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Crops Classification in Fragmented Agricultural Land Using Integrated Radar and Optical Remote Sensing Satellite Data

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ABSTRACT

This study aims to classify crops on fragmented agricultural land by integrating radar (Sentinel-1) and optical (Sentinel-2) satellite remote sensing data. The research responds to the pressing issue of decreasing agricultural land in Jember Regency due to land conversion, which threatens food security. Feature-level fusion is applied to combine spectral indices (NDVI, NDWI, NDBI) from Sentinel-2 and radar backscatter characteristics (VV, VH) from Sentinel-1. Classification was performed using the Random Forest algorithm in the Google Earth Engine (GEE) platform. The results showed that the combination of both datasets provided high overall accuracy (81.58%) in classifying eight land cover types including agricultural crops such as paddy, corn, sugarcane, and citrus. This integration enables better monitoring of complex agricultural landscapes, offering a practical tool for sustainable land management.

INTRODUCTION

The agricultural sector in Jember Regency is experiencing increasing pressure due to land conversion, driven by the growth of residential, industrial, and service areas (Rondhi *et. al.*, 2018). Between 2005 and 2013, data show that rice fields decreased by an average of 81.86 hectares annually, with a land-use conversion rate reaching 31.92% over that period. This transformation significantly threatens local food security, particularly because in 2015, Jember was once a leading rice producer in East Java, with more than one million tons harvested (Sunartomo, 2015). However, since then, production has consistently declined.

One of the major consequences of land conversion is the fragmentation of agricultural land, which refers to the division of continuous farmland into smaller, isolated parcels (Ansari, 2020). Fragmentation negatively impacts planting patterns, reduces agricultural productivity, and creates difficulties in monitoring and managing agricultural systems. Given the complexity of fragmented land and the high heterogeneity of crops, conventional field-based surveys are no longer sufficient to support sustainable agriculture planning (Pramesthy *et. al.*, 2023).

In response, remote sensing technology has become a vital tool for crop monitoring and land use classification (Soedarto & Ainiyah, 2022). Remote sensing technology has proven effective in land cover classification, especially in agricultural monitoring (Wang *et. al.*, 2023). Optical satellite imagery, such as from Sentinel-2 which provides high spatial and spectral resolution data, captures detailed spectral information of vegetation, enabling the calculation of vegetation indices like NDVI, NDBI, and NDWI for crop mapping (Sklenicka, 2016). However, optical data are often limited by cloud cover, especially in tropical regions like Indonesia. To overcome this limitation, Synthetic Aperture Radar (SAR) data from Sentinel-1 offer all-weather, day-and-night imaging capabilities (Filipponi, 2019). SAR data captures structural and moisture-related characteristics of the land surface (Sonobe *et. al.*, 2017). SAR data also inform surface texture and structural information through backscatter intensity, providing valuable features for distinguishing different land cover types, including agricultural crops (Carlier, 2000).

Several studies have reported improvements in classification accuracy when combining optical and radar data (Defourny *et. al.*, 2019). For example, the integration of Sentinel-1 and Sentinel-2 using machine learning classifiers such as Random Forest and Support Vector Machine has achieved accuracies of over 80% in land cover mapping. Yet, most of these studies do not address the specific challenges posed by fragmented agricultural lands, where spatial complexity and mixed cropping systems are common.

Studies by Dagne *et. al.* (2023) demonstrated that combining Sentinel-1 and Sentinel-2 data significantly increases classification accuracy. Using Support Vector Machine (SVM) and Random Forest (RF), they achieved overall accuracies of 91% and 81%, respectively, when fusing radar and optical datasets. Their findings validate the effectiveness of multi-source integration in land cover classification, particularly in heterogeneous landscapes.

Moreover, Chen & Zhang (2023) employed a fusion framework using Landsat-7/8, Sentinel-2, and Sentinel-1 to monitor alfalfa fields. The study reported a significant reduction in RMSE for vegetation index estimations, confirming the reliability of integrating radar and optical data for precision agriculture. Similarly, Eramudadi & Rokhmana (2024) applied an object-based approach in Google Earth Engine using Sentinel-1 and Sentinel-2, obtaining high classification accuracy for urban settlement mapping.

Despite these advancements, limited studies focus explicitly on fragmented agricultural land, where small-scale, irregular field boundaries and crop heterogeneity pose unique challenges to classification accuracy. Mayele *et. al.* (2024) emphasized that land fragmentation disrupts spatial consistency, making remote sensing analysis more complex. This study contributes by addressing the classification of fragmented agricultural lands in Jember Regency using radar-optical data fusion. The approach builds on previous works by introducing feature-level fusion techniques to better capture the spatial complexity and seasonal crop variation in highly fragmented areas.,

Thus, this study aims to explore the integration of Sentinel-1 and Sentinel-2 data for crop classification in fragmented agricultural regions in Jember Regency. Using feature-level fusion and the Random Forest algorithm within the Google Earth Engine (GEE) platform, the study seeks to generate a high-accuracy classification map that reflects the diversity and complexity of local land use. This research is expected to contribute to sustainable agricultural monitoring and land management in regions facing similar challenges.

MATERIALS AND METHODS

This study was conducted in Jember Regency, East Java, Indonesia. There are 2 types of utilized data that are satellite data and ground data. Using multi-temporal imagery from Sentinel-1 (radar) and Sentinel-2 (optical) satellites covering the period from 2021 to 2024.

Prior to the classification stage, a data fusion process was carried out at the feature level. This fusion involved the integration of information derived from two distinct types of remote sensing imagery—optical imagery from Sentinel-2 and radar imagery from Sentinel-1. The rationale behind this approach lies in harnessing the complementary strengths of both data sources: the rich spectral information provided by optical imagery and the structural and moisture-related insights obtained from radar data. By combining these features, a more robust and comprehensive representation of land cover conditions was achieved, particularly in complex and heterogeneous agricultural landscapes.

Following the data fusion process, ground truth data were overlaid onto the fused imagery to facilitate the classification and accuracy assessment stages. As illustrated in Figure 1, the spatial distribution of training and validation samples covers the entirety of the study area. Each land cover class was assigned a unique color to enhance visual distinction. This stratified sampling ensured adequate representation of all classes, thereby supporting a robust and unbiased classification process. The methodological framework included data pre-processing, feature extraction, image fusion, classification, and accuracy assessment.

Pre-processing:

Sentinel-2 images were processed using cloud masking based on the QA60 band to eliminate cloudy pixels, ensuring high-quality composite imagery. Sentinel-1 imagery was corrected for speckle noise using the Lee filter to retain essential surface texture characteristics, which are critical in radar image analysis.

Feature Extraction:

Vegetation and land characteristics were quantified using spectral indices derived from Sentinel-2. There are three spectral indices applied in this study that are NDVI, NDWI, and NDBI.

- NDVI (Normalized Difference Vegetation Index) for vegetation vigor

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

- NDWI (Normalized Difference Water Index) for surface moisture

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{2}$$

- NDBI (Normalized Difference Built-up Index) for urban area identification

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{3}$$

Where:

NIR = Reflectance value of band 8 (NIR)
Red = Reflectance value of band 4 (Red)
Green = Reflectance value of band 3 (Green)
SWIR = Reflectance value of band 11 (SWIR)

From Sentinel-1, backscatter coefficients VV and VH were extracted along with the VH/VV ratio to represent surface structure and moisture content. These radar features complemented the spectral indices by providing texture and penetration-based information.

Image Fusion:

Feature-level fusion was applied by stacking all derived indices and radar features into a single dataset. This comprehensive layer combined both spectral and structural insights, enabling more accurate classification in fragmented and heterogeneous agricultural landscapes.

Classification:

A supervised classification was carried out using the Random Forest (RF) algorithm, implemented in the Google Earth Engine (GEE) platform. RF was chosen due to its robustness in handling high-dimensional input features and its effectiveness in non-parametric classification tasks. A total of 122 ground truth points were used for training, while 51 validation points, stratified across all land cover classes, were used to evaluate classification accuracy.

Ground truth data were imported into GEE as a Feature Collection and labelled according to the eight land cover classes. The fused image stack—consisting of Sentinel-1 and Sentinel-2 derived features (NDVI, NDWI, NDBI, VV, VH, VH/VV)—was used as input. The dataset was then randomly split into training data (122 samples) and validation data (51 samples) using stratified sampling techniques to ensure representative distribution across all classes.

A Random Forest classifier with 100 decision trees was initialized and trained using the 122 ground truth points. The algorithm evaluated feature importance and built multiple decision trees through bootstrap sampling. Each pixel in the image was classified based on majority voting from the ensemble of trees. The trained model was applied to the entire image to produce the classified land cover map.

Accuracy Assessment:

Confusion matrix analysis was used to assess the performance of the classification model. One key accuracy metric was calculated Overall Accuracy (OA). Accuracy assessment was conducted by comparing predicted labels with the 51 validation points and mathematically expressed in equation 4.

$$OA = \left(\frac{Totalcorrectclassification}{TotalSampel}\right) x100\% \tag{4}$$

Finally, a majority filter was optionally applied to reduce speckle noise and smoothen classification boundaries. This classification strategy allowed for efficient identification of land cover types by leveraging the complementary strengths of radar and optical remote sensing data. This classification strategy allowed for efficient identification of land cover types by leveraging the complementary strengths of radar and optical remote sensing data.

Training Sample Collection: A total of 51 reference points were used to represent seven land cover classes: Built-up Land, Paddy Fields, Corn, Sugarcane, Citrus, Non-agricultural Vegetation, Shrubs, and Water Bodies. Each point was manually labelled based on known ground truth or verified image characteristics.

Random Forest Classification: The Random Forest classifier in GEE was configured with a number of decision trees and applied bootstrap sampling. It evaluated input features (e.g., NDVI, VH/VV) to determine their importance. During training, an ensemble of decision trees was built, each trained on a subset of data. For each pixel, the RF model aggregated predictions from all trees (majority voting) to assign the class label.

Classification Output: The trained RF model was applied to the entire study area to produce a classified land cover map. Each pixel was labelled into one of the seven predefined classes. Optional post-processing, such as mode filtering, was applied to reduce noise. The final classification map visually displayed land cover types and supported further spatial analysis.

Size of Dataset

The dataset comprised fused imagery over 2,855 hectares of agricultural and non-agricultural land. Ground truth data included 122 training points and 51 validation points, categorized into the following eight land cover classes: built-up land, paddy fields, corn, sugarcane, citrus, non-agricultural vegetation, shrubs, and water body.

The spatial distribution of all ground truth samples is visualized in Google Earth Engine. Each land cover class was assigned a unique color, and the points were distributed proportionally across the study area to ensure adequate spatial coverage and representativeness. Training samples are denoted with solid color pins, while validation points are represented by lighter or outlined markers. This stratified sampling approach supports robust classification performance and accurate validation outcomes.The fused dataset covered approximately 2,855 hectares in Jember Regency and was categorized into the following eight land cover classes:

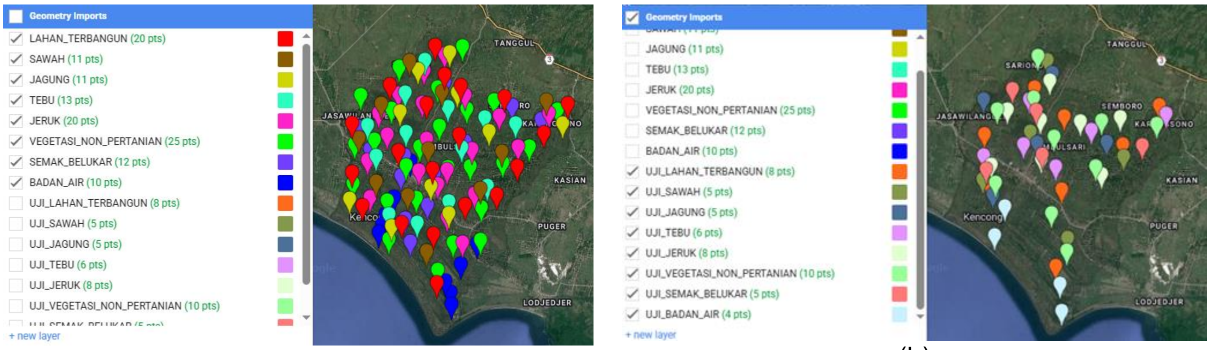
Table 1. Land Cover Type

Class	Land Cover Type	Training Point	Validation Point
1	Built-up Land	20	8
2	Paddy Fields	11	5
3	Corn	11	5
4	Sugarcane	13	6
5	Citrus	20	8
6	Non agricultural Vegetation	25	10
7	Shrubs	12	5
8	Water Bodies	10	4

Table 1 shows the distribution of training and validation data points for eight land cover classes, namely Built-up Land, Paddy Fields, Corn, Sugarcane, Citrus, Non-agricultural Vegetation, Shrubs, and Water Bodies. Overall, there were 122 training points and 51 validation points used in the classification process. The class with the highest number of training points is Non-agricultural Vegetation with 25 points, while the classes with the least number of training points are Paddy Fields, Corn, and Water Bodies, each with only about 10-11 points. The split ratio between training and validation data ranges from 70:30 for almost all classes, which is a commonly used split in classification model development to ensure the model does not suffer from overfitting and can still be objectively validated.

RESULTS AND DISCUSSION

Trainig Point and Validation Point



(a) (b)

Figure 1. Training points in the study area (a) and Validation points in the study area (b)

Figure 1 shows the distribution of training and validation points obtained through the stratified random sampling method in the study area, where the training points (Figure a) are used to train the classification algorithm in recognizing the spectral and textural characteristics of each land cover class, while the validation points (Figure b) are arranged independently to ensure an objective and unbiased evaluation of classification accuracy. The point generation process begins with defining the boundaries of the study area and creating a reference layer based on high-resolution imagery or manual interpretation, which is then used as a reference in generating a proportional number of random sample points evenly distributed across each land cover class. Visualization of these points is done on the base image by assigning different colors to each class, so that their spatial distribution can be validated visually and potential overlap between training and validation points can be avoided.

Fusion of Sentinel-1 and Sentinel-2 Imagery

The integration of Sentinel-1 and Sentinel-2 datasets at the feature level significantly enhanced the ability to distinguish various land cover types within the study area. Sentinel-2 provided detailed spectral information through vegetation and built-up indices (NDVI, NDWI, NDBI), while Sentinel-1 contributed backscatter intensity and texture features (VV, VH, VH/VV ratio) that are not affected by atmospheric conditions.

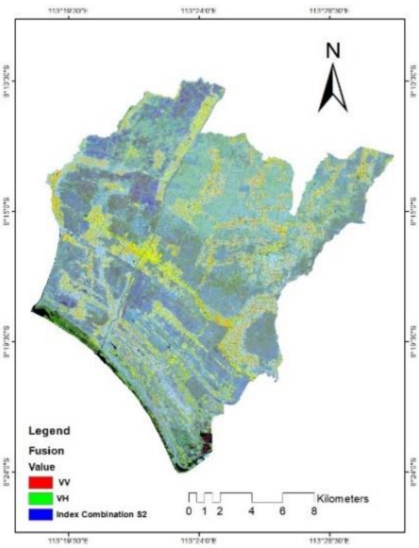


Figure 2. result of sentinel-1 and sentinel-2 Fusion combined

The fusion process allowed the generation of a composite image with enriched dimensionality, capturing both spectral and structural differences across land covers. This approach was particularly effective in fragmented agricultural landscapes, where single-source imagery often fails to differentiate between closely related crop types or between agricultural and non-agricultural vegetation.

Land Cover Classification Result

The classification process was performed using Random Forest algorithm in the Google Earth Engine environment and it produced a thematic map containing seven land cover classes as shown in Figure 3.

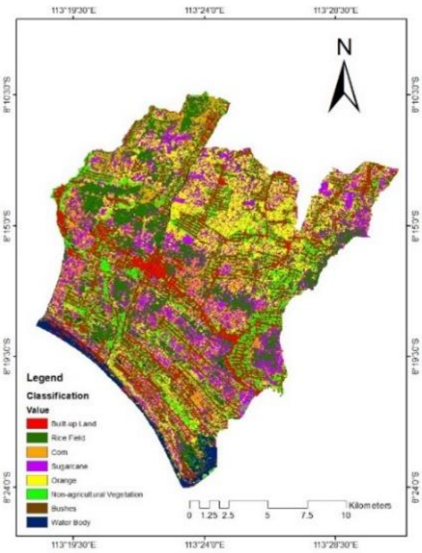


Figure 3. results from combined sentinel-1 and sentinel-2 crop classification

Based on the classification result, it can be calculated the area of each land cover type as described in the table 2.

Table 2. Land Cover Type and Area (ha)

Class	Land Cover Type	Area (ha)
1	Built-up Land	217.070
2	Paddy Fields	464.514
3	Corn	260.333
4	Sugarcane	502.687
5	Citrus	497.122
6	Non-agricultural Vegetation	301.691
7	Shrubs	517.962
8	Water Bodies	94.090
	Total	2855.469

The data of land cover type area show that the largest land cover identified was shrubs (517.96 ha), followed by sugarcane (502.69 ha), and citrus (497.12 ha). Paddy fields also covered a significant area (464.51 ha), reflecting their importance in the region. Corn occupied 260.33 ha, while built-up land and non-agricultural vegetation covered smaller areas. These results confirm the mixed and fragmented nature of agricultural use in Jember Regency.

Classification Accuracy

The accuracy assessment was conducted using 51 validation points. The confusion matrix revealed that overall classification accuracy reached 84.37%, indicating strong agreement between the classified map and reference data.

Confusion matrix of the evaluation results of the land cover classification consisting of eight classes, namely Built-up Land, Rice Field, Corn, Sugarcane, Orange, Non-Agricultural Vegetation, Shrub, and Water Body, which were evaluated using a number of validation points. Based on the matrix, the diagonal values indicate the number of validation points that were correctly classified in each class, with the best accuracy achieved by the Built-up Land and Non-Agricultural Vegetation classes, both of which showed perfect classification results. However, notable misclassifications occurred in the Rice Field and Shrub classes, where Rice Field was not correctly classified at all, while Shrub showed predominant classification confusion especially with the Non-Agricultural Vegetation and Water Body classes. These errors indicate spectral overlaps between similar classes or possible limitations in the features used in the classification process. Therefore, the results of this confusion matrix confirm the need for improved training data quality and feature enrichment, such as the addition of temporal vegetation indices or texture attributes, to improve classification accuracy in low-performing classes.

The overall accuracy value obtained of 0.84375 or 84.375% indicates relatively good model performance, but the presence of several classes with low individual accuracies indicates the need for improved training data quality or the use of additional features such as temporal vegetation indices, image texture, or DEM data integration to reduce the level of confusion between spectrally similar classes. This matrix is an important indicator in assessing the reliability of the classification model and informs strategic recommendations for improving classification methods in land cover research in the study area.

This result surpasses the accuracy reported by Dagne *et al.* (2023) who achieved 81% accuracy using similar radar-optical fusion and Random Forest classification techniques. The slightly higher accuracy in this study can be attributed to the use of additional indices (NDVI, NDWI, NDBI), optimized cloud masking, and the inclusion of structural backscatter features (VV, VH) from radar imagery. These enhancements likely improved class separability, particularly between vegetation and non-vegetation categories. Nevertheless, further improvements are recommended, such as integrating temporal composites, DEM variables, and texture features to address the remaining misclassifications among spectrally similar crop types.

CONCLUSIONS

This study demonstrates the effectiveness of integrating Sentinel-1 and Sentinel-2 satellite imagery for classifying crops in fragmented agricultural areas. The fusion of spectral indices from Sentinel-2 (NDVI, NDWI, NDBI) with radar backscatter features from Sentinel-1 (VV, VH, VH/VV) enhanced the representation of both surface structure and vegetation characteristics.

Using the Random Forest algorithm within the Google Earth Engine (GEE) platform, the classification achieved an overall accuracy of 84.37% across seven land cover classes. The fusion approach successfully distinguished between major crop types and non-agricultural covers, despite some spectral overlap between crops with similar growth stages.

The findings highlight the potential of multi-source remote sensing for supporting precision agriculture, particularly in regions where land fragmentation and cloud cover limit traditional monitoring methods. Further improvements could be achieved by integrating additional features such as temporal composites, texture metrics, and topographic data to reduce class confusion and improve accuracy.

This method provides a scalable and cost-effective solution for agricultural land monitoring, aiding policymakers and agricultural agencies in planning and managing land resources more sustainably.

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