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Predicting the Water Requirement for Rice Production as Affected by Projected Climate Change in Bihar, India

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Received: 22 September 2020; Accepted: 23 November 2020; Published: 25 November 2020

Abstract: Climate change is a well-known phenomenon all over the globe. The influence of projected climate change on agricultural production, either positive or negative, can be assessed for various locations. The present study was conducted to investigate the impact of projected climate change on rice's production, water demand and phenology for the state of Bihar, India. Furthermore, this study assessed the irrigation water requirement to increase the rice production by 60%, for the existing current climate scenario and all the four IPCC climate change scenarios (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) by the 2050s (2050–2059). Various management practices were used as adaptation methods to analyze the requirement of irrigation water for a 60% increase in rice production. The climate data obtained from the four General Circulation Models (GCMs) (bcc_csm1.1, csiro_mk3_6_0, ipsl_cm5a_mr and miroc_miroc5) were used in the crop growth model, with the Decision Support System for Agrotechnology Transfer (DSSAT) used to simulate the rice yield, phenological days and water demand under all four climate change scenarios. The results obtained from the CERES-Rice model in the DSSAT, corresponding to all four GCMs, were ensembled together to obtain the overall change in yield, phenology and water demand for 10 years of interval from 2020 to 2059. We investigated several strategies: increasing the rice's yield by 60% with current agronomic practice; increasing the yield by 60% with conservation agricultural practice; and increasing the rice yield by 30% with current agronomic practice as well as with conservation agricultural practices (assuming that the other 30% increase in yield would be achieved by reducing post-harvest losses by 30%). The average increase in precipitation between 2020 and 2059 was observed to be 5.23%, 13.96%, 9.30% and 9.29%, respectively, for RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. The decrease in yield during the 2050s, from the baseline period (1980–2004), was observed to be 2.94%, 3.87%, 4.02% and 5.84% for RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5, respectively. The irrigation requirement was predicted to increase by a range of 39% to 45% for a 60% increase in yield using the current agronomic practice in current climate scenario and by 2050s with all the four climate change scenarios from the baseline period (1980–2004). We found that if we combine both conservation agriculture and removal of 30% of the post-harvest losses, the irrigation requirement would be reduced by 26% (45 to 19%), 20% (44 to 24%), 21% (43 to 22%), 22% (39 to 17%) and 20% (41 to 21%) with current climate scenario, RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 conditions, respectively. This combination of conservation practices suggests that the irrigation water requirement can be reduced by a large percentage, even if we produce 60% more food under the projected climate change conditions.

Keywords: water requirement; rice production; phenology; food security; climate change scenarios

1. Introduction

Food security is a big concern globally for the near future. The rising global population will increase the global food demand between 60 to 100% by 2050 [1–3]. In order to ensure optimum food production, the weather, with its various factors, plays an important role through proper crop growth and development. However, in the long run, climate change is expected to have an impact on the food availability and water requirement for crop cultivation [4–6]. Under the climatic factors, precipitation, temperature, solar radiation and carbon dioxide are the primary causes for altering crop production. The global future climate projection by the Intergovernmental Panel on Climate Change (IPCC) predicts that the average annual temperature is expected to increase by 0.3 to 1.7 °C under RCP 2.6, 1.1 to 2.6 °C under RCP 4.5, 1.4 to 3.1 °C under RCP 6.0 and 2.6 to 4.8 °C under RCP 8.5 by the end of the 21st century [7].

Rice is a staple food of South Asia, where 7% of the total land is used for rice cultivation [8,9]. In India, rice is grown in a 43 million ha area, around 27% of the total arable land [10]. With the rapid population growth in India, which also leads to urbanization, the land used for rice production is gradually shrinking [11–13]. The projected change in climate will add additional challenges on rice production in the country [14,15]. Moreover, as per the 2014–2015 census by the Government of India, Bihar is the 6th largest rice producing state in India, and the monsoon rainfall is very important for rice production in the state. This state has a dearth of resources for agricultural production. Thus, even a inconsiderable change in weather in any particular year causes a reduction in crop yield [16]. Therefore, a study of the effect of climate change on rice production is necessary to understand and develop strategies for the future of agriculture in the state of Bihar.

Several studies have assessed the impact of climate change on crop production. Abeysingha et al. [17] found an increase in the annual rice yield from the 2020s to 2080s with the Special Report on Emission Scenarios (SRES)—A2, A1B and B1—for the Gomti river basin region in Uttarpradesh, India. They observed an increase in water demand, but the irrigation water was observed to decrease in the future due to an increase in monsoon rainfall. Shah and Srivastava [18] indicated that higher temperature causes a reduction in Kharif rice in India, and showed the temperature as an important function of rice yield. Furthermore, a study by Rao et al. [19] found that the impact of climate change can reduce rice production in the range of 4.5–9% from 2020 to 2039 in India. A study on the average climate change impact by Auffhammer et al. [20], based on the collected data during 1966–2002 from all the states in India, showed the adverse impact of water stress and excess rainfall on rice yield. Their analysis using Monte Carlo simulation showed the drought frequency as a reason for the reduction in yield by 1.7%.

The impact of climate change scenario A2 during 2020–2080 on potato, in Bihar, showed a decrease in yield by a maximum of 5.9%, 15% and 24.8% by 2020, 2050 and 2080, respectively [21]. Under a similar climate change scenario, A2, the rice yield was estimated to increase by 2.7% in 2020, but decrease by 0.3% and 31.3 % by 2050 and 2080, respectively [22]. In order to assess the climate smartness of current land use for agriculture in Bihar, Shirsath et al. [23] used productivity, incomes and emissions as benchmarks, and recommended the derivation of the various evidence and reasoning from the outline of the database for climate-smart intervention through a bio-economic land-use analysis. These studies, to investigate the impact of climate change on crop yield, used the crop growth model INFOCROP by Aggarwal et al. [24]. Several other climate change studies have been performed for other parts of India [25–28] but the assessment of climate variation on rice crop production with current climate change scenarios in Bihar has not been performed yet.

The objectives of this study are to apply the crop growth model Decision Support System for Agrotechnology Transfer (DSSAT) to predict the changes in the rice yield, water demand and

phenological growth in Bihar, India, due to the effect of the projected change in climate by the 2050s. The CERES-rice model in DSSAT was assessed for its robustness for the rice crop [29], and hence used in this current climate change study for Bihar, India. We also predicted the requirement of irrigation water for a 60% increase in rice yield by the 2050s. We investigated various management practices to maximize rice production and minimize the irrigation requirement.

2. Material and Methods

2.1. Study Area Description and Agricultural Dataset for Crop Modeling

The study area for this experiment is located on the farm of the Borlaug Institute of South Asia (BISA), Pusa, Bihar, India, which is situated at a latitude of 25°58′ N and longitude of 85°40′ E, with an elevation of 52 m above sea level (Figure 1). The climate of the study area is hot and humid summer and cold winters with an average annual rainfall of 1297 mm, mainly received in the monsoon season (June to September). Rice is the primary crop that is grown by farmers, followed by wheat and maize. Monsoon season is utilized to cultivate the rice crop because of its high water demand, and wheat, which needs relatively less water, is grown in the Rabi season (November to May).

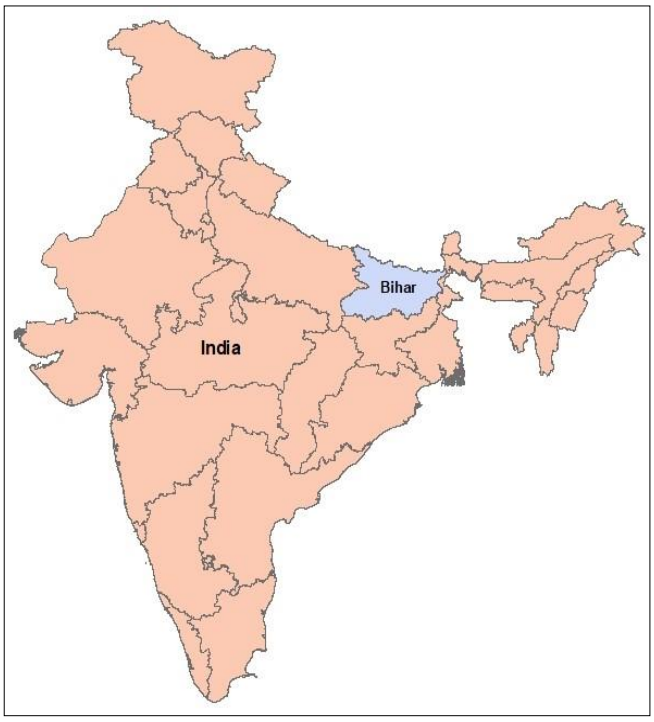

Figure 1. The study area: Bihar, a state in India.

The long-term puddling-transplanted rice experimental data during the monsoon season from 2006 to 2015 were collected (the current climate scenario) [29]. These 10 years of data were used to calibrate and validate the CERES-Rice model in the DSSAT, and based on its excellent performance, found to be good for the decision-making process in agricultural modeling, hence the same model was used for this study [29]. The statistical measures to assess model performance, from calibration to validation, have been presented in the article by Jha et al. [29].

2.2. Climate Data

The baseline and projected future climate data to use in this study were collected from Climate Change, Agriculture and Food Security (CCAFS) (www.ccafs-climate.org/data/), developed by the Consultative Group on International Agricultural Research (CGIAR). The AgMIP Modern-Era

Retrospective Analysis for Research and Applications (AgMERRA) was used as an observation dataset for an available historical period of 25 years (1980–2004). These daily time series climatic data provided high-resolution (0.25° × 0.25°) and consistent climate data and was designed particularly to assess the impact of climate change and variability on agricultural production. The AgMERRA dataset is a combination of reanalysis data (the Modern-Era Retrospective Analysis for Research and Applications, MERRA, and the Climate Forecast System Reanalysis, CFSR) and the dataset collected from various observatory networks and satellites. This dataset has been widely used by researchers for agricultural modelling [30–32]. Thus, we have also used this dataset, which is specifically used for agricultural modelling purposes. To assess the significance of this dataset for our modelling objectives, we performed several statistical analyses and, based on a strong correlation between the historical observed and historical simulated data, we used the projected future climate data after bias-correction for agriculture modelling.

The baseline data were generated using four recent global climate models (bcc_csm1.1, csiro_mk3_6_0, ipsl_cm5a_mr and miroc_miroc5). The model bcc_csm1.1 was developed at the Beijing Climate Center (BCC), China Meteorological Administration (CMA), China [33]. This model simulates the interaction between the global carbon cycle and vegetation and is an integration of several climatic components models—the atmospheric model (bcc_agcm2.1), ocean model (mom4_l40), land surface model (bcc_avim1.0) and sea ice model (SIS) [34]. The csiro_mk3_6_0 model was developed in Australia under a collaboration between the Commonwealth Scientific and Industrial Research Organization (CSIRO) and the Queensland Climate Change Center of Excellence (QCCCE). This model incorporates aerosol treatment and an updated radiation scheme, which were not included in the previous version of this model [35,36]. Another selected climate model in this study, ipsl_cm5a_mr, was developed at Institut Pierre-Simon Laplace, France. The atmospheric component model (LMDz), the NEMO model for ocean and sea ice components, ORCHIDEE (vegetation model), and INCA (atmospheric chemical compositions model) are coupled using the OASIS coupler in the climate model ipsl_cm5a_mr [37,38]. The climate model miroc_miroc5 was developed in collaboration among the University of Tokyo, National Institute for Environmental Studies (NIES) and Japan Agency for Marine-Earth Science and Technology. All atmospheric components, except the atmospheric dynamical core part, land surface, oceanic, sea ice and vegetation components, were modified in this version of the model [39]. All the four selected global climate models are incorporated in the fifth phase of Coupled Model Intercomparison Project (CMIP5). These GCMs were selected based on the four selection approaches, namely, the vintage, resolution, validity and representativeness of the results, suggested by the team of the Task Group on Scenarios for Climate Impact Assessment (TGCIA), developed under the IPCC [40]. The description of these selected models is provided in Table 1 [33,35,36,38,39].

Further, this baseline period (1980–2004) was used to produce the projected future climate data of 40 years (2020–2059) for all the four representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5), which are the future climate change scenarios adopted in the IPCC's 5th assessment report [41]. We have shown the projected change in maximum temperature (Tmax) (Figure 2a), minimum temperature (Tmin) (Figure 2b) and solar radiation (Figure 3) for a 10-year (decade) interval from 2020 to 2059, with all four future climate change scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

Table 1. Selection of global climate models [33,35,36,38,39].

Model	Research Center	Resolution	
		Atmosphere	Ocean
bcc_csm1.1	Beijing Climate Center (BCC), China Meteorological Administration (CMA), China	2.8° × 2.8°	0.8° × 1.0°
csiro_mk3_6.0	Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Queensland Climate Change Centre of Excellence (QCCCE), Australia	1.85° × 1.875°	1.0° × 1.875°
ipsl_cm5a_mr	Institut Pierre-Simon Laplace, France	1.27° × 2.5°	—
miroc_miroc5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	1.4° × 1.4°	0.8° × 1.4°

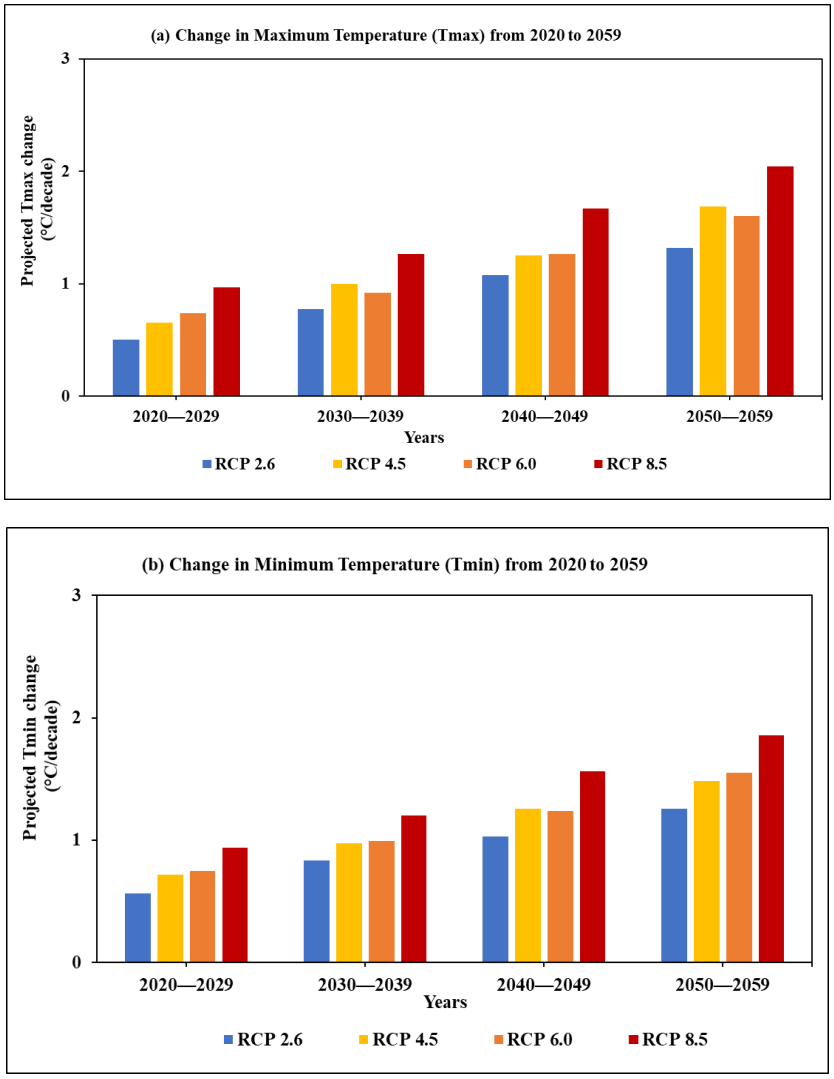

Figure 2. Projected change in maximum temperature (Tmax) (**a**) and minimum temperature (Tmin) (**b**) for a 10-year (decade) interval from 2020 to 2059, with RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

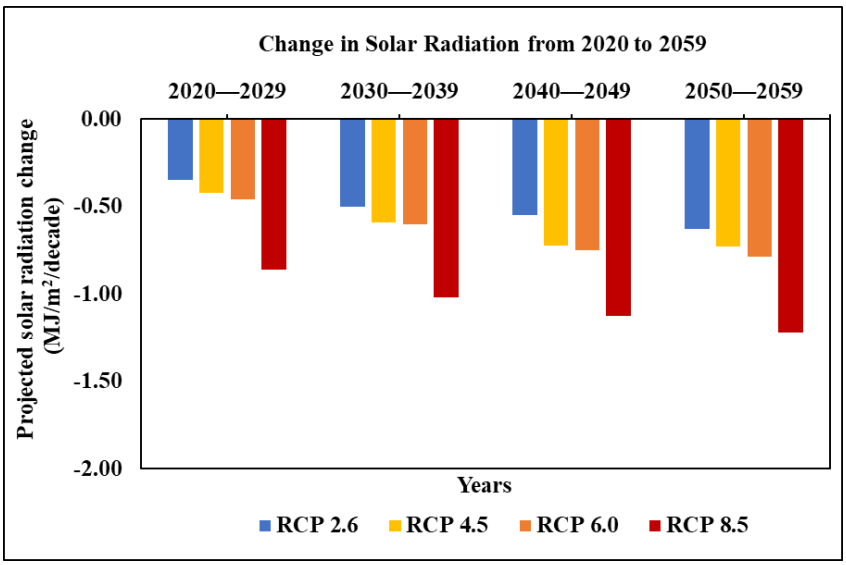

Figure 3. Projected change in solar radiation for a 10-year (decade) interval from 2020 to 2059 with RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

All the four RCPs refer to the net radiative forcing taken up by the earth due to an increase in greenhouse gases and pollutants. RCP 2.6 is a low greenhouse gas emissions scenario in which radiative forcing reaches the peak value of 3.1 W/m^2 before 2100 and then returns to 2.6 W/m^2 by 2100 [42]. RCP 4.5 and RCP 6.0 are both intermediate emission of greenhouse gas scenarios, where radiative forcings of 4.5 W/m^2 and 6.0 W/m^2, respectively, stabilize shortly after 2100 [43,44]. RCP 8.5 is a high greenhouse gas emission scenario, where the rise in radiative forcing reaches 8.5 W/m^2 by 2100 [45,46]. We considered the projected CO_2 concentrations for the 2050s, corresponding to all the RCPs, to comprehensively understand the impact of climate change on rice yield and water demand.

2.3. Processing of Climate Data

Global climate models are the primary source of generating climate data for analysis of climate change impact at global and local scales. However, the raw data obtained from the GCM simulations contain large deviations from the observed baseline data [47]. The models' outputs are projected at a limited spatial resolution (>50 km) and may contain systematic errors due to the coarse resolution. Therefore, errors and biases need to be removed in order to make the raw climate data of the GCMs to use in crop modeling studies. The bias correction method is applied to correct any flaws in the GCMs' raw data [48]. Quantile mapping, a bias correction method, was selected to correct the GCMs' data, which works well for both stochastic and non-stochastic variables.

2.4. DSSAT Simulation to Assess the Impact of Climate Change on Rice Yield, Phenology and Water Demand

The DSSAT [49] was simulated using the baseline period (1980–2004) and projected future climate (2020–2059) data generated from each of the four GCMs, for all four scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. The ensemble mean of the outputs from the DSSAT simulation for each of the four GCMs was taken as the average crop growth, yield and water demand for the baseline period and future years. The impact of climate change on rice yield, phenological days and water demand were computed in 10-year intervals between 2020 and 2059, relative to the baseline period (1980–2004), using Equation (1).

$$\begin{aligned}&\text{Percentage change in rice yield, phenology, and water demand}\\&= ((\text{Future simulated value} - \text{Baseline value})/(\text{Baseline value})) \times 100\end{aligned} \tag{1}$$

The flow chart of the estimation of the climate change impact on rice production, phenological days and water demand is shown in Figure 4.

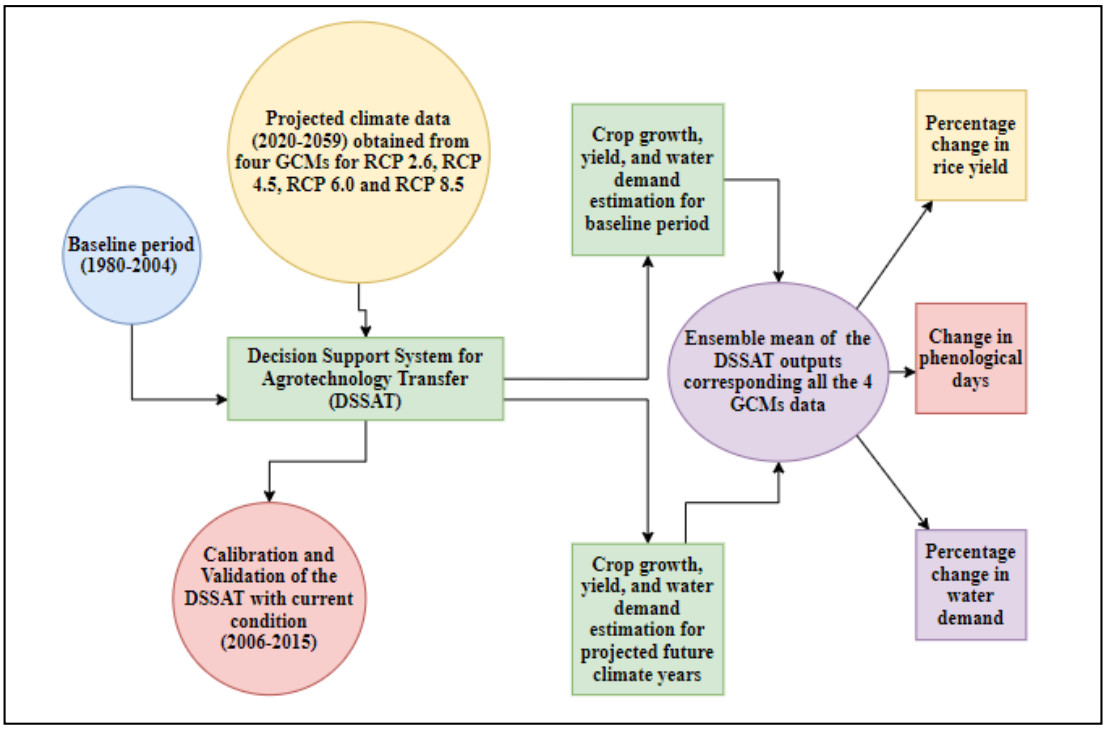

Figure 4. Flow chart for estimating the impact of climate change on rice production, phenological days and water demand, using the Decision Support System for Agrotechnology Transfer (DSSAT) simulation.

2.5. Estimation of Irrigation Water Requirement for Rice Production

The CERES-Rice model [49] was used to study the irrigation requirement for rice production for the current (2006–2015) and projected future climate change conditions (2020–2059). Since crop yield is a function of various factors, such as irrigation water, fertilizer and weather, the mathematical form of Equation [50] can be written as in Equation (2).

$$Y = f(W,\ We,\ F) \tag{2}$$

where Y is the yield and W represents the irrigation water requirement; We, the weather parameters (precipitation, temperature and solar radiation); and F, the fertilizer input. Furthermore, the crop growth model also computes the yield productivity, as a function of irrigation water, precipitation, temperature and fertilizer input. Thus, the yield productivity will provide the fraction of percentage yield obtained from these factors, which can be expressed as given in Equation (3).

$$Y_p = f(PPT,\ Ir,\ ET,\ Nu) \tag{3}$$

where Y_p is the yield productivity, PPT represents the percentage of yield productivity from precipitation, Ir is the percent of yield productivity from irrigation water, ET represents the percentage of yield productivity from evapotranspiration and Nu shows the percent yield productivity from the fertilizer inputs.

Based on the simulated yield productivity from various predictor variables, given in Equation (3), by the DSSAT, the percentage of irrigation requirement for a 60% increase in rice production was estimated. Considering precipitation and nutrient inputs as constants, the yield productivity as affected by these two factors is considered unchanged. The change in yield productivity from ET, due to the increase in irrigation requirement, was assumed negligible. The DSSAT model

was simulated for conservation agriculture, with direct-seeded rice and keeping the crop residue of 2500 kg/ha; these conditions produced the maximum yield through the model simulation [29]. Conservation agriculture (direct-seeded rice with residue use) is becoming a desired agricultural practice for rice production because it does not require much water during seedlings, eliminate current agronomic practice (transplanting) and eliminate the need for a continuous ponding depth of 5–6 cm in the rice field. Additionally, this practice also helps preserving moisture in soil by reducing the evaporation from the soil surface due to the presence of crop residue on the topsoil. Therefore, the yield productivity from the different predictor variables, as given in Equation (3), obtained with the conservation agriculture method, was used to estimate the irrigation requirement to increase the yield by 60%. Furthermore, we assumed that if the post-harvest loss of rice of 30% [51,52] is totally eliminated, we would only need to increase the yield by 30% (meaning that the combination of 30% yield increase and elimination of 30% losses that happens globally at present will give a 60% increase in rice yield). Thus, the requirement of irrigation water with reducing the post-harvest loss was computed using a similar method for increasing the yield by 60%.

2.6. Management Scenarios for Predicting the Rice Yield and Irrigation Water Requirement

Since Bihar, India, is mostly an agricultural state and rice is a staple food, we developed management practices for maximizing the rice production and associated irrigation water requirements. In addition to estimating the irrigation water requirement for sustaining the current level of rice yield, we also investigated the possible irrigation water requirement for a 60% increase in rice production (as described in Section 2.5). The following scenarios are developed.

(a) Estimate the change in irrigation water requirement for increasing the rice yield by 60% with current agronomic practice and climate change scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5;
(b) Estimate the change in irrigation water requirement for increasing the rice yield by 60% with conservation agricultural practices and under climate change scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5;
(c) Estimate the change in the irrigation water requirement for increasing the rice yield by 30% (assuming that the other 30% increase in yield would be achieved by reducing the post-harvest losses by 30%) with the current agronomic practice and under climate change scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5;
(d) Estimate the change in irrigation water requirement for increasing the rice yield by 30% with conservation agricultural practices (and assuming a post-harvest loss reduction by 30%) and under climate change scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

3. Results

3.1. Current and Projected Future Climate Change Impact on the Rice Yield, Phenology and Water Demand

Table 2 describes the changes in yield, precipitation, irrigation water requirement, rice water demand and CO_2 concentration with the current climate scenario and projected future climate change scenarios—RCP 2.6, RCP 4.5, and RCP 6.0 and RCP 8.5, respectively.

It can be seen from Table 2 that the yield with the current climate scenario has increased from the baseline period associated with the increase in precipitation and CO_2 concentration that have been observed for the 10 years of the period. Furthermore, the increase in rice yield leads to an increase in water demand. The change in yield, water demand and phenology under all four scenarios—RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5—from the baseline period (1980–2004), are described below.

Table 2. Yield, water inputs (precipitation + irrigation water), water demand and CO_2 concentration, for the baseline period (1980–2004), current climate scenario (2006–2015) and projected future climate change scenarios up to 2050s, under RCP 2.6, RCP 4.5 RCP 6.0 and RCP 8.5.

Climate Scenarios		Yield (kg ha^{-1})	Precipitation (mm)	Irrigation (mm)	Water Demand (mm)	CO_2 Concentration (ppm)
Baseline (1980–2004)		5467	729	290	494	359
Current climate scenario (2006–2015)		5580	742	288	512	390
RCP 2.6	2020–2029	5590	797	271	519	421
	2030–2039	5423	763	274	485	436
	2040–2049	5302	730	270	488	441
	2050–2059	5306	779	281	490	443
RCP 4.5	2020–2029	5760	865	254	523	464
	2030–2039	5574	814	275	508	447
	2040–2049	5667	869	252	510	473
	2050–2059	5255	775	272	481	497
RCP 6.0	2020–2029	5591	800	274	504	456
	2030–2039	5239	734	278	482	438
	2040–2049	5277	809	273	485	462
	2050–2059	5247	844	257	474	492
RCP 8.5	2020–2029	5624	759	285	501	435
	2030–2039	5665	820	266	509	466
	2040–2049	5542	774	277	496	511
	2050–2059	5148	834	265	468	567

3.1.1. RCP 2.6

The change in yield with RCP 2.6 shows that the yield during 2020–2029 increased by 2.25% from the baseline period (Figure 5a and Table 2). In addition to that, an increase in rice yield during 2020–2029 was associated with an increase in water demand by 5.06% (Figure 5a). Moreover, Figure 5b shows a decrease in total phenological days of 1.38 days during 2020–2029 for RCP 2.6. Although the change in panicle initiation days was small during this period, anthesis and maturity days decreased by 0.32 days and 1.07 days, respectively.

Figure 5a and Table 2 demonstrate that the rice yield during 2030–2039 for RCP 2.6 decreased by 0.80%. Even though the precipitation and CO_2 concentration increased by 4.58% and 77 ppm, respectively, the model-generated rice yield was lower compared to that in 2020–2029. Despite a relatively small increase in temperature from the previous decade, a decrease in rice phenology by 2.36 days was accompanied by a reduction of 0.80% in the rice yield (Figure 5b). The reduction in rice yield and a decrease in phenological days was associated with a decrease in water demand by 1.82% (Figure 5a). However, contrary to the previous decade, the duration of all three phenological stages—panicle initiation, anthesis and maturity—can be seen as reduced during 2030–2039.

During 2040–2049 for RCP 2.6, rice yield, water demand and phenological days decreased by 3%, 1.21% and 3.40 days, respectively (Figure 5a,b). The precipitation increased by 0.14% in the period 2040–2049 compared to baseline level, which is one of the reasons for the adverse impact on rice yield. However, the CO_2 concentration increased by 82 ppm from the baseline period.

The change in yield during the 2050s (2050–2059) for RCP 2.6 decreased by 2.94% (Figure 5a). The decrease in rice yield during this period was associated with a reduction of water demand by 0.81% (Figure 5a). Moreover, the decrease in solar radiation and increase in temperature were associated with a decrease in panicle initiation, anthesis and maturity days by 0.92 days, 1 day and 2.68 days, respectively (Figure 5b). This total reduction of 4.6 days in phenological days, affected by temperature and solar radiation, also influenced the yield to decrease during the 2050s.

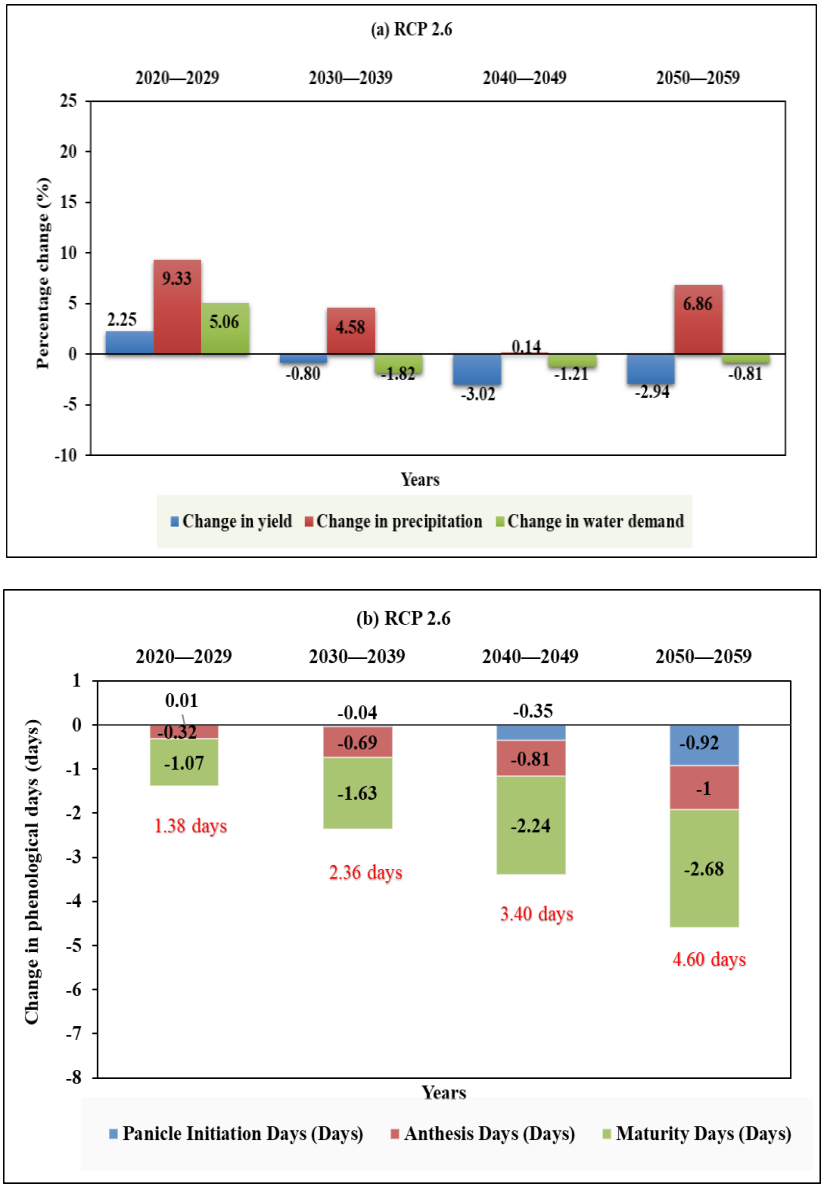

Figure 5. Climate change impact on rice yield and water demand (**a**) and phenology (**b**) for RCP 2.6.

3.1.2. RCP 4.5

During 2020–2029, increases in precipitation and CO_2 concentration of 18.66% and 105 ppm, respectively, over the baseline period were accompanied by the yield increasing by 5.36% for RCP 4.5 (Figure 6a and Table 2). An increase in rice yield was associated with an increase in water demand by 5.87% (Figure 6a). Similar to RCP 2.6, the panicle initiation days increased by 0.05 days during 2020–2029. However, anthesis and maturity days were reduced by 0.41 days and 1.32 days, respectively.

Figure 6a shows the increase in rice yield of 1.95% during 2030–2039 for RCP 4.5. Predictions of the rise in precipitation and CO_2 concentration of 11.66% and 89 ppm, respectively, were accompanied by an increase in yield during this period. Nevertheless, the increase in water demand of 2.83% was observed during 2030–2039 for RCP 4.5 (Figure 6a). Changes in climatic factors influenced to decrease the panicle initiation, anthesis and maturity days by 0.08 days, 0.74 days and 1.76 days, respectively.

Increases in rice yield of 3.66% was observed during 2040–2049 for the intermediate scenario, RCP 4.5 (Figure 6a). The water demand for the increase in yield was found to be 3.24% during 2040–2049 for RCP 4.5 (Figure 6a). Further, panicle initiation, anthesis and maturity days decreased by 0.52 days, 0.91 days and 2.48 days, respectively (Figure 6b).

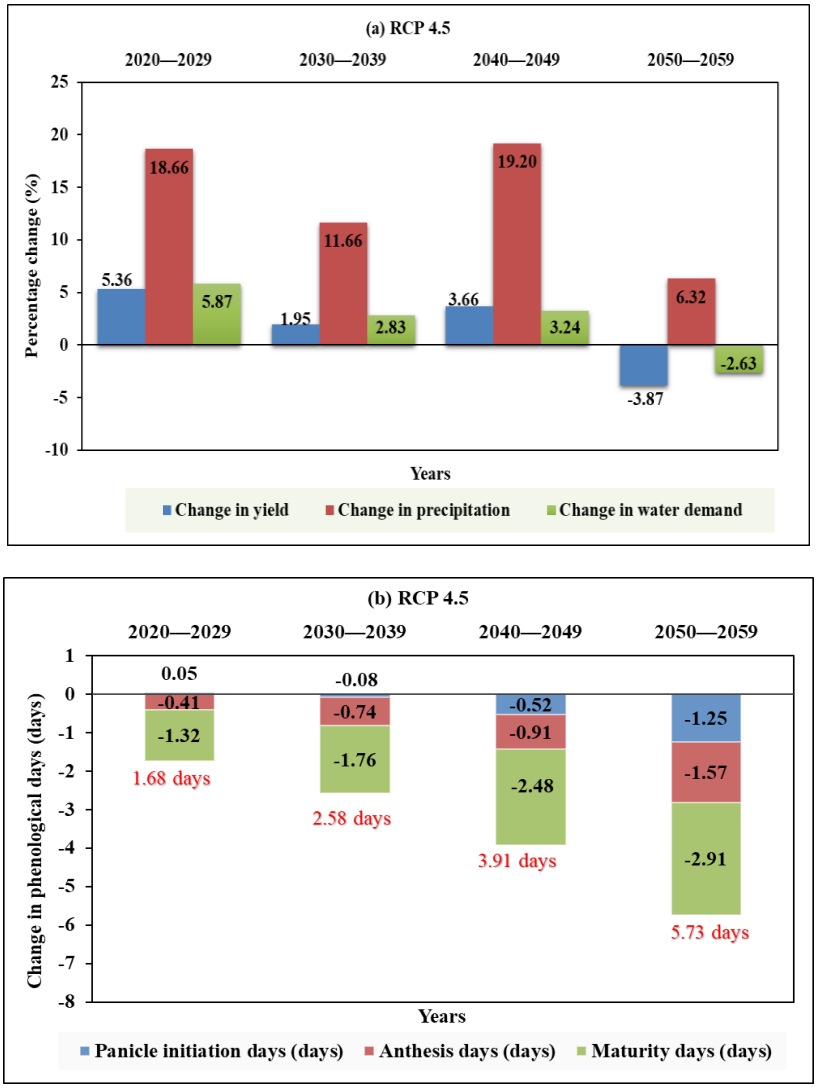

Figure 6. Climate change impact on rice yield and water demand (**a**) and phenology (**b**) for RCP 4.5.

Figure 5a shows the decrease in rice yield by 3.87% during the 2050s (2050–2059). Water demand also decreased by 2.63 % over the baseline period for the predicted yield (Figure 6a). It can be seen from Figure 6b that the panicle initiation, anthesis and maturity days decreased by 1.25 days, 1.57 days and 2.91 days, respectively, with a total decrease by 5.73 days.

3.1.3. RCP 6.0

An increase in rice yield of 2.27% was predicted during 2020–2029, when precipitation was higher by 9.74%, for RCP 6.0 (Figure 7a and Table 2). The CO_2 concentration decreased by 8 ppm from RCP 4.5, but a few months during the growing season was faced with projected higher temperatures and lower solar radiation in this scenario. These non-uniform changes in climatic factors influenced the yield to increase by 2.27% during 2020–2029. A reduction in yield of 4.17%, 3.48% and 4.02% can be seen from Figure 7a, during 2030–2039, 2040–2049 and 2050–2059, respectively, for RCP 6.0. Precipitation was found decreasing with this scenario from 2030 onwards till 2050 and the CO_2 concentrations were observed to be reduced till 2059, compared to the intermediate scenario, RCP 4.5. Similarly, water demand also increased by 2.02% during 2020–2029, and the effects of a reduction in yield were seen for the decrease in water demand of 2.43%, 1.82% and 4.05%, during 2030–2039, 2040–2049 and 2050–2059, respectively (Figure 7a). Thus, with all the climatic factors changing simultaneously,

it altered the water demand and rice yield. Furthermore, Figure 7b demonstrates the decrease in phenological days of 1.89 days, 2.23 days, 4.08 days and 6.03 days during 2020–2029, 2030–2039, 2040–2049 and 2050–2059, respectively, with RCP 6.0.

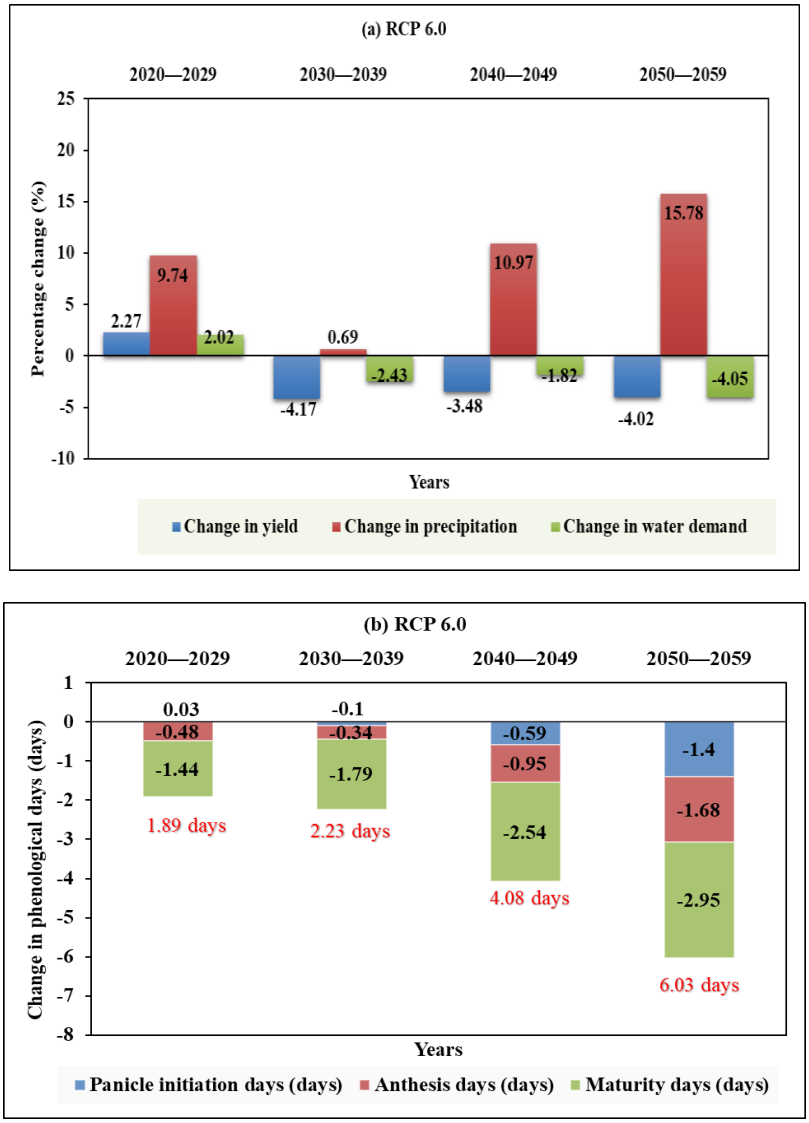

Figure 7. Climate change impact on rice yield and water demand (**a**) and phenology (**b**) in the scenario RCP 6.0.

3.1.4. RCP 8.5

Figure 8a illustrates the increase in rice yield of 2.87% during 2020–2029. However, the increase in precipitation and CO_2 concentration was predicted as 4.12% and 76 ppm, respectively. Furthermore, Figure 8a shows the increase in water demand of 1.42% during 2020–2029. Similarly, for this scenario, panicle initiation days increased by 0.07 days, which also supported the increase in yield (Figure 8b). All other growth stages, anthesis and maturity days, decreased by 0.58 days and 1.64 days, respectively, and reduced the total phenological days by 2.15 days, during 2020–2029 (Figure 8b).

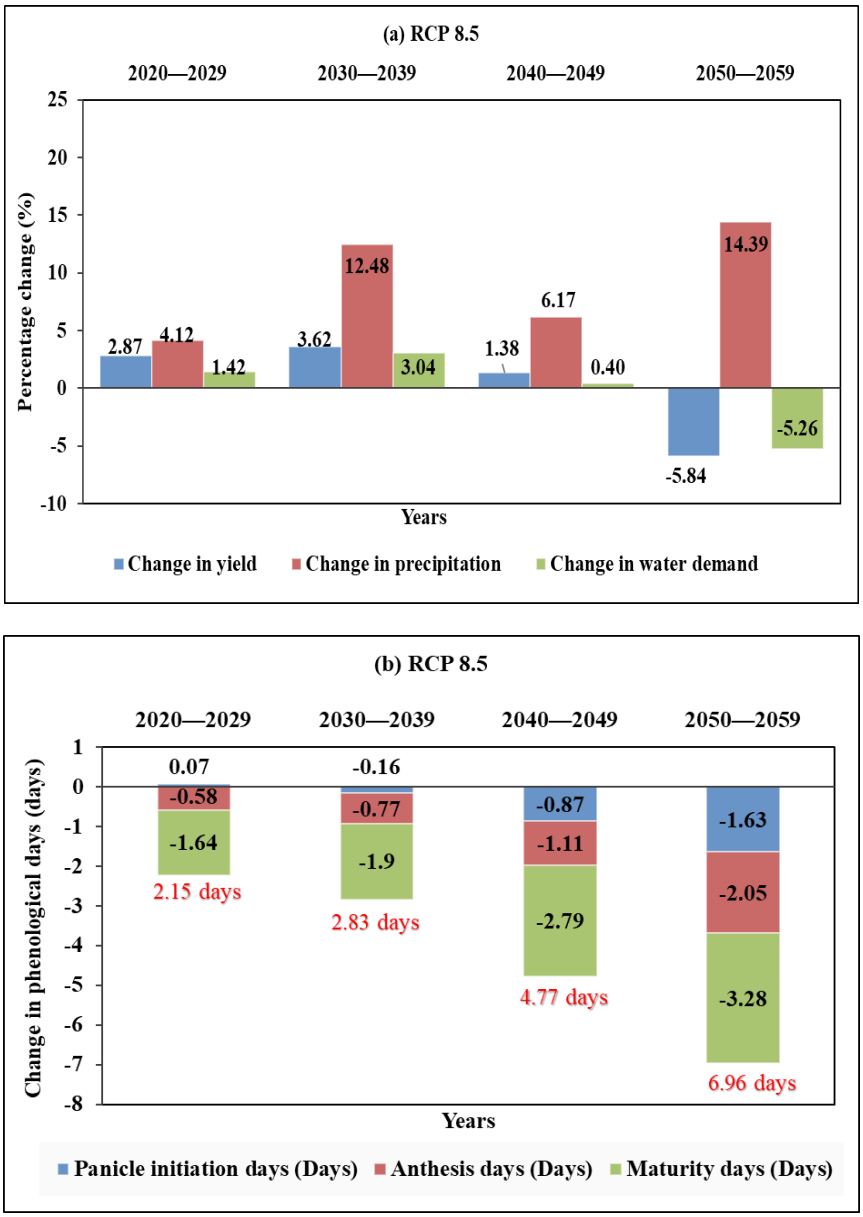

Figure 8. Climate change impact on rice yield and water demand (**a**) and phenology (**b**) in the scenario RCP 8.5.

During 2030–2039, rice yield increased by 3.62% for RCP 8.5 (Figure 8a). For this increase in yield, precipitation and CO_2 concentration increased by 12.48% and 107 ppm, respectively. Predicted water demand for this period increased by 3.04%, and total phenological days decreased by 2.83 days. Panicle initiation, anthesis and maturity days decreased by 0.16 days, 0.77 days and 1.9 days, respectively, during 2030–2039 (Figure 8a,b). Figure 8a and Table 2 also demonstrate the increase in yield, precipitation and CO_2 concentration of 1.38%, 6.17% and 152 ppm, respectively, during 2040–2049. A decline in the panicle initiation, anthesis and maturity days was observed to be 0.87 day, 1.11 days and 2.79 days, which also affected the rice yield (Figure 8b).

The decrease in rice yield was observed to be 5.84% from the baseline period during the 2050s with RCP 8.5. Water demand also decreased by 5.26% during this period (Figure 8a). It is worthwhile to notice that the total phenological days under this scenario decreased by 6.96 days with panicle initiation, anthesis and maturity days reduced by 1.63 days, 2.05 days and 3.28 days, respectively (Figure 8b).

3.2. Irrigation Water Requirement of the Total Water Input (Precipitation + Irrigation Water) for Different Management Practices under (a) the Current Climate Scenario, (b) RCP 2.6, (c) RCP 4.5, (d) RCP 6.0 and (e) RCP 8.5.

This section deals with the predicted results of the change in irrigation requirement of the total water input for different management practices under the current climate scenario and projected future climate change scenarios. In addition, it describes the irrigation requirement of the total water input for a 60% increase in rice production by the 2050s.

3.2.1. Current Climatic Scenario

Figure 9 and Table 3 illustrate the need for irrigation water of the total water input (i.e., precipitation + irrigation) with different management practices under the current climate scenario that exists in the state of Bihar. Under the current climate scenario, for the present rice yield levels and agronomic practices, 28% of the total water input is derived from irrigation water. If the rice yield needs to be increased by 60% (in order to fulfill the food demand of the increasing population), the rice cultivation with an existing transplanting method will need 45% of the total water input to be derived from irrigation water. If conservation agriculture (direct-seeded rice with the residue of 2.5 ton/ha) is adapted for the same 60% higher production from the current climate scenario, the irrigation requirement of the total water input will be 32% by saving 13% irrigation water. However, when the post-harvest loss of the rice yield is reduced by 30%, the irrigation requirement will become 36%. Further, if we combine both conservation agriculture and a 30% reduction in post-harvest losses, the irrigation requirement would be 19% of total water input, thereby, reducing it by 26% (45 to 19%).

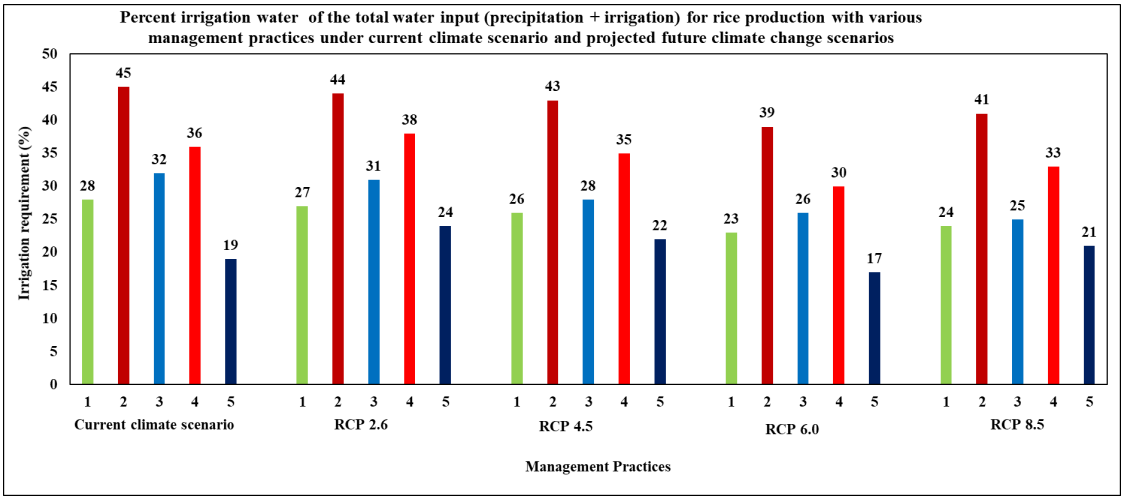

Figure 9. Change in irrigation water of the total water input (precipitation + irrigation water), for the obtained yield and increase in yield by 60% with different management practices under the current climate scenario and projected future climate change scenarios. **Note:** Management Practice 1: For the obtained yield with the current agronomic practice in the current climate scenario and by the 2050s with the projected future climate change scenarios. Management Practice 2: For an increase in yield by 60% with the current agronomic practice in the current climate scenario and by the 2050s with the projected future climate change scenarios. Management Practice 3: For an increase in yield by 60% with conservation agriculture (direct-seeded rice with residue (2500 kg/ha)) in the current climate scenario and by the 2050s with the projected future climate change scenarios. Management Practice 4: For an increase in yield by 30% (and reducing the post-harvest loss by 30%) in the current climate scenario and by the 2050s with the projected future climate change scenarios. Management Practice 5: For an increase in yield by 30% (and reducing the post-harvest loss by 30% and applying conservation agriculture) in the current climate scenario and by the 2050s with the projected future climate change scenarios.

Table 3. Change in irrigation water of the total water input (precipitation + irrigation water), a requirement for an increase in yield by 60% with the current climate scenario and projected future climate change scenarios, with application of various management practices.

	Irrigation Requirement (%)				
Climate Scenarios	**Management Practice 1**	**Management Practice 2**	**Management Practice 3**	**Management Practice 4**	**Management Practice 5**
Current Climate Scenario	28	45	32	36	19
RCP 2.6	27	44	31	38	24
RCP 4.5	26	43	28	35	22
RCP 6.0	23	39	26	30	17
RCP 8.5	24	41	25	33	21

Note: Management Practice 1: For the obtained yield with the current agronomic practice in the current climate scenario and by the 2050s with future climate change scenarios. Management Practice 2: For an increase in yield by 60% with the current agronomic practice in the current climate scenario and by the 2050s with future climate change scenarios. Management Practice 3: For an increase in yield by 60% with conservation agriculture (direct-seeded rice with residue (2500 kg/ha)) in the current climate scenario and by the 2050s with future climate change scenarios. Management Practice 4: For an increase in yield by 30% (and reducing post-harvest loss by 30%) in the current climate scenario and by the 2050s with future climate change scenarios. Management Practice 5: For an increase in yield by 30% (and reducing the post-harvest loss by 30% and applying conservation agriculture) in the current climate scenario and by 2050s with future climate change scenarios.

3.2.2. RCP 2.6

Figure 9 and Table 3 demonstrate the irrigation requirement with the lowest greenhouse gases emission scenario (RCP 2.6). Irrigation requirement of the total water input for the predicted rice yield during the 2050s was computed to be 27%. For the 60% increase in rice yield with the transplantation method of rice cultivation, the irrigation requirement of the total water input was estimated to be 44%. Using the conservation agriculture method for the same increase in yield, the irrigation requirement will be reduced to 31%. If the post-harvest losses of 30% are reduced with the current cultivation method of rice, the irrigation requirement would be 38% of the total water input, saving 6% of the irrigation water. When the post-harvest loss reduction of 30% is combined with conservation agriculture, the irrigation requirement of the total water input would be reduced by 20% (44 to 24%).

3.2.3. RCP 4.5

Figure 9 and Table 3 show the irrigation requirement of the total water input for the climate change scenario RCP 4.5. The decreased yield of 3.87% by the 2050s will need 26% irrigation water of the total water input. The irrigation requirement for a 60% increase in rice yield with the transplanting method of rice cultivation was estimated to be 43% of the total water input. If Management Practice 3, conservation agriculture, is used to increase the rice yield by 60%, the irrigation requirement of the total water input will be reduced to 28%. Since the CO_2 concentration is high and the residue is applied in this practice, both will contribute toward saving the irrigation water. However, only reducing 30% of the post-harvest losses with the transplanting method, one will need 35% of the total water input to be derived from irrigation water. Furthermore, when Management Practice 5 is used, the irrigation requirement of the total water input will decrease to 22%, indicating a water-saving strategy under a high CO_2 concentration, crop residue, and a reduction of the post-harvest losses.

3.2.4. RCP 6.0

Figure 9 and Table 3 illustrate the irrigation requirement of the total water input with the intermediate scenario, RCP 6.0. The irrigation requirement of the total water input during the 2050s with this scenario was observed to be only 23%, which is the least amongst all scenarios. It was also observed that the CO_2 concentration was less during this period with RCP 6.0, which might have led to an increase in irrigation productivity and reduced the irrigation water of the total water

input. It can also be seen that for a 60% increase in rice yield with the current agronomic practice, the irrigation requirement of the total water input was observed to be 39%. Using Management Practice 3, when the conservation agriculture technique was applied for 60% higher rice production, the irrigation requirement of the total water input reduced to 26%. If the reduction in post-harvest loss of 30% is incorporated with the current agronomic practice, the irrigation requirement would be 30% of the total water input. If we combine conservation agriculture with a reduction in post-harvest losses, the irrigation requirement would be 17% of the total water input, saving 22% (39 to 17%) of the irrigation water for a 60% increase in rice yield.

3.2.5. RCP 8.5

Figure 9 and Table 3 demonstrate the irrigation requirement of the total water input for the extreme climate change scenario (RCP 8.5). Since the precipitation and CO_2 concentration during the 2050s are predicted to be very high, there was a decreased rice yield of 5.84%, resulting in an irrigation water requirement of 24% of the total water input. With this condition, achieving a 60% higher rice yield would require 41% irrigation water of the total water input. If conservation agriculture is applied, the crop residue will help preserve soil moisture and the irrigation requirement would be reduced to 25% of the total water input. Reducing the post-harvest losses of rice by 30% with current agronomic practice (Management Practice 4) would reduce the irrigation requirement by 8% (41 to 33%) of the total water input. The best-case scenario could be the strategy of reducing the post-harvest loss and applying conservation agriculture (Management Practice 5), which would reduce the irrigation requirement of the total water input to 21%.

4. Discussions

The results obtained in this study showed that crop yield and water demand were very responsive to future climate change scenarios. The prediction of reduction in rice yield was possibly due to a large increase in temperature (Figure 2a,b) and a reduction in solar radiation (Figure 3), for all the climate change scenarios. The rise in temperature (Figure 2a,b) would increase the water demand and decrease the yield; however, an increase in CO_2 concentration would induce the decrease in water demand. It has also been predicted that the increase in temperature (Figure 2a,b) and decrease in solar radiation (Figure 3) would decrease the phenological days [53,54]. The decrease in solar radiation (Figure 3) would affect the photosynthetic process and metabolic growth in rice plants, which could result in the reduction of rice yield [55]. Both factors (increase in temperature and decrease in solar radiation) would reduce the panicle initiation, anthesis and maturity days altogether. The obtained results showed that a decrease in phenological days was accompanied by a reduction in rice yield [56]. This can be inferred that, when the duration of the crop growth period (phenological days) decreased, crops would not require water for those days that were eliminated from the growth period. The decrease in phenological days would also result in a shorter period for crop biomass accumulation and prevent proper growth, and thus will decrease the yield as well [56,57]. It can be also inferred that a significant decrease in rice phenology can influence the water demand and reduce the rice yield. Moreover, the higher precipitation and higher CO_2 concentration were associated with an increase in yield; otherwise, temperature change (Figure 2a,b) would reduce the rice yield [58,59].

If the CO_2 concentration did not increase for the selected 10-year interval, the water demand could have been even higher for those periods. Thus, it is our understanding that increased CO_2 concentration would ultimately reduce the water demand. Krujit et al. [60] has also supported that the rise in CO_2 concentration decreases the stomatal conductance in a plant, which leads to a reduction in the transpiration rate and, as a result, water demand decreases [59,61]. The increase in water demand was also found to be associated with an increase in rice yield. The decrease in yield during the 2050s can be a clear indication that temperature played a dominant role (Figure 2a,b) in rice growth and development. Changes in temperature and solar radiation were observed to be unfavorable for conducive growth of rice during the 2050s. The adverse impact of high temperatures (Figure 2a,b)

and low solar radiation (Figure 3), which decreased the total phenological days, also affected the rice growth phases and ultimately reduced the rice yield. Consequently, rice yield declined despite high precipitation and CO_2 concentration. However, an increase in the CO_2 concentration of 208 ppm during the 2050s with RCP 8.5 can also indicate that, above a certain threshold limit of CO_2, it may have no impact on crop yield [62,63]. An increase in temperature (Figure 2a,b) and decrease in solar radiation (Figure 3) were found to be extreme with RCP 8.5, compared to other scenarios, which resulted in the highest reduction of phenological days. Therefore, even with an increasing CO_2 concentration, the rice yield did not increase in the same ratio; it showed the predominant effects of temperature and solar radiation [4,61,64].

It can also be seen that panicle initiation days increased for all the scenarios during 2020–2029; the growing degree days (GDD) for this stage was possibly not affected by an increase in temperature and solar radiation. Furthermore, all the growth stages (panicle initiation, anthesis and maturity) during each decade from 2020–2059 also validate the reasoning of an adverse impact of temperature and solar radiation on rice growth and development [56,65].

All these changes seem to be a combined effect of the future projected climate change's impact on rice production. This complex phenomenon strongly supports the idea of the crop growth and yield depending on the local microclimatic conditions, because each crop has different climatic requirements for sufficient development and optimum production [66,67]. Therefore, the rice crop may vary in their production, water demand and phenology with the climatic conditions of the growing place [14,68,69].

This study clearly supported that conservation agricultural practices helped increase the rice yield and reduced the irrigation water requirement. Conservation agriculture practices with direct-seeded rice and incorporation of crop residue save a greater amount of water by cutting down evaporation losses from soil surface; these ultimately result in requiring less irrigation water compared to the transplanting method of rice production and to an increase in rice production of 60% by 2050s. If the post-harvest loss of rice is reduced by 30%, applying conservation agriculture practices can help in saving a large amount of irrigation water.

5. Conclusions

Rice is the primary staple food that is mostly grown during the monsoon season in Bihar, where most farmers are dependent upon the monsoon rainfall for growing rice crops. This dependence will cause a profound impact on rice production in Bihar under projected climate change conditions. This study was carried out to examine the projected climate change impact on the rice production, water requirement and crop phenology by the 2050s. We also examined the change in irrigation requirement with different scenarios for a need to increase rice production by 60% by the 2050s.

RCP 2.6 and RCP 6.0 showed an increase in yield during 2020–2029, but after this period, the yield was observed to decrease till the 2050s with both the scenarios. The rice yield was found increasing over the baseline period for RCP 4.5 and RCP 8.5 by 2049. The dominance of the increase in precipitation and CO_2 concentration over the change in temperature during this period were associated with an increase in rice yield. During the 2050s, a change in temperature had more influence on rice growth and yield compared to precipitation and the CO_2 concentration. A change in water demand was observed to vary with fluctuation in rice yield. The change in water demand was affected by the change in CO_2 concentration (which reduces the water requirement and increases the yield). In addition to that, the gradual decrease in phenological days reflected that rice growth was affected by an increase in temperature and decrease in solar radiation.

The decline in irrigation requirement with future scenarios during the 2050s compared to the current climate scenario was due to an increase in precipitation and CO_2 concentration. These two factors (precipitation and CO_2 concentration) supported rice growth and yield without needing much supplemental irrigation water. In order to increase the yield by 60% with the current agronomic practice, the highest amount of irrigation water would be used with the current climatic scenario. An increase in 60% rice yield with various management practices shows that the adaptation of conservation

agriculture and a reduction in post-harvest loss by 30% require a lower amount of irrigation water compared to all other strategies.

Author Contributions: This research work was a part of Doctoral Thesis of R.K.J., which was supervised by P.K.K. Conceptualization—R.K.J. and P.K.K.; methodology—R.K.J. and P.K.K.; formal analysis—R.K.J.; investigation—R.K.J., P.K.K. and P.K.; resources—R.K.J. and P.K.K.; data curation—R.K.J. and R.J.; writing—original draft preparation—R.K.J.; writing—review and editing—R.K.J., P.K.K., P.K., P.C.D., and R.A.C.; visualization—R.K.J., P.K.K., P.K., P.C.D., and R.A.C.; supervision—P.K.K.; project administration—P.K.; funding acquisition—P.K.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partly funded by the University of Illinois at Urbana-Champaign, and USDA-NIFA.

Conflicts of Interest: The authors declare no conflict of interest.

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