Benthic habitats mapping in Pari Island, Kepulauan Seribu, Indonesia using drone and sentinel-2B imagery with object based image analysis method

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Abstract. Benthic habitats are living places and shelters for various types of aquatic organisms, including seagrass, seaweed, algae, dead corals, and living corals with different types of substrates, such as rubble, sand, and mud. This habitat has the potential to change, so it is necessary to monitor it regularly by mapping shallow-water habitats using remote sensing technology such as satellite imagery and drones. This study aims to classify and map benthic habitats in the shallow waters of Pari Island using drone and satellite images using the object-based image analysis (OBIA) classification method. A total of 1052 aerial photographs with a resolution of 3.6 cm / pixel and Sentinel-2B images with a spatial resolution of 10 m were processed using the support vector machine (SVM) algorithm. Both images produced six classes: live corals, macroalgae, seagrass, dead corals with algae, sand, and rubble. The overall accuracy test results for drone imagery and satellite imagery were 81.88% and 69.57%, respectively. Based on the overall accuracy, the drone images proved to be better than Sentinel-2 imagery.

1 Introduction

Indonesia is a country with a coral reef area reaching 39,583 km2 with 18% in the form of world coral reef cover and 45.7% in the form of coral triangle area [4]. The amount of potential possessed must be optimized and utilized on an ongoing basis. One way to accomplish thisis to utilize remote sensing technology to inventory basic habitat cover [5]. A shallow sea water habitat is a place to live and shelter various types of aquatic organisms, including seagrass, seaweed, algae, dead coral, and living corals with different types of substrates, such as coral fragments, sand, and mud [11].

Pari Island is one of the islands located in the waters of the Thousand Islands. This water area is situated in the DKI Jakarta region, outside Jakarta Bay. Geographically, this water area plays an important and significant role in regional economic growth through the development of marine industries such as sea transportation services and tourism. The Pari

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Island group consists of Pari Island, Kongsi Island, Tengah Island, Burung Island, and Tikus Island, which are all surrounded by an atoll reef. The water conditions in the area outside the atoll are deep, while the water inside the atoll is relatively shallow, and in some places, there are lagoons [18].

Remote sensing technology has been widely used for the detection of benthic habitats in Indonesia because this method works faster and with sufficient accuracy. In addition to satellite imagery, currently the increasing use of remote sensing using drone technology has been widely used [23]. High-resolution aerial photography images produced with drones can be repeated in time series at the same location so that studies can be conducted on the impact of changes on the closure of coral reef ecosystems associated with certain phenomena [22]. Drones produce image data with higher spatial resolution, are more economical, avoid cloud cover, provide more flexible data acquisition while maintaining high accuracy potential, and real-time. Digital classification consists of two approaches: pixel and object-based classification. Object-Based Image Analysis (OBIA) is a object-based remote sensing image analysis method that can detect several objects with certain similarities. OBIA classifies satellite images based on spectral values and optimizes the spatial features of images according to interpretation elements, such as texture, shape, and other parameters [19]. A wide variety of algorithms can be used in the image classification process. The SVM algorithm is an algorithm whose classification method uses a hypothetical space in the form of a linear function in a feature space. The SVM algorithm has been proven to produce better accuracy than other classification algorithms, such as Decision Tree (DT), Bayes, and K-Nearest Neighbor (KNN), in image-based classification.

Benthic habitat mapping needs to be done regularly because this habitat has the potential to change due to certain factors, such as habitat utilization, which causes pressure on shallow sea-bottom habitats [21]. In general, shallow water areas on small islands are vulnerable to climate change, which results in potential habitat destruction, changes in natural processes in ecosystems, and pollution [20].

2 Methods

2.1 Study Site

This study was conducted from October 2023 to May 2024. The data used are from field observations carried out on Pari Island, Kepulauan Seribu. The research sites are shown in Figure 1.

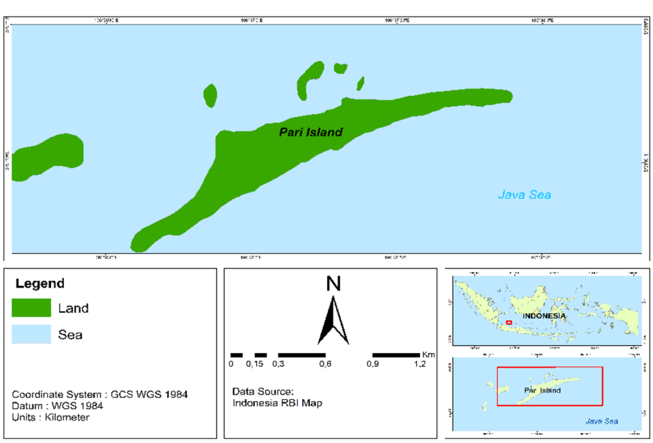

Fig. 1. Study area at Pari Island.

2.2 Data Collection

Field observations were conducted by taking aerial photos using drones and observing benthic habitats by taking the coordinates and documentation of objects. The process of taking aerial photos consists of creating a flight plan using a drone deployment application. A flight area plan that includes three flight plans with flight altitude settings of 120 mfrontlap 70%, sidelap 70%, and drone flight speed set at 12 m/s and camera viewing angle -90°. Drone flights were carried out at 16.00-17.00) [9]. There were 242 points of benthic habitat divided into two different inputs: 104 points for classification and 138 points for accuracy tests.

2.3 Data Processing and Analysis

2.3.1 Photogrammetry

The process of processing aerial photos until the results of obtaining mosaic images includes the following processes: 1) input aerial photos, 2) aligned photos, 3) building a dense cloud, 4) building 3D polygon model, 5) building texture, 6) building orthophotos, and 7) exporting aerial photo mosaic results. Photos taken using drones already have coordinate points and are in JPEG format. The drone design track is shown in Figure 2.

Fig. 2. Drone track design at Pari Island.

2.3.2 Image Preprocessing

Preprocessing is the initial process of repairing an image to remove noise. Preprocessing removes parts that are not required in the input image for the next process [15]. The image preprocessing stage began with cropping and composite imagery. Cropping on the image serves to determine exactly which part of the image will be used as an area of the object to be processed, so that it can be separated from areas that are not needed in the next processing. The composite band is the process of composite (merging) three bands to obtain red, green, and blue colors for the image [13]. Atmospheric correction was then carried out to eliminate errors caused by atmospheric influences on the image [8]. Dark object subtraction (DOS) was used. DOS is an empirical method of atmospheric correction for satellite imagery, which assumes that reflectance from dark objects includes a substantial component of atmospheric scattering.

2.3.3 Water Column Correction

Water column correction is performed to improve image quality by red (3)
the water column so that the appearance of objects is clearer, making it e
contained in the image [1]. The information obtained in the previous image was mixed with reflections from several components in the water. Water column correction improves the accuracy of digital image classification performed [6]. In drone imagery, water column correction is not carried out because drone data collection is carried out at low tide such that the appearance of the object is clearly visible. The method used to correct the influence of the water column is the Depth Invariant Index (DII) using the Lyzenga algorithm (1981)[10] with the following equation:

$$Y = ln\, ln\, (Li)\ - \left[\left(\frac{ki}{kj}\right) \times ln\, (Lj)\right]$$

With,

$$\frac{ki}{kj} = a + \sqrt{a^2 + 1}$$

$$a = \frac{(\sigma_{ii} - \sigma_{jj})}{(2\sigma_{ij})}$$

Where:

Y:	Depth-invariant index.
Li:	Reflectance value of blue band
Lj:	Reflectance value of green band
ki/kj:	Attenuation ratio
a:	Coefficient of attenuation
σ_{ii}:	Variance band blue
σ_{jj}:	Variance band green
σ_{ij}:	Covariance of bands blue and green

2.3.4 Segmentation (4)

Segmentation is the concept of building objects or segmentation from pixels into segments or objects that have the same properties. The segmentation algorithm used was multi resolution segmentation (MRS) [12]. In this study, three main segmentation parameters were selected:scale, shape, and compactness, with different variation values to obtain optimal segmentation parameters for land cover classification [7].

2.3.5 Level Classification

Image classification is carried out using contextual editing method: (1)
application of machine learning algorithms at level 2. Machine lea
mathematical algorithms that use data as a way of learning and produce predictions or decisions [16]. Level 1 classification (reef level) is used to assign classes with a certain threshold value so that it becomes the desired object class, while leve
used classifier with the Supported Vector Machine (SVM) algorithm. (2)
classes that are classified which is life coral, macroalgae, seagrass, rubble, sand, and dead coral with algae. SVM algorithm equation are:

$$f(x) = \Sigma_{i \epsilon S} \lambda_i y_i K(x_i x) + w_0 \quad (5)$$

Where:
K = Kernel function (6)
y_i dan x_i = Represent training sample
λ_i = Lagrange multiplier
S = Part of the training sample corresponds to the multiplier. (7)
w_0 = Hyperplane parameter

2.3.6 Accuracy Test

Accuracy tests were performed to determine the optimal results of each machine learning algorithm used and to determine the results of mapping shallow marine habitats. A confusion matrix was used as the accuracy test formula. The confusion matrix is one of the accuracy testing methods used to determine the overall accuracy value of the clas results by comparing the classification result classes with data training (can be calculated using the following equation [2]: (8)

$$\textit{Producer accuracy} = \frac{n_{jj}}{n_{+j}} \times 100\%$$

$$\textit{User accuracy} = \frac{n_{ii}}{n_{i+}} \times 100\%$$

$$\textit{Overall accuracy} = \frac{\sum_{i=1}^{k} \; n_{ii}}{n} \times 100\%$$

The value of the kappa coefficient describes the condition of whether or not the accuracy of the data being compared is used to determine the closeness or agreement of the results of testing two datasets. The kappa coefficient value has a range of up to 1.00, with value categories referring to Congalton and Green (2019)[2] The equation and range of kappa coefficient values can be expressed as follows:

$$K = \frac{\sum_{i=1}^{k} \; n_{ii} - \sum_{i=1}^{k} \; n_{i+} n_{i+i}}{n^2 - \sum_{i=1}^{k} \; n_{i+} n_{i+i}}$$

Where
K = kappa coefficient
k = number of rows in the matrix
n = number of observations
nii = number of observations in the i column and i row
njj = number of observations in the j column and j row
ni+ = total marginal row i
n+i = total marginal column i
n+j = total column

3 Result and Discussion

3.1 Ortophoto

Drone flights were carried out three times in the North, South and East regions, and 1052 aerial photographs were obtained. Aerial photographs of the three regions were then processed using orthophotos to produce images of Pari Island. An aerial photograph map is shown in Figure 3.

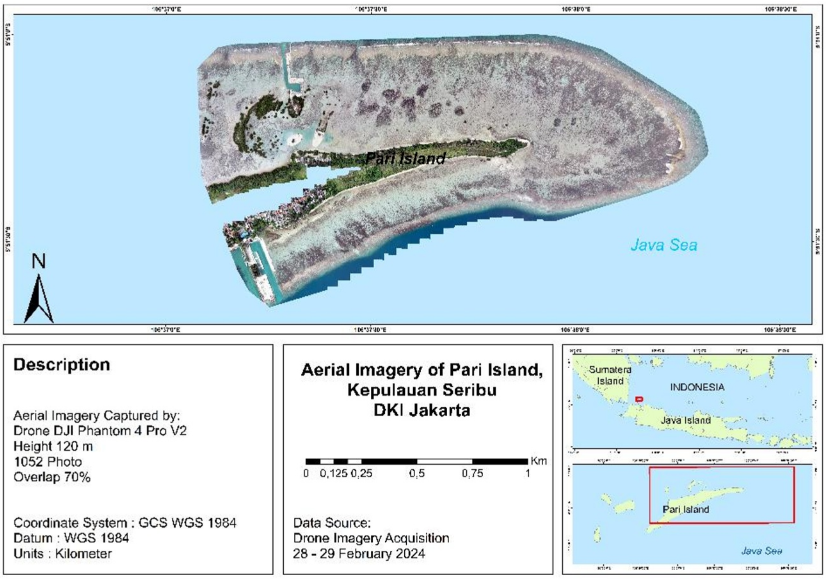

Fig. 3. Aerial imagery using drone at Pari Island.

The aerial photography acquisition process acquired an area of 161 ha with a flight time of ±30 min per flight plan and a spatial resolution of 3.6 cm/px. In the aerial photo image of Pari Island, there was a difference in brightness caused by the angle of incidence of the sun and the ability of the camera sensor to focus on an object. In addition, other weather conditions such as clouds and wind also affect the results of aerial photography and the duration of aerial photo acquisition. The orthophoto results were used to segment the benthic habitat.

3.2 Image Preprocessing

3.2.1 Atmospheric Correction

Atmospheric corrections were made to the satellite images using the DOS. The DOS searches each band for the darkest pixel value. Scattering was eliminated by subtracting the value of each pixel in the band [14]. Satellite images before and after correction show visual differences, where the results of images from the application of atmospheric correction are sharper and brighter compared to images before correction. The differences in satellite imagery before and after correction are shown in Figures 4 and 5.

Fig. 4. Sentinel-2B image before atmospheric correction.

Fig. 5. Sentinel-2B image after atmospheric correction.

3.2.2 Water Column Correction

Water column correction is applied to improve the image quality so that objects at the bottom of shallow water can be better distinguished. The Sentinel-2B imagery acquired on February 29, 2024, was taken by satellite at 2:55 p.m. and the receding time of Pari Island waters was at around 4:00 p.m., making it necessary to correct the water column for the Sentinel-2B imagery. Image transformation is carried out using a combination of blue and green canals, which are excellent bands for penetrating visible light energy into the water column and are highly dependent on water conditions (attenuation coefficient) [17]. Lyzenga (1981)[10] stated that obtaining an appropriate linear correction requires training areas on the same bottomwater substrate at different depths. In this study, training areas were in sand habitats with different depths to extract their pixel values and search for variant values of each band and covariance values between bands. The seabed information can be determined from the attenuation coefficient between channels i and j (ki/kj).

Band	Attenuation Ratio (ki/kj)
Blue – Green	0.361738

3.3 Segmentation and Classification

Level 1 segmentation of individual drones and satellite imagery resulted in land, shallow water, and deep-sea classes. The segmentation process is performed using a multi resolution segmentation algorithm with shape parameters valued at 0.1, compactness valued at 0.5 (default), and scale using a value of 250 for drone imagery and a scale of 50 for satellite imagery. Level 2 segmentation is carried out by resegmentation of the shallow water class. Each drone image and imagery produced six classes of benthic habitats, namely corals, seagrass, sand, macroalgae, DCA, and rubble. For drone imagery, segmentation was performed with a shape parameter value of 0.1, compactness of 0.5 (default), and scale of 50 and 10, respectively, because benthic habitats have a smaller area, and the scale value of level 2 segmentation must be smaller than level 1 to be more focused and avoid under-segmentation.

The results of level 1 segmentation (reef level) are then classified into three classes: land, shallow sea, and deep sea, and the shallow sea area is used for level 2 segmentation. The benthic habitat classification scheme in the Pari Island area is classified into six classes: seagrass, rubble, sand, macroalgae, dead coral with algae, and coral. In determining the benthic habitat classification scheme with six classes used, there are no standard provisions in Indonesia, so the determination of these six classes uses ad hoc classification, namely, the determination of classes with what is appropriate found in field conditions. Benthic habitat classification was performed based on the results of shallow sea segmentation, where the segment was trained using 104 field observation points. Classification of benthic habitat distribution in aerial photographic imagery using the support vector machine (SVM) algorithm. The results of benthic habitat classification are shown in Figures 6 and 7, and the overall area of each benthic habitat class is shown in Table 5.

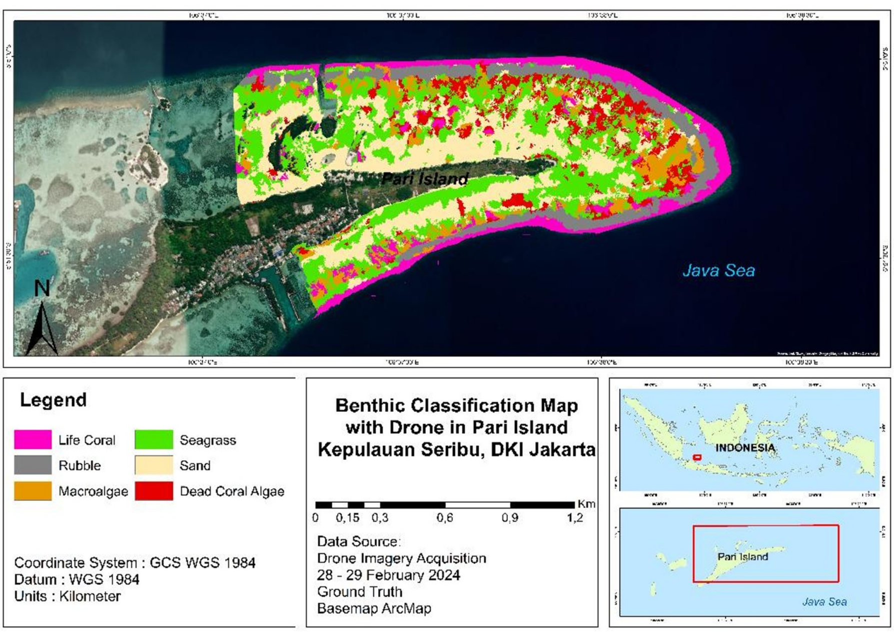

Fig. 6. Benthic map with drone at Pari Island.

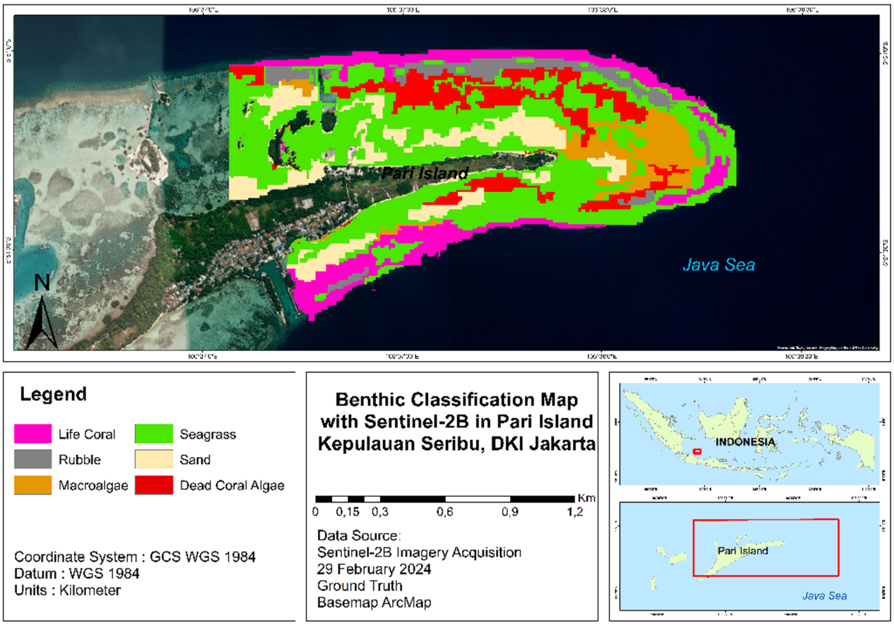

Fig. 7. Benthic map with Sentinel-2B at Pari Island.

The benthic habitats found on Pari Island are quite diverse and evenly distributed in shallow water areas. There were differences in the area of the benthic habitat in each image due to differences in the spatial resolution of each image used. Significant differences were observed in the results of the object-based classification using Sentinel-2B imagery. This is due to the lower resolution of Sentinel-2B imagery compared to drone imagery to perform object-based classification in classifying a relatively small spatial area, namely, Pari Island. The low spatial resolution of Sentinel-2B images affects the segmentation process, which causes satellite images to experience errors in the form of under-segmentation. In the results of drone images, the distribution pattern formed is very complex, and is influenced by the data source used (drone imagery) having a high spatial resolution of 3.6 cm/pixel so that it is able to classify objects on Pari Island quite well.

3.4 Accuracy Test

An accuracy test was conducted to determine the accuracy of the data from the classification process determined through 138 observation points from a total of 242 observation points. Accuracy tests were performed using the confusion matrix method, including overall accuracy (OA), producer accuracy (PA), and user accuracy (UA).

Drone Imagery Result									
		DCA	LC	SG	M	S	R	Total	UA (%)
Field Points	DCA	15		4				19	78.95
	LC		17	2			1	20	85.00
	SG	2	1	33		3		39	84.62
	M	1			10	2		13	76.92
	S	2		3		24		29	82.76
	R		3		1		14	18	77.78
	Total	20	21	42	11	29	15	138	
	PA (%)	75.00	80.95	78.57	90.91	82.76	93.33		
	OA (%)	81.88							
	Kappa	0.80							

Satellite Imagery Result									
		DCA	LC	SG	M	S	R	Total	UA (%)
Field Points	DCA	12		2	3	1	1	19	63.16
	LC		11	1	1		2	20	73.33
	SG	2	5	44	6	2	5	64	68.75
	M	1	1	2	10	1		15	66.67
	S			4	1	15		20	75.00
	R	1					4	5	80.00
	Total	16	17	53	21	19	12	138	
	PA (%)	75.00	64.71	83.02	47.62	78.95	33.33		
	OA (%)	69.57							
	Kappa	0.68							

Based on Table 7 and 8 it can be seen that the OA value for drone imagery is 81.88% and for satellite imagery is 69.57%. Compared to previous studies by Ari Anggoro (2017), which achieved 75% overall accuracy by using Worldview 2, benthic habitat mapping using drones showed higher spatial resolution and overall accuracy. The kappa coefficient for drone imagery, with a value of 0.80 is included in the very good category, and the kappa coefficient for satellite imagery with a value of 0.68 is included in the good category. There is a difference in OA values from the results of the drone and Sentinel-2B image classification owing to differences in the spatial resolution of the images. The spatial resolution of drone imagery in one pixel is 3.6 cm/pixel while in Sentinel-2B imagery, it is 10 m. According to Firansyah *et al*. (2019), the higher the spatial resolution of the image data, the better the accuracy strength. Referring to SNI 7716:2011, the value of the acceptable overall accuracy test results for mapping shallow seawater habitats was ≥ 60% [9] . Compared to previous studies by Ari Anggoro (2017), which achieved 75% overall accuracy by using Worldview 2, benthic habitat mapping using drones showed higher spatial resolution and overall accuracy.

4 Conclusion

Object-based benthic habitat mapping on Pari Island using drone imagery and Sentinel-2B satellite imagery resulted in a scheme of six classes: seagrass, macroalgae, rubble, sand, coral, and dead coral with algae. Drone and satellite imagery produced OA values of 81.88% and 69.57%, respectively, with kappa coefficient values of 0.80 (very good) and 0.68 (good) respectively. The results of the kappa accuracy and coefficient test indicate that the results of drone image classification are better than those of satellite images, and the spatial resolution of the image affects the accuracy value. Further research is expected on the collection of coordinate point data using geodetic GPS so that it can produce classification and test values with better accuracy.

References

[1] Aldin F, Prasetyo Y, Helmi M. 2020. Studi pemetaan habitat dasar perairan laut dangkal berdasarkan analisis digital menggunakan citra Pleiades multispektral di Perairan Pulau Menjangan Besar, Kepulauan Karimunjawa, Jawa Tengah. *Jurnal Geodesi Undip*. 9(1): 77-86.

[2] Congalton RG, Green K. 2019. *Assessing the Accuracy of Remotely Sensed Data*. New York (NY): CRC Press.

[3] Firansyah S, Gaol J, Susilo SB. 2019. Perbandingan klasifikasi SVM dan *decision tree* untuk pemetaan mangrove berbasis objek menggunakan citra satelit Sentinel-2B di Gili Sulat, Lombok Timur. *Journal of Natural Resources and Environmental Management*. 9 (3): 746 – 757.

[4] Giyanto, Winardi, Kusmanto E, Salmin, Soeroyo, Manuputty A. 2014. Panduan Monitoring Kesehatan Karang. Jakarta (ID): CRITC COREMAP LIPI.

[5] Hafizt M, Iswaril MY, Prayudha B. 2017. Kajian Metode Klasifikasi citra landsat-8 untuk pemetaan habitat bentik di Kepulauan Padaido, Papua. *Oseanologi dan Limnologi di Indonesia*. 2(1): 1-13.

[6] Ilyas TP, Nababan B, Maduppa H, Kushardono D. 2020. Pemetaan ekosistem lamun dengan dan tanpa koreksi kolom air di Perairan Pulau Pajenekang, Sulawesi Selatan. *Jurnal Ilmu dan Teknologi Kelautan Tropis*. 12(1): 9-23.

[7] Koman WAF, Izza AS, Candraningtyas D. 2022. Perbandingan parameter segmentasi OBIA dalam klasifikasi tutupan lahan. *Jurnal Paradigma: Jurnal Multidisipliner Mahasiswa Pascasarjana Indonesia*. 3(2): 104-113.

[8] Kristianingsih L, Wijaya A, Sukmono A. 2016. Analisis pengaruh koreksi atmosfer terhadap estimasi kandungan klorofil-a menggunakan citra Landsat 8. *Jurnal Geodesi Undip*. 5(4): 56–64.

[9] LIPI. 2014. Panduan Teknis Pemetaan Habitat Dasar Perairan Laut Dangkal. Jakarta (ID): CRITC COREMAP LIPI.

[10] Lyzenga DR. 1981. Passive remote sensing techniques for mapping water depth and bottom features. A*pplied Optics*. 17: 379-383.

[11] Mastu LOK, Nababan B, Panjaitan JP. 2018. Pemetaan habitat bentik berbasis objek menggunakan citra sentinel-2 di Perairan Pulau Wangi-Wangi Kabupaten Wakatobi. *Jurnal Ilmu dan Teknologi Kelautan Tropis*. 10(20): 381-396.

[12] Prabowo NW, Siregar VP, Agus SB. 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.

[13] Putra RD, Napitupulu HS, Nugraha AH, Suhana MP, Ritonga AR, Sari TEY. 2022. Pemetaan luasan hutan mangrove dengan menggunakan citra satelit di Pulau Mapur, Provinsi Kepulauan Riau. *Jurnal Kelautan Tropis*. 25(1): 20-30.

[14] Rahman A, Siregar VP, Panjaitan JP. 2020. Estimasi kedalaman perairan dangkal menggunakan citra satelit multispektral Sentinel-2A. *Jurnal Segara*. 16(3): 151-162.

[15] Rohpandi D, Sugiharti A, Winara GA. 2015. Aplikasi pengolahan citra dalam pengenalan pola huruf ngalagena menggunakan MATLAB. Konferensi Nasional Sistem dan Informatika 2015.

[16] Roihan A, Sunarya PA, Rafika AS. 2020. Pemanfaatan *machine learning* dalam berbagai bidang: review paper. *Indonesian Journal on Computer and Information Technology*. 5(1): 75-82.

[17] Sabilah AA. 2021. Performa algoritma *maximum likelihood*, *support vector machine,* dan logika *fuzzy* dalam memetakan sebaran lamun menggunakan citra multi-sensor. [tesis]. Bogor (ID): Institut Pertanian Bogor

[18] Salim H, Ahmad L. 2013. Karakteristik pantai Gugusan Pulau Pari. *Jurnal Region* 5(1): 1-11.

[19] Saputra R, Gaol JL, Agus SB. 2021. Studi perubahan tutupan lahan mangrove berbasis objek (OBIA) menggunakan citra satelit di Pulau Dompak Provinsi Kepulauan Riau. *J. Ilmu dan Teknologi Kelautan Tropis*. 13(1): 39-55.

[20] Sari CA, Syah AF, Prayudha B, Salatahol A. 2020. Pemetaan habitat bentik menggunakan citra satelit sentinel-2A di Pulau Liki, Papua. *Jurnal Penginderaan Jauh*. 17(1): 33-42.

[21] Siregar VP, Agus SB, Sunuddin A, Subarno T, Aziizah NN. 2020. Analisis perubahan habitat dasar perairan dangkal menggunakan citra satelit resolusi tinggi di Karang Lebar, Kepulauan Seribu. *Jurnal Ilmu dan Teknologi Kelautan Tropis*. 12(1): 37- 51.

[22] Sugara A, Siregar VP, Agus SB. 2020. Klasifikasi habitat bentik perairan dangkal dari citra worldview-2 menggunakan data in-situ dan *drone*. *Jurnal Ilmu dan Teknologi Kelautan Tropis*. 12(1): 135-150.

[23] Thenu IM, Makailipessy MM. 2017. Pemetaan perubahan ekosistem wilayah pesisir Kecamatan Dullah Utara Kota Tual. *Jurnal Teknologi Perikanan dan Kelautan*. 8(1): 39-48.