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Evaluation of the CMS-CERES rice crop growth model

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ABSTRACT

Food security of world is a serious problem because of the ever growing population. The climate variability is more prevalent in recent years and thus worsens the problem of food security. Agriculture and climate are interconnected and the availability of food may be significantly impacted by climate change. Climate factors such as rising temperatures, CO_2 levels, and precipitation patterns have an impact on crop yields . The average global atmospheric carbon dioxide in 2023 was 419.3 parts per million. Between 2022 and 2023, the amount of carbon dioxide in the atmosphere increased by more than 2 parts per million. Since 1850, the average annual increase in Earth's temperature has been 0.11° Fahrenheit (0.06° Celsius), or almost 2° F. The increased concentration of greenhouse gases in the atmosphere is expected to cause an increase in the global mean surface temperature of 1.4 to 5.8°C between 1990 and 2100. Potential changes in the global climate may have an effect on the yield of food crops like rice which provides 21% of the energy needed by humans and meets the nutritional demands for more than half of the world's population.

Key words: *CMS, CERES, Crop growth model and Rice*

India is consistently ranked as the second-largest producer of rice in the world with a remarkable production rate of 2,798 kg ha^{-1}. The country contributed 129.5 million metric tons, i.e., 20% of the crop's total output from 46.3 million hectares. Andhra Pradesh produced 13.1 million metric tons of rice from 2.6 million hectares. The state has produced 5,130 kg of rice per acre (DES, 2021).

According to Prodhan *et al.* (2017), temperature variation is one of the key factors affecting rice yield during the blossoming, grain filling, and maturity stages of the crop. Rice yield decreases by 10% for each 1 °C rise in minimum temperature during the growing season due to factors such as shortened growth periods (Jagadish *et al.,* 2015), reduced light absorption (Jagadish *et al.,* 2007) and poorer kernel development. Despite the beneficial effects of elevated CO_2 levels on growth, the concurrent increase in temperature offsets these gains, leading to overall diminished rice yields. Elevated daily maximum temperatures have the potential to decrease rice spikelet fertility, thereby reducing overall yield potential. Conversely, increasing atmospheric CO_2 levels could positively impact rice yields by promoting enhanced growth and productivity. Projected declines in rice yield in China vary between 3.7% and 16.4% across climate change scenarios (RCP2.6, RCP4.5, RCP8.5) affecting both rainfed and fully irrigated rice production systems and sustained. Substantial increase in rice yields (+28% by 2071–2099) under higher greenhouse gas emissions (RCP 8.5)(Alvar Beltran *et al.,* 2022).

In the Godavari zone in Andhra Pradesh, MTU 7029 rice variety is grown on 1.85 lakh hectares, or around 51.67% of the zone's total rice area. It is one of the most popular types of rice cultivated in this area during the *kharif* season. The area under rice cultivation decreases gradually over the years because of decreasing productivity due to climate change and management practices. The impact of climate change on rice yield has been extensively researched . However, mitigating these effects through strategic adaptations in agricultural practices is essential. Adaptations include adjusting transplanting schedules optimizing plant density and improving nutrient management tailored to specific cultivars and regions. Effective selection of these strategies is crucial for minimizing the future impacts of climate change.

Crop weather models are useful tools for combining information and studying the intricate relationships between a variety of factors, such as weather, soil characteristics, and crop management, that affect crop performance. In order to help farmers make decisions about crop management operations, the CERES Rice model is integrated into the Decision Support System for Agro-technology Transfer (DSSAT) program. It has been found to be a useful research tool for predicting phenological occurrence, genetic coefficients, grain yield, and harvest index of the rice crop (Shamim *et al.,* 2012). DSSAT Model can be used to study the interactions between Genotype, Environment and Management and helps to achieve sustainable agricultural production by alternation of management strategies like change in dates of sowing, irrigation and fertilizer management in approaching increase in crop yield and quality, optimum resource utilization and reducing the negative impact of climate change. Numerous processes are simulated by this model, including the crop's phenological development, the growth of the leaves, stems, and roots, the accumulation and distribution of biomass among the leaves, stems, panicles, grains, and roots, the crop's use of the soil's water balance, and the changes and crop uptake of soil nitrogen.

MATERIAL AND METHODS

Field experiment

The field experiment conducted at RARS, Maruteru, Andhra Pradesh during *kharif* 2023 employed in Randomized Block Design and consisted of seven different nitrogen levels ranging from 0% to 150% of the recommended Dose of Nitrogen (RDN) (0% RDN, 25% RDN, 50% RDN, 75% RDN, 100% RDN, 125% RDN, 150% RDN). Nitrogen was applied at a rate of 60 kg ha^{-1} as urea, 40 kg ha^{-1} of phosphorus as SSP and 40 kg ha^{-1} of potash as murate of potash. Fertilizers were administered with phosphorus, potash, and a one-third nitrogen applied at transplanting, while the remaining nitrogen was split into two doses during the maximum tillering and panicle initiation stages.

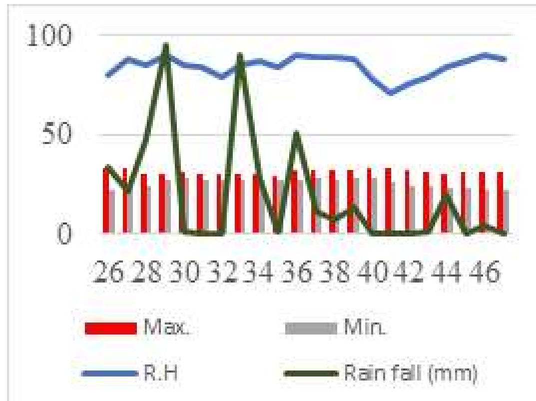
Input files for model to run

Crop management file

Information related to crop management such as transplanting dates, planting density, row spacing, planting methods, and the specifics of fertilizer and irrigation management (including application dates, quantities, and timings) was compiled to generate the input files for the model.

Weather file

Daily maximum temperatures of 31.18°C, minimum temperatures of 25.44°C, total rainfall of 425.6 mm, and an average relative humidity of 81.19% were collected from weather station RARS, Maruteru for the year 2023. For modeling purposes, solar radiation data was obtained from NASA POWER.



Soil file

Before the cropping season, soil data was systematically gathered at different depths. This included information on soil classification, bulk density, organic carbon content, and the percentages of sand, silt, and clay. Other parameters assessed were soil texture, pH, cation exchange capacity (CEC), and concentrations of total nitrogen, potassium, and phosphorus.

Collection of experimental data

Phenological data of crop including days to panicle initiation, anthesis, and physiological maturity, were taken by marking ten plants from the middle of each experimental row. Growth measurements, such as the number of hills per meter and total dry matter (TDM), were taken at 30, 60, and 90 days after transplanting (DAT), and at harvest. Additionally, grain and biological yield data were recorded by harvesting the crops at maturity.

Genetic coefficient file

The genetic coefficients detailed in are integral to rice cultivar growth simulations. Which were generated through GLUE by using the previous year field data. Crop genetic coefficients are pivotal in differentiating performance among rice cultivars. Estimation methods such as field experiments or the GLUE module within the CERES-Rice model are utilized, with GLUE being favoured for its efficiency in diverse geographic settings. The GLUE tool was iteratively executed 30,000 times to estimate the genetic parameters as part of the calibration process (Gao *et al.,* 2026). P coefficients aid in predicting milestones such as flowering and maturity, while G coefficients estimate potential grain yield for each specific cultivar.

Model calibration and validation

To achieve credible results, crop models require rigorous calibration, validation, and evaluation tailored to specific varieties and environments to ensure accurate simulation and predictive capability. Model calibration is the process of refining cultivar coefficients to align simulated outputs closely with observed data for phenology, biomass, and yield. The model calibration was done by using the previous year's crop data. The coefficients obtained from simulations were applied to forecast experimental outcomes, comparing them with observed phenology and growth values. Evaluation was conducted upon achieving a favourable match between predicted and observed results. The evaluation process involved running the model using treatments that were not part of the calibration process. This evaluation used RMSE, NRMSE and coefficient of determination (R^2) as metrics to gauge the model's accuracy in predicting flowering and maturity dates, as well as final yield, by comparing simulated and observed values (Yang *et al.,* 2014).

$$R^2 = 1 - \frac{\sum_{i=0}^{n} X_{obs_i} - X_{sim_i})^2}{\sum_{i=1}^{n} X_{obs_i} - \overline{X_{obs_i}})^2}$$

$$RMSE = \frac{\sum_{i=1}^{n}(X_{obs_i} - X_{sim_i})^2}{n}$$

$$NRMSE = \frac{RMSE \times 100}{\bar{Q}}$$

Where X_{obsi} is observed value and X_{simi} is modeled value at time/place *i*

The computed values of RMSE and NRMSE serve as metrics to assess how closely the model's predictions match the actual observed values. A low RMSE suggests that the model's predictions are close to the observed data points on average. Meanwhile, NRMSE, which normalizes RMSE by dividing it by the range of observed values, approaching one indicates that the model's predictions are reliable across the range of observed data. Therefore, lower RMSE and NRMSE value below 10% indicate excellent and below 20% indicate well and R^2 values below one are desirable as they signify better model accuracy and precision in predicting outcomes.

Climate change scenarios

The baseline year 2023 was used to develop projections of climate data for the year 2100 across four Representative Concentration Pathways (RCPs) 2.6, 4.5, 6.0, and 8.5. These scenarios, detailed in the IPCC's fifth assessment report, reflect various levels of greenhouse gas emissions. Projections cover changes in temperature extremes and solar radiation over each decade. RCP 2.6 represents a low emissions scenario with radiative forcing peaking at 3.1 W/m² and then decreasing. RCP 4.5 and RCP 6.0 are intermediate scenarios with stabilizing radiative forcings of 4.5 W/m² and 6.0 W/m², respectively. RCP 8.5, the high emissions scenario, sees radiative forcing reach 8.5 W/m².

Climate impact studies on crop models generally assume constant crop, soil, and management conditions, with climate being the sole variable. This study adhered to that assumption, using fixed rice cultivar, soil, and agricultural practices to simulate climate change impacts on rice production for the year 2100 under (RCPs) 2.6, 4.5, 6.0, and 8.5 scenarios. The analysis involved comparing CERES-Rice model outputs from the baseline period (2023) with those from the IPCC (RCPs) 2.6, 4.5, 6.0, and 8.5. scenarios. We also assessed the effects of CO_2

fertilization and temperature changes with and without the CO2 fertilization effects.

To ensure the reliability of crop simulation models, precise estimation of flowering duration and grain yield are essential (Yao *et al.,* 2007). Thus the present experimental data was won for validation of the model.

RESULTS AND DISCUSSIONS

Model validation

One year of field data collected at RARS, Maruteru was utilized to validate the model. The findings from this validation process are summarized below

Crop phenophases

The comparison of observed and simulated data for days to panicle initiation, anthesis and physiological maturity under different nitrogen levels are presented in Table 1,2 and 3 and showed that the CERES-Rice model's predictions closely matched with the observed values. The model's performance metrics were: RMSE of 1.25, NRMSE of 1.43%, and an R^2 value of 0.96 for panicle initiation, RMSE of 1.12 NRMSE of 1.01%, and an R^2 value of 0.94 for days to anthesis and RMSE of 4.11, NRMSE of 2.84%, and an R^2 value of 0.90 for physiological maturity. This indicates a minor overestimation of 1.27% for days to panicle initiation, 1% for days to anthesis and 0.83% for physiological maturity by the model. Overall, the simulation was deemed excellent, as the NRMSE was below 10% and the R^2 value was high. The low RMSE reflects the model's accuracy in predicting days to panicle initiation. Goswami and Dutta (2021) reviewed the model's performance globally and found it to be highly accurate, with NRMSE ranging from 1-5% for anthesis and 1-4% for physiological maturity. These results confirm that the model provides reliable predictions and closely aligns with actual observations. The CERES-Rice model accurately predicted phenological events in rice, with its simulated dates closely matching the observed data (Kant *et al.,* 2018, Deka *et al.,* 2016, Hadiya *et al.,* 2016, Mote *et al*., 2016, and Vilayvong *et al.,* 2015.

Grain yield

The CERES-Rice model was evaluated for simulating rice grain yield at different nitrogen levels and was presented in Table 4. Analysis showed that the simulated grain yields were well-correlated with observed values, with an RMSE of 446.35, an NRMSE of 9.63%, and R^2 of 0.7, indicating a slight overestimation of 1.6% by the model. This performance is considered excellent, as the NRMSE is below 10% and the R^2 is within the expected range. The model provided a close match to the actual grain yields for the MTU 7029 cultivar, demonstrating its capability in predicting rice growth and yield under varying nitrogen conditions. This suggests a strong potential for CERES-Rice in modeling rice development.

Tari *et al.* (2023) found that the CERES-Rice model showed a strong correlation between observed and simulated grain yields, with R^2 values from 0.83 to 0.90 and RMSE values from 225 to 464 kg ha^{-1}, indicating effective predictions under different nitrogen levels. Goswami and Dutta (2021) reported NRMSE values between 0.05% and 5.00%, noting occasional discrepancies, particularly under water stress. Ahmad *et al.* (2012) observed that the model's simulated grain yields were in good agreement with actual yields, showing normalized RMSE between 2.1% and 3.4%. Sharma and Kumar (2006) noted a substantial correlation in the North Western Himalayas, with an R^2 of 0.78. Kant *et al.* (2018), Hadiya *et al.* (2017) Deka *et al.* (2016), Yarnia (2016) and Mote *et al*. (2016) showed that the model's predictions for grain yield is closely align with actual observed data.

CONCLUSION

The application of 125% RDN @ 75 kg N ha^{-1} was found to be the optimum for realizing a higher grain yield, net returns, and returns per rupee investment. However it shoued on par results with the recommended dose of 100% RDN holds good for the rice test variety MTU 7029. Evaluation of CMS-CERES Rice model result in good agreement between observed and simulated values of phenophases and grain yield. Genetic coefficients of variety MTU 7029, a modified by using the previous year field data through GLUE module.

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Table 1. Comparison of simulated and observed days taken to reach panicle divation under different levels of nitrogen in rice

Treatments	Days to panicle initiation (Days)		
	Observed	**Simulated**	**% Deviation**
T_1 (Control (No nitrogen)	85.5	87.3	2.1
T_2 (25% RDN @ 15 kg N ha^{-1})	86.3	87.8	1.7
T_3 (50% RDN @ 30 kg N ha^{-1})	86.5	87.8	1.5
T_4 (75% RDN @ 45 kg N ha^{-1})	87.0	88.0	1.2
T_5 (100% RDN @ 60 kg N ha^{-1})	87.0	88.0	1.2
T_6 (125% RDN @ 75 kg N ha^{-1})	88.3	89.3	1.1
T_7 (150% RDN @ 90 kg N ha^{-1})	88.8	89.8	1.1
RNSE	1.25		
NRMSE (%)	1.43		
R^2	0.96		

Table 2. Comparison of simulated and observed days to attain anthesis of rice under different levels of nitrogen

Treatments	Days to anthesis (Days)		
	Observed	**Simulated**	**% Deviation**
T_1 (Control (No nitrogen)	112.3	115.3	2.8
T_2 (25% RDN @ 15 kg N ha^{-1})	114.3	115.5	1.1
T_3 (50% RDN @ 30 kg N ha^{-1})	114.5	115.5	0.9
T_4 (75% RDN @ 45 kg N ha^{-1})	115.0	116.0	0.9
T_5 (100% RDN @ 60 kg N ha^{-1})	115.0	116.5	1.3
T_6 (125% RDN @ 75 kg N ha^{-1})	117.3	117.5	0.2
T_7 (150% RDN @ 90 kg N ha^{-1})	117.8	117.8	0.0
RNSE	1.12		
NRMSE (%)	1.01		
R^2	0.94		

Table 3. Comparison of simulated and observed days to attain physiological maturity of rice under different levels of nitrogen.

Treatments	Days to physiological maturity (Days)		
	Observed	**Simulated**	**% Deviation**
T_1 (Control (No nitrogen)	140.5	147.3	4.8
T_2 (25% RDN @ 15 kg N ha^{-1})	142.3	147.3	3.5
T_3 (50% RDN @ 30 kg N ha^{-1})	143.3	147.8	3.1
T_4 (75% RDN @ 45 kg N ha^{-1})	145.3	148.3	2.1
T_5 (100% RDN @ 60 kg N ha^{-1})	145.3	148.8	2.4
T_6 (125% RDN @ 75 kg N ha^{-1})	147.3	149.6	1.6
T_7 (150% RDN @ 90 kg N ha^{-1})	148.8	149.8	0.7
RMSE	4.11		
NRMSE (%)	2.84		
R^2	0.90		

Table 4. Comparison of simulated and observed grain yield (kg ha^{-1}) of rice under variable nitrogen levels.

Treatments	Grain yield (kg ha^{-1})		
	Observed	simulated	Difference (O-S)
T_1 (Control (No nitrogen)	3322	2786	-536
T_2 (25% RDN @ 15 kg N ha^{-1})	3840	4732	892
T_3 (50% RDN @ 30 kg N ha^{-1})	4745	5059	314
T_4 (75% RDN @ 45 kg N ha^{-1})	4815	5068	253
T_5 (100% RDN @ 60 kg N ha^{-1})	5150	5096	-54
T_6 (125% RDN @ 75 kg N ha^{-1})	5499	5118	-381
T_7 (150% RDN @ 90 kg N ha^{-1})	5090	5121	31
RMSE	446.35		
nRMSE (%)	9.63		
R^2	0.70		

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