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Evaluation of DSSAT model (CERES rice) on rice production: A review

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Abstract
Rice is the staple food for over half of the world population. Crop models potentially offer a means to readily explore management options to increase yield, and to determine trade-off between yield, resource-use efficiency and environmental outcomes. This paper reviews the performance of CERES-Rice model in different regions of the world in relation to their potential application towards increasing resource use efficiency and yield of rice. In this article, the CERES-Rice model evaluation by using the simulated and observed values on crop phenology (anthesis, physiological maturity) and final grain yield mainly over Asian countries by different authors has been compiled and described. Mainly the model was evaluated based on different statistical measures such as RMSE and D-index. Several datasets for the prediction of grain yield and phenological period across different parts of Asia were examined. This particular model predicted those with high-accuracy (nRMSE1-5% for anthesis and 1-4% for physiological maturity days). For various data sets for grain yield, the nRMSE varied between 0.05–5.00 percent with error percentage of 2-5%. The model sometimes over-estimated or under-estimated the values of grain yield, especially under water stress conditions.

Keywords: Crop modelling, DSSAT CERES

Introduction
The need for increasing agricultural productivity on a sustainable basis is the primary concern for the agricultural research and development community (Singh *et al*. 2002) [1]. Rice is the staple food for over half of the world population. Asia produces and consumes about 90% of the global rice. Hence, the key for global food security is Asia's rice production. Climate change also posed threat on global rice production. In the Philippines with low latitude, increased temperature by 4 °C due to climate change decreased yield by 20-50% (Timsina *et al*. 2006) [2] In rainfed areas of both India and Indonesia, any decrease in rainfall due to climate change would decrease rainfed rice yield while increased rainfall would increase yield (Saseendran *et al*., 2000) [3].The expansion in rice production in a sustainable way has been a matter of concern to gain food security, particularly in developing countries. There are many factors that impact rice production including management practices such as cultivar use, transplanting date, plant density, fertilizer application, irrigation amongst others. Identification of suitable crop management practices could provide information to increase the rice yield of this production area. However, this process is time consuming and expensive as many years of experimental trials are required. In addition, cropping systems are extremely complex and many factors have to be considered to achieve long-term sustainability (Geng *et al.*, 1990) [4] in major rice growing areas.
The decision support system for agro technology transfer (DSSAT) developed by the International Benchmark Systems Network for Agro technology Transfer (IBSNAT) contains multiple crop models including CERES-Rice. The CERES-Rice model simulate crop growth, development and yield, taking into account the effects of weather, genetics, soil water, carbon and N and planting, irrigation and N fertilizer management (Ritchie *et al*., 1998) [5]. These models can also be run in sequence under the DSSAT system, offering the ability to evaluate options for increasing yield and water-and N-use efficiency (Timsina *et al*., 1995) [6].
All crop models should be evaluated in the environment of interest if the results of applications are to be credible. There are many studies on the calibration and validation of CERES-Rice around the world, but there has been very little quantitative and systematic evaluation on their

performance using robust statistical criteria, and no attempt to synthesise the results of those evaluations. The objectives of this review are (i) to compile and analyse results of the performance of CERES Rice using various statistical criteria; (ii) to identify the capabilities and limitations of these models for application in Rice systems.

Model evaluation and testing

Evaluation involves comparison of model output with observed data and a determination of suitability for an intended purpose. It is useful to think of model evaluation as a documentation of its accuracy for specific predictions in specified environments, with appropriate consideration given to possible errors in input variables or data evaluation. Essential parts of any minimum data set for evaluation are: (1) a complete record of the information required to run the model, and (2) field information on the aspect(s) for which the model is being validated. The data sets should not have been used previously for calibration and should represent the complete array of environments and crop sequences for which the model will be applied (Jones *et al*., 2003) [7].

Several statistical methods for analysing model performance are available (Jones and Kiniry, 1986; Willmott, 1982; Willmott *et al*., 1985) [8-10]. Jones and Kiniry (1986) [8] used means and standard deviations (SD) for observed and simulated data and linear regression parameters such as intercept (a), slope (b), and coefficient of determination (R^2). However, Thornton and Hansen (1996) concluded that use of the F-test (to test the null hypothesis that the regression line has unit slope and an intercept of zero) can be severely misleading. They showed that the probability of rejection of a valid model may increase with sample size, and pointed out that this is not an acceptable behaviour for a validation test of complex simulation models. Rodríguez *et al*. (2010) [11] indicate that two criteria were used to evaluate the calibration, that is, root mean square error (RMSE) and r^2. The first corresponds to the square root of the mean square error RMSE = [Ó{(simulated-observed)2 /N] 0.5}, which provides the degree of dispersion between simulated and observed values, while r^2 provides the degree of association between simulated and observed data. Willmott (1982) [9] and Willmott *et al*. (1985) [10] recommended the use of RMSE or RMSD (root mean square error or deviation), RMSEs (root mean square error systematic), RMSEu (root mean square error unsystematic), and D-index (index of agreement), but suggested that RMSE is the ‘‘best’’ measure as it summarises the mean difference in the units of observed and predicted values.

To evaluate the performance of the models, we compiled the published data on simulated and observed results from several studies across Asia, and then showed a range of statistical parameters for each data set that were presented by the authors (Tables 3). These included RMSE, nRMSE, D-index and percentage of error. A model is said to be good fit when RMSE (and RMSEs) is 0 and D-index is 1. These parameters were calculated as follows:

$$RMSE = \left[N^{-1}\sum_{i=1}^{n}(P_i - O_i)^2\right]^{0.5}$$

$$nRMSE = \left[\sum_{i=1}^{n}[(P_i - O_i)^2/n]\right]^{0.5} \times 100/M$$

$$D\ Index = 1 - \left[\sum_{i=1}^{n}(P_i - O_i)^2 / \sum_{i=1}^{n}[|P'_i| + |O'_i|]^2\right]$$

$$|P'_i| = a + bO_i$$

$$P_i = P'_i - \bar{O}\ ;\ O'_i = O_i - \bar{O}$$

$$Error\ Percent = [(P_i - O_i)/P_i]^{0.5}\ \times 100$$

Where P_i and O_i are predicted and observed values and $\bar{O}$ is the mean observed value over several replicates. $\bar{O}$ has an associated standard deviation which is often ignored in model evaluation, and any difference between simulations and observations is attributed solely to model inadequacies (e.g., Kobayashi and Salam, 2000; Gauch *et al*., 2003) [12, 13]. In this review, model performance was judged on various qualitative and quantitative criteria, but with more weight on RMSE and D-index.

Model Calibration of DSSAT CERES-Rice

Model was calibrated by the adjustment of parameters so that simulated values compare well with observed values (Boote, 1999) [14]. The genetic coefficients were derived iteratively, by manipulating the relevant coefficients to achieve the best possible match between the simulated and observed values. The genetic coefficients used in CERES models characterise the growth and development of crop varieties differing in maturity. The coefficients for CERES-Rice reported in various literatures are summarised in Table2. The coefficients reported in Table 2 were mostly derived from results of experiment in different location, different varieties, different duration of experiment and different climatic situation. Many studies did not even report the model version used, nor provide cultivar names or phenological information, making it difficult for the reader to calculate or assign any coefficients. The details of the genetic-coefficient are given in the table 1.

Table 1: Description of different genetic co-efficient used in CERES-Rice model

Genetic co-efficient	Description
P1	Time period (expressed as growing days) [GDD] in 0oc over as a base temperature of (100 ºC) from seeding emergence during which the rice plant is not responsive to change in photoperiod of the plant. This period is also referred to as the basic vegetative phase of the plant.
P2O	Critical photoperiod of the longest day length (in hours) at which the development occurs at a maximum rate. At values higher than P20 development rate is slowed hence there is a delay owing to longer day lengths.
P2R	Extent to which phase development leading to panicle initiation is delayed. (Expressed as GDD in ºC for each hour increase in photoperiod above P20.
P5	Time period in GDD (ºC) from beginning of grain filling (3-4 days after flowering) to physiological maturity with a base temperature of 90 ºC.
G1	Potential spike let no. Coefficient as estimated from the no. Spike let per g of main culms dry weight is less lead blades and sheaths plus spikes of anthesis a typical value is 55.
G2	Single grains a right (g) under ideal growing conditions i.e. Non-limiting light, water nutrients and in the absence of

	pest and diseases.
G3	Tillering coefficient (sealer value) relative to Pusa Basmati cultivar under ideal condition. Higher tillering cultivars would have a coefficient greater than 1.0.
G4	Temperature tolerance coefficient usually 1.0 for varieties growth in normal environment G4 for Japonica type rice growing in a warmer environment would be 1.0 or greater. Likewise, the G4 value for indicia type rice in very cool environment or season would be less than 1.0.

Table 2: Genetic co-efficient of various cultivar over different countries for CERES-Rice

Cultivar	Duration of experiment	Location	Climate	Coefficients								Source
				P1	P2R	P5	P2O	G1	G2	G3	G4	
Sarjoo-52	2010, 2012	Faizabad, U.P, India	Semi-arid	650.0	200.0	520.0	12.0	59.0	0.025	1.00	1.00	Surya Prakash Singh *et al.* (2018) [15]
NDR-359	2010, 2012	Faizabad, U.P, India	Semi-arid	1150.0	120.0	150.0	11.0	60.0	0.018	1.00	1.00	Surya Prakash Singh *et al.* (2018) [15]
Swarnasub-1	2010, 2012	Faizabad, U.P, India	Semi-arid	750.0	150.0	400.0	11.3	59.0	0.022	1.00	1.00	Surya Prakash Singh *et al.* (2018) [15]
NDR-359	2012-2018	Prayagraj, U.P, India	Sub-tropical	500.0	200.0	450.0	12.5	62.0	0.190	1.00	1.00	Sanadya Anurag *et al.* (2019) [16]
NDR-97	2012-2018	Prayagraj, U.P, India	Sub-tropical	300.0	120.0	390.0	11.5	59.0	0.220	1.00	1.00	Sanadya Anurag *et al.* (2019) [16]
SARJU-52	2012-2018	Prayagraj, U.P, India	Sub-tropical	450.0	170.0	365.0	12.2	47.0	0.238	1.00	1.00	Sanadya Anurag *et al.* (2019) [16]
BR-22		Jessore, Bangladesh	Sub-tropical	645.0	120.0	405.0	13.5	70.0	0.026	1.10	1.20	Hasan *et al.* [17]
BR-22		Barisal, Bangladesh	Sub-tropical	648.0	120.0	402.0	12.0	62.0	0.025	1.10	1.20	Hasan *et al.* [17]
BR-22		Comilla, Bangladesh	Sub-tropical	655.0	115.0	400.0	10.5	70.0	0.027	1.00	1.10	Hasan *et al.* [17]
BR-22		Sylhet, Bangladesh	Sub-tropical	652.0	120.0	399.0	10.2	63.0	0.027	1.10	1.00	Hasan *et al.* [17]
IR-36		IRRI, Philippines	Tropical	450	149.0	350.0	11.7	68.0	0.023	1.00	1.00	Hoogenboom *et al.* (1997) [18]
Jaya	1993-1994	Kerala, India	Tropical	830.0	50.0	277.0	15	72.8	0.028	1.00	1.00	Saseendran *et al.*(1998) [19]
IR-8	1993-1994	Kerala, India	Tropical	880.0	52.2	550.0	12.1	65.0	0.028	1.00	1.00	Saseendran *et al.*(1998) [19]
Swarna	2015	Odisha, India	Sub-tropical	620.0	180.0	490.0	11.8	70.0	0.020	1.00	1.00	M.Ray *et al.* (2018) [20]
China early				100.0	130.0	332.0	12.4	55.0	0.025	1.00	1.00	Hoogenboom *et al.* (1997) [18]
IR-72		Philippines	Tropical	400.0	100.0	580.0	12.0	76.0	0.023	1.00	1.00	Hoogenboom *et al.* (1997)[18]
Masuli		Nepal	Sub-tropical	830.0	200.0	600.0	11.4	35.0	0.030	1.00	1.00	Timsina *et al.* (1997) [21]
Amaroo		Southern NSW, Australia	Temperate	370.0	750.0	85.0	14.5	80.0	0.026	1.00	1.00	Meyer *et al.* (1994) [22]

For grain yield

Sanadya Anurag *et al*. (2019) [16] reported that, the deviation between simulated and grain yield varied between 89 kg ha-1 to 569 kg ha-1. The values of RMSE is 335.31, 643.76 and 267.59 for NDR – 359, NDR – 97 and SARJU – 52 respectively, NRMSE is 0.05, 0.08, 4.45 for NDR – 359, NDR – 97 and SARJU – 52 respectively with an average percent error of 2.36, 4.84 and 3.23 for NDR – 359, NDR – 97 and SARJU – 52 respectively, which indicated that model performed well in all the years in predicting the grain yield of rice for every cultivar in sub-tropical zone of Uttar Pradesh, India.

In tropics (Thailand), Saythong Vilayvong *et al*. (2014) [23] found that differences between the simulated data and observed data for grain yield were low, ranging from 31 to 154 kg ha−1 for RMSE values and 1 to 6% for NRMSE values. However, the highest RMSE value of 556 kg ha−1 and NRMSE value of 16% were found for TDK8 transplanted on 7 July 2012.

Kaushik Sar *et al*. (2017) [24] showed that over the 6 years of simulation, the model overestimated the grain yield in all the years of simulation except during the year 2009 and 2013, where model underestimated yield in agro-climatic zone of Bihar. The model successfully predicted growth, phenology and yield of crop with error values within 10%.In nutshell, the model prediction was reasonably good for predicting crop duration, and leaf area index and grain yield for rice varity Rajendra Mahsuri-1. In fact this study provides an insight into the complex issue of evaluation and model performance.

M.Ray (2018) [20] showed a good match was between observed and simulated grain yield of Swarna variety with a RMSE of 0.817 t/ha and a normalized RMSE (RMSEn) of 14.943% in the field trial performed in Orissa, India. An index of agreement for grain yield closer to 1 (0.869) also revealed that the model performed well in predicting the yield. The simulated results show that an increase in both maximum and minimum temperature led to a decrease in grain yield. As compared to maximum temperature, increase in minimum temperature had more pronounced negative effects on the yield of Swarna. This more pronounced negative impact of minimum temperature on rice yield could be explained by increased respiration losses during the vegetative phase (Peng *et al*., 2004) [25] and reduced grain-filling duration and endosperm cell size during the ripening phase (Morita *et al*., 2005) [26].

Ravikant Chandrvavanshi *et al*. (2019) [27] showed that there was a good agreement between observed and simulated grain yield of rice with RMSE of 0.35 in M.P, India.

NT Son *et al*. (2016) [28] compared the DSSAT predicted yield with the government's rice yield statistics in Taiwan, indicating that the RMSE value obtained for the first crop in 2014 were 11.7%. This study demonstrates the potential of DSSAT-rice model integrating with remotely sensed data for yield estimation over a large region. But in case of this particular study, several factors may have influence on the accuracy of yield simulation results, including limitations of spatial and temporal resolutions of remotely sensed data and limited number of rain gauge stations used to derive weather data. For example, the resolution bias between remotely sensed data (e.g., LAI and soil data) and weather data, which were created by the spatial interpolation. Moreover, the model could also be affected by the mixed-pixel problems and the uncertainty of the data used in this study for the simulation.

Hasan *et al*. [17] suggested the predicted crop yields (BR-22) in the validation period was in close agreement with the observed yields (9.90 < RMSE < 14.87; 0.71 < R2 < 0.82). The calibrated and validated model was then used for scenario analysis at various climatic zones of Bangladesh. There are many climatic factors that have very much influence on rice production. Some factors have significant roles such as daily maximum and minimum temperature, rainfall, solar radiation and CO2 which were taken into consideration while model simulation. In order to assess the importance of climatic parameters on predicted rice yield, sensitivity analysis for T. aman (BR-22) was carried out by predicting rice yield in Madaripur district of Bangladesh using predicted climatic parameters for the years 2008 and 2070 by changing the value of one parameter, while all other parameters remain the same. Interestingly the yield of the predicted cultivar will be decreased from 3105 kg/ha in 2008 to 2007 kg/ha in 2070.

Ranjit K Jha (2020) [29] showed a good relationship between measured and predicted values for rice yield. The value of RMSEn for yield was 2.73%, which shows minimal deviation between the simulated and measured value of grain yield in Bihar, India. The d-index between observed and simulated values for grain yield was 0.62 which reveal a good agreement for yield, and excellent agreement for rice yield. The ME for prediction of yield was calculated 0.75, which shows the high accuracy of the CERES-Rice model to use for the decision-making process. He also demonstrated the effect of water stress condition on yield during different growth phases of Rajendra Mahsuri rice, showing that the average decrease in yield was estimated to be 24% during the vegetative phase. Kumar *et al.* (2014) [30] also informed that due to increased spikelet sterility because of water stress during reproductive phase results in a reduction in grain yield.

Kropff *et al.* (1994) [31] reported that ORYZA1, CERES-Rice, SIMRIW, and TRYM overestimated yields in the wet season at IRRI and, with the exception of ORYZA1, predicted LAI inaccurately in the dry and wet season at IRRI, and at Kyoto, Japan and Yanco, Australia. Mall and Aggarwal (2002) [32], however, concluded that both CERES-Rice and ORYZA1N predicted grain yields satisfactorily (within ±15%), especially for yields above 4 t/ha, with RMSE of 0.7 and 0.6 t/ha, respectively. Both models predicted grain number fairly accurately over the range 15,000–32,000 grains/m2, with ORYZA1N performing better than CERES-Rice at lower, but the latter performing better at higher, yield levels. Both models were unable to adequately simulate growth and yield under N and water deficit stresses.

Phenology

Ravikant Chandrvavanshi *et al.* (2019) [27] used Ceres-rice model of DSSAT v 4.5 in Madhya Pradesh region of India. He concluded that the model performed well in validation of phenology, Validation results showed that model predicted number of days to flowering with the RMSE values of 0.98. Four days difference was recorded between observed and simulated days to flowering in different varieties. The model simulated number of days from planting to physiological maturity with a RMSE value of 0.65. Maximum LAI was simulated with RMSE of 0.38 for this cultivar khandagiri. Another study also showed similar pattern of the response in Pusa Basmati-1 when simulated with CERES-Rice model the anthesis with RMSE 1.53, maturity with RMSE 0.79, maximum LAI with RMSE 2.35, and Grain yield with RMSE 0.

Jha *et al.* (2020) [29] showed that phenological day's prediction in total crop duration was less than 5%, supporting the use of CERES-Rice model of DSSAT v 4.6 for prediction of management practices in Bihar. The d-index values between observed and simulated values for PI, AD, and PM was 0.92, 0.91, and 0.81, respectively, which reveal high accuracy and good agreement for rice phenology. It can be seen from this study that large amount of rainfall was received during maturity phase of that year, but when the researchers imposed the water stress condition at that phase in the simulation, the yield decreased. The water stress during maturity stage affects the grain size and 1000-grain weight; consequently, it decreases the rice yield (Akram *et al.* 2013) [33]. The significant reduction during reproductive phase among all the three rice growth phases shows that the reproductive phase is a major rice growth period where the plant needs more water and scarcity of that will adversely affect the rice production.

In sub-tropical northern Bangladesh (Timsina *et al*., 1998) [34], suggested very good fit for anthesis and maturity dates of cultivar BR11 and BR14, with normalised RMSE of 5% and 4%, and D-index of 0.98 and 0.96, respectively.

The CERES-Rice model predicted the phenological events of anthesis and maturity in rice accurately with low RMSE (0.93% and 1.93% respectively) and high d-index values of 0.98 and 0.94. this clearly shows a high accuracy model prediction in the experimental site was located in the Southern Telangana Agro climatic zone of Andhra Pradesh, India (Kadiyala *et al*., 2014) [35].

Table 3: Results of evaluation for CERES-RICE for rice phenology and grain yield as published by various authors

Source	Parameter	Rmse (% or T/ha or kg/ha)	Nrmse (%)	D-Index	PE (percentage error)
	Grain yield				
Sanadyaanurag (2019) [16]		335.31 kg/ha (NDR-359)	0.05		2.36
		643.76 kg/ha (NDR-97)	0.08		4.84
		267.59 kg/ha(SARJU-52)	4.41		3.23
Saythong Vilayvong (2014) [23]		175 kg/ha (TDK8)	4.67		
Saythong Vilayvong (2014) [23]		84 kg/ha (TDK11)	2.67		
KaushikSar (2017) [24]		266.72 kg/ha			1.46
M. Ray (2018) [20]		0.817 T/ha	14.94		
Ravikant Chandrvavanshi (2019) [27]		0.35%			
NT Son (2016) [28]		11.7%			
Hasan (BR22) [17]		26.02% (Rajshahi)			
		9.90% (Barishal)			
Ranjit K Jha(2020) [29]			2.73	0.62	
Kadiyala (2014) [35]		0.57T/ha	10.30	0.97	
	Anthesis Days (AD)				

Ranjit K Jha (2020) [29]			1.06	0.91	
Ravikant Chandrvavanshi (2019) [27]		0.98%			
Kadiyala (2015) [35]		0.93%	1.00	0.98	
Timsina *et al*. (1998) [34]		4.09%	5.00	0.98	
	Physiological Maturity Days (PM)				
Kadiyala (2015) [35]		1.93%	1.00	0.94	
RavikantChandrvavanshi (2019) [27]		0.65%			
Ranjit K Jha (2020) [29]			1.01	0.81	
Timsina *et al*. (1998) [34]		5.00%	4.00	0.96	

Conclusion

The variable performance of the models is probably due to a combination of deficiencies in model inputs, experimental observations, inclusion of non-modelled factors (such as disease, lodging, pests, storms) in model validation, and insufficient capture of model processes. Possible input deficiencies include insufficient data for derivation of robust genetic coefficients, lack of data on initial soil mineral N and water, and lack of proper soil characterisation (especially hydraulic properties). Few of the above reports of model evaluation state how these inputs were derived or how genetic coefficients were determined.

The variable performance of the models, and in particular of CERES-Rice, highlights the importance of proper calibration and evaluation in the environment of interest before applying them to evaluate management options. This is especially important in the absence of information regarding variety, location, year of study of model processes as reflected in the models' relative inabilities to predict a range of crop, soil and water parameters.

Better evidence of the ability of the models to simulate a range of important parameters other than yield, such as time course of biomass production, leaf area development, N uptake, soil water and mineral N dynamics, and components of the water and N balances, is also highly desirable to demonstrate the robustness of model processes and to increase the confidence in the use of model. The results of the few studies where some of these components have been determined are, however, generally encouraging.

In conclusion, while it seems that CERES-Rice has performed reasonably well in different regions of Asia, evaluations and applications addressing resource use efficiency and sustainability issues are lacking. Better data from field experiments designed to address these issues, and further model evaluations, improvements and applications, are needed to address the issues of yield stagnation or decline and increasing yield gaps, and finally to contribute to solving the resource and food security problems in different regions of the Asia.

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