A COMPARISON OF OBJECT-BASED AND PIXEL-BASED APPROACHES FOR LAND USE/LAND COVER CLASSIFICATION USING LAPAN-A2 MICROSATELLITE DATA

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Received: 7 June 2017; Revised: 15 June 2017; Approved: 16 June 2017

Abstract. In recent years, small satellite industry has been a rapid trend and become important especially when associated with operational cost, technology adaptation and the missions. One mission of LAPAN-A2, the 2nd generation of microsatellite that developed by Indonesian National Institute of Aeronautics and Space (LAPAN), is Earth observation using digital camera that provides imagery with 3.5 m spatial resolution. The aim of this research is to compare between object-based and pixel-based classification of land use/land cover (LU/LC) in order to determine the appropriate classification method in LAPAN-A2 data processing (case study Semarang, Central Java).The LU/LC were classified into eleven classes, as follows: sea, river, fish pond, tree, grass, road, building 1, building 2, building 3, building 4 and rice field. The accuracy of classification outputs were assessed using confusion matrix. The object-based and pixel-based classification methods result for overall accuracy are 31.63% and 61.61%, respectively. According to accuracy result, it was thought that blurring effect on LAPAN-A2 data may be the main cause of accuracy decrease. Furthermore, the result is suggested to use pixel-based classification to be applied in LAPAN-A2 data processing.

Keywords: *LAPAN-A2 microsatellite, LU/LC, object-based, pixel-based*

1 INTRODUCTION

The utilization of small satellite for remote sensing is increasing in recent years. Over the past 50 years, more than 1500 small satellites have been launched worldwide with well-focus on Earth observation missions. More than half of them are classified as micro satellites with the mass between 10 and 100 kg (Sandau and Brieb 2008; Gupta *et al.* 2016). The term "faster, cheaper and smaller" that addressed to this satellite, generally explains that the microsatellite technology is developed by countries who want to start with effective costs and affordable technology (Vincent *et al.* 1998; Gardner *et al.* 1996).

The diverse Earth monitoring based on microsatellite data has been done, included: a) hotspot detection, fires and volcanic eruptions (Walter *et al.* 2005), b) environment monitoring, such as land use classification (Qian 2008), land surface and vegetation analysis (Becker *et al.* 1996), agriculture, hydrology, urban and coastal area (Laguarde *et al.* 2010), water quality (Matjafri *et al.* 2002), global 3D imaging (Yang and Yang 2002) and c) disaster monitoring, such as cyclone, flood, drought, landslide, pollution, (Yong *et al.* 2008; Sandau and Brieb 2008), impending earthquake forecast (Qiang *et al.* 2000), etc.

Microsatellite development is also becoming a concern of Indonesian National Institute of Aeronautics and Space (LAPAN). The mission of LAPAN-A2, as first equatorial microsatellite developed by LAPAN, are maritime monitoring, disaster mitigation supporting and Earth observing by using RGB matrix camera (Hardhienata *et al.* 2011). This microsatellite has altitude 650 km the digital spaceCam c4000 matrix camera can provide 3.5 m spatial resolution and 7 km of swath. The microsatellite also has an equatorial orbit with 6º inclination (on-nadir). It can cover Indonesia region around 9º for off-nadir view.

This research was carried due to high resolution imagery is intended for commercial purpose. In addition, the utilization of optical-based satellite has limitation in tropical countries, such as Indonesia, regarding to cloud cover, fog and smoke. Thus, LAPAN-A2 is expected to complement the need of the data since it has high spatial and temporal resolution (14 times a day). It is important to evaluate the data quality of LAPAN-A2 and to assess the appropriate method applied to the data, both visual and digital classification. Previous study has shown that the overall accuracy of LAPAN-A2 for LU/LC classification in Semarang by visual interpretation is about 61.77%. Camera quality, off-nadir view and weather condition are some factors which may affect in accuracy (Nugroho *et al.* 2017). It is considered necessary to assess the LU/LC classification by using digital classification since visual interpretation is subjective and requires experienced interpreter while digital classification also offers faster results (Zylshal *et al.* 2016).

The aim of this research is to compare the object-based and pixel-based classification of LU/LC and determine the most appropriate classification method in processing LAPAN-A2 data. The result of this research is expected to be useful as reference in development program of LAPAN satellite in the future.

2 MATERIALS AND METHODOLOGY

In this section we simply introduce about data, location and method that used in this study.

2.1 Location and Data

The study area is located in Semarang, Central Java province with total population 1.584.906 (Semarang City Central Bureau of Statistics 2014). This area has some remarkable land cover changes due to urban expansion, population pressure and the development of various economic activities (Dewi and Rudiarto 2013). Hence, LU/LC information is needed for effective land management. We used LAPAN-A2 satellite imagery with acquisition date on 24 February 2016. The study area extends between longitudes 110º21'9.31" E -110º24'3.22" E and latitudes 6º56'3.5" S - 6º58'57.72" S (Figure 2-1). The data has been geometric corrected using 25 control points extracted with total RMSE about 5.62 (Nugroho *et al.* 2017).

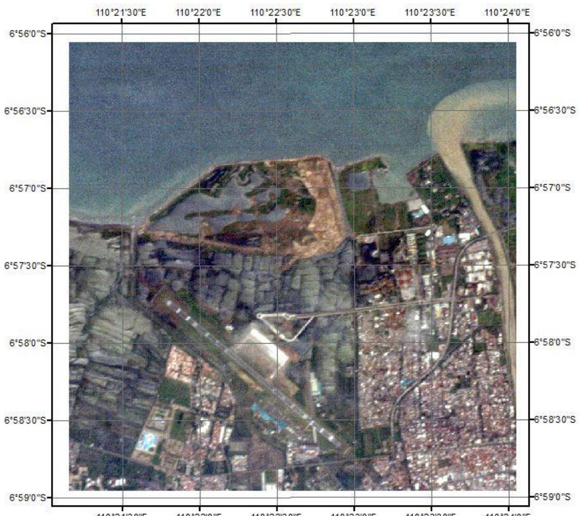


Figure 2-1: LAPAN-A2 data used in this study

Pleiades-1A Orthorectified imagery was used as reference data with 0.5 m spatial resolution (acquisition time in 2013). LAPAN-A2 data was obtained from Satellite Technology Center of LAPAN, while Pleiades-1A data was gained from Remote Sensing Technology and Data Center, LAPAN.

2.2 Methods

Object-based classification already widely used as an efficient method for classifying high resolution image data. The method allows to explore in image classification not only digital value of pixel but also other features like shape, size, texture, pattern and context (Blaschke 2010; Chmiel and Fijalkowska 2010; Sari and Kushardono 2016). The method basically consists of two phases, which are segmentation and classification (Baatz and Schape 2000). A segmentation algorithm was carried out based on statistical analysis of the neighbouring pixels around and merges homogeneous pixels in a one boundary. This research used multiresolution segmentation that classifying data into some segments based on its spectral properties. Segmentation process generated data into region which has similar pixels to identify the LC/LU classes. The next stage of this research was supervised classification process by selecting the training samples of the classes. The object features that used in classification stage are brightness, area, length to width ratio, rectangular fit and roundness. Training samples were selected based on existing LU/LC to represent the entire class. The classes were sea, river, fish pond, tree, grass, road, building 1, building 2, building 3, building 4 and rice field. Table 2-1 shows the summarizes of class legend that represented in different colour. Finally, the accuracy assessment was conducted using confusion matrix (Congalton 1991) to evaluate the classification results, which consist of Overall Accuracy, Users Accuracy, Producer Accuracy and Kappa Coefficient. As reference the Pleiades-1A data has resized to 3.5 meter refers to LAPAN-A2 data. Resampling is conducted by nearest neighbor method.

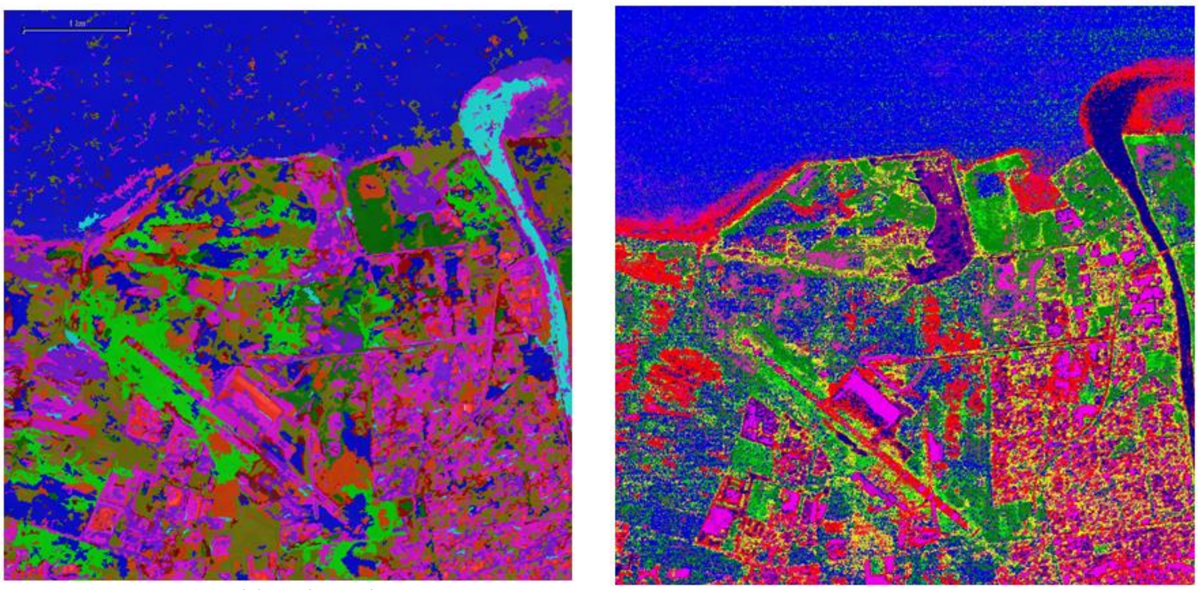
Table 2-1: Legend for LU/LC classes

No	Class	Color	No	Class	Color
1	Sea		7	Building 1	
2	River		8	Building 2	
3	Fish pond		9	Building 3	
4	Tree		10	Building 4	
5	Grass		11	Rice fields	
6	Road				

Pixel-based supervised classification is defined as an approach of image classification that depend on spectral differences between different surface features. This method referred o as a parametric approach of classification since most classifiers imply Gaussian distribution (Santos *et al.* 2006). The maximum likelihood method (MLL) classifies a pixel from the spectral response pattern of each category and then assigned to a class (Rujoiu-Mare and Mihai 2016). This method is conducted on individual pixels and the training samples are selected based on visual interpretation which will be further processed to assist in determining signatures of certain class (Lin *et al.* 2015). Pixel-based classification was performed using the same training data which used in object-based classification. The difference between the two methods is the segmentation process, where pixel-based classification did not use in the segmentation stage.

3 RESULTS AND DISCUSSION

Figure 3-1 shows the comparison result of (a) object-based and (b) pixel-based approaches for LU/LC classification using LAPAN-A2 data. Each class is distinguished by using different color as described in Table 2-1. Table 3-1 displays in detail the accuracy assessment using object-based classification. The numbers from 1 through 11 at the header and first column of the table denote the class of sea, river, fish pond, tree, grass, road, building 1, building 3, building 4 and rice field, linked to Table 2-1. The total correct pixel for class 1 (sea) to class 11 (rice field) in percent are 92.81, 79.77, 0, 0, 0, 0, 0, 25.06, 55.79, 0 and 94.54. The total analyzed pixel is 110.842. Table 3-2 also summarizes the same result for pixel-based classification. According to total pixel of 120.885 we can see the total correct pixel for all classes in percent is 76.51, 88.51, 19.29, 74.72, 31.3, 63.42, 91.26, 80.54, 91.64, 22.83 and 37.78, respectively.



(a) object-based (b) pixel-based

Figure 3-1: Result of LU/LC conducted to LAPAN-A2 data for (a) object-based and (b) pixel-based

Table 3-1: The result of assessment accuracy for LC/LU using object-based classification (%)

Class	1	2	3	4	5	6	7	8	9	10	11
1	**92.81**	0.65	2.64	0.48	4.37	1.27	1.04	0.76	4.86	0	1.68
2	0	**79.77**	2.63	0	0	0	0.2	0	0.28	0	0
3	0	7.27	**0**	0	0	15.72	11	3.62	2.43	15.01	0
4	0	0	0	**0**	0	0	0	0	0	0	0
5	0	0	0	95.74	**0**	0	0	0	0	0	0
6	0	0	0	0	0	**0**	0	0	0	28.11	0
7	0	0	25.18	0	90.69	0.81	**0**	0.4	0	0	0
8	4.6	6.78	43.47	0.16	0.06	68.73	5.95	**25.06**	16.89	14.64	0
9	1.69	5.53	9.42	0	2.51	8.33	81.78	62.3	**55.79**	42.24	1.34
10	0.9	0	16.66	3.62	1.94	5.14	0.03	4.34	14.07	**0**	2.44
11	0	0	0	0	0.43	0	0	3.92	5.77	0	**94.54**
Total	100	100	100	100	100	100	100	100	100	100	100

Overall accuracy : 31.63%
Kappa coefficient : 0.28

Table 3-2: The result of assessment accuracy for LC/LU using pixel-based classification (%)

Class	1	2	3	4	5	6	7	8	9	10	11
1	**76.51**	0	4.2	0.2	2.6	0.62	0	8.79	0	0.46	0.99
2	0	**88.51**	6.57	0	0	10.16	7.67	0.4	2.03	0.28	0.07
3	10.6	0.27	**19.29**	2.25	9.79	5.05	0	2.63	0	17.14	16.8
4	0.13	0.01	2.53	**74.72**	44.67	0.01	0	0	1.69	2.78	1.01
5	3.73	0.49	11.35	17.14	**31.3**	1.14	0	0.24	0.06	4.77	6.9
6	0.91	5.56	40.52	0.01	0.15	**63.42**	0.89	4.97	0.73	20.61	14.54
7	0	1.83	3.2	0.18	0.04	1.1	**91.26**	1.75	0.17	0.05	0.01
8	8	0.03	2.02	0	0.08	0.97	0	**80.54**	0	0	0
9	0	1.34	0.14	0.4	0.73	1.33	0.05	0	**91.64**	1.07	2.13
10	0.06	0.12	3.7	1.22	3.42	9.31	0.03	0.44	0.79	**22.83**	19.77
11	0.05	1.84	6.47	3.9	7.22	6.89	0.1	0.24	2.88	30.01	**37.78**
Total	100	100	100	100	100	100	100	100	100	100	100

Overall accuracy : 61.61%
Kappa coefficient : 0.56

Table 3-1 shows that some classes are identified as other class. For example, tree class as grass class; road class as building 2 class; and building 2 class as building 3 class which affect the accuracy. It is supposed that the similar object would affect misclassified class due to the limitation of sensor spectral separability factor. Camera sensors seem to be good at identifying water objects as evidenced by corrected pixels was about 92.81% and 79.77% for sea and river class. As well as for rice field the corrected pixel reached 94.54%. Class reduction for building object can be considered for increase the accuracy. Slightly different, in general most objects are well classified for pixel-based classification. Corrected pixel for four objects (river, building 1, building 2 and building 3) are more than 90%. Selection of training areas became determining factor of classification results. Table 3-2 summarize the result of assessment accuracy using pixel-based classification.

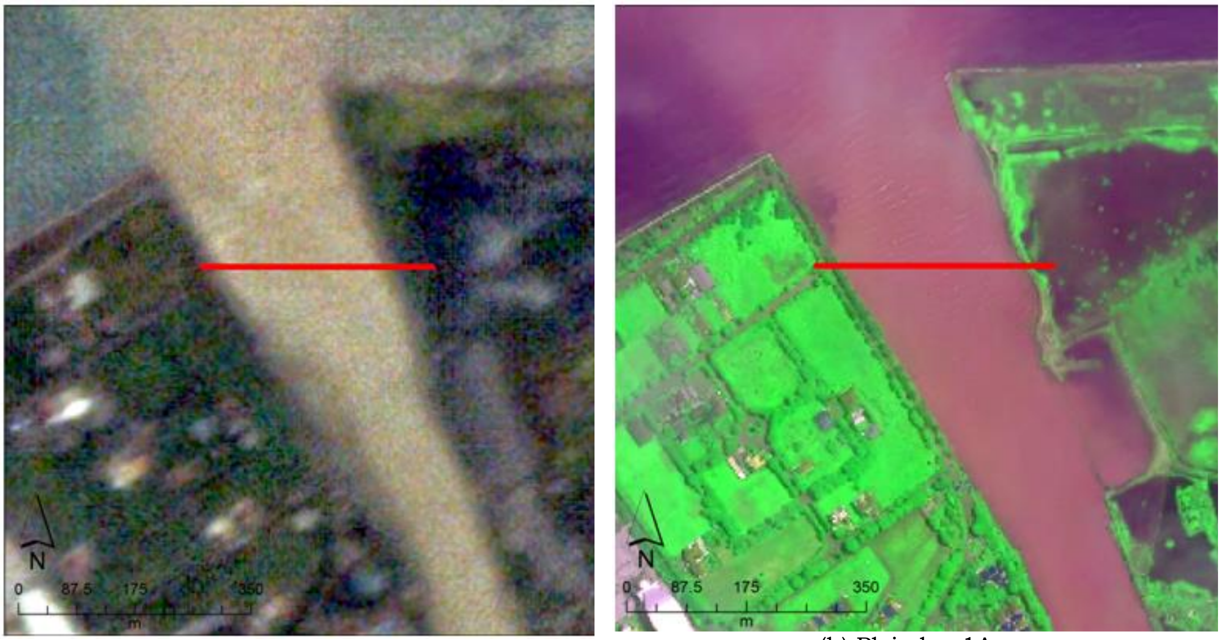
Table 3-3: Comparison of producer's accuracy and user's accuracy for abject based and pixel-based

No	Class	Producer's Accuracy		User's Accuracy	
		Object-based %	Pixel-based %	Object-based %	Pixel-based %
1	Sea	92.81	76.51	90.38	92.2
2	River	79.77	88.51	96.69	83.73
3	Fish pond	0	19.29	0	38.02
4	Tree	0	74.72	0	63.86
5	Grass	0	31.3	0	34.13
6	Road	0	63.42	0	31.03
7	Building 1	0	91.26	0	90.17
8	Building 2	25.06	80.54	1.98	45.94
9	Building 3	55.79	91.64	15.64	68.55
10	Building 4	0	22.83	0	10.92
11	Rice field	94.54	37.78	87.71	46.91

Based on the total correct pixels for each class, the calculation result of producer's and user's accuracy has shown in Table 3-3. The overall accuracy for LU/LC classification in Semarang, Central Java using object-based is about 31.63% and 61.61% for pixel-based. It is found that there is a tendency that the object-based accuracy is lower than pixel-based classification in almost all classes except for sea and rice field class. The producer's accuracy of sea class is 92.81% for object-based classification and 76.51% for pixel-based classification while rice field is 94.54% for object-based classification and 37.78% for pixel-based classification. In other class, such as river, fish pond, tree, grass, road, building 1, building 2, building 3, and building 4 the accuracy obtained by pixel-based method is higher than object-based method.

Blurring effect on LAPAN-A2 data seems to be the main cause why the object-based method cannot optimize the selected feature parameter to classify the objects. Blurring effect makes the edge between objects become unclear. By comparing side by side (a) the blurring of LAPAN-A2 with (b) Pleiades-1A data it was clearly seen the existance of this blur as shown in Figure 3-2. For this purpose, the Pleiades-1A data was resampled from 0.5 meters to 3.5 meters to match LAPAN-A2 pixel size using nearest neighbor algorithm.

The blurring may be caused by an inadequate dynamic range on LAPAN-A2's sensor that leads the spectral separability of the examined LU/LC classes being not optimal. The comparison of spectral separability over transect line for red band of two images (as noted by red line in Figure 3-2) has shown in Figure 3-3. Figure 3-3 illustrates the profile of spectral separability on edge between two objects (vegetation and water in this case and indicated by dashed arrow) for Pleiades-1A (noted by red line) and LAPAN-A2 (noted blue line). This profile shows that Pleiades-1A data curve seems to be more straight line (noted by red line) than LAPAN-A2 (blue line). It means that in segmentation process of two objects on LAPAN-A2 data is less distinguishable that cause lower accuracy. Edge enhancement and class reduction are some suggestion which may possible be to resolve the problem.



(a) LAPAN-A2 (b) Pleiades-1A

Figure 3-2: Side by side of (a) blurring on LAPAN-A2 data compared with (b) Pleiades-1A data

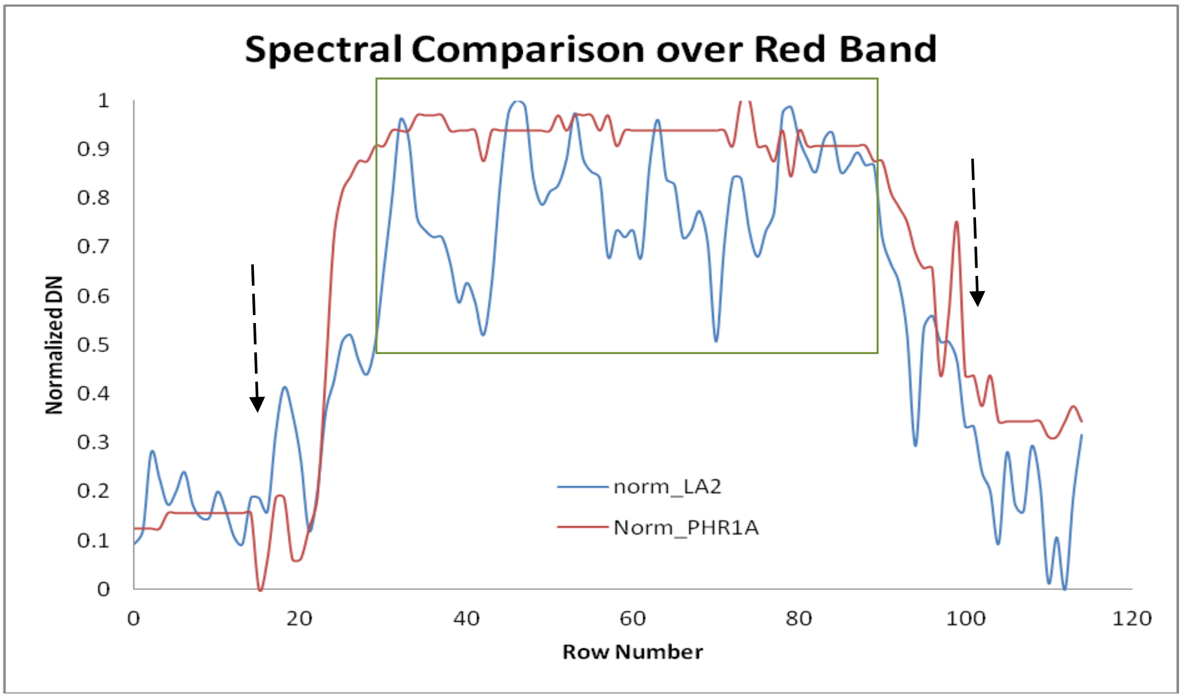


Figure 3-3: Spectral profile over transect line on Figure 3-2

Misclassified object on the relatively homogenous area such as the water body may also be caused by the high variation of LAPAN-A2 spectral value over this area. Figure 3-2 and 3-3 further show that a relatively homogenous water body (indicates by green rectangle on Figure 3-3) tends to have a high variation of digital number on LAPAN-A2 data compared with Pleiades-1A data. Performing smoothing algorithm prior to segmentation and classification process might be able to reduce this effect.

Overall performance of object-based classification on LAPAN-A2 on extracting LC/LU information was lower than pixel-based classification or visual interpretation previously done by Nugroho *et al.* (2017) with 61.77% accuracy. This result indicates that interpretability of LAPAN-A2 data is around 62%. The use of LAPAN-A2 data as a primary source of LU/LC classification is still lower compared to other well established high resolution satellite data. One of the advantages of LAPAN-A2 data is from the high temporal resolution. This microsatellite should pass over Indonesia and other near equatorial locations 14 times a day that very useful to be used as surveillance purpose.

4 CONCLUSION

Based on the findings from digital classification on LAPAN-A2, pixel based classification method perform better than object-based classification method. Off-nadir acquisition, sensor quality, as well as weather condition are other factors that may contibute to low accuracy. Further research work about perform of LAPAN-A2 data in other location, on-nadir view, weather analysis and the constraint of cloud cover during acquisition time that may affect the data quality are still needed to optimize the benefit of data utilizations. This research is expected to provide a reference of development program of LAPAN satellite in the future.

ACKNOWLEDGEMENTS

The authors would like to thank the Satellite Technology Center and Remote Sensing Technology and Data Center, LAPAN as data provider.

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