

Identifying Rice Transplantation Dates using Sentinel-1 Synthetic Aperture Radar data and Machine Learning

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Received 06 December 2024; revised 11 July 2025; accepted 26 November 2025

This study evaluates the effectiveness of Sentinel-1 Synthetic Aperture Radar (SAR) data, acquired at a 10-m spatial resolution with 12-day intervals, for accurately mapping rice transplantation dates during the Kharif season of 2023 in Kakinada district, Andhra Pradesh. SAR's ability to penetrate clouds and provide all-weather observations was particularly valuable for tracking rice cultivation under monsoon conditions. The study integrated the Random Forest algorithm to classify rice crop pixels, achieving precise identification of transplantation dates using Google Earth Engine (GEE) platform. A comparison between satellite-based estimates and the Agriculture Department's records demonstrated strong alignment. Sentinel-1 SAR observations from 28th July, 9th August, 21st August, and 2nd September 2023 closely matched Agriculture Department records from 2nd August, 9th August, 23rd August, and 6th September. On 2nd August, satellite data estimated 44,672.42 hectares, compared to the Department's 43,414 hectares with a 2.9% deviation. By 9th August, satellite estimates were 61,199.22 hectares, while the Department's estimation was 62,563 hectares, showing a -2.18% deviation. By 23rd August, estimates reached 81,064.94 hectares, with the Department recording 81,889 hectares with a -1.01% difference. Finally, on 6th September, the satellite estimate was 84,049.53 hectares, closely aligning with the Department's 83,685 hectares, reflecting a minimal 0.44% deviation. These minor variations, likely due to timing or reporting differences, underscore the reliability of SAR data for near-real-time monitoring. Accurately identifying transplantation dates and mapping is crucial, as it significantly aids in the precise estimation of rice crop biomass, which is a key parameter for forecasting rice yields.

Keywords: Crop, GEE, Random forest, Transplantation date, VH Polarization

Introduction

Paddy cultivation is critical for global food security, providing sustenance to millions of people worldwide. Efficient management of paddy cultivation requires timely and accurate information about key agricultural activities, particularly the transplantation of paddy seedlings. Mapping transplantation dates is essential for optimizing irrigation schedules, assessing crop health, and predicting yield outcomes. However, traditional methods for monitoring transplantation dates rely on labor-intensive ground surveys or manual observations, which are time-consuming and limited in spatial coverage and accuracy.

The use of SAR imagery, especially from satellites like Sentinel-1, has emerged as a powerful tool for agricultural monitoring. SAR data offers distinct advantages for paddy crop mapping, including its all-

weather imaging capability, high spatial resolution, and ability to penetrate clouds and vegetation cover. These features make SAR particularly useful for monitoring paddy fields, especially during the monsoon season when optical data is often obstructed by clouds. By leveraging SAR data alongside advanced machine learning techniques, such as the Random Forest algorithm, there is an opportunity to automate the mapping of paddy transplantation dates at scale, enabling more efficient and accurate agricultural management. In the realm of paddy crop classification, the VH polarization channel of Sentinel-1 SAR data has garnered attention for its sensitivity to vegetation's structural and moisture content characteristics. The utility of VH polarization SAR data has been demonstrated in accurately mapping paddy fields through texture analysis and machine learning techniques.¹ Similarly, applied polarimetric decomposition techniques to extract relevant features from VH polarization SAR data for classifying paddy crops.²

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Random Forest classifiers have emerged as a prominent tool for image classification in remote sensing due to their robustness and scalability. Studies have showcased RF's effectiveness in land cover classification and its suitability for mapping complex environments.^{3,4} Further analyses have highlighted RF's superior performance compared to traditional decision trees,⁵ while researchers have reviewed RF's versatility and effectiveness across various remote sensing domains, reinforcing its reliability in land cover mapping and crop classification.⁶

One platform that has facilitated the processing and analysis of large volumes of remote sensing data is GEE. It is a cloud-based platform that allows researchers and practitioners to analyze geospatial data at planetary scale, including Sentinel-1 SAR imagery. By integrating SAR data with the Random Forest algorithm within GEE, researchers can efficiently map paddy transplantation dates over large agricultural landscapes, which is vital for timely decision-making and sustainable crop management.

Despite the promising potential of remote sensing for rice crop classification, a significant research gap remains in accurately detecting and mapping paddy transplantation dates. While studies have successfully demonstrated the utility of SAR data for crop mapping, the specific task of identifying transplantation dates has not been extensively explored. This gap limits the scalability of automated systems for large-scale agricultural management, particularly in regions where manual monitoring is not feasible.

This study, therefore, aims to explore the feasibility of mapping paddy transplantation dates using Sentinel-1 SAR data and the Random Forest technique through GEE. Accurately identifying transplantation dates is crucial, as it significantly aids in the precise estimation of rice crop biomass, which is a key parameter for forecasting rice yields.

Study Area

Kakinada district, located in the southeastern part of Andhra Pradesh, India, is a newly established administrative area. Its central coordinates are 16.9891° N latitude and 82.2475° E longitude. Kakinada district shares borders with Anakapalli and Alluri Sitaramaraju districts to the north, East Godavari district to the south, and Konaseema district to the southwest, with the Bay of Bengal lying to the east. The district spans a total area

of 3020 km² and features diverse landscapes, including forests covering 330 km², barren land constituting 4.66%, and non-agricultural land accounting for 20.10%. Agriculture plays a significant role in the district's economy, with fertile plains supporting the cultivation of rice, sugarcane, coconut, banana, mango, and various vegetables. (Source: <https://kakinada.ap.gov.in/>)

The climate in Kakinada district is generally moderate, with May being the warmest month and January the coolest. For the year 2023, Kakinada received a total of 920.82 mm of rainfall by the end of August, which is slightly lower than the same period in 2022, which recorded 924.19 mm. The Godavari River is the primary source of water for Kakinada district. Additionally, irrigation channels such as the Yeleru, Thandava, and Pampa rivers, along with various irrigation projects and tube wells, supplement groundwater irrigation, ensuring a steady supply of water for agricultural activities in the region. The study area map is shown in Fig. 1.

Materials and Methods

The study employs data from the Sentinel-1 C-band Synthetic Aperture Radar (SAR) instrument, operating at a frequency of 5.405 GHz, specifically focusing on the S1 Ground Range Detected (GRD) scenes. These scenes, accessed through the Earth Engine Snippet `ee.ImageCollection("COPERNICUS/S1_GRD")`, offer varying resolutions of 10, 25, or 40 m. Each scene presents one of four band combinations, corresponding to different polarization settings of the instrument: VV (single co-polarization with vertical transmit/vertical receive), HH (single co-polarization with horizontal transmit/horizontal receive), VV + VH (dual-band cross-polarization with vertical transmit/horizontal receive), and HH + HV (dual-band cross-polarization with horizontal transmit/vertical receive). For this study, the focus lies on the 10 m spatial resolution data specifically from the VH polarization band, captured at intervals of 12 days. The date wise details of Sentinel-1 data are shown in Table 1.

By utilizing the VH polarization data with a 10 m resolution and a temporal interval of 12 days, this study aims to provide valuable insights into rice cultivation dynamics. The focus on VH polarization is motivated by its sensitivity to various surface properties, making it particularly suitable for

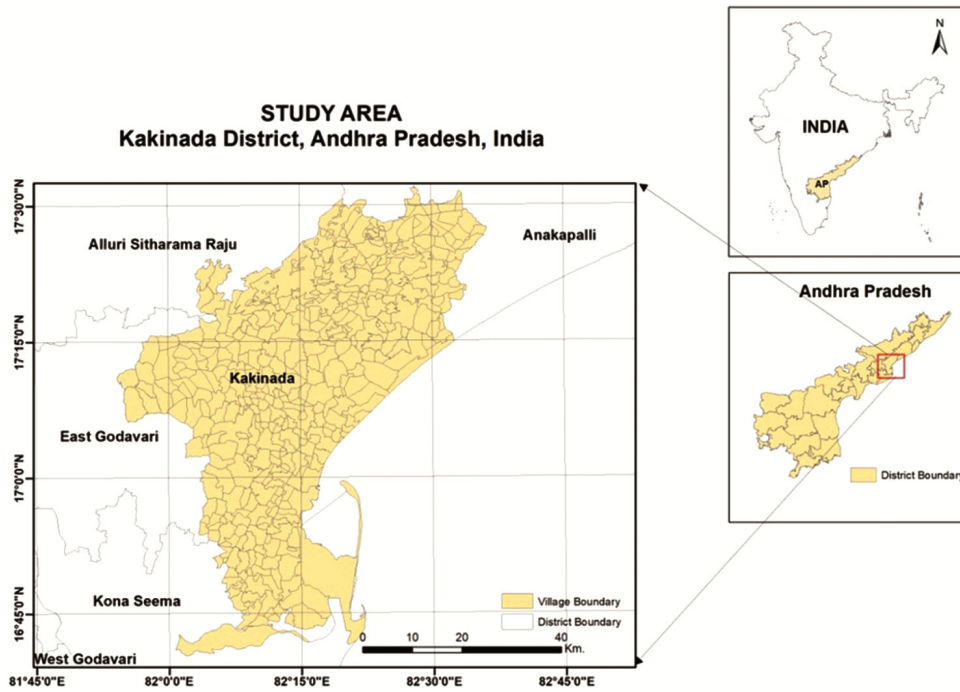


Fig. 1 — Study area

Table 1 — Date wise Sentinel-1 data set used

S. no.	Date of acquisition	Polarization	Instrument mode	Orbit
2	22 nd June 2023	VH	Interferometric Wide	Descending
3	4 th July 2023	VH	Interferometric Wide	Descending
4	16 th July 2023	VH	Interferometric Wide	Descending
5	28 th July 2023	VH	Interferometric Wide	Descending
6	9 th August 2023	VH	Interferometric Wide	Descending
7	21 st August 2023	VH	Interferometric Wide	Descending
8	2 nd September 2023	VH	Interferometric Wide	Descending

discriminating rice fields and detecting changes associated with the transplantation process. Through rigorous classification techniques applied to the SAR imagery, coupled with ancillary data on rice cultivation practices, the study endeavors to establish a robust framework for accurately estimating rice transplantation dates, thereby enhancing our understanding of agricultural processes and facilitating informed decision-making in resource management.

The methodology has been explained below in flow chart illustrated in Fig. 2, outlining the steps involved in mapping rice crops using Sentinel-1 data and the Random Forest technique through GEE:

Data Acquisition: Access the Sentinel-1 SAR imagery from GEE Snippet `ee.ImageCollection("COPERNICUS/S1_GRD")` and filter the date of

acquisition, in this study the Sentinel-1 data has been acquired from June 2023 to September 2023 as per the rice crop growth cycle in the Kakinada district of Andhra Pradesh.

Land Use/Land Cover (LULC) Masking

The LULC mask: ("ESA/WorldCover/v100") was accessed through GEE and used to extract an agriculture land mask for the study area. This mask was then applied to the Sentinel-1 data, effectively excluding non-agricultural regions from the rice classification workflow. By focusing only on agricultural areas, this masking step refined the classification by reducing confusion from urban, water, forest, and barren land classes. It also helped in improving classification accuracy and reducing processing time by eliminating irrelevant regions.

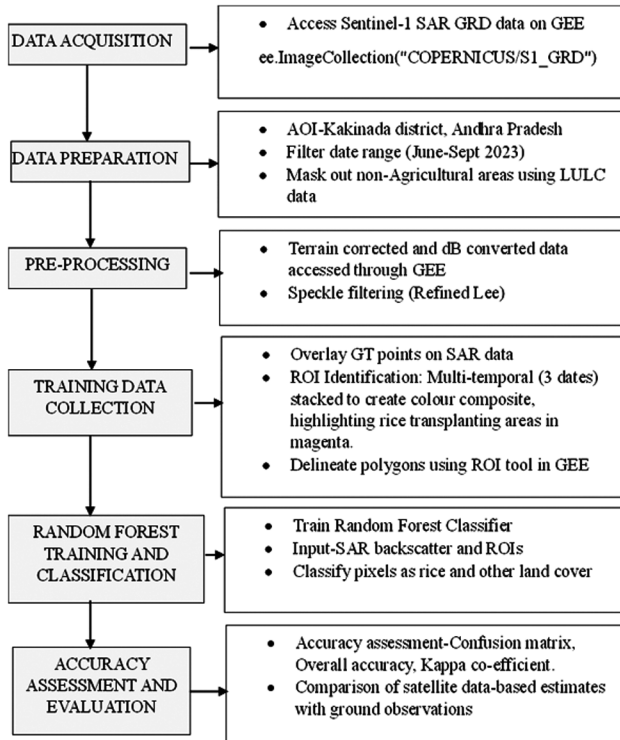


Fig. 2 — Flowchart of the methodology

Preprocessing

Calibration of Sentinel-1 SAR data: In this study, each Sentinel-1 GRD scene had already undergone standard pre-processing and was accessed through GEE snippet. As per the GEE data catalog, the pre-processing was performed using the Sentinel-1 Toolbox and included the following steps:

- Thermal noise removal to eliminate additive noise effects;
- Radiometric calibration to convert raw digital numbers into sigma naught (σ^0) backscatter values;
- Terrain correction using SRTM 30 m DEM to correct geometric distortions caused by topography;
- Finally, the terrain-corrected backscatter values were converted from power to decibels (dB) using the logarithmic transformation is formulated in Eq. 1.

$$dB = 10 \cdot \log_{10}(\sigma^0) \quad \dots (1)$$

These steps ensure that the Sentinel-1 data are radiometrically and geometrically corrected, making them suitable for time-series analysis, classification, and crop monitoring.

Perform Speckle Filtering to Reduce Noise and Improve Image Quality: Refined Lee Filter⁷ (3×3 windows) was applied to reduce speckle noise in the polarimetric

SAR images. Refined Lee Filter is an advanced version of the traditional Lee speckle filter, specifically designed to improve speckle reduction in Synthetic Aperture Radar (SAR) imagery, including Sentinel-1 data. Speckle noise is inherent in SAR imagery and can significantly degrade image quality, making interpretation and analysis challenging. Refined Lee Filter enhances the traditional Lee filter by integrating local statistical properties of the SAR data, allowing for better preservation of image features while effectively suppressing speckle noise. This approach helps maintain the integrity of the image's key features, such as edges and textures, while reducing noise. Speckle filtering has been applied across the entire acquired Sentinel-1 dataset using the GEE platform, ensuring improved image clarity for further analysis.

Field Data Collection: A field visit was conducted during 12–13th October 2023 to collect ground-truth data essential for training and validating the rice crop mapping process. During the field observations, rice and non-rice information was systematically recorded at various locations within the study area using a GPS-enabled camera with an accuracy of approximately ± 1 m. The total dataset consisted of 124 points, which included 84 points representing rice fields and 40 points representing non-rice areas.

Training and Validation Data Preparation

The dataset was split into training and validation subsets to ensure a robust and unbiased assessment of the classification model. The total dataset consisted of 124 points, divided into the following categories:

Rice points: 84

Non-rice points: 40

These points were split using a 60:40 ratio:

Training Data (60%): 74 points (50 rice points and 24 non-rice points)

Validation Data (40%): 50 points (34 rice points and 16 non-rice points)

Identification of Regions of Interest (ROIs): To identify regions of interest (ROIs) containing rice fields and other land cover types, multi-temporal Sentinel-1 data from three specific dates were combined and stacked to generate a composite image. This composite image, represented in color, visualized temporal changes in the study area, highlighting regions of rice transplantation prominently in magenta.

To finalize the ROIs for the rice crop, a total of 74 training data point locations (50 rice points and 24 non-rice points) were collected and overlaid on the

composite Sentinel-1 image. This overlay process validated and refined the boundaries of the identified rice areas, ensuring that the training data accurately represented the rice crop regions within the study area.

Collection of Training Samples: Using the Region of Interest (ROI) collection tool in the GEE code editor, training samples were systematically collected by delineating polygons around the finalized ROIs. Six dates were sampled to ensure comprehensive representation of both rice and non-rice areas. The training data formed the basis for the classification model, capturing essential land cover characteristics for accurate mapping.

Random Forest Training and Validation

The Random Forest algorithm⁸ plays a pivotal role in classifying Synthetic Aperture Radar (SAR) data, particularly in distinguishing rice from non-rice areas. By using an ensemble of decision trees, each trained on different subsets of both the data and features, Random Forest captures complex patterns and variations in SAR imagery, which includes backscatter intensity, texture, and temporal changes. This ensemble approach reduces overfitting and improves classification accuracy, especially in the presence of noise. After training, the algorithm applies majority voting across the decision trees to classify each pixel, ensuring robust and precise identification of rice crop regions. Its ability to process large datasets with high-dimensional features makes it a powerful tool for land cover classification, effectively supporting agricultural monitoring through accurate delineation of rice cultivation areas.

The Random Forest (RF) classifier assigns a label to a given input pixel based on majority voting from multiple decision trees. For a pixel x with feature vector $F = \{f_1, f_2, \dots, f_k\}$, the classification label $L(x)$ is given in Eq. 2:

$$L(x) = \text{Mode}(T_1(x), T_2(x), \dots, T_n(x)) \quad \dots (2)$$

where,

- $T_i(x)$: The classification result (label) from the i -th decision tree for the pixel x .

- n : The total number of decision trees in the Random Forest.

- Mode: The most frequently occurring label (majority vote) across all trees.

Training the Random Forest (RF) classifier: The Random Forest (RF) classifier was trained using the training

samples collected in the previous process, which consisted of a total of 74 points—50 rice points and 24 non-rice points. These training samples enabled the classifier to learn the distinct patterns and characteristics associated with rice and non-rice regions. Once trained, the classifier was applied to the entire SAR dataset, where each pixel was systematically classified as either rice or non-rice. The trained Random Forest classifier utilized the learned patterns from the training phase to assign labels to each pixel based on the feature values, ensuring precise classification across the entire study area.

Validation Process of Classified Rice Map: The validation dataset, consisting of 50 points (34 rice points and 16 non-rice points), was used to independently assess the accuracy of the classified rice map. These points were systematically sampled to evaluate the performance of the classification model. To ensure the reliability and robustness of the rice mapping process, several validation metrics were calculated:

Confusion Matrix: A matrix that compares the classification with the actual reference data, showing the true positives, false positives, true negatives, and false negatives. It is used to validate the accuracy of classification results, such as distinguishing between rice and non-rice areas. From the confusion matrix, several performance metrics can be derived: such as overall accuracy, producers accuracy, users accuracy and kappa co-efficient.

Overall Accuracy (OA): The proportion of correctly classified pixels out of the total pixels, providing an overall measure of classification success.⁹

The Overall Accuracy (OA) is formulated in Eq. 3.

$$OA = \frac{O_i}{O_t} * 100 \quad \dots (3)$$

where,

O_i = Correctly classified points.

O_t = Total points.

Producer's Accuracy: The producer accuracy is the probability of a sample spatial data unit being correctly classified and is a measure of the error of omission for the particular category to which the sample data belong.⁹

The Producer accuracy (PA) is calculated from Eq. 4.

$$PA = \frac{P_i}{P_t} * 100 \quad \dots (4)$$

where,

P_i = Correctly classified sample locations in column.

P_t = Total number of sample locations in column.

User's Accuracy: This is the probability that a spatial data unit classified on the map or image actually represents that particular category on the ground.⁹

The User's accuracy (UA) is formulated in Eq. 5.

$$UA = \frac{U_i}{U_t} * 100 \quad \dots (5)$$

where,

U_i = Correctly classified sample locations in row.

U_t = Total number of sample locations in row.

Kappa Coefficient: The Kappa Coefficient, also known as Cohen's Kappa, is a measure of agreement between two classifiers when they categorize items into multiple classes. Cohen's Kappa takes into account the possibility of agreement occurring by chance and provides a measure of agreement beyond what would be expected due to random chance alone. The coefficient ranges from -1 to 1.⁽¹⁰⁾

Kappa Coefficient (\hat{k}) is calculated from Eq. 6.

$$\hat{k} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \cdot x_{+i})} \quad \dots (6)$$

where,

r = number of rows in the error matrix

x_{ii} = number of observations in row i and column i (on the major diagonal)

x_{i+} = total of observations in row i (shown as marginal total to right of the matrix)

x_{+i} = total of observations in column i (shown as marginal total at bottom of the matrix)

N = total number of observations included in matrix

Evaluation process of Rice Crop Transplanted Area: The evaluation process between satellite data estimates and the area reported by the Agriculture Department involves a systematic comparison of the two datasets to assess accuracy and discrepancies. Initially, satellite-derived estimates of transplanted rice area are calculated using remote sensing techniques, which capture land cover changes over time. These estimates are then compared to the officially reported areas from the Agriculture Department, which are typically

based on ground surveys and administrative records. The cumulative transplanted rice area is tracked over specific observation dates to identify trends and deviations. Statistical analysis is conducted to calculate the percentage deviation between the satellite estimates and the reported figures, allowing for an assessment of the reliability and validity of the satellite data.

Result and Discussion

SAR (Synthetic Aperture Radar) data is highly effective in distinguishing various objects on the Earth's surface due to its sensitivity to surface roughness, dielectric properties, and moisture content. Water bodies exhibit a distinct signature as the radar signals are absorbed and scattered due to the high dielectric constant of water, resulting in a low backscatter response. Similarly, moist soil and wetland areas also show low backscatter due to their moisture content. On the other hand, surfaces like fallow land, built-up areas, and different crop types, such as rice and cotton, exhibit varying levels of backscatter depending on their structural characteristics and moisture content. For instance, rice crops, particularly during their growth stages, tend to show higher backscatter due to their canopy structure and moisture levels, while built-up areas, with their complex structures, show strong reflections. This variability in backscatter signatures makes SAR data a powerful tool for monitoring and mapping land cover types and their changes.¹¹⁻¹³

To analyze the behavior of various land cover types in response to SAR (Synthetic Aperture Radar) signals, data was collected at 12-days intervals from June to September 2023 from a consistent location, capturing samples from water bodies, rice crops, cotton crops, plantations, built-up areas, and fallow land. The temporal signatures of these objects were plotted on a graph, revealing that the rice crop exhibits a distinct SAR signature throughout its growth cycle. Notably, during the field preparation stage, where fields are flooded for transplanting, the rice crop's backscatter response undergoes significant changes. These changes differentiate rice from other crops and land cover types, making it easily identifiable in SAR data. The variations in backscatter among different objects are as shown in the graph (Fig. 3).

Progress of Paddy transplantation observed on Sentinel-1 satellite data

In Kakinada district, the transplantation activities were observed to commence on 4th July 2023 and concluded on 2nd September 2023. As per the classification methodology mentioned the rice crop area was classified and spatial map with statistics were generated. The area transplanted on various dates during this period was recorded as follows: 13,187 hectares on 4th July, 6,381 hectares on 16th July, 27,755 hectares on 28th July, 16,808 hectares on 9th August,

20,442 hectares on 21st August, and 3,378 hectares on 2nd September 2023. Consequently, the total rice area transplanted during the Kharif 2023 season in the Kakinada district of Andhra Pradesh amounted to 87,750 hectares.

The recorded transplantation figures indicate a fluctuating pattern in the pace of agricultural operations over the course of the season. Initially, on July 4th, a substantial area of 13,187 hectares was transplanted, signifying a robust start to the cultivation process. This was followed by fluctuations in transplantation rates, with subsequent dates showing variations in the hectares transplanted, ranging from 6,381 hectares on July 16th to 27,755 hectares on July 28th. The progress transplantation rice map is shown in Fig. 4.

By the end of the transplantation period, a total of 87,750 hectares of rice area had been transplanted in the Kakinada district during the Kharif 2023 season. The composite map of rice crop is shown in Fig. 5.

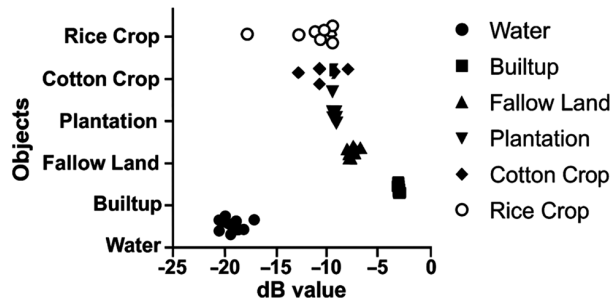


Fig. 3 — SAR signature plots of different earth object

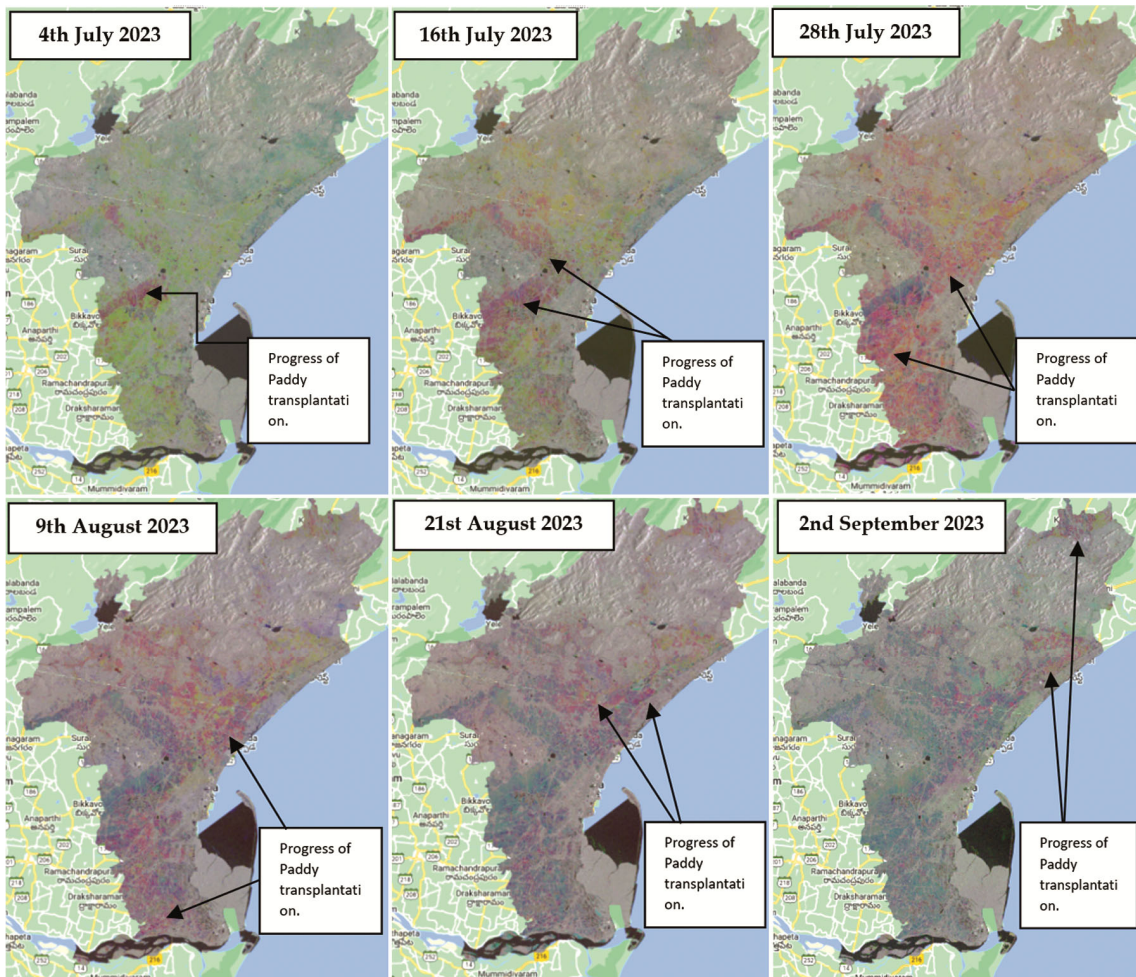


Fig. 4 — Progress of Paddy transplantation observed on Sentinel-1 satellite data

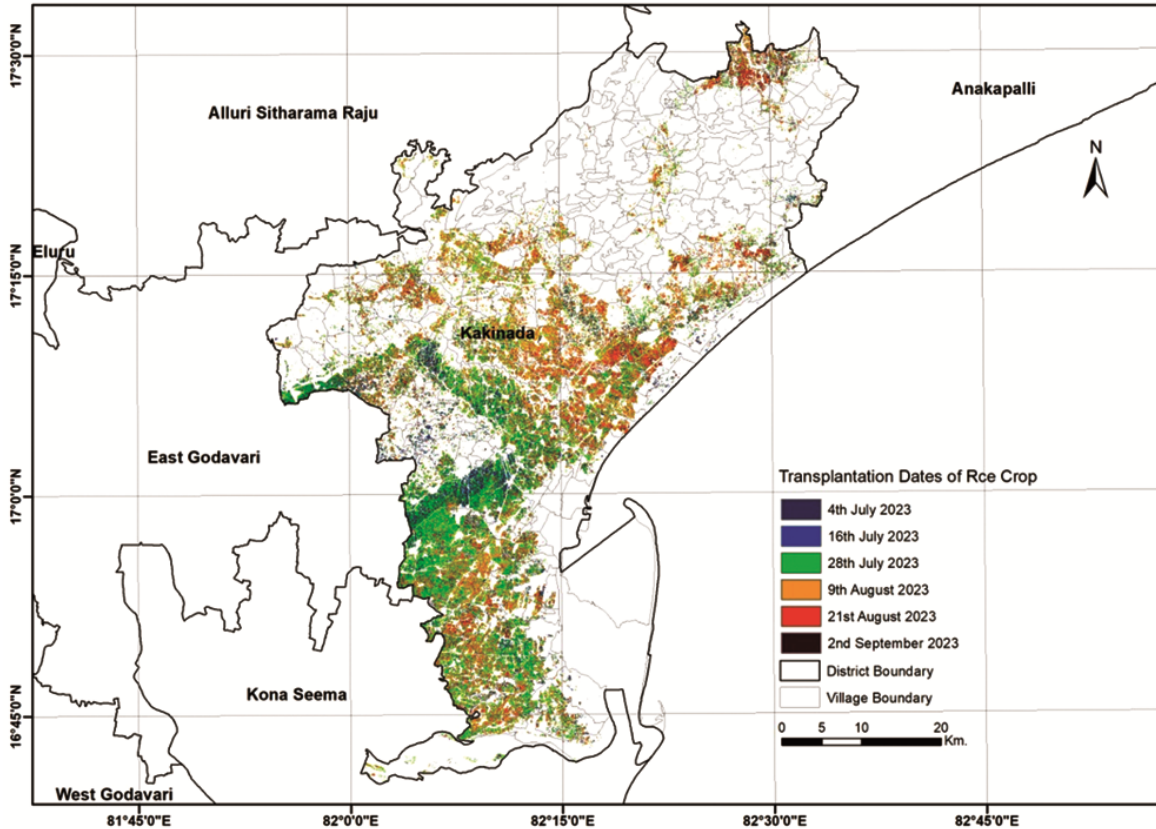


Fig. 5 — Date wise classified Rice map

Validation Analysis

The validation of the rice crop classification model, developed using Sentinel-1 SAR VH polarization data and the Random Forest algorithm, was conducted using 40% of the total field data, comprising 124 ground truth points. From this, 50 points (34 rice and 16 non-rice) were used for independent validation. The confusion matrix, presented in Table 2, showed 32 True Positives (TP), 14 True Negatives (TN), 2 False Positives (FP), and 2 False Negatives (FN). The model achieved an overall accuracy of 92%, demonstrating strong performance in distinguishing rice from non-rice classes. The Producer’s Accuracy and User’s Accuracy for rice were both 94.12%, indicating the model’s high sensitivity and reliability in identifying rice pixels. For non-rice samples, both accuracy metrics were 87.50%, further supporting the robustness of the classification. The Kappa coefficient of 0.816, presented in Table 3, indicates substantial agreement between predicted and observed classifications, validating the reliability of the model.

These results are consistent with recent advancements in rice mapping using Sentinel-1 SAR

Table 2 — Confusion Matrix generated from the validation points

Crop	Rice	Non-rice	Total
Rice	32 (TP)	2 (FN)	34
Non-rice	2 (FP)	14 (TN)	16
Total	34	16	50

Table 3 — Summary of validation results

Metric	Value
Total points	124
Training points	74
Validation points	50
Overall accuracy	92%
Producer’s accuracy	Rice: 94.12%, Non-rice: 87.5%
User’s accuracy	Rice: 94.12%, Non-rice: 87.5%
Kappa coefficient	0.816

time-series data. In a 2023 study, researchers developed a U-Net deep learning model incorporating Sentinel-1 features and ESA World Cover land cover masks, achieving an accuracy of 92.2% and a strong correlation with national statistics (R^2 up to 0.97) across five Southeast Asian countries.¹⁴ Likewise, researchers applied a Random Forest classifier to smoothed Sentinel-1 VH time-series data in Taiwan

for the 2019–2020 rice seasons, reporting an overall accuracy exceeding 87.7%, a Kappa coefficient over 0.76, and a county-level RMSE below 19.7%.¹⁵

Aligned with these studies, the present research demonstrates that using only VH polarization, along with agricultural land masking from ESA World Cover, is effective in accurately classifying rice-transplanted areas. The approach not only enhances classification accuracy but also reduces computational load by focusing exclusively on agricultural zones. These findings underscore the strength of integrating SAR time-series with machine learning algorithms for operational rice mapping, offering a scalable and efficient method for large-area agricultural monitoring.

Evaluation statistics of Transplanted Rice Crop Area

The evaluation process systematically compares satellite-derived estimates with the areas reported by the Agriculture Department to assess accuracy and identify discrepancies. This analysis provides insights into the alignment between remote sensing-based estimates and ground-truth data. The statistics derived from satellite data are compared with the statistics provided by the Agriculture Department, as presented in Table 4, to highlight any variations or inconsistencies between the two datasets.

Table 4 presents a comparison of rice area estimates between satellite observations and the Agriculture Department's reported statistics for the dates 4th July, 16th July, 28th July, 9th August, 21st August, and 2nd September. The table shows the estimated transplanted rice area based on satellite data alongside the cumulative area reported by the Agriculture Department.

An evaluation was conducted using statistics provided by the Agriculture Department on rice crop areas transplanted on 2nd August, 9th August, 23rd August, and 6th September 2023. The cumulative sown area reported by the Agriculture Department on

these dates was compared with the transplanted area estimated using satellite data. Satellite-based estimates were derived from observations on 28th July, 9th August, 21st August, and 2nd September 2023, aligning as closely as possible with the corresponding ground observations.

The 28th July satellite estimates indicated a cumulative sown area of 44,672.42 hectares, which was compared with the Agriculture Department's recorded area of 43,414 hectares on 2nd August. This results in a deviation of 1,258.42 hectares (2.9%), reflecting minor differences likely due to the ongoing transplanting process between the two dates.

The 9th August satellite observation closely matches the Agriculture Department's report. The satellite estimate indicates 61,199.22 hectares, while the Agriculture Department's estimates is slightly higher i.e., 62,563 hectares, resulting in a deviation of 1,363.78 hectares (−2.18%). This alignment demonstrates that both sources captured the sown area with minimal discrepancy, likely reflecting minor differences in timing or ground conditions.

For the 23rd August ground report, the Agriculture Department recorded a cumulative sown area of 81,889 hectares. This was compared with the 21st August satellite observation, which estimated 81,064.94 hectares, leading to a deviation of 824.06 hectares (−1.01%). This minor variation suggests that the satellite data captured most of the sown area accurately, though some ongoing transplanting activities in the two-day interval between the 21st and 23rd may have contributed to the slight underestimation.

Similarly, for the 6th September Agriculture Department report, the recorded sown area was 83,685 hectares, while the 2nd September satellite observation estimated it at 84,049.53 hectares, resulting in a deviation of 364.53 hectares (0.44%). This small difference could be attributed to the dynamic nature of agricultural operations, including

Table 4 — Evaluation of estimates from satellite data and reported by Agriculture department

Date of observation (Satellite/Agri. Dept)	Estimated transplanted rice area (ha) (Satellite)	Cumulative transplanted rice area (ha) (Satellite)	Area reported by agriculture dept. (ha)	Deviation (%)
4 th July 2023/NA*	12223.12	12223.12	NA	NA
16 th July 2023/NA	5505.98	17729.1	NA	NA
28 th July 2023/2 nd August 2023	26943.32	44672.42	43413	2.90
9 th August 2023/9 th August 2023	16526.8	61199.22	62563	−2.18
21 st August 2023/23 rd August 2023	19865.72	81064.94	81889	−1.01
2 nd September/6 th September 2023	2984.59	84049.53	83685	0.44

*NA-Not Applicable

possible late sowing, discrepancies in data aggregation, or differences in how sown and transplanted areas were categorized by both sources.

In summary, the comparison between satellite-based estimates and Agriculture Department statistics shows strong alignment across all dates, with only minor variations. These differences are well within acceptable limits, reinforcing the reliability of satellite data for monitoring sown areas in near-real-time. The slight mismatches are likely due to the inherent temporal gaps between field observations and satellite overpasses or minor differences in reporting methodologies.

The utilization of Sentinel-1 SAR data in conjunction with the Random Forest algorithm and GEE platform has demonstrated exceptional performance in accurately mapping rice crop areas during the Kharif 2023 season in Kakinada district. Sentinel-1 SAR's ability to capture temporal backscatter variations, particularly during critical growth stages of rice, such as field preparation and canopy development, has proven effective for distinguishing rice from other land cover types. The Random Forest classification algorithm further enhanced the model's accuracy by leveraging its robustness in handling non-linear relationships and its capability to work efficiently with SAR data's multi-dimensional feature set. GEE's cloud-based processing capabilities facilitated the analysis of large datasets, enabling rapid processing and visualization of classification outputs.

In comparison to traditional optical remote sensing methods, which are often hampered by cloud cover during the monsoon season, SAR data offers a distinct advantage due to its all-weather imaging capability. However, optical satellite data has also been widely used for rice crop mapping in areas with minimal cloud interference. Studies have demonstrated the effectiveness of MODIS for large-scale rice mapping in Vietnam using temporal NDVI profiles.¹⁶ Similarly, another study highlighted the use of Sentinel-2 data for high-resolution rice mapping, showing its capability to differentiate crop types during specific phenological stages.¹⁷ Comparatively, SAR-based methods, as used in this study, outperform optical approaches in cloudy regions while maintaining high classification accuracy.

In the present study, the integration of Sentinel-1 SAR, Random Forest, and GEE has achieved comparable or even superior mapping accuracy,

ensuring reliable and consistent results. Furthermore, the temporal analysis of SAR backscatter from rice fields has proven instrumental in detecting the progression of transplanting activities and estimating total rice area.

Conclusions

In conclusion, the accurate mapping of rice transplantation dates is crucial for biomass generation and yield estimation, as it provides vital temporal information for assessing crop development. This study demonstrates the effectiveness of Sentinel-1 Synthetic Aperture Radar (SAR) data combined with advanced machine learning techniques, particularly the Random Forest algorithm, in accurately identifying rice transplantation events. The integration of Sentinel-1 SAR data, Random Forest classification, and the GEE platform offered an efficient and scalable solution for processing and analyzing large datasets. The strong alignment between satellite-based estimates and the Agriculture Department's reported estimates, with minimal deviations on key observation dates (e.g., 2.90% on July 28, -2.18% on August 9, -1.01% on August 23, and 0.44% on September 2), highlights the accuracy and reliability of this methodology. These small discrepancies emphasize the robustness of the SAR-based approach, which proves to be an invaluable tool for agricultural monitoring, particularly in biomass generation and yield estimation. This study offers strong potential for scaling to state- or national-level applications. Moreover, the estimated transplantation dates can be integrated into crop growth models to support biomass and yield forecasting.

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