APPLICATION OF LAPAN A3 SATELLITE DATA FOR THE IDENTIFICATION OF PADDY FIELDS USING OBJECT BASED IMAGE ANALYSIS (OBIA)

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Abstract. The role of agriculture is directly related to SDG No.2, which is running a programme until 2030 to reduce national poverty, eradicate hunger by increasing food security and improving nutrition and support sustainable agriculture. Problems faced include the reduction in agricultural land, which results in lower rice production, and the limited information on the monitoring of paddy fields using spatial data. The purpose of this study is to identify paddy fields using LAPAN A3 satellite imagery based on OBIA classification. The data used were from LAPAN A3 multispectral imagery dated 19 June 2017, Landsat 8 imagery dated 17 June 2017, DEM SRTM (BIG), and the Administrative Boundary Map (BIG). The analysis method was segmentation by grouping image pixels, and supervised classification by taking several sample areas based on Random Stratified Sampling. The results will be carried using a confusion matrix. The classification results produced four classes; watery paddy fields, vegetation paddy fields, fallow paddy fields, and non-paddy fields, using of the green, red, and NIR bands for the LAPAN A3 data. From the results of the segmentation process, there remain some oversegmented features in the appearance of the same object. Oversegmentation is due to an inaccurate value assignment to each algorithm parameter when the segmentation process is performed. For example, watery paddy fields appear almost the same as open land (fallow paddy fields), the water object is darker purple. The visual classification results (Landsat 8 data) are considered as the reference for the digital classification results (LAPAN A3). Forty-eight samples were taken and divided into four classes, with each class consisting of 12 samples. The results of the accuracy test show that the total accuracy of the object-based digital classification for visual classification is 62.5% with a Kappa accuracy value of 0.5. The conclusion is that LAPAN A3 data can be used to identify paddy fields based on spectral resolution and to complement Landsat 8 data. To improve the accuracy of the classification results, more samples and the correct RGB composition are needed.

Keywords: *paddy field, LAPAN A3, Landsat 8, object based image analysis (OBIA), supervised classification*

1 INTRODUCTION

Indonesia is an agricultural country with most of its territory beings agricultural land which is used as a source of food security. Information related to the availability of such land must be obtained and managed quickly and accurately so that it can be used immediately d by the community (Setiawan, Y., Prasetyo, L. B., Pawitan, H., Liyantono, L., Syartinilia, S., Wijayanto, A. K., Hakim, P. R. (2018)). According to Nugroho (2015), agricultural land plays a strategic role and function in the community, as most of Indonesia's population depends on the agricultural sector.

It plays a very important role in providing and realising national food security. However, a problems faced is

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the reduction in agricultural land, which results lower rice production (Singawilastra, D. H., Wikantika, K., & Harto, A. B. (2016)). Therefore, the national programme must be implemented as soon as possible so that sustainable agricultural development can be realised.

The role of agriculture is directly related to SDG No.2, which runs programme until 2030, to reduce national poverty, hunger by increasing food security and providing better nutrition, and supporting sustainable agriculture. This goal is in line with Indonesia's development priorities, which include food security and job creation. To support the SDG programme, monitoring of paddy fields in Indonesia must be conducted continuously so that changes that occur can be identified quickly and in a structured manner. Identification of paddy fields is one way to obtain the spatial information needed. The use of remote sensing technology is very helpful in obtaining, processing and interpreting images that can be used in various applications and information generation (Ardiansyah et al., 2015).

Such technology is an effective and fast tool for detecting the dynamics of land use and its changes. The spatial information obtained from the identification of paddy fields can be categorised based on cropping patterns, which can be classified as watery paddy fields, vegetative paddy fields, generative paddy fields, fallow paddy fields and non- paddy fields. The dynamics of changing cropping patterns can occur from year to year in line with climatic conditions and land characteristics (Setiawan et al., 2018; Setiawan et al., 2014).

A problem that occurs is that the monitoring of spatial data on paddy fields is still based on very limited information, so additional spatial information is needed, which must be continuously updated. There is considerable satellite data that can provide this information. One approach is utility satellite imagery from the LAPAN A3 experimental Indonesian microsatellite undertaking Earth monitoring and remote sensing missions (Tahir et al, 2016).

The LAPAN-A3/IPB satellite is the first experimental satellite imagery programme conducted by the Indonesian Institute of Aeronautics and Space. It aims to accelerate the national programme of developing operational imagery satellites (Judianto et al, 2015). Indonesia, which is rich in biodiversity, has abundant marine and land natural resources. However, it also faces various types of disasters that often occur and whose impact causes damage and loss to the community. The LAPAN-A3 satellite is designed to provide real time, fast, accurate and easily accessible data that can be used to monitor and predict the situation in Indonesia. In response to the limitations and high cost of data purchased from abroad, the introduction of the LAPAN A3 satellite is expected to help solve the problems that occur. Indonesia's decision to have its own earth observation satellite started with the micro satellite imagery project, which was deemed appropriate for strengthening innovation and national development. To maximise the utilisation of LAPAN A3 satellite data, optimal preparation is needed before launching.

Currently, there are numerous developments in data processing technology for various applications, which will make it easier for users to produce spatial information. One such technology is OBIA classification. The segmentation process performed is grouped based on contiguous pixels of the same quality (spectral similarity) (Wibowo et al., 2010, cited in Hurd et al.

2006). In general, the classification process using the OBIA method involves two main stages; image segmentation and classification for each segment (Wibowo et al., 2010, cited in Xiaoxia, et al. 2004). The object-based classification approach is considered better than pixel-based classification, because it gives more consideration to spectral and spatial aspects. Spectral characteristics are expressed in the form of the hue or colour of an object, while spatial characteristics need to be based on interpretation keys, namely shape, size, association, site, texture, and pattern (Yaisa et al., cited in Projo, 2019).

The purpose of this study is to identify paddy fields using LAPAN A3 satellite imagery based on OBIA classification. The use of the LAPAN A3 satellite is expected to be able to produce spatial information from the identification of growth phases in paddy fields, classified as watery paddy fields, vegetative paddy fields, fallow paddy fields, and non-paddy.

2 MATERIALS AND METHODOLOGY

2.1 Location and Data

The research location was Subang Regency, West Java Province (see Figure 2.1). The data used were from LAPAN A3 multispectral satellite imagery dated 19 June 2017, Landsat 8 imagery dated 17 June 2017, DEM SRTM (BIG), and the Administrative Boundary Map (BIG).

The LAPAN A3 satellite has a multispectral imagery characteristic with four charged-coupled Device (CCD) detectors that produce four red, green, blue, and NIR channels. With the lens system used by the LAPAN A3 satellite, the beam-splitter is divided into three parts, namely the blue-green detector, the red detector, and the NIR detector. Each detector chip has 8002 detector units with a width of 9 m. In addition, the colour filter for each channel placed one shows an illustration of the light geometry on the LAPAN-A3 satellite multispectral imagery optical system, starting from the light entering the lens system until it is divided by the beam-splitter is received to each detector. More details can be seen in Table 1.

Table 2-1: Characteristics of the LAPAN-A3 and Landsat-8 Satellites

Satellite	Sensor	Band	Spectral Range
LAPAN A3	LISA (Line Imager Space Application)	B1-Blue	0.41 - 0.49 µm
		B2-Green	0.51 – 0.58 µm
		B3-Red	0.63 – 0.70 µm
		B4-NIR	0.77 – 0.99 µm
Spatial Resolution: 18 m, Swath Width: 122,4 km , Revisit Time: 21 Days, Radiometric Quantification : 16 BIT			
Landsat 8		1- Blue	433-453 µm
		2- Blue	450-515 µm
		3-Green	525-600 µm
		4-Red	630-680 µm
		5-NIR	845-885 µm
		6-SWIR 2	1560-1660 µm
		7-SWIR 3	2100-2300 µm
		8-PAN	500-680 µm
		9-SWIR	1360-1390 µm
Spatial Resolution: 15 m (B8) and 30 m, Revisit Time: 16 Days, Radiometric Quantification : 8 BIT			

Figure 2.1: Reseach Location

2.2 Methods

The data processing method used in the research was geometric correction of the LAPAN A3 data by taking the control point / GCP (ground control point), with the GCP point is obtained using corrected Landsat 8 georeference images.

The DEM data were used as height information for an area and provided additional information in identifying the paddy fields. The method used in the segmentation was multi-resolution segmentation, which groups the pixels in the image into polygons based on parameters such as scale, color, shape factor, compactness and smoothness (Singawilastra et al., 2016). At the classification stage, the method used was supervised, by taking several sample areas. Sampling was performed based on Random Stratified Sampling with the sample spread out and not resting on a particular object. In addition, each sampling represents members of each class (Wasil, 2013; Sari, 2014). The selection of training sample areas is very important in order to obtain better results. The classification of the paddy fields can be seen by their spectral characteristics, each phase has a different appearance. The determination of the parameters in the classification was based on the physical properties of the classified object, with the parameters being watery paddy fields, vegetative paddy fields, fallow paddy fields, and non-paddy fields.

The accuracy value was tested using a confusion matrix as a contingency table or error matrix. A contingency table was used to measure the relationship (association) between two categorical variables, the table summarised the shared frequency of observations in each variable category. Accuracy value can be divided into two types; overall accuracy, the total class classified divided by the total reference class; while the individual category accuracy value is further divided into two parts, namely producer accuracy and user accuracy (Jaya, 2010).

Table 2.2: Error (Confusion Matrix)

Classification Data	Reference Class			Total Pixel	User Accuracy
Map	A	B	C		
A	X_{11}	X_{12}	X_{13}	X_{1+}	X_{11}/X_{1+}
B	X_{21}	X_{22}	X_{23}	X_{2+}	X_{22}/X_{2+}
C	X_{31}	X_{32}	X_{33}	X_{3+}	X_{33}/X_{3+}
Total Pixel	X_{+1}	X_{+2}	X_{+3}	N	
Accuracy User	X_{11}/X_{+1}	X_{22}/X_{+2}	X_{33}/X_{+3}		

Testing the accuracy value was performed from the results of the digital classification of the LAPAN A3 data overlay with the Landsat 8 data which was classified visually (see Figure 2.2). The equation used was Kappa Accuracy,

User Accuracy = (Xii / X + i) x 100%
Accuracy = (Xii/Xi+i)x 100%
Overall Accuracy = (∑ Xii r I+2)/N)x 100%

N is the number of pixels
Xi + is the number of pixels in the ith row.
X + i is the number of pixels in the ith column.
Xii is the diagonal value of the contingency matrix of row i and column i.

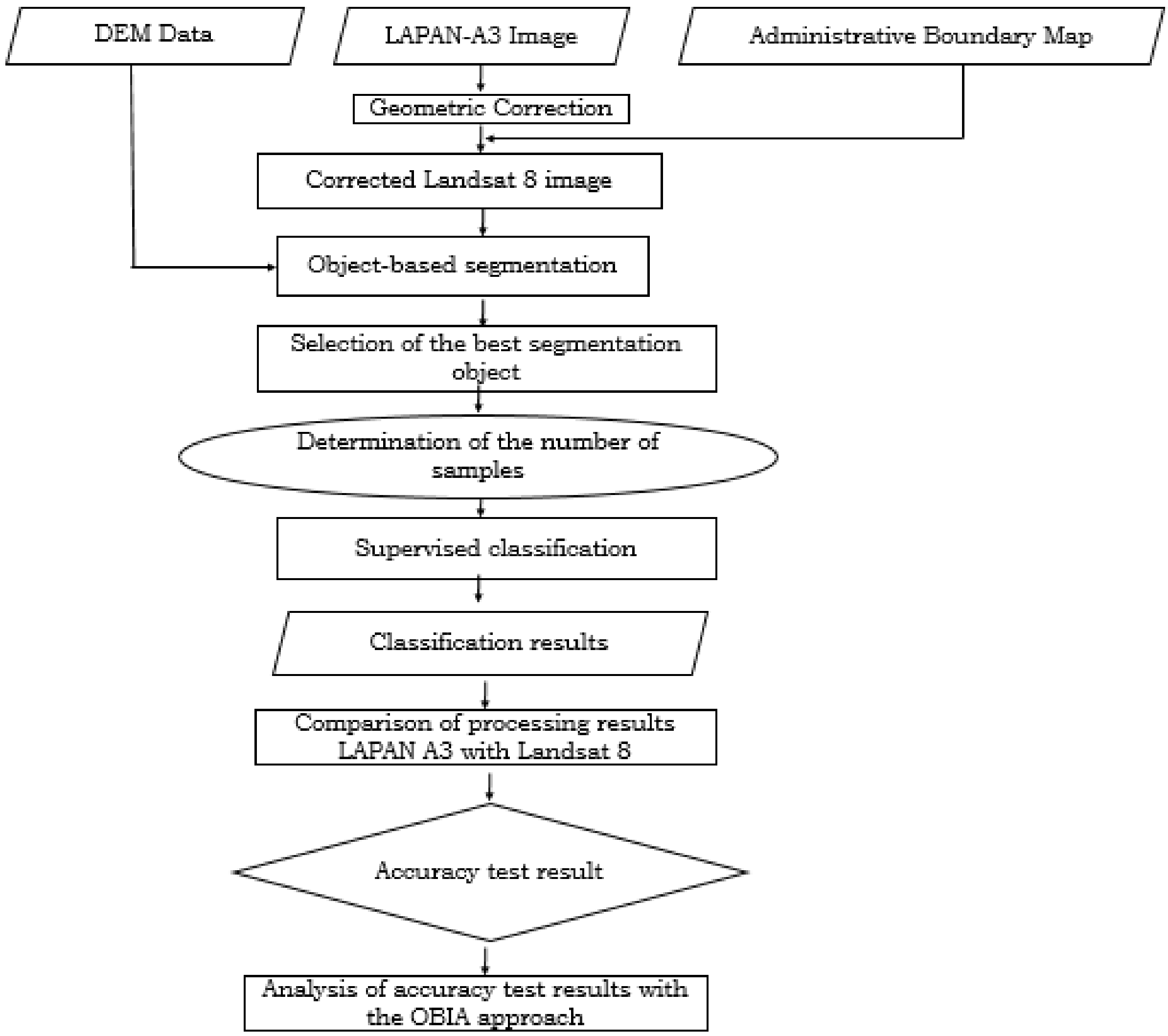


Figure 2.2: Research flow chart

3 RESULTS AND DISCUSSION

Based on the results of the OBIA classification process on the LAPAN A3 data used to identify paddy fields in Subang Regency, four classes were produced, namely watery paddy fields, vegetative paddy fields, fallow paddy fields, and non-paddy fields. In classifying the data, the green, red, and NIR bands were employed as they have a spectral resolution that is easy to use in identifying vegetation and water. To identify the four classes, several samples that had the same shape, colour and texture were used (Figure 3.1).

From the results of the segmentation process, there remained some oversegmented features in the appearance of the same object. Oversegmentation is due to inaccurate value assignment to each algorithm parameter when the segmentation process is conducted. Grading is very influential on the results displayed. For example, watery rice fields appear almost the same as open land.

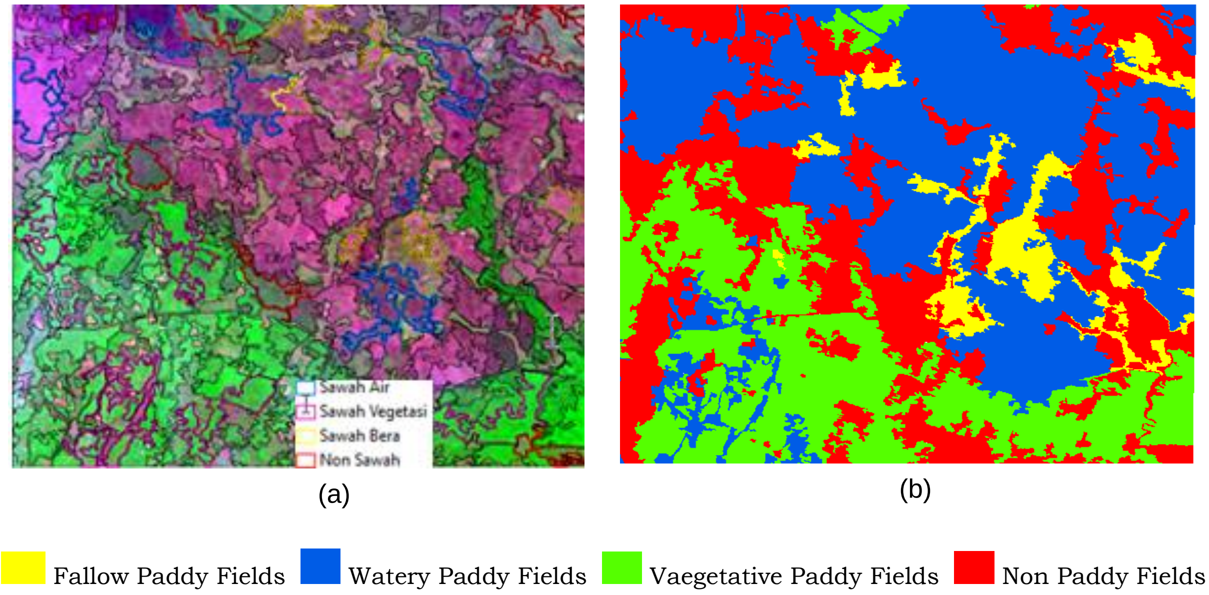


Figure 3.1: Results of the object-based digital segmentation; (a) sampling of objects with similarities and (b) results of classification using LAPAN A3 data from 19 June 2017.

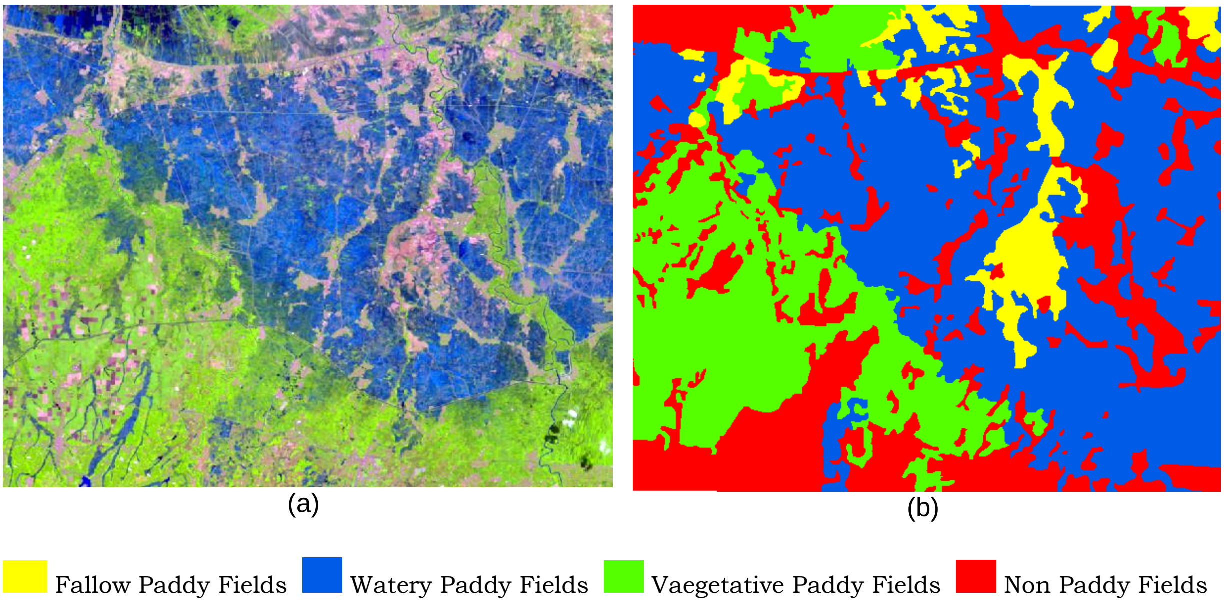


Figure 3.2: (a) Landsat 8 Data; (b) Results of the visual classification of the Landsat 8 data dated 17 June 2017.

Visual interpretation was performed on the Landsat 8 data to identify the potential for paddy fields based on interpretation keys (hue and color, texture, shape, size, pattern, site, shadow, and association) (see Figure 3.2). in the LAPAN A3 and Landsat 8 data, there is only a difference of two days between the recording dates, so they show similarities in classification. Visual interpretation requires accuracy by intepreter in identifying an object, which usually takes a long time if the area to be classified is very large. On the other hand, object-based digital classification using computer skills requires a relatively shorter time. In identifying the potential of paddy fields using LAPAN A3 data with the object-based digital classification process, several samples that have the same colour, pattern and texture are needed to obtain accurately results. The results of this visual interpretation of the Landsat data were used as a reference in testing the accuracy of the configuration matrix.

Based on these two classifications, an overlay was then applied to observe the differences in the results between the visual and digital classifications. The accuracy of the classification results was tested by using a contingency/error matrix, or confusion matrix (Hendrawan, 2003). The visual classification results (Landsat 8 data) were considered as the reference for the digital classification results (LAPAN A3). 48 samples were taken and divided into four classes, with each class consisting of 12 samples. The results of the confusion matrix (see Table 3.1) show that the total accuracy of object-based digital classification compare to the visual classification was 62.5% with a Kappa accuracy value of 0.5. The minimum level of classification accuracy using remote sensing must be not less than 85% (Affan, 2010).

Table 3.1. OBIA classification accuracy level with visual classification

Accuracy Test of LAPAN A3 with Landsat 8 in 2017						
		Landsat 8				Totally
		WPF	VPF	FPF	NPF	
Lapan A3	WPF	8	3	1	0	12
	VPF	0	10	0	2	12
	FPF	7	0	3	2	12
	NPF	0	3	0	9	12
Totally		15	16	4	13	48

Information:

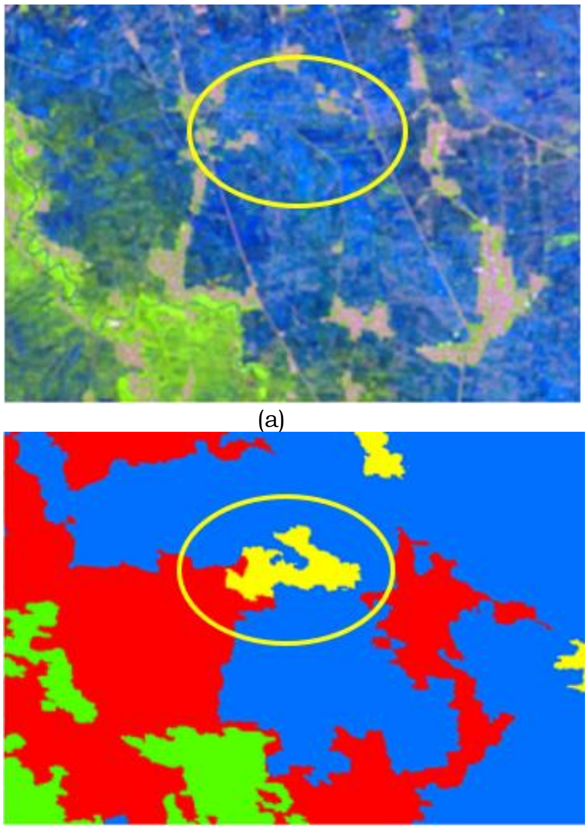
FPF = Fallow Paddy Fields

WPF = Watery Paddy Fields

VPF = Vegetative Paddy Fields

NPF = Non-Paddy Fields

Several errors occurred when performing the test. This was because in the sample selection there were mixed objects with a level of similarity in colour and texture, meaning that the resulting class tended to be different from the one in the image. As an input in the classification process, band selection also affects the classification results, as each object has a different sensitivity to certain wavelengths (Nugroho et al., 2015).



(a)

(b)

Figure 3.4: (a) Watery paddy fields from in Landsat 8 data and (b) fallow paddy fields from LAPAN A3 data

4 CONCLUSION

The conclusion is that the total accuracy value of digital classification using OBIA LAPAN A3 data with reference to Landsat 8 data is 65%, with a Kappa accuracy 0.5. This shows that LAPAN A3 data can be used in identifying paddy fields based on spectral resolution and also to complement Landsat 8 data. To increase the accuracy value of the classification results, more samples and the correct RGB composition are needed.

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AUTHOR CONTRIBUTIONS

Application of Lapan A3 Satellite Data for The Identification of Paddy Fields Using Object Based Image Analysis (OBIA). Lead Author: Mukhoriyah, Co-Author: Dony Kushardono. Author contributions are as follows:

1. Mukhoriyah: Provision and processing data, Introduction, map layouting, and results analysis
2. Dony Kushardono: Draft manuscripts and Review result analysis

REFERENCES

Affan M., Faizah, & Dahlan. (2010). Land Cover Change Analysis Using Satellite Images. Jurnal Natural. 10(1): 50-55.

Ardiansyah, & Sawitri Subyanto, A. S. (2015). *Identification of Paddy FIelds Using NDVI and PCA in Landsat 8 Image (Case Study*: Demak Regency, Central Java). UNDIP Geodetic Journal. 4 (4), 316–324.

Jaya I.N.S. (2010). Digital Image Analysis Remote Sensing Perspective for Natural Resource Management. Faculty of Forestry, Bogor Agricultural University.

Judianto, C.T., & Nasser, E.N. (2015). The Analysis of LAPAN-A3/IPB Satellite Image Data Simulation Using High Data Rate Modem. ScienceDirect. *Procedia Environmental Sciences*, 24, 285-296. https://doi.org/10.1016/j.proenv.2015.03.037

Nugroho, J. T., Zylshal, Z., & Kushardono, D. (2018). LAPAN-A3 Satellite Data Analysis for Land Cover Classification (Case Study: Toba Lake Area, North Sumatra). *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, 15 (1), 71-80. https://doi.org/10.30536/j.ijreses.2018.v15.a2782

Nugroho, U. C., Susanto, Yudhatama, D., & Mukhoriyah. (2015). Identification of Tin Mining Land Using Maximum Likelihood Guided Method in Landsat. *Globe Magazine*, 17 (1), 9-15. http://jurnal.big.go.id/index.php/GL/article/view/213

Setiawan, Y., Prasetyo, L. B., Pawitan, H., Liyantono, L., Syartinilia, S., Wijayanto, A. K., & Hakim, P. R. (2018). Utilization of Satellite Data Fusion LAPAN-A3 / Ipb and Landsat 8 for Monitoring Rice Fields. *Journal of Natural Resources and Environmental Management*, 8 (1), 67–76. https://doi.org/10.29244/jpsl.8.1.67-76.

Setiawan, Y., & Yoshino, K. (2014). Detecting land-use change from seasonal vegetation dynamics on a regional scale with MODIS EVI 250-m time-series imagery. *Journal of Land Use Science*, 9 (3), 304-330. https://doi.org/10.1080/1747423X.2013.786151

Singawilastra, D. H., Wikantika., K., & Harto, A. B. (2016). Analysis and Validation of the 2010 Ministry of Agriculture's 2010 Paddy Field Survey Results Based on the OBIA Classification Approach (Study Cases, Juntiyuat District, Indramayu District). ResearchGate. DOI: 10.13140/RG.2.2.34258.81609

Tahir. A.M., Hakim. P.R., & Syafruddin, A.H. (2016). Image-Focusing Quality Improvement on LAPAN-A3 Satellite Multispectral Imager. *Aerospace Technology Journal*, 14 (1), 37-50.

Wibowo, T. S. (2012). Application of object-based image analysis (OBIA) for land-use change detection using ALOS-2 AVNIR. *Indonesian Earth Journal*, I (3), 130-138. https://doi.org/10.1007/978-3-540-79132-4_8

Wibowo, T. W., & Danoedoro, P. (2010). Comparison of Multispectral Classification with Object Oriented Classification for Alos Avnir-2 Image-Based Land Cover Extraction. *Thesis*, Gajah Madja University. https://doi.org/10.13140/RG.2.1.2100.9366

Yaisa, S.N., Yanuarsyah, I., & Hudjimartsu, S. A. (2019). Identification of Paddy Field with Object-Base Image Analysis (OBIA) Combination on Aerial Image Images. .

Semnati, 2, 227-231. http://prosiding.uika-bogor.ac.id/index.php/semnati/article/view/295.

Zylshal, Z., Sari, N. M., Nugroho, J. T., & Kushardono, D. (2017). Comparison of Spectral Characteristics between LAPAN-A3 and Sentinel-2A. *The 5th Geoinformation Science Symposium, IOP Conference Series: Earth and Environmental Science*, 98, 012051. DOI: 10.1088/1755-1315/98/1/01205