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Using AquaCrop as a decision-support tool for improved irrigation management in the Sahel region

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ABSTRACT

Operational systems providing irrigation advisories to agricultural extension workers are paramount, particularly in West Africa where the yield gap represents the greatest agriculture growth-led opportunity. The proposed framework for Burkina Faso, an irrigation decision support system (DSS), is based on in-situ weather and field observations necessary for feeding the atmosphere, soil, and crop modules of crop-water productivity models (e.g., AquaCrop). To optimize water resources, incoming irrigation and precipitation, and outgoing evapotranspiration are constantly monitored and adjusted. The findings of the proposed semi-automatic irrigation DSS indicate that water stresses affecting the canopy cover and stomatal closure are minimized if the proposed irrigation schemes are generated and improved with five-day weather observations. The source of uncertainty in crop models' evapotranspiration estimations is reduced by systematically comparing the observed crop evapotranspiration (ETc) with historical ETc records. An increase in yields is observed in all studied crops, from 1960 to 2018 kg/ha (tomato dry yields), from 2571 to 2799 kg/ha (maize), and from 1279 to 1385 kg/ha (quinoa) when comparing the 2020–21 and 2021–22 experiments. Results show an optimization of water resources, with a higher evapotranspired water productivity (WP_{ET}, expressed as dry weight) when comparing the two experiments, from 0.86 to 0.97 kg/m^3 for tomato, from 0.85 to 0.86 kg/m^3 for maize, and from 0.67 to 0.73 kg/m^3 for quinoa, respectively in 2020–21 and 2021–22. The proposed irrigation DSS can be used to inform extension workers and technical agronomic experts about real-time crop water requirements and, thus, assist the Climate Risk and Early Warning Systems (CREWS) initiative that aims to improve access to weather information for decision-support in agriculture. Afterwards, extension agents can catalyze irrigation advisories and support farmers improve irrigation management at the field level to, ultimately, obtain higher yields.

1. Introduction

In Burkina Faso, agriculture is subsistence-based and rainfed, subjected to favorable weather conditions during the rainy season (May to October) to meet the country's food demand. Unreliable and erratic rainfall, together with a low soil fertility and poor structured soils, are the main abiotic stresses constraining crop production. The latter are hindered by inadequate water management systems as well as technological agronomic solutions, except for some agricultural practices traditionally adopted by Sahelian farmers (e.g., zaï pits, stone bunds, agroforestry, and mulching), rendering agricultural systems and livelihoods highly vulnerable and exposed to climate threats, including in-season rainfall variability and weather extremes. As a result, between 2019 and 2021, 3.8 million Burkinabè suffered from undernourishment, roughly 20 % of the population (FAO, 2022a). What's more, due to the lack of water resources, agricultural production during the dry season has been limited to vegetable gardening, mainly practiced through intensive production systems adjacent to water basins. In recent years, the nationwide harvested area of tomato has folded, from 1226 to 2045 ha (ha) between 2011 and 2020, while the production of tomato fresh yields has remained constant (10.8 t/ha) over time (FAO, 2022b). On the other hand, the production of staple crops (e.g., millet, sorghum, and

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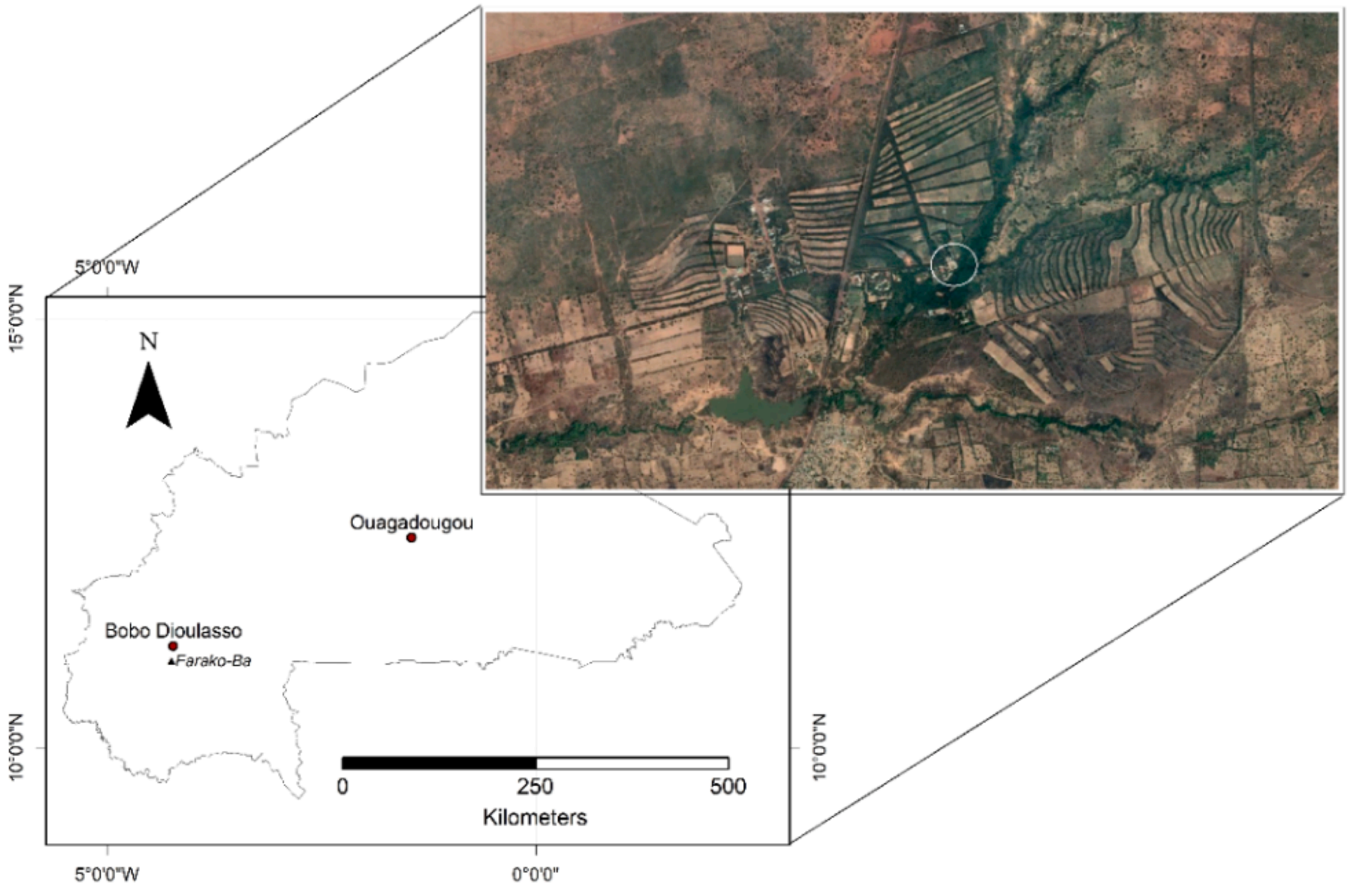

Fig. 1. Selected site for testing an irrigation DSS in Burkina Faso.

maize) during the wet season has become vital to ensure the minimum calorie intake for healthy diets and improved nutrition (Laudien et al., 2022). Thereby, to cope with increasing food demand, the harvested area of staple crops has increased in the past-decade (2011–2020), especially that of maize, by about 400000 ha, up to 1.13 million ha in 2020 – likewise to that of sorghum (1.18 million ha), but lower to that of millet (1.86 million ha) (FAO, 2022b). Despite the increase in harvested area, there is a major production gap during the lean season, also described as the hunger gap comprising the three months (June to August) preceding the harvesting of rainfed crops. As a result of low food availability during the wet season, food assistance programs have sought to improve food production during the dry season, particularly along traditional lowlands of southwestern Burkina Faso.

To increase food production during the dry season and to ameliorate nutritional and food safety, the Food and Agriculture Organization (FAO) alongside with national agricultural research centers and academia, have promoted drought-tolerant crops (e.g., quinoa) capable of tackling both malnutrition and the impacts of increasing abiotic stresses associated with weather extremes and climate variability (Alvar-Beltrán et al., 2019; Dao et al., 2020). However, while crop breeding programs have played a key role on increasing crop water productivity (CWP) in the past, such gains are not foreseen into the future (Molden et al., 2010). Thereby, modelling crop water consumption and CWP is a key step towards optimizing water resources in the Sahel region. In recent years, a considerable amount of research has been conducted to assess the impacts of climate change and improve agricultural water management through water conservation methods, yet little is known about ways of coping with dry-spells during the agricultural campaign through small-scale irrigation for highly water demanding crops (e.g., maize and tomato). The latter is key to reduce the yield gaps of subsistence (maize), highly nutritious (quinoa) and cash crops (tomato), particularly among rural and resource constrained communities.

Therefore, the Sahel region, continues to have a paucity of literature applying CWP models, which are essential to support farmers and agricultural extension workers make agricultural water management informed decisions during the growing season. Existing CWP experiments have aimed to increase crop yields (per unit of land area) by using similar or less amount of water inputs. For example, in Burkina Faso, Wellens et al. (2013a) and Alvar-Beltrán et al. (2021a, b) have successfully applied CWP models (AquaCrop) to optimize cabbage and quinoa yields, while minimizing crop water use. The General Large Area Model for Annual Crops (GLAM) has also been used to improve maize planting dates (Waongo et al., 2014) and the Système d'Analyse Régionale des Risques Agroclimatiques (SARRA) has been tested by agronomists and agrometeorologists working in the Sahel for risk analysis and yield forecasting (Traoré et al., 2011; Genesio et al., 2011). In West Africa, the Agricultural Production Systems sIMulator (APSIM) and the Decision Support System for Agrotechnology Transfer (DSSAT) have been widely used to assess climate change impacts on sorghum yields (Guan et al., 2017; Arumugam et al., 2023) and to support decision making on nitrogen management for pearl millet (Akponikpè et al., 2010). In Burkina Faso, APSIM has been tested to evaluate the effect of soil, climate, and sowing dates on the temporal variability of maize yields (Waha et al., 2015). Some of the existing literature using AquaCrop in West Africa for irrigated maize and tomato show that, if management practices are not improved, climate change might adversely impact crop production (Raes et al., 2021). At the regional level, the AGRHYMET center has worked for decades on research, development, and implementation of crop models for Sahelian cereals based on the SARRA model family (Oettli et al., 2011; Vintrou et al., 2014). However, AGRHYMET acknowledges new challenges such as the need to enhance

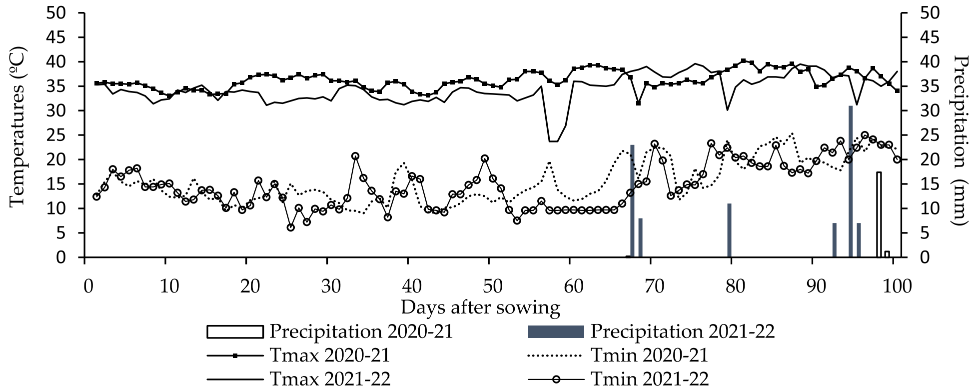

Fig. 2. Daily maximum and minimum temperatures (ºC) and precipitation (mm) recorded in 2020–21 and 2021–22.

the production of irrigated vegetables and cash crops and, thus, has requested a wider scope of solutions based on other crop models, including AquaCrop. In addition, the AGRHYMET regional center calls for action to strengthen in-situ data collection for model calibration and operational use as well as to develop and implement an integrated climate, hydro, and crop modelling framework for operational crop monitoring and yield forecasting at the regional level.

Besides of partially fulfilling AGRHYMET needs in the region, the herein pilot study rolls-out a hybrid approach that fills the gap in literature by blending weather and agronomic observations with CWP models (AquaCrop) with the objective of (i) developing an irrigation DSS to increase staple crop (maize) production and food availability both during the dry and lean season, (ii) diversifying household income by enhancing the production of cash crops (tomato) during the dry season, (iii) ameliorating the diet of food insecure people by promoting highly nutritious crops (quinoa) recently introduced in the region, and (iv) assisting extension workers in the development of irrigation advisory services. As a result, this study monitors the phenological development of tomato, maize, and quinoa, besides quantifying crop water requirements during the growing season to ultimately provide extension workers with guiding material to minimize water use and modulate the adverse effects of abiotic stresses. In addition, the here presented innovative task force and inter-agency communication approach represents a steppingstone towards developing a comprehensive DSS for improved irrigation management in the Sahel region. This is achieved by systematically running CWP models that estimate crop water requirements during the growing season which, consequently, improve weather-informed decision making at the farm level.

2. Materials and methods

2.1. Area of study

According to Köppen's climatic classification, Burkina Faso is divided into three climatic regions: (i) hot-desert climate (BWh), (ii) hot semi-arid climate (BSh), and (iii) tropical savanna climate (Aw). This study is performed at the Institut de l'Environnement et des Recherches Agricoles (INERA), Farako-Ba research station (11° 05′ N, 4° 19′ W, 421 m.a.s.l) (Fig. 1). INERAs research station is found within the tropical savanna region (so-called Soudanian agroclimatic zone), characterized by dry winters and warm year-round temperatures. In this region, the total annual precipitation ranges between 900 and 1200 mm, scarce from November to April and abundant over the summer months.

2.2. Experimental design

The here presented pilot agronomic experiment is rolled-out during two consecutive dry seasons, comprising the 2020–2021 and 2021–2022 periods. Agronomic experiments are deployed over a surface area of 680 m^2, including 140 m^2 of bare soil left between field plots to avoid side-effects. An area of 180 m^2 is assigned to each crop (tomato, maize, and quinoa), where each field is divided into three replicates sizing 60 m^2, and split into 15 rows spaced by 0.8 m. In both years, the sowing of maize and quinoa is done on December 14; whereas tomato plants are, first, sown on seedling trays and, afterwards, transplanted into the field on December 14. Upon proper calibration of the AquaCrop model, the proposed irrigation DSS uses daily crop evapotranspiration (ETc) simulated values under net irrigation to, afterwards, estimate crop water requirements (reference value necessary to determine the timing and amount of water application at a given time) under optimal water growing conditions. While the ETc values for the first experiment (2020–2021) are merely based on simulated reference evapotranspiration (ETo) derived from daily meteorological data from the field using the Penman-Monteith equation, the second experiment (2021–2022) uses a learning approach (based on historical simulated ETc values from the first experiment) to enhance the irrigation DSS and, consequently, improve water use efficiency and crop yields during the second year.

2.3. Model theory

The AquaCrop model has been developed by the Land and Water Division at FAO to assess the effect of different environmental conditions and field management practices on crop production. The model simulates yield in four steps: (i) crop development, (ii) crop transpiration, (iii) biomass production, and (iv) yield formation (Steduto et al., 2012; Vanuytrecht et al., 2014; Raes, 2017). The first step, i.e., the development of the crop green canopy cover (thereafter CC), is simulated as the soil fraction covered by the canopy of the crop. Afterwards, the crop transpiration (Tr) is calculated by multiplying the reference evapotranspiration (ETo) by the crop coefficient (Kc) that depends on the CC. Then, the actual transpiration (Ta) is calculated from the potential evapotranspiration. The third step estimates the production of above-ground crop biomass, which is proportional to the cumulative water transpired by the crop (Eq. 1). Lastly, through the harvest index (HI), corresponding to the share of harvestable product to the total above-ground biomass, the crop yield is obtained (Eq. 2).

$$\text{Crop biomass (B)} = \sum \text{Tr} * \text{WP} \tag{1}$$

$$\text{Crop yield (Y)} = \text{HI} * \text{B} \tag{2}$$

2.4. Model parametrization

2.4.1. Climate module

The National Meteorological Service of Burkina Faso (ANAM) has provided this work with the weather data necessary for running the climate module in AquaCrop. Weather data (Fig. 2), automatically

Table 1
Summary of field observations per experiment.

Weather	Observation frequency	Sample size
Maximum temperature	every 3h	±800 readings
Minimum temperature	every 3h	±800 readings
Precipitation	daily	±100 readings
Crop	Observation frequency	Sample size per replicate (tomato/maize/quinoa)
Plant density at sowing	once/season	25/125/250 plants
Time to emergence	once/season	25/125/250 plants
Time to flowering	once/season	25/125/250 plants
Duration of flowering	once/season	25/125/250 plants
Time to senescence	once/season	25/125/250 plants
Time to maturity	once/season	25/125/250 plants
Canopy cover	weekly	10/10/10 images
Yield	once/season	10/125/100 plants
Soil management	Application frequency	Total fertilizer amount (tomato/ maize/quinoa)
NPK	twice/season	450/200/100 kg/ha
Urea (CH_4N_2O)	twice/season	200/150/150 kg/ha

recorded every 3 h, including maximum and minimum temperatures (ºC) and precipitation (mm), has been transferred (twice a week) to crop modelers responsible for computing crop water requirements under net irrigation requirements over the entire experimental period (see Section 2.4.3). Afterwards, climate files have been uploaded into AquaCrop to compute twice a week the ETo derived from daily meteorological data using the Penman-Monteith equation, which includes all the parameters governing the energy exchange and latent heat-flux (Raes, 2017). In the case weather data (e.g., humidity, solar radiation and windspeed) necessary to compute ETo through the Penman-Monteith equation is missing, procedures to estimate missing climatic data are used according to the methodologies outlined in the Irrigation and Drainage Paper No 56 (FAO, 1998).

2.4.2. Crop module

In AquaCrop, the fine tuning of crop parameters is achieved using field information on the planting method and plant density, field management, plant phenology and soil profile conditions (Table 2). Additional crop parameters, affected by crop's responses to abiotic stresses, such as water, temperature, soil salinity and fertility, are calibrated based on an extensive search of literature (Alam et al., 2017; Alvar-Beltrán et al., 2020; FAO, 2012; Wahid et al., 2007). Crop development, including the canopy cover (CC) and the crop phenological phases, is monitored on weekly basis for the CC and when 50 % of the plants have reached a specific growing stage (time for plant emergence, time for maximum CC, time/duration of flowering, start of canopy senescence, and physiological maturity) (Table 1). In addition, the Canopeo App., tool for measuring the fractional green CC of the plants (at 60 cm distance from the top of the canopy), is employed to monitor the development of the CC in the field. Emerging CC findings are used to complement the field data section in AquaCrop. Lastly, to avoid any side effects, readings from the five middle-rows in each plot are collected to monitor both the crop growth and development.

$$\text{Tomato yields}(\text{in kg} \Big/ \text{ha}) = (FW * PD) * (\frac{(100 - MC)}{100}) \quad (3)$$

Where FW corresponds to the fruit weight (in kg) produced by one plant calculated as the average of 10 plants/replicate, PD to the plant density (25,000 plants/ha), and MC to the moisture content adjusted at 90 % necessary to convert fresh tomato yields into dry yields in AquaCrop (FAO, 2012).

Table 2
Parametrization of AquaCrop for quinoa, maize, and tomato.

Inputs	Units	Tomato Observed 20/21-21/22 [calibrated]	Maize Observed 20/21-21/22 [calibrated]	Quinoa Observed 20/21-21/22 [calibrated]
Crop module				
Development				
Plant density	plants/ha	25,000 [idem]	62,500 [idem]	125,000 [idem]
Type of planting method	-	Transplanting [idem]	Direct sowing [idem]	Direct sowing [idem]
Initial canopy cover	%	n/d [0.38]	n/d [0.41]	n/d [0.63]
Canopy size seedling	cm^2/plant	n/d [25.0]	n/d [6.5]	n/d [5.0]
Canopy expansion	%/day	n/d [10.0/9.9]	n/d [12.0/12.2]	n/d [10.2/11.6]
Canopy decline	%/day	n/d [4.3/3.7]	n/d [3.8/6.0]	n/d [13.0/15.0]
Time to recovery/emergence	days	4/4 [idem]	5/5 [5/4]	4/4 [5/3]
Time to maximum canopy cover	days	63-70/63-70 [68/70]	63-70/63-70 [67/65]	56-63/49-56 [65/56]
Time to senescence	days	70/70 [idem]	70/75 [69/75]	69/56-63 [67/63]
Time to maturity	days	80/69 [80/73]	91/92 [idem]	75/70 [idem]
Maximum canopy cover	%	31/34 [idem]	56/57 [idem]	23/24 [idem]
Time to flowering	days	30/29 [32/32]	66/63 [66/57]	35/34 [idem]
Duration of the flowering	days	17/17 [idem]	12/13 [12/11]	16/15 [idem]
Length building up harvest index	days	50/40 [48/41]	25/35 [idem]	40/36 [idem]
Max. effective rooting depth	cm	n/d [45]	n/d [100/100]	30[2] [idem]
Crop Production				
Crop water productivity	kg/m^3	18[1] [idem]	33.7[1] [idem]	10.5[1] [12.0]
Harvest index	%	55/60 [56]	34/31 [34/32]	63/63 [64]
Crop response to water stresses				
Maximum crop transpiration	-	1.10[1] [idem]	1.05[1] [idem]	1.10[1] [idem]
Canopy expansion	p: upper/lower	0.15/0.55[1] [idem]	0.14/0.72[1] [idem]	0.50/0.80[1] [idem]
Stomatal closure	p: upper	0.50[1] [idem]	0.69[1] [idem]	0.60[1] [idem]
Early canopy senescence	p: upper	0.70[1] [idem]	0.69[1] [idem]	0.98[1] [idem]
Crop response to temperature stresses				
Base temperature	ºC	7[1] [idem]	8[1] [idem]	2[1] [idem]
Upper temperature	ºC	28[1] [idem]	30[1] [idem]	30[1] [idem]
Pollination affected by heat stress	ºC	32-37[3] [idem]	33-38[4] [idem]	36-41[5] [idem]
Pollination affected by cold stress	ºC	5-10[1] [idem]	5-10[1] [idem]	3-8[1] [idem]
Soil module				
Soil texture (0-20/20-100cm)	USDA	Sandy-Loam/Sandy-Clay-Loam[1] [idem]		
Permanent wilting point	Vol %	10/20[2] [idem]		

(continued on next page)

Table 2 (*continued*)

Inputs	Units	Tomato Observed 20/21-21/22 [calibrated]	Maize Observed 20/21-21/22 [calibrated]	Quinoa Observed 20/21-21/22 [calibrated]
(0-20/20-100cm)				
Field capacity (0-20/20-100cm)			Vol %	22/32[2] [idem]
Saturation point (0-20/20-100cm)	Vol %	41/47[2] [idem]		
Hydraulic conductivity (0-20/20-100cm)	mm/day	800/125[2] [idem]		

[1]FAO (2012); [2]Alvar-Beltrán et al. (2019); [3]Wahid et al. (2007); [4]Alam et al. (2017); [5]Alvar-Beltrán et al. (2021a)

$$\text{Maize yields(in kg}\Big/\text{ha)} = GW * \left(\frac{(100-H)}{85}\right) * \left(\frac{10}{S}\right) \tag{4}$$

Where GW corresponds to the grain weight (in kg) produced by one plant as the average of plants in 20 m^2 (125 plants/replicate), H to the humidity level when measuring grain weight (18 % in 2020–21 % and 13 % in 2021–2022), (100−15)/85 to the yield adjusted at 15 % moisture, and S to the surface area (20 m^2) of the five middle-rows comprising 125 maize plants/replicate.

$$\text{Quinoa yields(in kg/ha)} = SW * \quad PD \tag{5}$$

Where SW corresponds to the weight of seeds (in g) produced by one plant calculated as the average of 100 plants/replicate, while PD to the plant density (125,000 plants/ha).

2.4.3. Irrigation module

To calculate the amount of irrigation in the field, a water counter is placed (⌀ 1/2") at the entry of each experimental block. Every row, spaced by 0.8 m, within each plot is equipped with a drip-irrigation pipeline (at a flow rate of 1.05 l/hour per emitter) and where emitters are spaced 30 cm from each other. Afterwards, to determine the crop water requirements in AquaCrop, crop evapotranspiration (ETc) is derived from in-situ weather observations necessary for estimating reference evapotranspiration (ETo) and crop characteristics necessary for determining crop evapotranspiration (Kc). To adjust the irrigation quantity in the field based on ETc simulations from AquaCrop, an iterative ETc simulation process in AquaCrop is performed for the previous five-days and, afterwards, extrapolated for the succeeding week. Although the AquaCrop model does not allow the user to perform sub-daily crop water requirement simulations, and to minimize losses from direct evaporation in the field, irrigation is applied either at dawn and or at dusk. In addition, to minimize potential water stresses to the canopy expansion, stomata closure and early senescence, field (observed) and simulated (AquaCrop) net irrigation requirements (quantity of water necessary for optimal crop growth) are regularly monitored and adequately adjusted in the field. This approach has ensured an optimization of water resources in the field and has likewise minimized physiological water stresses to the plant. To achieve so, the root zone depletion is parametrized in AquaCrop to a level where water resources may not drop below 30 % readily available water (RAW), and where 0 % RAW corresponded to the field capacity and 100 % RAW to the threshold triggering stomatal closure. The former is a steppingstone towards improving the irrigation DSS in the 2021–22 experiment, where ETc daily values from the 2020–21 experiment, together with in-situ daily weather observations from the 2021–22 experiment, are used as a baseline to anticipate crop water requirements in the forthcoming days. This approach allowed a better estimation of crop water requirements in the 2021–22 experiment, besides optimizing water resources and improving crop yields without incurring in crop water stresses (see results in Sections 3.1 and 3.2).

2.4.4. Field management module

To guarantee an optimal crop development in the field, adequate levels of soil fertilization and frequent management of weeds (every three weeks) is performed during the entire growing cycle. For example, two NPK fertilizations (nitrogen, phosphorus, and potassium) are applied to tomato plants, 250 kg/ha of NPK during transplanting and 200 kg/ha of NPK 15 days after transplanting, amounting to a total of 450 kg/ha of NPK (Table 1). An additional 100 kg/ha of urea (equivalent to 46 kg N/ha) are applied both at 25 and 40 days after transplanting. For maize, at the time of sowing, the field is fertilized at a rate of 200 kg/ha of NPK, with an additional 100 kg/ha and 50 kg/ha of urea at 20 and 30 days after sowing, respectively. Lastly, at the time of quinoa sowing, NPK is applied at a rate of 100 kg/ha, with an additional 100 kg/ha and 50 kg/ha of urea at 25 and 35 days after sowing, respectively.

2.4.5. Soil module

The soil profile in AquaCrop is composed by different soil horizons, each with its own physical characteristics. Therefore, to determine soil-classes at two different depths (0–20 and 20–40 cm), five soil samples are randomly collected from the experimental field. Overall, the experimental field displayed a sandy-loam and sandy-clay-loam soil characteristics, respectively at the upper and lower depths (Table 2). Additional values regarding the soil water content at saturation, field capacity, and permanent wilting for the different soil-classes are retrieved from the soil curve numbers publicly available in AquaCrop's manuals on calculation procedures (Raes et al., 2018a).

2.5. Statistical analysis

To test the performance of the AquaCrop model against observed values in the field, different statistical indicators are used. For example, the Pearson correlation coefficient (r, Eq. 6) measures the strength and direction of the relationship between two variables (e.g., observed and simulated CC), while the Nash-Sutcliffe model efficiency coefficient (NSE, Eq. 7) is used to assess the predictive skill of the AquaCrop model. In addition, the root-mean square error (RMSE, Eq. 8) is useful for testing the differences between predicted and observed values (Jacovides and Kontoyiannis, 1995) and the normalized-RMSE (NRMSE, Eq. 9) provides relevant information about the average of the measured data ranges. For the NRMSE, AquaCrop findings are considered highly performant if the differences between observed and simulated values are below 5 %, and good when ranging between 6 % and 15 % (Raes et al., 2018b). Lastly, the Willmott's index of agreement (d, Eq. 10) provides a measure of the agreement of the deviation between modelled and observed values from the observed mean, where 0 indicates disagreement and 1 perfect agreement between simulated and observed values (Willmott, 1984).

$$\mathrm{R} = \frac{\sum(Oi-\widehat{O})(Pi-\widehat{P})}{\sqrt{\sum(Oi-\widehat{O})2 \quad \sum(Pi-\widehat{P})2}} \tag{6}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Oi-Pi)^2}{\sum_{i=1}^{n}(Oi-\widehat{O})^2} \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Oi-Pi)^2} \tag{8}$$

Table 3
Summary of crop-water information.

Variable	Units	Tomato		Maize		Quinoa	
		2020-21	2021-22	2020-21	2021-22	2020-21	2021-22
Accumulated water inputs (I+P) (DSS)	mm	328	341	359	458	254	271
Accumulated water inputs (I+P) (net irrigation)	mm	332	285	366	370	279	258
N° irrigation events (DSS)	-	29	25	32	31	28	22
N° irrigation events (net irrigation)	-	76	66	86	81	71	64
Accumulated ETc (DSS)	mm	229	208	303	324	191	189
Accumulated ETc (net irrigation)	mm	341	288	389	384	285	254
WP_{ET} (observed/ simulated DSS)	kg/ m^3	0.86/ 0.85	0.97/ 1.00	0.85/ 0.88	0.86/ 0.83	0.67/ 0.64	0.73/ 0.69
WP_{ET} (net irrigation)	kg/ m	0.57	0.72	0.67	0.69	0.43	0.51

Note: I (irrigation), P (precipitation), ETc (crop evapotranspiration)

$$\text{NRMSE} = \left(\frac{RMSE}{\widehat{O}}\right) * 100 \tag{9}$$

$$\text{d} = 1 - \frac{\sum_{i=1}^{n} (Oi - Pi)^2}{\sum_{i=1}^{n} (P_i' + O_i')^2} \tag{10}$$

Where O_i and P_i corresponds to the observed and simulated values, respectively, and n to the number of observations. While the RMSE has the same units as that of the variable being simulated (kg/ha), NRMSE units are displayed as a percentage. In addition, $O'_I = [O_i - \widehat{O}]$ and $P'_I = [P_i - \widehat{P}]$ shows the differences between observed and simulated values, with $\widehat{O}$ and $\widehat{P}$ as the observed and simulated means, respectively.

3. Results

3.1. Agroclimatic information

There are significant precipitation differences between the 2020–21 and 2021–22 dry-season experiments, respectively recording 19 and 87 mm/season (Fig. 2). The average Tmax and Tmin recorded during the 2020–21 and 2021–22 experiments is of 36.3/34.4 °C and of 15.6/14.8 °C, respectively. In addition, the average (absolute) Tmax observed during the pollination phase of tomato, maize, and quinoa is of 35.1/33.1 °C (36.8/35.2 °C), 35.7/32.9 °C (38.3/38.0 °C) and of 35.0/32.8 °C (36.8/34.7 °C), respectively in 2020–21 and 2021–22. For tomato and quinoa, the AquaCrop simulations suggest that the average crop cycle temperature stress and the average crop cycle water stress affecting the canopy expansion and stomatal closure is of 0 % for both years. For maize, the average crop cycle temperature stress affecting crop transpiration is of 0 % for 2020–21 and of 1 % for 2021–22, while the average crop cycle water stress affecting the canopy expansion and stomatal closure is of 0 % for both years.

These simulation findings suggest that the soil water stresses affecting the CC development and the expansion of the root zone, inducing stomata closure and reducing crop transpiration rates, are minimal in both experiments. This is because the total available water in the root zone during the entire growing cycle is constantly above the plant's wilting point and below the field capacity, thus indicating that neither biomass production nor yields are constrained by reduced transpiration. Lastly, with regards to air temperature stresses, although temperatures occasionally breached the critical threshold for pollination (see calibrated values in Table 2), its effects on pollination are considered null because the duration and intensity of the stress are limited in time.

3.2. Crop water requirements

In this study, to sustain maximum crop productivity and, at the same time, minimize water use and reduce the number of irrigation events,

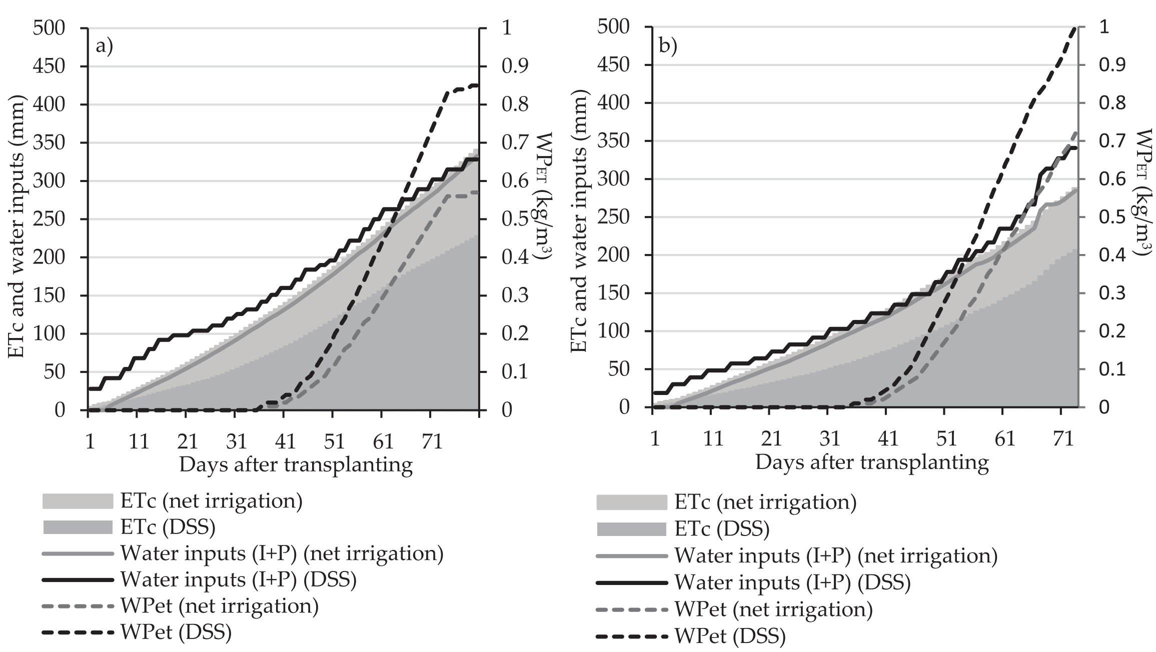

Fig. 3. Tomato: accumulated crop evapotranspiration (ETc in mm), water inputs (from irrigation (I) and precipitation (P)), and evapotranspired water productivity (WP_{ET} in kg/m^3) under a DSS and net irrigation requirements in (a) 2020–21 and (b) 2021–22.

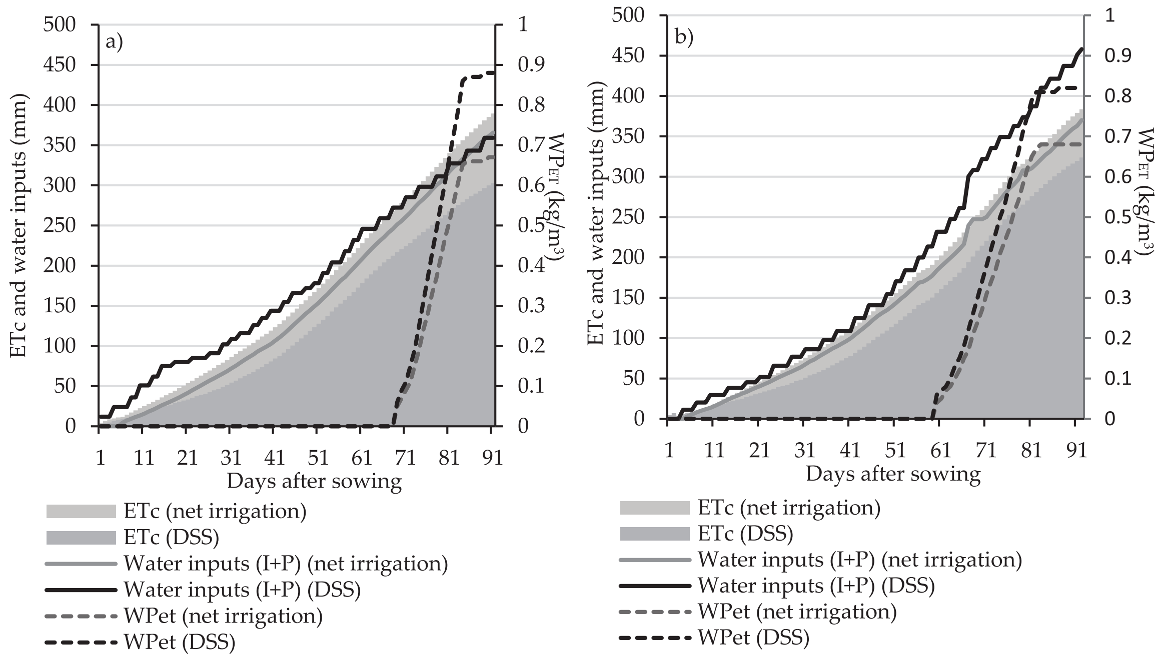

Fig. 4. Maize: accumulated crop evapotranspiration (ETc in mm), water inputs (from irrigation (I) and precipitation (P)), and evapotranspired water productivity (WP_{ET} in kg/m^3) under a DSS and net irrigation requirements in (a) 2020–21 and (b) 2021–22.

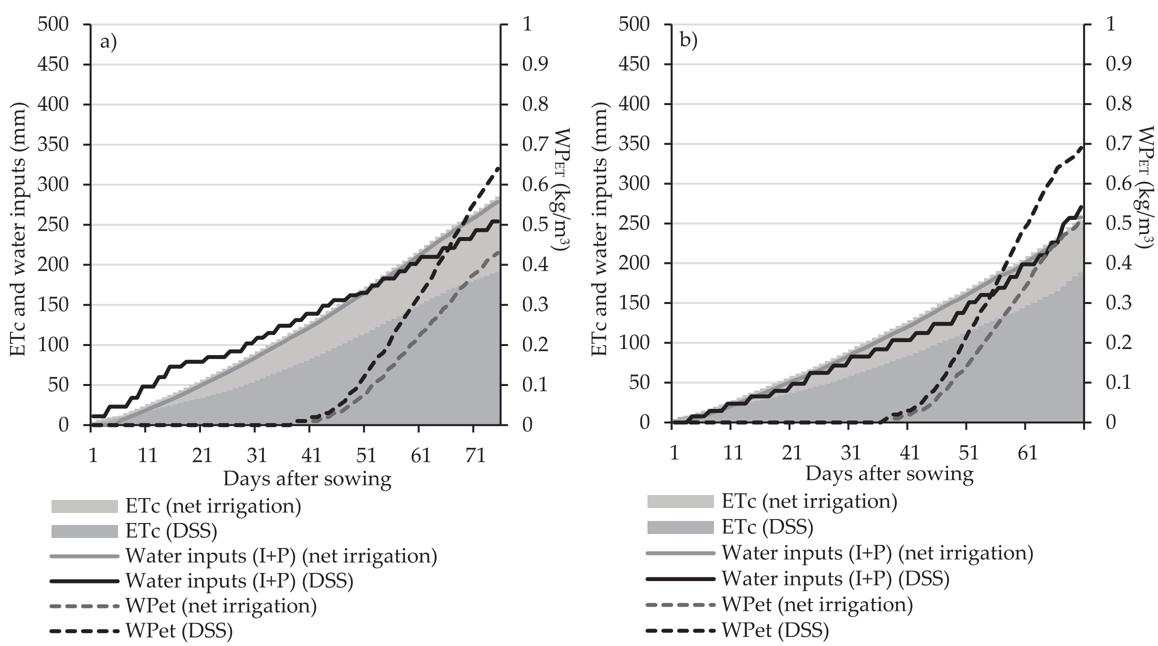

Fig. 5. Quinoa: accumulated crop evapotranspiration (ETc in mm), water inputs (from irrigation (I) and precipitation (P)), and evapotranspired water productivity (WP_{ET} in kg/m^3) under a DSS and net irrigation requirements in (a) 2020–21 and (b) 2021–22.

the progress of crop water requirements is constantly monitored and assessed during the entire growing cycle. The observed precipitation and applied irrigation, as well as the crop evapotranspiration (ETc) during the 2020–21 and 2021–22 experiments are displayed in Table 3 and Figs. 3–5.

For tomato, the accumulated ETc under net irrigation requirements during the 80- and 73-day growing period is of 341 mm/season (2020–21) and of 288 mm/season (2021–22), while the accumulated ETc using a DSS is of 229 mm/season (2020–21) and of 208 mm/season (2021–22), respectively after transplanting (Fig. 3). Although dry yields using a DSS are similar in both experiments (1960 and 2018 kg/ha of dry weight), a higher ET water productivity (WP_{ET} expressed as kg of dry yield per m^3 of water evapotranspired) is observed in 2021–22 (0.97 kg/m^3) compared to 2020–21 (0.86 kg/m^3). These WP_{ET} differences are explained by lower ETc requirements during the 2021–22 experiment compared to 2020–21. In addition, the observed WP_{ET} using a DSS is 42 % higher to that simulated under net irrigation requirements (average of both years). Despite rainfall downpours in the 2021–22 experiment, irrigation management is improved during the second year because similar or slightly higher yields are obtained with a lower number of irrigation events, 25 events in 2021–22 instead of 29 events in 2020–21.

For maize, the accumulated ETc under net irrigation requirements

Table 4
Statistical evaluation of AquaCrop simulations.

	Units	Tomato		Maize		Quinoa	
		2020-21	2021-22	2020-21	2021-22	2020-21	2021-22
Canopy cover							
Pearson correlation coefficient (r)	-	0.99	0.99	0.99	0.99	0.99	0.99
Root-mean square error (RMSE)	-	1.8	1.5	3.0	3.1	1.5	1.9
Nash-Sutcliffe model efficiency coefficient (NSE)	-	0.98	0.99	0.98	0.98	0.97	0.96
Willmott's index of agreement (d)	-	0.99	1.00	1.00	0.99	0.99	0.99
Normalized RMSE (NRMSE)	%	12.9	9.2	8.8	8.7	14.2	15.2
Yield							
Observed (DSS)	kg/ha	1960	2018	2571	2799	1279	1385
Simulated (DSS)	kg/ha	1944	2071	2664	2673	1227	1297
Simulated (net irrigation)	kg/ha	1930	2064	2600	2638	1227	1300
Normalized RMSE (NRMSE) (DSS)	%	1.97		4.11		5.43	

during the 91- and 92-day growing period is of 389 mm/season (2020–21) and of 384 mm/season (2021–22), while the accumulated ETc using a DSS is of 303 mm/season (2020–21) and of 324 mm/season (2021–22) (Fig. 4). Although water inputs in 2020–21 are 22 % lower than in 2021–22, the yield loss is not more than 8 % compared to 2021–22. This is because increasing water inputs, in the form of precipitation in 2021–22, occur once the crop is fully developed and, therefore, do not have a negative effect on crop yields. Lastly, the observed and simulated WP_{ET} using a DSS requirements is similar in both years; though, the WP_{ET} using a DSS is 27 % higher to that simulated under net irrigation requirements (average of both years).

For quinoa, the accumulated ETc during the 75- and 70-day growing period is of 285 mm/season (2020–21) and of 254 mm/season (2021–22), respectively, while the accumulated ETc using a DSS is of 191 mm/season (2020–21) and of 189 mm/season (2021–22) (Fig. 5). Since higher yields are observed with a similar amount of water evapotranspired, the WP_{ET} in 2021–22 is slightly higher (0.73 kg/m^3) to that of 2020–21 (0.67 kg/m^3). For quinoa, as for tomato and maize, the observed WP_{ET} using a DSS is 49 % higher to that simulated under net irrigation requirements (average of both years). Lastly, the number of irrigation events in 2021–22 is reduced due to a higher number of rainy days and increased water application per irrigation event, 10.9 mm/event in 2021–22 instead of 9.1 mm/event in 2020–21.

3.3. Model performance

A successful parametrization of the canopy cover (CC) curve over the growing season is key to provide accurate soil evaporation, crop transpiration, biomass, and yield estimates. The AquaCrop model is calibrated based on field observations, resulting in a good model performance as indicated by the NRMSE for the CC development of tomato (12.9 % and 9.2 %), maize (8.8 % and 8.7 %), and quinoa (14.2 % and 15.2 %), respectively in 2020–21 and 2021–22 (Table 4, Figs. 6–8). A high Pearson correlation coefficient and Wilmott's index agreement indicates a well modelled CC estimates against observed values. The calibrated model also elucidates a high model performance when comparing the observed and simulated yield values, as indicated by the NRSME for tomato (1.97 %), maize (4.11 %), and quinoa (5.43 %) yields on average for both years (Table 4). In addition, the observed (simulated) tomato (after converting fresh fruit into dry weight), maize and quinoa yields are of 1989 (2007), 2685 (2668), and 1332 (1253) kg/ha, respectively on average for both experiments.

4. Discussion

4.1. Yield gap reduction and water optimization

Real-time and precision irrigation scheduling can improve or maintain crop yields with similar or less amount of water applied. The average tomato (19890 kg/ha of fresh yield), maize (2685 kg/ha), and quinoa (1332 kg/ha) yields observed in this study, using an enhanced DSS, together with optimal fertilizer and weeding conditions, are double (+90 %) to those reported for tomato (10449 kg/ha), notably higher (+59 %) to those of maize (1691 kg/ha), and slightly higher (+8 %) to those of quinoa (1233 kg/ha) in Burkina Faso (Alvar-Beltrán et al., 2019; FAO 2022a). These differences between actual and potential yields are described by improved water and soil management in the field. In addition, AquaCrop simulations on crop water requirements are, to some extent, in harmony with satellite remote sensing estimations. For maize, for example, actual ET satellite estimations along the Kou Valley (southwestern Burkina Faso) are of 549 mm/season (Sawadogo et al., 2020), while those reported in this study are of

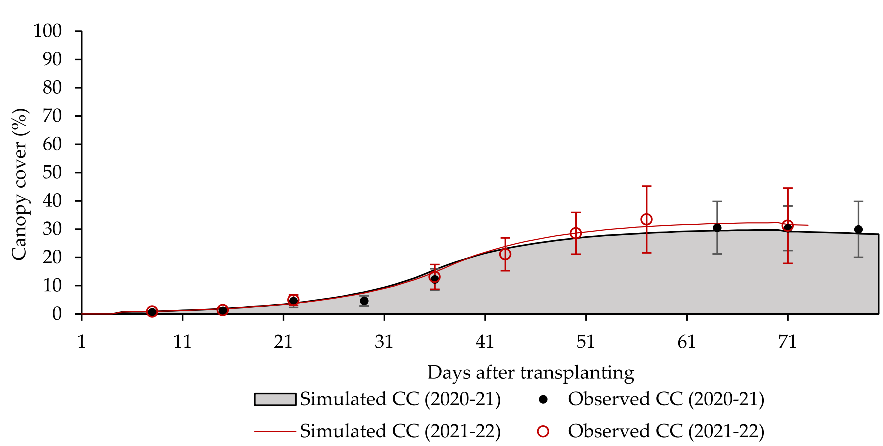

Fig. 6. Simulated and observed canopy cover (CC) for tomato in 2020–21 and 2021–22.

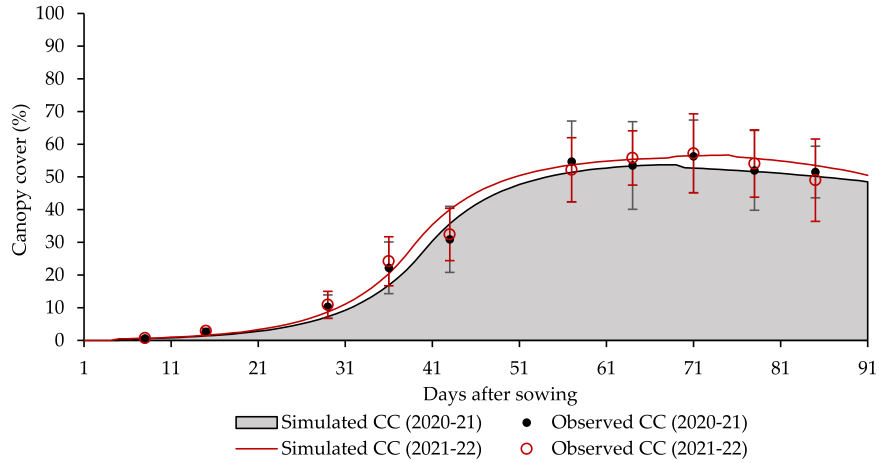

Fig. 7. Simulated and observed canopy cover (CC) for maize in 2020–21 and 2021–22.

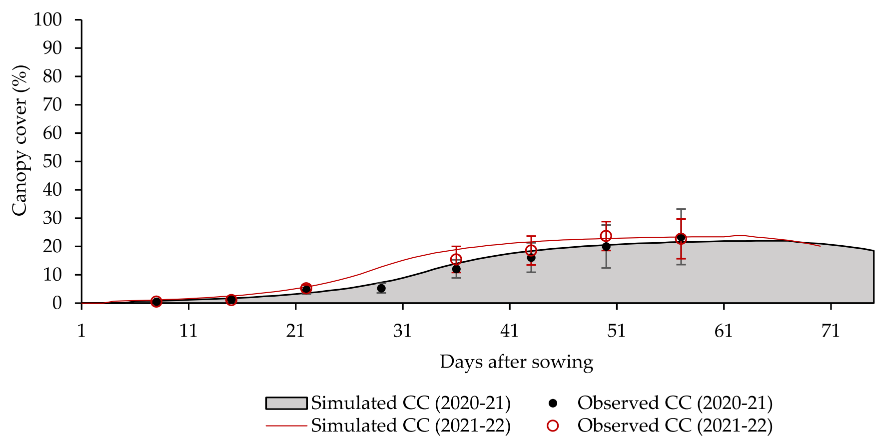

Fig. 8. Simulated and observed canopy cover (CC) for quinoa in 2020–21 and 2021–22.

387 mm/season under net irrigation requirements. These ET differences for maize are explained by a delayed sowing date in Sawadogo's et al. (2020) study, which is affected by higher ET rates occurring during the pre-rainy season (March and April). Higher ETc findings to those of this study (315 mm/season under net irrigation requirements) are reported for tomato during the dry season (413 mm/season) in Tougou valley (Sahelian agroclimatic zone) during the dry season (Mandé, 2006). The latter ET differences are described by a longer crop cycle, 10 weeks instead of 8 weeks, and higher latitudes to those of this study and, consequently, with higher ET rates. For quinoa, lower ETc values under net irrigation requirements (270 mm/season) are simulated in this study compared to full irrigated conditions (394 mm/season) for the same location (Alvar-Beltrán et al., 2019). These differences are explained by an optimization of water resources in this study and, consequently, lower ETc rates, as well as by a different ET calculation method when computing crop water requirements to those of this study, Hargreaves and Samani equation instead of Penman Monteith.

4.2. Evaluation of an improved irrigation DSS

Real-time irrigation scheduling, on daily and hourly basis, has received little attention in the Sahel region. New DSS tools (e.g., AquaCrop) for improved irrigation management are increasingly used in Burkina Faso for developing efficient irrigation schemes (Wellens et al., 2013a; Alvar-Beltrán et al., 2021a). Additional studies on vegetables have identified irrigation calendars using satellite information together with the assistance of AquaCrop (Wellens et al., 2013b; Traore, 2018). Overall, the high performance of AquaCrop when considering the four steps describing yield production is improved thanks to increasing number of model inputs, particularly those related to the plant phenology, canopy development and final yield are essential for accurate estimates of tomato, quinoa, and maize yields in Burkina Faso. This study also reveals the capacity of the model to deliver semi-automated support at the field level by determining both the irrigation intervals and thresholds when the total available water in the soil is above the lower and below the upper thresholds affecting canopy development, inducing stomata closure, and triggering early canopy senescence.

4.2.1. Usefulness of the DSS

This study's findings highlight the usefulness of applying a DSS that integrates crop-water productivity tools to facilitate planning and management of irrigation schemes at the field level, besides displaying a yield reduction gap with the same or less amount of water resources. In addition, since ETc is constantly monitored on AquaCrop, crop water stresses are avoided in both experiments. Water optimization during the 2021–22 is constantly enhanced through historical ETc observations collected during the 2020–21 experiment. The former allows the crop modeler to estimate ETc beforehand and, with high confidence, forecast ETc values regardless of the weather conditions, which generally do not display large daily variations at this latitude. Moreover, improved irrigation schemes are extremely useful to the scheme manager for deciding the timing to switch from the arranged schedule, when water demand is low, to the fixed rotation, when water demand is high (Lozano and Mateos, 2008). The latter is particularly relevant for vegetable crops,

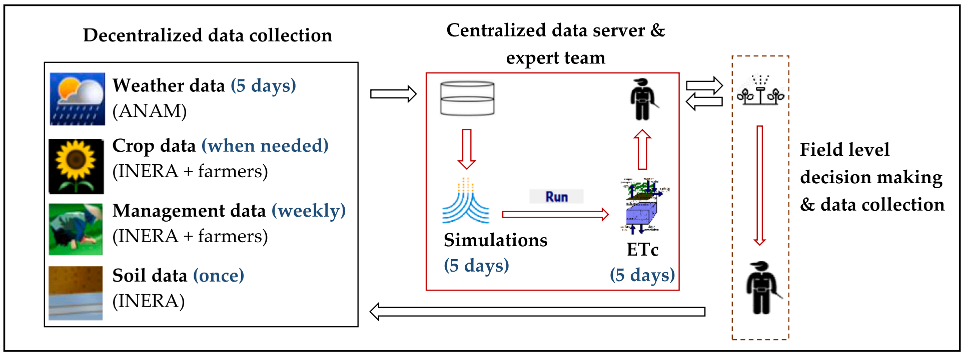

Fig. 9. Proposed real-time irrigation advice and communication workflow.

Table 5
Proposed irrigation scheme for tomato, maize, and quinoa during the dry-season along the Soudano-Sahelian agroclimatic zone of Burkina Faso.

	Month	December			January			February			March		
Crop	Dekadal	1	2	3	1	2	3	1	2	3	1	2	3
Tomato	Amount (mm)	20 + 25[1]	35	35	45	50	55	60	55	45[2]	35[2]		
	Nº events	4	3	3	3	4	4	5	4	3	3		
Maize	Amount (mm)	15 + 25[1]	30	30	35	45	55	60	60	50	50[2]	40[2]	
	Nº events	4	3	3	3	3	4	4	4	4	4	3	
Quinoa	Amount (mm)	15 + 20[1]	30	35	45	45	45	45	35	30[2]			
	Nº events	3	3	3	3	3	4	4	3	2			

[1] Irrigation requirements prior to sowing/transplanting
[2] Additional irrigation may be required according to the physiological maturity of the plant
Note: estimated crop water requirements during the dry-season, thereby considering no precipitation.

where difficulties related to communally managed waters resources often results in conflicts among farmers in Burkina Faso (De Fraiture et al., 2014). Lastly, another advantage of the proposed DSS is that the user can make real-time decisions on whether it's necessary or not to irrigate the field and avoid unnecessary motorized travelling and ignition of fuel propelled pumps with the associated economic costs to the farmer as well as to the environment.

4.2.2. Limitations of the DDS and solutions

One of the major drawbacks of AquaCrop standalone program is regularly assessing crop water requirements. This iterative process is time consuming, however it can be overcome by developing a semi-automated R-environment that simultaneously runs and evaluates the ensemble of field level simulations, as described by Sallah et al. (2019). Some of the shortfalls of AquaCrop is that the field is assumed to be uniformed without spatial differences in crop development, transpiration, soil characteristics or management. In addition, only vertical incoming (precipitation, irrigation, and capillary rise) and outgoing fluxes (evaporation, transpiration, and deep percolation) are considered, whereas the horizontal movement of water is overlooked. Developing an irrigation DSS that is scalable and robust in a non-controlled environment is extremely complex. The latter requires bringing together different national institutions and research institutions, and, foremost, their targeted audiences (farmers) that make decisions based on weather-informed agricultural advisories provided by agricultural extension workers. A solution to bridge the last-mile gap is creating a dashboard that allows user-friendly consultations for irrigation programming and monitoring, as described by Ferrández-Pastor et al. (2018).

5. Conclusions

Although it is widely understood that full irrigation can increase crop yields, new irrigation control methods can substantially improve yields and evapotranspired water productivity in arid environments. The proposed irrigation DSS using the AquaCrop model has proven suitable and useful for assisting and enhancing irrigation management in the field (Fig. 9). The model has supported the field technician in a semi-automated way to calculate real-time crop water requirements based on daily ETc values. Several years of experiments are essential in designing iterative learning processes and, foremost, to adjust in an effective and fast manner irrigation schemes to ensure that the soil-water balance is kept above the upper threshold reducing canopy expansion and below the field capacity to avoid water losses into the environment, including plant transpiration interferences. Overall, the proposed DSS is viewed as a benchmark for future research studies and projects/programmes such as CREWS. The piloted framework is a steppingstone towards operationalizing the irrigation DSS within the region (Table 5). This can be achieved by creating a digital portal that provides a gateway to automatically access, through an application programming interface, climate, crop, soil, and management site-specific and geospatial information collected by National Agricultural Research Centers and National Meteorological and Hydrological Services within the region. While technical agronomic experts are still required to feed the system, no additional interaction is required to process the batch (AquaCrop plugin), which can run automatically and release outputs for users to make weather-informed decisions at the field level. In addition, weather observations can likewise be complemented by a network of soil moisture sensors that provide more accurate and reliable information about the soil-water balance. The proposed DSS should also be tested during the rainy season to modulate the adverse effects of more recurrent and prolonged dry-spells on rainfed crops, which are essential for sustaining agricultural production and food security along the Sahel region. Ongoing agricultural meteorology programs within the region could roll-out and test this methodology during the rainy season and scale-up this intervention during the dry season. This might improve the quality of existing weather-informed irrigation advisories, besides partially fulfilling the call for action made by AGRHYMET regional center to operationalize the use of crop-water productivity models such as AquaCrop in the Sahel.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

Acknowledgements

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