

Predicting Irrigated and Rainfed Rice Yield Under Projected Climate Change Scenarios in the Eastern Region of India

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Abstract Numerous estimates for the coming decades project changes in precipitation resulting in more frequent droughts and floods, rise in atmospheric CO₂ and temperature, extensive runoff leading to leaching of soil nutrients, and decrease in freshwater availability. Among these changes, elevated CO₂ can affect crop yields in many ways. It is imperative to understand the consequences of elevated CO₂ on the productivity of important agricultural crop species in order to devise adaptation and mitigation strategies to combat impending climate change. In this study, we have modeled rice phenology, growth phase, and yield with the “Decision Support System for Agrotechnology Transfer (DSSAT) CERES rice model” and arrived at predicted values of yield under different CO₂ concentrations at four different locations in Eastern India out of which three locations were irrigated and one location was rainfed. The ECHAM climate scenario, Model for Interdisciplinary Research on Climate (MIROC)3.0 climate scenario, and ensemble models showed different levels of yield increase with a clear reduction in yield under rainfed rice as compared to irrigated rice. A distinct regional and cultivar difference in response of rice yield to elevated CO₂ was seen in this study.

Results obtained by simulation modeling at different climate change scenarios support the hypothesis that rice plant responses to elevated CO₂ are through stimulation of photosynthesis. Realization of higher yields is linked with source sink dynamics and partitioning of assimilates wherein sink capacity plays an important role under elevated CO₂ conditions.

Keywords Climate change · Simulation modeling · Elevated CO₂ · Sink capacity · Photosynthesis

1 Introduction

Global climate change will have a decisive impact on crop production, and the prediction of the extent of this has emerged as a major research priority during the past decade. Numerous estimates for the coming decades project changes in precipitation resulting in more frequent droughts and floods, rise in atmospheric CO₂ and temperature, extensive runoff leading to leaching of soil nutrients, and decrease in freshwater availability. World agriculture faces overwhelming

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challenges to meet rising demands for food, energy, and other agricultural products, and this coupled with increasing population and dwindling natural resources makes it imperative for us to understand the consequences of climate change on the productivity of important agricultural crop species. Climate trends since 1980 were large enough in many countries to offset a significant proportion of the potential increases in average crop yields due to technological advances, CO₂ fertilization, and other factors [9, 18]. The AR5 report of Stocker et al. [28] shows an estimated warming of 0.85 °C since 1880 with the fastest rate of warming in the Arctic. By the end of the twenty-first century, the global surface temperature increase is likely to exceed 1.5 °C relative to the 1850 to 1900 period for most scenarios (except representative concentration pathways (RCPs) RCP 2.6) and is likely to exceed 2.0 °C for many scenarios (RCP 6.0 and RCP 8.5). In addition, precipitation will become more variable, and episodes of extreme weather will become more frequent and intense and last longer. Projected climate change scenarios will affect crop productivity and also food security. Kii et al. [14] analyzed food availability and risk of hunger under the combined scenarios of food demands and agroproductivity with and without climate change by 2100 for the B2 scenario and concluded that future food demand can be satisfied globally under all assumed combined scenarios and also that a reduction of food access disparity and increased progress in productivity are as important as climate change mitigation for reducing the risk of hunger.

Crop production system involving complete input management with recommended package of practices including scheduling irrigation, nutrient application, and crop protection is cost intensive for experimental data generation especially when done at different sowing dates and multiple locations. Appropriately validated crop simulation models could be used to test many such combinations in a brief time with limited expense. Such simulations can adequately describe relative trends in yields caused by environmental variation [21, 27].

Mechanistic models predict crop productivity based on quantitative functional relationships essentially fundamental to the processes studied such as photosynthesis, water relations, source sink relationship, and their interaction with changing environmental variables. This makes these models suitable for projecting the impact of predicted climate scenarios on crop productivity; in addition, these models can be used at multiple levels which include experimental field, regional, national, and global. Local-gridded approaches to crop modeling using climate change scenarios can also assist to identify suitable adaptation and mitigation measures. Lenzen et al. [16] developed a modeling approach for examining selected drivers of ecosystem functioning and agricultural productivity and carried out a number of scenario projections of country-level consumption, production, land use, energy use, greenhouse gas emissions, species diversity, and agricultural production up to 2050. Recently, application of the crop yield

simulation systems approach to climate change adaptation and mitigation initiatives has been gaining popularity. This is due to the increasing availability of information on the processes that are affected by changing climate, thus helping us to devise possible adaptation measures [6, 20, 30, 31]. The effects of CO₂ fertilization on crop production have also been widely studied and have been reported to reduce some of the potential damages caused by the climatic impacts of greenhouse gases but by significantly less than that indicated in earlier research [5].

Rice (*Oryza sativa* L.) is one of the major crops in the world. It is grown in diverse climatic zones and is the staple diet of about 2.7 billion people. In India, it is cultivated in about 150 million hectares, producing 132,013,000 metric tons, which covers about 26 % of the global rice production [29]. Climate change impacts on the yields of rice in relation to temperature, carbon dioxide, and rainfall change have been studied by using the crop growth model InfoCrop in the uplands of the Hill Tracts of Chittagong [3]. Rice cultivars respond differently to elevated CO₂ concentrations, and CO₂ × cultivar interaction has also been studied under open-field conditions and it was found to increase yield in rice [7]. In view of the above facts, we devised a study with the objectives of calibrating and validating rice phenological stages with special reference to anthesis days and physiological maturity in different cultivars at different locations in Eastern India including locations of the Indo-Gangetic Plains (IGP) of India and to model the effect of elevated CO₂ on rice yield under different climate change scenarios.

2 Materials and Methods

2.1 Study Area

In the present study, four representative locations were selected, viz., Faizabad (IGP), Kanpur (IGP), Raipur, and Ranchi in Eastern India. These locations varied in their geographical placement and differed in climate as well as soils (Table 1). Seasonal rainfall in these locations varied from 697.7 to 1148.3 mm. The mean maximum temperatures varied between 28.4 and 38 °C and the mean minimum temperatures ranged between 15.5 and 27.5 °C. Rice is grown under an irrigated ecosystem in Faizabad, Kanpur, and Raipur, whereas at Ranchi, it is grown under a rainfed ecosystem. In the irrigated ecosystem, the amount of irrigation differed from location to location.

2.2 Experimental Data

Experimental crop data for rice was collected from the date of sowing experiments (early, normal, and late sowings) carried out at Faizabad, Kanpur, Raipur, and Ranchi locations which

Table 1 Agroclimatic and edaphic details of the selected locations

Station	Latitude	Longitude	Altitude (m)	Cultivar	Soil	Ecotype	Period of experiment	T_{max} (°C)	T_{min} (°C)	Rainfall (mm)	Sunshine (h)
Faizabad	26° 47' N	82° 12' E	113	Sarjoo-52	Silty loam	Irrigated	2008–2012	33.8	19.4	812	7.2
Kanpur	26° 39' 35" N	80° 18' 25" E	125.9	NDR359	Sandy loam	Irrigated	2008–2012	31.3	18.7	867	5.9
Raipur	21° 15' 00" N	81° 41' 00" E	289	Mahamaya	Matasil soil	Irrigated	2007–2011	32.7	19.7	1180	6.7
Ranchi	23° 17' 00" N	85° 10' 00" E	289	Vandana	Loamy	Rainfed	2007–2012	28.6	16.7	1397	6.02

are part of All India Coordinated Research Project on Agrometeorology (AICRPAM), Indian Council of Agricultural Research (ICAR), Central Research Institute for Dryland Agriculture (CRIDA), Hyderabad, India. A minimum data set of the summer (*kharif*) rice crop which includes crop management data, viz., cultivar information, crop duration, date of sowing, date of anthesis or 50 % flowering, date of physiological maturity, application schedule, and amount of fertilizer and irrigation, is given in Table 2. Soil profile data comprising the physical and chemical properties of the soil up to 60 cm depth with an interval of 5 cm was collected from the study area of the four locations. Further, locationwise daily weather data (solar radiation, maximum and minimum temperatures, and rainfall) was collected and arranged in the CERES rice model weather input format. All this crop management data along with soil profile and daily weather data sets of the selected locations was converted to model data sets for further simulation process.

2.3 Decision Support System for Agrotechnology Transfer CERES Rice Model

The CERES rice model in decision support system for agrotechnology transfer (DSSAT) developed by Hoogenboom et al. [8] is a process-based model that can simulate the growth and development of cereal crops under varying weather, soil, and management levels. It simulates soil water balance and water use by the crop and soil nitrogen transformations and uptake by the crop besides growth and different phenophases of the crop. Crop growth rate (CGR) is simulated by employing a carbon balance approach in a source sink system [23] and crop duration through thermal time concept [11]. A schematic representation of the model is given in Fig. 1. The model simulates total biomass of the crop as the product of the growth duration and average growth rate. The model uses phenology, nitrogen and water input, and growth and development as components wherein day length and temperature are taken into consideration for the phenological stages. Biomass production is taken into account as a result of partitioning of assimilates; in addition, source sink relationship is also considered in the model. The simulation of yields at the process level involves the prediction of these two important processes. The yield of the crop is the fraction of total biomass partitioned to grain.

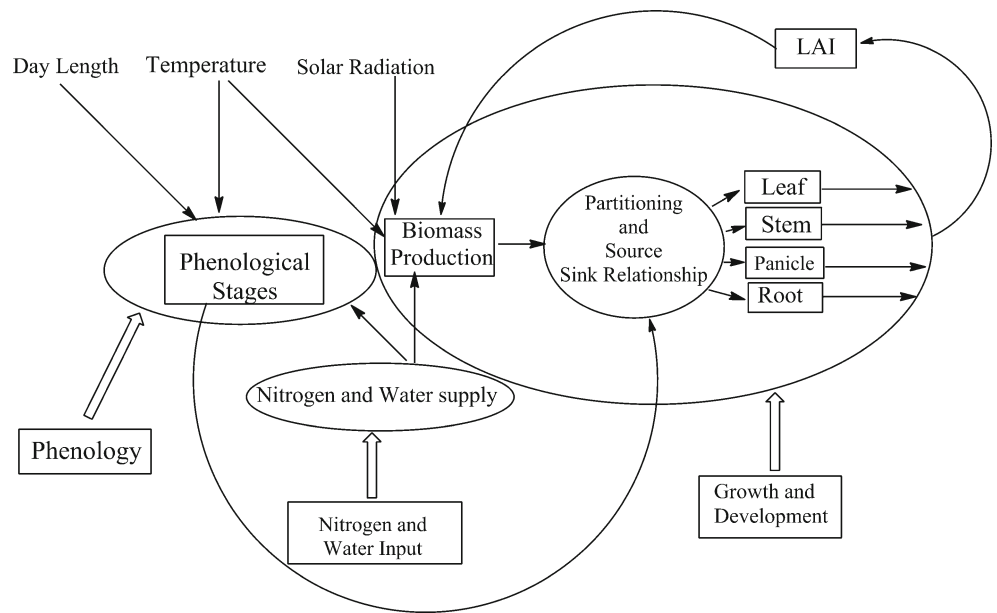
2.4 Model Calibration and Validation

Calibration is adjustment of the system parameters so that simulated results reach a predetermined level, usually that of an observation. Genotype coefficients of the rice cultivars ‘Sarjoo-52 (Faizabad), NDR359 (Kanpur), Mahamaya (Raipur), and Vandana (Ranchi)’ were calibrated and validated using the experimental data on phenology and grain yield

Table 2 Cultivation and input application details of varieties in different locations

Location	Cultivar	Dates of sowing	Dates of irrigation	Amount of irrigation	Dates of fertilizer application	Type of fertilizer	Amount of fertilizer (N, P, and K) application (kg ha ⁻¹)		
Faizabad	Sarjoo-52	Early	24th July	60 mm	5th July	Urea, DAP, MOP	50 % N+P and K		
			19th August		29th July			25 % N	
		Normal	9th September	60 mm	2nd September	Urea, DAP, MOP	50 % N+P and K		
			10th August		15th July			25 % N	
		Late	25th August	60 mm	10th August	Urea, DAP, MOP	50 % N+P and K		
			10th September		10th August			25 % N	
		Kampur	NDR359	Early	15th August	Check basin	25th July	Urea, DAP, MOP	50 % N+P and K
					30th August		17th August		
				Normal	15th September	Check basin	15th September	Urea, DAP, MOP	50 % N+P and K
					12th July		05th July		
Late	11th August			Check basin	3rd August	Urea, DAP, MOP	50 % N		
	26th August				04th September			25 % N	
Raipur	Mahamaya			Normal	22nd July	75 mm	15th July	Urea, DAP, MOP	25 % N+P and K
					21st August		13th August		
				Late	05th September	75 mm	14th September	Urea, DAP, MOP	25 % N+P and K
					25th September		25th July		
		Early	1st August	75 mm	23rd August	Urea, DAP, MOP	33 % (N+P and K)		
			31st August		24th September			25 % N	
		Normal	15th September	75 mm	15th July	Urea, DAP, MOP	33 % (N+P and K)		
			5th October		12th August			33 % (N+P and K)	
		Ranchi	Vandana	Normal	26th July	No irrigation	14th September	Urea, DAP, MOP	25 % N+P and K
					23rd October		25th July		
Late	03rd August			No irrigation	25th August	Urea, DAP, MOP	25 % N+P and K		
	31st October				23rd September			50 % N	
Early	No irrigation			No irrigation	5th August	Urea, DAP, MOP	25 % N+P and K		
	No irrigation				4th September			25 % N	
Normal	No irrigation			No irrigation	2nd October	Urea, DAP, MOP	34 % (N+P and K)		
					20th June			20th July	25 % N+P and K
Late	No irrigation			No irrigation	7th July	Urea, SSP, MOP	131:188:35		
					26th July			30th June	25 % N
Normal	No irrigation	No irrigation	30th July	Urea, SSP, MOP	25 % N+P and K				
			20th July			5th August	50 % N		
Late	No irrigation	No irrigation	10th July	Urea, SSP, MOP	25 % N+P and K				
			30th July			10th July	50 % N		
			15th August						

Fig. 1 Schematic representation of the rice growth simulation model CERES rice



for different years (Table 3). Statistical methods were selected to compare the results from simulation and observation. Model performance evaluation is presented by the root mean square error (RMSE) and *D*-index [32, 33].

$$RMSE = \left\{ \frac{\sum_{i=1}^n (S_i - Ob_i)^2}{n} \right\}^{0.5}$$

$$D = 1 - \frac{\sum_{i=1}^n (S_i - Ob_i)^2}{\sum_{i=1}^n (|S_i - \overline{Ob}_{avg}| + |S_i - \overline{Ob}_{avg}|)^2}$$

where S_i and Ob_i are the model simulated and experimental observation points, respectively. Ob_{avg} is the average of experimental observations and n is the number of observations.

2.5 Climate Change Scenarios

Climate change influences rice crop mainly through increased atmospheric CO₂, temperature, and change in rainfall. The Climate Change Agriculture and Food Security (CCAFS) Institute under the CGIAR system has hosted a web site for providing the downscaled projection data on point basis (<http://gismap.ciat.cgiar.org/MarkSimGCM/>), through Mark Sim™ DSSAT weather file generator [10]. This generator converts the downscaled weather data from global climate

models (GCMs) to DSSAT weather input file format. Projected data collected from two GCMs, viz., ECHAM5 [24] and Model for Interdisciplinary Research on Climate (MIROC)3.2 (K-1 Model Developers, 2004) data for 2020, 2040, and 2080, were used for simulation.

2.5.1 The ECHAM5 Climate Model

This climate model has been developed from the European Center for Medium Range Weather Forecasting (ECMWF) forecast atmospheric model and has a comprehensive parameterization package which allows the model to be used for climate simulations. The model is a spectral transform model with 19 atmospheric layers and derived from experiments performed with spatial resolution T42 (which approximates to about 2.8° longitude/latitude resolution). ECHAM5 is the current generation in the line of ECHAM models [25]. A summary of developments regarding model physics in ECHAM and a description of the simulated climate obtained with the uncoupled ECHAM model are given in Roeckner et al. [26].

2.5.2 MIROC3.2

The MIROC, updated in 2004 to version 3.2, was jointly developed in Japan by the Centre for Climate System

Table 3 Genetic coefficients of different rice cultivars grown at different locations

Station	Cultivar/genotype	P1	P2R	P5	P2O	G1	G2	G3	G4
Faizabad	Sarjoo-52	680	163	365	12.3	70	0.0275	1	1
Kanpur	NDR359	395.9	211.9	352.3	10.8	60	0.028	0.7	1.05
Raipur	Mahamaya	618.4	233.9	384	11.9	56.6	0.026	1	1
Ranchi	Vandana	258	60.2	216.5	12.5	72.4	0.028	1	1

Research (CCSR), University of Tokyo; the National Institute for Environmental Studies (NIES); the Frontier Research Centre for Global Change (FRCGC); and the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) [13]. This coupled model is comprised of the following models:

- Atmospheric model: AGCM5.7b
- Oceanic and sea ice model: COCO3.3
- Land surface model: minimal advanced treatments of surface interaction and runoff (MATSIRO)
- Coupling model: MIROC3.2

2.5.3 Ensemble Model

The ensemble mean of four models, viz., CNRM-CM3, CSIRO-Mk3_5, along with the above-described ECHAM5 and MIROC3.2, was used for the same years. CNRM-CM3 is a global coupled system, the third version of the ocean-atmosphere model initially developed at CERFACS (Toulouse, France), and then regularly updated at the Center National Weather Research. CNRM-CM3 also now includes a parameterization of the homogeneous and heterogeneous chemistry of ozone and a sea ice model, and it corresponds to a resolution of about 2° in longitude, the latitudinal resolution varying from 0.5° near the equator to roughly 2° in polar regions. CSIRO-Mk3_5 is a climate system model containing a comprehensive representation of the four major components of the climate system (atmosphere, land surface, oceans, and sea ice). There are simulations for a range of scenarios available for this model. This simulation uses scenario SRESA2 which represents the SRESA2 scenario 2001 to 2100. The scenario includes standard daily and monthly meteorological and monthly oceanographic variables. It is also a contribution to the WCRP CMIP3 multimodel database and meets their formatting standards [4].

3 Results

3.1 Rice Growth and Yield Calibration and Validation

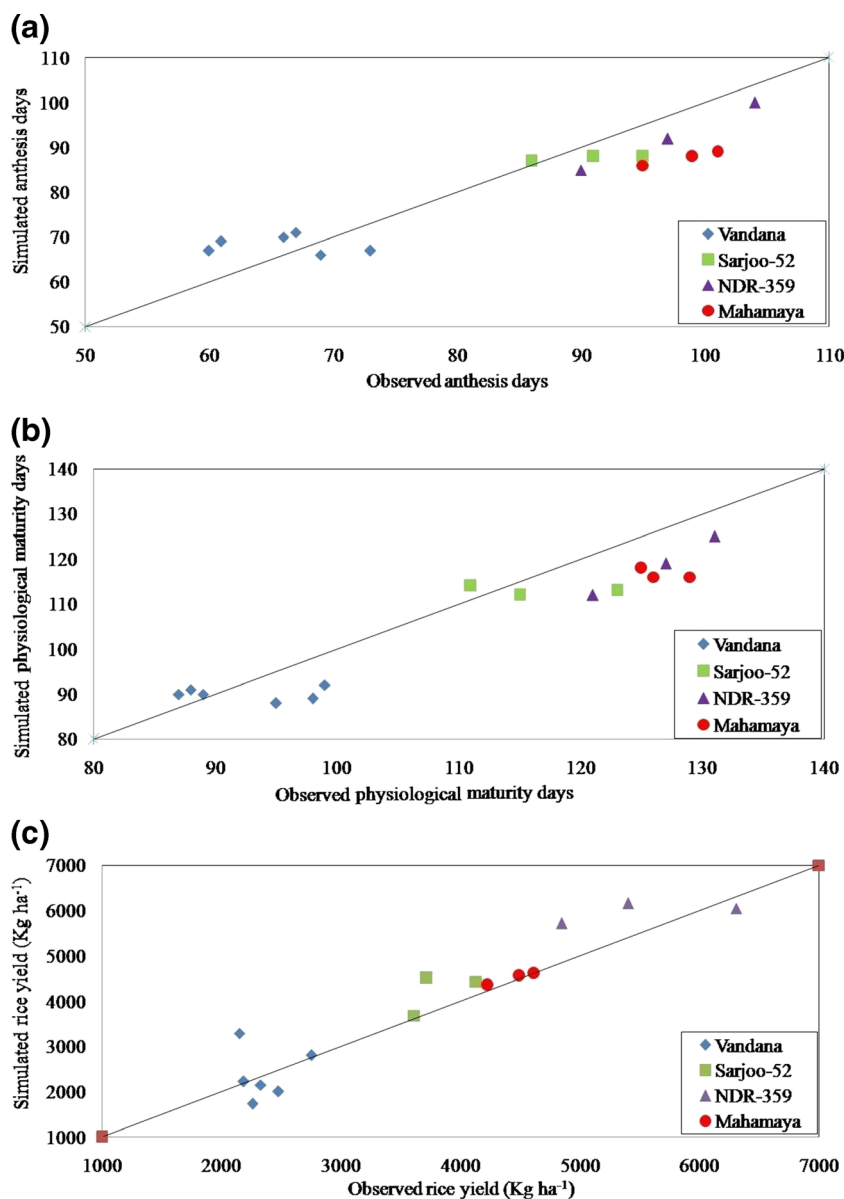
Rice calibration in relation to growth and development in terms of anthesis and physiological maturity at four locations, viz., Ranchi, Faizabad, Kanpur, and Raipur, is shown in Fig. 2. Figure 2a shows the relationship between simulated and observed anthesis days from 50 to 110 days and Fig. 2b shows physiological maturity between 80 and 140 days. The simulated and observed anthesis days and physiological maturity days, respectively, in the case of Ranchi did not overlap with the other locations, namely Faizabad, Kanpur, and Raipur. On the other hand, rice calibration for anthesis and maturity in the other locations, viz., Faizabad, Kanpur, and Raipur,

exhibited overlap with anthesis clustering between 85 and 105 days, with the earliest anthesis among these locations being in Faizabad followed by Kanpur and Raipur. Rice calibrated in Kanpur exhibited a wider range in the number of days for anthesis, starting from 90 to 105 days. A similar trend was seen in the case of physiological maturity in the calibration of rice for the three locations, i.e., Faizabad, Kanpur, and Raipur. Among these three locations, Faizabad rice came earliest to maturity at 100 days and extended up to 125 days, whereas two samples of Kanpur and Raipur rice were clustered around 130 days showing late physiological maturity. Maturity in all the locations did not extend beyond 132 days. Calibration of rice in relation to growth and development was closest to a linear trend in the case of locations Kanpur and Faizabad and was slightly away in Raipur. A similar trend was seen in the case of physiological maturity as well, although the distance from the linear was a little more than that observed in the case of anthesis. Ranchi also exhibited similar trends in the case of both days to anthesis and physiological maturity. Rice calibration in relation to simulated and observed yield (kg ha^{-1}) is shown in Fig. 2c. Rice yield in Ranchi was significantly less compared to the other three locations, Faizabad, Kanpur, and Raipur, ranging from 2200 to about 2800 kg ha^{-1} . The yields in the other locations were more than 1000 kg ha^{-1} and above the yield at Ranchi. The highest yield was seen in Kanpur and the lowest yield among the three locations other than Ranchi was seen in Faizabad. Yield in Raipur was clustered between 4200 and 4800 kg ha^{-1} . On the other hand, yield in Kanpur was spread apart between 4800 and 6400 kg ha^{-1} . Raipur exhibited closest to linearity among the locations. A trend similar to the one observed in the case of anthesis and maturity was also observed in yield in the case of Ranchi.

Validation of data in rice in the four locations—Ranchi, Faizabad, Kanpur, and Raipur—is depicted in Fig. 3. Validation of observed and simulated data on days to anthesis in Ranchi followed a linear pattern and the anthesis was observed between 65 and 70 days (Fig. 3a). Data were clustered around these days and exhibited linearity, with only three sample points being outliers. The other three locations were closely clustered between 85 and 105 days. The validation data for observed anthesis days in rice showed maximum variation and spread in Kanpur with anthesis extending from 87 to about 103 days. On the other hand, the locations, namely Faizabad and Raipur, did not exhibit a high degree of spread in anthesis days, and they varied from 85 to 85 and 93 to 103 days in Faizabad and Raipur, respectively.

Similar to the validation data in rice for anthesis days in the four selected locations, the validation data on physiological maturity also showed that rice at Ranchi came to maturity significantly earlier than the other three locations by about 10–15 days. In Raipur, unlike anthesis days (Fig. 3b), physiological maturity was more spread out, ranging from 119 to

Fig. 2 Rice calibration in relation to growth and development in terms of anthesis (a), physiological maturity (b), and yield (c) at four locations, viz., Ranchi (Vandana), Faizabad (Sarjoo-52), Kanpur (NDR359), and Raipur (Mahamaya)

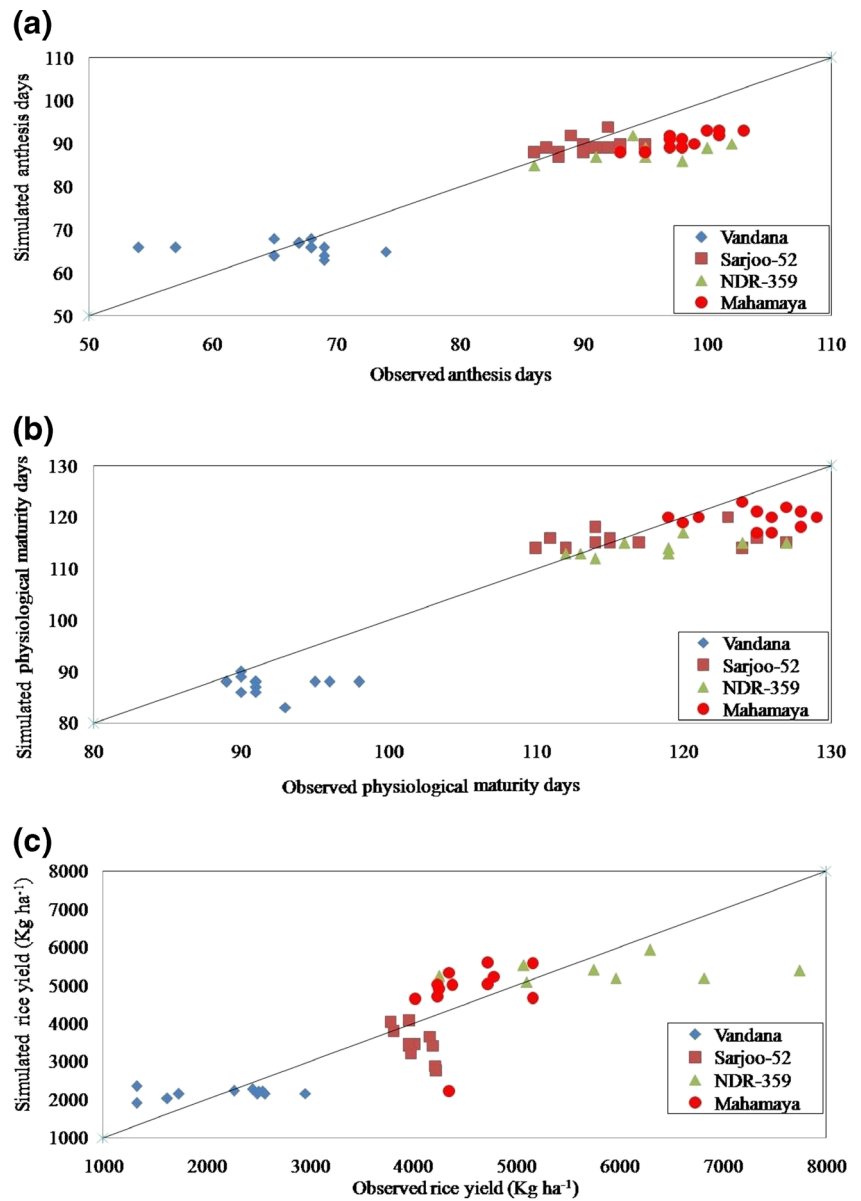


130 days, whereas in the case of Faizabad, the same type of clustering was seen in anthesis days. The highest degree of variation in the days to maturity was seen in Kanpur starting from as early as 118 days to as late as 131 days.

The relationship between simulated and observed rice yields in the validation data in the four locations, viz., Ranchi, Faizabad, Kanpur, and Raipur, is shown in Fig. 3c. Unlike that seen in the anthesis and maturity, the difference between the outlier Ranchi and the other states was not evident. The three locations—Faizabad, Kanpur, and Raipur—did not exhibit close clustering as seen in anthesis and maturity. In this case, they exhibited a high degree of spread. Ranchi showed the minimum yield with a range of 1200 to near 3000 kg ha⁻¹. The highest yield observed in Ranchi was less than the lowest observed in the other three locations, namely Faizabad, Kanpur, and Raipur. Similar to the observations in anthesis days, the location Kanpur

exhibited a wide range in yield ranging from 4000 to 8000 kg ha⁻¹. On the other hand, Faizabad and Raipur did not exhibit this degree of variation as observed in Kanpur. Data from Faizabad was clustered closely and was deviating from linearity, whereas data from Raipur was spread out but close to linearity. Table 4 shows the rice anthesis day calibration at Ranchi, Faizabad, Kanpur, and Raipur, and a 2-day difference between observed and simulated was seen in the cultivar Vandana in Ranchi in anthesis days. The cultivar Vandana came to anthesis at the earliest as compared with the other three varieties. A maximum difference was seen in the variety Mahamaya which was 10 days with an RMSE value of 10.739. With regard to rice physiological maturity day calibration (Table 5), again, it was seen that cultivar Vandana attained physiological maturity as compared to the other varieties in the other locations at 93 days and varied only 3 days from the simulated value

Fig. 3 Rice validation in relation to growth and development in terms of anthesis (a), physiological maturity (b), and yield (c) at four locations, viz., Ranchi (Vandana), Faizabad (Sarjoo-52), Kanpur (NDR359), and Raipur (Mahamaya)



because the variety Vandana is a short duration variety with 100-day duration. The physiological maturity date of this cultivar at Ranchi was earlier than the anthesis days of other varieties in the other three locations. In Kanpur and Raipur, varieties

NDR359 and Mahamaya, respectively, came to observed physiological maturity 1 day apart at 126 and 127 days, and the simulated values for these varieties were 119 and 117 days, respectively. Table 6 shows rice yield calibration at Ranchi,

Table 4 Rice anthesis day calibration at Ranchi, Faizabad, Kanpur, and Raipur

Station	Cultivar	Anthesis days		RMSE	D-stat
		Observed	Simulated		
Faizabad	Sarjoo-52	91	88	4.435	0.537
Kanpur	NDR359	97	92	4.69	0.864
Raipur	Mahamaya	98	88	10.739	0.322
Ranchi	Vandana	66	68	5.627	0.202

Table 5 Rice maturity day calibration at Ranchi, Faizabad, Kanpur, and Raipur

Station	Cultivar	Maturity days		RMSE	D-stat
		Observed	Simulated		
Faizabad	Sarjoo-52	116	113	6.272	0.382
Kanpur	NDR359	126	119	7.767	0.628
Raipur	Mahamaya	127	117	10.296	0.213
Ranchi	Vandana	93	90	5.745	0.398

Table 6 Rice yield calibration at Ranchi, Faizabad, Kanpur, and Raipur

Station	Cultivar	Yield		RMSE	D-stat
		Observed	Simulated		
Faizabad	Sarjoo-52	3822	4208	490.626	0.546
Kanpur	NDR359	5518	5979	686.676	0.543
Raipur	Mahamaya	4445	4508	83.694	0.909
Ranchi	Vandana	2359	2370	553.508	0.364

Faizabad, Kanpur, and Raipur, and the Ranchi cultivar Vandana recorded the least yield and the difference in yield between observed and simulated was only 11 kg ha⁻¹. The highest observed yield of 5518 kg ha⁻¹ was recorded by variety NDR359 in Kanpur. The difference between observed and simulated yield in the case of locations Faizabad, Kanpur, and Raipur was much higher as compared to Ranchi.

4 Discussion

Calibration was done with the independent data sets of four rice cultivars, viz., Ranchi (Vandana), Faizabad (Sarjoo-52), Kanpur (NDR359), and Raipur (Mahamaya), for different genetic coefficients with the aim to characterize the rice performance. Accuracy in simulation of yield, phenology, and growth requires the use of accurate genetic coefficients [19, 22]. These coefficients were adjusted and recalibrated until there was a high degree of similarity between the observed and simulated dates of anthesis, physiological maturity, and grain yield. Model validation was done with observations on anthesis days, physiological maturity days, and grain yield. Calibration and validation showed that there was good agreement between predicted and observed values for all the phenology and yield parameters. It was seen that in rice calibration at Ranchi, the anthesis days were between 60 and 75 days and physiological maturity was between 85 and 100 days. Ranchi rice was grown under upland conditions and was not irrigated or flooded; hence, it was seen that the growth and development of rice in the location Ranchi was markedly different from the other locations wherein phenology was delayed with respect to Ranchi. This could be because there is hastening of phenology under nonirrigated conditions in rice possibly to adjust source sink partitioning so that maximum source strength and sink capacity can be achieved under given conditions. This can also be explained due to the fact that, in general, time of day of flowering is regulated at the level of the individual spikelet because anthesis events on a panicle are spread over an extended period, probably due to different physiological ages and topological positions among spikelets [12]. Changes in environmental conditions preceding the anthesis event and immediately after the anthesis event can influence the time of flowering. This suggests the involvement

of regulatory processes occurring prior to anthesis as well as after the anthesis event. It was seen in this study that physiological maturity varied significantly in the cultivar that came to early maturity in Ranchi. It has been observed in this study that Ranchi cultivars advanced its phenology and growth phase under growing conditions so that its flowering time effectively escaped severe water stress which is frequently seen after the end of the rainy season. This ability to maintain growth during drought can contribute to yield determining processes.

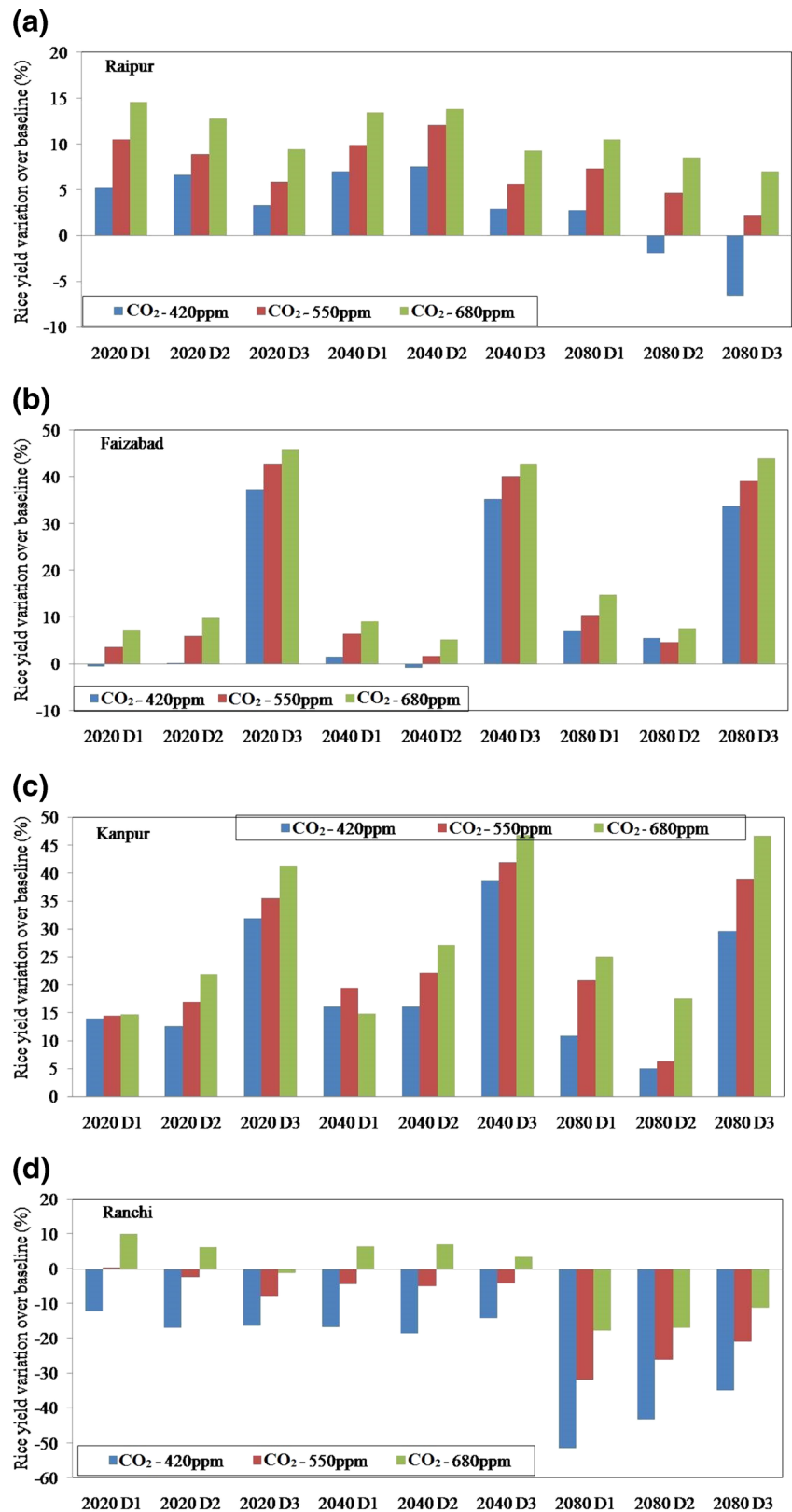
4.1 Genetic Coefficients

Genetic coefficients of the four baseline cultivars used in the study with respect to rice grown in different locations are given in Table 3. The data shows P1—the time period (expressed as growing degree days [GDD] in °C above a base temperature of 9 °C) from seedling emergence during which the rice plant is not responsive to changes in photoperiod. This period is also referred to as the basic vegetative phase of the plant. P2O is the critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate. At values higher than P2O, developmental rate is slowed; hence, there is a delay due to longer day lengths. P2R is the extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in photoperiod above P2O. P5 is the time period in GDD (°C) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 °C. G1 is the potential spikelet number coefficient as estimated from the number of spikelets per gram of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis. G2 is the single grain weight (g) under ideal growing conditions, i.e., nonlimiting light, water, and nutrients and absence of pests and diseases. G3 is the tillering coefficient (scaler value) relative to IR64 cultivar under ideal conditions. A higher tillering cultivar would have coefficient greater than 1. G4 is the temperature tolerance coefficient.

4.2 Rice Yield Prediction in Different Scenarios

Rice yield variation as reduction or increase from baseline in the MIROC3.0 climate scenario under different CO₂ levels in 2020, 2040, and 2080 at different dates of sowing—D1, D2, and D3—wherein D1 is the early-sown, D2 is the normal-sown, and D3 is the late-sown rice, is shown in Fig. 4. Elevated CO₂ concentration of 680 ppm showed the highest yield in all the locations in all the dates of sowing studied and in all the 3 years 2020, 2040, and 2080, and a reduction in yield was seen to be least in Ranchi wherein the yields expressed as percentage difference over baseline were seen to be negative. Normal and late date of sowing at an elevated CO₂ concentration of 420 ppm showed high reduction in yield in 2080 in

Fig. 4 Rice yield variation over baseline (%) in MIROC3.0 climate scenario model under different CO₂ levels (420, 550, and 680 ppm) in 2020, 2040, and 2080 at different dates of sowing—D1 (early sown), D2 (normal sowing), and D3 (late sowing)—at Raipur (Mahamaya) (a), Faizabad (Sarjoo-52) (b), Kanpur (NDR359) (c), and Ranchi (Vandana) (d)



Ranchi, whereas this was not the case in the other years with all the dates of sowing. In general, in all the locations, all concentrations of CO₂ in all dates of sowing at 420 ppm

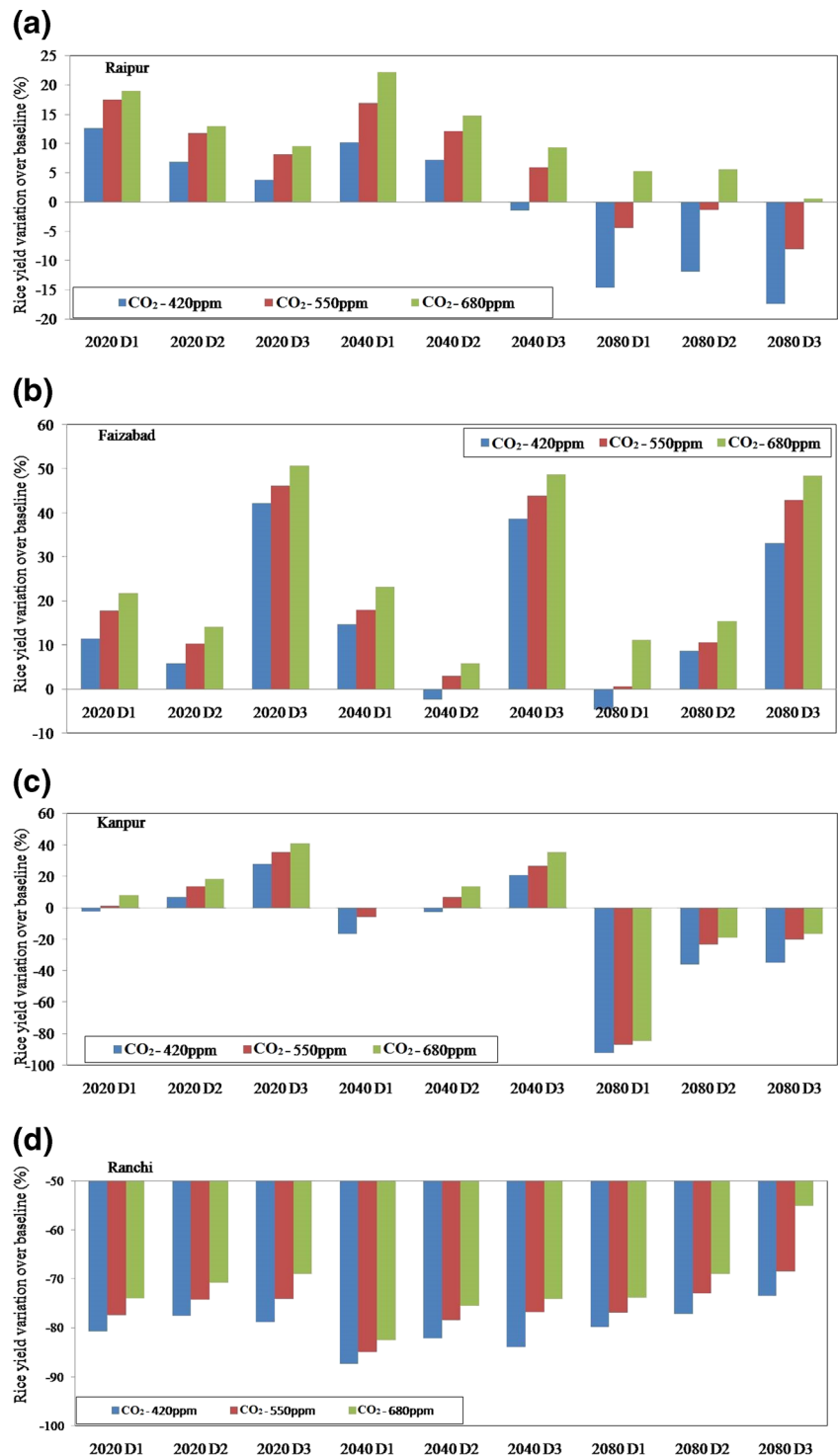
showed the least increase over baseline with reduction seen in Ranchi. In Faizabad, there was a high increase in yield from 30 to 45 % in all the concentrations of elevated CO₂.

Unlike Faizabad and Kanpur, Raipur showed a decreasing trend in yield as the date of sowing advanced.

Rice yield variation as reduction or increase from baseline in ECHAM5 climate scenario under different CO₂ levels in 2020, 2040, and 2080 at different dates of sowing—D1, D2, and D3—is shown in the ECHAM5 scenario model is shown in Fig. 5. Unlike the MIROC3.0 climate

scenario, this model shows a decline in yield in 2080 in three locations, namely Raipur, Kanpur, and Ranchi. An elevated concentration of CO₂ at 680 ppm showed the maximum increase in all dates of sowing in 2080, and in Faizabad, it was seen as negative as it showed the minimum reduction as compared to the other concentrations. In Faizabad, which was the only location where there was an

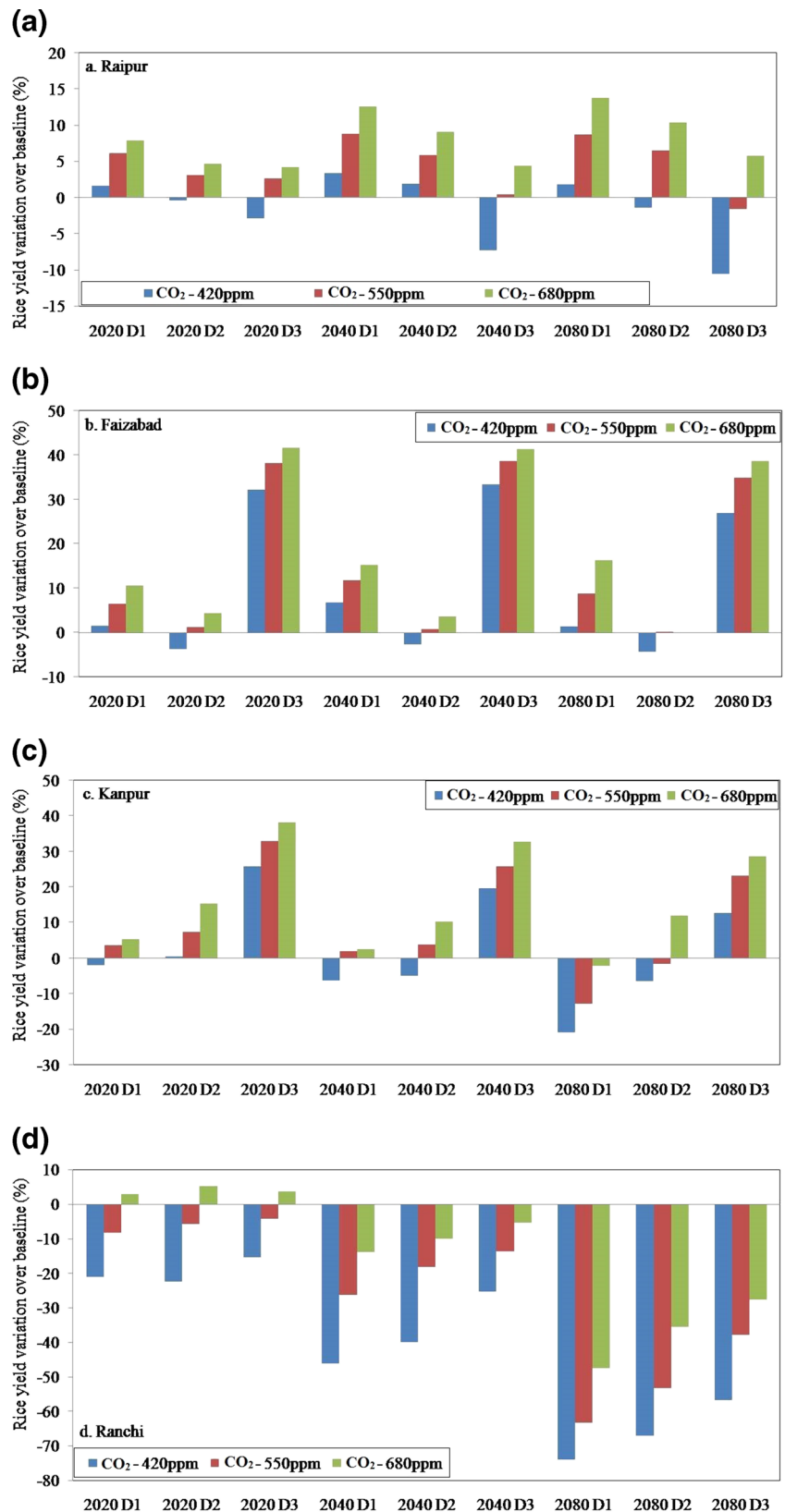
Fig. 5 Rice yield variation over baseline (%) in ECHAM climate scenario model under different CO₂ levels (420, 550, and 680 ppm) in 2020, 2040, and 2080 at different dates of sowing—D1 (early sown), D2 (normal sowing), and D3 (late sowing)—at Raipur (Mahamaya) (a), Faizabad (Sarjoo-52) (b), Kanpur (NDR359) (c), and Ranchi (Vandana) (d)



increase in predicted yield, it was seen that the late sowing date (D3) showed a high increase in yield under all three elevated CO₂ concentrations.

Rice yield variation as reduction or increase from baseline in the climate scenario ensemble models is shown in Fig. 6. In general, CO₂ concentration of 420 ppm in all the locations

Fig. 6 Rice yield variation over baseline (%) in ensemble climate scenario models under different CO₂ levels (420, 550, and 680 ppm) in 2020, 2040, and 2080 at different dates of sowing—D1 (early sown), D2 (normal sowing), and D3 (late sowing)—at Raipur (Mahamaya) (a), Faizabad (Sarjoo-52) (b), Kanpur (NDR359) (c), and Ranchi (Vandana) (d)



showed a marked decline in predicted yield, with the maximum reduction seen in 2080 in Ranchi. Late-sown rice in Faizabad and Kanpur in 2040 and 2080 showed a yield increase up to 40 % in all the three elevated CO₂ concentrations, with higher elevation showing a higher percentage increase. In Ranchi, the ensemble model showed a decrease in yield in all the dates of sowing and all the years at all the elevated concentrations of CO₂ except 680 ppm in 2020 wherein at all sowing dates a slight increase over the baseline yield was predicted. The increase in CO₂ concentration increased yield in general in all the scenarios simulated, and this is agreement with many other researchers who have reported increasing rice yield with increasing CO₂ level [1, 2, 15, 17, 34]. Results obtained by simulation and scenarios support the hypothesis that rice plant responses to elevated CO₂ are through stimulation of photosynthesis and eventual realization of higher yields. A distinct regional and cultivar difference in response of rice yield to elevated CO₂ was seen in this study, and this can be explained by the fact that while crop yield normally responds positively to increased atmospheric CO₂ concentration, in our study, it was seen that the response depended on the location and cultivar and, to a large extent, on the input given as well as on the environmental conditions. Our results are in confirmation with Hasegawa et al. [7] who reported that rice cultivars respond differently to elevated CO₂ concentrations. Here we see that CO₂ × cultivar interaction tested by model prediction showed a yield increase which could be due to larger sink capacity under higher CO₂ concentrations. Therefore, we can infer that in spite of increasing CO₂ as predicted by climate change scenarios, regional and local yield response to elevated CO₂ will vary due to differences in the local climate and the input used.

5 Conclusions

Rice is one of the major crops in India. The ongoing climatic aberrations may impact the yields and, hence, the food security of the country. The present study was conducted by selecting four rice-growing locations in Eastern India including locations of the IGP of India using the DSSAT CERES rice model, and a simulation was carried out by incorporating the future climate change scenarios from individual and ensemble models. It was found that the rice yields are impacted at all locations, viz., Kanpur, Faizabad, Raipur, and Ranchi. Ranchi was seen to have maximum losses in terms of yield because of the rainfed rice growing ecosystem. Increase in CO₂ concentrations increased the yields of rice in all the locations except Ranchi. In Ranchi, yields were not influenced by any concentration of elevated CO₂ except at 680 ppm during the 2020 scenario. Hastening of phenology under rainfed conditions in rice is a possible physiological mechanism to regulate source sink partitioning so that

maximum source strength and sink capacity can be attained under given conditions. Adjusting the date of sowings can become helpful as an adaptation strategy to identify the optimum date of sowing under future climate change scenarios and, in turn, increase productivity.

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