

1 Increased temperature stress reduces future yields despite
2 intensification of irrigation

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15 **Keypoints:**

- 16 • Increased temperature stress strongly reduces future crop yields.
17 • Lowered plant productivity due to heat stress markedly reduces plant water demand.
18 • Intensified irrigation to increase future crop yields is not a viable climate change adaptation
19 measure.

20 **Abstract**

21 Climate change and variability threatens the sustainability of future food productions, especially in
22 semi-arid regions where water resources are limited, and irrigated agriculture is widespread.
23 Increasing temperatures will exacerbate evaporative losses and increase plant water needs.
24 Consequently, higher irrigation intensities would be a logical measure to mitigate climate change
25 impacts in these regions. Using an ensemble of well-parameterized crop model simulations, we
26 show that this mitigation measure is oversimplified and that besides water resources availability,
27 strong temperature increases play a crucial role in crop developments and resulting plant water
28 needs. Our analysis encompasses agricultural areas of the Lower Chenab Canal System in Pakistan
29 (15 000 km²), which is part of the Indus River irrigation system, the largest irrigation system in the
30 world; and covers economically important crop growing areas (e.g., of cotton, rice and maize crops).
31 Climate models project an above average increase in temperature over the study region, and the
32 agro-hydrological and biophysical crops models respond with a strong decline of up to -24% ($\pm 12\%$)
33 in future crop productions. Our modeling results further suggest that evaporative and irrigation
34 demands do not align with increasing future temperature trends. The resulting decline in crop
35 productions is consistent among model projections despite an intensification of irrigation measures
36 and the positive effect of future CO₂ enrichments. Overall, our study emphasizes the role of elevated
37 temperature stress, its effects on agricultural production as well as water demand, and its
38 implications for climate change adaption strategies to mitigate adverse impacts in an intensively
39 irrigated region.

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41 **Keywords:** Climate change, agricultural yield decline, SWAT, APSIM, temperature stress

42 **1. Introduction**

43 In recent years, climate change and its impact on the environment have become one of the main
44 concerns worldwide. Especially, its effect on agricultural systems has become a major problem,
45 considering the alarming global developments regarding water and food security (Hanjra and
46 Qureshi, 2010; Schewe et al., 2014). The latest special report of the UN Intergovernmental Panel on
47 Climate Change (IPCC 2019) predicts, with high confidence, that future changes in climatic conditions
48 will exacerbate existing water and food shortages for billions of people. One of the main reasons
49 considered responsible for the expected food shortage is the inability to meet future agricultural
50 water demands (Fader et al., 2016). Globally, irrigation volumes have more than doubled since the
51 1960s (IPCC 2019) and are likely to increase further due to climate change in regions with already
52 limited water supply (Wada et al., 2013; Wang et al., 2016).

53 In semi-arid and developing regions like Pakistan, agriculture is the most important economic sector,
54 employing nearly half of the population (Qureshi, 2011). A large part of agricultural workers are small
55 scale farmers, highly dependent on maintaining their productivity levels and becoming increasingly
56 vulnerable to climate change impacts and potential losses of income (Oxfam, 2009). The projected
57 increase in water scarcity, due to climate change along with the increasing demand of the fast-
58 growing population, poses a severe threat to the national food supply and to the productivity of
59 economically important cash crops such cotton, maize and rice (Khan et al., 2016; Qureshi, 2011;
60 Schewe et al., 2014).

61 Especially the Indus Basin in Pakistan's Punjab province is a hot spot for the impact of climate change
62 on water availability and agricultural productivity, as it constitutes one of the world's largest closed
63 irrigation areas (Mekonnen and Hoekstra, 2011). Currently irrigation water in the region accounts for
64 over 90% of the total water demand (Fischer et al., 2007). Significant climate induced changes in the
65 upstream glacio-hydrology – the major water source for the Indus Basin - are threatening future
66 water availability in the basin (Immerzeel et al., 2010); along with the rising temperatures that are
67 generally projected to increase faster than on global average in the region (Saeed and Athar, 2018).

68 Under such conditions, water related adaptation strategies, such as increased irrigation amounts,
69 and enhanced irrigation efficiency are possible solutions to cope with these challenges. The benefits
70 of such adaptation measures have been studied for agricultural systems experiencing similar climate
71 change pressures and have been suggested as possible actions (Elliott et al., 2014; Fader et al., 2016;
72 Molden et al., 2010). Yet, sensitivities of crops to changes in temperature can be higher than those
73 due to water availability changes (Lobell and Burke, 2008). Temperature induced stress on crop
74 growth and productivity could counteract the potential of optimized water management for
75 increased productivity (Lobell et al., 2015; Zaveri and Lobell, 2019). It is therefore imperative to
76 understand the role of temperature stress on crop growth and resulting plant water demand, in
77 connection to water (availability) stress. Furthermore, improved knowledge about possible impacts
78 of temperature and water stress as well as their interlinkages on future crop growth will help
79 defining adequate adaptation strategies. In terms of adequate water availability for crop growths,
80 especially in semi-arid regions, previous studies highlight that there is still very limited understanding
81 of the potentials and limits of irrigation related climate change adaptation (Tack et al., 2017; Taraz,
82 2018); and that more research is needed to disentangle the effects of temperature and water stress
83 related climate change impacts on agricultural yields (Carter *et al* 2016).

84 This study elaborates on how temperature stress controls agricultural productivity and plant water
85 requirements in an intensively irrigated agricultural system in Pakistan's Punjab province. It suggests
86 that the intuitive assumption, that increasing temperatures will inevitably lead to higher
87 transpiration and thus to increasing irrigation demands, might not be a universal principle. This is
88 shown by the application of two models from two different scientific disciplines. In order to tackle
89 diversity in crop model parameterization, we consider the hydrological SWAT model (Arnold et al.,
90 2012) and the biophysical-crop modelling framework APSIM (Holzworth et al., 2014) to analyze
91 climate change impacts on yield and water demand. Numerous modeling studies regarding negative
92 climate change impacts on yields and the potential of irrigation to mitigate these impacts exist. These
93 studies, however, have been conducted using either hydrological models or crop models (Elliott et

94 al., 2014). The combination of both model types is expected to allow a more detailed understanding
95 of strengths and weaknesses of either model and thus, might result in a more reliable assessments of
96 changes in future yield and water demand dynamics. Both models are used in an ensemble
97 framework to analyse the climate change impacts on resulting crop growth over the study area. To
98 this end, we use 9 climate model realizations; bias-corrected and downscaled to force both crop
99 models under moderate (Representative Concentration Pathways (RCP) 4.5) and high-end (RCP 8.5)
100 future carbon emission scenarios. We design a careful modelling experiment to analyse the impacts
101 of increased temperature stress on future crop yields in connection to potential water stress.
102 Through these analyses, we aim to provide a better understanding on the interlinkages between
103 temperature and water stress and to detect dominant drivers of declining (future) agricultural
104 productivity - which could then aid in defining effective adaptation measures.

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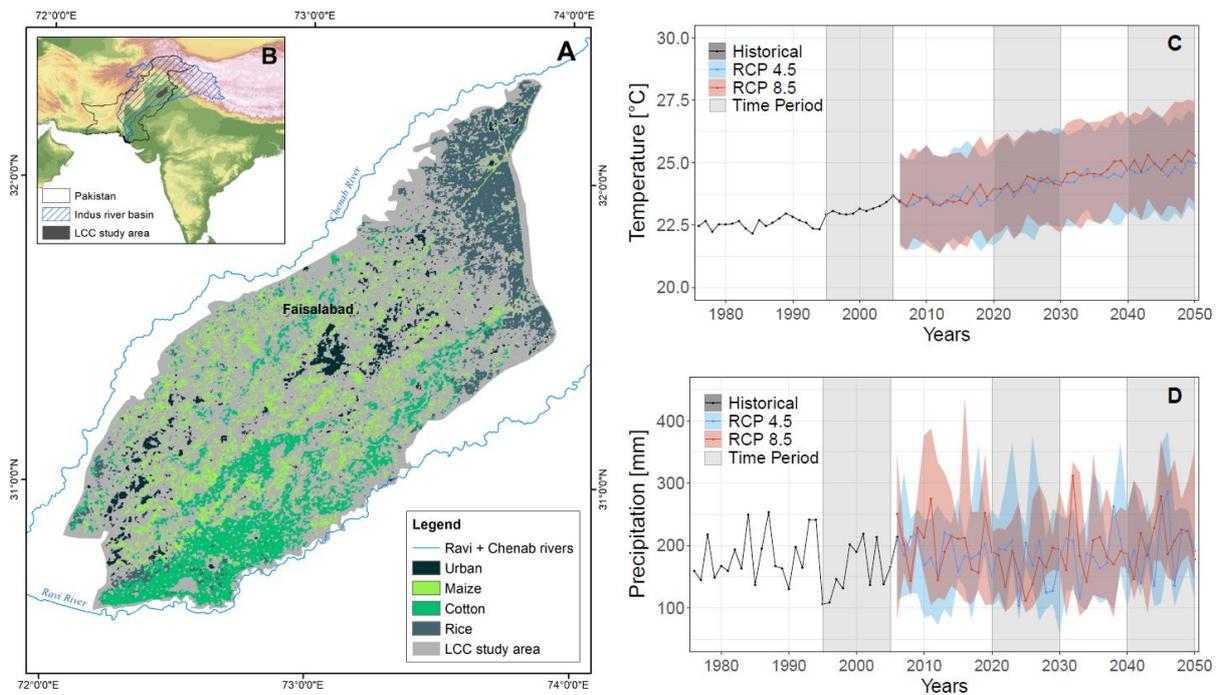
106 **2. Methods and Materials**

107 **2.1 Study Area**

108 The study area is part of the Lower Chenab Canal System Area (LCC) in Pakistan, which comprises
109 about 15 000 km² of agricultural land on the floodplains between the Rivers Chenab and Ravi (Fig. 1A
110 and 1B). The LCC region is part of the Indus Basin Irrigation System (IBIS), the world largest irrigation
111 system, feeding more than 200 million people (Immerzeel et al., 2010). The area is characterized by
112 small-scale and highly fragmented agricultural cropping patterns. During dry winter season (Rabi) the
113 dominating crop type is winter wheat while during the wetter and hot summer (Kharif) the crop
114 pattern diversifies and mainly cotton, maize, rice and fodder are grown on small scale farm plots.
115 Annual potential evaporation (1800 mm/a) is more than three times larger than annual precipitation
116 (500 mm/a), resulting in a strong demand for additional irrigation. Knowing about potential negative
117 impacts on agricultural productivity and defining possible adaptation strategies is therefore of
118 paramount importance for water and food security in this region.

119 In this study we focus on analyzing the impacts of future climate change on summer crops, namely
 120 cotton, maize and rice, grown between May and October. The impact is evaluated based on changes
 121 in crop yield and relevant hydrologic and biophysical variables including evapotranspiration,
 122 irrigation demand, leaf-area growth, and biomass production (Fig. 2A). Due to high summer
 123 temperatures in our study region (mean daily Temperature > 30 °C), evaporative loss is highest
 124 during this time and changes in irrigation needs have a particularly strong impact on basin wide
 125 water demand. The selected crops represent high value crops with a wide distribution in the study
 126 area (Fig. 1A) and changes in yield will have significant economic impacts.

127



128

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

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135 2.2 Models: SWAT and APSIM

136 The hydrological model SWAT (Soil & Water Assessment Tool) simulates the quantity and quality of
 137 water flow within catchments, incorporates detailed management strategies (e.g. irrigation schedule,

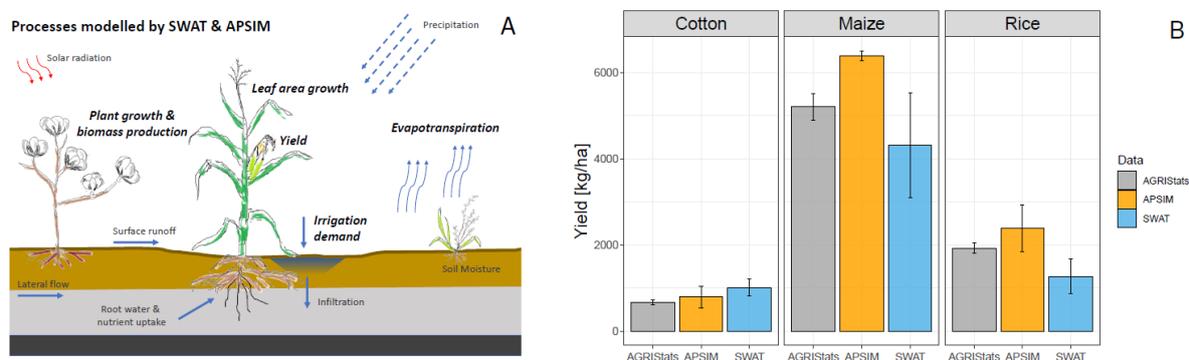
138 planting schedule) and basic plant physiognomic stages, e.g. root development, leaf area
139 development, biomass change (Arnold et al., 2012; Gassman et al., 2014). The main underlying
140 principle for the simulation of water fluxes is the water balance equation (Neitsch et al., 2009). By
141 accounting for spatially distributed environmental changes, it simulates their effects on individual
142 water balance components. Its strengths are therefore the closing of the hydrological cycle and the
143 detection of spatially distributed changes in water availability and demand. Impacts of changing
144 atmospheric CO₂ concentrations are accounted for in the estimation of potential evapotranspiration,
145 affecting (i.e., reducing) plant water demand as well as in the estimation of plant radiation use
146 efficiency, affecting (i.e., enhancing) the biomass production. To ensure correct and spatially
147 differentiated parameterization, the model is calibrated following an automated and spatially
148 distributed calibration approach (Becker et al. 2019). In this study the model is run on a daily
149 timescale, with daily climate input data. Yield levels are taken at the end of each growing period.

150 The Agricultural Production System Simulator (APSIM; Holzworth et al., 2014) is a biophysical crop
151 modelling framework which simulates agricultural crop dynamics with respect to varying climatic and
152 environmental conditions. It has been used extensively to assess climate change impacts on
153 agricultural productivity (e.g. Deihimfard et al., 2018; Liu et al., 2013; Williams et al., 2015). Model
154 performance and applications are studied in depths within the scope of the Agricultural Modelling
155 Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2014), in which the APSIM
156 model was applied in the same study region of southern Punjab to assess climate change impact on
157 crop production. Focus and strength of the APSIM framework is the plant-specific simulation of
158 biophysical dynamics with respect to changes in the environment. Due to its modular approach, with
159 individual sub-models for each crop type, it can account for plant specific reactions to climate
160 change. For example, with individual models for cotton, rice, and maize it accounts for plant type
161 specific carbon assimilation processes (C3 vs. C4-plants) and hence, differentiates between plant type
162 reactions to increased atmospheric CO₂ levels. The APSIM model parameterization for the study area
163 was established (calibrated) following the guidelines given for the APSIM classic model (APSIM model

164 documentation, 2021) for three crop specific modules for cotton, maize and rice. Like the SWAT
 165 model the APSIM model is run on a daily time scale, with daily climate input data. Yield estimates are
 166 taken at the time of harvest at the end of the growing season.

167 To allow comparison between the SWAT and the APSIM models, we adopted the soil and
 168 management parameter configurations from the calibrated SWAT model. Soil parameters were
 169 furthermore verified through laboratory analysis of soil samples collected during a field campaign in
 170 the study region (Schulz et al., 2021 and Supplementary Section 2.3). We also conducted a sensitivity
 171 analysis to analyze the effect of varying soil parameters on the APSIM simulated crop yields that
 172 further allowed to constrain appropriate parameters for the APSIM soil module. Details of the
 173 employed parameters and underlying estimation procedure for both crop models are described in
 174 the Supplementary Information S2 and Tables S1-S3.

175 Finally we compared and contrasted the modeled crop yields with observed data provided by the
 176 Agricultural Statistics of Pakistan, published by the Ministry of National Food Security & Research
 177 (MNFSR, 2021) (Fig. 2B). Yield data for cotton, rice, and maize from the province of Punjab was taken
 178 for the years 2009-2013 and compared to simulated yield levels by SWAT and APSIM for the same
 179 period (mean of all years is shown in Fig. 2B). Details of the model validation can be found in the
 180 Supplementary Information S2.5.



181
 182 *Figure 2: (A) Schematics of the main processes simulated by SWAT and APSIM models and analyzed in this study (bold italic).*
 183 *(B) Evaluation results of simulated yield simulations compared to observations; with the latter based on the AGRISStats =*
 184 *Agricultural Statistics of Pakistan. Bar heights show the mean of the years 2009-2013 and uncertainty bars show +/- one*
 185 *standard deviation.*

186

187 **2.3 Climate data sets**

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

193 Climate projection datasets are taken from the Coordinated Regional Downscaling Experiment
194 (CORDEX), which provides a suite of regional climate projections based on the Global Climate Models
195 of the Coupled Model Intercomparison Project, Phase 5 (CMIP5; Taylor *et al* 2012). We consider
196 medium (RCP 4.5) and high (RCP 8.5) greenhouse gas emission scenarios from the IPCC - Fifth
197 Assessment Record (AR5); and analyze the impacts in the near future (short; until 2030) and the mid
198 future (medium; until 2050). The short-term time frame is selected to show the potential changes
199 expected to occur in the coming next decade, and to show the necessity for immediate actions. The
200 medium-term scenario is chosen to show the consequences of climate change at a time scale still
201 relevant for today's population. Due to the capabilities of management and plants to adapt to
202 changes in climate as well as long-term reactions of farming community to adapt to new
203 environmental conditions, we do not include a long-term impact assessment. For the short- and
204 medium-term scenarios, we assume that factors such as plant genetics and management strategies
205 remain constant and at a current level.

206 The projections of future CO₂ concentration are based on van Vuuren *et al.* (2011) and are assumed
207 to be 420 ppm and 450ppm CO₂ for RCP 4.5 and RCP 8.5, respectively during the time period 2021-
208 2030; and 470 and 520 ppm CO₂ for RCP 8.5 are projected for the time period 2041-2050.

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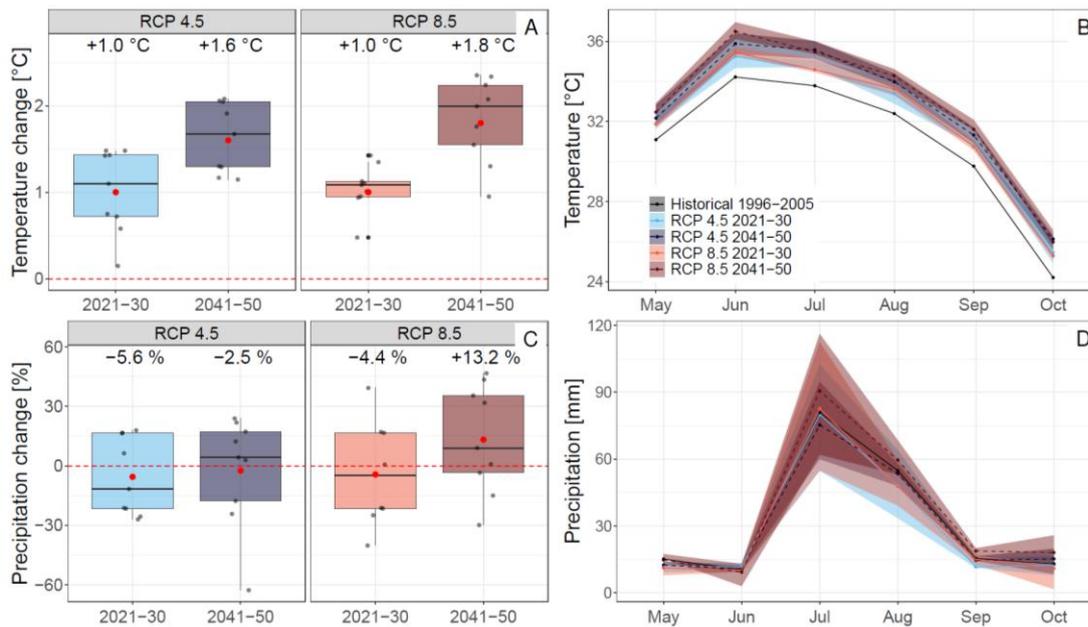
210 **3. Results and Discussions**

211 **3.1 Future climate trends in the LCC study area**

212 The climate models project a strong increase in temperature over the study region, under the high-
213 emission scenario RCP 8.5 as well as under the moderate emission scenario RCP 4.5 (Fig. 1C). For the
214 summer season (May-October), the ensemble means predict an increase of 1.0 °C ($\pm 0.4^\circ\text{C}$) for RCP
215 4.5 and 1.0 °C ($\pm 0.3^\circ\text{C}$) for RCP 8.5 until 2030, compared to the historical period of 1996-2005. A
216 warming of 1.6 °C ($\pm 0.5^\circ\text{C}$) and 1.8 °C ($\pm 0.5^\circ\text{C}$) is projected for RCP 4.5 and 8.5, respectively, until
217 2050 (Fig. 3A). Strong increases in temperature under both scenarios points towards higher pressure
218 on agricultural production resulting from increased temperature stress on crop growth, especially
219 during summer months (Fig. 3B). A high agreement between the climate model ensemble members
220 regarding consistent increase in future temperature indicates that the future summer season
221 warming in the LCC area can be projected with high confidence (Fig. 1C; Fig. 3A and 3B).

222 Precipitation projections, on the other hand, are highly uncertain and there is no clear trend in
223 annual or monthly precipitation amounts (Fig. 1D, Fig. 3C and 3D). Future water availability in terms
224 of precipitation projections over the study area is therefore difficult to predict. In this study, we
225 assume that due to the constant irrigation activities in the LCC irrigation system, agricultural water
226 availability is always assured, and plant water demand is met. Thus, impacts of changes in
227 precipitation on our model results are small and water stress is kept low.

228 Scenarios that future water availability either by water abstractions from the river Chenab or from
229 ground water resources can no longer meet irrigation demands are not analyzed in this study, as we
230 purely focus on the effect of climate change impacts of agricultural productivity given enough water.



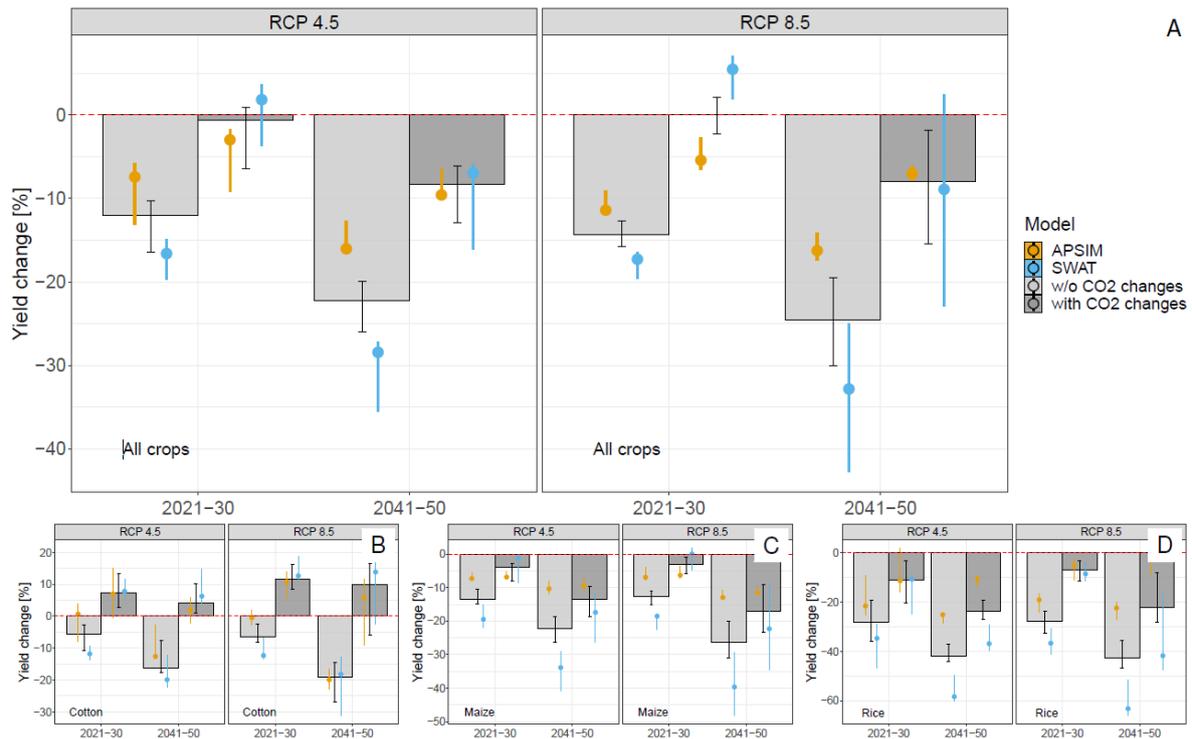
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232 *Figure 3: Projected temperature and precipitation change during Kharif (summer) months, for selected time periods 2021-*
 233 *2030 and 2041-2050, with respect to historical data (1996-2005). Absolute seasonal temperature change (A) and absolute*
 234 *monthly temperature changes (B). Relative seasonal precipitation changes (C) and absolute monthly precipitation changes*
 235 *(D). Red dots and the displayed percentages show ensemble mean changes. Grey dots represent single ensemble members.*
 236 *Right panels show model ensemble uncertainty bands of 25th and 75th percentiles.*

237

238 **3.2 Declining yield levels under climate change**

239 Both models show that climate change will lead to a substantial reduction of future yield levels in the
 240 study area. Under current CO₂ concentrations, mean yield levels are projected to decrease by up to -
 241 24% (±12%) under the high emission and mid-century scenario (Fig. 4A, light grey bar, RCP 8.5 2041-
 242 50). Despite their differences in predicted magnitudes of yield declines (SWAT: -32% (±12%) and
 243 APSIM: -16% (±2%)), the models agree in their trends (sign) and show increasing yield losses with
 244 increasing temperatures for all crop types (Fig. 4B-4D). Considering that water demand is assumed to
 245 be met, these results underline that the increasing temperature stress alone will have a strong
 246 negative effect on crop growth, which is in-line with findings of previous studies (Deryng et al., 2014;
 247 Saddique et al., 2020; Siebert and Ewert, 2014; Zhao et al., 2017).



248

249 *Figure 4: Projected changes in future crop yield under the RCP 4.5 and RCP 8.5 scenario, neglecting (light grey bars) and*
 250 *considering (dark grey bars) the impact of CO₂ changes. Results are shown for all crops combined (A) as well as separately*
 251 *for cotton (B), maize (C) and rice (D). Filled bars show the model ensemble median and black error bars show the respective*
 252 *25th and 75th percentiles of the model ensemble (SWAT and APSIM with nine climate models). Separate results for SWAT and*
 253 *APSIM models are shown as colored dots (median) and error lines (25th and 75th percentiles for the model ensemble of nine*
 254 *climate models).*

255

256 Accounting for increasing CO₂-concentrations (Fig. 4, dark grey bars) dampens the negative impact of
 257 the temperature increase on yields, revealing the significant positive effect of higher CO₂ levels on
 258 agricultural productivity due higher photosynthesis rates, also known as CO₂-fertilization. For the
 259 short-term scenario (2021-2030), increasing CO₂-concentrations prevent the strong decline in
 260 simulated crop yields. This is generally in-agreement with previous studies showing this strong
 261 positive effect of increasing CO₂ concentrations on plant growth and its ability to counteract plant
 262 growth limiting effects (Parry et al., 2004). Yet, the effectiveness of CO₂-fertilization is still a large
 263 source of uncertainty (Elliott et al., 2014; McGrath and Lobell, 2013). In the context of our study,
 264 uncertainty arises through the differences in representing CO₂-impacts on plant physiology by SWAT
 265 and APSIM. The hydrological SWAT model does not account for plant type specific impacts of CO₂
 266 (e.g. different reactions of C3-plant and C4-plant) and might overestimates the positive effects of CO₂

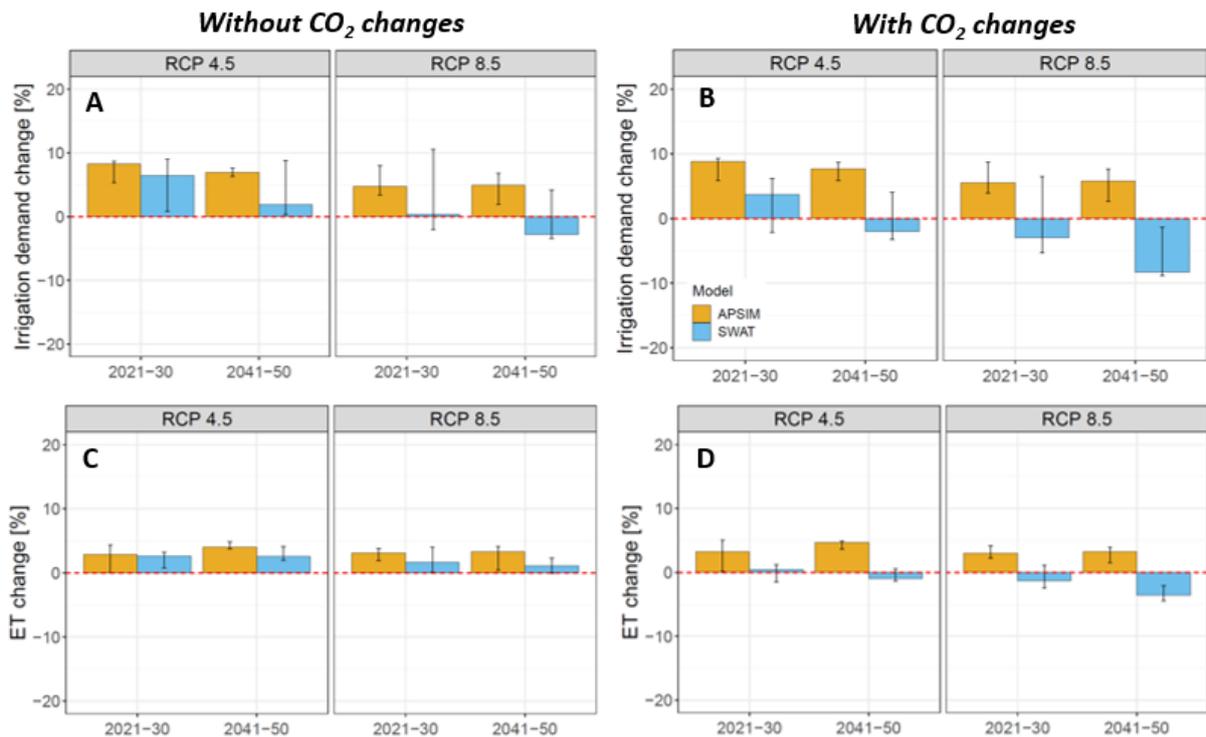
267 (Wu et al., 2012). The APSIM crop models, on the other hand, consider plant specific impacts, e.g. the
268 maize-model (Fig. 4C) correctly assumes maize-insensitivity to changing CO₂ effects (maize = C4-
269 plant). In the case of cotton, which shows a lower yield reduction than rice and maize, the enhanced
270 productivity under rising CO₂ levels even leads to an increasing yield (Fig. 4B). The sensitivities of rice
271 and SWAT-maize yield to CO₂-concentrations are comparable, but their yield reductions due to
272 temperature stress are too severe for increasing CO₂ emissions to compensate (Fig. 4D).

273 Overall, APSIM results show declining yields even for the short-term future, indicating that elevated
274 CO₂ concentrations are not able to compensate for reduced yield due to higher temperature stress.
275 Under further rising temperatures (2041-2050), both models project decline in crop yields (-8%
276 (±9%), RCP 4.5 and -7% (±12%), RCP 8.5); and disclose that even with further elevated CO₂-
277 concentrations and unlimited water availability climate change induced yield declines cannot be
278 prevented. All estimated crop productivities show that yields are expected to benefit less from
279 increasing CO₂ levels, as temperatures continue to rise (Fig. 4B).

280 Previous studies have indicated that increasing CO₂ improves water use efficiency by reducing plant
281 transpiration which facilitates plant growth during dry/drought conditions (Wullschleger et al., 2002;
282 Yoo et al., 2009). At the same time, it has been also reported that reduced plant transpiration leads
283 to increased temperature stress, due to a reduced evaporative cooling effect (Siebert et al., 2014;
284 Vanuytrecht et al., 2012). Both these effects are not covered presently by either of the models. As
285 the strong increase in future temperature is projected under both RCPs and together with abundance
286 of water due to irrigation, the positive effect of CO₂ on yield levels is most likely overestimated by
287 both crop models. Recently, Wang et al., 2020 noted the positive effects of CO₂ tend to be
288 overestimated by crop models based on their analysis of a global reduction in CO₂ fertilization effect
289 on vegetation photosynthesis, which most models do not account for.

290

291 ***3.3 Future irrigation and evaporative demand***



292

293 *Figure 5: Projections of future irrigation demand (A and B) and future ET rates (C and D). Changes under the baseline CO₂-*
 294 *scenario (A and C) and with increased CO₂-levels (B and D).*

295 In the following, we discuss the reasons behind the estimated yield declines based on changes in
 296 irrigation demand, evapotranspiration, leaf area index and biomass productivity. Results presented
 297 here are averaged over the selected summer crops cotton, maize and rice. Crop specific results are
 298 presented in the supplementary material (Supplementary Figures S4-S5).

299 Considering the significant temperature increase one would expect a strong increasing signal in plant
 300 water demand (Döll, 2002; Wada et al., 2013). Examining irrigation and evaporative demands in the
 301 study area, however, reveals that trends in future water demand do not align with projected
 302 temperature trends. Increasing water demands are surprisingly moderate and do not increase by
 303 more than 5% (average of both models; Fig. 5C). Against the expectation of a strong increase in
 304 irrigation needs under rising temperatures, both crop models show that average irrigation demands
 305 increase less under higher temperatures. Under both emission scenarios, a maximum increase is
 306 predicted for the moderate scenario (RCP 4.5, 2021-2030) while a minimum increase is predicted for
 307 the high-end emission scenario (RCP 8.5, 2041-2050). Figure 5 displays the results for APSIM and
 308 SWAT separately to reveal important differences in their simulation results. SWAT projects the

309 lowest increase in water demand for the RCP 8.5 and mid-term future scenario ($1\pm 8\%$). Under
310 elevated CO_2 concentrations (Fig. 5B), water demand even further reduces ($-4\pm 7\%$), which generally
311 agrees with the effect of reduced plant water demand due to reduced stomatal conductance (Kimball
312 et al., 2002).

313 The APSIM model simulated irrigation demand appears insensitive to CO_2 changes, as irrigation
314 demands remain constant regardless of changes in CO_2 levels (Fig. 5A vs. 5B). Yet, the significant
315 increase in LAI (leaf area index) under elevated CO_2 levels (see below, Fig. 6B) and the negligible
316 change in irrigation demand illustrates that the APSIM model likewise account for the positive CO_2
317 effects on water demand and show decreasing irrigation demands relative to leaf area growth.

318 The reason for the surprisingly low increase in irrigation demand can be explained by the low
319 increase in actual evapotranspiration (Fig. 5C and 5D), which prevents irrigation demands to
320 significantly increase. Despite the strong temperature rise, increases in ET are projected by both crop
321 models to stay on average below 3% ($\pm 4\%$), and do not increase with higher temperatures, even
322 under the assumption of unchanged CO_2 emissions.

323 Noting that water supply is guaranteed in both crop models, the low ET rates under rising
324 temperatures cannot be related to water shortages and should be explained by ET controlling plant
325 parameters, such as LAI and biomass production (as discussed below in the following section). The
326 limited changes in water demand also reveal that even if more water for intensified irrigation activity
327 would be available, it would not help to reduce yield losses.

328 ***3.4 Future plant growth and agricultural productivity***

329 The SWAT model estimates LAI development based on the influence of the predominant
330 environmental stress factor (Neitsch et al., 2009), i.e. heat stress in this study. This results in a
331 significant reduction in LAI by up to -27% ($\pm 6\%$) under the high-emission scenario (RCP 8.5, 2041-
332 2050). The decreasing LAI trend clearly follows the increasing temperature trend, with highest LAI
333 reductions under the RCP8.5 scenario (Fig. 5A) and confirms the LAI sensitivity towards temperature.

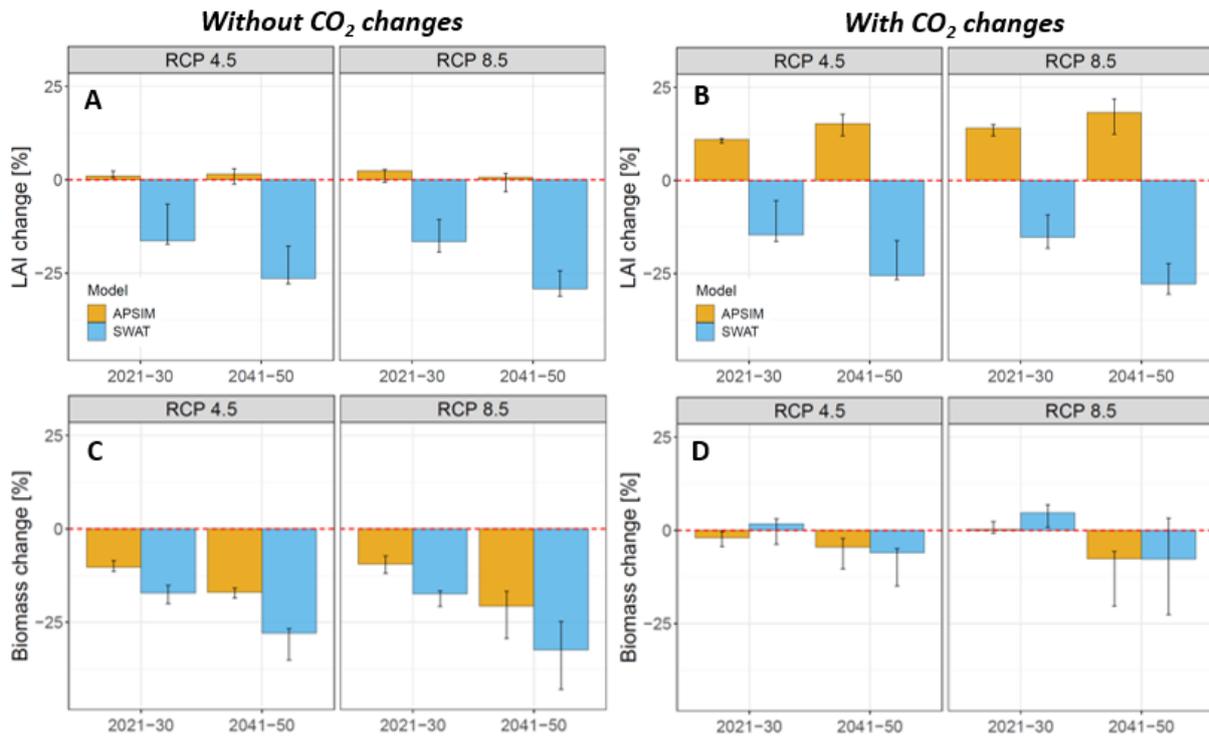
334 In combination with the reduction of stomatal conductance, a significant decline in LAIs therefore
335 seems to be one of the main reasons for the overall low ET rates simulated by the SWAT model
336 under high temperatures (Fig. 5C). LAI calculations in SWAT do not account for CO₂ effects (Fig. 6A vs
337 6B), which leads to strong LAI decreases even under higher CO₂ concentrations (Fig. 6B) and to
338 decreasing ET rates (Fig. 5D).

339 APSIM on the other hand, which does not account for a specific heat stress factor in parts of its LAI
340 calculations, shows a clear LAI insensitivity to temperature (Fig. 6A and 6B). Yet, APSIM-LAI
341 predictions show a notable sensitivity to CO₂-concentrations and increasing leaf growth under rising
342 CO₂ levels. APSIM based simulated LAIs are projected to increase by up to 15% ($\pm 10\%$) under the high
343 emission scenario, which explains why APSIM-ET rates do not decrease despite ET reducing CO₂-
344 effects (Fig. 5D). Similar effects were described recently by Singh et al., 2020, revealing a strong
345 increase in LAI due to CO₂ increases which can offset higher water use efficiency.

346 As the leaf area growth and temperature increase jointly control the evaporative demands and
347 ultimately irrigation water needs, the differences in LAI projections underline the importance of
348 model sensitivity with respect to temperature stress. These differences in the underlying model
349 parameterizations between both models leads to two different conclusions. On the one hand, the
350 SWAT model projects a decline in future plant growth, which is strong enough to reduce ET and
351 irrigation demand -- this leads to the conclusion that irrigation intensification cannot help to mitigate
352 future yield losses. APSIM on the other hand, forecast increasing leaf area growth and indicates that
353 due to its (even if only moderately) rising irrigation demands, intensified irrigation is necessary to not
354 further strengthen the predicted yield losses.

355 The apparent inconsistency in decreasing LAI and at the same time increasing biomass in SWAT
356 under elevated CO₂ concentrations (Fig. 6B and 6D) can be explained by the sensitivity of biomass
357 production in SWAT to changes in CO₂. In SWAT, the biomass production is dependent on radiation
358 use efficiency and available light for photosynthesis (see Supplementary Material S.2.1.1). While the
359 availability of light is dependent on LAI development, radiation use efficiency is positively affected by

360 changes in CO₂-concentrations (Neitsch et al., 2009). Increasing CO₂ concentrations thus enhance
 361 biomass production. In this study, this biomass enhancing effect is stronger than the negative effect
 362 due to decreasing LAI (SWAT results Fig. 6D, RCP 4.5). Yet, for RCP 8.5 and a further temperature
 363 increase, this effect is dominated by a further reduction in LAI, leading to a reduction in biomass even
 364 under further elevated CO₂ concentrations (Fig. 6D).



365
 366 *Figure 6: Projections of future LAI changes (A and B) and future biomass changes (C and D). Changes under the baseline CO₂-*
 367 *scenario (A and C) and with increased atmospheric CO₂-levels (B and D).*

368 Despite their differences in LAI estimation procedures, both models show that even if the increased
 369 future water demand is fulfilled, a substantial reduction in plant biomass (and thereafter yields) due
 370 to increasing temperatures is projected in future (Fig. 6C). To this end, both models show a good
 371 agreement in their predicting trends. Rising CO₂ levels might compensate negative temperature
 372 effects in the near future but already for the mid-century scenario (2041-2050), biomass is projected
 373 to decline despite further elevated CO₂ levels (Fig 6D).

374 The reason for the discrepancy between increasing LAI predictions and decreasing biomass estimates
 375 by APSIM, can be found in the way APSIM accounts for biomass partitioning processes. As a
 376 biophysical crop model, the APSIM model accounts for carbon assimilation in different plant parts

377 (i.e. leaves, stem, fruit). Leaf area can therefore remain constant or even increase while the overall
378 biomass decreases (APSIM model documentation, 2021).

379 Recalling that both models assure a sufficient supply of irrigation water to meet changing water
380 demands, our results reveal that temperature stress alone is responsible for the simulated yield
381 declines in this study. We therefore conclude that increased water use has a strong limit in mitigating
382 future yield losses. Intensification of irrigation might be able to mitigate yield declines in the near
383 future, when positive CO₂ effects balance the harmful temperature effects and irrigation demands
384 are still increasing (Fig. 5B). For the mid-century scenario however, when positive CO₂ effects are no
385 longer sufficient and irrigation demand decrease, irrigation intensification will not be able to mitigate
386 the projected yield losses.

387 It should be mentioned that our deductions are based on the average trends estimated for maize,
388 cotton, and rice crops. Plant specific reactions should be considered, when impacts on individual crop
389 types are the focus. The effects of climate change on each crop type showed that even though crop
390 reactions differ, they agree in their overall responses to temperature stress and sensitivity to CO₂
391 (see Supplementary Section S3 for details). The exception to this general trend is the maize crop
392 simulated by the APSIM model due its particular physiologies as a C4-plant (Supplementary Section
393 S3).

394

395 **4. Conclusions**

396 The main finding of our study is that under the expected climate change scenarios a substantial
397 reduction in summer crop yields is likely to occur in the study region, even though enough irrigation
398 water is assumed to be available. It could be shown that plant development is dominantly controlled
399 by temperature stress and that therefore the negative climate change impact on agricultural
400 productivity cannot be mitigated by an intensification of irrigation.

401 Assuming a constantly satisfied plant water demand, our results indicate that in the intensively
402 irrigated agricultural system we looked at, the limit of additional water as adaptation measure could
403 be reached in the near future. The dominant future factor, likely causing a substantial yield decline,
404 seems to be plant heat stress. Under these circumstances, temperature related adaptation strategies
405 such as the selection of more heat resistant crops, or changes in crop planting schedules to avoid
406 high temperature stress seem more suitable than water related adaptation measures.

407 The results contradict previous studies, which suggest that increased irrigation amounts can help to
408 reduce crop heat sensitivity in such a way that it partially or even entirely offsets temperature
409 induced yield reduction (Shaw et al., 2014; Tack et al., 2017; Zaveri and Lobell, 2019). However, these
410 studies also argue that yield gains from intensified irrigation have already slowed down in recent
411 years and that the application of more water has its limits as a potential adaptation strategy to
412 prevent harmful effects of rising temperatures.

413 Finally, by using two crop models from two different scientific disciplines, this study showed that
414 while both models agree in their overall yield simulations, their predictions of future water demand
415 and the capability of irrigation to counteract the dominating temperature stress can vary
416 significantly. Hence, when using models as decision support systems for future water resources
417 planning, it needs a careful examination of their respective model structures and especially their
418 sensitivities with respect to temperature stress in order to draw the reliable conclusion about future
419 irrigation demands.

420

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433 **Data Availability Statement**

434 The data produced in this study can be accessed through the following data repository:

435 <https://doi.org/10.5281/zenodo.4603703>

436

437

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