TEA PLANTATION MAPPING USING UAV MULTISPECTRAL IMAGERY

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ABSTRACT. Tea is one of Indonesia's most famous commodities, which is dominantly planted on the Java Island of Indonesia. Tea is one of the leading sources of exports, and the Indonesian government is very concerned about the stability of their export commodity sustainability. Therefore, monitoring and evaluating its sustainability and availability become necessary. One of the solutions to the tea plantation monitoring and management program is mapping through remote sensing and GIS. In this study, high-resolution multispectral imageries are captured from a UAV and used to map the tea plantation with three vegetation indexes (VIs). An Object-Based Image Analysis (OBIA) is used to classify the tea field's condition based on spectral characteristics. The results of this study are: (i) high-resolution multispectral imageries can be used to map the tea plantation with different VIs, and (ii) SAVI is the best VI to map the tea plantation since it has the lowest RMSE value of 0.4173. Hopefully, this study can support the government program on their export commodity with valuable baseline information on the tea plantation.

Keywords: *tea plantation mapping, OBIA, spatial analysis, vegetation index, UAV*

1 INTRODUCTION

Tea has become a worldwide product, with the consumption rate reaching almost 7.5 thousand tons per capita (Food and Agriculture Organization of the United Nations, 2022). Price and income variables influence the demand for tea. FAO tea price peaked in 2017 with a value of US$3.1 per kilogram and declined to US$2.4 per kilogram in 2022 (Food and Agriculture Organization of the United Nations, 2022). Indonesia is one of the countries with high production and export of tea, with the total export value reaching US$147 million in 2019 (Department of Agriculture, 2020). Java island holds the highest tonnage of production, reaching 107 tons. West Java is the highest tea producer in Indonesia, reaching 90.3 tons of tea in 2019 (Department of Agriculture, 2020).

Due to the high production and demand for tea, there is a need for practical, inexpensive, and efficient asset management. Mapping tea plants from a distance using remote sensing, such as unmanned aerial vehicles (UAV) and satellite imagery, is one of the assets managements that can be done. Nowadays, the necessity for spatial data is becoming more prominent. It is not just about the accuracy and proper planning, monitoring, and evaluation process but also depends on the temporal coverage of the data (Foody et al., 2017). Agriculture is one of the critical sectors in Indonesia (Rokhmatuloh et al., 2019). Vegetation and forestry data are one example of many spatial databases highly needed by the government and agricultural sector (Putut Ash Shidiq et al., 2017), especially in Indonesia. The nation's total land area is around 190 million hectares. From the total, 55 million hectares is an agricultural area, and 129 million hectares are forested. Twenty-four million hectares are arable land, and 20 million hectares are planted with permanent crops. Indonesia has a total tea plantation area of 121,034 hectares, based on plantation statistics data in 2014 (Quincieu, 2015). In this sector, agricultural areal mapping has been essential to providing a database for management, improvement, and food security purposes.

Along with technological advancements in mapping, remote sensing technology has a significant advantage over conventional terrestrial mapping. This technology allows rapid data collection for a larger mapping area, which can be done by satellite imagery. However, the spatial resolution of the satellite imagery is coarse. With the introduction of drones (unmanned aircraft vehicles/UAV), terrestrial mapping can be carried out at high resolution. UAV system presents as an alternative to the more-conventional airborne or satellite remote sensing system (Foody et al., 2017; Zhang et al., 2021). Thus, this study aims to test the ability of a UAV-based multispectral system to map tea plantations, generate a vegetation index from UAV, and use the value of the vegetation index to classify different types of crops.

2 MATERIALS AND METHODOLOGY

2.1 Study Area

The study area is conducted in the Nyalindung District, Sukabumi Regency, West Java Province. Nyalindung District has a total area of 10,448 hectares, with a total of ten villages. Located in a steep hill area, Nyalindung District is located at an elevation of 500-1,000 meters above sea level. In this study, the area comprises around 13.34 hectares. The area is used as paddy fields, tea plantations, mixed gardens, and settlements. This study area was chosen because it has large tea plantation area. The study area is shown in Figure 2-1.

2.2 Data Collection

This study uses DJI Phantom 4 Multispectral to map the study area. It has five bands of multispectral sensors:

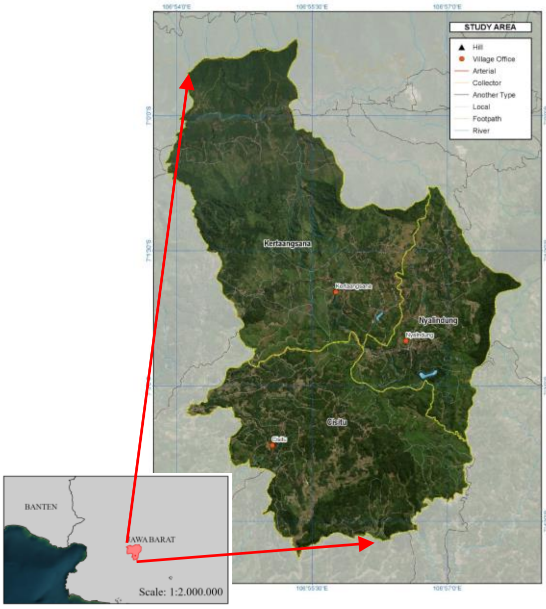

Figure 2-1: Study area

green, blue, red, red edge, and near-infrared, and each sensor is equipped with 2.08 megapixels and a 5.74 mm focal length (Furukawa et al., 2021). The UAV, coupled with a Sunshine sensor, contained similar bands and multiple navigation satellite systems, including GPS, BeiDou, GLONASS, and Galileo.

Several factors must be considered in mapping operations using UAV, such as altitude, overlap, flight time, and flight plan. The elevation is related to the image resolution. Overlap determines image quality, especially when creating a Digital Elevation Model (DEM). Flight time is closely related to battery capacity. Then, the flight plan defines the mapping area. The flight plan is designed using the DJI GS Pro application. The criteria used in this study are shown in Table 2-1.

Table 2-1: Flying criteria in this study

Factors	Criteria
Flight time	10-15 minutes
Flight plan	± 17 ha
Overlap and sidelap	80% and 60%
Altitude	120 meters above the ground

After the pictures have been taken, the next step is to do the mosaicking so that an orthophoto can be produced and ready to be processed in the next step. The construction of the orthophoto was done by Agisoft Metashape Professional software, with the workflow in Figure 2-2. The photo is aligned, the dense cloud is built, the mesh is built, and the texture is built. Finally, a mosaic image was carried out, which produced an orthophoto. The image can be seen in Figure 2-3.

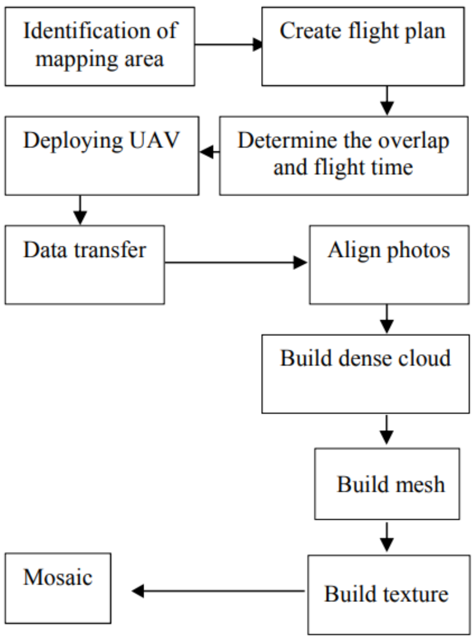

Figure 2-2: Workflow of image generation from UAV

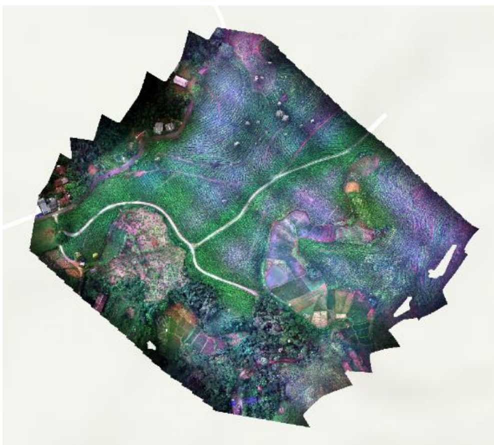

Figure 2-3: An image from the UAV, with 80% overlap and 60% sidelap

A field survey was conducted to measure the wave spectrum of tea plants in the tea plantation in the study area. OceanInsight™ Spectrophotometer was used to measure the tea plants' wave spectrum. A field survey was conducted in August 2022. This study used the purposive grid sampling method to get the samples for each feature, with a grid size of 20 × 20 meters. However, this study only collects tea plants' wave spectrums during the field survey. There were 71 sampling points collected during the field survey. The collected data (observed value) was used to calculate the RMSE over the model. The distribution of the sampling points is shown in Figure 2-4. Other vegetation inside the study area, such as paddy fields and trees, are also chosen to map each feature. Table 2-2 shows the number of samples for each feature.

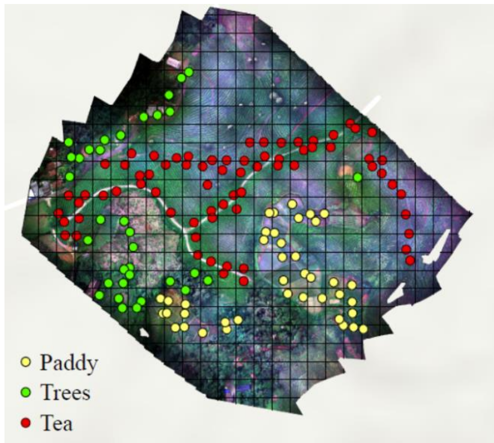

Figure 2-4: Ground samples distribution

Table 2-2: Number of samples in this study

Vegetation	Number of samples
Tea plants	71
Paddy fields	40
Trees	34

2.3 Data Processing

This study uses three vegetation indices (VIs) to map each feature: NDVI, GNDVI, and SAVI. The orthophoto that was already processed from the previous step is used to calculate three vegetation indices. Using ArcGIS Pro 3.0.2, the vegetation indices are produced by applying the indices formula using the "Raster Calculator" tools. The formula of NDVI, GNDVI, and SAVI is shown in Equation 1 to Equation 3 (Gitelson et al., 1996; Huete, 1988; Rouse et al., 1973). Afterward, the value of each vegetation index is extracted by "Extract Multi Values to Point" tools from each sample point.

$$NDVI = \frac{\rho NIR - \rho red}{\rho NIR + \rho red} \quad \text{........................(1)}$$

$$GNDVI = \frac{\rho NIR - \rho green}{\rho NIR + \rho green} \quad \text{....................(2)}$$

$$SAVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red} + L} \times (1 + L) \quad \text{..........(3)}$$

where:

ρ_{NIR} : near-infrared spectrum

ρ_{red} : red spectrum

L : vegetation canopy reflectance adjustment constant (L = 0.5)

3 RESULTS AND DISCUSSION

This study has only one flight plan, with an area of 13.34 hectares. The flight plan covers the entire area, and the resulting vegetation indices, such as NDVI, GNDVI, and SAVI, are presented in Figure 3-1. The area is mainly planted with tea plants and other vegetation, such as paddy fields and trees. There are also settlements area in the captured imagery.

The results of different vegetation characteristics and crops are based on different vegetation indices shown in Figure 3-2. The value for the NDVI, GNDVI, and SAVI vary depending on the vegetation type and crops. All the vegetation index values can be used with further processing to distinguish between different crops. This study used mean and standard deviation to distinguish between crops. After applying the NDVI algorithm, the NDVI values varied from 0.11 (tea plants) to 0.66 (trees). The NDVI values are presented in Table 3-1. In Table 3-2, the GNDVI values varied from -0.40 (paddy fields) to 0.66 (trees). Meanwhile, the SAVI values varied from -0.73 (paddy fields) to 1.24 (trees), as shown in Table 3-3. From all vegetation indices, trees have the broadest range of minimum and maximum vegetation index values than other vegetation features. However, the mean value of tea plants is close to the mean value of trees.

From the processing of the descriptive statistics above, a box plot can be made in Figure 3-2, showing a clear separation between each vegetation type for three vegetation indices (VIs). Unfortunately, the separation is somewhat scrambled for tea plants as it can be misinterpreted.

After processing the three vegetation indices, the vegetation index values are compared with the measurement of tea leaves' wave spectrum using the OceanInsight™ Spectrophotometer to produce the RMSE value. The vegetation index with the smallest RMSE value indicates that the vegetation index is suitable for mapping tea plantations and other vegetation features. Table 3-4 shows the RMSE value for each vegetation index. From the RMSE calculation between observed and predicted data, the SAVI algorithm produces the smallest RMSE value. It means the SAVI index is the best algorithm to map tea plants and other vegetation types in this study (Parida & Kumari, 2021; Singh & Frazier, 2018).

Mapping of tea plantations was carried out in this study, where an area of 5.88 hectares from a total area of

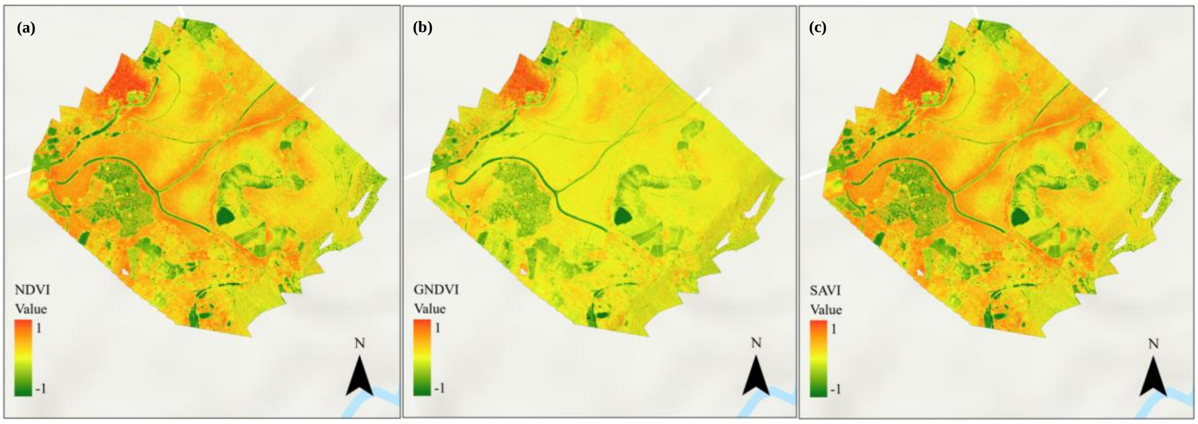

Figure 3-1: Map of (a) NDVI, (b) GNDVI, and (c) SAVI

Table 3-1: Range of NDVI values for each vegetation type

Vegetation	Min	Max	Mean	Stdev

Tea plants	0.11	0.70	0.40	0.14
Paddy fields	-0.49	0.56	0.03	0.33
Trees	-0.03	0.83	0.42	0.21

Table 3-2: Range of GNDVI values for each vegetation type

Vegetation	Min	Max	Mean	Stdev
Tea plants	-0.14	0.45	0.13	0.11
Paddy fields	-0.40	0.28	-0.06	0.19
Trees	-0.16	0.66	0.19	0.20

Table3-3: Range of SAVI values for each vegetation type

Vegetation	Min	Max	Mean	Stdev
Tea plants	0.16	1.04	0.61	0.22
Paddy fields	-0.73	0.85	0.05	0.49
Trees	-0.05	1.24	0.64	0.32

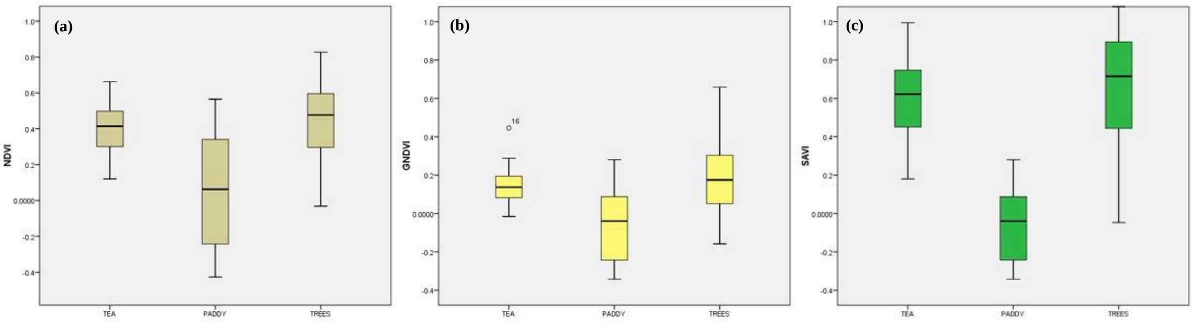

Figure 3-2: Separation plot of tea, paddy, and trees based on (a) NDVI, (b) GNDVI, and (c) SAVI values

Table 3-4: RMSE value for each vegetation index

Vegetation Index	RMSE
NDVI	0.4575
GNDVI	0.6702
SAVI	0.4173

13.34 hectares is tea plantations, as shown in Figure 3-3. The mapping of tea plants from UAV was carried out using a supervised support vector machine (SVM) classification, with Object-Based Image Analysis (OBIA). This method was chosen because it produces the best mapping of agriculture, especially tea plants (Tu et al., 2018).

The same mapping method was done for the three VIs, including NDVI, GNDVI, and SAVI. Mapping tea plantations with VIs was done by extracting the value range of tea plantations from each VIs. Figure 3-4 shows the mapping of each VIs, and the results of mapping tea plants are similar between those three VIs. The results spread throughout the drone imagery area. The results of tea plantation mapping using the NDVI, GNDVI, and SAVI indices generated a tea plantation area of 9.62 hectares, 11.29 hectares, and 9.61 hectares respectively.

Figure 3-3: Tea plantation mapping using drone imagery

The mapping of tea plantations carried out with the three VIs is still not in accordance with the mapping from drone imagery. This is because the sampling still uses a 20 × 20 meters sampling grid, so the sampling is too general, which causes the samplings to be biased with other vegetation features, as shown in Figure 3-4. Some features that should not be tea plants, such as in

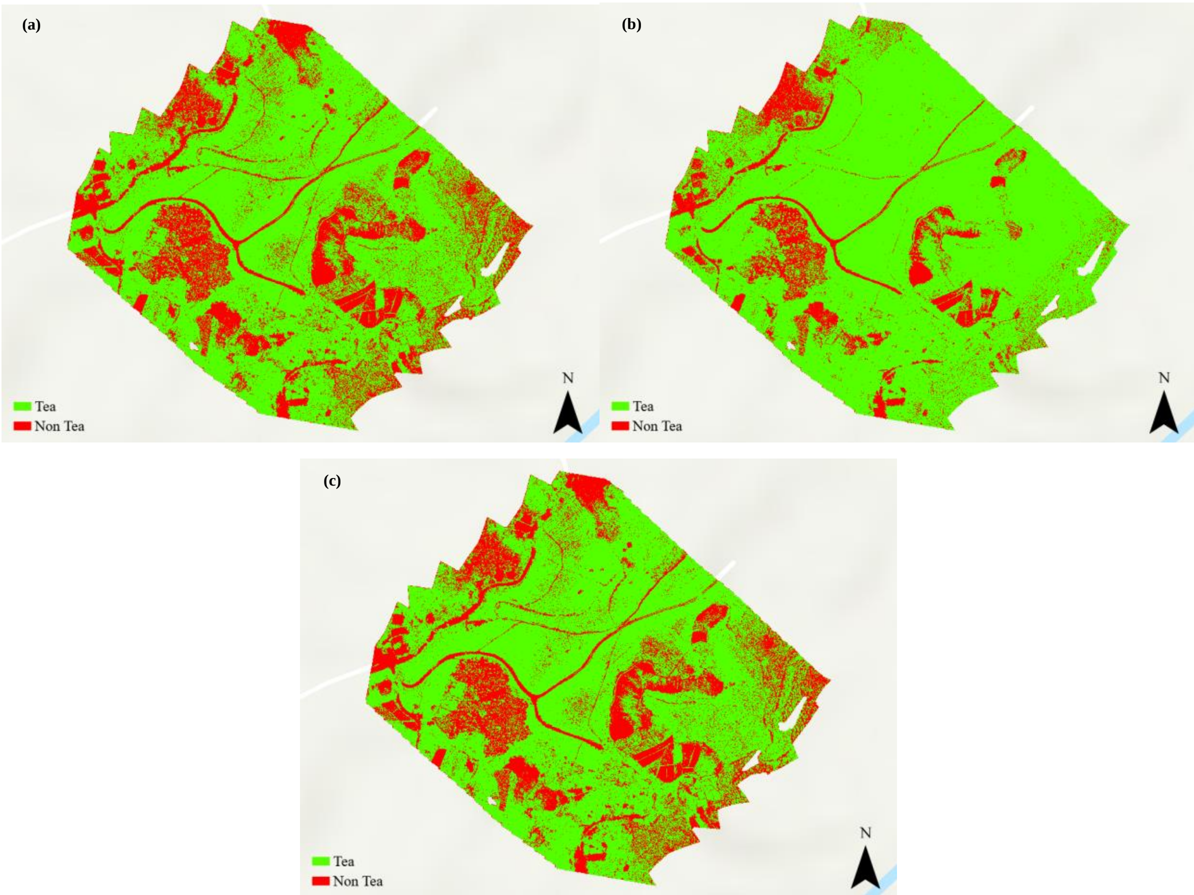

Figure 3-4: Tea plantation mapping based on (a) NDVI, (b) GNDVI, and (c) SAVI values

the south of drone imagery, are mapped to be tea plants. This is due to the bias of VIs values between tea and other vegetation features. When the grid sampling size is reduced according to drone resolution, the values of the three VIs for tea plants will be more accurate for better tea plantation and other vegetation mapping. Moreover, the number of samples for each feature can be increased to obtain better spectral library and mapping results.

4 CONCLUSION

The multispectral sensor on the UAV platform has been successfully used to generate NDVI, GNDVI, and SAVI. NDVI, GNDVI, and SAVI produce the RMSE values of 0.4575, 0.6702, and 0.4173, respectively. With RMSE value for each vegetation index, SAVI has least error for tea plantation mapping. Therefore, this study considers SAVI as the best vegetation index algorithm for image separation processing and mapping vegetation features. SAVI index is helpful in discriminating different crop types, such as tea plants, paddy fields, and trees, and lessening soil reflectance's effect on the values. However, the SAVI index still varied in results. The same types of crops have different values. Hence, future works are needed to verify the indices as accurately as possible with modifying the sampling method and number of samplings.

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