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Monitoring Dynamics of Vegetation Cover with the Integration of OBIA and Random Forest Classifier Using Sentinel-2 Multitemporal Satellite Imagery

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Abstract

The existence of vegetation in an area has an important role to maintain the carrying capacity of the environment and create a comfortable environment as a place to live. In an effort to create a sustainable environment, there are various pressures on vegetation that cause a decrease in vegetation area. Economic activity, population growth and other anthropogenic activities trigger the dynamics of vegetation cover in an area that causes land cover changes from vegetation to non-vegetation. Majalengka Regency as one of the areas with intensive regional physical development in line with the operation of BIJB Kertajati and the Cipali toll road became the study area in this research. This study aims to monitor the dynamics of vegetation cover with the proposed method namely the integration of the OBIA and Random Forest classifier using multi temporal Sentinel-2 satellite imagery. The results show that there is a decrease in the area of vegetation in the research area as much as 4,329.6 hectares to non-vegetation areas in the period 2016-2020. The vegetation area in 2020 is 84,716.07 hectares and non-vegetation area is 35,708 hectares. Thus, there has been a decrease in the percentage of vegetation area from 73.94% in 2016 to 70.35% in 2020, meanwhile for non-vegetation areas there has been an increase from 26.06% in 2016 to 29.65% in 2020.

1. Introduction

Vegetation in an area has an important role in maintaining a comfortable and sustainable environment for all residents (Wolch et al., 2014). Sustainability is closely related to the realization of equitable public health and environmental justice for all people, wherever they live and wherever they come from (Wolch et al., 2014). To maintain the carrying capacity of the environment, in regional development a harmonious synergy is needed between spatial planning and physical development (Priyanta, 2015). In relation to vegetation cover, the synergy can realize regional development that maintains the existence of vegetation to preserve the environment.

The role of vegetation in an area is controlling the impact of climate change. This climate change, at the city or district level, indicated by an increase in surface temperature due to anthropogenic activities that increase the concentration of greenhouse gases (Direktorat Jenderal Pengendalian Perubahan Iklim KLHK, 2020). The increase in surface temperature due to human activities can be controlled by planting vegetation in the area (Nse et al., 2020). Various studies have shown how vegetation in an area has a strong negative relationship with surface temperature (Guha & Govil, 2020). Furthermore, anthropogenic activities can lead to environmental degradation, especially air pollution (Referowska-Chodak, 2019). In this case, vegetation in an area can reduce air pollution by $PM_{2.5}$ pollutants (Wu et al., 2019).

In realizing a sustainable environment, there are various pressures on vegetation. This pressure causes a decrease in vegetation area due to the increasing need for residential land (Mukhoriyah et al., 2019). Increased economic activity also triggers changes in land use into settlements and industries (Cao et al., 2019). Not only that, the vegetation in the protected forest area also experiences land conversion into agricultural land and other anthropogenic forms (Fonge et al., 2019). Disturbances in an area also occur along with the expansion of urban areas (Gui et al., 2019).

Majalengka Regency is one of the areas in West Java Province that has experienced very intensive regional development along with the operation of the West Java International Airport (BIJB) and the Cipali toll road. BIJB has been operating and is located in a strategic location supported by excellence in accessibility (Syafarudin & Mulyana, 2019). The aerocity business concept promoted in the BIJB development or called the aerotropolis is a stimulant for economic growth, especially with the government's partnership with various business sectors (Tjahjono & Yuliawati, 2017). Another phenomenon related to physical development in Majalengka Regency is the construction of the Cipali toll road and train line which further increases accessibility to and from the Majalengka Regency area (Naipospos et al., 2020). With this condition, the development of other related physical developments such as settlements and industry in Majalengka Regency will increase and have the potential to increase land conversion from vegetation to built-up land, as has happened around BIJB Kertajati where the area of vegetation cover has been converted into built-up land and airport infrastructure (Sari & Kushardono, 2019).

Analysis of vegetation distribution in an area can be done using remote sensing techniques, as has been done in various studies, including the extraction of vegetation indices using multitemporal low spatial resolution remote sensing data for the study of urban vegetation dynamics (Lu et al., 2019). The use of medium spatial resolution satellite imagery data to determine the spatial and temporal dynamics of vegetation distribution in green spaces has also been carried out using Landsat (Sathyakumar et al., 2020). For remote sensing data with higher resolution, green space mapping has been carried out using GaoFen-2 imagery by looking at the physical features of green space such as vegetation types, as well as a combination of GaoFen-2 and Landsat images to see changes in the green space area (Chen et al., 2018; Yang et al., 2020). With the high spatial resolution of Sentinel-2, applications for vegetation studies have been carried out in various studies, including mapping of wetland vegetation, mapping of urban land cover and phenology of broadleaf plants in spring (Bhatnagar et al., 2020; Kowalski et al., 2020; Schug et al., 2020).

In the development of remote sensing data processing technology, image classification is effectively carried out based on objects and no longer based on pixels. This method is known as the Object Based Image Analysis (OBIA) method as a method of segmentation and classification based on objects in the image (Blaschke et al., 2000). The hybrid OBIA method with Random Forest (RF) is one of the most current and reliable methods for the analysis of vegetation distribution (Fu et al., 2017; Puissant et al., 2014). In research related to vegetation mapping in urban environments, the RF algorithm integrated with the OBIA method has been used for Quickbird satellite imagery and obtained good accuracy (Puissant et al., 2014).

Research to compare OBIA with pixel-based methods and RF algorithms has been conducted for mapping vegetation in wetlands using GF-1 imagery and SAR data and produces better accuracy using the OBIA method (Fu et al., 2017). In addition, mapping of sugarcane and riparian vegetation with the integration of OBIA and RF has been carried out with good accuracy (Luciano et al., 2019; Nguyen et al., 2019). By looking at the specifications possessed by Sentinel-2 imagery and the results achieved by integrating the OBIA and Random Forest methods in various studies, this study aimed to monitor the dynamics of vegetation cover by integrating the OBIA and Random Forest methods using multitemporal Sentinel-2 satellite imagery.

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2. Methods

This research was conducted in Majalengka Regency, West Java Province. Sentinel-2 satellite imagery data used in this study were acquired in the period 26 July 2016 and 23 September 2020. These two dates were chosen with the consideration that both data are the clearest data from cloud cover. The availability of the clear optical imagery or the lowest cloud cover throughout the year is very difficult for tropical regions such as Indonesia, especially in areas with highlands or mountains as in some of the study areas.

In both acquisition periods, cloud cover was the lowest so that the vegetation analysis could be carried out optimally. Moreover, both are in the acquisition period with the closest month having the same season, namely the end of the dry season to the beginning of rainy season so as to minimize the effect of seasonal differences on the research results.

The research continued with the extraction of vegetation and non-vegetation using the OBIA method approach. This object-based classification is carried out using multi resolution segmentation and random forest classifier algorithms. In the multi resolution segmentation process, the input parameters scale and homogeneity namely compactness and shape were used. This approach is carried out by starting with segmentation or separation of objects (Labib & Harris, 2018; Sari & Kushardono, 2016; Uca Avci et al., 2014). After doing this step, the vegetation and non-vegetation classes will be generated. The research flowchart is shown in Figure 1. This segmentation describes the relationship between the level of concordance or suitability (h) with the dimension-feature space (d) of two adjacent image objects as follows:

$$h = \sqrt{\sum_{d} (f1d - f2d)^2}$$

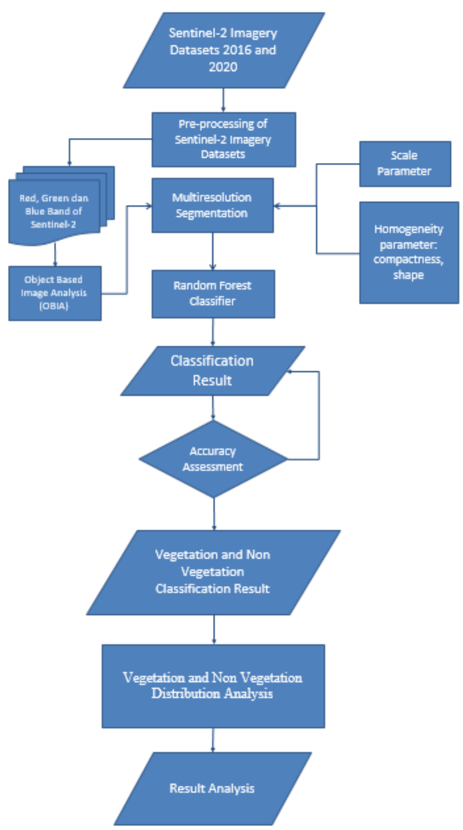

Figure 1. Flowchart of the vegetation cover dynamics analysis

3. Results and Discussion

Segmentation in this research is done by multiresolution segmentation algorithm. This segmentation algorithm has advantages in classification results compared to other methods (Kavzoglu & Tonbul, 2017). Table 1 shows the results of segmentation of satellite imagery in the acquisition period of 26 July 2016. Based on the results of data processing for Sentinel-2 satellite imagery in the acquisition period, the best segment results are obtained at a parameter value of 200 scale with a processing time of about 2 minutes. In this scale parameter, the number of objects formed from a total of 24,278,610 pixels is 12,062 objects. As for the shape and compactness variables used for all parameters of the same scale, namely shape 0.1 and compactness of 0.5. For a scale parameter smaller than 200, the object segment formed is less than optimal because there are homogeneous objects whose segments are separated, while for a larger scale parameter of 250, there are different object segments that are joined.

Table 1. Segmentation Results of Sentinel-2 Satellite Image (Period 26 July 2016)

No	Shape	Compactness	Scale Parameter	Total Objects
1	0.1	0.5	50	162,046
2	0.1	0.5	100	43,606
3	0.1	0.5	150	20,321
4	0.1	0.5	200	12,062 (optimal)
5	0.1	0.5	250	8,058 (There are segments of paddy fields and settlements combined)
Total pixels: 24,278,610 (Time: 2 minutes)				

Source: Analysis, 2021

Figure 2 shows the visualization of the segment at the optimal segmentation stage at a scale parameter of 200 for the image acquisition period on July 26, 2016. In the results of the first segmentation area, it can be seen that the objects contained in the area are built up land as part of the airport infrastructure in the form of an airplane runway, vegetation of paddy fields, rivers and built up land in the form of settlements. In the results of the segmentation of the second region for the same period in 2016, it can be seen objects in the form of clouds and shadows, built up land and forest vegetation. From the results of segmentation of this scale parameter, it can be seen that the object segments are well separated, where the built-up land object is separated from the paddy field vegetation although it has similar visual characteristics. In addition to the river object, the meandering river and the vegetation around the river are also well separated. As for rice fields that have different phases, the object segments are separate. At the time of classification, samples for wetland vegetation can be selected to represent each existing phase.

Furthermore, Figure 3 is a map showing the distribution of vegetation in Majalengka Regency in 2016. From the total area of Majalengka Regency of 120,424 hectares, the area which includes vegetation in 2016 is 89,045.69 hectares and non-vegetation area is 31,378 hectares. By looking at this total area, it can be seen that the percentage of vegetation area is 73.94% while non-vegetation in 2016 is 26.06%. On the map it can be seen that the vegetation in this area is evenly distributed in almost all districts. Classification is carried out using the OBIA method and the random forest classifier algorithm which produces vegetation and non-vegetation objects. The resulting non-vegetated objects are built up land, bodies of water, clouds and shadows. Non-vegetation objects in the form of clouds and shadows are found in the highlands and slopes of Mount Ciremai. Other non-vegetation objects are scattered in Kertajati District, Dawuan District, Ligung District, Palasah District, Jatiwangi District, Sukahaji District, Kasokandel District, Majalengka District, Leuwimunding District, Banjaran District, Bantarujeg District, Cikijing District and Talaga District. Meanwhile, vegetation objects are found in almost all sub-districts in Majalengka Regency.

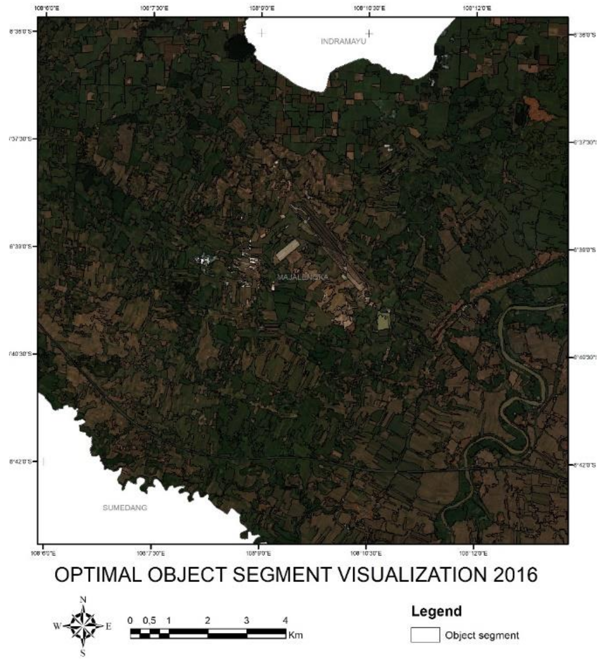

Figure 2. Visualization of Optimal Object Segmentation Results in 2016

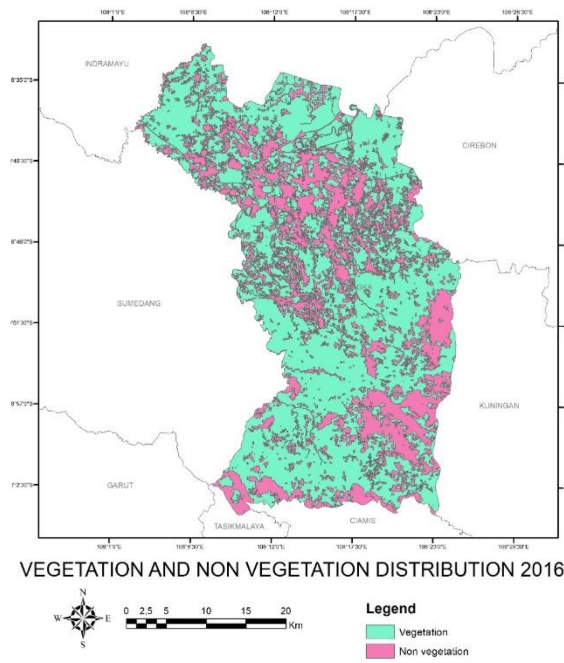

Figure 3. Distribution of Vegetation in Majalengka Regency in 2016

Table 2 shows the results of the accuracy test carried out on the classification of vegetation and non-vegetation land cover in Majalengka Regency in 2016. It can be seen in the table that there are three types of non-vegetation land cover, namely built-up land, water bodies and clouds/ shadows. Thus there are four classes in the accuracy test table. The overall accuracy obtained is 0.86 with a Kappa Index of 0.715. This shows that the classification results obtained in the form of vegetated and non-vegetated land cover in the study area are classified as high and reliable. With this fairly high level of accuracy, the obtained vegetated and non-vegetated areas can be accepted and analyzed further.

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Table 2. Accuracy Assessment of Land Cover Classification Result in 2016

User \ Reference Class	**Built-up land**	**Water bodies**	**Vegetation**	**Cloud/ shadows**	**Sum**
Built-up land	129,452	709	45,418	761	176,340
Water bodies	0	27,022	0	0	27,022
Vegetation	42,773	0	367,439	166	410,378
Cloud/ shadows	0	0	0	19,421	19,421
Unclassified	0	0	0	0	0
Sum	172,225	27,731	412,857	20,348	
Producer	0.75	0.97	0.89	0.95	
User	0.73	1	0.89	1	
Hellden	0.74	0.98	0.89	0.98	
Short	0.59	0.97	0.81	0.95	
KIA Per Class	0.65	0.97	0.68	0.95	
Overall Accuracy	0.86				
KIA	0.71				

Source: Analysis, 2021

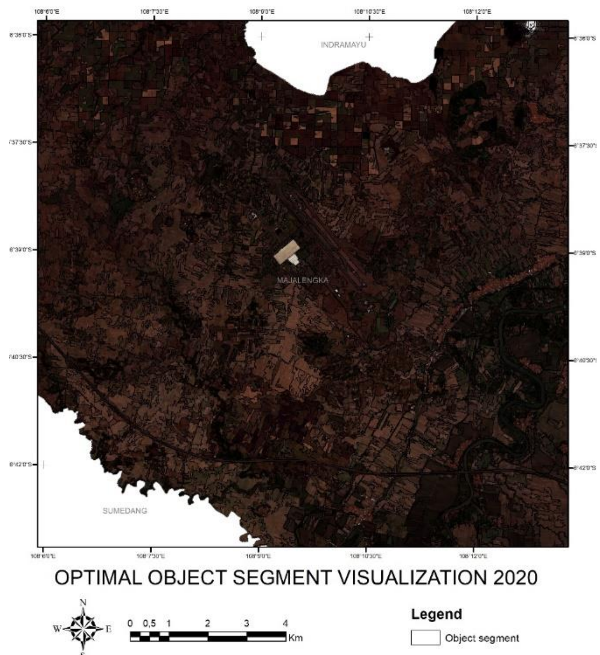

Figure 4. Visualization of Optimal Object Segmentation Results in 2020

Figure 4 shows segment visualization at the optimal segmentation stage at a scale parameter of 150 for the image acquisition period of 23 September 2020. In the results of the first segmentation, it can be seen that during this period, the built-up area in BIJB Kertajati has more extensive coverage area including buildings and airport infrastructure. Around the airport, we can see paddy fields in the fallow phase and built-up area or settlements. At this scale parameter, the objects can be separated properly, making it easier to take samples for different objects during classification. As for river objects, these objects can also be separated well from surrounding objects such as vegetation, although visually they have almost the same roughness. However, the scale parameter of 150 is able to differentiate river objects from the shape and color which are different from the vegetation. In the second area for the same acquisition period, it can be seen that cloud and shadow objects can be separated well, as well as vegetation objects that are well separated from residential built-up area even though the settlements are relatively small. This scale parameter was chosen because at the 200 scale parameter, objects that should be different are combined, on the contrary at the 100 scale parameter, there are still many homogeneous objects that are separated by segments so that they are less effective when selecting samples in the next process.

To determine the dynamics of vegetation in the study area, land cover classification was carried out on the Sentinel-2 satellite imagery which was acquired on September 23, 2020. As Table 3 below, it describes the results of image segmentation during the acquisition period. In the table, it can be seen that the best segment results are obtained at the scale parameter of 150 value which is different from 2016. The processing time is approximately 2 minutes. This is because at this scale parameter, the number of objects formed from a total of 24,224,198 pixels, namely 20,761 objects, is the optimal result in delineating objects in the study area. Meanwhile, on a scale parameter of 200, there are segments of settlements and vegetation that are combined, while for parameters smaller than 150, there are several homogeneous objects such as vegetation but still separated by segments. As for the shape and compactness variables used for all scale parameters, the shape value is 0.1 and the compactness is 0.5.

Table 3. Segmentation Results of Sentinel-2 Satellite Image (Period 23 September 2020)

No	Shape	Compactness	Scale Parameter	Total Objects
1	0.1	0.5	50	167,075
2	0.1	0.5	100	45,085
3	0.1	0.5	150	20,761 (optimal)
4	0.1	0.5	200	12,156 (residential and vegetation segments are combined)
Total pixels: 24,224,198 (Time: 2 minutes)				

Source: Analysis, 2021

Furthermore, Figure 5 is a map that shows the distribution of vegetation in Majalengka Regency in 2020. In the image of this period, there is a decrease in vegetation area compared to the previous image acquisition period in 2016. Of the total area of Majalengka Regency which is 120,424 hectares, the area which includes vegetation in 2020 is an area of 84,716.07 hectares and non-vegetation area of 35,708 hectares. By looking at this total area, it can be seen that there is a decrease in the percentage of vegetation area, from 73.94% to 70.35%, while non-vegetation in 2020 has increased from 26.06% to 29.65%.

On the map it can be seen that the vegetation in this area is still evenly distributed in almost all districts. The resulting non-vegetation objects are built up, water bodies, clouds and shadows. As in the 2016 image, in the 2020 image, non-vegetation objects including clouds and shadows are found in the highlands and slopes of Mount Ciremai which are covered with clouds throughout the year. Non-vegetation objects appeared to increase in Kertajati District, Jati Tujuh District, Dawuan District, Ligung District, Palasah District, Kadipaten District, Jatiwangi District, Sukahaji District, Kasokandel District, Cigasong District, Majalengka District, Leuwimunding District, Banjaran District, Bantarujeg District, Cikijing District and Talaga District. Meanwhile, vegetation objects are found in almost all sub-districts in Majalengka Regency.

In the period 2016 - 2020, there was a decrease in vegetation area of 4,329.6 hectares which became a non-vegetation area. Most of this land conversion occurred in the area of West Java International Airport (BIJB) Kertajati and its surroundings which became built-up land in the form of settlements. Besides, the addition of non-vegetation areas also occurred in other sub-districts such as Dawuan District, Jatiwangi District, Kadipaten District, Kasokandel District, Cigasong District, Majalengka District, Maja District and Bantarujeg District in the form of additional transportation access like roads and settlements. The vegetation that has undergone conversion is mostly paddy fields which are still widely found around settlements.

Table 4 below shows the result of the accuracy assessment carried out on the classification of vegetated and non-vegetation land cover in Majalengka Regency for the acquisition period on 23 September 2020. It can be seen in the table that there are three types of non-vegetation land cover, namely built-up area, water bodies and clouds/ shadows. Thus, there are a total of four classes in the accuracy test table. In each class, it can be seen the number of pixels used as test data for accuracy tests. The test data were chosen evenly in their location distribution and optimally selected in each class so that they were representative of the accuracy of the classification results per class. The overall accuracy obtained is 0.87 with a Kappa Index of 0.757. This shows that the classification results obtained in the form of vegetation and non-vegetation land cover in the study area for satellite imagery in 2020 are high and reliable. With a fairly high level of accuracy, the results of the calculation of the area of vegetation and non-vegetation areas obtained can be accepted and analyzed further.

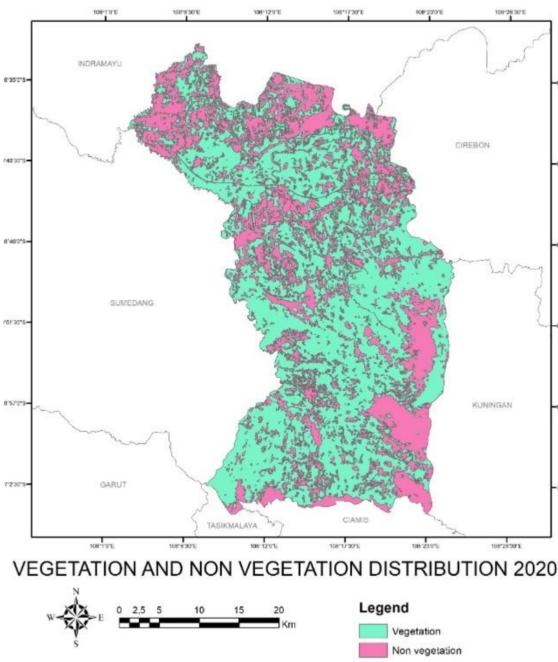

Figure 5. Distribution of Vegetation in Majalengka Regency in 2020

Table 4. Accuracy Assessment of Land Cover Classification Result in 2020

User \ Reference Class	Built-up land	Vegetation	Water bodies	Cloud/ shadows	Sum
Built-up land	41,045	14,027	0	0	55,072
Vegetation	2,303	112,337	205	930	115,775
Water bodies	0	0	8,522	0	8,522
Cloud/ shadows	6,744	0	0	5,236	11,980
Unclassified	0	0	0	0	0
Sum	50,092	126,364	8,727	6,166	
Producer	0.82	0.89	0.98	0.85	
User	0.74	0.97	1	0.44	
Hellden	0.78	0.93	0.99	0.58	
Short	0.64	0.86	0.98	0.40	
KIA Per Class	0.75	0.72	0.97	0.84	
Overall Accuracy	0.87				
KIA	0.76				

Source: Analysis, 2021

4. Conclusion

Analysis of the distribution model of vegetation and non-vegetation in 2016 and 2020 has been carried out using Sentinel-2 satellite imagery data. The multi temporal distribution of vegetation and non-vegetation models shows that there is a decrease in vegetation area of 4,329.6 hectares to non-vegetation areas in the 2016-2020 period. The area including vegetation in 2020 is 84,716.07 hectares and non-vegetation area is 35,708 hectares. Thus, there has been a decrease in the percentage of vegetation area from 73.94% in 2016 to 70.35% in 2020, meanwhile for non-vegetation areas there was an increase from 26.06% to 29.65% in 2020.

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6. Conflict of interests

The authors declare that there is no conflict of interest with any financial, personal, or other relationships with other people or organizations related to the material discussed in the article.

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