VEGETATION INDICES FROM LANDSAT-8 DATA IN PALABUHANRATU

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Abstract. Land cover will change due to population pressure, resource use, and human interest in space. Measuring the land area is essential to determining how much positive and negative is converted. The vegetation on land was determined by how densely the plants were spread out. This study is conducted in Palabuhanratu, Sukabumi Regency. It aims to test and compare how accurate EVI and SAVI are at seeing vegetation density. The images used are from Landsat 8 in 2018 and 2022. Calibration is performed using high-resolution images, followed by field surveys with 98 points from polygon sampling. The average accuracy of the results from EVI is 49%, while the average accuracy of the results from SAVI is 45%. So, we can say that the EVI or SAVI based-input gives a similar result on observing the vegetation density in Palabuhanratu.

Keywords*: Vegetation Index, Remote Sensing, Sukabumi, Multispectral*

1 INTRODUCTION

In a changing world, the land cover area will constantly change because of population growth, the need for wood and building materials, the spread of agriculture, and government policies(Wubie et al., 2016)If it is correlated with Indonesia's forest area, in 2020, legally (de jure), Indonesia's forest area will be 120.5 million hectares, while in fact (*de facto*), it will only be 86.9 million hectares, with 33.4 million hectares without forest cover (Nurbaya et al., 2022) This means there is a reduction in land cover, and 33.4 million hectares that do not have land cover are now areas of competition for non-burning development areas (Forest Digest, 2022).

Java Island is the most populous island in Indonesia. In 2015, it had a forest area based on a land cover of 3,206 million hectares, which decreased to 2,711 million hectares in 2020 (BPS, 2021b). The ratio of forest area in 2021 on Java Island is only 24%, with 19% having forest cover and the other 5% being botanical gardens and biological conservation parks (LIPI, 2021). The province of West Java is the most populous on the island of Java (BPS, 2022), and if it is correlated with the level of change in land area, it indeed becomes a synthesis that land change is likely.

One of the urban areas in West Java, Palabuhanratu, is on the coast of the Sukabumi Regency. Since it was designated as a regency city in 1998, the level of land use in Palabuhanratu has been high due to economic growth, population growth, and connectivity support for various types of activities and services for the population (BPS, 2022). Changes in use, if uncontrolled, will result in losses, including the balance of water supplies (Woyessa & Welderufael, 2021) In addition, it can be even worse, namely land degradation and reduced forest land, which can then indicate reduced soil fertility, clean water quality, and even poverty and hunger (Obubu et al., 2022).

Between 2018 and 2021, there was a change in the demographic dynamics at Palabuhanratu; in 2018, there were 107,666 people (BPS, 2018), while in 2021, there were 116,677 people (BPS, 2021a). Then there was an increase of 4,078 people in Palabuhanratu. This indicates a change in land use, particularly land cover conversion (Li et al., 2015). With this, it becomes interesting to study land use change using the vegetation index.

Changes in land cover require periodic monitoring to be seen in real-time. One way to do this is through satellite imagery, which can provide two-dimensional or three-dimensional variations of objects on the earth's surface (Danoedoro, 2012)). Remote sensing offers excellent resolution for sustainable coastal management to reduce degradation due to anthropogenic activities (Olubunmi Adegun, 2015). Thus, a method is needed to analyze the land cover to produce accurate results.

The Soil Adjustment Vegetation Index (SAVI) and Enhanced Vegetation Index (EVI) methods were developed based on the algorithm from the Normalized Difference Vegetation Index (NDVI). The Enhanced Vegetation Index (EVI) method can reduce the background from the tree canopy, resulting in a better analysis (Ibnu Lonita et al., 2015), and better and more accurate than NDVI (Son et al., 2014). The SAVI method, on the other hand, can suppress the soil background at canopy brightness levels by focusing on the NIR and RED bands (Gilabert et al., 2002).

This study determined the features, area, and precision of the two EVI and SAVI vegetation indices techniques based on the preceding description. Then this may be understood, and the excesses can be used as stakeholder concerns connected to the research object to determine sustainable space utilization.

2 MATERIALS AND METHODOLOGY

2.1 Location and Data

This research was conducted in Palabuhanratu Village, Palabuhanratu District, Sukabumi Regency, West Java Province. Palabuhanratu Village is located at coordinates 106° 32' 14.653" E, 6° 58' 54.087" S to 106° 34' 41.972" E, 6° 59' 13.949" S, has an area of 564 hectares or 5.64 km2, has a population density 6,300 people/km2. In contrast, Palabuhan Ratu sub-district has an area of 94.09 km2 with a population density of 7,119 people/km2, with the most negligible density in Cimangu Village with 1,084 people/km2. Palabuhanratu District is bordered by Cikakak District (North), Simpenan District (South), Bantargadung District (East), and the Indian Ocean (West) (BPS, 2021a).

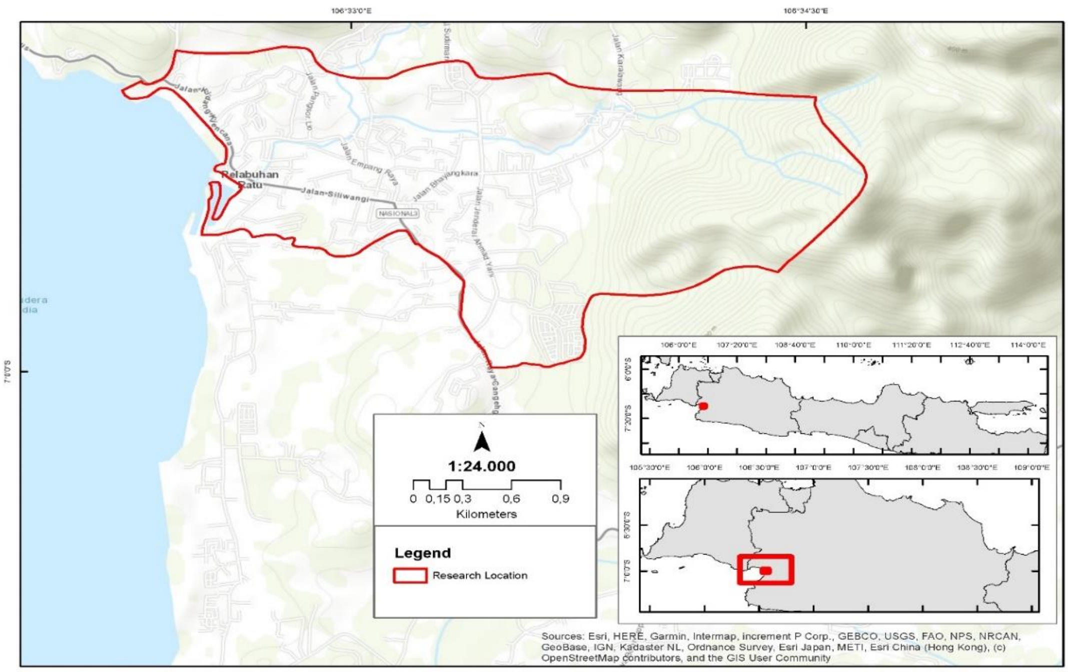

Figure 1. Research Location, Palabuhanratu Sub-District

2.2 Data Used

The information for this investigation came from pictures taken by the Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) in 2018 and 2021. Those materials are available for download from the official website of the United States Geological Survey (USGS, 2022a). The two images are used to compare the EVI and SAVI vegetation indices and predict how much land will be converted into something else in 2018 and 2021 by comparing the EVI and SAVI vegetation indices. The two images were created with the cloud cover in Palabuhanratu in mind, which will be corrected in the future. In addition to field surveys, Geospatial Information Agency (BIG Indonesia) high-resolution pictures were employed in the calibration procedure.

2.3 Methods

The data collection process consists of primary and secondary data. Between October 29 and November 2, 2022, 98 sample points were taken from Palabuhanratu to collect the first data set. The data collection process in the field used the Avenza Map application. At the same time, secondary data was collected before field calibration in the form of OLI-TIRS Landsat 8 satellite and Orthorectification high-resolution images from the Geospatial Information Agency, Indonesia.

2.3.1. Satellite image processing and analysis

The division of data processing is divided into pre-processing, processing, and post-processing. The tools used to help with the analysis are ArcGis 10.8 (ESRI 2020), Microsoft Excel, Avanza Map, and Global Mapper.

2.3.2. Pre-processing

2.3.2.1. Radiometric and Atmospheric correction

Radiometric and atmospheric corrections ensure that the actual spectral radian values are correct. The image can be wrong because of things like the weather, the recording angle of the angle of incidence of sunlight, and other things (Kustiyo et al., 2014). In this study, a radiometric correction was performed to change the number of pixels to a value of no physical units. There were two steps: changing the data to TOA radiance and surface reflectance (USGS, 2022b).

2.3.2.2. Band Combination

In ArcGIS, composite bands help combine several layers to create a true or false color composite. According to the principle of amalgamate image color, which consists of 7 bands of red, green, and blue, The true composite bands used in this study are the original colors without cloud obstructions, namely 7, 5, and 3 (Eid et al., 2020)

2.3.2.3. Image Clipping

The satellite image was obtained from the website usgs.gov. Covers a large area, so it is necessary to crop the image in the area of interest (AOI) as the object of research. Image cropping using the spatial analysis Clip in the Palabuhanratu area, both in 2018 and 2021.

2.3.3. Processing

In this process, researchers will describe the EVI and SAVI vegetation indices as an analytical comparison to determine the accuracy of the two indices.

2.3.3.1. Remote Sensing Indices

2.3.3.1.1. Soil-adjusted vegetation index (SAVI)

The SAVI index was created by modifying the NDVI algorithm to account for the influence of soil brightness when vegetation is lacking (Huete, 1988). This vegetation index is based on distance (Santos *et al.* 2019). The SAVI index is very accurate for analyzing surface land cover properly. The SAVI equation is based on red imagery or band 4, near-infrared (NIR) or band 5. The soil brightness correction factor ranges from the lowest vegetation value of 0 to a high vegetation cover value of 1 (Li et al., 2015). The average study defines the L value for accommodating each land cover type (Jara et al., 2019)

$SAVI = (1.5 * (NIR - RED))/(NIR + RED + L)$

Where:

NIR = band 5
RED = band 4
L = the adjustment for the canopy background is 0.5

2.3.3.1.2. Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) is a vegetation index that emphasizes areas with a high enough signal or biomass that increases greenery, reducing the background of soil and canopy signals (Ibnu Lonita et al., 2015). The EVI formula calculates the index (Zhong et al., 2021)

$$EVI = G\left(\frac{NIR - RED}{NIR + C1 \times RED - C2 \times BLUE + L}\right)$$

Where:
G = Gain factor, which is 2.5
NIR = Band 5
Red = Band 4
Blue = Band 2
L = canopy background adjustment to address non-linear, differential NIR, and red beam transfer through the canopy, which is 1
C1 = aerosol resistance coefficient of 6
C2 = aerosol resistance coefficient of 7.5

2.3.3.2. Image classification

This study used EVI and SAVI to detect non-vegetated and vegetated areas. The geoprocessing raster calculator tool is then used to obtain the maximum and minimum values of the two indices based on the Landsat time series for 2018 and 2021. Using supervised classification, the maximum likelihood algorithm is then used to look at built-up areas and plants. In this guided classification, images of Palabuhanratu are divided into two types of land cover: built-up areas and plant-covered areas. After that, both the EVI and SAVI indices were reclassified. They were split into four groups: non-vegetation, low vegetation density, medium vegetation density, and high vegetation density. A built-up area is one without vegetation, while a vegetated area is one with a range of low to high plant density. Then do the conversion from a raster to a polygon using the raster-to-polygon tools.

Then look at the open attribute table and choose a polygon to determine the sample in that study after calculating and using the Slovin sampling method with the formula(Khan et al., 2021)

$n = N/(1 + Ne^2 \quad)$

Where:

n = code of samples
N = total population
e = margin of error

2.3.4. Post-processing

2.3.4.1. Change detection

Digital change detection is a method that uses multispectral image data to look at any changes in land cover in a particular area over a specific time period. It was built on comparing two or more images of a given site at different times, such as post-classification and pixel-to-pixel comparisons (Othman et al., 2012)

This study analyses changes using a time series in 2018 and 2021, which can show how much land cover has changed in terms of area and location. This is helpful for figuring out more about the site based on the percentage of each of the four classes.

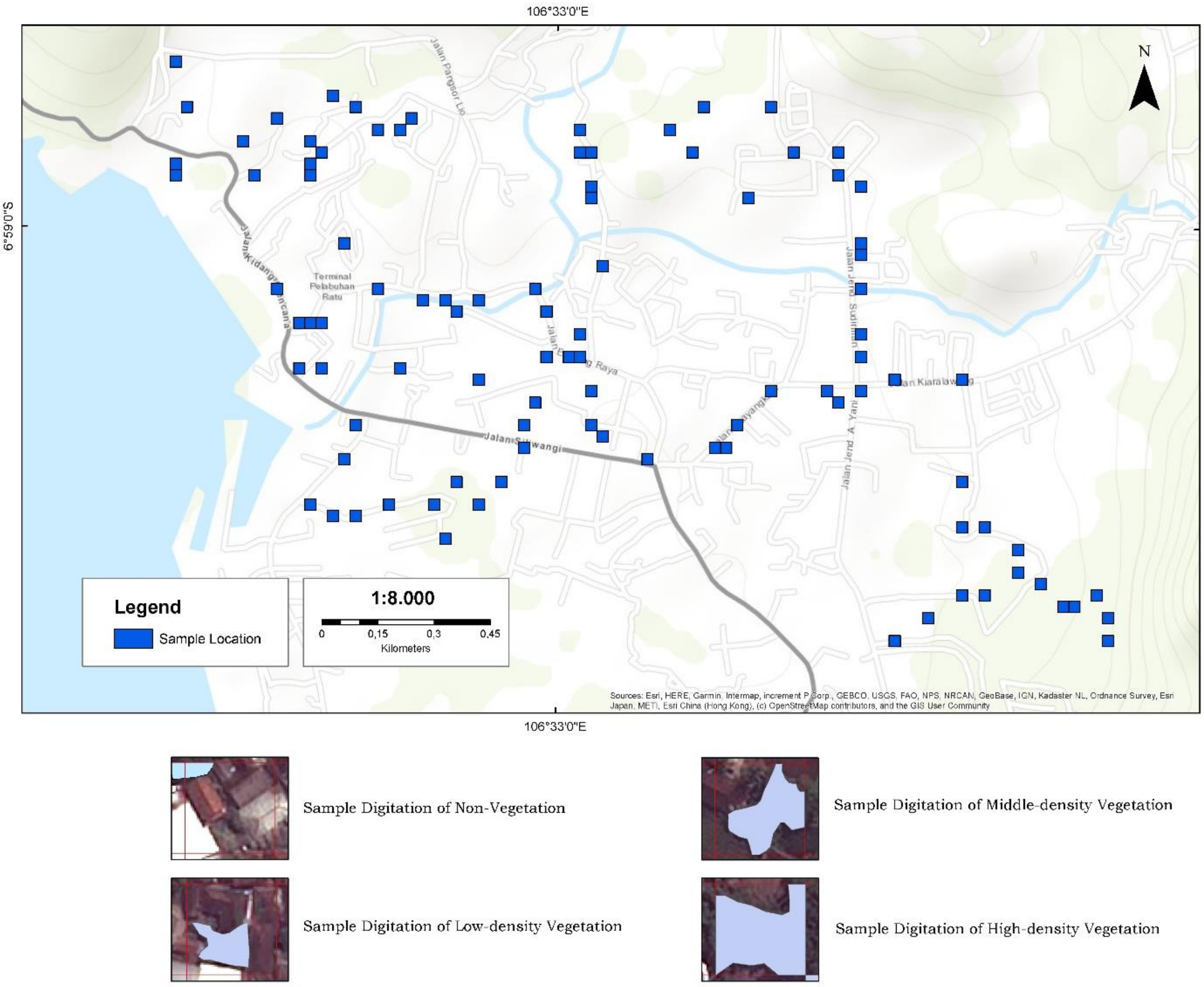

Figure 2. Sampling Location in Palabuhanratu Sub-District

Table 1. Area (Ha) and percentage of EVI

Code	Class Name	2018			2021		
		Pixels	Area (Hectares)	%	Pixels	Area (Hectares)	%
1	Non-Vegetation	1530	137.70	24%	1720	154.80	27%
2	Low-density Vegetation	1536	138.24	24%	1562	140.58	25%
3	Middle-density Vegetation	1857	167.13	30%	1633	146.97	26%
4	High-density Vegetation	1349	121.41	22%	1357	122.13	22%

Table 2. Area (Ha) and percentage of SAVI

Code	Class Name	2018			2021		
		Pixels	Area (Hectares)	%	Pixels	Area (Hectares)	%
1	Non-Vegetation	1425	128.25	23%	1549	139.41	25%
2	Low-density Vegetation	1499	134.91	24%	1401	126.09	22%
3	Middle-density Vegetation	1815	163.35	29%	1719	154.71	27%
4	High-density Vegetation	1533	137.97	24%	1603	144.27	26%

2.3.4.2. Accuracy Assessment

In the Palabuhanratu research area, accuracy is measured by looking at a sample of 98 points on the ground and in high-resolution images. This was done to see how well the EVI and SAVI algorithms for measuring plant growth compare. Due to limited access to the location or coordinate points, the calibration process is done carefully based on field observation.

3. Results and Discussion

3.3. Change detection

Based on the images taken in 2018 and 2021, the land cover was divided into four groups (Table 1). According to the SAVI Vegetation Index analysis, there were 128.25 hectares of non-vegetation areas in 2018, 139.41 hectares will be non-vegetation areas in 2021, and an additional 11.16 hectares, or 2% of the total area, will be non-vegetation areas. This indicates that there is land conversion in the village of Palabuhanratu. Areas with low and medium density also experienced a decline in 2018, and there were 134.91 and 163.35 hectares, respectively. The area was then reduced to 126.09 hectares, or 2% of the total area. Interestingly, there was an increase in high-density vegetation, from 137.97 to 144.27 hectares, or an increase of 2% for this area.

Whereas for the EVI vegetation analysis, it can be explained that in 2018, the non-vegetation area had an area of 137.70 hectares, while in 2021, it had an area of 154.80 hectares. There is an additional 17.10 hectares or 3% of the total area of Palabuhanratu village. Whereas for low vegetation density, there was an increase in the area of 2.34 hectares, or 0.4%, and what is interesting for vegetation density is a significant decrease of 20.16 hectares or 4%; starting in 2018, there were 167.13 hectares, and in 2021, there were 146.97 hectares. High vegetation density is relatively constant, adding 0.72 hectares, or 0.1%.

These changes will be a driving factor for land change if they are associated with population growth. The most notable thing is the addition of non-vegetation land cover areas, based on an EVI of 3% and SAVI of 2%. If it is further identified, the use of the land is in the form of built-up areas, housing, shops, lodging, hotels, and others. As for the land cover areas, there was a significant reduction, namely in areas with low and medium vegetation, meaning that some land use areas, such as agricultural land, became built-up areas. Whereas for areas with high densities, there is no significant change, with a range of 0.1-1% of the total area.

the change in land use is terrible for both the people who live there and the environment (Hu et al., 2015). The factor that influences land change is that it can increase the surface area (LST) and indirectly affect electricity consumption (Wang et al., 2022); besides that, it can cause loss of biodiversity (Zabel et al., 2019) and reduce carbon stocks (Molotoks et al., 2018). Apart from that, it can reduce healthy food, and unplanned housing, of course, will have adverse effects, especially in developing countries (Khan et al., 2021). Thus, changes in land cover can affect other variables in an environment.

3.4. Accuracy Analysis

This accuracy analysis was carried out by checking the field with 98 samples in Palabuhanratu. Checking is carried out in two stages: high-resolution imagery and field surveys. This is done to prevent each pixel, which produces four color gradations and 45% accuracy. The two vegetation indices have a relatively small difference (4%). According to EVI data, 49% of the land is non-vegetated (21%), and has low (20%), medium (3%) or high (4%) vegetation density. As per the SAVI data, the classes of non-vegetation (21%), low (15%), medium (3%) and high (5%) vegetation density.

By putting these data together, we can see that the two indices have the same value for detecting non-vegetation classes, which means that their accuracy is the same. For the low vegetation density class, there is a difference of 5%, meaning that the EVI is higher than the SAVI, which shows that the EVI does an excellent job of spotting low-class cover. Whereas the middle-class density has the same value, 3%, and the high-density class has a difference of 1%, where EVI is more accurate than SAVI.

This is in line with the fact that the EVI index can be used for tropical areas with high land cover (H. & Dodge-Wan, 2020)); besides, it can accurately analyze land conversion into rubber plantation areas (Fan et al., 2015)). EVI has proven to be very effective for measuring leaf area index (LAI) in densely vegetated and grassland areas (Yang et al., 2023), so it is possible to develop sustainable forest and grassland management

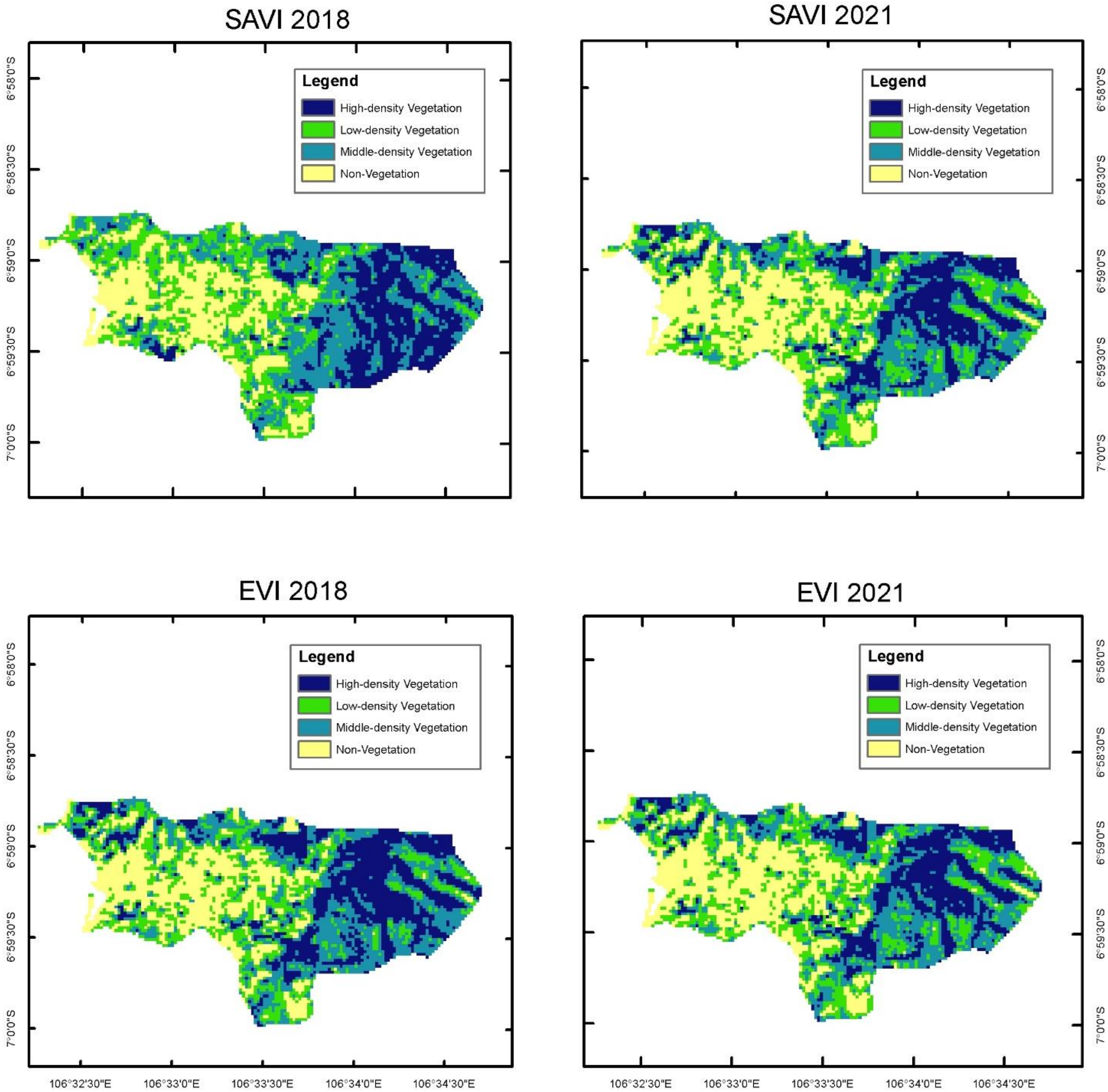

Figure 3. EVI and SAVI value in each vegetation conversion class

Table 3. Canopy Criteria

Code	Class	Canopy Criteria Cover Interval
1	Non-Vegetation	<10%
2	Low-density Vegetation	10 - 40%
3	Middle-density Vegetation	41 - 69%
4	High-density Vegetation	70 - 100%

Table 4. Results Comparison of EVI and SAVI with Vegetation Density Class

Code	Class	Samples	EVI		SAVI	
			Number of correct pixels	Producer Accuracy	Number of correct pixels	Producer Accuracy
1	Non-Vegetation	34	21	21.43%	21	21.43%
2	Low-density Vegetation	43	20	20.41%	15	15.31%
3	Middle-density Vegetation	12	3	3.06%	3	3.06%
4	High-density Vegetation	9	4	4.08%	5	5.10%
	Total	98	48	48.98%	44	44.90%

4 CONCLUSION

This study found that there is land conversion in both indices into a non-vegetative land cover class, which can take the form of built-up land that is used for housing, shops, lodging, empty land, and other things. This suggests that it may be related to population growth. The EVI index, with a value of 49% compared to a SAVI value of 45%, is stated as an accurate index in measuring the area of land in Palabuhanratu, as indicates in a comparative analysis between the two indices. EVI is very good at figuring out how dense the plants are in the tropics because of this analysis and the fact that the land cover has leafy variables.

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