

THE COMPARISON OF VERSATILE LAND USE MAPPING (SCALE 1:50.000) USING VISUAL IMAGE INTERPRETATION AND SUPERVISED MULTISPECTRAL CLASSIFICATION METHOD

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ABSTRACT: Versatile land use classification offers a multi-dimensional land use classification scheme, i.e. spectral dimension. The spectral dimension is used to support remote sensing imagery mapping; however, the better technique is not discovered yet. This research aims to compare versatile land use mapping which is generated by visual interpretation and digital image processing. Both techniques use Landsat 8 OLI imagery as main data and SPOT 7 imagery as supporting data. The visual interpretation is conducted using the key interpretation as the main derivation parameter, while the digital image processing is conducted using maximum likelihood supervised classification. A field assessment is needed for image reinterpretation in visual technique, and an accuracy assessment is needed for both visual and digital techniques. The research in Sorolangun District, Sorolangun Regency, Jambi Province, Indonesia shows different mapping result for both techniques. The visual interpretation generates an optimum generalisation, as the private forest is the widest land use area (27,311.90 hectares). Meanwhile, the digital image processing generates the minimum generalisation based on the pixel, as the oil palm plantation is the widest land use area (10,011.24 hectares). Moreover, the data distribution in this part is more likely dispersal due to mix pixel effect. Even though the versatile land use classification has been arranged based on a spectral characteristic of the land use object, the application says it is not effective yet to be conducted using supervised multispectral classification method, since the geometric boundary detection of land use needs association parameter of the object visually. Meanwhile, the supervised multispectral classification only capable to generate the object boundary based on spectral value on each pixel with overall accuracy 90.60%. Contrarily, the visual interpretation classification generates lower accuracy by 84.78%.

1. INTRODUCTION

Indonesia, as a tropical country, has a unique land characteristic which is resulted in a wide variety of land cover and land use (LC/LU). There were many LC/LU classification schemes developed to be applied in Indonesia such as Darmojuwono (1964), Sandy (1975), and Malingreau (1978). Each scheme has a different function, naming, and level of classification. Nowadays, a classification scheme has been developed to fulfil Indonesia needs of satisfying mapping for LC/LU. This scheme is being called with Versatile Land Use Information System (VLUIS). Different from the previous schemes, one characteristic of VLUIS is designed by considering the multidimensional and multilevel framework. Those are the spectral, spatial, temporal, ecological, socio-economic dimension with different level of classification which is associated with spatial resolution of the data. Besides these characteristics make it suitable for data extraction by remote sensing in Indonesia. VLUIS now is developed to use by Indonesia government for the standardization of land use/land cover mapping.

The assumption of VLUIS will only require a spectral dimension for full spectral image classification because the land use classification needs other dimensions as the approach (Danoedoro, 2004). One of the pilot projects related to this scheme has used visual interpretation technique to derive LC/LU information in Sumatera. That project gave 90% accuracy for all area of mapping. This study aims to look for proof whether digital image classification might give the same level of accuracy concerning how the classification scheme has developed with spectral category as the first dimension. The overall accuracy between the previous project and this study might be different because this study localizes the assessment in Sorolangun Regency of Sumatera.

2. DATA AND METHOD

2.1 Data

The versatile land use classification had been done in Sorolangun regency as one of the pilot projects from Information Geospatial Agency of Indonesia and Universitas Gadjah Mada at 2018. Due to the aim of this study is to compare the result between visual and digital information technique using versatile land use scheme, this paper uses the same data as that project, those are Landsat 8 OLI recorded at August 6, 2016, as the main data and SPOT 7 imagery year 2015 as the supporting data.

2.2 Method

Lillesand, 2015, said that the best way to interpret the image is with the experience and understanding of the environment. That way we can do the image interpretation for land use classification. According to that statement, field orientation is needed to be conducted before the image begins to be interpreted. On the other hand, vegetation and land use mapping within an ecological landscape perspective is frequently used by remote sensing. This perspective is seeing the land unit as the unique analysis units that have homogeneity in the biophysical characteristic such as climate, soil, and hydrology (Danoedoro, 2004).

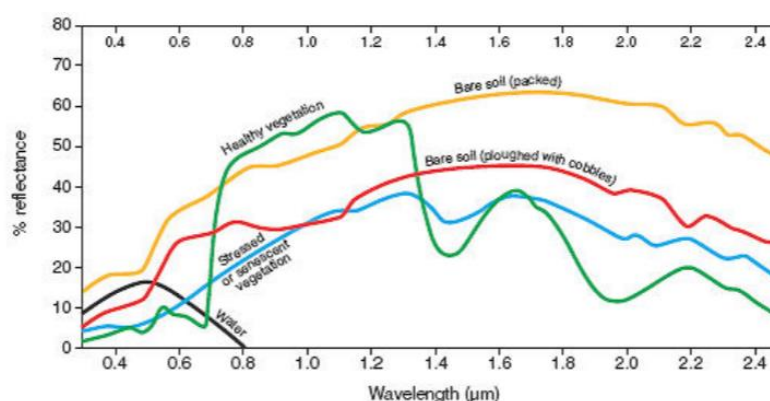


Figure 1. Spectral Reflection Curve which is Showed Different Spectral Signature for Different Land Cover (Barret & Curtis, 1999)

There are two techniques for land use mapping by image interpretation. The first technique to classify land use is visual interpretation. Tone, texture, shadow, pattern, shape, size, site, and association are eight elements to interpret the image (Campbell, 2011). To apply this

technique, we need to prepare the calibrated image to ease the visual recognition of the land use. The pixel of Landsat OLI needs to be sharpened as 15 m spatial resolution to make it optimum to map the land use with the scale of 1:50.000 (Tobler, 1987). Brovey method of pan-sharpening is used because of its suitability for the visual interpretation which prioritises the colour composite (Hidayati, 2017). Landsat 8 pan-sharpened and calibrated images are displayed on-screen with 562 and 652 RGB composite to highlight the land cover based on the spectral signature.

Another way to classify land use is digital image interpretation. This study used supervised classification with the popular maximum likelihood algorithm to classify the land use. Using maximum likelihood algorithm, the class of each pixel is approximated by decision volume of hyper-ellipsoid, while the unknown pixel is calculated by the probability of membership (Duda & Hart, 1973; Jia et al 2013). This technique is started with collecting the region of interest (ROI) for each land-use class. The minimum pixel for ROI within each land use category should not be less than 100 pixels, with 10 - 16 hectares as a minimum area for Landsat MSS (Joyce 1978; Campbel, 2011).

2.3 Sampling

The good sample should consider the population, therefore Slovin is one of the suitable sampling methods for remote sensing application. Slovin method calculates sample by this formula: $N / (N \times d^2 + 1)$, where N is the population of the data, and d is the accepted error. Based on that calculation, the land use is being proportionally random sampled by the accumulation area for each land use. All collected samples are calculated with a confusion matrix to see the accuracy assessment for each result of the classification technique. For the area of the sample, the minimum of polygon area is the 2500 m² (more than 10 times of spatial resolution of the imagery).

3. RESULT AND DISCUSSION

Each land use has its own main land-cover to be highlighted based on the spectral characteristics. Therefore, the RGB (red, green, blue) band composites used in this study involve some electromagnetic spectrums such as blue for water bodies, near-infrared (NIR) for vegetations, and short-wave infrared (SWIR) for bare lands or built-up areas. Meanwhile, the red electromagnetic spectrum is used to represent the main land-use. This is considered because the red colour tends to be easier for the human to recognise.

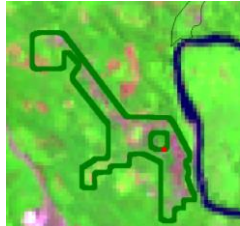
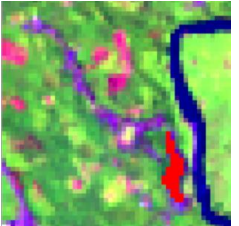

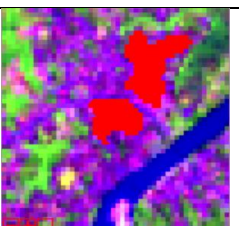

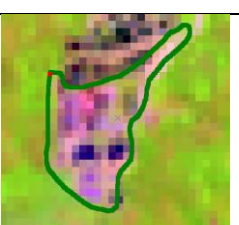
3.1 Mapping Process

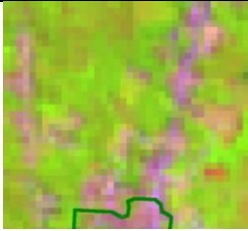
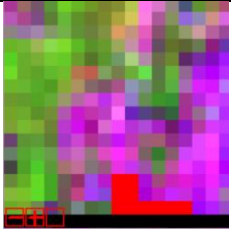
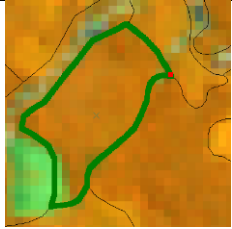
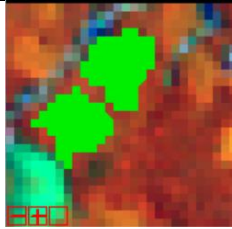
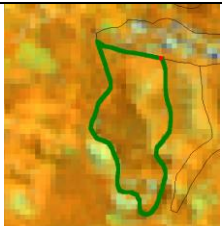
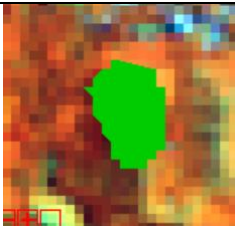

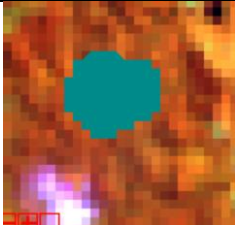
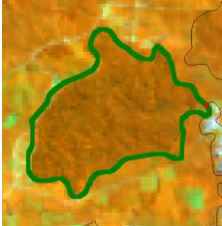
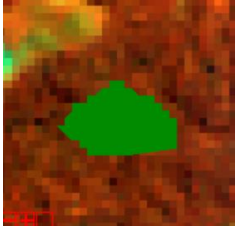

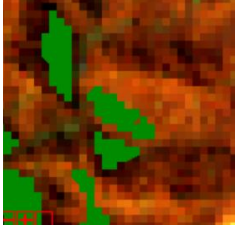

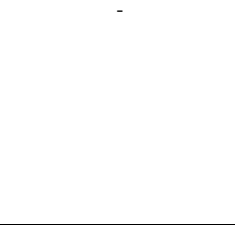
The built-up area displayed on Landsat-8 652 composite gives radiant purple colour for various kinds of settlement, green colour for vegetations, and blue colour for water bodies. The rural settlement is displayed as some ranges of purple pixels on screen at 652 composite. The purple colour range looks radiant and it is not evenly distributed as mono-colour, with the shade showing the height of the building. The rural settlement has a pattern of a single row or dispersed single building surrounded by vegetation coverage. The difference between image interpretation key of the rural and urban settlement is the pattern as well as the association. The rural settlement is associated with natural or semi-natural vegetation coverage, while the urban settlement is associated with the built-up area and man-made vegetation coverage.

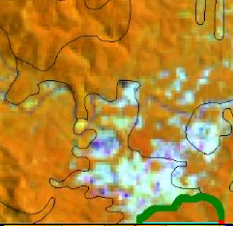
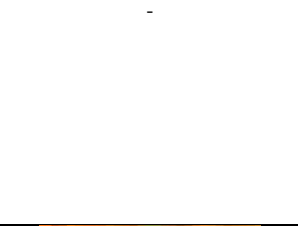
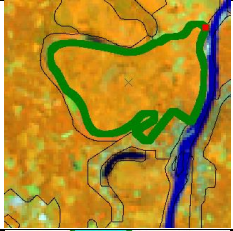
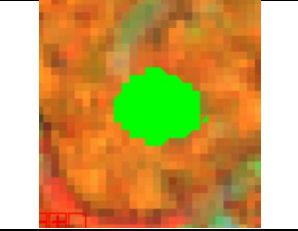
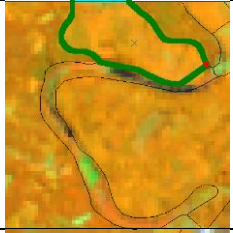

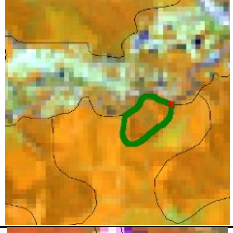
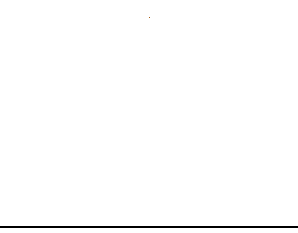

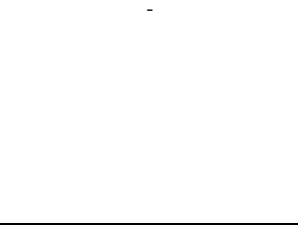
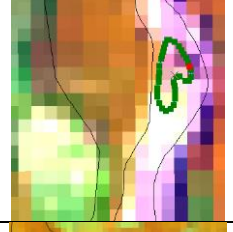
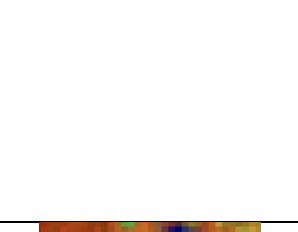
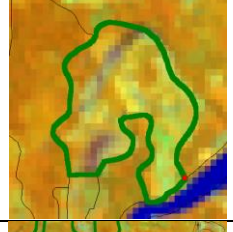
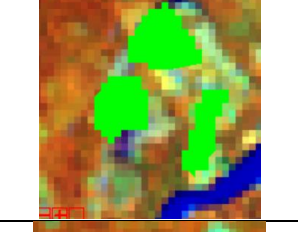
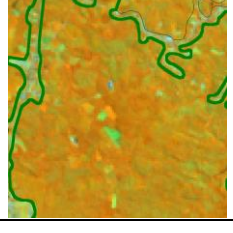
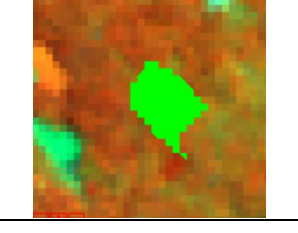
Other existing built-up areas in Sorolangun are industrial building and other non-settlement buildings. Those land uses have the same scale of colour as the settlement but is differentiated by the range of colour, pattern, shape, and association. While the settlement generally has a wide range of purple shade and clustered as a group of building, industrial building and other non-settlement buildings tend to have mono-colour due to its standalone formation characteristic. They also have an association with bare land and/or man-made vegetation coverage.

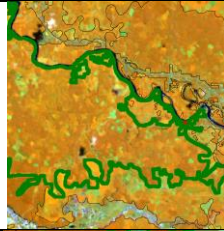
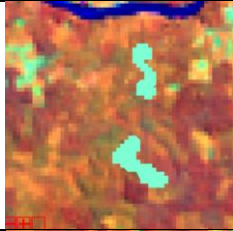
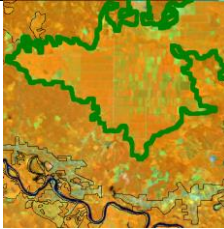
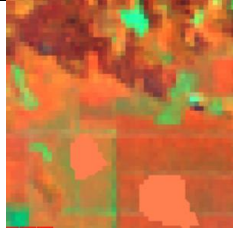
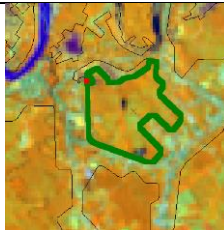
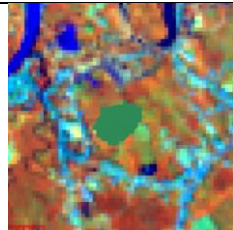
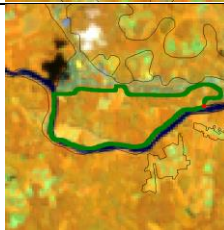
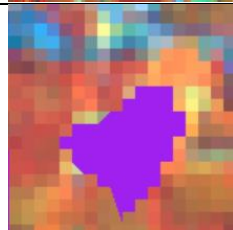
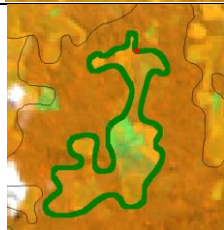
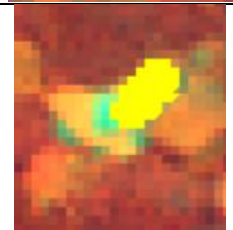
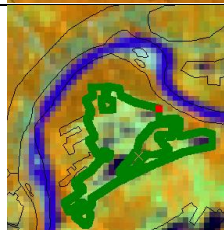
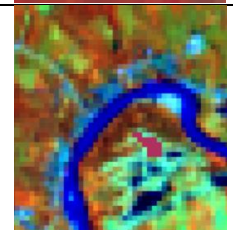
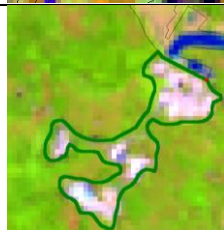

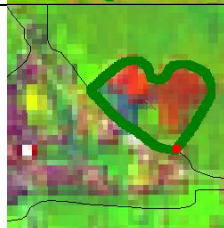
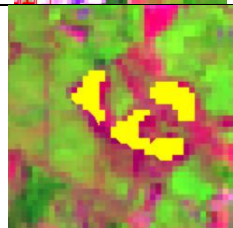
Otherwise, the vegetation area is represented by band 5 (near-infrared spectrum) of Landsat-8 imagery. So that 562 composites are used at this study to highlight every land use with vegetation as the main land-cover. For each vegetation coverage, the tone can be divided as light orange, Seville orange, and umber. The homogeneity of height, the spacing between crowns, pattern, and soil make difference interpretation key of each vegetation land use. For example, the primary highland forest is vegetation in the dry soil with topography above 300 metres AMSL. It has semi-homogeneity of height without exact pattern and spacing between the dense crown, therefore it's displayed as pixels with raw umber colour and shaded. However, the private forest has a variety of height between vegetation, therefore, it's displayed with light – Seville orange. The association of each coverage is important to make sure which is the real class of land use. The summary of image interpretation keys is shown in the table below:

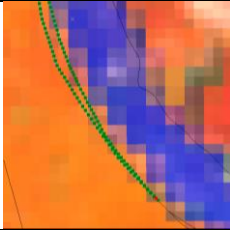
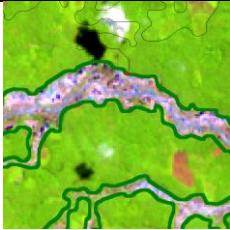
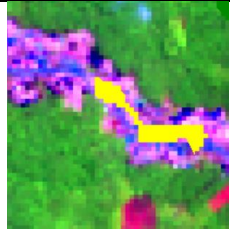
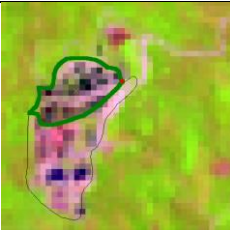
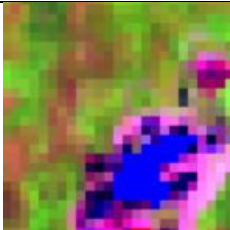
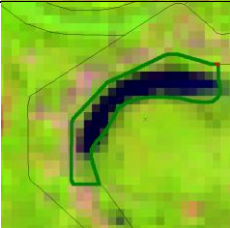
Table 1. Image Interpretation Keys of the Different Mapping Technique

No	Land Use	Image Interpretation Key	Visual Digitization	Digital ROI Sampling
1.	Rural settlement	Composite: 652 Colour/ tone: purple-green range Shadow: shaded Pattern: a form of rows or a dispersed single building Association: natural/semi-natural vegetation coverage.		
2.	Urban settlement	Composite: 652 Colour/tone: purple-green range Shadow: shaded Pattern: clustered Association: built-up area		
3.	Other non-settlement building	Composite: 652 Colour/tone: purple Shadow: shaded Pattern: a single form of building Association: bare soil		

4.	Industrial building	Composite: 652 Colour/tone: purple Shadow: shaded Pattern: single/clustered form of building Shape: Identifiable (e.g. letter L) Association: manmade vegetation coverage		
5.	Primary lowland forest medium density	Composite: 562 Colour/tone: Seville orange Shadow: shaded Pattern: clustered Site: <300 metres AMSL Association: river		
6.	Secondary lowland forest low density	Composite: 562 Colour/tone: Light orange Shadow: shaded Pattern: clustered Site: <300 metres AMSL Association: street, bare land, rural settlement		
7.	Secondary lowland forest medium density	Composite: 562 Colour/tone: Seville orange Shadow: shaded Pattern: clustered Site: <300 metres AMSL Association: street, bare land, rural settlement		
8.	Secondary lowland forest high density	Composite: 562 Colour/tone: Raw umber Shadow: shaded Pattern: clustered Site: <300 metres AMSL Association: street, bare land, rural settlement		
9.	Primary highland forest high density	Composite: 562 Colour/tone: Raw umber Shadow: shaded Pattern: clustered Site: >300 metres AMSL Association: hills		
10.	Secondary highland forest medium density	Composite: 562 Colour/tone: Seville orange Shadow: shaded Pattern: clustered Site: >300 metres AMSL Association: street, bare land, rural settlement		

11.	Secondary highland forest high density	Composite: 562 Colour/tone: Raw umber Shadow: shaded Pattern: clustered Site: >300 metres AMSL Association: street, bare land, rural settlement		
12.	Natural/semi-natural vegetation cover	Composite: 562 Colour/tone: Light orange Shadow: soft-shaded Pattern: clustered Association: river, forest, settlement		
13.	Bushes	Composite: 562 Colour/tone: Greenish - orange Shadow: very soft-shaded Pattern: clustered Association: river, forest, bare land		
14.	Shrubs	Composite: 562 Colour/tone: Greenish - umber Shadow: soft-shaded Pattern: clustered Association: river, forest, bare land		
15.	Primary peat swamp forest low density	Composite: 562 Colour/tone: Purple - umber Shadow: shaded Pattern: clustered Association: river, forest		
16.	Primary peat swamp forest medium density	Composite: 562 Colour/tone: Purple - yellow Shadow: shaded Pattern: clustered Association: river, forest		
17.	Secondary peat swamp forest medium density	Composite: 562 Colour/tone: Blue-green - yellow Shadow: shaded Pattern: clustered Association: river, forest		
18.	Private forest	Composite: 562 Colour/tone: Range of orange - green Shadow: shaded - unshaded Pattern: clustered Association: forest, settlement		

19.	Rubber plantation	Composite: 562 Colour/tone: Range of pale umber - green Shadow: soft-shaded Pattern: clustered Shape: likely rectangular Association: forest		
20.	Oil palm plantation	Composite: 562 Colour/tone: Range of radiant orange - green Shadow: soft-shaded Pattern: clustered Shape: likely rectangular Association: forest		
21.	Mixed garden	Composite: 562 Colour/tone: Range of orange - green Shadow: soft - unshaded Pattern: clustered Association: settlement		
22.	Cultivation field	Composite: 562 Colour/tone: Range of orange-yellow Shadow: unshaded Pattern: clustered Association: mixed garden, forest		
23.	Shifting cultivation	Composite: 562 Colour/tone: Range of orange - yellow-green Shadow: unshaded Pattern: clustered Association: mixed garden, forest		
24.	Paddy field	Composite: 562 Colour/tone: Range of yellow - green - blue Shadow: unshaded Shape: likely rectangular Pattern: clustered Association: mixed garden, settlement, forest		
25.	Open-pit mining - ore	Composite: 652 Colour/tone: Range of white - magenta Shadow: unshaded Pattern: dispersed - clustered Association: forest, industrial building		
26.	Other bare lands	Composite: 652 Colour/tone: a range of red Shadow: unshaded Pattern: dispersed - clustered Association: forest, open- pit, settlement		

27.	Inland swamp	Composite: 562 Colour/tone: a range of blue - orange Shadow: unshaded Association: river		-
28.	Mud flat	Composite: 652 Colour/tone: a range of blue - magenta Shadow: unshaded Association: river, open-pit mining		
29.	Oxidation ponds and wastewater treatment	Composite: 652 Colour/tone: dark blue Shadow: unshaded Association: other building		
30.	Other water reservoirs	Composite: 652 Colour/tone: dark blue Shadow: unshaded Association: river, settlement		

Those image interpretation keys give a different result for visual and digital technic of land use mapping. In general, the result from the visual technique for land use mapping has more variety of land uses than the result from the digital technique. Still, the result gives more generalization for each polygon of land use due to the boundary is created from visual recognising where the same land use might not always have the same land cover. Meanwhile, the digital technique makes more complex polygon of land use due to how the digital technique classifies each pixel based on spectral recognising. With maximum likelihood algorithm, each pixel is identified as certain land cover despite the land use is not only recognise with the type of existing land cover. This reason affected the result while the map from visual interpretation is much more readable for general usage than the map from digital interpretation. The comparison of each land use mapping is shown in figure below.

3.2 The Result of the Comparison

The comparison between each land use from the visual and digital technique is distinguished from the size, pattern and accuracy of the result. The widest area from the visual technique is a private forest with 27.311,9 hectares, while the oil palm plantation is the widest area with 10.011,24 hectares from the digital technique. These different results related to the pattern of polygon identified from both techniques. The classification with the visual technique gives the pattern result up to the operator, while the digital technique creates the pattern result by the spectral recognition. All land uses which have single main land-cover give the nearly similar pattern, while all land uses which is described as a group of multiple land cover have different pattern between those techniques.

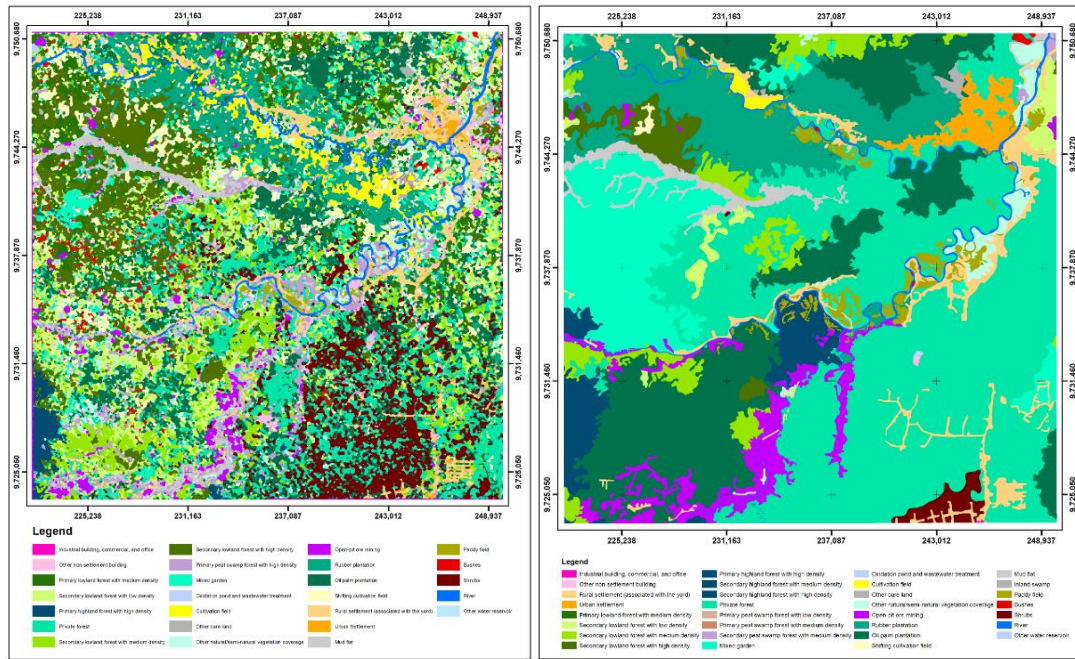


Figure 3. The Comparison of the Map from Visual Technique (Left) which is Copyright from Information Geospatial Agency of Indonesia. The Patterns Vary between each Land-use, so Does the Accuracies.

The result for vegetation areas also has a similar pattern with different size of polygon between visual and digitation technique. Those areas are primary highland forest high density, secondary lowland forest medium density, and rubber plantation. Due to consideration of the land cover homogeneity from each land use, oil palm plantation should also have a similar pattern for both techniques. Other land uses have a very dispersed pattern for the digital technique. That is probably because the region of interested collected to supervise the classification is not the pure pixel of land cover. The mixed pixel is not easy to recognised by maximum likelihood algorithm as a certain class of land cover.

Confusion Matrix	Total (ms)	Error of Omission (%)	User Accuracy (%)
Total (ms)	221,358	15.22%	84.78%
Error of Omission (%)	13.10%	89,22%	
Producer Accuracy (%)	86.90%		
Overall Accuracy			

Confusion Matrix	Total (ms)	Error of Omission (%)	User Accuracy (%)
Total (ms)	187,526	13.21%	86.79%
Error of Commision (%)	11.02%	90,60%	
Producer Accuracy (%)	88.98%		
Overall Accuracy			

Figure 5. The Comparison of Accuracy Assessment from Visual Mapping (Upper) and Digital Mapping (Lower).

The confusion matrix is used to know the accuracy of both techniques. From the accuracy assessment, the mapping of land use from digital techniques has slightly better accuracy in 90,6%, while the visual technique has 89,2%. This value of accuracy might be caused by the samples are intersected with the detailed result of spectral recognising, although it's not fully overlapped. While the samples are polygon of areas, every intersection is also calculated. Nevertheless, all of the accuracy difference values are not significant.

4. CONCLUSION

In general, even though this new scheme of land use classification is considering the spectral dimension, this scheme is still more suitable and applicable with visual interpretation technique due to the better accuracy and visualization. The spectral dimension of this land use classification helps the application for mapping land use with homogeneous land cover, but still cannot accurately recognise the land use with mixed spectral characteristic. For example, the private forest might be one polygon in visual mapping but might content many polygons of vegetation land-use combinations.

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REFERENCE

- Barrett E. C. and Curtis L F. 1999. Introduction to Environmental Remote Sensing (4rd ed), Chapman & Hall, London.
- Campbell, J. B. 2011. Introduction to Remote Sensing (3rd ed), Guilford Press, New York.
- Danoedoro, P. 2004. Geographic Information Science from Image Processing and Analysis to The Mapping and Spatial Modelling (1st ed), Cartography and Remote Sensing Department of Geography UGM, Yogyakarta, pp. 219-247.
- Danoedoro, P. 2004. Developing A Versatile Land-use Information System Based on Satellite Imagery for Local Planning in Indonesia Phase I: Establishment of Classification System. Conference: The Seventh International Seminar on GIS for Developing Countries. 'GIS Capacity Building and Infrastructure' Universiti Teknologi Malaysia, Skudai, Johar, Malaysia.
- Jia, et al. 2014. Land Cover Classification using Landsat 8 Operational Land Imager Data in Beijing, China. *Geocarto International*, 29 (8). p 941-951.
- Tejada, Jeffry J. and B, Punzalan. Joyce, Raymond. 2012. On the Misuse of Slovin's Formula, *The Philippine Statistician Journal*, Vol. 61, No. 1: p129-136
- Hidayati, et. al. 2017. Pan-Analysis Pan-Sharpening to Upgrade the Quality of Remote Sensing Imagery within Classification for Soil Use and Management. *Bhumi* 3 (1): 122-135.
- Lillesand, T. M., Kiefer, R. W. and Chipman, J. W. 2008. Remote Sensing and Image Interpretation, 6th ed., John Wiley & Sons, New York.
- Tobler. 1987. Measuring Spatial Resolution. Conference: Beijing Conference on Land Use and Remote Sensing.