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CLIMATE CHANGE

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Modelling climate change impacts on wet and dry season rice in Cambodia

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Abstract

Irregular rainfall, rising temperatures and changing frequency and intensity of extreme weather events are projected to reduce crop yields and threaten food security across the tropical monsoon sub-region. However, the anticipated extent of impact on crop yields and crop water productivity (CWP) is not yet thoroughly understood. The impacts of climate change on rice yields and CWP are assessed over the Northern Tonle Sap Basin in Cambodia by applying the AquaCrop model into the mid- (2041–2070) to long-future (2071–2099) under two Representative Concentration Pathways (RCPs) (4.5 and 8.5). Short (95 days), medium (125 days) and long (155 days) cycle varieties are tested during the wet and dry seasons. An assessment of different sowing dates and irrigation strategies (fixed and net irrigation during the dry season) elucidated the variation in response to changing environmental conditions. Higher yields (+15% by 2041–2070 and +30% by 2071–2099) and CWP values (+42% by 2071–2099) are expected if using short-cycle varieties, in particular when sown in July. Dry season rice yields are also projected to increase (+28% by 2071–2099), especially under a higher greenhouse gas emission scenario (RCP 8.5) compared to a medium emission scenario (RCP 4.5) as a result of the CO_2 fertilization effect. Depending on the climatic scenario, rice variety, irrigation scheme, and sowing date, increasing heat and drought-stress conditions are likely to have different impacts on rice yields and CWP over time. Overall, this study highlights the benefits of adjusting crop calendars to identify the most suitable irrigation schedules and rice varieties to effectively adapt to projected future climate.

KEYWORDS
agricultural meteorology, AquaCrop, climate risks, crop water productivity, food security

Key Points

- Rice is a stable crop ensuring food security in Cambodia
- Adverse climate change impacts are expected on rice production if appropriate agriculture transformation and adaptation to climate change are not considered.
- C_3 crops (rice) may benefit from the CO_2 fertilization effect, mostly under irrigated conditions

1 | INTRODUCTION

The agricultural sector contributes to 20.8% of Cambodia's gross domestic product, and crop production accounts for 57.7% of this sector, followed by fisheries, livestock, and forestry (MAFF, 2020a; MAFF, 2020b). Rice (*Oryza sativa* L.) is of high importance for food security in Cambodia. National estimates indicate a harvest area of 3.0 million hectares (ha) and a production of 10.9 million tonnes in 2019 (FAO, 2021a). Wet season rice accounts for more than 80% of the national rice production (FAO, 2021b). Rice production, processing, and marketing employ 3 million people, equivalent to 20% of the country's workforce (IFC, 2015) and is the backbone of subsistence farming. While the production of wet season rice extends across the country, dry season rice is found in areas where water resources are abundant (Takeo, Prey Veng, Kandal, Kampong Thom and Banteay Meanchey provinces) and often using high-yielding varieties. Over the past decades, an improvement in rice yields is observed among smallholder farmers benefiting of enhanced irrigation infrastructure, extension services, agricultural inputs, and rising market demand. As a result, national rice yields have improved from 2.1 tons/ha in 2000 to 3.3 tons/ha in 2019. In addition, the national irrigated areas (wet and dry season rice) have been estimated at 1.8 million ha in 2018 (RGC, 2019). However, the irrigation infrastructure faces many operational and maintenance challenges and water delivery has not reached many remote areas of Cambodia. This has posed water constraints and significant risks in rice areas furthest from the primary canal network, besides generating water management conflicts among downstream and upstream water users (Sithirith, 2017).

According to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment report on climate change (IPCC, 2021), there is high confidence in the weakening of the Southeast Asia monsoon in the second half of the 20th century. In the near term, South and Southeast Asian monsoon is likely to be dominated by the effects of internal variability, while temperature rise is expected to be lower than the global average increase. In Cambodia, future changes in river flow are projected to decline in a medium to high-emission scenario (RCP 6.0) (Oeurng et al., 2019). Out of all the rivers within the Mekong River Basin, the water levels of the Tonle Sap Lake tributaries are anticipated to experience the greatest water decline. These changes in water levels are attributed to shifts in seasonal rainfall distribution and prolonged dry periods.

Translating the aforementioned climate trends into potential impacts on crop yields requires the use of well-parameterized crop models. Such models have been used in this region to evaluate climate change impacts on rice production and to strengthen agricultural adaptation interventions (Boonwichai et al., 2018; Boonwichai et al., 2019; Chhogyel et al., 2020; Hayashi et al., 2018). For example, Masutomi et al. (2009) foresee an −11.7% (Vietnam), −8.2% (Thailand) and −0.5% (Myanmar) decrease in rice yields by 2080 under the A1B fossil intensive scenario. Another study shows how improved irrigation and CO_2 fertilization effect may increase rice yields by +8.2% to +42.7% in Cambodia and Thailand under RCP 8.5 by 2080 (Chun et al., 2016). In this line, Kontgis et al. (2019) confirm a decrease in rice yields along the Vietnamese Mekong Delta, where increasing water and fertilizer application is not sufficient to offset yield decline, except when accounting for the CO_2 fertilization effect. Another study using five global climate models (GCMs) projects a notable decrease in rainfed rice production for three GCMs, with small changes in two GCMs (Tsujimoto et al., 2022). The CROPWAT model has also been tested on rice along the lower Mekong River Basin (Mainuddin & Kirby, 2009). Matthews et al. (1997) evaluated the impact of climate change and increasing atmospheric CO_2 concentration on Asian rice yields. The results suggest yield changes ranging from +6.5% to −5.6% and from +4.2% to −12.8% over the century, respectively when using the ORYZA1 and SIMRIW models.

AquaCrop is a crop-water productivity model developed by the Food and Agriculture Organization (FAO) of the United Nations, supporting food security by identifying environmental constraints that affect crop production and crop water productivity (CWP). In Cambodia, the AquaCrop model has been applied to assess climate change impacts on lettuce (Ket et al., 2018) and maize (Na et al., 2017), but has not yet been tested on rice. Previous studies indicate an overestimation of heat sterility in arid environments when using ORYZA2000 model (van Oort et al., 2015). The successful implementation of AquaCrop in numerous South and Southeast Asian countries supported the model selection for this study (Maniruzzaman et al., 2015; Mondal et al., 2015; Xu et al., 2019). Furthermore, over the 1993–2004 period, a lower rice productivity has been observed in Laos, Thailand and Cambodia presumably as a result of the combination of lower rainfall, longer dry periods, poorer soil fertility, cultivation of local varieties, and inadequate field management practices. Similarly, analysis of Global Agro-Ecological Zoning V4 shows stable to moderate decreases in yield productivity in Laos, Thailand and Cambodia under low (RCP 2.6) to high (RCP 8.5) emission scenarios (Fischer et al., 2021).

The aforementioned studies have either examined the regional impacts of climate change on rice production and/or focused on rainfed lowland rice production without assessing climate impacts on dry season rice. Our study fills the gap in the literature by assessing the main climatic drivers (atmospheric CO_2, temperature and precipitation) posing a risk to rice production both during the wet and dry season in an agriculturally important basin in Cambodia. To do so, we consider local projections of several climate variables for site-specific areas of Cambodia under two RCPs (4.5 and 8.5) from 2017 until 2099. This approach allows us to determine the effect of abiotic stresses on rice yields and on water consumption. In sum, a comprehensive analysis is presented by testing different sowing dates and varieties, allowing a comparison between treatments and the identification of most suitable sowing dates and irrigation strategies that increase the efficiency of agricultural water use in a sustainable manner, both in rainfed and irrigated fields.

2 | MATERIALS AND METHODS

2.1 | Site description

According to the Köppen climatic classification, Cambodia has a tropical monsoon climate (Kottek et al., 2006). Total annual precipitation exceeds 1400 mm/year in central lowlands and reaches 4000 mm/year in coastal zones and/or highlands (Thoeun, 2015). The Tonle Sap Basin is characterized by warm year-round temperatures (28°C), higher before the start of the monsoon season (March and April) and lower during the boreal winter (December–February). Intense monsoon rains occur during May–October, carrying abundant organic matter and nutrient-rich sediments deposited along the floodplains (Marcaida III et al., 2021).

AquaCrop simulations are ran along the four eastern provinces (Oddar Meanchey, hereafter location 1; Preah Vihear, location 2; Kampong Thom, location 3; Siem Reap, location 4) around the Tonle Sap Lake (Figure 1). The Tonle Sap Basin is one of the most important agricultural zones in Cambodia. About a fifth of the cereal production and a third of the national agricultural households are found along the Tonle Sap Lake and surrounding provinces (NIS, 2015; NIS, 2020). Due to suitable agroclimatic conditions, the majority of rice production occurs along the Tonle Sap basin (Figure 2). Three varieties of rice are grown during the wet season (early-, medium-, and late-maturing varieties) and one over the dry season (early maturing).

2.2 | The AquaCrop model

To estimate climate change impacts on rice production and to assist management decisions in both irrigated and rainfed agriculture we used the AquaCrop model. The model considers crop responses to climate change via the standard simulation of crop responses to water and temperature (stresses) in combination with the responsiveness of transpiration and biomass production (through the Water Productivity parameter [WP*]) to atmospheric CO_2 concentration (Vanuytrecht et al., 2011). In brief, the increase in CO_2, which induces CO_2 fertilization, reduces the crop transpiration and increases the biomass water productivity (Raes, 2017). In addition, the model uses thermal units for calculating the growing degree days and determining crop development and the length of different phenological phases (Raes, 2017). Thus, when using thermal units to parametrize crop development, the model is capable of detecting an acceleration of phenological phases linked to warmer temperatures. However, since the purpose of this study is to assess the impact of climate change on different growing cycles, growing calendar days have been selected instead of growing degree days.

In addition, the AquaCrop model simulates yield in four steps: (i) crop development, (ii) crop transpiration, (iii) biomass production, and (iv) yield formation. The first step, the development of the green canopy cover, is simulated by the fraction of the soil surface covered by the canopy. Secondly, the crop transpiration is calculated by multiplying the reference evapotranspiration by the crop coefficient that depends on the canopy cover. In this case, water stresses not only affect the canopy development but may also induce stomata closure and affect crop transpiration. The third step estimates the above-ground ground biomass production, proportional to the cumulative water transpired by the crop. Then, through the harvest index, which is the fraction of harvestable product to above-ground ground biomass, the crop yield is obtained. Lastly, if there are any water and temperature stresses during the growing cycle, the reference harvest index is altered, and consequently, the magnitude and duration of the stress determines the overall effect on the harvest index.

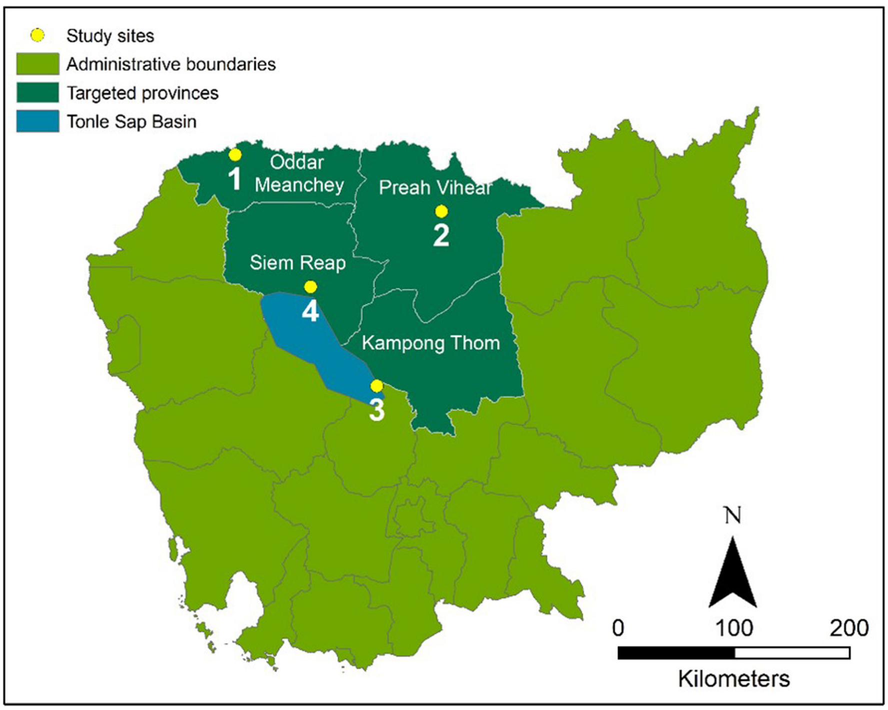

FIGURE 1 The four sites considered in this study

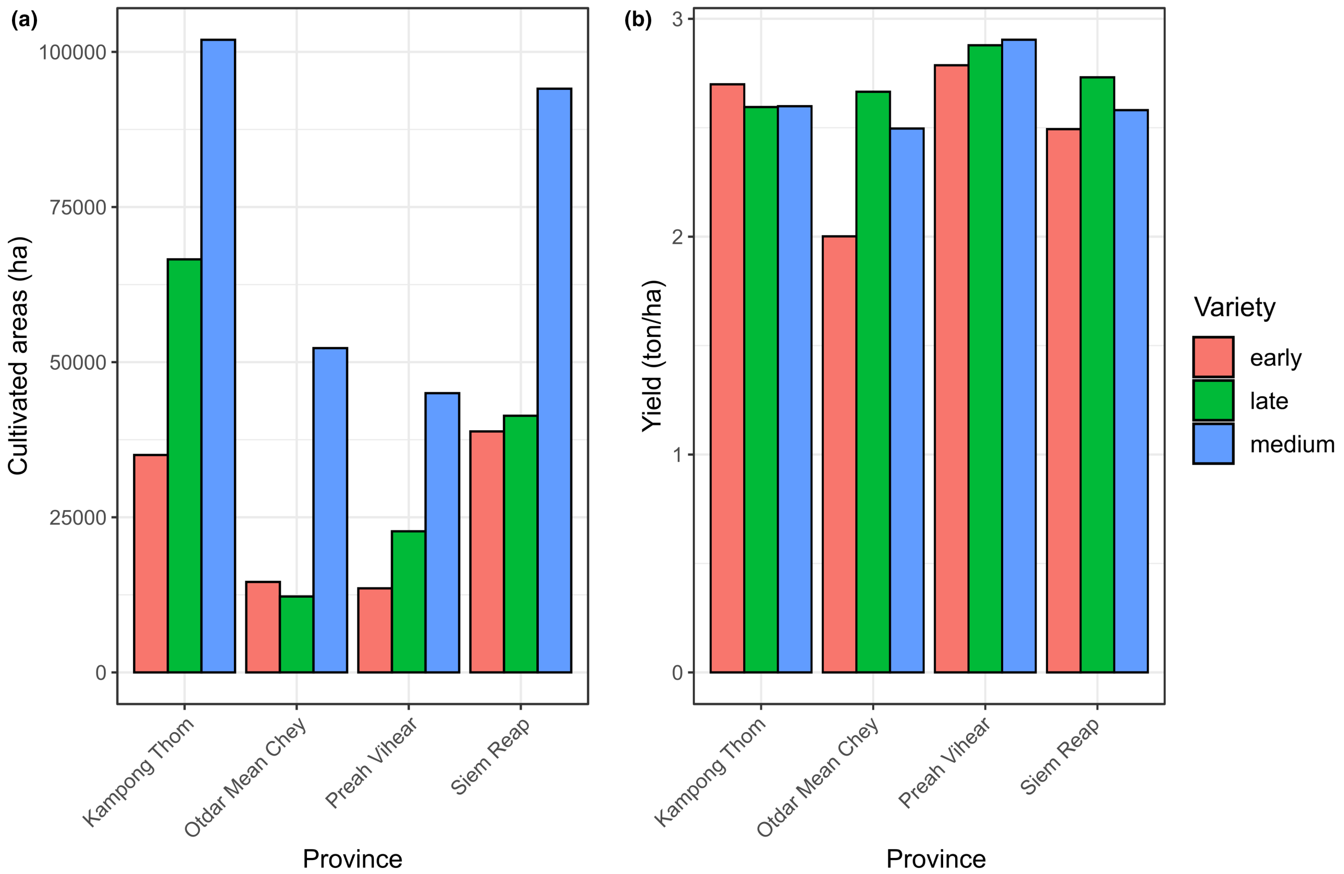

FIGURE 2 Cultivated area (a) and average yields (b) from 2014 to 2019 of early-, medium-, and late-maturing rice varieties during the wet season along the four sites of interest (MAFF, 2020a; MAFF, 2020b)

A validation of model outputs is done using yield data for the 2014–2019 period. We first validate model outputs with field observations, and afterwards, simulate crop responses into the future. Lastly, an analysis of the model outputs is done using the adjusted-R^2, which is a corrected goodness (model accuracy) of fit measure for linear models that allows the user to identify the percentage of variance in the output variable (yield) explained by the input variable (rice variety, location, sowing date, and RCP).

2.2.1 | Weather parameters

In this work, we considered daily maximum and minimum temperature, precipitation, wind speed, and solar radiation, derived from the COnsortium for Small-scale MOdelling (COSMO) model in CLimate Mode (CCLM) version 5–0-2 (Sørland et al., 2021). The CCLM5 regional climate model was driven by the CNRM-CM5 global climate model (Voldoire et al., 2013) within the framework of the Coordinated Regional Downscaling Experiment (CORDEX), providing dynamically downscaled (at 0.44° spatial resolution) outputs over the East Asian (EAS) domain (Giorgi A Gutowski Jr, 2015). In addition to the historical scenario (which ends in 2005), two future Representative Concentration Pathways (RCPs, which extend up to 2100) accounting for different socio-economic and emission scenarios were considered, namely, the RCP 4.5 (Clarke et al., 2007) and the RCP 8.5 (Riahi et al., 2011). While the former assumes a radiative forcing of 4.5 w/m^2 and 550 CO_2 ppm by 2100, the latter reaches 8.5 w/m^2 and 1000 CO_2 ppm by the end-century. Furthermore, to remove systematic model biases (see, e.g., Sørland et al., 2021 and references therein), the future simulations provided by the CCLM5 were re-scaled based on the differences (quotient for the case of precipitation) between the observed and simulated means over the 1979–2005 period. To do this, the WFDE5 (Cucchi et al., 2020) dataset, which provides daily reanalysis data for different meteorological variables at 0.5° resolution globally for the 1979–2016 period, was used as a historical reference. The nearest WFDE5 grid box was employed in each of the four sites. Then, the reference evapotranspiration (ETo) was calculated based on the approximated Penman Monteith equation (Raes, 2017). Note that WFDE5 builds on the ERA5 reanalysis (Hersbach et al., 2020) and was calibrated using the WATCH Forcing Data methodology, having proved suitable for hydrological and crop modelling purposes across the world (see, e.g., Cucchi et al., 2020 and references therein) and supporting impact assessments of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b).

2.2.2 | Crop parameters

The crop file prepared in AquaCrop included crop-specific parameters related to crop management strategies (plant density and method), crop development (phenological stages), crop production (harvest index) and crop's responses to abiotic stresses (water, temperature and soil fertility). In this study, a blend of primary and secondary data sources (Table 1) were used to parametrize crop parameters (CARDI et al., 2017; Flor et al., 2018; Poulton et al., 2015; Raes et al., 2010). Additional field data on crop development supported the previous, including observations on plant phenology provided by the Ministry of Agriculture, Forestry, and Fisheries (MAFF) of Cambodia for the purpose of this study (Table 1).

Three rice varieties with different sensitivity to photoperiodicity were simulated: short (95 days), medium (125 days), and long (155 days) cycle. Simulations using short-cycle varieties were run over the wet and dry season, whereas medium- and long-cycle varieties were simulated over the wet season. To develop strategies that reduced crop's exposure to abiotic stresses, increase yields, and crop water productivity, four sowing dates at 15-day intervals were selected over the wet season (from 15 June until 1 August) and three over the dry season (from 1 November until 1 December). In addition, based on a search of literature, maximum temperatures above 35°C were considered detrimental for the pollination of rice, and consequently parametrized on AquaCrop as the threshold at which heat-stresses started to occur (Julia and Dingkuhn, 2013; Kobayasi et al., 2010; Shah et al., 2011; Yoshida et al., 1981). Lastly, the threshold at which water stresses affected the canopy expansion, stomata closure, and early canopy senescence was retrieved from a 2-year experimental study conducted in low-lying areas of the Terai, Nepal (Shrestha, 2014).

2.2.3 | Soil parameters

The soil file in AquaCrop included information about the soil horizons, soil texture, field capacity, permanent wilting point, saturated hydraulic conductivity, and volumetric content at saturation. If only the soil texture class was available, default values for the remaining soil parameters were accessible in AquaCrop (Raes et al., 2013). In this work, soil information was provided by the Department of Agricultural Land Resources Management (DALRM), General Directorate of Agriculture (GDA), Ministry of Agriculture, Forestry and Fisheries (MAFF) for the four provinces of interest: Oddar Meanchey, Preah Vihear, Kampong Thom, and Siem Reap (Table 1) (White et al., 1997). To keep consistency between agroclimatic variables, we used the same geographical coordinates both for soil information and for downscaling climate information. While heavy clay soils were found in backslopes (location 3), soils with a coarse texture (sandy and loam) were present in slightly higher areas, such as levee crests or slopes (locations 1, 2, and 4).

2.2.4 | Irrigation and field management parameters

To simulate crop growth under irrigated conditions, the AquaCrop model allowed the user to apply specific irrigation options. It included the determination of net irrigation requirements as well as the generation of an irrigation schedule based upon irrigated and rainfed management strategies. The model provided alternatives for different application methods, such as sprinkler irrigation, surface irrigation, and drip irrigation. In the present study, surface (basin) irrigation was selected and where 100% of soil surface area was wetted (Table 1). In addition, to maximize production and identify constraints to crop production and water productivity, we selected different irrigation schemes. While wet season rice was simulated under rainfed conditions, dry season rice (short-cycle varieties) was run under irrigated conditions using two irrigation schemes: (i) net irrigation based on a selected threshold of allowable root zone depletion and (ii) fixed irrigation based on a time interval with fixed application depth. Under net irrigation, 20 mm of water were added to the field every time the soil reached field capacity, and this was done up until 20 days before harvesting when irrigation ceased. Under fixed irrigation, a weekly interval was used to provide the field with the sufficient amount of water to return soil–water levels back to field capacity. In addition to the irrigation module, the field management components in AquaCrop were related to fertility levels, mulching to reduce evaporation from soil surface, field surface practices, and weed management. Since rice cultivation in Cambodia was based on high-nutrient application, in this work, we did not consider soil fertility as a limiting factor for biomass production. Weed management was also calibrated as good, but not optimal, due to a high planting density making it difficult for farmers to conduct manual weeding (Flor et al., 2018).

3 | RESULTS

3.1 | Wet season rice

3.1.1 | Crop yields and crop water productivity

Figure 3 displays the yield changes (a) and crop water productivity (b) of short, medium, and long-maturing varieties for different sowing dates (15 June, 1 July, 15 July and 1 August) in the four study areas for both RCPs. The yields of medium/long-cycle varieties decline in most simulations, but differently depending on the site. For example, in locations 1 and 2, the yields of medium and long-cycle varieties decrease in 25 out of the 32 simulations (78%); whereas in locations 3 and 4, it decreases in 13 out of 32 simulations (40%). In contrast to medium/long-cycle varieties, the yields of short-cycle varieties increase in 25 out of the 32 simulations (78%). An in-depth analysis for locations 1 and 2 shows a yield improvement from 2.86 ton/ha in the near-term (2017–2040) to 3.30 ton/ha in the medium-term (2041–2070) and up to 3.78 ton/ha in the far-future (2071–2099) when sowing short-cycle varieties between the 1 and 15 July. The latter is equivalent to a 15%–30% yield enhancement by the end-century (2071–2099) compared to the baseline period (2017–2040). Furthermore, based on the adjusted-R^2, the rice variety is the most important independent

TABLE 1 Variables parametrized for short-, medium- and long-cycle varieties of rice

Inputs	Units	Value – Short-cycle observed (calibrated)	Value – Medium-cycle observed (calibrated)	Value – Long-cycle observed (calibrated)
Climate (past/future)				
Maximum temperature	°C	n/a	n/a	n/a
Minimum temperature	°C	n/a	n/a	n/a
Precipitation	mm	n/a	n/a	n/a
Wind speed	m/s	n/a	n/a	n/a
Solar radiation	w/m^2	n/a	n/a	n/a
Crop				
Development				
Plant density	Plants/ha	3,000,450	3,000,450	3,000,450
Type of planting method	-	Direct sowing	Direct sowing	Direct sowing
Initial canopy cover	-	Very high cover	Very high cover	Very high cover
Canopy size seedling	cm^2/plant	(3)	(3)	(3)
Canopy expansion	%/day	(13.2)	(7.9)	(5.7)
Canopy decline	Days	(30)	(38)	(27)
Time to recovery/emergence	Days	(7)	(7)	(8)
Time to maximum canopy cover	Days	35–55 (45)	55–75 (75)	75–95 (105)
Time to senescence	Days	105 (75)	125 (105)	145 (135)
Time to maturity	Days	100–120 (95)	120–140 (125)	140–160 (155)
Maximum Canopy cover	%	(70)	(75)	(75)
Time to flowering	Days	70–90 (60)	90–110 (90)	110–130 (115)
Duration of the flowering	Days	35 (15)	35 (17)	35 (17)
Length building up harvest index	Days	30 (30)	30 (30)	30 (30)
Max. effective rooting depth	cm	(50)	(55)	(60)
Time for maximum root depth	Days	(50)	(80)	(110)
Crop production				
Crop water productivity	kg/m^3	(19.0)	(19.0)	(19.0)
Harvest index	%	45–60 (55)	24–45 (42)	24–45 (35)
Response to stresses (water)				
Effect of crop transpiration (KcTr)	-	1.10	1.10	1.10
Canopy expansion	-	Extremely sensitive to water stress	Extremely sensitive to water stress	Extremely sensitive to water stress
Stomatal closure	-	Moderately sensitive to water stress	Moderately sensitive to water stress	Moderately sensitive to water stress
Early canopy senescence		Moderately sensitive to water stress	Moderately sensitive to water stress	Moderately sensitive to water stress
Response to stresses (temperature)				
Base temperature	°C	8	8	8
Upper temperature	°C	30	30	30
Start of heat-stress effect	°C	35	35	35
Maximum heat-stress effect	°C	40	40	40
Field				
Management				
Soil fertility stress	%	(0)	(0)	(0)
Mulches	-	(None)	(None)	(None)

(Continues)

TABLE 1 (Continued)

Inputs	Units	Value – Short-cycle observed (calibrated)	Value – Medium-cycle observed (calibrated)	Value – Long-cycle observed (calibrated)
Relative cover of weeds	%	(35)	(35)	(35)
Net irrigation (dry season)				
Method	-	Surface irrigation	n/a	n/a
Time criteria	-	Allowable depletion	n/a	n/a
Interval (up until 75 DAS)	mm	n/a	n/a	n/a
Depth criteria	-	Field capacity	n/a	n/a
Amount	mm	20		
Fixed irrigation (dry season)				
Method	-	Surface irrigation	n/a	n/a
Time criteria	-	Fixed irrigation	n/a	n/a
Interval (up until 84 DAS)	Days	7	n/a	n/a
Depth criteria	-	Back to field capacity	n/a	n/a
Amount	mm	n/a	n/a	n/a
Soil				
Location 1: texture at 0–120 cm	USDA	Loamy-sand (idem)	Loamy-sand (idem)	Loamy-sand (idem)
Location 2: texture at 0–65 cm	USDA	Loamy-sand (idem)	Loamy-sand (idem)	Loamy-sand (idem)
Location 2: texture at 65-120 cm	USDA	Clay (idem)	Clay (idem)	Clay (idem)
Location 3: texture at 0-120 cm	USDA	Clay (idem)	Clay (idem)	Clay (idem)
Location 4: texture at 0-50 cm	USDA	Sandy-loam (idem)	Sandy-loam (idem)	Sandy-loam (idem)
Location 4: texture at 50-95 cm	USDA	Sandy-clay-loam (idem)	Sandy-clay-loam (idem)	Sandy-clay-loam (idem)
Location 4: texture at 95-120 cm	USDA	Clay-loam (idem)	Clay-loam (idem)	Clay-loam (idem)

variable explaining the yield changes over time, followed by the location and sowing date (Figure 4). However, the share of variation explained by the input variable (rice variety) is not large enough (12%) to draw robust conclusions of the variation in the output variable (yield) over time.

The crop water productivity (CWP) of short-cycle varieties increases by 42% in the long-term period, and consequently, the agricultural product (yield) rises without increasing water inputs. Although, there are not yield and CWP differences between future climate scenarios (RCPs 4.5 and 8.5), there are notable differences between different growing cycles. For instance, the CWP of short-cycle varieties rises from 1.09 to 1.55 kg of seed per m^3 of water evapotranspired when the near (2011–2040) and far-future are compared (2071–2099). In contrast to short-cycle varieties, the CWP of medium/long-cycle varieties decreases from 0.69 to 0.61 kg/m^3 and from 0.32 to 0.21 kg/m^3 when the average of both RCPs in the near (2011–2040) and far-future are compared (2071–2099). While 15 June is a more suitable sowing date for medium/long-cycle varieties, short-cycle varieties outperform when seeding in July. However, until the mid-century, the yields of short-cycle varieties are higher when sowing in early August rather than in early July. With regards to the spatial suitability, the herein simulations confirm that location 2 is the most appropriate site for growing short-cycle varieties, followed by location 1.

3.1.2 | Impacts of future climate on wet season rice

Due to a shorter growing period, short-cycle (95 days) varieties are less exposed to more frequent and intensified weather extremes than medium- (125 days) and long-(155 days) cycle varieties. Rainfall projections show a high inter-annual rainfall variability under both RCPs, with a comparable decreasing precipitation trend (19% between 2017–2040 and 2071–2099) across all locations, rice varieties, sowing dates, and RCPs (Figure 5a). In a warmer climate, the number of days with heat-stress conditions increases, especially under RCP 8.5 (Figure 5b). The exposure to heat-stress conditions (Tmax ≥35°C) is substantial among long-cycle varieties. For example, when sowing on 15 June, the number of days with heat-stress conditions increases from 74 to 98 days/season and from 86 to 124 days/season, respectively under RCPs 4.5 and 8.5 when the near-future (2017–2040) and far-future (2071–2099) are compared. As a result, long-cycle varieties are affected by heat-stress on average 63% (RCP 4.5) and 80% (RCP 8.5) of the growing season. Although short-cycle varieties experience a lower number of days with high temperatures during the growing season, they are comparably as exposed as long-cycle varieties. For instance, if sowing on 15 June under RCP 8.5, short-cycle varieties experience heat around 88% of the growing season in the far-future (2071–2099). Despite these findings, an increase in exposure to weather hazards does not necessarily imply an

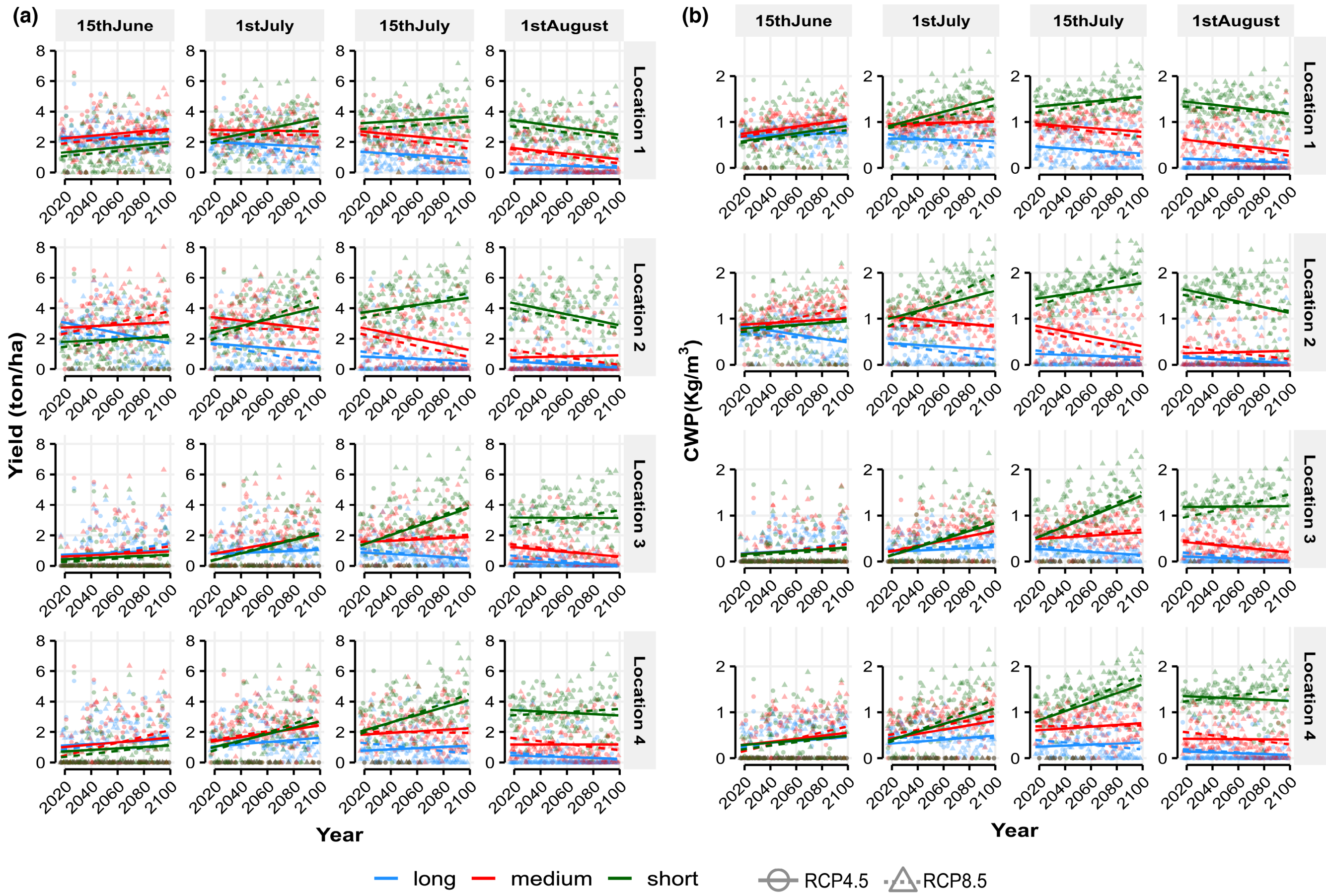

FIGURE 3 (a) Projected rice yields (ton/ha) and (b) crop water productivity (kg of yield per m^3 of water evapotranspired) during the wet season under future climate scenarios (RCPs 4.5 and 8.5) over the 2017–2099 period. Blue, red, and green circles and triangles correspond to long, medium, and short-cycle varieties under RCPs 4.5 and 8.5, respectively; while blue, red, and green straight and dotted lines correspond to the yield and CWP trends

increase in plant's sensitivity. In this line, AquaCrop allows the user to elucidate further the duration and extent of heat damage to the plant. Findings indicate that the percentage of heat-stress affecting crop transpiration is very low (close to 0) for all rice varieties, location, sowing date, and RCPs. This is because the threshold at which heat-stress starts to affect pollination occurs at 35°C, whereas full stress happens only when temperatures exceed 40°C.

3.2 | Dry season rice

3.2.1 | Crop water requirements

There are no major changes in irrigation requirements (IR) when sowing rice in November over the analysed period, though a slight increase is observed in early December under net irrigation (Figure 6). The IR of dry season rice in locations 1, 2, and 4 are considerably lower under fixed irrigation (250–400 mm/season) to that of net irrigation (600–750 mm/season). Considering the type of irrigation scheme and the much higher water-holding capacity of clay soils, the soil–water levels in location 3 are constantly above field capacity throughout the growing cycle. Due to the saturation of the soil with water, clay soils have a much higher evaporative area. The latter is reflected in the losses as atmospheric evaporation from the ground, which triple, in many cases, those of sandy and loam soils. For example, the average IR in location 3 under fixed irrigation (±500 mm/season) and net irrigation (±1000 mm/season) are 30%–50% higher to that simulated in locations 1, 2, and 4. As IR increases so does the rate of transpiration in location 3, mostly under net irrigation compared with fixed irrigation. These results are similar to the transpiration rates simulated in locations 1, 2, and 4, where crop evapotranspiration rates are in the range of 350–400 mm/season (Figure 7).

3.2.2 | Crop yields and crop water productivity

The interaction between closer to optimal growing temperatures for crop development during the boreal winter (December–February) and higher CO_2 concentrations (RCP 8.5) may have a positive impact on crop yields than moderate increases in CO_2 (RCP 4.5). Differences between RCPs are heightened in the second half of the 21st century

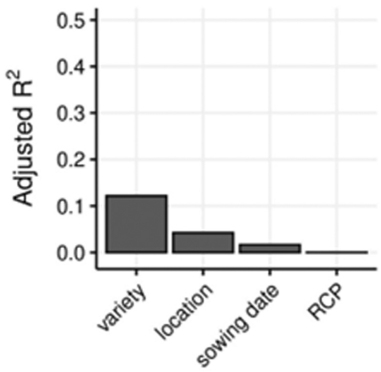

FIGURE 4 Adjusted- R^2 values for different input variables (rice variety, location, sowing date, and RCP) over the wet season. A lower adjusted- R^2 value indicates that the additional input variables are not adding value to the model. For example, if the R^2 value is 0.5, 50% of the variation in the output variable (yield) is explained by the input variables (rice variety, location, sowing date, and RCP)

compared with the first half, where yields stabilize under RCP 4.5 but continue to increase under RCP 8.5 (Figure 8a). Under RCP 4.5, the yields increase from 5.79 to 6.20 and 6.35 ton/ha when the near-term (2011–2040), medium-term (2041–2070), and far-future (2071–2099) are respectively compared. For RCP 8.5, the positive yield changes over time are larger, increasing from 5.88 to 6.67 and 7.52 ton/ha when the near (2011–2040), medium (2041–2070), and far-future (2071–2099) are compared. The latter changes are equivalent to a 13% and 28% yield improvement with regards to the near-term. There are also no major yield differences between sowing dates, with identical yield trends over time. Similar increasing yield trends are displayed in the four locations, with yields varying between 5.0 and 7.0 ton/ha when the near (2017–2040) and far-future (2071–2099) are compared, except for location 3 under fixed irrigation. The interaction between soil type (i.e., clay) and irrigation scheme (i.e., fixed irrigation) in location 3 explains, to a large extent, the potential evaporation rate compared with other types of soil texture and irrigation schemes.

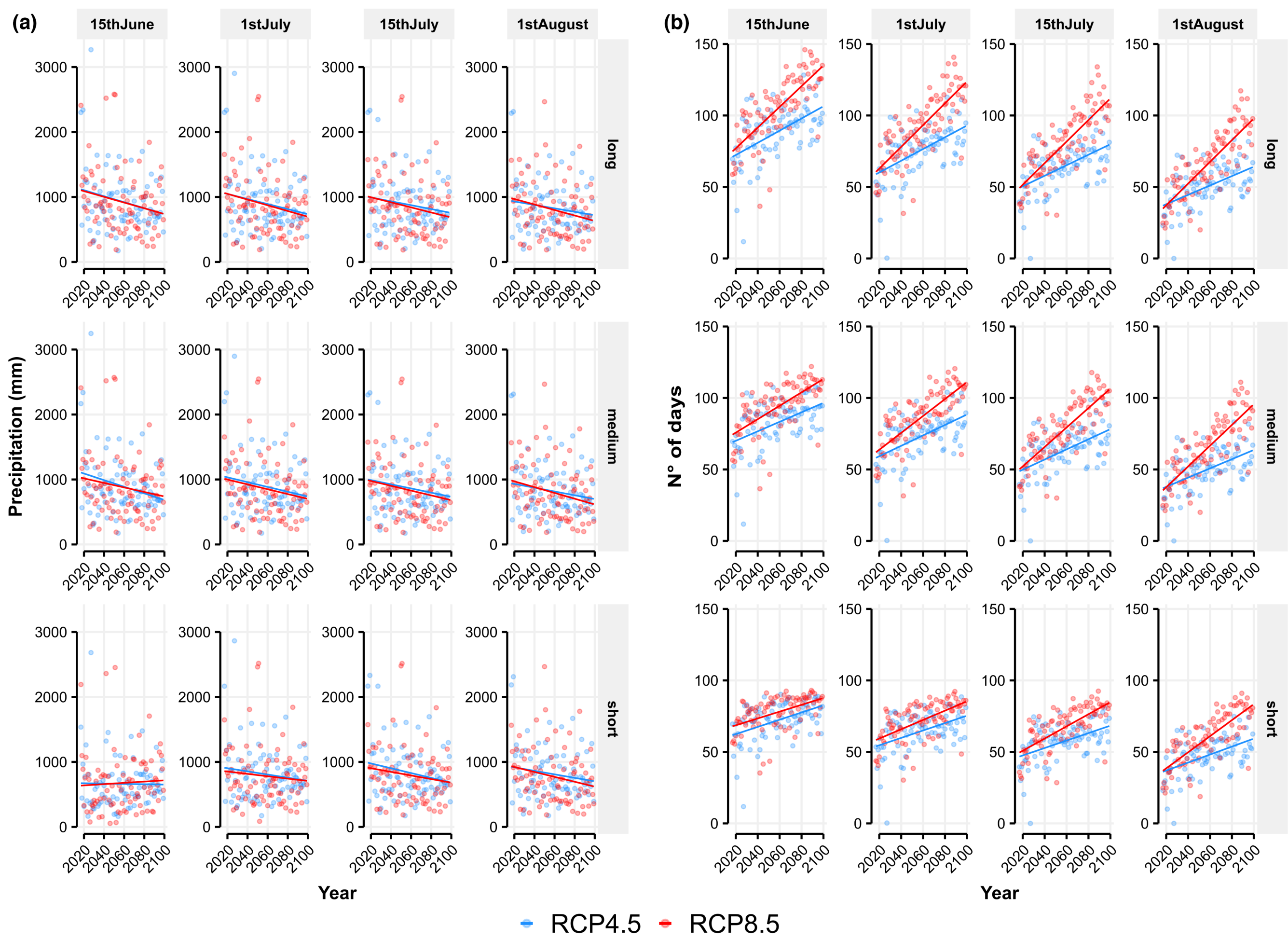

FIGURE 5 (a) Precipitation changes (mm) during the wet season and (b) number of days during the growing season with maximum temperatures above 35°C over the 2017–2099 period. Blue and red circles correspond to RCPs 4.5 and 8.5, respectively. Regressed lines are given for both RCPs. Because of the small differences in precipitation and temperature between the four locations the results are averaged

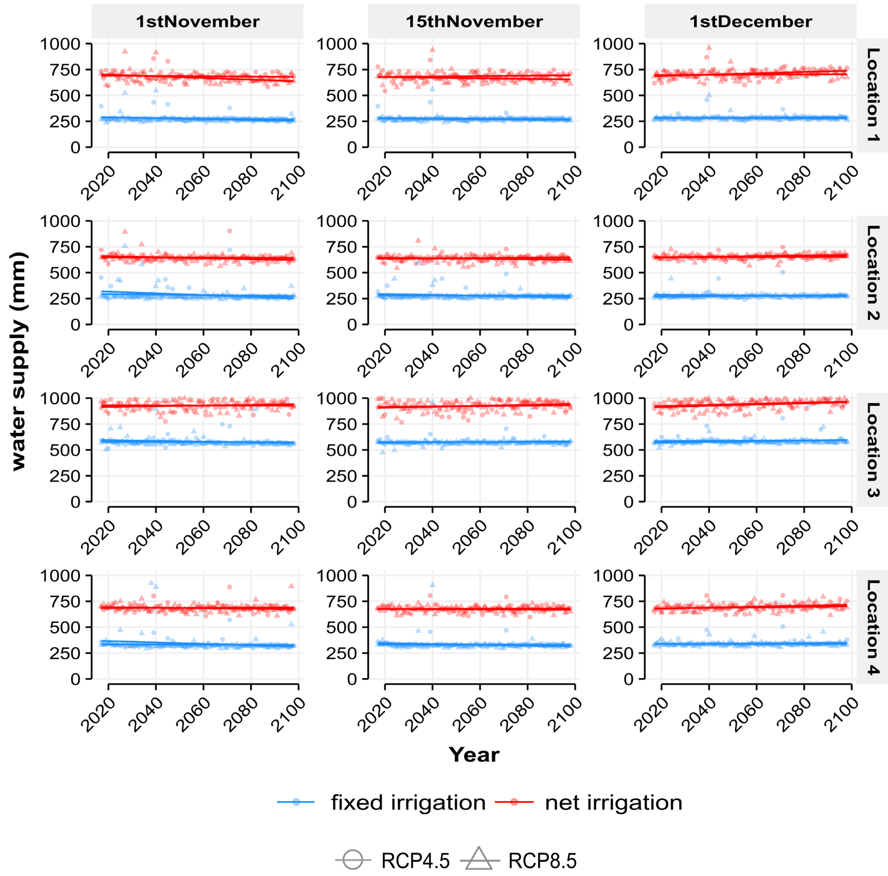

FIGURE 6 Simulated irrigation requirements (mm) during the dry season under future climate scenarios (RCPs 4.5 and 8.5) over the 2017–2099 period. Blue and red circles and triangles correspond to fixed and net irrigation under RCPs 4.5 and 8.5

AquaCrop monitors the water stress affecting the canopy expansion and resulting in stomatal closure and early senescence. For example, in location 3, while the average duration of water stress under fixed irrigation is of 61.7% (86.3% of the time reducing canopy expansion and 37.1% inducing stomata closure), in locations 1, 2, and 4 is of 22.5% (38.4% of the time reducing canopy expansion and 6.6% inducing stomata closure) average of all sowing dates and RCPs (figure not shown for brevity). In addition, the adjusted-R^2 measures the percentage of variation explained by the independent variable (Figure 9). For dry season rice, over 30% of the variation in yield over time is described by the location, followed by the irrigation scheme with 12%. While changes in future climate are comparable between locations, the yield variation is driven by differences in soil texture between locations. On the contrary, RCPs and sowing dates explain <5% of the yield variation. Lastly, minor crop water productivity (CWP) differences are expected when comparing the two irrigation schemes under both RCPs (Figure 8b). However, slightly higher CWP values are foreseen under fixed irrigation in RCP 8.5 than for net irrigation in RCP 4.5.

3.2.3 | Impacts of future climate on dry season rice

During the boreal winter, dry season rice is closer to optimal growing conditions than the wet season rice. In the near-future (2017–2040), heat-stress conditions (Tmax ≥35°C) remain below 10 days/season for all sowing dates, particularly if seeding early in November (Figure 10). However, the projected temperature rise over the 21st century projects an increase in the number of days with heat-stress conditions over the growing season. The number of days with heat-stress conditions, for example, rises from 4 to 8 days/season and from 5 to 17 days/season under RCPs 4.5 and 8.5, respectively when the near (2017–2040) and far-future (2071–2099) are compared (average of sowing dates and locations). These differences are heightened when comparing different sowing dates. For example, when seeding on 1 December, the number of days with heat-stress conditions increases from 8 to 12 days/season and from 9 to 20 days/season under RCPs 4.5 and 8.5, respectively when the near (2017–2040) and far-future (2071–2099) are compared. However, as for wet season rice, an increase in exposure does not necessarily translate in an increase in plant sensitivity. Overall, under future climatic conditions, heat-stress conditions in the study areas are not considered a major limiting factor negatively affecting crop transpiration and spikelet sterility, and thus, the final yield.

4 | DISCUSSION

Rising temperatures may disturb vital functions of plants, such as enzyme efficiency, cell division, growth and productivity (Mittler et al., 2012). The flowering stage of rice is found to be the most

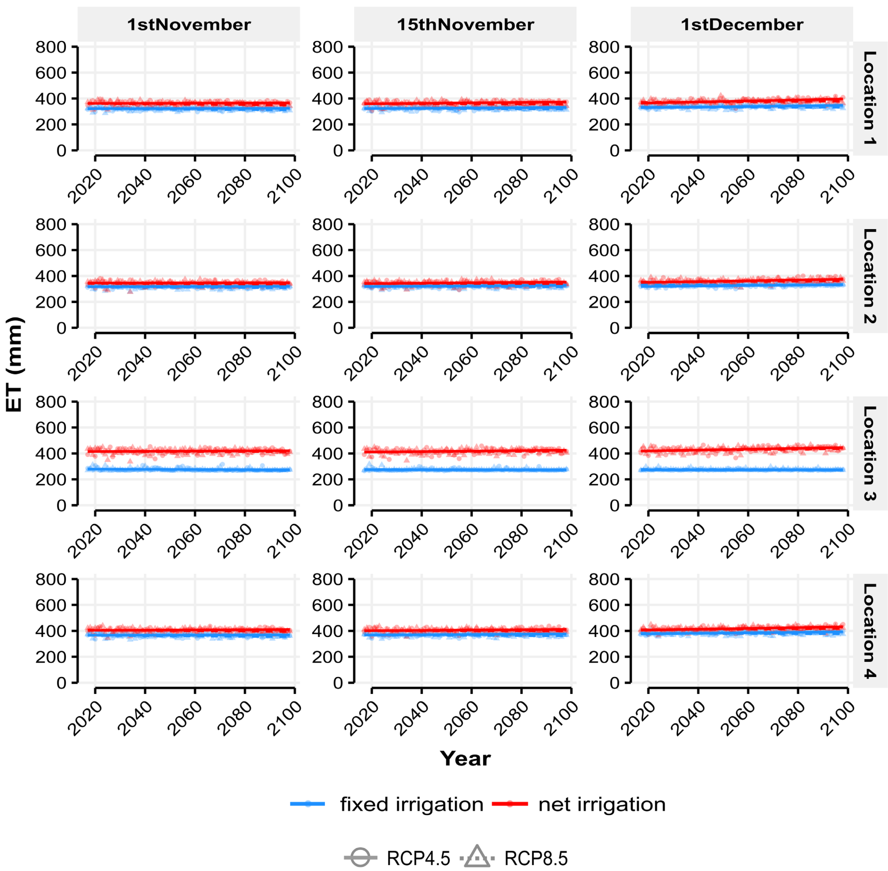

FIGURE 7 Simulated evapotranspiration (mm) during the dry season under future climate scenarios (RCPs 4.5 and 8.5) over the 2017–2099 period. Blue and red circles and triangles correspond to fixed and net irrigation under RCPs 4.5 and 8.5

sensitive to heat-stress (Lawas et al., 2018; Wu et al., 2020). Even few hours of high temperatures coinciding with flowering leads to a decrease in pollen viability and spikelet sterility (Jagadish et al., 2007), with a quantitative impact observed with more than 1 day of heat-stress (Rang et al., 2011). The damage caused by heat-stress strongly depends on the timing and duration of the stress. Although most of the scientific literature defines 33–35°C as the critical temperature threshold at which spikelet sterility starts to occur (Julia and Dingkuhn, 2013; Kobayasi et al., 2010; Yoshida et al., 1981, among others), a study in Australia indicates that even under extreme heat (40°C) conditions during anthesis, heat-induced flower sterility does not appear to be detrimental for rice growers (Matsui et al., 2007). In this regard, some of the research questions raised in the literature, including the timing and duration of heat-stress responsible for yield reduction through spikelet sterility, are addressed here (Van Oort and Dingkuhn, 2021). For example, our study reveals that heat-stress (Tmax ≥35°C) conditions are exceeded during the wet season, but the threshold at which full pollination stress (Tmax ≥40°C) starts to occur is not exceeded until the far-future. However, the timing at which the stress occurs varies depending on the growing cycle and sowing date. While early season rice (mid-June) is increasingly exposed to heat, rice sown during the mid-season (July) is frequently exposed to the concurrent effect of heat and water stress. This affects mainly the medium/long-cycle varieties at the flowering (90–115 days after sowing) and grain filling stage. Hence, simultaneous abiotic stresses exacerbate the reduction in final yield in medium/long-cycle varieties when seeding in July. If late sowing (early August), heat-stress has a minor effect in medium/long-cycle varieties than in short-cycle varieties. This is due to the timing at which flowering is reached by medium/long-cycle varieties, coinciding with fall (November) and the departure of the boreal winter (December) with closer to optimal flowering temperatures. Nevertheless, the absence of precipitation in late seeding (early August) counteracts the benefits of mild temperatures during the boreal winter, and thus, adversely affecting the final yields of medium/long-cycle varieties. Likewise, short-cycle varieties sown in August are increasingly exposed to an earlier offset of the rainy season and future precipitation decline.

Although sterility rates associated with extreme high temperatures are only expected to occur in the high-emission scenario (RCP 8.5), the overall sterility rates increase faster in a wet than in a dry environment. This is because of the greater increase of the panicle temperature caused by reduced loss of water vapour in transpiration (Yoshimoto et al., 2022). Furthermore, rising temperatures and lower relative humidity, from a decline in precipitation, results in increasing evaporative demand. The simulated ETc outputs under net irrigation (350–400 mm/season), respectively, are comparable to those measured in Cambodia using lysimeters (ETc 490 mm/season) during the dry season, but over the warmest months (February–April) (Smith and Hornbuckle, 2013). Similar findings have been reported in China and Bangladesh, where there are no appreciable changes in seasonal water requirements for dry season rice due to climate change (Luo et al., 2015; Shahid, 2011). In this work, although ETc and irrigation requirements (IR) under net and fixed irrigation do not experience

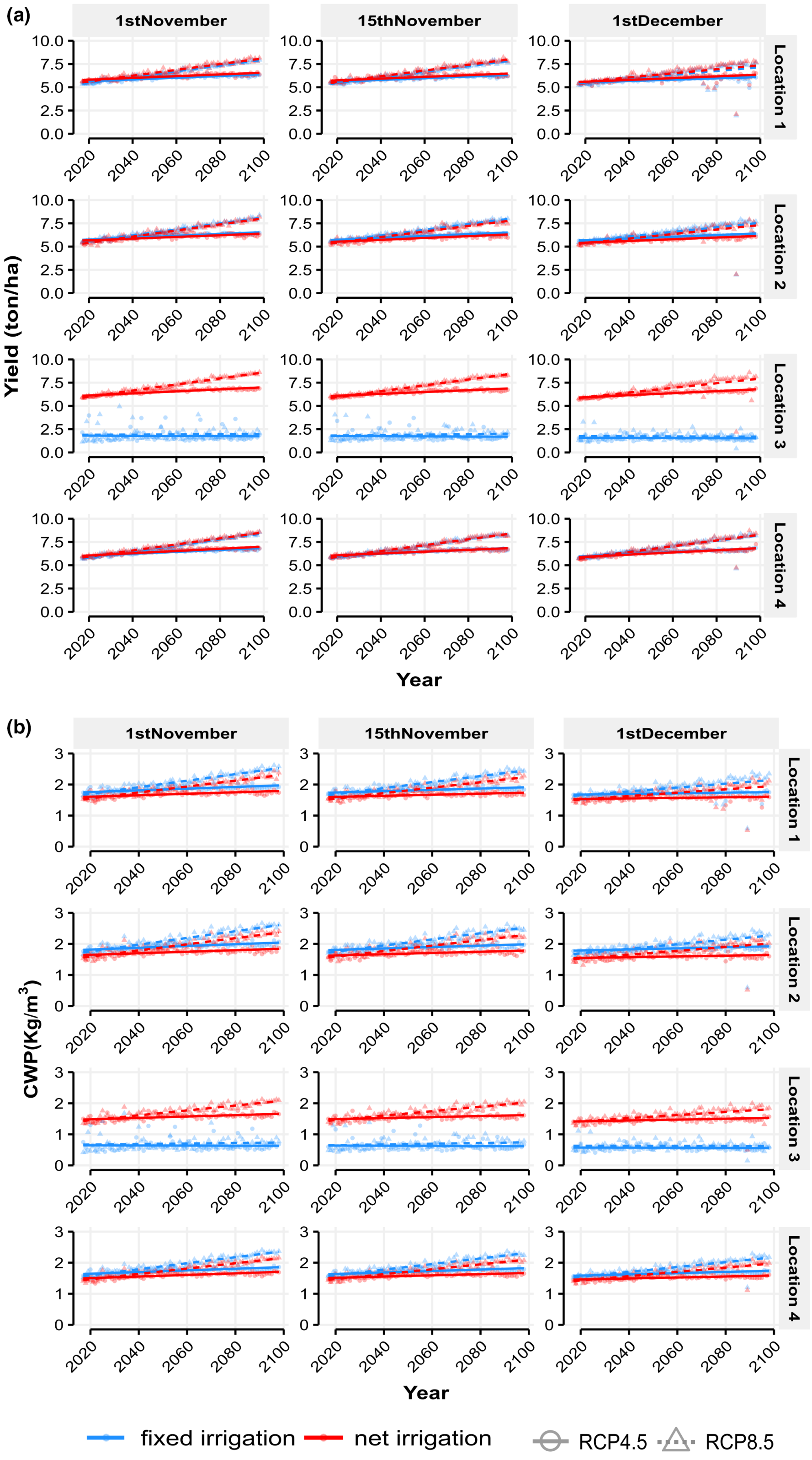

FIGURE 8 (a) Projected rice yields (ton/ha) and (b) crop water productivity (kg of yield per m^3 of water evapotranspired) during the dry season under future climate scenarios (RCPs 4.5 and 8.5) over the 2017–2099 period. Blue and red circles and triangles correspond to fixed and net irrigation under RCPs 4.5 and 8.5, respectively; while blue and red straight and dotted lines correspond to the yield and CWP trends

major variations over time, an increase in crop water productivity (CWP) is projected under both irrigation schemes, heightened under RCP 8.5. Increasing CO_2 (RCP 8.5 vs. 4.5) under moderate temperatures (dry vs. wet season) may enhance the plant's water use efficiency. However, as temperature increases above the optimal temperature threshold for growth and development, the positive impact of increasing water use efficiency is counteracted. Hence, AquaCrop is capable of depicting crop responses to climate change via the standard simulation of crop responses to water and temperature stresses in combination with the responsiveness of transpiration and biomass production to atmospheric CO_2 concentration (Vanuytrecht et al., 2011). In addition, the increased productivity of C_3 plants compared with C_4 grown in adequate conditions is widely understood, as C_3 plants require higher concentrations of CO_2 to reach higher enzyme efficiency than C_4 plants (Lawlor and Mitchell, 1991). While C_4 crops are more productive in a CO_2-enriched environment, except for drought conditions, the yield responses of C_3 plants may diminish in a nitrogen deficient and wet environment (Ainsworth and Long, 2021). The latter work also reveals that rice has the highest yield potential (35%) in an elevated CO_2 environment than the average C_3 crops (14%). The latter is confirmed in this study with an increase in dry season rice yields by up to 28% under RCP 8.5 in the far-future (2071–2099).

In this work, we also highlight the importance of assessing a sowing window for farmers to obtain the highest agriculture outputs (yields) with lower water inputs and higher water use efficiency. As observed in regional (Li et al., 2015) and national studies, for example, in Bangladesh (Acharjee et al., 2019), China (Ding et al., 2020), and Thailand (Babel et al., 2011), adequate irrigation during the dry season and adjustment of sowing dates during the rainy season can be a viable solution for modulating climate change impacts on rice production. Although these interventions may not be sufficient in all possible scenarios, the combination of the latter together with short-cycle varieties is likely to reduce crop's exposure, and consequently, sensitivity to increasing and more frequent abiotic stresses. In addition, as the life cycle of the plant shortens so does the available time for rice to acquire radiation, CO_2, and nutrients for biomass accumulation. However, in Cambodia, the yields of short-cycle varieties are not adversely affected by shortened growth duration, as observed in other regions, for example, north-eastern China where rice yields are reduced by 19% (Ding et al., 2020). Therefore, genotypes with faster growth cycles adapt to shorter growing seasons at high latitudes or allow multiple plantings in longer seasons at middle and low latitudes (Qiu et al., 2021). This practice is already observed in the Mekong River Delta (Vietnam) where short-cycle varieties allow rice farmers to produce twice during the rainfed 6-month rainy season (FAO, 2012). Evidence from Myanmar also show that farmers are successfully adapting to altered rainfall conditions through the use of rice varieties with a shorter vegetation period (SeinnSeinn et al., 2015). For Cambodia, the implications of climate change and climate variability on rice production may vary between regions. First, because the number of days with heat-stress conditions is expected to increase faster in continental areas than in the coastline and, secondly, because projected precipitation decline is greater in western and central parts of Cambodia than in north-eastern parts bordering Laos (Tangang et al., 2018; Teixeira et al., 2013).

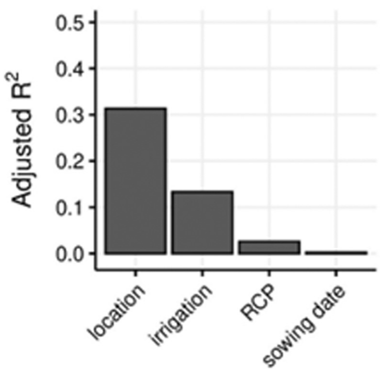

FIGURE 9 Adjusted- R^2 values for different input variables (location, irrigation, RCP and sowing date) over the dry season. A lower adjusted- R^2 value indicates that the additional input variables are not adding value to the model. For example, if the R^2 value is 0.5, 50% of the variation in the output variable (yield) is explained by the input variables (location, irrigation, RCP, and sowing date)

5 | CONCLUSION

In this study, we explored the responses of three rice varieties with multiple sowing dates to different climate change scenarios in the wet and dry season along the Northern Tonle Sap Basin in Cambodia. We

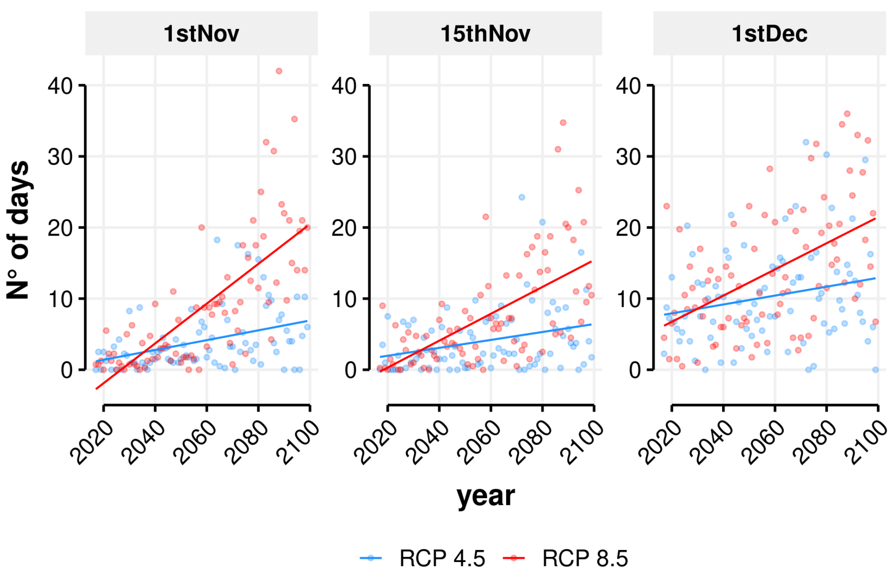

FIGURE 10 Number of days during the growing season with maximum temperature above 35°C for different RCPs (4.5 and 8.5) over the 2017–2099 period. Blue and red circles correspond to RCPs 4.5 and 8.5, respectively

found that a CO_2-enriched environment has a positive impact on rice yields. Yield losses are caused by the exposure to abiotic stresses, mostly as a result of the duration and timing of the stress. Water, and to a minor extent, heat-stress are detrimental for crop development and productivity during the wet season, while drought is the main climatological hazard affecting dry season rice. Both abiotic stresses are projected to exacerbate into the future, as heat-stress conditions are expected to intensify and become more recurrent, while precipitation may decline. As a result, medium/long-cycle varieties are increasingly exposed to abiotic stresses, whereas short-cycle varieties are affected to a lesser extent. An acceleration of plant's phenological phases from rising temperatures may lead to a shorter growing cycle, and as a consequence, less water consumption by the crop. However, a lower water consumption is likely to be counteracted by increasing evaporation rates, and consequently, no substantial changes in crop evapotranspiration are expected over time.

Basic agronomic interventions on rice production systems (i.e., selection of appropriate varieties, sowing dates, and irrigation schemes), have proven to be an effective adaptation solution to changing environmental conditions and to growing water demand over the Northern Tonle Sap Basin. Although we recommend using short-cycle varieties, these varieties often require intensive use of agrochemical inputs, especially fertilizers. Thereby, breeding/research programs should be centred on short-cycle varieties requiring less use of agrochemical inputs and varieties less prone to pests and diseases. In addition, medium-cycle varieties have the best quality fragrant rice with a better market price than short-cycle varieties. Local consumers also prefer long-grain aromatic rice varieties rather than short-rice grains, and therefore, it is as important to meet consumer preferences (quality/fragrance) in order to promote agricultural transformation of rice production in Cambodia. Meanwhile, the adjustment of sowing dates would further increase crop yields during the wet season. Yields during the dry season are likely to tolerate future climate and benefit from optimal growing temperatures. The simulation results from different irrigation schemes show the advantages of developing sustainable and highly efficient irrigation systems. They also highlight Cambodia's potential compared with other regions to produce rice over the dry season, while using low water inputs. This is essential to meet agricultural water demand while avoiding water shortages and potential conflicts between rice growers. The findings of this study highlight the importance of increasing investment in irrigation infrastructure, in particular for secondary and tertiary canals that reach rural farmers, outreach and engagement of communities in water use associations while encouraging agricultural diversification. To better understand the negative/positive effects of climate change on rice production, we suggest transferring knowledge on crop-modelling approaches as it is an easy and non-expensive way of identifying best adaptation strategies. The AquaCrop results, and those of other models (e.g., ORYZA2000), are useful to assist farm-level management decisions in both rainfed and irrigation agriculture. Hence, we also encourage its use among agricultural extension workers to further support decision-making on water allocation as well as to sustainably use water resources essential for achieving food security in Cambodia. Lastly, since precipitation patterns may experience spatial and temporal differences, new perspectives for further research should aim at analysing climate change impacts on rice production at national scale and regional scale.

AUTHOR CONTRIBUTION

Writing and editing JAB; data collection RS, KS, VS; data analysis JAB, RS, RM, GF; review AH,GF, PY, KS, and VS.

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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 manuscript.

DATA AVAILABILITY STATEMENT

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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