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Deforestation Analysis in Taba Penanjung District with NDVI

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Abstract. Forests are cleared to expand residential areas and plantations or change the allocation of forest land to non-forest (deforestation). This study aims to create a map of the condition of the forest area and find out the areas affected by deforestation and determine the rate of change in the forest area in the Taba Penanjung District forest area. First data on Landsat 8 images geometric correction performed to position image data so that it matches the actual coordinates and performing Radiometric Correction is used to correct if an error or distortion occurs due to imperfect operation and sensors. NDVI Method is the method used for comparing the greenness of vegetation in satellite imagery, which uses band 4 (Red) and band 5 (NIR), which is processed by ArcMap software. The results of this study produced a map of the condition of forest areas and the area of land affected by deforestation. Forest turn-over rates were described in the annual trend from 2013 to 2018. Furthermore, this research shows that deforestation in the Taba Penanjung district has happened in 58% of the total area of 23, 747 ha. Although the deforestation has decreasing value in 2015 by 1.6%, it showed that there were increasing values in deforestation rate in 2014, 206, 2017 by 1.4%, 1.9%, and 9.5% respectively from the total area of 23, 747 ha.

Keywords: Deforestation, Taba Penanjung, NDVI, Landsat 8, ArcMap.

1. INTRODUCTION

Deforestation in Indonesia has increased in recent years. The entire area under the moratorium has lost 2.5 million ha of primary forest since 2002 to 2012 [1], [2]. In the seven years before the moratorium was announced (2005-2011) total deforestation in these areas was 800,000 ha [3]. In the seven years since its entry into force (2012-2018), total deforestation has reached 1.2 million ha [4], [5]. The average annual deforestation rate in these areas is 97,000 ha for the period 2005-2011, rising to 137,000 ha for 2012-2018. Although there was a significant decrease in deforestation in 2018 compared to previous years for that period (fell to 112,000 ha for that year), this rate of deforestation is still higher than the average deforestation in these areas before the moratorium entered into force. This shows that the recent public claims about improved governance in protected areas (such as areas under the moratorium) are premature claims [6].

During the period 2017-2018, Greenpeace found that there was a slight increase in the loss of primary forest in Papua in the moratorium area. Therefore, a moratorium is not an effective tool for consolidating deforestation reduction. In addition, during the moratorium period (2011 - 2018), data showed that total deforestation in the moratorium area reached 1.2 million ha, while Indonesia's total deforestation (inside and outside the moratorium area) reached 4.38 million ha. This condition showed that deforestation in the moratorium area is equivalent to 27.4% of the total deforestation that occurred in Indonesia [7]. Furthermore, the rate of deforestation or forest damage in Bengkulu is already quite high, namely 231.157.75 hectares of the total forest area of 924,631 hectares, both protection forests, conservation and production forests [3],. Based on data from the Bengkulu Province Forestry Service alerts earlier, the condition of our forests is worsened by the number of forest encroachment activities, illegal logging, land conversion and forest fires. Research like [8], [9] also confirmed that there is a problem in forest management in Sumatra, especially Bengkulu, so it can't achieve the best approach in managing the forest in Bengkulu.

Taba Penanjung is one of the districts at Bengkulu Province where the area is around 14.838 ha. Based on data, 71 % of forest area in Bengkulu was damaged. It is located approximately 30 km from Bengkulu city center, the location is shown in Figure 1. Taba Penanjung forest is the upper stream river region of Bengkulu Province which guarantees water quality in the downstream. Worse, the condition of Taba Penanjung forest is currently run into degradation and it is no longer has a function as it should be. Here, we showed the how forest is changed over Taba Penanjung District in Bengkulu with the method of NDVI to see the trend of the expanding area of deforestation.

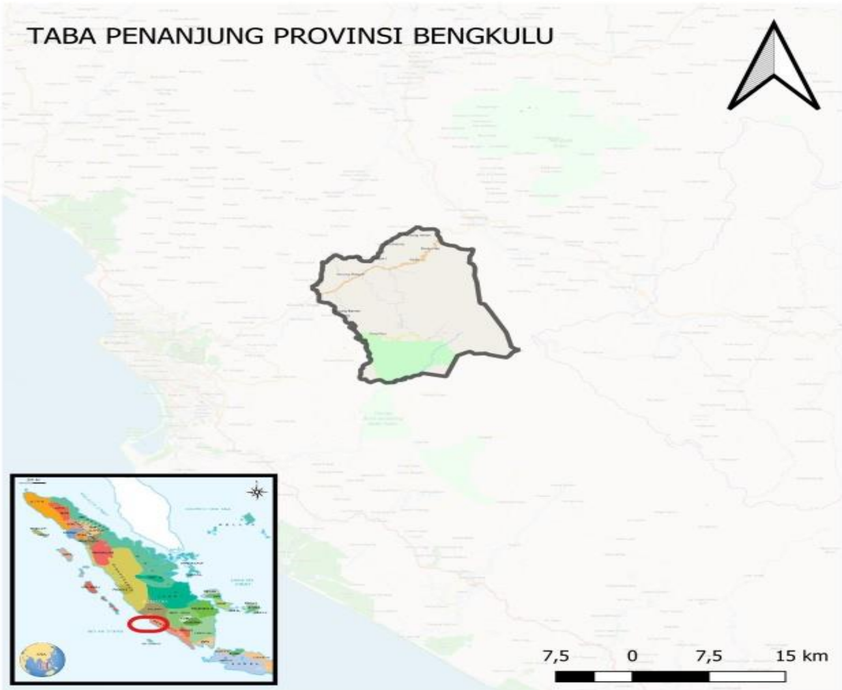

FIGURE 1. Taba Penanjung District

2. MATERIAL AND METHODS

The Indonesian Forest Zone is determined by the Minister of Forestry in the form of a ministerial decree concerning the selection of forest areas and changes in the Province. The appointment of forest areas includes areas that are part of the Nature

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Reserve Area (*KSA*) and Nature Conservation Area (*KPA*). Based on Law No. 41 of 1999 concerning Forestry, forest areas divided into Conservation Forests, Protection Forests and Production Forests [10]. In another hand, deforestation is the process of removing natural forests by logging for timber or changing the designation of forest land to non-forest. It can also be caused by intentional or natural forest fires [11]. Gaveau et al., (2009) and Kimberly M & Lisa M (2009) showed that the biggest factor that causes deforestation are plantation conversion, illegal logging, forest fire, use of firewood. Deforestation detection has been an emerging issue to halt the process of forest turns over to protect the sustainable ecology. Some technology approach already been used to help the process [14], [15]. Remote sensing is one of science or art to identify, observe and measure an object without direct contact with the object that involved technology for processing it. The process that occurs in it includes the detection and measurement of different wavelengths of radiation reflected or emitted from a particular object or material, with which it can be identified and categorized in class/type, existing material and spatial distribution [16], [17]. Geometric Correction to position image data so that it matches the actual coordinates, while doing Radiometric Correction is used to correct if there is an error or distortion caused by imperfect operation and sensors [18].

The 8 Landsat is the latest satellite consists of two science instruments - Operational Land Imager (*OLI*) and Thermal Infrared Sensor (*TIRS*). These two sensors provide seasonal coverage from the global mainland with a spatial resolution of 30 meters (*visible, NIR, SWIR*); 100 meters (*heat*); and 15 meters (*panchromatic*) [19], [20]. It includes the preprocessing scheme to provide the better result of classification. In this research we used NDVI approached to see the classification land use over the area. The Normalized Difference Vegetation Index (*NDVI*) method is a method used to compare the greenness of vegetation in satellite images, the NDVI method using band 4 (*Red*) is used to distinguish slopes and vegetation and band 5 (*NIR*) to emphasize the biomass content. NDVI is formulated as follows [21], [22]:

$$NDVI = \frac{Band\ 5\ (NIR) - Band\ 4\ (Red)}{Band\ 4\ (Red) + Band\ 5 (NIR)} \quad (1)$$

Map layout (*Layout*) is the last job after inputting data, changing data, analyzing data, adding labels, and setting legendary table of contents [23]. Thematic maps are a special map designed and presented to show specific themes that are connected to a specific geographical area. Thematic maps commonly used in planning include cadastral maps (*ownership limits*), legal land use map design (*Zone Map*), land use maps, population density maps, slope maps, geological maps, rainfall maps and agricultural productivity maps [24], [25].

Taba Penanjung is one of the critical areas in the Air Bengkulu sub-watershed. The various land uses in this area affect the watershed and the sustainability of the downstream areas. Recently, this area has become a destination for toll road construction because of its strategic position. In addition, this area has long been a coal mining area which affects waste pollution and sedimentation in rivers. Therefore, it is very important to know how the land is used in this area from year to year to become the basis for government policy in developing and developing this area without endangering the sustainability of other regions [26]. The images used in this research were the chain of image from Landsat 8, which already equipped by the cirrus band to reduce the cloud cover over the area of this research. The tile images of P125R63 were downloaded for each year to be processed with NDVI. The data were collected with the parameter of cloud coverage less than 30% to improve the accuracy of NDVI method. The method of NDVI was chosen because its ability to defined the density of canopy cover from the plantation in Remote Sensing image [21], [22]. This could be the benefit to determine the land cover inside the area of interest in this project. Thus would be the future research to see the forest turn over on the site. Research such as [27], [28] have proof the efficiency value of this method to process remote sensing image.

This study will utilize remote sensing data, namely Landsat 8 Image data downloaded on the Landsat 8 official website, namely https://earthexplorer.usgs.gov which is useful for data analysis of points of forest affected by deforestation using the Normalization Method Differences in Vegetation or NDVI Indices (Normalized Difference Vegetation Index). Can be seen the workflow in this study in Figure 2. The required data in this research is Landsat 8 image of Taba Penanjung form 2013 to 2018. Landsat image has 9 OLI bands and 2 thermal bands, to get the best results in image processing accordingly merging several bands. The next step is geometric correction and radiometric correction to make the image more representative by improving pixel values by considering atmospheric disturbance factors as the main source of error using the histogram approach. The input data used in this process is the GCP point georeference of the 6 Landsat 8 band image. To get a representative map the next step is image cutting followed by the Normalized Difference Vegetation Index (NDVI) to analyze vegetation on the earth's surface. The next step is image classification process, which is grouping all pixels into groups so that it can be interpreted as a specific property. After all the steps are taken, then make a map of the distribution of vegetation density with information that is overlaid with vegetation maps. Preprocessing was done by using the software of Er-Mapper to make the images from the satellite ready to be processed. The band 6, 5, and 4 were choose to be composited by the software. Each of bands from the year of 2013, 2014, 2015, 2016, 2017, and 2018 were proceed to be used for further process. Geometric corrections are performed to avoid geometric distortion of the distorted image. This can be achieved by determining the relationship between the image coordinate system and the geographic coordinate system using calibration data from sensors, position and altitude from measurement data, ground control points, atmospheric conditions, and so on. The method chosen should be appropriate after considering the geometric distortion characteristics and available reference data. Unknown parameters defining the mathematical equation between the image coordinate system and the geographic coordinate system should be determined using calibration data and/or ground control points. Here we are going to use a polynomial approach to process the image. The accuracy of the geometric corrections must be tested and verified. If the resulting accuracy does not meet the criteria, the method or data used should be tested and corrected in order to avoid mistakes. Images that have been identified with features on Earth should be produced using resampling and interpolation techniques. When the geometric or geometric reference data of the sensor is known or measured, theoretically or systematically, geometric distortion can be avoided. In general, a systematic correction is sufficient to eliminate all errors

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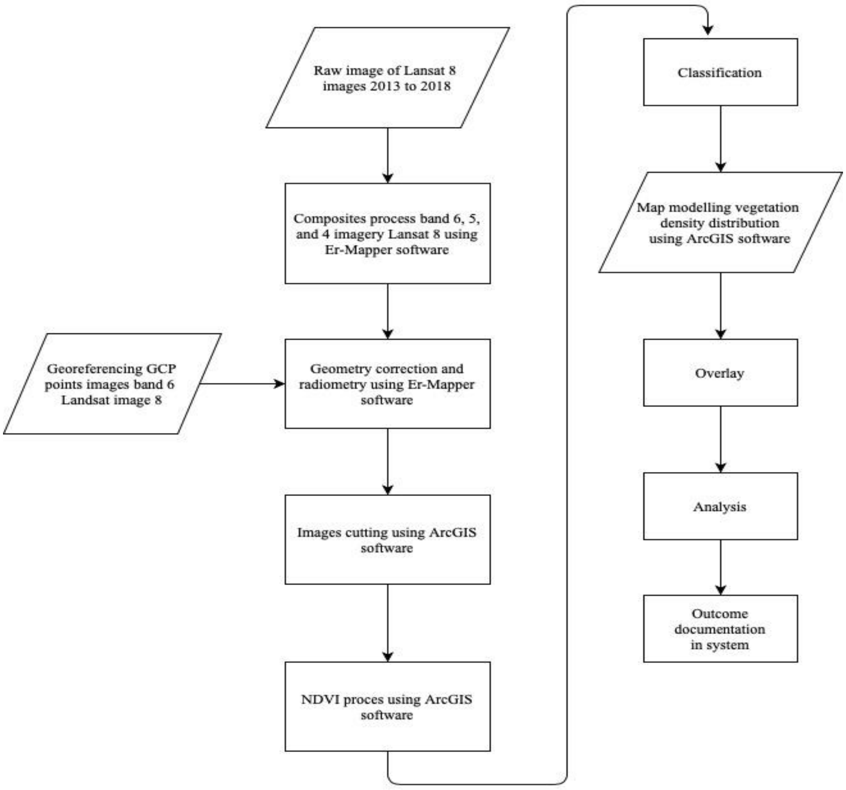

FIGURE 2. Flowchart of research work

Radiometric Calibration is the first step that must be done when we are processing satellite image data. The main purpose of this radiometric calibration is to convert the data in the image which is (generally) stored in the form of a Digital Number (DN) into radiance and / or reflectance, or also to brightness temperature (for Infrared Thermal channels). Radiometric correction is done because there is an error by the sensor and the sensor system on the detector response and the influence of a stationary atmosphere. Radiometric correction is carried out to correct or distortion caused by imperfect operation and sensors, attenuation of electromagnetic waves by the atmosphere, variations in data angles, variations in the angle of elimination, angles of reflection and others that may occur, data transmission and recording. There are two groups in the implementation of radio metrics namely radiometric calibration and. Radiometric calibration is the first step that must be taken when processing satellite image data. The main result of radiometric calibration is to convert the data in the image stored in the form of a digital number (DN) into radiance and / or reflectance. In addition, this radiometric calibration can change the digital number to the brightness temperature. In radiometric calibration, there are two ways based on increasing data, namely: the first method uses gain and offset, the data required is the radiance or reflectance multiple rescaling factor (GAIN) and additive rescaling factor offset then the second method uses the maximum and minimum radian or reflectance values. Vegetation index is the amount of green value of vegetation obtained from digital signal processing of brightness value data from several satellite sensor data channels. The process of comparing the brightness of the red light channel (red) and the near infrared light channel is carried out for vegetation monitoring. The phenomenon of absorption of red light by chlorophyll and reflection of near infrared light by the mesophyll network found on leaves will make the brightness values received by satellite sensors on these channels much different. On non-vegetation land, including water areas, residential areas, open vacant land, and areas with damaged vegetation conditions, will not show a high (minimum) ratio value. In contrast, in very tightly vegetated areas, with healthy conditions, the ratio of the two canals will be very high (maximum). The comparison value of the red light channel brightness with near infrared light or NIR / RED, is the value of a vegetation index (simple ratio) that is no longer used. This is because the value of the NIR / RED ratio will give a very large value for healthy plants.

3. RESULT AND DISCUSSION

Classification results of Landsat 8 image in the forest area of Taba Penanjung district:

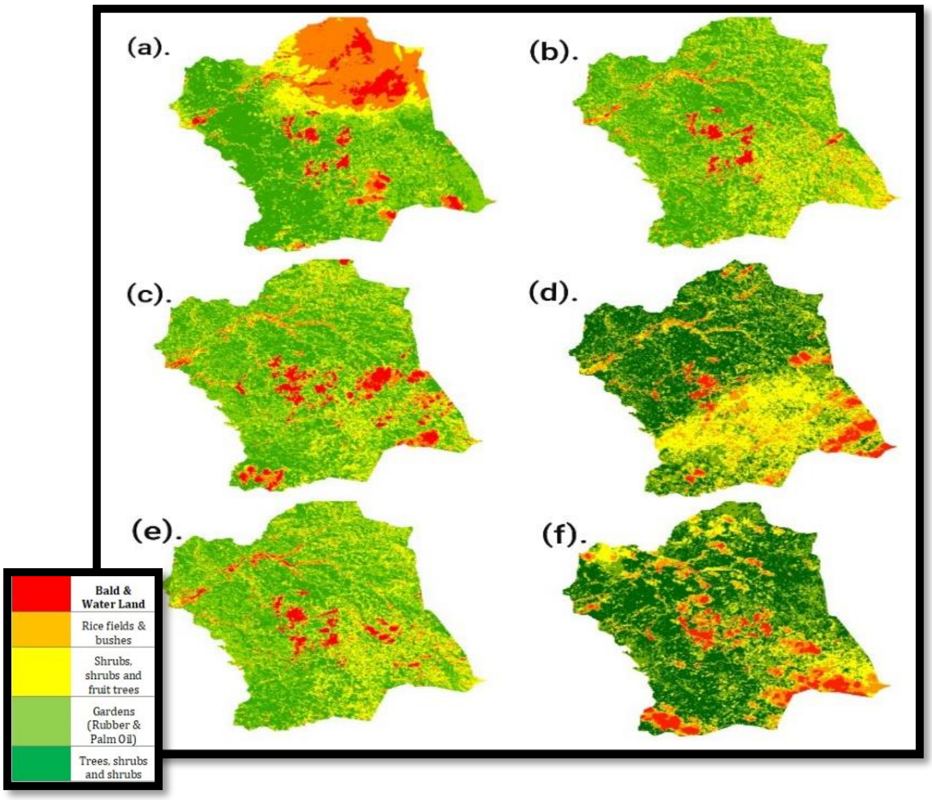

FIGURE 3. Results of Classification of Land Cover of Deforestation of Forest Areas in Taba Penanjung District In (a) 2013, (b) 2014, (c) 2015, (d) 2016, (e) 2017 and (f) 2018

In Figure 3 shows the results of classification using Landsat 8 image data from 2013 to 2018, in figure 3 (a) of the 2013 classification results, (b) 2014 classification results, (c) 2015 classification results, (d) year classification results. 2016, (e) the results of the 2017 classification, and (f) the results of the classification in 2018. The

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results of the analysis showing the extent of each classification and knowing the land cover of each classification can be seen in Table 1.

TABLE 1.
The results of analysis Lansat 8 image from 2013-2018

ear	Image Pixel Density	Image Pixel Amount	Classification Color	Information Field	Large (Ha)
2013	-0.189453721-0.17971028	16543 (6%)	Red	Bald & Water Land	1,489
	0.17971028 - 0.279224054	53135 (20%)	Orange	Rice fields & bushes	4,782
	0.279224054 - 0.391578315	33661 (13%)	Yellow	Shrubs, shrubs and fruit trees	3,029
	0.391578315 - 0.487881967	68036 (26%)	Light Green	Gardens (Rubber & Palm Oil)	6,123
	0.487881967 - 1	92469 (35%)	Dark Green	Trees, shrubs and shrubs	8,322
	TOTAL	263,896			23,745
2014	-0.235642567 - 0.193067117	5749 (2%)	Red	Bald & Water Land	517
	0.193067117 - 0.32809379	15698 (6%)	Orange	Rice fields & bushes	1,413
	0.32809379 - 0.41248546	49740 (19%)	Yellow	Shrubs, shrubs and fruit trees	4,477
	0.41248546 - 0.476623129	98919 (37%)	Light Green	Gardens (Rubber & Palm Oil)	8,903
	0.476623129 - 1	93738 (36%)	Dark Green	Trees, shrubs and shrubs	8,436
	TOTAL	263,844			23,746
2015	-1 - 0.174509804	7995 (3%)	Red	Bald & Water Land	720
	0.174509804 - 0.318039216	7995 (6%)	Orange	Rice fields & bushes	1476
	0.318039216 - 0.429803922	50095 (19%)	Yellow	Shrubs, shrubs and fruit trees	4509
	0.429803922 - 0.499607843	101024 (38 %)	Light Green	Gardens (Rubber & Palm Oil)	9092
	0.499607843 - 1	88335 (33%)	Dark Green	Trees, shrubs and shrubs	7950
	TOTAL	263,847			23,746
2016	-0.174449891 - 0.210215376	11190 (4%)	Red	Bald & Water Land	1007
	0.210215376 - 0.317791256	24279 (9%)	Orange	Rice fields & bushes	2185
	0.317791256 - 0.40254801	63624 (24%)	Yellow	Shrubs, shrubs and fruit trees	5726
	0.40254801 - 0.474265263	78085 (30%)	Light Green	Gardens (Rubber & Palm Oil)	7028
	0.474265263 - 1	86666 (33%)	Dark Green	Trees, shrubs and shrubs	7800
	TOTAL	263,844			23,746
2017	-0.158734471 - 0.188304466	13898 (5%)	Red	Bald & Water Land	1251
	0.188304466 - 0.312474361	20680	Orange	Rice fields &	1861

		(8%)		bushes	
	0.312474361 - 0.411173508	42909 (16%)	Yellow	Shrubs, shrubs and fruit trees	3862
	0.411173508 - 0.481218065	97269 (37%)	Light Green	Gardens (Rubber & Palm Oil)	8754
	0.481218065 - 1	89088 (34%)	Dark Green	Trees, shrubs and shrubs	8018
	TOTAL	263,844			23,746
2018	-0.146711633 - 0.171256905	15812 (6%)	Red	Bald & Water Land	1,423
	0.171256905 - 0.294550827	26707 (10%)	Orange	Rice fields & bushes	2,404
	0.294550827 - 0.401621865	37187 (14%)	Yellow	Shrubs, shrubs and fruit trees	3,347
	0.401621865 - 0.482736288	74046 (28%)	Light Green	Gardens (Rubber & Palm Oil)	6,664
	0.482736288 - 0.680655479	111580 (42 %)	Dark Green	Trees, shrubs and shrubs	10.042
	TOTAL	263,843			23,747

In Figure 4 shows the results of the analysis of Landsat 8 images from 2013-2018 which have been carried out by the classification process of NDVI Method, the data shows that in 2013 dominated 35% of Very Solid Vegetation Classification with an area of 8,322 Ha, 2014 dominated by Vegetation classification Solid with a percentage of 37% with an area of 8,903 Ha, in 2015 dominated by classification of Solid Vegetation with a percentage of 38% with an area of 9,092 Ha from a total area of 23,746 Ha, in 2016 dominated by classification of Very Solid Vegetation with a percentage of 33% with an area of 7,800 Ha, 2017 dominated by classification Solid Vegetation with a percentage of 37% with an area of 8,754 Ha, in 2018 dominated by classification of Very Solid Vegetation with a percentage of 42% with an area of 10,042 Ha, the following results of data in graphical form can be seen in Figure 4.

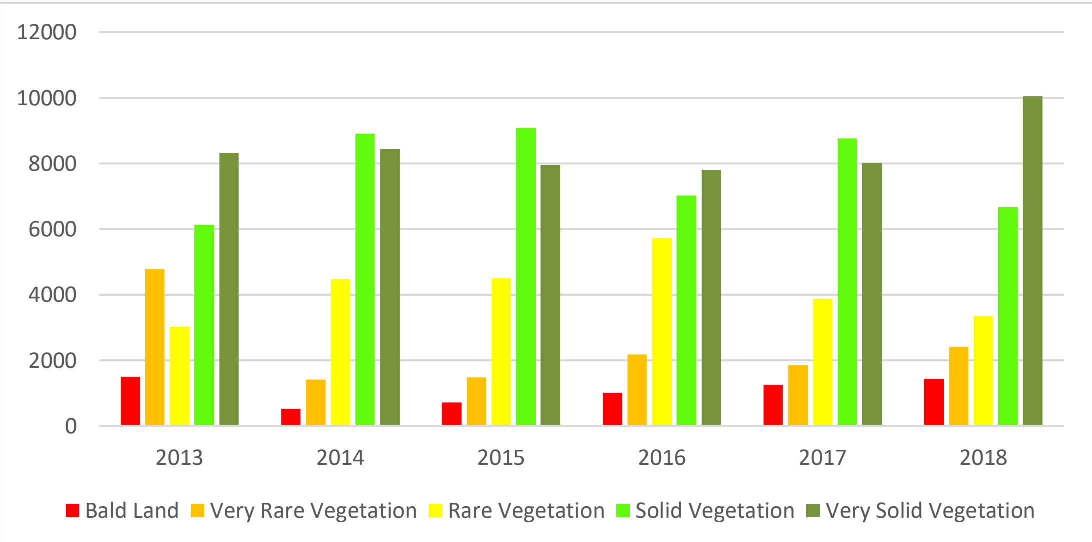

FIGURE 4. Results of Analysis of Deforestation

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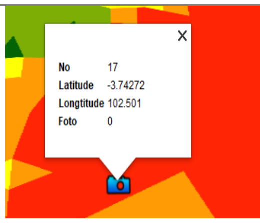
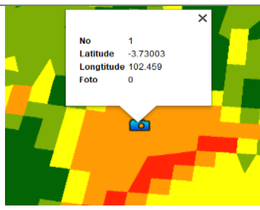
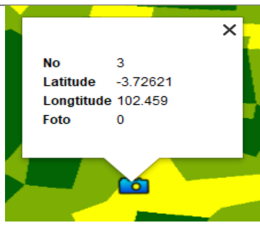
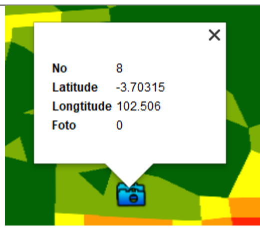
3.1.GROUND CKECKING

In the process of checking the field it is useful to determine the success rate of the method used, namely the NDVI method and also useful to be a limitation in calculating the area of forest and non-forest. Ground check is done by checking the area based on Landsat 8 imagery with the actual conditions and record on land changes. The method is simply picking the point on the classification process and checks the truth on the area based on the position in latitude and longitude on the ground. The following are the results of checking the field in the area of Taba Penanjung Subdistrict in Table 2. All of the definition of the classification refers to the standard process of MoEF of Indonesia, including the definition of forest and tree [10].

TABLE 2.
Ground Checking Result

No.	Location	Figure	Image	Information
1.	Tj. Raman village			y: -3.742715 x: 102.50115 Image Classification: Bald land Field: Coal mining
2.	Tj. Raman village			y: -3.73003 x: 102.458738 Image Classification: Very rare vegetation Field: Rice fields
3.	Tj. Raman village			y: -3.726213 x: 102.458926 Image Classification: Rare vegetation Field: Rubber plantation
4.	Lubuk Sini village			y: -3.703153 x: 102.505679 Image Classification: Solid vegetation Field: Trees, shrubs and bamboo plants.

5.	Tj. Raman village			y: -3.72886 x: 102.482878 Image Classification: Very Solid Vegetation Field: Tree/forest.

In Table 3 the results of checking the fields show the results of checking that is in the real field, by random sampling, then each point that has the coordinates coordinated then the coordinates obtained are entered into the Google Earth Software. The results of checking this field are as follows.

TABLE 3.
Field Check Results

No.	Classification Color	Type of Land in Field
1.	Red	Water, Bald Land, mine coal mine
2.	Orange	Bush and Rice Field
3.	Yellow	Shrubs, shrubs and fruit trees (Coconut tree, rambutan)
4.	Light Green	Palm plantation & rubber plantation
5.	Dark Green	Trees and shrubs

The stipulation of the Minister of Forestry Regulation on Procedures for Reducing Emissions from Deforestation and Forest Degradation (REDD) stipulates that:

1. *Article 1 paragraph 1*: Forest is an ecosystem unit in the form of a stretch of land containing biological natural resources dominated by trees in the fellowship of their natural environment, which cannot be separated from one another.
2. *Article 1 paragraph 2:* Deforestation is the permanent change of forested areas to non-forested caused by human activities.

Then from the above provisions and supported by the results of checking the fields in Table 3, it was found that forest areas used classification of Very Solid Vegetation, whereas for non-forest areas using the limitation of classification of Bald Land, vegetation was very rare, vegetation was rare, vegetation was dense, determination of classification limits was obtained. from the ground check analysis. The following is a graph of the results of the rate of change in forest and non-forest area in the Taba Penanjung district forest area.

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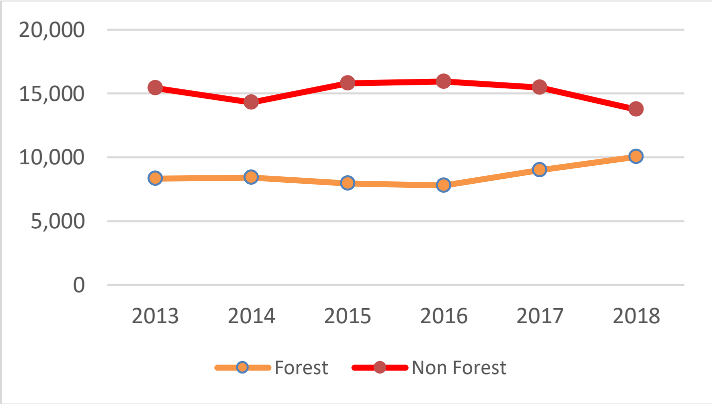

FIGURE 5. Graph of forest and non-forest areas

In Figure 5 shows the results of the area of forest and non-forest areas. In the calculation of forest and non-forest areas there are still shortcomings, such as the data used, namely Landsat 8 image data in the Taba Penanjung district area, there are still thick clouds, thin clouds which affect the results of the calculations carried out, which of the regions the cloud covered means there is still land that cannot be analyzed by *ArcGIS Software* because of the closure of a forest or land area by the cloud and affects the process of data analysis performed on *ArcGIS Softw*are using the *NDVI* method.

4. CONCLUSION

This research have been succeed to establish Thematic Map of forest conditions in the Taba Penanjung district area from 2013-2018. For that period, we found thatthe area of forest land affected by deforestation in the forest area of the district of Taba Penanjung is 13,750 Ha. Forest turn-over rates were described in the annual trend from 2013 to 2018. Furthermore, this research shows that deforestation in the Taba Penanjung district has happened in 58% of the total area of 23, 747 ha. Although the deforestation has decreasing value in 2015 by 1.6%, it showed that there were increasing values in deforestation rate in 2014, 206, 2017 by 1.4%, 1.9%, and 9.5% respectively from the total area of 23, 747 ha. Furthermore, this research also found that there is no reforestration activity during this period of time. This research still can be expand to a braoder solution for further decion maker and policy. We recommend some research that can be expand from this research are: (a)This result still contains area with cloud covered that could be leads to different group of the land cover classification, involving the algorithm to reduce the cloud would be useful for further research; (b) Some latest classification methods have been published while this paper in progress of publication. Further research direction could be the using of another method to improve the result of classification with Remote Sensing image. (c) This data has limited chunk of the years, further research can be processing with additional year backward and forward.

REFERENCES

[1] M. C. Hansen *et al.*, “High-Resolution Global Maps of 21st-Century Forest Cover Change,” *Science (80-.).*, vol. 342, no. 6160, pp. 850–853, 2013, doi: 10.1126/science.1244693.

[2] A. Langner and F. Siegert, “Spatiotemporal fire occurrence in Borneo over a period of 10 years,” *Glob. Chang. Biol.*, vol. 15, no. 1, pp. 48–62, 2009, doi: 10.1111/j.1365-2486.2008.01828.x.

[3] B. A. Margono, P. V. Potapov, S. Turubanova, F. Stolle, and M. C. Hansen, “Primary forest cover loss in Indonesia over 2000–2012,” *Nat. Clim. Chang.*, vol. 4, no. 8, pp. 730–735, 2014, doi: 10.1038/nclimate2277.

[4] L. Tacconi, R. J. Rodrigues, and A. Maryudi, “Forest Policy and Economics Law enforcement and deforestation : Lessons for Indonesia from Brazil ☆,” *For. Policy Econ.*, vol. 108, no. September 2018, p. 101943, 2019, doi: 10.1016/j.forpol.2019.05.029.

[5] C. Kubitza, V. V Krishna, K. Urban, Z. Alamsyah, and M. Qaim, “Land Property Rights, Agricultural Intensification, and Deforestation in Indonesia,” *Ecol. Econ.*, vol. 147, pp. 312–321, 2018, doi: https://doi.org/10.1016/j.ecolecon.2018.01.021.

[6] B. A. Margono *et al.*, “Mapping and monitoring deforestation and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010,” *Environ. Res. Lett.*, vol. 7, no. 3, p. 034010, 2012, doi: 10.1088/1748-9326/7/3/034010.

[7] T. Cadman, T. Sarker, Z. Muttaqin, F. Nurfatriani, M. Salminah, and T. Maraseni, “The role of fiscal instruments in encouraging the private sector and smallholders to reduce emissions from deforestation and forest degradation: Evidence from Indonesia,” *For. Policy Econ.*, vol. 108, no. April, p. 101913, 2019, doi: 10.1016/j.forpol.2019.04.017.

[8] K. G. Austin, A. Mosnier, J. Pirker, I. McCallum, S. Fritz, and P. S. Kasibhatla, “Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments,” *Land use policy*, vol. 69, 2017, doi: 10.1016/j.landusepol.2017.08.036.

[9] R. B. Thapa, T. Itoh, M. Shimada, M. Watanabe, M. Takeshi, and T. Shiraishi, “Evaluation of ALOS PALSAR sensitivity for characterizing natural forest cover in wider tropical areas,” *Remote Sens. Environ.*, vol. 155, pp. 32–41, 2014, doi: 10.1016/j.rse.2013.04.025.

[10] Ministry of Forestry of the Republic of Indonesia, “Consolidation Report Reducing Emissions From Deforestation And Forest Degradation In Indonesia,” 2008.

[11] K. M. Carlson *et al.*, “Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia,” *Proc. Natl. Acad. Sci.*, vol. 109, no. 19, pp. 7559–7564, 2012, doi: 10.1073/pnas.1200452109.

[12] C. Kimberly M and C. Lisa M, “REDD pilot project scenarios: are costs and benefits altered by spatial scale?,” *Environ. Res. Lett.*, 2009, doi: 10.1088/1748-9326/4/3/031003.

[13] D. L. A. A. Gaveau, S. Wich, J. Epting, D. Juhn, M. Kanninen, and N. Leader-Williams, “The future of forests and orangutans (Pongoabelii) in Sumatra: Predicting impacts of oil palm plantations, road construction, and mechanisms for reducing carbon emissions from deforestation,” *Environ. Res.*

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

Lett., vol. 4, no. 3, 2009, doi: 10.1088/1748-9326/4/3/034013.

[14] J. P. Shim, M. Warkentin, J. F. Courtney, D. J. Power, R. Sharda, and C. Carlsson, “Past, present, and future of decision support technology,” *Decis. Support Syst.*, vol. 33, no. 2, pp. 111–126, 2002, doi: 10.1016/S0167-9236(01)00139-7.

[15] A. Vatresia, J. P. Sadler, R. R. Rais, and E. Imandeka, “The development of mobile application for conservation activity and wildlife in Indonesia,” in *Proceeding - 2016 International Conference on Computer, Control, Informatics and its Applications: Recent Progress in Computer, Control, and Informatics for Data Science, IC3INA 2016*, 2017, vol. 2016-Septe, pp. 203–208, doi: 10.1109/IC3INA.2016.7863050.

[16] N. E. Young, R. S. Anderson, S. M. Chignell, A. G. Vorster, R. Lawrence, and P. H. Evangelista, “A survival guide to Landsat preprocessing,” *Ecology*, vol. 98, no. 4, pp. 920–932, 2017, doi: 10.1002/ecy.1730.

[17] J. Southworth *et al.*, “Land cover change and landscape fragmentation—comparing the utility of continuous and discrete analyses for a western Honduras region,” *Glob. Environ. Chang.*, vol. 101, no. 2–3, pp. 185–205, 2016, doi: 10.1146/annurev.energy.28.050302.105459.

[18] P. M. Mather and M. Koch, “Preprocessing of Remotely-Sensed Data,” in *Computer Processing of Remotely-Sensed Images*, John Wiley & Sons, Ltd, 2011, pp. 87–124.

[19] S. Anwar and A. Stein, “Use of spatial statistics to investigate early forest degradation activities as detected from satellite images,” *Spat. Stat.*, vol. 12, pp. 50–64, 2015, doi: 10.1016/j.spasta.2015.01.003.

[20] M. Panta, K. Kim, and C. Joshi, “Temporal mapping of deforestation and forest degradation in Nepal: Applications to forest conservation,” *For. Ecol. Manage.*, vol. 256, no. 9, pp. 1587–1595, 2009, doi: 10.1016/j.foreco.2008.07.023.

[21] K. Prabhakara, W. D. Hively, and G. W. McCarty, “Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 39, pp. 88–102, 2015, doi: https://doi.org/10.1016/j.jag.2015.03.002.

[22] W. Wu, “Derivation of tree canopy cover by multiscale remote sensing approach,” *Work. Geospatial Data Infrastruct. from data Acquis. Updat. to smarter Serv.*, no. Cc, pp. 142–149, 2002, doi: 10.5194/isprsarchives-XXXVIII-4-W25-142-2011.

[23] M. Broich, M. Hansen, F. Stolle, P. Potapov, B. A. Margono, and B. Adusei, “Remotely sensed forest cover loss shows high spatial and temporal variation across Sumatera and Kalimantan, Indonesia 2000-2008,” *Environ. Res. Lett.*, vol. 6, no. 1, 2011, doi: 10.1088/1748-9326/6/1/014010.

[24] C. Song, C. E. Woodcock, K. C. Seto, M. P. Lenney, and S. A. Macomber, “Classification and change detection using Landsat TM data: When and how to correct atmospheric effects?,” *Remote Sens. Environ.*, vol. 75, no. 2, pp. 230–244, 2001, doi: 10.1016/S0034-4257(00)00169-3.

[25] T. Hermosilla, M. A. Wulder, J. C. White, N. C. Coops, and G. W. Hobart, “An integrated Landsat time series protocol for change detection and generation of annual gap-free surface reflectance composites,” *Remote Sens.*

Environ., vol. 158, pp. 220–234, 2015, doi: 10.1016/j.rse.2014.11.005.

[26] A. S. Cohen, R. Bills, C. Z. Cocquyt, and A. G. Caljon, "The Impact of Sediment Pollution on Biodiversity in Lake Tanganyika," *Conserv. Biol.*, vol. 7, no. 3, pp. 667–677, 1993, doi: 10.1046/j.1523-1739.1993.07030667.x.

[27] B. DeVries, J. Verbesselt, L. Kooistra, and M. Herold, "Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series," *Remote Sens. Environ.*, vol. 161, pp. 107–121, 2015, doi: 10.1016/j.rse.2015.02.012.

[28] Z. Zhu *et al.*, "Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014)," *Remote Sens. Environ.*, vol. 185, pp. 243–257, 2016, doi: 10.1016/j.rse.2016.03.036.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)