation	Observed mean	Simulated mean	Diff %	*NRMSE*[a]	*r*[b]	*d*[c]
2021	*RED-20*	*CC*	*%*	7	61.3	62.9	2.6	9.2	0.89	0.99
		TDM	$t\ ha^{-1}$	7	6.1	5.6	8.2	18.6	0.97	0.99
		Y	$t\ ha^{-1}$	7	2.9	2.8	3.4	24.3	0.89	0.99
		SWC	*mm*	6	90.8	85.6	5.7	7.8	0.98	0.72
2022	*FARM*	*CC*	*%*	7	69.7	73.0	4.7	14.3	0.92	0.98
		TDM	$t\ ha^{-1}$	6	5.4	6.1	13.0	32.3	0,92	0.97
		Y	$t\ ha^{-1}$	6	2.5	2.9	16.0	37.6	0.94	0.98
		SWC	*mm*	4	49.7	54.2	9.1	9.5	0.99	0.90
2022	*RED-40*	*CC*	*%*	7	64.4	70.3	9.2	23.2	0.85	0.94
		TDM	$t\ ha^{-1}$	7	6.4	7.2	12.5	26.0	0.93	0.98
		Y	$t\ ha^{-1}$	6	2.8	3.1	10.7	22.0	0.90	0.99
		SWC	*mm*	5	49.4	54.8	10.9	11.2	0.90	0.63
Overhall		***CC***	*%*	21	65.2	68.8	5.5	16.7	0.92	0.98
		TDM	$t\ ha^{-1}$	20	6.0	6.3	5.0	25.2	0.93	0.98
		Y	$t\ ha^{-1}$	19	2.7	2.9	7.4	28.3	0.97	0.99
		SWC	*mm*	15	66.0	67.0	1.5	9.3	0.95	0.99

[a] Normalized root mean square error.
[b] Correlation coefficient.
[c] Index of agreement of Willmott

performance across different irrigation strategies and climatic conditions was confirmed, with *r* and *d* values remaining consistently above 0.90 for all variables. Similarly, for the validation step, *NRMSE* calculated for *TDM* and *Y* remained almost always in the range of 20 % to 30 %, as in the calibration process. This confirms that the high variability in the formation of yield in the tomato crop is a component of the cultivation system that is not easy to simulate accurately in the absence of specific algorithms in this regard.

The parameters and coefficients reported in Table 2 and 3 were derived from the same set defined through the iterative trial-and-error procedure. This process involved continuous feedback and feedforward between the calibration and validation phases, ensuring that the calibrated parameters were sufficiently robust to represent various experimental conditions without needing further adjustments.

3.3. Analysis of the irrigation-related parameters of processing tomato

Regarding crop productivity, simulations revealed that the increase in seasonal irrigation volumes led to an improvement in fruit yield (Fig. S2, supplementary material), with values ranging from 1.89 t ha^{-1} with 65 mm of seasonal water supply to a maximum of 12.14 t ha^{-1} with 406 mm of water supply.

It is noteworthy that this increase was linear as it progressed from approximately 70 mm to 324 mm of water supply, then the progression slowed around 400 mm, and finally stabilized up to volumes of 660 mm.

The net and linear increase in tomato productivity as the crop was exposed to seasonal irrigation scenarios ranging from reduced (around 100 mm) to intermediate (400 mm) water amounts, although followed by a smaller increase at higher irrigation levels (700 mm), indicated a "very strong" impact of irrigation on crop productivity, as reflected by the quantitative and qualitative assessment of the framework (Table 4 and 5).

The environmental impact of irrigation was assessed based on water loss due to drainage and *Blue_FP*, where increases resulting from higher irrigation volumes indicated an excess of water supply not effectively used by the crop (Fig. S3, supplementary material).

The drainage was almost negligible with irrigation up to 440 mm, after which it increased sharply, reaching values of up to 150 mm at higher seasonal irrigation volumes.

However, based on the framework judgements, it emerged that the influence of irrigation on this environmental parameter was judged to be *poor*. This could be attributed to the fact that an increase in drainage (even though abrupt) occurred only at irrigation volumes exceeding 500 mm and, in some "year x management" combinations, even at higher volumes (Fig. S3a, supplementary material).

Simulations established a consistent value for *Blue_FP* (24.43 mm kg^{-1}, on average) for cropping scenarios irrigated with water ranging from 90 to 330 mm (Fig. S3b, supplementary material).

Beyond this threshold, *Blue_FP* increased linearly up in the most extreme irrigation scenarios, with water consumption increasing by 0.08 mm per mm of water supplied to produce one kg of dry fruits.

In Fig. S3b (supplementary material), one can observe some *Blue_FP* values above the "average" path recorded for management between 65 and 350 mm of irrigation water. This was caused by the trend of ET_0 in 2019 higher than the average of the other growing seasons (623 mm in 2019 vs 572 mm as average for the remaining years), resulting in higher water consumption by the system without a proportional increase in yield, especially in scenarios with reduced water supply.

Unlike drainage, the synthetic score judged *Blue_FP* to be "moderately" responsive to irrigation management, but with higher water consumption by the system after 300 mm, meaning more water was used inefficiently to produce one kilogram of tomato fruits compared to lower seasonal irrigation volumes.

Regarding *IrrUE* and *WP*, two findings emerged (Fig. S4a and Fig. S4b, supplementary material). In scenarios with low to moderate irrigation supply (100–350 mm), these efficiencies exhibited high variability, due to the limited capacity of such volumes to mitigate water stress caused by meteorological conditions. Conversely, irrigation volumes exceeding 360 mm stabilized served to stabilize the responses of these two efficiencies, with values of 24.22 kg mm^{-1} for *IrrUE* and 19.38 kg mm^{-1} for *WP*, thus reducing their erraticism across years.

However, no increase in efficiency values observed with further water supply; instead, a decrease occurred as irrigation volumes increased.

The lack of a clear correlation between *IrrUE*, *WP*, and irrigations was also reflected in the poor scores obtained for both parameters in Table 5.

The profitability of tomato cultivation exhibited a wide-range, showing negligible profits at the lowest irrigation volumes (approximately 100 mm) and reaching a net income of € 15,000–16,000 ha^{-1} for seasonal water volumes exceeding 380 mm (Fig. S5a, supplementary material). Notably, *NetInc* remained relatively stable, with only minor fluctuations at higher water inputs (450–660 mm).

In terms of *IrrEcEff*, increasing irrigation from 220 mm to 390 mm resulted in a substantial increase in this metric, rising from 7.42 kg €$^{-1}$ to 28.77 kg €$^{-1}$, representing more than a fourfold increase in economic

Table 5
Values of the parameters involved in Eq. 12–17 and the synthetic judgment for the investigated variables in the processing tomato cropping system. Very strong, Strong, Moderate, Poor, and Not significant refer to the impact that irrigation has on the investigated variables.

Variable	Parameter						Judgment
	WR_f $\_\beta_{ii}$	WR_f $\_\beta_i$	WR_f $\_B_0$	$WR_{\_R2}$	StV_i	WV_i	
Y	1.00	1.00	1.00	1.00	4.64	1.00	*Very strong*
Drainage	1.00	1.00	0.00	1.00	0.76	−0.30	*Poor*
Blue_FP	1.00	1.00	1.00	1.00	1.00	−0.59	*Moderate*
IrrUE	0.33	0.33	0.33	0.75	0.75	0.29	*Poor*
WP	1.00	1.00	1.00	0.00	0.75	0.30	*Poor*
IrrEcEff	0.33	0.00	0.00	1.00	1.67	0.98	*Very strong*
NetInc	1.00	1.00	0.33	0.75	3.38	1.00	*Very strong*

Y = yield; *Blue_FP* = blue footprint; *IrrUE* = irrigation use efficiency; *WP* = water productivity; *IrrEcEff* = irrigation economic efficiency; *NetInc* = net income.

Table 4
Regressor values (βs), their corresponding *p*-values (α), and R-squared (R^2) from the second-order regression analysis between seasonal irrigation volumes and the standardized examined variables.

Variable	Parameter						
	β_{ii}	β_i	B_0	R^2	$\alpha\_\ \beta_{ii}$	$\alpha\_\ \beta_i$	$\alpha\_\ \beta_0$
Y	-1.79E-05	1.79E-02	-3.62E+00	8.96E-01	0.00E+00	0.00E+00	0.00E+00
Drainage	1.98E-05	-9.71E-03	4.52E-01	7.46E-01	2.90E-07	1.72E-04	2.36E-01
Blue_FP	-1.04E-05	1.24E-02	-2.64E+00	9.40E-01	0.00E+00	0.00E+00	0.00E+00
IrrUE	1.19E-05	−8.98E-03	1.28E+00	1.24E-01	2.75E-02	2.26E-02	4.07E-02
WP	−1.20E-05	1.34E-02	−2.72E+00	9.30E-01	0.00E+00	0.00E+00	0.00E+00
IrrEcEff	−8.18E-06	1.03E-03	8.63E-01	6.45E-01	3.83E-02	7.12E-01	5.96E-02
NetInc	−2.17E-05	1.35E-02	−1.49E+00	3.89E-01	9.64E-05	6.55E-04	1.47E-02

Y = yield; *Blue_FP* = blue footprint; *IrrUE* = irrigation use efficiency; *WP* = water productivity; *IrrEcEff* = irrigation economic efficiency; *NetInc* = net income.

efficiency (Fig. S5b, supplementary material). Beyond this threshold, *IrrEcEff* exhibited a consistent, albeit modest, decline with increasing irrigation levels, reaching 9.69 kg €$^{-1}$ at the highest water regime (approaching 700 mm).

Particularly, the data points at lower irrigation levels (65–195 mm) achieved. An *IrrEcEff* of up to 38.77 kg €$^{-1}$ partly due to particularly favourable water costs applied by the local irrigation consortium compared to the other two price brackets for higher seasonal irrigation volumes.

The evaluative framework, based on the outcomes of AquaCrop exhibited a "very strong" sensitivity for both profitability-related parameters regarding variations in irrigation volumes (Table 5). However, the effects of different irrigation strategies followed contrasting paths: an increase in income with higher levels of irrigation and an enhancement of economic efficiency with reduced water inputs.

3.4. Multi-objective analysis of processing tomato

The impact of different irrigation strategies (seasonal volumes from 100 to 700 mm with 100 mm intervals between each management) on the evaluative parameters of processing tomato was assessed using truth scores (TW_i; Eq. 17). TW_i allowed for the evaluation of the trade-off among various water-related parameters (productivity and economic performance, environmental sustainability, water use efficiency, and economic efficiency of irrigation) by assigning scores to each variable, which can be compared both within and across different irrigation scenarios.

Reduced seasonal irrigation volumes (100–200 mm) led to a decline in crop productivity, compared with higher water regimes, subsequently affecting economic profitability and resulting in negative TW_i values (Fig. 3). Furthermore, the lowest water supply resulted in a negative TW_i value (−0.11) associated with *WP,* which was only better than the TW_i recorded for the two highest seasonal irrigation volumes (600 mm and 700 mm), with TW_i values of −0.37 and − 0.81, respectively.

Based on the TW_i score, it emerged that the irrigation regime with the lowest water input (100 mm) favored only two variables (*Blue_FP* and *IrrEcEff*), while it was detrimental to the remaining variables in comparison with seasonal irrigation volumes up to 400 mm.

As irrigation regimes with higher water supply were considered (up to 600 mm), the positive effect of irrigation on productivity and economic returns became more evident. However, this improvement was more pronounced with a seasonal water supply of 500 mm quantity compared to the other water treatments, with TW_i increasing from negative values at 100 mm and 200 mm of water supply to 0.85 in terms of yield and *NetInc*.

However, with a seasonal water supply exceeding 400 mm, *IrrEcEff*, *WP,* and *IrrUE* were negatively affected compared to the other water regimes, with TW_i scores shifting from positive to negative values (Fig. 4).

The best TW_i score for drainage was achieved with seasonal irrigation volumes of 200 mm and 300 mm, while the worst scores (with negative values) were observed for seasonal volumes of 500 mm and above (with intermediate values in the remaining two irrigation scenarios). This indicated that irrigation volumes exceeding 400 mm (under the climatic and environmental conditions investigated) resulted in water supplies that exceeded the crop's potential to utilize water, with irrigation water not intercepted by the roots.

This finding was also supported by the TW_i score for *Blue_FP*. In fact, from 100 mm up to 300 mm of seasonal water supply, TW_i recorded values between 0.35 and 0.47, which decreased to 0.06 for 400 mm of seasonal water, and then dropped to negative values (down to −1.84 in the most abundant irrigation scenario). This indicated that under the most irrigated scenarios, the system used more water to produce the same unit (1 kg) of product compared to the scenarios with less irrigation water.

The TW_i assessment strongly discouraged pursuing irrigation volumes of 700 mm. In this regard, the scores for productivity and profitability variables indicated a worsening of TW_i performance compared to those obtained with irrigation volumes ranging between 400 mm and 600 mm.

Additionally, indicators such as *IrrUE, WP,* and *IrrEcEff* recorded the worst TW_i values compared to other irrigation strategies.

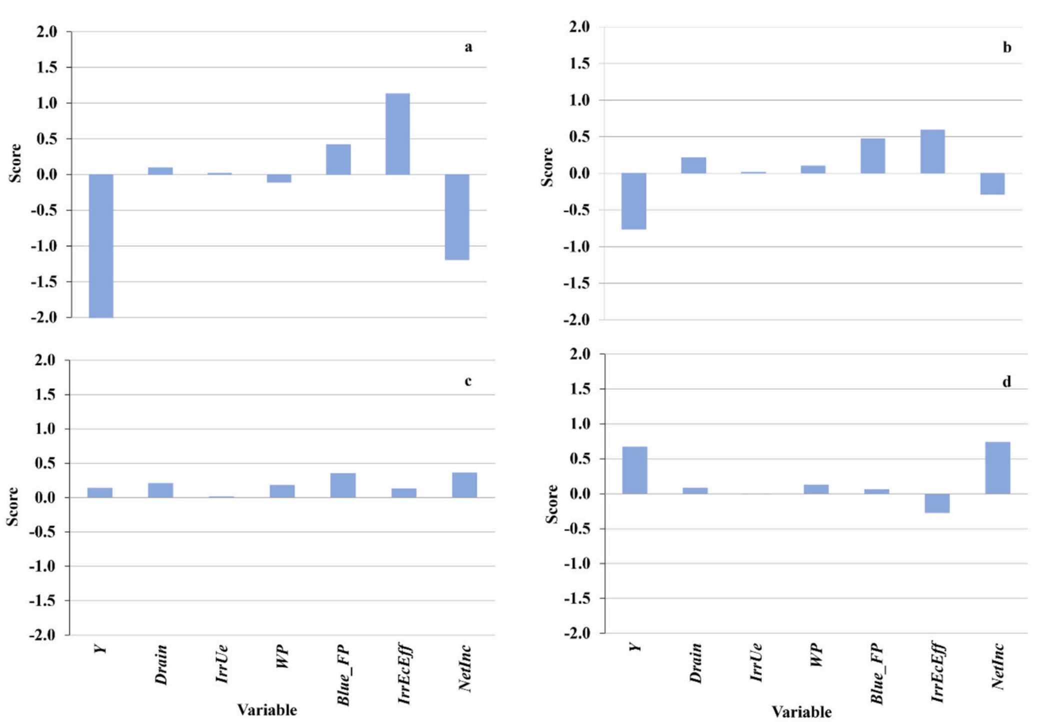

Fig. 3. Truth values of normalized index (Score; *TWi*) for all the water-related parameters (Variable) of the processing tomato cropping system in response to seasonal irrigation regimes of *a)* 100 mm, *b)* 200 mm, *c)* 300 mm, and *d)* 400 mm.

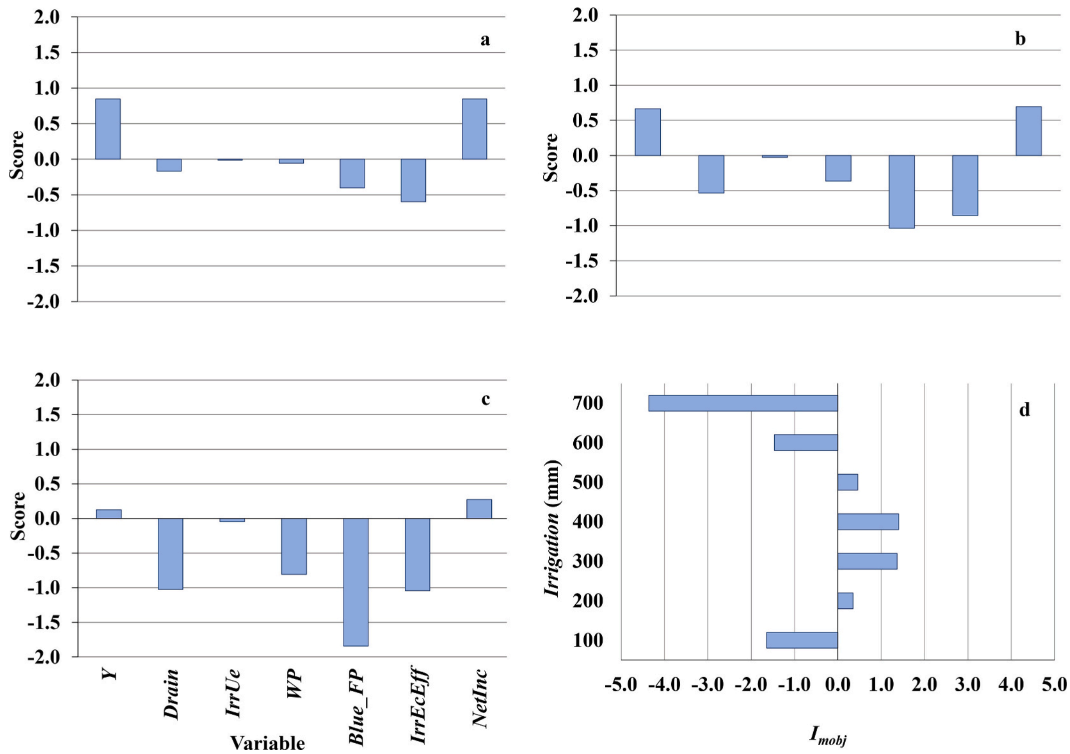

Fig. 4. Truth values of normalized index (Score; *TWi*) for all water-related parameters (Variable) of the processing tomato cropping system in response to seasonal irrigation regimes of *a)* 500 mm, *b)* 600 mm, *c)* 700 mm and *d)* aggregated multi-objective index score (I_{mobj}).

Each irrigation strategy presented its own set of advantages and disadvantages across the variables investigated, making it difficult to pinpoint the optimal strategy for maximizing the overall performance of processing tomato cultivation. Evaluating these variables in isolation proved challenging when trying to integrate yield, water use efficiency, environmental sustainability and economic returns into a cohesive irrigation management approach. To address this complexity, the I_{mobj}, index was employed, offering clear and interpretable insights into the effects of different irrigation volumes on the performance of the cropping system (Fig. 4d).

According to the multi-aggregate index, the extreme irrigation strategies (100 mm and 700 mm) were judged to be the least sustainable, as they led to poor overall system performance. Similarly, even the 600 mm irrigation volume, which supplied an ample amount of water, was deemed suboptimal based on I_{mobj} evaluations due to its inefficiency and negative environmental impacts.

Moderate irrigation volumes of 200 mm and 500 mm provided positive I_{mobj} scores, indicating some improvements in productivity but not sustainability (500 mm) and sustainability but not productivity (200 mm).

However, these strategies still fell short compared to the optimal irrigation regimes identified through I_{mobj}, which were300 mm and 400 mm.

Among these two options, the 400 mm irrigation strategy proved to be the superior choice, delivering a 13 % improvement in overall system performance compared to the 300 mm strategy.

4. Discussion

In this paper, has been proposed a new methodological framework to screen the most efficient irrigation strategies based on seasonal water supply volumes. This approach considered various aspects of the cropping system - productive, environmental, and economic - individually and then integrated them into a unified multi-aggregated index. The framework was structured as a hierarchical pyramid, with AquaCrop outputs at the base and the I_{mobj} index at the top. The robustness of the framework's base was ensured by thorough calibration and validation, as demonstrated by the performance of statistical indices such as *r*, *d*, and *NRMSE*.

The high values of *r* and *d* reflect AquaCrop's excellent capacity to replicate field data across different growth stages, including canopy development, biomass accumulation, and fruit development. AquaCrop also performed well in simulating *SWC*, with *NRMSE* values below 10 %, further confirming the model's accuracy for this parameter.

However, the intrinsic variability of field measurements, particularly in the middle to latter stages of tomato crop growth (e.g., variability in fruit appearance, senescence, and presence of cull fruits), presented a challenge for crop models like AquaCrop, which lack specific options to account for these dissimilarities. This contributed to *NRMSE* values for *TDM* and *Y* that were higher than optimal but still within acceptable range, given the observed variability in field data.

The parameterization of AquaCrop primarily aimed to accurately replicate water consumption and final marketable yield (with a good alignment between observed and simulated data), upon which the rest of the framework was built. Thus, the reliability of AquaCrop was assessed in accurately replicating the crop yield and water use, ensuring the framework's suitability for evaluating the productive and economic aspects, as well as the environmental sustainability of the processing tomato cropping system under different irrigation scenarios.

4.1. Impact of irrigation on water-related processing tomato parameters

The cultivation of processing tomatoes in the Mediterranean region is heavily dependent on irrigation due to low rainfall and high evaporative demand during the growing season.

The evaluation of irrigation volumes on processing tomato revealed critical insights into the balance between productivity, economic returns and environmental sustainability.

AquaCrop simulations, conducted across a range of irrigation volumes (from a minimum of 65 mm to a maximum of 661 mm), demonstrated a clear dependency of crop yield and profitability on adequate water supply, aligning with similar findings through modelling exercises (Rinaldi et al., 2011).

Specifically, irrigation volumes of 400 and beyond mm were identified as beneficial for enhancing crop yields, aligning with previous studies that have shown the positive effects of increased water availability (between 400 mm and 600 mm) on tomato productivity in Mediterranean environments (Giuliani et al., 2005; Rana et al., 2000).

However, this research goes beyond traditional productivity assessments by examining the broader implications of varying irrigation strategies. The increase in irrigation volumes did not uniformly translate to improvements in all aspects of the cropping system. While higher water availability boosted productivity and economic returns, significant challenges were observed in terms of water use efficiency and environmental sustainability.

Our findings indicated that *WP* and water efficiencies initially improved with increased irrigation but plateaued and subsequently declined at volumes above 350–400 mm. This suggests a threshold beyond which the crop's capacity to utilize additional water effectively diminishes, leading to inefficiencies. Similarly, Katerji et al. (2013) in simulated scenarios, experienced increasing values of *WP* as irrigation volumes increased up to approximately 380 mm, after which it stabilized until seasonal irrigation volumes of 460 mm, and then decreased with higher volumes up to around 500 mm.

Environmental impacts, particularly those related to drainage and *Blue_FP,* showed a marked response to increased irrigation volumes.

Seasonal volumes below 400 mm did not generate drainage losses, indicating efficient use of water within the crop's root zone. However, as irrigation volumes exceeded this threshold, a pronounced increase in drainage was observed, indicating that the excess water bypassed the crop's uptake capacity and was lost to deeper soil layers. What was found under the simulated scenarios was corroborated by observations from field experiments, where it was observed that increasing seasonal irrigation from 400 mm to 600 mm resulted in almost all the additional water being surplus, with drainage of approximately 175 mm (Vázquez et al., 2006).

Concerning *Blue_FP,* our findings aligned with previous studies carried out under similar Mediterranean conditions, where increasing irrigation volumes beyond crop requirements resulted in a linear rise in *Blue_FP* (Chouchane et al., 2015). The additional water consumed beyond optimal volumes was not fully utilized by the crop, leading to higher water wastage and environmental burden. In this context, the increase in *Blue_FP* under surplus irrigation (from 500 mm to 700 mm) mirrored observations from other Mediterranean cropping systems, where excessive irrigation volumes were linked to higher environmental footprints without corresponding gains in yield (Ventrella et al., 2018).

This is a critical finding, as it highlights the point at which irrigation practices shift from being beneficial to potentially harmful, contributing, for example, to water wastage and increased leaching of nutrients, as well as to a water supply that exceeds the actual needs of the crop.

The simulated scenarios demonstrated that as seasonal irrigation volumes increased, mainly from limited water inputs up to 500 mm, there was a marked increase in the profitability of processing tomato cultivation. Beyond this threshold, additional water inputs did not result in further increases in *NetInc*, aligning with findings reported by several other authors (Rinaldi et al., 2015; Rinaldi and Ubaldo, 2007; Sarker et al., 2016). Moreover, pushing irrigation volumes beyond these levels led to drastic reductions in economic efficiency of irrigation, with declines of up to 66 % in the most intensive irrigation regime.

While crop productivity and profitability are confined to specific spatial and temporal contexts (limited to the farm and the cropping year), the consequences of drainage and *Blue_FP* extend beyond individual farms and growing seasons, both spatially and temporally.

Excessive drainage and surplus irrigation water relative to the crop's actual needs can lead to nitrate leaching, posing a significant risk of groundwater contamination. This leaching can result in the degradation of water quality in aquifers, contributing to eutrophication in nearby water bodies and negatively impacting aquatic ecosystems (Dupas et al., 2015).

Furthermore, the waste of irrigation resources due to over-irrigation not only diminishes the efficiency of water use but also reduces the availability of water for other essential purposes, such as domestic consumption and industrial applications. This over-extraction increases competition for water resources, exacerbating the challenges associated with water scarcity, especially in regions already facing significant water stress (Rosa et al., 2020).

Regression analysis is a widely used method in agronomy to quantify the relationships between water supply and crop response across various variables, as demonstrated in this study. It can provide a general understanding of how dependent variables change in response to independent variables, such as increased yield with higher irrigation or reduced water efficiency with more irrigation. In this context, the non-standardized regressions used to assess individual water-related parameters revealed that while increased irrigation volumes enhanced yields and economic returns, they did not yield comparable benefits in environmental terms.

The lack of clear convergence among various water-related parameters has made it challenging to identify the optimal balance between maximum productivity and environmental sustainability, underscoring the inherent trade-offs in irrigation management. Regression analysis has previously been applied in a multi-objective approach. Methods like Central Composite Design (*CCD*) require an initial assessment to determine the most appropriate model type (e.g., linear, multiple) and order (e.g., quadratic, cubic) to describe the relationships between irrigation parameters and crop productivity or water consumption. This process involves defining key factors such as the number of levels for each variable and positioning axial points, which extend beyond the factorial design to capture non-linear relationships. Additionally, statistical indicators such as R^2, adjusted R^2, and lack of fit are used to evaluate the model's accuracy and its suitability for decision-making (Mahmoodi-Eshkaftaki and Rafiee, 2020). This complexity poses challenges, requiring substantial statistical expertise and time.

The framework developed in this paper aims to reduce the complexity of these analyses while maintaining a balance between replicability, usability, readability, and reliability of the resulting estimates.

4.2. Shifting paradigms: introducing TW_i for a holistic evaluation of irrigation strategies

The evaluation of irrigation strategies through TW_i provides a valuable tool for understanding the impact of varying irrigation volumes on multiple performance metrics. Unlike traditional methods that might assess variables in isolation, TW_i offers a unified approach to quantify how changes in irrigation volumes affect productivity, economic returns, and efficiency, enabling a comprehensive comparison across different irrigation regimes.

The development of TW_i focused on ease of application (using standardized polynomial regressions and weighting of the related parameters), robustness of its foundations (utilizing a process model like AquaCrop), and its replicability in different pedo-climatic contexts.

Although this approach is based on methods already widely used in other studies (irrigation response curves for water-related parameters; use of crop simulation models), it integrates them to provide both qualitative assessments (the impact of irrigation ranging from strong to non-significant on cropping system parameters) and quantitative evaluations (TW_i values).

In this regard, under the pedo-climatic conditions used for field trials and replicated in the simulation scenarios, it emerged that irrigation had a "very strong" impact on certain variables such as crop productivity and profitability. However, on other parameters, such as water use efficiencies, the impact of different irrigation regimes was found to be poor.

This confirms that parameters like *WUE* or *WP* represent the balance between gains (such as carbon acquisition or crop yield) and costs (such as transpiration and water applied; Wang et al., 2024) and are extensively used in simulation models as constant parameters (e.g., CropSyst) throughout or for most of the crop growing cycle (e.g., AquaCrop). The qualitative assessment provided by TW_i offers an initial guide for the decision-making process, highlighting which aspects to prioritize when balancing the benefits and costs associated with different irrigation regimes. Specifically, to streamline the decision-making process concerning which cropping system water related parameters need evaluation, water use efficiencies could be excluded a priori, as they are either unaffected by or minimally impacted by different water supply strategies. This preliminary check becomes even more valuable when the water-related parameters to be analyzed are numerous. In such cases, the proposed framework - highly flexible and adaptable to user needs - provides an initial ranking. This ranking offers insights into which parameters require greater attention and which can be disregarded due to their minimal influence from irrigation regimes.

After this initial screening (if deemed necessary), the framework using TW_i can quantify how (increasing or decreasing) and to what extent the various water-related parameters change with different irrigation regimes. As previously mentioned, this verification process is crucial when the user's goal is a comprehensive evaluation of the impacts of irrigation management on different aspects of the cropping system, including productive and economic performance, environmental impacts, and water use efficiencies. Indeed, the framework, through the algorithms implemented for calculating TW_i, assigns a numerical value to each parameter of the cropping system, making them comparable. These values are obtained through a process of standardization (StV_i; Eq. 14) and normalization (WV_i; Eq. 15). This approach allowed for the quantification of the actual impact of irrigation on each water-related parameter, thereby isolating it from other factors that could influence the same parameter.

The framework suggested, for example, that the impact of irrigation was very strong with respect to production ($WV_i = 1$; Table 6), but weaker concerning water use efficiencies ($WV_i = 0.29$ for *IrrUE* and $WV_i = 0.30$ for *WP*; Table 6).

In fact, the dynamics of *WP* and *IrrUE* could be influenced not only by irrigation but also by other factors, such as rainfall during the crop cycle and canopy development, which affected the amount of water evaporated, intercepted and drained.

Moreover, if specific analytical needs require placing more emphasis on specific targets (e.g., environmental variables rather than on crop productivity and profitability) with respect to the irrigation regime, the value of *k* can be adjusted, accordingly.

The application of unbalanced values of *k* across different variables became even more crucial in the multi objective analysis when aggregating the TW_i of individual water-related parameters into I_{mobj} for screening, ranking, and ultimately optimizing the seasonal irrigation volume. The use of the aggregated index facilitated practical decision-making by, consolidating diverse criteria into a single scalar value while accounting for the complex trade-offs inherent in multi-objective optimization. TW_i and I_{mobj} offer a more practical and user-friendly alternative to other multi-objective functions (i.e. AHP and TOPSIS), making it particularly suitable for applications where simplicity, efficiency, and clear interpretation of results are paramount. Unlike AHP (Ren et al., 2019), which necessitates a complex series of pairwise comparisons and intricate calculations to derive weights and consistency ratios, TW_i simplifies this by leveraging regression-based approach and straightforward weighting of parameters that integrate directly with simulation outputs, allowing for a more intuitive and less resource-intensive evaluation.

Similarly, TOPSIS (Wang et al., 2019) requires the normalization of decision matrices, the identification of ideal and negative-ideal solutions, and the calculation of distances from these solutions. This multi-step process can be complex and time-consuming, especially when dealing with large datasets or numerous criteria. The framework proposed in this paper streamlines this by providing a single composite score for each irrigation scenario based on its impact on various parameters. This not only simplifies the analysis but also enhances the clarity of the results, allowing for easier comparison across different irrigation strategies.

Under the environmental conditions of the experimental trials and as reflected in the simulated irrigation scenarios, assigning equal importance to each variable ($k = 5$ in Eq. 15), the optimal range of seasonal water supply to enhance the overall performance of the system by maximizing I_{mobj}, which was found to be between 300 and 400 mm, with a slight superiority of the index for the 400 mm scenario compared to that of the 300 mm scenario (Fig. 4d).

These results were closely interconnected with the pedo-climatic context under which the field trials were carried out, and thus used for the calibration of AquaCrop and subsequently for the parameterization of the evaluative framework. For example, factors such as the amount of natural water inputs (e.g., rainfall) at the experimental site, the hydrogeological characteristics of the soil (including depth, infiltration capacity, and water storage potential available for the crop), and the irrigation volumes specified for different irrigation scenarios all influenced AquaCrop's response. This response was reflected in terms of evapotranspiration, plant growth, productivity, as well as any water surplus that resulted in drainage and unproductive water use.

Analyzing in depth what led I_{mobj} to indicate this volume as preferable (to optimize both agronomic and ecological aspects), it could be highlighted that, from an agronomic perspective, 400 mm of seasonal water supply returned higher productivity values compared to lower irrigation levels, while being in line with those of higher levels (as clearly expressed by the TW_i values, Figs. 3 and 4).

Considering the ecological aspect (therefore water use efficiencies and environmental sustainability), it was highlighted that 400 mm of irrigation volume resulted in a neutral situation between the more performing irrigation options and the less performing ones in eco-friendly terms. It never reached critical TW_i values (negative, except for a negligible −0.001 for *IrrUE*) as recorded at higher irrigation volumes but was slightly lower than the values seen with the lower irrigation regimes (200 mm and 300 mm), even though these were less effective in terms of productivity and profitability.

However, as the calculation of I_{mobj} is set up, one can obtain an exact value (rather than a range) for the seasonal irrigation volume by using an objective function aimed at maximizing I_{mobj}. By building the framework within Excel, it is then possible to use the generalized reduced gradient code for nonlinear programming in the Excel add-in Solver (Lasdon et al., 1978), setting I_{mobj} as the objective cell and establishing a maximum irrigation constraint of 700 mm. In this specific case, the framework returns an optimized value of 354 mm as the seasonal irrigation volume to maximize I_{mobj}.

In cases where one wants to compare not only different irrigation scenarios but also identify the best irrigation scenario while emphasizing certain variables over others, I_{mobj} with an unbalanced *k* comes into play.

To clarify this concept, an additional analysis was conducted, emphasizing the importance of water use efficiencies, *IrrEcEff*, drainage, and *Blue_FP*, while reducing the weight on crop yield and *NetInc* when verifying the irrigation scenario with the highest score in terms of I_{mobj} and comparing it with scenarios with balanced importance ($k = 5$). This approach can be useful in circumstances where reducing environmental impacts is a priority (e.g. in polluted areas), particularly in addressing issues caused by the unproductive use of irrigation water, such as drainage, nitrate leaching, impacts on aquifers, and water diversion for other sectors (i.e. human consumption and/or industrial use), as highlighted in section 4.1.

Weights were assigned accordingly, with a value of *k* equal to 0 (lowest importance) for yield and *NetInc* parameters, *k* equal to 10 (highest importance) for *Blue_FP* and *IrrEcEff*, and *k* equal to 0 (highest importance) for drainage and the two water efficiencies (set at 0 because StV_i for these parameters was found to be less than b, see Eq. 15–16).

By prioritizing aspects related to environmental sustainability and water use efficiencies, it emerged that the two scenarios with the highest irrigation volumes (600 mm and 700 mm) were even more penalizing in terms of irrigation resource management, as indicated by even lower I_{mobj} values compared to the same scenarios with equal and balanced k values (Fig. 5a). Conversely, in the scenarios with lower water supply, water savings resulted in an I_{mobj} that shifted from a negative value (−1.64) for seasonal volumes of 100 mm to a positive value (0.46), while for a seasonal water amount of 200 mm, I_{mobj} experienced a marked improvement, increasing from 0.35 when k was set to 5 to 1.52 when unbalanced k values were used in favour of parameters related to water savings.

The I_{mobj} values result from the aggregation of TW_i specifically for each water-related parameter of the cropping system. The analysis of TW_i for instance, comparing the scenario of 400 mm (with $k = 5$) versus 300 mm (with unbalanced k values for prioritizing the water saving), provided a clear picture of the effect of different k values on system score. (Fig. 5b). The TW_i values for yield and *NetInc* under the 400 mm water supply scenario were significantly higher than those of the other parameters, despite almost none of these parameters reaching critical scores. As a result, the I_{mobj} was higher for the 400 mm scenario compared to the 300 mm seasonal irrigation volume scenario with balanced k, even though the environmental sustainability parameters were superior in the latter. However, when comparing the 400 mm scenario with the 300 mm scenario, the I_{mobj} score for the 300 mm scenario was higher, indicating greater environmental sustainability. This was supported by particularly favourable *TWi* scores for environmental parameters and water use efficiency in the 300 mm scenario compared to the 400 mm scenario, despite a substantial reduction in scores for productivity and profitability with 300 mm of water supply.

Although the information presented thus far is based on the industrial tomato cropping system cultivated in Capitanata and calibrated on climatic trends from several years closely correlated with the experimental fields, the framework is highly adaptable to specific water resource and pedo-climatic conditions, as well as to various herbaceous crops. These conditions - such as rainfall inputs and soil type - impact the response of the first layer of the system (namely, the AquaCrop simulations), which subsequently influences the upper layers and ultimately the final output of the system. In our study, the results obtained and the associated discussions were based on an average trend spread over multiple simulated crop years, providing a general indication for optimizing seasonal irrigation volumes rather than offering specific recommendations for individual years. Additionally, the modularity of the response based on parameter k allows for the adaptation of the framework to meet specific needs, such as prioritizing water savings over maximum productivity in contexts with limited water resources.

Therefore, any productive agricultural system can be fed into this new multi-objective tool, as it does not have a rigid structure (the AquaCrop crop model can be replaced by other process models or utilize independent experimental data if sufficiently numerous to adequately support the regression analysis) and is adaptable to specific analytical needs (it is possible to add additional parameters of the cropping system beyond those analyzed in this paper). Moreover, all analyses and equations presented in the text are easily importable and executable in the most common electronic spreadsheets, as well as the processing of all outputs derived from these analyses (i.e., parameters of the regression models) to arrive at TW_i and I_{mobj}, thereby expanding the fields of application to various production systems.

In any case, certain limitations must be acknowledged when selecting the mechanistic model to replicate real scenarios. In our study, compared to more complex simulation models, the lower complexity of AquaCrop - due to the limited number of parameters and coefficients that need to be calibrated - makes it an ideal choice as a balanced compromise between ease of use and the adequacy of the outputs necessary to form the foundational basis of the proposed framework (i.e., the response of water-related parameters to seasonal irrigation volumes). However, since AquaCrop is essentially based on water dynamics and crop productivity, it lacks certain features that account for the impacts of climate change on crop responses. For instance, heat waves - which are expected to become increasingly frequent and intense during the growing cycle of spring-summer crops like tomatoes - can significantly reduce yield under field conditions and compromise the accuracy of model's simulations.

5. Conclusions

The study presented a comprehensive framework for evaluating the impact of irrigation strategies on processing tomato cultivation in Mediterranean environments. By combining AquaCrop simulations with a weighted empirical model, the framework identified optimal irrigation volumes that balance productivity, profitability, water use efficiency, and environmental sustainability. The results showed that seasonal irrigation volumes around 400 mm optimize overall system performance, while volumes closer to 300 mm may be preferable when prioritizing water conservation and environmental sustainability without compromising profitability.

This approach emphasizes the importance of integrating multiple parameters to provide a balanced assessment of irrigation strategies.

Limitations of this research included the specific pedo-climatic context in which the framework was developed and calibrated, which

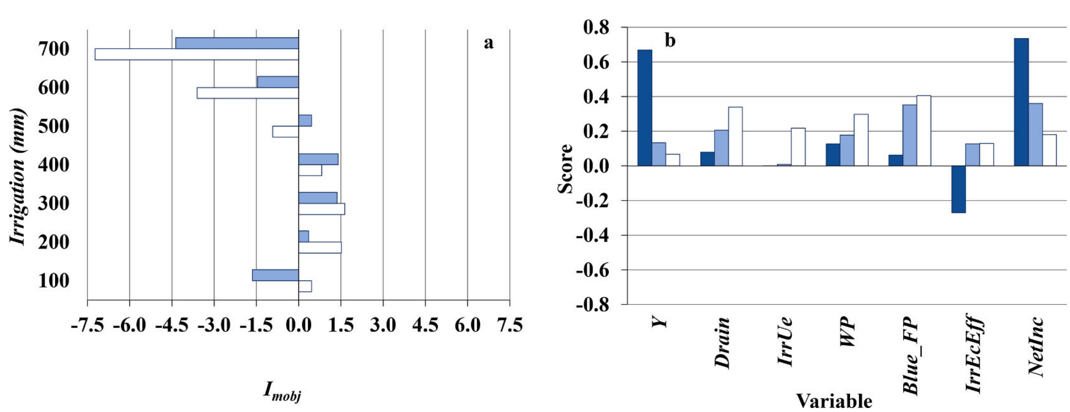

Fig. 5. Comparison between *a)* the aggregated multi-objective index score (I_{mobj}) resulting from application of equal (light blue bars) k values (see Eq. 15–16) and unbalanced k values (white bars) and *b)* the related TW_i (Score) when applying 400 mm ($k = 5$; dark blue bars), 300 mm ($k = 5$; light blue bars) and 300 mm (unbalanced k; white bars) of seasonal water supply. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

may limit its generalizability to other regions. The findings from this paper can be adapted to similar climatic contexts of the study area, but in different cultivation regions, recalibration of the proposed framework will be required (although the layers that constitute it remain unchanged) to obtain responses tailored to specific pedo-climatic contexts. Moreover, validation of the framework is necessary under climate change scenarios, where the impacts of varying environmental conditions (e.g., heat waves) must be carefully evaluated due to the lack of specific algorithms implemented in AquaCrop and other simulation models to replicate such conditions. Furthermore, the integration of this approach into a dedicated Decision Support System (DSS) remains an ongoing development to enhance practical application. Currently, the spreadsheet, where the fully functional framework is structured, can be provided upon request to the authors.

CRediT authorship contribution statement

P. Garofalo: Writing – review & editing, Writing – original draft, Conceptualization. **M. Riccardi:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **P. Di Tommasi:** Writing – review & editing, Methodology, Data curation. **A. Tedeschi:** Writing – review & editing, Methodology, Data curation. **M. Rinaldi:** Writing – review & editing, Methodology, Data curation. **F. De Lorenzi:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Data curation.

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

The authors do not have permission to share data.

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Appendix A. Supplementary data

List of acronyms used in the text, meaning, and units of measure is reported in Table S1 in supplementary materials.

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