

Feature-level fusion of Sentinel-1 SAR and Sentinel-2 optical imagery for crop-type mapping in humid tropical mountainous terrain

Indarto Indarto^{*1)}, Gunawan Gunawan²⁾, Mahrus Irsyam¹⁾ and Fahmi Arif Kurnanto³⁾

¹⁾Department of Agricultural Engineering, Faculty of Agricultural Technology, University of Jember, Jember, Indonesia

²⁾Department of Information System, Faculty of Engineering and Computer Science, Panca Sakti University, Tegal, Indonesia

³⁾Department of Geography Education, University of Jember, Jember, Indonesia

Received 8 August 2025

Revised 27 May 2026

Accepted 5 August 2026

Abstract

Accurate crop-type mapping in humid tropical mountains is challenged by persistent cloud cover, rugged topography, and fragmented smallholder parcels. This study evaluates a feature-level fusion workflow that integrates Sentinel-2 optical indices and Sentinel-1 SAR backscatter for crop-type mapping in Candipuro District, Lumajang, East Java, Indonesia. Sentinel-2 surface reflectance and Sentinel-1 IW data acquired in June–July 2023 were harmonised in Google Earth Engine to a common 10 m pixel grid, so that all comparison maps were evaluated on the same spatial support. The optical component comprised NDVI, NDBI, and NDWI, whereas the radar component used the VH/VV polarisation ratio. A DEM was used only to characterise the mountainous setting and to assist terrain interpretation, and was not included as a predictor in the classifier. The stacked feature image was classified using a Random Forest model trained with 101 field-survey ground control points representing eight land-cover/crop-related classes. Accuracy was assessed using 393 stratified random validation points. The fused-image classification achieved an overall accuracy of 93% and a kappa coefficient of 0.90. The fusion workflow yielded richer thematic differentiation than the optical-only comparison scenarios, particularly for water bodies, sugarcane, and shrubland. However, class-level results reveal substantial uncertainty for corn fields and moderate confusion in built-up and water classes. Therefore, the present workflow should be interpreted as a site-specific, single-date proof of concept rather than a fully transferable operational solution. The results indicate that Sentinel-1/Sentinel-2 feature fusion is promising for crop-type mapping in cloud-prone mountainous landscapes, while future work should incorporate multi-temporal phenology, richer vegetation indices, SAR texture features, uncertainty mapping, and broader field sampling.

Keywords: Crop type mapping, Feature fusion, Sentinel, Google Earth Engine, Mountainous terrain, Humid tropics

1. Introduction

Crop type mapping (CTM) aims to identify and classify different types of crops grown in specific areas using various data sources and techniques. Then, remote sensing images, such as Sentinel-1 (SAR) and Sentinel-2 (optical), are widely used for monitoring crop growth and health. Combining data from multiple sources is usually used to improve crop-type mapping accuracy. Deep and machine-learning techniques analyse satellite data to produce crop-type (CT) maps [1]. Furthermore, CT maps can be used for broader applications, such as yield prediction, crop management, environmental monitoring, disaster assessment, policy making, and economic planning. For example, Crop-type maps help forecast grain supplies to estimate crop yields [1]. The maps then facilitate effective farm management practices by providing detailed crop inventory. In advance, a CT map also assists in understanding environmental conditions and optimising land use. Moreover, the maps also identify factors influencing crop stress, assess damage due to storms and drought, inform agricultural policies, and contribute to national food security. Finally, crop-type maps are used to support the collection of crop production statistics and aid in economic planning [2].

Sentinel-2 imagery was obtained from the optical imaging satellite launched in 2015. This satellite has a high-resolution passive multispectral sensor featuring 13 spectral bands. The Sentinel-2 mission supports terrestrial observations for various services, such as forest monitoring, land cover change detection, and natural disaster management. Sentinel-2 satellite is capable of terrestrial observations, such as land cover change detection and disaster management, covering an area of 290 km (swath-width) with three types of spatial resolution: 10 meters for bands (B2, B3, B4, B8), 20 meters for six bands (B5, B6, B7, B8, B11, B12), and 60 meters for three bands (B1, B9, B10). The Sentinel-2 satellite has a temporal resolution, returning to the same point every five days, allowing for comprehensive coverage of our planet [3, 4].

Broad applications of Sentinel-2 images have been found in the literature during the last decade. Sentinel-2 is used for land use and land cover (LULC) change, crop monitoring and development, crop type classification, vegetation index derivation, estimating yield, disaster mitigation, urban area, and other wide area applications [5, 6].

Furthermore, the Sentinel-1a satellite image is obtained from the Sentinel-1 radar imaging satellite, which was launched in 2014 by the European Space Agency (ESA). Sentinel-1 consists of a constellation mission of two types of satellites, namely Sentinel-1a and 1b. This satellite carries a C-band SAR instrument (505 GHz) capable of acquiring images in various conditions and weather, day or

*Corresponding author.

Email address: indarto.ftp@unej.ac.id

<https://doi.org/10.64960/easr.2026.263460>

night, with a temporal resolution of 6 days. This satellite operates for 7 to 12 years. Sentinel-1a moves in a polar orbit with an orbital altitude of 697 km. Sentinel-1a is operational for land and ocean services such as marine environment observation, oil spill detection, ice monitoring, sea transportation monitoring, land surface mapping, land cover and vegetation mapping, and natural disaster observations like floods and earthquakes [7, 8]. Sentinel-1 is used to map plant species in southern Russia. The area is often covered by snow and clouds, benefiting from Sentinel-1's ability to penetrate cloud and snow cover for vegetation and plant monitoring to create the map [9]. A previous study [10] used Sentinel-1 SAR to detect floating macroalgae and other floating objects.

Researchers worldwide have developed several Image Fusion (IF) remote sensing data processing methods. IF uses information from several sources for optimal or compact data representation, supporting better description and decision-making. IF technique enhances the quality and content of the resulting image, making it more useful for human and machine perception [11, 12]. The fused images are more robust and reliable [13, 14]. Image data fusion techniques promise several advantages, including (a) enhanced image data quality, (b) Improved classification, (c) Feature enhancement, (d) Noise reduction, (e) Wider coverage, (f) Increased robustness, and (g) Creation of stereo data sets [13, 15].

Although many procedures for image fusion exist, they may point to different aspects of IF. IF methods are still being developed and integrated with more advanced artificial intelligence technology. Previously, Sentinel-1 and Sentinel-2 data were used to map and monitor wetlands [3]. In parallel, the time series of Sentinel-1 and Sentinel-2 are also applied to monitor irrigation events and plant dynamics [16]. In addition, the 2019 floods in Mozambique caused by tropical cyclone Idai were studied and monitored from Sentinel-1 and Sentinel-2 images [17]. Next, Habibie et al. [18] maps and monitors urban areas using Sentinel-1 and Sentinel-2.

Furthermore, many research works have combined Sentinel-1 and Sentinel-2 to solve many problems. For example, Wang et al. [19] conducted the Research by combining ESA sentinel-1 and sentinel-2 to produce a 10m automatic forest cover map in the Han River Valley, China. Then, similar work on land use and land cover maps using Sentinel-1 and Sentinel-2 has been reported by several authors [9, 20, 21].

CTM also uses Sentinel-1 and Sentinel-2 fusion. For example, Sentinel-2 and machine learning map the crop type, while Sentinel-1 backscatter time series monitor the plant phenology [22]. Then, Sentinel-1 and Sentinel-2 images time series were integrated for CTM in the oasis agricultural area [23]. Moreover, the Fusion of Sentinel-1 and Sentinel-2 data is used for savannah land cover mapping by optimising a combination of sensors and seasons [24]. Later, Asam et al. [25] mapped the German plant types by combining temporal statistical metrics of the Sentinel-1 and Sentinel-2 time series with LPIS data.

Despite these advances, relatively fewer studies address smallholder agricultural areas in humid tropical mountainous terrain, where cloud contamination, steep slopes, and fragmented parcels occur simultaneously. In such environments, a computationally simple feature-level fusion workflow may still be useful as a practical baseline, especially when the number of clear optical scenes is limited. Nevertheless, a single-date or short-period fusion strategy cannot fully capture crop phenology and should not be interpreted as a substitute for a full time-series framework.

Against this background, the present study investigates whether feature-level fusion of Sentinel-1 and Sentinel-2 can improve crop-type mapping in Candipuro, Lumajang, East Java, Indonesia. The study specifically focuses on a mountainous humid-tropical landscape dominated by small agricultural parcels. Rather than proposing a fully operational regional product, the study evaluates a site-specific baseline workflow implemented in Google Earth Engine and examines its accuracy, class-level weaknesses, and practical limitations.

The contributions of this study are threefold. First, it documents a harmonised 10 m feature-stacking workflow for combining optical and radar predictors in a cloud-prone mountainous setting. Second, it compares the fused classification with two optical-only scenarios to show how the choice of predictor set affects the resulting map. Third, it explicitly discusses class imbalance, local confusion, scale support, and methodological limitations so that the conclusions remain proportional to the presented evidence.

Accordingly, the objective of this study is to assess the usefulness of feature-level Sentinel-1/Sentinel-2 fusion for crop-type mapping in a humid tropical mountainous area, while identifying the circumstances under which the resulting classification is reliable and where additional methodological development is still required.

2. Materials and methods

2.1 Study area

This Research was conducted from 2023 to 2024 at Candipuro District, Lumajang Regency, East Java, Indonesia (Figure 1). Administratively, Candipuro is located around several sub-districts, namely Pasrujambe, Tempursari, Pronojiwo, and Pasirian. Candipuro has an altitude of 322 meters above sea level, and this area receives an average annual rainfall of 5075 mm per year.

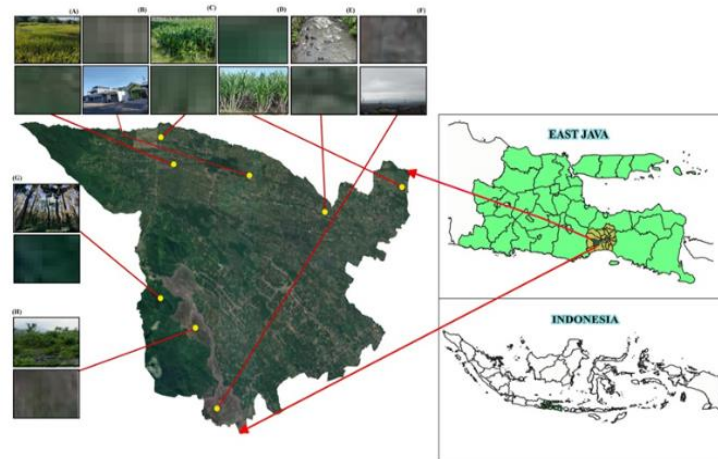


Figure 1 The study site collected GCPs and nomenclature classes.

Fieldwork and image processing were conducted from 2023 to 2024. Candipuro is located in the Mount Semeru region and is characterised by steep terrain, high annual rainfall, and highly fragmented agricultural parcels. For terrain description and map interpretation, the mountainous setting was checked against the NASA SRTM Digital Elevation 30 m dataset ('USGS/SRTMGL1_003') available in Google Earth Engine; however, the DEM was not included as a predictive variable in the classification model. This distinction is important because the present study evaluates feature fusion based on Sentinel-1 and Sentinel-2 predictors only.

Most of the village is on the steepest plateau near Mount Semeru. Terraced farming areas and dense vegetation dominate the agricultural land. The farmland is composed of small-scale terraced lands. The farming system is dominated by small and irregular plots, in which paddy, corn, sugarcane, vegetables, shrubs, and mixed vegetation occur in close proximity. These conditions increase within-pixel heterogeneity and complicate crop discrimination, especially when the map is produced at medium spatial resolution.

2.2 Input data

2.2.1 Optic and radar satellite data

Sentinel-2 Surface Reflectance and Sentinel-1 SAR data were used as the main remote-sensing inputs. Sentinel-2 optical imagery was accessed in Google Earth Engine (GEE) from the Harmonized Sentinel-2 MSI Level-2A Surface Reflectance collection, 'COPERNICUS/S2_SR_HARMONIZED', for the period June–July 2023. Sentinel-2 bands B2, B3, B4, and B8 provide 10 m spatial resolution, whereas band B11 used for NDBI is natively 20 m. Sentinel-1 radar imagery was accessed from the GEE collection 'COPERNICUS/S1_GRD', which provides C-band SAR Ground Range Detected (GRD) data including VH and VV polarisation channels. In this study, Sentinel-1 IW dual-polarisation data acquired during the same period were used to derive the VH/VV ratio. For terrain interpretation, topographic context was checked using the NASA SRTM Digital Elevation 30 m dataset, 'USGS/SRTMGL1_003', although the DEM was not incorporated as a predictive variable in the classifier. To make feature stacking and map comparison consistent, all predictor layers were harmonised to a common 10 m pixel grid within the same area of interest and temporal window. The comparison maps shown later in the manuscript therefore differ in feature composition, not in spatial support.

The data was selected only for cloud cover less than 3%. We used the median composite image for Sentinel-2 and interferometric-wide for Sentinel-1. Sentinel-1 imagery available in GEE has been corrected using the Sentinel-1 Toolbox (i.e., thermal noise removal, radiometric calibration, and terrain correction for each scene). Therefore, all scenes used for this study have been corrected using the Sentinel-1 Toolbox. Then, the filter area and date are used to obtain Sentinel-1 and Sentinel-2 images for the appropriate area of interest (AOI). Finally, an algorithm called "filter. eqquicision" and "filter ee.Filter.listContains" are selected to obtain polarisation VH-VV of the ascending and descending phase of Sentinel-1 using mode Informetric Wide [26-28].

2.2.2 Ground truth data collection

A total of 101 ground control points GCPs were collected from June to August 2023, through field survey using GPS, ground photographs, and Avenza Maps. Each point was assigned only after direct visual confirmation of the dominant land-cover/crop-related class in the field. Eight nomenclature classes, i.e.: (a) paddy field, (b) pavement area, (c) corn field, (d) sugar cane field, (e) water body, (f) sand, (g) dense vegetation, and (h) shrubland (Figure 1). Then, GCP and classes are used for validation processes during the image classification. Classification is done on top of the GEE engine using Random Forest (RF) algorithms. Many research studies have recommended that the RF algorithm is the best for classification processes of Sentinel images using GEE [29-31].

2.3 Procedures

The workflow focused on feature-level fusion of Sentinel-1 and Sentinel-2 predictors. First, vegetation indices were derived from Sentinel-2 imagery. Second, the radar-derived VH/VV polarisation ratio was obtained from Sentinel-1. Third, these predictors were stacked into a single multiband feature image and classified using a Random Forest (RF) model in GEE. Finally, the fused classification was compared with two optical-only scenarios to assess how predictor design affects map detail and thematic separation.

The workflow was intentionally designed as a simple and reproducible baseline suitable for cloud-prone areas with limited clear-sky observations. Consequently, the present experiment does not yet include multi-temporal phenological metrics, SAR texture measures, or algorithm benchmarking, all of which are discussed later as important directions for future work. In this case, a feature fusion combines the vegetation indexes derived from Sentinel-2 and the polarisation VH/VV of Sentinel-1.

The Fusion Image (FI) is therefore expressed as $FI = (NDVI + NDBI + NDWI) + (VH/VV)$. Moreover, a random forest (RF) algorithm is used to classify FI to produce a crop-type map. The classification process is executed on top of the GEE platform [29-31].

2.3.1 Image pre-processing

Google Earth Engine (GEE) was used to collect and preprocess all Sentinel-1 and Sentinel-2 imagery. For Sentinel-2, cloud-affected pixels were masked prior to compositing in order to minimise cloud contamination during the June–July 2023 acquisition window. Cloud masking was conducted using the Sentinel-2 cloud-probability information available in GEE, after which the selected scenes were composited over the study period and clipped to the same area of interest. The resulting cloud-reduced Sentinel-2 surface reflectance data were then used to derive NDVI, NDBI, and NDWI.

For Sentinel-1, the 'COPERNICUS/S1_GRD' collection available in GEE was used. These GRD data are provided in Earth Engine after standard preprocessing steps, including thermal-noise removal, radiometric calibration, and terrain correction. To reduce local speckle effects and improve visual consistency, an additional speckle-reduction step was applied before deriving the VH/VV ratio. The Sentinel-1 scenes were then filtered to match the area of interest and acquisition period used for the optical imagery.

Finally, all optical and SAR predictor layers were harmonised to a common 10 m pixel grid so that the stacked feature image could be used consistently in the subsequent fusion and classification stages. This harmonisation ensured that differences among the comparison maps reflected feature composition rather than differences in spatial support.

2.3.2 Deriving vegetation index

First, the selected vegetation indices, i.e., Normalised Difference Vegetation Index (NDVI), Normalised Difference Build-Up Index (NDBI), and Normalised Difference Water Index (NDWI), are derived from Sentinel-2 data. Then, derived vegetation indices (NDVI, NDBI, and NDWI) produce an index combination from Sentinel-2. The combination index is supposed to improve the interpretation of similar spectral responses of surface features in the optical bands.

NDVI uses and performs better to identify vegetation greenness [32]. The formulas for these indices are presented in Table 1. Then, NDBI better maps the built-up or pavement area using a Sentinel-2 image [33, 34]. Moreover, NDWI is used mainly to identify the presence of water bodies [35, 36]. Hence, combining (NDVI + NDBI + NDWI) can simultaneously improve the detailed separation of main surface features, such as vegetation types, water bodies, and built-up areas. Figure 2 shows the research procedures.

Table 1 Vegetation indices used in this study and the formula

Index	Formulas	Reference
NDVI	$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$	[33, 37-39]
NDBI	$(\text{SWIR}-\text{NIR})/(\text{SWIR}+\text{NIR})$	[17, 40, 41]
NDWI	$(\text{Green}-\text{NIR})/(\text{Green}+\text{NIR})$	[41-43]

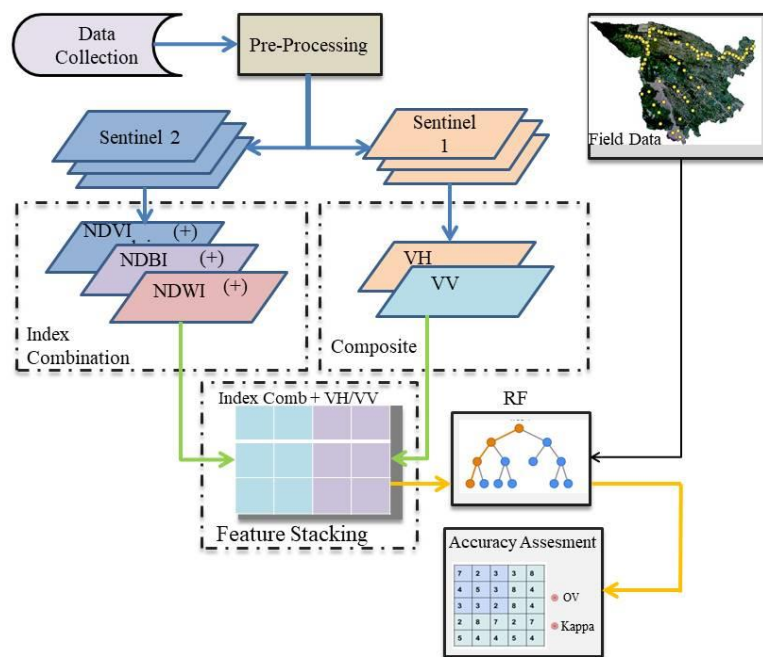


Figure 2 Research Procedures

2.3.3 Fusion method

In this Research, the fusion technique uses image feature extraction and stacking. Firstly, features are extracted from each image separately. For instance, spectral features are extracted from optical images, and textural features are extracted from SAR images. Feature stacking in satellite image fusion involves combining multiple features extracted from different satellite images into a single, unified dataset. This technique enhances the accuracy and richness of the information derived from satellite imagery. Then, the extracted features are stacked together to form a comprehensive feature set. This stacked dataset is then used for further analysis or classification [43-45].

In this case, the spectral features of NDVI, NDBI, and NDWI are extracted from the optical image (Sentinel-2), while textural features (backscattered image or VH/VV) are derived from radar Sentinel-1. Then, each value of all these features is stacked to form a new single image using equation (Eq. 1), as follows.

$$\text{Fusion Image (FI)} = \text{Stack (NDVI, NDWI, VH/VV)} \quad (1)$$

where FI denotes the fused multiband image and Stack(.) denotes band-wise concatenation rather than numerical summation.

In Sentinel-1 terminology, VV is the co-polarised backscatter acquired with vertical transmit and vertical receive, whereas VH is the cross-polarised backscatter acquired with vertical transmit and horizontal receive. The VH/VV ratio was used to represent relative structural differences in surface scattering and vegetation cover.

The present study uses this simple stacking strategy as a baseline. More advanced fusion procedures, including feature selection, multiscale fusion, or deep-learning-based integration, may further improve class separability, but these were beyond the scope of the current single-date experiment.

The fused classification achieved an overall accuracy of 93% and a kappa coefficient of 0.90, indicating good agreement between the classified map and the independent validation data. However, the class-level results are more heterogeneous than the summary metrics alone suggest. Dense vegetation, paddy field, sandy land, and shrubland performed well, whereas water bodies showed only moderate user accuracy (0.71) and corn fields performed poorly. The user accuracy of 0.00 for corn fields indicates that this class was not mapped reliably in the present experiment, most likely because of limited and unbalanced reference samples, spectral confusion with neighbouring vegetation classes, and the fragmented character of the parcels. For this reason, the manuscript now avoids claiming that all crop classes were mapped equally well.

3.3 Crop type maps: Comparisons

Figure 4 (a, b, c) shows crop-type maps of the same areas of interest, classified by three different methods. Method-1 (Figure 4a) visualises the crop type map produced from a composite of bands 2,3,4, and 8 of the Sentinel 2 image. The classification was done on top of the GEE platform using the RF algorithm. Figure 4a shows only the five (5) classes, consisting of (1) Paddy fields, (2) built-up or pavement areas, (3) dense/annual vegetation, (4) sugarcane, and (5) sand (Table 3).

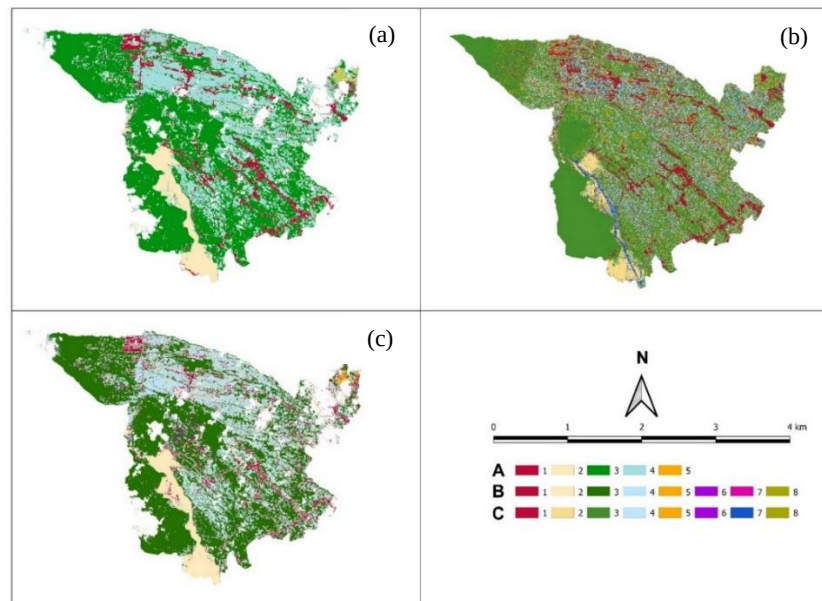


Figure 4 Crop-type classified maps

Table 3 The area occupied by each class (in ha and %), method 1, 2, and 3

No	Classes	Metode-1 (A)		Metode-2 (Fusion / B)		Metode-3 (C)	
		Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
1	Paddy field	334,55	29,90	193,97	16,79	206,90	20,51
2	Built-up/pavement	84,68	7,57	128,84	11,15	48,30	4,79
3	Dense Vegetation	571,77	51,11	647,63	56,06	419,70	41,60
4	Waterbody	0	0	55,13	4,77	0	0
5	Sugarcane	14,46	1,29	58,10	5,03	21	2,08
6	Maise	0	0	12,69	1,10	37,20	3,69
7	Sand	113,34	10,13	50,21	4,35	80,20	7,95
8	Shrubland	0	0	8,77	0,76	75,20	7,45
9	Sweet Potato	0	0	0	0	2,20	0,22
Total		1118,79	100	1155,3	100	890,7	100

Then, method-2 (Figure 4b) shows the crop type map produced from the fusion technique using the procedure described in Figure 2. Figure (4b) presents the eight (8) classes including (1) Paddy fields, (2) built-up or pavement areas, (3) dense or annual vegetation, (4) water bodies, (5) sugar canes, (6) corn field, (7) sand, and (8) scrubland.

Finally, method-3 (Figure 4c) shows the crop type map processed using a combination of vegetation indices from a composite of band B2, B3, B4, B8, NDVI, SAVI, and MBI. The composites were created from Sentinel-2 optical imagery. Figure 4c also show eight (8) classes, including (1) Paddy fields, (2) built-up or pavement areas, (3) dense or annual vegetation, (4) sweet potatoes, (5) sugar canes, (6) cornfield, (7) sand, and (8) scrubland. In Figure 4c, the water body is not detected, contrary to method 2, which can capture the area of sweet potato cultivation.

Method 3 (Figure 4c) also captures small-scale variability, but unlike Method 2 it does not detect water bodies and instead identifies a small sweet-potato class. This difference illustrates that crop-type maps in fragmented mountainous terrain are sensitive to feature composition, particularly when classes share similar spectral responses or when parcel sizes approach the pixel size.

Figure 4 and Table 3 show that different composite methods, including fusion techniques, will propagate the classified crop type maps. Many factors may cause the results. However, it is interesting to research the best method according to the local conditions to produce more appropriate maps with the same data input.

Method 2 (Figure 4B) appears to provide the most balanced representation of the heterogeneous landscape, including water bodies and shrubland that are not clearly represented in Method 1. In addition, the fused result yields a more conservative estimate of paddy-field area and a higher proportion of dense vegetation than Method 1, suggesting that the predictor set materially affects the final land-cover allocation.

Overall, Figure 4 and Table 3 show that different predictor combinations propagate substantially different crop-type maps even when the same classifier, area of interest, and spatial support are used. In practical terms, this means that map users should interpret class areas together with the underlying feature design, validation results, and intended scale of application rather than relying on overall accuracy alone.

4. Discussion

Figure 5 shows the zoomed-in view of small areas and respective crop-type maps produced by different methods. Figure 5 visualises how different methods will produce different map results. Figure 5a shows the agricultural land in the Google Earth image. Figure 5b shows a similar area captured from the raw image of Sentinel-2. Figure 5c shows the map produced from Sentinel-2 using method (1). Figure 5d shows the map classified using the method fusion (method-2), and Figure 5e shows a classified map using method-3. Method 1 is crop type mapping using GEE, a machine-learning approach, and a derived vegetation index [46]. Method 2 uses a fusion of Sentinel-2 and Sentinel-1 images (this Research). Method-3 is a crop-type mapping from the Sentinel-2 image using a scenario of vegetation index.

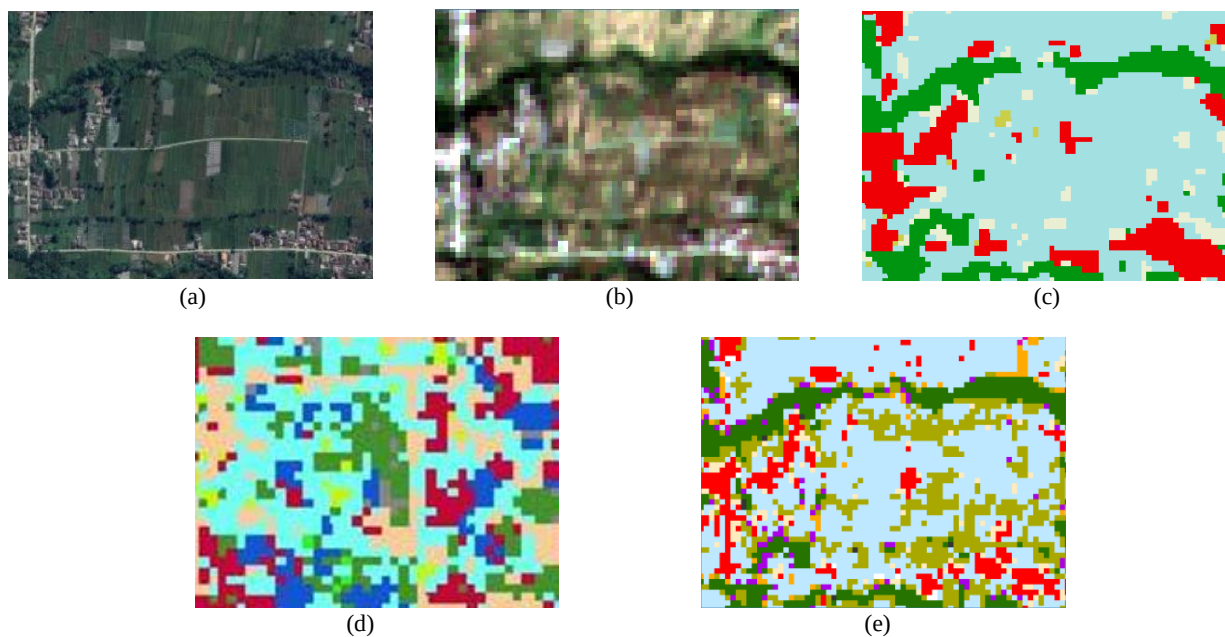


Figure 5 Comparison: (a) Google Earth, (b) Sentinel-2 image, (c) method-1, (d) method-2 (fusion), (e) method-3.

Misclassification is most evident in the built-up, water, and corn classes. Built-up areas can exhibit spectral responses similar to dry soil, sparse vegetation, or irrigated paddy at the time of image acquisition. In addition, the parcel structure in Candipuro is highly fragmented, so a single 10 m pixel may contain mixed signals from crops, boundaries, soil, or nearby vegetation. These factors help explain why class-level performance is uneven even though the overall accuracy is high. The present results therefore support the usefulness of fusion as a local mapping aid, but they do not justify a blanket claim that all crop classes were mapped accurately.

Several limitations should be considered when interpreting the present results. First, the analysis was conducted using imagery from a short acquisition window (June–July 2023), whereas crop discrimination is inherently phenology-dependent; therefore, a multi-temporal design would be more appropriate for operational CTM. Second, the optical predictor set was intentionally compact and did not include richer vegetation or red-edge indices. Third, the SAR contribution was limited to the VH/VV ratio and did not include textural descriptors that may improve discrimination in heterogeneous terrain. Fourth, the reference dataset consisted of 101 field points and remained limited for a complex fragmented landscape; moreover, the archived revision materials do not preserve the full class-by-class distribution of the training GCPs in tabulated form, which constrains more detailed discussion of training-data balance. Fifth, the study did not include classifier benchmarking, spatial transferability tests, or explicit uncertainty analysis. Finally, DEM information was used only for terrain interpretation and was not incorporated as a predictive variable, although topographic effects may influence class separability in mountainous environments. Taken together, these limitations indicate that the proposed workflow should be regarded as an exploratory, site-specific baseline for humid tropical mountainous terrain rather than a fully transferable operational mapping framework.

Theoretically, some aspects will constrain the CTM in humid tropical regions, including (a) frequent cloud cover, (b) complex crop dynamics, (c) limited ground truth data, (d) High Vegetation density or heterogeneity, (e) socioeconomic factors, and (f) technological limitations.

Firstly, persistent cloud cover in humid tropical regions limits the use of optical remote sensing data, making it challenging to obtain clear images for crop mapping. The favourable weather conditions for multiple cropping cycles and diverse crop types lead to complex crop dynamics that are difficult to monitor and classify accurately. Secondly, dense vegetation can obscure crops, making it difficult to distinguish between crop types using remote sensing technologies. Thirdly, Small-scale, non-mechanised farming practices prevalent in tropical regions can vary widely, adding another layer of complexity to crop type mapping [47]. Finally, advanced

technologies like Synthetic Aperture Radar (SAR) and deep learning are required to overcome these challenges, but their implementation can be resource-intensive. Therefore, these constraints necessitate innovative techniques and technologies to improve the accuracy and reliability of crop-type mapping in humid tropical regions [46, 48].

5. Conclusions

Feature-level fusion of Sentinel-1 and Sentinel-2 showed promising performance for crop-type mapping in the Candipuro mountainous landscape, yielding an overall accuracy of 93% and a kappa coefficient of 0.90 on a harmonised 10 m grid. The fused workflow produced a more detailed thematic representation than the optical-only baseline, particularly for several non-crop and mixed classes in this cloud-prone environment. Nevertheless, the uneven class-level performance, limited field reference data, incomplete class-by-class archival documentation of the training samples, short temporal acquisition window, and absence of uncertainty and transferability analysis indicate that the present workflow should be interpreted as a site-specific proof of concept rather than a generalisable operational solution. Future work should prioritise multi-temporal phenology, richer optical and SAR features, broader and more balanced field samples, terrain predictors, classifier benchmarking, and explicit uncertainty assessment.

6. Acknowledgements

This publication is an additional output from an internal research grant (Hibah PrGb) funded by LP2M Universitas Jember, from 2023 to 2025. (Contract from DGHE-RI No: 7554/UN25/KP/2024 Date: 20 Maret 2024 and Derivative contract from University of Jember No: 3143/UN.25.3.1/LT/2024). The Research focuses on integrating Sentinel-1 and Sentinel-2 images for crop type mapping. Indarto coordinates the project.

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