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Object based classification of benthic habitat using Sentinel 2 imagery by applying with support vector machine and random forest algorithms in shallow waters of Kepulauan Seribu, Indonesia

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Abstract. *Hartoni, Siregar VP, Wouthuyzen S, Agus SB. 2021. Object based classification of benthic habitat using Sentinel 2 imagery by applying with support vector machine and random forest algorithms in shallow waters of Kepulauan Seribu. Biodiversitas 23: 514-520.* Benthic habitats have very high complexity and are home to many types of aquatic organisms. Benthic habitats have various functions, including habitat for flora and fauna, sediment traps, nursery areas, and foraging areas for aquatic fauna that are susceptible to damage due to human activities or natural factors. Therefore, more accurate spatial information is needed. The purpose of this study was to examine the ability of object-based classification techniques for mapping shallow waters benthic habitats using Sentinel 2A imagery. The two classification algorithms used are support vector machine (SVM) and random forest (RF). The input image layer (IIL) used for classification is the natural color band (Band 432). The results showed that the SVM and RF classification algorithms could classify eight classes of benthic habitats. The overall accuracy (OA) of the SVM algorithm is 65%, while the RF accuracy is 67%, with kappa values of 0.59 and 0.60, respectively. The significant test applied to Sentinel 2 images with SVM and RF algorithms for benthic habitats has a Z test value of-0.41. These results indicate that the classification results between the SVM and RF algorithms are not significantly different.

Keywords: Benthic habitat, Kepulauan Seribu, object-based, random forest, support vector machine

INTRODUCTION

The biodiversity of coastal ecosystems such as coral reefs, seagrasses, and mangroves is under threat worldwide due to the impacts of climate change (Waycott et al. 2011) and, anthropogenic pressures from such as overfishing, coastal development, and tourism activities (Hughes et al. 2003). As a part coastal ecosystem, shallow water benthic habitats are very highly complex and comprises of diverse ecosystem which are used as a place to live for various types of marine biota. It is also composed of biotic components such as seaweed, seagrass, algae, live coral, and non-biotic component such as sand, mud, and coral rubble (Zhang et al. 2013). As an addition, shallow waters benthic habitats have various functions, included as sediment traps, nursery grounds, and foraging for aquatic fauna. These benthic habitats are vulnerable to damage due to human activities or natural factors and change dynamically (Eugenio et al. 2017).

Benthic habitat mapping using satellite imagery along with accuracy assessments have been carried out by several researchers (Phinn et al. 2011; Wahidin et al. 2015; Hafizt et al. 2017; Siregar et al. 2020). Pixel-based classification is the most frequently applied technique in mapping. The pixel-based classification method with conventional algorithms such as maximum likelihood (MLH) only utilizes spectral information in classifying multispectral images. The results of pixel-based classification tend to produce a salt and pepper effect, where one pixel classed is different from the surrounding classes (Duro et al. 2012; Pande-Chhetri et al. 2017). This effect is due to the complexity of the biophysical environment, which results in spectral similarities between land cover classes or classification schemes used (Whiteside et al. 2011).

In the last decade, object-based image analysis (OBIA) has been accepted as an effective method for extracting and classifying information from high spatial resolution satellite images (Blaschke 2010; Roelfsema et al. 2018). OBIA involves segmenting images into homogeneous areas and object characteristics with a set of features related to spectral, spatial, and contextual properties (Draˇgut et al. 2014). Machine learning classification algorithms have grown rapidly enough to be used to classify spatial data from various sources. Support vector machine (SVM) and random forest (RF) classification algorithms, including machine learning algorithms, have received increasing attention (Rodriguez-Galiano et al. 2012; Du et al. 2015) and are applied in the OBIA classification because of its excellent classification results and processing speed (Zhang et al. 2013).

So far, Landsat imagery is a medium spatial resolution satellite image used in various uses in mapping resources both on land and in waters. Landsat is one of the satellites with a long history, a spatial resolution of 30 meters, and good spectral resolution, and the data is time series and can be obtained free of charge. However, in recent years the presence of the sentinel2 satellite, which was launched in 2015 with specifications consisting of 13 bands, a spatial resolution of 10 meters includes four multispectral bands that can penetrate the water column and have a temporal resolution of 10 days. The data can be accessed free of charge, is expected to be a source of information, spatial data of benthic habitat mapping. Benthic habitat mapping research using medium resolution image data with the OBIA technique approach with the application of machine learning algorithms needs to be done to determine the ability of the algorithm to classify benthic habitats. This study aims to analyze the ability of object-based classification techniques for mapping benthic habitats using Sentinel 2 imagery with SVM and RF classification algorithms in the shallow waters of the Kepulauan Seribu (Seribu Islands), Jakarta, Indonesia.

MATERIALS AND METHODS

Study area

The research was conducted from August to December 2018, while the field survey was conducted in September 2018. The location of this research was carried out in shallow waters around Pramuka Island, Panggang Island, and Karya Island in the Kepulauan Seribu District, Jakarta, Indonesia (Figure 1).

Procedures

Data and data sources

The satellite image data used in this study is the Sentinel 2A sensor which is downloaded via https://scihub.copernicus.eu. This imagery was acquired on 07 September 2018. Data obtained consist of 13 spectral bands in VNIR and SWIR. The bands used have a spatial resolution of 10 m that is band 2 (0.458-0.523 µm), band 3 (0.543-0.578 µm) and band 4 (0.650-0.680 µm).

The field data collected was the type of shallow waters benthic habitat. The observation stations were determined using a random sampling method. The benthic habitats type was observed by direct visual observation and combined with a quadratic transect photo technique (Phinn et al. 2011; Roelfsema et al. 2013). The quadratic transect also makes it easier to determine the dominant component of shallow-water benthic habitat. At each point of the observation, benthic habitat data were collected by placing five transects of 1 m x 1 m in an area of 10 m x 10 m so that there were five transects squared. This component of the benthic habitat is used as the basis for the formation of the benthic habitat classification scheme at the study site. Benthic habitat type information obtained from 310 observation points are used for determining the classification scheme, classification process with satellite imagery, and for accuracy testing. Each observation station is recorded its position using a global positioning system (GPS).

Classification scheme

The benthic habitat classification scheme is a structured system to classify the benthic habitat types into several classes defined based on its ecological characteristics. The initial stage to produce the map is to identify these classes and describe their attributes. The determination of the benthic habitat classes is based on the dominant cover of the benthic habitat component obtained from field observations using the quadratic transect. The benthic habitat components found in each quadratic transect might be composed of single benthic habitat composition, dominated by one benthic habitat component or a mixture of several benthic habitat components. The classification scheme refers to the dominant benthic habitat cover principle, which modifies the scheme used by Green et al. (2000).

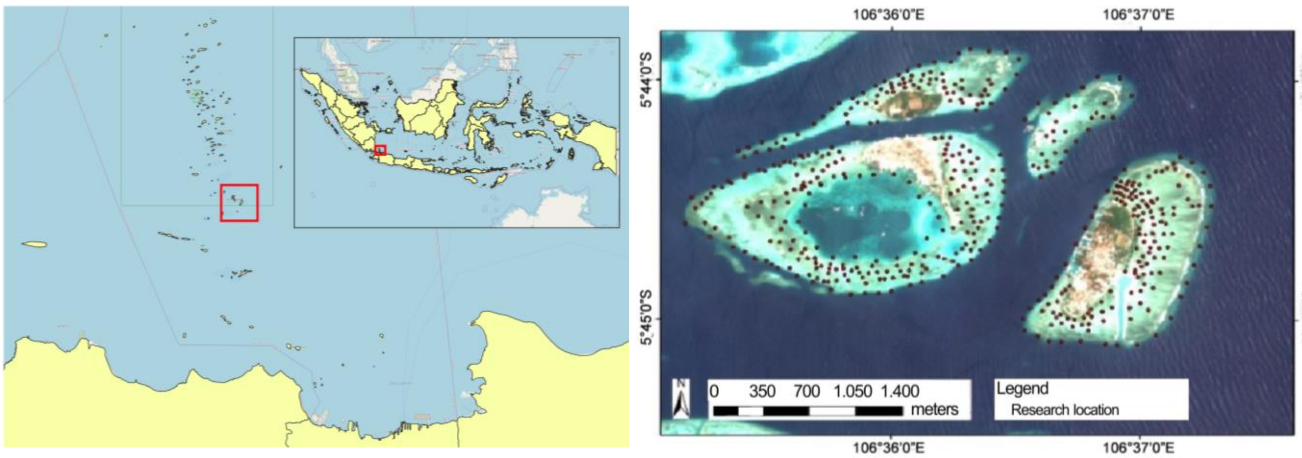

Figure 1. Map of research location in shallow waters around Pramuka Island, Panggang Island, and Karya Island of Seribu Islands, Jakarta Bay, Indonesia

The classes were determined based on the analysis of the percentage cover grouping of the components that make up the benthic habitat using cluster analysis (Agglomerative Hierarchical clustering, AHC) with a dissimilarity of 35%. AHC is a classification method based on the value of dissimilarities between objects to be grouped. The number of dissimilarities can be adjusted to the subject studied based on the nature of the data. This analysis produces a dendrogram that shows the grouping so that it is possible to obtain several similar classes in which the data can be grouped (Ripley 1996). The similarity was measured using the Bray-Curtis distance similarity coefficient (Clarke 1993). This analysis accommodates the desired biological properties and is suitable for ecological distance measurements. Shallow waters benthic classes with the frequency of presence of less than 3% were eliminated (Green et al. 2000).

Image preprocessing

The preprocessing stage consists of atmospheric correction, image cropping, and masking of land and water areas. Atmospheric correction is a process to eliminate errors caused by the influence of the atmosphere on the image. Atmospheric correction was performed using the dark object subtraction method (Chavez 1988) with the help of QGIS software.

Shallow waters benthic habitat mapping and accuracy test

Mapping of shallow waters benthic habitats using OBIA technic is carried out in two stages, namely, image segmentation and classification in each segment (Zhang et al. 2013; Dra˘gut et al. 2014). The process of image segmentation and classification was done using ArcGIS Pro software. The natural color composite images (Band RGB 432) were used as the input image layer (IIL) in the OBIA classification process. The segmentation process uses the Mean Shift Segmentation (MSS) algorithm (Lourenço et al. 2021). MSS parameters consist of spectral detail, spatial detail, and minimum segment size. The spectral detail and spatial detail parameters use values of 20 and 5, respectively, while the minimum segment size as the segmentation size parameter has a value of 1. There is no standard set of standards in determining the standard score of segmentation parameters in object-based classification (Wahidin et al. 2015).

The machine learning classification algorithms used in this studied were the support vector machine and random forest. The OBIA classification parameters in both algorithms used were the attribute features on the mean digital number and standard deviation. The final stage of the classification process is to determine the accuracy of the classification (map) results, which consists of overall accuracy (OA), kappa coefficient, Z test statistics referring to Congalton and Green (2009).

RESULTS AND DISCUSSION

Classification scheme

The description of the classification scheme is derived from the percentage value of the seven benthic components based on the Bray-Curtis coefficient dissimilarity of 35% using AHC statistical calculations. The dissimilarity of 35% indicates that each habitat class built has a minimum of 65% similarity to the benthic components. Because there is no standardization in standard class naming in the development of classification schemes, the class naming in this study is adjusted to the benthic composition of the constituents observed in the field. The dendrogram showed as many as 14 benthic habitat classes (Figure 2), that is C1: sparse sand seagrass (PLj); C2: sand medium seagrass (PLs); C3: coral (K); C4: coral rubble (KPk); C5: coral algae (KA); C6: algae rubble (APk); C7: sand rubble (PPk); C8: rubble (Pk); C9: dense seagrass sand (LpP); C10: sand algae sparse seagrass (PALj); C11: coral sand (KP); C12: algae medium seagrass sand (ALsP); C13: algae coral (AK); and C14: dense seagrass algae (LpA).

The application of the classification scheme to satellite imagery considers the number of samples at least 3% of the total sample. Of the total 14 habitat classes, only eight classes, namely PLj, PLs, K, KPk, PPk, Pk, LpP, and PALj classes that meet the minimum number, while six classes, namely KA, APK, KP, AlsP, AK, and LpA classes are not used in the classification process with satellite imagery. The similarity value in defining the classification scheme does not have a standard provision based on grouping analysis. It is caused by conditions and variations of different observation locations and is adapted to the satellite imagery platform used (Mumby and Edwards 2002; Wahidin et al. 2015). The 8 classes shallow waters benthic habitat classification scheme is applied in the mapping (Figure 3).

The PLj class consists of a benthic sand component with sparse seagrass. The PLs class consists of a benthic sand component with medium seagrass. Class K consists of a benthic component of coral reefs. The KPk class consists of a benthic component of coral reefs with rubble. The PPk class consists of a benthic sand component with rubble. The Pk class consists of a benthic component of rubble. The LpP class consists of a benthic component of dense seagrass with sand. The PALj class consists of benthic sand, algae and sparse seagrass components.

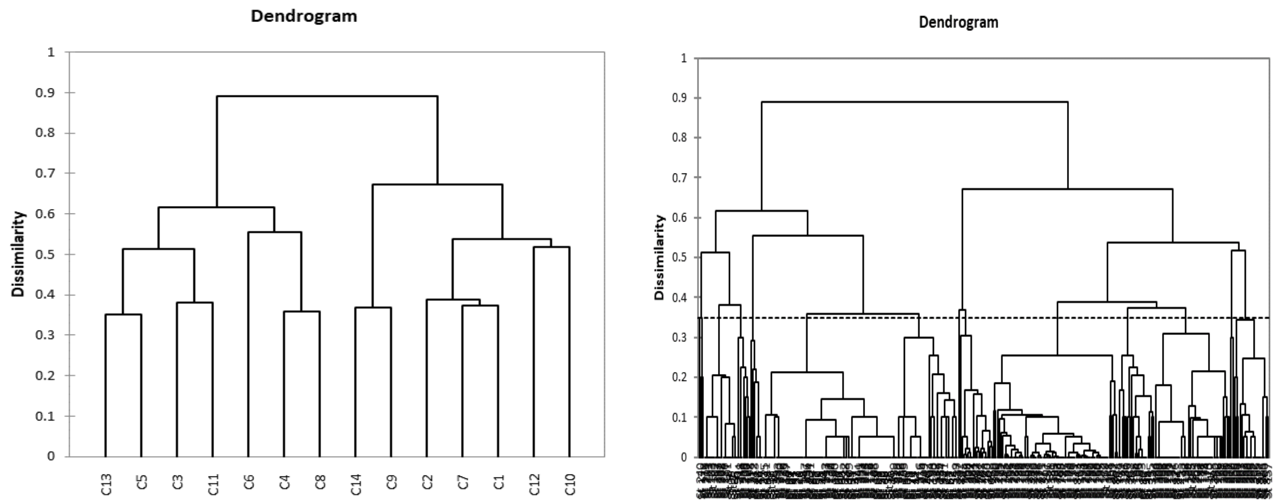

Figure 2. Dendogram of habitat class grouping

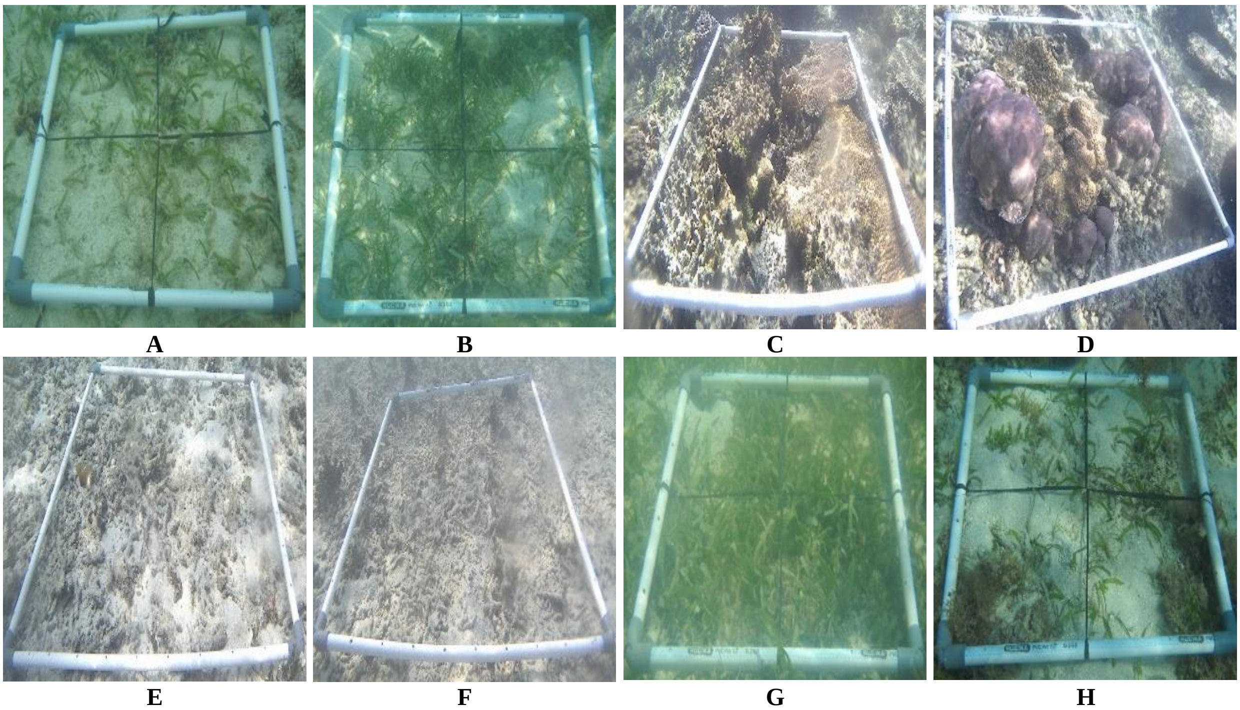

Figure 3. The eight classes shallow waters benthic habitat in Kepulauan Seribu, Jakarta, Indonesia. A. PLj; B. PLs; C. K; D. KPk; E. PPk; F. Pk; G. LpP; H. PALj

Benthic habitat classification

The results of the classification of shallow-water benthic habitats based on the object that was applying SVM and RF algorithms provided eight classes of benthic habitat as proposed in the classification scheme, were presented in Figure 4.

Visually, the two algorithms provided eight classes of benthic habitat, but there are differences in the spatial distribution of benthic habitat classes. Classification using the SVM algorithm showed that sand rubble (PPk) is dominant in the area, followed by sand algae sparse seagrass (PALj), and coral rubble (KPk). In the contrary, using the RF algorithm, the sand rubble (PPk) seems more dominant in the area, followed by coral rubble (KPk) and sand sparse seagrass (PLj). The two algorithms showed that the sand is very dominant in the research location but is mixed with other benthic components and does not showed the dominance of one benthic habitat component; this is because the shallow-water benthic habitat is a habitat that has a complexity, unique ecosystem and rapidly changing environmental conditions that affect the types of benthic components in shallow waters.

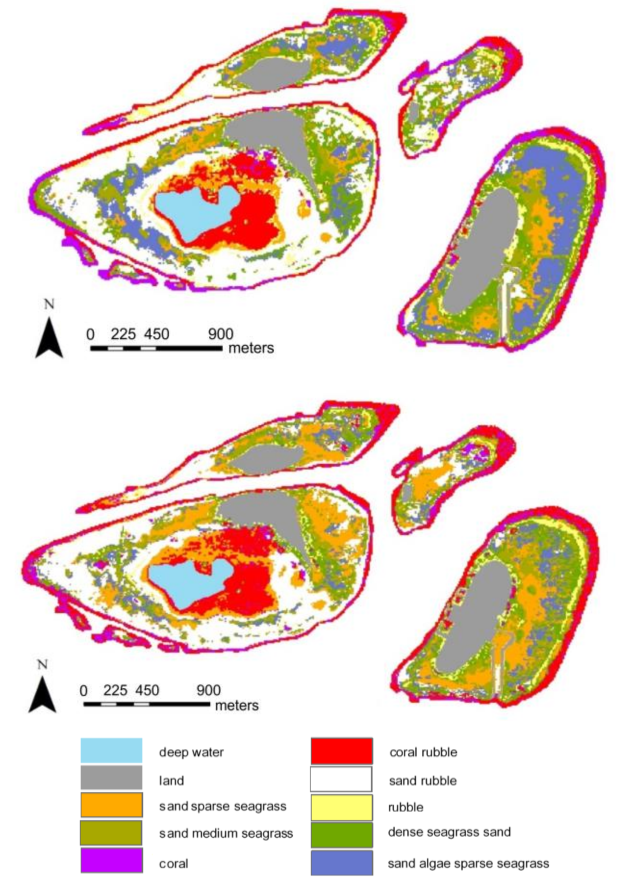

Figure 4. Shallow waters benthic habitat classification of the Sentinel 2A images using (A) the SVM algorithm and (B) the RF algorithm

The area of each benthic habitat class can be derived by spatial analysis. The total area of eight benthic habitat classes classified using the SVM and RF algorithms is presented in Table 1.

The area classified in eight benthic habitat classes showed that the sand rubble (PPk) is the highest area in both algorithms dominated the shallow water area with an area of 95.11 ha and 88.18 ha, respectively. In contrast, the benthic habitat class, which has the lowest area, namely rubble (Pk), has an area of 28.12 ha and 13.93 ha, respectively. The difference in the area shows the implications of the application of the two classification methods used. The difference in the area can be caused by overlaps between classes of classified benthic habitats and errors in segment features that are not classified correctly; this depends on the selection of the classification method used. According to Green et al. (2000), differences in mapping classification results from several studies are caused by differences in classification methods, number of field observation points, number of benthic habitat classes, and images used. Errors in classifying will affect the area in each class resulting in low accuracy.

Table 1 also showed that the distribution of the seagrass ecosystem is dominated by medium seagrass and sparse seagrasses, in line with the coral reef ecosystem, which is dominated by coral rubble in the study area; This indicates that the ecosystem is experiencing disturbances. According to field observations, seagrass and coral reefs are under pressure due to community activities in densely populated land areas that produce household waste around shallow waters, and the impact of coastal development and tourism activities significantly affects the distribution and condition of coral reefs and seagrass. In addition, the research area is directly dealing with open waters whose environmental changes are very dynamic.

Test accuracy

The accuracy test of the SVM and RF classification algorithms produces overall accuracy (OA) values of 65.00% and 67.00%, respectively, and kappa values of 0.59 and 0.60, respectively (Table 2).

The RF algorithm has higher accuracy than the SVM algorithm. The number of classes influences the difference in accuracy results; the higher the number of classes, the lower the accuracy percentage. The study of Andrefouet et al. (2003) using Landsat and IKONOS images applying several classes, showed the result of different OA which decreases with the increasing of the number of classes used, that is 77% (4-5 classes), 71% (7-8 classes), 56% (9-11 classes), and 53% (>13 classes). Mastu et al. (2018), classified the benthic habitat using Sentinel-2 imagery and the SVM algorithm, which has an OA of 60.4% in 12 classes and 64.1% in 9 classes. Meanwhile, Wicaksono et al. (2019) in his research, using WorldView-2 imageries, informed that the OA of RF was 94.17% (4 classes) and 88.54% (14 classes). Wahidin et al. (2015), using Landsat 8 OLI images with support vector machine (SVM), random tree (RT), bayyesian, k-nearest neighbor (KNN) and decision tree (DT) shows that the algorithm SVM has a better ability than other algorithms with an overall accuracy rate of 73% with seven classes. Nababan et al. (2021), using drone imagery and applying the SVM algorithm, resulted in an overall accuracy of 77.4 % in 12 classes and 81.1% in 9 classes.

Table 1. Area of benthic habitat class at the study site

Class	Class code	Habitat thematic class area (Ha)	
		SVM Algorithm	**RF Algorithm**
Sand sparse seagrass	PLj	32.48	68.99
Sand medium seagrass	PLs	54.63	59.94
Coral	K	28.83	23.76
Coral rubble	KPk	56.67	75.44
Sand rubble	PPk	95.11	88.18
Rubble	Pk	28.12	13.93
Dense seagrass sand	LpP	39.19	32.41
Sand algae sparse seagrass	PALj	53.96	26.39
Total		389.03	389.04

Table 2. Overall accuracy(%), kappa test, and Z test for benthic habitat classification using SVM and RF algorithms.

Test	Algorithms	
	SVM	**RF**
Overall accuracy (%)	65.00	67.00
Kappa	0.59	0.60
Z test	-0.41	

The Z test is used to determine whether two or more image classifications differ significantly or not (Congalton and Green 2009). Comparison tests of the different classification is carried out to determine the difference in perform of each treatment. Overall, the significant test applied to Sentinel 2 images with SVM and RF algorithms for benthic habitats classification has a Z test value of-0.41. These results indicate that the classification results between the SVM and RF algorithms are not significantly different. According to Congalton and Green (2009), the Z test value between-1.96 to 1.96 is an accuracy category in a normal distribution. According to Sesnie et al. (2010), Dalponte et al. (2013), and Ghosh et al. (2014), the ability of the RF and SVM classification algorithms are equally reliable, with the results of the RF classification being slightly better for high-dimensional data input such as hyperspectral images.

The results of mapping benthic habitats are influenced by several factors, namely resolution, number of classes, an algorithm used, and data collection errors in the field and aquatic environmental conditions. Errors in data collection were related to technicalities in the field, namely errors in taking the number of samples, sampling techniques (size transect quadrat), and errors in the presentation of benthic habitat cover. Errors in the classification process will affect the area; this can result in low accuracy. The scale segmentation is determined by the resolution of the image used, the level of heterogeneity or complexity of shallow-water benthic habitats, and the study site area. These factors can cause differences in the number, shape of polygons, and the area of each habitat class, thus affecting the mapping of the distribution of benthic habitats.

The condition of the aquatic environment, namely the optical properties of seawater and the turbidity of the waters, can affect the results of satellite imagery. In clear waters, energy is absorbed more optimally, so it will be seen into the waters. Hochberg and Atkinson (2003) stated that low accuracy in benthic habitat mapping could be influenced by various things, namely the type of sensor, image resolution, and aquatic environmental conditions such as depth, water quality, and sea surface conditions. Absorption and scattering are essential factors in describing the value of attenuation in the waters. Waters characteristics affect the absorption and scattering process of the light energy entering the water column (Saulquin et al. 2013).

In conclusion, the classification of benthic habitats using Sentinel 2A images applying the SVM and RF classification algorithms can classify eight benthic habitats. The classification of benthic habitats with both classification algorithms, the accuracy of the SVM algorithm and the RF classification algorithm produces OA values of 65.00% and 67.00%, respectively, and kappa values of 0.59 and 0.60, respectively. Of the two classification algorithms used in the classification of benthic habitats in this study, the accuracy of the RF algorithm is higher than the SVM algorithm. The significant test applied to Sentinel 2 images with SVM and RF algorithms for benthic habitats has a Z test value of-0.41. These results indicate that the classification results between the SVM and RF algorithms are not significantly different.

REFERENCES

Andrefouet S, Kramer P, Torres-Pulliza D, Joyce KE, Hochberg EJ, Garza-Pe´rez R, Mumby PJ, Riegl B, Yamano H, White WH, Zubia M, Brock JC, Phinn SR, Naseer A, Hatcher BG, Muller-Karger FE. 2003. Multi-site evaluation of ikonos data for classification of tropical coral reef environments. Remote Sens Environ 88: 128-143. DOI: 10.1016/j.rse.2003.04.005.

Blaschke T. 2010. Object based image analysis for remote sensing. J Photogr Remote Sens 65 (1): 2-16. DOI: 10.1016/j.isprsjprs.2009.06.004.

Chavez PS. 1988. An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. Remote Sens Environ 24: 459-479. DOI: 10.1016/0034-4257(88)90019-3.

Clarke KR. 1993. Non-parametric multivariate analyses of changes in community structure. Aust J Ecol 18: 117-143. DOI: 10.1111/j.1442-9993.1993.tb00438.x.

Congalton RG, Green K. 2009. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. CRC Press Indiana, United States.

Dalponte M, Ørka HO, Gobakken T, Gianelle D, Næsset E. 2013. Tree species classification in Boreal Forests with hyperspectral data. IEEE Transact Geosci Remote Sens 51: 2632-2645. DOI: 10.1109/TGRS.2012.2216272.

Du P, Samat A, Waske B, Liu S, Li Z. 2015. Random forest and rotation forest for fully polarized SAR image classification using polarimetric and spatial features. J Photogr Remote Sens 105: 38-53. DOI: 10.1016/j.isprsjprs.2015.03.002.

Duro DC, Franklin SE, Dube MG. 2012. A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. Remote Sens Environ 118: 259-272. DOI: 10.1016/j.rse.2011.11.020.

Dra˘gut L, Csillik O, Eisank C, Tiede D. 2014. Automated parameterisation for multi-scale image segmentation on multiple layers. J Photogr Remote Sens 88: 119-127. DOI: 10.1016/j.isprsjprs.2013.11.018.

Eugenio F, Marcello J, Martin J, Rodríguez-Esparragón D. 2017. Benthic habitat mapping using multispectral high-resolution imagery: Evaluation of shallow water atmospheric correction techniques. Sensors 17: 2639. DOI: 10.3390/s17112639.

Ghosh A, Fassnacht FE, Joshi PK, Koch B. 2014. A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales. Intl J Appl Earth Observ Geoinfo 26: 49-63. DOI: 10.1016/j.jag.2013.05.017.

Green E, Edwards AJ, Clark C. 2000. Remote Sensing Handbook for Tropical Coastal Management. Unesco Pub Paris, France.

Hafizt M, Manessa MDM, Prayudha. 2017. Benthic habitat mapping by combining lyzenga's optical model and relative water depth model in Lintea Island, Southeast Sulawesi. Earth Environ Sci 98: 012037. DOI: 10.1088/1755-1315/98/1/012037.

Hughes TP, Baird AH, Bellwood DR, Card M, Connolly SR, Folke C, Grosberg R, Hoegh-Guldberg O, Jackson JB, Kleypas J, lougH JM, Marshall P, NyströM M, Palumbi SR, Pandolfi JM, Rosen B, Roughgarden J. 2003. Climate change, human impacts, and the resilience of coral reefs. Science 301: 929-933. DOI: 10.1126/science.1085046.

Hochberg EJ, Atkinson MJ. 2003. Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. Remote Sens Environ 85: 174-189. DOI: 10.1016/S0034-4257(02)00202-X.

Lourenço P, Teodoro AC, Gonçalves JA, Honrado JP, Cunha M, Sillero N. 2021. Assessing the performance of different OBIA software approaches for mapping invasive alien plants along roads with remote sensing data. Intl J Appl Earth Observ Geoinfo 95: 102263. DOI: 10.1016/j.jag.2020.102263.

Mastu LOK, Nababan B, Panjaitan JP. 2018. Object based mapping on benthic habitat using Sentinel-2 imagery of the Wangi-wangi Island waters of the Wakatobi district. Jurnal Ilmu dan Teknologi Kelautan Tropis 10 (2): 381-396. DOI: 10.29244/jitkt.v10i2.21039.

Mumby PJ, Edwards AJ. 2002. Mapping marine environments with IKONOS imagery: Enhanced spatial resolution can deliver greater thematic accuracy. Remote Sens Environ 82: 248-257. DOI: 10.1016/S0034-4257(02)00041-X.

Nababan B, Mastu LOK, Idris NH, Panjaitan JP. 2021. Shallow-water benthic habitat mapping using drone with object based image analyses. Remote Sens 13: 4452. DOI: 10.3390/rs13214452.

Pande-Chhetri R, Elrahmana AA, Liua T, Morton J, Wilhelm VL. 2017. Object-based classification of wetland vegetation using very high-resolution unmanned air system imagery. Eur J Remote Sens 50 (1): 564-576. DOI: 10.1080/22797254.2017.1373602.

Phinn SR, Roelfsema CM, Mumby PJ. 2011. Multi-scale, object-based image analysis for mapping geomorphic and ecological zones on coral reefs. Intl J Remote Sens 33: 3768-3797. DOI: 10.1080/01431161.2011.633122.

Roelfsema C, Phinn S, Jupiter S, Comley S, Albert S. 2013. Mapping coral reefs at reef to reef-system scales. 10s-1000s km^2. using objectbased image analysis. Intl J Remote Sens 34: 6367-6388. DOI: 10.1080/01431161.2013.800660.

Roelfsema C, Kovacs E, Ortiz JC, Wolff NH, Callaghan D, Wetle M, Phinn S. 2018. Coral reef habitat mapping: A combination of basedimage analysis and ecological modelling. Remote Sens Environ 208: 27-41. DOI: 10.1016/j.rse.2018.02.005.

Rodriguez-Galiano VF, Ghimire B, Rogan J, Chica-Olmo M, Rigol-Sanchez JP. 2012. An assessment of the effectiveness of a random forest classifier for land-cover classification. J Photogr Remote Sens 67: 93-104. DOI: 10.1016/j.isprsjprs.2011.11.002.

Ripley BD. 1996. Pattern Recognition and Neural Networks. Cambridge Univ Press. United Kingdom.

Saulquin B, Hamdi A, Gohin F, Populus J, Mangin A, d'Andon OF. 2013. Estimation of the diffuse attenuation coefficient KdPAR using MERIS and application to seabed habitat mapping. Remote Sens Environ 128: 224-233. DOI: 10.1016/j.rse.2012.10.002.

Sesnie S, Finegan B, Gessler PE, Thessler S, Bendana Z, Smith AMS. 2010. The multispectral separability of Costa Rican rainforest types with support vector machines and random forest decision trees. Intl J Remote Sens 31 (11): 2885-2909. DOI: 10.1080/01431160903140803.

Siregar VP, Agus SB, Sunuddin A, Pasaribu RA, Sangadji MS, Sugara A, Kurniawati. 2020. Benthic habitat classification using high resolution satellite imagery in Sebaru Besar Island, Kepulauan Seribu. Earth Environ Sci 429: 012040. DOI: 10.1088/1755-1315/429/1/012040.

Wahidin N, Siregar VP, Nababan B, Jaya I, Wouthuyzen S. 2015. Object based image analysis for coral reef benthic habitat mapping with several classification alghorithms. Proc Environ Sci 24: 222-227. DOI: 10.1016/j.proenv.2015.03.029.

Waycott M, McKenzie LM, Mellors JE, Ellison JC, Sheaves MT, Collier C, Schwarz A, Webb A, Johnson JE, Payri CE. 2011. Vulnerability of mangroves, seagrasses and intertidal flats in the tropical Pacific to climate change. In: Bell JD, Johnson JE, Hobday AJ (eds). Vulnerability of Tropical Pacific Fisheries and Aquaculture to Climate Change. Secretariat of the Pacific Community, New Caledonia.

Whiteside TG, Boggs GS, Maier SW. 2011. Comparing object-based and pixelbased classifications for mapping savannas. Intl J Appl Earth Observ Geoinfo 13 (6): 884-893. DOI: 10.1016/j.jag.2011.06.008.

Wicaksono P, Aryaguna PA, Lazuardi W. 2019. Benthic habitat mapping model and cross validation using machine-learning classification algorithms. Remote Sens 11: 1279. DOI: 10.3390/rs11111279.

Zhang C, Selch D, Xie Z, Roberts C, Cooper H, Chen G. 2013. Object-based benthic habitat mapping in the Florida Keys from hyperspectral imagery. Estuar Coast Shelf Sci 134: 88-97. DOI: 10.1016/j.ecss.2013.09.018.