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Strengthening food security through rice crop area monitoring in India using EOS-04 (RISAT-1A) SAR data

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ABSTRACT

Timely and accurate estimation of rice crop area and production is crucial for effective crop management and strengthening food security initiatives. Unlike optical sensors, Synthetic Aperture Radar (SAR) provides a significant advantage by penetrating cloud cover and enabling uninterrupted monitoring of croplands, even under persistent cloudy conditions. This study presents a decision rule-based rice crop mapping approach using temporal HH and HV dual-polarization data acquired in Medium Resolution ScanSAR (MRS) mode from Earth Observation Satellite-04 (EOS-04), the successor to Radar Imaging Satellite-1 (RISAT-1). Distinct backscatter responses observed at different growth stages of rice were used to establish decision rules, enabling reliable classification of rice versus non-rice areas. To ensure operational scalability, an automated framework was developed that directly retrieves satellite data from archives, integrates with the Data Processing (DP) Chain at the National Remote Sensing Centre (NRSC), and applies decision rules within a streamlined workflow for large-scale mapping. The methodology was first validated across eight test sites in diverse regions of India, achieving classification accuracies between 81% and 96% depending on data continuity. It was subsequently deployed to over 340 major rice-growing districts during the Kharif 2024 season, consistently achieving accuracies above 80%. Comparison with official government statistics further confirmed its robustness, with rice area estimates showing strong agreement ($R^2 > 0.9$) across 343 districts. These results demonstrate the reliability and scalability of the EOS-04 dual-polarized SAR-based methodology, paving the way for operational, nationwide rice crop monitoring to support agricultural planning and food security.

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EOS-04; RISAT-1A; decision rule; rice; India; automation

1. Introduction

Rice, scientifically known as *Oryza Sativa*, holds a paramount position in India's agricultural landscape. It stands as the nation's most crucial food crop and ranks as the world's second-largest rice producer, following only China. Beyond being a dietary staple in India, rice serves

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as a fundamental source of livelihood for millions of households, carrying profound economic significance and playing a central role in safeguarding the country's food security. Rice constitutes the staple diet for over 65% of India's population, thereby, is pivotal to the food and livelihood security of people (Pathak et al. 2020). The timely and accurate estimation of crop area and production is imperative to support food crop management and bolster food security initiatives. In this context, the analysis of satellite-based remote sensing data has emerged as an indispensable tool for pre-harvest crop acreage estimation. Remote Sensing technology provides scalable and unbiased estimates of rice cultivation, complementing traditional surveys and statistical methods (Guo and Ren 2023; Nelson et al. 2014; Yuan et al. 2025; Zhan, Zhu, and Li 2021). Remote Sensing's transformative role in rice crop mapping within India offers effective agricultural management and enhances food security measures. This method utilizes satellite imagery and advanced technologies to systematically monitor, assess, and understand rice cultivation across large areas. Remote sensing plays a crucial role in collecting and analysing information about the growth stages, health, and spatial distribution of rice crops. This information enables farmers, policymakers, and researchers to make well-informed decisions related to crop management, yield forecasting, resource allocation, and food security planning. Specifically, Synthetic Aperture Radar (SAR) data has the advantage over optical data for its operational capability in all weather conditions providing the continuous data even under persistent cloudy conditions. The use of Synthetic Aperture Radar (SAR) data marked a significant advancement in remote sensing applications for agriculture (Ma et al. 2022; Wang et al. 2022a). Notably, data from the first European Remote Sensing satellite (ERS-1) was employed by Le Toan et al. (1997) to develop a methodology for mapping rice fields. This approach relies on detecting the distinctive temporal variations in radar backscattering coefficients, which are characteristic of flooded rice areas during different growth stages. SAR has exhibited a well-established capability to detect various lowland rice systems, encompassing both irrigated and rainfed fields, by leveraging the distinctive temporal patterns exhibited in the crop's backscatter coefficient (Bouvet et al. 2011; Chang et al. 2021; Clauss et al. 2018; Inoue et al. 2014; Nguyen et al. 2015).

Several researchers advanced the application of SAR technology for rice detection and monitoring (Bazzi et al. 2019; Bouvet, le Toan, and Lam-Dao 2009; Choudhury and Chakraborty 2006; Gao et al. 2023; Inoue et al. 2002; Kobayashi and Ide 2022; Nelson et al. 2014; Suga and Konishi 2008). Inoue et al. (2002) observed that the Leaf Area Index (LAI) exhibited a strong correlation with HH- and cross-polarized backscatter in the C-band, indicating its effectiveness for monitoring canopy development in rice fields. Further, multi-temporal SAR data from various platforms – including TerraSAR-X (X-band), ENVISAT-1/ASAR (C-band), and ALOS/PALSAR (L-band) – were utilized by Suga and Konishi (2008) to monitor rice crop growth stages and to accurately delineate rice-planted areas. These sensors, operating at different frequencies, enabled a comprehensive understanding of structural and moisture-related changes throughout the crop cycle. Bouvet, le Toan, and Lam-Dao (2009) utilized a time series of dual-polarized ENVISAT ASAR data (HH and VV) to effectively identify rice crop pixels. By analysing the temporal behaviour of the HH/VV backscatter ratio and applying fixed threshold values, they achieved a classification accuracy of approximately 90%.

A rule-based classification approach, which analyzes the correlation between the temporal evolution of rice crops and corresponding temporal backscatter patterns, has been

suggested as an effective method for operational rice crop mapping over large areas. This technique relies on a small set of rules and parameters that can be quickly adapted across different sites and seasons, offering scalability and simplicity in implementation (Choudhury and Chakraborty 2006; Nelson et al. 2014). Sentinel-1 time series data in VV and VH polarizations has been widely explored by researchers for accurate delineation of rice crop areas across diverse geographical regions using multiple approaches (Bazzi et al. 2019; Kobayashi and Ide 2022; Lasko et al. 2018; Nguyen, Gruber, and Wagner 2016; Wang et al. 2022b). Bazzi et al. (2019) extended the work on rice mapping by utilizing Sentinel-1 SAR data to develop a technique for identifying rice crop dynamics across Italy, emphasizing the advantages of radar-based approaches for monitoring crops in regions with challenging optical data acquisition conditions. These studies have demonstrated the effectiveness of Sentinel-1's dual-polarization SAR data in capturing rice phenology and field-level variability. In a more recent study, Mansaray et al. (2021) applied machine learning techniques to Sentinel-1 and Sentinel-2 data to enhance the mapping of rice fields in Sierra Leone, underlining the potential of these modern remote sensing platforms for large-scale agricultural monitoring.

The multi-date SAR data analysis approach leverages the distinct temporal variations in radar backscatter observed in rice fields, ranging from the initial transplanting phase to later growth stages (Choudhury et al. 2012). This dynamic behaviour of backscatter enables effective tracking of crop phenology. Numerous studies conducted across various regions of India have successfully demonstrated the use of this approach for mapping rice crops with reasonably high accuracies, reinforcing its suitability for operational agricultural monitoring in monsoon-dependent rice-growing areas. Recently, the Earth Observation Satellite-04 (EOS-04) also referred to as RISAT-1A was launched by the Indian Space Research Organisation (ISRO) in 2022 as a continuation of the RISAT-1 mission. EOS-04 carries a C-band synthetic aperture radar (SAR) and provides dual-polarized data (HH and HV). This opens up new opportunities to explore its potential for operational rice crop monitoring in India and beyond. This breakthrough laid the groundwork for operational rice monitoring systems, particularly in Asia, and continues to influence current practices using modern SAR sensors like Sentinel-1 and RISAT-1A.

The EOS-04 data has been utilized for mapping *Kharif* sown areas and inventorying specific *Kharif* crops using various methodologies (Bhattacharya et al. 2024; Srikanth et al. 2025). However, these studies have been confined to small areas or a few districts, and the methods developed have not yet been automated for large-scale operational implementation, limiting their broader applicability for regional or national crop monitoring. This study aims (i) to develop a rice crop mapping procedure using temporal HH and HV polarization data from EOS-04, and (ii) to evaluate the methodology across multiple sites to ensure its scalability and applicability for large-area rice crop mapping, making it suitable for operational implementation across diverse geographical regions. Further, an automated framework is proposed to directly fetch the satellite data from the archives, and the pre-processing steps within the Data Processing (DP) Chain at the National Remote Sensing Centre (NRSC), and implementation of decision rules that ensure a streamlined and efficient workflow for large-scale rice crop mapping at the national scale. Thus, this study focused on utilizing dual-polarization (dual-pol) radar data, specifically HH (horizontal transmit, horizontal receive) and HV (horizontal transmit, vertical receive), for mapping rice crops across various regions in India.

2. Study area

India experiences a wide range of climatic patterns, primarily due to its vast geographical expanse, diverse topography, and the significant influence of the Himalayas and surrounding seas. The country's climate is predominantly classified as tropical monsoon, marked by distinct wet and dry seasons. The Southwest Monsoon (June to September) is the most significant, accounting for nearly 75% of the annual rainfall. It originates over the Indian Ocean and brings heavy rains to the west coast, northeastern states, and the Indo-Gangetic plains. In contrast, the Northeast Monsoon (October to December) primarily impacts the southeastern coast, especially Tamil Nadu, bringing moderate rainfall during the post-monsoon period (Lal 2003).

Rice is a major *kharif* crop in India, and while it is grown in nearly every state, the bulk of its cultivation is concentrated in a few key states due to favourable climatic and soil conditions, as well as availability of water. Rice cultivation during the *kharif* season (June to October) coincides with the southwest monsoon, which provides the necessary water for rice fields, especially in rain-fed areas. Developing a decision rule methodology for rice crop mapping to ensure that the methodology can be generalized across the country's diverse agricultural environments necessitates to test and evaluate the methodology for selected test districts spread across various regions of India (Figure 1(a)) with distinct rice-growing characteristics. Among the study sites, Karnal, Rewa, Bhandara, Karimnagar, Purba Bardhaman, and East Godavari districts are characterized by predominant rice cultivation, making them essentially mono-cropped areas. In contrast, the Siddipet and Narayanpur study sites feature a diversified cropping pattern, with a mix of other *kharif* crops alongside rice cultivation. Following the development of a decision rule-based approach for rice mapping in the eight test sites (Figure 1(a)), the major rice-growing states of India, namely, 1. Andhra Pradesh, 2. Bihar, 3. Chhattisgarh, 4. Haryana, 5. Jharkhand, 6. Karnataka, 7. Madhya Pradesh, 8. Maharashtra, 9. Odisha, 10. Punjab, 11.

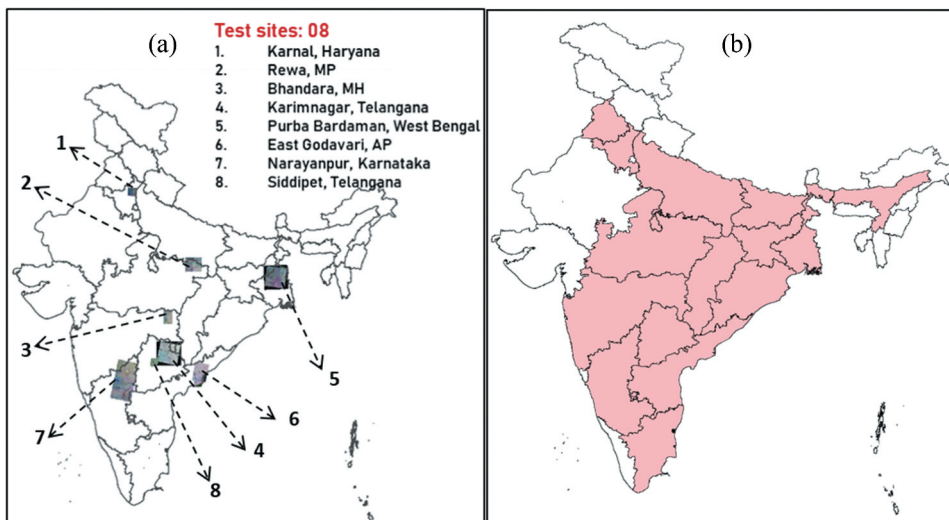


Figure 1. (a) Map showing the locations of test sites areas across India (b) Major Rice growing states of India.

Tamil Nadu, 12. Telangana, 13. Uttar Pradesh, 14. West Bengal, and 15. Assam is selected to test its applicability for regional-scale implementation (Figure 1(b)).

3. Data used

This study utilized Medium Resolution ScanSAR (MRS) mode data acquired by the EOS-04 satellite. EOS-04 captures Synthetic Aperture Radar (SAR) data across a range of incidence angles from 23° to 49°, with a swath width of 160 km. The sensor's azimuth and range resolutions, considering weighting, are 33 m and a variable range from 43 m to 22 m, respectively. The output products are available at a sampling resolution of 18 × 18 m for MRS mode and 36 × 36 m for CRS mode. The SAR data is captured in dual polarization (HH and HV bands), and the output images are provided as Beta-Naught (Beta0) products. The MRS data, collected systematically at 17-day intervals in both HH (Horizontal-Horizontal) and HV (Horizontal-Vertical) polarizations during descending passes, ensures consistent acquisition geometry throughout the study period. The Level-2A enhanced geo-referenced GeoTIFF datasets with a spatial resolution of 18 m were used for the analysis. A minimum of four acquisition cycles (or coverages) is required to reliably detect a rice-sown pixel and generate an accurate rice crop map. Data acquisitions from the end of May or the first week of June through to the end of September or mid-October were included in the analysis, aligned with the rice crop calendar for these test sites as shown in Figure 2. The datasets used for methodology development spread across eight test sites are listed in Table 1.

Further, data from 10 acquisition cycles, i.e. approximately 2700 scenes per polarization were analysed for both HH and HV polarizations to assess the *kharif* rice crop area across 15 major rice growing states of India. A tentative transplantation windows for rice crop were identified for each state under study by analysing the data from June to October, in conjunction with district-wise contingency plans developed by the Central Research Institute for Dryland Agriculture (CRIDA) (https://www.icar-crida.res.in/Crop_Contingency_Plan.html). These acquisition cycles spanned the period from June to October, covering the early stages of the cropping season to the pre-harvest phase. For states such as Karnataka and Tamil Nadu, data from an additional 11th acquisition cycle in november were incorporated to account for delayed sowing activities observed in these regions. The temporal False Color Composite (FCC) of MRS HV polarization data for the months of June, July, and August across India is presented in Figure 3.

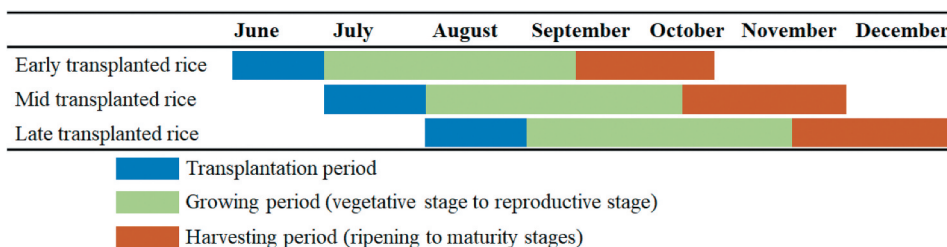


Figure 2. Crop calendar of rice in India (source: https://www.icar-crida.res.in/Crop_Contingency_Plan.html).

Table 1. EOS-04 satellite data acquisitions are used for methodology development across the eight test sites.

Study sites	MRS data acquisition date	Study area	MRS data acquisition date
1. Karnal (Haryana)	02-06-2022	2. Rewa (Madhya Pradesh)	04-06-2022
	19-06-2022		21-06-2022
	06-07-2022		08-07-2022
	23-07-2022		11-08-2022
	09-08-2022		28-08-2022
	26-08-2022		14-09-2022
	12-09-2022		01-10-2022
	29-09-2022		18-10-2022
3.Bhandara (Maharashtra)	04-06-2022	4. Karimnagar (Telangana)	04-06-2022
	21-06-2022		21-06-2022
	08-07-2022		08-07-2022
	11-08-2022		11-08-2022
	28-08-2022		28-08-2022
	14-09-2022		14-09-2022
	01-10-2022		01-10-2022
	18-10-2022		18-10-2022
5. Purba Bardhaman (West Bengal)	29-05-2022	6. East Godavari (Andhra Pradesh)	05-06-2022
	02-07-2022		22-06-2022
	19-07-2022		09-07-2022
	05-08-2022		26-07-2022
	08-09-2022		12-08-2022
	25-09-2022		29-08-2022
	12-10-2022		15-09-2022
			02-10-2022
7.Narayanpur (Karnataka)	03-06-2022	8. Siddipet (Telangana)	19-10-2022
	20-06-2022		12-06-2022
	07-07-2022		29-06-2022
	24-07-2022		16-07-2022
	10-08-2022		02-08-2022
	27-08-2022		19-08-2022
	13-09-2022		05-09-2022
	30-09-2022		22-09-2022
	17-10-2022		09-10-2022

4. Methodology

The methodology was developed using *Kharif* season data from 2022 for the eight test sites. For upscaling, testing, and evaluation, data from *kharif* 2024 was considered. This comprehensive dataset enabled a detailed temporal and spatial evaluation of rice crop development and distribution, leveraging dual-polarized MRS data to enhance the accuracy of crop assessment.

4.1. Pre-processing

The RISAT-1A Level-2A data, initially received in Digital Numbers (DN) format, was enhanced using a speckle filtering process before being converted to Sigma0 values on a decibel (dB) scale, as shown in Equation 1. In this study, an Enhanced Lee filter with a 5×5 window size was applied independently to both

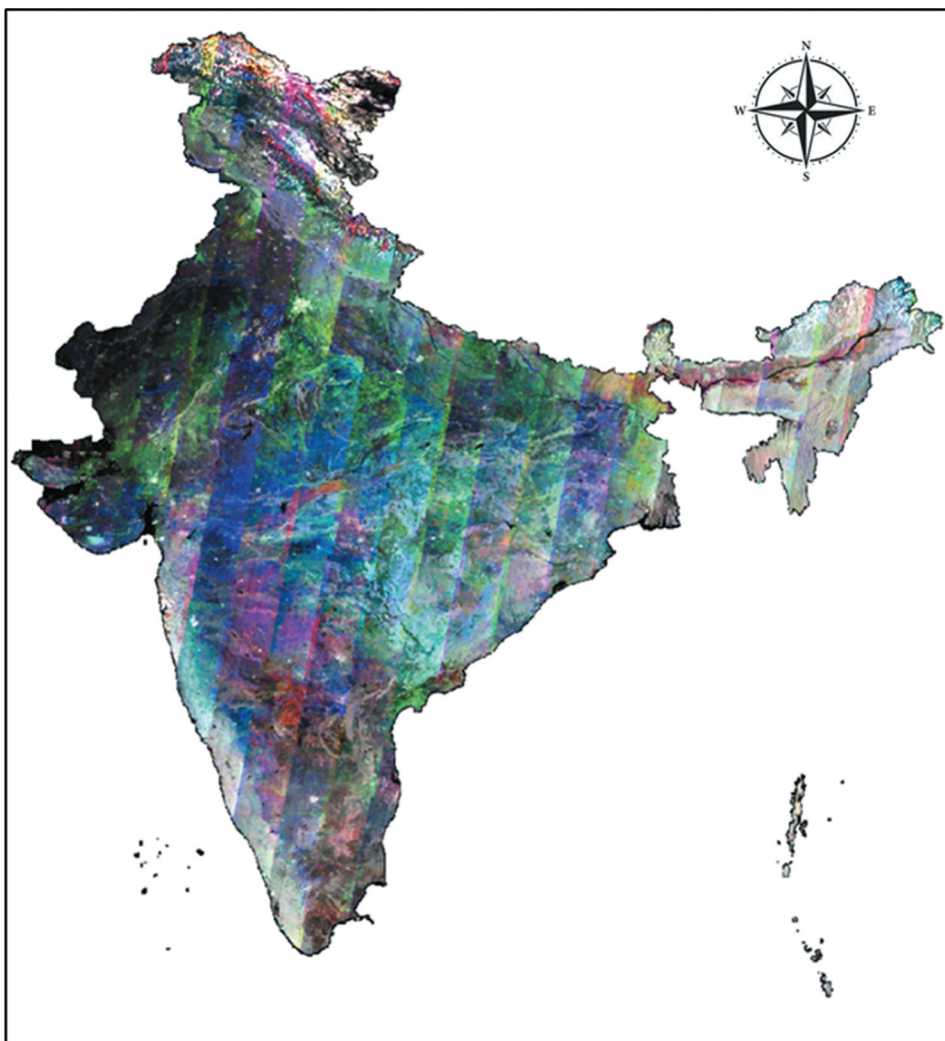


Figure 3. Temporal False Color Composite (FCC) of MRS HV polarization for the months of June, July, and August (2024) across India.

HH and HV polarizations. Additionally, a multi-temporal stack image was generated as part of the analysis.

$$\sigma_0(\text{dB}) = 10\log_{10}(DN^2 - N) + 10\log_{10}(\sin i_p) - K_{dB} \quad (1)$$

where, where σ_0 (dB) is the backscattering coefficient Sigma0 in dB, DN is the digital number, N is the image noise bias, i_p is the per pixel incidence angle, and K_{dB} is the beta0 calibration constant. Further, based on the analysis of data from the eight test sites, the pre-processing steps were automated in the Data Processing (DP) Chain. Upon data acquisition, it is automatically fetched from the server, followed by speckle filtering and Sigma0 conversion for each polarization, thereby preparing the data for the implementation of the rice crop mapping algorithm.

4.2. Generation of temporal backscatter profiles and formulation of decision rules for rice crop classification

The temporal pattern of backscatter responses of rice crop for both HH and HV polarizations from RISAT-1A were generated using multi-temporal stack data for the selected Areas of Interest (AOIs) at each of the eight test sites. These AOIs were carefully chosen based on ground truth data from various locations. This analysis provides valuable insights into the backscatter responses of rice crop during the pre-transplantation, transplantation, and post-transplantation stages. The range of backscatter values observed at each stage of rice crop growth served as the basis for establishing decision rules, which were used to classify pixels as either rice or non-rice crops. This study utilized data from four specific dates, the first corresponds to the pre-transplantation phase, the second to the transplantation phase, and the remaining two to post-transplantation stages. These data points were used to classify pixels as either rice or non-rice crop pixels. The methodology flowchart, which illustrates the various steps involved in rice crop classification, is presented in [Figure 4](#). Additionally, identifying the probable sowing window for each state during the upscaling phase helped prevent potential mix-ups with other crop pixels, particularly during the early part of the season.

4.3. Classification of rice crop pixels based on decision criteria

The process of identifying rice crop pixels involves a multi-stage approach designed to account for staggered transplantation practices in the field. This sequence of observations ensures the accurate discrimination of rice pixels from non-rice classes while effectively handling the temporal variability and staggered transplanting events commonly observed across large agricultural landscapes. The transplantation phase of the rice crop was distinctly identified by a sudden drop in backscatter values, attributed to agronomic flooding, which was subsequently followed by a gradual increase in backscatter due to crop establishment and growth. This characteristic 'V'-shaped temporal backscatter profile formed the fundamental basis for distinguishing rice pixels from non-rice pixels in the classification process. This iterative mapping process is initiated at the onset of the rainy season (from late May to early June) and continues through to August, coinciding with the completion of the majority of rice transplantations across India. At each iteration, rice crop layers are generated corresponding to the detected transplantation events at staggered intervals. Upon completion of the entire transplantation window, the individual rice crop layers generated at different stages are systematically amalgamated, resulting in the production of a comprehensive rice crop map, accurately capturing the spatial and temporal variability of rice cultivation across the landscape.

In India, rice crop transplantation typically begins in the first week of June, coinciding with the onset of the southwest monsoon. The majority of transplantations are completed by the end of July; however, in regions with higher irrigation requirements, the process may extend into mid-August. In Tamil Nadu, rice transplantation is often delayed due to the late arrival of rainfall, which typically coincides with the northeast monsoon. To account for these regional variations, different time periods were considered for each state when implementing the

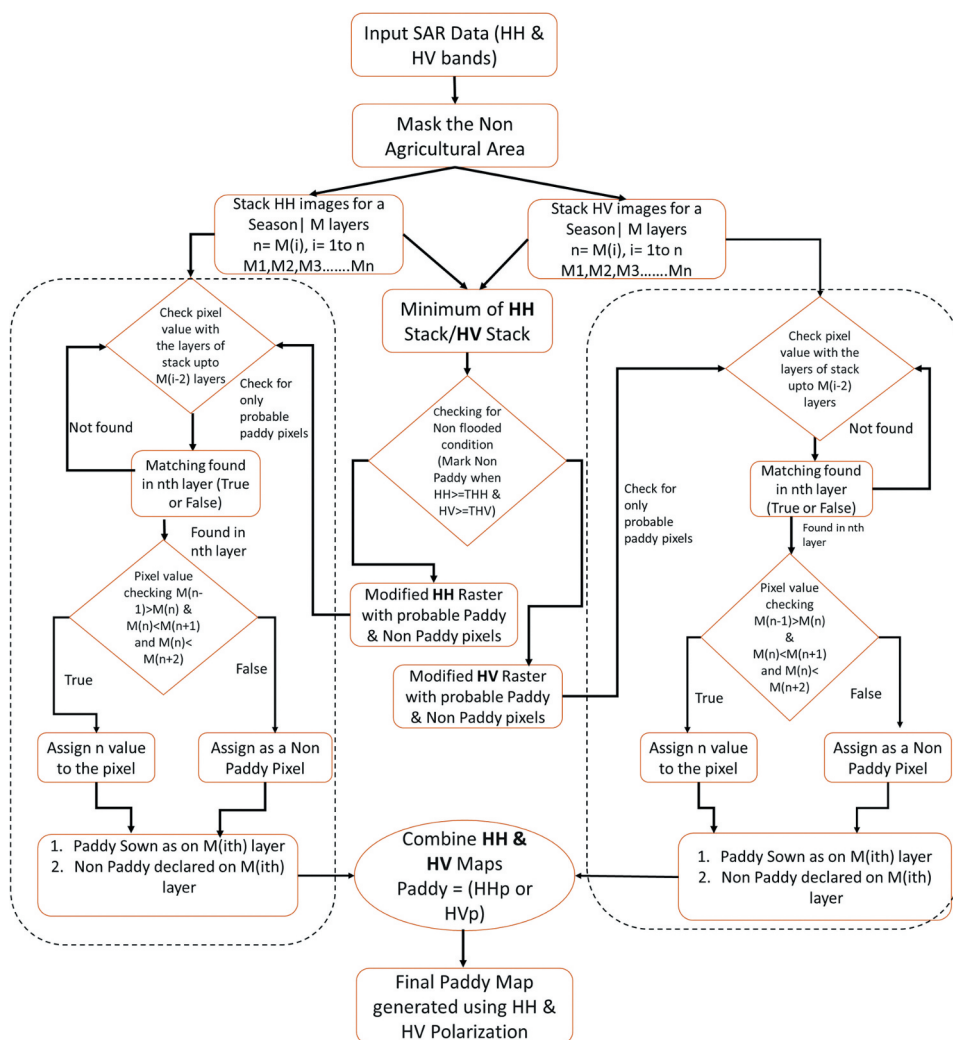


Figure 4. Methodology flow chart for rice crop classification using temporal MRS data and automation in DP chain.

decision criteria for rice crop mapping. The classification process was carried out iteratively to accurately capture the staggered transplantation timelines across the various states.

4.4. Framework for automatic generation of Rice Crop Map (RCM) through Integrated Multi mission Ground Segment for Earth Observation Satellites (IMGEOS)

Proposed automated framework for rice crop map generation can be effectively organized into three main modules, each focusing on specific aspects of the overall process. These modules ensure that the overall system is modular, efficient, and capable of handling large-scale datasets automatically.

- (i) Data Fetch Modules: Handle the acquisition of required input datasets,
- (ii) Data Pre-Processing Modules: Perform essential transformations and calibrations on the raw data, and
- (iii) Rice Crop Map Generation Modules: Carry out the final mapping and classification processes.

4.4.1. Data fetch Modules

The Data Input Module plays a crucial role in the rice crop mapping system by ensuring that the required datasets are gathered, transformed, and pre-processed efficiently for the subsequent stages of classification and mapping. The key functionalities of this module are given as follows:

- (a) Data Fetching: Retrieve EOS-MRS Enhanced Terrain Corrected (L2A) data for the specified time period and geographic region from the IMGEOS Storage. The system automatically unzips or extracts the downloaded data files to prepare them for the next steps in the processing chain.
- (b) Data Segregation: The Data Segregation process ensures that only the most relevant satellite data is selected for rice crop mapping. By filtering the data based on Indian geographic coverage, descending passes, and the specific polarizations (HH and HV), the system improves the accuracy and relevance of the input data for the rice crop mapping process. This segmentation also minimizes computational overhead by excluding unnecessary data, ensuring faster and more efficient processing in subsequent stages.
- (c) Reference Mask : Reference mask refers to agricultural areas thereby limiting the analysis within agricultural areas, which was generated using 1:50000 Land Use Land Cover (LULC) map generated by NRSC LULC at national scale
- (d) Cycle-wise File Listing: For each scene, generate a list of cycle-wise files from the input data, organizing them for easy access and processing in subsequent stages.

4.4.2. Data pre-processing Modules

The Data Pre-processing Module is designed to prepare the filtered data for analysis by applying essential pre-processing techniques. The functionalities of this module are as follows:

- (a) Speckle Noise Removal: Implementation of a 5×5 Enhanced Lee Filter for speckle noise reduction in radar images, enhancing the quality of the data for subsequent processing.
- (b) Radiometric Calibration and Sigma0 Conversion from DN values
- (c) Data Stacking: Stack the data from all the consecutive five cycles to create an active common area defined by the reference mask, i.e. agricultural area. This helps to form an 'active common area' - a spatial-temporal composite that captures consistent observations for analysis like crop growth dynamics.

4.4.3. Rice crop map generation module

The Rice Crop Map Generation Module is designed to classify rice crops based on temporal backscatter profiles from SAR data and generate cumulative rice crop

maps for different sowing windows. The major functionalities of this module are as follows:

- Pixel Evaluation and Classification:** For each scene extent, evaluate each pixel to create a temporal profile corresponding to stacked file, and apply decision rule-based classification to categorize each pixel either as rice crop or non-rice crop.
- Cumulative Output Map Generation:** Generate six cumulative output maps to represent different staggered rice crop sowing periods, where each map reflects the rice crop areas for specific timeframes based on the classification.
- Single Rice Crop Map Creation:** Combine the six cumulative output maps into a single comprehensive rice crop map, providing an overall view of rice cultivation across the study area.

4.5. System configuration for automated framework

A completely automated software has been developed in Python to streamline the process of rice crop map (RCM) generation. The overall processing flow for the Rice Crop Mapping (RCM) generation is presented in Figure 5, which illustrates the sequence of steps involved. Further, specifications and technical details related to the software and processing workflow are provided in Table 2.

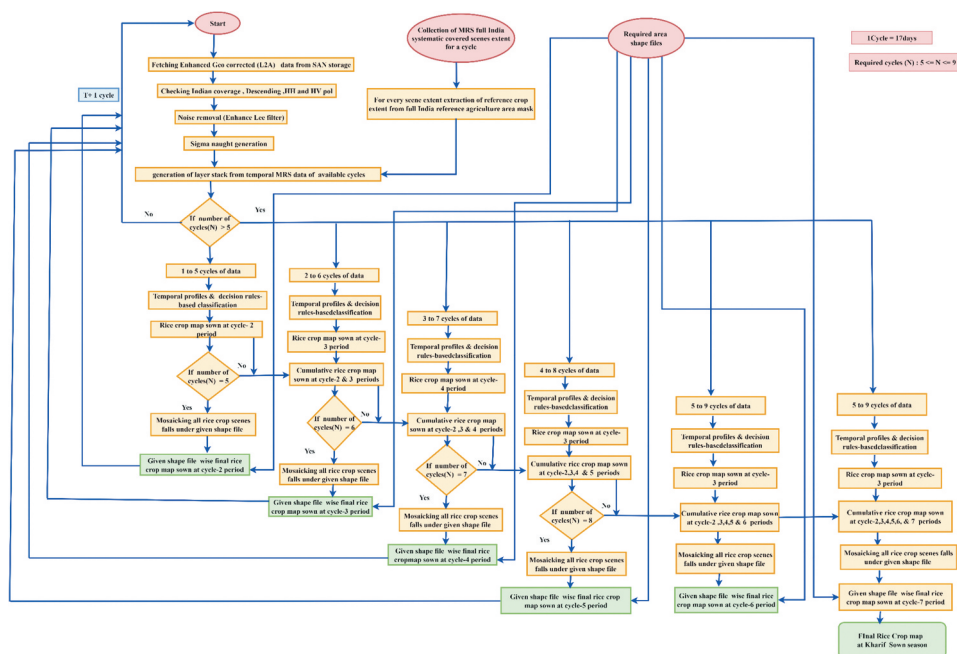


Figure 5. Process flow of rice crop map generation in IMGEOS chain.

Table 2. Software development specifications.

Development Environment	Hardware: RHEL 7.5, 256 GB RAM, CPU cores –24 Software: Python with GDAL & PROJ4 Libraries
Turn-around-Time	10 min per scene
Output RCM file specifications	Shape file-based Product, Bits per pixel: 4 File format: Geo-Tiff Projection: GCS, Datum: WGS-84 Grid spacing: 18 m

4.6. Implementation of methodology for upscaling to major rice growing states of India

The methodology, initially tested and validated at selected study sites across India, was systematically upscaled to cover major rice-growing states. To ensure regional applicability and accuracy, the decision rules were fine-tuned considering the state-specific sowing and transplantation windows, reflecting the agro-climatic variability across different rice ecosystems. These refined rules were integrated into the Data Processing (DP) Chain, enabling operational execution within the IMGEOs automation framework. The pre-processed SAR data, generated through the automated workflow, was subsequently classified for rice crop mapping by strictly adhering to the state-specific Standard Operating Procedures (SOPs) established for rice crop monitoring. This approach ensured consistency, scalability, and accuracy in generating rice crop maps at the state level, facilitating seamless integration of the outputs into national agriculture monitoring systems. The rice crop maps were generated iteratively, starting from the end of the last cycle in May/early June and continuing until October for most states. However, for Karnataka and Tamil Nadu, the data acquisition period was extended from July to November, reflecting the unique cropping patterns and sowing times in these regions.

4.7. Accuracy assessment

Initially, accuracy assessment for the identified study districts was carried out using Ground Truth (GT) points collected during the crop season, which helps to evaluate the effectiveness of the mapping methodology and its reliability in capturing the spatial extent of rice cultivation across India. The classified rice crop maps were validated against these GT points to generate standard accuracy metrics. Further, the accuracy assessment of the rice crop maps for major rice growing districts of India for the *Kharif* 2024 season was carried out using two approaches. First, district-wise rice crop statistics were extracted using the major rice-growing district shape file and compared with data from the Department of Economics and Statistics (DES). Second, the rice crop map was validated using ground truth (GT) points obtained from the Bhuvan FASAL FDC app for Andhra Pradesh, Odisha, Haryana, Punjab, Jharkhand, and West Bengal, where sufficient GT data was available. The GT points were used to perform pixel-by-pixel validation, allowing for the accuracy of these regions. Spatial distribution of the GT points collected from the states of Andhra Pradesh, Odisha, West Bengal, Punjab, Haryana, and Jharkhand for the *kharif*-2024 season are presented in [Figure 6](#).

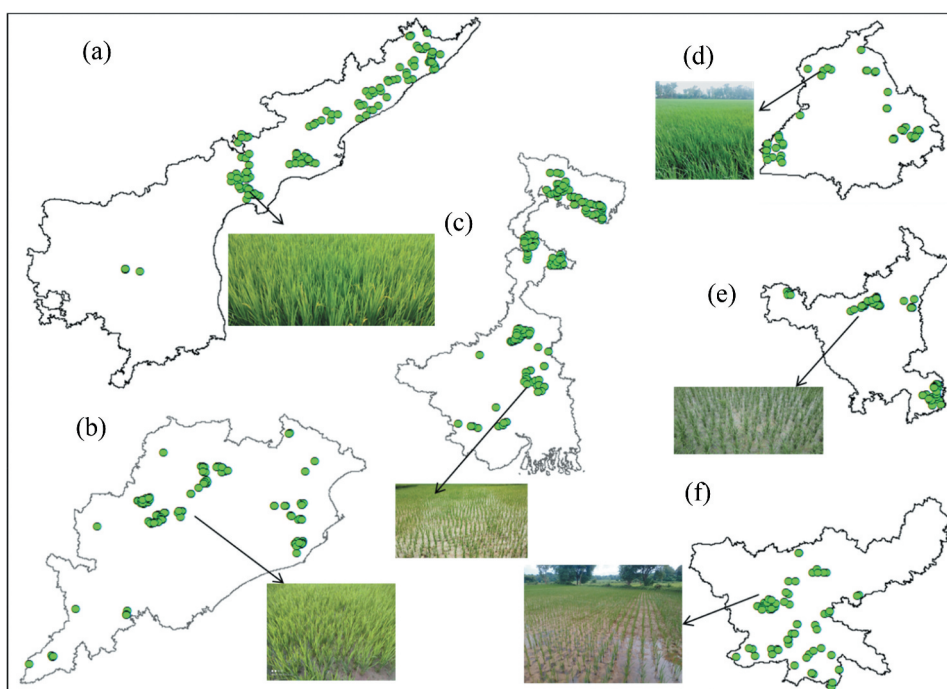


Figure 6. Spatial distribution of the GT points over the Indian states (a) Andhra Pradesh, (b) Odisha, (c) West Bengal, (d) Punjab, (e) Haryana, (f) Jharkhand for the *kharif*-2024 season.

5. Results

5.1. Analysis of temporal backscatter profiles of rice crop in EOS-04 data

Regional variations in rice cultivation practices were analysed by examining the temporal backscatter profiles (HH and HV polarizations) of rice crops across eight representative test sites, covering diverse agro-climatic zones of India (Figure 8). The analysis of temporal backscatter profiles (HH and HV) across the selected test sites revealed considerable variability in the transplantation period of rice crops; these profiles indicated staggered transplantation patterns, reflecting local variations in rainfall onset, water availability, and farming practices, thereby emphasizing the need for site-specific calibration of classification rules to accurately capture the rice crop dynamics. The characteristic backscatter signatures corresponding to different sowing and transplantation periods were studied to refine the decision rules for rice crop mapping. The transplantation window of rice crops exhibited notable spatial variability across the test sites, ranging from the second fortnight of June at Karnal (a test site in North India) to the last week of August at Narayanpur (a test site in South India). This variation reflects regional differences in monsoon onset, irrigation practices, and farmer preferences. The transplantation phase was distinctly captured in the temporal SAR backscatter profiles (HH and HV polarizations), characterized by a sudden drop in backscatter values due to agronomic flooding of the fields, which smoothens the surface and reduces backscatter. This is subsequently followed by a progressive increase in backscatter as the rice crop establishes and grows, contributing to enhanced volume scattering from the crop canopy. This distinct 'V'-shaped temporal

backscatter signature serves as a key indicator for differentiating rice crops from non-rice areas, and forms the basis for pixel-wise classification in the rice crop mapping algorithm.

Furthermore, the temporal backscatter profiles provided critical insights into the presence of staggered rice transplanting practices within individual sites (Figure 7). For instance, in the East Godavari district, the transplantation events were observed around July 9 July 200126, and 12 August, while in Karnal, they occurred approximately on June 19 July 200106, and 23 July. Similarly, in Narayanpur, the transplantation phases were detected around 24 July, 10 August, and 27 August. To effectively capture these variations, it is essential to analyse satellite SAR data spanning from the first week of June to the third week of October, ensuring comprehensive coverage of the entire transplantation and early growth phases of rice crops across regions. Notably, during the transplantation phase, the backscatter values were consistently below -12 dB in HH polarization and below -18 dB in HV polarization across all the test sites, followed by an increase of at least 2 dB in both polarizations during the subsequent crop growth period (Figure 8). These thresholds formed the basis for the decision rules applied in the classification algorithm.

However, in certain regions, particularly in areas where rice fields remain consistently inundated due to frequent rainfall or continuous irrigation, the increase in backscatter during the early growth phase was limited to approximately 1 dB, rather than the typical 2 dB observed elsewhere. This subtle backscatter response necessitated the adoption of slightly modified decision criteria specific to such regions. To address this, state-wise

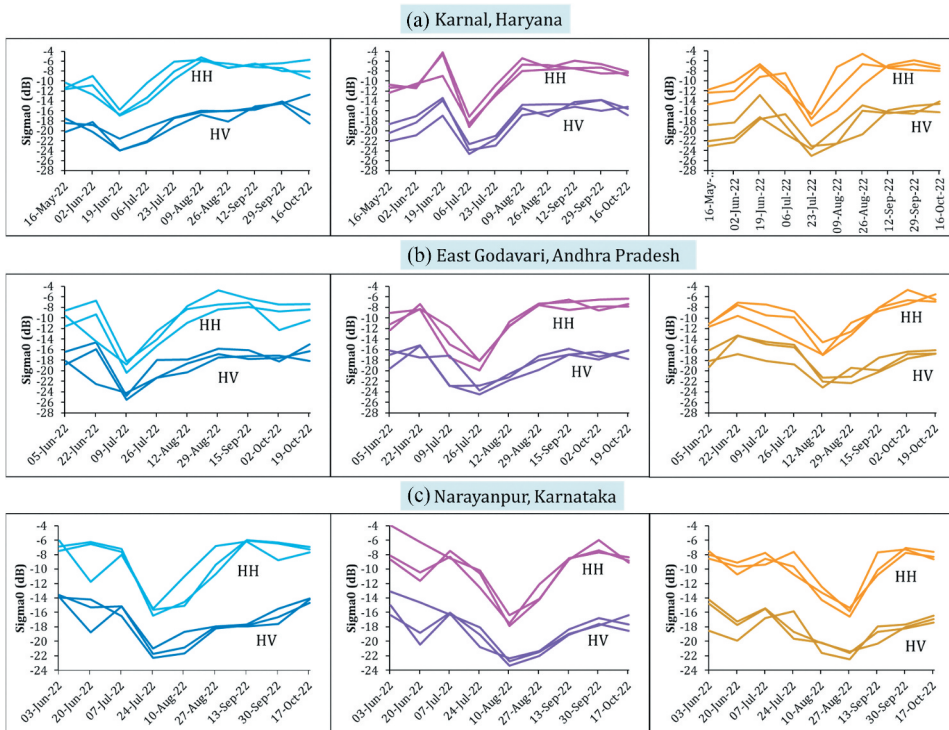


Figure 7. Temporal backscatter (HH and HV) profiles of rice crop in EOS-04 data.

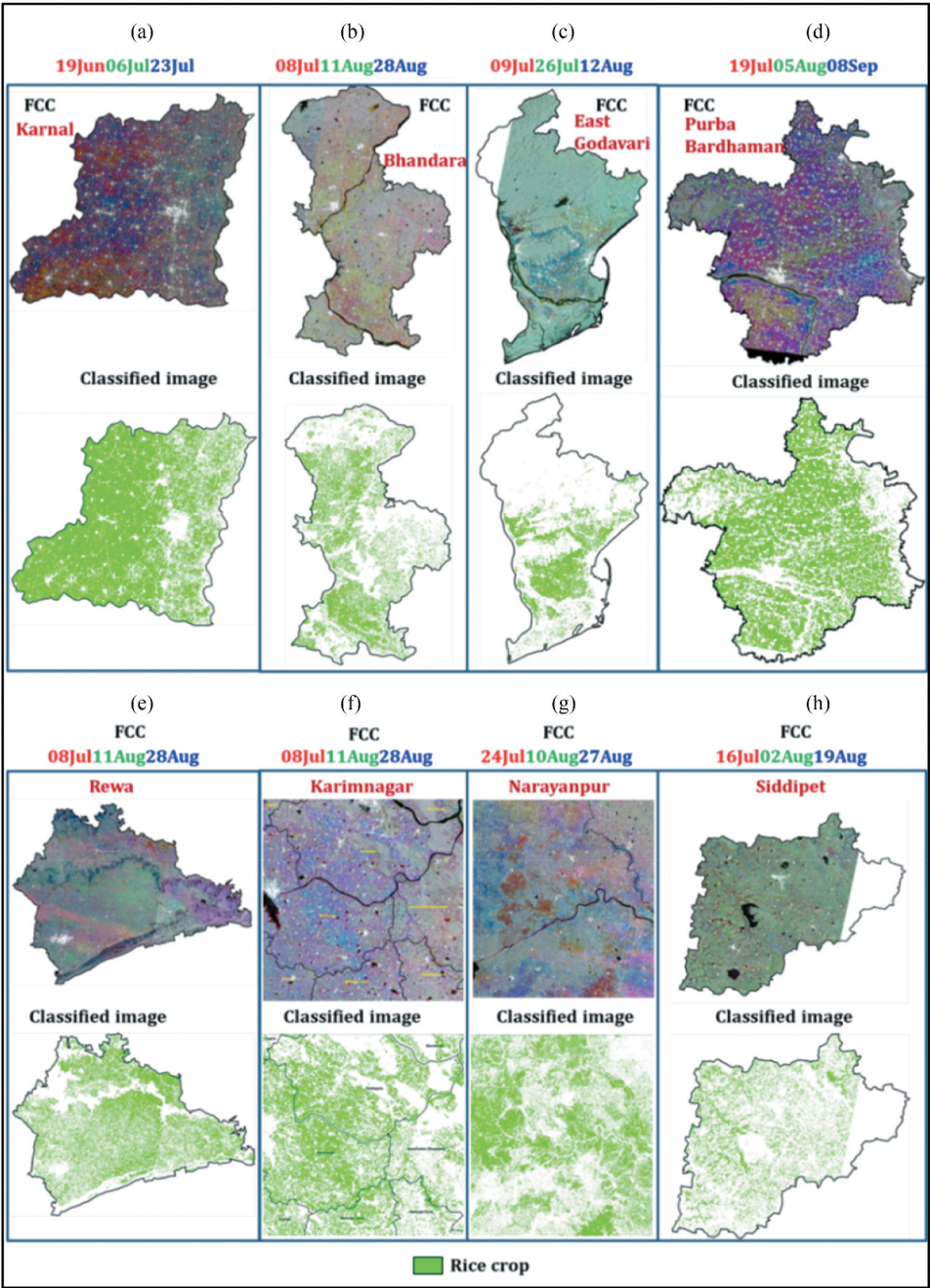


Figure 8. FCC of EOS-04 data along with classified rice crop maps for test sites (a) Karnal, (b) Bhandara, (c) East Godavari, (d) PurbaBardhaman, (e) Rewa, (f) Karimnagar, (g) Narayanpur, (h) Siddipet.

decision rules were developed by systematically analysing the temporal backscatter profiles at randomly selected locations within each state, considering local cropping practices, water management, and backscatter behaviour. These state-specific Standard Operating Procedures (SOPs) were subsequently integrated into the Data Processing (DP)

Chain, ensuring that the rice crop mapping algorithm was tailored to the agro-climatic conditions and farming practices of each state, thereby improving the classification accuracy and operational scalability.

5.2. Classification of rice crop pixels based on decision rules

The decision-making framework was uniformly applied across all eight test districts to maintain consistency and comparability in rice crop mapping outcomes. The framework is based on the systematic analysis of temporal backscatter profiles derived from both HH and HV polarizations, using carefully selected ground truth points at each location as reference. It was observed that when HH or HV polarization data were used independently, the rice crop extent was often underestimated, likely due to the limited sensitivity of a single polarization to capture the full range of crop and water conditions across diverse sites. In contrast, the combined use of both HH and HV polarizations significantly enhanced classification accuracy, enabling a more robust detection of rice crop dynamics and yielding more reliable and comprehensive rice crop extent maps. [Figure 8](#) presents the False Colour Composite (FCC) images and the corresponding classified rice crop maps for all eight test sites. The selected sites encompass a range of cropping patterns and agro-ecological conditions. Among them, Karnal, Bhandara, East Godavari, Purba Bardhaman, Rewa, and Karimnagar are characterized as rice-dominant regions with limited presence of other crops, providing relatively homogeneous conditions for rice mapping. In contrast, the Narayanpur and Siddipet districts exhibit heterogeneous agricultural landscapes, with a substantial presence of non-rice crops alongside rice cultivation, presenting a more challenging mixed-cropping scenario. Accordingly, the classification performance of the rice crop mapping approach was evaluated under both rice-dominant and mixed-crop conditions, providing insights into the robustness and adaptability of the developed methodology across diverse agricultural settings.

5.3. Accuracy assessment for identified test sites

The accuracy assessment of rice crop mapping, conducted using the available ground truth (GT) points, demonstrated that rice crop could be delineated with an accuracy exceeding 90% in the districts of Karnal, Purba Bardhaman, East Godavari, and Siddipet ([Table 3](#)). In the remaining test sites, the classification accuracy ranged between 81% and 88%. These variations in accuracy are primarily attributed to data gaps during the critical rice transplantation phase in certain areas, as well as weaker backscatter signal manifestation, prolonged inundation, or mixed cropping patterns. This multi-tiered validation approach ensured reliability and operational readiness of the rice crop maps at both district and state levels.

5.4. Automatic generation of Rice Crop Map (RCM) in IMGEOs framework

A unified, data-centric framework has been established at IMGEOs to automate the generation of national and state-level rice crop maps from the Level-2A Enhanced

Table 3. Accuracy of rice crop mapping in different test districts across India.

SNo.	Test district	Accuracy
1	Karnal	94%
2	Rewa	88%
3	Bhandara	81%
4	Karimnagar	87%
5	Purba Bardhaman	96%
6	East Godavari	95%
7	Narayanpur	83%
8	Siddipet	92%

Terrain Geo-Referenced Products provided by EOS-04 in MRS mode. To generate a comprehensive rice crop map for all of India, a total of 12 MRS cycles of data (spanning from 15th May to 4th December) was used. This extended period accommodates the different sowing windows adopted by various states across India. The software is designed to ensure that each cycle-wise Rice Crop Map (RCM) generation begins from the end of the 5th cycle and continues until the end of the 12th cycle, utilizing data from the five most recent cycles at any given time. As a result, six sets of cycle-wise RCMs are produced, allowing for the analysis of rice sown area progression at various intervals of time. These six cycle-wise RCM sets are then combined to create the final, comprehensive rice crop map (RCM), ensuring accurate representation of rice cultivation dynamics over the entire period. The rice crop map algorithm incorporates temporal profile analysis and a decision rule-based classification approach for accurate rice crop delineation.

5.5. Implementation of the methodology in the major rice growing states of India

The methodology developed for rice crop mapping was extended and implemented across 343 major rice growing districts in 15 key rice-producing states of India to assess its scalability and applicability. The classification of rice crop pixels was performed using four-date data (pre-transplantation, transplantation, and two post-transplantation dates) in an iterative manner, where one date was shifted forwards on the time scale accounted for staggered rice transplantations both within and across states. Prior to deployment in the Data Processing (DP) Chain, the decision rules were fine-tuned based on the sowing and transplantation windows specific to each state. The pre-processed data, generated through the automation chain, was then classified for rice cultivation according to state-specific Standard Operating Procedures (SOPs) for rice crop mapping. The rice crop maps were generated iteratively, beginning from the end of the last cycle in May or the first cycle in June, and continuing through October for most states. By the end of October/November, the cumulative rice crop area for each state was determined by combining all rice pixels corresponding to the transplantation period. For Karnataka and Tamil Nadu, however, data from July to November was utilized to account for their unique cropping patterns. The final rice crop map for the major rice-growing states of India during the *Kharif* 2024 season is presented in [Figure 9](#).

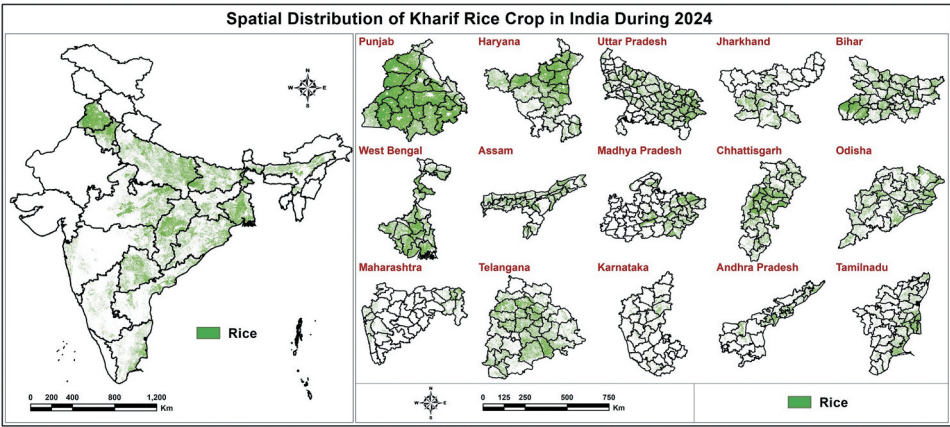


Figure 9. Kharif rice map (2024) for the major rice growing states of India.

5.6. Accuracy assessment of national level rice map for the kharif 2024 season

The district-wise comparison between the rice crop area estimated using the proposed methodology and the official Department of Economics and Statistics (DES) reported statistics exhibited a strong correlation (Figure 10). Higher coefficient of determination (R^2) value of 0.91 reinforces the effectiveness of the implemented decision-rule-based classification and validates the suitability of the methodology for operational rice crop

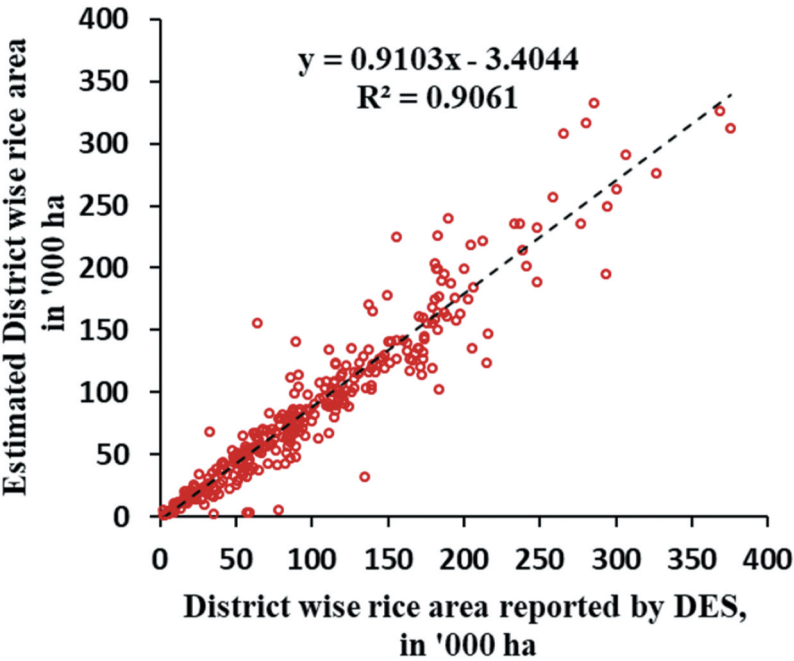


Figure 10. Correlation of estimated district-wise rice crop area statistics from satellite-based classification and the area reported by department of Economics and statistics (DES) reported data for the Kharif 2024 season.

area estimation at the national scale. The district-wise comparison of the rice crop area statistics estimated from satellite data and the area reported by the DES is presented in [Figures 11a and b](#). accounted that accounted

The results suggest that the methodology consistently performs well, achieving an accuracy of approximately 80% in the majority of districts. These findings validate the robustness of the approach for large-scale rice crop mapping and underscore its potential for operational implementation in agricultural monitoring and decision support systems. The state-wise rice crop area statistics for the *Kharif* 2024 season, excluding Maharashtra and Tamil Nadu are presented in [Table 4](#).

The independent validation of the rice crop map using ground truth (GT) points further confirmed the high reliability of the methodology across diverse agro-climatic regions ([Table 5](#)). In Andhra Pradesh, 113 out of 123 GT points were correctly classified as rice, achieving an accuracy of 91.86%. Similarly, in Odisha, 145 out of 165 GT points were accurately identified, resulting in an accuracy of 87.87%. West Bengal also demonstrated strong classification performance, with 139 out of 156 GT points correctly mapped, corresponding to an accuracy of 89.10%. In the states of Punjab, Haryana, and Jharkhand, despite the relatively low availability

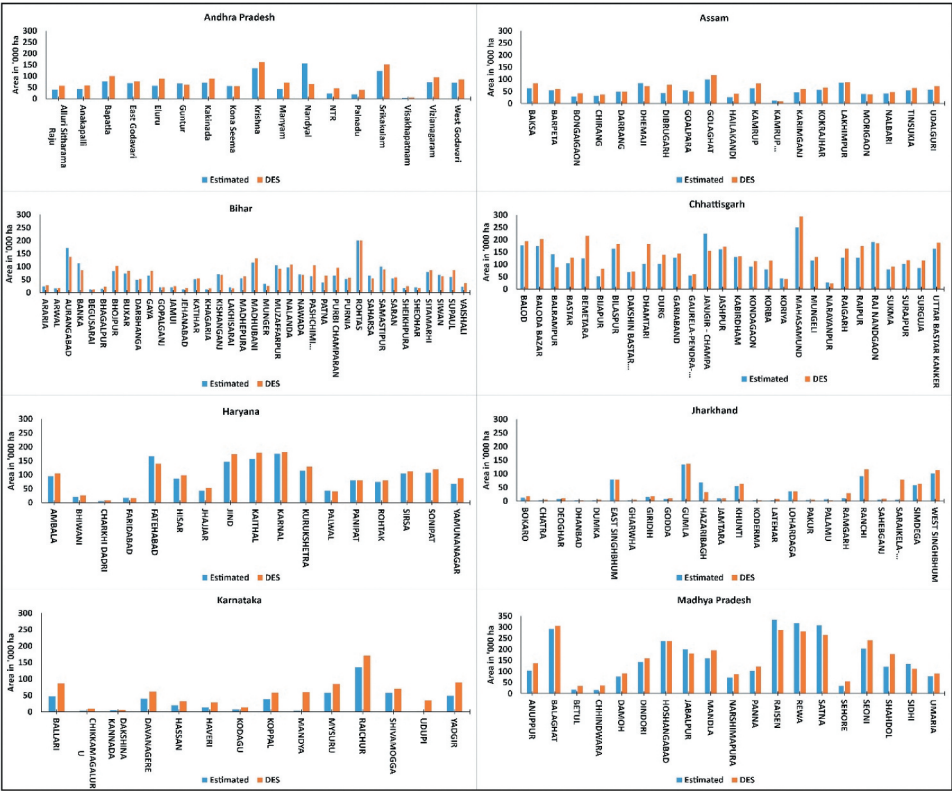


Figure 11a. Comparison of district-wise rice crop area statistics derived from satellite-based classification with Department of Economics and Statistics (DES) reported data for the Kharif 2024 season.

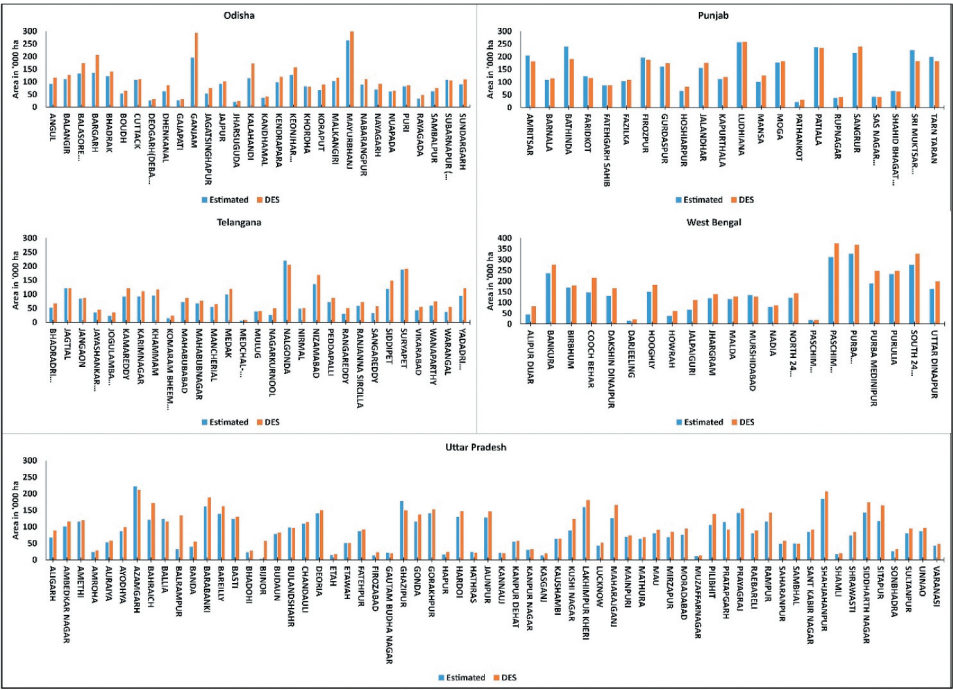


Figure 11b. Comparison of district-wise rice crop area statistics derived from satellite-based classification with Department of Economics and Statistics (DES) reported data for the Kharif 2024 season.

Table 4. State-wise rice crop area statistics for the major rice-growing states of India during the Kharif 2024 season (area in thousand ha).

S.No.	State	Estimated Area	DES Reported Area
1	ANDHRA PRADESH	1127	1451
2	ASSAM	986	1956
3	BIHAR	2203	2965
4	CHHATTISGARH	3388	3786
5	HARYANA	1498	1423
6	JHARKHAND	717	1203
7	KARNATAKA	545	960
8	MADHYA PRADESH	2921	2761
9	ODISHA	2718	3692
10	PUNJAB	3130	3044
11	TELANGANA	2105	2322
12	UTTAR PRADESH	5271	5732
13	WEST BENGAL	3090	4041

Table 5. Accuracy of rice crop mapping in selected states of India.

Sl.	States	Accuracy
1	Andhra Pradesh	91.86%
2	Odisha	87.87%
3	Punjab	86.53%
4	Haryana	88.46%
5	Jharkhand	85.71%
6	West Bengal	89.10

of GT points (52, 78, and 70 points, respectively), the classification accuracies remained robust, ranging from 85% to 88%.

6. Discussion

In this study, 10 to 12 cycles of MRS data from EOS-04 were utilized, encompassing the critical phases of the rice-growing season across India. The decision rules for rice crop mapping were initially formulated using observations from eight representative test sites, leading to the development of state-specific rule sets that were subsequently embedded into the automated Data Processing (DP) Chain. The consistently high classification accuracies achieved over two Kharif seasons underscore the robustness and reliability of the methodology, reinforcing its suitability for operational applications in future cropping seasons. At each stage, a rice crop map is generated using a set of four strategically selected SAR acquisition dates corresponding to one date prior to agronomic flooding, capturing the baseline backscatter from dry or partially moist fields followed by another date during the agronomic flooding phase, characterized by a significant drop in backscatter due to standing water. Two subsequent dates during the early vegetative phase were used to confirm rice crop presence by verifying the progressive increase in backscatter, indicating active crop growth.

Importantly, the approach capitalizes on the distinct temporal backscatter response of rice crops – characterized by a dip during transplantation followed by a progressive increase during growth – without the need for ground truth (GT) data for national-level scaling of decision rules. Validation of the rice crop maps using GT data provided by national agencies (Mahalanobis National Crop Forecast Centre (MNCFC)) and crowd-sourced sources demonstrated classification accuracies consistently above 80%, further affirming the scalability, robustness, and operational viability of the methodology for large-area rice crop monitoring and decision support.

The comparison of district-wise rice crop area statistics derived from the methodology with the DES reported statistics yielded a strong correlation, with an R^2 value of 0.91, indicating a high level of agreement at the national scale. However, despite the high overall correlation, notable deviations were observed in certain districts, which can be attributed to specific local conditions. In areas with undulating terrain or where direct seeded rice (DSR) practices are prevalent, the characteristic backscatter response of rice is less pronounced, leading to underestimation of rice areas using SAR data. Conversely, in some regions, rice area tends to be overestimated, likely due to spectral overlaps or similar backscatter signatures from other crops or land uses. Larger deviations observed in Assam, Jharkhand, and Karnataka states can primarily be ascribed to the presence of undulating terrain in Assam, Jharkhand, and coastal Karnataka, leading to complex scattering behaviour and reduced discrimination of rice crops. Similarly, in Odisha, Andhra Pradesh, and West Bengal, the deviations in rice crop area statistics could also be attributed to the presence of undulating terrains in parts of these states and the predominance of DSR practices, which complicate the accurate delineation of rice fields using radar backscatter-based approaches. These observations highlight the need for further refinement of decision rules in such challenging agro-ecological zones and crop management systems. Nonetheless, these deviations are generally within the 10–20%

range, contributing to an overall classification accuracy of approximately 80% at the national level.

This study is in line with earlier research efforts aimed at improving rice crop mapping using optical and SAR remote sensing data, as demonstrated by Qiu BingWen et al. (2017), Liu et al. (2018), Talema and Hailu (2020), Thorp and Drajat (2021), and Zhan, Zhu, and Li (2021). Notably, Qiu BingWen et al. (2017) implemented a combined vegetation phenology and surface water variation approach (CCVS) using 8-day composite Landsat-8 OLI time-series data to develop a robust rice mapping algorithm in Northeast China, demonstrating the effectiveness of time-series analysis for detecting paddy rice phenology. Similarly, Liu et al. (2018) introduced a sub-pixel estimation approach for paddy rice planting fraction, utilizing the relationship between the coefficient of variation (CV) of the Land Surface Water Index (LSWI) derived from MODIS data and the planting fraction, which further highlighted the potential of combining surface water dynamics and vegetation indices for large-area rice crop mapping. Similarly, Talema and Hailu (2020) explored the use of Sentinel-1 and Sentinel-2 data for mapping rice and other crops in Ethiopia, proposing a hybrid method that combined radar and optical data for improved accuracy in regions with complex landscapes and agricultural practices. Additionally, Thorp and Drajat (2021) demonstrated the utility of multi-temporal SAR data for identifying paddy rice fields in the United States, focusing on seasonal water changes and the relationship between backscatter characteristics and crop development stages. Zhan, Zhu, and Li (2021) further expanded this field of research by investigating the synergy of optical and SAR data in monitoring rice cultivation in China and proposing a novel data fusion approach that improved mapping accuracy by addressing the limitations of each data type when used independently.

The operational integration of Sentinel-1A time-series data with Sentinel-2A optical indices for mapping rice fields in tropical regions was also explored by Talema and Hailu (2020). Furthermore, Zhan, Zhu, and Li (2021) developed a rice mapping method that combined rice phenology features with Sentinel-1 data to improve the accuracy of rice field classification. While previous studies have explored rice crop mapping using optical or time-series SAR data, primarily from Sentinel-1 (VV and VH polarizations), they did not assess the potential of EOS-04 HH and HV polarization data for large-scale rice crop mapping. This study, however, leveraged dual-polarized EOS-04 systematic coverage data (HH and HV) to delineate rice crop areas. It employed multiple decision criteria tailored for different states and demonstrated the operational implementation of rice crop mapping in India through automated SAR data pre-processing. Additionally, it established the standardization of Standard Operating Procedures (SOPs), facilitating consistent and scalable rice crop mapping across diverse regions. However, the methodology does have certain limitations. Extremely delayed transplantations may not be detectable, as their signal manifestation may be too weak. Furthermore, the rice crop mapping approach heavily relies on the transplantation signature, which could lead to the underestimation of direct-seeded rice crop pixels due to the absence of a distinct transplantation phase in the crop cycle. The unified, data-centric framework established at IMGEOs for the automated generation of national- or state-level rice crop maps is a significant advancement in leveraging Earth Observation (EO) data for large-scale agricultural monitoring. This framework works, specifically focusing on the use of Level-2A Enhanced Terrain Geo-Referenced Products from the

EOS-04 satellite in MRS (Medium-Resolution Mode) and the fully automated Python-based solution.

7. Conclusions

In this study, a decision rule-based framework for rice crop mapping using temporal backscatter signatures was developed, which did not rely on ground truth (GT) data. This framework was automated and scaled to a national level, covering all major rice-growing districts across India. When HH or HV polarization data were used independently, the extent of the rice crop was often underestimated. However, the integration of both HH and HV polarizations resulted in significantly improved classification accuracy and more reliable rice crop extent estimation, all achieved without the need for ground truth data in the national-scale implementation. The classification results were further validated using ground truth (GT) points provided by a national agency and crowd-sourced data, confirming that the mapping accuracy remained above 80%. This validates the robustness and scalability of the developed methodology. A comparison of district-wise rice area estimates with the Directorate of Economics and Statistics (DES) reported figures showed a strong correlation, with an R^2 value of 0.91. While the overall correlation was high, larger deviations were observed in some districts, primarily due to factors such as undulating terrain and the prevalence of direct-seeded rice, which are challenging to capture accurately with satellite data alone. The development of these automated procedures is highly relevant for upcoming ISRO missions and will play a crucial role in refining methodologies for the NISAR mission. Further improvements, particularly through the integration of additional SAR data from the Sentinel-1 satellite series, are expected to enhance rice crop mapping accuracies, potentially surpassing 90% in the near future.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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