PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol x(x): xx–xx
https://doi.org/10.14719/pst.7442

HORIZON
e-Publishing Group
HePG

RESEARCH ARTICLE

Remote sensing and simulation: A novel approach to rice yield estimation in the Cauvery delta

S Manikandan [1], S Pazhanivelan[2*], K P Ragunath[2], R Kumaraperumal[1], A P Sivamurugan[2], M Raju[3], N S Sudarmanian[2] & S Satheesh[1]

[1]Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore 641 003, India

[2]Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore 641 003, India

[3]Cotton Research Station, Tamil Nadu Agricultural University, Srivilliputhur, Virudhunagar 626 125, India

*Email: pazhanivelans@gmail.com

OPEN ACCESS

ARTICLE HISTORY
Received: 26 January 2025
Accepted: 03 March 2025
Available online
Version 1.0 : 16 March 2025

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

CITE THIS ARTICLE
Manikandan S, Pazhanivelan S, Ragunath KP, Kumaraperumal R, Sivamurugan AP, Raju M, Sudarmanian NS, Satheesh S. Remote sensing and simulation: A novel approach to rice yield estimation in the Cauvery delta. Plant Science Today (Early Access). https:/doi.org/10.14719/pst.7442

Abstract

This study explores the use of the C-band Synthetic Aperture Radar (SAR) dataset from Sentinel-1A for crop area delineation and its integration with the DSSAT crop simulation model for spatial yield estimation for rice crop in the Cauvery Delta region of Tamil Nadu, India. With the global population increasing at a rapid rate, precision agriculture is critical for addressing food security challenges. The near-real-time monitoring capabilities of remote sensing techniques, especially microwave datasets made all season crop monitoring possible. The DSSAT model has demonstrated its capability to simulate yields under varying climatic and management scenarios. This approach offers timely and scalable solutions for monitoring crop health and forecasting yields, which are critical for mitigating the impact of climate change on agriculture. The estimated rice area using the Parameterized classification technique was 118104 ha in the Thanjavur district and 102138 ha in the Thiruvarur district, with an accuracy of 86 %. Upon validation against crop-cutting experiments, the DSSAT approach achieved average RMSE values of 440 kg ha^{-1} and 450 kg ha^{-1}, along with yield agreements of 90 % and 89 % in Thanjavur and Thiruvarur respectively. These quantitative results highlight the enhanced precision of the integrated remote sensing and simulation framework for rice yield estimation, offering a robust tool for precision agriculture and improved decision-making under variable climatic conditions.

Keywords

crop monitoring; food security; remote sensing; rice; yield

Introduction

Global population estimates projects that the ten billion mark will be surpassed by the 2080s, followed by a decline in the 2100s. India's population is expected to reach 1.7 billion by the end of the 2050s (1). Nearly 1 in 10 people globally faced hunger and 2.4 billion people experienced moderate to severe food insecurity in 2022 (2). Estimated food grain production over the past decade had an increase of about 687 lakh t (3). The food grain production during the period 2022-2023 surpassed the five-year average by 31 million t, with major food grains such as rice and wheat exceeded the five-year average by 12.8 and 5.7 % respectively (4). To address these issues, India has implemented policies like the National Food Security Act (NFSA) (5), Rashtriya Krishi Vikas Yojana (RKVY) - Remunerative Approaches for Agriculture and Allied sector Rejuvenation (RAFTAAR) (6) and the National Nutrition Mission (7), ensuring every individual gets proper nourishment.

Remote sensing has emerged as an asset for policymakers by providing near-real-time crop monitoring and yield forecasting. By providing critical insights, remote sensing enables informed decision-makers that significantly impact agricultural productivity, food security and sustainability. The integration of satellite datasets and advanced simulation models presents a more comprehensive approach to crop yield estimation, especially in the context of changing climatic conditions.

Spectral signatures derived from optical dataset show distinct patterns in the Near Infrared (NIR) and Shortwave Infrared (SWIR) regions, allowing for crops differentiation throughout the crop growth cycle (8). Dual-polarimetric SAR sensors provide high temporal and spatial resolutions with a large swath width (9). In SARsystem, the C-band was more effective at the early stages of crop and is highly sensitive to biomass, whereas the L-band is more effective in later growth stages (10). The Spectral Matching Technique (SMT) applied on NDVI derived from optical datasets improves cropping pattern analysis (11). Single and double cropping of rice can be distinguished through a combination of slope information and VH backscatter values (12).

Utilization of the linear regression model and bivariate model to spectral indices has proven effective in yield estimation for sugarcane (13, 14). Crop simulation models was found to be a valuable asset in the impact analysis of climate change on crop yields (15, 16). Additionally, drone technology, with its ability to capture high-resolution imagery, provides valuable insights into crop health and growth, enabling more precise yield predictions (17). Spectral indices derived from satellite and drones imagery have demonstrated effectiveness in terms of microscale yield estimation (18). Multiple regression models have been found to outperform linear regression models in pre-harvest crop yield prediction using spectral indices (19). The integration of spectral indices, climate data, field measurements and simulation models significantly enhance the accuracy, reliability and early estimation of crop yield (20-23).

In a climate-sensitive region like the Cauvery Delta, remote sensing provides extensive and timely data for continuous crop monitoring, while crop simulation models like DSSAT offer a detailed understanding of yield outcomes under varying environmental conditions. Together, they form a robust system that supports sustainable agriculture, improves food security and enables informed decision-making in the face of climate challenges.

Materials and Methods

Study area

The Thanjavur and Thiruvarur districts of the Cauvery delta region in Tamil Nadu, covering approximately 5773 km^2, were considered as the study areas for this research during the *Samba* 2023 season (Fig. 1). The geographical extent of the study area ranges from 11° 11' 5.3772" to 10° 8' 12.289 2" North latitude and 78° 46' 34.6656" to 79° 45' 48.456" East longitude. This region is popularly termed as “Granary of South India” due to the wealthy agricultural activities, particularly rice growing ability (24, 25).

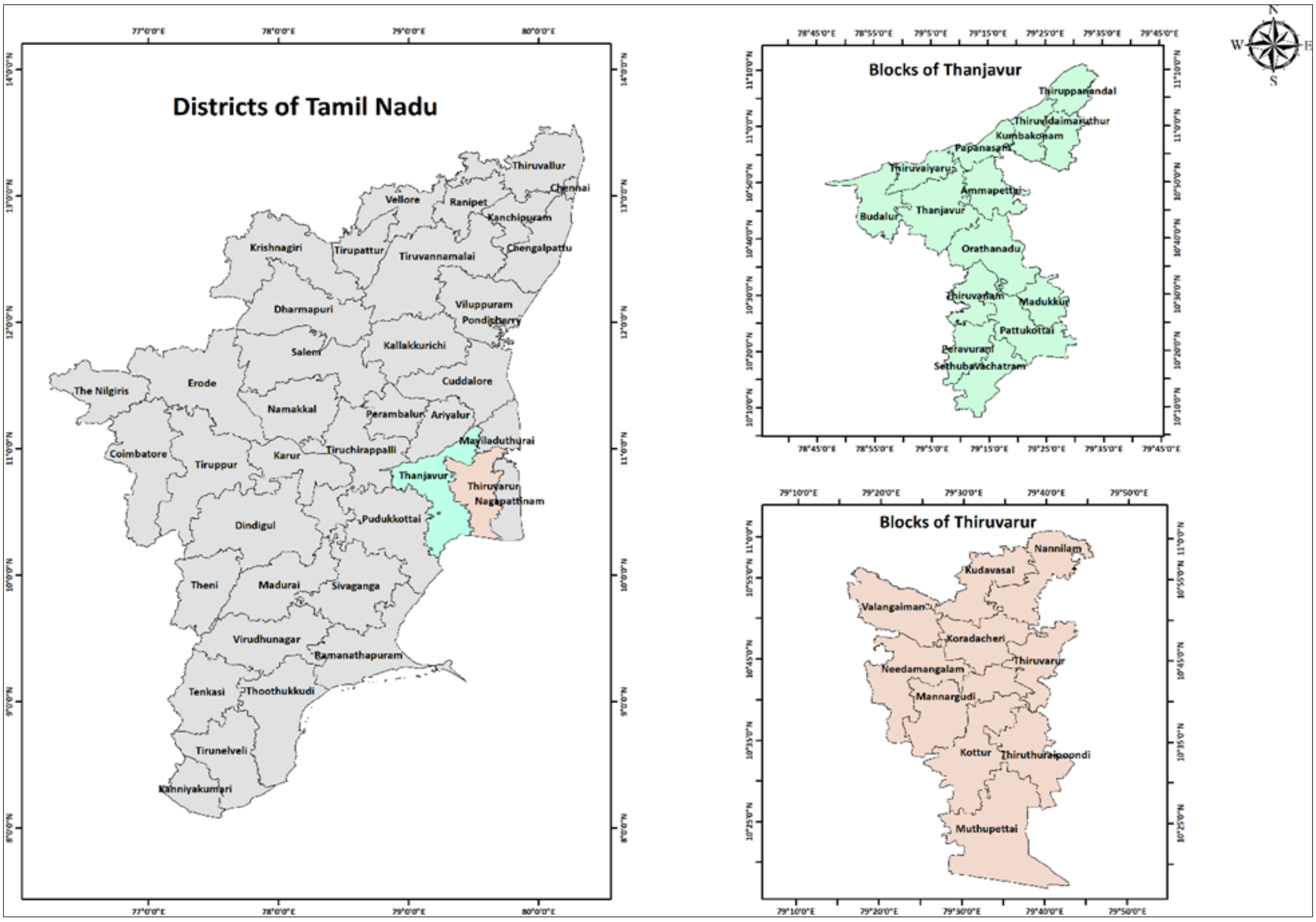

Fig. 1. Study area map.

Rice area estimation

For this study, rice crop areas were identified using data from the Sentinel-1A dataset, a C-band SAR Level 1 Ground Range Detected (GRD) dataset, acquired in Interferometric Wide Swath mode with dual VV and VH polarization. This dataset offers 20-m spatial resolution and a 12-day temporal resolution (26). With cloud-penetrative capability, dual polarization and adequate temporal resolution, Sentinel-1A SAR provides a more reliable and consistent dataset for rice monitoring in the climate-sensitive Cauvery Delta.

VV polarization, which measures the backscattering coefficient of vertically transmitted and received radar waves, is effective in differentiating crop types due to variations in canopy structure and moisture (27). Monitoring temporal changes in backscatter allows the estimation of variations in leaf area index and biomass, which serves as key indicators of crop health and potential yield (28).

Rice area estimation was performed using MAPscape-5.7 software for dataset preprocessing and classification. In MAPscape-5.7, classification parameters for crop area estimation were selected based on the temporal backscatter signatures of rice fields. Sentinel-1A VH polarization data played a crucial role, as rice exhibited a strong dynamic range, with mean backscatter values ranging from -24.46 dB at the start of the season (coinciding with agronomic flooding) to a peak of -13.72 dB during the tillering to flowering stages in the Samba season. These temporal variations were analyzed to develop rule-based classification models, where threshold values were set to differentiate rice from other land cover types.

The classification process also incorporated contextual information, such as field boundaries and temporal consistency, to enhance accuracy. Parameter selection was refined through iterative validation using reference datasets and expert knowledge of regional cropping patterns. The estimated rice area was subsequently used as a crop area mask for spatial yield estimation. The complete methodology for rice area estimation is illustrated in Fig. 2.

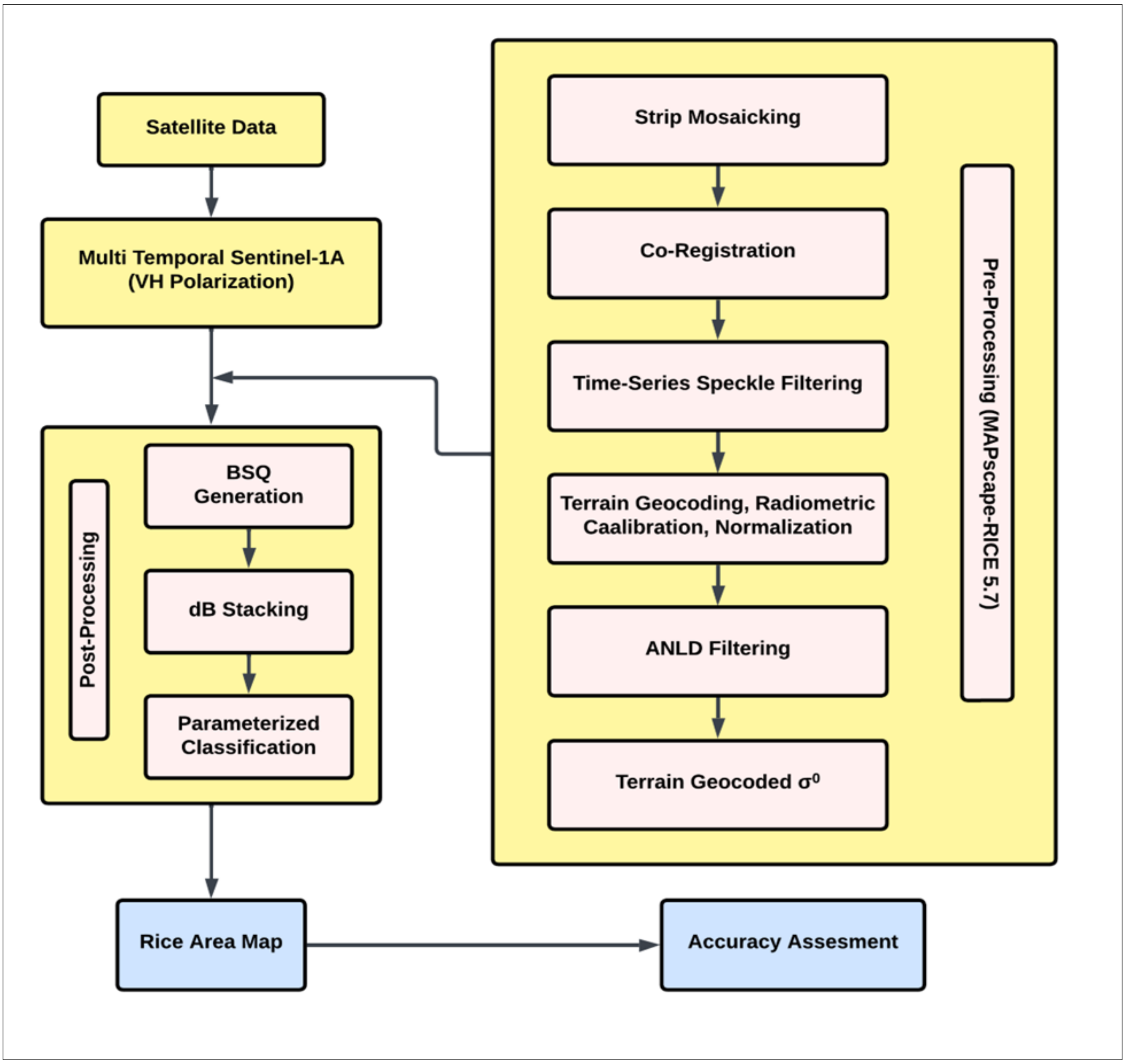

Fig. 2. Flow chart of rice area estimation.

Rice yield estimation

The Decision Support System for Agrotechnology Transfer (DSSAT) was initiated under the auspices of the International Benchmark Sites Network for Agrotechnology Transfer Project (IBSNAT) project. It is a powerful software tool that simulates plant growth, development and yield for over 42 crops, incorporating real-world factors like weather conditions, soil characteristics and management practices (29, 30).

Soil data

Physico-chemical soil data obtained from the Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, was processed into soil input files for integration into the DSSAT model.

Weather data

Meteorological data, including minimum and maximum temperature, precipitation, solar radiation, relative humidity and wind speed, were sourced from NASA POWER, a component of NASA's Earth Science Research Program. The data, available in CSV format, was extracted from the NASA POWER data portal at a spatial resolution of approximately 0.5 x 0.625 degrees, covering the period from August 2023 to January 2024. This dataset was obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project, which is funded through the NASA Earth Science/Applied Science Program (31).

Genetic coefficient

Genetic coefficients, including P1 (photoperiod insensitivity period), P20 (critical photoperiod), P2R (photoperiod sensitivity coefficient), P5 (grain filling period), G1 (potential spikelet number coefficient), G2 (ideal grain weight), G3 (tillering coefficient) and G4 (temperature tolerance coefficient), were determined for rice varieties CR1009, ADT(R) 45 and BPT 5204 using GENCALCULATOR. These coefficients, relevant to the study area, were used in subsequent analyses (32).

Crop management

DSSAT XBuild was utilized to generate comprehensive crop management scenarios. The experimental conditions, including soil and field properties, planting geometry, irrigation and fertilization regimes, organic residue and chemical inputs, tillage practices, environmental modifications, harvest procedures and simulation control settings, were input into the DSSAT model.The methodology for DSSAT - based yield estimation is illustrated in Fig. 3.

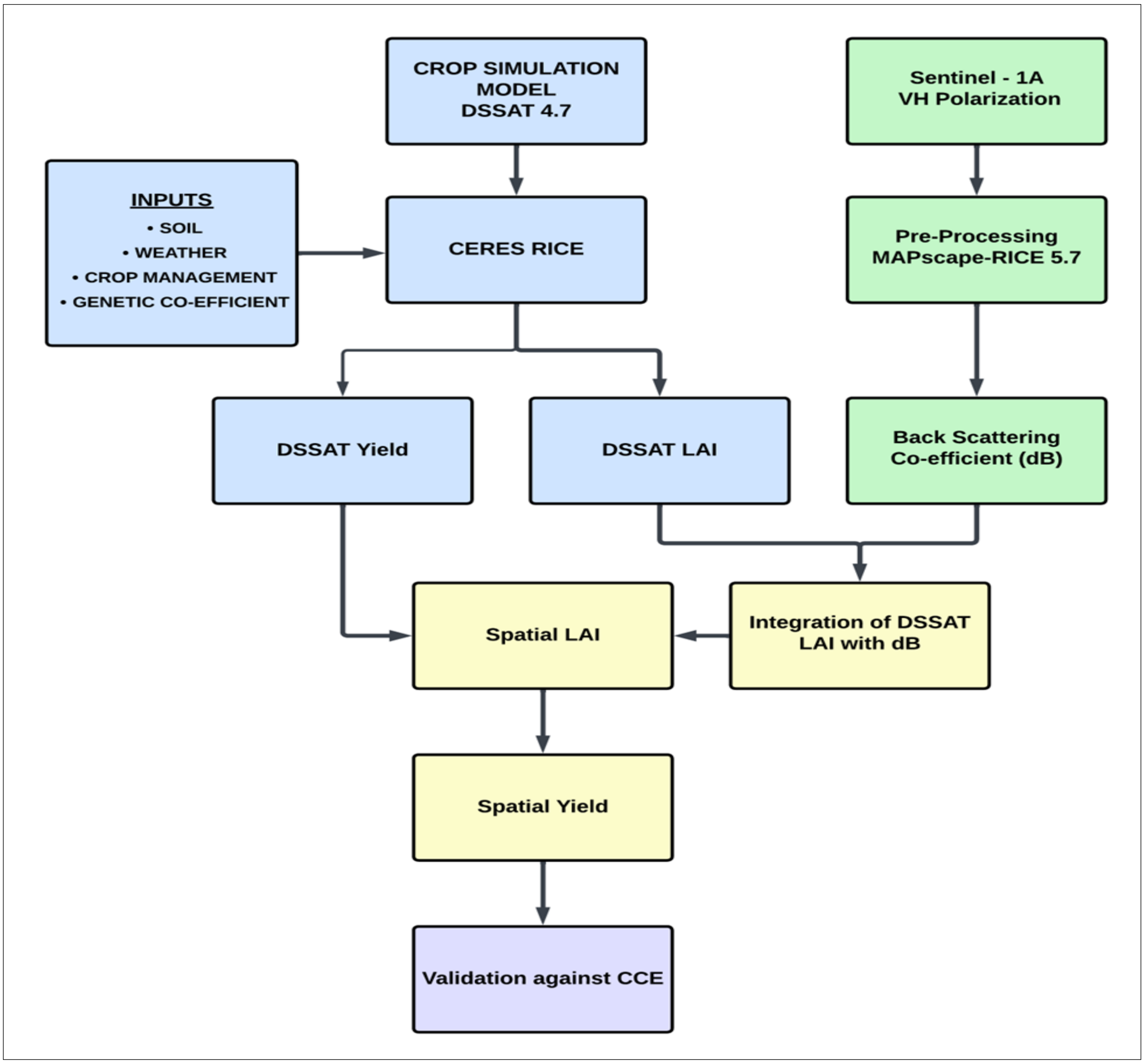

Fig. 3. Flow chart of DSSAT model-based yield estimation.

Results

Rice area estimation

The estimated rice crop area, derived from the Sentinel-1 SAR dataset, was 118104 ha in Thanjavur district and 102138 ha in Thiruvarur district. Among the blocks in Thanjavur, Orathanadu recorded the highest rice cultivation area, covering 15656 ha, while in Thiruvarur district, Needamangalam had the highest area of 13377 ha. The block-wise distribution of rice is represented in Table 1.

Table 1. Block wise rice area of study area

Blocks of Thanjavur	Area in Hectares	Blocks of Thiruvarur	Area in Hectares
Ammapettai	14094	Koradacheri	7972
Budalur	8837	Kottur	13184
Kumbakonam	6982	Kudavasal	9144
Madukkur	3908	Mannargudi	11477
Orathanadu	15656	Muthupettai	9366
Papanasam	3890	Nannilam	9745
Pattukottai	5857	Needamangalam	13377
Peravurani	5927	Thiruthuraipoondi	10479
Sethubavachatram	7157	Thiruvarur	5227
Thanjavur	13140	Valangaiman	12167
Thiruppanandal	8942		
Thiruvaiyaru	6369		
Thiruvanam	9015		
Thiruvidaimaruthur	8328		

A total of 314 ground truth points were collected at different stages of crop growth to validate the estimated crop area. A confusion matrix was computed to estimate the accuracy of crop classification. The assessed accuracy for rice crop classification was 86 %, while the accuracy for non-rice crops was 79 %. The rice crop area map of the study area is shown in Fig. 4.

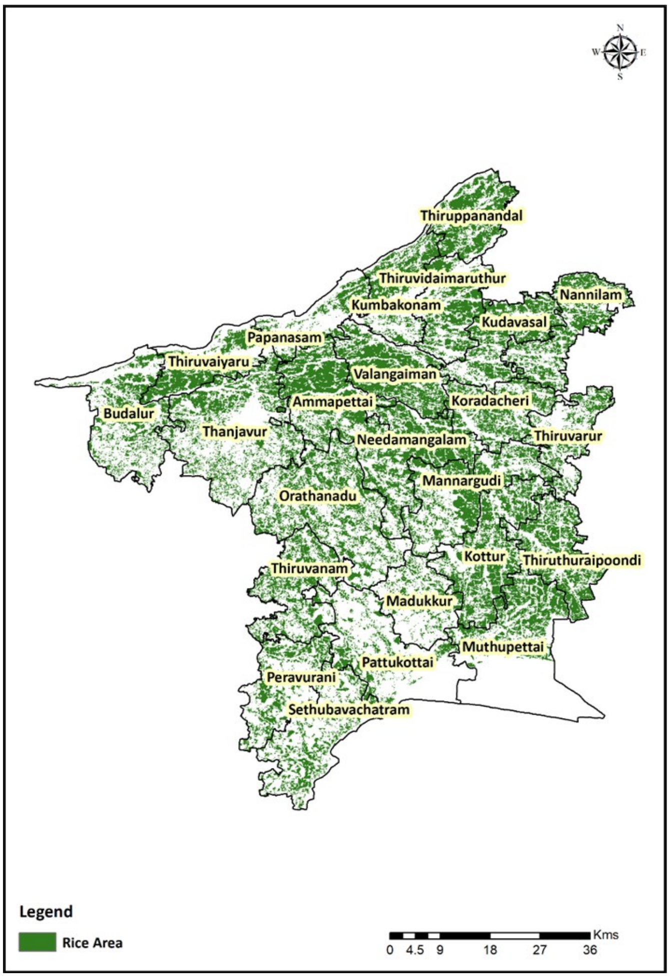

Fig. 4. Rice area map.

Rice yield estimation

The average yield obtained from 14 blocks in Thanjavur district, as estimated using the DSSAT model, was 3920 Kg ha^{-1}. The estimated yield distribution is shown in Fig. 5, while the statistical comparisons are tabulated in Table. 2 and graphically visualized in Fig. 6. Among the fourteen blocks, Ammapettai recorded the highest yield of 4150 Kg ha^{-1}, whereas Sethubavachatram had the lowest yield of 3619 Kg ha^{-1}.

Estimated yields were compared with results from Crop Cutting Experiments (CCE) to calculate Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Agreement percent. For Thanjavur district, the average RMSE was 440 Kg ha^{-1}, NRMSE was 10 % and Agreement Percentage was 90 %.

Similarly, the average rice yield obtained from 10 blocks in Thiruvarur district, as estimated using the DSSAT model, was 3732 Kg ha^{-1}. The estimated yield distribution is shown in Fig. 5, with statistical comparisons tabulated in Table. 3 and graphically visualized in Fig. 7. Among the ten blocks, Thiruvarur recorded the highest yield of 3930 Kg ha^{-1} and Muthupettai had the lowest yield of 3577 Kg ha^{-1}.

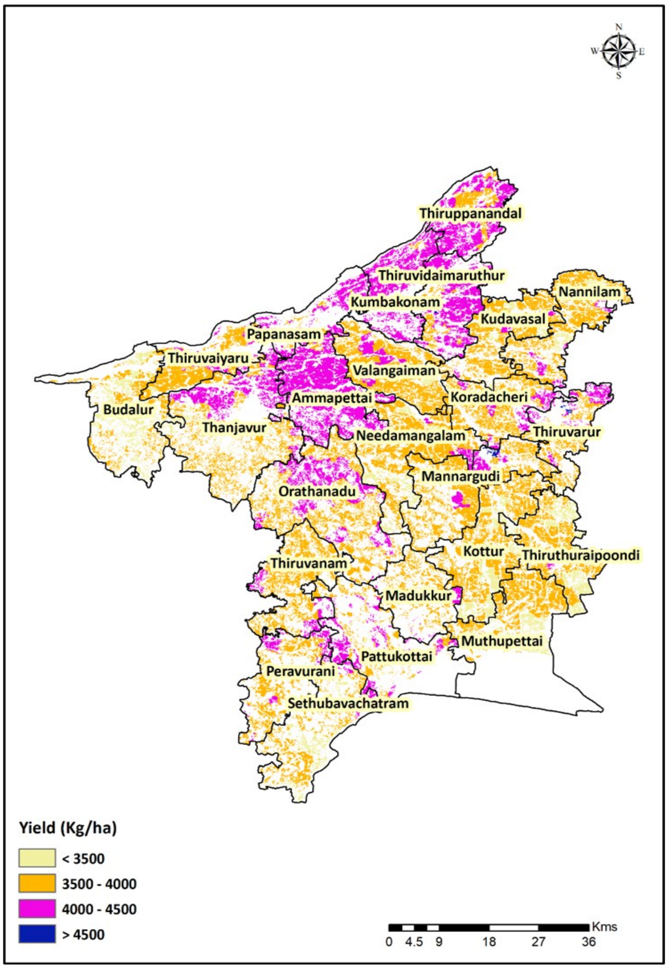

Fig. 5. DSSAT model-based yield map.

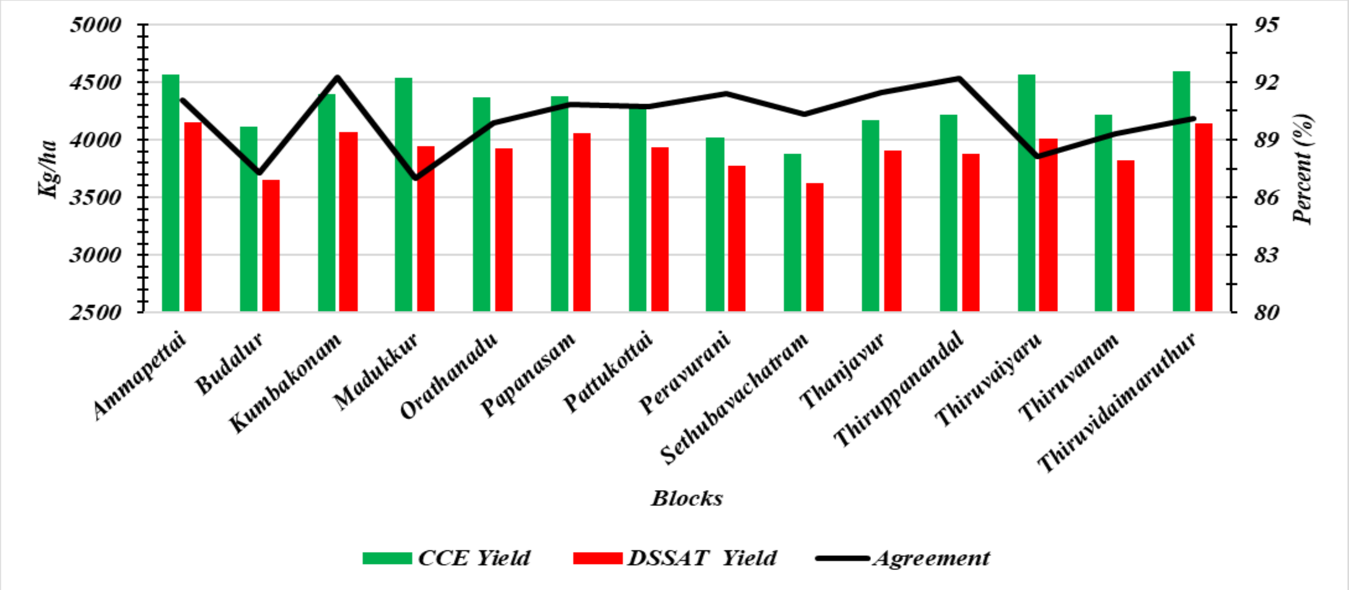

Fig. 6. Comparison of block wise rice yield in Thanjavur district.

Table 2. Comparison of block wise rice yield in Thanjavur district

Block	CCE Yield (Kg/ha)	DSSAT Yield (Kg/ha)	DSSAT RMSE (kg/ha)	DSSAT NRMSE (%)	Agreement (%) DSSAT vs CCE
Ammapettai	4569	4150	430	9	91
Budalur	4118	3655	539	13	87
Kumbakonam	4393	4070	355	8	92
Madukkur	4536	3939	597	13	87
Orathanadu	4367	3928	459	10	90
Papanasam	4381	4052	415	9	91
Pattukottai	4291	3934	413	9	91
Peravurani	4022	3772	359	9	91
Sethubavachatram	3881	3619	385	10	90
Thanjavur	4166	3907	366	9	91
Thiruppanandal	4219	3881	341	8	92
Thiruvaiyaru	4568	4008	564	12	88
Thiruvanam	4213	3823	469	11	89
Thiruvidaimaruthur	4595	4143	472	10	90
AVERAGE	**4309**	**3920**	**440**	**10**	**90**

Table 3. Comparison of block wise rice yield in Thiruvarur district

Block	CCE Yield (Kg/ha)	DSSAT Model based Yield (Kg/ha)	DSSAT Model based RMSE (kg/ha)	DSSAT Model based NRMSE (%)	Agreement (%) DSSAT vs CCE
Koradacheri	4385	3825	564	13	87
Kottur	4088	3603	490	12	88
Kudavasal	4207	3703	507	12	88
Mannargudi	4201	3832	401	9	91
Muthupettai	3935	3577	399	10	90
Nannilam	4141	3732	428	10	90
Needamangalam	4105	3700	410	10	90
Thiruthuraipoondi	4000	3606	411	10	90
Thiruvarur	4358	3930	464	10	90
Valangaiman	4226	3815	426	10	90
AVERAGE	**4165**	**3732**	**450**	**11**	**89**

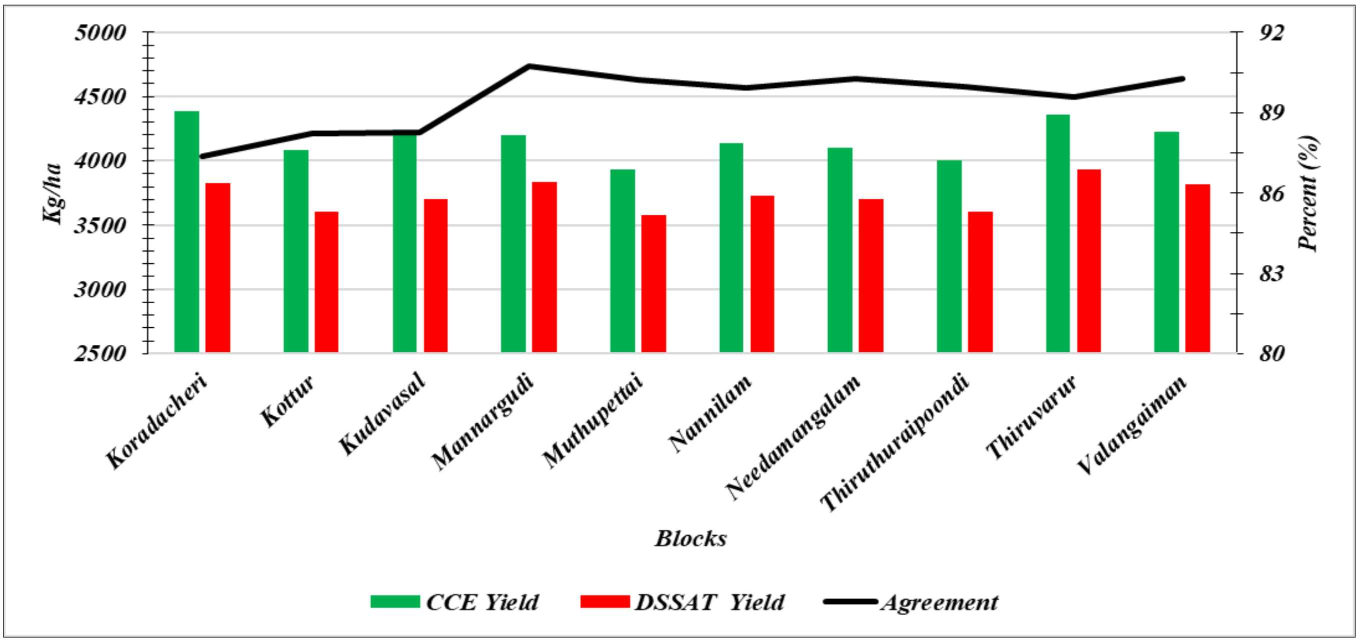

Fig. 7. Comparison of block wise rice yield in Thiruvarur district.

The estimated yields were compared with Crop Cutting Experiments (CCE) for computing Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Agreement percent. For Thanjavur district, the average RMSE was 450 Kg ha^{-1}, NRMSE was 11 % and Agreement percentage 89 %.

Discussion

Sentinel-1A SAR is an active microwave sensor that transmits and receives radar signals at various polarizations. The C-band SAR sensor is particularly effective for continuous agricultural monitoring and crop area estimation. It is suitable for penetrating cloud cover and improves crop monitoring even during the monsoon period. SAR's sensitivity to dielectric properties, surface roughness and crop canopy structure enables the detection of changes in crop growth and development. Cross-polarization channels (VH or HV) are especially useful in distinguishing and estimating crop area by utilising the unique backscattering signatures of different crop canopies (10).

Among various radar bands, Sentinel-1B's C-band had a higher accuracy than the L-band ALOS-2, although t both these bands showed a lower coefficient of variation in classification (33).

An automated rice estimation system, Phenorice had the ability to delineate rice crops with an R^2 range of 0.75-0.92 across India, Italy and the Philippines. However, the study found that the mixed pixels in fragmented rice ecosystem limits the overall estimation capability (34).

The backscattering coefficient of VV polarization was found to be maximum during the tillering stage and minimum during the agronomic flooding (35). Sentinel-1A's VV polarization was found to be particularly sensitive in the early growth stages of rice, whereas VH polarization demonstrated greater sensitivity during the later stages, from tillering to maturity and provided a more reliable assessment of the crop's temporal behaviour compared to VV polarization (36). The parametric classification of rice crops through MAPscape software used in this study was in line with results from (37-39).

Crop simulation models, which integrate climate, soil, water and management practices, are valuable tools for determining optimal crop management. Their growing use in spatial simulation enables effective technology transfer and aids in identifying production limitations across landscapes. The DSSAT CERES-Rice model was used here to spatially assess the influence of soil, hydrological, agronomic and climatic factors on rice production and its variability (40).

The DSSAT model simulates crop growth by considering soil, crop variety, weather and management practices. It uses inputs like planting date, seed type, soil conditions and daily weather data to predict crop yield, nutrient uptake, soil moisture and potential plant stress at the end of the season (41). The CERES-Rice model within the DSSAT model accurately simulated key rice growth stages, including the time to germinate, flower and maturity. It also effectively predicted yield, leaf area, harvest index and overall plant biomass. A previous study determined that DSSAT was a decision-making tool for crop management after optimizing the maize sowing date and irrigation to enhance yield outcome (42).

The integration of remote sensing data with crop simulation models allows for the expansion of point-based simulations to broader agricultural landscapes. This approach employs remotely sensed data as a proxy for various agricultural variables. For instance, Leaf Area Index (LAI) values derived from remote sensing were spatially assimilated into DSSAT as a generating variable (43). It was demonstrated that the micro level yield estimates might be improved by combining satellite-derived LAI with simulated rice growth factors. It was discovered that weather variability, soil and rainfall affected the LAI of rice at the field level and related to the variation in yield.

Accordingly, suitable regression models were employed in the current investigation to estimate rice LAI from dB images, utilizing simulated LAI from DSSAT models. Despite the diversity of monitoring fields and the variety of conditions in which rice was cultivated, it was determined that sentinel 1A SAR data was reliable in estimating the area of rice in Thanjavur and Thiruvarur districts and may offer inputs for excellent spatial estimation of rice yields in the region when combined with DSSAT CERES-Rice crop simulation model.

DSSAT allows farmers to optimize crop management by simulating various strategies, such as irrigation schedules, fertilizer applications and planting dates, to identify the most effective practices for specific field conditions. It also enables yield prediction under different environmental scenarios, helping farmers in making informed decisions about resource allocation and farm planning. Additionally, DSSAT assists in risk assessment by evaluating the impact of climate variability and extreme weather events, allowing farmers to develop effective mitigation strategies (44).

Policymakers can use DSSAT to evaluate the impact of agricultural policies on crop productivity and sustainability, aiding in the development of policies that promote sustainable agriculture. It also helps assess the effects of climate change on agriculture, enabling the formulation of climate-resilient strategies. Additionally, its outputs support efficient resource allocation by identifying critical areas that require intervention, ensuring optimal use of national resources (45).

Conclusion

This study exploits the capability of remote sensing and crop simulation for rice yield estimation in the Cauvery delta region of Tamil Nadu, India. We employed a robust framework that enables timely and accurate yield prediction using Sentinel-1 and DSSAT crop simulation model. This approach is efficient in estimating the rice yield with reasonable accuracy and holds further potential for further improvement through feature engineering and hyperparameter tuning. Generally, linking DSSAT with remote sensing data is valuable for understanding the effects of climate variability and management practices on rice yields. Additionally, researchers and policymakers can identify methods to reduce the impact of climate change through the simulation of different scenarios and optimize agricultural practices.

Although this study provides a solid foundation for rice yield estimation, further research should focus on integrating additional data sources, including soil moisture data and weather forecasts, to enhance the accuracy of predictions. The development of user-friendly interfaces and tools can facilitate the adoption of these techniques by farmers and agricultural extension services. Advanced knowledge can be integrated with traditional knowledge, hence striving for sustainable and resilient systems in food production during the rising global challenges.

Furthermore, this approach can be extended to other crops and Agro-climatic conditions through calibration of model for different crop types and climatic conditions. The integration of Machine Learning and Artificial Intelligence tools for data analytics ensures early predictions.

Acknowledgements

Authors wish to thank Department of Remote Sensing and GIS and Centre for Water and Geospatial Studies of Tamil Nadu Agricultural University, Coimbatore for providing financial assistance for conducting this research.

Authors' contributions

SM carried out the experiment, observation and drafted the manuscript. SP guided the research by formulating the research concept and approved the final manuscript. KPR guided the research by formulating the research concept and helped in securing research funds. RK performed the statistical analysis. APS and MR conceived of the study and participated in its design and coordination. NSS and SS participated in the data analysis and revised manuscript. All authors reviewed the results and approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare no conflict of interest.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly and ChatGPT by OpenAI to enhance language clarity and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

1. Nations U. World Population Prospects 2024: Summary of Results. New York: Department of Economic and Social Affairs, United Nations Affairs DoEaS; 2024. Contract No.: UN DESA/POP/2024/TR/NO. 9.
2. The Sustainable Development Goals Report 2024. New York, USA: United Nations - Department of Economic and Social Affairs, Affairs DoEaS; 2024.
3. Final Estimates of Production of Foodgrains, Oilseeds and other Commercial Crops for the 2023-24 [Internet]. Department of Agriculture & Farmers Welfare | MoA & FW | Government of India. 2024 [cited 06/12/2024]. https://agriwelfare.gov.in/en/AgricultureEstimates
4. Department of Agriculture & Farmers Welfare, Ministry of Agriculture & Farmers Welfare, India. Go. Annual Report 2023-2024. New Delhi: Ministry of Agriculture & Farmers Welfare, Government of India., Welfare DoAF; 2024 26/07/2024.
5. National Food Security Portal: Department of Food and Public Distribution, Government of India.; 2024 [updated 11/12/2024; cited 2024 06/12/2024]. https://nfsa.gov.in/portal/AboutUs
6. Rashtriya Krishi Vikas Yojana (RKVY): Agricultural Informatics Division, National Informatics Centre; 2024 [cited 2024 12/12/2024]. https://rkvy.da.gov.in/#
7. POSHAN Abhiyaan [press release]. Ministry of Women and Child Development, 24/03/2023 2023.

8. Verma A, Kumar A, Lal K. Kharif crop characterization using combination of SAR and MSI Optical Sentinel Satellite datasets. Journal of Earth System Science. 2019;128(8):230. https://doi.org/10.1007/s12040-019-1260-0

9. Dey S, Bhogapurapu N, Homayouni S, Bhattacharya A, McNairn H. Unsupervised classification of crop growth stages with scattering parameters from dual-pol Sentinel-1 SAR data. Remote Sensing. 2021;13(21):4412. https://doi.org/10.3390/rs13214412

10. Kalecinski NI, Skakun S, Torbick N, Huang X, Franch B, Roger JC, et al. Crop yield estimation at different growing stages using a synergy of SAR and optical remote sensing data. Science of Remote Sensing. 2024;10:100153. https://doi.org/10.1016/j.srs.2024.100153

11. Gumma MK, Tummala K, Dixit S, Collivignarelli F, Holecz F, Kolli RN, et al. Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information. Geocarto International. 2022;37(7):1833-49. https://doi.org/10.1080/10106049.2020.1805029

12. Hegde A, Umesh P, Tahiliani MP. Automated rice mapping using multitemporal Sentinel-1 SAR imagery using dynamic threshold and slope-based index methods. Remote Sensing Applications: Society and Environment. 2024:101410. https://doi.org/10.1016/j.rsase.2024.101410

13. Pande CB, Kadam SA, Rajesh J, Gorantiwar SD, Shinde MG. Predication of Sugarcane Yield in the Semi-Arid Region Based on the Sentinel-2 Data Using Vegetation's Indices and Mathematical Modeling. In: Pande CB, Moharir KN, Singh SK, Pham QB, Elbeltagi A, editors. Climate Change Impacts on Natural Resources, Ecosystems and Agricultural Systems. Cham: Springer International Publishing; 2023. p. 327-43. https://doi.org/10.1007/978-3-031-19059-9_12

14. Tripathy R, Nigam R, Bhattacharya B. Agrometeorological approach for sugarcane yield estimation at regional scale using satellite remote sensing. Journal of the Indian Society of Remote Sensing. 2023;51(8):1715-28. https://doi.org/10.1007/s12524-023-01724-x

15. Geethalakshmi V, Gowtham R, Gopinath R, Priyanka S, Rajavel M, Senthilraja K, et al. Potential impacts of future climate changes on crop productivity of cereals and legumes in Tamil Nadu, India: A Mid‐Century Time Slice Approach. Advances in Meteorology. 2023;2023(1):4540454. https://doi.org/10.1155/2023/4540454

16. Awad MM. Toward precision in crop yield estimation using remote sensing and optimization techniques. Agriculture. 2019;9(3):54. https://doi.org/10.3390/agriculture9030054

17. Shaikh TA, Rasool T, Lone FR. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Computers and Electronics in Agriculture. 2022;198:107119. https://doi.org/10.1016/j.compag.2022.107119

18. Singha C, Swain KC. Vegetation indices-based rice and potato yield estimation through Sentinel 2B satellite imagery. Advancement of GI-Science and sustainable agriculture: A Multi-dimensional Approach. GI Science and Geo-environmental Modelling: Springer; 2023. p. 113-34. https://doi.org/10.1007/978-3-031-36825-7_8

19. Htun AM, Shamsuzzoha M, Ahamed T. Rice yield prediction model using normalized vegetation and water indices from Sentinel-2A satellite imagery datasets. Asia-Pacific Journal of Regional Science. 2023;7(2):491-519. https://doi.org/10.1007/s41685-023-00299-2

20. Sadeh Y, Zhu X, Dunkerley D, Walker JP, Chen Y, Chenu K. Versatile crop yield estimator. Agronomy for Sustainable Development. 2024;44(4):42. https://doi.org/10.1007/s13593-024-00974-4

21. Mandapati R, Gumma MK, Metuku DR, Bellam PK, Panjala P, Maitra S, et al. Crop yield assessment using field-based data and crop models at the village level: A case study on a homogeneous rice area in Telangana, India. AgriEngineering. 2023;5(4):1909-24. https://doi.org/10.3390/agriengineering5040117

22. Bazkiaee P, Kamkar B, Amiri E, Kazemi H, Rezaei M, López-Bernal A. The rice yield gap estimation using integrated system approaches: a case study-Guilan province, Iran. International Journal of Environmental Science and Technology. 2022;19(9):8451-64. https://doi.org/10.1007/s13762-022-04093-z

23. Bhoutika K, Kumar A, Das DP, Pandey A. Geospatial Technology for Crop Yield Forecasting-A Case Study of SW Uttarakhand. Geospatial Technologies for Resources Planning and Management: Springer; 2022. p. 315-30. https://doi.org/10.1007/978-3-030-98981-1_14

24. Official Website of Thanjavur District, Tamil Nadu: National Informatics Centre. Ministry of Electronics & Information Technology, Government of India; 2024 [updated 12-12-2024. https://thanjavur.nic.in/

25. Official Website of Thiruvarur District, Tamil Nadu: National Informatics Centre. Ministry of Electronics & Information Technology, Government of India; 2024 [updated 11-12-2024. https://tiruvarur.nic.in/

26. Agency ES. Overview of Sentinel-1 Mission: European Space Agency; 2024 [cited 2024 12/12/2024]. https://sentiwiki.copernicus.eu/web/s1-mission

27. Liu Y, Pu X, Shen Z. Crop type mapping based on polarization information of time series sentinel-1 images using patch-based neural network. Remote Sensing. 2023;15(13):3384. https://doi.org/10.3390/rs15133384

28. Mansaray LR, Zhang D, Zhou Z, Huang J. Evaluating the potential of temporal Sentinel-1A data for paddy rice discrimination at local scales. Remote Sensing Letters. 2017;8(10):967-76. https://doi.org/10.1080/2150704X.2017.1331472

29. Abayechaw D. Review on decision support system for agrotechnology transfer (DSSAT) model. Information Systems. 2021;10(6):126-33. https://doi.org/10.11648/j.ijiis.20211006.13

30. DSSAT-History: DSSAT Foundation; 2024 [cited 2024 12/12/2024]. https://dssat.net/development/history/

31. (LaRC) NAaSANLRC. NASA POWER. In: (LaRC) NAaSANLRC, editor. 2024.

32. Amiri E, Rezaei M, Bannayan M, Soufizadeh S. Calibration and evaluation of CERES rice model under different nitrogen-and water-management options in semi-mediterranean climate condition. Communications in soil science and plant analysis. 2013;44(12):1814-30. https://doi.org/10.1080/00103624.2013.769565

33. Kraatz S, Torbick N, Jiao X, Huang X, Robertson LD, Davidson A, et al. Comparison between dense l-band and c-band synthetic aperture radar (sar) time series for crop area mapping over a nisar calibration-validation site. Agronomy. 2021;11(2):273. https://doi.org/10.3390/agronomy11020273

34. Boschetti M, Busetto L, Manfron G, Laborte A, Asilo S, Pazhanivelan S, et al. PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series. Remote Sensing of Environment. 2017;194:347-65. https://doi.org/10.1016/j.rse.2017.03.029

35. Raman MG, Kaliaperumal R, Pazhanivelan S. Rice Area Estimation in Tiruvarur District of Tamil Nadu using VV Polarized Sentinel 1A SAR Data. Indian Journal of Natural Sciences. 2017;8(44):12782-93.

36. Kumar M, Podila P, Sireesha G. Response of the direct sown and transplanted rice crop to multi-temporal Sentinel-1A data and estimate the rice sown area by synergetic use of Senteil-1A and Sentinel-2. 2022;1:73-82. https://doi.org/10.5281/zenodo.7054508

37. Prakash MA, Pazhanivelan S, Muthumanickam D, Ragunath K, Sivamurugan A. Mapping rice area in the Cauvery Delta Zone of Tamil Nadu using Sentinel 1A Synthetic Aperture Radar (SAR) Data. International Journal of Environment and Climate Change. 2023;13(10):195-204. https://doi.org/10.9734/ijecc/2023/v13i102630

38. Pazhanivelan S, Ragunath K, Sudarmanian N, Kumaraperumal R, Setiyono T, Quicho E. Integrating time-series SAR data and ORYZA crop growth model in Rice area mapping and yield estimation for crop insurances. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2019;42:239-43. https://doi.org/10.5194/isprs-archives-XLII-3-W6-239-2019

39. Raman MG, Kaliaperumal R, Pazhanivelan S, Kannan B. Rice area estimation using parameterized classification of sentinel 1A SAR data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2019;42:141-7. https://doi.org/10.5194/isprs-archives-XLII-3-W6-141-2019

40. Venugopalan M, Tiwary P, Ray S, Chatterji, Velmourougane K, Bhattacharyya T, et al. InfoCrop-cotton simulation model–its application in land quality assessment for cotton cultivation. Current Science. 2014:1512-8.

41. Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt L, et al. The DSSAT cropping system model. European Journal of Agronomy. 2003;18(3-4):235-65. https://doi.org/10.1016/S1161-0301(02)00107-7

42. Rugira P, Ma J, Zheng L, Wu C, Liu E. Application of DSSAT CERES-maize to identify the optimum irrigation management and sowing dates on improving maize yield in Northern China. Agronomy. 2021;11(04):674. https://doi.org/10.3390/agronomy11040674

43. Rui L, Li C-j, Dong Y-y, Feng L, Wang J-h, Yang X-d, et al. Assimilation of remote sensing and crop model for LAI estimation based on ensemble Kaiman Filter. Agricultural Sciences in China. 2011;10 (10):1595-602. https://doi.org/10.1016/S1671-2927(11)60156-9

44. Zechariah Jeremaiho A-GS, Abdul-Halim Abubakari, Muna Mohamed Elhag. Methodology: The Decision Support System for Agrotechnology Transfer (DSSAT) Software Crop Model for Agriculture Decision. Agrotechnology. 2023;12(03):08. https://doi.org/10.35248/2168-9881.23.12.327

45. Hoogenboom G, Porter CH, Boote KJ, Shelia V, Wilkens PW, Singh U, et al. The DSSAT crop modeling ecosystem. Advances in crop modelling for a sustainable agriculture: Burleigh Dodds Science Publishing; 2019. p. 173-216. http://doi.org/10.19103/AS.2019.0061.10