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Increased heat stress reduces future yields of three major crops in Pakistan's Punjab region despite intensification of irrigation.

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ABSTRACT

Climate change and variability threaten the sustainability of future food production, especially in semi-arid regions where water resources are limited and irrigated agriculture is widespread. Increasing temperatures will exacerbate evaporative losses and increase plant water needs. In this regard, higher irrigation intensities have been posited as a solution to mitigate climate change impacts in these regions. Here, using the agro-hydrological model SWAT and the biophysical crop model APSIM, we show that this mitigation measure is oversimplified. We find that heat stress, driven by strong temperature increases, might be the dominating factor in controlling future crop yields and plant water needs. Our analysis encompasses agricultural areas of the Lower Chenab Canal System in Punjab, Pakistan (15,000 km^2), which is part of the Indus River irrigation system, the largest irrigation system in the world, covering major cotton, rice and maize cropping zones. Climate models project a strong increase in temperature over the study region of up to 1.8 °C (±0.5 °C) until the mid-century. Both models predict a decline in future crop yields for maize and rice crops, while cotton yields are less effected by rising temperatures and strongly benefit from elevated atmospheric CO_2 concentrations. For a high carbon emission scenario, the models simulate yield declines for maize of up to −10% (APSIM) and −19% (SWAT); for rice yields of up to −4% (APSIM) to −26% (SWAT), and for cotton yields of −1% (APSIM) to +11% (SWAT), until 2050, relative to the baseline scenario 1996–2005. Our modeling results further suggest that irrigation demands do not align with increasing temperature trends. Average irrigation demands increase less under higher temperatures. Overall, our study emphasizes the role of elevated heat stress, its effects on agricultural productivity as well as water demand, and its implications for climate change adaption strategies to mitigate adverse impacts in an intensively irrigated region.

Plain language summary: Climate change is one of the most important challenge facing agriculture, and hence future food security. Farmers struggle more and more to ensure a reliable food production. This is especially true for semi-arid regions where water resources are limited but at the same time urgently needed for irrigation, such as in the Lower Chenab Canal Area, in Punjab, Pakistan. The search for adaptation measures to weaken the negative impacts of climate change on agricultural systems becomes increasingly important. One option could be the intensification of irrigation. We use two models to simulate crop growth processes under various climate conditions. Our results show that heat stress would be the dominating stress for plants in the selected study region and that this heat stress might even lead to a reduction in water demand. Intensive irrigation can not necessarily help to prevent climate change-related yield losses. The models further predict that rising CO_2 can have a positive effect on crop yield by enhancing plant growth. Nevertheless, our results indicate that these positive effects could not compensate the negative impacts of heat stress under constantly rising temperatures.

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1. Introduction

In recent years, climate change and its impact on the environment is one of the main concerns facing societies globally. Specifically, its effect on agricultural systems has become a major problem considering the alarming global developments regarding water and food security (Hanjra and Qureshi, 2010; Schewe et al., 2014). One of the latest special report of the UN Intergovernmental Panel on Climate Change (Shukla et al., 2019) predicts with high confidence that future changes in climatic conditions will exacerbate existing water and food shortages for billions of people. One of the main reasons considered responsible for the predicted food shortage is the inability to meet future agricultural water demands (Fader et al., 2016). Globally, irrigation volumes have more than doubled since the 1960s (Shukla et al., 2019) and are likely to increase further due to climate change in regions with already limited water supply (Wada et al., 2013; Wang et al., 2016).

In semi-arid and developing regions like Pakistan, agriculture is the most important economic sector, employing nearly half of the population (Qureshi, 2011). A large part of agricultural workers are small-scale farmers who are highly vulnerable to yield losses, which have become increasingly frequent in the recent decades (Oxfam, 2009). The projected increase in water scarcity due to climate change, along with the increasing demand of the fast-growing population, poses a severe threat to the national food supply and the production of economically important cash crops such as cotton, maize, and rice (Ahmad et al., 2015; Khan et al., 2016; Schewe et al., 2014).

The Indus Basin in Pakistan's Punjab province is a hot spot for climate change impacts on water availability and agricultural production, as it constitutes one of the world's largest closed irrigation areas (Mekonnen and Hoekstra, 2011). Irrigation water accounts for over 90% of the total water demand in the region (Fischer et al., 2007). Significant climate-induced changes in the upstream glacier-hydrology – the major water source for the Indus Basin - are threatening future water availability in the basin (Immerzeel et al., 2010); along with the rising temperatures which are projected to increase faster than the global average (Saeed and Athar, 2018). Under such conditions, water-related adaptation strategies, such as increased irrigation amounts, and enhanced irrigation efficiency are potential solutions to cope with these challenges. The effects of such adaptation measures have been studied for agricultural systems experiencing similar climate change pressures and have been suggested as possible actions (Elliott et al., 2014; Fader et al., 2016; Molden et al., 2010). However, the direct role of increasing temperatures in affecting crop yields is gaining importance across the globe, and could be an important factor in the Indus Basin. Temperature-induced stress on crop growth could counteract the potential of enhanced irrigation to increase productivity (Zaveri and Lobell, 2019). It is therefore imperative to understand the role of temperature stress on crop growth and resulting plant water demand in combination with water stress. Improved knowledge on the potential impacts of temperature and water stress as well as their interlinkages is important to define adequate adaptation strategies (Lesk et al., 2022). In terms of adequate water availability for crop growth, especially in semi-arid regions, previous studies highlight that there is still very limited understanding of the potentials and limits of irrigation-related climate change adaptation (Tack et al., 2017; Taraz, 2018); and that more research is needed to disentangle the effects of temperature and water stress-related climate change impacts on agricultural yields (Carter et al., 2016).

The main objective of this study is to quantify the impact of heat stress on yield and crop water demand, in the Lower Chenab Canal System, in Pakistan. We hypothesize that future temperature conditions will have a strong negative impact on crop yields in our study area. Further, we propose the counter-intuitive hypothesis: increasing temperatures will lead to a reduction in irrigation requirements driven by a strong decrease in crop growth which leads to reduced plant water needs.

To assess these hypotheses, the study elaborates on how temperature stress controls agricultural productivity and plant water requirements in an intensively irrigated agricultural system. To explore whether our counter-intuitive assumption that increasing temperatures will lead to decreasing irrigation demands, holds true, we apply two models: the hydrological SWAT model (Arnold et al., 2012) and the biophysical-crop modelling framework APSIM (Holzworth et al., 2014). While biophysical crop models are the classical models to be used to assess climate change impacts on crops, studies have shown their low performance in reproducing hydrodynamics such as soil moisture storage or plant water availability (Faria and Bowen, 2003), which are crucial processes for the estimation of water requirements and demands. Hydrological models on the other hand, show low performances in simulating plant physiological behaviour and yield estimations. In this study we therefore use a hydrological and a biophysical crop model in an ensemble framework to assess climate change impacts on crop production as well as climate change impacts on plant water demands. A hard coupling of both models is beyond the scope of this study. Yet, the profound comparative analysis of both model types is expected to allow a more detailed understanding of strengths and weaknesses of either model and will result in a more reliable assessment of changes in future yield and water demands. Uncertainties of the respective model applications are discussed in detail and give valuable insights for modellers of both modelling communities, as they reveal important limits of climate impact assessment based on process-based hydrological as well as crop models.

2. Materials and methods

2.1. Study area

The study area is part of the Lower Chenab Canal System Area (LCC) in Pakistan, which comprises about 15,000 km^2 of agricultural land on the floodplains between the Rivers Chenab and Ravi (Fig. 1A and B). It belongs to the Indus Basin Irrigation System (IBIS), the world's largest irrigation system, feeding more than 200 million people (Immerzeel et al., 2010). The area is characterized by small-scale and highly fragmented agricultural cropping patterns. During the dry winter season (Rabi) the dominating crop type is winter wheat while during the wetter and hot summer (Kharif) the crop pattern diversifies and mainly cotton, maize, rice, and fodder are grown on small-scale farms. Annual reference evaporation (approx. 1800 mm/a) is more than three times larger than annual precipitation (approx. 500 mm/a), resulting in a strong demand for additional irrigation. Knowing about potential negative impacts on agricultural production and defining possible adaptation strategies is therefore of paramount importance for water and food security in this region.

In this study, we focused on analysing the impacts of future climate change on summer crops, namely cotton, maize, and rice, grown between May and October. Impacts are evaluated based on changes in crop yield and relevant hydrologic and biophysical variables including evapotranspiration, irrigation demand, leaf-area growth, and biomass production. The selected crops represent high-value crops with a wide distribution in the study area (Fig. 1A). Thus, changes in their production levels will have significant economic impacts and changes in irrigation needs will have a strong impact on basin-wide water demand.

2.2. Models: SWAT and APSIM

To analyse climate change impacts on yield and water demand, we apply two models from different scientific disciplines. We consider the agro-hydrological SWAT model (Arnold et al., 2012), with high performance in simulating complex hydrological plant-soil-atmosphere interactions and the biophysical crop modelling framework APSIM (Holzworth et al., 2014), with high performance in simulating complex plant growth dynamics. The models are briefly described below:

The agro-hydrological SWAT model (Soil & Water Assessment Tool) simulates the quantity and quality of water flow within catchments, incorporates detailed management strategies (e.g. irrigation schedules, planting schedules) and basic plant physiognomic stages, e.g. root development, leaf area development, and biomass change (Arnold et al., 2012; Gassman et al., 2014). The main underlying principle for the simulation of water fluxes is the water balance closure (Neitsch et al., 2009). SWAT accounts for spatially distributed environmental and climatic changes and it simulates their effects on individual water balance components, such as evapotranspiration, infiltration, soil moisture changes and runoff (Fig. 2). Its strengths are therefore the detection of spatially distributed changes in water availability and demand. Impacts of increasing atmospheric CO_2 concentrations are accounted for in the estimation of potential evapotranspiration, affecting (i.e., reducing) plant water demand as well as in the estimation of plant radiation use efficiency, affecting (i.e., enhancing) biomass production. To ensure correct and spatially differentiated parameterization, the model is calibrated following an automated and spatially distributed calibration approach. A detailed description of this calibration procedure can be found in Becker et al. (2019). In this study, the model was run on a daily timescale, with daily climate input data. The spatially distributed SWAT results are averaged over each respective crop growing region, resulting in one maize, one rice, and one cotton data set.

The Agricultural Production System Simulator (APSIM) is a biophysical crop modelling framework which simulates agricultural crop dynamics with respect to varying climatic and environmental conditions (Holzworth et al., 2014). It has been extensively used to assess climate change impacts on agricultural productivity (Deihimfard et al., 2018; Gaydon et al., 2021; Khaliq et al., 2019). Model performance and applications are studied in depths within the scope of the Agricultural Modelling Intercomparison and Improvement Project - AgMIP (Boote et al., 2021; Rosenzweig et al., 2014), in which APSIM was applied in the same study region of southern Punjab to assess climate change impact on crop production. Focus and strength of the APSIM framework is the plant-specific simulation of biophysical dynamics such as biomass production, yield or root growths (Fig. 2). Due to its modular approach, with individual sub-models for each crop type, it can account for plant specific reactions to climate change. For example, with individual models for cotton, rice, and maize it accounts for plant type specific carbon assimilation processes (C3 vs. C4-plants) and hence, differentiates between plant type reactions to increased atmospheric CO_2 levels.

Different to SWAT, APSIM is a plot-scale model. To allow for a model comparison between the spatially distributed SWAT model and APSIM, we calibrated the APSIM model by adopting the most important soil and management parameter configurations from the calibrated SWAT model. To rule out uncertainties which would arise due to spatial differences in soil and climate conditions over the large LCC area, we conducted a sensitivity analysis to analyse the effect of varying soil and climate parameters on APSIM simulated crop yields. This further allowed us to constrain appropriate parameters for the APSIM model. Soil parameters were furthermore verified through laboratory analysis of soil samples collected during a field campaign in the study region (Schulz et al., 2021). Details of the used parameters and underlying estimation procedure for both crop models are described in the Supplementary Information S2 and Tables S1-S3. Like the SWAT model, APSIM was run on a daily time scale, with daily climate input data.

Two central management-related assumptions were made in both models: i. water stress is minimized by including regular irrigation events, as soon as soil moisture drops below 90%; and ii. nutrient stress is minimized by assuring sufficient fertilizer application, applying 100 kg/ha of nitrogenous fertilizer at each irrigation event. Simulated trends of future yield, biomass production, evapotranspiration, LAI and water demand can therefore be ascribed to the effect of temperature increase, by ruling out the influence of irrigation and nutrient management.

The skill of both models to correctly reproduce plant water demands was validated against observed crop specific evapotranspiration (ET)

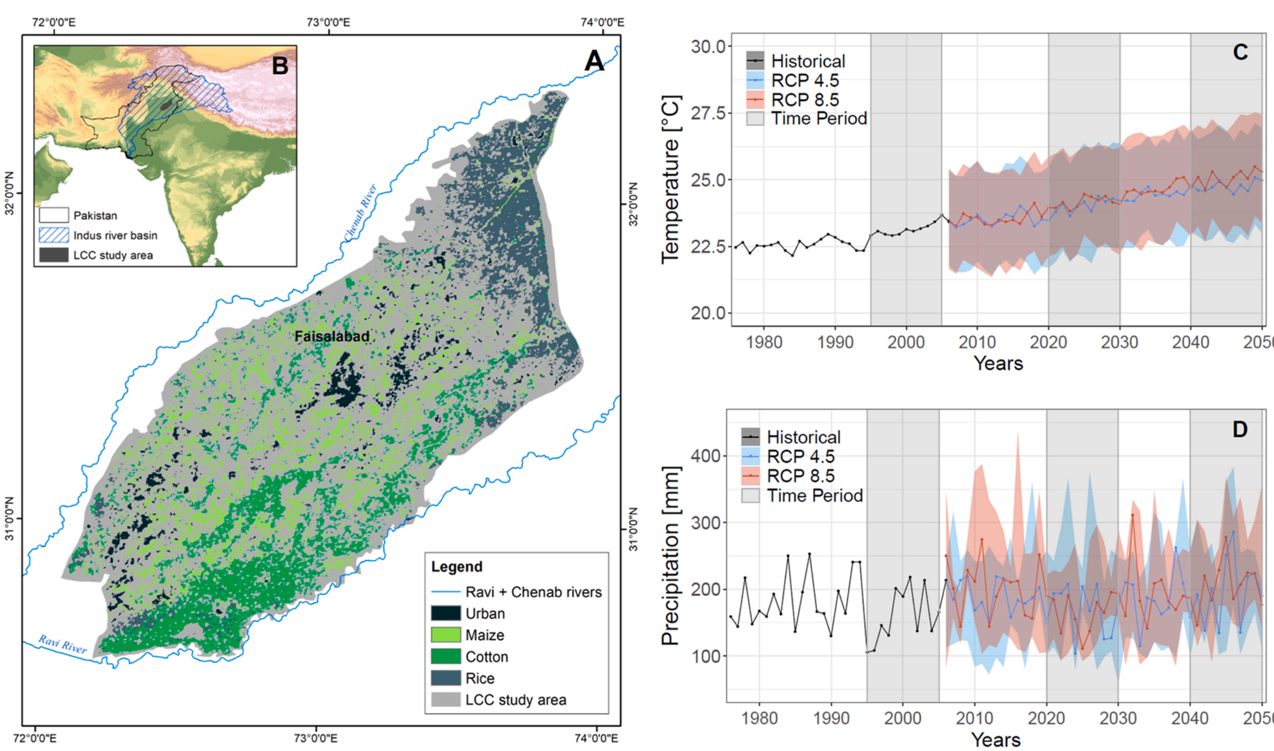

Fig. 1. (A) Lower Chenab Canal (LCC) study area and spatial distribution of cotton, maize and rice growing regions (Land-use data from Awan et al., 2016). (B) Overview of LCC study area, Pakistan, and the Indus River Basin. (C) Mean annual temperature and (D) precipitation trends of historical data (black line) and future climate projection of 9 CORDEX models (red and blue lines are ensemble means; coloured uncertainty band span between 25th and 75th percentiles). Shaded grey areas (C and D) show the reference period (1996–2005) and future periods of 2021–2030 and 2041–2050, examined in this study.

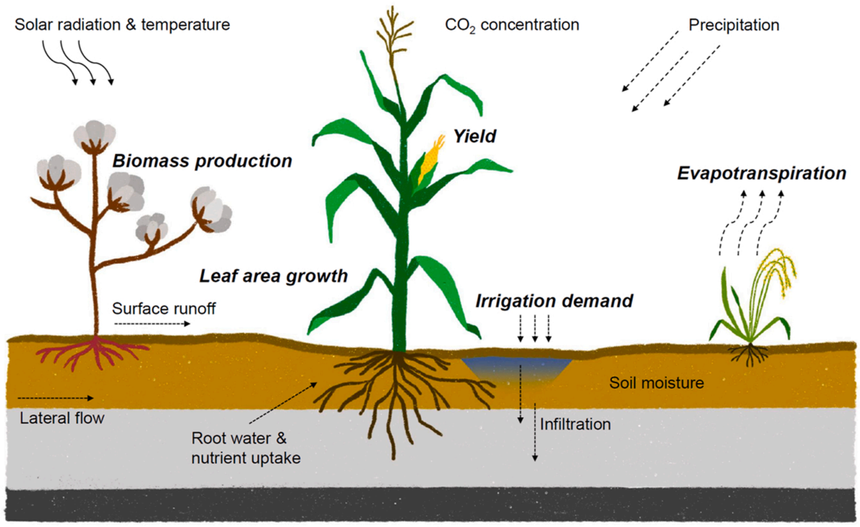

Fig. 2. Schematics of the main processes simulated by SWAT and APSIM models. Processes analysed in this study are written in bold and italic letters.

rates, for the years 2009–2010. This time period was chosen based on the availability of high resolution and crop specific ET data. To validate the model performances with respect to yield simulations annual yield estimates were validated using observed yield data provided by Agricultural Statistics of Pakistan, published by the Ministry of National Food Security & Research (MNFSR, 2021). Observed yield data could be obtained for the years 2002–2013, at the province level for the province of Punjab.

2.3. Climate data sets

Daily Climate Forecast System Reanalysis data (Saha et al., 2010) was taken as historical reference climate data for a baseline period (1996–2005). The data set encompasses temperature, precipitation, relative humidity, solar radiation, and wind speed. To ensure the accuracy of the baseline data set, the CFSR data was bias-corrected using climate records of three available local climate stations (Supplementary Section 1.1).

Climate projection datasets were taken from the Coordinated Regional Downscaling Experiment (CORDEX), which provides a suite of regional climate projections based on the Global Climate Models of the Coupled Model Intercomparison Project, Phase 5 (Taylor et al., 2012). We considered medium (RCP 4.5) and high (RCP 8.5) greenhouse gas emission scenarios from the IPCC - Fifth Assessment Record (AR5); and analysed the impacts in the near future (short; until 2030) and the mid future (medium; until 2050). The short-term time frame was selected to show the potential changes expected to occur in the coming next decade, and to show the necessity for immediate actions. The medium-term scenario was chosen to show the consequences of climate change at a time scale still relevant for today's population. Due to the capabilities of management and plants to adapt to changes in climate as well as long-term reactions of the farming community to adapt to new environmental conditions, we do not include a long-term impact assessment. For the short- and medium-term scenarios, we assumed that factors such as plant genetics and management strategies remain constant and at a current level.

The projections of future CO_2 concentration were based on (van Vuuren et al., 2011) and were assumed to be 420 ppm CO_2 (RCP 4.5) and 450 ppm CO_2 (RCP 8.5), during the time period 2021–2030, and 470 ppm CO_2 (RCP 4.5) and 520 ppm CO_2 (RCP 8.5) for the period 2041–2050. The study uses climate projections based on the older Representative Concentration Pathway (RCP) scenarios used in CMIP5 rather than the newer Shared Socio-economic Pathways (SSP) scenarios from CMIP6. In terms of CO_2 emission scenarios, the scenarios RCP 4.5 and RCP 8.5 used in this study can be compared with the SSP2–4.5 and the early century SSP5–8.5 scenario, respectively (Fuglestvedt et al., 2021). We acknowledge that the newer climate projections might yield slightly different results, however, these are rather small given the mid-century time frame of the analysis (until 2050), in which CMIP5 and CMIP6 scenarios are still comparable (Fig. 3).

3. Results and discussion

3.1. Validation results of SWAT and APSIM

The skill of both the models to correctly reproduce plant water demands was validated against observed crop specific evapotranspiration (ET) rates, for the years 2009–2010. Validation results are given in terms of mean monthly absolute ET values and the coefficient of determination (R^2) in Table 1. The skill of the models to correctly reproduce plant growths dynamics was validated against observed yield data, for the province Punjab, for the years 2002–2013. Validation results of yield simulations are given in terms of mean absolute yields and the relative error (RE) in Table 2 and are visualised in Fig. 2.

Both models show their strengths in their respective domains. SWAT performs slightly better in reproducing ET, due to its focus on hydrological processes and APSIM performs better in yields, due to its focus on plant growth dynamics. All models overestimate evapotranspiration rates and, with the exemption of the SWAT-Rice model, they all overestimate crop yields. This consistent overestimation of ET and yield is not surprising, considering the fact that we simulate hypothetical cases in which farm management practices are assumed to be close to optimal, with sufficient water and fertilizer supply. Even though this is not a perfect representation of reality, it is an important assumption in order to rule out yield variations due to management, while studying the potential risks of climate impacts on agricultural production. Note that in this study we use the models for studying relative changes for two future time periods, rather than studying the change in absolute values. The model structural reasons for the discrepancies in their performances are discussed in more detail further below. They give important insights into model uncertainties and their use as climate impact assessment tools.

3.2. Future climate trends in the LCC study area

Climate models project a strong increase in temperature over the

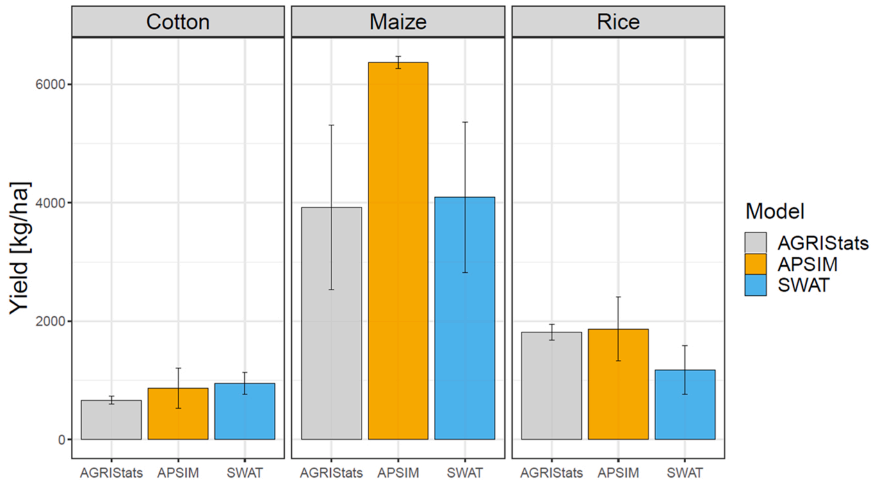

Fig. 3. Simulated yield estimates compared to observations; observations are the AGRIStats data = Agricultural Statistics of Pakistan. Bar heights show the mean of the years 2002–2013 and uncertainty bars show + /- one standard deviation.

Table 1
Validation results for simulated evapotranspiration rates.

Crop type	Observed ET	SWAT ET and R^2		APSIM ET and R^2	
	Mean absolute ET [mm/month]	mean absolute ET [mm/ month]	R^2	Mean absolute ET [mm/ month]	R^2
Rice	75	83	0.65	84	0.26
Cotton	50	86	0.36	97	0.59
Maize	60	73	0.54	69	0.44

Table 2
Validation results for simulated yields.

Crop type	Observed Yield	SWAT Yield and RE		APSIM Yield and RE	
	Mean absolute yield [kg/ha]	Mean absolute yield [kg/ha]	RE [%]	Mean absolute yield [kg/ha]	RE [%]
Rice	1813	1174	-35	1867	3
Cotton	666	950	30	867	23
Maize	3922	4092	4	6370	38

study region, under the high-emission scenario RCP 8.5 as well as under the moderate emission scenario RCP 4.5 (Fig. 1C). For the summer season (May-October), the ensemble means predict an increase of 1.0 °C (± 0.4 °C) for RCP 4.5 and 1.0 °C (± 0.3 °C) for RCP 8.5 until 2030, compared to the reference period of 1996–2005. A warming of 1.6 °C (± 0.5 °C) and 1.8 °C (± 0.5 °C) is projected for RCP 4.5 and 8.5, respectively, until 2050 (Fig. 4A). Strong increases in temperature under both scenarios point towards higher pressure on agricultural production resulting from increased heat stress on crop growth, especially during summer months (Ahmad et al., 2015; Awan et al., 2021; Yasin et al., 2022). During the four central months of the growing season (May-August), mean monthly temperatures are projected to exceed 32 °C (Fig. 4B). A high agreement between single climate model ensemble members regarding the consistent increase in future temperature, indicates that the future summer season warming in the LCC area can be projected with high confidence (Fig. 1C; Fig. 4A and B).

Precipitation projections, on the other hand, are highly uncertain and no clear trend in annual or monthly precipitation amounts can be detected (Fig. 1D, Fig. 4C and D). Estimations of future water availability based on precipitation projections for the study area, are therefore difficult. In this study, we assume that due to the constant irrigation activities in the LCC irrigation system, agricultural water availability is always assured, and plant water demand is met. Thus, impacts of changes in precipitation are small and water stress is kept low. Scenarios in which future water availability can no longer meet irrigation demands, e.g. due to shrinking surface or groundwater resources, are not analysed in this study. We focus exclusively on the effects of climate change on agricultural production given sufficient water supply and examine if the pressure on water resources will increase in future.

3.3. Declining yield levels under increasing temperatures

Both models (SWAT and APSIM) show that climate change will lead to a substantial reduction of future yield levels in the study area. Under current CO_2 concentrations, mean yield levels of all three crops are projected to decrease by up to – 24% (± 12%) under the high emission and mid-century scenario (Fig. 5A, light grey bar, RCP 8.5 2041–50). SWAT simulates yield reductions of up to – 63% (± 19%) for rice, – 18% (± 12%) for cotton, and – 40% (± 12%) for maize. APSIM simulates yield reductions of up to – 22% (± 4%) for rice, – 20% (± 11%) for cotton, and – 12% (± 3%) for maize (Fig. 5 A-C). Despite differences in the predicted magnitudes of yield declines, SWAT and APSIM models agree in their trends (sign) and show that increasing yield losses align with increasing temperatures for all crop types. Considering that water demand and nutrient availability is assumed to be met, the results underline that increasing heat stress will play an important role in the decline of future crop yields. This is in-line with the findings of previous studies, which show that declining yields can be strongly related to temperature increases (Ortiz-Bobea et al., 2019; Saddique et al., 2020; Yasin et al., 2022; Zhao et al., 2017). Regional studies from Pakistan agree with our results and show that heat stress is the major factor threatening future yields in important agricultural regions in Pakistan (Awan et al., 2021; Khan et al., 2021; Yasin et al., 2022). Exact estimates of projected yield declines for our study region and our selected crops vary. The above cited studies suggest yield declines of approx. up to – 17% to – 25% in rice yields (Khan et al., 2021), up to – 30% in cotton yields (Awan et al., 2021), and – 8% to – 55% in maize yields (Yasin et al., 2022), for mid-century climate change scenarios.

In addition it is worth noticing that the negative effects of rising temperatures on yields are often non-linear (Lobell et al., 2011; Schauberger et al., 2017; Schlenker and Roberts, 2009). Of particular importance is the exceedance of crop specific critical temperature thresholds, above which crops experience significant yield reductions. Cotton, which has a higher optimal temperature (approx. 30–32 °C, (Reddy et al., 1999; Schlenker and Roberts, 2009) and thus a higher heat resistance than rice (approx. 25 °C, Luo, 2011) and maize (approx. 29 °C, Schlenker and Roberts, 2009), can therefore better cope with elevated temperatures. This is also reflected in the results of this study,

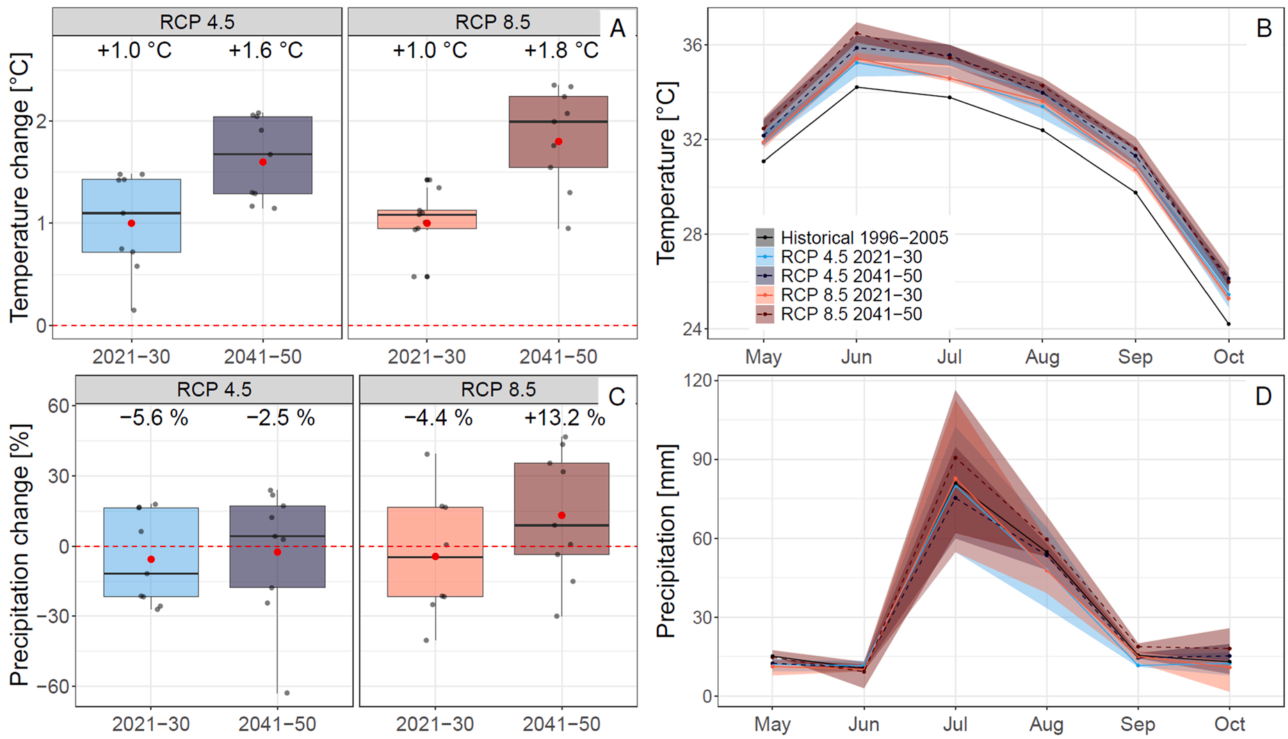

Fig. 4. Projected temperature and precipitation change during Kharif (summer) months, for selected time periods 2021–2030 and 2041–2050, with respect to historical data (1996–2005). (A) Absolute seasonal temperature change and (B) absolute monthly temperature changes. (C) Relative seasonal precipitation changes and (D) absolute monthly precipitation changes. Red dots and displayed percentages show ensemble mean changes. Grey dots represent single ensemble members. The right panels show model ensemble uncertainty bands of 25th and 75th percentiles.

which show a strong crop specific sensitivity to heat stress, with stronger heat stress impacts for rice and maize and a lower heat stress impact for cotton. Furthermore, SWAT shows significantly higher sensitivities to temperature than APSIM, resulting in strong yield declines for all three crops. The stronger temperature sensitivity of SWAT explains the larger uncertainties in SWAT yield predictions, as temperature projections of the nine selected climate models are stronger reflected in the final SWAT results compared to ASPIM results. Despite the differences between APSIM and SWAT estimates, simulated yield losses of both models are unequivocal and would have large implications for future agricultural productivity in the study area.

3.4. Impact of rising CO_2 on plant development

Increasing atmospheric CO_2 levels dampen the negative effects of rising temperatures on yields and reveals the significant positive effect of elevated CO_2 concentrations on agricultural productivity (Fig. 5, dark grey bars). This effect is also known as CO_2 fertilization. For the short-term scenario (2021–2030), increasing CO_2 concentrations could even prevent a significant decline in simulated crop yields. APSIM results show that average yield losses could be approx. 4.4% (RCP4.5, 2021–2030) to 6% (RCP8.5, 2021–2030) less severe due to increasing CO_2 concentrations. Averaging yield levels of all tree crops, SWAT projects a full offset of climate-related yield losses under enhanced CO_2 levels. For the short-term scenario, SWAT simulates increasing yields of + 1.8% (RCP4.5) to + 5.5% (RCP8.5; Fig. 5A). Strong positive effects of increasing CO_2 concentrations on plant growth, as seen in our results, have proven to counteract plant growth-limiting effects (Parry et al., 2004; Singh et al., 2020). At this point, it is worth to recall that, in this study, we assume a sufficient supply of nutrients at any time. Nutrient stress would limit the CO_2 fertilization effect (Reich et al., 2014), but in this study the positive effect of CO_2 enrichment on plant development is unimpeded. Overall, the effectiveness of CO_2 fertilization is still a large source of uncertainty (Elliott et al., 2014; McGrath and Lobell, 2013), which is yet to be improved in bio-physical crop models (Toreti et al., 2020). In the context of our study, uncertainty arises through the differences in representing CO_2 impacts on plant physiology by SWAT and APSIM.

SWAT accounts for the positive effects of CO_2 by increasing the radiation use efficiency of plants under rising CO_2 levels (Eqs. (S1) and (S2)). This increases the plants' ability to capture photosynthetically active radiation and leads to more efficient biomass production. Yet, the model equally applies this formulation to all crops, irrespective of their different photosynthetic pathways, i.e. C3- or C4-pathway. Hence, the agro-hydrological SWAT model does not account for plant-type-specific impacts of CO_2 and might overestimate the positive effects of CO_2 (Wu et al., 2012).

The APSIM crop models, on the other hand, consider plant-specific impacts (Vanuytrecht and Thorburn, 2017). In the case of C3-plants, such as rice and cotton, the models account for the photorespiratory part in the photosynthetic process (e.g. Eq. (S8) for cotton). Higher photorespiration lowers carbon assimilation under stress conditions and elevates it under higher CO_2 concentrations (Morison and Lawlor D.W, 1999). The APSIM maize-model (Fig. 5C) correctly assumes insensitivity to changing CO_2 effects for C4-plants. While this leads to unchanged maize yields with respect to CO_2 changes in APSIM simulations, SWAT assumes positive effects of CO_2 on maize growth. For cotton, rising CO_2 levels lead to increased cotton yields of approx. up to + 6% (APSIM) and + 14% (SWAT) until 2050, under the high emission scenario (Fig. 5B). Likewise, the simulated rice dynamics are consistent in both models. Rice yields (Fig. 5D) experience similar positive impacts under rising CO_2 levels compared to cotton (both C3-plants), but their yield reductions due to heat stress are too severe to be compensated by increasing CO_2 concentrations (Fig. 5D). Large discrepancies in the rice

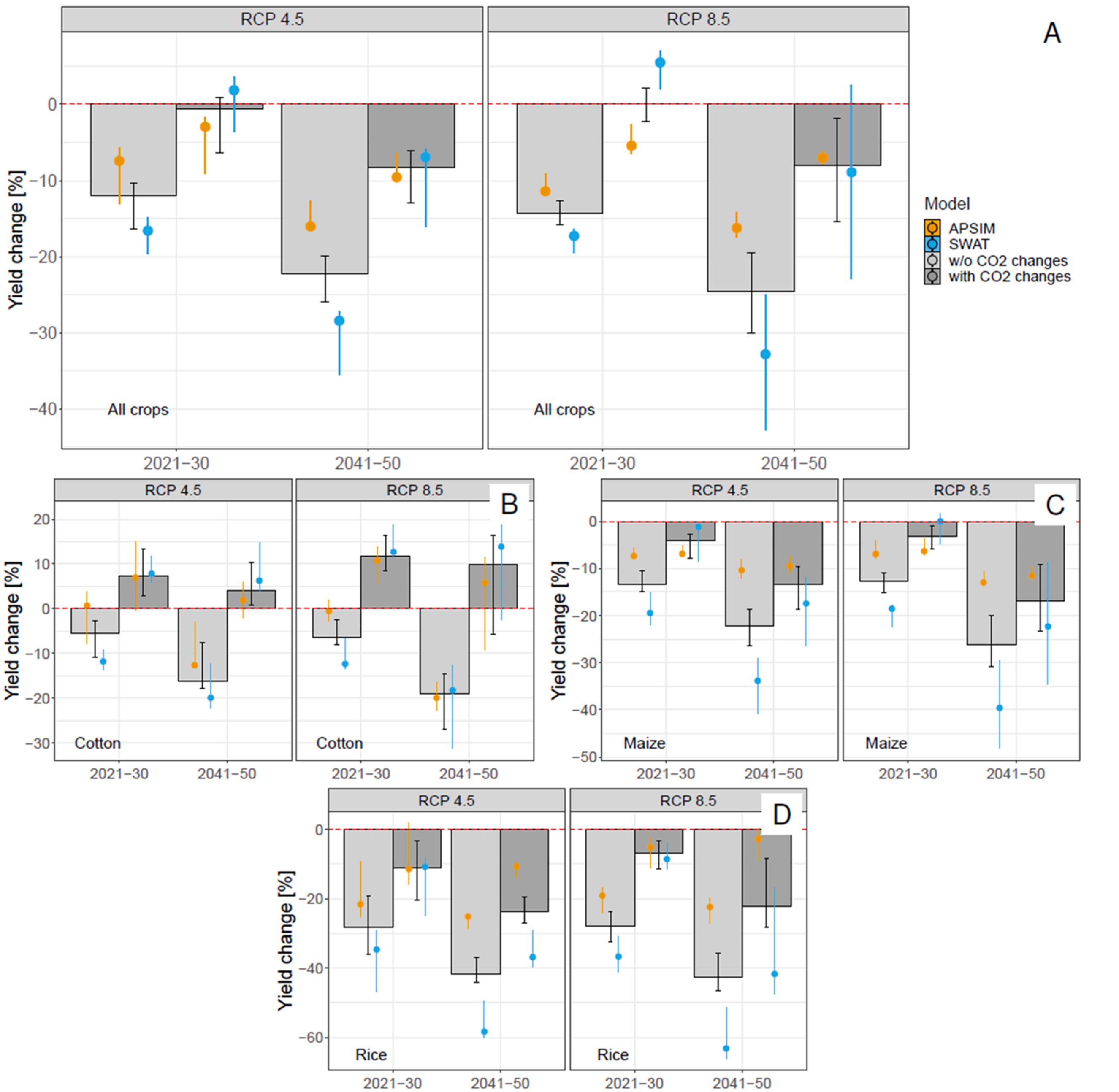

Fig. 5. Projected changes in future crop yield under the RCP 4.5 and RCP 8.5 scenario, neglecting (light grey bars) and considering (dark grey bars) the impact of CO_2 changes. (A) Results are shown for all crops combined as well as separately for (B) cotton, (C) maize and (D) rice. Filled bars show the median estimate and black bars the respective 25th and 75th percentiles of the model ensemble (SWAT and APSIM with nine climate models). Separate results for SWAT and APSIM models are shown as coloured dots (median), and coloured line with the respective 25th and 75th percentiles for the model ensemble of nine climate models.

and maize simulations of the two models can be seen with respect to temperature changes. These are further discussed below.

Previous studies have indicated that increasing CO_2 improves water use efficiency by reducing plant transpiration which facilitates plant growth during drought conditions (Singh et al., 2020; Wullschleger et al., 2002; Yoo et al., 2009). At the same time, it has also been reported that reduced plant transpiration leads to increased heat stress, due to reduced evaporative cooling (Siebert et al., 2014; Vanuytrecht et al., 2012). These two effects are currently not captured by either of the models. As the strong increase in future temperature is projected under both RCP scenarios and together with the abundance of water due to irrigation, the positive effect of CO_2 on yield levels is most likely overestimated by both crop models.

Under further rising temperatures (scenarios for the period 2041–2050), APSIM and SWAT project a decline in crop yields indicating that even with further elevated CO_2 concentrations and unlimited water and nutrient availability, climate change induced yield declines cannot be prevented. APSIM projects an average yield decline of − 8% (± 3%, RCP 4.5) and − 7% (± 2.3%, RCP 8.5), while SWAT projects a similar yield decline with larger uncertainties of − 7% (± 13%, RCP 4.5) and − 7% (± 18%, RCP 8.5). All estimated crop yields show that the positive effects of increasing CO_2 levels are likely to diminish as temperatures continue to rise (Fig. 5A).

3.5. Future irrigation and evaporative demand

In the following, we analyse if rising temperatures will lead to an increase in irrigation demand and if irrigation is an effective measure to counteract the severe yield losses. Further, we discuss the reasons behind estimated yield declines in the context of changes in irrigation demand and evapotranspiration (ET).

Considering the significant temperature increase one would expect a strong increasing signal in plant water demand (Döll, 2002; Wada et al., 2013). Examining irrigation and evaporative demands in the study area, however, reveals that trends in future water demand do not align with projected temperature trends. Against the expectation of increasing irrigation needs due to rising temperatures, both crop models show that average irrigation demands increase less under higher temperatures. Under both emission scenarios and for both models, the strongest increase in irrigation demand is predicted for the moderate short-term scenario (RCP 4.5, 2021–2030), while less increase is predicted for the high-end emission scenario (RCP 8.5, 2041–2050). Fig. 6 displays the results for APSIM and SWAT separately to reveal important differences in their simulation results. Results are averaged over the selected summer crops cotton, maize and rice to focus on unraveling the complex dynamics of heat and water stress interactions under different climate scenarios. Crop specific results are presented in more detail the supplementary material (Figs. S4-S5).

For conditions with historical CO_2 levels, SWAT projects the lowest irrigation needs for the RCP 8.5 and mid-term future scenario (increase of irrigation needs by $1 \pm 8\%$; Fig. 6A). Under elevated CO_2 concentrations (Fig. 6B), water demand even reduces ($-4 \pm 7\%$), which agrees with the effect of reduced plant water needs due to reduced stomatal conductance (Fernández-Martínez et al., 2019; Kimball et al., 2002). For the same scenario, irrigation demand simulated by APSIM will increase by approx. $5 \pm 5\%$. It appears insensitive to CO_2 changes, as irrigation demand remains constant regardless of changes in CO_2 levels (Fig. 6A vs. B). Yet, the significant increase in LAI under elevated CO_2 levels (Fig. 6B) as well as the negligible change in irrigation demand illustrates that APSIM likewise accounts for positive CO_2 effects on water demand and shows decreasing irrigation demand relative to leaf area growth. The reason for the surprisingly low increase in irrigation needs can be explained by a similarly low increase in actual evapotranspiration rates (Fig. 6C and D). Irrespective of the strong temperature rise (up to 1.8 °C until 2041–2050), increases in ET are projected by both crop models to stay on average below 3% ($\pm$ 4%; for model differences see Fig. 6), and do not increase with further rising temperatures.

Finally, the fact that biomass and yield strongly decline while future irrigation demands do not align with future temperature trends indicates that even if more water for intensified irrigation activity would be applied, it would not help to prevent yield losses when significant heat stress is the main yield controlling factor. This is further underlined by the strong impact of heat stress on leaf area growth and the already mentioned dynamics of biomass production, which are discussed in more detail below.

3.6. Future plant growth and plant productivity

SWAT model results suggest a significant reduction in LAI by up to − 27% ($\pm$ 6%) under the high-emission scenario (median of all three crop models for RCP 8.5, 2041–2050). Crop specific declines are estimated to be up to − 31% for maize, − 25% for cotton, and − 58% for rice (Fig. S8). The decreasing LAI trend clearly follows the increasing temperature trend, with the highest LAI reductions under the RCP 8.5 scenario (Fig. 6A), and reveals a strong sensitivity of leaf area growth to temperature changes (Fig. 6C). The reason for this strong temperature sensitivity is the following: SWAT estimates LAI development based on the influence of one predominant environmental stress factor (Eq. (S4)), which is heat stress in this study. Further, LAI calculations in SWAT do not account for CO_2 effects (Fig. 7A vs B), which results in strong LAI decreases even under higher CO_2 concentrations (Fig. 7B) and in decreasing ET rates (Fig. 7D).

APSIM on the other hand, which does not account for a specific heat stress factor in its LAI calculations, shows a clear LAI insensitivity to temperature (Fig. 7A vs. B). APSIM leaf area calculations are primarily controlled by water stress, but as constant water supply is guaranteed in

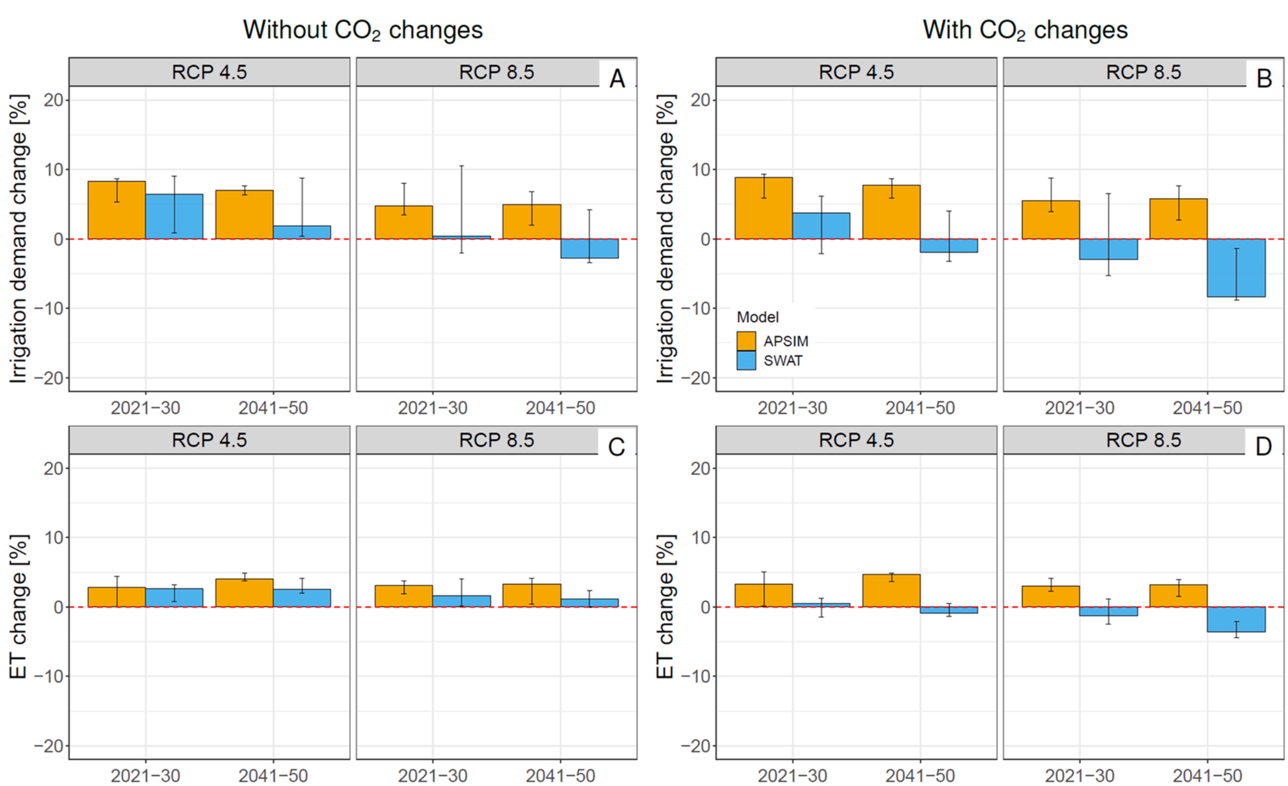

Fig. 6. (A and B) Projections of future irrigation demand and (C and D) future ET rates. (A and C) Changes under the baseline CO_2-scenario and (B and D) with increased CO_2-levels.

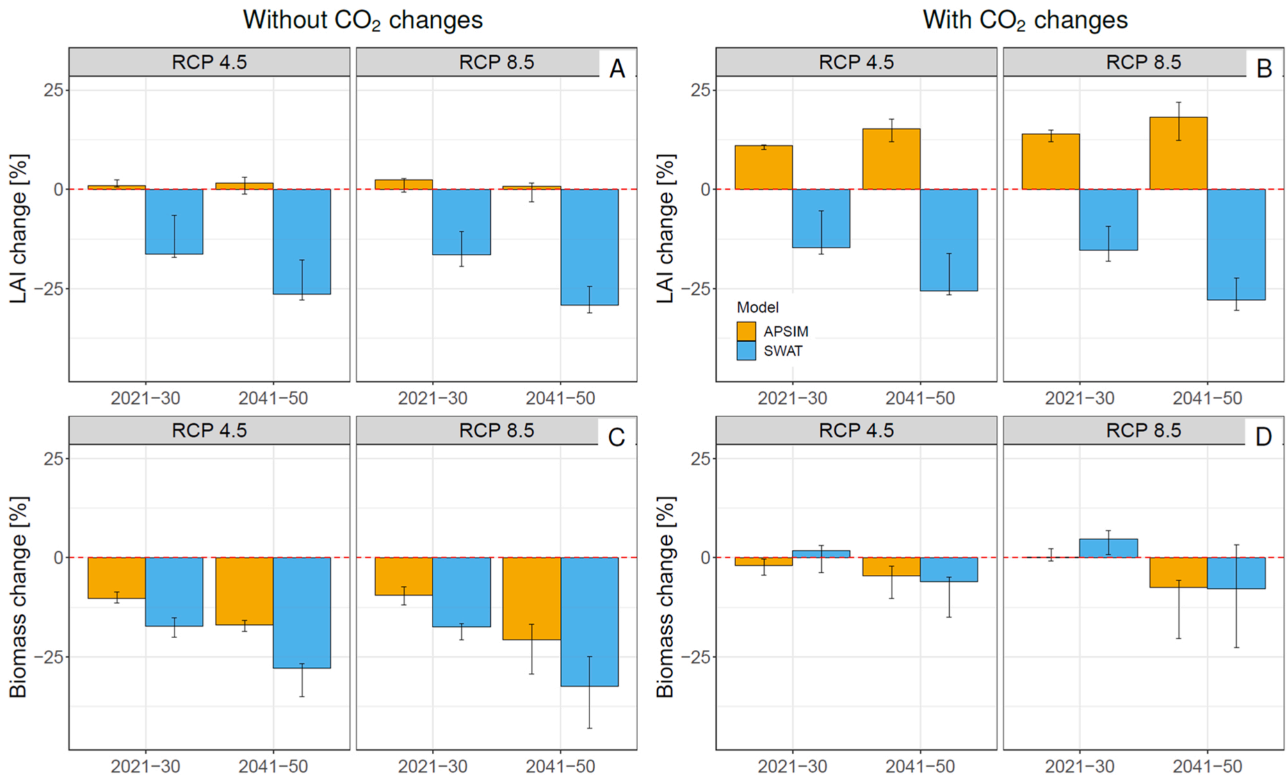

Fig. 7. (A and B) Projections of future LAI changes and (C and D) future biomass changes. (A and C) Changes under the baseline CO_2-scenario and (B and D) with increased CO_2-levels.

this study, LAI development is unimpeded. Yet, APSIM-LAI predictions show a notable sensitivity to CO_2-concentrations and increasing leaf growth under rising CO_2 levels, for C3-plants. Consequently, APSIM based simulated LAIs are projected to increase by up to 15% (± 10%) under the high emission scenario, which explains why APSIM-ET rates do not decrease despite ET reducing CO_2-effects (Fig. 5D). Crop specific results are − 1% for maize (C4-plant), + 24% for cotton, and + 29% for rice (both C3-plants; Fig. S8). Similar effects were observed and described by Singh et al. (2020), revealing a strong increase in LAI due to CO_2 increases, offsetting higher water use efficiency.

As leaf area and temperature jointly control the evaporative demands and ultimately irrigation water needs, the differences in LAI simulations highlight the importance of model sensitivity to heat stress. The differences in the underlying model structures result in two dissimilar conclusions. On the one hand, SWAT projects a decline in future plant growth, which is strong enough to reduce ET and irrigation demand. This leads to the conclusion that irrigation intensification cannot help to mitigate future yield losses. APSIM, on the other hand, forecast increasing leaf area growth and indicates that intensified irrigation will be needed due to the resulting (albeit modest) rise in water demands. Yet, even in the latter case, intensified irrigation cannot prevent future yield losses.

The discrepancy between the projected increase in LAI and the decrease in biomass estimates by APSIM results from the way APSIM accounts for biomass partitioning processes. As a biophysical crop model, APSIM accounts for carbon assimilation in different plant fragments such as leaves, stem, fruits, and roots. The produced biomass can dynamically be allocated to different plant parts. Leaf area can therefore remain constant or even increase while the overall biomass decreases.

While SWAT and APSIM disagree in their LAI estimates, both models predict a substantial reduction in plant biomass under increasing temperatures (Fig. 7C). Under historical CO_2-levels SWAT predicts a reduction in biomass of up to − 33% (± 11%; up to −41% for maize, −20% for cotton, and −64% for rice), while APSIM predicts a reduction of up to − 25% (± 11%; up to −17% for maize, −23% for cotton, and −5% for rice; RCP 8.5, 2041–2050). To this end, both models show a good agreement in their predicting trends and in their sensitivity towards CO_2 changes. Rising CO_2 levels might compensate negative temperature effects in the near future but for the mid-century scenario (2041–2050), biomass is projected to decline despite further elevated CO_2 levels (Fig. 7D). This aligns with observations which show a clear temperature dependent CO_2 fertilization effect (Fernández-Martínez et al., 2019). As mentioned above, elevated CO_2 concentrations can lead to an enhanced carbon fixation rate under higher CO_2 concentrations. Yet, at the same time, it has been reported that reduced plant transpiration due to enhanced CO_2 availability leads to increased heat stress. The reason is reduced evaporative cooling which induces higher leaf and plant organ temperatures (Siebert et al., 2014; Vanuytrecht et al., 2012). At the same time, the temperature increase can speed up the plant development and lead to less time for carbon assimilation and reduced biomass production. The results are supported by Morison and Lawlor D. W. (1999), who point out that a temperature increase of just a few tenths of a degree can act cumulatively over time and can significantly accelerate plant development and reduce time for biomass production.

Recalling that both models assume a sufficient supply of irrigation water and enough nutrient supply, our results reveal once more that heat stress is the dominating factor controlling future yield developments. We, therefore, conclude that the mitigation potential of irrigation to counteract future yield losses is severely limited under further rising temperatures. An intensification of irrigation might be able to mitigate yield declines in the near future, when positive CO_2 effects balance the harmful temperature effects and irrigation demands are still increasing (Fig. 6B). For the mid-century scenario, however, the positive CO_2 effects as well as irrigation intensification will not be able to compensate for the yield losses.

4. Conclusions

The study examines potential climate change impacts on cotton, maize and rice crops in the Punjab region of Pakistan. The main finding is that under expected climate change scenarios a substantial reduction in summer crop yields is likely to occur in the study region. It could be shown that plant development is dominantly controlled by heat stress and that negative climate change impacts on agricultural production can only be marginally mitigated by an intensification of irrigation. In the medium-term future, under further rising temperatures, irrigation cannot prevent increasing yield losses. Temperature related adaptation strategies such as the selection of more heat resistant crops, or changes in crop planting schedules seem therefore more suitable than water related adaptation measures. This aligns with current efforts in Pakistan to re-define eco-agrological zones according to changing climate patterns and to choose earlier planting dates to avoid summer heat waves.

By using two models from different scientific disciplines, and with two different model architectures, the study is able to point out important model structural limitations which influence the final results of climate impacts on local crop production and water demands. LAI simulations and the simulation of CO_2-sensitivities were identified as important model routines, leading to discrepancies in the results of our climate change impact assessment using the SWAT and the APSIM models. This also leads to important differences in the estimation of irrigation water demand. We therefore conclude by suggesting a better combination of the strengths of hydrological and biophysical crop models. The integration of more robust hydrological routines into biophysical crop models is a promising way forward. Such a hard-coupled model integration will be valuable for agricultural climate change impact studies as it enables a simultaneous consideration of the hydro-climatic environment with specific bio-physical responses of plants to climate change.

Declaration of Competing Interest

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

Data availability

The data is freely available and I have shared the link to the repository in the manuscript.

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Open Research

The data produced in this study can be accessed through the following data repository: **https://doi.org/10.5281/zenodo.4603703**.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2023.108243.

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