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Identification and classification of cloud computing-based vegetation index values on several lands used in Bogor Regency, Indonesia

H S Aprilianti[1,2,3], R A Ari[1,2,4,5], A Ranti[1,2] and M F Aslam[1,2]

[1]Department of Forest Management, Faculty of Forestry and Environment, IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[2]Sustainable Science Research Student Association (IPB SSRS Association), IPB University, Bogor Regency 16680, Indonesia
[3]International Forestry Student Association, Faculty of Forestry and Environment, IPB University, IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[4]Fauna Conservation Union (UKF IPB), IPB Dramaga Campus, Bogor Regency 16680, Indonesia
[5]CNT Tourism Information and Research Center, Community Nature Traveler (CNT Batui), Banggai Regency 94762, Central Sulawesi, Indonesia

E-mail: hasnaaprilianti@apps.ipb.ac.id

Abstract. Understanding the threshold value classification from various vegetation types may help distinguish spectral reflectance differences in detailed land use studies. However, conducting all of the processes requires relatively large resources regarding manual computation, which could be surpassed by cloud computing. Unfortunately, in Bogor Regency, there is still a lack of research that studies the threshold value of various vegetation types related to forestry and plantation sectors. Land use categories were classified, and threshold values were determined, especially for selected vegetation types including teak, oil palm, rubber, pine, bamboo, and tea based on several vegetation indices in Bogor Regency using the Cloud-Computing platform. The data source was retrieved from 10-meters Sentinel-2 Satellite median imagery of January 2019 - June 2021. Land use maps were generated using Random Forest Algorithm from composite images. Meanwhile, the threshold value of each vegetation type was calculated from the average and standard deviation of NDVI, SAVI, EVI, ARVI, SLAVI, and GNDVI index. The result of the study showed forest and plantation area covers about 158,168.13 ha or 48.92 % of the study area. NDVI was found suitable to identify teak, SLAVI for rubber and pine, EVI for bamboo and tea, and GNDVI for oil palm vegetation.

1. Introduction
Land use is any form of human intervention or intervention on land in order to meet their daily needs, both materially and spiritually (socioeconomic). This means that land use includes all types of

appearances and has been linked to human activities in utilizing land. There are many classifications of land use types, such as the study of Hardy and Anderson [1], which divided into 11 classes, namely urban and built-up, transportation-communications-utilities, farming (agriculture), grassland (grazing), forest land (forestry), extractive, water, marshland, tundra, barren land, and permanent snowfields. In Indonesia, the Ministry of Environment and Forestry classified land use in the form of land cover, which is divided based on a map scale including 1: 1,000,000, 1: 250,000, 1: 50,000, and 1: 25,000 regarding the Land Cover Classification System of the United Nation - Food and Agriculture Organization (LCCS-UNFAO) [2]. Bogor Regency land use in 2019 is based on data from the Food Crops, Horticulture and Plantation Service, dominated by settlements and offices covering 122,527 hectares, while the area for land planted with trees/forests is only 44,609 hectares.

Each type of land use reflects, transmits, and absorbs a particular wavelength range related to its properties [3, 4, 5]. However, distinguishing land use categories could pose certain challenges due to several confounding factors, such as variations of canopy properties [6], background soil reflectance [7], viewing geometry [8], solar illumination, and atmospheric composition [9]. Vegetation indices (VI) have been widely applied and proven to maximize interpretation and minimize erroneous factors [10-12]. Currently, a lot of vegetation index development is being carried out to identify specific vegetation types. The results of the vegetation index produce different values and are generally referred to as threshold values. For example, Lyon et al. [13] used seven indices, including the Difference Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), Transformed Vegetation Index (TVI), Ratio Vegetation Index (RVI), Soil and Atmospherically Resistant Vegetation Index (SARVI), Soil Adjusted Vegetation Index (SAVI), and Transformed-SAVI (TSAVI) indices and then compared the values generated by each index in the detection of vegetation and land cover changes in the Chiapas area, Mexico. Meanwhile, the study of Sonobe *et al*. [14] involved 82 indices to evaluate the performance of random forests (RF) and support vector machines (SVM) in classifying plant types using MSI (Multispectral Instrument) data. Baloloy *et al*. [15] formulated the Mangrove Vegetation Index (MVI) specific vegetation index for mangrove vegetation.

The threshold value approach of vegetation is one way to identify the types of vegetation incorporated in a land use stretch [16]. The application of the calculation of the threshold value is used by Sun *et al*. [17], who conducted research on calculating the threshold value of the Modified Normalized Difference Impervious Surface Index (MNDISI) method for urban areas using Landsat image sources. In addition, research by Jia *et al*. [18] explained that the submerged mangrove vegetation has a threshold value that is quite difficult to determine. However, determining the threshold value of vegetation requires a combination of many analytical methods to increase the accuracy level [18].

Advances in science and technology in the use of statistical, computational methods in geographic information systems help humans produce more accurate analyses. Until now, there are many ways to visualize a spatial database for mapping purposes, especially in the identification and monitoring of land cover areas [19-21]. Cloud Computing-based mapping through the Google Earth Engine (GEE) platform is an alternative scheme that reduces one of the challenges in analyzing a larger number of satellite images so that it can produce analysis results with a high degree of accuracy [22-24]. In addition, the GEE Platform provides easy access to many satellites as an option for determining the source of image data [25,26]. However, the application of the Cloud Computing-based mapping method in a study to find information on the threshold value of a vegetation type in the land use classification is currently not widely applied. This study is expected to provide information regarding the identification of vegetation types using several index algorithms, making it easier to determine the involvement of the index in the process of classifying land use types in the study location. Later, this paper will be useful as a reference for further research.

2. Methods

2.1. Study area

Astronomically, Bogor Regency is located between -6° 18 'North Latitude and -6° 47' South Latitude and between 106° 01' - 107°103' East Longitude (figure 1), with an area of 2,663.85 km² [27]. This area has a morphological type of area that varies from lowlands in the north and mountains in the south, where around 29.28% is at an altitude of 15 - 100 meters above sea level (masl), 42.62% at an altitude of 100 - 500 masl, 19.53% at an altitude of 500 - 1,000 masl, 8.43% at an altitude of 1,000-2,000 masl, and 0.22% at an altitude of 2,000 - 2,500 masl [28]. This research took place from April to May 2021, focusing on vegetation types from several land use types. Bogor Regency is one of the urban buffer areas with a rapid land cover change and many land uses. Types of land use in this area include primary forest, secondary forest, plantation forest, homogeneous plantations, mixed plantations, dryland agricultural savanna, mixed dryland agriculture, settlements, bare land, water bodies (rivers, lakes, and ponds), as well as mining.
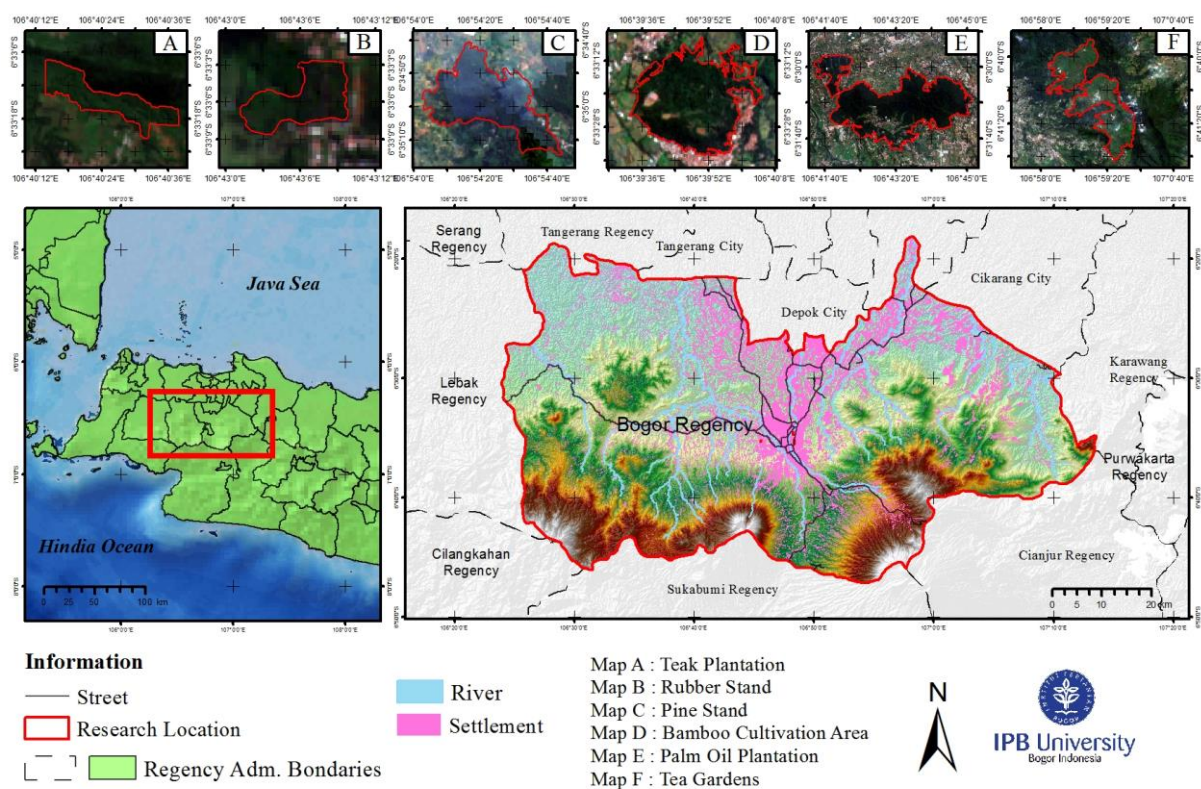
Figure 1. Location research map.

2.2. Data and GIS processing

The main data source of this research is Sentinel-2 Satellite Imagery which is a type of high-resolution image (MSI: MultiSpectral Instrument) with a spatial resolution of 10 m (Band-2, Band-3, Band-4, Band-8), 20 m (Band-5, Band-6, Band-7, Band-8A, B11, Band-12), and 60 m (Band-1, Band-9, Band-10) [29-31]. Sentinel-2 imagery used is an image with a recording time series in January 2019 - December 2020. Other secondary data used are the Indonesian Topographical Map (Rupa Bumi Indonesia Map) and the Shuttle Radar Topography Mission Digital Elevation Model (DEM-SRTM). The spatial data processing in this study was carried out in two stages: the classification of land use types and the calculation of the threshold value for each vegetation type. Classification of land use types

using the Random Forest Algorithm (a combination of Sentinel-2 bands with NDVI, NDWI, EVI, SAVI, ARVI, SLAVI, IBI, and GNDVI) based on Cloud Computing via the Google Earth Engine platform. Furthermore, the analysis for calculating the threshold value for vegetation types uses vegetation analysis methods including NDVI, EVI, SAVI, ARVI, SLAVI, and GNDVI. The application of this method is made by creating training sample data as a classification reference point for the introduction of land use and vegetation types (table 1).

Table 1. Training sample data.

No	Variable	Total training sample
	Land use type	
1	Waterbody	121
2	Forest area	105
3	Build up area	100
4	Plantation area	100
5	Agricultural area	100
6	Barren land	100
	Vegetation type	
7	Teak (*Tectona grandis*)	71
8	Rubber (*Hevea brasiliensis*)	32
9	Pine (*Pinus merkusii*)	340
10	Oil palm (*Elaeis guineensis*)	185
11	Bamboo (Bambusoideae)	20
12	Tea (*Camellia sinensis*)	485

2.3. Random Forest algorithm for land use classification

Data processing is performed using the Cloud Computing-based Random Forest Algorithm through the Google Earth Engine platform. The use of this method and platform is one of our reasons for classifying land use accurately and quickly due to a large amount of data and involving many analytical methods [22-24,32]. According to Zhuang et al. [33], the use of classification methods with algorithms aims to improve the quality of the desired results. The initial stage of this research is to map land use types with the Random Forest classification method, a collection of regression trees, and one part of the Machine Learning algorithm [34-36]. There are several types of land use that will be classified, including forest areas, plantations, water bodies, settlements, open land, and agriculture. The formation of the Random Forest Algorithm formula involves several analyzes, including NDVI, NDWI, EVI, SAVI, ARVI, IBI, SLAVI, and GNDVI (table 2), and is combined with several additional bands consisting of Band-2, Band-3, Band-4, Band-5, Band-8, and Band-9.

2.4. Analysis of threshold values

The next stage is to classify vegetation on the type of vegetated land use. The types of land use in the form of forest, plantation, and mixed gardens will be reclassified, and the threshold value for each vegetation that dominates the land use will be calculated. Calculated the threshold value by performing a vegetation analysis with each analysis method, including NDVI, EVI, SAVI, ARVI, SLAVI, and GNDVI analysis (table 2). Some of these analytical methods are derivative products of spatial-based vegetation analysis methods that are often used to identify and monitor vegetation on the earth's surface [45]. Curran *et al*. [3] said the chlorophyll content was positively related to the point of maximum slope in the reflected vegetation spectrum, which occurs at a wavelength between 690 - 740 nm and is known as the "red edge". The spectral reflection of each vegetation is used to identify or detect the level of tree

condition based on the index range value (threshold value). The value of the two vegetation indices shows that the results obtained are related to each other so that they can present the reflectance value [46].

Table 2. Several analytical formulas were used in this study.

No	Method	Formula	References
1	Normalized Difference Vegetation Index (NDVI)	$NDVI = \dfrac{NIR - RED}{NIR + RED}$	[37]
2	Normalized difference water index (NDWI)	$NDWI = \dfrac{GREEN - NIR}{GREEN + NIR}$	[38]
3	Enhanced Vegetation Index (EVI)	$EVI = G\dfrac{NIR + RED}{NIR + C1 \times RED - C2 \times BLUE + L}$	[39]
4	Soil Adjusted Vegetation Index (SAVI)	$SAVI = \dfrac{1{,}5\,[NIR - RED]}{NIR + RED + 0{,}5}$	[40]
5	Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = \dfrac{NIR - [RED - \gamma\,(BLUE - RED)]}{NIR + [RED - \gamma\,(BLUE - RED)]}$	[41]
6	Specific Leaf Area Vegetation Index (SLAVI)	$SLAVI = \dfrac{NIR}{RED + SWIR}$	[42]
7	Index-Based Built-up Index (IBI)	$IBI = \dfrac{NIR}{NIR + RED} + \dfrac{GREEN}{GREEN + SWIR1}$	[43]
8	Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = \dfrac{NIR - GREEN}{NIR + GREEN}$	[44]

Note: Blue = blue band (Band-2); Green = green band (Band-3); Red = red band (Band-4); NIR = near-infrared band (Band-8); SWIR = shortwave-infrared band (Band-11); L = calibration factor of canopy and soil effects (value 1); C1 C2 = the aerosol coefficients were 6.0 and 7.5, respectively; G = gain factor (value 2.5)

3. Results and discussion

3.1. Location research

Bogor Regency has an area of 2,663.85 km² which consists of various types of land use [27]. The results of the classification of land use types show that there are six types of land use and forest areas (151,754.40 ha) and agriculture (88,422.86 ha) dominate the Bogor Regency area with percentages of 46.94% and 27.35%, respectively (Table 4). Geographically, the status of the Bogor Regency area as a buffer zone for the state capital is the reason for the government to develop the agricultural and plantation sectors around the Greater Jakarta area (Jakarta - Bogor - Depok - Tangerang - Bekasi) [27,28]. However, the status of Bogor Regency as a buffer for the capital city also causes Bogor Regency and other surrounding areas to have a fairly high tendency of land conversion. Trisasongko *et al.* [47] said the conversion of agricultural land in the Jabodetabek area occurs due to the introduction of toll road construction, making it easier for people to access Jakarta to areas around Jakarta. This resulted in a threat in the form of regional development caused by the demographic bonus with a population growth rate of 3.16%, thereby increasing the conversion of land into settlements. According to a report from the Ministry of Agriculture, Bogor Regency experienced changes in land area in the form of agriculture in 2015, covering an area of 40,912 ha to 46,141 ha in 2019 and plantations in 2015 covering an area of 56,440 ha to 52,795 ha in 2019. These data indicate that there is a potential for agricultural land crises in urban areas due to human actions in the future [48]. Smith *et al.* [49] states that the distribution of land use and cover patterns impacts human decisions on landscape use. As a result, the agricultural land crisis in this region will have a negative impact on productivity and food supply in urban areas.

**Table 3.** Total area in several types of land use.

No	Land use type	Land area	
		Hectares (ha)	Presentation (%)
1	Waterbody	23,090.01	7.14
2	Forest area	151,754.40	46.94
3	Build up area	18,956.27	5.86
4	Plantation area	6,413.73	1.98
5	Agricultural area	88,422.86	27.35
6	Barren land	34,685.85	10.73
	Total	323,323.12	100

In addition to agriculture and plantations, the study area is one area that has forest areas in which there are two national parks, namely Mount Gede Pangrango National Park (TNGGP) and Mount Halimun Salak National Park (TNGHS) [50]. The spatial analysis resulted in the area of land use in the forest category of 151,754.40 ha, or 46.94% of the total area of Bogor Regency, and most of the area is in the national park area (table 3; figure 2). Looking at the annual trend, in the last five years, the condition of Bogor Regency's forests is in a critical situation. The Bogor Regency area's critical land and forest conditions cover around 31,800 ha according to research data. The report also stated that this damage occurred due to the conversion of forest land functions, exploitation of natural resources to accelerate economic development growth, and encroachment of people who depend on local forest resources.
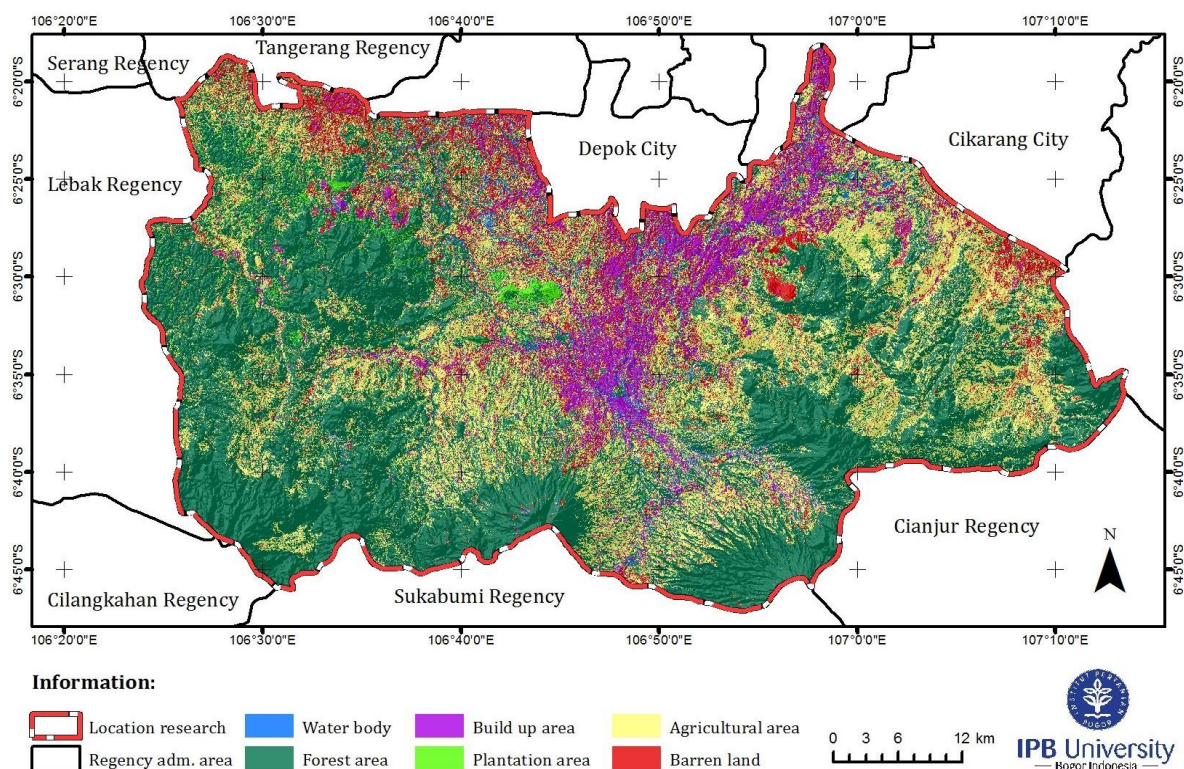
Figure 2. Land use map in Bogor Regency.

3.2. Threshold index value

The process of classifying land use types is influenced by several factors that must be explored in depth to obtain the appropriate classification results. Cheng *et al*. [51] argue that the difference in sensor characteristics is one of the reasons that affect the classification results. Tso dan Mather [4] explained that atmospheric conditions greatly affect the value of the wavelength recorded by the satellite. Furthermore, each type of vegetation has a threshold value of wavelength in pixel scale and can be used in the identification of land use changes. Kumar *et al*. [46] stated that the spectral reflectance of vegetation types is used to identify or detect the level of tree condition based on the index range value (threshold value). To determine the threshold value obtained from the calculation of the mean and standard deviation of each variable. In this study, the distribution of threshold values for each type of vegetation varies for each index.
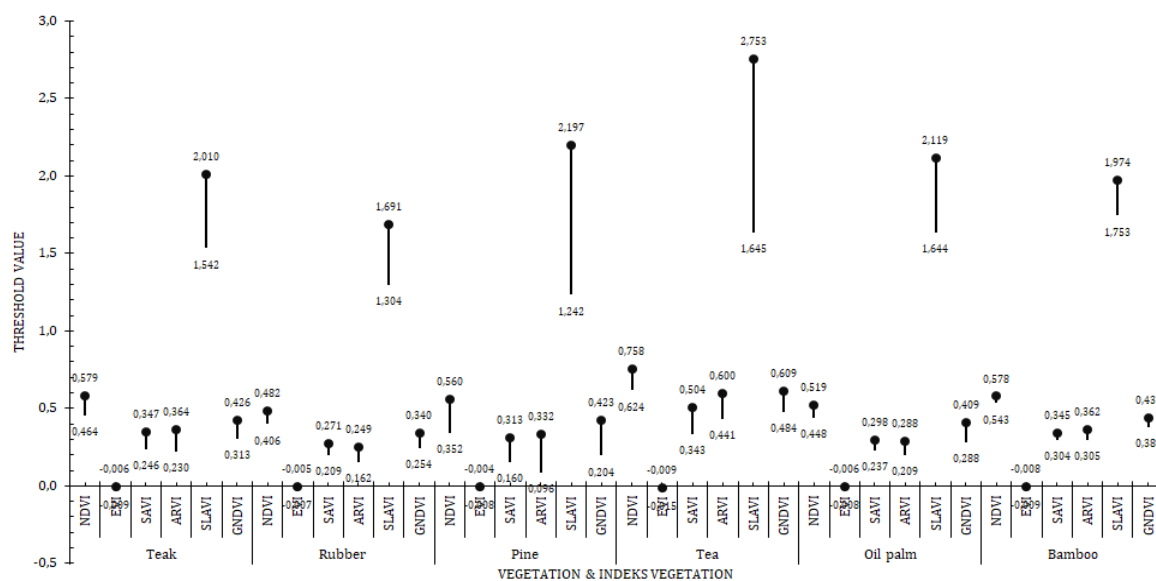
Figure 3. Graph of the distribution of the threshold value of an index for each type of vegetation.

3.2.1. Threshold index value for oil palm. Oil palm plantations are a strategic industry in Indonesia, where since 2000, the Indonesian palm oil industry has grown rapidly in Indonesia [52]. Currently, remote sensing technology cannot be separated from the oil palm plantation industry sector. Kanniah *et al*. [53] argue that classifying oil palm plantations and knowing their geographical distribution is important to distinguish oil palm from vegetation with other nearby land covers such as forest, other vegetation, buildings, barren land, and others. The area of our study is an oil palm plantation owned by PT Perkebunan Nusantara VIII (Persero) under the auspices of the Ministry of State-Owned Enterprises (BUMN). The area is Cikasungka Plantation, located in Bogor Regency with 21,331.08 hectares of oil palm. Furthermore, the results of our spatial analysis explain that this oil palm plantation has a specific threshold value for each index. The distribution of the threshold values, among others, is for the NDVI value with a range of 0.448327 - 0.519225; EVI (-0.00767217) - (-0.00586702); SAVI 0.236883 - 0.297776; ARVI 0.208717 - 0.288435; SLAVI 1.64446 - 2.11935; GNDVI 0.288434 - 0.4085 (Figure 3). The results show that the highest threshold value is through the SLAVI index, and the lowest is the EVI index. The size of the threshold value of each index represents the characteristics of the vegetation. Kumar *et al*. [46] stated in their research that the higher the reflectance value in oil palm plantations, the higher the vegetation cover.
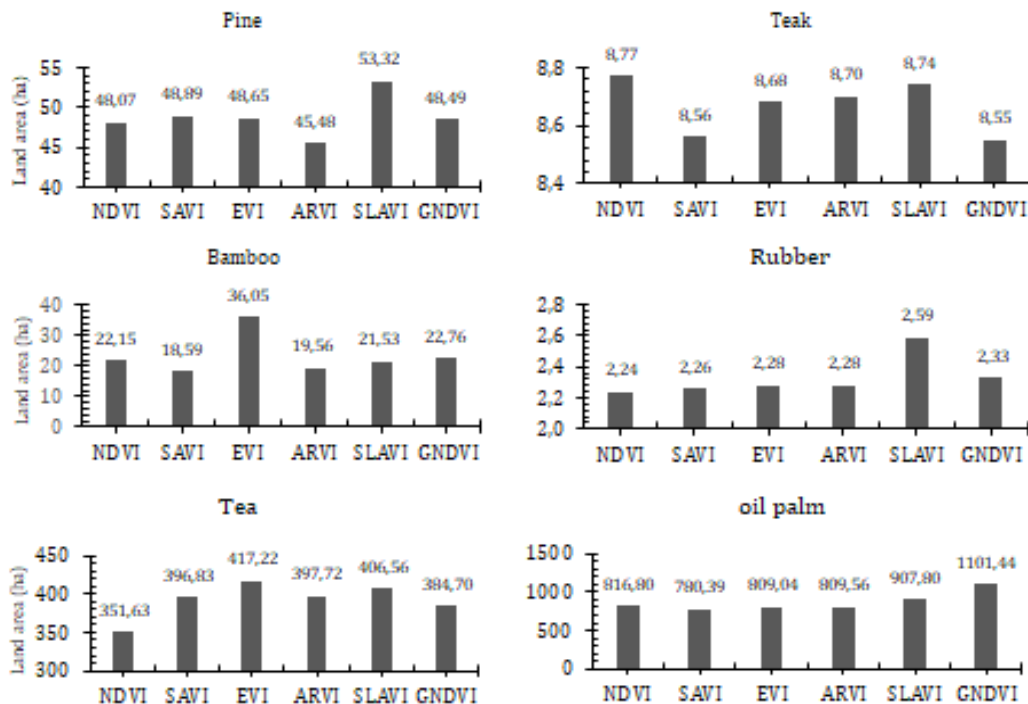
Figure 4. Distribution of land area (ha) identified from the application of vegetation threshold values

Figure 5 (Map 1A-1F) interprets that there are differences in the ability of the index in classifying the class of threshold values for vegetation types in the form of oil palm plantations. For example, the NDVI, SAVI, ARVI, SLAVI, and GNDVI indexes are opposite to the value of the EVI index, which is in the same location when the values of the five indexes are in a class smaller than the threshold value, in contrast to the EVI index which is in a larger class of the threshold value (figure 5: Map 1B). This is different from what was revealed in the research of Oon *et al.* [54] that the value of NDVI, EVI, and SAVI in large-scale oil palm plantations (companies/industries) has a fairly high value. The minimum value or less than the threshold value indicates that it is not an oil palm plantation. While the maximum value class or a value that exceeds the vegetation threshold value indicates that the area is densely vegetated with a high index value. If viewed, there is a collection of pixels in a class smaller than the threshold value in that area. This shows that there are other types of use in the oil palm plantation area, such as built-up land and barren land. In addition, the results of field observations show that the area contains settlements for garden workers and company offices.

Spatially, the results of the analysis of all indices for the specified threshold value can classify oil palm and non-oil palm vegetation. Each index has a different ability to interpret the wavelengths that are read in each vegetation. The index value in the oil palm plantation area depends on the treatment and condition of the oil palm vegetation, such as fertilization and medicinal plants [54]. Meanwhile, Fayech dan Tarhouni [55] explained that climate or weather conditions greatly affect the value produced by an index of each vegetation. In this case, the GNDVI index has a higher tendency to classify oil palm plantations, and the lowest is the SAVI index. It was found that the GNDVI index was able to interpret areas with oil palm vegetation and resulted in a land area of 1101.44 ha of the total area, followed by other indices, namely SLAVI (907.80 ha), NDVI (816.80 ha), ARVI (809.56 ha), EVI (809.04 ha), EVI (809.04 ha), and SAVI (780.39 ha) (figure 4). Similarly, the study of Samseemoung *et al.* [56] uses the GNDVI and NDVI indices for the purpose of measuring plant health in oil palm plantations with the

image source coming from helicopter-mounted aerial photographs. That research explained that the use of image sources originating from satellites has weaknesses ranging from how to obtain data and data processing, so it is not suitable for small-scale garden objects.

The results of the analysis show that spatial-based identification in oil palm plantations has one of the factors that affect the vegetation that takes shelter under it. In addition, the condition of the canopy on oil palm plants also affects the identification of the value of the vegetation. According to the results of field observations carried out at the research location, the condition of the oil palm canopy is quite tight. The leaves are crossed with each other with a distance between trees of about 6 x 6 m. Looking at the spatial resolution of the satellite measuring 10 m, it is possible that the results produced will be affected by undergrowth, with the area of the canopy cover still within the pixel size. The understorey species found were *Chromolaena odorata, Phyllanthus urinaria, Pennisetum purpureum, Brachiaria mutica, Megathyrsus maximus, Eleusine indica, Xanthosoma sagittifolium, Elephantopus scaber, Amaranthus spinosus,* and *Ageratum conyzoides.*
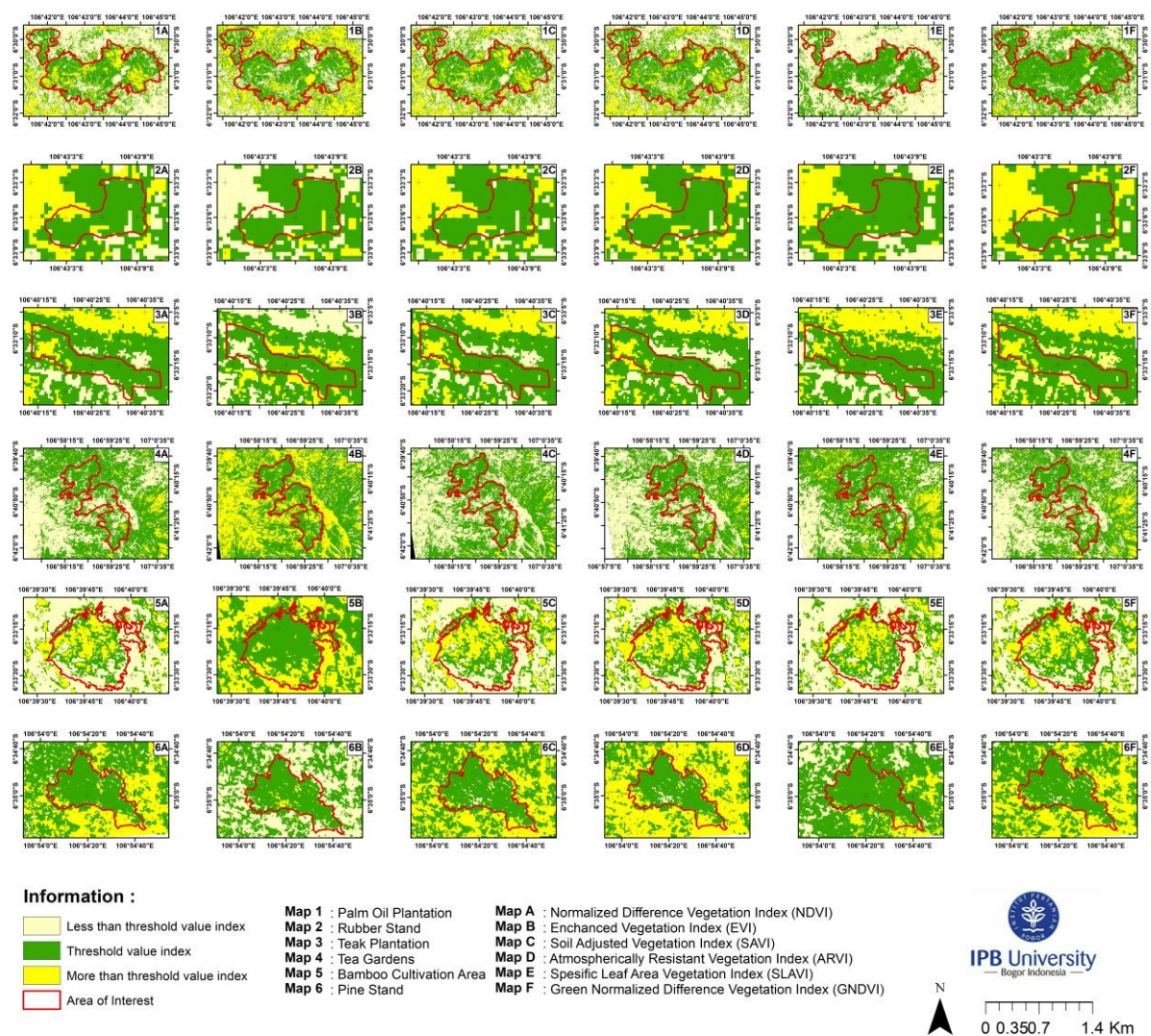
Figure 5. Simulation map of the application of the threshold value for palm vegetation.

3.2.2. Threshold index value for rubber plantation. Rubber plantations are important plantations, both in the context of the community's economy and as a source of non-oil and gas foreign exchange for the country. The area of rubber plantations in Indonesia in 2018 was 3,671,302 hectares with a total production of 3,630,268 tons [57]. In 2019, the total area of rubber plantations in Bogor Regency was 1,619.1 hectares [58]. Rubber plantations are divided into three areas that are distinguished according to their ownership status, people's plantations, large private plantations, and large state plantations. The research area is located within the Bogor Agricultural Institute campus. This location is close to the Rubber Technology Research Agency (BPKT), which has a research and development mandate for post-harvest technology for rubber commodities. Geographic information systems on rubber plantations can be used for various activities such as monitoring and development planning. Utilizing an integrated GIS website to provide information about the location and potential of rubber plantations is one example of its use [59]. From the results of the study, it was found that the threshold values for rubber plantations, namely NDVI 0.40613 - 0.481827; EVI (-0.00690026) - (-0.00509917); SAVI 0.208936 - 0.270971; ARVI 0.162128 - 0.249016; SLAVI 1.30419 - 1.69102; GNDVI 0.254272 - 0.339765 (figure 3). It is read, as with oil palm vegetation, the SLAVI index has a fairly high threshold value, and the EVI index indicates the lowest. However, when compared with oil palm vegetation, the threshold value of the NDVI-EVI-SAVI-ARVI-GNDVI index found in rubber vegetation is greater than the index recorded in oil palm vegetation. While the SLAVI index for oil palm is greater than the threshold value through the SLAVI index for teak plantations.

Basically, each index has a different ability to classify a type of vegetation. Figure 5 shows that the results of the six index methods are almost the same, except for the SLAVI index. The SLAVI index classifies the best area for rubber vegetation types. This is different from the results of class classification on oil palm vegetation types, which have a better classification tendency for the GNDVI index. The EVI index shows more areas that are below the threshold value (figure 5: Map 2B) and is inversely proportional to the other five index methods. The green color indicates that the area is at the threshold value, meaning that the land is filled with rubber type vegetation. Based on field observations, the height of rubber plants in the study area ranged from 13-16 meters. The condition of the plants under the stands was observed to be dense, and locations were found, including *Brachiaria mutica, Pandanus tectorius,* and *Megathyrsus maximus*. In addition, there is the use of agroforestry for the type of cocoa grown under rubber stands. This will certainly make rubber plants have a fairly high pixel value compared to normal rubber stands. Green pixels were also found outside the area, indicating the area was overgrown with rubber-like vegetation. Meanwhile, the surrounding area is non-rubber plantation land, which is depicted by yellow pixels. This is in accordance with field observations carried out at the research site that there are types of built-up land around the rubber stands, namely lecturer housing. The vegetation index method used is concluded to be able to distinguish rubber and non-rubber vegetation areas.

3.2.3. Threshold index value for teak plantation. Spatial results show the threshold value of teak plantations, namely NDVI ranging from 0.464159 - 0.578821; EVI (-0.00920116) - (-0.00607199); SAVI 0.245853 - 0.346708; ARVI 0.229802 - 0.364369; SLAVI 1.75325 - 1.97375; GNDVI 1.54185 - 2.0972. The result of the threshold value is that SLAVI has the highest threshold value compared to other indices. In contrast, the lowest threshold value is owned by the EVI index. This is the same as the palm-bamboo-pine vegetation, which has the same pattern (figure 5). In Indonesia, the type of land used with teak vegetation is known as teak plantation forest. Teak plantation forest is one of the forests with commodity types that have high selling value because of the quality of the strong and durable wood [60]. Teak plantation forests on the island of Java are mostly managed by Perhutani, which are mostly found in Central and East Java. The provinces of West Java and Banten, which are in one regional division, have an area of 192,723.58 hectares for the teak company class [61].

Simulation results of the application of threshold values on teak vegetation (figure 5: Map 3A-3F) illustrate that the NDVI vegetation index has the largest distribution of threshold values and dominates the teak plantation area. Values that are not included in the threshold value class indicate that the area is not a vegetated teak area. This is in accordance with the results of field observations that show that the area is a mixed forest area with various types of weeds mixed with bamboo forests. It is known that the NDVI index is one of the highest indexes in mapping the distribution of teak vegetation with a cover area of 8.77 ha. In contrast, the lowest index is the GNDVI index which has successfully identified an area of 8.55 ha (figure 4). The ability of the index when identifying teak vegetation depends on the spectral received by the satellite. In addition, other factors such as understory vegetation, canopy cover and atmosphere can affect the results of the analysis. It is known from field studies that the understory vegetation in teak plantations includes *Pteridophyta* sp, *Brachiaria mutica, Eclipta prostrata, Mangifera indica, Lantana camara, Chromolaena odorata, Pennisetum purpureum, Acalypha indica, Mimosa pudica, Psidium guajava, Bidens pilosa, Bambusoideae, Xanthosoma sagittifolium, Euphorbia hirta, Medicago lupulina, Heliotropium indicum, Pandanus amaryllifolius, Pandanus tectorius, Amaranthus spinosus, Solanum torvum, Imperata cylindrica, Megathyrsus maximus, Eleusine indica,* and *Muntingia calabura.*

3.2.4. Threshold index value for tea gardens. Spatial analysis shows that tea plantations have a threshold value for the NDVI index of 0.623762 - 0.75837; EVI (-0.0148138) - (-0.00879656); SAVI 0.342565 - 0.503846; ARVI 0.440582 - 0.599911; SLAVI 1.64454 - 2.75279; and GNDVI 0.484015 - 0.60895 (figure 3). From the threshold values obtained, the SLAVI index was detected to have a fairly high threshold value compared to other indices, and the EVI index was in the lowest value range. If seen from the simulation results of the application of the threshold value (figure 5: Map 4B), the EVI index chose a very broad coverage of 417.22 ha and the lowest was the NDVI index with an area of 351.63 ha (figure 4). This is influenced by the wide scope of determining the location of the simulation application, and in it there is a land use that is not tea vegetation. Meanwhile, in determining the threshold, it is necessary to minimize the land and take a coverage area that only has tea vegetation.

Figure 5 (Map 4A-4F) reported that there are some pixels that do not belong to the threshold value class of tea vegetation. After being compared with the observation results, the pixels that show the area are non-tea vegetation areas. The area has tea vegetation with a density level that is not comparable to the location where the threshold value is taken. The area in question is on a ridge, and has an avalanche that is impossible for tea vegetation to grow. In addition, there are access roads and several settlements for tea plantation workers in the simulation location and contribute pixels that do not include the threshold value. Spatially, it shows that outside the area there are areas identified as tea-vegetated land. However, the area is a forest area that does not include tea plantations at all. This indicates that the spectral value reflected by the tea vegetation is almost similar to the surrounding forest area. In contrast to other vegetation types, the spectral values obtained are in the low range (figure 5), so that it becomes a limitation in classifying vegetation spatially.

3.2.5. Threshold index value for bamboo cultivation plantation. Bamboo is one of the commodities classified as non-timber forest products. The development of bamboo plantation forest has been regulated in Permenhut No. 36 of 2008 through the IUPHHBK scheme. However, no company has yet applied for the business license. The area of bamboo forest based on ownership status is 1.4 million ha (67%) for privately owned bamboo forest and 723,000 ha (37%) for state-owned bamboo forest or growing on public land [62]. In 2007, Indonesia's bamboo production potential was 10.4 million tons of bamboo. Based on the analysis in the field, the identified bamboo has a growing distance between 3 - 4 m in length and 3 - 6 m in width. The research area is located in the Leuwiliang bamboo cultivation

area, Bogor Regency. The use of remote sensing on bamboo vegetation has been widely used, for example to identify the location of its distribution [63] and how the microclimate is related to the water content of bamboo litter in bamboo forests. From the results of the study, it was found that the threshold value of the bamboo cultivation area, namely NDVI 0.542857 - 0578405; EVI (-0.00913627) - 0.00777112; SAVI 0.303762 - 0.344763; ARVI 0.30509 - 0.362304; SLAVI 1.75325 - 1.97375; GNDVI 0.387545 - 0.436589.

Figure 5 (Map 5A-5F) presents the different results of each method. The EVI method shows the best results for identifying bamboo vegetation seen from the number of green pixels in the area (figure 4). The conclusion is the same as the best method for identifying tea gardens, but different from the results in teak plantations. Shi *et al.* [64] mention that EVI will identify better on plantation land than forest. This method is also the chosen one. Zhou *et al.* [65] to identify variations in bamboo forests to obtain future carbon predictions. Some green pixels are also visible outside the area. This result occurs because bamboo is indeed found there, but it is mixed with other agricultural plants in the area as evidenced by field observations. In addition, the results of the analysis of the EVI method are inversely proportional to the other five methods (figure 5: Map 5B). The results of the analysis of the NDVI-ARVI-SAVI-SLAVI-GNDVI method show a lot of yellow pixels in the area. This means that the area within the area is below the threshold value, which means it does not show bamboo vegetation. The factor that makes NDVI results inaccurate is their inability to identify very small changes in leaf area and greenness [66]. The yellow pixels found in the area indicate the presence of buildings and barren land in it. Meanwhile, those found outside the area are residential areas and agricultural areas. Confirmation of this is done through field observations that prove these conditions. The types of understorey found were *Mimosa pudica*, *Imperata cylindrica*, *Chromolaena odorata*, dan *Manihot esculenta*. Selain itu beberapa tumbuhan penghasil buah seperti *Artocarpus heterophyllus*, *Mangifera indica*, *Persea americana*, and *Ananas comosus* were also found in the study area.

3.2.6. Threshold index value for pine stands. Pine (*Pinus merkusii*) is a coniferous tree with an economic function from its wood and sap which has high economic value. In addition to economic value, pine also provides benefits from an ecological perspective such as good hydrological and erosion prevention functions and from a social point of view, it can provide employment and absorb adequate amounts of labor [67]. Pine stand classification maps can be useful in land use planning around existing population identifying conservation sites, and selecting new sites for reintroduction of species in their natural habitats [68]. One of the pine stands on the island of Java is located in the Gunung Pancar Tourism Park covering an area of 447.5 ha [69] with an area of 80 ha of pine forest which is used as a potential tourist attraction [70]. As a form of vegetation and remote sensing is one of the needs in identifying the distribution of spatial-based vegetation. We got the threshold value for pine stands, namely NDVI 0.351548 - 0.559664; EVI (-0.00804581) - (-0.00371463); SAVI 0.160412 - 0.313166; ARVI 0.096302 - 0.332379; SLAVI 1.24184 - 2.19697; and GNDVI 0.203931 - 0.422876.

Figure 5 (Map 6A-6F) displays the results of the vegetation index using the six methods on pine stands (*Pinus merkusii*) and their surroundings in the Gunung Pancar Nature Tourism Park. Just like rubber stands, SLAVI can classify pine vegetation types well. The green area inside the pine stand boundary is at the threshold value identifying the pine stand while the green area outside the pine stand boundary represents other vegetation. The yellow area identifies land uses other than pine vegetation such as vacant land and settlements that are at an index value less than the threshold value or more than the threshold value. The EVI index classifies locations differently from other indices, many areas with values below the identified threshold, such as rubber stands. In contrast, Waring *et al.* [71] stated that EVI is superior to other methods because it is sensitive to site-specific variations, local variations in leaf canopy area and chlorophyll concentration. In contrast the results show that SLAVI is the index with

the most indications of pine vegetation area with a land area of 53.32 (figure 5: Map 6E; figure 4). NDVI, SAVI, ARVI and GNDVI indexes resulted in almost the same classification in pine stands.
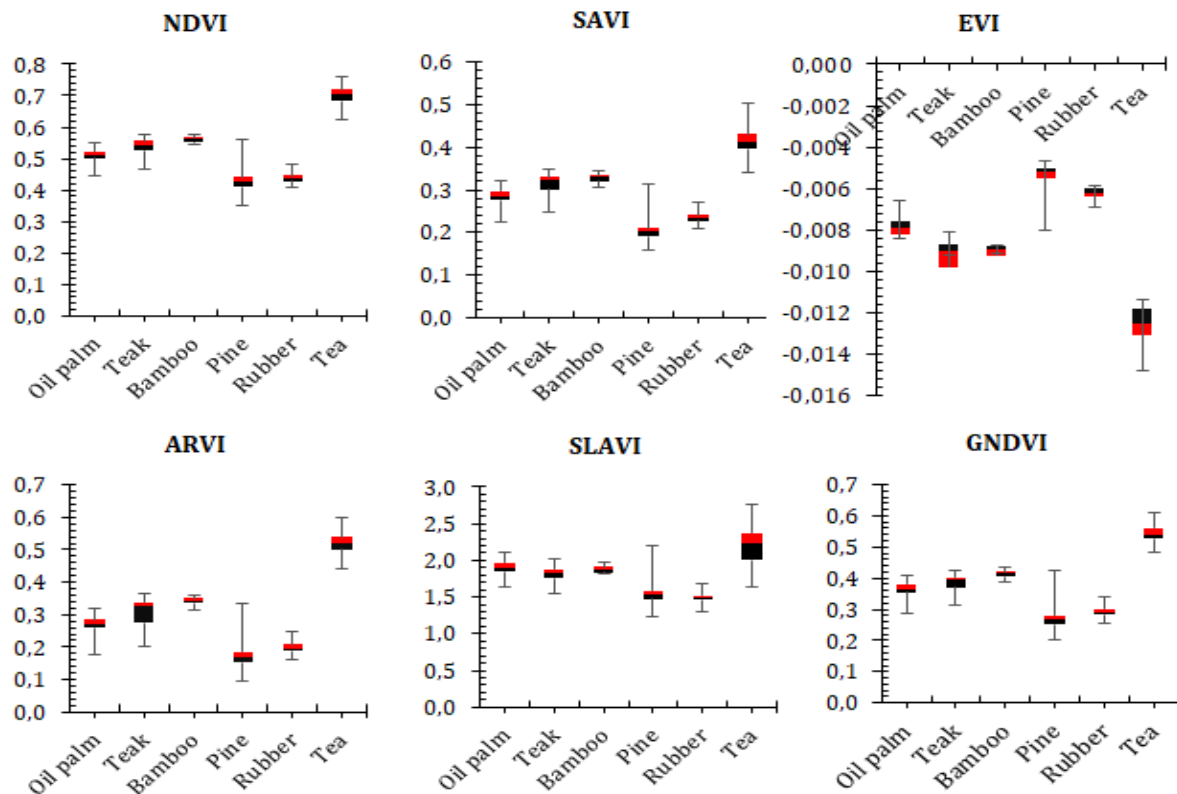
Figure 6. Graph of the distribution of pixel values at each index.

3.3. Distribution of vegetation index value

The results showed that there were fundamental differences regarding the distribution of threshold values for each vegetation. Figure 6 reported that tea plants have different threshold values from the others except for the SLAVI index. The rest of the vegetation is indistinguishable or nearly identical. According to the results of the analysis, vegetation of oil palm, teak, bamboo, pine and rubber has a much lower threshold value than tea vegetation and only occurs in the NDVI-EVI-SAVI-ARVI-SLAVI-GNDVI index. The threshold values of some of these vegetations are almost similar and not much different, indicating that these vegetations are difficult to distinguish under the same conditions. In contrast to the SLAVI Index, which does not succeed in describing the spectral differences between tea and other vegetation, it can only distinguish between teak and rubber (figure 5: Map 2E). In addition, the EVI index can not only distinguish between bamboo-tea-rubber or tea vegetation with other vegetation, but can distinguish between tea-teak-rubber and other vegetation (figure 5: Map 2B). This one affects the ability of the index to classify land use types at the vegetation level. However, tea vegetation has a weakness in terms of spectral reflection. The threshold value of this type of vegetation cannot be distinguished by a few pixels of vegetation in the forest area around the location of the tea research station (figure 5: Map 4). In addition, all of the indices involved fail to differentiate between vegetation and forest as a whole. It is believed that the spectral values received by the Sentinel 2 satellite from forest areas are very similar to the spectral values in tea-vegetated areas (figure 6; figure 3). Thus, the use of these six indices cannot be applied to map the distribution of tea with locations adjacent to

forest areas. From this problem, the combination of the new index is one solution that can be offered to map the distribution of tea vegetation.

Judging from the results that have been obtained, overall there is an index that can be used for classification purposes and predicting the distribution of vegetation. The results show that the NDVI-EVI-SAVI-ARVI-GNDVI index has the advantage that it can distinguish tea, rubber and bamboo vegetation. Meanwhile, all indexes can be used to classify bamboo and rubber. The ability of an index to classify vegetation depends on the type of band involved in the index formula and the spectral values read and recorded by the satellite. For spectral values, there are several factors that affect the condition of the canopy cover, understory vegetation, and atmosphere. In their research, as de Oliveira Silveira *et al.* [72] and Pocewicz *et al.* [73], understorey affects vegetation identification results. In addition, Eskelson *et al.* [74] and Karlson *et al.* [75] explained that the understorey vegetation community is an important component of forest ecosystems and has specific characteristics in terms of spatial size. Finally, the distribution pattern of this threshold value can be recommended for the classification and identification process of vegetation according to the indexing capability.

4. Conclusions

Land use in the study area is dominated by land use types such as forest (46.9%) and followed by agriculture (27.4%), barren land (10.7%), water bodies (7.1%), built-up land (5.9%), and plantations (2%). Our study found various threshold values for each vegetation index (VI). Spatially, one index, namely the EVI index, is inversely proportional to the other five indices. The simulation results of the application of threshold values to map the distribution of vegetation types produce a suitable index and can distinguish between vegetation and non-vegetation types. The suitable indexes include NDVI for teak vegetation, SLAVI for rubber and pine vegetation, GNDVI for oil palm vegetation, and EVI for bamboo and tea vegetation. The distribution of index pixel values shows that tea vegetation is the type of vegetation that has the highest distribution of values on the NDVI-SAVI-ARVI-SLAVI-GNDVI index and the lowest on the SLAVI index. Seeing the difference in distribution patterns, the value of the tea type vegetation index can help classify land use types with tea and non-tea vegetation types. However, the threshold value of tea vegetation cannot be applied to locations adjacent to forest vegetation because it has a fairly high spectral value and is similar to vegetation in forest areas. In addition, the entire index can be used to classify bamboo and rubber

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