Smart Harvest Monitoring of paddy Using UAV and ML in Bargarh District, Odisha

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Abstract

Accurate crop monitoring during the harvest period is crucial for agricultural planning, procurement, insurance claims, and post-harvest management. This study presents a comprehensive analysis using high-resolution Unmanned Aerial Vehicle (UAV) imagery and machine learning (ML) techniques to classify harvest-stage crops in Rajborsambar Block of Bargarh District, Odisha — a predominantly paddy-growing region in eastern India. UAV surveys were conducted during the harvest phase to capture multispectral and RGB imagery across selected agricultural fields. Based on field observations and ground truth data, crops were categorized into four classes: (1) harvested crop, (2) standing crop, (3) cut and spread crop, and (4) other land use/cover. Notably, traditional satellite imagery such as Sentinel-2 (S2) lacks the spatial detail required to accurately detect cut and spread crops due to coarse resolution and mixed pixel effects. In contrast, UAV imagery, with centimetre-level detail, provides rich surface texture and crop residue patterns that enhance classification accuracy. Key features extracted from the UAV imagery included vegetation indices (Vegetation Atmospherically Resistant Index), canopy cover, and texture metrics. These were used to train and validate multiple machine learning classifiers: Support Vector Machine (SVM), Random Forest (RF). Ground truth data were collected through field surveys and farmer consultations. Among the models, SVM achieved the highest classification accuracy of 82.3%, followed by RF (90.7%). The models showed significant improvement in detecting the cut and spread crop classes, which is typically indistinguishable in medium-resolution satellite imagery.

1. Introduction

Agriculture has manifested to multiple hazards leading to frequent crop losses worldwide. Due to this, in agriculture sector, crop insurance sector has become an essential risk management tool. In today's world, agricultural risk-sharing through crop insurance has been in existence, but in developed and developing nations, there is still a need for evolved innovative crop insurance products. Risk reducing financial device like a crop insurance agreement is quite relevant for the crops to confirm its sustained production. Rice is a vital food crop ensuring the food security of India. The considerable potential for crop insurance in India is denoted by low growth of crops and outreach of crop insurance which is likely the risks agriculturists face in growing rice and other crops. To reduce the impact of covariate risks and encourage innovations and investments in the farming sector, a vigorous crop insurance system is very vital. India has a history of executing different crop insurance schemes with improvements from every so often (Mishra 1996, Singh 2013). Remote sensing and Geoinformatics techniques are efficacious tool for spatially monitoring the health conditions of agricultural crops throughout the crop growth period. Sowing and harvesting periods of crops planted in the same region may vary between years according to seasonal dynamics. To attain the desired level of accuracy in crop classification, numerous spectral bands including different temporal images of multispectral time series and vegetation indices derived from these bands are effectively used.

In the present study, Random Forest (RF) Classification and Support Vector Machine (SVM) has been used. Random Forest is a machine learning algorithm that uses innumerable decision trees to make better predictions. Each tree checks at different random parts of the dataset and their results are combined by voting for classification or averaging for regression which makes it as ensemble learning technique. This helps in reducing errors and improving accuracy. Whereas, Support Vector Machine is a supervised machine learning algorithm used for regression and classification tasks. It tries to find out the best boundary called hyperplane that separates different classes in the dataset. The main objective of SVM is to maximize the margin between the two classes. The larger the margin the better the model performs on advanced and undetectable data.

It has been observed that random forest (RF) surpasses Support Vector Machine (SVM) marginally but persistent throughout. The evaluation of the effectiveness of RF classifiers for complex land use and land cover categories is extracted from Sentinel-2 (S2) data. The result shows that RF accomplish high classification accuracy and worked well for small training datasets as well as strong to the noise. The chances of highest vitality for crop classification characteristics are gathered from Sentinel-2 (S2) which highlights the band 4 (Red Band) of Sentinel-2 (S2). In the study, the utilization of Support Vector Machine (SVM) model effectively for crop type identification using time-series of Sentinel-2 (S2) Normalized Difference Vegetation Index (NDVI) data, results in the achievement of higher classification accuracy as compared to the stratified random approach. The identification of crops with accuracy and timely, holds chief significance for effective crop management and yield estimation. As compared to satellite-based remote sensing, Unmanned Aerial Vehicle (UAV), with their higher spatial and temporal resolution, offer a novel solution for precise crop identification. The study evaluates a methodology that integrates object-oriented method and random forest (RF) algorithm for crop identification using multispectral UAV images. The process involves a multiscale segmentation algorithm, utilizing the optimal segmentation scale determined by Estimation of Scale Parameter 2 (ESP2). Eight classification schemes (S1–S8) were then developed by incorporating index (INDE), textural (GLCM), and geometric (GEOM) features based on the spectrum (SPEC) features of segmented objects. The best-trained RF model was established through three steps: feature selection, parameter tuning, and model training. Subsequently, feature importance for different classification schemes and generated a prediction map of vegetation for the entire study area based on the best-trained RF model. In concise, the proposed method, RF algorithms based on multispectral UAV images, displayed high accuracy of crop classification. This study gives valuable insights for the accurate identification of paddy crop. Thus, helping as a reference for future developments in agricultural technology and crop management strategies.

2. Study Area

Rajborasambar is a block situated at 20.9988° N, 83.0620° E coordinates in the Bargarh district of Odisha, India. This block is one of the 12 Community Development (CD) blocks in the district. Bargarh district is situated in the western part of Odisha, close to the border of neighbouring state of Chhattisgarh. It is defined by an undulating plain between high hills to the north and south. The Ong River flows through this plain, and its valley is considered well-suited for agriculture. The soil in this area is a mixture of sand, gravel, and clay, and is enriched by river silt and hill drainage. Agriculture is the primary source of livelihood for many people in the Rajborasambar block of the Bargarh district, Odisha. This block lies in a rain-fed area, which makes farmers vulnerable to natural disasters like drought and floods. The government has implemented schemes to support farmers, such as providing incentives for new irrigation potentials like dug wells and river lift points. There are also programs such as Pradhan Mantri Fasal Bima Yojana (PMFBY), that encourages farmers to protect their agricultural products from unforeseen weather events and provide financial support to stabilize their income. Farmers in Odisha, in general, face challenges such as low yields due to factors like modest soil quality, limited fertilizer use, and variable monsoon rains. The average landholding is small, with a majority of farmers being small and marginal landholders.

The block is known for its agricultural activities and is surrounded by fertile land. UAV which was operated for the study (Figure 1), was conducted in seven (7) Area of Interests (AOIs) of the block in 16th December, 2023. UAV operations were conducted to monitor plot-wise paddy crop status.

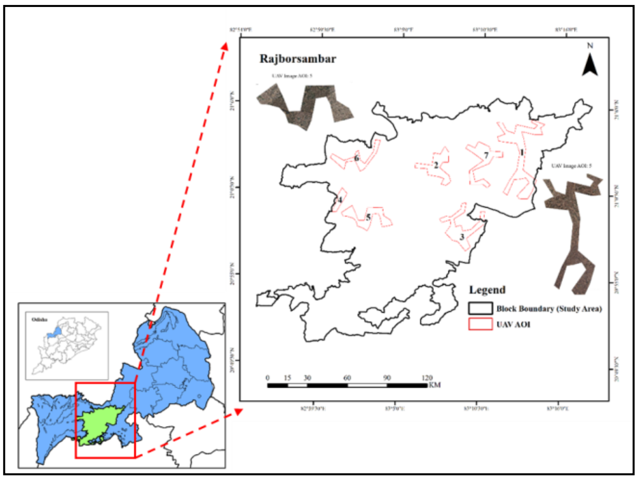

Figure 1. Map of seven locations (AOI) of Rajborasambar block where UAV operations are conducted.

3. Methodology

In this study, ML techniques are integrated with multitemporal Sentinel-2 (S2) and UAV imageries to evaluate the classification accuracy of paddy crop. To analyze the paddy crop of Rajborasambar Block, the analysis was divided into two categories based on the occurrence of Cyclone “Michung”, during the time period of 1st to 6th December, 2023. The first category is the pre-Cyclonic event, and the second category is post-Cyclonic event. In pre-Cyclonic event, the analysis was done with the help of Random Forest (RF) algorithm in Google Earth Engine (GEE) using Sentinel-2 (S2) data. Crop health was also monitored with these datasets using NDVI. In Post-Cyclonic event, re-analysis of paddy crop area was done with the help of Random Forest (RF) algorithm in Google Earth Engine (GEE) using Sentinel-2 (S2) data. The traditional satellite imagery of Sentinel-2 (S2), lacks the spatial details required to accurately detect paddy crop stages due to coarse resolution, mixed pixel and cloud cover effects. To overcome these limitations and analysis purpose, Reliance General Insurance Company Limited (RGICL) has flown the UAV for identifying the paddy crop stages. Thus, during the harvest phase, UAV surveys were conducted to capture multispectral and RGB imagery across selected agricultural fields. For UAV both classification Support Vector Machine (SVM), Random Forest (RF) methods are used. The classification accuracy was evaluated through a confusion matrix, and the best feature selection model was determined. Following the analysis, ground truthing data were also used to validate the study.

The study utilizes both primary and secondary datasets, encompassing remote sensing data, ground truthing data. The remote sensing data include Sentinel-2 satellite imageries and UAV dataset. Satellite data of Sentinel-2, The European Space Agency satellite that provides multispectral sensors with spatial resolution of 10 meters, was used for the calculation of remote sensing driven perimeter in Bargarh District, whereas UAV data, with spatial resolution of 2.1 cm is used in the study area.
These datasets are used to generate the False Colour Composite (FCC), Normalized Difference Vegetation Index (NDVI), Crop Mask, and other intermediate outputs. A Global Positioning System (GPS) survey was conducted to collect ground control points (GCPs) for the of crop classification (training and testing) and validation.

The NDVI is obtained with the formula:

$$NDVI = (NIR-Red) / (NIR+Red) \qquad (1)$$

where

NDVI = Normalized Difference Vegetation Index,
NIR (Near Infrared Band) is the band 8 of Sentinel 2 satellite data,
Red (Red Band) is the band 4 of Sentinel 2 satellite data.

The mentioned formula necessitates the Red and Near-Infrared bands of each scene. The numbers of these spectral reflectance bands are different for various satellites, but the wavelengths are almost similar for the Red and Infrared bands, respectively. Figure 2 describes the methodology used in the present study. This study engages two machine learning classification methods, i.e., Random Forest (RF) and Support Vector Machine (SVM). Both the methods are state-of-the-art algorithms for land use classification from satellite imagery. RF and SVM are powerful devices in remote sensing, each with its own firmness.

RF is popular for its robustness, ease of use, and ability to handle large datasets with missed out values.

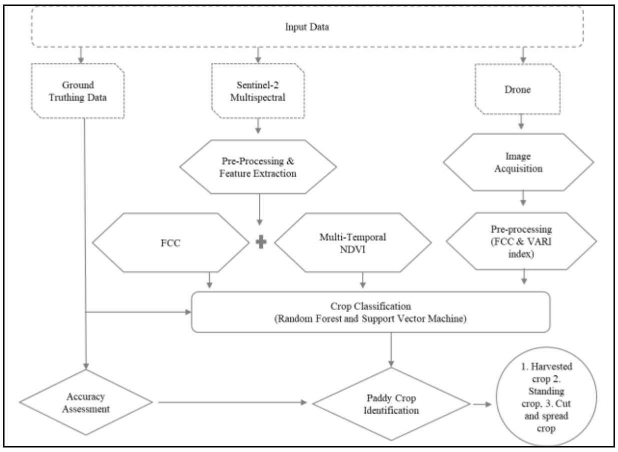

Figure 2. Methodology flowchart.

RF operates by aggregating predictions from multiple decision trees to make a final prediction. This ensemble approach improves the accuracy and robustness of the model. In context of classification, the final prediction is based on the majority poll of all the trees, as shown in the following equation (Equation 2):

$$\hat{y} = Mode\ \{h1(x), h2(x), \ldots, hB(x)\} \qquad (2)$$

where

hB(x) = the prediction of the bbbth tree.
Mode = the most frequent class label among the tree prediction.

Alternatively, SVM performs expertly in high dimensional spaces and complex classification tasks but requires careful parameter regulation. SVM is fundamentally a binary classifier, where, for multi-class classification, strategies such as One-vs-One (OvO) or One-vs-Rest (OvR) are used. In OvO, each pair of classes has a separate SVM, and the final class prediction is generally determined by majority voting among all the SVMs. In OvR, one SVM is trained for each class against all other classes, and the final class prediction is based on the SVM with the highest confidence score. Therefore, the option between RF and SVM often depends on the specific requisite of the remote sensing task at hand, including the features of the data and practical outcome needs. It is not unfamiliar to use both methods complementarity and to compare results to ensure maximum accuracy in remote sensing applications. This study aims to differentiate the capabilities of RF and SVM in land use classification and paddy crop cultivation area classification using both methods.

4. Results And Discussion

4.1 Pre -Event Analysis

Paddy crop for the Kharif 2023 season was classified and identified paddy sown area using Sentinel-2 (S2) images at the block level with Random Forest method (Figure 3). This analysis was conducted during the peak vegetative period of the paddy crop, utilizing time-series Normalized Difference Vegetation Index (NDVI) images. The Random Forest (RF) method achieved an overall accuracy of 89.85% with a kappa coefficient of 79.13%. The total paddy area of the Rajborasambar block was calculated as 13,583.69 hectares, while the seven Areas of Interest (AOI) locations (Figure 4) comprised 1,989.90 hectares of paddy crop area.

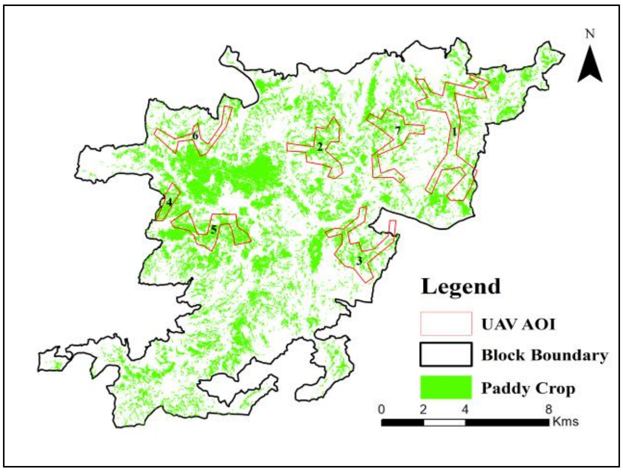

Figure 3. Paddy crop Map of Rajborasambar block using multi-date NDVI (Normalized Difference Vegetation Index) images were generated from Sentinel-2 data.

The combined geographical area of all seven Areas of Interest (AOIs) was 5041.51 hectares, of which 1869.90 hectares were identified as paddy crop cultivation areas. AOI 1 comprised 1463.64 hectares, with a paddy crop area of 459.62 hectares, representing 31% of its total area. AOI 2 and 3 is having total area of 674.66 and 854.87 hectares of land, having 253.81 and 269.79 hectares of paddy crop in it, representing 38% and 32% of its total area. AOI 4 and 5 exhibited the highest proportions of land dedicated to paddy area. Out of the total geographical area of 189.96 and 652.77 hectares, 121.51 and 394.31 hectares were identified as paddy crop, representing 64% and 60%. AOI 6 is consisting total area of 461.43 hectares with paddy area of 103.08 hectares, with 22% paddy crop area. AOI 7, having an area of 744.18 hectares of land with 267.78 hectares of paddy crop, with 36% of area.

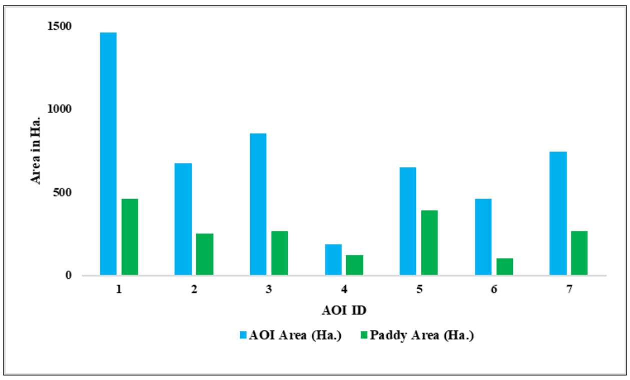

Figure 4. Graphical representation of total geographical and paddy sown area of seven AOIs (Rajborasambar block).

The NDVI-based analysis provided condemnatory perception into the temporal dynamics of paddy crop growth during Kharif 2023 season. NDVI, being a vigorous indicator of vegetation strength and biomass, was used to monitor the crop from sowing to harvesting stages. As shown in Figure 5, NDVI values displayed a gradual increase during the sowing (2nd

Fortnight of July) and early vegetative stages (2nd Fortnight of September to 1st Fortnight of October), followed by a sharp decline as the crop approached maturity and harvest (1st Fortnight of December). This trend precisely captures the phenological stages of paddy growth in Rajborasambar block. The NDVI time-series maps generated from Sentinel-2 imagery (Figure 6) comprises of data from 16th November to 26th December 2023. These maps reveal the progressive changes in crop health condition across the Rajborasambar block. During mid-November, NDVI values were moderate (0.4–0.6), indicating the post-vegetative stage of crop growth and gradually declined thereafter, corresponding to the harvesting period in mid to late December. This gradual decline is consistent with ground observations, where crops were either harvested or in the drying phase. Due to the rainfall event, occurred during 1st to 6th December 2023, re-analysis of paddy identification was done using Sentinel-2 satellite data, dated, 16th December 2023, to understand the actual crop scenario on the field.

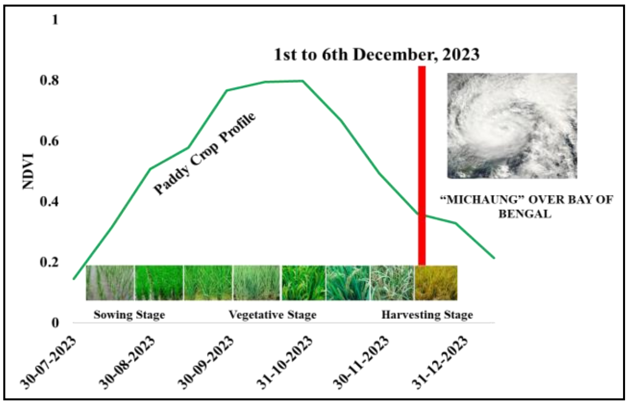

Figure 5. Seasonal Paddy crop profile from the period of sowing to harvesting (Rajborasambar block) using Sentinel-2 (S2) satellite imagery. The graph is marked with a vertical red line on December 1-6, 2023, coinciding with a satellite image of a cyclonic storm labelled as ‘Michaung’ over the Bay of Bengal.

4.2 Post-Event Analysis

A rainfall event occurred between December 1st and 6th, 2023, during the harvest period. Post rainfall event, the immediate available cloud-free Sentinel-2 (S2) image was classified for the entire block (Figure 7). As per the re-analysis of paddy area, post rainfall event, the paddy area identified for all seven AOIs were 322.84 hectares. The Random Forest (RF) method achieved an overall accuracy of 83.45%. Out of 1869.9 hectares, 1547 hectares was harvested before 16th December 2023 (Figure 8). Among all the seven AOIs, the maximum paddy crop area with 60.11 hectares and 9% of total geographical area of AOI 5 has been observed. Whereas, the minimum areas for paddy are 76.91 and 31.95 hectares for AOIs 1 and 2, with 5% of the total geographical area for each AOI. As per field observations, another class was needed to add in the study, that is, ‘cut and spread’.

Due to the lack of high spatial resolution, the cut and spread condition was not properly visible. As the cut and spread condition is the most vulnerable state for paddy crop loss, UAV data was used to immediately analyse the crop situation. Thus, Reliance General Insurance Company Limited (RGICL) has used UAV data to monitor the crop condition for Kharif season, 2023. The classification has been done using UAV images post rainfall event. The data is then classified into four categories, that is, harvested, standing, cut and spread, and other class (Figure 9). The overall accuracy assessment of RF classification is 90.7%, which shows higher accuracy as compared to SVM classification method which was 82.3%. Hence, Random Forest classification (RF) has performed better in this study area because of its higher accuracy.

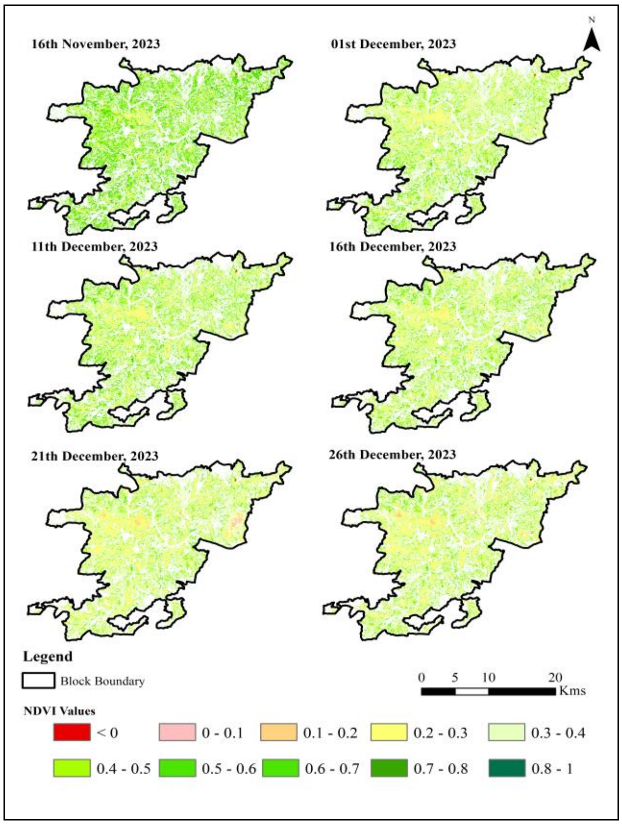

Figure 6. The NDVI series of maps with different shades, labelled with dates from 16th November to 26th December, 2023.

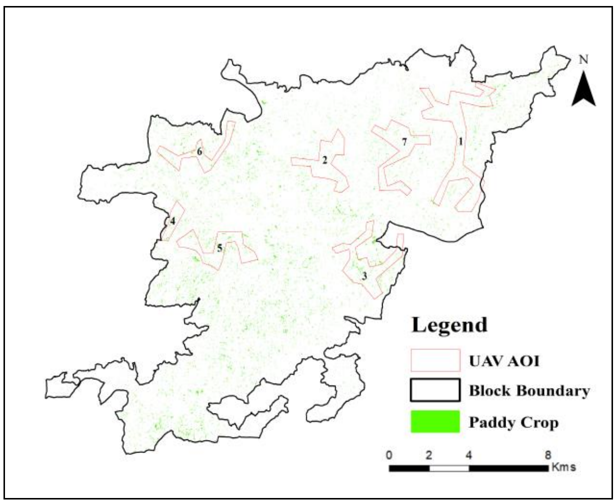

Figure 7. Paddy crop Map of Rajborasambar block using 16th December 2023, NDVI (Normalized Difference Vegetation Index) images were generated from Sentinel-2 data.

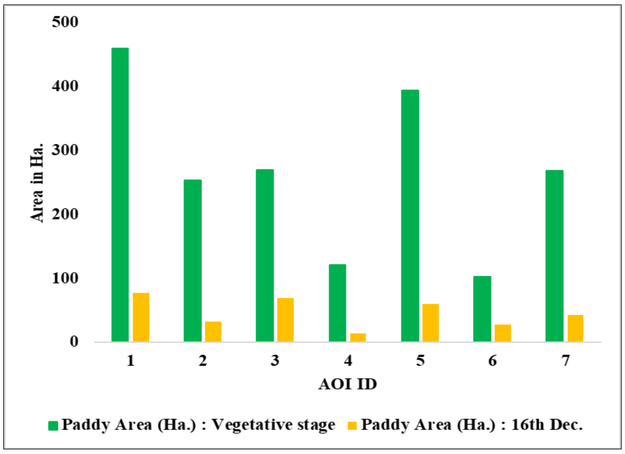

Figure 8. Graphical representation of paddy sown area during the vegetative stage and 16th December after the event.

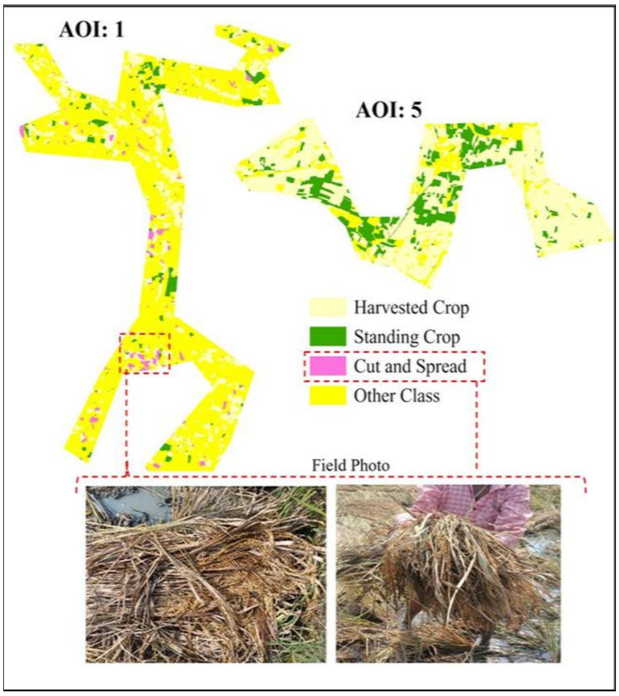

Figure 9. UAV classified image with classes, i.e., "Harvested Crop," "Standing Crop," "Cut and Spread," and "Other Class." of the AOI-1 and 5.

The total geographical area for all seven AOIs were 5,041.51 hectares, with land-use categories including harvested land, standing crop, cut and spread, and other class. Harvested land constituted the area with 1,735.23 hectares (34%). Standing crop comprising 301.29 hectares (6%), whereas, cut and spread areas were significantly smaller with 45.87 hectares (1%), respectively. The majority of the land was classified as ‘other’ class, accounting for 2,958.24 hectares (59%) of the total area. Among all the seven AOIs, the area for cut and spread cases are found in only two locations, that is, AOI 1 and AOI 6. AOI 1 is having harvested area of 363 hectares, standing crop area of 58.48 hectares, cut and spread area of 38.07 hectares and other class having 1003.21 hectares of area. Whereas, AOI 6 is having harvested area of 120.5 hectares, standing crop area of 0.91 hectares, cut and spread area of 7.8 hectares and other class having 332.22 hectares of area. Apart from these two AOIs, rest of the locations are having no cut and spread areas. Thus, AOI 2 and AOI 3 is having harvested area of 278.31 and 221.18 hectares, standing crop area of 13.35 and 46.25 hectares and other class area of 383 and 587.44 hectares. Whereas, AOI 4, AOI 5 and AOI 7 are having harvested areas of 119.51, 294.62 and 338.11 hectares, standing crop areas of 28.94, 116 and 37.36 hectares and other class areas of 41.51, 242.15 and 368.71 hectares.

AOI ID	Area in Ha.			
	Harvested	**Standing Crop**	**Cut and spread**	**Other**
1	363.00	58.48	38.07	1003.21
2	278.31	13.35	0	383.00
3	221.18	46.25	0	587.44
4	119.51	28.94	0	41.51
5	294.62	116.00	0	242.15
6	120.50	0.91	7.80	332.22
7	338.11	37.36	0	368.71
Total Area	**1735.23**	**301.29**	**45.87**	**2958.24**

Table 1: Area showing harvest, standing crop, cut and spread and other class data for UAV operations in seven locations.

The comparison of paddy crop data from two sources, i.e., Sentinel-2 (S2) satellite imagery and UAV for seven AOIs has been performed. The Sentinel-2 (S2) and UAV data are collected on December 16th, 2023. Sentinel-2 (S2) data shows a total paddy area of 322.84 hectares across all AOIs. In contrast, the UAV data, differentiates between standing crops and cut and spread, recorded an overall area of 301.29 hectares as standing crop, whereas, cut and spread class is having 45.87 hectares.

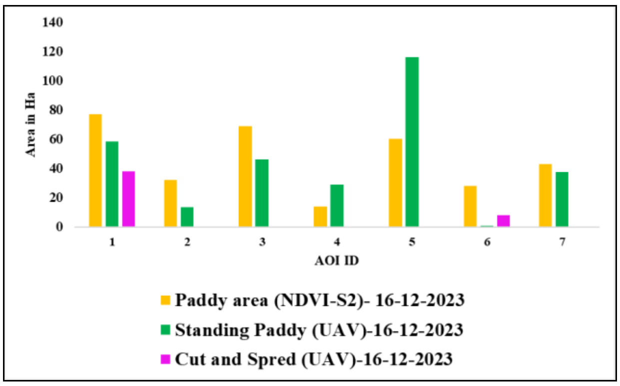

Figure 10. The graphical representation shows comparison of paddy crop area of AOIs that are classified by two distinct images.

5. Conclusion

The study successfully works as a multi-layered approach to monitor and assess the paddy crop in the Rajborasambar block during Kharif 2023 season, utilizing both satellite and UAV data. The initial analysis, conducted using Sentinel-2 satellite imagery from Google earth Engine platform and the Random Forest (RF) method during the peak vegetative period, constructively classified the paddy crop with a high overall accuracy of 89.85% and a kappa coefficient of 79.13%. This analysis resolute the total paddy area in the block to be 13,583.69 hectares.

The use of NDVI time-series data provided critical insights into the temporal dynamics of the growth of crops, accurately capturing the phenological stages from sowing to harvesting. The analysis revealed a gradual increase in NDVI values during the early vegetative stages, followed by a sharp decline as the crop reached maturity. This trend aligned with ground observations, confirming the effectiveness of the methodology.

A key finding of the study was the impact of a specific rainfall event that occurred from 1st to 6th December 2023, during the harvesting period. To evaluate the resulting crop damage, a re-analysis was performed using Sentinel-2 image from 16th December, 2023. The post-rainfall analysis depicts a decrease in overall accuracy to 83.45% and identified a remaining paddy area of 322.84 hectares across the seven Areas of Interest (AOIs). This illustrated that a significant portion of the crop (1,547 hectares) had been harvested before the rainfall event.

To overcome the obstacles of satellite data, particularly the inability to properly assess the 'cut and spread' condition, the study integrated high-spatial-resolution UAV imagery. The UAV data, classified using the Random Forest method, executed an even higher overall accuracy of 90.7% and effectively categorized the crop into harvested, standing, cut and spread, and other classes. This confirmed the higher-level performance of Random Forest over other methods like SVM and bring out the value of integrating UAV data for thorough, plot-level crop assessment, especially for vulnerable crop stages that are difficult to monitor with satellite imagery alone.

6. Acknowledgment

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7. References

Cuaran, J., Leon, J., 2021. Crop Monitoring using Unmanned Aerial Vehicles: A Review. AG. https://doi.org/10.18805/ag.R-180

De Castro, A., Torres-Sánchez, J., Peña, J., Jiménez-Brenes, F., Csillik, O., López-Granados, F., 2018. An Automatic Random Forest-OBIA Algorithm for Early Weed Mapping between and within Crop Rows Using UAV Imagery. Remote Sensing 10, 285. https://doi.org/10.3390/rs10020285

Deng, H., Zhang, W., Zheng, X., Zhang, H., 2024. Crop Classification Combining Object-Oriented Method and Random Forest Model Using Unmanned Aerial Vehicle (UAV) Multispectral Image. Agriculture 14, 548. https://doi.org/10.3390/agriculture14040548

Eskandari, R., Mahdianpari, M., Mohammadimanesh, F., Salehi, B., Brisco, B., Homayouni, S., 2020. Meta-analysis of Unmanned Aerial Vehicle (UAV) Imagery for Agro-environmental Monitoring Using Machine Learning and Statistical Models. Remote Sensing 12, 3511. https://doi.org/10.3390/rs12213511

Gokool, S., Mahomed, M., Kunz, R., Clulow, A., Sibanda, M., Naiken, V., Chetty, K., Mabhaudhi, T., 2023. Crop Monitoring in Smallholder Farms Using Unmanned Aerial Vehicles to Facilitate Precision Agriculture Practices: A Scoping Review and Bibliometric Analysis. Sustainability 15, 3557. https://doi.org/10.3390/su15043557

Gupta, G., Abrol, V., Pradhan, S.R., 2023. Smart Farming: Boosting Crop Management with SVM and Random Forest. https://doi.org/10.21203/rs.3.rs-3160171/v1

Lee, H., Wang, J., Leblon, B., 2020. Using Linear Regression, Random Forests, and Support Vector Machine with Unmanned Aerial Vehicle Multispectral Images to Predict Canopy Nitrogen Weight in Corn. Remote Sensing 12, 2071. https://doi.org/10.3390/rs12132071

Liu, B., Shi, Y., Duan, Y., Wu, W., 2018. UAV-BASED CROPS CLASSIFICATION WITH JOINT FEATURES FROM ORTHOIMAGE AND DSM DATA. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII–3, 1023–1028. https://doi.org/10.5194/isprs-archives-XLII-3-1023-2018

Ma, L., Fu, T., Blaschke, T., Li, M., Tiede, D., Zhou, Z., Ma, X., Chen, D., 2017. Evaluation of Feature Selection Methods for Object-Based Land Cover Mapping of Unmanned Aerial Vehicle Imagery Using Random Forest and Support Vector Machine Classifiers. IJGI 6, 51. https://doi.org/10.3390/ijgi6020051

Maimaitijiang, M., Sagan, V., Sidike, P., Daloye, A.M., Erkbol, H., Fritschi, F.B., 2020. Crop Monitoring Using Satellite/UAV Data Fusion and Machine Learning. Remote Sensing 12, 1357. https://doi.org/10.3390/rs12091357

Murthy, C.S., Poddar, M.K., Choudhary, K.K., Pandey, V., Srikanth, P., Ramasubramanian, S., Senthil Kumar, G., 2022. Paddy crop insurance using satellite-based composite index of crop performance. Geomatics, Natural Hazards and Risk 13, 310–336. https://doi.org/10.1080/19475705.2021.2025155

Saini, R., Ghosh, S.K., 2018. CROP CLASSIFICATION ON SINGLE DATE SENTINEL-2 IMAGERY USING RANDOM FOREST AND SUPPOR VECTOR MACHINE. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII–5, 683–688. https://doi.org/10.5194/isprs-archives-XLII-5-683-2018

UAV Remote Sensing for Urban Vegetation Mapping Using Random Forest and Texture Analysis, n.d.

Wang, Z., Zhao, Z., Yin, C., 2022. Fine Crop Classification Based on UAV Hyperspectral Images and Random Forest. IJGI 11, 252. https://doi.org/10.3390/ijgi11040252

Yuan, H., Yang, G., Li, C., Wang, Y., Liu, J., Yu, H., Feng, H., Xu, B., Zhao, X., Yang, X., 2017. Retrieving Soybean Leaf Area Index from Unmanned Aerial Vehicle Hyperspectral Remote Sensing: Analysis of RF, ANN, and SVM Regression Models. Remote Sensing 9, 309. https://doi.org/10.3390/rs9040309