DoI: https://doi.org/10.58537/jorangrau.2025.53.5.11

J. Res. ANGRAU 53 (5) 63-69, 2025

IDENTIFICATION AND ESTIMATION OF RICE SOWN AREA IN GUNTUR DISTRICT USING SENTINEL 1A SATELLITE DATA

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Date of Receipt : 10.09.2025 Date of Acceptance : 24.11.2025

ABSTRACT

Accurate estimation of rice-sown area is critical for informed agricultural planning, particularly in Andhra Pradesh's complex irrigated landscapes. This study mapped rice cultivation in Guntur district using Sentinel-1A SAR (Synthetic Aperture Radar) data integrated with machine learning classifiers. A total of 84 ground-truth observations supported supervised classification using Random Forest (RF) and K-Nearest Neighbours (KNN). Both models overestimated rice extent, but RF showed superior performance with 94% user's accuracy, 96% producer's accuracy and kappa coefficient of 0.76. Overestimation by KNN was largely due to confusion with waterlogged fallow areas. Results confirm the utility of SAR and RF for precise rice area assessment and underscore the importance of localized model calibration in heterogeneous agroecosystems.

Key words: Crop classification, Random Forest, Rice, SAR, Sentinel-1A

INTRODUCTION

Accurate and timely estimation of crop-sown area is crucial for effective agricultural management, efficient resource allotment and informed policy planning, particularly in regions where agriculture plays a major economic role. Rice is a dominant crop in India's agrarian economy, mainly in Andhra Pradesh, where cultivation is concentrated in the Krishna Western Delta (KWD) and Nagarjuna Sagar Project (NSP) command areas. Estimating rice area in these regions is challenging due to fragmented landholdings, large spatial extent, and variability in cropping patterns and water availability, which limit the reliability of conventional assessment methods. These command areas are economically important and exhibit pronounced spatial and temporal variation in rice cultivation driven by irrigation dynamics and cropping intensity.

Traditional field-based surveys for crop area mapping are labor-intensive, costly, and constrained in spatial coverage. Their effectiveness further declines during the monsoon season, when persistent cloud cover restricts the make use of optical remote sensing (Choudhary *et al*., 2014). These restrictions have raised interest in remote sensing–based approaches that can provide consistent and scalable observations.

Synthetic Aperture Radar (SAR) has appeared as an important tool for agricultural monitoring because it operates independently of weather conditions and sunlight (Liu *et al*., 2019). Sentinel-1A, under the European Space

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Agency's (ESA) Copernicus program, offers frequent revisit cycles and free access to high-resolution data, making it well suited for monitoring rice-growing regions affected by seasonal cloud cover. Many studies have demonstrated its effectiveness in identifying rice fields, including flooded paddies, under diverse environmental conditions (ESA, 2024).

Despite these advantages, SAR-based rice mapping remains challenging due to the similarity in backscatter between rice fields and other land types, such as waterlogged fallows and shallow water bodies, which can develop misclassification (Singh *et al*., 2015). Machine learning classifiers, including Random Forest (RF) and K-Nearest Neighbours (KNN), have shown potential for upgrading classification accuracy, but their performance depends on careful calibration and high-quality training data, particularly in heterogeneous agricultural landscapes (Kumar *et al*., 2022).

With this context, the present study evaluates the effectiveness of RF and KNN classifiers for estimating rice-sown areas in the KWD and NSP command regions. Special attention is given to reducing misclassification caused by saturated lowlands, shallow inundation, and uncultivated seasonal fallows that exhibit SAR backscatter characteristics similar to rice. The study further explores improvements in model performance through the integration of local agricultural knowledge and finer temporal resolution in model calibration.

MATERIAL AND METHODS

The study was done during the 2024 *kharif* season in Guntur district, Andhra Pradesh, India, an area known for extensive canal-irrigated rice cultivation under the KWD and NSP command areas. Time-series Sentinel-1A SAR data were received from the ESA Copernicus Open Access Hub for the kharif season, when rice growth is at its maximum. Multiple SAR acquisitions were selected to capture the peak vegetative and reproductive stages of the rice crop.

SAR data preprocessing was carried out using ESA's Sentinel Application Platform (SNAP) version 10. This involved orbit correction, speckle filtering to reduce inherent SAR noise, and geometric terrain correction to minimize topographic distortions. Backscatter values were converted from digital numbers to decibels to normalize the data and allow comparison across different acquisition dates. The processed SAR data were then used to derive information related to key rice growth stages.

To support model development, ground-truth data were collected from 84 locations across the study area. These sites represented different rice cultivation practices and landscape conditions, ensuring broad spatial coverage. Field visits during the kharif season provided GPS coordinates and visual confirmation of land-cover types.

The ground-truth observations were utilized to train two supervised machine learning models, RF and KNN, to distinguish rice fields from other land types, including waterlogged fallow areas with similar radar backscatter. Cross-validation was applied to reduce overfitting and improve model reliability.

Model performance was assed using user's accuracy, producer's accuracy, and the kappa coefficient (Singh *et al*., 2015). User's accuracy indicates how often pixels classified as rice are actually rice, while producer's accuracy reflects how well rice fields were correctly identified. The kappa coefficient assessed the agreement between classified results and field observations beyond chance.

RESULTS AND DISCUSSION

In this investigation, two machine learning classifiers, RF and KNN, were applied to estimate the rice-sown area in Guntur district using SAR data presented in Fig.1 & 2. Both models overestimated the actual rice-sown area, with KNN showing a stronger overestimation tendency compared to RF (Table 1). The misclassification was largely on account of the spectral similarity between rice fields and other land types, particularly shallow water bodies and water-retaining fallow lands, which present similar radar backscatter signatures. This spectral confusion is a well-documented challenge in SAR-based classification, as various land covers in agricultural landscapes often have overlapping backscatter characteristics, leading to inaccuracies (Gao *et al*., 2017).

Among the two classifiers, RF outperformed KNN, particularly in regions with complex land-use patterns such as the KWD and NSP command areas. RF is known for its ability to manage heterogeneous datasets and to capture complex relationships between input variables, which is a key strength when dealing with complex agricultural environments (Liu *et al*., 2020). The RF classifier achieved user's accuracy of 94%, producer's accuracy of 96%, and a kappa coefficient of 0.76, showing strong agreement with field data. These results are in accordance with previous studies that have demonstrated RF's effectiveness in classifying land cover using SAR data, especially in regions with diverse land use (Yu *et al*., 2020; Surya *et al*., 2024). The relatively high kappa coefficient further confirms that RF delivers reliable results with minimal random misclassification, making it suitable for large-scale monitoring.

In contrast, the KNN classifier displayed a higher degree of overestimation, especially in areas where mixed land types were present. This issue was especially noticed in zones where rice fields were adjacent to waterlogged fallow lands or shallow water bodies, which share similar radar signatures with rice paddies. KNN's reliance on pixel-level classification without considering spatial context can lead to confusion in areas with complex or mixed land covers (Benediktsson *et al*., 2018). While KNN is a simple and widely-used classification method, its performance is often compromised in heterogeneous landscapes where contextual relationships between neighbouring pixels are vital for discriminate land types.

Another crucial observation from this investigation was the spatial variability in the rice area estimates across Guntur district. Specifically, RF underestimated the rice area in the KWD, likely due to the heterogeneity of the fields and varying cropping intensities that were not fully characterised in the training samples. Previous study has highlighted that crop classification can be difficult in regions with highly variable field sizes, land use patterns, and cropping intensity, as these factors introduce significant spatial complexity (Li *et al*., 2021). In this case, the limited number of ground-truth points available for training might have contributed to the underestimation by failing to capture the diversity of field patterns in this region.

Conversely, the NSP command areas showed the highest overestimation in rice area estimates. This could be attributed to late water availability and the existence of self-sown rice from the previous season. While self-sown rice is inactively cultivated, its radar backscatter signature closely resembles that of actively cultivated rice, leading to misclassification. A similar issue was observed by Huang *et al*. (2021), where residual crop growth or land with standing water was mistakenly identified as active crop fields. This issue underscores the importance of incorporating temporal

Table 1: Estimated rice crop areas using random forest and KNN algorthims

S.No	Mandal Name	Normal	Estimated area (ha)		S.No	Mandal Name	Normal	Estimated area (ha)	
			RF	KNN				RF	KNN
1	Amaravathi	294	1088	1240	30	Nagaram	11016	10664	10514
2	Amruthalur	10502	9233	10521	31	Nekarikallu	4742	423	652
3	Atchampet	609	557	745	32	Narasaraopet	1451	5147	6814
4	Bapatla	13453	13401	12564	33	Nizampatnam	5437	8747	9538
5	Bellamkonda	557	1313	1473	34	Nuzendla	1077	2593	4834
6	Bhattiprolu	6031	5855	5128	35	Pittalavanipalem	4921	4949	5949
7	Bollapalle	1143	2622	2463	36	Pedakakani	4967	410	628
8	Chebrolu	5908	6155	5864	37	Pedakurapadu	131	420	592
9	Cherukupalle	7491	5989	5637	38	Pedanandipadu	115	1087	1450
10	Chilakaluripet	92	3736	3296	39	Sattenapalle	1405	2364	4109
11	Dachepalle	352	830	1008	40	Phirangipuram	768	2715	3716
12	Duggirala	8531	8180	10985	41	Piduguralla	1959	4716	5072
13	Durgi	379	2322	2224	42	Ponnur	13210	13072	11588
14	Guntur	145	470	494	43	Prathipadu	362	588	712
15	Edlapadu	657	956	908	44	Rajupalem	1432	2280	2814
16	Gurazala	1249	2691	3055	45	Rentachintala	2203	11214	13485
17	Ipur	2805	3064	3894	46	Repalle	10677	4215	3778
18	Kakumanu	9921	10463	10643	47	Rompicherla	3368	1778	2319
19	Karempudi	2839	2652	2968	48	Savalyapuram	2056	724	621
20	Karlapalem	6453	6575	5724	49	Tadepalle	661	1851	2147
21	Kollipara	6308	5638	4931	50	Tadikonda	385	6763	6249
22	Kollur	5088	5422	4957	51	Tenali	8279	920	1230
23	Krosuru	1226	717	920	52	Thullur	109	7111	7612
24	Machavaram	664	1209	1720	53	Tsundur	8089	3807	3462
25	Macherla	700	2357	3303	54	Vatticherukuru	3622	2138	2810
26	Mangalagiri	2584	1822	2104	55	Veldurthi	22	8453	9568
27	Medikonduru	140	1465	1379	56	Vemuru	8142	1964	2420
28	Muppalla	1872	2584	2486	57	Vinukonda	828	2048	3607
29	Nadendla	153	449	310	**Total**	**199581**	**222978**	241234	

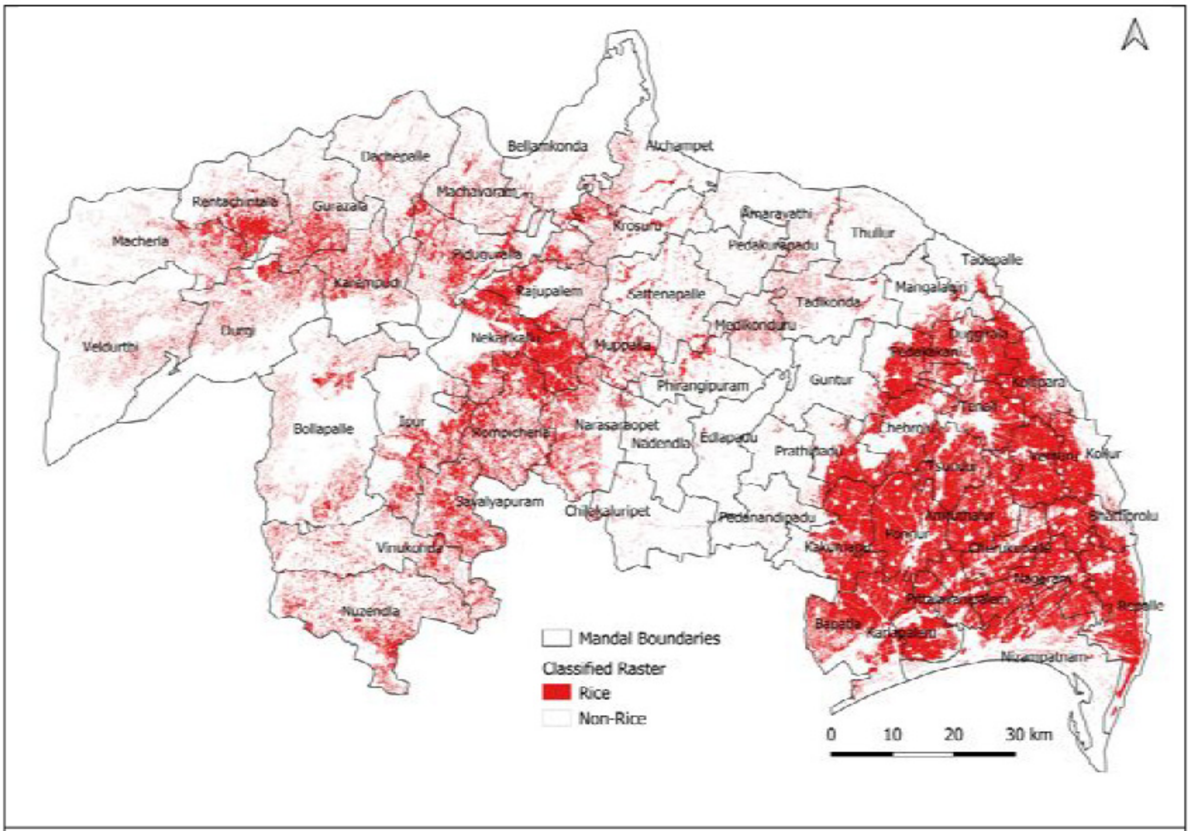

Fig1: Estimated rice area of Guntur district using RF algorithm

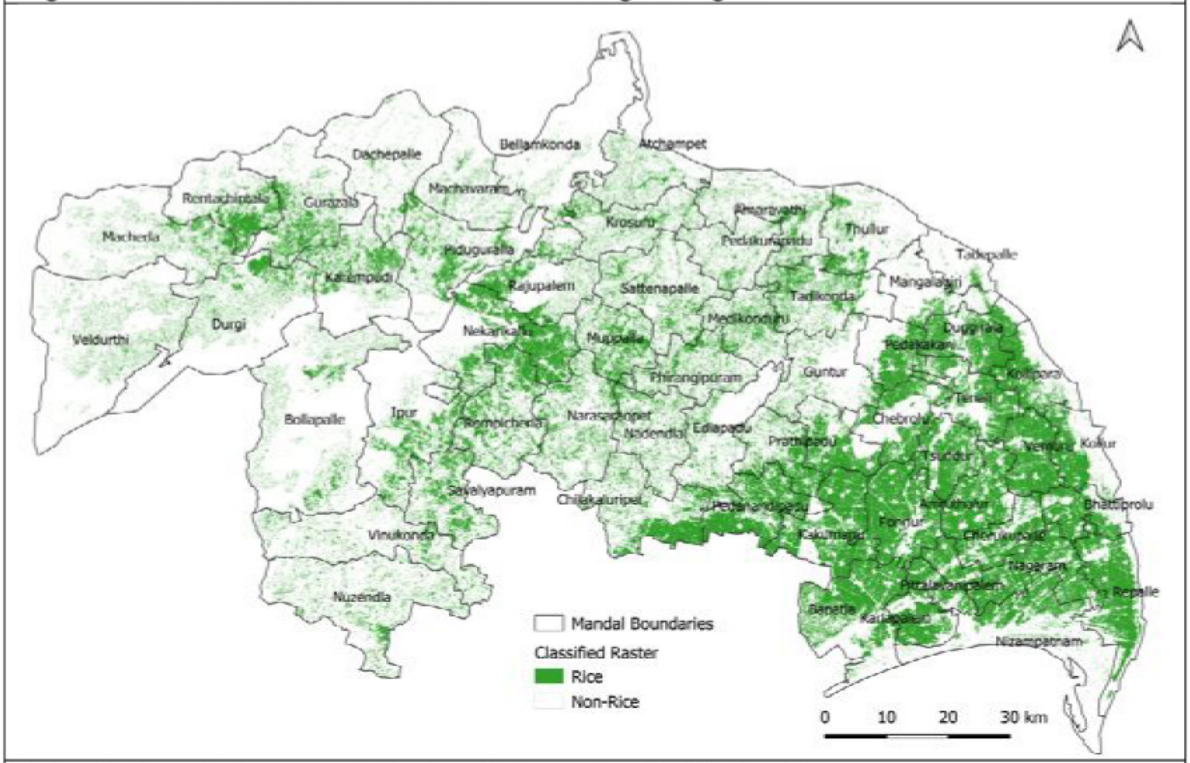

Fig2: Estimated rice area of Guntur district using KNN algorithm

dynamics, such as variations in crop growth stages and water availability, into the classification model for more accurate estimations.

Both the RF and KNN classifiers highlighted the importance of using high-quality, region-specific training datasets for improving classification accuracy. The performance of these algorithms is more sensitive to the diversity and quality of the input training data, which must reflect the spatial and temporal variability of land cover types and crop growth stages. In this study, although 84 ground-truth reference points were collected from different locations, the limited number of samples might not have fully recorded the full range of spatial complexities, particularly in regions with varying cropping intensities and land use. The inclusion of more detailed agronomic data and better representation of crop phenology could further enhance model performance (Kumar *et al*., 2022).

The results also emphasize the need for model calibration specific to local conditions, as machine learning algorithms such as RF and KNN benefit significantly from incorporating region-specific parameters, such as local crop calendars, irrigation practices, and field sizes (Benediktsson *et al*., 2018). Additionally, integrating multi-source remote sensing data, such as combining SAR data from Sentinel-1 with optical imagery from Sentinel-2, could improve classification accuracy. Combining these data sets allow for complementary data that can assist to resolve ambiguities in land cover classification, especially in mixed and heterogeneous agricultural landscapes (Wang *et al*., 2021). This multi-source approach has been successfully implemented in previous studies to enhance classification accuracy and overcome the limitations of using a single remote sensing source.

CONCLUSION

This investigation established that Sentinel-1A SAR imagery, integrated with RF and KNN, is effective for estimating rice-sown areas in irrigated regions. RF outperformed KNN, achieving higher accuracy with a kappa coefficient of 0.76. However, overestimation due to confusion with waterlogged fallow lands where self-sown rice was observed. The results emphasize the importance of region-specific training datasets and temporal dynamics in model calibration. Future work should focus on integrating multi-source remote sensing data and expanding ground-truth data to enhance classification accuracy for real-time agricultural monitoring.

REFERENCES

Benediktsson, J. A., Pesaresi, M, and Amato, U. 2018. Advances in remote sensing for precision agriculture: Current state and future directions.Remote Sensing of Environment, 205: 26-36.

Choudhary, B.U., Das, A., Maji, A.K. and Bandyopadhyay, A. 2014. Remote sensing and GIS for rice area estimation and production forecasting: A review. Journal of AgriSearch, 1(1): 1–10.

European Space Agency. 2024. Sentinel-1A Synthetic Aperture Radar data. Copernicus Data Space Ecosystem, European Space Agency. Available at: https://dataspace.copernicus.eu (Accessed November 2024).

Gao, F., Liu, Y., and Zhao, X. 2017. Evaluation of machine learning algorithms for land cover classification using Sentinel-1 SAR data.Journal of Remote Sensing, 39(12): 124-139.

Huang, X., Wang, L., & Zhang, X. 2021. Mapping crop acreage using SAR data: A review and analysis of classification approaches.International Journal of Remote Sensing, 42(15): 5530-5552.

Kumar, S.M., Podila, P. and Sireesha, G. 2022. 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 Sentinel-1A and Sentinel-2. Scientist*,* 1(3):73-82

Li, X., Zhang, L., & Xu, L. 2021. Machine learning techniques for crop classification and mapping in agriculture: A review of methods and applications. Computers and Electronics in Agriculture, 184, 105865.

Liu, C.-A., Chen, Z.-X., Shao, Y., Chen, J.-S., Tuya Hasi and Pan, H.-Z. 2019. Research advances of SAR remote sensing for agriculture applications: A review. Journal of Integrative Agriculture, 18(3): 506–525

Liu, D., Yang, H., and Liu, Y. 2020. Random Forest for crop classification using remote sensing data: A comparative analysis. Remote Sensing Letters,11(5): 424-433.

Singh, R.P., Ghosh, S. and Roy, P.S. 2015. Application of SAR data in agriculture: A review. Journal of Environmental Biology, 36(2): 311–318.

Surya, S, M., Medida, S. K., Mrudhula, K. A., Sridhar, T.V. and Pradeep, K. M. 2024. Estimation of rice area in KWD region using geospatial tools. International Journal of Environment, Agriculture and Biotechnology, 9(5): 273–279.

Wang, C., Zhang, L., and Yu, Y. 2021. Multi-source remote sensing data fusion for improving crop classification: A case study using Sentinel-1 and Sentinel-2 data.Remote Sensing, 13(5): 909.

Yu, Y., Zhang, L., and Li, J. 2020. Remote sensing-based Random Forest classification for crop mapping: A case study in a heterogeneous agricultural area. Remote Sensing, 12(6), 1024.

Sunil kumar, M. and Asha Jyothi, B. 2025. Identification and estimation of Rice sown area in Guntur district, Andhra pradesh, India, using sentinel 1a satellite data. The Journal of Research ANGRAU,53(5): 63-69