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Detection of Deforestation Using Low Resolution Satellite Images in the Islands of Sumatra 2000-2012

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Abstract

In the last two decades, the international community has given great attention to the issues of deforestation and degradation. In Indonesia, these issues had been a very critical as they were related to the Indonesian government's commitment in reducing greenhouse gases by 2020 through the Reducing Emission from Deforestation and forest Degradation (REDD) mechanism. This paper describes the use of low resolution satellite imagery, i.e., MODIS (Moderate Resolution Imaging Spectroradiometer) for monitoring deforestation in Sumatra during the period of 2000-2012. The main objective of the study was to derive rapid forest and land cover change information from low resolution imageries in Sumatra between 2000 - 2012.

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This study used level 2 Terra MODIS (*MOD13Q1*) imageries, acquired in 2000, 2006 and 2012 as the main data source, where the 16-day composite imageries were derived from NASA – USGS (United States Geological Survey). The selection of cloud-free MODIS image was based on pixel reliability and VI quality bands. Change detection method applied to detect deforestation was the post-classification comparison, in which each image set representing each date was classified independently using pixel-based supervised classification method. The study found that deforestation rate in Sumatra Islands for the period 2000 – 2006 is approximately 292,029.2 ha per year, then decrease drastically in the period of 2006 – 2012 to approximately 72,905.3 ha per year. As for regional level, the study shows that MODIS data may provide reliable information for deforestation detection.

Keywords: MODIS; forest cover change; supervised classification; deforestation

1. Introduction

Tropical forest is one of the natural resources that have an important role in Indonesia. The issue of climate change has become a serious concern, considering its impact that may affect human life and other living components in the world as a result of the accumulation of greenhouse gases in the atmosphere [1, 2]. Forest sustainability becomes important in maintaining global climate, carbon storage, hydrological process and biodiversity [1, 3, 4].

Deforestation, as part of land use change on a regional scale has become a global environmental issues, in addition to the issues of land degradation, biodiversity, food security and environmental sustainability [5, 6]. Many studies expressed that deforestation in tropical forests occurred in 1990 has led to emissions of greenhouse gases by 17% [7]. The increase of greenhouse gases emissions was believed to increase the temperature of the earth worldwide [8-10].

Forest monitoring is an important part of REDD scheme. Monitoring plays a role in the case of a warning for the danger of deforestation. United Nations Framework Convention on Climate Change (UNFCCC) has emphasized the importance of accurate and consistent forest cover data availability in monitoring deforestation. It is important to calculate the amount of greenhouse gas emissions. One of the technical problems highlighted by the UNFCCC in REDD mechanism is that all estimations should be as transparent, consistent and accurate as possible, and open to be assessed independently [11, 12]. Monitoring of forest/land cover on a regional scale using field measurement system may time consuming and costly. Therefore, a fast, consistent and accurate method is required. The purpose of remote sensing in forestry is to obtain recent information on land cover [13-15] including the monitoring of forest cover [16-18]. Remote sensing technology is a quite powerful tool to obtain information on land cover change by understanding the dynamics of change in the land surface [19-21]. Data from satellite images to detect changes in vegetation are strongly associated with spatial resolution, temporal resolution and spectral resolution [22, 23].

The use of MODIS satellite data could be one of the solutions for forest monitoring activities to provide forest cover information either at regional or national level. These capabilities are due to the daily temporal resolution, high spectral resolution (36 channels) and low spatial resolution (250m, 500m, 1km) of the areas. The

MOD13Q1 product has several advantages for land use and land cover (LULC) mapping. First, the product includes EVI (Enhanced Vegetation Index) and NDVI (Normalized Difference Index), as well as blue, red, NIR and mid-infrared bands, with a 16-day compositing scheme that helps eliminate cloudy and other unreliable pixels. Although there are alternative compositing techniques for MODIS daily imagery [24], MOD13Q1 is favourable because image compositing is done prior to download, greatly reducing data download time, storage costs and processing time. Second, the MOD13Q1 VI, red and NIR bands have 250m resolution, whereas other MODIS products, such as the Nadir BRDF-Adjusted Reflectance (NBAR) based on Aqua and Terra (MCD43A4) have ≥500m resolution [25].

Research on the dynamics of land cover change using Terra MODIS MOD13Q1 satellite images has been widely conducted [26, 27]. The use of EVI and NDVI bands found in that satellite images has been widely used to detect changes in land cover, including detect deforestation. Temporal dynamics of these indices are useful to distinguish soil surface conditions, including changes and distribution of land cover [20, 28]. In this study, detection of deforestation implemented was post classification comparison [17, 22, 29]. The main objective of the study is to derive rapid information of forest and land cover change from low resolution imageries occurred in Sumatra between 2000 – 2012 periods.

2. Materials and methods

2.1 Research Location

The research was mainly conducted in Sumatra Island including small islands in its surrounding that located between 95° E-109.2° E and 6° N-6.2° S (see Figure 1). Administratively, Sumatra Island is divided into 10 Provinces and 141 Regencies/Cities with a total area of 47.322.331.3 Ha. The selection of study sites in Sumatra Island is based on the fact that this island is suffering from the high rate of deforestation. Sumatra had been ranked to the third largest island in Indonesia with a high rate of deforestation. A high level of forest conversion into agricultural land in Indonesia, particularly in Sumatra, has attracted many international researchers to conduct studies [30-33].

2.2 Data

Terra MODIS MOD13Q1 satellite image data that used in this study were obtained from http://modis.gsfc.nasa.gov or at https://lpdaac.usgs.gov/data_access/data_pool [34]. MODIS images for the islands of Sumatra include 4 grids, namely h27v08, h27v09, h28v08 and h28v09. These MODIS satellite images have level-2 with 16 day-composite. MODIS level-2 was generated from the level-1 product whereas the main data content was a geophysical value for each pixel derived from the level-1 data by applying sensor calibration, atmospheric correction, and biooptic algorithms. Each level-2 product is associated with geographic coverage of level 1-A product and stored in HDF format [35]. The data conversion process from HDF format to TIF format, as well as mosaics of each band in the study were performed using MODIS Reprojection Tool software [36]. Terra MODIS MOD13Q1 satellite images data that used in this research were acquired in 2000, 2006 and 2012 with 250 m spatial resolution.

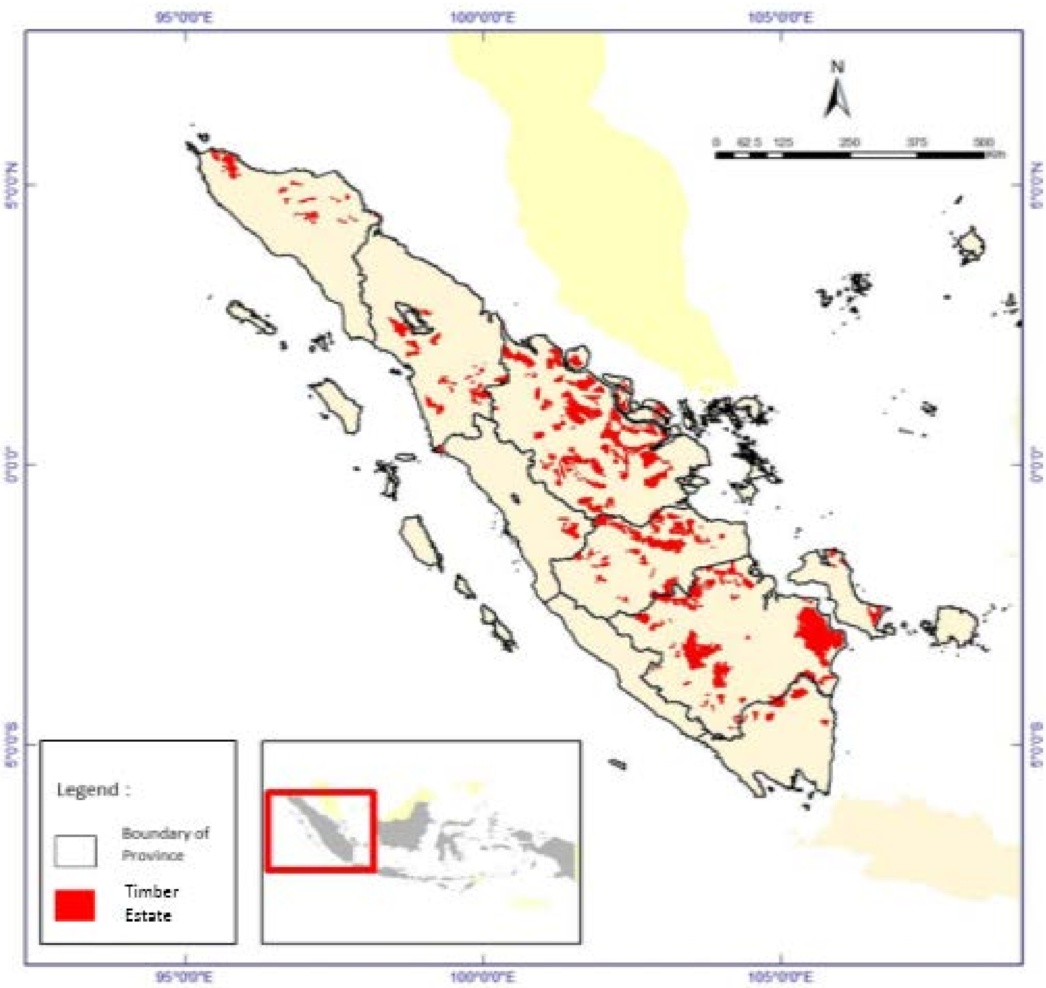

Figure 1: Research location (Timber Estates were excluded from study area)

2.3 Research Steps

Multi temporal land cover analysis was conducted by classifying each date independently. This process was intended to obtain land and forest cover representing each date, then would be used as a basis in determining the rate of deforestation. Detection of forest cover changes was done using post-classification comparison method [37-39]. Detection was conducted through pixel-by-pixel comparison to obtain detailed information on current forest cover change. The steps of this research can be described as follows:

2.3.1 Data set making (Stacking)

In this study, the used data sets were the MIR (Middle Infrared), NIR (Near Infrared), Blue, Pixel Reliability and VI Quality bands. MIR, NIR and blue bands were used to create a composite image, while Pixel Reliability and VI Quality were used to select image data quality to be used [22].

2.3.2 Data selection (Masking)

Cloud cover is a major problem in remote sensing using optical satellite images, especially in tropical forest regions such as Indonesia and Brazil [13, 40]. Sixteen day-composite data product of Terra MODIS may contain poor data due to the presence of clouds, haze or bad reflectance value, thus it needs a selection (masking) process in order to obtain cloud-free or haze-free [22]. Selection of good images was based on the band information that determines the image quality, i.e. Pixel Reliability and VI Quality bands [41]. Pixel reliability was used to select the quality of image bands. The criteria of a good image was based on the criteria as shown in Table 1. The zero value was considered to be good and the higher value of the pixel reliability was considered to be unfavorable data. If the pixel reliability was insufficient to determine land cover information, then the VI quality band was used [22]. In this study, it is preferable to use good quality data (rank key 0) and visually acceptable marginal data (rank key 1).

Table 1: Description of pixel reliability value Terra MODIS MOD13Q1 satellite images

Rank Key	Summary QA	Description
-1	Fill/No Data	Not Processed
0	Good Data	Use with confidence
1	Marginal data	Useful, but look at other QA information
2	Snow/Ice	Target covered with snow/ice
3	Cloudy	Target not visible, covered with cloud

Masking process was applied to all masked image data sets of Terra MODIS MOD13Q1 started from the coverage of day-049 to day-353 in each year of observation. Terra MODIS MOD13Q1 satellite image data for the coverage of day-1, day-17 and day-33 were not included in the analysis because in year 2000 this satellite data was available on the coverage of day-049. Thus to unify the observation, the coverage of data of day-1, day-17 and day-33 in 2006 and 2012 were also excluded from the analysis. The illustration of Terra MODIS MOD13Q1 satellite images mosaic process is presented in Figure 2.

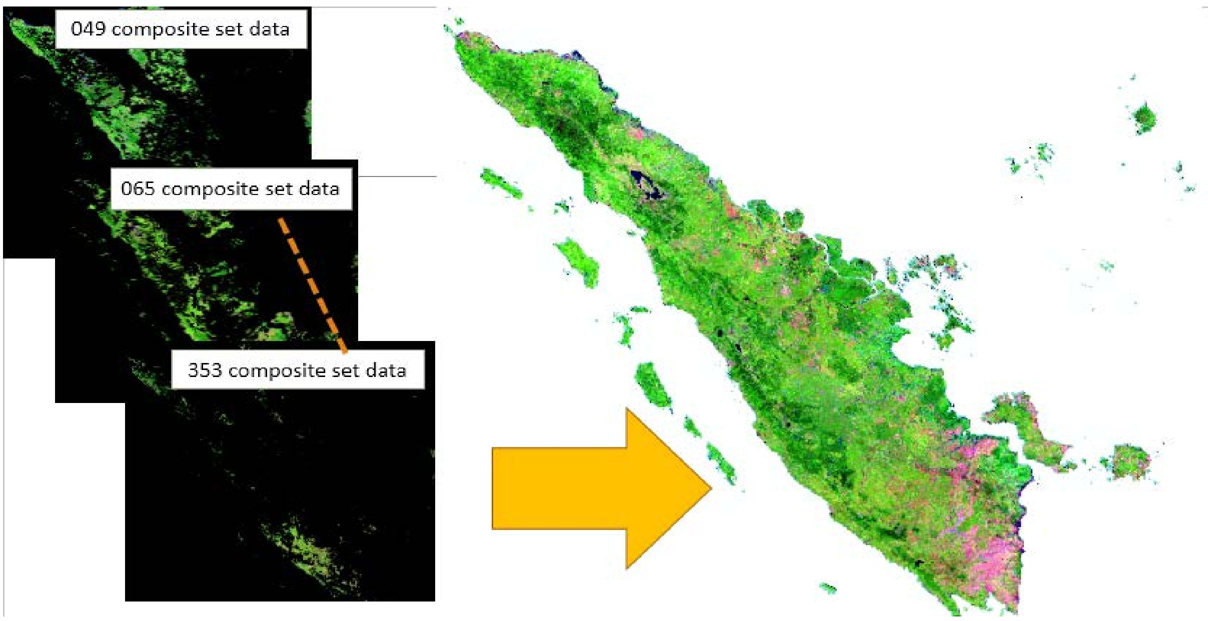

Figure 2: Mosaic process of Terra MODIS MOD13Q1 satellite images after masking

2.3.3 Quantitative Classification of Land Cover

Analysis of land cover classification on Terra MODIS satellite images was performed using supervised classification approach [42, 43] with maximum likelihood classifier. The maximum likelihood classifier considers several factors such as the probability of a pixel to be classified into classes or specific categories. The maximum likelihood classifier categorizes pixels that have not been identified based on the average vector of multivariate sample and variance-covariance matrix between bands of any class or category [44-46]. All band combinations of image data were classified by sample pixels (training area) that have been made. Processing of land cover classification from the continuous pixel values was performed using ERDAS Imagine (image processing software). In this study, there were three land cover classes created, i.e. forest cover, non-forest cover, and water bodies and cloud cover class. The limitations of this study were the lack of ground check data from study area and unavailable high resolution image on google earth for ground truth process. Hence, the process of making the training area and the validation is only performed on a grid that visually correct.

Evaluation of separation between classes was conducted based on the separability analysis. Separability measurement was conducted to obtain the degree of separation that in line with the accuracy of classification. Transformed Divergence (TD) measure was selected because its capability to provide the level of separation and able to be used to evaluate interclass separation [47-49]. Separability analysis is necessary to show statistical separation between land cover classes based on the statistical examination [50, 51]. This may conclude whether a class should be merged with another class or not. The TD was calculated using the following formula :

$$Dij = 0.5\, tr[(Ci - Cj)(Cj^{-1} - Ci^{-1})] + 0.5\, tr[(Ci^{-1} + Cj^{-1})(Mi - Mj)\,(Mi - Mj)^T]$$

$$TD_{ij} = 2000\left[1 - \exp\left[\frac{-D_{ij}}{8}\right]\right]$$

Note:

i and j = the two signature (classes) being compared

Ci = the variance – covariance matrix of signature i

M = the mean vector of signature i

tr = the trace function (matrix algebra)

T = the transposition function

TDij = separability measure between class i and j

Dij = divergence value between class i and j

TD value criteria used in separating classes of land cover in this study were as follow [44, 47-49, 52] :

(1) Inseparable : ≤ 1600

(2) Poor separability : 1601 – 1699

(3) Fair separability : 1700 – 1899

(4) Good separability : 1900 – 1999, and

(5) Excellent separability : 2000

2.3.4 Validation

Validation process was conducted on the newest land cover in 2012 on the basis of various ground truth data such as google map, ground survey, interviews etc. [30]. This validation process was conducted by looking at the dominant land cover on the randomly selected sample grid with the size of 250 x 250 m. Determination of accuracy value from land cover classification results was conducted using the confusion matrix [43, 48, 49, 53] to calculate Overall and Kappa Accuracy using the following formula:

$$Overall = \frac{\sum_{k}^{r} X_{kk}}{N} \times 100\%$$

$$Kappa(\kappa) = \frac{N\sum_{k}^{r} X_{kk} - \sum_{k}^{r} X_{k+} X_{+k}}{N^2 - \sum_{k}^{r} X_{k+} X_{+k}} \times 100\%$$

Note:

N = the sum of all pixels used for accuracy assessment

r = the number of classes examined in the confusion matrix

X_{kk} = the number of pixels in the relevant class (The sum of pixels on the diagonal matrix)

X_{k+} = $\sum X_{ij}$ (the sum of all columns in the i-th row)

X_{+k} = $\sum X_{ij}$ (the sum of all rows in the j-th column)

Kappa Accuracy was used because it considered all elements in the contingency matrix. Kappa Accuracy was also used to test its significance between two-confusion matrix of different methods or different bands combination [54]. Overall Accuracy, including the producer's and user's accuracy, describes the truth, but do not consider the possibility of map agreement regarding to the reference data. Kappa Accuracy becomes a good method of accuracy calculation for comparing different maps generated from different classification techniques.

2.3.5 Analysis of Deforestation

Deforestation was defined as the change in forest cover to be a non-permanent forest. In this study, forest cover changes that occur in the timber estate were not included in the calculation of deforestation. Land cover changes that occur in the timber estate were caused by regular and non-permanent logging activities.

Based on the results from multi-date Terra MODIS image classification, the analysis of land cover changes was conducted by overlaying images that obtained from different date, i.e. in 2000-2006 and 2006-2012. Overlays of two images from classification results would generate a transition matrix that expressed the extent/area or numbers of pixels of a land cover class in the first-date image that changed into other land cover classes in the following date.

3. Results and Discussion

In general, the separability analysis results show that the separation between classes was ranging from good to excellent (Table 2). Separability value of the land cover classification analysis in 2000, 2006 and 2012 were more than 1900 and categorized as excellent [54], thus the training area which was used as a sample in the classification of land cover, can be used. The result of the confusion matrix which is also called a contingency matrix was shown in Table 3.

Table 2: Separability matrix of supervised classification using Terra MODIS (*MOD13Q1*) imageries

	Year	No	Land Cover	Reference Data		
				Forest	Non Forest	Water Body and Cloud
Classified Data	2000	1	Forest	0	1970	1999
		2	Non Forest	1970	0	1952
		3	Water Body and Cloud	1999	1952	0
	2006	1	Forest	0	1999	2000
		2	Non Forest	1999	0	1995
		3	Water Body and Cloud	2000	1995	0
	2012	1	Forest	0	1998	1999
		2	Non Forest	1998	0	1999
		3	Water Body and Cloud	1999	1999	0

Table 3: Error matrix of supervised classification using Terra MODIS (*MOD13Q1*) imageries

	Year	No	Land Cover	Reference data: Forest	Non Forest	Water Body and Cloud	Row Total	User's Accuracy
Classified Data	2000	1	Forest	4370	228	0	4598	0.950
		2	Non Forest	81	2486	28	2595	0.958
		3	Water Body and Cloud	17	109	2143	2269	0.945
			Column Total	4468	2823	2171	9462	
			Producer's Accuracy	0.978	0.881	0.987		
	2006	1	Forest	1793	49	26	1868	0.959
		2	Non Forest	78	2206	76	2360	0.935
		3	Water Body and Cloud	2	76	2898	2976	0.974
			Column Total	1873	2331	3000	7204	
			Producer's Accuracy	0.957	0.946	0.966		
	2012	1	Forest	2300	208	2	2510	0.916
		2	Non Forest	62	2975	122	3159	0.942
		3	Water Body and Cloud	74	31	4573	4678	0.978
			Column Total	2436	3214	4697	10347	
			Producer's Accuracy	0.944	0.926	0.974		

Based on the result of accuracy assessment in Table 3, the Producer's Accuracy of forest class showed that 97.8% of 4370 forest pixel could be true classified in 2000, 95.7% of 1793 forest pixel could be true classified in 2006 and 94.4% of 2300 forest pixel could be true classified in 2012. In this study, the digital image classification using supervised method provided good results, as seen from the high Overall and Kappa Accuracy. The Overall Accuracy resulting 95.1%, 95.7% and 95.2% of correctly classified land cover in 2000, 2006 and 2012 respectively, while the Kappa Accuracy values were 92.3%, 93.5 % and 92.5%, respectively.

The result of Supervised Classification from Terra MODIS MOD13Q1 Satellite Images of year 2000, 2006 and 2012 is presented in Figure 3 and the area of land cover changes in the Islands of Sumatra for each province excluding timber estate are tabulated in Table 4.

The accuracy test of land cover classification from 538 randomly selected sample grids in 2012 showed the overall accuracy of 76.4% and Kappa accuracy of 56.7%. This result was lower than accuracy test result from the study of [55] with overall accuracy of 79% in mid-Appalachian highland region of the United States. Clark and his colleagues [25] also reported that the accuracy of land cover classification from the MODIS 250m vegetation index product (MOD13Q1) in the Dry Chaco ecoregion of South America had an Overall Accuracy of 79.3%, producer's accuracy from 51.4% (plantation) to 95.8% (woody vegetation), and user's accuracy from 58.9% (herbaceous vegetation) to 100.0% (water).

Figure 3: The map of land cover using supervised classification from Terra MODIS (*MOD13Q1*) imageries year 2000 (a), 2006 (b), 2012 (c)

The size of the ground truth validation result was greatly influenced by the extent of mixed pixels in a particular class and the presence of human activity in causing deforestation. However, the small patches with area of less than 6.25 ha or smaller than the smallest pixel size of Terra MODIS MOD13Q1 satellite images was not detected as deforestation [30]. Disadvantages and limitations of the MODIS NDVI-based change detection approach are substantially associated with the low spatial data resolution (250 m). In particular, change events less than approximately 1.5 ha will have a low probability of being detected. One impact of this resolution limitation is potentially poorer accuracies for urban areas that tend to change at finer resolution [28]. MODIS land cover was very successful at mapping extensive cover types (e.g. coniferous forest and grasslands) and less successful at mapping smaller habitats (e.g. wetlands, deciduous tree cover) that typically occur in patches that are smaller than the MODIS pixels [56]. The spatial resolution of the MODIS NDVI data significantly limits their use for certain applications such as the monitoring of change in riparian buffer zones and urban areas and the monitoring of other relatively fine-scale conversion events that may be associated with high ecological value resources[28].

The pixel of moderate resolution sensor images, due to its spatial resolution, generally includes more than one type of land cover [57]. When these sensors observe the Earth, the measured radiance is the integration of the radiance of all the objects that are contained within the pixel, implying the existence of the so-called mixture problem [58]. The value of accuracy is also influenced by the quality of Terra MODIS MOD13Q1 satellite image that resulted from mosaic of the coverage of day-049 until day-353. Clouds were still remain even after masking process on each coverage of Terra MODIS MOD13Q1 satellite images. This was caused by a defective or inaccuracy of reliability pixel band in showing image quality information on several pixels in the study area. In addition, it was also caused by several areas in the Islands of Sumatra that were always covered with clouds at all coverage, thus the presence of clouds was inevitable.

Table 4: Recapitulation of land cover changes in Sumatra Islands per province

No	Province	Forest Area (ha)			Deforestation rate (ha/year)	Percentages of Deforestation rate (%)
		2000	2006	2012		
1	Bengkulu	843,768.8	678,637.5	673,668.8	14,175.0	1.7
2	Jambi	1,138,918.8	1,179,200.0	1,117,975.0	1,745.3	0.2
3	Bangka Belitung	224,900.0	112,825.0	179,418.8	3,790.1	1.7
4	Riau Islands	189,762.5	174,931.3	251,931.3	-5,180.7	-2.7
5	Lampung	245,718.8	204,631.3	301,825.0	-4,675.5	-1.9
6	Nanggroe Aceh Darussalam	2,687,631.3	2,515,750.0	2,156,781.3	44,237.5	1.6
7	Riau	2,277,787.5	1,264,962.5	1,569,493.8	59,024.5	2.6
8	West Sumatra	1,861,643.8	1,605,456.3	1,405,443.8	38,016.7	2.0
9	South Sumatra	801,812.5	1,015,662.5	962,456.3	-13,387.0	-1.7
10	North Sumatra	1,876,556.3	1,644,262.5	1,339,887.5	44,722.4	2.4
		12,150,500.0	10,398,324.8	9,960,893.3		

The coverage of forest area in the Islands of Sumatra continues to decline rapidly (Table 4). Forest area excluding timber estate in 2000 was about 12,150,500.0 Ha (25.7%), then decreased in 2006 to 10,398,324.8 Ha (22.0%) and by 2012 it was detected about 9,960,893.3 Ha (21.0%). These results are also consistent with the study results of [33] who mentions that forest area in the Islands of Sumatra continued to decline from 2000 to 2010. Study result of Wedastra and his colleagues [22] using Terra MODIS MOD13Q1 satellite images with unsupervised and supervised combination method (hybrid method) provided forest cover of Sumatra in 2008 covering an area of about 21.964.100 Ha, then declined in 2012 covering an area of about 11.270.050 Ha . The Ministry of Forestry (MoF) stated that forest cover area in 2011 was 14.84 million Ha [59] and declined to 13.97 million Ha [60] in 2012. The study results of Margono and her colleagues [33] using satellite images of Landsat 7 + Enhanced Thematic Mapper Plus (ETM+) and Landsat 5 Thematic Mapper (TM) show that forest area in the Islands of Sumatra in 2000 was about 15.69 million Ha then decreased in 2010 to 13.58 million Ha.

The highest rate of deforestation was found in Riau and North Sumatra Provinces, where wide area of forest cover was converted into oil palm plantations. The expansion of oil palm plantations is mostly done both by large companies as well as in small scale by community. Conversion of forest to other land uses has become a major issue in Indonesia [32], in particular the reduction of natural forests in Sumatra were converted into oil palm plantations [61]. During the past 10 years, the extent of oil palm plantations in Indonesia has increased from 4.16 million ha in 2000 to 8.25 million ha in 2009.

Table 5: Comparism of forest area result classification using Terra MODIS (*MOD13Q1*) imageries with MoF classfication using landsat

Year	Forest Cover Area (ha)			Percentage (%)
	MODIS	MoF	Difference	
2000	12,150,500.0	13,423,712.5	1,273,212.5	10.5
2006	10,398,324.8	12,886,393.8	2,488,068.9	23.9
2012	9,960,893.3	11,509,125.0	1,548,231.7	15.5

The study shows that the deforestation rate from 2000 to 2006 was 292,029.2 ha per year, while from 2006 to 2012 the deforestation rate decreased to 72,905.3 ha per year. These results are lower than the results of classification by the MoF by using Landsat imagery. The difference percentage of MoF and MODIS classification was in the range of 10.5 – 23.9% (Table 5).

4. Conclusion

The coverage of forest area in the Islands of Sumatra continues to decline rapidly. Forest area excluding timber estate in 2000 was about at 12,150,500.0 Ha (25.7%), then decreased in 2006 to 10,398,324.8 Ha (22.0%) and by 2012 it was detected at 9,960,893.3 Ha (21.0%). These results are lower than the results of classification by the MoF by using Landsat imagery. The difference between MoF and MODIS MOD13Q1 classification was in the range of 10.5 – 23.9%. Based on post classification comparison using Terra MODIS MOD13Q1, the deforestation rate from 2000 to 2006 was 292,029.2 ha per year, while from 2006 to 2012 the deforestation rate decreased to 72,905.3 ha per year.

References

[1] C. M. P. Ozanne, D. Anhuf, S. L. Boulter, M. Keller, R. L. Kitching, C. Körner, *et al.*, "Biodiversity meets the atmosphere. A global view of forest

canopies," *Science*, vol. 301, pp. 183–186, 2003.

[2] G. Heal and B. Kriström, "Uncertainty and climate change," *Environmental and Resource Economics*, vol. 22, pp. 3-39, 2002.

[3] FAO. (2012, 2 Januari 2015). *State of the World's Forests*. Available: http://www.fao.org/docrep/016/i3010e/i3010e00.htm

[4] F. Achard, H. D. Eva, H. J. Stibig, P. Mayaux, J. Gallego, T. Richards, *et al.*, "Determination of

deforestation rates of the world's humid tropical forests," *Science,* vol. 297, pp. 999–1002, 2002.

[5] J. A. Foley, R. DeFries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter*, et al.*, "Global Consequences of Land Use," *Science,* vol. 309, pp. 570-574, 2005.

[6] J. M. Olson, S. Misana, D. J. Campbell, M. Mbonile, and S. A. Mugisha, "Research framework to identify the root causes of land use change leading to Land degradation and changing biodiversity," International Livestock Research Institute, Nairobi (Kenya).2004.

[7] R. E. Gullison, P. C. Frumhoff, Josep G. Canadell, C. B. Field, D. C. Nepstad, K. Hayhoe*, et al.*, "Tropical forests and climate policy," *Science,* vol. 316, pp. 985-986, 2007.

[8] D. T. Shindell and G. A. Schmidt, "Southern Hemisphere climate response to ozone changes and greenhouse gas increases," *Geophysical Research Letters,* vol. 31, 2004.

[9] J. F. Mitchell, "The "greenhouse" effect and climate change," *Reviews of Geophysics,* vol. 27, pp. 115-139, 1989.

[10] J. Hansen, M. Sato, R. Ruedy, K. Lo, D. W. Lea, and M. Medina-Elizade, "Global temperature change," *Proceedings of the National Academy of Sciences,* vol. 103, pp. 14288-14293, 2006.

[11] F. e. Achard, H.-J. Stibig, H. D. Eva, E. J. Lindquist, A. Bouvet, O. Arino*, et al.*, "Estimating tropical deforestation from Earth observation data. Carbon Management," *Carbon Management,* vol. 1, pp. 271 - 287, 2010.

[12] S. Eckert, H. R. Ratsimba, L. O. Rakotondrasoa, L. G. Rajoelison, and A. Ehrensperger, "Deforestation and forest degradation monitoring and assessment of biomass and carbon stock of lowland rainforest in the Analanjirofo region, Madagascar," *Forest Ecology and Management,* vol. 262, pp. 1996-2007, 2011.

[13] M. C. Hansen, Y. E. Shimabukuro, P. Potapov, and K. Pittman, "Comparing annual MODIS and PRODES forest cover change data for advancing monitoring of Brazilian forest cover," *Remote Sensing of Environment,* vol. 112, pp. 3784-3793, 2008.

[14] R. DeFries, M. Hansen, J. Townshend, A. Janetos, and T. Loveland, "A new global 1-km dataset of percentage tree cover derived from remote sensing," *Global Change Biology,* vol. 6, pp. 247-254, 2000.

[15] P. Mayaux, P. Holmgren, F. Achard, H. Eva, H.-J. Stibig, and A. Branthomme, *Tropical forest cover change in the 1990s and options for future monitoring* vol. 360, 2005.

[16] C. A. Portillo-Quintero, A. M. Sanchez, C. A. Valbuena, Y. Y. Gonzalez, and J. T. Larreal, "Forest cover and deforestation patterns in the Northern Andes (Lake Maracaibo Basin): A synoptic assessment using MODIS and Landsat imagery," *Applied Geography,* vol. 35, pp. 152-163, 11// 2012.

[17] J.-F. Mas, "Monitoring land-cover changes: a comparison of change detection techniques," *International journal of remote sensing*, vol. 20, pp. 139-152, 1999.

[18] E. F. Lambin, "Monitoring forest degradation in tropical regions by remote sensing: some methodological issues," *Global ecology and biogeography*, vol. 8, pp. 191-198, 1999.

[19] M. Herold, C. E.Woodcock, A. d. Gregorio, P. Mayaux, A. S. Belward, J. Latham, *et al.*, "A Joint Initiative for Harmonization and Validation of Land Cover Datasets," *IEEE Transactions On Geoscience And Remote Sensing*, vol. 44, pp. 1719-1727, 2006.

[20] Y. Setiawan and K. Yoshino, "Detecting land-use change from seasonal vegetation dynamics on regional scale with MODIS EVI 250-m time-series imagery," *Journal of Land Use Science*, 2013.

[21] G. L. Galford, J. F. Mustard, J. Melillo, A. Gendrin, C. C. Cerri, and C. E. P. Cerri, "Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil," *Remote Sensing of Environment*, vol. 112, pp. 576-587, 2008.

[22] I. B. K. Wedastra, A. Shapiro, E. Apriani, and T. Widiastomo, "Sistem Pemantauan Penutupan Lahan Pulau Dan Wilayah (Pemanfaatan Teknologi Penginderaan Jauh – MODIS)," *WWF INDONESIA*, 2013.

[23] P. R. Coppin and M. E. Bauer, "Digital change detection in forest ecosystems with remote sensing imagery," *Remote sensing reviews*, vol. 13, pp. 207-234, 1996.

[24] P. E. Dennison, D. A. Roberts, and S. H. Peterson, "Spectral shape-based temporal compositing algorithms for MODIS surface reflectance data," *Remote Sensing of Environment*, vol. 109, pp. 510-522, 2007.

[25] M. L. Clark, T. M. Aide, H. R. Grau, and G. Riner, "A scalable approach to mapping annual land cover at 250 m using MODIS time series data: A case study in the Dry Chaco ecoregion of South America," *Remote Sensing of Environment*, vol. 114, pp. 2816-2832, 2010.

[26] J. Verbesselt, R. Hyndman, G. Newnham, and D. Culvenor, "Detecting trend and seasonal changes in satellite image time series," *Remote sensing of Environment*, vol. 114, pp. 106-115, 2010.

[27] J. F. Knight, R. S. Lunetta, J. Ediriwickrema, and S. Khorram, "Regional scale land cover characterization using MODIS-NDVI 250 m multi-temporal imagery: A phenology-based approach," *GIScience & Remote Sensing*, vol. 43, pp. 1-23, 2006.

[28] R. S. Lunetta, J. F. Knight, J. Ediriwickrema, J. G. Lyon, and L. D. Worthy, "Land-cover change detection using multi-temporal MODIS NDVI data," *Remote Sensing of Environment*, vol. 105, pp. 142-154, 2006.

[29] K. Kafi, H. Shafri, and A. Shariff, "An analysis of LULC change detection using remotely sensed data; A Case study of Bauchi City," in *IOP Conference Series: Earth and Environmental Science*, 2014, p. 012056.

[30] Y. Setiawan, M. I. Lubis, S. M. Yusuf, and L. B. Prasetyo, "Identifying change trajectory over the Sumatra's forestlands using moderate image resolution imagery," *Procedia Environmental Sciences,* vol. 24, pp. 189-198, 2015.

[31] T. P. Tomich, M. van Noordwijk, S. Budidarsono, A. Gillison, T. Kusumanto, D. Murdiyarso*, et al.*, "Agricultural intensification, deforestation, and the environment: assessing tradeoffs in Sumatra, Indonesia," *Tradeoffs or synergies,* pp. 221-244, 2001.

[32] E. Romijn, J. H. Ainembabazi, A. Wijaya, M. Herold, A. Angelsen, L. Verchot*, et al.*, "Exploring different forest definitions and their impact on developing REDD+ reference emission levels: A case study for Indonesia," *Environmental Science & Policy,* vol. 33, pp. 246-259, 2013.

[33] B. A. Margono, S. Turubanova, I. Zhuravleva, P. Potapov, A. Tyukavina, A. Baccini*, et al.*, "Mapping and monitoring deforestation and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010," *Environmental Research Letters,* vol. 7, p. 034010, 2012.

[34] LPDAAC. Data Pool [Online]. Available: https://lpdaac.usgs.gov/data_access/data_pool

[35] LPDAAC. MODIS Overview [Online]. Available: https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool.

[36] LPDAAC. MODIS Reprojection Tool [Online]. Available: https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool.

[37] K. O. Were, Ø. B. Dick, and B. R. Singh, "Remotely sensing the spatial and temporal land cover changes in Eastern Mau forest reserve and Lake Nakuru drainage basin, Kenya," *Applied Geography,* vol. 41, pp. 75-86, 2013.

[38] Z. Huiping, J. Hong, and H. Qinghua, "Landscape and water quality change detection in urban wetland: a post-classification comparison method with IKONOS data," *Procedia Environmental Sciences,* vol. 10, pp. 1726-1731, 2011.

[39] O. R. Abd El-Kawy, J. K. Rød, H. A. Ismail, and A. S. Suliman, "Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data," *Applied Geography,* vol. 31, pp. 483-494, 2011.

[40] D. H. Hoekman, "Radar monitoring system for sustainable forest management in Indonesia " in *IGARSS '97: 1997 Int. Geoscience and Remote Sensing Symposium*, Singapore, 1997, pp. 1731–3.

[41] R. Solano, K. Didan, A. Jacobson, and A. Huete, *MODIS Vegetation Index User's Guide (MOD13 Series)*: Vegetation Index and Phenology Lab. The University of Arizona, 2010.

[42] J. R. Otukeia and T. Blaschke, "Land cover change assessment using decision trees, support vector

machines and maximum likelihood classification algorithms," *International Journal of Applied Earth Observation and Geoinformation*, vol. 12, pp. S27–S31, 2010.

[43] C. E. Churches, P. J. Wampler, W. Sun, and A. J. Smith, "Evaluation of forest cover estimates for Haiti using supervised classification of Landsat data," *International Journal of Applied Earth Observation and Geoinformation,* vol. 30, pp. 203-216, 8// 2014.

[44] I. N. S. Jaya, *Analisis Citra Digital. Persepektif Penginderaan Jauh Untuk Pengelolaan Sumberdaya Alam. Teori dan Praktik Menggunakan Erdas Imagine*. Indonesia: Fakultas Kehutanan. Institut Pertanian Bogor, 2010.

[45] R. M. Hord, *Digital image processing of remotely sensed data*. London: Academic Press, 1982.

[46] J. R. Eastman, S. Crema, H. Zhu, J. Toledano, and H. Jiang, "In-Process Classification Assessment of Remotely Sensed Imagery," *GeoCarto International*, vol. 20, pp. 33-43, 2005.

[47] J. R. Jensen, *Introductory digital image processing: A remote sensing perspective*. New Jersey: Prentice Hall, 1996.

[48] I. Jaya and S. Kobayashi, "Classification of detailed forest cover types based upon the separability algorithm: a case study in the Yahiko Mountain and Shibata Forest Area," *Journal of the Remote Sensing Society of Japan,* vol. 15, pp. 40-53, 1995.

[49] I. Jaya and S. Kobayashi, "Detecting Changes in Forest Vegetation using Multitemporal Landsat TM Data: A case study in the Shibata Forest, Niigata Prefecture," *Journal of Forest Planning,* vol. 1, pp. 23-38, 1995.

[50] A. Singh, "Some clarifications about the pairwise divergence measure in remote sensing," *Remote Sensing,* vol. 5, pp. 623-627, 1984.

[51] P. H. Swain and S. M. Davis, *Remote sensing: The Quantitative Approach*. New York: McGraw Hill Book Company, 1978.

[52] P. Mather, M. Steven, and J. Clark, "Theoretical problems in image classification," *Application of RS in Agriculture*, pp. 127-135, 1990.

[53] P. Olofsson, G. M. Foody, M. Herold, S. V. Stehman, C. E. Woodcock, and M. A. Wulder, "Good practices for estimating area and assessing accuracy of land change," *Remote Sensing of Environment*, vol. 148, pp. 42-57, 2014.

[54] I. N. S. Jaya, "Monitoring Forest Cover Change Using Multitemporal Landsat TM Data," PhD Disertasi, Graduate School of Science and Technology, Niigata University, Japan, 1996.

[55] J. P. Spruce, S. Sader, R. E. Ryan, J. Smoot, P. Kuper, K. Ross, *et al.*, "Assessment of MODIS NDVI time series data products for detecting forest defoliation by gypsy moth outbreaks," *Remote sensing of environment,* vol. 115, pp. 427-437, 2011.

[56] K. J. Wessels, R. S. De Fries, J. Dempewolf, L. O. Anderson, A. J. Hansen, S. L. Powell, *et al.*, "Mapping regional land cover with MODIS data for biological conservation: Examples from the Greater Yellowstone Ecosystem, USA and Pará State, Brazil," *Remote Sensing of Environment,* vol. 92, pp. 67-83, 7/15/ 2004.

[57] L. Anderson, Y. Shimabukuro, and E. Arai, "Cover: Multitemporal fraction images derived from Terra MODIS data for analysing land cover change over the Amazon region," *International Journal of Remote Sensing,* vol. 26, pp. 2251-2257, 2005.

[58] A. Aguiar, Y. Shimabukuro, and N. Mascarenhas, "Use of synthetic bands derived from mixing models in the multispectral classification of remote sensing images," *International Journal of Remote Sensing,* vol. 20, pp. 647-657, 1999.

[59] Ministry of Forestry, *Statistik Kehutanan Tahun 2011*. Jakarta: Kementerian Kehutanan, 2012.

[60] Ministry of Forestry, *Statistik Kehutanan Tahun 2013*. Jakarta: Kementerian Kehutanan, 2014.

[61] M. Broich, M. C. Hansen, P. Potapov, B. Adusei, E. Lindquist, and S. V. Stehman, "Time-series analysis of multi-resolution optical imagery for quantifying forest cover loss in Sumatra and Kalimantan, Indonesia," *International Journal of Applied Earth Observation and Geoinformation,* vol. 13, pp. 277-291, 4// 2011.