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Monitoring Rice Crop Dynamics in Koppal District using Time-Series Sentinel-1 Data on Google Earth Engine

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Abstract

Accurate estimation of crop area and timely assessment of crop losses are essential for empowering farmers, especially as technological advancements transform methods of area estimation, crop production, and crop insurance. This study focuses on mapping rice crop dynamics during the Kharif season (June to October) using satellite-based time-series data. We employed data from Sentinel-1 and Sentinel-2 satellites, combined with the Random Forest classification technique, to identify late transplantation and monitor rice growth at 15-day intervals. The study analyzed data from 2019 to 2023 and classified six crop categories using a robust sampling method. The methodology demonstrated high classification accuracy, ranging from 84.53% to 91.23% across different datasets and phases of crop growth. Results show that the total rice crop area in Koppal district fluctuated moderately between 2020 and 2023, ranging from 53,121.36 ha to 59,129.33 ha, indicating overall stability in rice cultivation despite seasonal variations and the effectiveness of spatiotemporal analysis for yield estimation, risk forecasting, and agricultural planning. This approach can contribute significantly to the development of sustainable agricultural strategies and policies, especially in densely populated countries like India.

Keywords: Crop mapping; Satellite remote sensing; Random Forest; Rice monitoring; Climate risk; Agricultural planning

1 Introduction

Rice is a stable food in India. To understand about food security, water use, greenhouse gas emission, and disease transmission, the information of area and spatial distribution of paddy rice is important. Due to the impacts of urbanization and recurring droughts, rice cultivation in Karnataka has been adversely affected. This work discusses the utilization of a paddy phenology-based algorithm for mapping paddy fields. The study was conducted in Koppal District, a region with extensive paddy cultivation. Landsat 8 data, known for its high revisit frequency and broad coverage, was used for the analysis. Data processing was carried out using ENVI software, while IDL 8.3 was employed for handling raster and vector data. The paddy rice map derived from the Koppal sample scene is expected to provide unprecedented insight into the number and spatial distribution of paddy rice fields, which will be helpful in food security assessment, freshwater resource management, greenhouse gas emissions, and disease control if it is extended the more scenes in South Asia [1].

In review of the study conducted by Job and Nandamohan (2004) [2], found that the research provides a comprehensive analysis of the transformation in rice production across different seasons autumn, winter, and summer in Kerala between 1975–76 and 1998–99. The study utilized secondary time-series data on area, output, and productivity, employing methodologies such as compound growth rate analysis, growth decomposition, and measures of instability. The exponential growth model was effectively applied to estimate the compound growth rates, while the area and productivity effects were derived using a multiplicative model. Additionally, the concept of elasticity of production was used to evaluate changes in output corresponding to variations in resource use.

As the population keeps growing and cities expand, paddy rice farming is shifting quite a bit in the two most populous countries China and India where ensuring food security is a top priority. Unfortunately, neither country has detailed and up-to-date information on rice grown areas. This gap in knowledge makes it tough to fully grasp how changes in rice cultivation affect critical issues like food and water security, climate change, and the spread of infectious diseases. To tackle this, created annual maps showing paddy rice planting areas for both countries from 2000 to 2015. This data came from a series of Moderate Resolution Imaging Spectroradiometer (MODIS) observations and a specialized rice mapping platform (RICE-MODIS). Their analysis revealed some interesting trends: in China, the area dedicated to paddy rice dropped by about 0.72 million hectares each year from 2000 to 2015. Meanwhile, India saw a important rise, with an increase of around 0.27 million hectares per year during the same period. They noticed that the spatial distribution of rice farming in China has shifted northeast, as areas in the northeast have expanded while southern regions have contracted. In contrast, India's paddy rice areas grew across the country, especially in the northwestern part of the Indo-Gangetic Plain and the central and southern plateaus. Overall, we see a clear trend of north-westward expansion in paddy rice agriculture in India. These changes raise important questions about how these shifts might impact national food security and environmental concerns related to water resources, climate change, and biodiversity [3].

A wide range of remote sensing datasets, from low-resolution to high-resolution imaging spectrometers such as Landsat-8 and Sentinel-1, have been widely used for mapping paddy fields [4–10]. Several studies have demonstrated the effectiveness of these datasets in rice crop mapping, particularly in Bangladesh [11,12]. Additional research has focused on mapping rice-growing areas in Bangladesh using a variety of classification techniques and temporal satellite imagery [13–16].

The main classification approaches adopted in these studies include supervised classifiers such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF), which have proven effective for accurately classifying rice fields [6,17,18]. Unsupervised classification methods, like the Iterative Self-Organizing Data Analysis Technique (ISODATA), have also been used [19,20]. In addition, knowledge-based classification methods, which incorporate expert domain knowledge into the classification process, have been employed in select studies [9,21].

To enhance classification accuracy and overcome limitations associated with individual methods, some researchers have developed hybrid classification approaches. These combine two or more techniques from supervised, unsupervised, or knowledge-based methods to leverage their respective strengths [7]. Collectively, this body of research demonstrates the growing sophistication and effectiveness of remote sensing and machine learning methods in rice mapping, particularly in regions where rice is a critical crop.

Understanding changes in cropping patterns across various regions is essential for improving agricultural knowledge and planning. A study conducted by Umesh et al. (2021) [22] focused on cropping pattern changes in Gangavathi Taluk from 2005 to 2016, using secondary data obtained from the Directorate of Economics and Statistics, Government of Karnataka. The study primarily examined how crop diversification evolved over time in the region. Analytical techniques, including crop diversification indices and chain analysis, were employed to interpret the trends and shifts in cropping patterns.

The objective of the current study is to evaluate the accuracy of a paddy rice map generated through a phenology-based algorithm by comparing it with statistical data. Additionally, this research aims to assess the potential of Sentinel-1 and Sentinel-2 time series datasets for mapping rice areas in Koppal District using machine learning algorithms, specifically Support Vector Machine (SVM) and Random Forest (RF), with a focus on VH polarization.

The specific research questions addressed in this study are:

1. To analyze the identification and spatial mapping of rice fields in Koppal District using time series Sentinel-1 and Sentinel-2 data from 2019 to 2023.
2. To monitor crop growth and estimate annual variations in rice cultivation area using the Google Earth Engine

platform.

3. To study the phenological stages of rice transplantation using time series data from Sentinel-1 (VH polarization) and Sentinel-2 imagery.

2 Materials and Methods

This study is conducted on one of the large rice production district in Karnataka, Koppal district, also known as the Rice Bowl of Karnataka due to its agricultural prominence, is located between 14°50′00″ to 16°10′00″ North latitude and 75°50′00″ to 76°50′00″ East longitude. Koppal district is approximately covered by 28.78 km^2. the Tungabhadra River is a significant water body in southern India flowing through Karnataka, including the Koppal district before joining the Krishna River this Tungabhadra River dam is located in the Koppal district it helps irrigation, electricity generation, and flood control also this Tungabhadra River dam has total capacity of 100.855 TMC (Thousand Million Cubic feet), with a live storage capacity of 95 TMC this dam approximately covered by 69,552 square kilometres up to Krishna River.

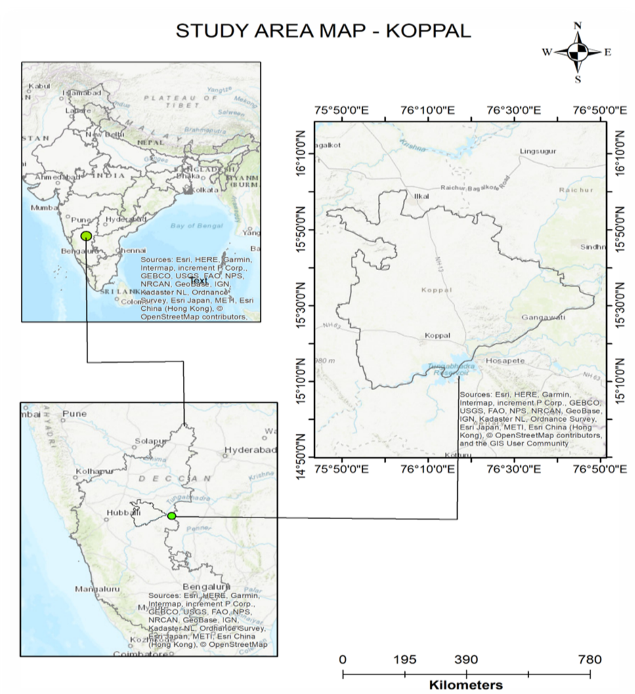

Fig. 1. Study Area Map of Koppal District, Karnataka. [Source: Esri, Garmin, Intermap, Increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Cadastre NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), OpenStreetMap contributors, and the GIS User Community]

The cloud-computing processing chain using GEE efficiently carries out all the steps of the processing chain from the temporal data fetching to the classification map generation in the framework of a single program. The main steps carried out in the GEE platform in this letter include the following. First, the Sentinel-1 data had to be fetched. Second, cloud filtering was applied to the scene. Third, a certain spatial filtering was applied to reduce speckle. Fourth, the backscatter coefficients were derived, and temporal analysis was performed. Fifth, the classification map was generated (see Figure 2for the scheme of the proposed processing chain for mapping the area of early and late rice transplanting and **S4 in the Supplementary Material** for the code developed in GEE).

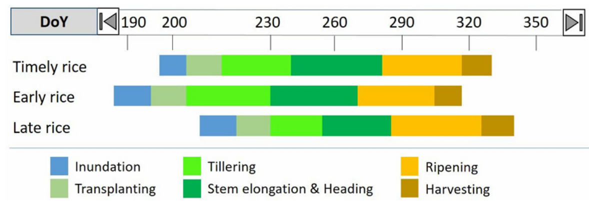

Fig. 2. Growing Stages of Paddy Crop as Observed Through Remote Sensing Data. [Source: IEEE Geoscience and Remote Sensing Letters]

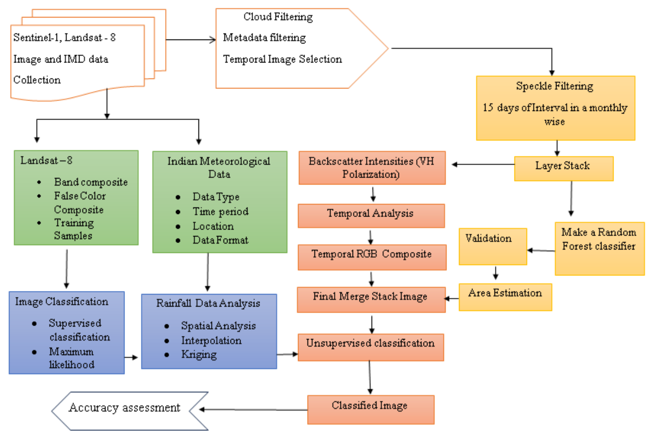

Fig. 3. Workflow for Satellite Data Processing and Classification Using Sentinel-1, Landsat-8, and IMD Data for Rice Crop Area Estimation

2.1 Sentinel-1 Data Retrieval

In this correspondence, 18 Sentinel-1A interferometric wide swath dual-pol (VV–VH) images in ground range detected (GRD) are employed. The high-density time-series Sentinel-1A data range from June 01, 2019 to October 31, 2019 (duration is from 2019 to 2023) with 15 days frequency. The data are retrieved directly from the GEE image collection into the GEE processing platform, and no need to download the data to a local workstation. It is comprised of Sentinel-1 GRD images, which are processed beforehand from SLC data based on the Sentinel-1 Toolbox to obtain a calibrated and orthocorrected product. So, the download time of the data and time spent in SLC to GRD product transformation could be preserved in the use of the GEE platform.

2.2 Filtering by cloud

The image collection in GEE holds a lot of information regarding Sentinel-1 images. These consist of the mode of acquisition, resolution, pass type, polarization, etc. The suitable image choice according to user requirements is referred to as "cloud filtering." It is performed in GEE using the Metadata and Filtering followed by spatial subset with the help of study area boundary. All images in this letter are chosen from the ascending orbit container of Sentinel-1 in GEE. Next, the temporal data are sorted based on the. filter Date argument.

2.3 Spatial Filtering for Speckle Reduction

To minimize the intrinsic speckle effect of SAR data, a speckle filtering (i.e., boxcar with 3×3 kernel) is applied in the GEE platform. Next, the speckle-filtered images of various dates are stacked into two sets of VV and VH polarizations.

2.4 Backscatter Coefficients and Temporal Extraction

Each location of in situ sampling's backscatter intensity $\sigma 0$ is extracted as a mean of 3×3 window using a pre-created Google Fusion Table. Backscattered coefficients of VV and VH channels, which are extracted, are temporally analyzed on the basis of the rice growth stage. To augment the temporal analysis, an RGB composite image of VH channels is produced.

2.5 Masking and Classification Map Generation

While the backscatter response of flooded fields during the transplanting period is a special feature for rice area delineation, the backscatter response from other land surfaces, like water bodies, could also be present during the transplanting period. Besides, there may be some mixing due to nonrice land covers like natural vegetation (forest) and urban or built-up areas whose temporal dynamics could be like rice. Therefore, for rice classification, threshold-based nonrice masks (forest, water bodies, and settlement) are created in GEE so that class mixing does not take place. These thresholds are determined based on the temporal dynamics of the said features.

This masking is followed by an unsupervised k-means clustering with which the life stages of the transplanted rice with different dates. The ee. of the GEE clustered. weakens argument uses Manhattan distance and calculates the centroids of all clusters. It must be pointed out here that Sentinel-1 acquisitions over the entire crop cycle were utilized for the temporal analysis, and acquisitions up to the early vegetative stage of rice were utilized for the early and late rice discrimination. The accuracy of classification was also evaluated by utilizing the in-situ measurements over the sample points. At the sample points, each labelled pixel (detected by the k-means algorithm) was associated with the ground observed rice class (timely transplanted rice or early late). The performance of the classification is measured using overall accuracy and κ-coefficient. It is to be noted that the validation points are sampled from various quadrants (as shown in **S2 of the Supplementary Material**), which are spread in the test area with diversified rice management practices which makes the strategy of validation robust and reliable enough to scale up for operational rice mapping.

Result and Discussion

3.1 Analyzing crop traits of rice and others during the transplantation and peak growth stages

3.1.1 Temporal Signatures – Backscatter:

The 2019 Sentinel-1 VH polarization backscatter profiles, analyzed using a Random Forest algorithm, effectively distinguish rice fields based on transplanting dates and land cover types. Temporal curves (yellow, green, blue, pink, etc.) reflect different rice transplanting times, showing increasing backscatter during growth stages and peaking around August–September. Early transplanted rice shows an earlier rise, while late-transplanted crops peak later. Red and blue curves represent built-up areas and water bodies, with stable high and low backscatter values, respectively. VH polarization is sensitive to vegetation structure and moisture, making it suitable for capturing crop phenology. The Random Forest classifier enhances accuracy by analyzing temporal variations at the pixel level. This method enables reliable identification of rice growth stages and separation from non-crop features. Overall, VH time-series data combined with machine learning supports precise rice crop monitoring, which is valuable for agricultural planning, food security assessments, and water resource management in mixed-use landscapes.

The 2020 Sentinel-1 VH polarization backscatter profile, shown above, illustrates temporal variations in rice crop dynamics using Random Forest classification. Each curve represents a different rice transplanting date or land cover type. The yellow, green, black, grey, and blue lines indicate rice transplanted at various times, each showing a gradual increase in backscatter as the crop progresses through its growth stages, peaking between August and September. The timing and shape of these peaks reflect phenological differences based on transplanting dates. In contrast, the red and pink curves, which remain relatively flat with consistently high backscatter, represent built-up areas, while the cyan curve with persistently low values indicates water bodies. VH polarization captures vegetation structure and moisture content effectively, allowing for clear separation between rice fields and non-crop areas. This time-series approach, combined with machine learning, enables accurate mapping of crop stages, offering valuable insights for agricultural monitoring, yield estimation, and sustainable resource management.

The 2021 VH polarization backscatter profile, generated from Sentinel-1 data using Random Forest classification, highlights the temporal variation in rice transplanting patterns and land cover types. The yellow, green, grey, and blue curves indicate rice transplanted at different dates, with increasing backscatter values during the crop growth phase, peaking around August–September. These variations reflect distinct phenological stages. Consistently high and flat red and pink curves denote built-up areas, while the cyan line with low, stable values indicates water bodies. The VH polarization effectively differentiates vegetation structures, supporting accurate rice crop monitoring and land cover classification in mixed-use agricultural regions.

The 2022 VH polarization backscatter profile from Sentinel-1 data illustrates rice crop dynamics and land cover variations using Random Forest classification. Temporal curves such as yellow, green, grey, and blue reflect rice transplanted at different times, showing characteristic backscatter dips during early growth and peaks around August–September. These trends indicate canopy development and moisture variations. The red and pink lines, with consistently high values, represent built-up areas, while the cyan curve indicates water bodies with low, stable backscatter. VH polarization effectively distinguishes vegetation and surface features, supporting accurate monitoring of crop phenology and land use in agricultural landscapes.

The 2023 VH polarization backscatter profile, derived from Sentinel-1 data using Random Forest classification, captures the temporal dynamics of rice cropping and land cover types. The yellow, green, blue, and grey curves represent rice fields transplanted at different dates, with characteristic low backscatter during early stages and peaks from September to October, indicating crop growth and canopy development. The red curve, showing consistently high values, represents built-up areas, while the pink curve with low, stable values identifies water bodies. VH polarization effectively highlights vegetation structure and moisture differences, aiding accurate classification and monitoring of rice fields and non-crop features.

An in-depth analysis of agricultural rice crop land use patterns in Koppal District, Karnataka, from 2020 to 2023, drawing insights from the provided dataset and contextualizing them with broader agricultural trends and reports. The validation overall accuracy figures, ranging from 0.881 to 0.908, attest to the reliability of the underlying data, making this analysis robust.

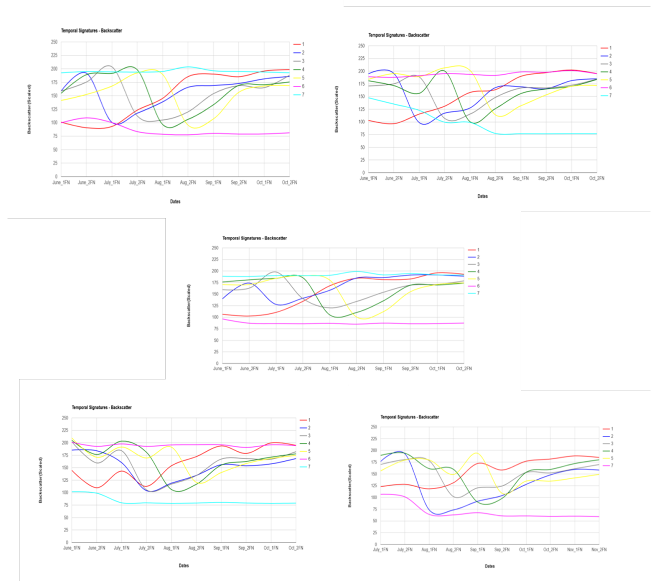

Fig. 4. VH Polarization Clusters for Rice Fields and Major Land Cover Types (2019–2023) Using Hierarchical Cluster Analysis (HCA)

Table 1. Agricultural Rice Crop Land Use in Koppal District (2020-2023)

Particulars	2020	2021	2022	2023
Tillage (June)	147489.48	242405.58	193865.82	167760.44
Rice 1 (July)	58788.44	8924.49	62359.49	58943.08
Rice 2 (August)	20422.34	25190.23	71862.21	50069.06
Late Rice Transplantation (September)	41106.79	42572.71	27730.33	11727.67
Maturity (October)	20511.73	43595.67	6658.28	26880.38
Total Rice crop Area	53121.36	54293.22	59129.33	55265.41
Training overall accuracy	Validation overall accuracy	Validation overall accuracy	Validation overall accuracy	Validation overall accuracy
0.908	0.898	0.906	0.902	0.881

3.1.2 Agricultural Rice Crop Land Use in Koppal District (2020-2023)

The examination of the provided data reveals discernible fluctuations across various stages of rice cultivation. Tillage area in June, for instance, exhibited a notable peak in 2021 at

242,405.58 hectares, signifying an initial strong intention for cultivation, but subsequently declined in the following years. This variability often reflects farmers' anticipations regarding monsoon onset and their strategic decisions influenced by preceding years' yields and prevailing market prices. Similarly, the area dedicated to Rice 1 (July) showed significant volatility, experiencing a sharp decline in 2021 to 8,924.49 hectares from 58,788.44 hectares in 2020, followed by a substantial rebound in 2022 to 82,359.49 hectares, before a slight reduction in 2023. Such fluctuations are intimately linked to the timely and adequate distribution of monsoon rainfall, which is critical for successful early paddy transplantation.

A notable observation is the increased prominence of Rice 2 (August) sowing in 2022, reaching 71,862.21 hectares, suggesting a potential shift in planting schedules or a delayed planting response to monsoon patterns in that particular year. Conversely, the trend for Late Rice Transplantation (September) indicates a consistent decline from 2021, culminating in a stark drop to 11,727.67 hectares in 2023. This point towards a reduction in late-season rice cultivation, likely due to increased risks associated with lower productivity or the approaching dry season. Furthermore, the area reaching maturity in October displayed considerable variability, with a remarkably low figure of 6,658.28 hectares in 2022 despite higher sowing areas in July and August. This discrepancy could imply significant crop loss or abandonment at later growth stages, possibly due to adverse weather conditions or failed yields.

Focusing on the aggregate, the total rice crop area demonstrated a marginal increase from 53121.36 hectares in 2020 to 59129.33 hectares in 2022, marking the peak in the observed period. However, a significant decline of approximately 12.67% was recorded between 2022 and 2023, with the total rice crop area shrinking to 55265.41 hectares.

To understand the reasons behind this notable decrease in rice cropland area from 2022 to 2023 in Koppal District, a review of general agricultural reports and trends for Karnataka and India is crucial. Research indicates that India's rice production in 2023 was projected to decline due to an uneven monsoon distribution and widespread drought conditions. The Ministry of Agriculture and Farmers' Welfare estimated a 3.7% reduction in Kharif rice production for 2023-24 compared to the previous year, highlighting that even consistent planting areas might not translate into successful harvests under adverse climatic conditions. Specifically, a prolonged dry spell in August 2023 was widely cited as a major contributing factor to this decline (Farmonaut, October 2023).

Reports on Karnataka's agricultural landscape further corroborate these findings. A recent publication by The Times of India (April 2025) explicitly stated a plummeting rice yield in Karnataka over the past decade, with Koppal experiencing a 2.4% drop. This report projects a statewide decline in rice production from 4.69 million tonnes in 2023-24 to 4.21 million tonnes in 2024-25. The article also points to the degradation of soil fertility in paddy cultivation regions, attributing it to improper water management and monocropping, which has led to increased soil salinity and reduced yields.

Koppal District, being largely rainfed (74% of cultivable land), is particularly susceptible to water scarcity. Older reports by NABARD (2022-23 PLP) for Koppal highlight this dependency, with only 26% of cultivable land under irrigation, primarily from the Tungabhadra and Hirehall Projects. The extensive reliance on groundwater, especially during periods of erratic rainfall, has resulted in aquifer depletion and the availability of saline water, which is unsuitable for food crops, forcing farmers to leave land uncultivated or switch to less water-intensive cash crops, exacerbating groundwater exploitation and soil salinity (HimalDoc, BioOne Complete, 2003, and Deccan Herald, 2025). Moreover, industrial pollution from factories in the district has been reported to contaminate water sources and soil, rendering agricultural land infertile and further contributing to crop loss (Deccan Herald, March 2025).

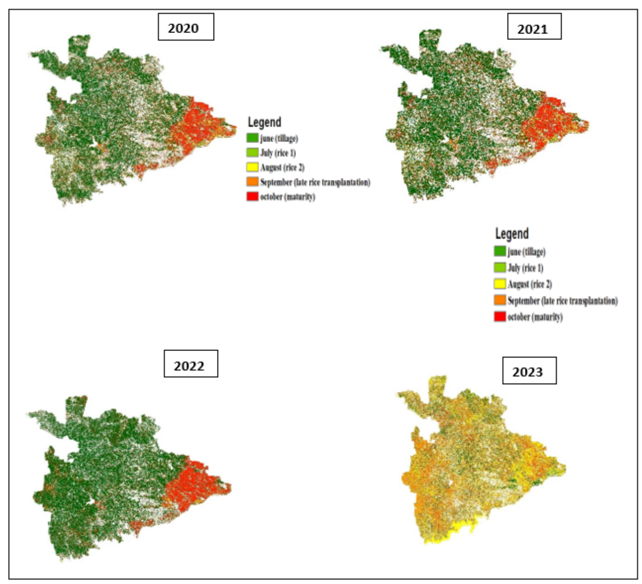

Fig. 5. Koppal District: Rice Transplantation from 2020 – 2023

Therefore, the observed decrease in rice cropland area in Koppal District from 2022 to 2023 can be primarily ascribed to a confluence of factors: the erratic and deficient monsoon in 2023, leading to severe drought conditions and water scarcity; the long-standing issue of depleting and saline groundwater resources; and the adverse impacts of soil health degradation and industrial pollution. Economic considerations, including declining yields and associated financial losses, may also have driven farmers to reduce their rice cultivation area or explore alternative cropping patterns. These challenges underscore the urgent need for integrated water management strategies, the promotion of climate-resilient agricultural practices, and policies supporting crop diversification to ensure the sustainability of rice cultivation and the livelihoods of farmers in Koppal District.

4 Conclusion

The temporal backscatter analysis using Sentinel-1 VH polarization and Random Forest classification effectively captured rice crop dynamics in Koppal District from 2019 to 2023. While rice cultivation showed resilience in early years, a notable decline in cropland area in 2023 reflects the growing vulnerability of the region's agriculture. Erratic monsoons, prolonged droughts, groundwater depletion, soil salinity, and industrial pollution emerged as key stressors. The synergy of remote sensing and machine learning proved essential in monitoring these trends. This highlights the urgent need for sustainable water management, crop diversification, and soil restoration to ensure food security and climate-resilient agriculture in Koppal.

References

1) Babu KG, Gnanpazham M. The Utilization of Paddy Phenology for Paddy Field Mapping. In: Proceedings of the 2nd International Conference on Geospatial Technologies and Applications (ICGTSA 2017). 2017.
2) Job MK, Nandamohan M. Growth of Rice in Kerala: An Economic Analysis. 2004.
3) Zhang M, Li H, Liu L, Deng C, Li C. Annual maps of paddy rice planting areas in China and India from 2000 to 2015. *Scientific Data*. 2017;4:170068.
4) Shew AM, Ghosh A. Mapping rice cultivation with Sentinel-1 SAR time series data: A case study in India. *Remote Sensing Applications: Society and Environment*. 2019;13:148–158.
5) Shapla SR, Rahman MM, Al-Amin M. Rice area mapping using MODIS time series data in Bangladesh. *Journal of Geomatics, Planning and Development*. 2015;3(2):1–8.
6) Singha M, Islam MA, Rahman MM. Rice area mapping using Sentinel-1 SAR and Sentinel-2 optical data in Bangladesh. *International Journal of Remote Sensing*. 2019;40(10):3907–3929.
7) Tiwari V, Singh K, Roy C. Rice crop mapping using Sentinel-1 and Sentinel-2 data in Eastern India. *Journal of the Indian Society of Remote Sensing*. 2021;49(10):2235–2247.
8) Gumma MK. Rice area mapping using MODIS time series data for Asia. *Journal of Environmental Science and Engineering (JESE)*. 2011;53(3):329–336.
9) Islam MA. Paddy rice mapping using Google Earth Engine and Sentinel-1 data in Bangladesh. *Journal of Geoinformatics and Remote Sensing*. 2021;8(1):1–10.
10) Pena-Arancibia JI, Phongsai S, Bador M. Rice crop mapping in Southeast Asia using Sentinel-1 SAR time series data. *Remote Sensing*. 2021;13(22):4642.
11) Shamsuzzoha M, Islam MS, Rahman MM. Rice crop mapping using Sentinel-1 SAR time series data in Bangladesh. *Geocarto International*. 2022;37(10):3297–3315.
12) Islam MA, Rahman MM, Hossain MA. Rice crop mapping using Sentinel-1 SAR time series data in Bangladesh. *Geocarto International*. 2022;37(10):3297–3315.
13) Mahboob MN, Hassan MQ, Hoque MA. Mapping of rice areas in Bangladesh using MODIS time series data. *Journal of Agricultural and Environmental Sciences*. 2016;11(1):1–8.
14) Alam MM, Rashid MH, Zaman MM, Rahman MA. Mapping Boro rice area using MODIS satellite imagery and field data in Bangladesh. *Journal of Environmental Science and Natural Resources*. 2019;12(1):167–176.
15) Aziz AB, Rahman A, Alam MS. Rice crop mapping using Sentinel-1 SAR time series data in Bangladesh. *Journal of Remote Sensing Applications*. 2023;3(1):1–10.
16) Kamal MA, Islam MS, Akter S. Rice crop mapping using Sentinel-1 and Sentinel-2 time-series data and machine learning algorithms. *Remote Sensing Applications: Society and Environment*. 2020;19:100350.
17) Xiao X, Boles S, Liu J, Zhuang D, Frolking S, Li C, et al. Mapping paddy rice agriculture in southern China using multi-temporal MODIS images. *Remote Sensing of Environment*. 2005;95(4):480–492.
18) Jiang X, Zhang M, Wang Y. Rice mapping in subtropical regions using Sentinel-1 SAR and Sentinel-2 optical data. *Remote Sensing*. 2023;15(2):488.
19) Gumma MK, Mohammed IA, Mude J. Remote sensing for rice area mapping and yield estimation in Bangladesh. *Journal of Land Use Science*. 2014;9(3):346–361.
20) More SK, Manjunath KR. Rice crop acreage estimation using MODIS satellite data. *International Journal of Advanced Remote Sensing and GIS*. 2013;2(1):1–8.
21) Nelson A, Gumma MK, van der Velde M. Knowledge-based classification for mapping paddy rice areas. *Remote Sensing*. 2014;6(1):74–98.
22) Umesh B, et al. Changing cropping patterns in Gangavathi Taluk of Koppal District. *International Journal of Current Microbiology and Applied Sciences*. 2021;10(1):2288–2296.