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ORIGINAL PAPER

Modeling deficit irrigation water demand of maize and potato in Eastern Germany using ERA5-Land reanalysis climate time series

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Abstract
ERA5-Land reanalysis (ELR) climate time series has proven useful in (hydro)meteorological studies, however, its adoption for local studies is limited due to accuracies constraints. Meanwhile, local agricultural use of ELR could help data-scarce countries by addressing gaps in (hydro)meteorological variables. This study aimed to evaluate the first applicability of the ELR climate time series for modeling maize and potato irrigation water demand (IWD) at field scale and examined the performance of ELR precipitation with bias correction (DBC) and without bias correction (WBC). Yield, actual evapotranspiration (ETa), irrigation, water balance, and crop water productivity (CWP) were evaluated using the deficit irrigation toolbox. The study found that maize (13.98–14.49 ton/ha) and potato (6.84–8.20 tons/ha) had similar mean seasonal yield under different irrigation management strategies (IMS). The Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS_WS) IMS had the highest mean seasonal yields under DBC and WBC, while rainfall and constant IMS had the most crop failures. DBC had a higher mean seasonal ETa than WBC, except for the potato FIT and rainfall IMS. Global Evolutionary Technique for OPTimal Irrigation Scheduling: one common schedule per crop season (GET-OPTIS_OS) and GET-OPTIS_WS IMS outperformed conventional IMS in IWD by 44%. Overall, GET-OPTIS_OS and GET-OPTIS_WS performed best for maize and potato CWP in terms of IWD, scheduling, and timing. Therefore, adoption of ELR climate time series and advanced irrigation optimization strategies such as GET-OPTIS_OS and GET-OPTIS_WS can be beneficial for effective and efficient management of limited water resources, where agricultural water allocation/resource is limited.

Introduction

The increasing demand in crop production aimed at attaining food security, which has been constrained by highly competitive but limited water resources, has attracted a global research audience (Gleick and Palaniappan, 2010; Hristov et al. 2021; Liu et al. 2020; Tian et al. 2021). Irrigation water demand (IWD) is projected to rise (e.g., de Andrade Santana et al. 2019; Masia et al. 2021) due to population growth, industrial needs (Singh 2014a, b, 2022) and ecological demands. Water resources planning and management are becoming more challenging due to population expansion (Maja and Ayano 2021; Yaqoob et al. 2023), increase in IWD (Li et al. 2020; Puy et al. 2021), contamination of surface and groundwater resources (Ligate et al. 2021; Liu et al. 2021; Tokatli 2021), and climate change impacts (Aryal et al. 2020; Ngoma et al. 2021; Shahzad et al. 2021). Innovative water-saving strategies, such as deficit irrigation have been explored for efficient crop production while minimizing the amount of crop loss per unit of water application.

Crop models play a crucial role in mechanistic understanding, identifying, and designing irrigation management strategies (IMS) for maximum utilization of finite freshwater resources for crop production (Kelly and Foster 2021). Conventional IMS provides a rational understanding of "what if" strategies to minimize the cost per unit application of water, while deficit IMS demystifies the best IMS by adopting an

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intentional systemic reduction of irrigation application. Common crop models, such as EPIC (Williams 1990), DSSAT (Jones et al. 2003), Wageningen (van Ittersum et al. 2003), and APSIM (Keating et al. 2003) model, are complex and require expensive laboratory analysis and key experimental data (Gadédjisso-Tossou et al. 2018). However, the AquaCrop model (Raes et al. 2009; Steduto et al. 2009) uses straightforward parameters and simple methods (Vanuytrecht et al. 2014), making it more applicable in data-sparse regions. This study adopted the AquaCrop model to broadly assess two different IMS: conventional and deficit, establishing the best and most relatable IWD modeling approach.

ERA5-Land reanalysis (ELR) climate data is the fifth generation of European reanalysis global data, available from 1950 till date and produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) under the European Commission for Copernicus Climate Change Service (C3S). ELR has a 9 km spatial resolution and an hourly temporal resolution that is the same as older generations of European reanalysis global climate data (Bell et al. 2021; Hersbach et al. 2020; Jiang et al. 2021). ERA5 and ERA-Interim are the previous generations of ELR, with spatial resolutions of 31 km and 80 km, respectively. Downscaling of meteorological forcing and thermodynamic correction of elevation near the surface, embedded in the ECMWF land model (a 4-D model) that describes water and energy cycles (Bell et al. 2021; Hersbach et al. 2020), and the availability of over 240 meteorological products (Jiang et al. 2021) are some of the key advantages of ELR global data over ERA5 and ERA-Interim.

ERA5 and ELR have found great applications in (hydro) meteorological studies, mostly at regional and global scales (Bell et al. 2021; Hersbach et al. 2020; Jiang et al. 2021; Jiao et al. 2021; Longo-Minnolo et al. 2022) but have a very limited adoption for local scale studies. For instance, Jiang et al. (2021) compare the daily precipitation of ERA5 to the China Meteorological Administration (CMA) precipitation database, covering most of the China land area. Hassler and Lauer (2021) investigate six reanalyses of ERA5 and ELR climate data with five observation data on a monthly, seasonal, and inter-annual basis from 1983 to 2016 in central Europe, south Asia, the Pacific Inter-Tropical Convergence Zone (ITCZ), and the Tropics. It is also worth noting that most of these studies use monthly precipitation and, at times, runoff, soil moisture, and potential evapotranspiration (ETo) (Vorobevskii et al. 2020). Nonetheless, the dearth of application and verification of daily precipitation and temperature of ELR, especially for agriculture applications, have not received great attention in recent literature according to Scopus keyword search conducted on 17.02.2024 *(TITLE-ABS-KEY("ERA5-Land" AND "AQUACROP MODEL" OR "IRRIGATION WATER DEMAND" OR "IRRIGATION MANAGEMENT STRATEGIES")*. Application of ELR at the local scale, if verified, could be of high importance for data-scarce countries (particularly developing nations) and the gap-filling of missing (hydro)meteorological variables.

Maize and potato have immense potential for clean and eco-friendly renewable energy generation (Felten et al. 2013; Peichl et al. 2018; Pfeiffer and Thrän 2018), aside from their diverse household uses. Maize plays a crucial role in bioethanol (Torney et al. 2007) and biogas production (Herrmann 2013; Herrmann and Rath 2012), while potato holds great potential for biofuel production (Awogbemi et al. 2022; Liang and McDonald 2014). With Germany's (and Europe's) transition to clean and eco-friendly energy sources, large cultivation of these crops with an increased/constant yield will be paramount, to maintain Germany's industrial workload demands and provide a consistent source of energy (Huynh et al. 2019), apart from human and animal consumption of these crops.

In Germany, continuous changes in climate conditions and recently projected extreme conditions by several studies (Egerer et al. 2023; Grossmann and Dietrich 2012; Pe'er et al. 2020), particularly the projected decrease and increase in precipitation and ETo pose a threat that may warrant a stringent water allocation measure for different sectors, especially for agriculture (Fig. S1). Furthermore, previous studies have projected a likely shortage of water resources in Germany (Al-Mukhtar et al. 2014; Drastig et al. 2016; Huang et al. 2010; Schleich and Hillenbrand 2009), hence, it is imperative to assess the impact(s) of a reduction in water allocation on agriculture.

In this study, as input climate data for the AquaCrop model to model IWD at the local scale at a farm in eastern Germany, we use hourly ELR precipitation and temperature downloaded from the C3S website and processed into daily values, as well as ETo (Singer et al. 2021) derived from the ELR products. We assess the applicability of ELR climate time series for modeling conventional and deficit IWD for maize and potato using yield, actual evapotranspiration (ETa), irrigation amount, water balance (WB), and crop water productivity (CWP; in terms of ETa) (Zwart and Bastiaanssen 2004) as IWD assessment evaluators. We also evaluate the effect of with and without bias correction (BC) of ELR precipitation on IWD by analyzing the statistical differences that exist before and after BC.

Materials and methods

Study area description

One of the farms in Bautzen, Saxony Free State, was chosen as the model site to implement the IMS. The farm has an approximate area of 0.24 km^2 at an elevation of 234 m-asl. The farm, located at 51° 10′ 12″–51° 10′ 48″ N, 14° 22′

12″–14° 22′ 48″ °E, is close to Kubschütz Weather Station (KWS), less than 230 m away (Fig. 1). Saxony is approximately 11,582 km^2 and spans through two German Federal States: Brandenburg and the Saxony Free State. Saxony Free State has a population of 4.3 million (Fig. 1). According to Spänhoff et al. (2012), arable fields and forests are the most common land uses.

Arable fields cover 39% of the land, while the forest covers 27%. Other land uses include grassland (13%), urban (12%), military bases (4%), agricultural land (3%), and lignite mining regions (2%). According to KWS climate data (1936–2021) downloaded from German Weather Service (Deutscher Wetterdienst, www.dwd.de), the farm receives a mean annual rainfall of 620 mm, with around 34% and 24% of rainfall during the summer (June–August) and spring (April–May) seasons, respectively. July is the wettest month, while February is the driest. The highest daily precipitation recorded in the farm was 98.30 mm in July 2011. The precipitation distribution is unimodal (Fig. 2).

Deficit irrigation water demand estimation

Maize and potato crops were chosen for this study because of their environmental and socioeconomic benefits. IWD from 1981 to 2020 was examined using daily ELR climate data to assess the likely future sustainability of the irrigation system in eastern Germany. Due to the location of eastern Germany, the climate water balance (CWB) is mostly low, necessitating high IWD (Drastig et al. 2016). The majority of the IWD in summer is met by groundwater pumping, leading to a lowering of the water table, and increasing competing demands and pressure from other sectors like public water supply (Gerwin et al. 2023; Mirschel et al. 2019) and ecological demands.

Before the application of ELR climate data for modeling, ELR and KWS were compared for quality control. However, 1998 was excluded due to missing precipitation data from KWS. The study included only the summer growing season (39 growing seasons in total), from April to November. According to Drastig et al. (2016), the summer season mostly requires supplemental irrigation due to water stress.

Soil hydraulic properties generation

Food and Agriculture Organization (FAO) global soil map classification was adopted for this study, and the Saxony Free State soil was extracted from the global soil map (Fig. 3). The soil map has a resolution of 1:5,000,000. User soil from the soil and water assessment tool (SWAT) (Arnold et al. 2013) was used to regroup the soil textural class into

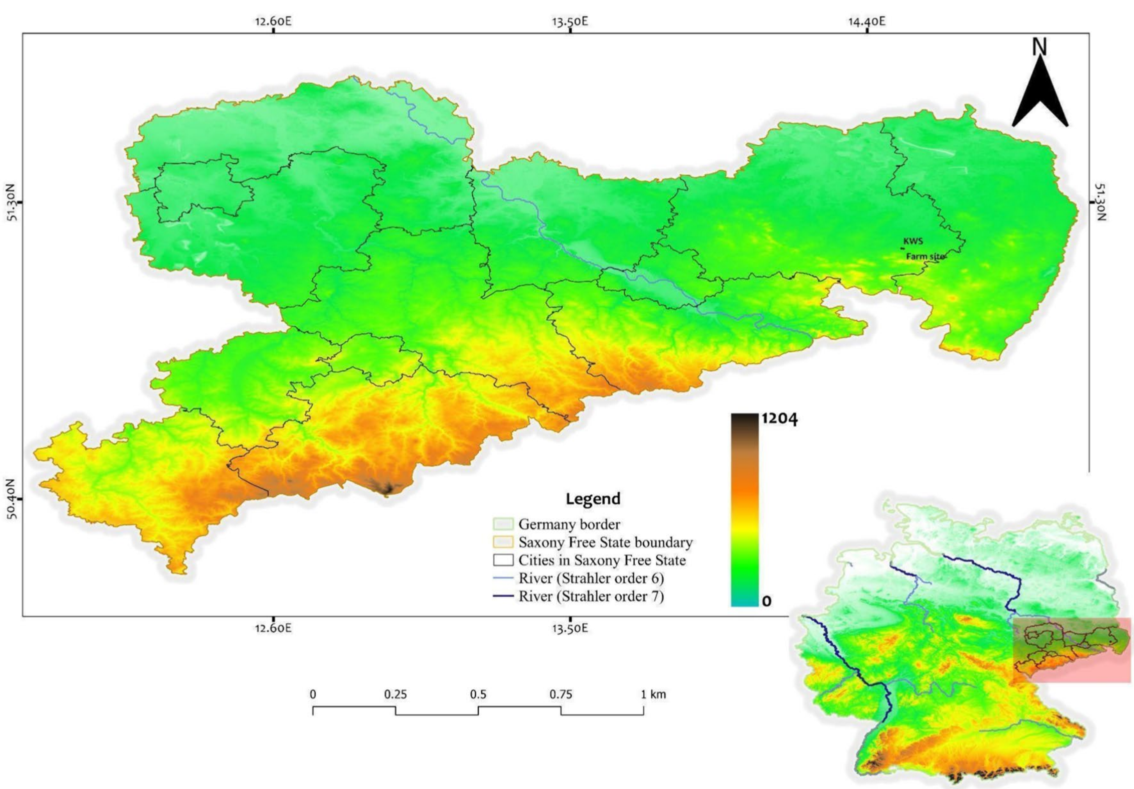

Fig. 1 Digital elevation model of Saxony Free State (DEM source: USGS SRTM 1 arc-sec; River source: Hydroshed)

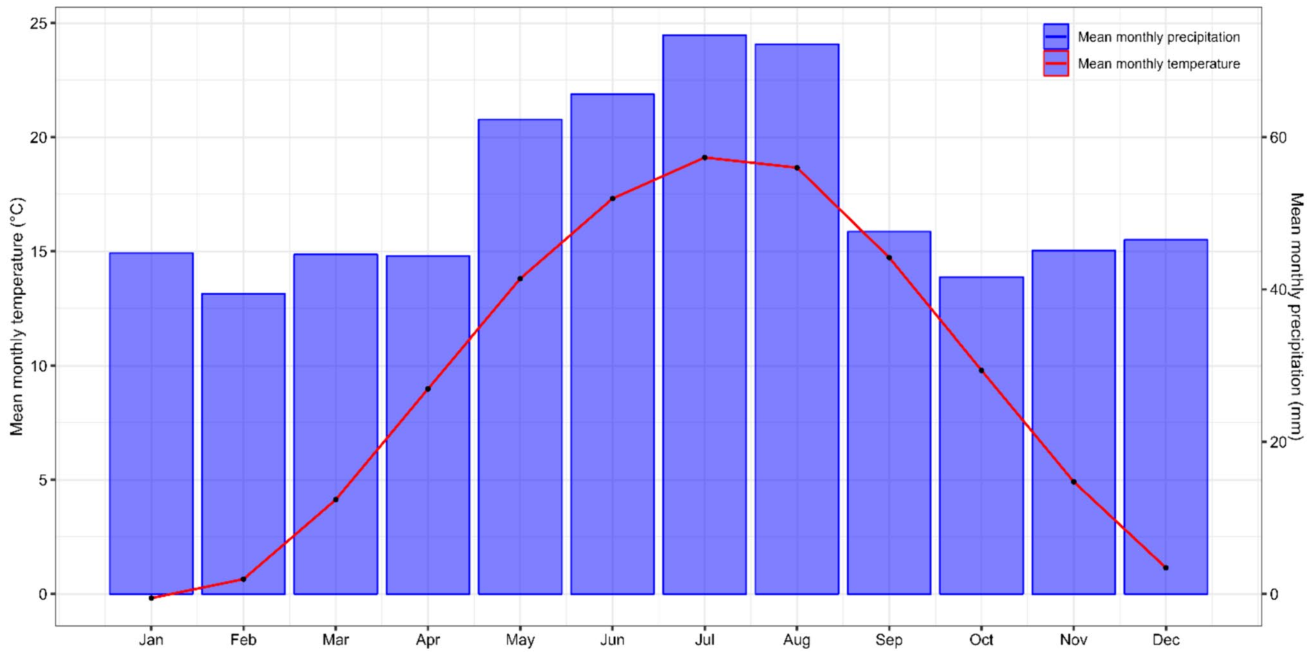

Fig. 2 Climograph of the Kubschütz weather station, Bautzen, for 83 years (1936–2021, excluding 1941 and 1942)

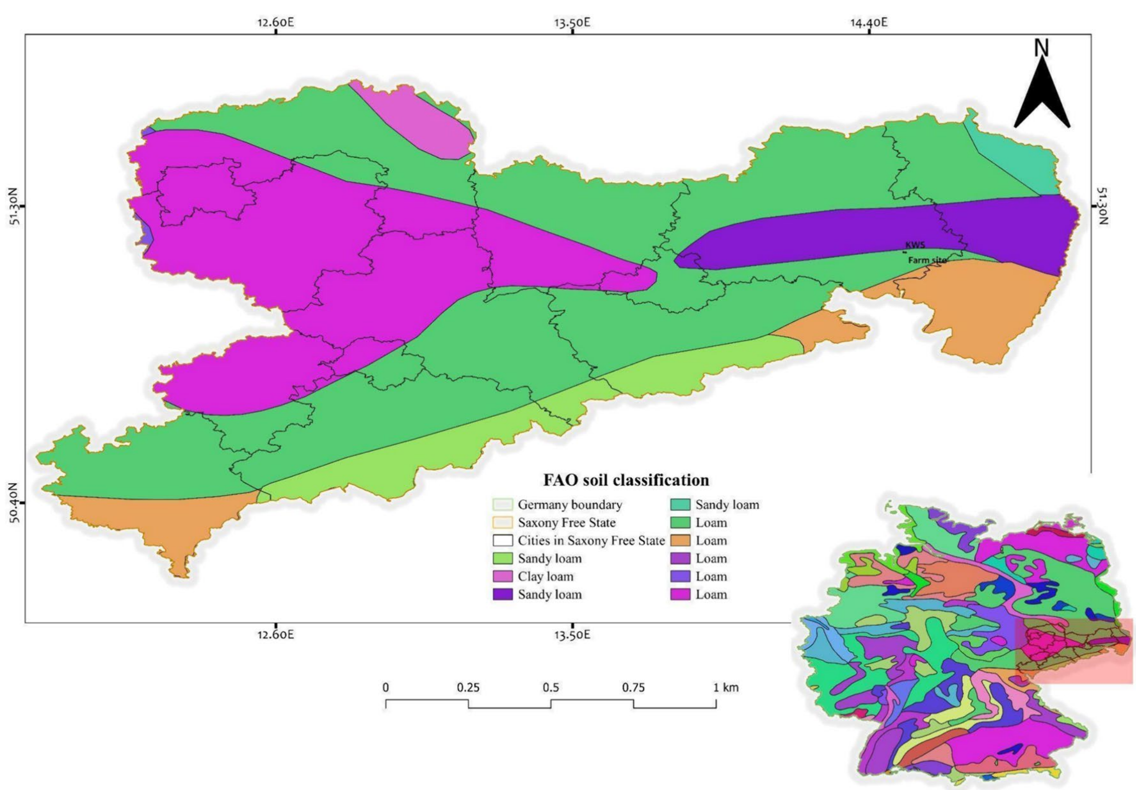

Fig. 3 FAO world soil map of Saxony Free State with the farm site and Kubschütz Weather station (Soil classification source: FAO)

the standard soil class using the soil name "sname" code of the SWAT. Arnold et al. (2013) methodology was used to adopt the physical soil characteristics of the FAO soil textural class.

The pedo-transfer function (PTF) developed by Saxton and Rawls (2006) was used to regenerate other necessary soil hydraulic properties. PTF analysis was carried out for two layers, with a total depth of 3 m. The assumed PTF estimation was based on previous engagement in the area, FAO and SWAT soil textural classifications, 2% organic matter content, and a density adjustment factor of 1.

The summary of the soil's physical properties and PTF output is given in Table 1. The PTF output was carefully compared with similar study that adopted field data in the region, to establish the representativeness of the result and the reliability of the IWD simulations. Krümmelbein et al. (2010) measured textural classes in Lusatia's first and second soil layers, revealing comparable hydraulic properties obtained from PTF, including bulk density and saturated hydraulic conductivity. The soil has good water-holding and draining capacity, which is essential for optimal crop cultivation and the adoption of an irrigation system. Notably, this study recognizes the limitations of PTF approach used and anticipates minimal land use change (Krümmelbein et al. 2010). Comparing PTF soil hydraulic properties with field and laboratory measurements would be vital in future research.

AquaCrop model

The AquaCrop model, developed by the Food and Agriculture Organization (FAO), is a water-based model that simulates crop biomass (Eq. 1) and harvestable yield (Eq. 3) in daily time steps, incorporating complex soil-water-plant interactions (Steduto et al. 2009) and normalized CWP (Razzaghi et al. 2017; Steduto et al. 2009), making it a conservative model adaptable to different climate conditions.

$$\frac{Y_x - Y_a}{Y_x} = K_y \frac{ET_o - ET_a}{ET_o} \tag{1}$$

$$B = WP * \Sigma Tr \tag{2}$$

$$cY = B * HI \tag{3}$$

The AquaCrop model is widely used for simulating crop responses to rainfall, full and supplemental irrigation, and deficit irrigation (Ezekiel et al. 2017; Gadédjisso-Tossou et al. 2018; Geerts et al. 2010; Igbadun et al. 2008), as well as other irrigation and field management operations. It is also widely used for planning, evaluating, and supporting strategic, tactical, and operational decisions on water resources management (Steduto et al. 2009).

Deficit irrigation toolbox (DIT)

DIT, written in the MATLAB programming language, is an extension of AquaCropOS, developed by Foster et al. (2017). DIT enables comprehensive analyses of crop yield responses to climate change, soil heterogeneity, and irrigation management practices (Schuetze and Mialyk 2019). The toolbox has two crop models: the soil water balance (SWB) model based on the Rao et al. (1988) method and the AquaCrop-OS version based on Foster et al. (2017).

Crop water production function (CWPF)

Crop water production function (CWPF) is the highest possible crop yield achievable under a given water application (Schütze and Schmitz 2010). Stochastic crop water production function (SCWPF), generated from stochastic weather behavior, aids in decision-making on a local scale by having a thorough understanding of modeling and implementation of IWD management (Schütze and Wagner 2016). SCWPF only generated information for the deficit IWD strategies, giving perfect information on IWD and corresponding yields. Figure 4 provides a concise overview of the SCWPF generation process.

Table 1 FAO world soil properties of the selected farm site. (adapted from SWAT (2012))

	Physical properties	Soil layer 1 (0–1.3 m)	Soil layer 2 (1.3–3 m)
FAO and SWAT classification	Sand (%)	48	56
	Silt (%)	32	24
	Clay (%)	20	20
	FAO soil textural class	Loam soil	
Pedo-transfer function	Permanent wilting point (%)	13	13
	Field capacity (%)	26	24
	Crop available soil water (%)	12	11
	Soil moisture at saturation /porosity (%)	44	43
	Moist bulk density (g/cm^3)	1.49	1.51
	Saturated hydraulic conductivity (cm/day)	36.73	40.77

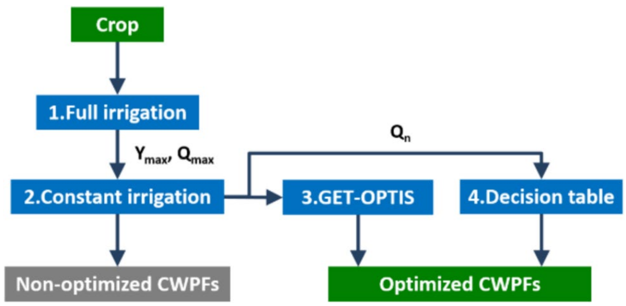

Fig. 4 SCWPF generation process (from Mialyk (2018))

Climate data generation and verification

Climate data processing

ELR climate time series was used as climate data input for the AquaCrop model. We downloaded hourly total precipitation and 2-m temperature of ELR climate data from Copernicus websites (Muñoz-Sabater 2022) from 1981 to 2020. Note that it is essential to validate and quantify the error margin associated with the ELR climate time series application for local adoption. To assess the applicability of ELR climate data for agricultural modeling applications, a comparison between the climate time series of ELR (total precipitation and 2-m mean temperature) and measured KWS (rainfall and mean temperature), was carried out. The hourly climate time series of ELR were converted to daily values using the climate data operator (CDO). CDO and R scripting language were adopted for the extraction of total precipitation. Gomis-Cebolla et al. (2023) highlighted that the daily value of ERA5-Land is the sum of total hourly precipitation values on a 24-hour basis. The World Meteorological Organization (WMO) recommends that 0.1 mm of precipitation is the lowest standard measurement for a high-resolution rain gauge. Therefore, daily precipitation below 0.1 mm was removed from the ELR daily precipitation time series. Moreover, precipitation less than 0.1 mm could easily evaporate.

For this study, the daily maximum and minimum hourly ELR 2-m temperature were considered as the maximum and minimum temperature values. Total precipitation and 2-m mean temperature of the ELR climate time series were compared with the KWS climate time series for daily, monthly, and annual assessments. ELR mean temperature is similar to the KWS mean temperature for daily, monthly, and annual comparisons (Fig. S2A). However, a significant deviation in ELR total precipitation was recorded (Fig. S2B). Therefore, BC of the ELR precipitation time series was conducted (to reduce the model underestimation of IWD).

Bias correction of ERA5 land reanalysis precipitation time series

BC approach is commonly used in hydrological modeling and processing to scale climate model-generated weather results to near-desired results (Soriano et al. 2019). BC helps to prevent unrealistic results between the observed and climate-generated results, as the statistical properties of the measured records do not always match the outputs of climate model results due to imprecise conceptualizing, discretization, and spatial averaging within the model grid cells (Soriano et al. 2019).

Xu and Xu (2023) developed the hyfo R package, which was used in the study to bias-correct ELR precipitation through various BC methods such as delta, scaling, empirical quantile mapping (EQM), and gamma quantile mapping (GQM). For Delta BC (DBC), the mean change signal from observations was added between KWS and ELR. Scaling BC used the difference quotient (multiplicative) method to scale the time series of precipitation between the observed and simulated means. EQM BC added the measured cumulative distribution function (CDF) climate time series quantiles to the average daily changes in the simulated precipitation climate time series quantiles. GQM approximates observed and simulated precipitation intensity distributions by gamma distributions Xu and Xu (2023). DBC outperformed other complex BC methods tested for daily, monthly, and annual comparison with KWS precipitation (Figs. S3, 4, and 5).

Deficit irrigation toolbox set-up for assessing irrigation water demand

The daily precipitation (DBC and ELR), and ETo calculated from ELR climate data (Singer et al. 2021) were used for simulations and optimization in the DIT. The AquaCrop model's default conservative crop parameter was used for maize and potato (Table S1). The base temperature of maize was adjusted to 5.5 °C, and the default value of 2 °C was used for potato. Adjusting the base temperature of maize to be different from the default value can lead to an extension of the growing season. Maize and potato belong to C4 and C3 crops. C4 species are usually more sensitive to the cold than C3 species (Singh et al. 2022; Wang et al. 2023). Nonetheless, the chosen base temperatures are within the maize and potato base temperatures specified by (Schmitz et al. 2007) for simulating crop growth models for temperate climates.

Dryland farming, conventional, and deficit IMS were implemented in the DIT to assess maize and potato productivity. Conventional IMS included full irrigation with a threshold (FIT, 80% of field capacity and 50% maximum irrigation depth) and full irrigation with filled soil water content (FIWC, irrigation starts when the water content is less than 90%). Deficit IMS explored in this study are constant irrigation (CI), decision table (DT), and Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS). DT: with phenological stages (DT-P) and without phenological stages (DT-NP) and GET-OPTIS: one common schedule per crop season (GET-OPTIS_OS) and one common schedule for all growing seasons (GET-OPTIS_WS) are examples of deficit IMS in DIT, following the study by Gadédjisso-Tossou et al. (2018).

Due to high evaporative demand of the study area, supplemental irrigation is mainly used to meet IWD, especially in the summer season (Drastig et al. 2016; Mirschel et al. 2019). Table 2 summarizes the rainfall, conventional and deficit IMS adopted for the study area.

Data analysis and visualization

Analyses of seasonal yield, ETa, irrigation, recharge, WB, and CWP to understand how rainfall, conventional and deficit IMS irrigation work in the study area. For the visualization, descriptive and inferential statistical analysis (analysis of variance (ANOVA) and Tukey post-hoc test), R programming language was used. Bar-plot was used to condense and visualize 39 growing season result distributions and variations for the different IMS. One-way ANOVA was used to verify the significant differences among all the IMS analyses, and the separation of group mean differences of the IMS was compared pairwise using the Tukey post-hoc test.

Results and discussion

The results of the ELR and the chosen BC method (DBC) for modeling the conventional and deficit IWD of maize and potato are presented in this section.

Deficit irrigation toolbox output

Though the simulation of all the conventional IMS took less than a minute as run-time, the heuristic deficit IMS took more time. For instance, DT-P has the highest run-time (4 days). It should be noted that two computers with different computing strengths (512 GB of RAM with a 2 GHz processor, and 8 GB of RAM with a 3.6 GHz processor) were used for the simulation and optimization of the IMS.

To compare the deficit IMS with the conventional IMS, 368 and 280 mm irrigation were chosen for maize and potato after examining SCWPF (Fig. S6). After these irrigations, a significant yield increase is not evident for both crops for an additional irrigation input. Non-beneficial components of ETa dominate after this period as the excess irrigation evaporates, runoff, or recharges the subsurface aquifer. These non-beneficial ETa are not necessarily useful for crop productivity and can lead to additional costs associated with pumping and labor.

Mean seasonal yield of maize and potato

Figure 5A shows the mean seasonal yield of maize and potato for the 39 growing seasons. The plot reveals that for the DBC and WBC, mean seasonal yields were relatively the same, with minimal variations for maize and potato yields, except for CI. In terms of conventional and deficit IMS, except for CI and rainfall, the mean seasonal yield is almost the same for all the conventional and deficit IMS, with minimal variations for maize. Similar observations could be noticed for potato except for the decrease in FIWC yield. This finding suggests that the DBC and WBC used as climate inputs for modeling the yield for maize and potato crops may be equally effective and efficient, with only differences in the CI and rainfall IMS.

GET-OPTIS_WS has the highest mean seasonal yield (14.49 ton/ha for DBC and 14.48 ton/ha for WBC, respectively) among all the IMS for maize. GET-OPTIS_WS mean seasonal yield is comparatively close to GET-OPTIS_OS mean seasonal yield (14.16 ton/ha for DBC and 14.29 ton/ha for WBC, respectively). Rainfall and CI also documented varying degrees of crop failure (maize). Figure 5A presents the total crop failure for rainfall conditions for DBC and WBC, while CI experienced 44% and 59% crop failure for DBC and WBC, respectively. This result suggests that GET-OPTIS_WS is more resilient to adverse water management

Table 2 Adopted IMS for managing IWD of the selected farm site during the summer growing season, Bautzen

Irrigation management strategy (IMS)	Conventional	Deficit
Rainfall	–	
Supplemental FIWC	✓	
Supplemental FIT	✓	
Supplemental CI		✓
Supplemental irrigation GET-OPTIS_OS (open-loop)		✓
Supplemental irrigation GET-OPTIS_WS (open-loop)		✓
Supplemental irrigation DT-NP (closed-loop, without phenological stages)		✓
Supplemental irrigation DT-P (closed-loop, with phenological stages)		✓

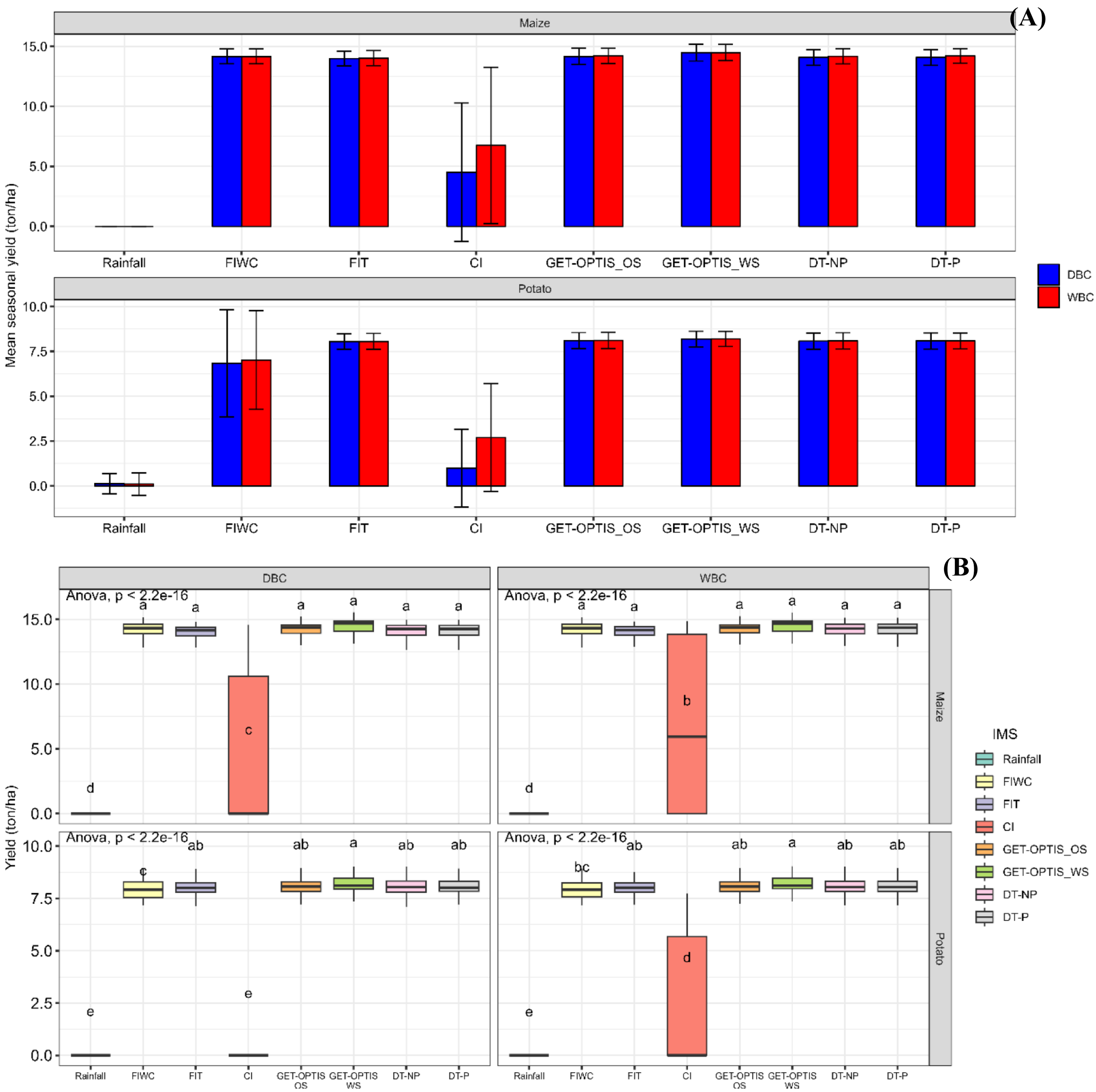

Fig. 5 Mean seasonal (**A**) and seasonal (**B**) yield of maize and potato from 1981 to 2020 summer growing season. $n = 39$, the error bar indicates standard deviation, and the letters represent Tukey pairwise comparison

conditions and has the potential to provide more stable maize production under water-stressed conditions. On the other hand, CI and rainfall farming have a higher susceptibility to crop failure.

GET-OPTIS_WS has the highest seasonal yield for potato (8.19 ton/ha for DBC and 8.20 ton/ha for WBC, respectively) compared to all other IMS. Similar to maize, the mean seasonal yield of GET-OPTIS_WS potato is close to the mean seasonal yield of GET-OPTIS_OS (8.10 ton/ha for DBC and 8.11 ton/ha for WBC, respectively), with similar variations. Conventional and deficit IMS recorded crop failure. Rainfall IMS records 95% crop failure for both DBC and WBC; FIWC records 15% and 13% crop failure for DBC and WBC; and CI recorded 77% and 51% crop failure for DBC and WBC, respectively. This shows that GET-OPTIS_OS and GET-OPTIS_WS are reliable and efficient IMS for potato, as compared to others. Also, the slight differences in the GET-OPTIS options' prediction accuracies between DBC and WBC further prove that the adopted approach in this study is reliable.

Solely practicing rainfed agriculture in this region may threaten food security. Some mild failure (FIWC) even for full irrigation was also documented for potato (as evident in Fig. 5A). Additionally, the standard deviation in the error bar (Fig. 5A) indicates a significant deviation from the mean seasonal yield, further highlighting the failure documented for the CI. Depending on the water availability, full (FIT) or sophisticated deficit IMS seem highly essential and necessary as supplemental IMS to protect the food security of this region.

Figure 5A shows a noticeable difference in yield between maize and potato. The crop species to which both crops belong could be responsible for these variations. Potato is classified as a C3 crop, but maize is a C4 crop. The photosynthetic active radiation (PAR) and photosynthetic process followed by the two crops generally affect their biomass production and thus their final yield. Compared to C3 crops, C4 crops like maize are more effective at converting PAR into biomass. C3 crops typically follow the Calvin cycle, whereas C4 crops usually follow the Hatch-Slack cycle (Singh et al. 2022; Wang et al. 2023).

Deficit irrigation can maintain or increase field crop yields, especially during the early growth stage. Past studies support this, especially for evolutionary algorithm optimized deficit IMS (Chai et al. 2016). Deficit IMS for maize has a similar or greater simulated mean seasonal yield than the conventional IMS. Potato, which are more sensitive to water stress than maize, yielded different findings. Badr et al. (2022) noted that early water deficits reduced potato yield. Doorenbos and Kassam (1979) found potato more responsive to water stress at the V1 and V stages. Due to shallow root systems, drought could adversely affect potato (Nasir and Toth 2022).

The recorded performance of the simulated maize yield in this study demonstrates the reliability of the model and its potential to greatly benefit end-users in IMS strategy recommendations. Although the model used in this investigation was not calibrated, the maize yield is within the AquaCrop model's documented range reported by previous studies. Hsiao et al. (2009) discovered that maize produced 9–15 ton/ha in response to irrigation and observed and simulated yields were well correlated. However, our modeled yields differed from field experiment yields. After testing deficit irrigation solutions on maize in Mkoji, Tanzania, Igbadun and Salim (2014) found a 7.0–12.7 ton/ha yield. Quantifying maize yield effects of tillage, crop rotation, and irrigation using a generalized linear model, in Müncheberg, Germany, (Huynh et al. 2019) found that irrigation, tillage, and crop rotation explain 35% of the range in maize production (6.8–10 ton/ha). These findings suggest that AquaCrop model calibration and validation may be needed to better represent field trials (Adeboye et al. 2021).

In 2017, Razzaghi et al. (2017) employed the AquaCrop model to assess and compare the potato yield in South Jutland, Denmark. They found that the model shows minimal variation from the actual field results. Razzaghi et al. (2017) reported that observed potato yield varies from about 7–9 tons/ha, while simulated yield ranges from about 7.4–8.2 ton/ha, which is similar to the observation of (Casa et al. 2013). This implies that the mean seasonal yield reported for potato in this study for conventional and deficit IMS is considered acceptable.

Figure 5B presents the boxplot of the pairwise comparison of WBC and DBC for maize and potato yields for all the growing seasons. The outliers from the visualization of the boxplot are excluded for this plot and other subsequent boxplots. ANOVA shows that the maize yield of all the IMS is significantly different ($p < 0.05$). All IMS adopted for the simulation and optimization of maize yield showed no significant difference ($p < 0.05$) for DBC and WBC, except for the rainfall and CI ($p < 0.05$). Excluding rainfall and CI, we observed a relative similarity between the conventional and deficit IMS in terms of statistical significance and median values. Among all the IMS, CI has the largest variation for DBC and WBC. The water management strategies adopted for rainfall and CI can be traced as the cause of these variations. This further highlights the importance of proper IMS in maximizing crop productivity and minimizing water usage.

Analysis of the pairwise comparison of potato shows that the simulated yields of the conventional and deficit IMS are statistically different ($p < 0.05$) for DBC and WBC. Similar significant differences between DBC and WBC for deficit IMS were noted, except for CI. Also, a significant difference ($p < 0.05$) of FIWC was observed for DBC and WBC. Although the pairwise comparison shows a significant difference between conventional and deficit IMS for DBC and WBC, their median values are relatively within the same range (except for rainfall and CI IMS). WBC of CI has the highest variation. It is noteworthy to state that the WBC of CI exhibits the highest variability in yield, suggesting that this IMS may be more sensitive to water application.

Mean seasonal actual evapotranspiration of maize and potato

Figure 6A presents the mean seasonal ETa of maize and potato for DBC and WBC. ETa of Rainfall and CI of maize and potato are generally lower than other IMS. DT-P of WBC has the highest ETa for maize (495.37 mm) and potato (337.73 mm), while Rainfall IMS of DBC has the lowest (60.64 and 71.87 mm) for maize and potato, respectively). Generally, the mean seasonal ETa of DBC is relatively lower

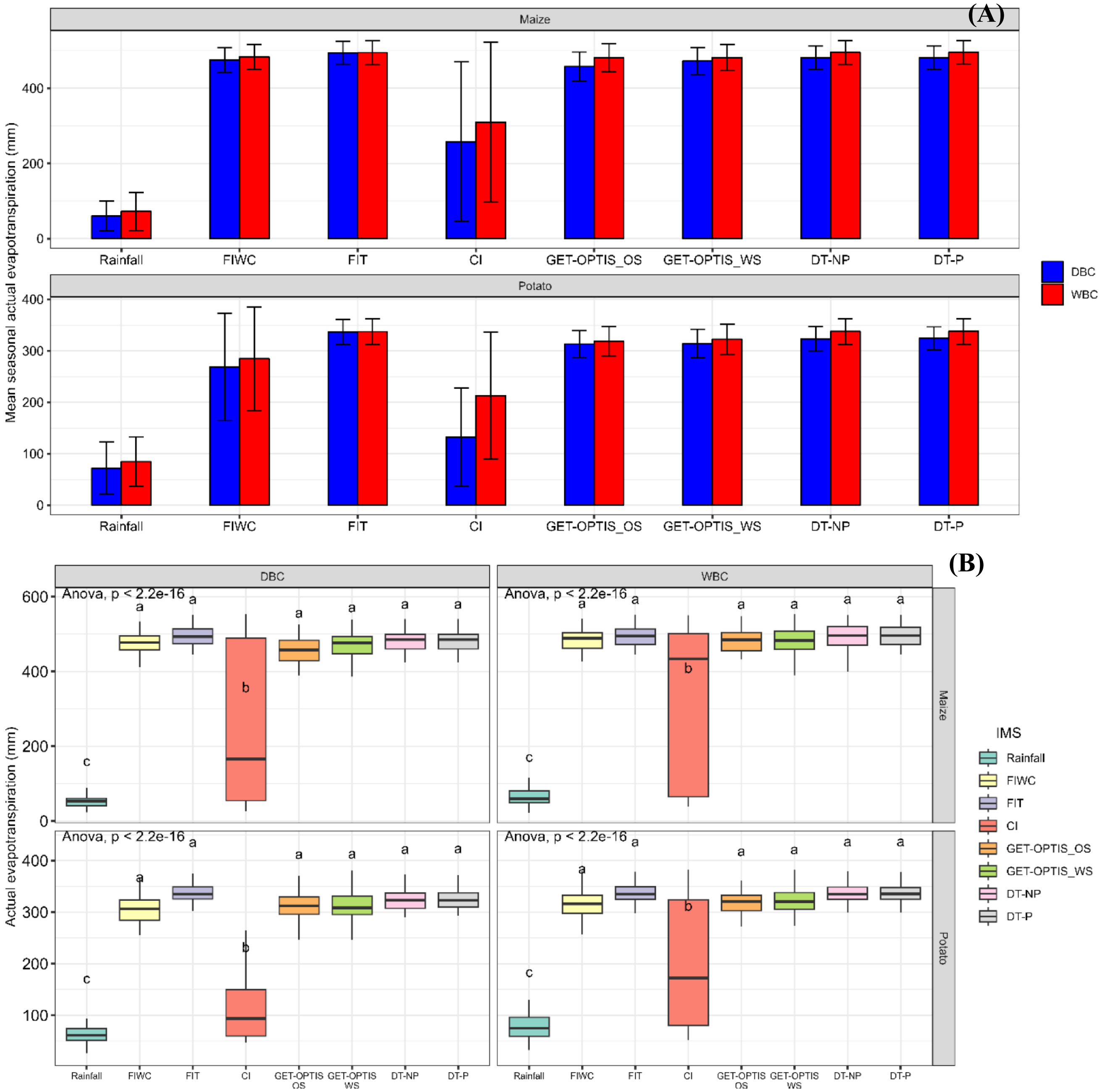

Fig. 6 Mean seasonal (**A**) and seasonal (**B**) actual evapotranspiration of maize and potato from 1981 to 2020 summer growing season. $n=39$, the error bar indicates standard deviation, and the letters represent Tukey pairwise comparison

than WBC for all the IMS except the FIT and Rainfall IMS of potato. Potato FIT IMS shows a similar mean seasonal ETa for DBC and WBC. A significant variation of ETa was noticed for CI. A slight reduction of ETa could also be illustrated by the application of deficit IMS.

Several factors contribute to the differences in ETa between rainfall and controlled irrigation systems. In rainfed conditions, crops rely solely on natural precipitation for water supply, which may be unpredictable and inconsistent. This could lead to periods of water stress for the crops. On the other hand, controlled irrigation (conventional and deficit) provides a more reliable and fairly consistent water supply to crops. This allows for more optimal growing conditions and higher water availability and reliability, leading to higher ETa values.

Table 3 presents the mean evaporation and transpiration components of ETa for DBC and WBC under conventional and deficit IMS. Thorough examination of the rainfall IMS

Table 3 Summary statistics of conventional and deficit IMS of DBC and WBC evaporation and transpiration of maize and potato

IMS	Maize				Potato			
	DBC		WBC		DBC		WBC	
	Evaporation (mm)	Transpiration (mm)	Evaporation (mm)	Transpiration (mm)	Evaporation (mm)	Transpiration (mm)	Evaporation (mm)	Transpiration (mm)
Rainfall	59.89	0.75	69.53	2.81	67.55	4.32	80.67	3.81
FIWC	169.68	305.34	177.79	305.34	108.23	160.47	120.46	164.19
FIT	192.96	301.39	192.50	302.26	149.43	187.22	149.77	187.57
CI	158.05	99.95	161.97	147.73	106.61	25.88	141.18	71.66
GET-OPTIS_OS	153.36	304.31	175.87	305.22	124.73	188.41	130.35	188.42
GET-OPTIS_WS	165.42	307.03	174.67	306.93	125.51	188.64	133.58	188.71
DT-NP	177.92	303.36	189.85	305.38	136.20	187.08	149.23	188.34
DT-P	177.92	303.36	190.28	305.10	136.60	187.55	149.14	188.59

reveals that most of the mean seasonal ETa comes from the evaporation of the soil surface during the growing seasons. Similar observations were seen for CI. There is no apparent difference between the conventional and deficit IMS of DBC and WBC in mean seasonal transpiration for all the IMS, except for CI and rainfall IMS.

Doorenbos and Kassam (1979) in their work on the yield response of crops to water, presented a range of 500–800 mm for maize and 500–700 mm for potato as the crop water requirement, noting that the climate of the region of cultivation and agronomic practices greatly influences ETa. Also, Igbadun and Salim (2014) reported 412–563 mm ETa for maize in Tanzania. Based on these findings, the mean seasonal ETa of maize aligns with the reported ETa values and earlier documented values in the literature.

The boxplot in Fig. 6B displays the pairwise comparison of WBC and DBC of ETa for maize and potato for all the growing seasons. ANOVA reveals a significant difference ($p < 0.05$) in the ETa of maize and potato across all the IMS. Comparing the ETa of all the IMS, except for the rainfall and CI, the analysis of the DBC and WBC of the maize ETa does not reveal any significant difference ($p < 0.05$). If rainfall and CI are excluded, the similarity between the conventional and deficit IMS based on statistical significance ($p < 0.05$) and median values could also be noted. CI exhibits the highest variation for both DBC and WBC across all the IMS. The high variation of both DBC and WBC in CI suggests that the approach may have a significant impact on the variability of maize crop water requirements.

Analysis of the pairwise comparison of potato demonstrates that the simulated ETa for the conventional and deficit IMS are statistically different ($p < 0.05$) for DBC and WBC. It is worth noting that there is a similarity in the significant difference ($p < 0.05$) between DBC and WBC for deficit IMS, except for CI. FIWC and FIT yielded similar results. It is also relevant to note that while the pairwise comparison indicates a significant difference ($p < 0.05$) between conventional and deficit IMS for DBC and WBC, their median values are quite similar (except for rainfall and CI). WBC of CI has the highest variation of ETa across all the IMS. Figure 6B indicates that deficit IMS has a greater positive impact on the ETa of potato crops for both DBC and WBC compared to conventional IMS. The high variation in ETa observed in WBC of CI further emphasizes the importance of implementing efficient IMS to maximize beneficial water use and minimize water loss.

Mean seasonal irrigation of maize and potato

The mean seasonal irrigation for all IMS is presented in Fig. 7A for the DBC and WBC of maize and potato. On average, excluding rainfall IMS, the mean seasonal conventional IMS is higher than the deficit IMS for DBC and WBC for both crops. DBC mean seasonal irrigation of DT-NP for maize (367.95 mm) and GET-OPTIS_OS for potato (280 mm) is the highest for deficit IMS. The WBC of FIWC for maize (540.10 mm) and the DBC of FIWC for potato (352.47 mm) are the highest under conventional irrigation. The seasonal mean seasonal irrigation for maize is comparable between DBC and WBC for both GET-OPTIS_OS and GET-OPTIS_WS. The smallest observed difference is 4.69 mm, and the largest observed difference is 15.76 mm.

Similarly, the mean seasonal irrigation for potato in DBC and WBC is also comparable when using GET-OPTIS_OS and GET-OPTIS_WS, with a minimum difference of 4.69 mm and a maximum difference of 76.11 mm. The results show that, on average, conventional IWD is higher than deficit IWD. Using GET-OPTIS_OS or GET-OPTIS_WS for deficit IWD can effectively achieve optimal crop growth and yield in maize and potato without having a big impact on the crops.

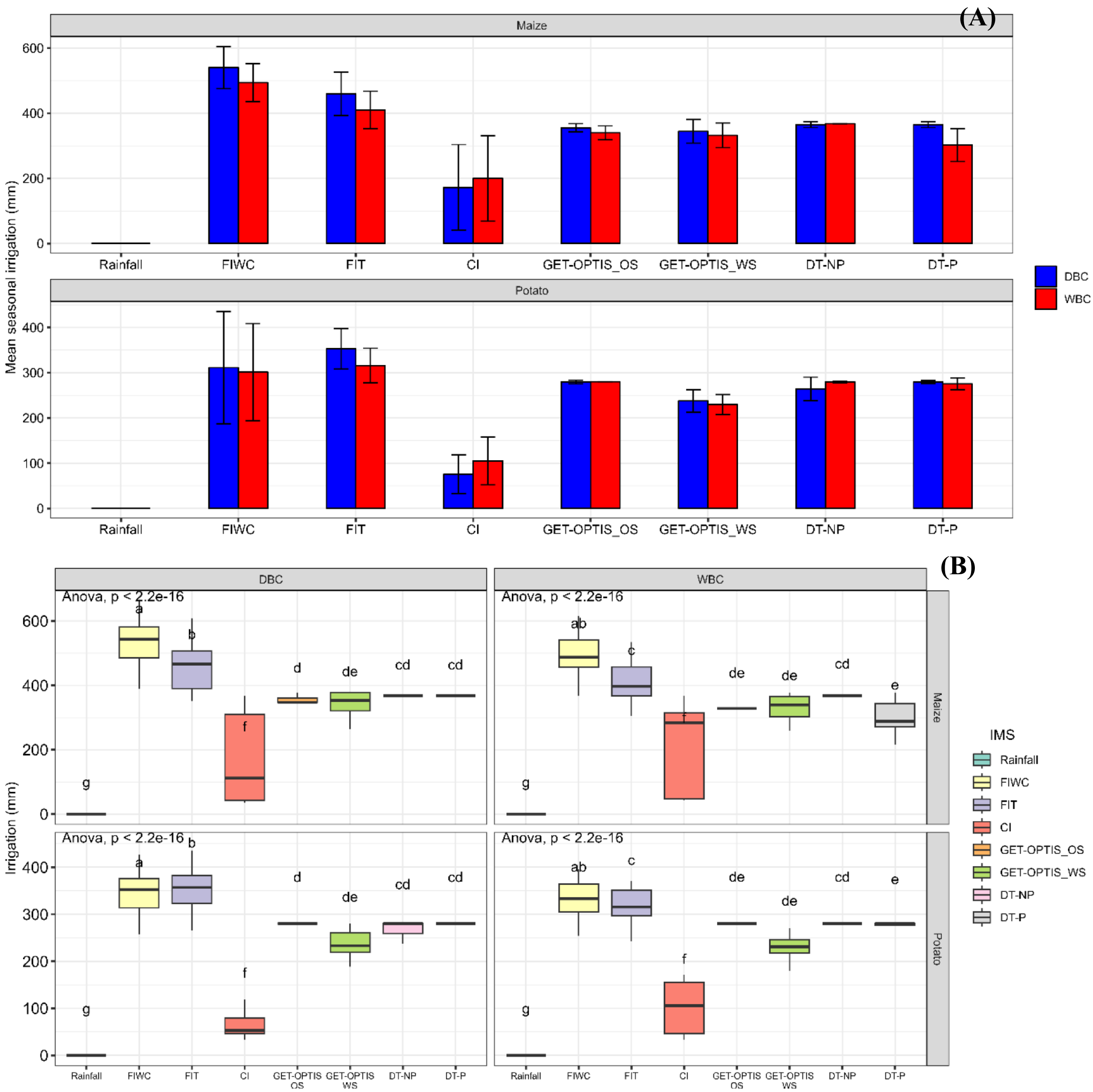

Fig. 7 Mean seasonal (**A**) and seasonal (**B**) irrigation of maize and potato from 1981 to 2020 summer growing season. $n = 39$, the error bar indicates standard deviation, and the letters represent Tukey pairwise comparison

Using deficit IMS reduces IWD by up to 26–44% for maize and 21–35% for potato, on average, compared to regular IMS (using FIWC as a reference). Without DBC, we observed that the mean seasonal IWD conventional IMS was about 50 mm lower, and the deficit IMS for maize was about 62 mm lower, on average. Almost the same trend, although mild, was also observed for potato. These findings suggest that deficit IMS, without the use of BC, can significantly reduce.

IWD for both maize and potato crops compared to conventional IMS. In addition, the yield remained consistent or even increased in some cases, indicating the potential benefits of implementing deficit IMS. These results highlight the potential of deficit IMS to improve crop yields and reduce water usage.

One way to assess an IMS's success is to analyze the recharge and overland flow during or after the irrigation event. Good IMS should have less water contributing to the recharge of the subsurface aquifer and overland flow. Assuming FIWC of DBC was chosen as the reference IMS, the deficit IMS effectively manages the irrigation water by reducing the mean seasonal recharge by more than 24–57% for maize and 2–58% for potato on average Fig. S10 and 11). This significant reduction in recharge indicates that the deficit IMS effectively manages the irrigation water. With the uncertainties in climate change impacts, this is crucial for sustainable agriculture and conserving water resources in areas where water scarcity is a concern. Schütze et al. (2012) stressed DT that deficit IMS tends to supply more water early in the growing season than GET-OPTIS.

The boxplot in Fig. 7B illustrates the pairwise comparison of WBC and DBC for the simulated supplemental irrigation application of maize and potato crops for all growing seasons. ANOVA indicates a significant difference ($p < 0.05$) in the irrigation of maize and potato across all the IMS. The analysis of the DBC and WBC in maize irrigation indicates a significant difference ($p < 0.05$) for all the IMS. Excluding CI, the median values for deficit IMS are similar for DBC only. Across all the IMS, CI shows the highest variation, while DT-P and DT-NP show the lowest variation for both DBC and WBC. This result suggests that the DBC and WBC of supplemental maize irrigation have a significant impact on the accurate prediction and planning of the irrigation management of maize.

Examination of the pairwise comparison of potato indicates that the simulated supplemental irrigation applications for the conventional and deficit IMS are statistically different ($p < 0.05$) for DBC and WBC. The median values for conventional IMS are comparable for DBC and WBC. WBC of CI has the highest variability. On the other hand, GET-OPTIS_OS, DT-P, and DT-NP demonstrate the lowest variations across all the IMS for DBC (and WBC). High variability observed in potato WBC may raise concerns among farmers and decision-makers about the consistency of the CI IMS. On the other hand, the low variability in GET-OPTIS_OS, DT-P, and DT-NP across all IMS for DBC (and WBC) suggests that these strategies may offer more stable and predictable results. These findings could provide valuable insights for farmers and researchers in making informed decisions regarding IMS for potato crops.

Mean seasonal water balance of maize and potato

The mean seasonal water balance of conventional IMS is generally higher than that of deficit IMS (as shown in Fig. 8A). FIWC (for DBC and WBC) recorded the highest mean seasonal water balance, while the rainfall IMS mean seasonal water balance was zero for the analyzed growing seasons. Excluding CI, deficit IMS showed noticeable differences in mean seasonal WB between DBC and WBC compared to conventional IMS. WBC mean seasonal water balance of the deficit IMS is generally higher than DBC, whereas the mean seasonal water balance of the conventional WBC and DBC is comparable. Most of all the IMS showed significant variations. Minimal variation of mean seasonal water balance was observed for FIT, both for maize and potato. These findings suggest that deficit IMS may have a greater impact on seasonal water balance compared to conventional IMS. This implies that the choice of IMS can significantly affect the overall WB in a growing season.

The CWB of Germany decreases with elevation and from west to east, from 1152 mm (2296 m-asl Allgäu, Bavaria State) at the highest elevation to -140 mm (-65 m-asl, eastern Harz Foreland) at the lowest in summer (Drastig et al. 2016). Due to increasing distance from the Atlantic and North Sea coasts, Lusatia, eastern Germany has a lower elevation and a summer CWB of -105 mm (Geoportal of the Federal Institute of Hydrology, https://geoportal.bafg.de/). According to the Helmholtz Centre for Environmental Research, this region shows exceptional drought conditions in Germany (Fig. S7). Negative CWB shows the possibility of high IWD, thus the need for irrigation.

Gerwin et al. (2023) noted that high IWD in the summer leads to a decrease in groundwater levels and an increase in competition between agriculture and public water supply. They also stressed the need for an optimized irrigation system to cushion these impacts (Gerwin et al. 2023). Andales et al. (2011) emphasize in their study that daily WB helps to determine when and how much daily IWD is required for crops, while seasonal WB is often used to determine the severity of any potential water deficit or surplus. Good IMS should not underestimate or overestimate WB, as this influences IWD directly. Our study only focuses on the summer season. As a result of this, it may be difficult to compare the annual CWB with the seasonal WB covered in this study. Despite this, zero seasonal WB for maize and potato (Fig. 8A) in the second-highest wettest season (summer season) gives an overview of the likely deficit condition the crop would have undergone without irrigation.

The boxplot in Fig. 8B depicts the pairwise comparison of WB, for WBC and DBC of maize and potato crops throughout all growing seasons. ANOVA reveals a significant difference ($p < 0.05$) in the WB of maize and potato across all the IMS. The examination of the DBC and WBC in maize WB reveals a significant difference for all the IMS ($p < 0.05$). It is important to mention that there is a similarity in significance difference between DBC and WBC for FIWC IMS. The median values for deficit IMS are comparable for DBC and WBC. Among all the IMS, GET-OPTIS_OS exhibits the highest variability of WB for both DBC and WBC. Across different IMS, the WB of maize for both WBC and DBC exhibits a consistent and significant difference, highlighting the impact of different IMS.

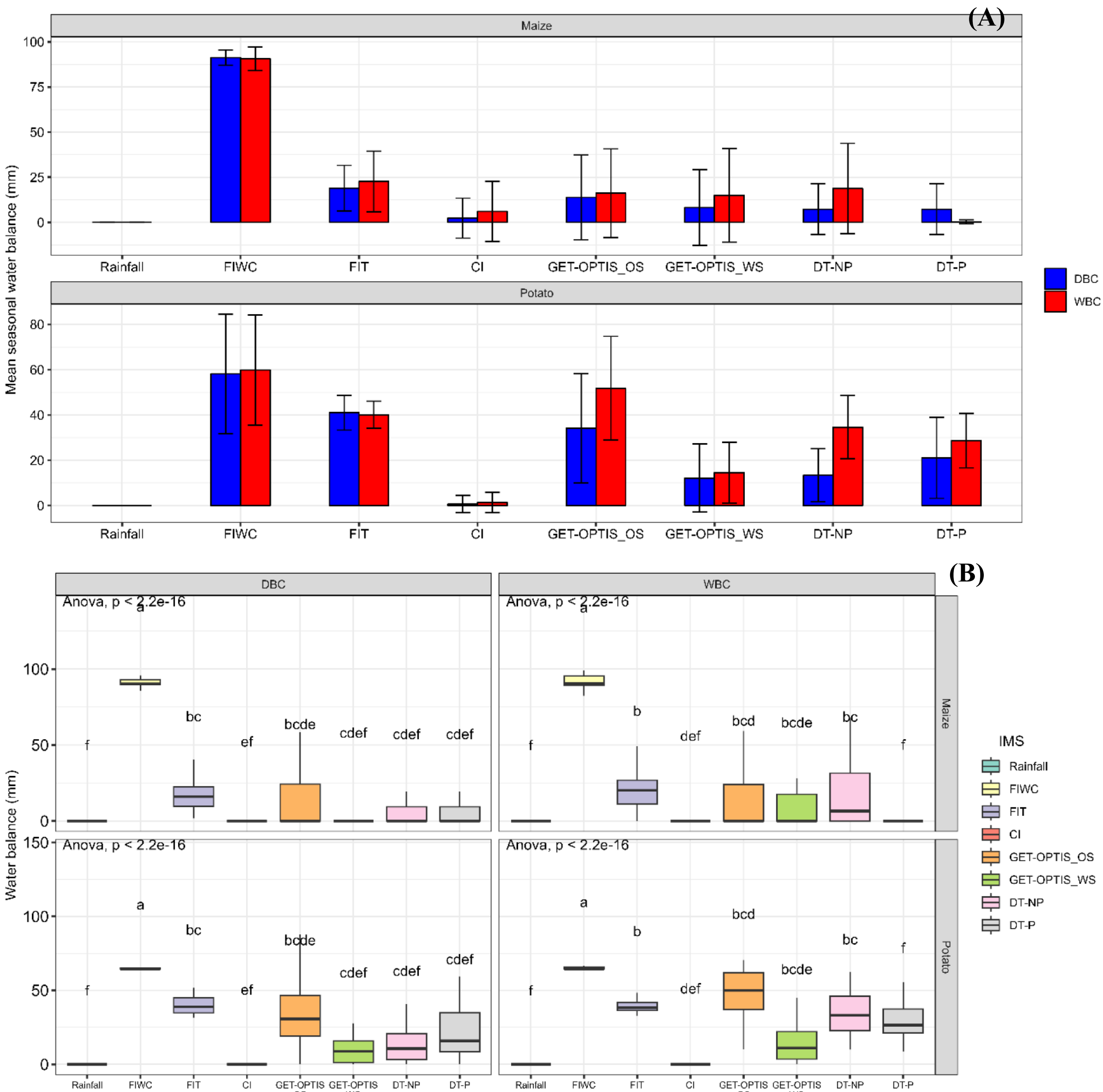

Fig. 8 Mean seasonal (**A**) and seasonal (**B**) water balance of maize and potato from 1981 to 2020 summer growing season. $n = 39$, the error bar indicates standard deviation, and the letters represent Tukey pairwise comparison

The analysis of the pairwise comparison of potato reveals that the WB of the conventional and deficit IMS exhibits significant differences ($p < 0.05$) for both the DBC and the WBC. Similar to maize WB, there is a similarity in the significant difference and median value between DBC and WBC for FIWC. GET-OPTIS_OS has the highest variability of WB for DBC and WBC among all the IMS. The pairwise examination of potato water balance (WB) underscores noteworthy distinctions between conventional and deficit IMS.

Mean seasonal crop water productivity of maize and potato (in terms of ETa)

Figure 9A shows the mean seasonal CWP of maize and potato for all the analyzed growing seasons for the WBC and DBC. DBC mean seasonal CWP is higher than WBC for both crops. Except for CI, the deficit IMS has a mildly higher mean seasonal CWP than the conventional IMS. Maize and potato IMS also show a significant variation

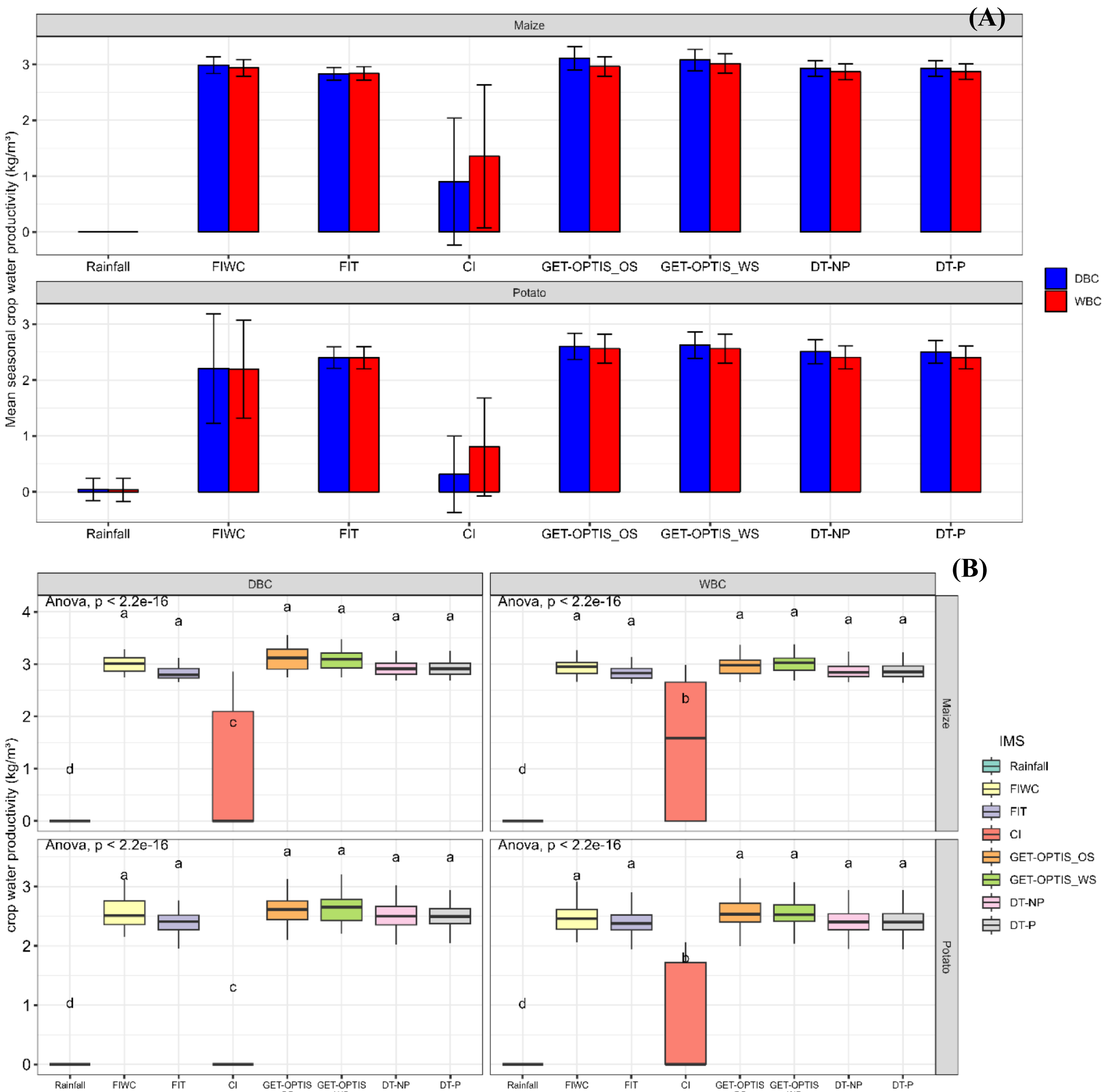

Fig. 9 Mean seasonal (**A**) and seasonal (**B**) crop water productivity of maize and potato from 1981 to 2020 summer growing season. $n = 39$, the error bar indicates standard deviation, and the letters represent Tukey pairwise comparison

for CI. The mean seasonal CWP for maize is highest in GET-OPTIS_OS (3.11 kg/m^3), while for potato, GET-OPTIS_WS has the highest CWP (2.62 kg/m^3). For all the deficits, CI has the lowest for both crops. Rainfall IMS has almost zero for potato and zero for maize. Unpredictable and inconsistent water availability from rainfall could have an impact on water uptake (ETa), which can then have an impact on the crop's CWP. With the application of deficit IMS, the mean seasonal CWP increased to 4% for maize and 10% for potato with less IWD. This shows that the deficit IMS has a higher CWP in terms of ETa than the conventional IMS. The analysis of the result suggests that deficit IMS could significantly improve CWP for both maize and potato (Chai et al. 2016). Furthermore, deficit IWD has the potential to achieve these improvements with minimal irrigation application, highlighting its efficiency in water use in agriculture. Overall, deficit IMS proved to be a promising approach for enhancing CWP and reducing water consumption in maize and potato production systems.

CWP of the mean seasonal maize is within the range of reported values (Hsiao et al. 2009; Zwart and Bastiaanssen 2004). Depending on the availability and cost of water, farmers would have to decide whether to focus on CWP or land productivity. Zamani et al. (2019) investigate the impact of timing and water supply availability on various cropping systems in Iran. Enhancing water use efficiency leads to increased financial returns for farmers and enables optimal utilization of the limited water supply allocated for irrigation, as demonstrated by Zamani et al. (2019). Deficit IMS have been proven to increase the CWP of field and woody crops (Chai et al. 2016; Gadédjisso-Tossou et al. 2018; Igbadun and Salim 2014; Zwart and Bastiaanssen 2004), as the strategy uses a limited amount of water for crop production. Minimal reduction in yield is often accepted as the penalty for reducing IWD (Chai et al. 2016; Gadédjisso-Tossou et al. 2018). As global changes tend to affect freshwater resource availability, Zwart and Bastiaanssen (2004) recommended that farmers start planning to move from "maximum irrigation–maximum yield strategies to less irrigation—maximum CWP policies.

In their global review of the CWP value of crops, Zwart and Bastiaanssen (2004) suggested that the ETa-Yield relationship should be locally determined due to the weak correlation between these two variables. ETa could not fully explain yield variation, judging by the coefficient of determination (R^2). They attributed climate, IMS, and soil management to the weak correlation (Zwart and Bastiaanssen 2004). These findings emphasize the importance of irrigation scheduling and timing, especially for deficit IMS, in yield prediction (Fig. S8 and 9). This study cannot validate the yield response to soil moisture since crop growth depends on daily soil moisture. To confirm Zwart and Bastiaanssen's (2004) assertion, crop responses to daily soil moisture management, especially deficit IMS, needed to be examined.

The boxplot in Fig. 9B illustrates the pairwise comparison of WBC and DBC for CWP in maize and potato overall growing seasons. ANOVA indicates a significant difference ($p < 0.05$) in the CWP of maize across all IMS. Excluding the rainfall and CI, there is no significant difference ($p < 0.05$) in the CWP for all the IMS when examining the DBC and WBC of the maize CWP. The conventional and deficit IMS median values showed relative similarity, except for the rainfall and CI. CI demonstrates the highest variability in both DBC and WBC among all the IMS. The high variability in both DBC and WBC observed in the CI suggests that CI may have a greater impact on CWP compared to other IMS. This variability of CI could be due to the strict IMS of CI. This result underscores the importance of developing strategies and technologies that can effectively address IMS and minimize any possible negative effects that may be associated with them.

The analysis of the pairwise comparison of potato reveals that CWP for the conventional and deficit IMS are not statistically different ($p < 0.05$) for the DBC and WBC, except for the rainfall and CI. Excluding rainfall and CI, we observe a similarity between the median values of conventional and deficit IMS. Comparative analysis reveals that CI exhibits the highest degree of variation in both DBC and WBC compared to all other IMS. These findings highlight the importance of considering different IMS and their potential implications for potato yield and CWP. Understanding the factors contributing to this high degree of variation could help inform decision-making and improve the effectiveness of IMS.

Conclusion

This study employed daily ELR climate time series data for precipitation, temperature, and ETo from a selected farm in the Saxony Free State, Germany, to simulate the IWD of maize and potato crops. Various irrigation techniques from the DIT of the AquaCrop model were examined and evaluated using DBC and WBC to enhance the accuracy of predictions. This study demonstrates that different IMS derived from the DIT of the AquaCrop model can predict the IWD of maize and potato crops. The findings indicated that the mean seasonal yield of maize and potato across various IMS exhibited a considerable degree of similarity, with just a few exceptions in specific IMS conditions (CI and Rainfall). GET-OPTIS_WS achieved the highest mean seasonal yield for maize and potato, 14.16–14.29 ton/ha and 8.19–8.20 ton/ha, respectively. Furthermore, the study revealed that DBC generally offered a more accurate representation of mean seasonal ETa in comparison to WBC, except in specific circumstances (CI and Rainfall).

GET-OPTIS_OS and GET-OPTIS_WS demonstrated superiority in reducing irrigation water by up to 44% compared to the conventional IMS. These IMS also showed better outcomes for maize and potato CWP in terms of IWD, scheduling, timing, and faster execution time than DT-P and DT-NP. Incorporating advanced irrigation optimization strategies like GET-OPTIS_OS and GET-OPTIS_WS can greatly improve CWP and overall performance in situations where there is a deficit of water for irrigation.

This study established that the GET-OPTIS_OS and GET-OPTIS_WS IMS offered the most favorable results for maize and potato crops, outperforming other IMS. Additionally, the study highlighted the importance of incorporating advanced irrigation optimization strategies in regions with a deficit of water for irrigation, as relying solely on rainfall may not guarantee food security. The study also showed that the use of daily ELR data can be efficient for specific local purposes.

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Author contributions O. Q. O. wrote the main manuscript text, prepared the figures and tables. O. Q. O., A. O. B., L. A. S., J. O. A., and A. A. M. reviewed and provided feedback on the methods, analysis, and interpretation of results.

Data availability The manuscript and supplementary information files include the data.

Declarations

Conflict of 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.

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