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Assessment of Different Frameworks for Addressing Climate Change Impact on Crop Production and Water Requirement

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Abstract: Various methodologies are used to estimate the impact of changing climatic factors, such as precipitation, temperature, and solar radiation, on crop production and water demand. In this study, the changes in rice yield, water demand, and crop phenology were estimated with varying CO_2 concentration and an ensemble of general circulation models (GCMs), using a decision support system for agrotechnology transfer (DSSAT), a crop growth model. The measured CO_2 concentration of 400 ppm from the Keeling curve, was used as the default CO_2 concentration to estimate yield, water demand, and phenology. These outputs, obtained with the default concentration, were compared with the results from climate change scenarios' concentrations. Further, the outputs corresponding to the ensembled GCMs' climate data were obtained, and the results were compared with the ensembled crop model outputs simulated with each GCM. The yield was found to increase with the increase in CO_2 concentration up to a certain threshold, whereas water demand and phenology were observed to decrease with the increase in CO_2 concentration. The two approaches of the ensemble technique to obtain final outputs from DSSAT results did not show a large difference in the predictions.

Keywords: crop production; climate change; CO_2 concentration; ensemble approach; water demand; phenology

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1. Introduction

Climate change is a global concern. The global average surface temperature is expected to increase between 3 °C and 4 °C and atmospheric carbon dioxide is likely to increase between 730 ppm and 1020 ppm by the end of the present century [1–3]. This change in future climate from the current climatic condition will have a dynamic impact on rice production around the world [4,5]. The impact associated with a rise in temperature, a change in carbon dioxide level, and unpredictable variation in rainfall will be of major economic and social importance for the regions where rice is the staple crop, affecting rice growth, yield, and water requirements [6,7].

Rice is the staple food for the people of India, and is grown on around 43 million hectares [8]. In India, Bihar contributes to the total rice production as the 6th largest rice producing state [9]. The population of the state is increasing rapidly, with 88.7% of the total population living in villages [10,11], and 80% of the population living in this state depends on agriculture for their livelihood [12]. This provides the insight that the state is far away from urbanization and the development of industries, and any significant change in carbon dioxide concentration in the state of Bihar may be uncertain. Therefore, we investigated the impact of changes in carbon dioxide concentration on crop production in case such changes become prominent during the next few decades in Bihar.

Various studies around the globe have assessed the combined climate change impacts on crop production. Drewry et al. [13] found a reduction in transpiration by 7% for soybean and negligible stimulation of photosynthesis for Maize, under elevated CO_2 concentration. Devkota et al. [14], using the B1 and A1F1 climate change scenarios under the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC), suggested the increase in rice yield with increased temperature and CO_2 concentration. They also found an adverse impact on the rice yield of short-duration varieties due to climate change. Elevated CO_2 increases the yield and water productivity and reduces the crop evapotranspiration by decreasing stomatal conductance (Vanuytrecht et al. [15]). Adachi et al. [16] examined the effects of elevated CO_2 concentration by 200 μmol mol^{-1} from the ambient concentration and increased soil and water temperatures by 2 °C on the rice photosynthesis rate and growth stages; they revealed that elevated CO_2 concentration with increased temperature reduces the light-saturated leaf photosynthesis rate with advancing rice growth stages. A sunlit growth chamber experiment on the rice variety IR72 at various levels of CO_2 concentration by Kumar et al. [17] demonstrated an increase in above-ground dry weight and water use efficiency with an increase in carbon dioxide concentration. Figueiredo et al. [18] observed that an increase in temperature limits crop yield. However, the combined effect of increased CO_2 concentration and temperature will increase crop yield up to a certain extent.

Moreover, in order to estimate crop production and water demand using climate models, several researchers have applied different methodologies. N'guessan et al. [19] ensembled the GCMs for robustness in the outputs obtained through crop models. An ensemble of seven GCMs was performed to project future precipitation and temperature, and these data were used in the CROPWAT model to predict crop water and net irrigation requirements (Agrawal et al. [20]). Martre et al. [21] compared the precision of outputs from an ensemble of 27 wheat models to various subsets of these models to determine the minimum ensemble size required for accurate results. In contrast, Rodríguez et al. [22] utilized an ensemble of 17 crop models to develop adaptation strategies for rainfed wheat in Lleida, NE Spain, under climate change conditions. From these studies, we observed that comparisons between ensembles of climate models and ensembles of crop model outputs corresponding to individual climate model data inputs have not been performed. Such comparisons would provide critical insights into the efficacy of different approaches, aiding in decision-making regarding the impacts of climate change on crop growth, production, and water use.

Therefore, as we have already completed the published research using an ensemble of crop model outputs run with individual GCMs (Jha et al. [23]), we performed this study to predict the yield, phenology, and water demand using an ensemble of four GCMs (bcc_csm1.1, csiro_mk3_6_0, ipsl_cm5a_mr, and miroc_miroc5) under the fifth phase of the Coupled Model Intercomparison Project (CMIP5). The details of these GCMs we have provided in our previous research article (Jha et al. [23]). Additionally, our research focused on investigating the comparison of both methods to estimate the impact of climate change on crop yield, water demand, and phenology.

Considering the discussions above, the objectives of this research were to: (i) investigate the total changes in rice yield, water demand, and phenology obtained with Keeling curve CO_2 concentrations and climate change scenario concentrations; and (ii) examine the total changes in rice yield, water demand, and phenological days between two approaches: crop growth model outputs obtained using ensembles of GCMs as input and ensembles of outputs obtained from the crop growth model, DSSAT, corresponding to each GCM's climate data as input.

The results obtained with the ensemble of crop growth model outputs using each GCM climate data as input in the model and outputs computed with varying CO_2 concentrations from all four climate change scenarios—representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5)—of the IPCC 5th assessment report [24] have been published in our previous article, Jha et al. [23].

2. Material and Methods

2.1. Study Area Description and Agricultural Dataset for Crop Modeling

The experimental site for this study was situated at the farm of the Borlaug Institute of South Asia, Pusa, Bihar, India, between the latitude of 25°58′ N and longitude of 85°40′ E. The elevation of the study area is 52 m from mean sea level. It receives a mean annual rainfall of 1297 mm, most of it falls in the monsoon season (June to September). The climate of the region is hot and humid summers with cold winters. Since most of the state lies in the Indo-Gangetic Plain, the soil type for the study area is alluvial sandy loam. Rice is the staple food for the state; thus, farmers mainly cultivate this crop for their livelihood. In order to cultivate this crop, they are totally dependent upon the monsoon rainfall.

The CERES-Rice model in DSSAT used in this study was calibrated and validated with 10 years (2006–2015) of long-term puddling-transplanted rice experiments at this site (Jha et al. [11]).

2.2. Use of Climate Data for This Study

The details of climate data of the baseline period (1980–2004) and future years (2020–2059) with all four climate change scenarios for this study have already been discussed in Jha et al. [23,25].

2.3. DSSAT Simulation to Assess the Implication of CO_2 on Crop Production, Water Requirement, and Phenology

The study reported in Jha et al. [23] was conducted with the changed CO_2 concentrations for all four climate change scenarios of the IPCC 5th assessment report [24]. Thus, it provided the outcomes incorporating the impact of changed CO_2 concentrations on rice production. In this current research work, the CERES-Rice model under DSSAT was simulated with a considered default value of 400 ppm of CO_2 for all four climate change scenarios. The reason for selecting a default value of 400 ppm was based on the measured value of CO_2 concentration by the Keeling curve for the present condition. The CERES-rice model was simulated for the future climate (2020–2059) data with keeping the default value of 400 ppm of CO_2 concentration for all four scenarios—RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. In the model, the selection of a default value of CO_2 concentration of 400 ppm was made by selecting the “Read from weather file” option under the “Simulation Options”. Then, CO_2 concentration under the “Environmental modifications” option was also used as 400 ppm for every year from 2020 to 2059. However, simulation for the historical period of 1980–2004 was simulated with the same CO_2 concentration obtained from the Keeling curve (Mauna Loa Observatory) [26]. The Keeling curve, monitored by Mauna Loa Observatory, Hawaii, provides the actual CO_2 concentration and is also used by the DSSAT model for crop modeling simulations with the recorded concentration. Other climatic factors, such as precipitation, temperature, and solar radiation, were not changed and kept similar to the obtained datasets corresponding to each of the GCMs. With the CO_2 concentration study, as similar to our previous study, the ensemble mean of the outputs from CERES-rice simulation corresponding to each of the four GCMs was used to dermine the average crop growth, yield, and water requirement for future years. The impact of climate change on rice yield, phenological days, and water demand were computed by using Equation (1), also used in Jha et al. [19], for every 10 years of the interval from 2020 to 2059 relative to the baseline period, as follows:

$$PC_{Y,\,P,\,W} = ((\mathrm{FSV} - \mathrm{BV})/(\mathrm{BV})) \times 100 \quad (1)$$

where $PC_{Y,P,W}$ = percent change in yield, water demand, and phenology;

FSV = future simulated value; BV = baseline value

2.4. Estimation of Crop Yield, Water Demand, and Phenology from the Ensemble Climate Data

In our previous study [23], the CERES-Rice model was run using the input of climate data of each GCM, and the outputs from the crop model obtained corresponding to each GCM were ensembled. This procedure was followed for all four climate change scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). However, in this study, the climate data of all four GCMs were first ensembled before providing these climate data as input into the CERES-Rice model. The simulation obtained from the CERES-rice model for yield, water demand, and phenology was used as a prediction from this study. The steps followed for this analysis are depicted in the flow chart in Figure 1. The flow chart of the estimation of climate change impact on rice production, phenological days, and water demand with the ensmble of crop model outputs' simulated corresponding input climate data of each GCM is already discussed in Jha et al. [23]. Furthermore, we investigated the difference between both of the methods if followed for future agricultural modeling prediction.

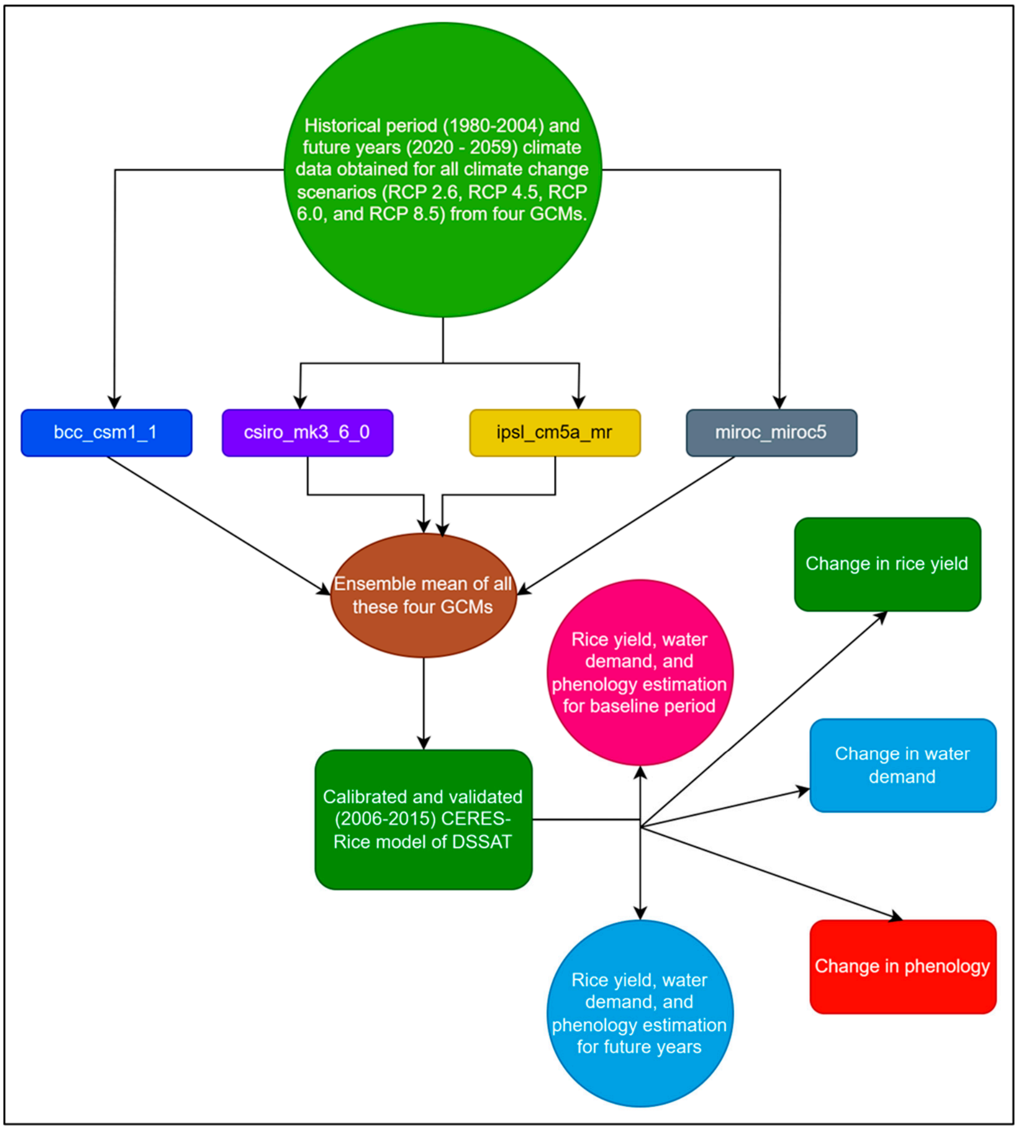


Figure 1. Flow chart of estimating the rice yield, water demand, and phenology from the ensemble climate data of GCMs.

3. Results

3.1. Assessment of Default CO_2 Concentration Impact on Rice Yield, Phenology, and Water Demand

The yield, water demand, and phenology predictions with the changed values of CO_2 concentrations have already been presented in the previous research article published by Jha et al. [23] in connection with this research work. The obtained values of yield, water demand, and phenological changes with a default value of CO_2 concentration of 400 ppm are presented in the following sections.

3.1.1. RCP 2.6

The decrease in yield with RCP 2.6 during 2020–2029 with a CO_2 concentration of 400 ppm was found to be 5.32% from the baseline period (Figure 2a). Since the yield with changed CO_2 concentration increased by 2.25% from the historical period (shown in Jha et al. [23]), the total change in yield was estimated to be decreased by 7.57%.

In addition, a decrease in CO_2 concentration of 21 ppm (421–400) from the default concentration during 2020–2029 was associated with an increase in water demand of 7.64% (Figure 2b). Moreover, Figure 2c shows a decrease in total phenological days of 3.83 days during 2020–2029 for RCP 2.6.

Figure 2a demonstrates that the rice yield during 2030–2039 for RCP 2.6 decreased by 8.93%. During this period, the increase in precipitation was also less compared to the previous decade, and CO_2 concentration decreased by 36 ppm. The decrease in rice phenology by 4.74 days reduced the rice yield dramatically (Figure 2c). Since rice yield decreased and the difference in a CO_2 reduction from the previous decade was also not very large, this resulted in a decrease in water demand of 5.58% from the baseline period (Figure 2b).

During 2040–2049 for RCP 2.6, rice yield and phenological days decreased by 14.20% and 9.64 days, respectively (Figure 2a,c). The increase in water demand due to the total decrease of 41 ppm in default CO_2 concentration from the changed concentration was found to be 7.90% (Figure 2b).

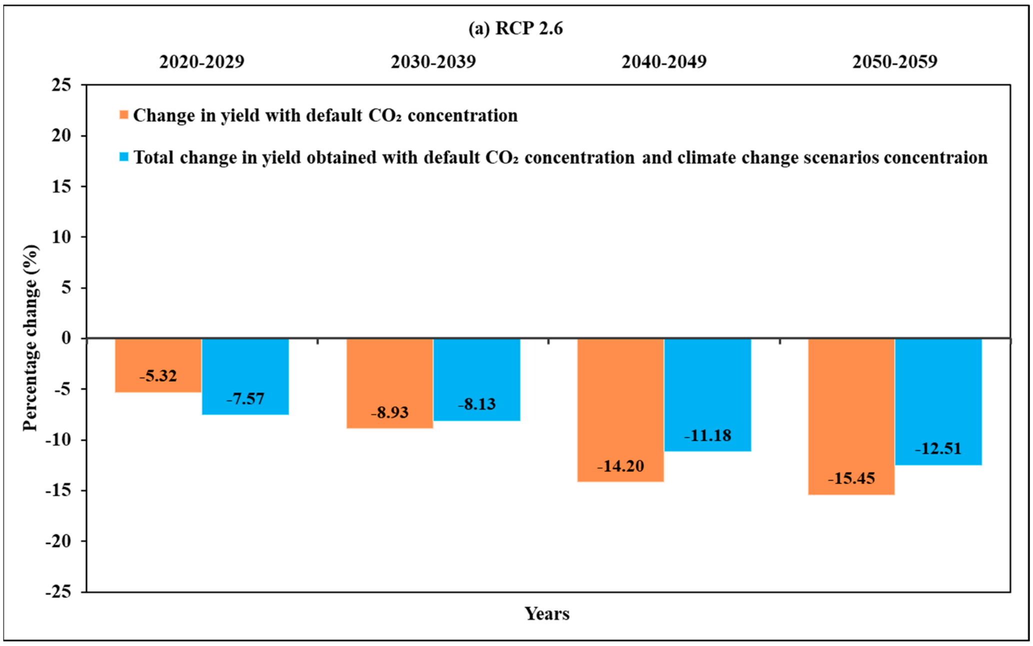


Figure 2. *Cont.*

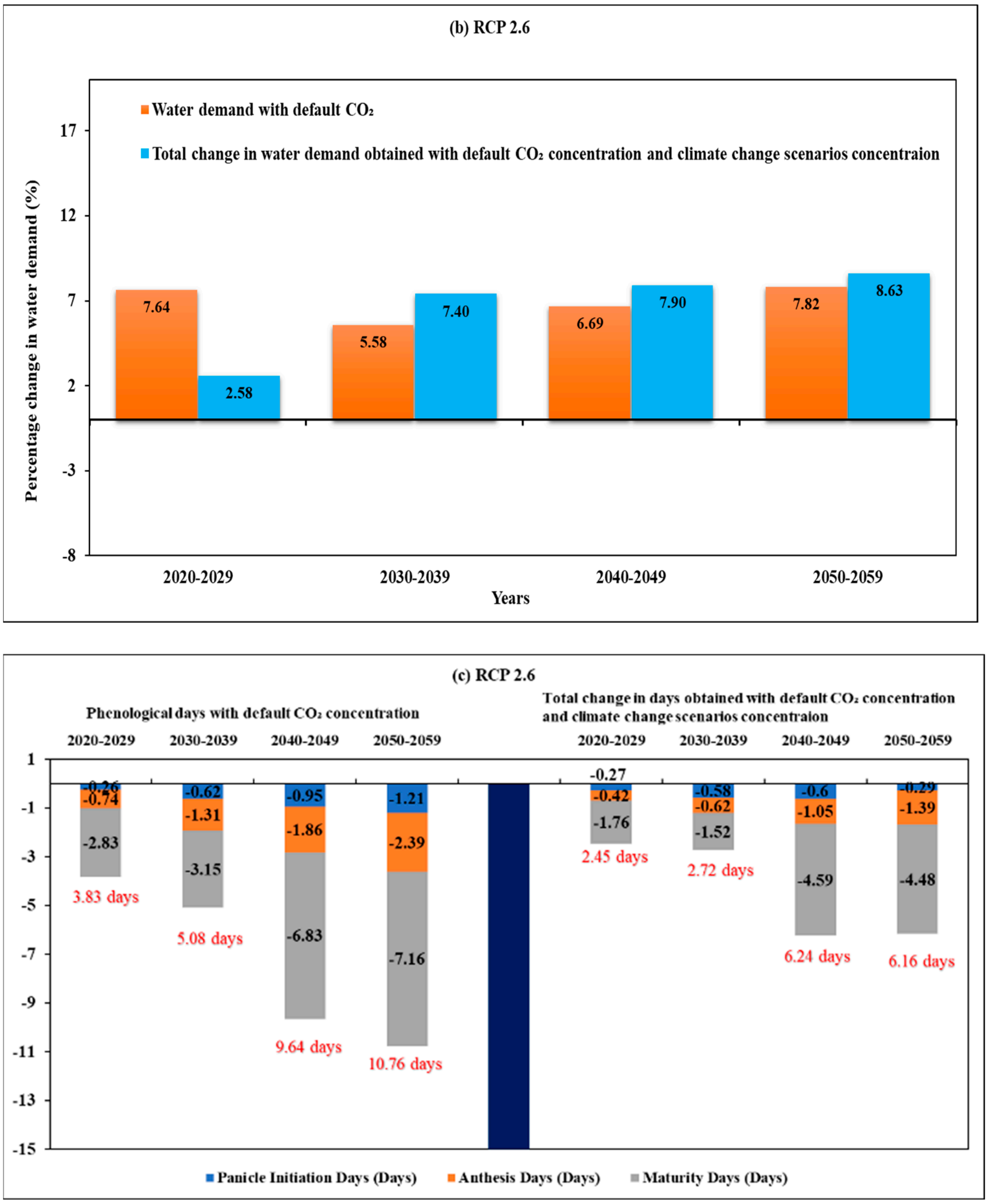


Figure 2. Impact of default CO_2 concentration on rice yield (**a**), water demand (**b**), and phenology (**c**) for RCP 2.6.

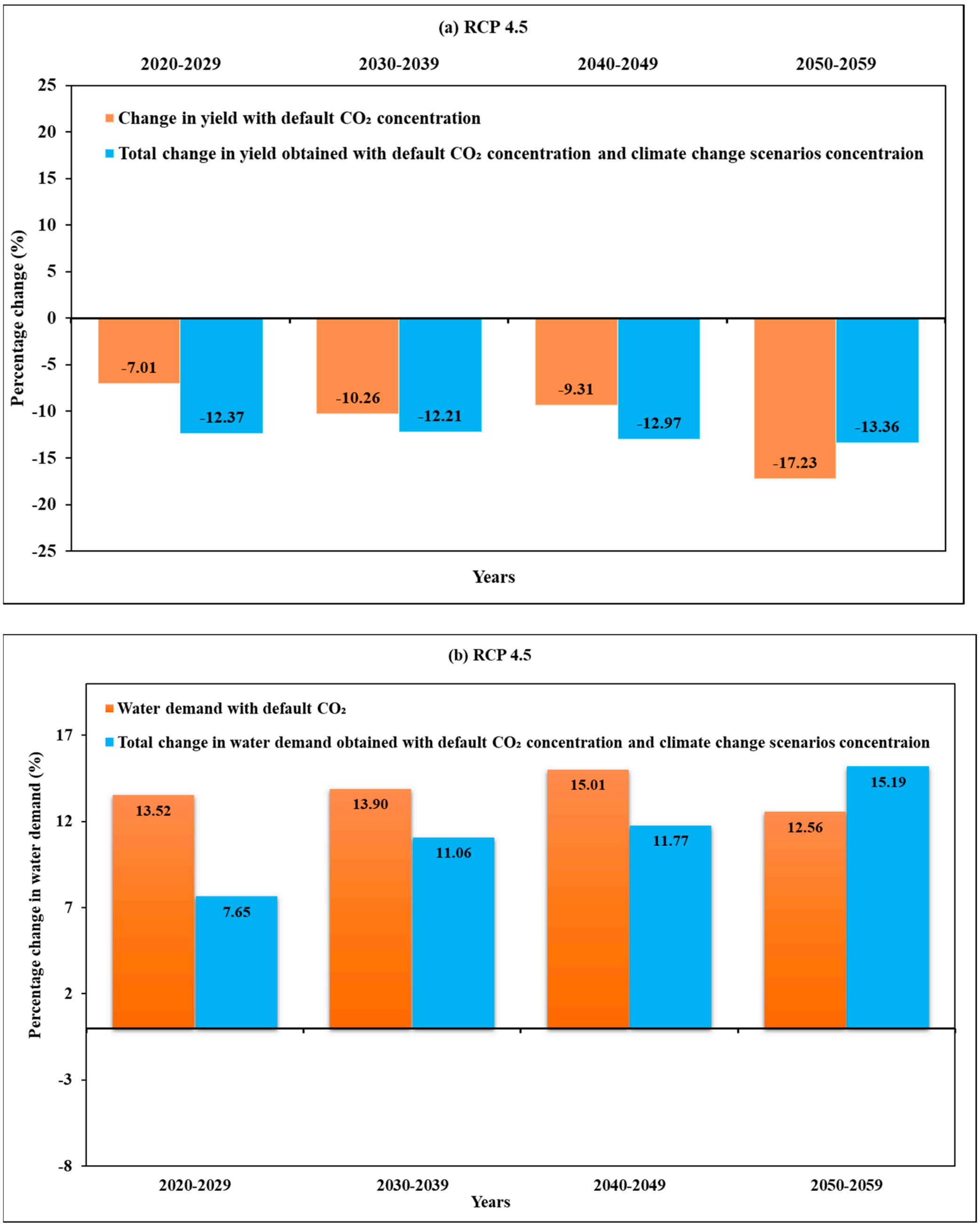
The change in yield during the 2050s (2050–2059) for RCP 2.6 decreased by 15.45% (Figure 2a). The decrease in CO_2 concentration during this period increased the water demand by 7.82% (Figure 2b). Moreover, the decrease in CO_2 concentration, solar radiation, and increase in temperature was accompanied by a decrease in panicle initiation, anthesis, and maturity days by 1.21 days, 2.05 days, and 7.65 days, respectively (Figure 2c).

3.1.2. RCP 4.5

During 2020–2029, a decrease in default CO_2 concentration of 64 ppm reduced the yield by 7.01% (Figure 3a). This decrease in CO_2 concentration and solar radiation and increase in temperature caused the water demand to increase by 13.52%, with a total change of 8% (Figure 3b). The total reduction of 4.29 days in rice phenology also caused the rice yield to decrease.

Figure 3a shows an increase in rice yield of 10.26% during 2030–2039 for RCP 4.5. A decrease in precipitation compared to the previous decade, and a reduction in CO_2 concentration and solar radiation caused more decrease in yield and an increase in water demand of 13.90% (Figure 3b). Furthermore, the reduction in total phenological days was found to be 6.19 days, where the decrease in panicle initiation, anthesis, and maturity days were 0.39 days, 1.64 days, and 4.16 days, respectively.

The increase in rice yield was observed to be 9.31% during 2040–2049 for the intermediate scenario, RCP 4.5 (Figure 3a). The water demand during this period increased by 15.01%, which showed that an increase in temperature, a decrease in CO_2 concentration, and solar radiation played an essential role in this high demand (Figure 3b). Moreover, panicle initiation, anthesis, and maturity days decreased by 1.19 days, 2.01 days, and 7.11 days, respectively (Figure 3c).



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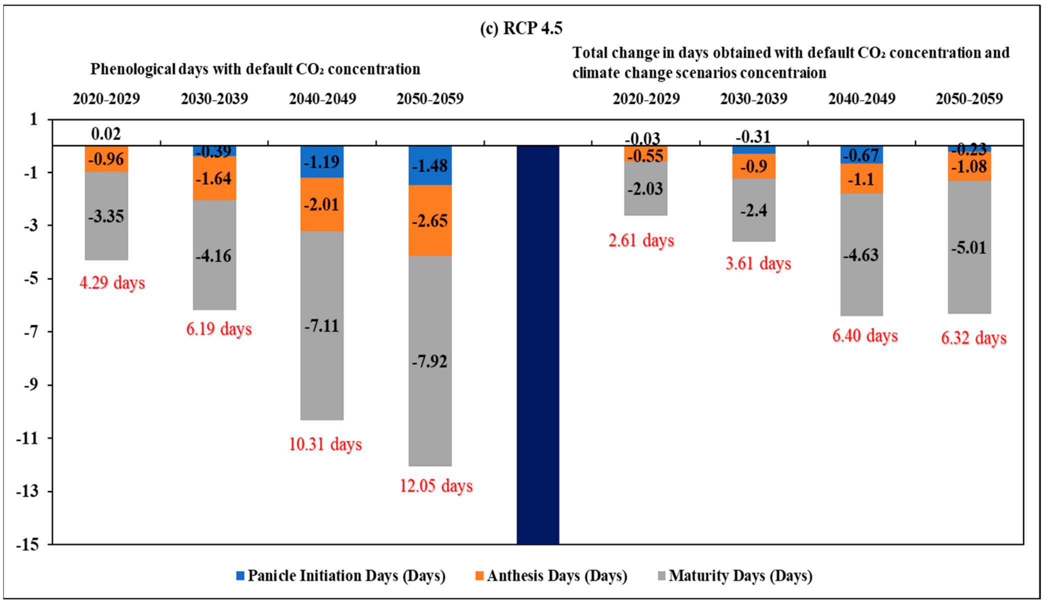


Figure 3. Impact of default CO_2 concentration on rice yield (**a**), water demand (**b**), and phenology (**c**) for RCP 4.5.

Figure 3a shows a decrease in rice yield of 17.23% during the 2050s (2050–2059). Therefore, a total decrease of 12.51% was observed during this period, with 400 ppm of CO_2 concentration. Water demand also increased by 12.56% from the baseline period with RCP 4.5 during the 2050s (Figure 3b). All the climatic factors, including a decrease in CO_2 concentration, reduced the total phenological days by 12.05 days (Figure 3c), also affected the rice growth phases and reduced the rice yield. It can be seen from Figure 3c that the panicle initiation, anthesis, and maturity days decreased by 1.48 days, 2.65 days, and 7.92 days, respectively, which affected rice growth stages severely.

3.1.3. RCP 6.0

The decrease in yield was estimated to be 9.86% during 2020–2029 (Figure 4a). The decrease in the default value of CO_2 concentration of 56 ppm indicates the impact of decreasing the rice yield and an increase in water demand of 11.98% (Figure 4b). The reduction in yield of 16.46%, 17.73%, and 18.74% can be seen from the Figure 4a, during 2030–2039, 2040–2049, and 2050–2059, respectively, for RCP 6.0. Similarly, water demand increased by 7.64% 5.58%, 6.69%, and 7.82%, during 2020–2029, 2030–2039, 2040–2049, and 2050–2059, respectively (Figure 4b). Moreover, Figure 4c demonstrates the decrease in phenological days of 4.42 days, 6.30 days, 10.51 days, and 12.10 days during 2020–2029, 2030–2039, 2040–2049 and 2050–2059, respectively, for RCP 6.0.

3.1.4. RCP 8.5

Figure 5a exhibits a decrease in yield of 8.56% during 2020–2029, which was associated with an increase in precipitation and a decrease in the default value of CO_2 concentration from the changed value of 4.12% and 35 ppm, respectively. Furthermore, Figure 5b indicates an increase in water demand of 10.15% during 2020–2029. Similarly, for this scenario, panicle initiation, anthesis, and maturity days decreased by 0.18, 1.24, and 4.86 days, respectively (Figure 5c).

During 2030–2039, rice yield decreased by 10.21% for RCP 8.5 (Figure 5a). Water demand for this period was found to have increased by 13.43%, and total phenological days decreased by 8.09 days.

Figure 5a illustrates a decrease in yield and increase in water demand of 14.10% and 14.79%, respectively. This large reduction in yield and the high water demand were caused by a decrease in CO_2 concentration, which dropped by 111 ppm from the changed value. Further, a combined effect—a decrease in CO_2 concentration, and a high increase in maximum and minimum temperature with a decrease in solar radiation—decreased the panicle initiation, anthesis, and maturity days by 1.26 days, 2.86 days, and 8.71 days, which also affected the rice yield (Figure 5c).

The decrease in rice yield of 23% during 2050–2059 for RCP 8.5 indicates that the decrease in CO_2 concentration of 167 ppm and high temperature caused a large reduction in rice yield (Figure 5a). Water demand increased by 13.98% during this period (Figure 5b). Further, total phenological days decreased by 14.55 days, where panicle initiation, anthesis, and maturity days were reduced by 1.79 days, 3.10 days, and 9.66 days, respectively (Figure 5c).

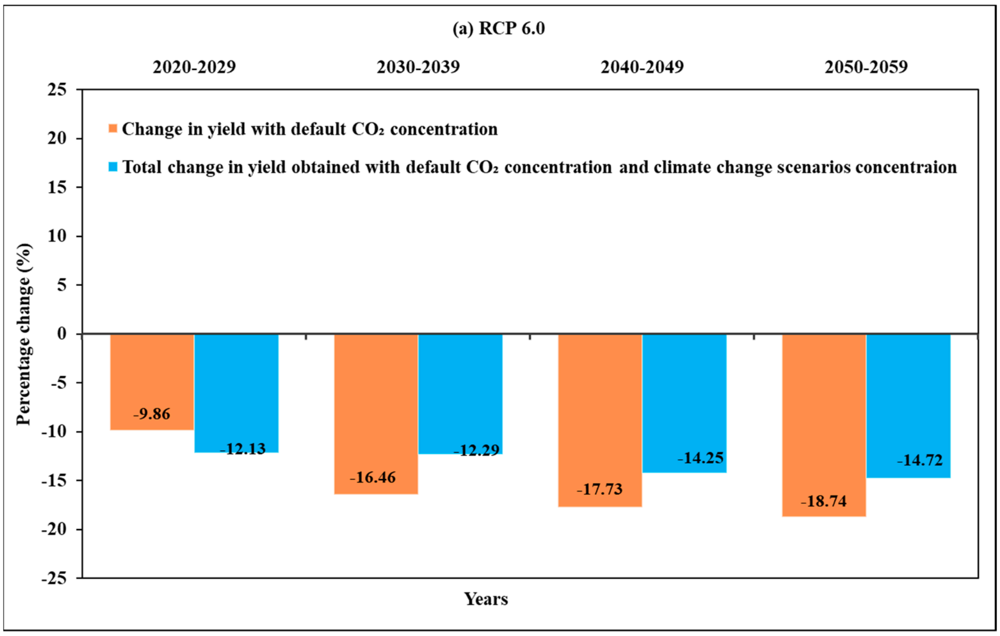
3.2. Change in Yield, Water Demand, and Phenological Days Obtained from CERES-Rice Simulation Using Ensembled Climate Data of GCMs, and Comparison with Ensembled Crop Model Outputs Obtained Corresponding to Each GCM

3.2.1. RCP 2.6

Figure 6a illustrates the change in rice yield with an ensemble of GCM simulation as an input in the CERES-rice model. During 2020–2029, the yield increased by 2.01% from the baseline period, which is 0.24% less than the yield obtained from the ensemble of crop model outputs corresponding to each GCM simulation. Water demand increased by 3.59% from the historical period, resulting in a large difference with the ensemble of crop model outputs of 1.49% (Figure 6b). Figure 6c corroborates the decrease in yield and water demand by showing a decrease in total phenological days of 0.20 days.

Figure 6a demonstrates that the rice yield during 2030–2039 for RCP 2.6 decreased by 0.34%. The total difference in results between the two methods is 0.46%. The water demand decreased by 1.47% from the baseline with the ensemble of GCMs (Figure 6b). The decrease in rice phenology of 2.18 days also depicts a small change in obtained results between the two methods (Figure 6c).

During 2050–2059 (2050s), the rice yield decreased by 2.16% from the historical period with an ensemble of GCMs (Figure 6a). The total change between the two methods of obtaining outputs showed a difference of 0.78%. The decrease in yield reduced the water demand in the same proportion by 0.16% (Figure 6b). Furthermore, the decrease in solar radiation and increase in temperature caused a decrease in panicle initiation, anthesis, and maturity days of 0.81 days, 0.95 days, and 2.51 days, respectively (Figure 6c).



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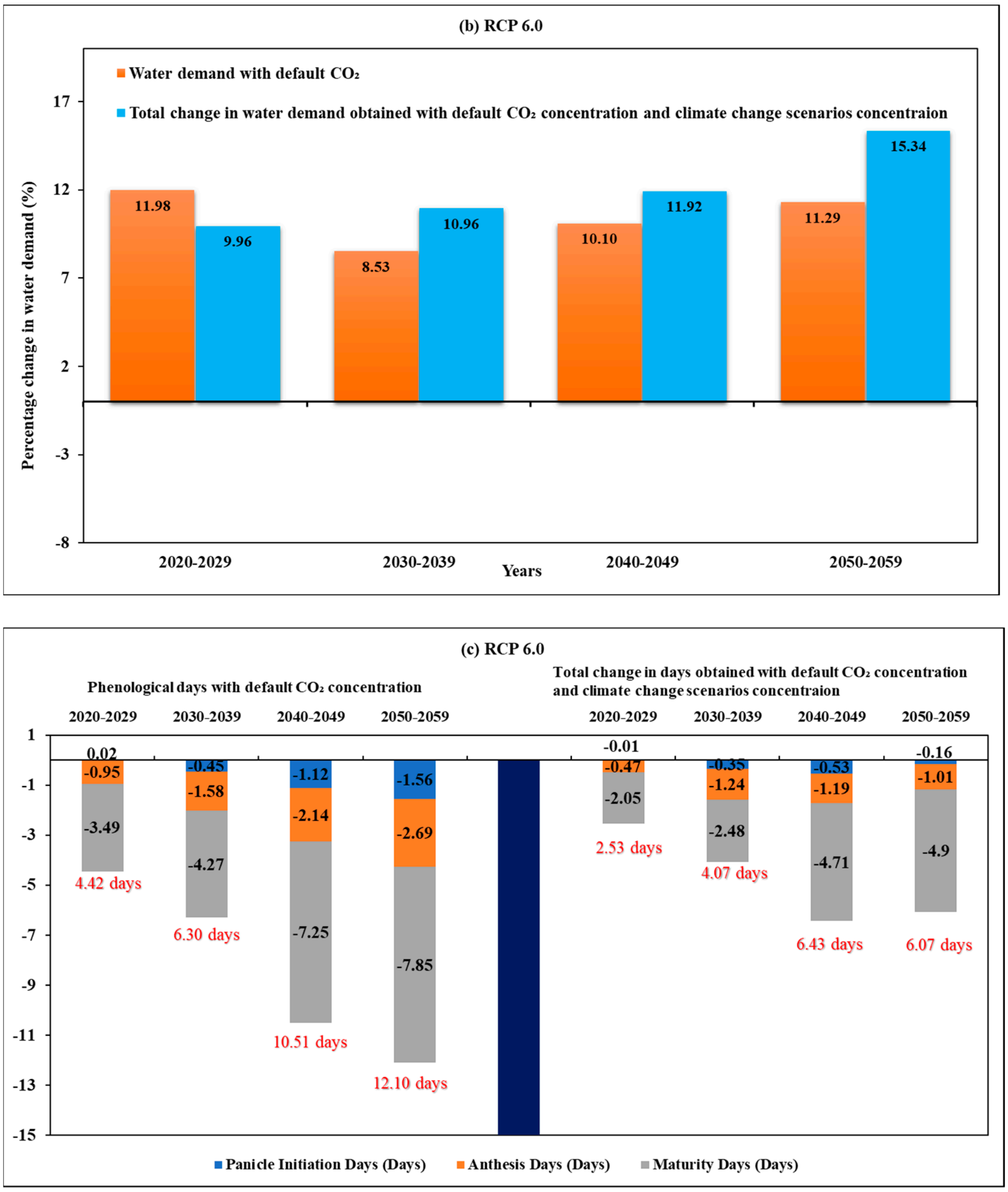

Figure 4. Impact of default CO_2 concentration on rice yield (**a**), water demand (**b**), and phenology (**c**) with the scenario RCP 6.0.

3.2.2. RCP 4.5

Figure 7a shows the increase in yield of 4.12% with an ensemble of GCMs during 2020–2029. This also led the water demand to be decreased by 4.29% from the baseline period (Figure 7b). The difference in water demand between both methods was determined to be 1.58%. The total decrease was estimated to be 1.58 days from the historical period.

The increase in rice yield was estimated to be 1.06% during 2030–2039 for RCP 4.5 (Figure 7a). The total decrease in yield from the ensemble of crop model outputs method was computed to be 0.89%. The water demand increased by 2.10% during this period, revealing a total difference of 0.73% from the ensemble results corresponding to individual GCMs (Figure 7b). The total decrease of 2.34 days predicts a difference of 0.24 days between the two methods of estimation.

Furthermore, Figure 7a also exhibits an increase in rice yield of 3.37% from the baseline period during 2040–2049. The water demand was also found to have increased by 3.01%, which is very close to the prediction with the ensembled crop model outputs method. (Figure 7b).

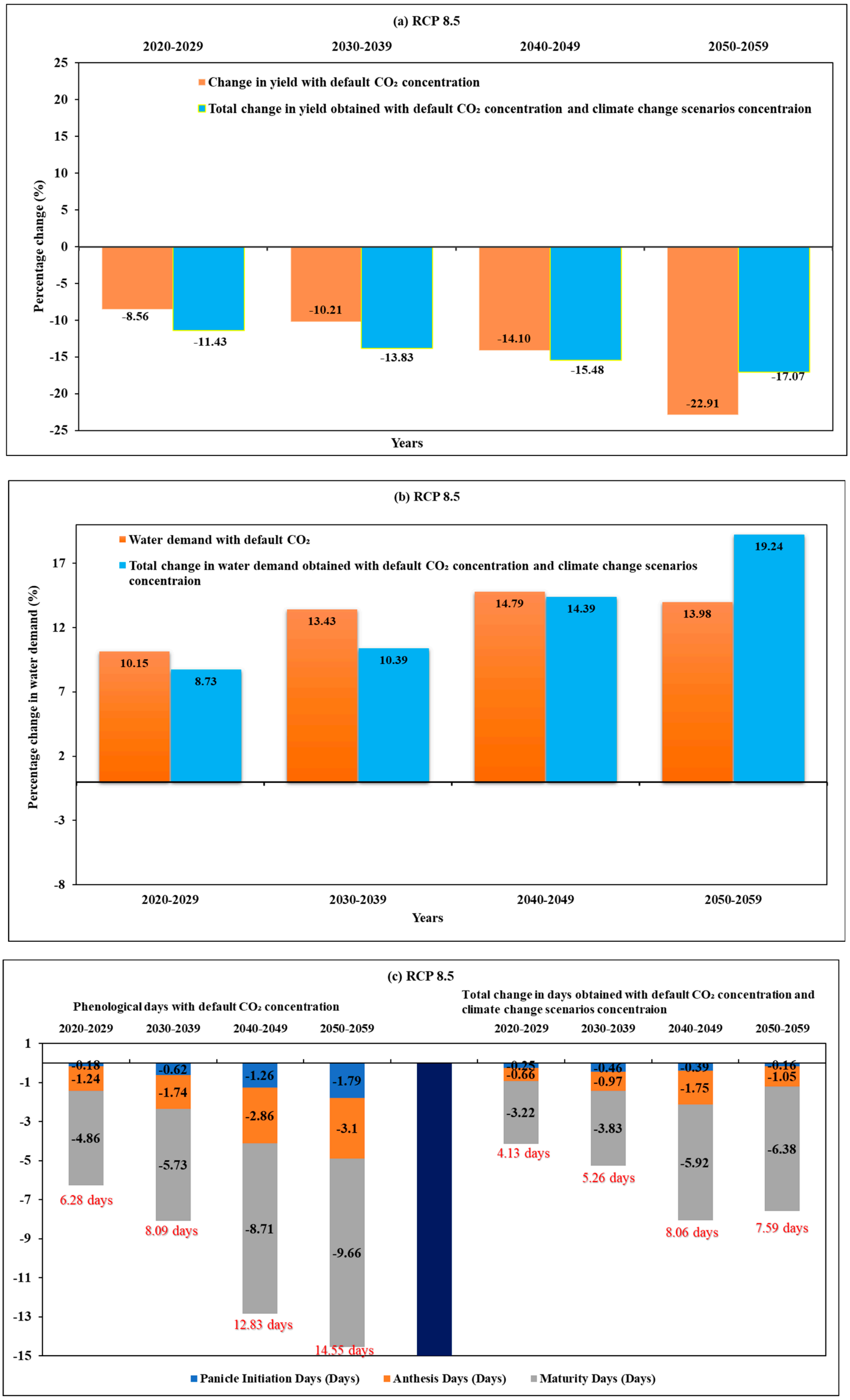

Figure 5. Impact of default CO_2 concentration on rice yield (**a**), water demand (**b**), and phenology (**c**) with the scenario RCP 8.5.

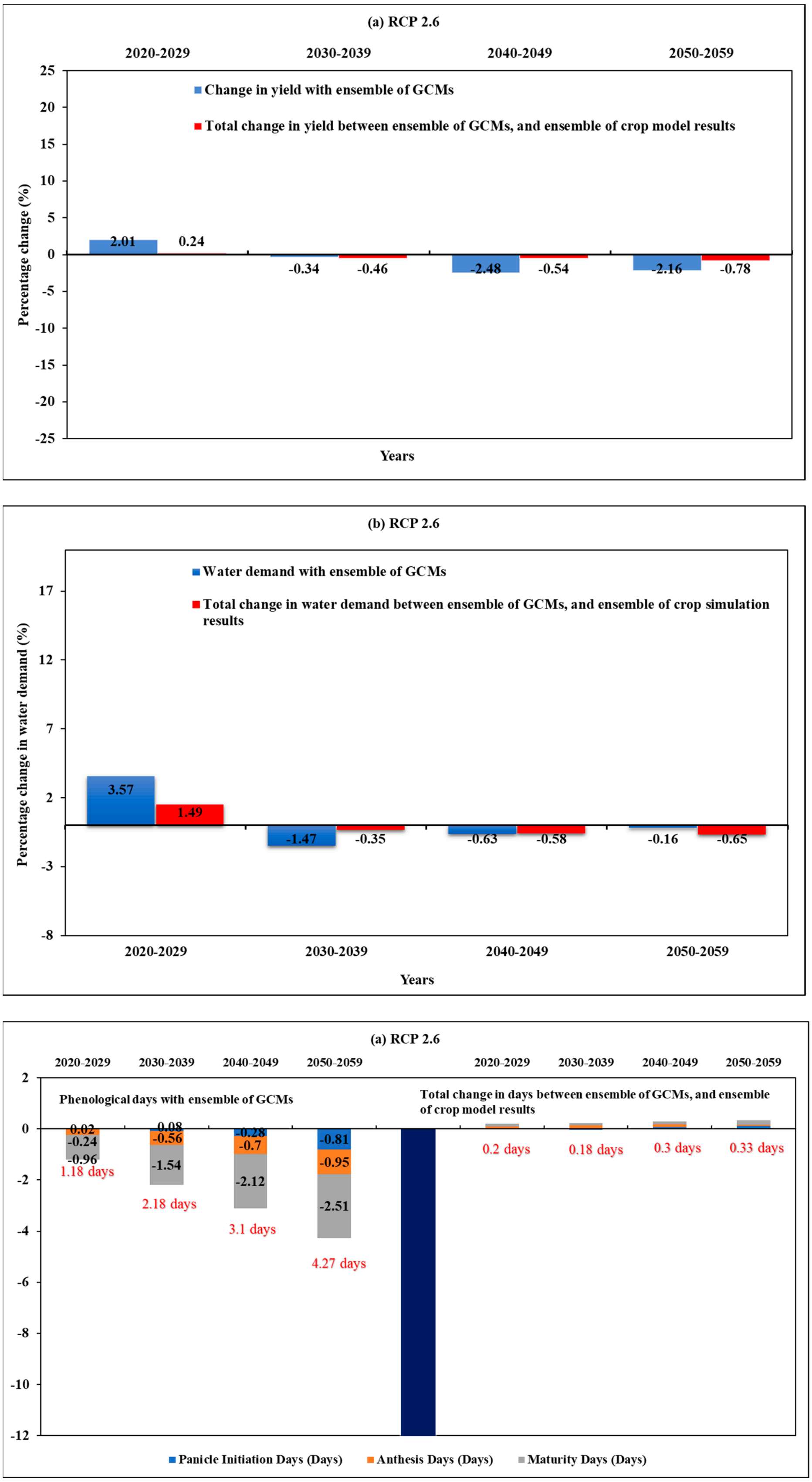

Figure 6. Climate change impacts on rice yield (**a**), water demand (**b**), and phenology (**c**) with the scenario RCP 2.6 using an ensemble of GCMs simulation.

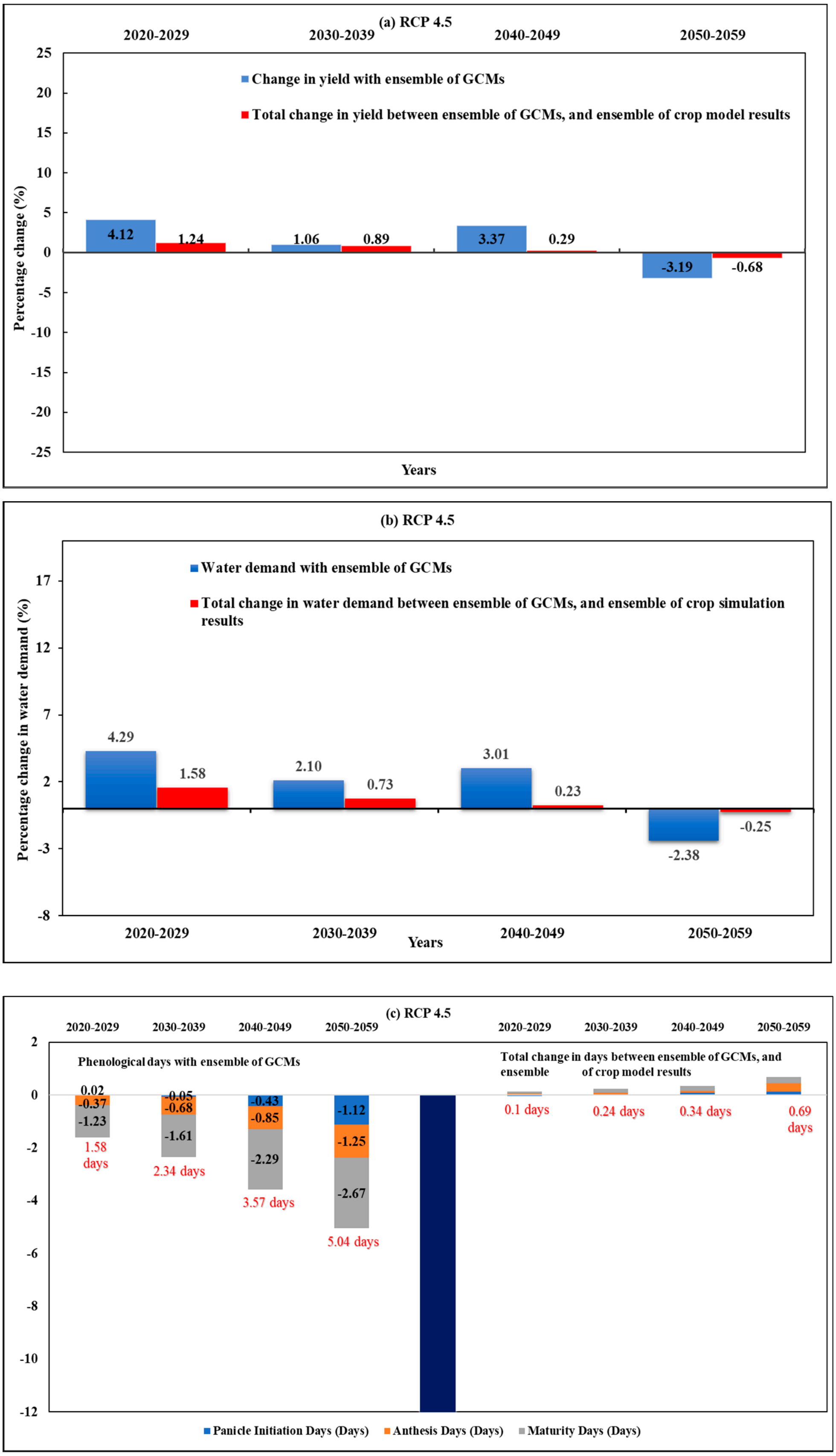

Figure 7. Climate change impact on rice yield (**a**), water demand (**b**), and phenology (**c**) with the scenario RCP 4.5 using an ensemble of GCMs simulation.

Figure 7a shows a decrease in rice yield of 3.19% during the 2050s (2050–2059). The decrease in rice yield also led to a proportional reduction in water demand, which was estimated to be decreased by 2.38%. (Figure 7b). High temperatures and low solar radiation decreased the total phenological days by 5.04 days (Figure 7c), as can be seen from Figure 7c, in which the panicle initiation, anthesis, and maturity days decreased by 1.12 days,
1.25 days, and 2.67 days, respectively.

3.2.3. RCP 6.0

An increase in yield of 1.89% can be seen in Figure 8a and Table 1 during 2020–2029. The difference in yield between the two methods of estimation was found to be 0.38%. A reduction in yield of 3.45%, 2.89%, and 3.76% is indicated from Figure 8a during 2030–2039, 2040–2049, and 2050–2059, respectively, for RCP 6.0. Similarly, water demand also increased by 1.48% during 2020–2029, and a decrease in yield caused a reduction in water demand of 1.47%, 0.84%, and 2.68%, during 2030–2039, 2040–2049, and 2050–2059, respectively (Figure 8b). Further, Figure 8c illustrates a decrease in phenological days by 1.72 days, 2.78 days, 3.61 days, and 5.53 days during 2020–2029, 2030–2039, 2040–2049, and 2050–2059, respectively, for RCP 6.0.

Table 1. Yield, water inputs (precipitation + irrigation water), and water demand, with baseline period (1980–2004), and projected future climate change scenarios up to 2050s with RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, with ensembled climate data of GCMs.

Climate Scenario		Yield (kg ha^{-1})	Precipitation (mm)	Irrigation (mm)	Water Demand (mm)
Baseline (1980–2004)		5372	729	282	476
RCP 2.6	**2020–2029**	5480	797	253	493
	2030–2039	5354	763	259	469
	2040–2049	5239	730	247	473
	2050–2059	5256	779	272	475
RCP 4.5	**2020–2029**	5593	865	240	496
	2030–2039	5429	814	267	486
	2040–2049	5553	869	239	490
	2050–2059	5201	775	261	465
RCP 6.0	**2020–2029**	5474	800	265	483
	2030–2039	5187	734	269	469
	2040–2049	5217	809	266	472
	2050–2059	5170	844	245	463
RCP 8.5	**2020–2029**	5499	759	271	483
	2030–2039	5556	820	254	493
	2040–2049	5439	774	262	480
	2050–2059	5040	834	236	452

3.2.4. RCP 8.5

Figure 9a shows an increase in yield of 2.37%, 3.43%, and 1.24% from the baseline period during 2020–2029, 2030–2039, and 2040–2049, respectively. The small changes between the two methods of 0.50%, 0.19%, and 0.14% for the periods of 2020–2029, 2030–2039, and 2040–2049, respectively, describe the increases in temperature that led to similar results. The increase in water demand was found to be 1.47%, 3.57%, and 0.78% during 2020–2029, 2030–2039, and 2040–2049, respectively (Figure 9b). The decrease in water demand for the 2050s was found to be 4.98%, and the difference between the two methods was very small at 0.34%. Furthermore, the decrease in phenological days was estimated to be 1.87 days, 2.52 days, 4.31 days, and 6.47 days, during 2020–2029, 2030–2039, 2040–2049, and 2050–2059, respectively (Figure 9c).

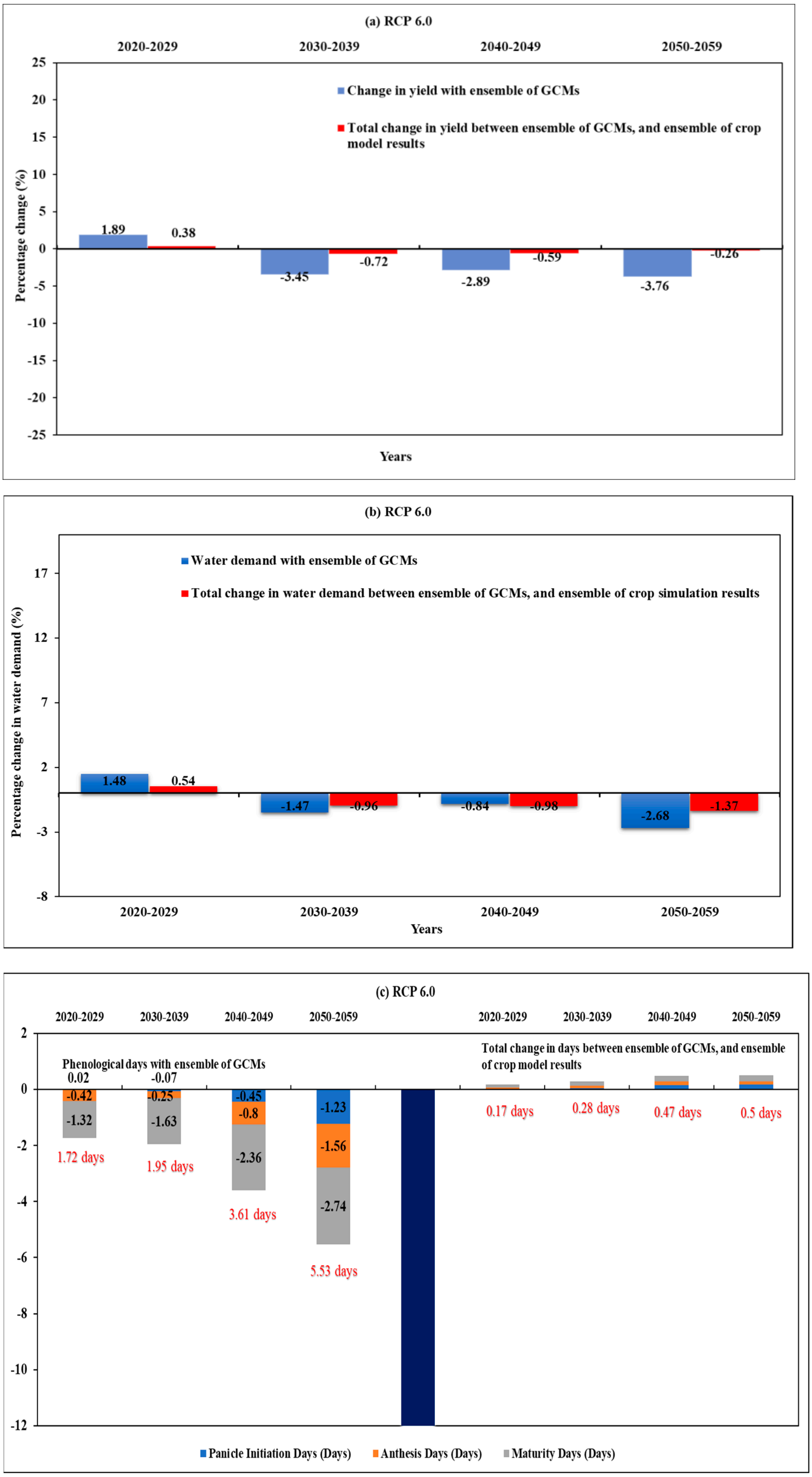

Figure 8. Climate change impacts on rice yield (**a**), water demand (**b**), and phenology (**c**) with the scenario RCP 6.0 using an ensemble of GCMs simulation.

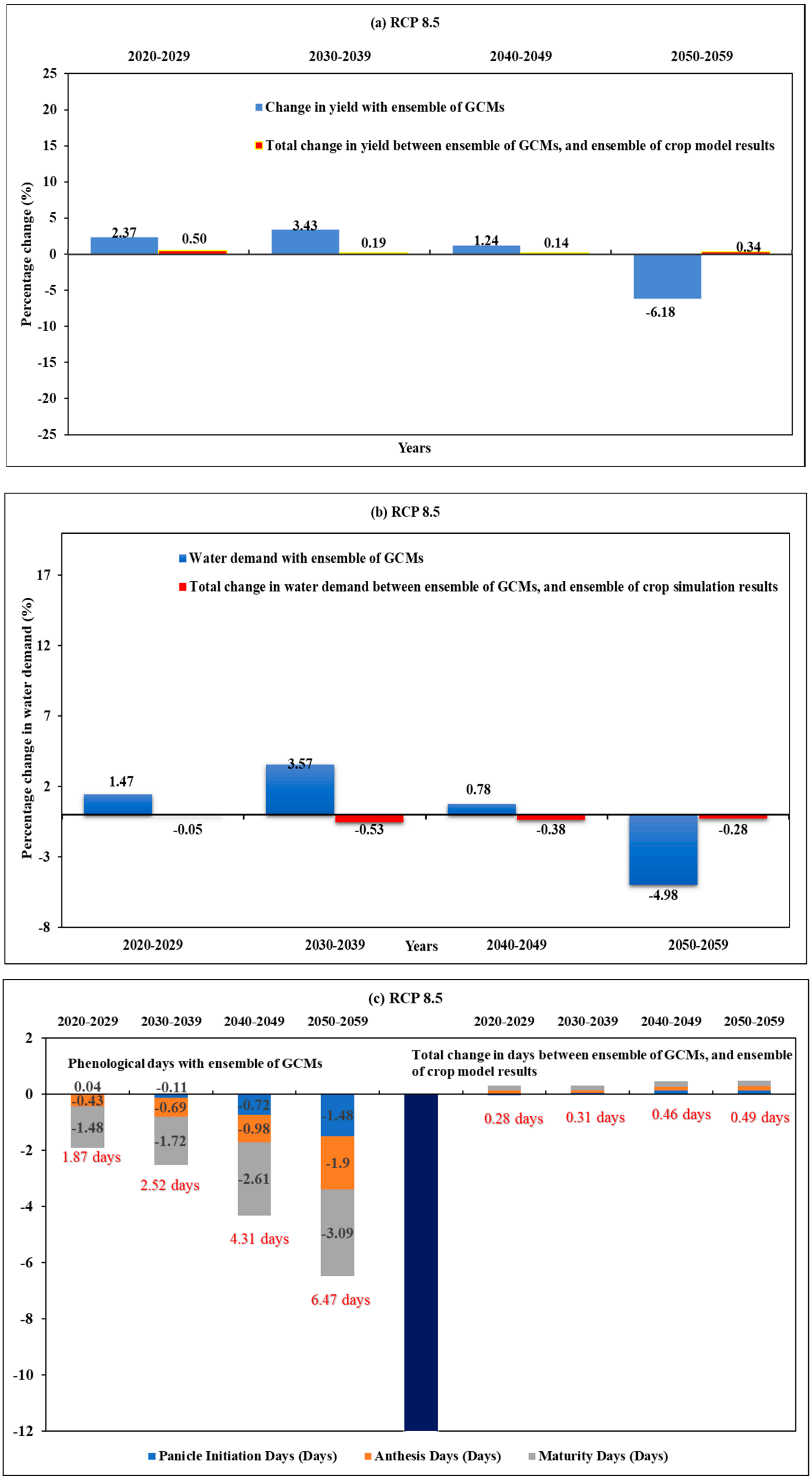

Figure 9. Climate change impact on rice yield (**a**), water demand (**b**) and phenology (**c**) with the scenario, RCP 8.5, using an ensemble of GCMs simulation.

4. Discussion

This research emphasized that the changes in yield, water demand, and phenology are highly correlated with CO_2 concentration, and altering this concentration will significantly affect the outputs. A large variation in climatic factors provides evidence of variation in yield for each decade. Although the CO_2 concentration has increased from the baseline period, an increase in temperature and a decrease in solar radiation influenced the change in yield (Figure 2a). Since the projection change in minimum temperature was found to be higher compared to the maximum temperature from the baseline period, both together affected the rice production. Despite a decrease in yield with all the climate change scenarios, an increase in water demand was most likely due to a decrease in CO_2 concentration and an increase in temperature [27,28]. The change in phenological days also showed that the decrease in CO_2 concentration affected the phenological days as well [29–31]. The decrease in yield during the 2050s shows that the reduction in CO_2 concentration caused a greater decrease in yield because it was the primary contributor to increase the in rice production in climate change conditions [32–34]. Therefore, with decreased CO_2 concentration, phenological days will also be reduced very significantly and will decrease the rice yield [35–37]. This large decrease in phenological days shows the adverse impact of the decrease in CO_2 concentration and solar radiation, an increase in temperature on the plant growth days (Figures 2c–6c). However, all the phenomena provide a complex relationship and wide impact of CO_2 concentration on rice yield, water demand, and phenology.

In addition to these results, an ensemble of GCMs as an input into the crop model demonstrates that the average weather of ensemble GCMs smoothed out the climate data and provided an average change in the yield, water demand, and phenology. The total difference between the two ensemble approaches—an ensemble of GCMs and an ensemble of crop model outputs run on the corresponding input of each GCM—was not very large, but a considerable difference was found where climatic factors change abruptly. This could be the rationale for there not being a greater difference when climatic factors have a significant trend (Jha et al., 2021) [25]. Nevertheless, the comparison between the two methods of obtaining results illustrated a decrease in outputs from baseline with the ensemble of GCMs. The increase in water demand for all the decades up to 2050 shows that higher temperatures from all the individual GCMs caused an increase in water demand. The change in phenological days demonstrated that panicle initiation days decreased for all the decades, and the difference in which the days between the two methods were maximum increased to 0.69 days.

Hence, this study elucidated the intricate interplay of climatic factors, demonstrating that fluctuations in, especially, CO_2 concentration influence rice yield, water demand, and phenology to a significant degree. Moreover, to estimate the climate change impact using climate and crop models, researchers need to study the climatic patterns and determine whether an ensemble of GCMs would be input into the model or whether an ensemble of crop model outputs corresponding to each GCM need to be considered for the final output for any decision-making strategies.

5. Conclusions

Climate change is an essential phenomenon that needs to be considered for future crop production. Various approaches are used to assess its impact, and understanding the differences among these approaches may influence decision-making guidelines. In this research, we have investigated the impact of changes in CO_2 concentration on rice production, water demand, and crop phenology. In addition to that, we have also studied the change in crop growth model outputs obtained using ensembled climate data of GCMs as input into the CERES-Rice model, which were compared with the ensemble of crop model outputs simulated with each individual GCM's climate data.

The CERES-Rice model simulation with the default CO_2 concentration (400 ppm) revealed a significant reduction in yield across all four climate change scenarios. During 2020–2029, the smallest decrease in yield of 5.32% was observed with RCP 2.6, while the largest decrease of 8.56% was estimated with RCP 8.5. The increase or decrease in yield was also found to be influenced by changes in precipitation, temperature, and solar radiation. By the 2050s, the decreases in yield ranged from 15.45% (RCP 2.6) to 22.91% (RCP 8.5). Additionally, the increase in water demand was associated with rising temperature and a decrease in CO_2 concentration from the changed CO_2 concentration. Furthermore, the decrease in CO_2 concentration, along with other factors, such as precipitation, temperature, and solar radiation, will reduce phenological days by a maximum of 14 days under RCP 8.5 during the 2050s.

The CERES-Rice model simulation using an ensemble of GCMs did not show very large differences in rice yield, water demand, and phenology compared to simulations using individual GCMs. However, yield and water demand were affected by variations in precipitation and temperature changes. Despite the yield decreasing under the worst-case scenario, water demand increased up to 2050 compared to the other ensemble approach. The variation in water demand with this ensemble of GCMs moved up or down in the same pattern as the values were changing with other methods. The total change in water demand between these two methods differed by a maximum of 1.58% during 2020–2029 with RCP 4.5, suggesting that differences could increase with drastic climatic changes. Nevertheless, the reduction in phenological days was relatively less compared to the simulation with individual GCMs.

Our research showed that a decrease in CO_2 concentration will reduce yield and phenological days while increasing water demand for rice production. Using an ensemble of GCMs will not drastically change the outputs of the CERES-Rice model compared to using individual GCMs. However, it will help to smooth out the variability and provide more consistent results.

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