COMPARATIVE ANALYSIS OF CLASSIFICATION METHODS FOR MAPPING SHALLOW WATER HABITATS USING SPOT-7 SATELLITE IMAGERY IN NUSA LEMBONGAN ISLAND, BALI

Kuncoro Teguh Setiawan[1]*, Gathot Winarso[1], Andi Ibrahim[1], Anang Dwi Purwanto[1], I Made Parsa[1]
[1]Remote Sensing Technology and Data Research Center, Aeronautics and Space Research Organization, National Research and Innovation Agency (BRIN)
*e-mail: kunteguhs@gmail.com

Received:11.03.2022; Revised:12.08.2022 ; Approved: 28.09.2022

Abstract. Shallow water habitat maps are critical for sustainable marine resource management. Using a better digital classification method can provide maps of shallow water habitats with the best accuracy capable of showing actual conditions. Experts are using the object-based classification method as an alternative to the pixel-based method. However, experts continue to rely on the pixel-based classification method when determining the condition of benthic habitat in shallow water. The objective of this study is to analyze the classification results and investigate the accuracy of shallow water habitat distribution using SPOT -7 satellite imagery in Nusa Lembongan Island, Bali. Water column correction based on the algorithm of Lyzenga (2006) was applied, while both object-based and pixel-based classification were used in this study. The benthic habitat classification scheme uses four classes: substrate, seagrass, macroalgae, and coral. The results show that the accuracy of pixel-based classification using maximum likelihood models and object-based classification using decision tree models are different. Mapping benthic habitats in Nusa Lembongan, Bali, with the object-based method and decision tree models has a higher classification accuracy than the pixel-based method with an overall accuracy of 68%.

Keywords: *object-based, pixel-based, coral, seagrass, macroalgae, Lyzenga 2006*

1 INTRODUCTION

Indonesia is one of the largest archipelagic countries in the world, located in a tropical climate and surrounded mostly by sea (Lasabuda 2013). As a maritime country, Indonesia is blessed with rich marine biodiversity, and its coral reef ecosystem is unique (Arief 2012). Coral reef ecosystems play an important ecological role by providing habitat for coastal inhabitants. These services include habitat for marine life, mixing of suspended sediments, coastal protection, and filtering of nutrients and sediments in runoff (Arief *et al.* 2017). This ecosystem is an important protection against climate change because it is vulnerable to climate change (Hoegh-Guldberg *et al.* 2017). Therefore, monitoring the presence and current conditions is critical for mitigating the effects of climate change. Information on the spatial distribution of current conditions is essential to support monitoring efforts.

Mapping of benthic habitats using remote sensing with satellite sensors is widely used because it is more efficient than direct observation in the field. Satellite imagery that has been used to obtain information on benthic habitats includes Landsat, Alos, Ikonos, Quickbird, and Worldview (Setyawan *et al.* 2014). Besides the advantage of large coverage in benthic habitat observation, this technology still poses a challenge in identifying these ecosystems in heterogeneous areas. For each observed object, a homogeneous area is required that meets the minimum standard for the area of a single pixel of the satellite imagery used (Setiawan et al., 2019). According to Winarso *et al.* (2015), the red-green-blue composite in the Band 4 3 2 combination in the Landsat 8 image is the most normative composite to visually interpret the appearance of the bottom substrate in the coastal area as the basis for coral reef ecosystems. In another study, Siregar (2010) showed that QuickBird imagery is able to distinguish live coral, dead coral, seagrass, sand, a mixture of sand and coral, and a mixture of sand and seagrass. Prawoto and Hartno (2018) have successfully used Sentinel-2 imagery to determine coral, seagrass, macroalgae, and sand.

The satellite imagery selected for this study is SPOT -7, the latest generation of the SPOT satellite with four multispectral bands with a spatial resolution of 6 meters for each band and a panchromatic band with a spatial resolution of 1.5 meters (Parabowo *et al.* 2018), which is suitable for spatial analysis of natural resources and the environment, especially for mapping shallow-water benthic habitats. This study aims to analyze the classification results of the distribution of benthic objects obtained using two different classification methods (pixel-based and object-based). Several studies have performed classification procedures using the OBIA (Object Based Image Analysis) method (Chris. Roelfsema *et al.* and Stuart. Phinn 2010; Leiper *et al.* 2014; Roelfsema *et al.* 2018) and pixel-based methods (Hafizt *et al.* 2017).

2 MATERIALS AND METHODOLOGY

2.1 Study Site and Data

The study site of the present investigation is located on the coast of Nusa Lembongan Island. The island of Nusa Lembongan in the province of Bali is home to one of the largest coral reef ecosystems in Indonesia. This island is the second largest island in the Nusa Penida sub-district. The waters of Nusa Penida, with the island of Nusa Lembongan located within it, are among the protected areas in Indonesia established by the Decree of the Minister of Maritime Affairs and Fisheries No. 24 of 2014. The geographical coordinates were 8°39'20'' - 8°42'00'' S and 115°25'20'' - 115°28'40'' E (Figure 2-1).

SPOT-7 satellite images acquired on June 6, 2019 were geometrically rectified with a spatial resolution of 6 m. The satellite images were obtained from the Remote Sensing Technology and Data Center, LAPAN in Indonesia.

As part of this study, a direct field observation was also conducted on June 2 and 3, 2019. The objective was to collect in-situ data to gather information about objects in shallow water habitats. The in-situ data collected will also be used as training input for the classification process and for accuracy assessment at 70% (training input): 30% (assessment input). The sampling method for retrieving in situ data is purposive and proportional random sampling, which is modeled on the measurement of field data associated with spatial coral reef information (BIG, 2014).

2.2 Research Method

The basic image classification concept in remote sensing is pixel-based analysis (Blaschke, et. al., 2015). The object-based concept was essentially adopted from the concept of photo interpretation for aerial photo analysis, which potentially offers the possibility of automating the process (Colwell 1965). The increase in spatial resolution of satellite imagery around 2000 led to a greater increase in object-based development and was supported by the introduction of the software OBIA (Blaschke *et. al.* 2015).

The main difference between pixel-based and object-based methods is the segmentation process, where some pixels are converted into a segment based on size, shape, etc. (Blaschke *et. al.* 2015). The pixels with different pixel attributes can be defined as a segment or an object. This process would increase accuracy because when pixels are used, the object is defined as multiple objects that are actually a single object with different pixel values due to the higher spatial resolution. The image processing procedure was almost the same except for the segmentation process.

The image processing procedure in this study consists of three main steps: (1) image preprocessing: radiometric correction, cropping, and masking; (2) advanced image processing such as water column correction, image classification, and interpretation; (3) accuracy evaluation (Figure 2-2). These three steps were performed to detect the distribution of coral reef ecosystems. In this study, both the pixel-based and object-based classification methods were applied to the image SPOT - 7 to classify benthic habitat objects in shallow water. The classes consist of four categories, namely coral, seagrass, macroalgae, and substrate.

2.2.1 Image Pre-Processing

Image preprocessing consists of atmospheric correction, radiometric

correction, geometric correction, cropping of the image in the research area, creation of an RGB composite, masking of land and water, and deletion of deep sea values. This activity supports further processing and analysis of image data for detection of benthic objects in shallow water habitats.
For atmospheric correction, the dark pixel subtraction (DPS) method was used in this study. Radiometric correction converts digital number data into reflective data. Cropping of image data is the determination of the location of the image in the study area to facilitate data processing and analysis. Masking is the process of separating the object of interest from objects that do not belong to the area of interest.

2.2.2 Advanced Image Processing

Advanced image processing began with the process of water column correction using Lyzenga's algorithm (2006). The correction process aims to remove the water column as a constraint in identifying objects below the sea surface. Then the process continues to classify the objects using two methods, pixel-based and object-based maximum likelihood classification and decision tree algorithm, respectively.
The water column presents an additional complexity in extracting information from flooded substrates through remote sensing that requires correction for its effects (Zoffoli *et al.* 2014).

In this study, the Depth Invariant Index (DII) method was used to correct for the water column. This method is based on the fact that electromagnetic waves emitted by the sun experience a gradual loss of intensity (attenuation) due to absorption and scattering by particles contained in the water (Manuputty *et al.* 2017). The equation for this method is as follows (Lyzenga 2006):

$$Y_{ij} = A - B$$
$$A = \log(L(\lambda)_i - \alpha(\lambda)_{i0} - \alpha(\lambda)_{i1}.L_{NIR}) \quad (2\text{-}1)$$
$$B = ki/kj.\log(L(\lambda)_j - \alpha(\lambda)_{j0} - \alpha(\lambda)_{j1}.L_{NIR})$$

$$\frac{k_i}{k_j} = a + \sqrt{a^2+1}\ ;\ a = \frac{\sigma_{ii} - \sigma_{jj}}{2\times\sigma_{ij}} \quad (2\text{-}2)$$

where

L_i : digital number for band i
L_j : digital number for band j
k_i/k_j : attenuation coefficient ratio for paired band i and band j
σ_{ii} : variance for band i
σ_{jj} : variance for band j
σ_{ij} : covariance for band i and j

The value of the attenuation coefficient in the calculation of the water column correction is obtained by creating practice areas for an area that assumes a homogeneous soil substrate found at different depths. In this study, the sand object was used as an example object in the ki/kj calculation.

The image output from the water column correction procedure with DII is then interpreted for the advanced classification procedure. In this study, two different classification methods were used, namely pixel-based classification and object-based classification. In the pixel-based classification, the maximum likelihood algorithm was used, and in the object-based classification, the decision tree algorithm was used.

The classification scheme for distinguishing objects in the benthic habitat into multiple classes follows the field observation data, which includes four classes. Both the maximum likelihood and decision tree classifiers are classified as supervised classification. The classification model was constructed from the calculation of field data (training area) with pixel/segment values. The difference between the two classifiers is that the decision tree performs the partitioning based on the Gini contamination, which is calculated from the likelihood value (for the C4.5 model) and the entropy value (for the C5.0 model) (Rokach and Mainon, 2005). The maximum likelihood method classifies by grouping into several classes with members that have maximum similarity of the average and standard deviation of two or more parameters (JARS, 1999). This method assumes that the data are normally distributed and that the parameters could be pairs of sensor bands. These objects were substrate, seagrass, macroalgae, and coral.

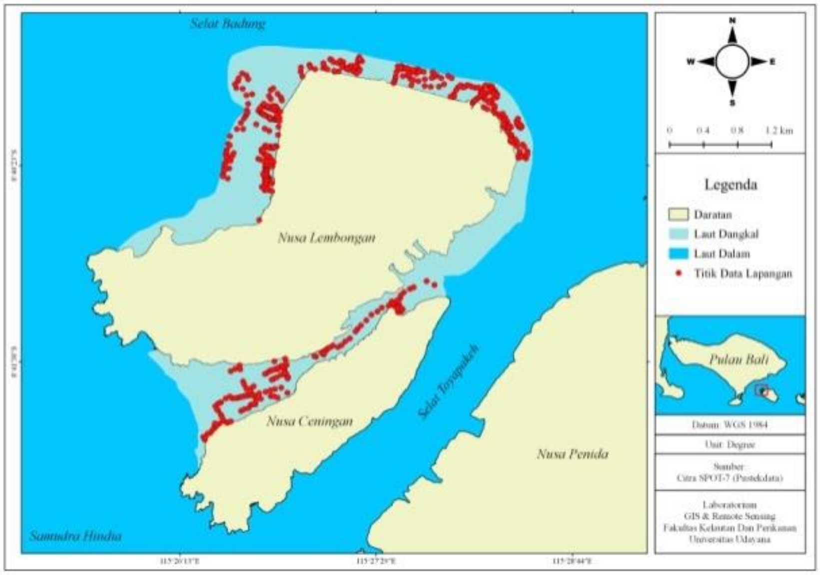


Figure 2-1. Study site

2.2.2 Accuracy Assessment

Accuracy assessment aims to measure the agreement with field observation data at a spatial point compared to the classified image. In this study, the confusion matrix technique was used to summarize the performance of the two classification algorithms used. The parameters in this technique determine the accuracy value with three parameters: User Accuracy (UA), Manufacturer Accuracy (PA), and Overall Accuracy (OA). According to the Indonesian National Standard (SNI) 7716: 2011, the standard accuracy that can be accepted for mapping benthic habitats in shallow waters is > 60% (Rahadiati et al., 2018). Mathematically, these three accuracy parameters can be represented as follows (Sampurno and Thoriq 2016):

$$\textit{Producer accuracy } (PA) = \frac{x_{ii}}{x_{i+}} \times 100\% \qquad (2\text{-}3)$$

$$\textit{User accuracy } (UA) = \frac{x_{ii}}{x_{+i}} \times 100\% \qquad (2\text{-}4)$$

$$\textit{Overall accuracy } (OA) = \frac{\sum_{i=1}^{k} x_{ii}}{N} \times 100\% \qquad (2\text{-}5)$$

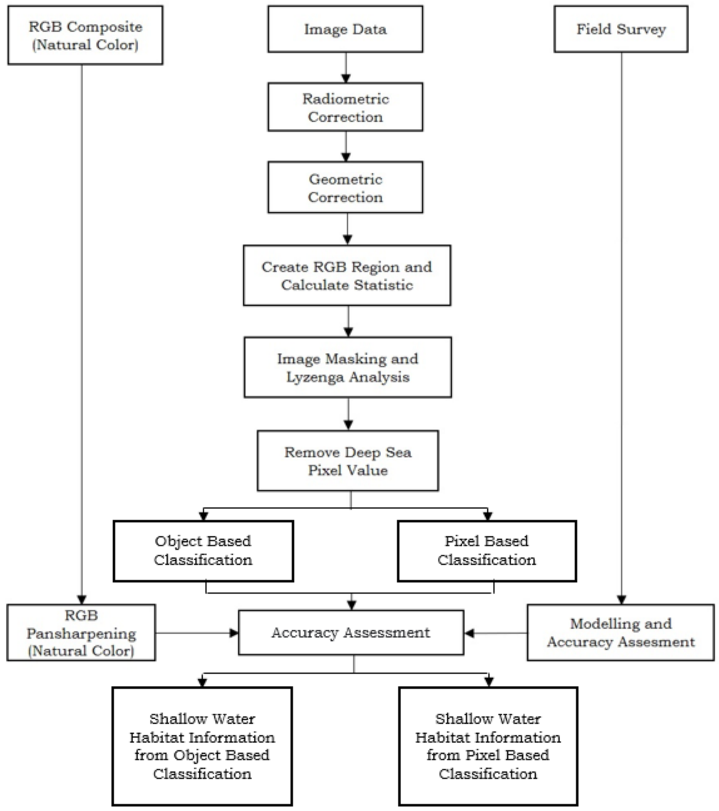
The confusion matrix is used not only to evaluate the accuracy rate, but also to calculate the error fraction of the classified image. In this matrix, there are two error scores, namely omission error (OE) and commission error (CE), which can be represented in the following formulas (Pamungkan and Jatmiko, 2016):

$$\textit{Omission error } (OE) = 100\% - PA_x \qquad (2\text{-}6)$$

$$\textit{Commission error } (CE) = 100\% - UA_x \qquad (2\text{-}7)$$

where:

N	:	total pixel in the experiment
x_{ii}	:	diagonal value of confusion matrix in row-i and column-i
x_{+i}	:	number of pixel in column-i
x_{i+}	:	number of pixel in row-i
PA_x	:	producer accuracy value for a class
UA_x	:	user accuracy value for a class



Gambar 2-2: Research flow-chart

3 RESULT AND DISCUSSION

3.1 Classification Result

Both the pixel-based and object-based classification processes yield four classes, namely coral, seagrass, macroalgae, and substrate. The classification result using a maximum likelihood algorithm for the shallow water benthic habitat of Nusa Lembongan Island is shown in Figure 3-1. Based on the classification result, it was clear that seagrass was dominant in the study area. Corals were found along the reef crest. This area was located at the boundary between the coast and the sea.

The detection and classification of the benthic habitat with the object-based classification method was performed using a decision tree algorithm. The classification result is shown in Figure 3-2. Corals were found mainly in the north of the island and also in the east and west. Macroalgae were found only in some places and in association with seagrass. The substrate class itself was distributed in some places on the island, dominating in the southern part.

Based on the classification process using two different classification methods, pixel-based and object-based, different area calculation results were obtained for four classes. The area calculation was performed for each class of benthic objects and is shown in detail in Table 3-1. In the area calculation in the pixel-based classification, substrate dominates with 35.76 %, to be exact 10.13 ha, followed by macroalgae with slightly different 30.24 % or 8.57 ha. Corals are found with 22.63% or 6.41 ha in the study area. Seagrass has the lowest area calculation with 11.37 % or 3.22 ha. The object-based classification leads to different results in the area calculation. Eelgrass is the most abundant compared to the other classes. It represents 30.89% of all observed objects with a calculated area of 8.75 ha. On the other hand, the other classes are not significantly different from each other: 24.14% (6.54 ha) for macroalgae, 23.09% (6.54 ha) for substrate, and 21.88% (6.20 ha) for corals. Overall, the pixel-based classification resulted in a higher variation in computational area for each benthic habitat object than the object-based classification. The spatial distribution of the object-based classification results is quite homogeneous for all four classes of benthic habitats

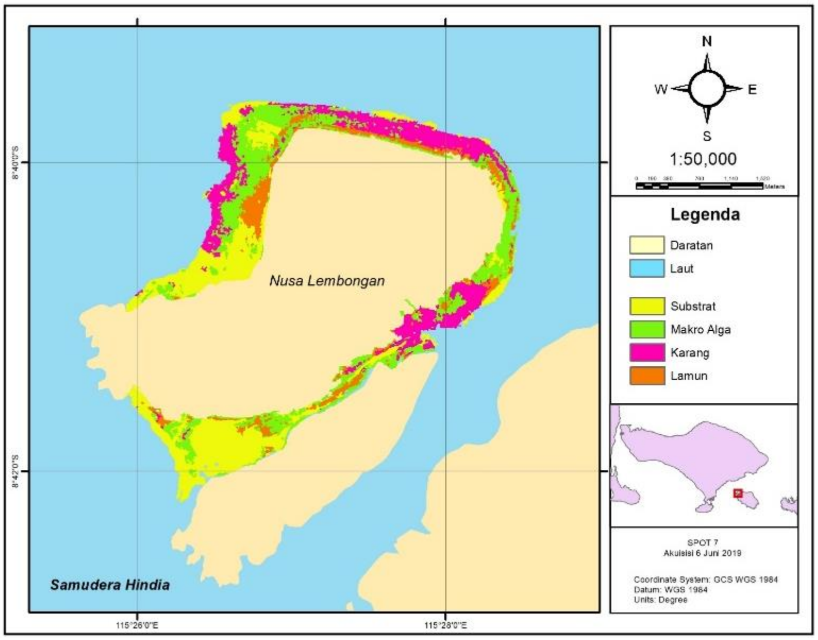


Figure 3-1: The results of pixel-based classification using the maximum likelihood algorithm

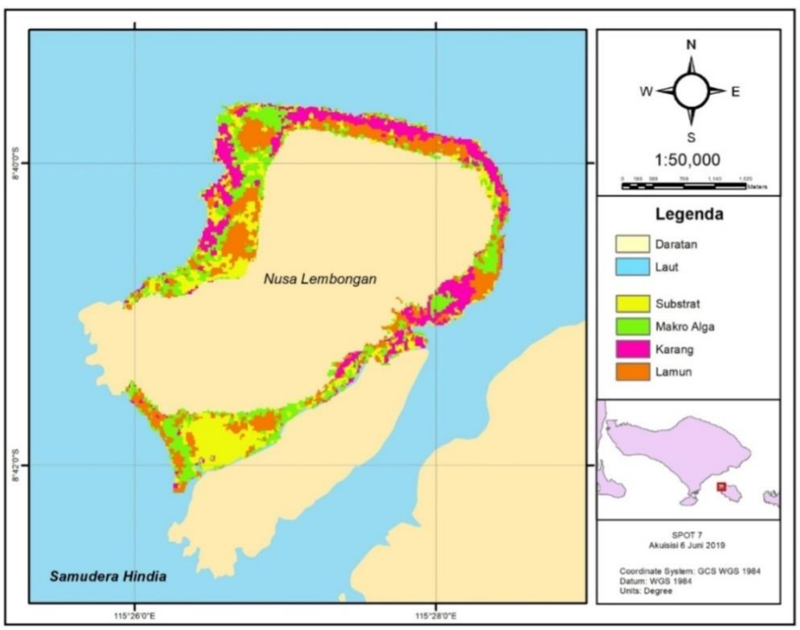


Figure 3-2: The results of object-based classification using the decision tree algorithm

Table 3.1: The calculation area for each class of benthic habitat based on the result of pixel-based classification and object-based classification

Classes	**Pixel-based classification**		**Object-based classification**	
	Area (ha)	**Percentage (%)**	**Area (ha)**	**Percentage (%)**
Substrate	10,13	35,76%	6,54	23,09%
Seagrass	3,22	11,37%	8,75	30,89%
Macroalgae	8,57	30,24%	6,84	24,14%
Coral	6,41	22,63%	6,20	21,88%
Total	28,33	100%	28,33	100%

3.2 Accuracy Assessment

The evaluation of the accuracy of the classified images was performed using five parameters: Overall Accuracy (OA), User Accuracy (UA), Producer Accuracy (PA), Omission Error (OE), and Commission Error (CE), which were then combined into a confusion matrix table. The error matrix compares the class-related relationship between the in situ data and the classified images. The result of the accuracy assessment is shown in Table 3-2 and Table 3-3.

The accuracy calculation showed an overall accuracy of 52.43% for the pixel-based image classification, while the object-based image classification had an accuracy value of 68.68%. This indicates that the spatial distribution of the benthic habitat is considered good, as the overall accuracy is above 50%.

The UA value is the probability of a pixel on the image, which refers to how the classified image is real on the ground. The UA value of pixel-based classification in this study shows that substrate has the highest UA value with 79.37% correctly classified. Macroalgae, on the other hand, has the smallest value of 30.67%. This means that only 30.67% were correctly classified as macroalgae. Seagrass has a huge UA value, while macroalgae has the smallest value for object-based classification with 70.73 % and 40.63 %, respectively.

The commission error (CE) in the confusion matrix can be defined as the part of the UA that is mutually satisfying. It represents the pixel values on the image that are predicted to belong to a particular class, but do not belong to that class. For example, the highest UA values in the pixel-based results are substrates, of which 79.37% were correctly classified and 20.63% were not assigned to their class. In contrast, 30.67% of the pixels were classified as macroalgae and 69.33% were defined as other class.

Producer accuracy (PA) indicates the proportion of a given class that was correctly classified compared to the reference data. The value PA corresponds to the omission error (OE). OE refers to the calculation in which the references are checked for incorrect classifications. PA Calculation results indicate that the coral class has the largest PA value among the other classes at 90.74%, while OE is 9.26%. Seagrass has the least value of PA with 30.85% , while OE has 69.15%. In the same way, coral has the highest PA value in object-based analysis with 92.16%, while OE is 7.84%. Macroalgae occupy the smallest place with a PA value of 43.33%, while OE is 56.67%.

Tabel 3-2: Confusion matrix of benthic habitat based on the results of the SPOT 7 classified image with pixel-based and maximum likelihood algorithm

Class	PA (%)	OE (%)	UA (%)	CE (%)
Substrat	45.87	54.13	79.37	20.63
Seagrass	30.85	69.15	52.73	47.27
Macroalgae	74.19	25.81	30.67	69.33
Coral	90.74	9.26	51.58	48.42
OA (%)	52.43			

Tabel 3-3: Confusion matrix of benthic habitat based on the results of the SPOT 7 classified image with object-based and decision tree algorithm

Class	PA (%)	OE (%)	UA (%)	CE (%)
Substrat	59.18	40.82	70.73	29.27
Seagrass	74.42	25.58	76.19	23.81
Macroalgae	43.33	56.67	40.63	59.37
Coral	92.16	7.84	70.15	29.85
OA (%)	68,68			

The classification results of the above two methods show that the overall accuracy values of pixel-based classification with the maximum likelihood algorithm and object-based classification with the decision tree algorithm are slightly different, 52.43% and 68.68%, respectively. The object-based classification with the decision tree algorithm shows a better quantitative result than the other method in detecting and classifying four object classes defined in the benthic habitat.

3.3 Discussion

In general, the accuracy of the two-way algorithm for classifying objects in shallow-water benthic habitats is moderate. The results show that the object-based method has higher accuracy than the pixel-based method. Considering the overall accuracy value obtained in this study, the object-based classification result can be accepted as 68.68%. The acceptable accuracy limit for shallow water habitat mapping is based on Indonesia National Standard (SNI) 7716:2011 and is 60% (Prayudha 2014).

The accuracy value obtained from the results of this study is more than 50%. Based on the accuracy value, this study is able to compete with previous studies. Wahidin *et al.* (2015) analyzed that the accuracy of mapping benthic habitats in shallow waters ranges from 40 to 73%. It could be even better if images with higher spatial and spectral resolution were used, such as CASI images used by Mumby *et al.* (1998) with accuracy close to 80%. This performance is determined by the classification scheme chosen. According to Selamat *et al.* (2012), the more classes displayed, the lower the accuracy of the mapping results. In addition, the largest factor influencing accuracy is the selected study site. Site differences are the largest factor affecting accuracy compared to other factors such as the classification method and atmospheric correction method used (Winarso *et al.* 2016). In addition, the training area defined for each object also affects the accuracy value. The errors in identifying benthic habitat objects on the ground based on the interpreter's knowledge and the occurrence of shifts in the position of the observed object due to the difference in position between the imagery and GPS can lead to low accuracy values (Siregar 2010).

Many methods have been developed and tested for classifying benthic habitat objects; OBIA is one of them. This study shows that the OBIA method gives a better result than the pixel-based method. This is consistent with the statement of Wahidin *et al.* (2015) that OBIA provides better accuracy than the pixel-based method. Hidayat (2017) proved that SPOT 6/7 images with the object-based method provides higher accuracy than the pixel-based one.

4 CONCLUSION

Analysis of shallow water habitat distribution in Nusa Lembongan Island, Bali, using SPOT -7 satellite imagery was performed by object and pixel based classification, results in four classes, namely substrate class, seagrass, macroalgae and coral. The results show that the accuracy of benthic habitat mapping in Nusa Lembongan, Bali with object-based classification of decision tree model has a higher overall accuracy of 68%. This result was good enough compared to the ground resolution of the SPOT -7 image, which is 6 m for multispectral images, because the dominance of object classes to 1 pixel was poor. Due to the heterogeneity of objects in the field, it was difficult to find 100% of the class within one pixel. The accuracy in this situation was improved by the object-based method, where some pixels were converted to 1 (one) segment, which means that non-dominant pixels in the segment were removed. This method could be applied in other areas because the supervised classification scheme is basically applicable to any area due to the field information required, although higher resolution is better for classifying benthic habitat objects, especially in tropical areas where diversity is high.

ACKNOWLEDGEMENTS

The authors would like to thank PUSFATJA, LAPAN for making this study possible. We would also like to thank the Bali Provincial Marine and Fisheries Service and Conservation International (CI) for their assistance with field data collection.

AUTHOR CONTRIBUTIONS

KTS is the main contributor. KTS: conceptualization, methodology, data processing, validation, analysis, and original design. GW: in situ data collection, analysis. AI and ADP: data processing, correction of original design and formal analysis. IMP: writing and editing.

REFERENCES

Arief, M. (2012). Aplikasi data satelit Spot-4 untuk mendeteksi terumbu karang: studi kasus di Pulau Pari. Majalah Ilmiah Globe, 14(1), 1-6.

Arief, M., Adawiah, S. W., Parwati, E., & Marpaung, S. (2017). Metode dual kanal untuk estimasi kedalaman di perairan dangkal menggunakan data Spot-6 studi kasus: Teluk Lampung. Jurnal Penginderaan Jauh dan Pengolahan Data Citra Digital, 14(1), 37-50.

BIG. (2014). Pedoman Teknis Pengumpulan dan Pengolahan Data Geospasial Habitat Dasar Perairan Laut Dangkal. Cibinong, Indonesia: Badan Informasi Geospasial.

Blaschke, T., Kelly, M., and Merschdorf, H. R. (2015). Object Based Image Analysis: Evolution, History, State-of-the-Art and Future Vision. Remotely Sensed Data Characterization, Classification, and Accuracies Chapter 14.

Chris. Roelfsema and Stuart. Phinn (2010) 'Object Based Analysis of High Spatial Resolution Imagery for Mapping Large Coral Reef Systems in the West Pacific At Geomorphic and Benthic Community Spatial Scales', pp. 4–7.

Hafizt, M., Iswari, M. Y. and Prayudha, B. (2017) 'Kajian Metode Klasifikasi Citra Landsat-8 untuk Pemetaan Habitat Bentik di Kepulauan Padaido , Papua Assessment of Landsat-8 Classification Method for Benthic Habitat Mapping in Padaido Islands , Papua Abstrak Pendahuluan Metodologi', Oseanologi dan Limnologi di Indonesia, 2(1), pp. 1–13. Available at: https://jurnal-oldi.or.id/index.php/oldi/article/view/69/67.

Hidayat, Aiman Munfih, (2017). Pemetaan Habitat Bentik Perairan Dangkal Pulau Opak Berbasis Objek dan Piksel Menggunakan Citra Satelit SPOT-7. Skripsi S1 FPIK IPB.

Hoegh-Guldberg, O., Poloczanska, E.S., Skirving, W., Dove, S. (2017). Coral Reef Ecosystems under Climate Change and Ocean Acidification. *Front. Mar. Sci.* 4:158. doi: 10.3389/fmars.2017.00158.

Japanese Ascotiation of Remote Sensing (JARS). (1999). Remote Sensing Note.

Lasabuda, R. (2013). Pembangunan wilayah pesisir dan lautan dalam perspektif Negara Kepulauan Republik Indonesia. Jurnal Ilmiah Platax, 1(2), 92-101.

Leiper, I. A. et al. (2014) 'Mapping coral reef benthos, substrates, and bathymetry, using compact airborne Spectrographic Imager (CASI) data', Remote Sensing, 6(7), pp. 6423–6445. doi: 10.3390/rs6076423.

Lyzenga, D.R.; Malinas, N.P.; Tanis, F.J. (2006) Multispectral bathymetry using a simple physically based algorithm. IEEE Trans. Geosci. Remote Sens 2006, 44, 2251–2259.

Manuputty, A., Lumban-Gaol, J., Agus, S., Nurjaya, I.W. (2017). The utilization of Depth Invariant Index and Principle Component Analysis for mapping seagrass ecosystem of Kotok Island and Karang Bongkok, Indonesia. IOP Conference Series: *Earth and Environmental Science*. 54. 012083. 10.1088/1755-1315/54/1/012083.

Mumby, P. J. et al. (1998) 'Benefits of water column correction and contex tual editing for mapping coral reefs', International Journal of Remote Sensing, 19(1), pp. 203–210.

Mumby, P. J. and Harborne, A. R. (1999) 'Development of a systematic classi ® cation scheme of marine habitats to facilitate regional management and mapping of Caribbean coral reefs', 88, pp. 155–163.

Pamungkas, B., & Jatmiko, R. H. (2016). Pemanfaatan citra penginderaan jauh dan sistem informasi geografis untuk pemetaan erosi di DAS Serang Kabupaten Kulonprogo. Jurnal Bumi Indonesia, 5(1), 1-10.

Prabowo, N. W., Siregar, V. P., & Agus, S.

B. (2018). Klasifikasi habitat bentik berbasis objek dengan algoritma support vector machines dan decision tree menggunakan citra multispektral Spot-7 di Pulau Harapan dan Pulau Kelapa. Jurnal Ilmu dan Teknologi Kelautan Tropis, 10(1), 123-134.

Prawoto, C. D., dan Hartono. (2018). Pemetaan habitat bentik dengan citra multispektral Sentinel-2A di perairan Pulau Menjangan Kecil dan Menjangan Besar, Kepulauan Karimunjawa. Jurnal Bumi Indonesia, 7(3), 1-8.

Prayudha, B. (2014). *Panduan Teknis Pemetaan Habitat Dasar Perairan Laut Dangkal*. Pusat Penelitian Oseanografi – LIPI.

Rahadiati, A., Soewardi, K., Wardiatno, Y., & Sutrisno, D. (2018). Pemetaan sebaran budidaya rumput laut: pendekatan analisis multitemporal. Majalah Ilmiah Globe, 20(1), 13-22.

Roelfsema, C. et al. (2018) 'Coral reef habitat mapping: A combination of object-based image analysis and ecological modelling', Remote Sensing of Environment, 208(December 2017), pp. 27–41. doi: 10.1016/j.rse.2018.02.005.

Rokach, L. and Maimon, O. (2005). Decision Trees. Data Mining And Knowledge Discovery Handbook Chapter 9. Department of Industrial Engineering. Tel-Aviv University. DOI: 10.1007/0-387-25465-X_9.

Sampurno, R. M., & Thoriq, A. (2016). Klasifikasi tutupan lahan menggunakan citra Landsat 8 operational land imager (OLI) di Kabupaten Sumedang. Jurnal Teknotan, 10(2), 61-70.

Selamat, M. B., Jaya, I., Siregar, V. P., & Hestirianoto, T. (2012). Akurasi tematik peta substrat dasar dari citra Quickbird (studi kasus Gusung Karang Lebar, Kepulauan Seribu, Jakarta). Journal of Marine Sciences, 17(3), 132-140.

Setiawan, K.T., Winarso, G., Ibrahim, A. 2019. Laporan Akhir Kegiatan Pemanfaatan Data Satelit Penginderaan Jauh Untuk Terumbu Karang Sebagai Parameter Pendukung Informasi Areal Budidaya Ikan. Pusfatja, LAPAN.

Setyawan, I. E., Siregar, V. P., Pramono, G. H., & Yuwono, D. M. (2014). Pemetaan profil habitat dasar perairan dangkal berdasarkan bentuk topografi: studi kasus Pulau Panggang, Kepulauan Seribu Jakarta. Majalah Ilmiah Globe, 16(2), 125-132.

Siregar, V. (2010). Pemetaan substrat dasar perairan dangkal Karang Congkak dan Lebar Kepulauan Seribu menggunakan citra satelit QuickBird. E-Jurnal Ilmu dan Teknologi Kelautan Tropis, 2(1), 19-30.

Wahidin, N. et al. (2015) 'Object-based image analysis for coral reef benthic habitat mapping with several classification algorithms', Procedia Environmental Sciences. Elsevier B.V., 24, pp. 222–227. doi: 10.1016/j.proenv.2015.03.029.

Winarso, G., Setiawan, K.T., Marini, Y., dan Hartuti, M. (2015). Interpretasi Visual Kenampakan Substrat Dasar Penyusun Ekosistem Terumbu Karang di Kepulauan seribu Menggunakan Data Landsat 8. Buku Buka Rampai Pemanfaatan Penginderaan jauh untuk Wilayah Pesisir dan Laut. IPB Press: Bogor.

Winarso, G. Manessa, MDM., Budhiman, S., dan Kano, A. Pemetaan Terumbu Karang di Indonesia : Komparasi 7 Metode Klasifikasi Terawasi dan Pengaruh Lokasi yang Berbeda. Prosiding Sinasja 2016.

Zoffoli, L., Frouin, R., Kampel, M. (2014). Water Column Correction for Coral Reef Studies by Remote Sensing. *Sensors (Basel, Switzerland)*. 14. 16881-16931. 10.3390/s140916881.