YSSP Report

Young Scientists Summer Program

Adjusting Cropping Calendars of Rice-based Systems to Mitigate Heat Stress Under Climate Change in South Asia

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Abstract

Climate change poses increasing risks to food security of South Asia with more severe heat stress, water scarcity, and flooding. As one of the major adaptation measures, adjusting crop calendars could be a feasible and effective solution to avoid adverse effects on crop yield potentials in a changing climate by allowing crops to grow in more favorable weather conditions. Previous single-crop and single-objective studies on the optimization of crop planting dates lack comprehensive consideration of multi-crop rotation systems, especially rice-based cropping systems with very short growing season intervals in Asian tropical monsoon regions. This study seeks to better understand potentials and limitations of adjusting crop calendars for climate change adaptation of double-rice and rice-wheat rotation systems, with a particular focus on the following questions: (1) Is it possible to avoid yield loss of rice and wheat through adjusting crop calendars in the study area? (2) How will fallow period between crop growing seasons change in the future? (3) What are relationships between crop yield improvement, irrigation water requirement, and heat stress mitigation in the study area?

To address these questions, we calibrated a spatial implementation of the Environmental Policy Integrated Climate (EPIC) agronomic model to estimate annual potential yields, irrigation water requirement, and heat stress days of irrigated double-rice and rice-wheat cropping systems in Bangladesh, India, and Myanmar (the BIM countries), and adjusted crop calendars (a) by single-objective optimization with maximum yield and (b) multi-objective optimization with least irrigation water requirement, minimum heat stress days, and highest potential yield under climate change.

Our results indicate that most yield loss in rice and wheat could be avoided through shifting planting dates while considering effects of elevated atmospheric CO_2 concentration on biomass assimilation and transpiration. The model indicates that fallow periods between kharif-rice harvest dates and rabi-rice planting dates in double-rice systems are likely to become longer due to shorter growing season duration meanwhile fallow periods between kharif-rice harvest dates and rabi-wheat planting dates in rice-wheat systems are likely to become shorter due to advanced planting dates of rabi wheat, which implies that double-rice systems in the BIM countries will have more flexibility to cope with smaller time windows for crop growth and development in the future. Moreover, nearly half of the study area has the potential to increase yield by more than 10% through changing crop calendars compared to the basic scenario with non-adjusted crop calendars under RCP8.5 in 2080s, but 59% of these areas would face contradictions in obtaining crop yield improvement, saving irrigation water, and mitigating heat stress in the future. We found those areas suitable for adopting shifting planting dates as one of adaptation strategies from the perspective of climate conditions, such as Punjab state in India and Rangpur in Bangladesh, are also the areas with shortened growing season intervals, which requires great efforts to achieve the adaptation objectives under climate change. Thus, the trade-off among economic cost, environmental impacts, and food security should be carefully considered for local governments and farmers to promote adjustment of crop calendars in the future.

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1 Introduction

Governments have agreed on a target to end hunger, food insecurity and all forms of malnutrition in the world by 2030, but there are many threats to achieve this sustainable development goal (United Nations, 2015; FAO et al., 2020). In South Asia, the rapid increase of food demand and limited scope for expanding cultivated area will be a challenge for ensuring regional food security, which requires great efforts in crop yield improvement. In addition, climate change is expected to present an array of challenging consequences, such as more severe heat stress, water scarcity, and flooding, leading to a general decline in food production over the next two to three decades and turn into a major cost driver of food in the near future according to previous research (Spijkers, 2010; FAO et al., 2020).

Future climate change scenarios highlight a widespread increase of high temperature events in India, the frequency of which at the end of the 21st century will be 30 times higher than that at the beginning of the century by 2°C of global warming (Mishra et al., 2017, Ruane et al., 2018). Increasing number of days with high temperatures will potentially reduce crop yield by affecting CO_2 assimilation rates, shortening crop development duration, raising the vapor pressure deficit (VPD), and leading to sterility (Wang et al., 2020). A systematic review of published simulation works reveals that temperature rise is expected to induce aggregate production losses of wheat, rice, and maize in tropical regions without any adaptation strategies (Challinor et al., 2014). Fortunately, most yield loss in rice and wheat may be avoided, or even reversed, in tropical regions with suitable adaptation strategies under the 2°C warming scenario. Crop-level adaptations including changes in planting times, varieties, irrigation, and residue management could increase simulated yields by an average of 7–15%, with adaptations more effective for wheat and rice than maize (Challinor et al., 2014).

As the largest water demand sector in South Asia, irrigation water saving for main food crops, rice, and wheat, needs special attention to deal with future food production. It is estimated that most river basins in India would be facing water scarcity due to the combined increase in water demand for irrigated agriculture, population growth, and higher standard of living by mid-century (Mujumdar, 2008; Hijioka et al., 2014). Moreover, climate change poses additional impacts on seasonal water scarcity. According to Coupled Model Intercomparison Project Phase 5 (CMIP5), the contrast in precipitation between wet and dry seasons in South Asia will be greater in the future, which means extreme high flows are likely to be higher in wet seasons and extreme low flows are likely to be lower in dry seasons, leading to more severe water scarcity in dry season and more frequent floods in wet season (IPCC, 2013).

Among the major adaptation measures, adjusting crop calendars could be a feasible and effective solution to offset adverse impacts of a changing climate on crop yield potentials. According to previous studies, the crop's phenological responses to climate change result in a shorter growing season of Boro rice and Rabi wheat in Bangladesh and India, which provides more flexibility to shift planting times and growth period (Lobell et al., 2012; Acharjee et al., 2019). Shifting planting dates allows crops to grow in more favorable weather conditions. It can be applied to not only avoid temperature stress (Basak et al., 2010; Karim et al., 2012; Shelley et al., 2016), but also significantly reduce water use (Mainuddin et al., 2011, Acharjeea et al., 2019). Nevertheless, avoiding heat stress, reducing irrigation water consumption, and mitigating potential yield loss are sometimes contradictory in regions with asymmetric water and thermal changes. Previous studies on the optimization of crop calendars mainly focused on one growing season or one aspect of the optimization, lack of comprehensive consideration in the context of food security and water scarcity at the regional scale, especially the impact of changing a crop's planting and harvest dates on the crops that are planted subsequently (Waha et al., 2013; Agnolucci et al., 2020).

Based on gaps identified in the literature, this study seeks to address the following research questions:

- Is it possible to avoid yield loss of rice and wheat through adjusting crop calendars in the study area?
- How will fallow period between crop growing seasons change under climate projections?
- What are relationships between crop yield improvement, irrigation water requirement, and heat stress mitigation in the study area?

To address these questions, we used a calibrated and validated spatial implementation of the Environmental Policy Integrated Climate (EPIC; Williams, 1990) model to estimate annual potential yields, irrigation water requirement, and heat stress days of irrigated double-rice and rice-wheat cropping systems with different crop calendars in India, Bangladesh, and Myanmar. We shifted crop calendars at a county level in main grain producing areas based on RiceAtlas and SAGE database, which are most comprehensive and detailed global crop calendars currently available. Optimal planting dates in double-rice and rice-wheat cropping systems of the study region were selected with the criteria of relative low irrigation needs, less heat stress days, and potential yields under multiple climate change scenarios by the mid and end century. It should be noted that "yield improvement" in this study refers to the yield increase in the optimized scenario with adjusted crop calendars compared to the basic scenario with non-adjusted crop calendars under the same weather conditions. This study will contribute to the understanding of potentials and limitations of crop growing season adaptation to climate change and provide scientific evidence for local policies to ensure food security.

2 Methodology

2.1 Study area

Bangladesh, India, and Myanmar (BIM countries), with about one fifth of the world's population, play a vital role in the fight against global hunger under climate change (Wheeler et al., 2013). The BIM countries are major food producing countries in the world, especially rice production of which accounted for nearly one-third of global rice production in 2020 (http://www.fao.org/faostat/en/). However, the crop yields in the BIM countries are lower than the world average and still have great potential to be improved (Wang et al., 2018).

Base on MapSPAM 2000 and RiceAtlas database, we selected the regions dominated by double-cropping systems with more than 1000 hectares per pixel (0.1°×0.1°) of rice or wheat harvest areas in the BIM countries as the study region (Laborte et al., 2017; International Food Policy Research Institute, 2019). Most of the rice-wheat rotation areas of the study region are distributed in upper and middle Indo-Gangetic plain, where rice and wheat are planted in Kharif season (wet season, May to October) and Rabi season (dry season, December to April), respectively. The multi-rice producing areas are widely distributed in the lower Indo-Gangetic plain, the Brahmaputra river plain, coastal areas of the Indian Peninsula, and the Irrawaddy Delta region, where rainfed rice and irrigated rice are mainly planted in Kharif season and Rabi season, respectively (Figure 1).

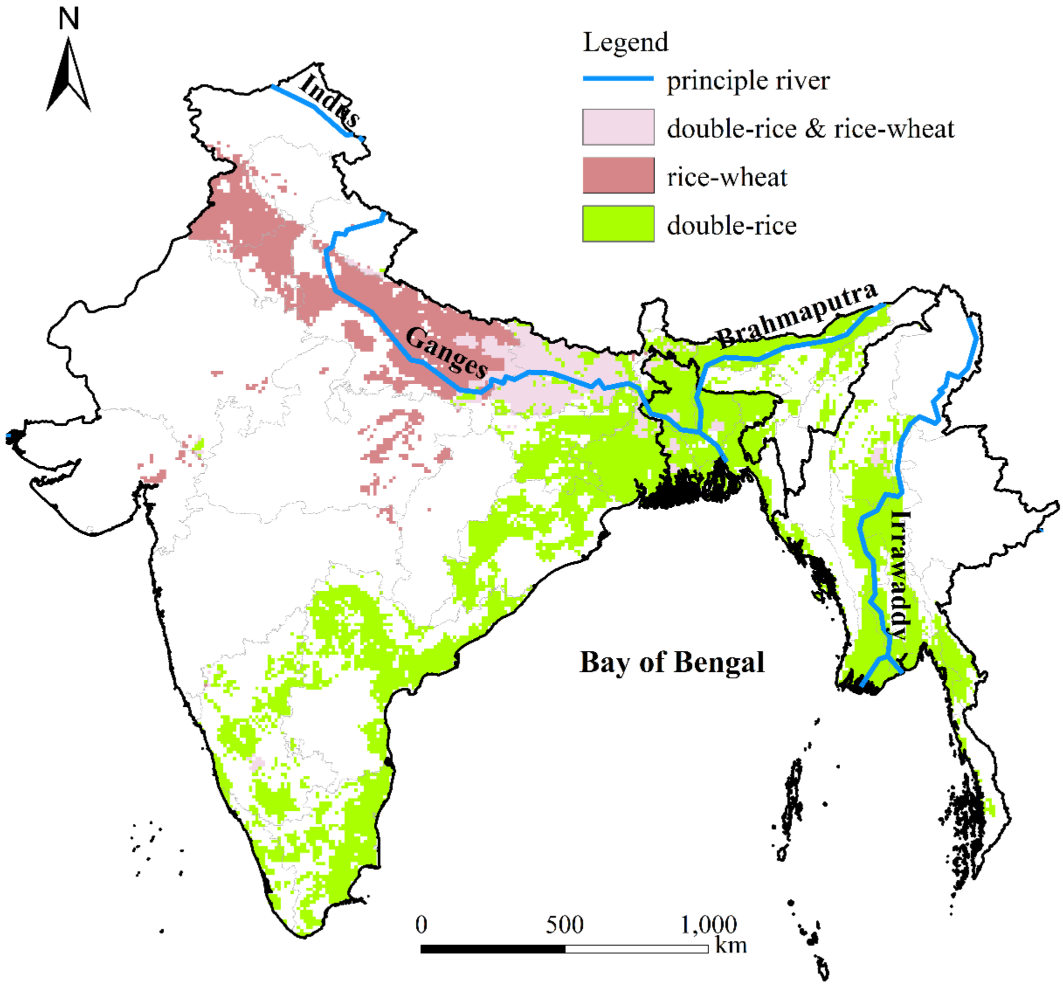

Figure 1 Principle rivers and dominant cropping systems in the study area

2.2 Model simulation

2.2.1 Data

The data and methods used in this study are shown in Figure 2**:**

Historical weather data: We obtained daily maximum temperature, daily minimum temperature, precipitation, solar radiation, relative humidity, and wind speed during 2001–2015 from the CRUNCEP Version 7 with a spatial resolution of 0.5° × 0.5° (Viovy, 2018).

Future climate scenarios: The climate change scenarios data used in the study are mean values of five regional climate products derived from the Coordinated Regional Climate Downscaling Experiment in South Asia (CORDEX-South Asia), including ACCESS1–0, CCSM4, GFDL-CM3, CNRM-CM5, and MPI-ESM-LR under the Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 during 2041-2070 and 2071-2099. Details of the model experiments for the south Asia region can be found in http://cccr.tropmet.res.in/home/ftp_data.jsp.

Crop calendars: In order to identify the start and end time of growing seasons for Kharif rice and Rabi rice, we used RiceAtlas (Laborte et al., 2017) to extract spatial distribution of peak planting/harvest dates of rice in the study area. RiceAtlas database is the most comprehensive and detailed global rice calendar currently available. The crop calendar of Rabi wheat was extracted from Sacks et al. (2010).

Crop growth parameters: Growth parameters of rice and wheat including base temperature (Tbase), optimum temperature (Topt), maximum potential leaf area index (DLMA), fraction of growing season when leaf area declines (DLAI), Biomass-Energy Ratio (WA), and harvest index (HI) were obtained from Jalota et al. (2012), Xiong et al. (2014), and Wang et al. (2020), which have been calibrated by the field experiments conducted in the study region (Table 1). Potential heat units (PHU) of rice and wheat were calculated at a pixel scale by the accumulation of the part of air temperatures higher than growth base temperatures between planting dates and harvest dates.

Table 1 Crop parameters used in the EPIC model

Crop parameters	Rice	Wheat	Units
WA	35.00	35.00	kg MJ^{-1}
HI	0.55	0.45	--
Tbase	10.00	3.00	°C
Topt	25.00	20.00	°C
PHU	2034±418	2010±327	°C
DLAI	0.80	0.64	--
DLMA	8.00	8.00	--

Soil data: Resources of soil data input into the crop model were spatial soil property estimates with 7 soil layers from WISE30sec database (Batjes, 2015).

MODIS LAI data: In order to discuss the uncertainty in modelling the effects of temperature change on growth season length (Lobell et al., 2012), we compared crop growth duration simulated by EPIC model and that observed by satellite remote sensing from 2003 to 2015 in pixels with harvest areas of rice or wheat more than 50 hectares/km^2. The observed growth season length was based on time-series LAI obtained from database MOD15A2, which is a MODIS product composited every 8 days at 1-kilometer resolution. The observed LAI series was processed by cubic spline interpolation and wavelet transform in each rice and wheat pixel (Sakamoto et al., 2005), and they were calibrated with ground measurements by linear transformation (Manikandan, 2019). Following Lobell et al. (2012), we computed growth season length of rice and wheat in each year as the number of days between the point when the LAI reaches 10% of its maximum amplitude for that season and the equivalent point on the declining portion of the LAI curve.

Potential yield estimates: To validate potential yields simulated by EPIC model, the robust site-specific estimates of potential yields based on field experiments of irrigated wheat and rice under optimal growing conditions were selected in the study region from Global Yield Gap Atlas (GYGA) database(http://www.yieldgap.org/web/guest/home). Also, we collected mean potential yields of rice in the BIM countries obtained by field experiments, statistical methods, and crop model simulation from published literature (Peng, 1999; Waddington et al.,2010; Neumann et al., 2010, Foley et al., 2011; Mueller et al., 2012, Wart et al., 2013, Ittersum et al., 2013; Wang et al., 2018).

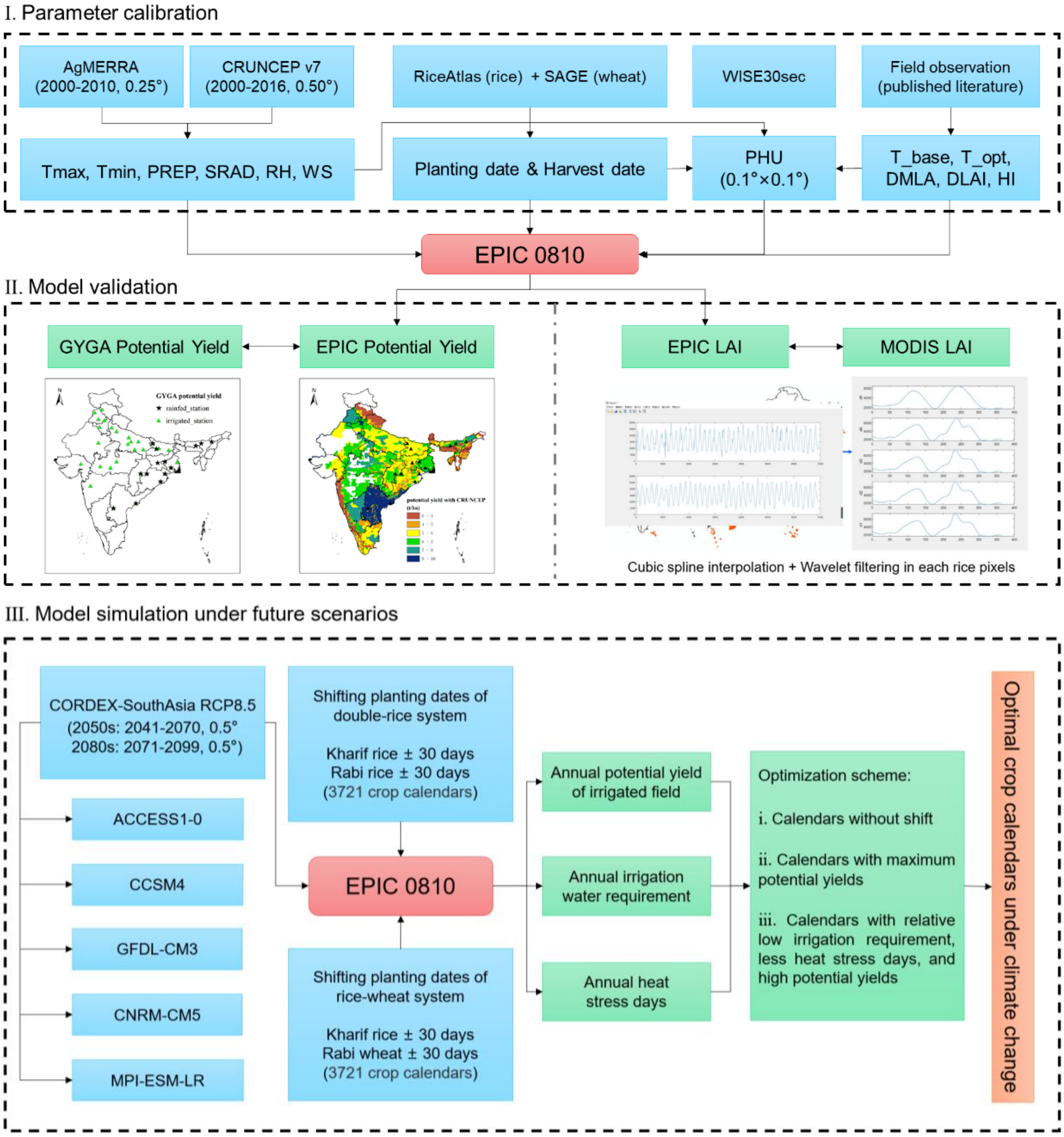

Figure 2 Schematic of the study design

2.2.2 EPIC model description

The Environmental Policy Integrated Climate (EPIC) agronomic model developed by United States Department of Agriculture (USDA) and Texas A&M University is a system dynamics model to simulate climate-vegetation-soil-management relationships in agricultural systems. The model was first used to quantitatively assess effects of soil erosion on crop yield, and then simulation functions were added to calculate the impacts of carbon dioxide (CO_2) fertilization, change of water quality, and cycles of soil carbon, nitrogen and phosphorus. The EPIC model has been widely used in crop yield estimation, climate change impact assessment, precision agriculture, and regional agriculture planning (Gassman et al., 2005; Fan et al., 2012). So far, many versions of EPIC model have been developed, and EPIC0810 is used in this study.

The EPIC0810 model simulates crop photosynthetic assimilation on a daily basis. The calculation of crop yield could fall into four steps (Williams, 1990). (1) Based on accumulated temperature, latent heat, and environmental stress, the EPIC model computes the daily variation of leaf area index and the daily photosynthetically active radiation (PAR) intercepted by the crop canopy. (2) The daily change of potential biomass is calculated by atmospheric CO_2 concentration, air humidity, and PAR. (3) The daily actual biomass of the crop was obtained by multiplying the potential biomass with the stress factors of that day. (4) The final yield of the crop is calculated by the product of the harvest index and the above-ground biomass accumulation in the whole growth period.

In the EPIC0810 simulation of rice and wheat, leaf area index (LAI) is initially zero or very small and increases exponentially at the early stage of vegetative growth, when the rates of leaf primordia development, leaf tip appearance, and blade expansion are linear functions of heat unit accumulation (Williams, 1990). After reaching a maximum, LAI begins to decline and approach zero at physiological maturity (Williams, 1990). In the EPIC model, leaf expansion, final LAI, and leaf duration are also reduced by stress factors (Williams, 1990).

Radiation use efficiency is sensitive to atmospheric CO_2 concentration in EPIC0810 model. CO_2 Concentration/Resulting WA value in the EPIC model (WAC2) is an "S" curve parameter used to describe the effect of CO_2 concentration on the crop parameter WA. The value on the left of the slash symbol ('/') is a value of CO_2 concentration higher than current ambient (i.e., 660 ppm) and the value on the right of the slash symbol is the corresponding value WA. This study set WA as 35 kg MJ^{-1} (Table 1) for both rice and wheat at 330 ppm CO_2, and elevated value of WA was set to 47 kg MJ^{-1} with the fertilization ratio of 1.35 commonly used in EPIC0810 model for C3 crops under 660 ppm CO_2 (Kimball, B.A., 1983).

2.2.3 EPIC model setup

In this study, the solar radiation absorbed by rice and wheat was calculated using the Beer law proposed by Monsi and Saeki (Hirose, 2005), and potential evapotranspiration was calculated by the Penman-Monteith method (Monteith and Moss, 1977) in the EPIC0810 model. Plant population for rice and wheat in the simulation is 300 plants/m^2. The soil profile was set to be static and all fields are set at zero slope to eliminate the long-term effects of soil erosion and nutrient deficiency on crop yield. The calculation of crop growth duration followed the heat unit (HU) accumulation approach, where the crop will not be harvested until the defined heat unit requirement to reach maturity is met. We selected auto-irrigation and auto-fertilization mode of EPIC0810 model to estimate non-nutrient-and-water-limited yields of rice and wheat, with the focus on the impacts of temperature rise and precipitation change on crop heat stress and irrigation water requirement under climate change scenarios. Additionally, we adopted furrow irrigation with furrow dikes in the study region.

2.2.4 Calculation of irrigation needs and temperature stress

In EPIC 0810 model, we input 0.99 as a plant water stress level to trigger automatic irrigation. The daily water stress level is the ratio of water supply and demand computed by formula (1):

$$WS_i = \frac{\sum_{l=1}^{M} u_i, l}{E_{Pi}} \tag{1}$$

where *WS* is the water stress level, *u* is the water use in layer *l*, and E_p is the potential plant water evaporation rate on day *i* (Williams, 1990).

In auto-irrigation mode, soil water content of the crop root zone is kept above field capacity and runoff losses are satisfied by adequate application volume. The irrigation volume is calculated with the equation (2):

$$IRRI = \frac{FC - SW}{1 - EIR} \tag{2}$$

where *IRRI* is the volume of irrigation water needs (mm), *FC* is the root zone field capacity (mm), *SW* is the soil water content of the root zone (mm), and *EIR* is the runoff ratio (Williams, 1990).

In EPIC model, temperature stress of the plant is estimated with the formula (3):

$$TS_i = \sin\left[\frac{\pi}{2}\left(\frac{TG - Tbase_j}{Topt_j - Tbase_j}\right)\right] \quad (3)$$

where *TS* is the plant temperature stress factor, *TG* is the soil surface temperature (°C), *Tbase* is the base temperature for crop *j*, and *Topt* is the optimal temperature for crop *j*. formula (3) produces symmetrical plant growth stress about the optimal temperature and considers average daily soil surface temperature as a stress indicator (Williams, 1990).

2.2.5 Structure of simulation units

The EPIC0810 model simulation is based on site scale with maximum field area of 250 acres, thus we need scale up the simulation results to a regional scale. In this study, simulation units adopted are based on a 0.1° x 0.1° spatial grid. The 30-second soil data was upscaled by taking the mode in each 0.1° x 0.1° unit intersected with the climate grid from CRUNCEP_v7 or Cordex_SouthAsia at 0.5° x 0.5°, study areas selected from MapSPAM 2000 at 0.1° x 0.1°, and grided crop calendars at 0.1° x 0.1° converted from county-level vector data (crop calendar of different units in the same county is homogeneous). The EPIC0810 model is forced with input data for each of these simulation units, which can be considered homogenous in terms of topographic, edaphic, climate, and management conditions, as a representative field. For model validation, the yield of rice and wheat on the regional scale was calculated by weighted mean of harvest area according to MapSPAM 2000. For double-rice systems, the annual potential yield is the sum of Kharif rice yield and Rabi rice yield in the corresponding simulation unit. For rice-wheat rotation systems, the annual potential yield is the sum of Kharif rice yield and Rabi wheat yield in the corresponding simulation unit. Additionally, in order to match the simulation units, the MODIS pixels in the region with harvest areas of rice or wheat more than 50 hectares/km^2 are resampled by arithmetic mean from 1km x 1km to 0.1° x 0.1° resolution, and only the units with bimodal shape in MODIS LAI curve are selected for comparison.

2.3 Multi-objective optimization of planting dates

We designed three scenarios to estimated crop yields in the future: the basic scenario with non-adjusted crop calendars and two optimized scenarios with adjusted crop calendars. Considering future changes in water and thermal conditions, we shifted current planting dates of rice and wheat by ±30 days in one-day steps, and combined them to obtain 7442 crop calendars of double-rice and rice-wheat systems (Figure 2). We removed calendar scenarios in which two growing seasons overlapped each other with altered planting and harvest dates. I The first optimization strategy is based on maximum annual yields of double-rice and rice-wheat cropping systems, and the second strategy to select optimal calendar follows these steps: 1) obtaining Pareto non-dominated solutions based on minimum irrigation need and least heat stress in each simulation unit; 2) selecting the point with highest yield in solved Pareto non-dominated solutions; 3) if the optimized yield potential is not higher than the original potential yield, then the simulation unit will not be adjusted for cropping calendar.

In such multiple-objective optimization, it is common that conflicts exist among crop yield maximization, irrigation water saving, and heat stress reduction. There is no single optimal solution; rather there is a set of alternative solutions, namely Pareto-optimal solutions, are optimal in the wider sense that no other solutions in the search space are superior when all the objectives are considered (Ripon et al., 2010). In a Pareto-optimal set, any two solutions of this set do not dominate each other, and one or more members of this set dominate all other solutions in the search space excluding this set. Figure 3 shows a Pareto front for irrigation water use and heat stress days, which are subject to minimization. In the study, we used non-dominated sorting in genetic algorithms-II (NSGA-II) (see more algorithmic details in Deb et al. (2002)) to calculate the Pareto front for minimum irrigation and least heat stress and selected the point with highest yield in the Pareto front as a best solution to shift planting dates.

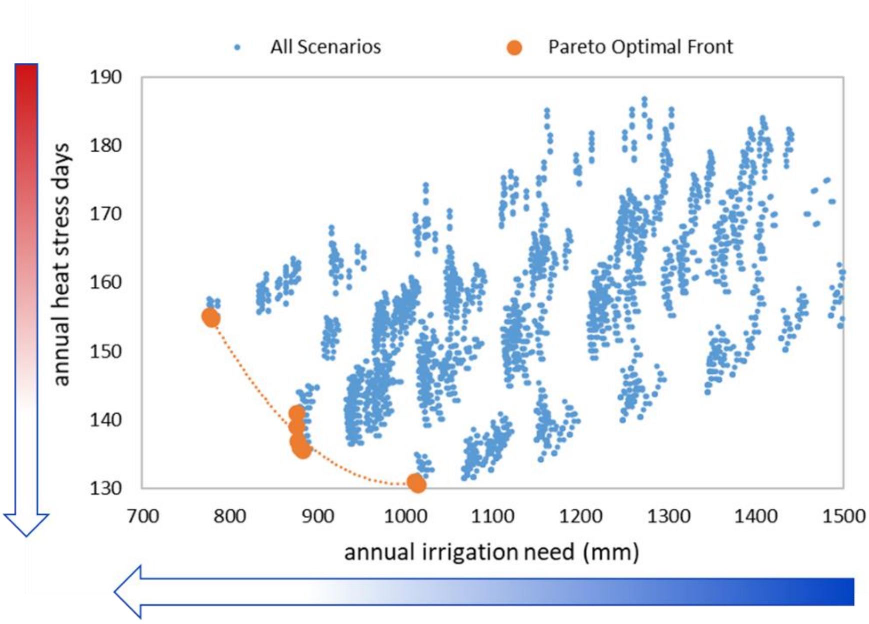

Figure 3 A Pareto front for minimum irrigation water use and heat stress days under different crop calendars in a simulation unit of Punjab, India

2.4 Definition of area classification

In order to discuss the spatial heterogeneity of relationships between crop yield improvement, irrigation water requirement, and heat stress mitigation in the study area, we computed the differences of these objectives between the two optimization scenarios and the non-optimization scenario in each simulation unit and divided the units into three regions with priority levels of A, B, and C, representing different relationships among the three objectives when shifting crop calendars.

Taking the scenario with non-adjusted calendars under RCP 8.5 in 2080s as a baseline, the ratio of yield improvement and the changes in irrigation volumes and heat stress days by single- and multi-optimized crop calenda are computed as follows:

$$\Delta Yield_{n\_max} = (Yield_{n\_max} - Yield_{n\_no})/Yield_{n\_no} \quad (4)$$
$$\Delta Irri_{n\_max} = (Irri_{n\_max} - Irri_{n\_no})/Irri_{n\_no} \quad (5)$$
$$\Delta Heat_{n\_max} = (Heat_{n\_max} - Heat_{n\_no})/Heat_{n\_no} \quad (6)$$
$$\Delta Yield_{n\_multi} = (Yield_{n\_multi} - Yield_{n\_no})/Yield_{n\_no} \quad (7)$$
$$\Delta Irri_{n\_multi} = (Irri_{n\_multi} - Irri_{n\_no})/Irri_{n\_no} \quad (8)$$
$$\Delta Heat_{n\_multi} = (Heat_{n\_multi} - Heat_{n\_no})/Heat_{n\_no} \quad (9)$$

where $\Delta Yield_n$, $\Delta Irri_n$, and $\Delta Heat_n$ are rates of changes in annual yield, irrigation water requirement, and heat stress days relative to baseline scenario in simulation unit *n*, respectively. The subscripts *'max'*, *'multi'*, and *'no'* mean the index simulated in max-yield optimization, multi-objective optimization, and non-optimization, respectively. Due to the optimization methods, $\Delta Yield_{n\_max}$ and $\Delta Yield_{n\_multi}$ are greater than or equal to 0 meanwhile $\Delta Irri_{n\_multi}$ and $\Delta Heat_{n\_multi}$ are less than or equal to 0.

In a specific simulation unit, if $\Delta Yield_{n\_multi} > 0.1$, then $unit\ n \in area\ A$. If $\Delta Yield_{n\_multi} < 0.1\ \&\ \Delta Yield_{n\_max} > 0.1$, then $unit\ n \in area\ B$. If $\Delta Yield_{n\_multi} < 0.1\ \&\ \Delta Yield_{n\_max} < 0.1$, then $unit\ n \in area\ C$. In this case, grain yields in region A could be improved by more than 10% with multi-objective optimization, which means significant yield improvement, irrigation water saving, and heat stress mitigation could be achieved simultaneously by adjusting crop calendars; region B is the area where grain yields could be improved by more than 10% with max-yield optimized crop calendars, but cropping systems are likely to consume more irrigation water and be attacked by more heat waves; region C represents the less favorable area to promote crop calendar adjustment, where the improvement of grain yields is limited to less than 10%.

3 Results

3.1 Model validation

The model parameters used in this study have been calibrated and validated in several sites in India and Bangladesh (Jalota et al. ,2012; Xiong et al. ,2014; Wang et al. ,2020) and we further evaluated the yield and phenology performance of EPIC model simulation based on pixel-scale crop calendars by RiceAtlas in the study region.

3.1.1 Crop yield potential evaluation

On the regional scale, the mean potential yield of main-season wheat in India during 2003-2015 simulated by calibrated EPIC model is 6.50 t/ha, which is 0.12 t/ha higher than the up-scaling location-specific estimate from GYGA in India. The mean potential yield of main-season rice is 10.43 t/ha, only 0.06 t/ha lower than the estimate from GYGA in India and Bangladesh. On the site scale, potential yields of rice and wheat estimated by EPIC model compare well with the data of GYGA (Figure 4).

In addition to GYGA data, we also compared the rice simulation results with those obtained by field experiments, statistical methods, and crop model simulation of previous studies in the BIM countries (Table 2). It can be found that potential yields estimated by empirical statistical methods, such as investigation of actual yields and analysis of boundary functions, are lower than the results from the model simulation in the study by 4.5 t/ha on average (Waddington et al.,2010; Neumann et al., 2010, Foley et al., 2011; Mueller et al., 2012), while potential yields estimated by EPIC model simulation and upscaling research with multiple models are slightly higher than the results in this study by 0.5 t/ha on average (Wart et al., 2013, Ittersum et al., 2013; Wang et al., 2018). Moreover, simulation results in this study basically fall in the range of potential yields estimated by field experimental methods (Peng, 1999). It can be found that potential yields estimated by crop models and field experiments are closer to our simulation results compared with statistical estimation.

Simulated total annual potential yields of double-rice systems and rice-wheat rotation systems in the study region are 19.40 t/ha and 17.06 t/ha during 2003-2015, respectively. The annual potential yields of double-rice and rice-wheat rotation systems in Andhra Pradesh, Punjab state, West Bengal state, and northwestern Bangladesh are over 20 t/ha due to longer crop growth seasons, better thermal conditions, and more solar radiation (Figure 5).

Table 2 Rice potential yield estimation by field experiments, statistical methods, and crop model simulation of previous studies in the BIM countries.

Methods	Area	Potential yield	
Field experimental methods	Asia tropical lowlands	10.80±0.40 t/ha	Peng *et al.*, 1999
Statistical methods	South Asia	6.98 t/ha	Waddington *et al.* , 2010
Statistical methods	Myanmar Bangladesh India	5~6 t/ha 5~6 t/ha 6~10 t/ha	Neumann *et al.* , 2010
Statistical methods	Bangladesh and India Myanmar	4.98 t/ha 5.85 t/ha	Foley *et al.*, 2011; Mueller *et al.*, 2012
Field experiments & model simulation	Bangladesh India	11.98 t/ha 9.01 t/ha	Wart *et al.* , 2013; Ittersum *et al.* , 2013
EPIC model simulation	Myanmar Bangladesh India	11.31 t/ha 11.78 t/ha 11.23 t/ha	Wang *et al.*, 2018

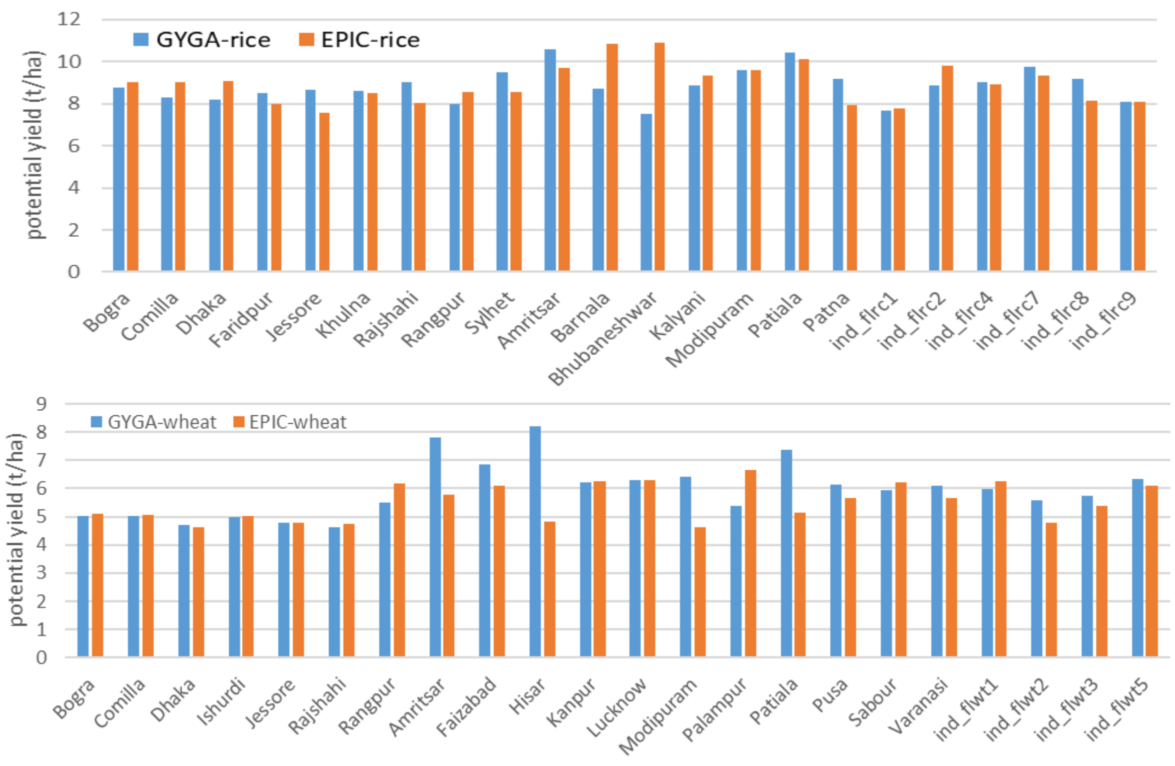

Figure 4 potential yields of rice and wheat estimated by EPIC model and GYGA database

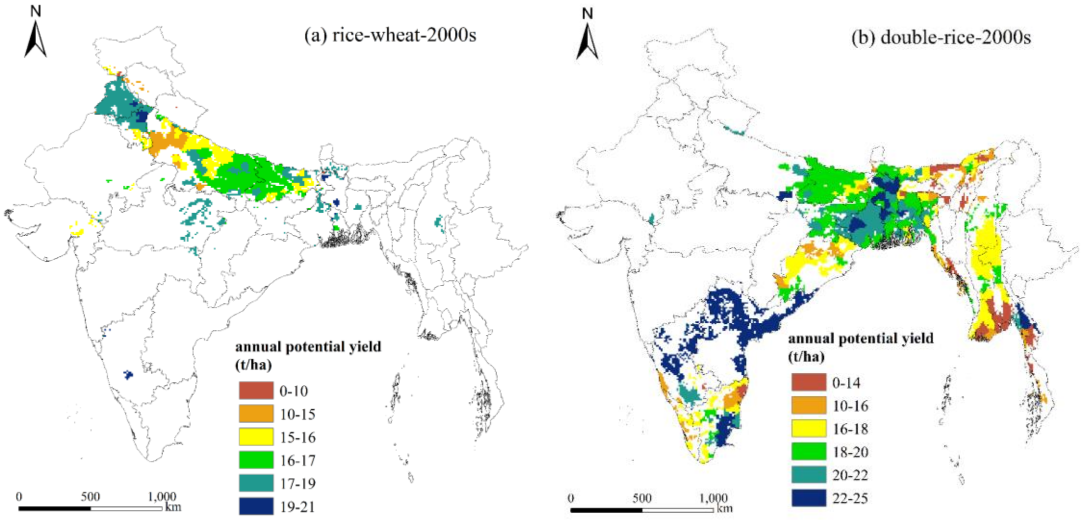

Figure 5 Spatial distribution of annual crop potential yields in the BIM countries simulated by the EPIC model

3.1.2 LAI phenology validation

We validated the LAI dynamic simulation in Punjab state, Andhra Pradesh, and Dhaka district with the mean values of selected simulation units. Punjab state of India is one of the regions with the most extensive distribution of rice-wheat rotation systems in the world meanwhile Andhra Pradesh of India and Dhaka district of Bangladesh have widely distributed double-rice cropping systems. There are short fallow periods between the harvest dates of Kharif crop seasons and the planting dates of Rabi crop seasons in Punjab state and Andhra Pradesh. Compared with them, fallow periods between dry and wet crop seasons in double-rice systems of Dhaka are relative longer. The LAI dynamics simulated by the EPIC model are in good agreement with satellite observations (Figure 6).

We also compared inter-annual variations (IAV) of growing season length observed by remote sensing and simulated by EPIC model in Punjab state during 2003-2015 (Figure 7). Although crop growing season length is affected by numerous environmental factors and field management, there is a clear negative correlation between crop season length and air temperature especially in rabi-wheat seasons of the study region. In general, results from the EPIC model are consistent with remote sensing observation in the length of crop growing season. Given that rabi wheat is more consistent than kharif rice in the IAV comparison between EPIC simulation and MODIS observation, the length of wheat growing season should be more affected by air temperature than that of rice in the study region because EPIC model calculates growing season lengths based on air temperature and potential heat units.

3.2 Projected climate change and crop calendar optimization

3.2.1 Projected changes in growing season climate

According to the future climate scenarios ensembled by ACCESS1–0, CCSM4, GFDL-CM3, CNRM-CM5, and MPI-ESM-LR in CORDEX-SouthAsia, mean annual air temperature and precipitation in the study area will continuously increase under different climate scenarios (Figure 8). Current mean temperature and future temperature increase in rice-wheat rotation areas are both higher than that in double-rice cropping areas. In the areas dominated by double-rice systems, mean annual temperature is likely to rise by 3.6 °C and mean precipitation is likely to increase by 6% from 2000s by the end of this century under RCP8.5. In the areas dominated by rice-wheat rotation systems, by the

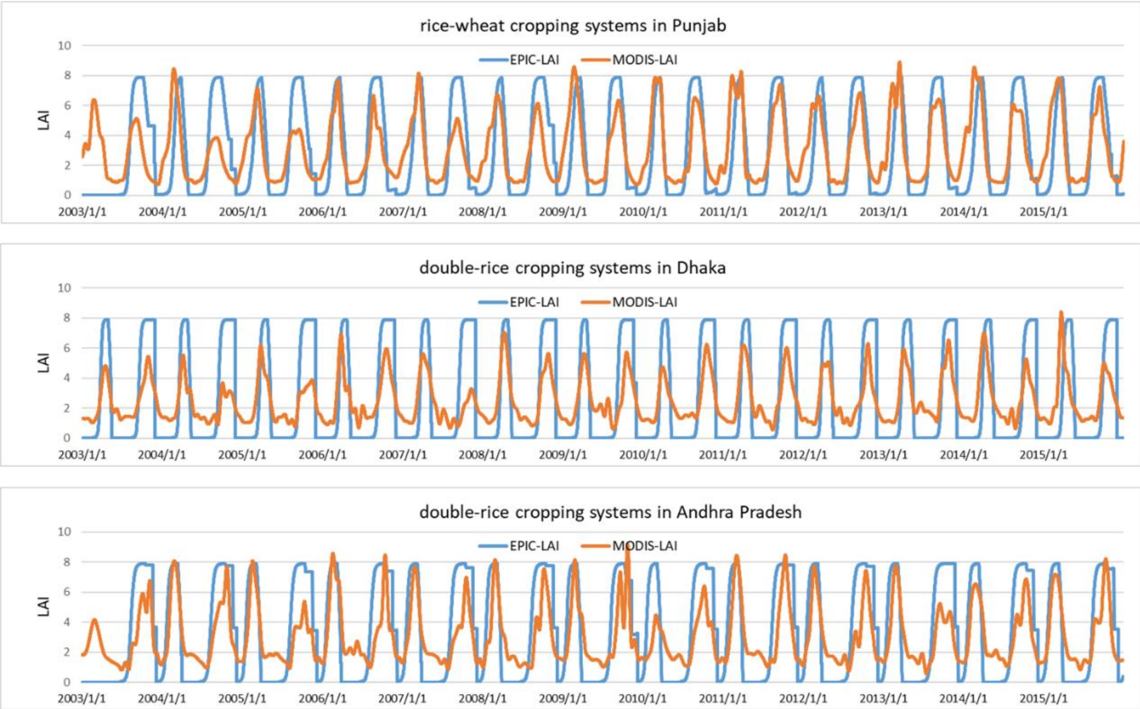

Figure 6 The LAI dynamics estimated by the EPIC model and MODIS data

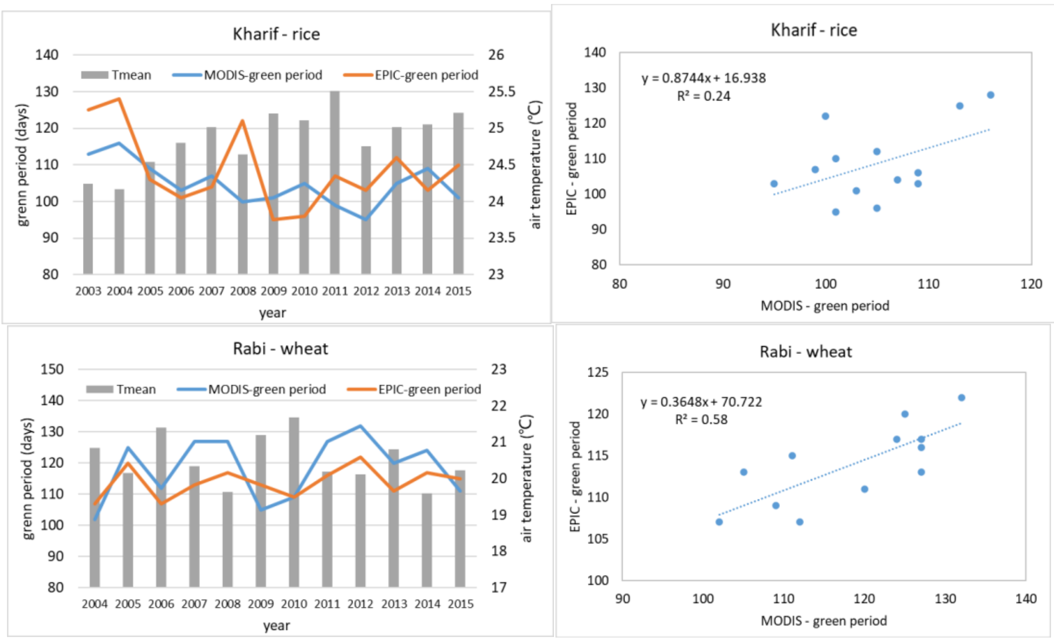

Figure 7 Inter-annual variations of growing season duration observed by remote sensing and simulated by EPIC model during 2003-2015

end of this century, mean annual temperature is likely to rise by 3.9°C and mean precipitation is likely to increase by 15%, which shows more significant climate changes than double-rice areas. Moreover, the changes of temperature and precipitation are asymmetric in different seasons. Generally, the temperature in winter will rise faster than that in summer, and the precipitation in wet season will increase more than that in dry season. The mean magnitude of temperature increase is 3.3°C in the warmest quarter (March-May) and 4.3 °C in the coldest quarter (November-January), and the precipitation is likely to increase by 7% in wet season while decrease by 9% in dry season in double-rice areas under RCP8.5 scenarios. In rice-wheat rotation areas, the average magnitude of temperature increase is 3.9°C in the warmest quarter (April-June) and 4.8 °C in the coldest quarter (November-January), and the precipitation is likely to increase by 18% in wet season and 12% in dry season.

Besides mean temperature change, critical temperature thresholds for wheat and rice growth is also important for evaluating the effect of temperature rise on wheat and rice production. Although winter temperatures rise faster than summer temperatures in the next decades, winter temperature mostly stays at or below the optimum growth temperatures for wheat and rice (20~30 °C), while summer periods with high temperatures exceeding critical temperature thresholds (30°C for wheat and 35 °C for rice) will be longer in the future. In double-rice areas, the period with daily temperatures above 30 °C is likely to increase from 65 days to 105 days in 2050s and to 246 days in 2080s according to RCP8.5 scenarios, but few days have an average temperature above 35 °C. In rice-wheat areas, the period with daily temperature above 35 °C is likely to increase from 6 days to 50 days in 2050s and to 70 days in 2080s under RCP8.5 scenarios. It is expected that the first day with temperature above 35 °C will come 25 days earlier and 37 days earlier than 2000s in rice-wheat rotation areas by 2050s and 2080s, which means the increasing possibility of high temperature occurence in the harvest season of wheat.

Cropping calendars of rice and wheat is well matched with local water and heat conditions in the study area at the present (Figure 8). Current growing seasons of Kharif rice makes full use of moderate precipitation during July to October and avoids previous rainstorms in the study area (especially in Bangladesh, Figure 9(a)). At the same time, the mean temperature of 25-30℃ during growing seasons is also the optimal temperature range for rice growth. During growing seasons of Rabi rice and wheat, temperatures are favorable for crop development on most days, but wheat may suffer from heat stress at the grain filling stage by the end of growing seasons (Figure 9(b)).

3.2.2 Optimization of crop growing seasons

According to the single- and multi- optimization results based on the crop model and optimization algorithms (Fig. 7), the optimal planting date of Kharif crop will be delayed and that of Rabi crop will be advanced, which results in both growing seasons being closer to winter season. This characteristic is more obvious in rice-wheat rotation areas, where summer temperature is higher than that in double-rice areas and the harvest day of rabi wheat is strictly limited by the critical time point of 30°C. In calendars adjusted by yield maximization under RCP8.5, the planting dates of kharif rice and rabi rice in double-rice systems are on average delayed by 16 days and 4 days, respectively, and the planting dates of kharif rice and rabi wheat in rice-wheat systems are on average delayed by 26 days and advanced by 4 days, respectively. In calendars adjusted by multi-objective optimization under RCP8.5, the planting dates of kharif rice and rabi rice in double-rice systems are averagely delayed by 15 days and 11 days, respectively, and the planting dates of kharif rice and rabi wheat in rice-wheat systems are averagely delayed by 18 days and advanced by 21 days, respectively.

Although the fallow period between planting dates of two season crops will be reduced in the optimized calendar, the shortened growing season duration under future warming scenarios may lead to an increase of growing season intervals. For rice-wheat rotation systems, the interval time between the harvest date of wheat and the planting date of rice increases with the temperature rise in optimized calendar, but it is shorter than the current interval under all climate change scenarios and the optimized calendar under multi-objective optimization requires shorter seasonal interval than that adjusted by yield maximization. On the contrary, compared with rice-wheat rotation systems, longer intervals and shorter lengths of growing seasons provide double-rice cropping systems more flexible adjustment space in crop calendars for climate change adaptation.

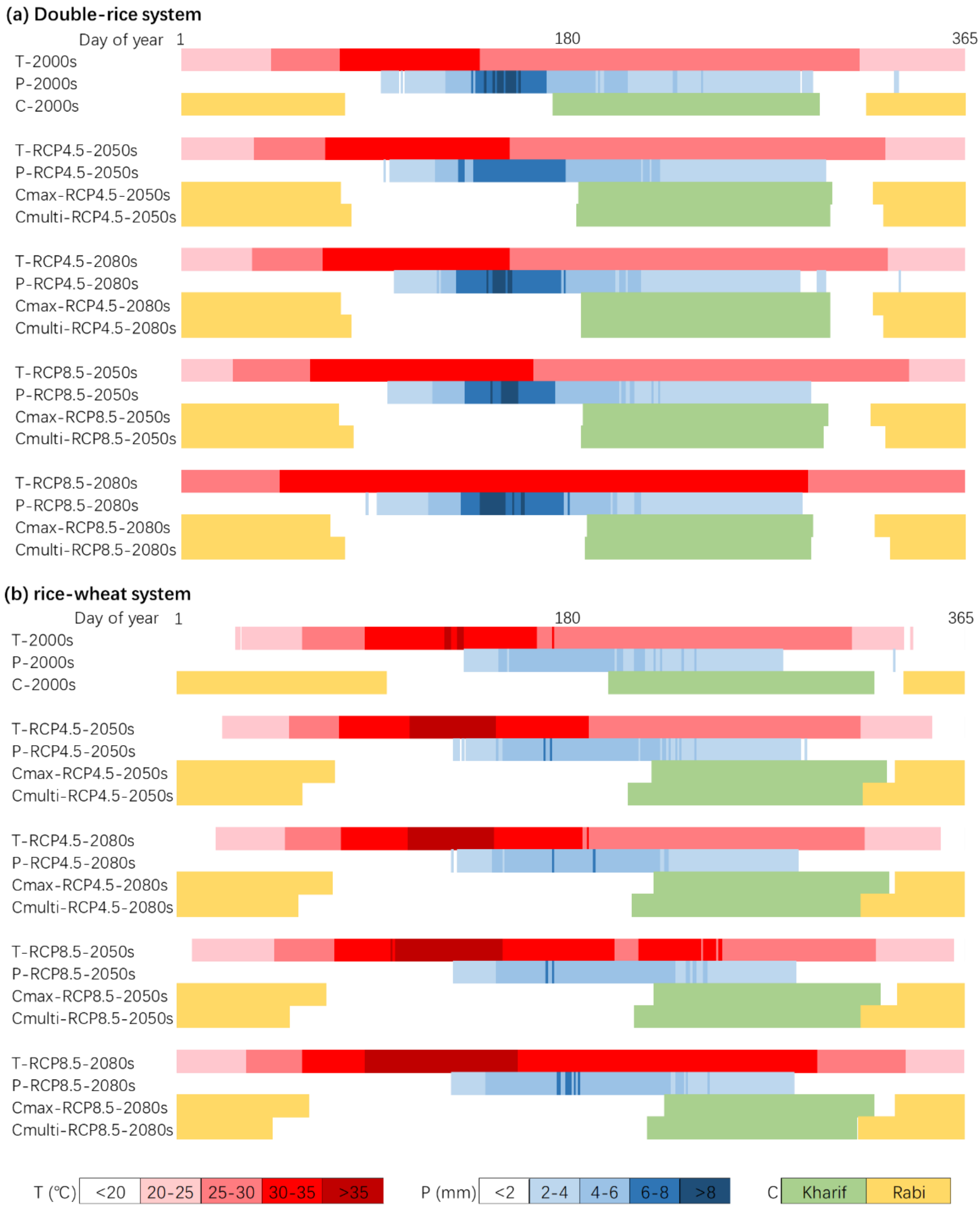

Figure 8 Temperature, precipitation and crop calendars in double-rice systems and rice-wheat systems of the BIM countries under baseline and projected climate for (a) rice-rice and (b) rice-wheat systems. T: temperature; P: precipitation; Cmax: crop calendars shifted with the criteria of yield maximization; Cmulti: crop calendars shifted with multi-objective optimization.

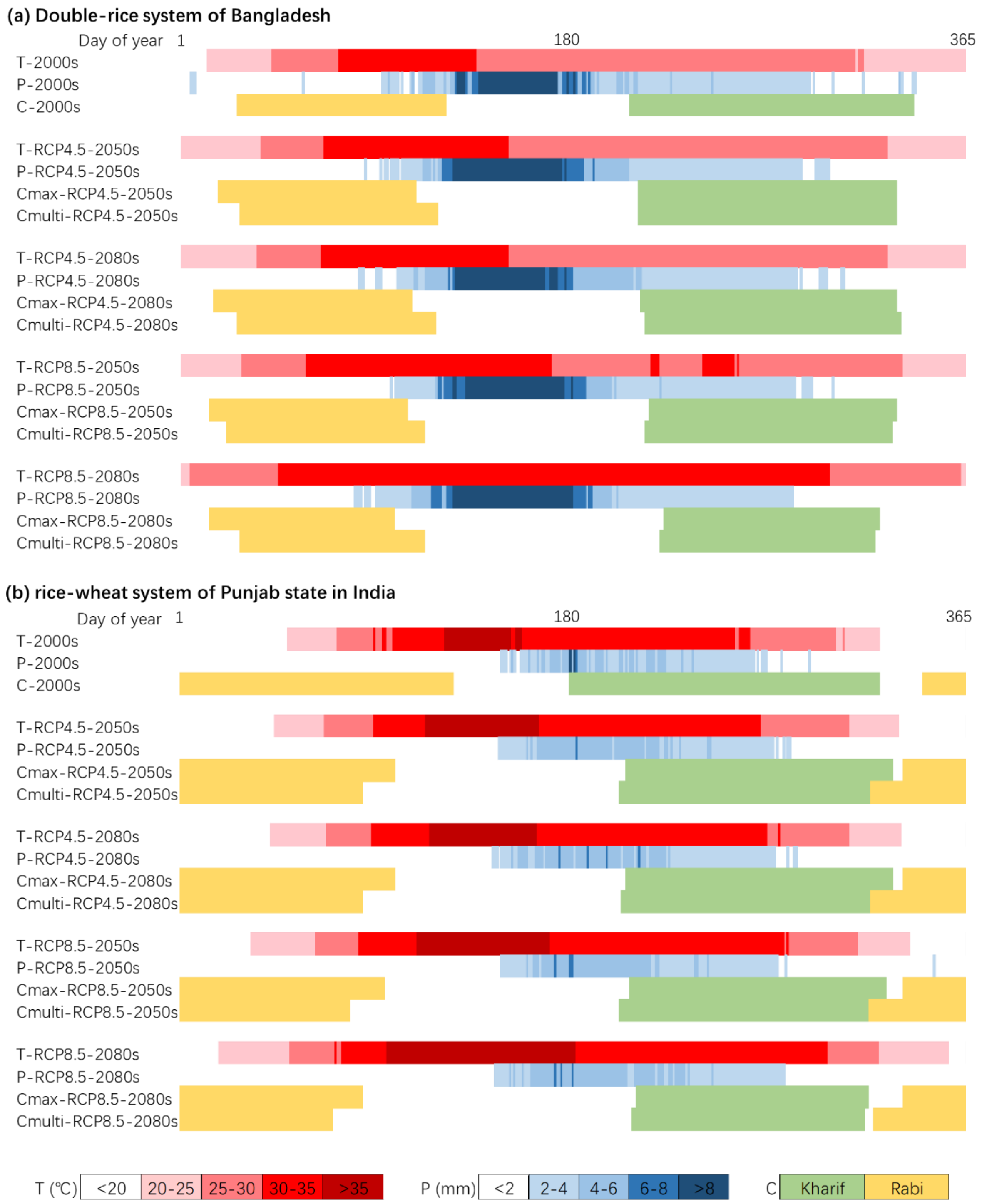

Figure 9 Temperature, precipitation and crop calendars in double-rice systems of Bangladesh and rice-wheat systems of Punjab state in India under baseline and projected climate for (a) rice-rice and (b) rice-wheat systems. T: temperature; P: precipitation; Cmax: crop calendars shifted with the criteria of yield maximization; Cmulti: crop calendars shifted with multi-objective optimization.

3.3 Climate impacts on crop yield potentials without shifting crop calendars

Grain yields would decrease under RCP4.5 and RCP8.5 scenarios with current cropping calendars, regardless of the consideration of CO_2 fertilization (Figure 10). Compared with the double-rice cultivation areas, the simulation results show that the rice-wheat rotation areas will have more heat stress days with temperature above 35 ℃ in the future, and the optimum temperature for wheat growth is lower than that for rice, so the negative response of rice-wheat rotation system to temperature rise is more significant. Nevertheless, the effect of CO_2 fertilization is likely to offset the yield loss caused by temperature rise and maintain the potential yield without a big drop. The average decline of double-rice yields, and rice-wheat yields are 1% and 6% with CO_2 fertilization under four climate change scenarios, respectively. In terms of spatial distribution, rice-wheat systems in the upper Ganges River Plain and the Indus River Plain, double-rice systems in the lower Ganges River Plain, and double-rice systems in Tamil Nadu may have a larger yield loss without changing the crop calendars under RCP8.5 scenarios (Figure 11 & 12).

Figure 10 Potential yield changes under different climate scenarios with current crop calendars and optimized crop calendars

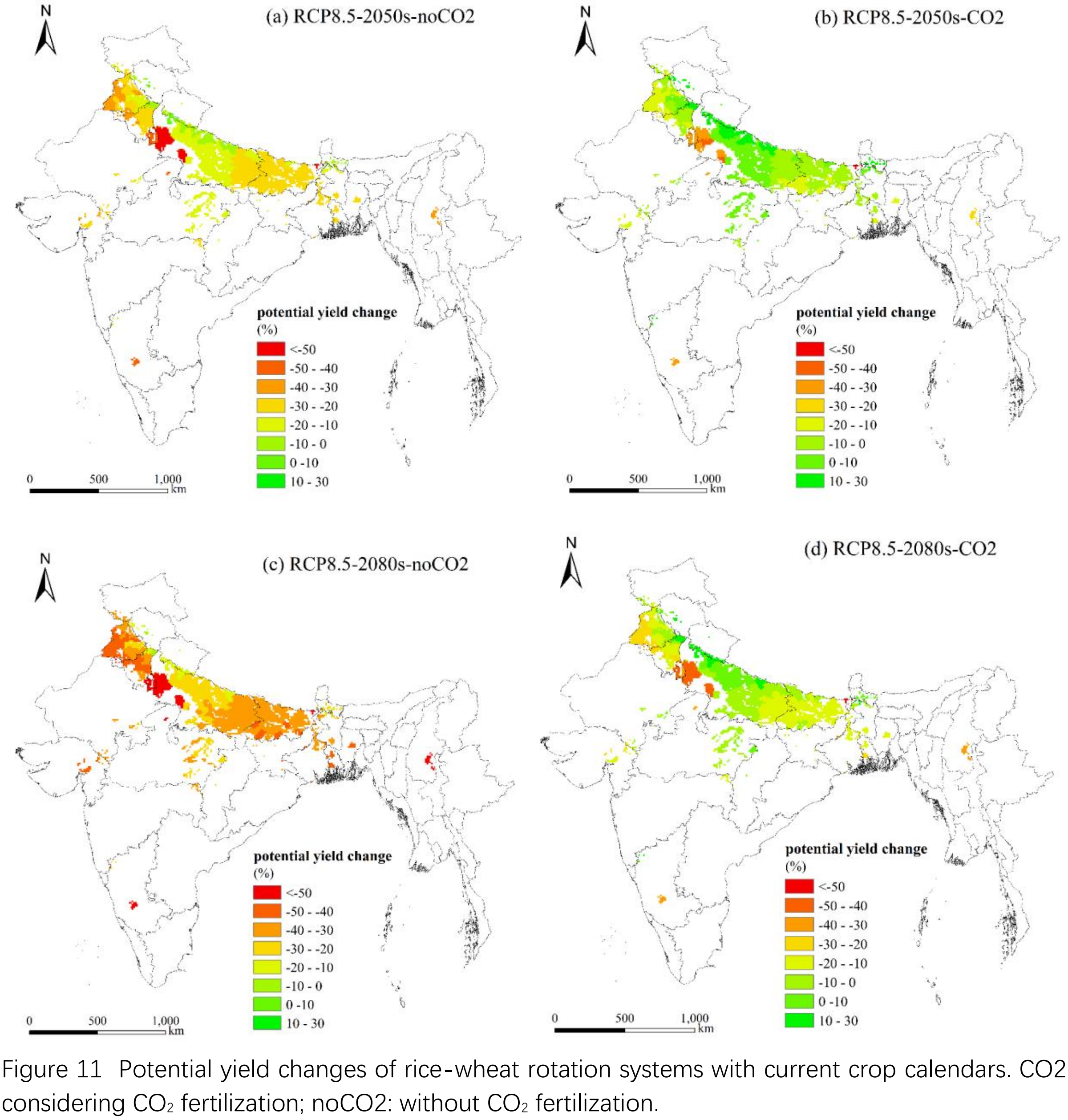

Figure 11 Potential yield changes of rice-wheat rotation systems with current crop calendars. CO2: considering CO_2 fertilization; noCO2: without CO_2 fertilization.

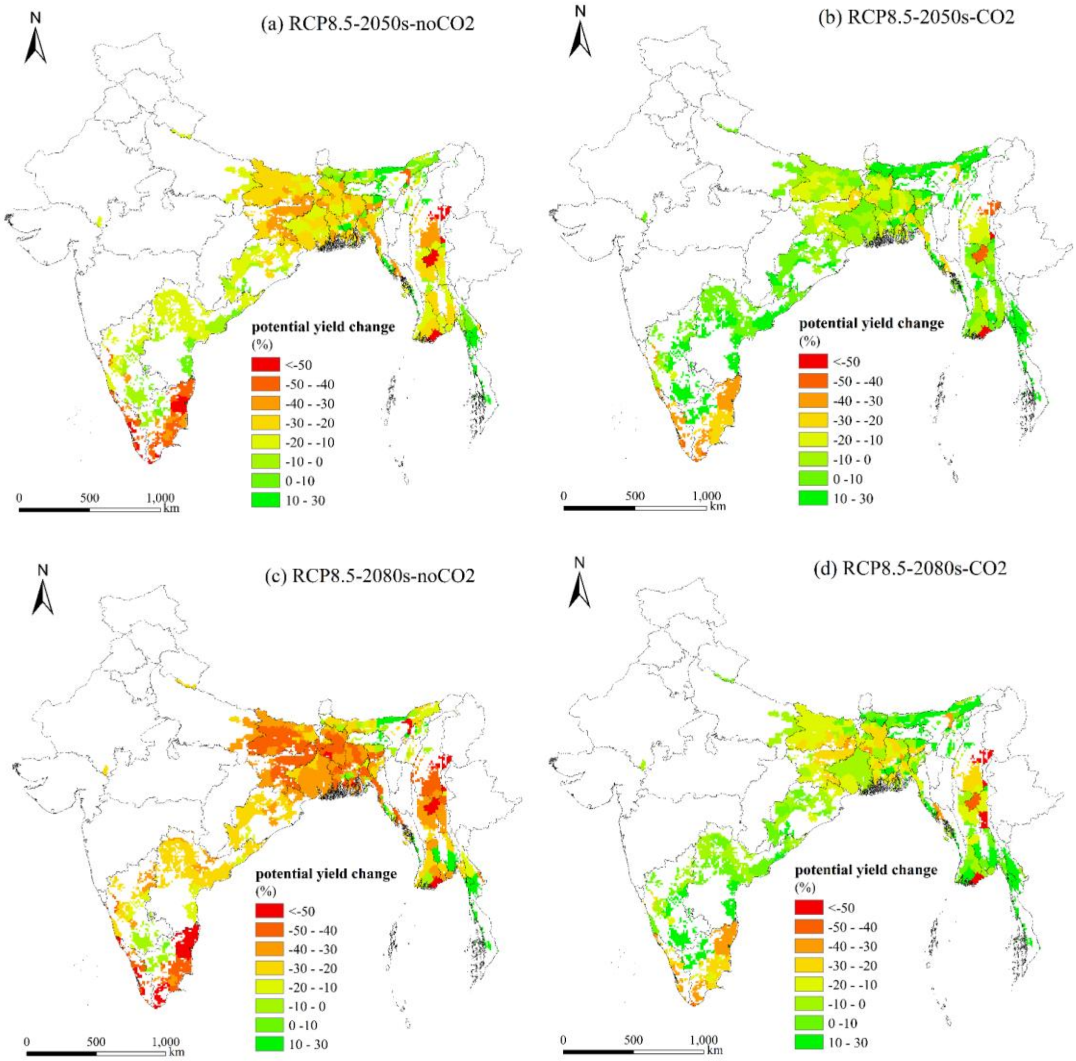

Figure 12 Potential yield changes of double-rice systems with current crop calendars. CO2: considering CO_2 fertilization; noCO2: without CO_2 fertilization.

3.4 Crop yield potentials under projected climate change with adjusted crop calendars

According to the model simulation, the yield loss may be reversed by shifting the crop calendars in the study area under most climate change scenarios (Figure 10). Adjustment of current crop calendars by yield maximization is likely to improve 15% of the double-rice yields and 3% of the rice-wheat yields, and adjustment of crop calendars by less irrigation need and heat stress days is likely to improve 6% of the double-rice yields and maintain the rice-wheat yields when considering CO_2 fertilization.

The effects of different optimization schemes on potential yields are highly heterogeneous in spatial distribution (Figure 13 & 14). Potential yield gap of rice-wheat systems between the basic scenario with non-adjusted crop calendars and the optimized scenarios with adjusted crop calendars under RCP8.5 reaches 15~20% in northwestern India, while it is only 5~10% in the middle Ganges River Plain. In double-rice areas, the potential yield gap in Bihar and Tamil Nadu of India, Rangpur of Bangladesh, central Myanmar, and parts of the Irrawaddy Delta is larger than other areas by optimized crop calendar with yield maximization. However, not all regions are able to achieve the maximum potential yields due to changes in irrigation water needs and heat wave effects on agricultural activities compared with scenarios simulated by original crop calendars. By comparing the results of max-yield and multi-objective optimization, most rice-wheat rotation systems in the study region could achieve a balance of mitigating yield loss, saving irrigation water, and avoiding heat wave. However, these optimization objectives are contradictory in many areas with double-rice systems, such as West Bengal, Bihar, and Tamil Nadu in India, most areas in Bangladesh, and the Irrawaddy Delta in Myanmar.

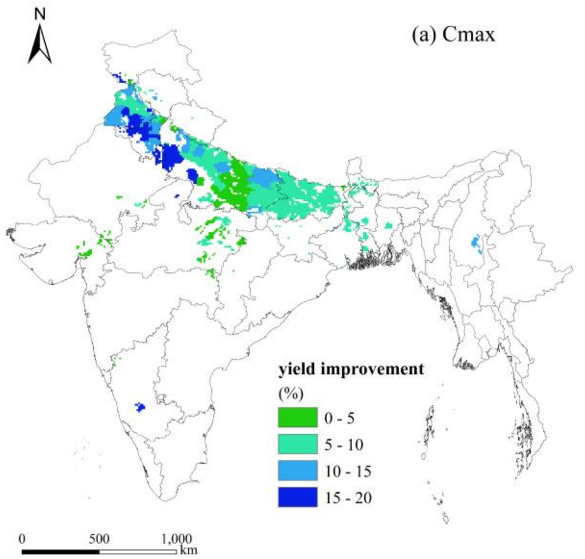

Figure 13 Potential yield improvement with adjusting crop calendars compared to the basic scenario with non-adjusted crop calendars in rice-wheat rotation systems under RCP 8.5. (a) Cmax: crop calendars shifted with the criteria of yield maximization; (b) Cmulti: crop calendars shifted with multi-objective optimization.

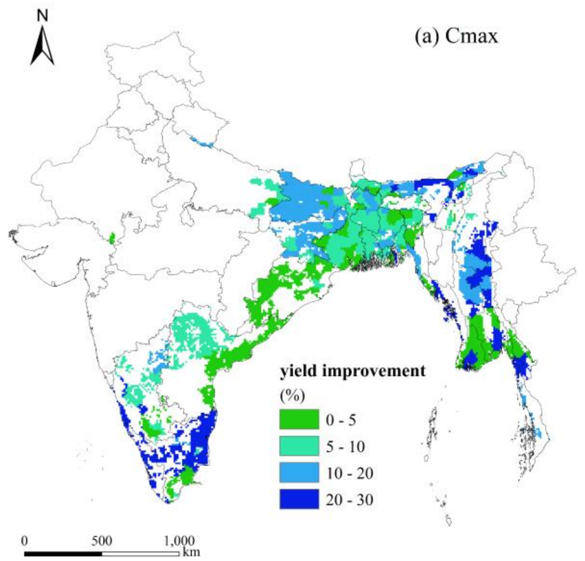

Figure 14 Potential yield improvement with adjusting crop calendars compared to the basic scenario with non-adjusted crop calendars in double-rice rotation systems under RCP 8.5 (a) Cmax: crop calendars shifted with the criteria of yield maximization; (b) Cmulti: crop calendars shifted with multi-objective optimization.

3.5 Relationships between crop yield improvement, irrigation water requirement, and heat stress mitigation in the study area

Shifting crop calendars may significantly mitigate yield losses in the future, but such climate adaptation measures are not suitable for all areas in the study region. According to the classification results, nearly half of the study area have the potential to increase yield by more than 10% through changing crop calendars, but 59% of these areas would face contradictions in obtaining crop yield improvement, saving irrigation water, and mitigating heat stress under climate change (Figure 15). The regions with the capacity to concurrently improve crop yield and reduce irrigation water requirement through adjusting local crop calendars only account for 18% of the total study area. In India, Punjab state is one of the most favorable areas to promote crop calendar adjustment, where potential yields of rice-wheat rotation systems could be improved by up to 20%, irrigation volume could be cut down by 127mm, and temperature stress days could be reduced by 24 days with multi-objective optimized crop calendars. In Bangladesh, Rangpur is the most favorable area to shift crop calendar in the future, where potential yields of double-rice cropping systems could be improved by up to 17% and irrigation volume could be reduced by 289mm. Since future temperature in Rangpur is suitable for crop growth, there is no significant change in heat stress days before and after adjusting the crop calendar. In Myanmar, central rain shadow area is a favorable area to adjust crop calendars, where potential yields of double-rice systems could be improved by up to 26%, irrigation volume could be cut down by up to 253mm, and temperature stress days could be reduced by 15 days in Mandalay through multi-objective optimization.

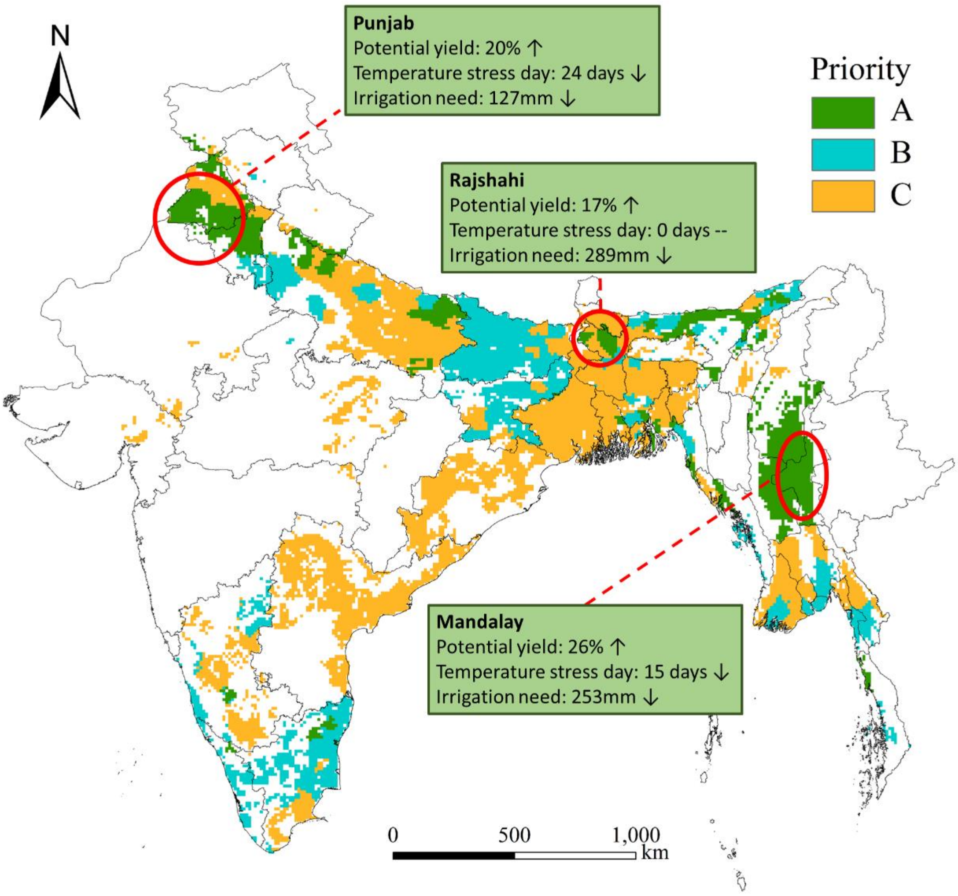

Figure 15 Priority of promoting crop calendar adjustment as an adaptation measure to climate change in India, Bangladesh, and Myanmar.

4 Discussion

4.1 Evaluation of potential yield simulation

This study focuses on the simulation of potential yield change driven by temperature rise and planting date adjustment with adequate fertilization and irrigation rather than actual yield variation, because low price of rice products, plant diseases and insect pests, inappropriate field management, weed competition, and soil fertility degradation were also important limitations for crop yields in southern Asian rice farming systems and rice-wheat rotation systems (Waddington et al., 2010). It is difficult for EPIC model to accurately distinguish and extract the effects of these factors, especially the influence of socio-economic factors, on actual yields under climate change.

Generally, the simulation result of rice potential yield is 0.5t/ha lower than the previous model simulation in the BIM countries (Table 2). One of the reasons is the consideration of spatially detailed crop calendars in the study. Due to socio-economic factors, not all crop seasons are fully matched with climatic conditions in the study area, leading to a reduction of potential yields. According to the model results based on RiceAtlas, in addition to the time phase of rice growing seasons, the length of rice growing seasons also has a great impact on the simulation of potential yield, which emphasized the significance of using fine spatial-resolution calendars in regional-scale simulation.

4.2 Uncertainties in simulating CO_2 fertilization

Rice and wheat are both C3 crops, which are more sensitive to elevated CO_2 compared with C4 crops (Kimball, 1983). In this study, simulated CO_2 fertilization - impacting biomass accumulation and transpiration efficiency - raised the crop yield by 11-39%, showing a similar tendency with field experiments conducted in South Asia by De Costa et al. (2007) and Roy et al. (2015). Nevertheless, CO_2 fertilization was found to reduce or disappear under wetter, drier, and/or hotter conditions when the forcing variable exceeded its intermediate regime (Obermeier et al., 2017). Compared with parameters of yield response to temperature change, those used to estimate CO_2 fertilization in process-based models are likely to be highly unreliable (Agnolucci, 2020). More experiments are needed to determine whether the effect of CO_2 fertilization can offset the negative effects of temperature rise under different field management practices in future.

4.3 Response of crop season length to temperature rise

In the study, we found that the response of wheat growing season to temperature rise evident in the MODIS data indicate greater sensitivities of season length to warming compared with that implied by EPIC models. Lobell et al. (2012) also found the same phenomenon in wheat simulation by CERES-Wheat and APSIM model. But this result doesn’t hold in rice, which has a higher growth temperature threshold than wheat. It reflects that the growing season length probably depend on the degree to which warming results in increased exposure to heat above critical thresholds and commonly used crop models underestimate the impacts of heat stress on wheat senescence in India. An another interesting finding is that, unlike what is generally believed, shortened growing season does not always result in a decrease in crop production if extreme heat can be avoided at the end of growing season, of which some rice-wheat rotation systems in northwestern India are good examples.

Because triple-cropping system is not as widely distributed as the double-cropping system in the study area and its calendar adjustment has less flexibility, we only discussed shifting planting dates of double-cropping systems in the BIM countries. Owing to more frequent heavy rain and shorter time window for crops to grow below 30 °C and 35 °C in the future (Figure 8 & 9), it will be a great challenge to improve cropping intensity from single-crop to double-crop or triple-crop in the study area.

4.4 Challenges from shortened fallow period in rice-wheat rotation system

Though areas with A-level priority (Figure 15) could significantly mitigate crop yield loss and reduce considerable irrigation water use by shifting crop planting dates, the values showed in results are theoretical maximums based on climate limitations and it requires a great effort to achieve in practice. For parts of rice-wheat rotation system in India, fallow periods between rice harvest dates and wheat planting dates are expected to be curtailed within one week to pursue the highest potential yield in the future. It is necessary for policy makers and farmers to work out a detailed farming scheme including selection of favorable crop varieties with suitable growth duration, preparation of seedbed in advance, application of direct-seed technology, agricultural machinery operation, and deepen the understanding of climate change impacts on these supporting technologies. It should be also considered that limitation of labor availability, cultivating improved varieties, and renting seeding machines will greatly increase food production costs, which will restrict farmers' ability to adopt shifting planting dates as an adaptation measure to cope with climate change. The relationships among technology, farmer decision making and climate change impacts are complex, underlining the importance of developing a subnational level dataset of economic variables at fairly fine resolution that provides information on farmer access to different levels of technology (Toshichika 2015).

5 Conclusions

We investigated potentials and limitations of adjusting crop calendars for climate change adaptation of two most widely distributed food production systems over India, Bangladesh, and Myanmar. Our results imply that most yield loss in rice and wheat could be avoided, or even reversed through shifting planting dates if CO_2 fertilization effects are realized. While there remains uncertainty around the effects of CO_2 on crop growth, model results indicate that adjusting crop calendars has great potential to mitigate yield reduction induced by temperature rise in the study area. Different from single-crop studies, we simulated double-rice and rice-wheat systems as a whole and considered the future variation of fallow periods between crop growing seasons under climate change with the multi-objective optimized scenarios. Fallow periods between kharif-rice harvest dates and rabi-rice planting dates in double-rice systems are likely to become longer due to shorter growing season duration in the future, meanwhile fallow periods between kharif-rice harvest dates and rabi-wheat planting dates in rice-wheat systems are likely to become shorter due to advanced planting dates of rabi wheat. It indicates that double-rice systems in the BIM countries will have more flexibility to cope with smaller time windows for crop growth and development: there will be longer fallow periods between two cropping seasons and more favorable air temperature range for double-rice systems than wheat-rice systems in South Asia. Moreover, nearly half of the study area have the potential to increase yield by more than 10% through changing crop calendars compared to the basic scenario with non-adjusted calendars under RCP8.5 in 2080s, but 59% of these areas would face contradictions in obtaining crop yield improvement, saving irrigation water, and mitigating heat stress under climate change. The areas suitable to adopt shifting planting dates as one of adaptation strategies, such as Punjab state in India and Rangpur in Bangladesh, are also the areas with shortened growing season intervals, which requires great efforts to achieve the adaptation objectives under climate change. Therefore, the trade-off among economic cost, environmental impacts, and food security should be carefully considered for local governments and farmers to promote adjustment of crop calendars in the future.

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