CROP TYPE MAPPING USING MACHINE LEARNING-BASED APPROACH AND SENTINEL-2: STUDY IN LUMAJANG, EAST JAVA, INDONESIA
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PEMETAAN JENIS TANAMAN MENGGUNAKAN PENDEKATAN MACHINE LEARNING DAN SENTINEL-2: STUDI DI LUMAJANG, JAWA TIMUR, INDONESIA

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ABSTRACT
In general, sentinel-2 imagery can be used for crop mapping. Crop types mapping aims to develop future strategies for sustainable agricultural systems. This study used Sentinel-2 from June 25 to July 6, 2023, with 10% cloud cover. The research was conducted in Pasrujambe and Candipuro sub-districts (± 242.23 km^2). The image is processed using a random forest on the GEE platform. Accuracy was generated using a confusion matrix with an overall accuracy of 85.82% and a kappa of 71.19%. Five main types of land use/cover were produced, namely: paddy (17.31%), sugarcane (0.93%), vegetation (69.74%), sand (7.4%) and built-up land (4.59%).

ABSTRAK
Secara umum, citra sentinel-2 dapat digunakan untuk pemetaan tanaman. Pemetaan jenis tanaman bertujuan untuk mengembangkan strategi masa depan untuk sistem pertanian berkelanjutan. Penelitian ini menggunakan Sentinel-2 pada tanggal 25 Juni hingga 6 Juli 2023 dengan tutupan awan 10%. Penelitian dilakukan di Kecamatan Pasrujambe dan Candipuro (± 242,23 km2). Gambar diproses menggunakan random forest pada platform GEE. Akurasi dihasilkan menggunakan matriks konfusi dengan akurasi keseluruhan sebesar 85,82% dan kappa sebesar 71,19%. Lima jenis penggunaan/tutupan lahan utama yang dihasilkan, yaitu: padi (17,31%), tebu (0,93%), vegetasi (69,74%), pasir (7,4%) dan lahan terbangun (4,59%).

INTRODUCTION
Crop Type Mapping indicates the intensity of land use in an area to develop sustainable future policy strategies in agriculture, plantations, and the like, both economically and ecologically *(Blickensdörfer et al., 2022).* In the agricultural sector, up-to-date information can be obtained by mapping crop types for planning and recognizing food security threats and their sustainability *(Hegarty-Craver et al., 2020).* Crop identification concerning the field of plant phenology, including the growth stage, has been carried out using remote sensing data *(Erdanaev et al., 2022a).* Remote sensing is a technique that has been proven effective in producing specific information on land cover and plant species *(Sun et al., 2020)*, both for its application in narrow *(Salas et al., 2020)* and large areas *(Griffiths et al., 2019).*

The Sentinel 2 platform is a remote sensing data widely used to map crop types in an area because of its multispectral sensor capabilities with 10 m, 20 m, and 60 m resolution and has an ideal wavelength *(Prins & Van Niekerk, 2021).* Several studies related to the mapping of crop types have been carried out, such as using sentinel 2 for crop type identification in small-plot agriculture land, which has a high accuracy value *(Gumma et al., 2022).* Xie and Niculescu 2022 *(Xie & Niculescu, 2022)* evaluated the Sentinel 2 image to map winter crops in the growing season. Furthermore, depending on the high precipitation frequency in their study location, they use Sentinel-1 C-band SAR data to monitor crop phenology. Sentinel-2 time series data for land cover mapping can reduce misclassification in its application to precision farming activities. It can also identify land cover features with small coverage, such as small fields, roads, and rivers *(Liu et al., 2020; Tran et al., 2022).* Different classification approaches and methods followed by pixel-based and object-based classifications were performed and evaluated using the Google Earth Engine (GEE) platform. No research can be found on mapping crop types using sentinel 2 in the Pasrujambe and Candipuro District of Lumajang.

Crop-type maps can be generated using a machine-learning approach applied to satellite images. Many studies on crop-type mapping used various machine-learning algorithms and Sentinel-2 data *(Alami Machichi et al., 2023; Luo et al., 2023).*

Machine Learning (ML) is a machine developed based on artificial intelligence (AI) to collect data independently using designed algorithms to imitate how humans learn (source). Machine learning has more features, such as simple operation, swiftness of operations, and the ability to process different data types (source). The use of machine learning for remote sensing, including Random Forests (RF), Neural Networks (NN), Support Vector Machines (SVM), and other processing methods, have proliferated with a high degree of accuracy *(Feng et al., 2019).* In several studies of various algorithms of machine learning for crop type identification, the random forest was recognized as one of the most efficient and accurate algorithms *(Akbari et al., 2020; Kpienbaareh et al., 2021; Wei et al., 2023).*

The objectives of this study are (1) to generate crop-type maps using 10 m Sentinel 2 of Pasrujambe and Candipuro District, Lumajang, and (2) to evaluate the random forest algorithm used to generate crop-type maps in the study area. The accuracy of the classification result is assessed using a confusion matrix derived from field data collection. Crop types have been widely mapped in large areas, and plant varieties have been uniform. This research was conducted in a limited area with various field sizes and plant varieties.

MATERIALS AND METHODS

Study Area

Two study areas were selected for crop type mapping, including Candipuro and Pasrujambe District, located in Lumajang Regency (Figure 1) and covering an area of 242.23 km2. Pasrujambe district, specifically, is located approximately 23 km south of the center of Lumajang city, with an average altitude of 75-2500 meters above sea level, and has an average rainfall of 952 mm with rainy days for 220 days within a year. Most of the Pasrujambe area is the mountainous area of Mount Semeru, and nearly 50% of its land cover is dense vegetation. Meanwhile, Candipuro District is 322 meters above sea level with a 2018 mm/year of rainfall.

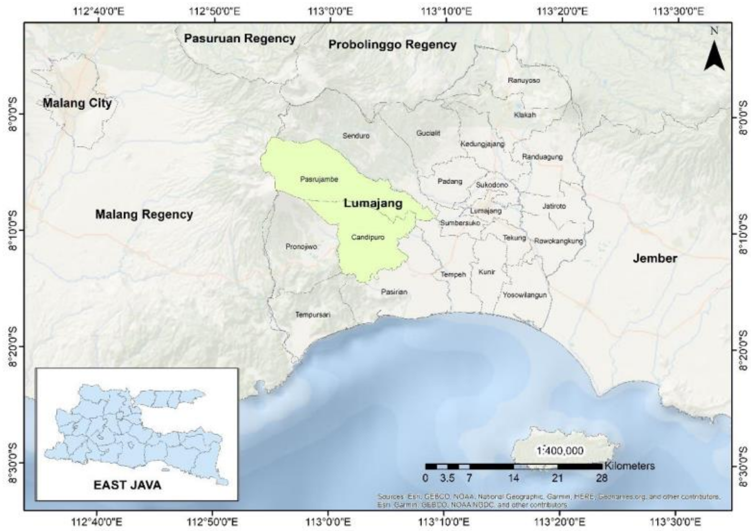

Fig. 1 - Study area in Candipuro and Pasrujambe District, Lumajang Regency

Input Data

Satellite Data

Spectral information from sentinel-2 imagery recorded in 2023 was used in this study. Sentinel-2 is a multispectral imaging mission based on a constellation of two high-resolution satellites launched in the sun-synchronous orbit *(Agency, 2015).* This study used time series data of Sentinel-2 from June 25 to July 6, 2023, with a minimum cloud cover of 10%. Due to the topography and climate conditions in the study area, the recorded images have a heavy cloud cover, and it is not easy to obtain satellite imagery with clear cloud cover.

Field Data Collection and Sampling

Field data on crop types were identified and collected from June to July 2023. The coordinates were recorded on each field using a GPS device at the center of the field boundaries. Crop types in each field were collected using a photo camera. One hundred sixty (160) ground truth samples from different crop types were collected, including paddy, built-up area, river, sugarcane, and dense vegetation (forest area, pine, teak plantations, and sengon trees). Field data collection is adjusted to the actual condition of vegetation cover in the field.

Fig. 2 - Example of field data in the study area captured using a digital camera and drone

Field data is used as a reference for making training areas. To improve the creation of training samples, Google Earth imagery was used to identify other types of land cover that are difficult to reach in the field data collection process. The training sample was divided into 70% training data and 30% validation data, as described by *(Adam et al., 2014)*. 70% of training data (31896 pixels) is used as input for classification, and 30% (13726 pixels) is used to validate the algorithm and assess the accuracy *(Shaharum et al., 2020).* The training data was used for training of the random forest classifier, while the validation data was used for accuracy assessment *(Adam et al., 2014)*. Optimization of the random forest parameters was done by repeated k-fold cross-validation using only the training sample *(Duro et al., 2012).*

Five (5) classes were identified and created using GEE, including built-up areas, sand, vegetation, paddy, and sugarcane. Samples were created using a polygon format. Table 1 illustrates the classes and number of each sample.

Table 1

Summary of the number of samples and the classes

Class	Number of samples (pixel)	Percentage (%)
Built-up Area	1229	3.27
Sand	11109	29.53
Vegetation	23062	61.31
Paddy	1184	3.15
Sugarcane	1032	2.74

Image Processing

The image processing was performed using the Google Earth Engine (GEE) platform. GEE provides a set of pixel-based classifiers to map crop types *(Shelestov et al., 2017).* GEE is used to collect a set of Sentinel-2 time series data, vegetation index transformation, and create a crop classification raster by performing a random forest classifier. A random forest classifier was used to produce crop-type maps and combine multiple vegetation indices to improve accuracy. The proposed workflow of the methodology of this study is shown in Figure 3.

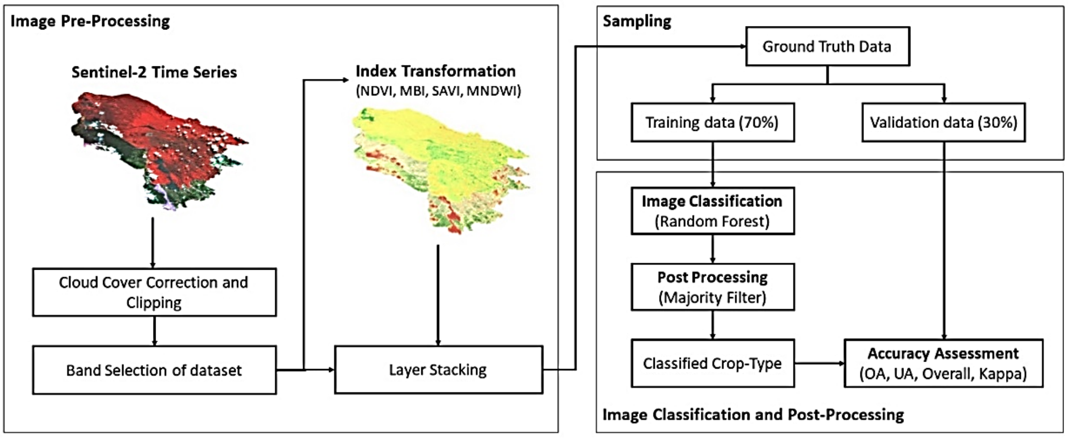

Fig. 3 - The workflow of this study was conducted in GEE to produce a crop-type map

a. Vegetation indices

Multiple vegetation indices were calculated as classification input data, including the Normalised Difference Vegetation Index (NDVI), Modified Bare Soil Index (MBI), Soil Adjusted Vegetation Index (SAVI), and Modified Normalised Difference Water Index (MNDWI). Each vegetation indices equation is shown in Table 2.

Table 2

Vegetation indices and the equation used in this study

Index	Formula	References
NDVI	(NIR – Red) / (NIR + Red)	*(Nouri et al., 2017)*
MBI	((SWIR1 – SWIR2 – NIR) / (SWIR1 + SWIR2 + NIR) + f))	*(Nguyen et al., 2021)*
SAVI	((NIR – Red) / (NIR + Red + L)(1 + L))	*(Huete et al., 1992)*
MNDWI	(Green – SWIR) / (Green + SWIR)	*(Xu, 2006)*

NDVI is an index widely used to produce crop-type classification maps *(Erdanaev et al., 2022b; HAO et al., 2020; Tariq et al., 2022)* by comparing the differences in the reflectance values of the red band (Red) and the near-infrared (NIR) band. NDVI values ranged from -1 to 1 *(Nouri et al., 2017)* and were calculated using the equation in Table 3.

MBI is used to distinguish between agricultural and non-agricultural fields. Specifically, it can identify bare soil and fallow land *(Nguyen et al., 2021).* The MBI value ranges from -0.5 to +1.5, where a higher MBI value indicates vacant land while a lower value indicates a body of water or vegetation. In MBI, an additional factor f is used with a value of 0.5 and is calculated using the equation in Table 3.

SAVI is a vegetation index aimed at minimizing the influence of soil on the calculation of vegetation values by using the L value as a soil adjustment factor. It has a value ranging from -1 to 1. The L value differs for each vegetation cover type, specifically 0 or 0.25 for dense vegetation, 1 for sparse vegetation, and 0.5 for moderate vegetation cover.

MNDWI is a modified form of NDWI *(McFeeters, 1996),* which computes using the SWIR band. This index is needed to delineate water bodies against other land covers.

b. Random Forest

Random Forest (RF) is a non-parametric supervised machine learning classification method. RF is a collection of decision trees combined to reduce variance and make data predictions more accurate. It can be used for classification and regression analysis *(Shaharum et al., 2020).* The random forest was selected because it is widely used and performs well for crop-type mapping.

RESULTS

Accuracy Assessment

The accuracy assessment was performed using the AcATaMa plugin provided by QGIS software. For sampling, response planning, and estimating in a framework for design-based inference, the AcATaMa plugin is a feature that offers thorough support *(Llano, 2019).* The crop type classification thematic map was evaluated using a confusion matrix (Table 3).

Table 3

Accuracy assessment of crop-type map

Class	Built-Up Area	Sand	Vegetation	Paddy	Sugarcane	Total	User Accuracy
Built-Up Area	36	3	0	6	1	46	78.26
Sand	1	48	9	18	1	77	62
Vegetation	3	3	665	60	8	739	89.99
Paddy	11	5	10	144	5	175	82.29
Sugarcane	0	0	1	3	3	7	43
Total	51	59	685	231	18	1044	
Producer Accuracy	70.59	81	97.08	62.34	17		
Overall Accuracy = 85.82%, Kappa Accuracy = 71.19%							

Table 4 - shows the accuracy of thematic maps, including PA, UA, OA, and Kappa. In general, crop type classification with NDVI, MBI, SAVI, and MNDWI index combination using RF classifier produced the accuracy derived from the confusion matrix shows good value where the Kappa of 71.19% and OA of 85.82%. In this study, paddy and sugarcane are the crop types that can be recognized. However, UA and PA of the sugarcane class showed the smallest value. The sugarcane class has a UA of 43% and a PA of 17%.

Identifying the crop type in Candipuro and Pasrujambe, Lumajang Regency is challenging due to the climatological and geographical conditions. The study area is a hillside area of Mount Semeru with relatively high rainfall, causing the image used as input for classification not to be free from cloud cover. On the other hand, the agricultural conditions in the study area are heterogeneous, and many farmers plant crops using an intercropping system. Due to the condition, the classification result is ambiguous.

This research uses limited sentinel-2 images and training samples illustrated in Table 2, recorded from June 25 to July 6, 2023. The classification accuracy can be improved using crop type label data in several years as training and test data. The experiment by Zhi et al. *(Zhi et al., 2022)* shows that classification accuracy will be low if only using data on plant species in one year. However, the accuracy can be increased when the coupling crop label from several years is used to classify crops, especially paddy and maize.

Thematic Maps of Crop Type Classification

This study used sentinel-2 level 2-A time series data computed by the GEE platform. The images were processed using an RF Classifier provided by GEE. The crop-type classification map identified using Sentinel-2 imagery obtained five (5) classes consisting of (1) built-up area, (2) sand, (3) vegetation, (4) paddy, and (5) sugarcane presented in Figure 3. The types of plant cover are identified using field data collection.

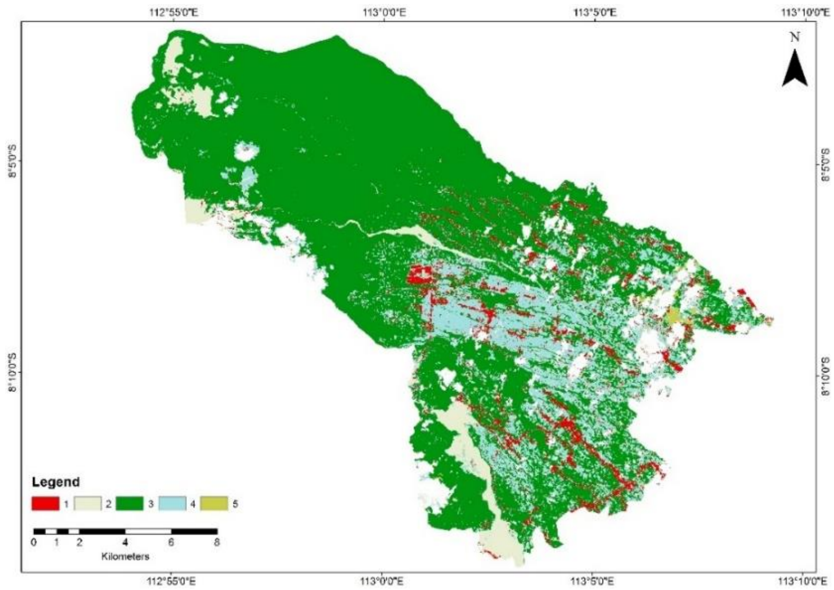

Fig. 3 - Thematic map of crop type classification of Candipuro and Pasrujambe, Lumajang Regency

Table 5- shows the area of each class, where two dominant food crops identified in the study area are paddy and sugarcane. In the study area, primary forests, pines, teak plantations, and sengon trees comprise most vegetation cover. Respectively, the classification results show that the paddy area is 46.22 ha (17.31%) and sugarcane is 2.49% (0.93%). In our study area, vegetation accounted for 69.74% of the total estimated area, so its effect on overall accuracy was relatively significant. Furthermore, the Built-Up Area shows an estimated area of 12.25 ha or approximately 4.59%, and sand of 19.87 ha or 7.44% of the study area.

Table 4

Summary of per-class estimated area

Class	Area (ha)	Percentage (%)
Built-Up Area	12.25	4.59
Sand	19.87	7.44
Vegetation	186.26	69.74
Paddy	46.22	17.31
Sugarcane	2.49	0.93
Total	267.09	100

DISCUSSION

Crop-type mapping is essential for various applications, especially in agriculture. However, mapping crop types in Candipuro and Pasrujambe Districts is challenging because this region is a heterogeneous environment with climatological and geographical conditions and temporal and spatial resolution of images. After all, the region has a tropical climate. Another challenge faced was the availability of cloud-free and shadow-free data, making it difficult to find optimal solutions for cloud-free temporal and composite resolution, leading to a lot of data loss. The solution offered for further studies is using Sentinel-1 images and a fusion of Sentinel-1 and Sentinel-2 images. Sentinel-1 uses a microwave sensor and operates day and night without any weather barriers, thus offering cloud-free data. The experiments conducted by Guo et al. and Kpeinbaareh et al. *(Guo et al., 2018; Kpienbaareh et al., 2021)* showed that fusing Sentinel-1 and Sentinel-2 data could improve the classification results of plant species in Northern Germany and Northern Malawi. In this research, the focus was on the uses of Sentinel-2 images combined with several vegetation indices (i.e., NDVI, MBI, SAVI, MNDWI) processed on the GEE cloud platform using an RF classifier to produce a thematic crop type map in Candipuro and Pasrujambe District, Lumajang Regency.

Random forest is an algorithm widely used in various studies and proved more accurate *(Dakir et al., 2023; Hudait & Patel, 2022).* Our result showed that the RF classifier can distinguish crop types in this study area in terms of overall accuracy (Table 4-). The overall accuracy obtained was 85.82%, and the kappa value of 71.19%. The causal factor that affects the accuracy is the occurrence of misclassification. For example, in this study, misclassification occurred due to similarities in pixel value between paddy (Band 02 = 0.1288, Band 03 = 0.1479, and Band 04 = 0.126) and vegetation (Band 02 =0.1238, Band 03 = 0.1385, Band 04 = 0.1206). Figure 4a shows how the paddy is classified as vegetation. A comparison of similarities between rice and vegetation in Sentinel-2 imagery is shown in Figure 4.

(a) (b) (c)

Fig. 4 - Comparison of the classified map, Sentinel-2 dataset, and Google image

This study uses the GEE cloud computing as a data processing platform. GEE is a geospatial analysis platform that provides multiple processing algorithms, an extensive database, and computing power and facilitates large amounts of high-resolution imagery to map crop types *(Liu et al., 2020).* Data processing by conventional methods (without cloud computing) will take quite a long time. With GEE, processing can be completed in just a few seconds, allowing for fast decision-making *(Shelestov et al., 2017).*

CONCLUSIONS

Crop-type maps in Candipuro and Pasrujambe Districts are generated using a machine learning approach provided by the Google Earth Engine (GEE) cloud computing platform. This study used Sentinel-2 time series data provided in large and free by GEE. The image was processed using a random forest classifier and showed an overall accuracy of about 85.82% and a kappa value of 71.19%. However, because of the climatological and geographical characteristics, identifying the crop type in the research area is difficult. The research region is a hillside area of Mount Semeru with relatively high rainfall, resulting in cloud cover in the photograph utilized as input for classification. On the other hand, the agricultural conditions in the research area are varied, and many farmers produce crops using an intercropping technique.

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