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Research Paper

Integration of CERES-rice crop simulation model and MODIS LAI (MOD15A2) for rice yield estimation

K. AJITH[1]*, V. GEETHALAKSHMI[2], K. BHUVANESWAR1[2], P. SHAJEESH JAN[3], ANU SUSAN SAM[1] and AJAI P. KRISHNA[4]

[1]*Regional Agricultural Research Station, Kerala Agricultural University, Kumarakom, Kerala, India*
[2]*Department of Agronomy, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India*
[3]*Regional Agricultural Research Station, Kerala Agricultural University, Ambalavayal, Kerala, India*
[4]*Government College, Mahatma Gandhi University, Kattappana, Kerala, India*
**Corresponding author Email id: ajith.k@kau.in*

ABSTRACT

In this study assimilation of MODIS LAI (MOD15A2) into DSSAT-CERES-rice crop simulation model was used to develop advance yield estimates of rice crop during pre-harvest stage (F3) in Palakkad district of Kerala during Mundakan (September- January) season 2022-23 and 2023-24. The free parameters identified as inputs for the DSSAT-CERES-rice crop simulation model were adjusted and optimized sequentially during assimilation process until a minimum value of cost function is reached. This helped to minimize the deviation between MODIS- LAI and model generated LAI and the yield predicted by the model consequently is taken as the predicted yield. The average predicted yield during 2022-23 and 2023-24 was 5590 kgha^{-1} and 5124 kgha^{-1} respectively. The yield prediction by simulation model integrated with remote sensing products had higher accuracy than using simulation model alone during both the years with number of panchayats having the BIAS above ± 10 per cent reduced from 20 to 12 and 23 to 11 during 2022-23 and 2023-24 respectively. The findings clearly show that incorporating satellite data into crop simulation models can produce more accurate rice production forecasts than crop simulation techniques used alone.

Keywords: DSSAT, CERES-rice, MODIS LAI, Remote sensing, Rice, Yield prediction

Rice is the staple food for more than half of the world's population and is considered as the most important crop in poor developing countries. Millions of small-scale farmers and landless labourers maintain their livelihood by rice cultivation. It is grown in more than hundred countries covering an area of 167.13 million hectare. Asia contributes 90.7 % of the world's production and India stands second (140.92 million tonnes), next to China (193.13 million tonnes) according to the FAOSTAT (2018). Due to a significant increase in India's food consumption and the worsening impact of climate change, problems to food security and local food inequality will continue to grow over time in India and thus causing challenges in achieving Sustainable Development Goal 2 (SDG-2) (Grebmer *et al.,* 2022).

Weather based models have been used to provide dependable forecast of crop yield well in advance and it envisages adoption of timely and suitable management strategies to protect the crops. Since crop simulation model approach is easier, quicker, and less expensive than actual experimentation, it is typically used to study how climate variability affects crop productivity (Mishra *et al.,* 2020). The crop simulation models are being used for various application including the yield forecasting, which is an important information in policy planning (Singh, 2023).

Integration of crop simulation models and remote sensing is one out of the prime approaches for forecast of crop yields at regional level (Yang *et al.,* 2010; Chaudhari *et al.,* 2010; Shanmugapriya *et al.,* 2022). The ready availability of remote sensing products at definite intervals and it's potential to reflect plant features with high precision could play a key role in establishing an efficient method of estimating preharvest yield. (Noureldin *et al.,* 2013). Patel *et al.,* (2023) reported that satellite-derived remote sensing data is the

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best option for predicting agricultural yield due to its multispectral and repeating nature. The majority of these studies have shown that assimilating remotely sensed data into crop growth models is a viable method for accurately estimating regional agricultural yields at wide spatial scales (Ma *et al.,* 2013). Gumma *et al.,* (2022) used the technique of re-parametrization of crop simulation models based on the several iterations using remote sensing leaf area index (LAI) obtained from Sentinel-2 time series data for yield estimation in Indian states of Telangana, Andra Pradesh and Odisha. Kuwata *et al.,* (2010) in his study assimilated satellite derived (MODIS) LAI and PAR into DSSAT-CERES crop simulation model and estimated wheat yield in advance. According to a study by Setiyono *et al.,* (2018), integrating MODIS and SAR data into a crop growth model can produce yield estimates that accurately reflect the spatial distribution of yield in the study area. Thus, integration of MODIS Leaf Area Index (LAI) data with the DSSAT model will be a potent tool for enhancing the precision of rice yield estimation. With this method, growth stages can be dynamically calibrated and validated making use of real time satellite satellite-derived data. Better geographical and temporal representation of crop conditions is made possible by this synergy, which makes the method especially helpful for regional agricultural monitoring and decision-making in rice-growing regions.

Therefore, efforts have been made to update one state variable ie. LAI in the CERES-Rice crop simulation model using MODIS LAI time series data in order to integrate remote sensing data with the model to forecast rice yield at different time scales and it's intercomparison with actual production estimates from the field to verify crop simulation model results.

MATERIALS AND METHODS

Study area

The study focuses on Palakkad one of largest rice-producing district in Kerala where paddy production is concentrated in the blocks of Chittur, Alathur, Kuzhalmannam, Kollengode, Nenmara, and Palakkad. Many farmers in this region are engaged in rice cultivation in relatively big plots of 5 to 10 acres, which is significantly larger than the average size of paddy fields in Kerala generally and hence, the study focused on these blocks in Palakkad district (Fig. 1).

LAI measurement and MODIS LAI retrieval

In this study, the leaf area index (LAI) was measured from 31 rice fields identified from 31 panchayats under study in Palakkad district by the method suggested by Yoshida *et al.,* (1976). The MODIS LAI product (MOD15A2) composited every 8 days at 0.5 km resolution on a sinusoidal grid was downloaded. A total of 16 scenes were accessed from September 2022 to January 2023 and September 2023 to January 2024 which coincides with the Mundakan (September to January) rice season of Palakkad. MOD15A2 data product was obtained in sinusoidal projection and was converted to Universal Transverse Mercator (UTM) co-ordinate system using HDF-EOS to GeoTIFF Conversion Tool (HEG) Tool. The imageries originally obtained in HDF format were converted to image raster files using ArcGIS. The Digital Number (DN) of each pixel is multiplied with a constant (0.1) with 'Raster calculator' provision in ArcGIS. Then the LAI was retrieved using 'Extract multivalues to points' facility in ArcGIS for 31 rice fields in Palakkad district. The peak MODIS-LAI values were validated using LAI data collected directly from the above 31 sites and a linear relationship was established between the two observations.

A fish net was developed with 0.5 km x 0.5 km grid size and rice pixels were classified from the image based on rice area. Pixels having more than 50% area covered with rice were considered as rice pixels. Then the LAI for each rice pixel was retrieved and the values were averaged panchayat wise. The time series LAI values for each panchayat were calculated using the relationship developed between MODIS-LAI and ground truth values.

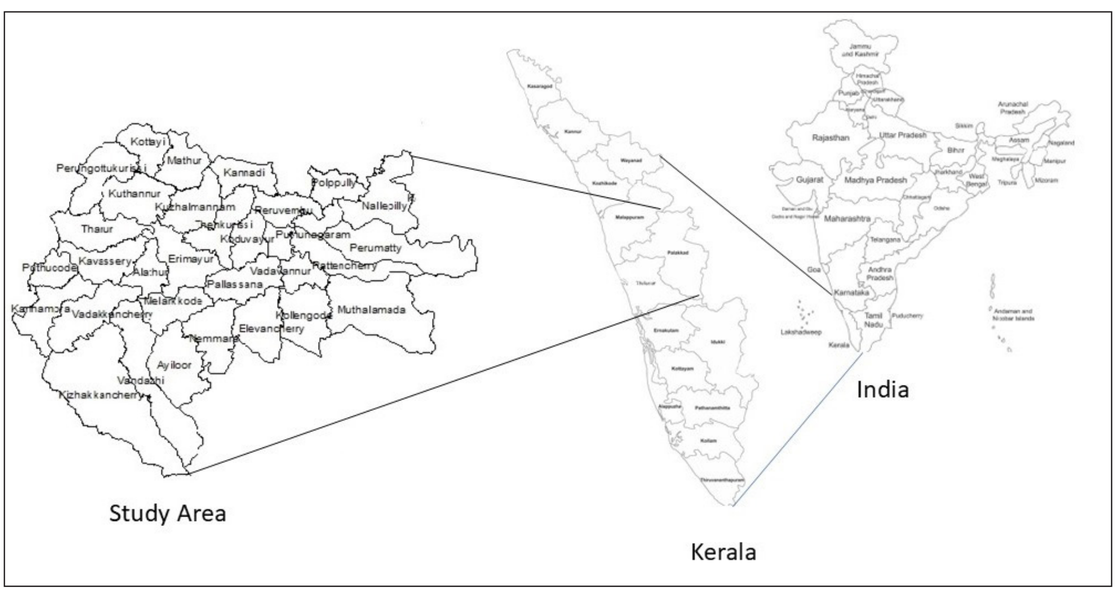

Fig 1: Location map of study area

Assimilation of MODIS LAI in DSSAT-CERES–Rice model

Input data, such as cultivar information, soil characteristics, crop management data and weather information, already prepared were used for DSSAT–CERES–Rice model. Using these input data, simulations were carried out with DSSAT and state variables (eg. LAI) were generated. The simulated LAI values were compared with MODIS derived LAI products, during corresponding crop stages to minimize the residual values between them by modifying the input parameters. In order to arrive this a set of free input parameters were identified and their range is presented in Table 1.

A cost function was constructed depending on the departure of the simulated LAI from MODIS-LAI using the optimization algorithm POWELL suggested by Press *et al.,* (1992). A minimum value of this cost function denotes a minimum deviation between LAI measured (LAI_M) and LAI simulated (LAI_S). This technique helped to skillfully lessen computation time to arrive at a minimum residual value. The cost function 'J' is given below.

$$J = \sum_{i=1}^{m} abs\ [(LAI)_S(t_i) - (LAI)_M(t_i)]\ /\ (LAI)_M(t_i)$$

where, LAI_M (t_i) and LAI_S (t_i) are measured LAI and simulated LAI at time ti, respectively.

Various iterations were carried out to obtain a minimum value of the cost function with optimum input parameters. Simulations were carried out with the optimized group of input parameters; to update the crop yield forecast values and the results of iterations gave minimum value for cost function was taken as the forecasted yield. The results of yield estimation were compared with the crop cutting experiments carried out at various locations in the district. The per cent BIAS (PBIAS) was worked out to assess the accuracy of prediction using the following formula.

$$PBIAS\ \% = \frac{Predicted\ yield - Actual\ Yield}{Actual\ Yield}\ X\ 100$$

RESULTS AND DISCUSSION

MODIS-LAI values at 500 m resolution were retrieved from MOD15A2 -8day time series product for 31 points in different panchayats of Palakkad district and was compared with LAI values observed from corresponding rice fields. A linear relationship was set between MODIS-LAI and the observed values ie. y=1.168 + 0.634x, where x is MODIS-LAI and y is the observed LAI. MODIS-LAI values were obtained at 8-day interval for each rice pixel which were already delineated from Sentinel-2 images. This was made panchayat wise by superimposing the panchayat boundaries over the images. The values thus obtained for each panchayat were corrected using the relationship already developed. A relationship developed between derived MODIS-LAI and Observed LAI during the crop season for one of the locations in Alathur Block is presented in Fig. 2.

DSSAT-CERES–Rice crop simulation model was run for rice variety Uma during 2022-23 and 2023-24 with planting date (date of transplanting), row spacing (cm), plant population, and nitrogen amount as free input parameters. A cost function was

Table 1 : Free input parameters and their range used for iterations in DSSAT–CERES-Rice model

Sr. No.	Free input parameters	Range
1.	Planting date (Julian day)	268-278
2.	Plant population (plants m^{-2})	55-65
3.	Row spacing (cm)	20-23
3.	Nitrogen amount (kg ha^{-1})	140- 160

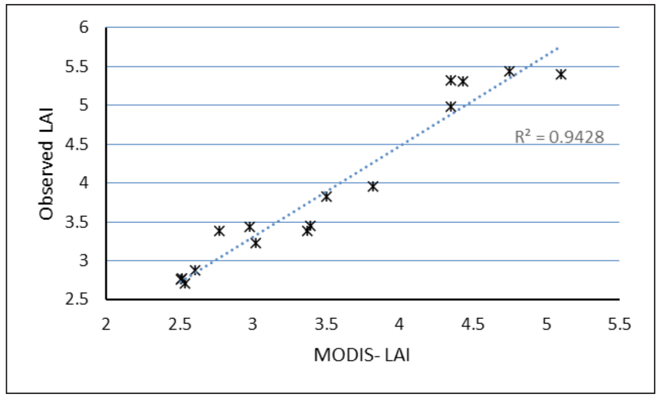

Fig. 2 : Relationship between MODIS-LAI and Observed LAI during 2022-23 in Alathur Block of Palakakd

created for each iteration depending on residuals between simulated LAI and MODIS-LAI. A gradual change was made for the free input parameters and iterations were continued till the cost function reached a minimum value. A representative optimization process for Kuzhalmannam block during 2022-23 is presented in Table 2. The last but one row represents the consequent optimized values for that block when the cost function reached the least value. Here the simulated LAI is influenced by the values of free variables given as input to the crop simulation model. For Kuzhalmannam panchayat planting at Julian day 270 with a plant population of 58, row spacing of 23 cm and Nitrogen amount of 150 kg ha^{-1} gave the least value for cost function (0.932). When the iterations were continued further by preponing the planting date there was an increase in the cost function. Thus the iterations were stopped with the minimum value of cost function.

The results obtained by running DSSAT-CERES-Rice model alone and CSM integrated with MODIS- LAI for the two years under study is presented in Table 3. During 2022-23 the highest yield (6848 kg ha^{-1}) was predicted for Alathur followed by Kannambra panchayat (6720 kg ha^{-1}). Estimated yield ranged between 4230 kg ha^{-1} to 6848 kg ha^{-1} with an average of 5453 kg ha^{-1}. Nalleppilly panchayat recorded least yield 4230 kg ha^{-1}. Yield forecast during 2023-24 revealed that the maximum yield (6350 kg ha^{-1}) is expected at Alathur panchayat followed by Kavasseri panchayat (6265kg ha^{-1}). The least yield (3163 kg ha^{-1}) was estimated for Thenkurisi panchayat and the average yield for the year was 4932 kg ha^{-1}

Several iterations were carried out using DSSAT CERES-Rice crop simulation model (CSM) with adjustment of free input parameters for rice variety Uma during pre-harvest stage (F3). The iterations were continued for various panchayats till the cost

Table 2: Adjustment of free input parameters (LAI) in the optimization process for rice variety Uma in Kuzhalmannam panchayat during 2022-23

Planting date in Julian day	Plant population	Row spacing (cm)	Nitrogen in kg ha^{-1}	Julian days									Cost function
				289	297	305	313	321	329	337	345	353	
				MODIS- LAI									
				1.76	2.31	2.45	2.64	3.95	4.21	3.85	3.76	3.52	
				Simulated LAI									
278	65	20.0	150	0.96	1.56	2.28	2.69	3.30	3.43	2.84	2.84	3.32	2.571
278	64	20.0	150	0.98	1.63	2.42	2.92	3.39	3.45	3.01	2.59	3.35	2.488
277	64	20.0	150	0.85	1.53	2.38	2.96	3.51	3.63	3.28	3.42	3.62	2.304
276	60	20.0	150	1.12	1.82	2.25	2.65	3.45	3.58	3.39	3.58	2.08	2.132
275	62	20.0	150	1.10	2.01	2.32	2.34	3.44	3.31	3.20	3.30	2.68	2.009
274	61	20.0	150	1.65	1.79	2.53	3.11	3.43	3.74	3.39	3.01	2.23	1.781
273	60	23.0	150	1.35	1.76	2.49	3.54	3.76	3.92	3.45	3.36	2.89	1.464
270	58	23.0	150	1.43	2.46	2.38	2.72	3.63	3.97	3.74	3.23	2.84	0.932
268	55	23.0	150	1.54	2.26	2.79	3.31	3.62	3.31	2.72	2.26	2.21	2.524

Table 3: Actual yield (kg ha^{-1}) and predicted yield (kg ha^{-1}) by CERES- rice model (CSM) alone and CSM integrated with MODIS-LAI during Mundakan 2022-23 and 2023-24

Sr. No.	Location	Actual yield	Predicted yield by		Actual yield	Predicted yield by	
			CSM	CSM with MODIS-LAI		CSM	CSM with MODIS-LAI
		2022-23			2023-24		
1	Alathur I	6500	6848	6645	6230	6350	6270
2	Kannambra	6500	6720	6320	5800	5405	5625
3	Kavasseri	5200	5600	5438	6015	6265	6255
4	Kizhakkenchery	5666	4588	4965	6250	6035	6205
5	Pudukkode	4900	5465	5358	4875	5705	5225
6	Tarur	5900	4380	5948	6175	4511	5425
7	Vadakkenchery	4743	5745	5586	5732	5075	5200
8	Erimayur	4250	5340	5220	5375	4789	4910
9	Ayilur	5250	4720	4810	5500	4311	4475
10	Melarkode	5250	5780	5740	5875	4165	4753
11	Vandazy	4250	5145	4848	4125	5375	4393
12	Nenmara	6400	4715	5425	5375	6074	5135
13	Elevenchery	6135	5224	5586	5375	4155	4225
14	Pallassana	5900	5250	6186	5745	4371	4555
15	Kollengode	5600	5900	5830	5450	4495	4705
16	Pattanchery	5400	6485	5850	5530	4693	5601
17	Muthalamada	5000	6295	6150	6125	5380	5290
18	Vadavannur	6000	5150	5120	5415	4335	4410
19	Koduvayur	5800	4648	5165	5825	5305	5610
20	Pudunagaram	6120	5246	5818	5975	4605	5480
21	Peruvemb	5800	5542	5884	5815	5321	5480
22	Perumatty	5250	5128	4980	4875	5213	5113
23	Nallepilly	3750	4230	4626	4125	5354	4983
24	Polpully	6250	4520	5350	5625	5245	5552
25	Chittur	5950	6240	6220	5415	4695	5025
26	Thenkurissi	5450	6020	5925	4055	3163	4370
27	Kuthanoor	5960	5729	5800	5825	4245	4713
28	Kuzhalmannam	5250	5588	5008	5695	4605	5210
29	Peringottukurissi	6050	5840	6230	5615	4245	5093
30	Mathur	5625	5940	5988	5200	4035	4805
31	Kottayi	6250	5020	5286	4075	5383	4770
	Mean	5560	5453	5590	5454	4932	5124

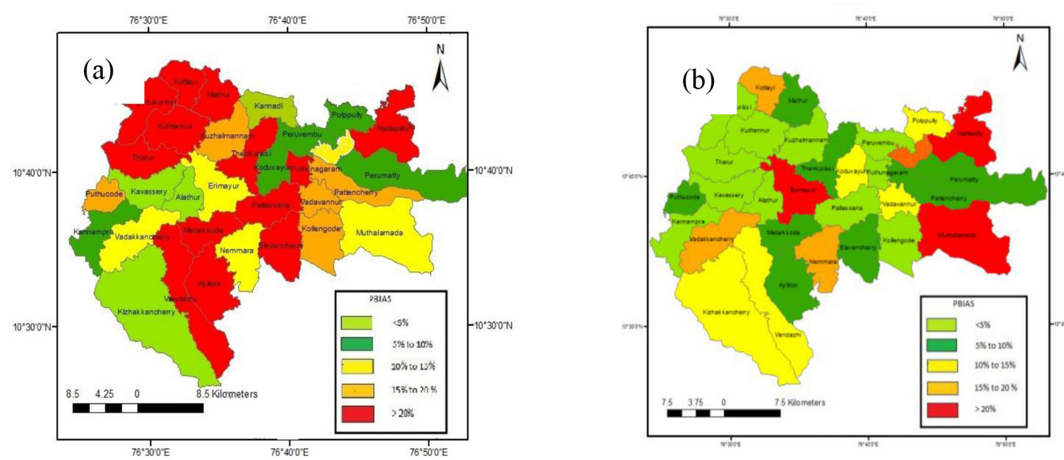

Fig. 3: Verification of yield forecast for rice by (a) crop simulation model alone and (b) crop simulation model integrated with MODIS LAI during 2022-23

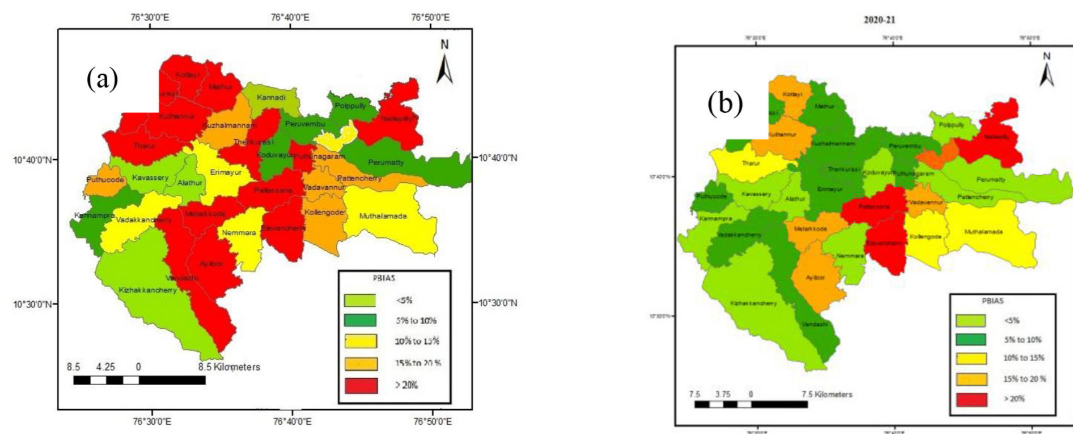

Fig. 4: Verification of yield forecast for rice by (a) crop simulation model alone and (b) crop simulation model integrated with MODIS LAI during 2023-24

function in relation to simulated LAI and MODIS-LAI reached a minimum value. Like F3 prediction obtained by running DSSAT-CERES-Rice crop simulation model alone, the trend in productivity among various panchayats remained the same during both the years under study when remote sensing products were integrated with crop simulation model. Alathur, Kannambra and Kavasseri panchayts recorded high productivity compared to other panchayats during both years. The average productivity of blocks during 2022-23 was higher (5590 kg ha^{-1}) compared to 2023-24 (5124 kg ha^{-1}). Since modification of LAI was done in CERES-rice crop simulation model with reference to MODIS-LAI the reason for higher yield during 2022-23 may be due to the higher MODIS-LAI values obtained during the year.

Inge *et al.,* (2013), opined that LAI is strongly dependent on the prevailing site conditions and the management practices. Alathur, Kannambra and Kavasseri panchayats had higher values of LAI_{max} (Maximum LAI value) during the year compared to 2023-24. Hashimoto *et al.,* (2023) suggested that the LAI could be used for monitoring trends in yield components in rice. According to Aschonitis *et al.,* (2014) the correlation between rice grain yield and LAI_{max} was significantly high. So higher rice yields reported during 2022-23 may be attributed to the higher MODIS-LAI values observed during the year. The low yields predicted during 2023-24 may be as a result of low LAI observed due to insufficient water availability, and adverse weather condition as rainfall and irrigation water was scarce during the year.

Verification of rice yield prediction

The absolute values of PBIAS of yield predicted for 31panchayats by crop simulation model alone and integration of crop simulation model and remote sensing products are presented in Fig 3 & 4.

From these two figures it is clear that yield prediction by integration of remote sensing products into crop simulation models gave better accuracy in majority of the panchayats as the PBIAS values of this method is low. When the overall accuracy of the deviation in yield prediction was assessed yield prediction by simulation model integrated with remote sensing products had higher accuracy than using simulation model alone during both the years.

The deviation ranged from -15.42 to 23.36 and -21.39 to 20.8 per cent during 2022-23 and 2023-24 respectively in integration method. During 2022-23, 20 panchayats had deviation above ± 10 per cent in simulation model method while only 12 panchayats had deviation above ± 10 per cent in integration method (Fig 3). During 2023-24 in crop simulation model method 23 panchayats showed deviation more than ±10 percent while in integration method the number of panchayats with PBIAS values above ±10 percent decreased to 11 panchayats (Fig 4). The study emphasized that using the DSSAT-CERES-RICE crop simulation model in conjunction with MODIS-LAI improved yield prediction accuracy for the Uma rice variety compared to using the crop simulation model alone. Doraiswamy *et al.,* (2005) and Fang *et al.,* (2008) assimilated MODIS-LAI in crop simulation models for yield prediction and obtained promising results. Pazhanivelan *et al.,* (2022) predicted rice yields for Cauvery delta region of Tamil Nadu by integrating synthetic-aperture radar (SAR) based LAI values with DSSAT crop simulation model and attained an accuracy of more than 80%. All attempts were aimed at minimizing the deviation between simulated LAI and remotely sensed LAI by arriving at optimum set of input parameters.

CONCLUSION

Though crop simulation models can estimate rice yields with better precision, this study revealed that by integrating remote sensing products with crop simulation models, rice yield estimates could be obtained with better accuracy.

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Data availability: All data are available with authors

Authors contribution: K. Ajith: Investigation, Analysis, Visualization, drafting original manuscript; V. Geethalakshmi: Conceptualization, Methodology, Supervision, Review, editing; K. Bhuvaneswari: Methodology, Analysis, Interpretation, editing; P. Shajeesh Jan: Data collection, Analysis, Review, editing; Anu Susan Sam: Interpretation, Review, editing; Ajai P. Krishna: Data collection, Analysis, Review, Editing

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