Assessing the impacts of climate change on aerobic rice production using the DSSAT-CERES-Rice model

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ABSTRACT

This study assessed the impacts of climate change on aerobic rice production using the DSSAT-CERES-Rice model. Actual data observed from four cropping seasons in two sites were used for calibration and validation. Four Representative Concentration Pathway scenarios were used to simulate climate change. The optimum planting windows were simulated across these scenarios. Results showed that DSSAT-CERES-Rice could adequately simulate aerobic rice production. Changes in seasonal rainfall and increases in temperature especially during dry seasons adversely affected aerobic rice production. Reduction of rainfall during the wet seasons favored aerobic rice production. Yield losses are twice as large as gains. Changes in climate could cause yield improvements to decline from 83% to 53% and yield reductions to increase from 150% to 177% towards the end of the 21st century. Selecting the best planting windows could optimize production to avoid huge economic losses. Optimum planting windows were simulated during normal, dry, and wet climate conditions. The derived set of genetic coefficients could be used to assess various aerobic rice farm crop and nutrient management strategies as well as other climate and soil conditions. The long-term projections on aerobic rice production could guide policy and decision-makers on designing long-term climate change adaptation and mitigation plans and programs.

Key words | aerobic rice, climate change, DSSAT, optimum planting window

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HIGHLIGHTS

- This paper pioneered the assessment of climate change impacts on aerobic rice using the DSSAT-CERES-Rice model.
- The DSSAT-CERES-Rice model has been proved to adequately mimic aerobic rice production.
- Optimum planting windows across climate change scenarios during the normal, dry, and wet years were identified for dry and wet seasons which can be used as reference for farmers, policy-, and decision-makers for climate change adaptation and mitigation.
- Impacts of climate change on aerobic rice production have been estimated to cause a decline in yield gains by as much as 83% and an increase in yield reductions by as much as 177%.
- The derived genetic coefficients can be used to assess impacts of other climatic conditions and crop management on aerobic rice production.

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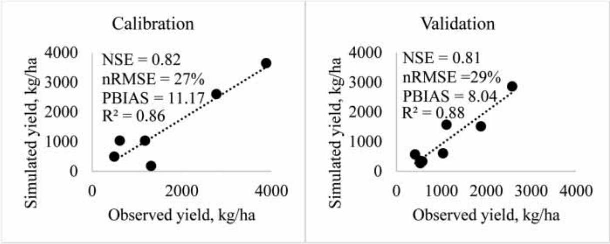
GRAPHICAL ABSTRACT



INTRODUCTION

Decreasing freshwater resources due to climate change has threatened rice production in many parts of the world. Climate-related disasters have caused the poor performance of agriculture in the Philippines (National Economic and Development Authority 2017). The country reported economic damages amounting to Php 163.6 billion (1 US dollar = 51.8 Php) from 2011 to 2015 due to climate-related disasters. The 2010 El Nino event alone has caused the country 12 billion pesos of economic losses. This has been one of the constraints in achieving the country's rice self-sufficiency targets. Moreover, the prices of rice due to supply shortage continued to rise, which prompted the government to remove the limitations on rice importation through the Rice Tarrification Bill. However, food security could be at risk when the sources of imported rice face disruptions due to many factors, one of which is climate change. There are already projections that most of the rice exporting countries in Asia will experience drought that could lead to a decrease in their rice production (VietNam News 2019). Every intervention possible to mitigate the effects of climate change is imperative, especially in the uplands and rainfed ecosystems. In the Philippines, most parts of the lowland irrigated rice frequently encounter water shortage during droughts and oftentimes become rainfed. Also, the upland rice farms are the primary victims of drought as they are dependent on rainfall for irrigation, which is oftentimes scarce during droughts. Phenomena like La Niña and El Niño are being monitored in the Pacific Ocean through indices, and countries are warned which provide an opportunity to prepare interventions to mitigate the adverse impacts. Climate projections are also available for use in studying the impacts of climate on crop production.

The Decision Support System for Agrotechnology Transfer (DSSAT) is a computer program, which includes the Cropping System Model (CSM)-Crop Environment Resource Synthesis (CERES)-Rice model, that can simulate rice crop growth, development, and yield based on the interactions between soil, water, weather, atmosphere, plant, and crop management (Jones *et al.* 2003). It also provides the environmental and stress factors from emergence to maturity that can be helpful to determine at which growth stage does water and nitrogen stress occur. The CERES-Rice model has been proved to accurately estimate phenology, biomass, and yield and has been increasingly used to assess the impacts of climate change in rice production especially during the 1990s (Timsina & Humphreys 2006). It has been extensively used for yield gap analysis of various crops (Singh *et al.* 2015; Balderama *et al.* 2016). The CERES-Rice integrated into DSSAT has also been employed in lowland and upland rice research to assess the effects of climate change (Nyang'au *et al.* 2014; Dar *et al.* 2017) and to further improve production through improved nutrient management (Singh *et al.* 2015; Vilayvong *et al.* 2015). These studies have shown beneficial impacts in yield because of the increase in CO_2 emissions and an increase in temperature to a certain extent. However, beyond the optimum levels, adverse impacts on rice production were reported. Azdawiyah Hariz & Fairuz (2015) used DSSAT to assess the shifting of planting dates by advancing and postponement of planting by 7 days increment and showed that shifted planting dates increased rice yield during main seasons but decreased during off-seasons.

Aerobic rice is a water-scarce production system with specially developed aerobic rice varieties that could produce a yield of at least 4–6 tons per hectare (Bouman *et al.* 2007). The use of aerobic rice varieties is one of the recommended crops to plant in water-scarce areas. They can be grown in a non-puddled and dry soil and has a water requirement the same as that of corn (Bouman 2001). Aerobic rice can also be grown in lowland rice paddies where they could produce more yields with more water. However, lowland rice paddies with adequate irrigation are not recommended for aerobic rice as high yielding lowland rice varieties still yield better. Aerobic rice is generally recommended in tail-ends of irrigation systems, upland areas, dryland areas, and during water-scarce seasons. Studies have shown a wide range of aerobic rice yields, which imply its potential for a favorable level of production even in water-scarce conditions (Atlin *et al.* 2006; Kato *et al.* 2009). Under well-watered conditions, aerobic rice can get as high as 7.4 tons/ha (George *et al.* 2002) but can still strive under dry conditions with yield ranging from 4 to 5.7 tons/ha with only 744–924 mm of total irrigation (Bouman *et al.* 2005; Peng *et al.* 2006). Aerobic rice yields can further be improved through appropriate nutrient management (Lampayan *et al.* 2010; Borja Reis *et al.* 2018). Based on the number of published studies on aerobic rice, it has garnered wide interest, especially in Asia. However, there are no available published studies yet on quantifying the impacts of climate change specifically for aerobic rice production using the latest climate projections for the mid- and late-21st century. Moreover, there are no studies yet on the optimum cropping calendar for aerobic rice, which needs to be adjusted during climate change both for dry and wet seasons. During extremely dry years, the timing of planting will be one of the most essential farm management to maximize the use of rainfall and ensure favorable levels of production. The present study will assess the impacts of climate change on the aerobic rice production using the variety NSIC Rc 192 and determine its optimum planting calendar across climate change scenarios.

The Methods section is described and explained in the study area, data gathering and experimental setup from two sites, the calibration and validation of DSSAT, the climate change scenarios based on the published climate projections, and the simulation of these scenarios. The Results and Discussion are detailed in the adequacy of the DSSAT model to simulate aerobic rice production. Besides, the impacts of climate change on aerobic rice production were analyzed and discussed. The optimum planting windows for each climate change scenario were determined based on the simulated yield of aerobic rice from daily planting dates over a year. A conclusion highlights the results of the study and its potential use for climate change mitigation and adaptation.

METHODS

The study area

The actual experiment was conducted in Isabela, Philippines (121°40″, 16°42″, and 81 masl). The site is under Type III climate with pronounced wet and dry months based on the Modified Coronas' Climate Classification in the Philippines. This type of climate is unimodal with the highest amount of rain falling between May and October. The available lowland rice-growing period is short, from July until October. Supplemental irrigation is needed for a second, rice or non-rice crop to grow. The average annual rainfall in the study area is around 2,000 mm. The month of June is the hottest in the area with a mean temperature value of 29 °C, and months of December to January are the coldest with a mean temperature of 23.8 °C. Two sites in the Isabela State University, Echague campus were chosen to represent flat and gently sloping areas. These topographies are normally planted with upland crops including upland rice in most areas of the country. The topography is flat in Site 1 and gently sloping in Site 2 (Figure 1).

Field experiment and data collection

Actual data on weather, soil, crop, crop management, and experimental data on agronomic variables such as biomass and yield are required to run, calibrate, and validate the

Figure 1 | Location of the study sites.

Table 1 | Soil characteristics in the two sites

Location	pH	OM, (%)	N, (%)	P, ppm (Bray)	K (me/100 g soil)
Site 1	4.3	2.41	0.15	3.6	0.76
Site 2	4.3	2.41	0.13	3.3	0.35

Note: pH, potential hydrogen; OM, organic matter; N, nitrogen; P, phosphorus; K, potassium.

DSSAT-CERES-Rice model. The daily weather data required to run the DSSAT model were taken from the Department of Science and Technology – Philippine Atmospheric, Geophysical and Astronomical Services Administration agrometeorological station inside the Isabela State University, Echague campus. The NSIC Rc 192 was chosen as an early maturing aerobic rice variety because it is highly recommended during drought conditions and farmers commonly referred this in the upland and rainfed ecosystems. The experiments were conducted for four cropping seasons. Site 1 was established during the dry season (planted on February 5) and the wet season (planted on August 25) of 2015. Sites 1 and 2 were planted during the wet season of 2016 (planted on July 15) and during the dry season of 2017 (planted on February 8). The soils are clay in both sites. Some chemical characteristics of the soils in the two sites are shown in Table 1. These chemical properties may improve or restrict the growth and yield of rice depending on their levels. The N, P, and K are determinants of soil fertility and essential soil macronutrients for crop production. The organic matter (OM) is a property of soil necessary for water holding capacity of the soil and crop root growth. Soil pH indicates soil health, which affects the availability of nutrients in the soil needed for rice production. The ideal soil condition for rice production in terms of pH is 5.5–7 and OM is greater than 3% (Sangatanan & Sangatanan 1990). Also, P is considered low if it is less than five, medium if value falls between 5 and 10 ppm, and high if value is greater than 10 ppm. The value of K is low with values between 20 and 80 ppm and high with values from 82 to 246 ppm (100 ppm K = 390 me/100 g soil). Relative to these, the soil in both sites had a low fertility condition.

The nutrient management employed was the zero rate of fertilizer (0-0-0 of N-P-K), the half rate of fertilization (60-30-30), and the full rate of fertilization (120-60-60) with basal and side dressing applications in Site 1 during the 2015 planting season. For both sites, during the 2016 and 2017 cropping, the zero rate of fertilizer (0-0-0 of N-P-K) and the full rate of fertilization (120-60-60) with basal and side dressing were applied. All crops were dry seeded and irrigated only when needed just enough to avoid permanent wilting. Biomass data of 10 samples were collected through destructive sampling at a 10-day interval throughout the growing seasons. These samples were weighed and oven dried at 80°C for 48 h (Table 2). The grain yield was taken from the 2 m × 2.5 m harvest area from every 5 m by 4 m plots.

The actual experimental data gathered were not statistically analyzed for the comparison of means as they were supposed to be used only in achieving the objectives under this study, which is for calibration and validation of the DSSAT-CERES-Rice model for an aerobic rice variety before climate change impact assessments. A DSSAT model only needs actual data and parameters on local conditions of soil, weather, crop, and crop management to carry on with calibration and validation. A well-calibrated and validated DSSAT model is necessary for reliable results of climate change scenario simulations.

The DSSAT-CERES-Rice model description

The DSSAT is a computer-based crop simulation model that offers its capability to estimate crop growth and yield. It contains 33 crop models, one of which is the DSSAT-CERES-Rice model. This crop model has been proved to adequately simulate the upland and lowland rice growth and yield and was used to study the effect of various climate conditions and crop management (Lakshmi & Singh 1998; Saseendran *et al.* 2000; Gerardeaux *et al.* 2012; Akinbile 2013; Azdawiyah *et al.* 2015; Vilayvong *et al.* 2015; Sar & Mahdi 2017; Ray *et al.* 2018). The present study pioneers the use of the DSSAT-CERES-Rice model for assessing the impact of climate change in aerobic rice. The actual conditions on soil, weather, crop management, and experimental data from the field experiment were inputted in DSSAT under the CERES-Rice model. The model simulation equations selected were the FAO-56 for evapotranspiration, soil conservation service for infiltration, canopy curve for photosynthesis, Ritchie water balance for the hydrology, Ceres (Godwin) for the method of soil OM, Suleiman–Ritchie for the soil evaporation method, and modified soil profile for the soil layer distribution. Further details on the DSSAT-CERES-Rice model are described in Hunt & Boote (1998) and Swain & Yadav (2009). The Generalized Likelihood Uncertainty Estimation (GLUE) was used to fit the model results based on the actual data on biomass and yield. The GLUE is a Bayesian estimation technique that employs Monte Carlo sampling from prior distributions of the genetic coefficients and a Gaussian likelihood function to derive the best set of coefficients based on the observed data that are inputted and used in the estimation process (Jones *et al.* 1864; He *et al.* 2008). The set of the genetic coefficients for the aerobic rice was the main output of calibration representing the NSIC Rc 192 CERES-Rice model. The DSSAT program also has a sensitivity analysis module where users can assess the impacts of a wide range of values of variables on crop growth and yield.

Table 2 | Number of experimental data points for biomass data and grain yield for calibration and validation

	Calibration		Validation	
Variable	Dry season 2015	Wet season 2015	Wet season 2016	Dry season 2017
Biomass data per treatment	10	10	10	10
Yield	6		8	

The model setup, calibration, and validation

The datasets from the dry and wet cropping in 2015 from Site 1 were used for calibration, while the datasets from the two sites in the 2016 wet season and the 2017 dry cropping season were used for validation. The performance of the model, both during the calibration and validation, was evaluated using four statistical indices, namely coefficient of determination (R^2), normalized root mean square error (nRMSE), percent bias (PBIAS), and Nash–Sutcliffe efficiency (NSE). All of these indices are explained in Moriasi *et al.* (2007). The value of R^2 describes the ratio of the variance in observed data explained by the model. The value of R^2 ranges from 0 to 1, with higher values indicating less error variance and typically values greater than 0.5 are considered acceptable. The nRMSE is a measure of the percentage overall deviation with respect to the mean of observed values. The values of nRMSE close to 0 indicate insignificant differences between simulated and observed means, thus indicating that little systematic deviation or bias in the entire dataset hence implies an accuracy of the model simulation for observed variables. The performance of the model is excellent if the nRMSE value is $<10\%$, good if it is $>10\%$ and $<20\%$, fair it is $>20\%$ and $<30\%$, and poor if it is $>30\%$. PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. A PBIAS of $+/-25\%$ is considered satisfactory. The NSE is a normalized index that compares the residual variance with that of the observed data variance and indicates how well the observed versus the simulated values fit the 1:1 plot. A value of NSE greater than 0.5 is generally considered as satisfactory.

Climate change scenarios

The Department of Science and Technology – Philippine Atmospheric, Geophysical and Astronomical Services Administration (Philippine Atmospheric Geophysical and Astronomical Services Administration 2018) published the downscaled local climate projections at the provincial level for the mid-21st century (2036–2065) and the end of the 21st century (2070–2099). They used the latest climate scenarios introduced by the Intergovernmental Panel for Climate Change (IPCC). Their climate projections were derived from the global climate models and were further downscaled to adequately replicate the local climate system using four regional climate models. Their downscaling methods are further detailed in Philippine Atmospheric Geophysical and Astronomical Services Administration (2018) publication. These climate projections were used to assess the impacts of climate change in aerobic rice. These projections represent the cumulative concentration of greenhouse gasses in the atmosphere and are labeled as the Representative Concentration Pathways (RCPs) (IPCC 2013). The present study considered the RCP4.5 (moderate level of GHG emissions) and RCP8.5 (high level of GHG emissions) scenarios. The numeric values in the RCPs indicate the total radiative forcing levels (W/m^2) that could lead to changes in the future climate. These levels are the resulting total energy that could be due to socio-economic and technological factors with no fixed quantitative estimates. The projections were further categorized into lower (10th percentile), median (50th percentile), and upper (90th percentile) bound ranges representing the driest, normal, and wettest years, respectively, that could occur in the mid- and late-21st century. These rainfall categories were named dry, normal, and wet years in this study. Rainfall is expected to decrease during the dry years that could trigger droughts and would increase during the wet years that could bring floods and crop lodging.

Table 3 shows the projected changes in temperature and percent changes in rainfall during the dry, normal, and wet years for the mid- and late-21st century. A large reduction in seasonal rainfall is seen to occur most frequently in the months of June–July–August (JJA) during the dry and normal years. The highest increase in rainfall may occur in the December–January–February (DJF) month during the dry and normal years. In the wet years, rainfall constantly increases with the largest increment during the DJF months. The projected temperature is expected to continuously increase towards the end of the 21st century. Table 3 shows that the RCP8.5 scenario has the most substantial increase in temperature, especially during the wettest years. Moreover, the projections show dry years to have the lowest increase in temperature. The majority of the largest increase in temperature can be observed during the JJA months.

The DSSAT needs daily weather data as input. The daily weather for the year 2013 was used as a baseline year since there are no indications of weather anomalies such as El Niño and La Niña during this year (NOAA Climate Prediction Center 2019). Thus, this year was considered as a normal year. To estimate the impact of climate change scenarios on the yield of aerobic rice, simulated yields for each date of planting across each scenario were compared with the yield from the baseline year (2013). Yield anomalies were computed as a departure from the mean yield during dry and wet seasons of the baseline year (2013).

Determination of the optimum planting window

The optimum planting window was identified through simulations of daily planting of aerobic rice starting from the first day until the last day of the baseline year (2013) using the sensitivity analysis module of DSSAT. These were done for

Table 3 | The projected changes in temperature and percent changes in rainfall for the province of Isabela

		Change in temperature (°C)				Percent change in rainfall (%)			
Scenario		**DJF**	**MAM**	**JJA**	**SON**	**DJF**	**MAM**	**JJA**	**SON**
Mid-21st century (2036–2065)									
RCP4.5	Dry year	1	0.9	1	1	3.5	1.1	−27.7	−4.4
	Normal year	1.2	1.2	1.3	1.1	11.5	10.3	−17.2	3
	Wet year	1.5	1.7	2	1.9	48.4	23.5	0.3	11.9
RCP8.5	Dry year	1.1	1.2	1.3	1.3	−1.5	−6.1	−24.2	−2.3
	Normal year	1.6	1.7	1.6	1.6	12.4	7	−2.6	11
	Wet year	1.8	2.3	2.5	2.3	34.8	17.3	25.7	16.2
Late-21st century (2065–2099)									
RCP4.5	Dry year	1.1	1.2	1.4	1.3	0.2	−6.7	−26.8	−5.2
	Normal year	1.5	1.7	1.6	1.5	16.5	2.4	−12.9	4.4
	Wet year	2.2	2.6	2.7	2.7	41.7	27.3	6.2	12.2
RCP8.5	Dry year	1.9	2.4	2.8	2.6	−10.2	−6.1	−31.2	−5.1
	Normal year	2.9	2.9	3.3	3.1	32.3	9.7	−21.6	5.7
	Wet year	3.5	4.0	4.5	4.3	51.1	28.4	15.2	24.7
Observed (1971–2000)		24.1	27.9	28.7	26.8	412.2	325	530.8	867

Note: DJF, December–January–February; MAM, March–April–May; JJA, June–July–August; SON, September–October–November.

each climate change scenario. This means that an everyday virtual planting experiment of aerobic rice in the same area was conducted to determine the best timing of planting across climate scenarios. The planting date under the sensitivity analysis module in the DSSAT program was set up for 365 days iteration with a 1-day increment starting on the first day of 2013 for the simulation of aerobic rice yield. The harvest yields from the simulated planting dates were plotted in graphs. The optimum planting windows were identified from the graph for the wet and dry cropping seasons. These dates had the best timing of rainfall that will provide the maximum level of production under rainfed conditions and the full rate of fertilization. These were done for the baseline (2013) and projected climate conditions. Differences in yield trend and yield losses relative to the baseline (2013) were analyzed.

RESULTS AND DISCUSSION

Model calibration and validation

The best set of genetic coefficients that provided the most adequate estimate of growth and yield of NSIC Rc 192 is presented in Table 4. These sets of genetic coefficients were finally selected when the model reliably replicated the observed values of biomass and yield taken from the 2015 dry and wet season experiments. The calibration process yielded high coefficients of determination for estimating biomass accumulation that ranged from 0.87 to 0.96, good to fair nRMSE that ranged from 17% to 29%, satisfactory PBIAS values that ranged from −0.37 to 18, and satisfactory NSE values in the range of 0.77–0.91 (Table 5). In terms of yield, the model performed adequately with simulated yield values close to the observed data (Figure 2). The calibration statistics for yield estimation resulted in a high R^2 value of 0.86, a fair nRMSE value of 27%, a satisfactory PBIAS value of 11.17, and a satisfactory NSE value of 0.82. In the calibration event, the actual yield of aerobic rice observed from the experiment ranged from 498 to 3,887 kg/ha. Aside from the variations in fertilizer management, low rainfall input and high temperature during the dry season caused the wide range in observed yield. The total amount of rainfall throughout the dry season was 231 mm only, and the mean temperature was 28.22 °C. During the wet season, rainfall amounted to 459 mm and the mean temperature was 26.74 °C. Also, variability in yield was attributed to the variations in fertilizer treatments applied.

Table 4 | The best set of genetic coefficients representing NSIC Rc 192

Cultivar	P1	P2R	P5	P2O	G1	G2	G3	G4
NSIC Rc 192	657.3	170	354.4	12.82	57.78	0.025	0.906	0.877

Note: P1, time period (expressed as growing degree days (GDD) in °C above a base temperature of 9 °C) from seedling emergence; P2O, critical photoperiod or the longest day length (in h) at which the development occurs at a maximum rate; P2R, extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in the photoperiod above P2O; P5, time period in GDD (°C) from the beginning of grain-filling to physiological maturity; G1, potential spikelet number coefficient; G2, single grain weight (g) under ideal growing conditions; G3, tillering coefficient; G4, temperature tolerance coefficient.

Table 5 | Calibration performance indices for the CERES-Rice model for NSIC Rc 192 in estimating biomass

		Mean biomass (kg/ha)					
Season	Nutrient management	Observed	Simulated	R^2	nRMSE (%)	PBIAS	NSE
Dry	Full	1,858	1,518	0.88	27	18	0.77
Dry	Half	1,570	1,521	0.87	29	3	0.84
Dry	Zero	947	976	0.95	17	−0.37	0.91
Wet	Full	2,733	2,716	0.93	22	0.62	0.92
Wet	Half	1,795	2,112	0.96	25	−18	0.90
Wet	Zero	285	243	0.93	24	15	0.88

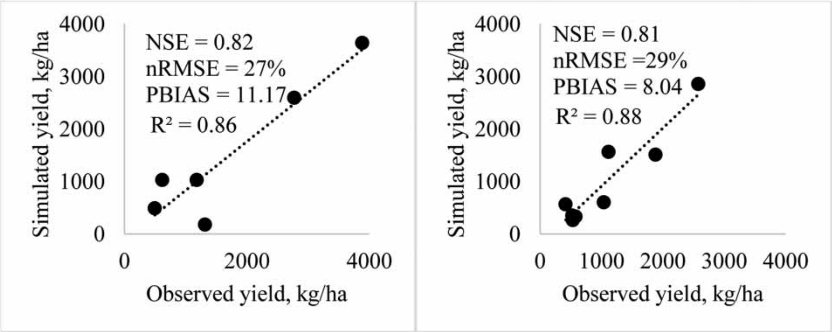


Figure 2 | Calibration (left) and validation (right) indices of the model performance in estimating the yield of NSIC Rc 192.

Likewise, the validation process proved that the model with the derived genetic coefficients could provide a satisfactory estimate of the growth of NSIC Rc 192 as manifest in its simulated biomass and yield. The validation statistics yielded high coefficients of determination for biomass simulation that ranged from 0.75 to 0.95, good to fair nRMSE values that ranged from 17% to 29%, satisfactory PBIAS values that ranged from −3 to 21, and satisfactory NSE values in the range of 0.55–0.91 (Table 6). The validation statistics for yield estimation similarly had good results with a high R^2 value of 0.88, a fair nRMSE value of 29%, a satisfactory PBIAS value of 8.04, and a satisfactory NSE value of 0.81. In the validation event, the actual yield of aerobic rice observed from the field experiment ranged from 419 to 2,579 kg/ha. A total rainfall amounting to 781 mm was recorded and a mean temperature was 27.3 °C during the dry season. During the wet season, the total rainfall amounted to 621.6 mm and the mean temperature was 28.6 °C. The wide yield range was due to the variable fertilizer treatments applied. Based on these results, the DSSAT-CERES-Rice model showed reliable estimates of biomass and yield of NSIC Rc 192 with nutrient management ranging from zero to full rate of fertilization during both wet and dry seasons.

Table 6 | Validation performance indices of the CERES-Rice model for NSIC Rc 192 in estimating biomass

			Mean biomass (kg/ha)					
Site	Season	Nutrient management	Observed	Simulated	R^2	nRMSE (%)	PBIAS	NSE
1	Wet	Full	4,074	4,842	0.94	21	−17	0.75
1	Wet	Zero	933	1,149	0.94	26	−21	0.66
2	Wet	Full	1,792	2,166	0.87	27	−19	0.61
2	Wet	Zero	1,007	913	0.95	19	13	0.69
1	Dry	Full	2,030	2,039	0.94	17	−3	0.91
1	Dry	Zero	848	737	0.84	22	12	0.68
2	Dry	Full	1,449	1,266	0.75	27	10	0.55
2	Dry	Zero	685	515	0.90	29	23	0.67

Climate change impacts

Figure 3 presents the yield anomalies for each simulated planting date across dry, normal, and wet years under each climate change scenario. The mean yield in the baseline year (2013) was 4.2 tons/ha during the wet season and 1.8 tons/ha during the dry season. Yield anomalies varied substantially in values across dry, normal, and wet years. However, the yield trends showed that the increase and the decrease in yields almost appear on the same planting dates for all the scenarios relative to the baseline period (2013).

Generally, during the wet seasons, the major increases in yields can be seen in aerobic rice planted in mid-July. Due to favorable weather conditions, improvement in yield during this season could reach up to 83% for normal years, 90% for dry years, and 68% for wet years. On the other hand, reduction in yield during the wet season could get as high as 293% for the normal years, 230% for the dry years, and 89% for the wet years. These yield losses occur within May and July planting dates.

During the dry seasons, the increases in yield are generally larger and occur predominantly in the planting dates in April and May. The maximum yield improvements during this season could be as high as 31–93% for the normal year, 35–70% for the dry year, and 66–126% for the wet years. The increases in yields during the wet and dry seasons are due to favorable water supply conditions that consequently favored better nitrogen transport. In effect, during these planting windows, there was no water and nitrogen stress as simulated by the model.

The annual average maximum yield reductions across all four scenarios were more than 150% with an increasing trend towards the end of the century. On the other hand, the annual average maximum yield increase ranged from 53% to 83% with a decreasing pattern towards the end of the century. Losses could be twice as large as gains. Yield losses are generally larger than yield improvements due to climate changes. Long-term projections showed that the increase in radiative forcing due to the increase in greenhouse gas emissions might cause yield improvements to decline and yield reductions to increase. Yield improvements during the dry seasons are due to sufficient rainfall to meet high water consumption from high temperatures. Water stress was the main reason for the decline in yield that also leads to nitrogen stress as water transports nitrogen from the soil to the crop. The model simulated higher water and nitrogen stress in growing periods with limited rainfall and high temperature. Water and nitrogen stress resulted in more yield reductions during dry years, dry seasons, and in the RCP8.5 towards the late-21st century, which could also be due to higher soil moisture variability. Larger fluctuations in soil water content during El Niño events were reported to cause yield anomalies in rice production (Stuecker *et al.* 2018).

Optimum planting windows

Figure 4 shows the estimated yield of the NSIC Rc 192 variety of aerobic rice across the climate change scenarios. Usually, the dry cropping season in the area starts from October to November, while the wet cropping season

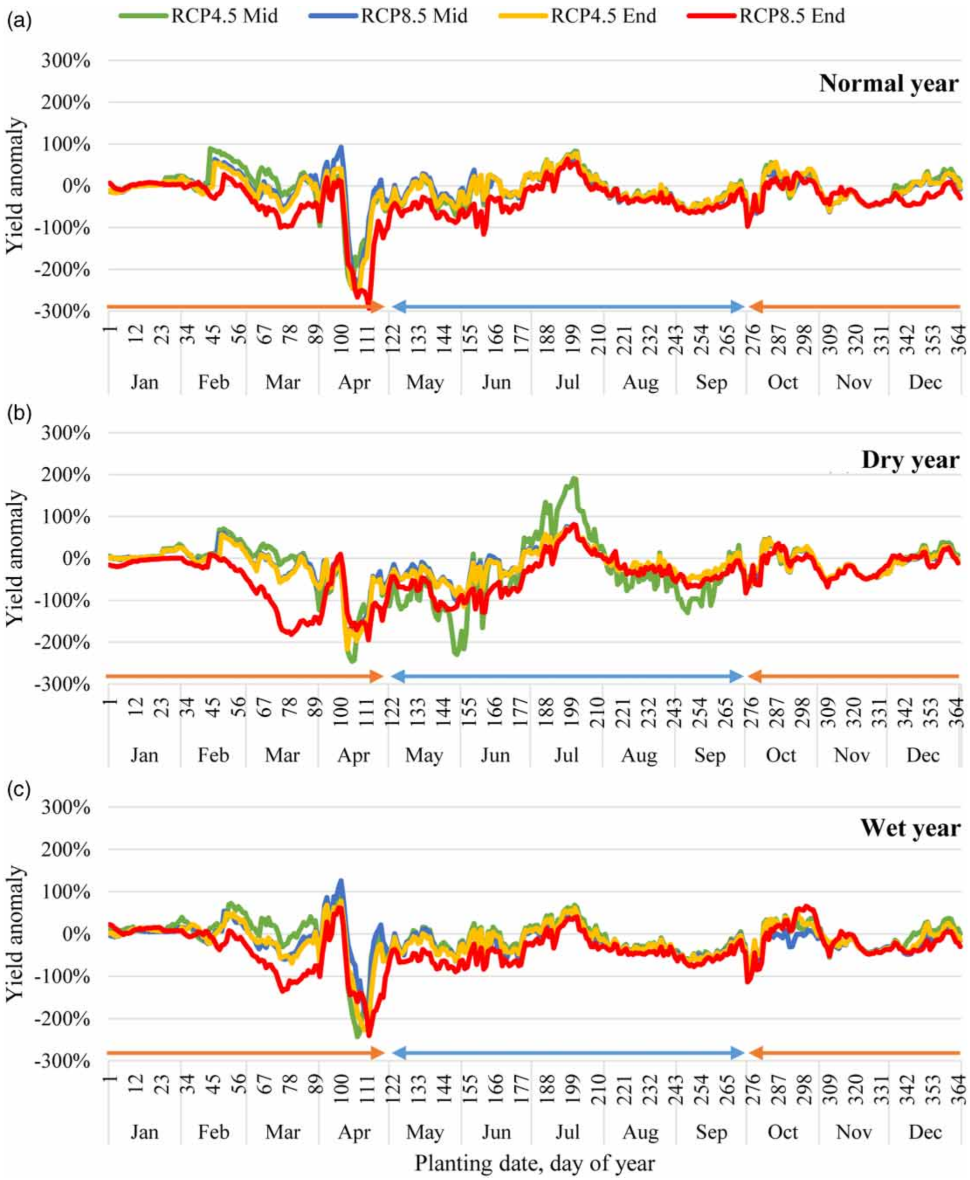


Figure 3 | Yield anomalies across climate scenarios during dry (orange horizontal line) and wet seasons (blue horizontal line) during normal, dry, and wet years. *Note*: Mid, mid-21st century; End, end of 21st century. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2020.286.

starts from May to June. Simulations showed that these usual planting dates during the dry seasons were found to have a low yield, especially during November. This implied that November planting for aerobic rice could be too late in the baseline year (2013). The month of September could be a better option in the current climate conditions.

The planting days within July and April showed a sudden production dip. The crops during the growth period within these months are highly exposed to water stress. Sowing of aerobic rice at these unproductive planting dates should be avoided. The well-calibrated and validated DSSAT model for aerobic rice had simulated water and nitrogen stress during these unproductive planting dates. If farmers opt to plant in September in the baseline year (2013), they could choose May for the first crop in a year to allow a month as a fallow period.

For the four RCP scenarios, simulations showed optimum yield performance up to more than 5 tons/ha

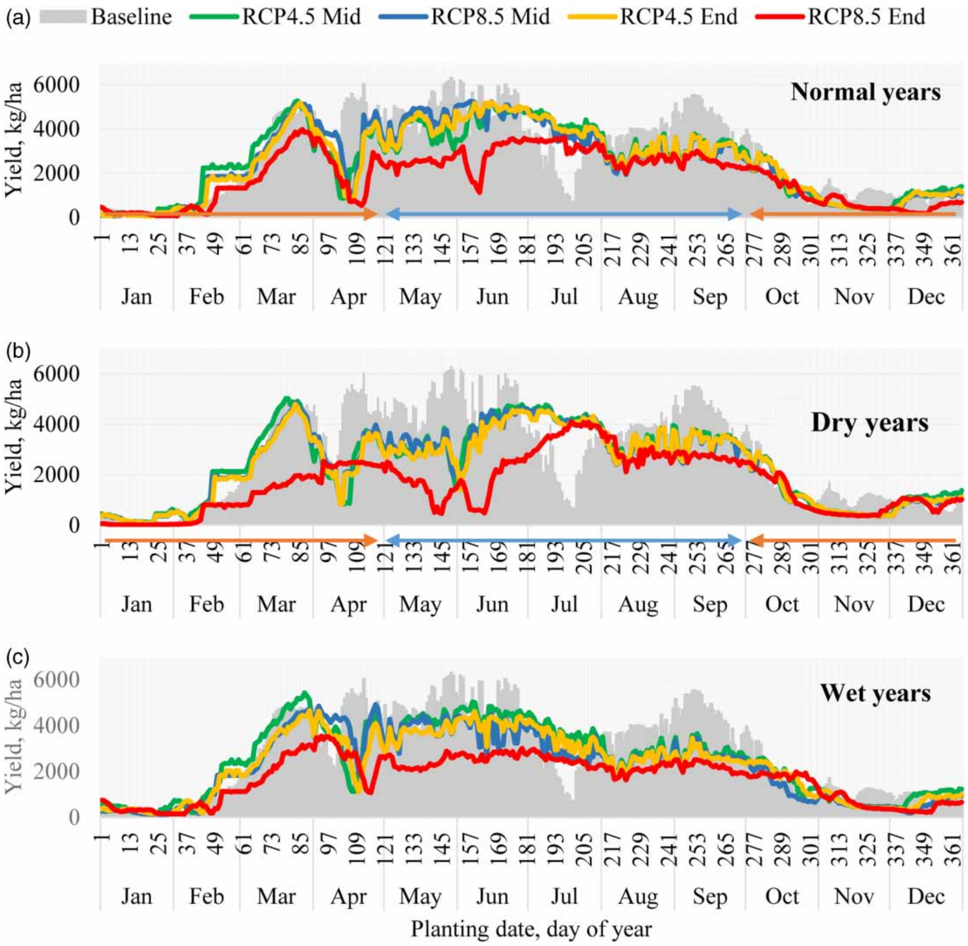


Figure 4 | Simulated aerobic rice yield for the normal and wet years across climate change scenarios. *Note*: Mid, mid-21st century; End, end of 21st century.

with planting dates in March for all the scenarios during dry seasons, except for the RCP8.5 late-21st century when rainfall is extremely scarce and the temperature is very high during the season. Water stress under this scenario is prevalent from the end of the juvenile phase until the grain-filling phase. At this range, rainfall is insufficiently available to provide water supply for the evapotranspiration rates. The best planting dates for the RCP8.5 scenario during the dry years occurred in the first and second week of April. However, the optimum yield it could produce could be two times lower than the other scenarios, which is up to 2 tons/ha only. This production level is comparable to a typical low yielding upland rice variety.

During the wet seasons, the optimum planting dates for all the RCP scenarios start in the last weeks of June until July where aerobic rice can produce up to more than 4 tons/ha. The month of July could be detrimental on the baseline year (2013) but the optimal planting window for the four RCP scenarios during the wet seasons regardless of the rainfall year category. This could be due to moderate rainfall and temperature conditions just enough for aerobic rice to jump-start the growing season. Normally, rainfall is excessive and intense during July. Aerobic rice is known to produce more with good root aeration. Zhu *et al.* (2015) proved in their study that root aeration improves growth and nitrogen accumulation of two lowland rice varieties. This could also be the reason why it performed best during the dry seasons. The reduction of rainfall during wet seasons in the climate scenarios had a favorable impact on aerobic rice production due to good root aeration.

CONCLUSION

In this study, the impacts of climate changes on aerobic rice production were estimated, and science-based decision support for selecting the optimum planting window of aerobic rice was developed. Results showed that the reduction of rainfall during the wet seasons is favorable for aerobic rice production. Large rainfall variability during the dry season adversely affects aerobic rice production. Choosing the optimum planting window for aerobic rice could minimize the impacts of climate change. The DSSAT-CERES-Rice model was successfully calibrated and validated for simulating aerobic rice production. The set of the genetic coefficients for aerobic rice can be used to simulate local conditions and crop management to improve aerobic rice production in other areas. With available seasonal daily weather forecasts, the derived DSSAT model for aerobic rice can be employed for seasonal crop forecasting. Further validation of its use in such applications is recommended to ensure model adequacy for aerobic rice yield forecasting. The long-term projections generated in this study provide an outlook of the future of aerobic rice production as affected by changes in climate. These can now be used by decision and policymakers in creating long-term action plans, climate change mitigation, and adaptation policies.

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CONFLICTS OF INTEREST

The author declares no conflicts of interest.

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