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An object-based classification of mangrove land cover using Support Vector Machine Algorithm

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Abstract. Accurate mapping of mangrove is necessary for effective planning and management of ecosystem and resources, due to the function of mangrove as a provider of natural products. The use of satellite remote sensing to map mangrove has become widespread as it can provide accurate, efficient, and repeatable assessments. The type of remote sensing that is based on imaging using the pixel method sometimes results in the misclassification of the imaging due to the “salt and pepper effects”. The aim of this study to use approach support vector machine (SVM) algorithm to classification mangrove land cover using sentinel-2B and Landsat 8 OLI imagery based on object-based classification method (OBIA). The field observation was done using Unmanned Aerial Vehicle (UAV) at Liong River, Bengkalis, Riau Province. The result by show overall accuracy classification using Sentinel-2B was better than Landsat 8 OLI imagery the value of 78.7% versus 62.7% and them were different significantly 7.23%.

1. Introduction

Mangroves are trees or shrubs unique [1-2] and salt tolerant [3] that grows at the surface between the land and the sea [4] in tropical and sub-tropical latitudes [5-7]. It is necessary for effective planning and management of ecosystem and resources, due to the function of mangrove as a provider of goods [8-11].

The satellite remote sensing has played an important role in mapping and monitoring mangroves, such as researchers preceding [12-21]. Furthermore, Kuenzer *et al.* [8] have conducted a review to see in more detail the various efforts that have been made by researchers in the use of remote sensing data in various regions of the world to map mangroves through various approaches. Despite the many efforts made by researchers to map mangroves with various approaches, there are still a number of challenges to mapping mangroves accurately. Due to mangrove mapping influenced such as the spatial and spectral resolution of the sensors used; condition of the study area; data availability and classification approach methods are used [8].

Heumann and Kuenzer [8,9] reported that the generally mangrove classification used pixel-based classification techniques. It was technique disadvantage as stated by Whiteside [22] the spectral heterogeneity within a particular land cover can lead to spurious (misclassified at that scale) pixels appearing within classes creating a ‘salt and pepper’ effect. Object-based classification is an alternative when classification based on pixel values is not able to define spatial objects properly. Object-based classification method is suitable for medium-resolution satellite imagery to high resolution, and it could be as an alternative method that has been used. Object-based classification try to build meaningful object through the process of image segmentation with similar characteristics based on spectral and spatial properties [23].

Studies on the application of OBIA have been widely carried out in the field of remote sensing, like Blaschke [12] which is review paper several about OBIA in the field of remote sensing. However, the application of this approach is still little done in the classification of mangroves, especially, in the Indonesian region. Previous application of OBIA for mangroves has been done by many researchers [2, 24-25].



SVM has a machine-learning technique that is well adapted to solving non-linear, high dimensional space classifications [26]. It can provide good accuracy compared to other machine learning classifications such as decision tree, random tree, k-nearest neighbor and Bayesian [9,27]. SVM statistical methods have been widely used for various applications. Mountrakis [28] has reviewed various paper that use SVM in the field of remote sensing. The results of that it is the best algorithm approach produced [28]. The use of SVM in the field of remote sensing is very interesting to study due to its ability to successfully handle data sets with little training with high classification accuracy than traditional methods such as pixel-based classification. Various efforts have been made to improve SVM performance applied in the field of remote sensing, such as: through image fusion [29], comparing SVM algorithms with other algorithms [24,25,30], the result showed SVM algorithm was better. Previous researchers have applied SVM algorithms in the field of remote sensing [28]. However, generally of the research used pixel-based classification and the application of this algorithm is still minimal for specific mangrove classifications in Indonesia. There are some who have used the application of this algorithm for object-based mangrove classification, such as Campomanes [24] but there are only 4 classes in the scheme.

Selection of suitable satellite imagery is also an important step in the success of classification for specific purposes [31]. Mangrove mapping generally uses Landsat series sensors [32], ASTER data [33], SPOT data [34], IKONOS [35], QuickBird [36], WorldView-2 [37]. Sentinel have a satellite mission developed by the European Space Agency. The existence of this satellite has relatively new, such as sentinel 2A which was released in 2015 and followed by sentinel-2B in 2017 compared to other similar satellites. The use of this image in extracting coastal area information has begun to be carried out by researchers, but its ability to map mangrove ecosystems is still not much used [39], so that it becomes an opportunity to be studied. An example of publication of this image utilization for mangrove was [38] and Kawamuna [40]. The purpose of this study was to implement the support vector machine algorithm to map mangrove land cover on Sentinel 2B and Landsat 8 OLI using the OBIA method.

2. Material and methodology

2.1. Location

The research was conducted in the mangrove ecosystem Liong River, Bengkalis Island, Riau Province. Field observations were conducted in January-February 2018. Geographically, the location of the study lies in 01°33'59.60"- 01°29'30.28"N and 102 °14'26.02 "- 102 ° 15'52.27" E (figure 1). The Liong River estuary has located on the Pantai Selat Baru which faces the Malacca Strait. These mangrove communities are established by 27 mangrove vegetation species which consist of 13 true mangrove species and 14 species of mangrove associate [50].

2.2. Satellite imagery and field data

Satellite imageries were used consist of: of sentinel-2B (<https://scihub.copernicus.eu/>) recorded on December 2nd, 2017 and Landsat 8 OLI (<https://earthexplorer.usgs.gov/>) recorded on March 17th, 2017. Field observations were carried out on land cover around mangroves, a maximum of 250 m from outside the mangrove border. The field observation was done using *Unmanned Aerial Vehicle* (UAV). UAV fly zone made using Arcgis 10.3 and that developed through a web-based DroneDeploy application (<https://www.dronedeploy.com>). A total of 483 observation used as the training area and the rest used for accuracy assessment. Land cover scheme based field study referred consists of 9 land cover classes such as: coconut tree (KA), rubber tree (KT), shrubs (SB), rubber oil palm (KS), agricultural area (DN), mangrove transition vegetation (VI), mangrove (ME), built-up area (LN) and water body (BA).

2.3. Data processing

The method proposed in this study consisted of four stages:

2.3.1. Data preparation (data download and image pre-processing)

Dark Object Subtraction (DOS) module was examined to Sentinel-2B and Landsat 8 OLI during atmospheric correction [41,42].

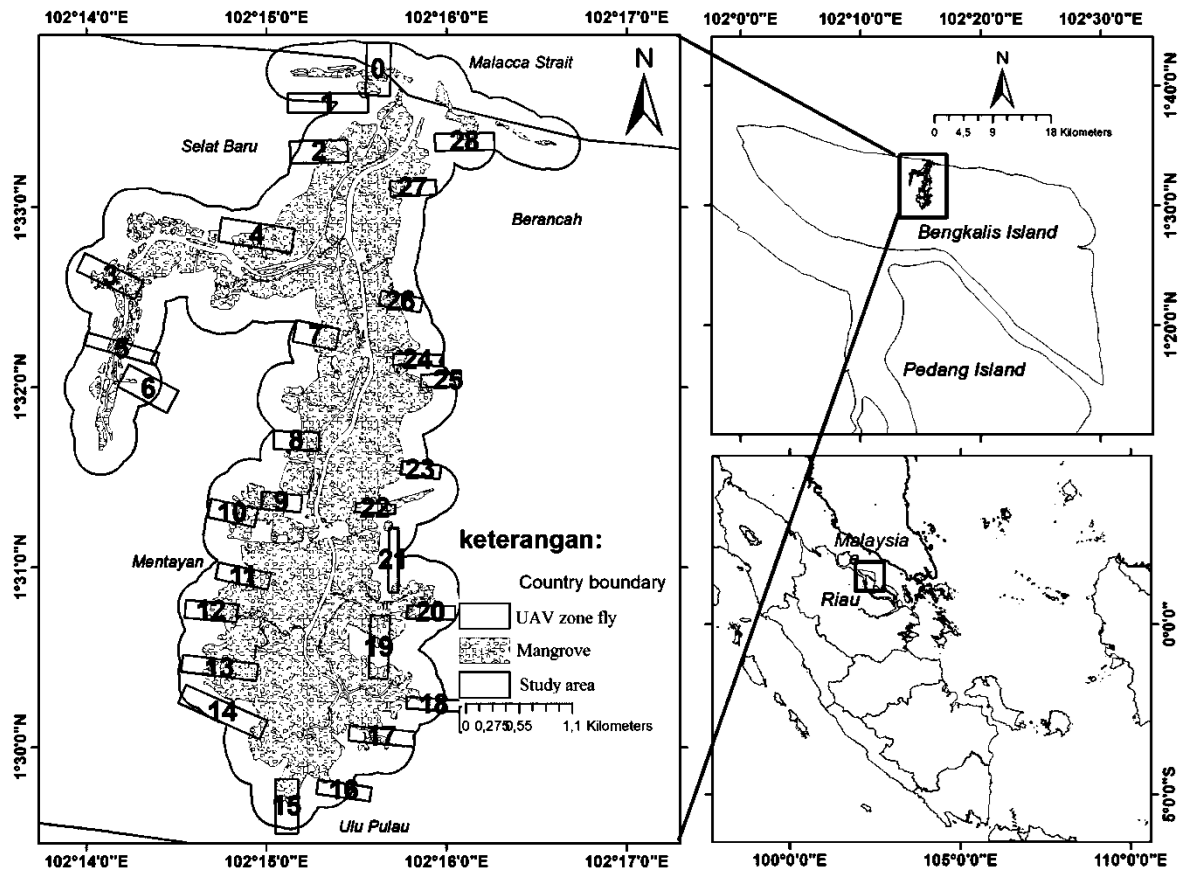


Figure 1. Location map of the study area.

2.3.2. Segmentation

Segmentation is the process of converting pixels to certain objects with a certain value. The algorithm used multiresolution segmentation (MRS). It is an optimization procedure, through minimizing the heterogeneity of object image, it used certain parameters (scale, color/shape, smoothness/compactness) [43]. These parameters provide certain qualities and build threshold values between objects based on the input used [44].

2.3.3. Classification using the Support Vector Machine (SVM) algorithm

The basic principle of SVM found the best hyperline that serves as a separator of the two data classes. Figure 2 shows some patterns that are members of two classes: +1 and -1. The pattern incorporated in class -1 is symbolized in red (box), while the pattern in class +1 is symbolized in yellow (circle). Classification problems can be translated by finding a line (hyperplane) that separates the both groups. Various discrimination boundaries were shown in figure 2a. Hyperplane the best separator between the two classes can be found by measuring the margin of the hyperplane and finding its maximum point. Margin is the distance between the hyperplane and the closest pattern of each class. The closest pattern called "support vector". The solid line (Fig. 2b) showed the best hyperplane, which located right in the middle of the two classes, while the red and yellow points in the black circle are support vector. The effort find the location of this hyperplane was the core of the learning process in SVM [45].

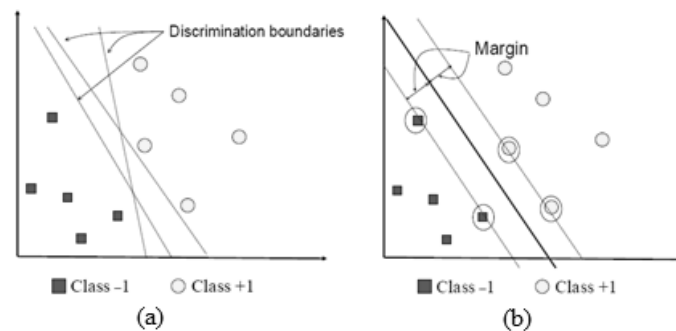


Figure 2. Margin hyperline.

2.3.4. Accuracy assessment

Mangrove land cover classification was validated by using error matrices [46], then overall accuracy, producers accuracy, and user accuracy as well as Kappa were calculated [47]. To make the comparison between classification method easier, thematic accuracy is only according to observation point-based reference.

3. Results and discussion

3.1. Optimization of segmentation parameter

The MRS segmentation algorithm has one solution in generating objects in the framework of object-based image analysis [2]. The effect of the value of the segmentation parameters proved to affect the object produced. It was of scale on the same shape and compactness values produces different size and number of objects. The large that value used, the greater is object segmentation that produced and the less is number of objects produced. The effect of scale parameters on the number of objects produced in each class of land cover around mangroves presented in table 1. Generally, the number of objects produced in each land cover class increased slightly with the increased in the scale value use. Mangrove class of Sentinel 2B the number of objects produced on a scale of 10 were 10,974 to 2,279 on a scale of 20 and continues to get smaller until it reaches scale 50 which were 336. Furthermore, mangrove class of Landsat 8 OLI on a scale of 10 the number of objects produced as much 1011 becomes 317 on a scale of 20 and continues to decline at a scale of 50 which were 19.

The overall accuracy of the object-based was classification using the SVM algorithm affected by segmentation parameters. Figure 3, the segmentation optimization process are produces optimum accuracy. Sentinel 2B of figure 3a, experiments with a scale of 10 to 40 produce accuracy with a tendency to increase by increasing the value of the scale applied. The accuracy value starts to fall when it is value reaches 50 (67.3%). The optimum segmentation accuracy obtained are 78.7% with a scale value of 40, shape 0.1 and compactness 0.5. While, Landsat 8 OLI (Fig 3b), optimum accuracy is produces on a scale of 20 with an accuracy value of 62.7%. The unit of analysis of this classification is the object resulted from segmentation process, each object has attribute features derived from the spectral statistical *i.e.* average and standard deviation band spectral, spatial information such as texture images that can be used in further analysis including image classification [48].

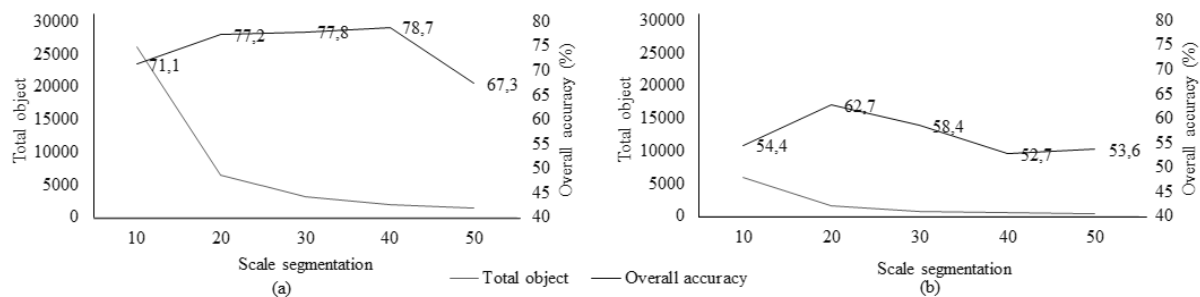


Figure 3. The effect of segmentation optimization process are produces optimum accuracy Shape: 0.1 and Compactness: 0.5 (a) Sentinel-2B; (b) Landsat 8 OLI.

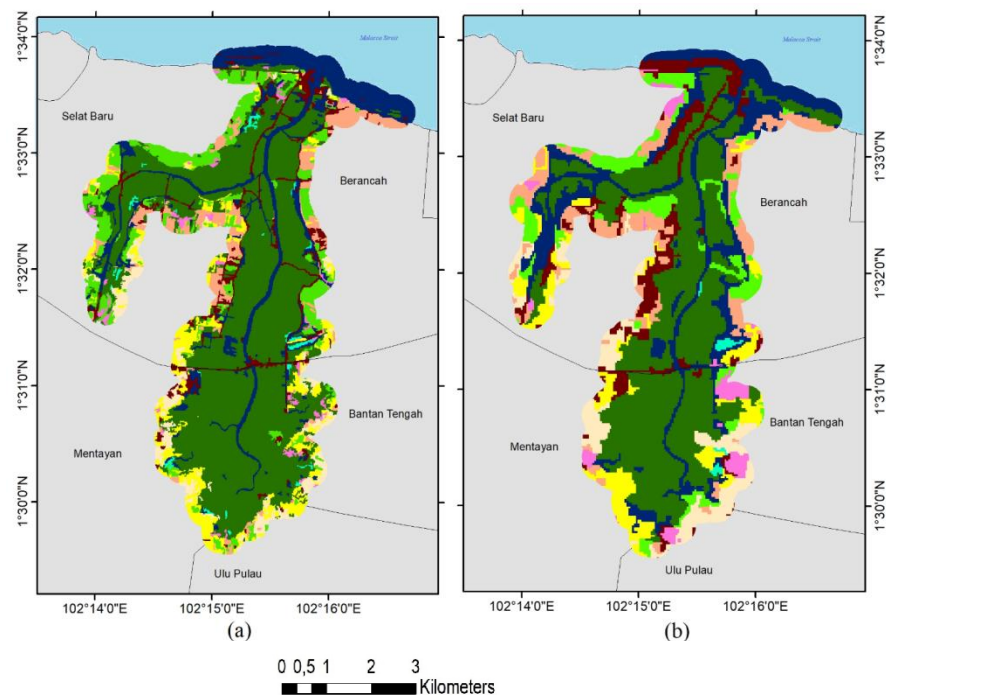
Table 1. The effect of segmentation scale (Shape: 0.1 and Compactness: 0.5).

N	Land cover	Sentinel-2B					Landsat 8 OLI				
		scale									
		10	20	30	40	50	10	20	30	40	50
1	Waterbody	2566	576	433	281	244	813	247	98	77	43
2	Agricultural area	2256	272	289	165	128	701	151	97	69	41
3	Rubber tree	1270	163	114	65	50	506	206	53	24	16
4	Coconut tree	305	262	121	35	76	151	72	47	32	32
5	Rubber oil palm	1632	563	158	142	118	969	81	67	42	58
6	Built-up area	3920	1495	392	233	136	1249	269	123	60	46
7	Mangrove	10974	2279	938	665	336	1011	317	154	65	19
8	Transtion vegetation	750	196	115	33	17	267	21	4	7	7
9	Shrubs	2356	552	427	210	144	260	121	43	33	19
	Total Objek	26029	6358	2987	1829	1249	5927	1485	686	409	281

3.2. Visual interpretation

Object-based classification try to build meaningful object through the process of image segmentation with similar characteristics [49]. Misclassifications were still found in both images, specifically to the land cover which was spectrally heterogeneous, for instance mangrove was affected by human being intervention such as land clearing with mangrove class. Result classification showed missclassification [effect salt and paper] such as mangrove grouped to rubber oil and coconut tree (figure 4b). Whiteside, Boggs [22] concluded that object-based classification can reduce spectral variability of land cover whose character is heterogeneous, while pixel-based classification still produces error clarification, especially the land cover which was spectrally heterogeneous to medium and high resolution satellite image. While object-based classification builds object based on value similarity around it, so it is possible that desired land cover class will be grouped to another land cover class. The application of scale segmentation and SVM algorithm showed overall accuracy of both images were 78.7% and 62.7%. Different spectral and spatial resolution of both images caused difference overall accuracy [27]. However, it was due to influence towards built scale segmentation.

Total area of the study area was estimate 1965.9 ha. The results of the area of the two images using an optimal scale was presented in figure 5. The mangrove transitional vegetation (VI) is a land cover class that has the smallest area in a row that is 1.3% (26.0 ha) for the Sentinel-2B image and 0.5% (9.4 ha) for Landsat 8 OLI imagery.



Legend :

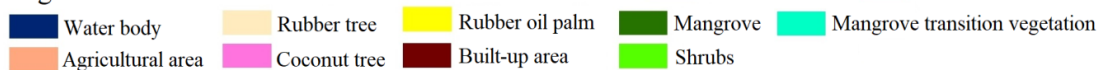


Figure 4. Classification result by using SVM algorithm (a) Sentinel-2B, (b) Landsat 8 OLI.

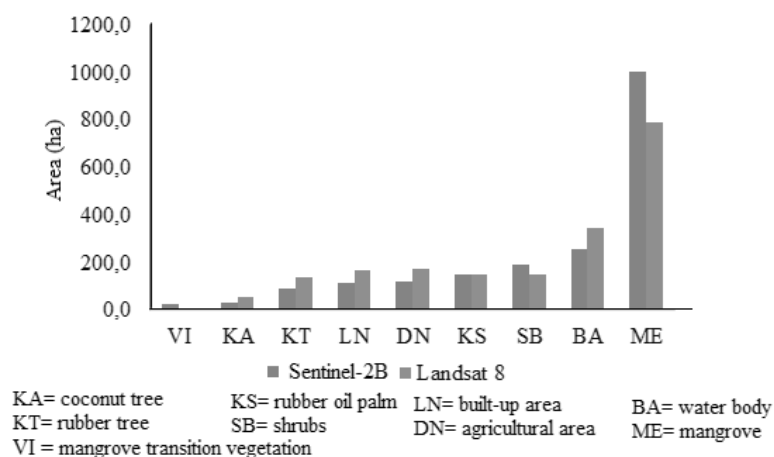


Figure 5. The results of the area of the two images using an optimal scale.

Area estimation of mangrove land cover class between both techniques were much different. The mangrove area provided by Object-based classification and pixel-based classification about 1004.3 hectares and 787.8 hectares (table 2). Object-based classification technique on Sentinel-2B is known

more accepted in mapping mangrove cover, due to its high user accuracy (UA) and producer accuracy (PA) compared on Landsat 8 OLI classification. UA and PA in Sentinel-2B were 83.3% and 89.4%, respectively, whereas UA and PA in Landsat 8 OLI were 77.5% and 81.9%. The presence of sensing optical sensors such as Sentinel-2B is one of the opportunities in scientific development and technology of remote sensing. Although the spatial resolution of Sentinel-2B varies (20 - 60 meters) for certain spectrums, it is a challenge in classification techniques to map mangrove ecosystems and result this study showed that Sentinel-2B can produce a relatively best for mapping of mangrove. The result classification of Landsat 8 OLI showed many mangroves classified into water bodies, built-up area and agricultural areas. It is can also be seen of the difference value UA in Sentinel-2 and Landsat 8 OLI, such as water body were 92.4% to 74.6, built-up areas were 5.4 to 43.6, agricultural area were 73.7% to 61.9%. While, PA of both images, such as water body were 91.4% to 53.8, built-up areas were 64.1 to 53.1% and agricultural area were and 73.7% to 68.4%. Landsat 8 OLI has mixed pixel, it is expected for increase accuracy with combination, but important variable analysis stated that input layer affecting object-based classification land cover mangrove was input layer derived from blue, green, red, NIR and MIR region. Therefore, it is cannot used to classification land cover mangrove.

Table 2. Estimation of land cover area produced by each classification.

Classes	Sentinel-2B			Landsat 8 OLI			Difference(ha)
	Area(Hectares)	UA(%)	PA(%)	Area(Hectares)	UA(%)	PA(%)	
VI	26.0	50.0	90.0	9.4	33.3	10.0	16.6
KA	28.2	11.1	8.3	52.9	28.6	100.0	24.7
KT	88.0	53.1	72.2	137.7	51.6	88.9	49.7
LN	111.5	85.4	64.1	165.1	43.6	53.1	53.6
DN	118.2	73.7	73.7	171.6	61.9	68.4	53.4
KS	147.1	70.3	52	151.0	70.6	48.0	3.9
SB	189.9	88.6	92.5	148.1	82.1	47.8	41.8
BA	252.8	92.4	91.4	346.7	74.6	53.8	93.9
ME	1004.3	83.3	89.4	787.8	77.5	81.9	216.5

This study, mangrove was can be mapping or separate with other class land cover. Result showed overall accuracy of Sentinel-2B was better of Landsat 8 OLI. Spectral and spatial resolution of images influence segmentation process. It influenced classification process used SVM and accuracy assesment. Therefore, Sentinel-2B have can be access with free and its can be alternative for mapping mangrove like Landsat 8 OLI.

The mangrove ecosystem is known for its difficult terrain to be reached and explored. Another problem in the classification of image data is to build representative sample cover land samples. It is not uncommon for these samples to be built with the help of very high-resolution imagery such as the WorldView, but sometimes the acquisition of very high resolution imagery has been obtained due to the relatively expensive price and optical mind often getting atmospheric disturbances. Another alternative that can be used to assist in identifying the class of mangrove land cover is by using unmanned aerial vehicle (UAV). This study, UAV used for observation altitude \pm 200 meters. Result showed accuracy of UAV not much different from observation conventional as well as preresearchers (table 3).

Table 3. The Overall accuracy with observation manually.

Researchers	Classification method	Images	Class of Land cover	Algoritma	Accuraction (%)
Jhonnerie (2015)	Object and Pixel	SPOT and Landsat	8 class	Random forest	81.6 and 78.1
Heumann (2011)	Object	Worldview-2	7 class	Combination Decision Tree and SVM	94
Ibrahim (2015)	Pixel	Rapideye and Landsat	7 class	MLH	85.7 and 88.9
Jalbuena <i>et al.</i> (2017)	Object	LIDAR	5 class	SVM	86.9
Long <i>et al.</i> (2016)	NDVI	Landsat	3 class	-	97

3.3. Difference of the overall accuracy land cover

Analisis Kappa and Z-test used to knows difference between both or more accuracy mapping of mangrove [17]. The result showed all of the Sentinel accuracy was better beside Landsat 8 OLI. The result of OA, Z-test, variance and kappa presented in table 4.

Table 4. The result of OA, Z-test, variance and kappa from both images.

Scale MRS	Sentinel-2B			Landsat 8 OLI			Significant
	Variant	Z	Kappa	Variant	Z	Kappa	
10	0.001485	16.9	0.65	0.005601	6.2	0.46	2.26
20	0.001399	19.5	0.73	0.003821	9.1	0.56	2.35
30	0.001354	19.9	0.73	0.004410	7.6	0.50	3.03
40	0.001108	22.4	0.75	0.002299	9.1	0.44	5.31
50	0.002718	11.8	0.62	0.002313	9.3	0.45	2.40

The result of test significant showed difference significance of both images because value Z-statistic not between ± 1.96 [17]. The comparison significant value Z-statistic of both images is 7.23. While, the comparison value Z-statistic be based of scale segmentation is scale MRS 40 with value 5.31 (table 4).

4. Conclusion

The application SVM algorithm was able to separate mangrove with other land cover classes Spatial resolution of the images influenced to process segmentation OBIA. The result showed that overall accuracy (OA) obtained for classification of land cover use Sentinel and Landsat imagery respectively MRS 40 were 78.7% and MRS 20 were 62.7%, them showed significant differences 7.23. In this study, the OBIA method can be a promising choice for mangrove mapping.

References

- [1] Rikimaru A, Roy P S, Miyatake S 2002 Tropical forest cover density mapping *Trop Ecol.* **43**(1) 39-47
- [2] Selvam V and Karunagaran V M 2004 *Ecology and Biology of Mangroves* (Chennai: M.S. Swaminathan Research Foundation) pp 1-61
- [3] Jhonnerie R, Siregar V P and Nababan B 2017 Comparison of random forest algorithm which implemented on object and pixel based classification for mangrove land cover mapping *ICST*

2016. **1** 292-302
- [4] Hogarth P J 2007 *The Biology of Mangroves and Seagrasses Third Edition* (Oxford: Oxford University Press)
 - [5] Ellison J and Stoddart D R 1991 Mangrove ecosystem collapse during predicted sea-level rise: Holocene analogues and implications *Journal of Coastal Research* **7** pp 151-165
 - [6] Giri C, Pengra B, Zhu Z, Singh A and Tieszen L L 2007 Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000 *Estuar. Coast. Shelf Sci.* **73** pp 91-100
 - [7] Zhang X and Tian Q 2013 A mangrove recognition index for remote sensing of mangrove forest from space *Curr. Sci.* **105** pp 1149-1154
 - [8] Kathiresan K B L and Bingham 2001 Biology of mangrove and mangrove ecosystems *advances in marine biology* **40**
 - [9] Heumann BW 2011 Satellite remote sensing of mangrove forests: Recent advances and future opportunities *Prog. Phys. Geogr.* **35** pp 87-108
 - [10] Kuenzer C, Bluemel A, Gebhardt S, Quoc T V and Dech S 2011 Remote Sensing of Mangrove Ecosystems: A Review *Remote Sensing* **3** pp 878
 - [11] Nascimento W R, Wal P, Proisy C and Lucas R M 2013 Mapping changes in the largest continuous Amazonian mangrove belt using object-based classification of multisensor satellite imagery *Estuar. Coast. Shelf Sci.* **117** pp 83-93
 - [12] Wang L, Sousa W P, Gong P and Biging G S 2004 Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama *Remote Sens. Environ.* **91**(3-4) pp 432-440
 - [13] Aslan A, Rahman A F, Warren M W and Robeson S M 2016 Mapping spatial distribution and biomass of coastal wetland vegetation in Indonesian Papua by combining active and passive remotely sensed data *Remote Sens. Environ.* **183** pp 65-81
 - [14] Chen C F, Son N T, Chang N B, Chen C R, Chang L Y, Valdez M, Centeno G, Thompson C and Aceituno J 2013 Multi-decadal mangrove forest change detection and prediction in Honduras. Central America. with landsat imagery and a markov chain model *Remote Sens.* **5**(12) pp 6408-6426
 - [15] Conchedda G, Durieux L and Mayaux P 2008 An object-based method for mapping and change analysis in mangrove ecosystems *ISPRS J. Photogramm. Remote Sens.* **63** pp 578-589
 - [16] Everitt J H, Yang C, Judd F W and Summy K R 2010 Use of archive aerial photography for monitoring black mangrove populations *J. Coast. Res.* **264** pp 649-653
 - [17] Ibharim N A, Mustapha M A, Lihan T and Mazlan A G 2015 Mapping mangrove changes in the Matang Mangrove Forest using multi temporal satellite imageries *Ocean Coast. Manag.* **114** pp 64-76
 - [18] Li M S, Mao L J, Shen W J, Liu S Q and Wei A S 2013 Change and fragmentation trends of Zhanjiang mangrove forests in southern China using multi-temporal Landsat imagery (1977-2010) *Estuar. Coast. Shelf Sci.* **130** pp 111-120
 - [19] Long J, Giri C, Primavera J and Trivedi M 2016 Damage and recovery assessment of the Philippines' mangroves following Super Typhoon Haiyan *Mar. Pollut. Bull.* **109**(2) pp 734-743
 - [20] Nascimento W R, Wal P, Proisy C and Lucas R M 2013 Mapping changes in the largest continuous Amazonian mangrove belt using object-based classification of multisensor satellite imagery *Estuar. Coast. Shelf Sci.* **117** pp 83-93
 - [21] Tran H, Tran T and Kervyn M 2015 Dynamics of land cover/land use changes in the Mekong Delta. 1973-2011: A Remote sensing analysis of the Tran Van Thoi District. Ca Mau Province. Vietnam *Remote Sens.* **7** pp 2899-2925
 - [22] Zhang X, Treitz P M, Chen D, Quan C, Shi L and Li X 2017 Mapping mangrove forests using multi-tidal remotely-sensed data and a decision-tree-based procedure *Int J Appl Earth Obs Geoinf.* **62** pp 201-214

- [23] Whiteside T G, Boggs G S and Maier S W 2011 Comparing object-based and pixel-based classifications for mapping savannas *Int. J. Appl. Earth Obs. Geoinf.* **13** pp 884–893
- [24] Blaschke T 2010 Object based image analysis for remote sensing *ISPRS J. Photogramm. Remote Sens.* **65** pp 2-16
- [25] Campomanes F, Pada A V, Silapan J, Avenue G and Avenue G 2016 Mangrove classification using support vector machines and random forest algorithm: A Comparative Study *Proceeding Conference: GEOBIA 2016 - Solutions & Synergies, At Enschede, Netherlands*
- [26] Madanguit C J C, Oñez J P L, Tan H G, Villanueva M D, Aurelio R M and Pasaporte M S 2017 Support Vector Machine(SVM) and Quick unbiased efficient mangrove and agricultural resource mapping using LiDAR Data Sets *Int. J. Appl. Environ. Sci.* **12** pp 1821–1830
- [27] Pal M, Mather P M 2005 Support vector machines for classification in remote sensing *Int. J. Remote Sens.* **26** pp 1007-1011
- [28] Wahidin N, Siregar V P, Nababan B, Jaya I, and Wouthuyzen S 2015 Object-based Image Analysis for Coral Reef Benthic Habitat Mapping with Several Classification Algorithms *Procedia Environ. Sci.* **24** pp 222-227
- [29] Mountrakis G, Im J and Ogole C 2011 Support vector machines in remote sensing: A review. *ISPRS J. Photogramm. Remote Sens.* **66** pp 247–259
- [30] Zhang L, Huang X, Huang B and Li P 2006 Information for Classification of High Spatial Resolution Remotely Sensed Imagery *IEEE Trans. Geosci. Remote Sens.* **44** pp 2950–2961
- [31] Mukhopadhyay A and Maulik U 2009 Unsupervised pixel classification in satellite imagery using multiobjective fuzzy clustering combined with SVM classifie *Fundam. Informaticae.* **86** pp 411–428
- [32] Phinn S R, Menges C, Hill G J E and Stanford M 2000 Optimizing remotely sensed solutions for monitoring, modeling, and managing coastal environments *Remote Sens. Environ.* **73** pp 117-132
- [33] Rahman M, Ullah R, Lan M, Sumantyo J T S, Kuze H and Tateishi R 2013 Comparison of Landsat image classification methods for detecting mangrove forests in Sundarbans *Int J Remote Sens.* **34** pp 1041-1056
- [34] Jean-Baptiste N and Jensen J R 2006 Measurement of Mangrove Biophysical Characteristics in the Bocozelle Ecosystem in Haiti Using ASTER Multispectral Data *Geocarto Inter.* **21**(4): 3-8
- [35] Santos L C M, Matos H R, Schaeffer-Novelli Y, Cunha-Lignon M, Bitencourt M D, Koedam N and Dahdouh-Guebas F 2014 Anthropogenic activities on mangrove areas (São Francisco River Estuary, Brazil Northeast): A GIS-based analysis of CBERS and SPOT images to aid in local management *Ocean Coast. Manage.* **89** pp 39-50
- [36] Chadwick J 2011 Integrated LiDAR and IKONOS multispectral imagery for mapping mangrove distribution and physical properties *Int. J. Remot. Sens.* **32** pp 6765-6781
- [37] Wang L, Sousa W P and Gong P 2004 Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery *Int J Remot Sens.* **25** pp 5655-5668
- [38] Kamal M and Phinn S 2011 Hyperspectral data for mangrove species mapping: A comparison of pixel-based and object-based approach *Remote Sens.* **3** pp 2222-2242
- [39] Vaglio Laurin G, Puletti N, Hawthorne W, Liesenberg V, Corona P, Papale D, Chen Q and Valentini R 2016 Discrimination of tropical forest types, dominant species, and mapping of functional guilds by hyperspectral and simulated multispectral Sentinel-2 data *Remote Sensing of Environment* **176** pp 163-176
- [40] Berger M and Aschbacher J 2012 Preface: The Sentinel missions—new opportunities for science *Remote Sensing of Environment* **120** pp 1-2
- [41] Kawamuna A, Suprayogi A and Wijaya A P 2017 Analisis Kesehatan hutan mangrove berdasarkan metode klasfikikasi NDVI pada citra Sentinel-2 *J. Geod. Undip.* **6** pp 277–284
- [42] Chavez PS 1996 Image-based atmospheric corrections revisited and improved *Photogrammetric Engineering & Remote Sensing* **62** pp 1025-1036

- [43] Sobrino J A, Jiménez-Muñoz J C and Paolini L 2004 Land surface temperature retrieval from LANDSAT TM 5 *Remote Sensing of Environment* **90** pp 434-440
- [44] Benz UC 2004 Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS ready information *ISPRS Journal of Photogrammetry and Remote Sensing* **58** pp 239-258
- [45] Vo Q, Oppelt N, Leinenkugel P and Kuenzer C 2013 Remote Sensing in Mapping Mangrove Ecosystems - An Object-Based Approach *Remote Sens.* **5** pp 183-201
- [46] Nugroho A S, Witarto A B and Handoko D 2003 *Support Vector Machine* (Indonesia).
- [47] Congalton R G 1991 A review of assessing the accuracy of classifications of remotely sensed data *Remote Sensing of Environment* **49** pp 1671-1678
- [48] Congalton R G and Green K 2009 *Assessing the Accuracy of Remotely Sensed Data Principle and Practices Second Edition ed.* (Boca Raton: CRC Press) p 192
- [49] De Santiago F, Kovacs J M, and Lafrance P 2013 An object-oriented classification method for mapping mangroves in Guinea, West Africa, using multipolarized ALOS PALSAR L-band data *International Journal of Remote Sensing* **34** pp 563-586
- [50] Daedonogoro 2012 *Pengantar penginderaan jauh digital* (Yogyakarta : ANDI press)
- [51] Rosmasita, Siregar V P and Agus S B 2018 Object and Pixel-based Mangrove Classification Using Satellite Imageri Multisensor at Liong River, Bengkalis, Riau Province [Thesis] (Bogor: Bogor Agriculture University)