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Simulating the impact of elevated thermal condition on wet-season rice grown in Eastern India by different crop growth models

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Abstract. Elevated thermal condition caused by global warming is a threat to major crops grown in India as well as other Asian and tropical countries, as it negatively affects the crop phenology, growth, dry-matter production and yield. The present research work aims to assess the impact of elevated temperature on rice production using three crop growth simulation models, namely, DSSAT, WOFOST and InfoCrop. Field experimental data-set of rice for seven years was used for model calibration and validation. After validation, three models were used to predict the yield under 1, 2 and3^{0}C rise over normal maximum and minimum temperature. The models were also used to assess the thermal impact on leaf area indices (LAI) and crop duration. It was observed that the crop duration was shortened by almost 10 days for 3^{0}C enhancement over normal and the LAI was also reduced considerably. The wet-season rice yield may be reduced by 8.7% for 1^{0}C, 12.5% for2^{0}C and 21.1% for 3^{0}C increase of normal temperature. Use of combination of more than one crop models can predict the climate change impact on rice production more reliably.

Keywords: rice, climate change, temperature, simulation technique, crop growth models.

1. INTRODUCTION

In most of the Asian countries including India, agriculture is expected to be adversely affected by the impact of climate change (IPCC, 2007). The increased climatic variability and anticipated temperature increase caused by global warming are the prime concern of rice crop scientists of Southeast Asia. The elevated thermal condition poses serious threat to rice productivity, which in turn disturb the socio-economic stability of different rice growing countries (Krishnan, et al., 2007). Globally rice is grown in 154 million ha land, out of which 137 million ha is grown in Asia alone. In Southeast Asia, rice is cultivated in 48 million ha land, i.e., 31 percent of the world rice is grown in this region (FAOSTAT, 2012). In India, rice is the most important food-grain, and it is cultivated in 43.8 million hectares land with 99.50 million tons of total national production (CRRI, 2011). Like all other crops, rice production is also dependent on prevailing weather situation to a considerable extent and therefore any changes in global climate will have major impact on rice production and productivity, causing socio-economic disturbance in Southeast Asia. Hence, in the present paper, rice crop has been chosen to observe the impact of elevated thermal conditions.

Significant warming trend in the tune of 0.51°C per 100 year has been observed in Indian sub-continent for the period 1901-2007(Kothawale et al., 2010). The regional climate models also predict increasing temperature trends for future. The all-India summer monsoon rainfall may increase 3 to 7% in the 2030's compared to 1970's (MoEF, 2010). Rice is water-loving crop and grown under stagnant water condition, hence the probability of getting reduced production under elevated rainfall situation will be less compared to elevated thermal condition. It was found that climate change is likely to reduce the yields of wheat, corn, and rice in Asia by 18.26, 45.10, and 36.25% until 2100 (Zhang, 2017). IFAD (2019) also reported that smallholder farmers cultivating rice will be the most vulnerable community due to climate change. On the contrary, few scientists reported that rice will perform better under elevated thermal condition if sown in optimal time (Devkota et al., 2013; Malhi et al., 2021). Although the impacts of climate change on crop production in Asia will vary by region, most of the regions will experience a decline in production level (IPCC, 2013). To assess the variations in climatic parameters on crop performance, Crop Growth Simulation Models (CGSMs)can be used very accurately, which are dynamic in nature (Hoogenboom et al., 1999; Jones et al., 1998). In near future, simulation will be used more extensively to assess the effects of climate change on agriculture and to find out the suitable adaptation options (Banerjee et al., 2014; Arbuckle et al., 2015). Many scientists are also working on comparison of various CGSMs to assess model's applicability and their interrelationship (Pirttioja et al., 2015; Sandor et al., 2017; Fronzek et al., 2018; Harkness et al. 2020). In this research paper the simulation results will provide some indication on change of LAI, maturity period, and overall yield of wet season rice under elevated thermal condition. Moreover, the calibration and validation processes for three important crop growth models are the part of the present research work.

2. MATERIALS AND METHODS

2.1 Study area

The study area was located under the New Alluvial Agro-climatic Zone of West Bengal, India. The zone is a part of lower Gangetic plain of India, where the climate is typically subtropical – hot and humid. Field experimentation was carried out at Agricultural University Farm of Kalyani (22.57°N, 88.20°E and 7.8 m above mean sea level), Nadia District, West Bengal. The characteristics of the region's climate are hot summers and moderately cool winters. The mean annual rainfall ranges from 140.0 to 160.0 cm. The potential evapotranspiration (PET) varies from 110.0 to 140.0 cm and the water deficit is about 40.0 cm. The length of crop-growing period is greater than 270 days. The seasons of this zone can broadly be divided into five main categories: spring, summer, rainy season, autumn, and winter. The autumn here is comparatively shorter than other parts of India, lasting only from beginning of October to the middle of November. The summer season is typically hot and the maximum temperature ranges between 38°C and 45°C, while the minimum is around 20°C. The monsoon season is observed during June to September and more than 75% of annual rainfall is received during the season. The wet-season rice is grown in this season. Mild winter in December-January is observed here with average minimum temperatures being somewhere around 15°C. Alluvium-derived soil is predominant in the region. The texture of the soil was sandy loam, with moderately well drainage capacity. The bulk density is around 1.55 g cm^{-3} and only 0.5 % soil organic carbon is observed here. The soil of this zone has high water holding capacity and it is less acidic.

2.2 Database generated for model calibration and validation

The crop data was generated through field experimentation under "All India Coordinated Research Program on Agrometeorology" (AICRPAM) of Kalyani center. The most popular rice cultivar of West Bengal State, namely, *Swarna* was grown with different dates of sowing during 2007 to 2013. Data on phenology, crop height, LAI, biomass and yield were recorded from the experiment field for the whole study period (2007 to 2013). Actual observation on phenology, especially days to crop maturity was recorded for all the treatments. The crop height and LAI were measured for different phonological stages along with final above ground biomass and yield. Data sets of 2007 and 2008 were considered for model calibration (done by simple trial-and-error or iteration method) and the remaining data sets were used for model validation. The weather data of nearby Meteorological Observatory, situated less than 50 m away from experimental field, were used as weather inputs. Soil-data inputs were taken from Annual Progress Report (APR) of FASAL Project (FASAL, 2013). The crop management inputs for the model (such as sowing dates, seed rate, irrigation scheduling, fertilizer applications, etc.) were considered as per State recommendation. With all the input parameters, the rice yield was simulated and compared with actual yield.

2.3 Description of models

In the present paper three models are used to simulate the rice yield, namely DSSAT (Version 4.5), WOFOST (Version 7.1), and Info Crop(Version 1.0). The "Decision support system for agrotechnology transfer" (DSSAT) was developed by the network of scientists associated with International Benchmark Sites Network for Agrotechnology Transfer project (IBSNAT, 1993; Jones et al., 1998). DSSAT is built with a modular approach, with different options available to represent such processes as evapotranspiration and soil organic matter accumulation, which facilitates testing different representations of processes important in crop growth. DSSAT typically requires input parameters related to soil condition, weather, and management practices, such as fertilizer use and irrigation, and characteristics of the crop variety being grown. DSSAT model is driven by CO_2, solar radiation, temperature and rainfall. In this model water level can be maintained like field level under management option interface. The InfoCrop model simulates daily dry matter production as a function of irradiance, maximum and minimum temperatures, water, nitrogen and biotic stresses (Aggarwal et al., 2006). The model provides integrated assessment of the effect of weather, variety, soil and management practices on crop growth and yield along with soil nitrogen and organic carbon dynamics. The WOFOST model computes the instantaneous photosynthesis, where irradiance plays the vital role (Boogaard et al., 1998). After subtracting the maintenance respiration, which described as a function of temperature, assimilates are partitioned over roots, stems, leaves and grains as a function of the development stage of the crop. The effect of soil moisture on crop growth is not considered and a continuously moist soil is assumed.

2.4 Future temperature scenarios

IPCC Fifth Assessment Report (IPCC AR5 WG1) has projected mean temperature increase in the tune of 1°C for RCP 2.6 and 2°C for RCP 8.5 during 2046-2065. During 2081-2100, the mean temperature may be enhanced by 3.6°C for RCP 8.5 (IPCC, 2013). Boomiraj et al., 2010 indicated that mean temperature increase in Eastern India will be about 1°C for 2020 and 3°C in 2050 if A2 scenario is considered. In view of the above referred climate change projections, the impact of 1°C, 2°C and 3°C temperature rise over normal temperature condition on production of wet-season rice has been assessed for Kalyani. The average weather data of thirty years (1981 to 2010) of Kalyani weather station was taken as normal weather data. Then 1°C, 2°C and 3°C were added with both normal maximum and minimum temperature to obtain elevated thermal regime. This regime was used to observe the effect of increased temperature on crop production.

2.5 Statistical procedure

The model performance was worked out using some statistical parameters, such as Coefficient of determination (R^2), Standard Error (SE), Root Mean Square Error (RMSE) and others, which were used to compare the simulated yield, biomass, LAI and crop duration with observed data (Fox, 1981). The linearity between simulated and actual values is denoted by R^2whereas the mean absolute deviation between the said values is described by RMSE. The combination of lower RMSE, higher R^2 values and lower SE indicates the accuracy of simulation model. The bias was also evaluated for testing reliability of the model. Bias indicates the extent up to which the prediction process can be trusted. In the present study, the used statistical tools are given below (Gordon and Shykewich, 2000):

(a) Bias indicates the mean of the predicted value minus the mean of observed value.

$$\text{Bias} = \frac{1}{N}\sum_{i\,1}^{N}(\text{fi} - \text{Oi}) \qquad (1)$$

Here, N is observation numbers, fi is the predicted yield and Oi is the observed yield.

(b) Mean absolute error (MAE) is the average of the absolute difference between predicted yield and observed yield.

$$\text{MAE} = \frac{1}{N}\sum_{i\,1}^{N}(|fi - Oi|) \qquad (2)$$

(c) Standard error (SE) can be calculated through comparing actual value (x) and predicted value (y). The equation of SE of the predicted yield value is as follows:

$$SE = \sqrt{\frac{1}{(N-2)}\left[\sum(y-y')^2 - \frac{[\sum(x-x')(y-y')]^2}{\sum(x-x')^2}\right]} \quad (3)$$

and are the average of $y_{i\text{-}N}$ and $x_{i\text{-}N}$ respectively.

(d) The mean of squares of the "errors" is termed as Mean Square Error (MSE).

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{fi}-\mathrm{Oi})^2 \quad (4)$$

(e) Root mean square error (RMSE) has the advantage over other error estimation methods as the RMSE is measured in the same units as the unit used in the data-set, rather than in squared units.

$$\sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{fi}-\mathrm{Oi})^2} \quad (5)$$

3. RESULT AND DISCUSSION

3.1 Comparison between simulated and observed yield of wet-season rice by different models

All the three models were used to simulate the rice yield for various dates of sowing. Before working out the simulated yield [termed as Forecast (F)], the genetic coefficients of the said variety were adjusted using iteration or 'trial-and-error' method. The derived genetic coefficients for DSSAT, WOFOST and InfoCrop are enumerated in Table 1, 2 and 3 respectively. The units of different coefficients are also included in the description. The variations of observed and simulated yield for different dates of sowing are shown in Table 4, 5 and 6 for DSSAT, WOFOST and InfoCrop models respectively. For DSSAT model, the difference between forecasted yield (F) and observed yield (O), i.e. bias was minimum compared to other two CGSMs. The highest correlation coefficient values and considerably lower RMSE also indicated the correctness of DSSAT simulated yield (Table 4). WOFOST model was used to predict the early and late transplanted wet season rice for two years. The WOFOST model slightly over-predicted the rice yield (Table 5). Here the RMSE value was more than DSSAT and InfoCrop models, although bias and SE were considerably low. The InfoCrop model output showed the lowest RMSE value indicating that the model can also provide near reliable yield (Table 6). Considering the R^2value, bias, SE and RMSE together, it is concluded that DSSAT and InfoCrop worked better in the study region.

The DSSAT model considers the maximum numbers of input-parameters for predicting the production, hence its performance is better than other two models. In this model, the crop growth rate is modified by stress-parameters like temperature; water deficit, nutrient defi-

Table 1. Genetic coefficients of *Swarna* Cultivar generated through iteration method in DSSAT Model.

Symbol	Description	Values
Juvenile phase coefficient (P1)	Time period (expressed as growing degree days [GDD] in °C over a base temperature of 9 °C) from seeding 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.	880
Critical photoperiod (P2O)	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate. At values higher than P2O development rate is slowed, hence there is delay owing to longer day lengths.	140
Photoperiodism coefficient (P2R)	Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in photoperiod above P2O.	200
Grain filling Duration coefficient (P5)	Time period in GDD (°C) from beginning of grain filling (3–4 days after flowering) to physiological maturity with a base temperature of 9 °C. Growth aspects	11.8
Spikelet number coefficient (G1)	Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry (less lead blades and sheaths and spikes) at anthesis	54
Single grain weight (G2)	Single grain weight (g) under ideal growing conditions, i.e. non-limiting light, water, nutrients, and in the absence of pests and diseases	0.024
Tillering coefficient (G3)	Tillering coefficient (scaler value) relative to IR64 cultivar under ideal conditions. A higher tillering cultivar would have a coefficient greater than 1.0.	1
Temperature tolerance coefficient (G4)	Temperature tolerance coefficient. Usually 1.0 for varieties growth in normal environments. G4 for japonica-type rice growing in a warmer environment would be 1.0 or greater. Likewise, the G4 value for indica-type rice in very cool environments or season would be less than 1.0	0.9

Table 2. Genetic coefficients of *Swarna* Cultivar generated through iteration method in WOFOST Model.

Symbol	Description	Values
DLO	Optimum daylength for development (Hr)	10.5
TSUM1	Temperature sum from emergence to anthesis (cel d)	1723
TSUM2	Temperature sum from anthesis to maturity (cel d)	526
TDW1	Initial total crop dry weight (kg ha^{-1})	50.00
CVL	Efficiency of conversion into leaves (kg kg^{-1})	0.754
CVO	Efficiency of conversion into storage organ (kg kg^{-1})	0.600
CVR	Efficiency of conversion into roots (kg kg^{-1})	0.754
CVS	Efficiency of conversion into stems (kg kg^{-1})	0.754

Table 3. Genetic coefficients of *Swarna* Cultivar generated through iteration method in InfoCrop Model.

Description	Values
Thermal time for sowing to germination (^{0}C days)	50
Thermal time for germination to 50% flowering (^{0}C days)	1650
Thermal time for 50% flowering to physiological maturity (^{0}C days)	430
Optimum temperature (^{0}C)	32.0
Maximum temperature (^{0}C)	45.0
Sensitivity to photoperiod	1.0
Relative growth rate of leaf area (^{0}C days^{-1})	0.009
Specific leaf area (dm^{2}mg^{-1})	0.0022
Index of greenness of leaves	1.0
Extinction coefficient of leaves at flowering	0.6
Radiation use efficiency (g MJ^{-1} day^{-1})	2.6
Root growth rate (mm day^{-1})	12.0
Sensitivity of crop to flooding scale	1.0
Index of N fixation	1.0
Slope of storage organ number/m^2 to dry matter during storage organ formation (storage organ/kg^{-1} day^{-1})	56000
Potential storage organ weight (mg^{-1} grain^{-1})	26
Nitrogen content of storage organ (fraction)	0.012
Sensitivity of storage organ setting to low temperature	1.0
Sensitivity of storage organ setting to high temperature	1.0

ciency and many others (Dhakar et al., 2018). Jain et al., 2018 compared the DSSAT with InfoCrop model and opined that production potential under DSSAT model is very high as compared to InfoCrop model. The absence of tillage effects in the InfoCrop model may be another reason for which the R^2 value between observed and predicted yield is less in InfoCrop compared to other two models. In general, the InfoCrop model utilizes the radiation use efficiency (RUE)-based approach for dry matter production and WOFOST calculates dry matter production as a function of gross canopy photosynthesis. The sensitivity of all the three used models to change in ambient temperature and radiation is not similar, which is reflected in the simulated results. Tapio et al., 2016 emphasized development of robust procedures for parameterizing the models, which is observed in all the models used in the present study. The procedural accuracy is reflected through very low RMSE value. Only 3.2%, 6.6% and 1.8% RMSE values (in respect to average actual yield) were observed for DSSAT, WOFOST and InfoCrop models, respectively. Up to 15% grain RMSE is well accepted (Tovihoudji et al, 2019) and the present predicted result is well within acceptable limit.

3.2 Thermal sensitivity of crop growth models

It is well known fact that the crop duration is highly dependent on prevailing temperature and with the temperature enhancement the crop duration decreases (Fatima et al., 2020). This section shows how different models can assess the impact of thermal imbalance on crop duration or other important growth parameter, like LAI. The DSSAT output showed the simulated LAI would decrease with increase of temperature. The decrease of LAI would be more in PI, heading and grain filling stages (**Fig. 1**). The lower LAI throughout the crop growth stages and shorter duration may be the main cause of yield reduction of wet-season rice under elevated thermal condition. **Figure 2** shows the decrease in crop duration for 1^0, 2^0 and 3^{0}C temperature enhancement over normal. DSSAT model predicted highest decrease in crop duration (10 days for NT + 3°C). On the contrary for 3°C enhancement, InfoCrop predicted only 5 days reduction in crop duration.

3.3 Production of wet-season rice under elevated thermal condition

The normal weather data of the region were used to simulate the yield. To run the model, the normal DOS (4th week of May) were considered, and the common management practices were taken into account. Although higher temperature in the future climatic scenario alters the sowing window of most of the crops (Perego et al., 2014), the wet-season rice sowing in Gangetic West Bengal mainly depends on monsoon rainfall. Hence, for simulating the rice yield for the future, same sowing time has been considered. 1^{0}C rise in temperature showed around 235 kg ha^{-1} yield reduction through DSSAT and WOFOST models and around 380 kg ha^{-1} yield reduction through InfoCrop model. For enhancement of 1°C rise in temperature, the crop duration will be decreased by 4

Table 4. Comparison between simulated and observed yield of wet-season rice for different sowing dates using DSSAT Model.

Treatments (Sowing date)	Forecast (F)	Observed (O)	F-O	Abs (F-O)	(F-O)^2	R^2	SE	RMSE
26.05.2010	4502	4750	-248	248	61504			
22.06.2010	4107	3940	167	167	27889			
24.05.2011	4156	4084	72	72	5184			
23.06.2011	4014	3943	71	71	5041			
17.05.2012	4610	4730	-120	120	14400			
01.06.2012	4195	4209	-14	14	196			
	4264.0 (Average)	4276.0 (Average)	-12.0 (Bias)	115.3 (ME)	19035.7 (MSE)	0.97	56.3	138

Table 5. Comparison between WOFOST simulated yield and observed yield of wet-season rice.

Treatments	Forecast (F)	Observed (O)	F-O	Abs (F-O)	$(FW-O)^2$	R^2	SE	RMSE
2012 d_0	4360	4469.5	-109.5	109.5	11990.25			
2012 d_1	4178	3663	515	515	265225			
2013 d_0	4541	4707.5	-166.5	166.5	27722.25			
2013 d_1	4287.5	4162.5	125	125	15625			
	4341.62 (Average)	4250.62 (Average)	91 (Bias)	229 (ME)	80140.63 (MSE)	0.95	58.2	283.09

d_0 = Early transplanting (15th June transplanted).
d_1 = Late transplanting (15th July transplanted).

Table 6. Measured and InfoCrop simulated yield of wet-season rice for different years.

Treatments (Days of sowing)	Forecast (F)	Observed (O)	F-O	Abs (F-O)	(F-O)^2	R^2	SE	RMSE
26.05.2009	4480	4375	105	105	11025			
09.06.2009	4710	4660	50	50	2500			
22.06.2009	4084	4105	-21	21	441			
26.05.2010	4637	4750	-113	113	12769			
09.06.2010	4212	4290	-78	78	6084			
22.06.2010	3853	3940	-87	87	7569			
	4329.3 (Average)	4353.3 (Average)	-24.0 (Bias)	75.7 (ME)	6731.3 (MSE)	0.94	95.1	82

days in DSSAT model. Sarath Chandran et al. (2021) also observed similar result for New Alluvial Zone of West Bengal. The reduction in crop duration has resulted less biomass accumulation and eventually lesser yield. Moreover, the higher photorespiration due to higher temperature is one of the major causes of yield reduction under elevated thermal condition. As discussed earlier, for enhancement of 3°C rise in temperature, the crop duration may decrease in the tune of 10 days which is reflected in yield reduction. More than 21% yield reduction is possible for 3°C temperature enhancement compared to normal condition. The InfoCrop predicted the highest yield reduction compared to other two models. Lowering of LAI mainly caused such reduction in InfoCrop, as the model proved less sensitive in case of crop duration. The LAI is another determining factor for yield prediction as pointed out by different scientists. For example, Pagani et al. (2019) used the assimilation of RS-derived LAI as an input parameter to improve the forecasting capability. All the three models' output under elevated thermal condition is shown in Table 7. At least 5% yield reduction would be observed for 1°C rise of normal temperature (NT + 1°C) and 10% yield would be decreased for 2^0C temperature rise (NT + 2°C).

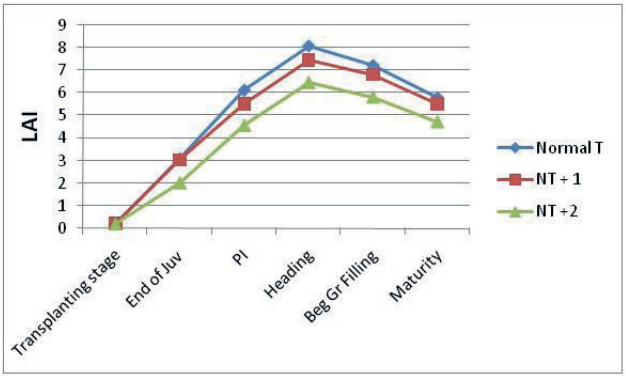

Fig. 1. Change of LAI at different crop growth stages under normal temperature and elevated thermal condition.

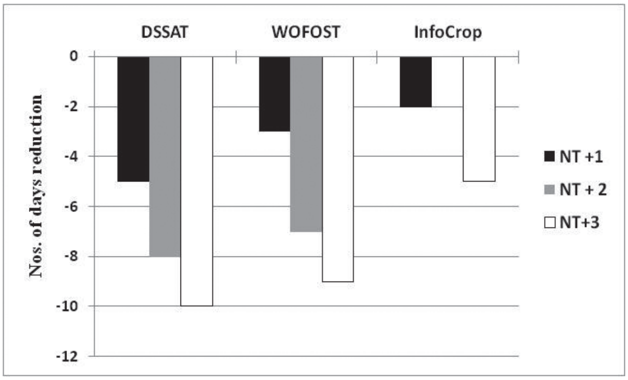

Fig. 2. Reduction in maturity period due to temperature increase (1°C, 2°C and 3°C) over normal temperature (NT).

Table 7. Rice yield under elevated thermal condition.

Models	Yield				% yield reduction		
	NT*	NT+1^{0}C	NT+2^{0}C	NT+3^{0}C	NT+1^{0}C	NT+2^{0}C	NT+3^{0}C
DSSAT	4145.0	3909.3	3625.3	-	5.7	12.5	-
WOFOST	4238.6	4006.5	3784.2	-	5.5	10.7	-
InfoCrop	4380.0	3997.6	-	3455.2	8.7	-	21.1

*Simulate yield under normal temperature (NT) condition

4. CONCLUSIONS

Due to temperature enhancement, the crop duration will be shortened by 2 to 10 days as simulated by different crop growth models. Due to early maturity of rice, farmers can grow short duration leafy vegetables (like spinach, coriander, etc., which takes only 40 days) and then sow the winter vegetables in mid-November. This may be regarded as the positive impact of climate change. There will be enhanced photorespiration and LAI will be reduced if temperature increases. These are the main reasons for reduction of simulated yield under elevated thermal condition. While developing new varieties, the plant breeders must look into these physiological factors to evolve climate resilient variety. All the three models under study predicted lower yield when higher temperature scenario was considered compared to normal weather situation of the study region. For one degree temperature rise, 5 to 8 percent yield will be reduced, whereas for two-degree temperature rise the reduction will be more than 10 percent. The adaptation options, such as added irrigation and fertilizer, choice of varieties, proper sowing window, etc., must be taken care of to reduce the negative impact of elevated thermal condition. DSSAT and InfoCrop models perform better for predicting the yield of wet-season rice in the Lower Gangetic Plains of West Bengal, India. The DSSAT model, being the most robust one, is recommended to assess the climate change impact and adaptation studies for most of the major crops.

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