IDENTIFICATION AND CLASSIFICATION OF FOREST TYPES USING DATA LANDSAT 8 IN KARO, DAIRI, AND SAMOSIR DISTRICTS, NORTH SUMATRA

Heru Noviar*), and Tatik Kartika
Remote Sensing Application Center, LAPAN
*) e-mail : herunov75@gmail.com
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Abstract. Forests have important roles in terms of carbon storage and other values. Various studies have been conducted to identify and distinguish the forest from non-forest classes. Several forest types classes such as secondary forests and plantations should be distinguished related to the restoration and rehabilitation program for dealing with climate change. *T*he study was carried out to distinguish several classes of important forests such as the primary dryland forests, secondary dryland forest, and plantation forests using Landsat 8 to develop identification techniques of specific forests classes. The study areas selected were forest areas *in* three districts, namely Karo, Dairi, and Samosir of North Sumatera Province. The results showed that using composite RGB 654 of Landsat 8 imagery based on test results OIF for the forest classification, the forests could be distinguished with other land covers. Digital classification can be combined with the visual classification known as a hybrid classification method, especially if there are difficulties in border demarcation between the two types of forest classes or two classes of land covers.

Keywords*: identification, classification, forest types, Landsat 8*

1 INTRODUCTION

Indonesia's forests have an important role in the world in terms of carbon storage and other values (FORDA Team for Climate Change, 2010; Sumargo, *et al.*, 2011).

Various studies have been conducted to identify and distinguish the forest and non-forest classes using Landsat data either using a single data or multitemporal data (Kartika, 2010; Kartika, *et al.*, 2012; Kartika, *et al.*, 2011).

Several forest types classes such as secondary forests and forest plantations are needed to be distinguished related to the restoration and rehabilitation program in dealing with climate change.

The methods used can be divided into digital and visual methods. Digital method is very dependent on atmospheric conditions of the data, and the method is divided into supervised and unsupervised methods. Supervised digital method, also depends on the sampling, while a visual method depends on the interpreter (Sutanto, 1986).

The Ministry of Environment and Forestry (KLHK) classifies forest types into 7 classes using Landsat data, namely: primary dryland forests, secondary dryland forests, primary swamp forests, secondary swamp forests, primary mangrove forests, secondary mangrove forests, and forest plantations (Rochmayanto, *et al.*, 2014).

While forest classification based on Indonesian National Standard (SNI) depends on the scale used; to a scale of 1: 1,000,000, forest types are divided into 2 classes, ie dryland forests and wetland forests; to a scale of 1: 250,000, forest types class are divided into four, namely primary dryland forests, secondary dryland forests, primary wetland forests, and secondary wetland forests. As for the scale of 1: 50,000 or 1: 25,000, each class of forest on a scale of 1: 250,000, divided by type, such as primary and secondary dryland forests, each consisting of Bamboo forests, mixed forests, Teak forests, Pine forests, woods Acacia, Eucalyptus forests, White Teak forests, Sengon forests, Sungkai forests, Mahogany forests, Rubber forests, and Jelutung forests. In addition, each type of the forest is divided into three classes again, is dense, moderate, and sparse. While primary and secondary wetland forests, each consisting of forest type such as mangroves, mixed forests, Nipah forests, and Sago forests. Each forest type is further divided into dense, moderate, and sparse, as on dryland forests (SNI, 2010).

With the availability of the newest generation of Landsat data (Landsat 8), the study aims to utilize these data in distinguishing several classes of forest types such as primary dryland forests, secondary dryland forests, and forest plantations by developing identification techniques on this forest classification. The case study area is forest areas in the province of North Sumatera, especially in 3 districts, namely Karo, Dairi, and Samosir.

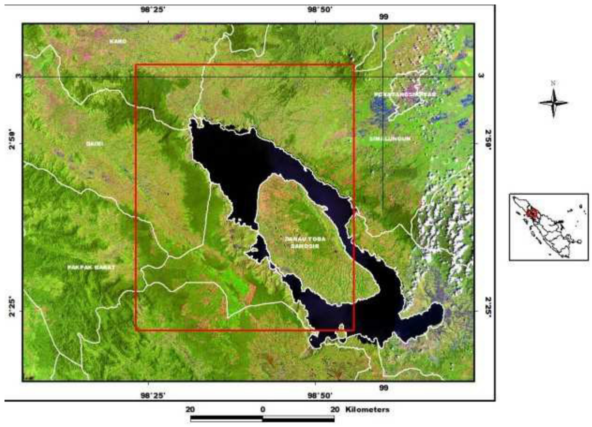


Figure 2-1: The Study Area in North Sumatera

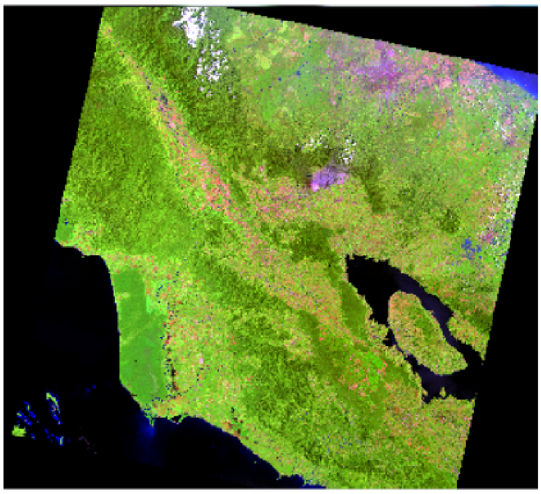


Figure 2-2: NCC RGB 653 Imagery of Landsat 8 path/row 129/58 acquired on February 21, 2015

2 MATERIALS AND METHODOLOGY

2.1 Data and Location

This study was located in North Sumatera Province, in the vicinity of Lake Toba, includes three districts namely Karo, Dairi and Samosir, as shown in Figure 2-1.

The data used is Landsat 8 path/ row 129/058 which was acquired on February 21, 2015.

2.3 Research Methods

The Landsat 8 data used on this study were data with path/row 129/058 dated February 21, 2015, covering most areas of the forest area surroundings Lake Toba. The Natural Color Composite (NCC) imagery using Red Green Blue (RGB) filters from Bands of 6, 5, and 3, so called RGB 653 as shown in Figure 2-2.

Bands selection for obtaining a natural color composite imagery (NCC) was conducted based on previous studies used Landsat previous generation (Landsat 5 and Landsat 7), the NCC imagery was composed of three selected spectral bands that can represent the natural color such as the vegetation color is green, the soil color is red, the water body color is blue. The NCC used composite bands of RGB 542, means, on the red filter using Band-5 (SWIR-1), on the green filter using Band-4 (Near Infra Red) and on the blue filter using Band-2 (green). In this study, because we used Landsat 8, to obtain the same composite, the spectral wavelengths bands used should be the same as the Landsat 5 and 7 above, namely the combination or color composite RGB 653, meaning the red filter using Band-6 (SWIR-1), the green filter using Band-5 (Near Infra Red) and the blue filter in Band-3 (Green).

In terms of the selection of the bands to composite the RGB imagery this could have used another technique, namely the method of OIF (Optimum Index Factor), i.e. the method of statistically to calculating the division between the number of standard deviation spectral numbers on the three bands with the number of the absolute value of the correlation coefficient between any two of the three bands (Jensen, 1986), where OIF algorithms can be written as follows:

$$OIF = \frac{\sum_{k=1}^{n} S_k}{\sum_{i=0}^{n} Abs\,(r_{jk})} \qquad (2\text{-}1)$$

where :

S_k = standard of deviation of the spectral value from the bands.

$Abs(r_j)$ = The absolute value of the correlation coefficient between each two of the three bands.

OIF Values which high, means a composite form presents color is more diversity so as to provide much spectral information.

In identifying the object of forest types visually using a combination of bands that had been chosen (natural color or test results OIF) on imagery other than the keys of interpretation, had used the help of a map of land cover current as a reference. The KLHK divides forest land cover classes into seven classes as mentioned above, the standard interpretation of Landsat imagery for forest types classification, are presented in Table 2-1. (MoF, 2003). KLHK identifying and updating land cover using visual interpretation of Landsat data and field survey.

After identification, next is created the training area for several classes of forest and non-forest of the study area in North Sumatera Province; then the classification was done digitally using the Maximum Likelihood method. In addition to the selection of training area with the help of maps of land cover from KLHK and the keys of interpretation, the training area was created homogeneous so that mixing class between classes with one another was small. The homogeneity test was done by calculating of coefficient of variation of each of channel of imagery in the training area which created. The mathematical equation

$$CV = SD/Mean \qquad (2\text{-}2)$$

Where:

SD = standard of deviation

Mean = the average digital value in the training area.

The smaller the CV value indicates more homogeneous variations, so that the classification results are expected not much mixing.

Table 2-1: Standard of Interpretation of Class of Forests Using Landsat data from KLHK (Source: MoF, 2003)

No.	Class of Forests	Visual Interpretation using Landsat Data
1.	Primary dry forest	All appearance of lowland hills forest, and mountains that have not seen the former logging, including dwarf forest,kerangas forest , forest on limestone,forests in the alkaline ultra rocks, needle leaf forest, and the moss forest.
2.	Secondary dry forest	The appearance of lowland forests, hills, and mountains that have appeared logged-over (groove and patches of logged).
3.	Primary swamp forest	All appearance of forests in swampy areas, including peat swamps and brackish marshes that have not appeared ex-logging.
4.	Secondary swamp forest	All appearance of forests in marshy areas and has appeared with the appearance of logged-over areas opening track (usually a rail line), and patches of logged.
5.	Primary mangroves forests	All appearance of mangroves forests, palm, and nibung located around the beach, and has not appeared ex-logging.
6.	Secondary mangroves forests	All appearance of mangroves forests, palm, and nibung which indicates the former logging, spots, or burn marks.
7.	Forest plantations	Class forest land cover is the result of human cultivation, covering industrial forest plantations and results reforestation forest plantations inside and outside the forest area (APL). From the imagery seen to have regular cropping patterns on flat areas, whereas for a bumpy area visible, image color that is different from the surrounding environment.

Meanwhile, to test the mixing of classes of forest and non-forest using Matrix Confusion methods, we used the mathematical equation as follows:

$$Overall\ Accuracy = \frac{1}{n}\sum_{i=1}^{k} n_{ii}\ User\ Accuracy = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ij}} \quad (2\text{-}3)$$

$$Kappa = \frac{P_0 - P_C}{1 - P_C} \quad (2\text{-}4)$$

Where,

n_{ii} = number of pixels from class i which classified correctly on class i of the reference data,

n_{ij} = number of pixels from class j of the reference data which classified as class i,

n = number of pixels totals,

k = number of class totals,

P_0 = *overall agreement,*

P_C = *chance agreement.*

To create the curve of spectral pattern that is formed from the channel imagery used in the classes of forest were obtained of the value of average (Mean) of the training area of from identification of objects. The complete study flow diagram was presented in Figure 2-3.

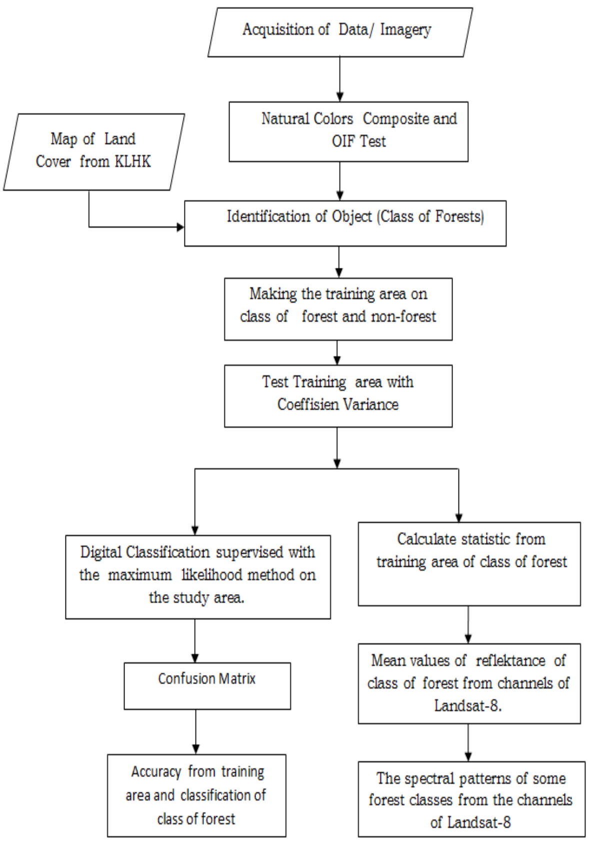


Figure 2-3: Flow diagram of the study

3 RESULTS AND DISCUSSION

In the NCC RGB 653 imagery, forest and other vegetations were seen as green, but different hue, brightness, texture and others. Visually, the green vegetation could be distinguished, but in interpreting as forests, plantations, rice fields and others require interpretation keys and experience of interpreter. Besides, also required secondary data such as field surveys and other supporting data such as maps land cover or the use of existing land.

The results of visual interpretation and maps of land cover that have been created by KLHK (newest updating in 2013) was used as a reference for identifying forest types classes in the study area.

The results of the composite selection using the OIF methods to obtain a combination of the bands used that provide a variety of information, was presented in Table 3-1 and Table 3-2.

Table 3-1: Test Result of OIF from Class of Forests

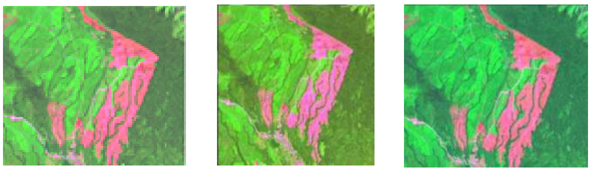
$R_1G_2B_3$	SD_1	SD_2	SD_3	r_{12}	r_{13}	r_{23}	SSD	S_r	OIF
751	59,22	525,549	46,591	0,072	0,413	0,137	631,36	0,622	1015,0482
752	59,22	525,549	37,627	0,072	0,513	0,108	622,396	0,693	898,11833
753	59,22	525,549	42,671	0,072	0,645	0,09	627,44	0,807	777,4969
754	59,22	525,549	31,891	0,072	0,787	0,027	616,66	0,886	696,00541
654	127,437	525,549	31,891	0,379	0,639	0,027	684,877	1,045	655,38469
651	127,437	525,549	46,591	0,379	0,597	0,137	699,577	1,113	628,55076
652	127,437	525,549	37,627	0,379	0,64	0,108	690,613	1,127	612,78882
653	127,437	525,549	42,671	0,379	0,691	0,09	695,657	1,16	599,70431

Table 3-2: Test Result of OIF from Class of Land Cover

$R_1G_2B_3$	SD_1	SD_2	SD_3	r_{12}	r_{13}	r_{23}	SSD	S_r	OIF
651	486,688	642,274	77,74	0,52	0,641	0,002	1206,702	1,163	1037,577
751	343,317	642,274	77,74	0,287	0,743	0,002	1063,331	1,032	1030,3595
652	486,688	642,274	92,492	0,52	0,714	0,038	1221,454	1,272	960,26258
752	343,317	642,274	92,492	0,087	0,818	0,038	1078,083	1,143	943,20472
654	486,688	642,274	178,708	0,52	0,844	0,151	1307,67	1,515	863,14851
754	343,317	642,274	178,708	0,287	0,928	0,151	1164,299	1,366	852,34187
753	343,317	642,274	134,466	0,287	0,875	0,327	1120,057	1,489	752,22095
653	486,688	642,274	134,466	0,52	0,852	0,327	12263,428	1,699	743,63037

Band 1 and band 2 should be removed or not used in the calculation of the value of OIF, because the band 1 and band 2 have high spectral scattering that causes the value of OIF be high, so it cannot represent the spectral value of the earth's surface (Chaves, 1982, in Jensen, 1986). Thus the composite using Bands-1 and 2 were ignored, resulting in the selection of the best composite for forest class was a combination of RGB 753, while on land cover classes, the selection of the best composite RGB 654.

If we compared the three composites were selected (RGB 653, 753, and 654) visually to distinguish the primary dry forest, the secondary dry forest, and plantation forests did not appear different, meaning that all three composite could be used for identification of land cover or forest types to equally provide natural color imagery. The results of this appeal can be seen in Figure 3-1.



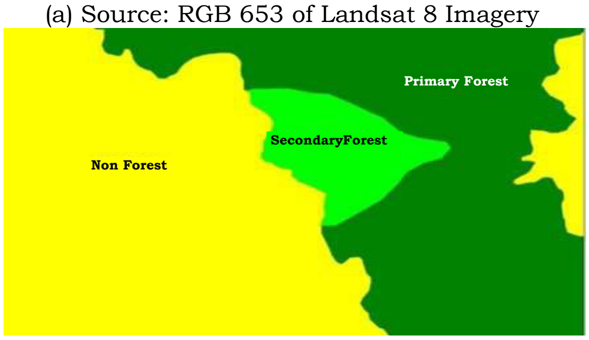
RGB 653 RGB 654 RGB 753

Figure 3-1: RGB Composite of Landsat 8 of the study area

This study used a RGB 654 composite imagery with consideration to distinguish forests with other land cover. Results overlay between an image and map land cover on area of study for class distinctions the primary and secondary dry forest are presented in Figure 3-2.

From Figure 3-2 (a) it could be seen that it was difficult to distinguish or draw the boundary between primary and secondary dryland forests, particularly in the example above, forest which was in the region of corrugated (mountains). From visual interpretation of KLHK that distinguish primary and secondary forests was that in secondary forests visible scars of logging the form of spots or rutting, indeed cursory look no blotches or in the form of stains green color on the delineation of secondary forests which created by KLHK above, but withdrawal of the boundary between primary and secondary forests in the image above was not clearly visible difference. In other regions the difference between secondary dry forests and forest plantations was presented in Figure 3-3.

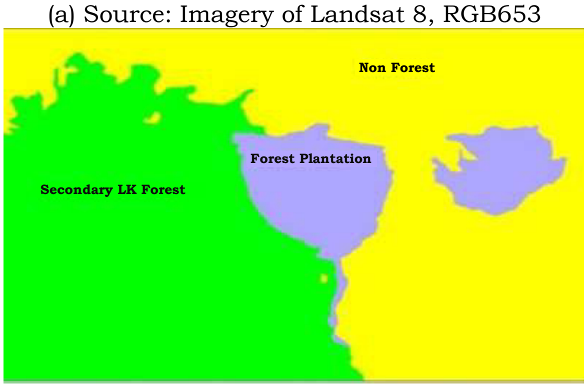
(a) Source: RGB 653 of Landsat 8 Imagery



(b) Source: Land Cover Map from KLHK

Figure 3-2: Difference of Classes between Primary and Secondary Dryland forests. (a) Seen from Landsat 8, and (b) Land Cover Map from KLHK.

(a) Source: Imagery of Landsat 8, RGB653

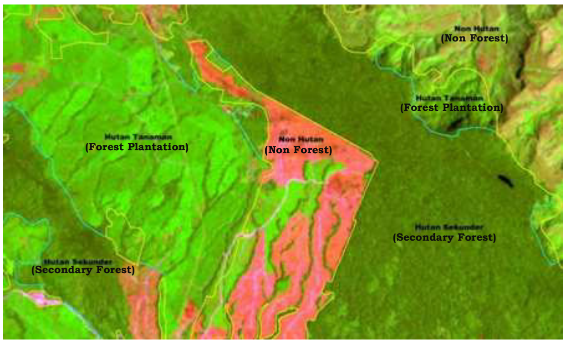


(b) Source: Land Cover Map from KLHK

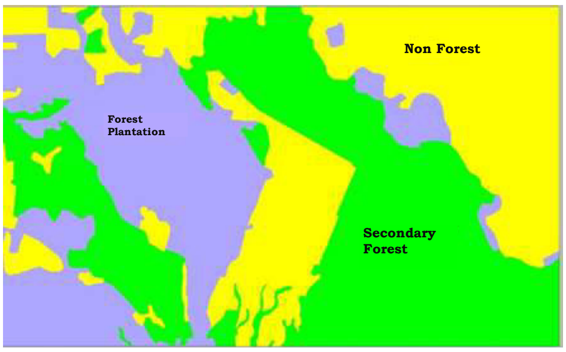
Figure 3-3: Difference of class between secondary dry forests and forest plantations. (a) Seen from Landsat 8, and (b) Land Cover Map from KLHK

From Figure 3-3 (a) it could also be seen that it was clearly visible the difference between secondary dryland forests and forest plantations. At forest plantations, color green looks somewhat different from the forest next (secondary dryland forests), also at forest plantations seen the appearance of smoother and homogeneous texture. In Figure 3-4 looks as well as differences between secondary dryland forests and forest plantations, either of the green hue, brightness and texture.

The results of a field survey which had been conducted on September 5 to 11, 2015, forest plantations were located in the region (Kecamatan Tele, Samosir) was a type of Eucalyptus plantations which is owned by PT. Indorayon (Toba Pulp Lestari). Results photo of field survey on the forest plantations in this region (Kecamatan Tele, Samosir) was presented in Figure 3-5. Plantation Forest Eucalyptus was also located in the forest area in Pulau Samosir (Figure 3-6.)



Source : RGB 653 Landsat 8 Imagery (a)

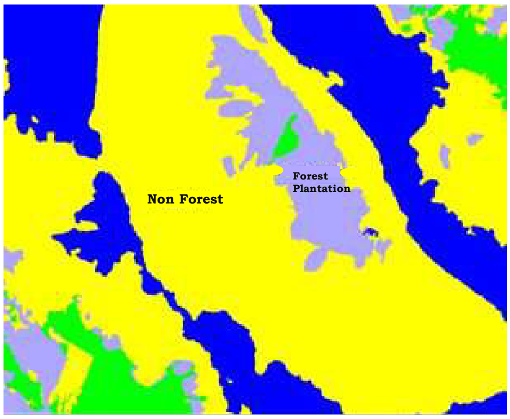


Source : The KLHK Land Cover Map (b)

Figure 3-4: Difference of Classes between Secondary Dryland forests and Forest Plantations (a) Seen from Landsat 8, and (b) The KLHK Land Cover Map

Figure 3-5: Plantation Forest Eucalyptus in Kecamatan Tele, Kabupaten Samosir

Source: RGB 653 Landsat 8 Imagery



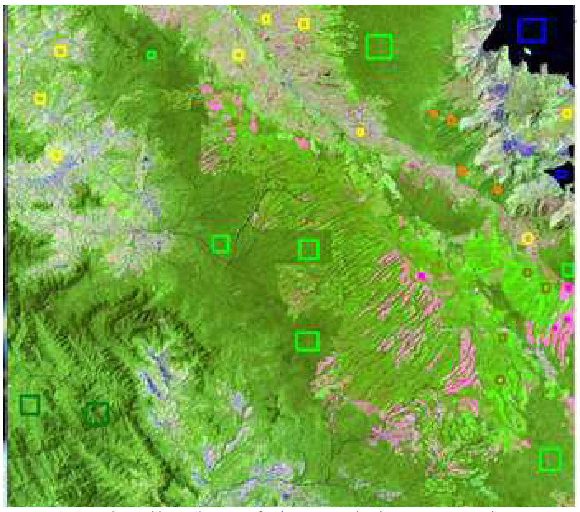
Source: The KLHK Land Cover Map

Photograph taken from Field Survey

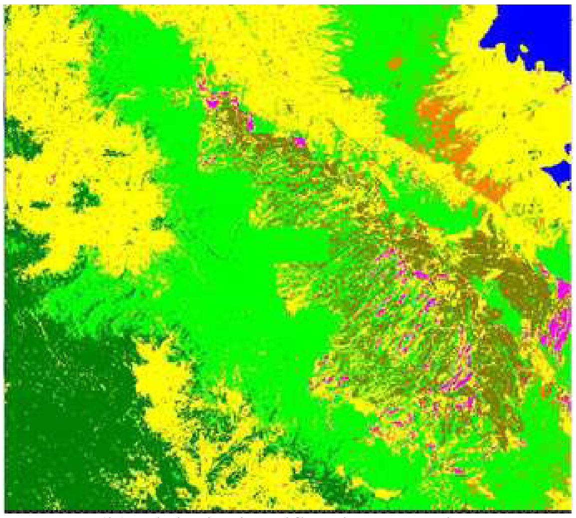
Figure 3-6: Plantation Forest Eucalyptus in Samosir Island

From the results of land cover classification, especially in forest areas, on the study area was only obtained three classes of forest, ie primary dry forest, secondary dry forest and forest plantation. After forest types classes were identified based on the KLHK land cover reference maps, next were done classification digitally with creating a training area on several classes of forests at sample area (Figure 3-7) and to determine the test mixing between the three classes of forest and non-forest and determine its accuracy digitally. In addition, from the training area which had been created, it will be calculated the average value of digital (reflectance) on each band used from Landsat 8 (1-7) which had the same spatial resolution, ie 30 meters. Subsequently made into the spectral curve of each class of forest type.

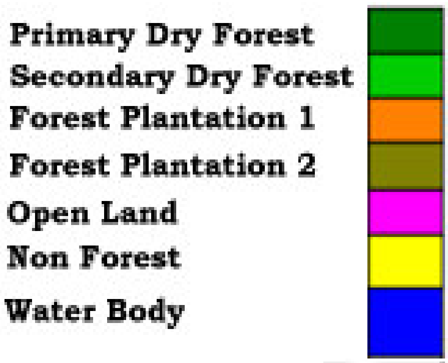
The test results of the selection of the training areas of forest type classes, whether it had been approached homogeneous, by looking at the coefficient of variation of the training areas which were taken on each band of Landsat used in the supervised classification process, were presented in Table 3-3. The result of the confusion matrix between training areas which created and the classification results were presented in Table 3-4, while the spectral curve of 3 classes of forests was presented in Figure 3-8, 3-9, 3-10, 3-11, 3-12, 3-13, and 3-14.



(a) Distribution of the Training Samples



(b) Digital Classification Results



(c) Legend

Figure 3-7: (a) Distribution of the Training Samples on Landsat 8 in the Study Areas, (b) Results of Digitally Classification using Maximum Likelihood Method, (c) Description of the Legend

From Table 3-3, the value of the CV coefficient of variation (color table) of all the training areas of forest class from all channels of Landsat 8, average, below 30%, it was considered good or fulfill the standard of selection of homogeneous training areas (training area is said good or nearly homogeneous if the CV is less than 30%).

Table 3-3: Coefficient of Variation of the training area on forest class of 7 channels Landsat 8

Mean							
	b1	b2	b3	b4	b5	b6	b7
Primary Dry Forest	936,2	715,4	566,3	333,9	2,541,8	1,039,9	383,1
Secondary Dry Forest	863,4	663,3	532,6	322,6	2,347,4	1,040,6	410,4
Forest Plantation1	847,4	652,6	557,6	326,6	2,382,5	918,8	373,9
Forest Plantation2	832,6	637,1	501,0	305,4	3,735,0	1,060,1	366,6
SD= Standar Deviasi							
	b1	b2	b3	b4	b5	b6	b7
Primary Dry Forest	25,9	24,7	53,0	30,4	583,5	233,7	80,0
Secondary Dry Forest	16,4	14,4	26,1	21,3	256,9	103,9	48,5
Forest Plantation1	11,1	11,5	25,6	15,2	283,7	138,2	48,2
Forest Plantation2	32,6	39,5	51,0	61,6	429,8	106,0	80,0
Coefisien of Variation (CV)=SD/Mean							
	b1	b2	b3	b4	b5	b6	b7
Primary Dry Forest	2,77	3,45	9,36	9,09	22,96	22,47	20,90
Secondary Dry Forest	1,90	2,17	4,90	6,61	10,95	9,99	11,81
Forest Plantation1	1,31	1,77	4,59	4,66	11,91	15,04	12,90
Forest Plantation2	3,91	6,21	10,19	20,19	11,51	10,00	21,82

From the confusion matrix between the training of areas with classification results on region samples were obtained overall accuracy, ie 98.27% of 27,652 pixels and the value of kappa value, ie 0.976. While the confusion matrix between the training area which are taken randomly and the classification results were shown in Table 3-5. From Table 3-5 was obtained overall accuracy of 97.14% and the kappa value, ie 0.961. When compared to Table 3-4, the result of confusion matrix in Table 3-5, the value of overall accuracy was not much different (equally good), above 97%, as well as the statistical value of kappa, meaning that accuracy was equally good.

From these results, the digital classification had provided good results to be able to distinguish the forest type classes. While the visual classification had shown more difficult to draw the line among forest type classes. Thus the digital classification could also be combined with visual classification, especially if there were difficulty in drawing the line between the two classes of forest or land cover two different classes. This method has also been known as a hybrid interpretation. The hybrid interpretation according to Suharyadi (2010) is a technique that combines the visual interpretation for the delineation of the object, and using the principles of digital spectral pattern recognition to identify the object.

Table 3-4: Results of confusion matrix between training of area with the classification results

	Primary Dry Forest	Secondary Dry Forest	Forest Plantation 1	Forest Plantation 2	Non-Forest	Open Land	Water Body
Primary Dry Forest	3966	0	0	0	0	0	0
Seconday Dry Forest	0	3468	15	1	33	34	1
Forest Plantation 1	0	0	1288	0	0	12	0
Forest Plantation 2	0	13	0	283	0	0	0
Non-Forest	0	17	0	0	4663	4	0
Open Land	0	7	25	0	0	12824	31
Water Body	0	0	3	0	0	282	682

Table 3-5: Results of confusion matrix between new training area with the classification results

	Primary Dry Forest	Secondary Dry Forest	Forest Plantation 1	Forest Plantation 2	Non-Forest	Open Land	Water Body
Primary Dry Forest	3911	0	0	0	0	0	0
Seconday Dry Forest	0	3566	15	7	78	79	14
Forest Plantation 1	0	38	1261	0	0	30	2
Forest Plantation 2	0	38	0	351	0	0	0
Non-Forest	0	7	0	0	4652	31	0
Open Land	0	4	45	0	0	10884	102
Water Body	0	2	10	0	0	277	581

Spectral pattern which formed (Figure 3-8, 3-9, 3-10, 3-11, 3-12, 3-13, and 3-14) of several types of forests in the study area was obtained from the value of the average reflectance of the training areas which were made based on the classes of forest types with the reference of the KLHK land cover map on the bands of the Landsat 8 used (Band-1 to Band-7), which had the same spatial resolution, ie 30 meters.

From Figure 3-8, 3-9, and 3-10 show that the spectral pattern between primary dry and secondary forests are similar, differences occur in the Band-5 (Near Infra Red) wherein reflectance of the primary dryland forests are higher than the secondary dry forest on this band.

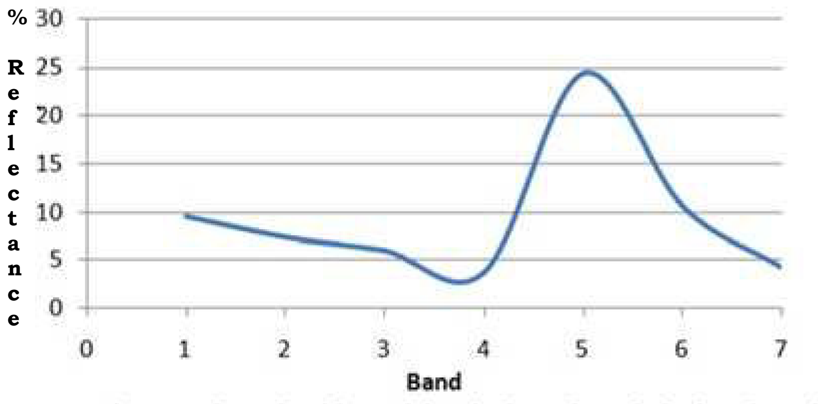


Figure 3-8: Spectral Pattern of Primary Dry Forests (Bands 1 to 7)

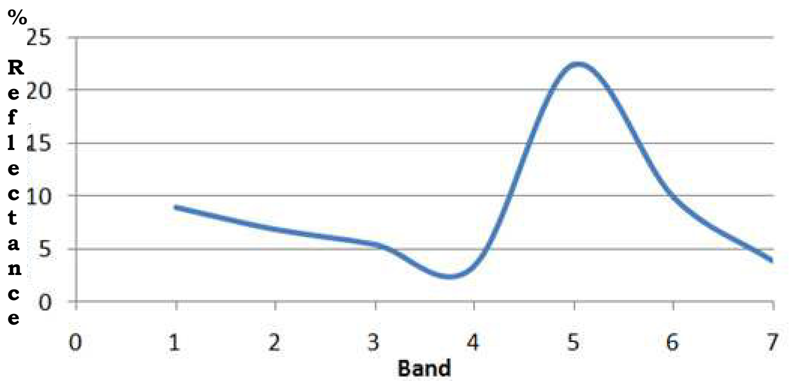


Figure 3-9: Spectral Pattern of Secondary Dry Forests (Bands 1 to 7)

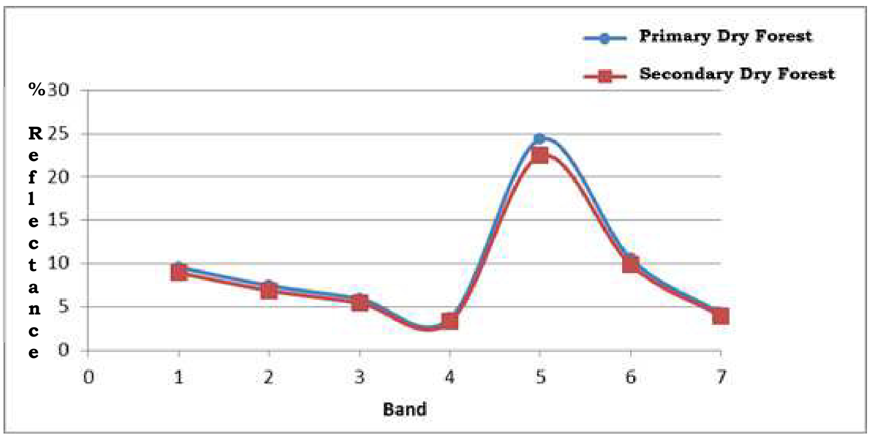


Figure 3-10: Spectral Pattern of Primary and Secondary Dry Forests (Bands 1 to 7)

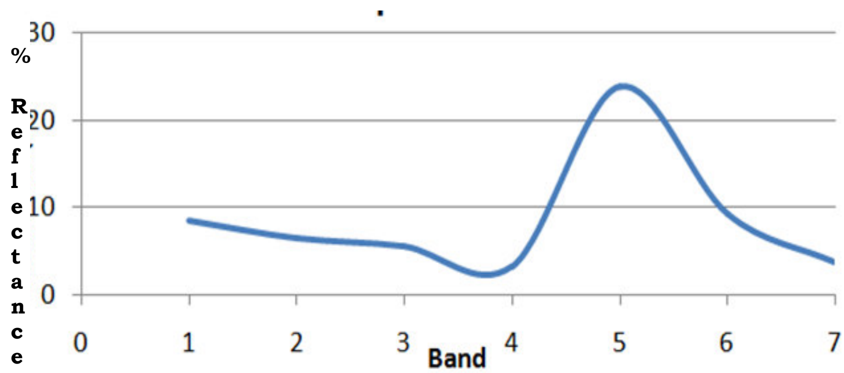


Figure 3-11: Spectral Pattern of Forests Plantation 1 (Bands 1 to 7)

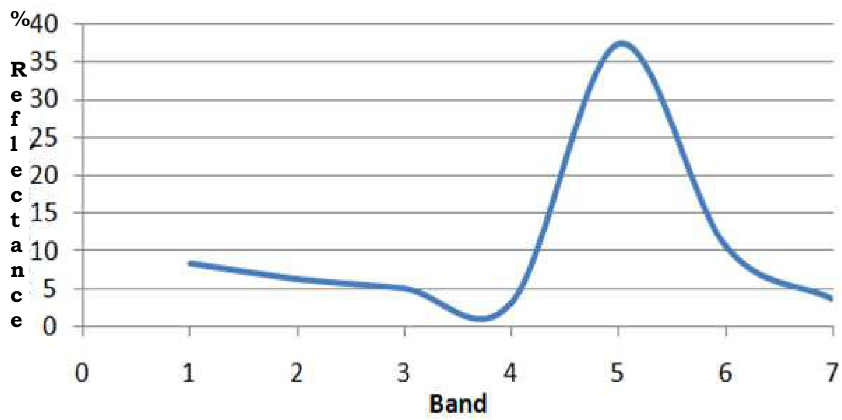


Figure 3-12: Spectral Pattern of Forests Plantation 2 (Bands 1 to 7).

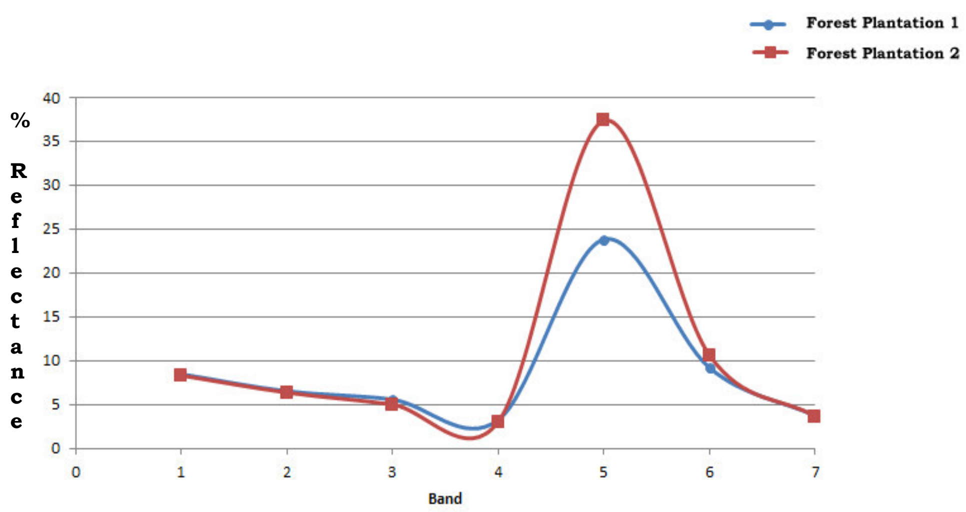


Figure 3-13: Spectral Pattern of Forests Plantation 1 and 2 (Bands 1 to 7)

In Figure 3-11, 3-12, and 3-13 were seen that spectral pattern of forest plantations 1 has reflectance numbers of Band-5 higher than forest plantation 2, in which from the results of a field survey which was conducted in September 2015, forest plantations 1 was pine forests, while forest plantations 2 was Eucalyptus forests (see Figure 3-6). While the spectral differences among four classes of the forest types (Figure 3-14) show that the forest plantations 2 has the highest reflectance numbers among all classes of the forests on Band-5.

Spectral patterns of the several forest types have the similar trends. In the study area, the spectral numbers of the primary dry forest are higher than the secondary dryland forests, with numbers between 20 and 25. Forest plantations 1 and 2 have a higher spectral value, but for plantations 1 did not differ significantly with the spectral value of forest land dry primary and secondary dry forest. Thus, there is difficulty distinguishing the forest classes based solely on spectral value.

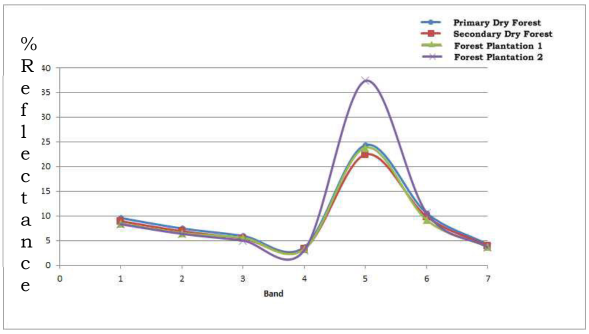


Figure 3-14: Spectral Pattern of Primary and Secondary Dryland Forests, Forests Plantations 1 and 2 (Bands 1 to 7)

4 CONCLUSION

The composite RGB 654 Landsat 8 imagery based on test results OIF for the forest classification, showed that the forests could be distinguished with other land covers. The results of the forest identification in the study area using Landsat 8, obtained four classes of forests; those were primary dryland forests, secondary dryland forests, and plantation forests which then was divided into two types, namely plantation forests 1 (Pine forests) and plantations forests 2 (Eucalyptus).

This study also provides results that the digital classification can be combined with the visual classification known as a hybrid classification method, especially if there are difficulties in border demarcation between the two types of forest classes or two classes of land covers. Spectral number of the forest types classes have the similar pattern, but it is quite difficult to conclude if the forest classes based solely on the spectral number.

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