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Interpretability Evaluation of Annual Mosaic Image of MTB Model for Land Cover Changes Analysis

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Abstract

To verify whether the annual mosaic image of MTB model is acceptable for further digital analysis, it is necessary to evaluate the visual interpretability. The MTB model is an effort to integrate multi-scene and multi-temporal data, to obtain a minimum cloud cover mosaic image in locations that are often covered by clouds and haze. This study is to evaluate the interpretability of the annual mosaic image for analysis of the land cover changes. The data used are the images of 2015, 2016, and 2017 covers a part of central Sumatra. Visual interpretations with a series of steps are used, starting with identification of the objects using interpretation keys, followed by spectral band correlations, scattergram analysis, and ended by consistency assessment. The consistency assessment step is performed to determine the level of clearness and easiness of the object recognition in the annual mosaic images. The results showed that the most optimal spectral bands used for RGB combinations for visual interpretation were Band SWIR-1, Band NIR, and Band Red. Based on the evaluation results, the annual mosaic image of MTB model performed the consistent results of the clearness objects and the easiness of the object recognition. Thus the annual mosaic image of MTB model of 0.02x0.02 degree tile is acceptable for further digital processing as well as digital land cover analysis.

Keywords: *interpretability evaluation, annual mosaic image, visual interpretations, scattergram analysis, consistency of the results, the level of clearness, the level of easiness, standardization of data processing*

1. Introduction

In order to obtain adequate accuracy of the information for the implementation of One Map Policy, the multi-temporal cloud free remote sensing satellite data is required [1-4]. The continuity and regularity of medium-scale multi-temporal satellite data availability, particularly for cloud-covered areas are still very low [4-8]. Several researchers have developed some solutions to address the availability of medium-scale data in a frequently cloud-covered areas, one of which is the Mosaic Tile Based (MTB) model developed by the authors [9-12]. The model is implemented with Landsat-8 Operational Land Imager (OLI) to obtain annual multi-temporal mosaic images with minimal cloud cover for central part of Sumatra. The problem is that the MTB model developed has not been proven its visual interpretability. The annual mosaic image of the MTB model to be used for digital interpretability, must be proven its visual interpretability with acceptable accuracies.

The MTB model is an approach constructed from a set of specified pixels (called tiles), which are integrated from the tiles of clear area from clouds and haze in the terrestrial areas that cover vegetation, open land, and water body of multi-temporal imageries without manipulation on the reflectance, that is oriented for digital analysis needs. Three tile sizes are used to examine the reliability and simultaneously the level of interpretability of the resulted image. Those tiles are the tile with a size of 0.10x0.10 degree (11kmx11km); 0.05x0.05 degrees (5.5kmx5.5km), and 0.02x0.02 degrees (2.2kmx2.2km). The quality of each tile in the mosaic image could be appraised using the IoCVO (Index of the Clear area, Vegetated Area, and Open Land) algorithm. This mosaicing process had adopted and modified various existing methods, such as NCAS (Australia), INCAS (Indonesia), University of Maryland (UM) [7],[11],[13-15], then developed a model with a simple algorithm that is MTB [12].

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The MTB model represents a new breakthrough in satellite image processing to overcome the cloud-covered areas and haze interference. The model can be a novelty in the standardization of the medium-scale data processing. In order to implement in digital interpretability, the acceptability of visual interpretability should be proven. Such acceptability will reduce the doubt that the annual mosaic image has a low accuracy, and will confirm an annual mosaic image that can be analyzed similar to non-mosaic or original data in digital image processing.

This study aims to evaluate the visual interpretability of the annual mosaic imagery for the analysis of land cover, and to examine its consistency for analysis of the land cover changes. The interpretability of the image can be measured by three parameters, namely (a) the clearness of the objects on the image, (b) the easiness of the object recognition, and (c) the national image interpretability rating scale. The evaluation of visual interpretability is one approach to measure the land cover changes [17-18]. If the results show that the annual mosaic image has a high level of interpretability so it can be accepted, then the MTB model will be one solution for providing satellite imagery in areas that are often covered by clouds and haze interference. This is in line with the efforts in the national standardization of data quality and remote sensing products, especially on the data processing [4],[2],[19-20]. This study will be a major contribution in proving that the MTB model is a new model that can be used for further digital analysis.

The data used for this study are the annual multi-temporal mosaic images of MTB model Landsat-8 OLI of 2015, 2016, and 2017 [12]. The study sites are the central part of Sumatra, part of Indonesia, which is often covered with clouds and haze interferences, so the availability of clear remote sensing satellite data is difficult [8-7]. The area has a relatively complete topography and varies, from flats to mountainous. The area also has relatively complete objects on land cover, i.e. forests, plantations, settlements, shrubs, bushes, agricultural fields, mangrove swamps, and water bodies. The changes occurring in land cover of this region are quite high, and properly representing the dynamic land use change analysis [10],[21-22]. The results of this study will be used to ensure that the annual mosaic of MTB image meets the requirements and quality to be used in the visual interpretation of land cover. Thus the MTB model will be able to be used as input in the national standardization of data quality and remote sensing products, particularly for data processing [17],[23-24].

2. Research Method

The data used for this study were the geometric and radiometric corrected Landsat-8 OLI with spatial resolution of 30 meters, for central part of Sumatra region, covering parts of Riau, West Sumatra, and North Sumatra Provinces as shown in Figure 1 [25-26]. The total data used consisted of 570 scenes, covers 10 (ten) scenes of data on path-row 125-59, 125-60, 126-59, 126-60, 126-61, 127-59, 127-60, 127-61, 128-59, and 128-60. However, for three year data of 2015, 2016, and 2017 in this study, only 478 scenes were used because of availability at the time of data collection. The orientation of this study was focused on detecting land cover objects in the terrestrial area, therefore only 5 (five) spectral bands most sensitives to land cover among 11 (eleven) available spectral bands were used, namely Band-2, Band-3, Band-4, Band-5, and Band-6 [12].

The cloud cover level of the data input in this study is shown in Figure 2. This figure shows that the cloud variation in the data used is very high, and even most of the data used indicates cloud coverage above 40%. The results of the Landsat-8 multi-temporal mosaic image developed using the MTB model with the best tile size of 0.02x0.02 degrees (2.2kmx2.2km) were evaluated for their visual interpretability and consistency assessment for the time series analysis of land cover changes. There are several land cover change detection techniques using time series data, and the evaluation of visual interpretability used in this study is one of the approaches in examining land cover changes [17],[3].

Evaluation of visual interpretability is done to find out how the clearness of the objects, the easiness of the object recognition, and national scale interpretability of the annual mosaic image. The clearness of the objects of the image is distinguished into 0 (unclear), 1 (somewhat obvious), 2 (clear enough), 3 (clear), and 4 (very obviously). While the easiness of the object recognition is divided into 0 (not recognizable), 1 (rather easy), 2 (easy enough), 3 (easy), and 4 (very easy). The national scale of image interpretability rating is divided into 10 levels, namely

Level-0, Level-1, Level-2, Level-3, Level-4, Level-5, Level-6, Level-7, Level-8, and Level-9 [16]. Due to the data availability reasons, only two of the three evaluations above mentioned will be done, that is the evaluation of the clearness of the objects, and the easiness of the object recognition.

The objective of this visual interpretability evaluation is to determine whether the annual mosaic image can be used for visual interpretation, and whether the results are consistent with the different year data. The interpretability evaluation is performed in the sequence of steps as shown in Figure 3.

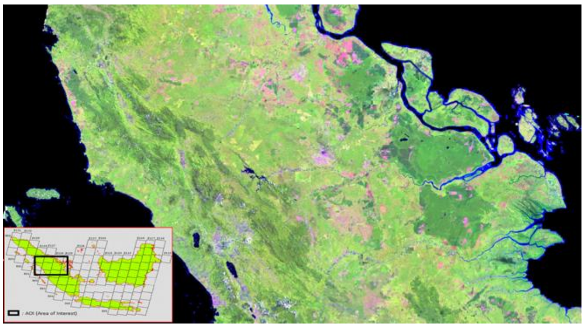
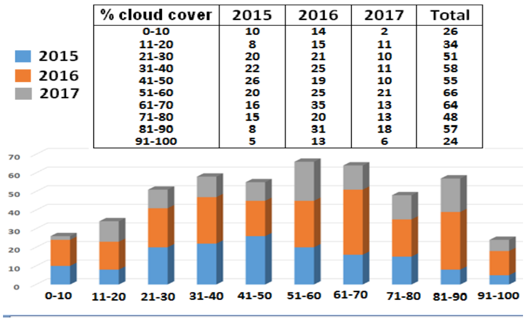


Figure 1. The RGB 654 of annual mosaic image of study area



% cloud cover	2015	2016	2017	Total
0-10	10	14	2	26
11-20	8	15	11	34
21-30	20	21	10	51
31-40	22	25	11	58
41-50	26	19	10	55
51-60	20	25	21	66
61-70	16	35	13	64
71-80	15	20	13	48
81-90	8	31	18	57
91-100	5	13	6	24

Figure 2. Cloud cover ranges of the data used in percent (%)

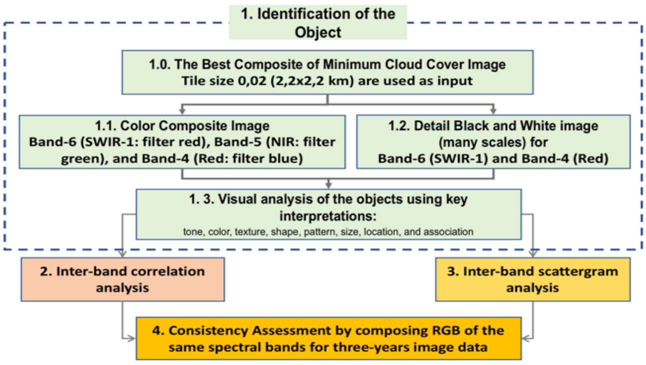


Figure 3. Model of Visual Interpretability Evaluation of Annual Mosaic Image of MTB

Firstly, identification of the object by comparing the original image of black and white that has not been mosaiced with a black-and-white image that has been in-mosaic. Identification of the object is done to determine the level of clearness of the object in the image and easiness of the object recognition. In order to examine the performance of the results, a color composite image was created. In certain parts of the color composite image was made more detailed image per band, with various scales. The scale used is 1: 250,000 for color composite images, and 1: 250.00, and 1: 100,000 for black-and-white image per band as the optimal scale for Landsat-8 OLI images [3].

The visual accuracy of the land cover objects was carried out using interpretation keys, such as tone, color, texture, shape, pattern, size, location, and association. The land cover category used is the categorization of Land Cover mapping using Landsat data in the scale of 1: 250,000 initiated by of the Ministry of Environment and Forestry (MEF) which categorized into 23 classes [24-23]. The number of classes is adapted to the level of clearness and easiness of object recognition.

Secondly, is to examine the correlation among spectral bands. This correlation test is performed to find out the most optimal spectral bands in visualizing the object, so that the clearness of the object and easiness to recognize the objects are high. The spectral bands have low correlations can be recommended to be selected as spectral bands for further analyzed in identifying objects, since those spectral bands can complement each other [27-28].

Thirdly, is creating scattergrams among spectral bands. The scattergrams can also perform the correlation results, to find out the most optimal spectral bands in visualizing the objects, so that the clearness of the objects can be optimized to easily recognizable. The scattergram distribution shows nearly a 45-degree angle trend is not recommended to be used in multispectral analysis in the form of color composite images, since it means those bands will be redundant and therefore does not show high contrast. The spectral bands recommended for color compositions in the visual analysis or taking the training samples in digital classifications, are spectral bands clustered into clear clusters.

Fourthly, is to examine the consistency of mosaic image of MTB model, consisting of superimpose analysis and comparative analysis. This consistency examination is by creating red-green-blue (RGB) among the same spectral bands on a three-year mosaic image. All five spectral bands SWIR-1 (Band-6), NIR (Band-5), Red (Band-4), Green (Band-3), and Blue (Band-2) are examined. Each spectral band is synthesized to create RGB, from which each spectral band for 2017 is filtered red, for 2016 filtered green, and for 2015 filtered blue. With the creation of RGB fusion of the three year images can be verified how is the consistency of mosaic image quality performance of MTB images. The annual image consistency can be known from the regularity of the form of changes in the five RGB images, by applying the principle of “no-color no-change”. This principle is significant if the image appears black to white (no color), meaning the land cover objects do not change, but if the objects appear in color, it means the land cover objects have changed into the image of the year [22],[29-33].

To determine the level of clearness of the objects and the level of easiness object recognition is performed for a visual land cover analysis, the several objects on the RGB of the selected spectral bands with the land cover map produced by the MEF of the same year are compared. The results of the comparison analysis will show how the acceptability level of the annual mosaic image can be used for the visual land cover analysis.

The results of the four implementation steps will give an idea of the level of clearness of the objects and the level of easiness of object recognition, as well as the level of consistency of the annual mosaic image in each spectral band. The end result will be the recommendation of the spectral bands which optimally provides the high clearness of the objects, and the easiness of the land cover object recognition.

3. RESULTS AND DISCUSSIONS

Evaluation of the visual interpretability of the annual mosaic image is performed to verify whether the MTB model results meet the requirements and might be accepted in the further digital analysis or not. In order to confirm the clearness of the objects and the easiness object recognition a series of assessment steps is carried out. Figure 4 shows the comparison between the original (un-mosaic) images and the mosaic images, both of the black-and-white and the color composite multi-temporal mosaic images. The tone, color, texture, shape, and pattern of the objects in the original images and in the multi-temporal mosaic images in various spectral bands and color composite image strongly indicates similarities. The appearance of the objects covered in the scenes is clearly visible and easily distinguishable from other objects on the mosaic color composite image.

Further analysis shows that cloud cover and haze found in original images have been greatly reduced in the image of multi-temporal mosaic results. On a very large enlargement scale of 1:50.000, the image of the mosaic results shows the boundary borders of the tile at several locations, for which the Landsat-8 multi-temporal mosaic image result is recommended to be used for the optimum scale of 1: 250,000, as shown in the Figure 4. It confirms that the annual mosaic image of the MTB model performs the clearness of the objects and the easiness object recognition for a visual land cover analysis. Thus the analysis of easiness of object recognition, as well as clearness of the objects in both the original and the mosaic images is relatively the same. However, this early conclusion is still needs to be further proved by the following analysis.

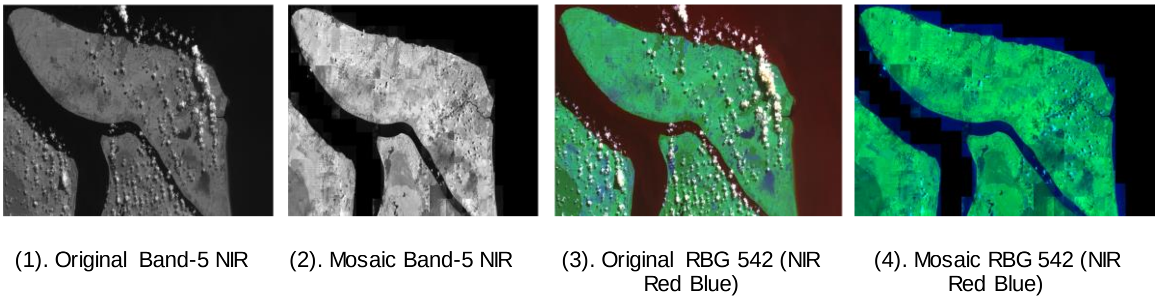


Figure 4. Comparison of Original and MTB Annual Mosaic Images of 2016
[Note: the images number (1)-(4) are recorded at July 12, 2016 located in the path-row 126-059]

According to the USGS, there are 5 (five) combinations of standard RGB channels for Landsat-8, namely Color Infrared 543, Natural Color 432, False Color 654, False Color 764, and False Color 753 [32]. While according to ESRI there are 10 (ten) spectral combinations band are introduced, namely Natural Color 432, False Color (urban) 764, Color Infrared (vegetation) 543, Agriculture 652, Atmospheric Penetration 765, Healthy Vegetation 562, Land/Water 564, Natural with Atmospheric Removal 753, Shortwave Infrared 754, and Vegetation Analysis 654.

As the objectives, the selected 5 (five) spectral band combinations based on correlations, stability of recording time, and atmospheric disturbance conditions were analyzed. The composing image of RGB 654 False Color/Vegetation Analysis, RGB 564 Land and Water, RGB 652 Agriculture, and RGB 562 Healthy Vegetation were created for the visual object recognition. Those images are shown in Figure 5. The scale used for this study is 1: 250,000 for color composite images, and 1: 250.00, and 1: 100,000 for black-and-white image per band as the optimal scale for Landsat-8 OLI images [33-35]**.** The enlargement of some parts on black-and-white and color composite images is performed to observe the detail objects for visual analysis.

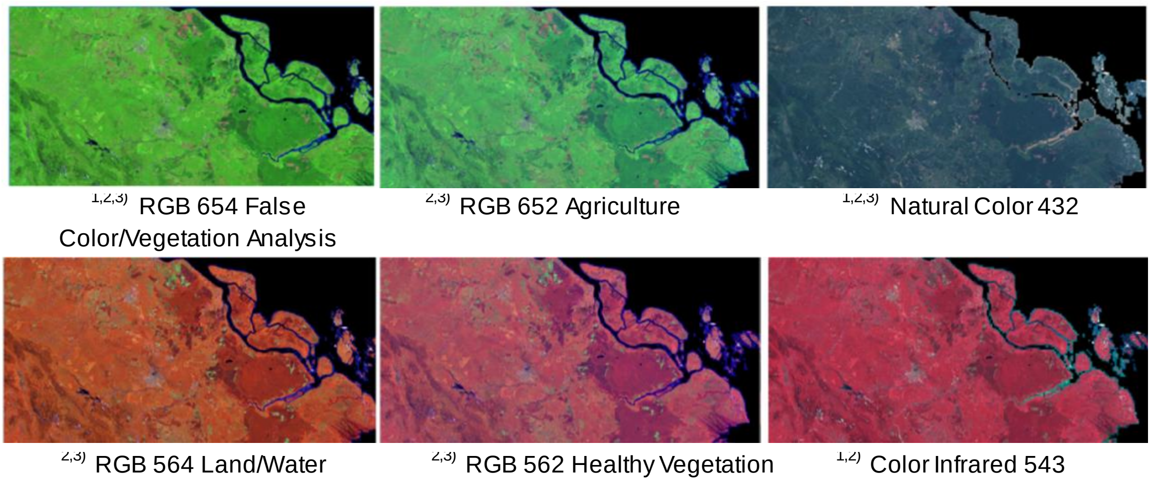
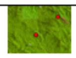
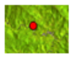
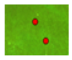
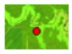
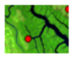
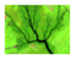
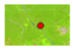
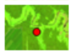
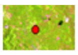
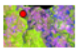
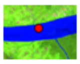
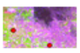
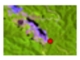


Figure 5. Standard of RGB Spectral Band Combination of Landsat-8 Image of a Part of the Study Area
1)Standard USGS, 2)Standard ESRI, 3)Used in this Study

The results of the visual analysis of the level of clearness of the objects and the level of easiness object recognition in both color composite and black-and-white images are shown in Table 1. From Table 1, it is known that the average scores of the clearness objects and the easiness of object recognition in RGB 654 (for Vegetation Analysis) or RGB 564 (for Land and Water analysis) are higher than in RGB 432 (Natural Color). The levels of the clearness objects in RGB are ranges from easy to very easy, and the easiness objects recognition ranges from easy to very obvious, rather than in each spectral band.

Table 1. The Clearness and Easiness Levels of Land Use/Cover Objects in the image of scale 1:250,000

No	Objects	A		B		C		D		E		F		G		H	I	J	Remarks
		a	b	a	b	a	b	a	b	a	b	a	b	a	b	Σ			
1	Primary Inland Forest (Hp)	1	1	1	1	1	1	2	2	3	3	4	4	3	3	30		2001 - Hp	easy to be recognized, somewhat obvious distinguished from other forests
2	Secondary Inland Forest (Hs)	1	1	1	1	1	1	2	2	2	2	3	2	2	2	23		2002 - Hs	easy to be recognized, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with Primary Inland Forest)
3	Primary Swamp Forest (Hrp)	1	1	1	1	2	2	2	2	3	3	4	4	3	3	32		2005 - Hrp	easy to be recognized, clearly distinguished from others
4	Secondary Swamp Forest (Hrs)	1	1	1	1	1	1	1	1	2	2	3	3	2	2	22		20051- Hrs	easy to be recognized, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with Primary Swamp)
5	Primary Mangrove Forest (Hmp)	1	1	1	1	2	2	2	2	4	4	4	4	3	3	34		2004 - Hmp	easy to be recognized, clearly distinguished from other
6	Secondary Mangrove Forest (Hms)	1	1	1	1	1	1	1	1	3	3	3	3	2	2	24		20041 - Hms	easy to be recognized, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with Primary Mangrove Forest)
7	Estate Forest (Ht)	1	1	1	1	2	2	3	3	4	4	4	4	3	3	36		2006 - Ht	very obvious and very easy to be recognized and distinguished from others
8	Plantation (Pk)	1	1	1	1	2	2	2	2	4	4	4	4	3	3	34		2010 - Pk	easy to be recognized, clearly distinguished from other
9	Shrub/Bush (B)	1	1	1	1	1	1	1	1	2	2	2	2	1	1	18		2007 - B	somewhat obvious to be detected, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with swampy schrub/bush)
10	Grasslands (S)	1	1	1	1	1	1	2	2	3	3	3	3	2	2	26		3000 - S	easy to be recognized, somewhat obvious distinguished from others
11	Swamp Bush/ Shrub (Br)	1	1	1	1	1	1	1	1	2	2	2	2	1	1	18		20071- Br	somewhat obvious to be detected, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with schrub/bush)
12	Dryland Agricultural mixed with Bush (Pc)	1	1	1	1	1	1	1	1	2	2	2	2	1	1	18		20092 - Pc	somewhat obvious to be detected, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with agricultural dryland)
13	Agricultural Dryland (Pt)	1	1	1	1	1	1	1	1	1	1	2	2	1	1	16		20091-Pt	somewhat obvious to be detected, somewhat obvious distinguished from others, need support data for interpretations (difficult to differenciate with agricultural dryland mixed with bush/schrub)
14	Paddy Fields (Sw)	1	1	1	1	2	2	1	1	2	2	3	3	3	3	26		20093-Sw	easy to be recognized, somewhat obvious distinguished from others
15	Swamp (Rw)	1	1	1	1	2	2	2	2	3	3	4	4	3	3	32		50011-Rw	easy to be recognized, clearly distinguished from other
16	Water Body (A)	1	1	2	2	3	3	4	4	4	4	4	4	3	3	42		5001-A	very obvious and very easy to be recognized and distinguished from others
17	Settlements (Pm)	1	1	1	1	3	3	2	2	2	2	4	4	3	3	32		2012-Pm	easy to be recognized, clearly distinguished from other
18	Other Built-up Areas (Pm)	1	1	1	1	1	1	1	1	2	2	3	3	2	2	22		2012-Pm	easy to be recognized, somewhat obvious distinguished from others, need support data for interpretations
19	Mining Areas (Pb)	1	1	1	1	2	2	2	2	2	2	3	3	2	2	26		20141-Pb	easy to be recognized, somewhat obvious distinguished from others
20	Open Lands – Airport (Bdr)	2	2	2	2	3	3	2	2	3	3	4	4	3	3	38		20121-Bdr	very obvious and very easy to be recognized and distinguished from others
21	Clouds (Aw)	4	4	3	3	3	3	1	1	2	2	3	3	4	4	40		2500-Aw	very obvious and very easy to be recognized and distinguished from others
22	Cloud Shadows (Aw)	3	3	2	2	2	2	2	2	2	2	3	3	4	4	36		2500-Aw	very obvious and very easy to be recognized and distinguished from others
Σ	Scores of Spectral Bands Quality	28	28	27	27	38	38	38	38	55	55	71	70	54	54				
	Average scores	1.3	1.3	1.2	1.2	1.7	1.7	1.7	1.7	2.5	2.5	3.3	3.2	2.5	2.5				

Note: A: Band-2 (Blue), B: Band-3 (Green), C: Band-4 (Red), D: Band-5 (NIR), E: Band-6 (SWIR-1), F: RGB 654/564 False Color-Veg Analysis/Land&Water, G: RGB 432 Natural Color, H: Interpretability Level, I: Object in Composite Image, J: Reference to MEF Map (Code & Toponimi); a → object clearness levels (0:unclear, 1:somewhat obvious, 2:clear enough, 3: clear, 4: very obvious); and b → object recognition easiness levels (0: not recognizable, 1:rather easy, 2: easy enough, 3:easy, 4:very easy); score ≥ 35 means very obvious and very easy to be recognized and distinguished from others; 31-34 means easy to be recognized, clearly distinguished from others; 26-30 means easy to be recognized, somewhat obvious distinguished from others; 21-25 means easy to be recognized, somewhat obvious distinguished from others, need support data for interpretations; and ≤ 20 means somewhat obvious to be detected, somewhat obvious distinguished from others, need support data for interpretations.

The clearness object of dense forest vegetation, such as primary forests and secondary forests can be clear-to-very obvious detected, but sometimes difficult to be distinguished from less dense vegetation coverage, such as plantations and agriculture. The easiness object of dense peat forests can be ease-to-very easily recognized and distinguished from other forests. The easiness object of estate forest and plantations can be easy enough-to-easily recognized from other forests. While easiness object of agricultural land can be fairly easy-to-easy enough recognized from other objects, and because of the color and the pattern of the object, the clearness and the easiness of object water and cloud covers can be very obvious clear and very ease recognized. The easiness of object recognition and the clearness of the object to be differentiated from the other objects is emphasized in the color composite samples listed in Table 1. All of samples selection listed in Table 1 is then confirmed with the map from MEF, and the results show strongly indicates similarities.

In order to optimize the object recognitions for visual interpretations in multi-temporal mosaic image, the selection of the spectral bands is analyzed. The selections are based on the correlation and scattergram values among the spectral bands. The spectral bands have low correlations are recommended to be selected as spectral bands for further analyzed in identifying objects, since those spectral bands can complement each other [27-28]. The results of correlation analysis, among the spectral bands are shown in Table 2. From the table, it can be concluded that the best of spectral bands for color composite analysis is Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green) with a correlation of 0.306, and a spectral band among the visible group.

Although the Band-2 (Blue) has the lowest correlation value, but it was not selected for multi-temporal analysis, because according to its wavelength the Band-2 is unstable against atmospheric disturbance conditions. For the spectral bands of visible group, the Band-4 (Red, filtered blue) was selected because this spectral band corresponds to the most stable wavelength characteristic of atmospheric disturbance, among the spectral bands of visible group. This condition is in line with the analysis of color composite of the original multi-temporal and multi-scene images [34-36]**.** Thus, for the color composite analysis the Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green), and Band-4 (Red, filtered blue) were selected. These combinations are the most optimal spectral bands in visualizing the objects.

Table 2. Correlation Analysis of Spectral Bands

Correlation Matrix	Band-2	Band-3	Band-4	Band-5	Band-6
Band-2	1.000	0.882	0.897	-0.238	0.359
Band-3	0.882	1.000	0.918	0.097	0.668
Band-4	0.897	0.918	1.000	-0.178	0.621
Band-5	-0.238	0.097	-0.178	1.000	0.306
Band-6	0.359	0.668	0.621	0.306	1.000
Average	0.594	0.641	0.653	0.205	0.488

Scattergram analysis results that have nearly a 45-degree angle trend is not recommended to be used in multispectral analysis in the form of color composite images, since it means those bands will be redundant and therefore does not show high contrast. From the scattergram analysis results as shown in Figure 6, it can be concluded that the spectral bands recommended for color compositions in the visual analysis or taking the training samples in digital classifications is Band-6 (SWIR-1, filtered red) on scattergram number 5 (2015), 10 (2016), and 15 (2017); Band-5 (NIR, filtered green) on scattergram number 19 (2015), 24 (2016), and 29 (2017); and Band-4 (Red, filtered blue) on scattergram number 20 (2015), 25 (2016), and 30 (2017). This condition is in line with the analysis of color composite of the original multi-temporal and multi-scene images [37].

In order to visually analyze the land cover changes, the superimposing of the selected spectral bands for the three years of 2015, 2016, and 2017 to a composite of RGB (red green blue) image is examined. The RGB composite image is intended to give the red filter to spectral bands of 2017, green filters on spectral bands of 2016, and blue filters on spectral bands of 2015 for each SWIR-1, NIR, Red, Green, and Blue spectral bands. The result of the RGB composite of three-year image is shown in Figure 7. From Figure 7, it is known that "no-color no-change". This is significant if the image appears black to white, it means the land cover objects do not change, but if the objects appear in color, it means the land cover objects have changed into the image of the year [22],[29-33]. The red color means the object exists in 2017, because the 2017 spectral band is given a red filter. The green color means the object existed in 2016, because the 2016 spectral band is given a green filter. And the blue color means the object existed in 2015, because the spectral band 2015 is given a blue filter. For example, a blue color means the object existed in 2015 and has changed in both of 2016 and 2017. The green color means the object existed in 2016, but it was changed from 2015 and has changed in 2017. The red color means the object exists in 2017 and it was not existed yet in both of 2016 and 2015. From the Figure it is also known that the color changes, which indicates the land cover changes is clearly visible and easily identifiable on Band-6 and Band-4.

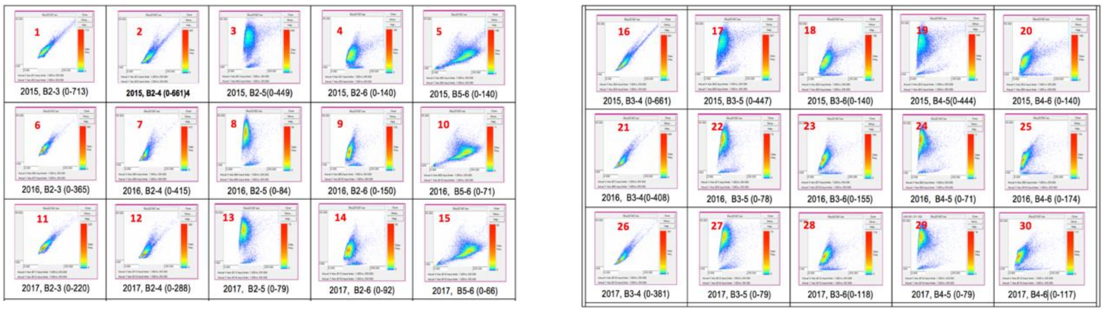
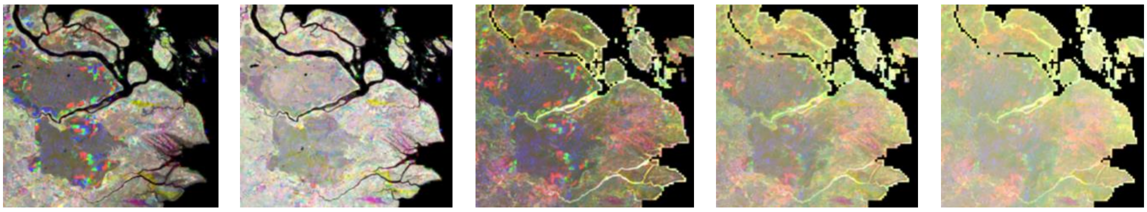


Figure 6. Scattergram Analysis of Spectral Bands of 2015, 2016, and 2017

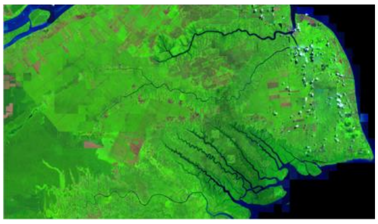


RGB of Band SWIR-1 (Band-6) R: 2017; G 2016, B: 2015	RGB of Band NIR (Band-5) R: 2017; G 2016, B: 2015	RGB of Band Red (Band-4) R: 2017; G 2016, B: 2015	RGB of Band Green (Band-3) R: 2017; G 2016, B: 2015	RGB of Band Blue (Band-2) R: 2017; G 2016, B: 2015

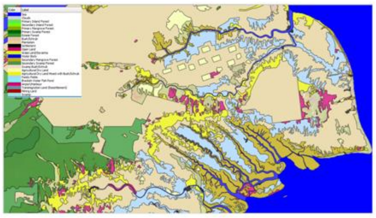
Figure 7. RGB Images of Each Spectral Band of 2015, 2016, and 2017, for Visual Analysis of Land Cover Changes

This condition is in line with the analysis of color composite of the original multi-temporal and multi-scene images [37],[27]. Thus, for the visual analysis of land cover changes through the RGB color composite for three year image data, the use of Band-6 (SWIR-1) and Band-4 (red) is recommended. These results mean that each spectral band of annual mosaic image MTB model shows the consistent result in performing the land cover objects for three years data.

The most optimum spectral bands to compose RGB in reflecting the object for the analysis of vegetations is the compositions of the Bands-6 (red filtered), Band-5 (green filtered), and Band-4 (blue filtered). While the best spectral band to compose RGB in reflecting the object for the analysis of Land/Water is the composition of Band-5 (red filtered), Band-6 (green filtered), and Band-4 (blue filtered). Those both images for the analysis of vegetation and Land/Waters are presented on the scale of 1: 250,000 are then compared and superimpose with the Land Cover map produced by the MEF of the same year and a scale of 1: 250,000 [12],[20-21]. From the comparison and superimpose analysis, as shown in Figure 8 known that some visual analyzed objects in the annual mosaic image are very closely suitable with the pattern of land cover on the map produced by the MEF. Base on the visual analysis of the superimposed image of the RGB 564 with the MEF Map on the detail scale of 1:250.000 and the superimposed image of the RGB 654 with the MEF Map on the detail scale of 1:100.000 known that for some objects in the annual mosaic image show a more detailed object classifications and not in the MEF map. It appears in the boundary of the class of bush/schrub on the MEF map after being superimposed with the annual mosaic image, it seems that there are some open land objects in the annual mosaic image. In addition, in the boundary of the class of estate forest on the MEF map after being superimposed with the annual mosaic image, it appears that there are some open land objects in the annual mosaic image. This is because the open land in both locations is part of the stages to become an estate forest and bush/shrubs. While in the larger scale image of the annual mosaic, it is recognize some tile boundaries. Visually the tile boundaries can be ignored because it clearly belongs to the class of the neighbouring object. One of them appears at the site in the middle of the swamp object, but because of base on the various key interpretations the tile boundaries belongs to the class of swamp, the tile boundaries can be ignored. Thus, the results of the comparison and superimpose analysis show that the annual mosaic image can be used for the visual land cover analysis as well as other digital analysis.

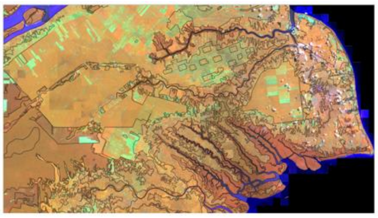


RGB 654 of 2016, Scale 1:250.000$^{*)}$

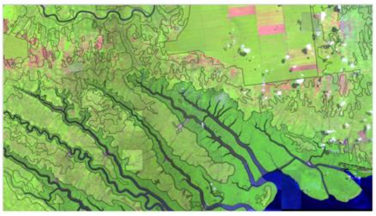


Land Cover Map Produced by the MEF of 2016, Scale 1:250.000$^{*)}$

RGB 564 of 2016, Scale 1:250.000$^{*)}$



Superimpose of RGB 564 and MEF Map of 2016, Scale 1:250.000$^{*)}$



Superimpose of RGB 654 of 2016 and MEF Map, Scale 1:100.000$^{*)}$

Superimpose of RGB 654 of 2016 and MEF Map, Scale 1:100.000$^{*)}$

Figure 8. Comparison and Superimpose of RGB 654 and RGB 564 with Land Cover Map Produced by the MEF, Scale 1:250.000
(Note: $^{+)}$ Scale at the display monitor)

From the evaluation of object recognition, correlation analysis, scattergram analysis, consistency assessment, superimpose analysis, and the comparative analysis with MEF land cover map, it is known as follows: (1) the annual mosaic image of the MTB model performs the clearness of the objects and the easiness object recognition for a visual land cover analysis, i.e. Forests, Plantations, Settlements, Schrubs, Bushes, Agricultural Fields, Mangrove Swamps, and Water Bodies; (2) the average scores of the clearness objects and the easiness of objects recognition in RGB 654 or RGB 564 are higher than in RGB 432; (3) the levels of the clearness objects in RGB are ranges from easy to very easy, and the easiness objects recognition ranges from easy to very obvious, rather than in each spectral bands; (4) the best of spectral bands for color composite analysis is Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green), and Band-4 (Red, filtered blue) with a correlation of 0.306. Means that these combinations are the most optimal spectral bands in visualizing the objects; (5**)** the spectral bands recommended for color compositions in the visual analysis of training samples in digital classifications is Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green), and Band-4 (Red, filtered blue); (6) from the creation of RGB fusion of the three year images can be verified that the land cover changes object is clearly visible and easily identifiable on Band-6 and Band-4. These results mean that each spectral band of annual mosaic image MTB model shows the consistent result in performing the land cover objects for three years data; (7) some visual analyzed objects in the annual mosaic image are very closely suitable with the pattern of land cover on the map produced by the MEF.

Thus, the results of the visual interpretability assessment confirm that the annual mosaic image can be used for the visual land cover analysis as well as other digital analysis. This condition is in line with the analysis of land cover of the original multi-temporal and multi-scene images [24],[34]. Thus the annual mosaic image of MTB model is acceptable for digital analysis of land cover as well as other digital analysis.

4. CONCLUSIONS

From the visual interpretation, analysis using the interpretation keys of tone, color, texture, shape, pattern, size, location and association concluded that for the land cover recognitions on the annual multi-temporal mosaic of color composite image, the use of RGB 654 or RGB 564 has the highest clearness objects as of 3.1, and the highest level of the easiness of object recognitions as of 3.2. The combinations of RGB 432 Natural Color have a clearness level of 2.5, and the easiness level for object recognitions as of 2.5. Among black and white spectral images, the Band-6 (SWIR-1) shows the highest level of the clearness and the easiness of object recognitions as of 2.5. Thus the compositions of RGB 654 or RGB 564 are the most recommended for the analysis of land cover (vegetations).

From the correlation analysis concluded that the best spectral bands for multi-temporal color composite analysis are the spectral bands with the lowest correlation, and the spectral bands with the most stable characteristic of atmospheric disturbance among the visible group. Meanwhile, from the scattergram analysis concluded that the most optimum spectral bands for multi-temporal color composite analysis are spectral bands clustered into clear groups. Both results of the correlation analysis and scattergram analysis confirm that the fusion of Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green), and Band-4 (Red, filtered blue) are the most recommended for visual analysis or taking the training samples in digital classifications of land cover analysis. All of three approaches, these are visual interpretations, correlation analysis, and scattergram analysis showing the strong similar results. Thus, for multi-temporal analysis of color composites, the recommended band compositions for vegetation analysis is the RGB 654 with Band-6 (SWIR-1, filtered red), Band-5 (NIR, filtered green), and Band-4 (Red, filtered blue). As for land/water analysis, the RGB 564 with Band-5 (SWIR-1, filter red), Band-6 (NIR, filtered green), and Band-4 (Red, filtered blue) are the most recommended.

For the visual analysis of land cover changes through the composites RGB of three years data, the composites of Band-6 and Band-4 provides a significant clearness level of the objects, and the easiness level of object recognitions on the annual multi-temporal mosaic image. Meanwhile, the results of comparison analysis between composite of RGB 654 and Land Cover Map produced by MEF shows the strong similar pattern of land covers. From the above approaches, concludes the more confidence results that the annual multi-temporal mosaic image of Landsat-8 OLI of MTB model with the tile size of 0,02x0,02 degrees performed the consistent quality outputs for the visual analysis of land covers. Thus, the MTB model can be accepted for further digital processing, and can be used as an input for the standardization of the quality of data and remote sensing product for the national data management.

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