Mapping of shallow-water benthic habitats in Nusa Lembongan, Bali using Sentinel-2B and Landsat 8 satellite data

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Abstract. The mapping of shallow-water benthic habitats using remote sensing techniques is critical for understanding responses to spatial and temporal environmental changes. However, the ongoing challenges in remote sensing are distribution assessments on the small island with high complexity ecosystem composition. The recently released and freely accessible Sentinel-2B (S2B) imagery presents a new opportunity for these challenges. Therefore, this study aimed to examine the ability of the S2B sensor in mapping shallow-water using two methods. These include a true color composite and images with water column correction using the Lyzenga algorithmwith or without water column correction. The results from S2B were compared with the maps from Landsat 8 data, and the error matrix was applied to test classification accuracy. The results show that the output maps had average overall accuracies of 65% for benthic coverage maps. In conclusion, S2B and Landsat 8 were good enough for mapping shallow-water benthic habitats, but water column correction on both sensors increased the accuracy.
Key Words: Benthic habitats, Remote Sensing, Nusa Lembongan, water column correction.

Introduction. Shallow-water habitat, consisting of seagrass, coral reefs, and mangrove, is the leading provider of species in the marine ecosystem. These species are crucial for the long-term viability and security of coastal resources. They are essential for providing food and other necessary services to coastal residents (Osinga et al 2011). Hoewever, shallow-water habitats such as seagrass and coral reefs have declined rapidly due to environmental and anthropogenic causes. These include climate change (Munday et al 2008; Ateweberhan et al 2013), sedimentation (Wooldridge 2009), marine tourism (Karang et al 2019), and destructive fishing (Hughes et al 2007; Caras & Pasternak 2009).

Bali Province is one area with diverse shallow-water ecosystems widely used as a tourism destination. The southern region is one area that is experiencing rapid development of tourism activities, one of which is the Nusa Lembongan. According to statistics issued by the statistical center, foreign visitor arrivals to Bali were 6,070,473 in 2018, an increase of 6.54% from 2017 (BPS 2018). The expansion of Nusa Lembongan occurs in areas of water in direct contact with underwater ecosystems, impacting changes in the extent of these ecosystems. Putra & Husrin (2017) stated that some of the southern coastal have degraded, indicating that the water quality on Kuta Beach has reached a predetermined threshold. Faiqoh et al (2017) reported a decrease in fish abundance in Samuh Beach due to the reduction in seagrass beds. Meanwhile, Rahadiarta et al (2019) reported that the area of seagrass in Mengiat Beach has decreased due to the installation of tourism amenities that affect carbon sequestration. The research above shows a decline in shallow water benthic habitats caused by anthropogenic activities without an appropriate policy strategy.

There is a growing need to map and track the distribution of these habitats around the globe to reverse the depletion trends. Information on the distribution can be the first step in making decisions and policies in ecology-based tourism management. The detection requires a fast and precise method due to the importance of accurate information from the region on spatial and temporal scales. Technological advances such as remote sensing have proven to be the ideal alternative for detecting shallow-water habitats. Remote sensing has long been identified as a technology capable of supporting the development of coastal zone monitoring and habitat mapping over large areas (Ouellette et al 2016). These processes require multi-temporal data from satellites or unmanned aerial systems (UAS) (Doukari et al 2019; Papakonstantinou et al 2020). This technology has been widely used for mapping and tracking shallow-water environments for the last two decades because of its advantages of large swath area, continuous resource data, and low-cost consumption (Hartono 1994; Mumby et al 1997; Fauzan et al 2017).

Medium-resolution multi-spectral imaging is the most commonly used data for mapping shallow-water habitats, and Aljenaed et al (2017) used Landsat 8 imagery in the Kingdom of Bahrain. Elenin et al (2020) also used this imagery integrated with a field survey method for marine habitat mapping in the Red Sea region. However, this multi-spectral medium resolution data may not be adequate for thorough analysis with a high complexity composition due to its limited spatial resolution and extent of the coral reef area (< 30 m) down the coast.

The majority of research used high-resolution multi-spectral imagery to differentiate between shallow water habitat class types. Indayani (2016) and Mustika (2013) used SPOT-5 imagery and Worldview-2 to map shallow-water habitats in the Riau and Panggang Islands respectively. The recent remote sensing technology Unmanned Surface Vehicle (USV) with high spatial resolution can be used for marine ecosystem monitoring with high accuracy results. For example, Mogstad et al (2019) successfully mapped shallow-water habitats in Norwegian water using USV – Underwater Hyperspectral Imaging (UHI) with an overall accuracy of 89-91%. Even though high-resolution imagery has attracted substantial interest, its constraints on high procurement costs and limited sizes impede continuous or broad regional coverage. As a result, the mapping of large-scale can lie in the potential of evolving sensors.

Sentinel-2A (S2A) and Sentinel-2B (S2B) are the two types of Sentinel-2 satellites launched on 23 June 2015 and 7 March 2017. Sentinel-2 sensor carries 13 multi-spectral bands of high spatial resolution for four traditional bands (red/green/blue/near-infrared) and high temporal resolution (11 days revisit time). It also has red-edged bands designed for vegetation detection (Drusch et al 2012) and the multi-spectral imager can cover a wide range of 290 km. Therefore, it can be freely obtained and likely used in various applications (ESA 2015). Due to the limitations of high-resolution satellites data (WorldView-2, IKONOS, SPOT, such as high cost, low temporal resolution, and small swath size) and Landsat 8 imagery (medium spatial and temporal resolution), the potential of Sentinel-2 can be used for shallow-water habitat study (Hedley et al 2012; Fauzan et al 2017; Immordino et al 2019). However, mapping in Nusa Lembongan has not been performed using data from Sentinel-2. This study, therefore, aims to explore the ability of Sentinel-2 sensors to map shallow-water habitats in small islands with high complexity ecosystem composition like Nusa Lembongan, Bali.

Material and Method

Research location. This study was conducted on February 2019 in the coastal area of Nusa Lembongan, Bali (as illustrated in Figure 1) where shallow-water habitats are optically distributed with depth less than 5 m. The coastal area is characterized by sand, rubber, coral reefs and seagrass. It is part of the Nusa Penida Islands as one of the protected areas defined by Decree No 24 of 2014 of the Minister of Marine Affairs and Fisheries concerning the Nusa Penida Marine Conservation Area (MPA), Klungkung Regency, Bali Province. The purpose MPA protects coastal and marine biodiversity, to create sustainable marine tourism, and fisheries (Darma et al 2010).

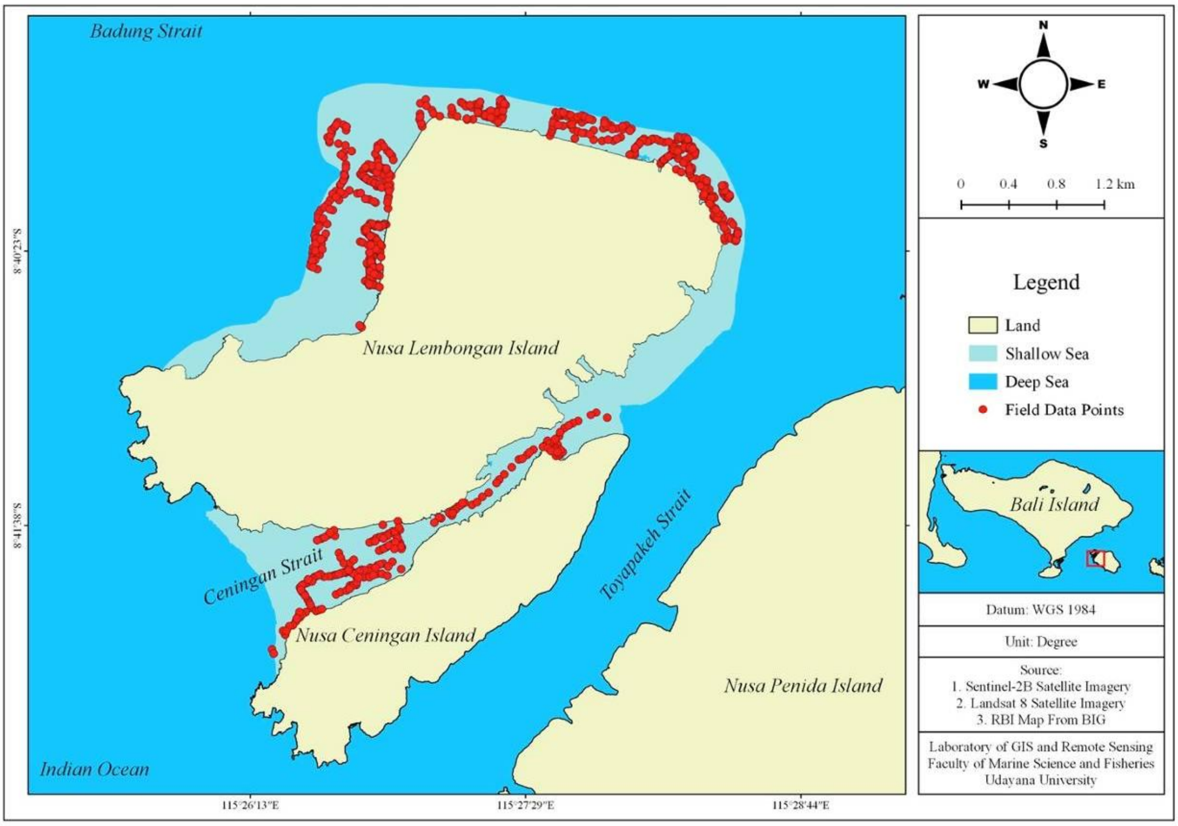


Figure 1. The location of the study area at Nusa Lembongan, Bali, Indonesia.

Field survey. The field survey was conducted in Nusa Lembongan coastal area from 13 to 24 February 2019. Countless filed samples were collected from point-based field data of underwater objects were collected with 700 field samples (as shown in Figure 1). From all these samples, 525 were input on an algorithm of maximum likelihood classification, while the remaining 175 were used for accurate test results.

Data processing. Satellite data for this analysis was the Sentinel-2B Level-1C (TOA; Top of Atmospheric reflectance) image, which covers Nusa Lembongan from Scientific Data Hub on 17 February 2019 (http:/scihub.copernicus.eu). As a comparison data, Landsat 8 Level-1T was acquired on 20 January 2019 from https:/earthexplorer.usgs.gov. Visible bands (4:red, 3:green, 2:blue) with 10 m and 30 m resolutions for S2B and Landsat 8 were selected. These bands can penetrate the water body, by allowing an image sensor to detect underwater objects (Green et al 2000). Atmospheric correction was applied to the S2B and Landsat 8 images using the Dark Object Subtraction (DOS) process (Chavez et al 1977). Water column correction was implemented based on the Lyzenga 81 algorithm (Lyzenga 1981), generating depth invariant index (DII) as b2b3, b2b4, and b3b4. It converts the reflectance information of seabed objects into a normalized DII to the depth variation (Fauzan et al 2017).

Shallow-water habitat mapping. The maximum likelihood algorithm for image classification was used for true-color composite and DII to produce shallow-water habitat maps. The six habitat classes used are seagrass, dead coral, sand, live coral, macroalgae, and rubble, as seen in Table 1. The S2B and Landsat 8 classification results were tested using an error matrix (confusion matrix). This is conducted by comparing the classified image as a map to the actual class obtained from field observations. The accuracy test refers to Congalton & Green (2008).

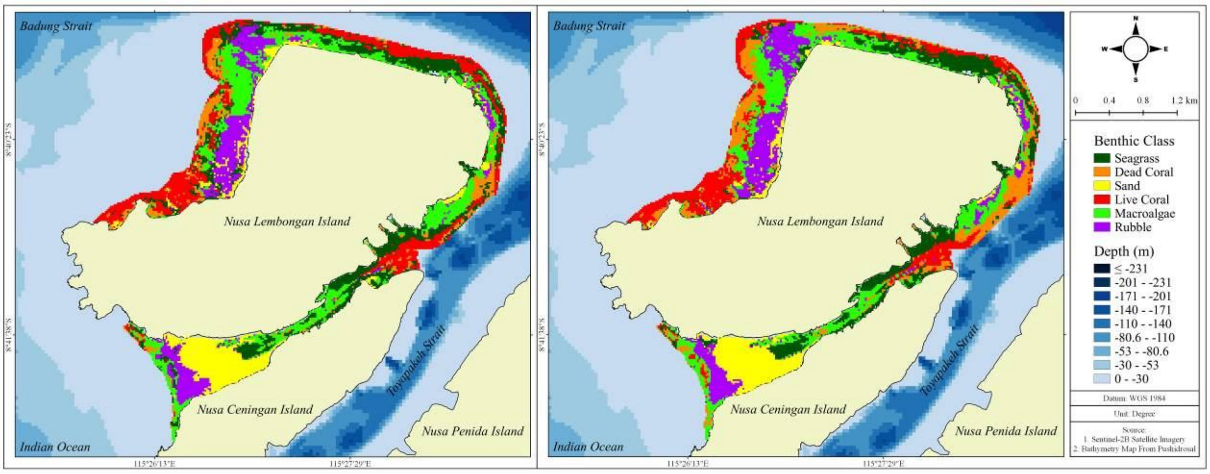
Table 1

Benthic classification scheme in Nusa Lembongan based on morphological structure

Benthic habitat class	*Description*	*Picture*
Sand	Granular material dominates (> 80%), while the remaining 20% consist of algae, seagrass and coral fragments.	
Seagrass	Dominated by seagrass meadows.	
Macroalgae	Habitat that grows on dead coral chunks and coral fragments.	
Rubble	Coral fragments with irregular shapes, where more than 60% is coral fragments, and the remaining 40% are sand substrate and macroalgae.	
Live coral	Habitats are composed of homogeneous coral material with a vast expanse and can be distinguished from other. There are found at the end of the reef area facing the sea, from the flat reef area and dominant in the crest area to the slope.	
Dead coral	Dead coral reefs dominate mainly in flat reef areas and slightly on the crest.	

Results and Discussion. Figure 2 shows the result of S2B using a supervised classification based on the composite RGB 432 and transformation (DII). This classification process was used by seagrass, macroalgae, live corals, dead corals, sand, and rubble.

An overall accuracy (OA) of 68% and Kappa index (K) = 0.62 from the DII image and 65% (K = 0.57) from the RGB composite were obtained (Tables 2 and 3). The lowest user accuracy (UA) also highest commission error (CE) class is macroalgae, with a UA of 47% for the RGB composite map and 51% for DII transformation. The CE is calculated by reviewing the classified sites for incorrect classifications. The CE values for the macroalgae are 52.63% and 48.57% for the RGB composite map and DII transformation, respectively. This means that nearly half of the classified images labeled as macroalgae were not found in the area. The lowest producer accuracy (PA) and also highest omission error (OE) is rubble, with an accuracy of 34.48% for the RGB composite map and 41.38% for DII transformation. The OE represents the fraction of values that belong to a class but were predicted to be in a different class. More than 50% of the rubble class containing macroalgae was misclassified.



a b

Figure 2. The result of maximum likelihood classification of S2B image: a. from RGB composite, b. from DII image.

Table 2

Confusion matrix for classification of S2B without DII

Classification	*Field data*						*Total*	*UA (%)*	*CE (%)*
	Live coral	*Macro algae*	*Seagrass*	*Sand*	*Dead coral*	*Rubble*			
Live coral	25	2	3	0	1	0	31	80.65	19.35
Macroalgae	1	18	3	0	4	12	38	47.37	52.63
Seagrass	3	4	18	0	6	1	32	56.25	43.75
Sand	0	1	0	24	0	6	31	77.42	22.58
Dead coral	0	3	0	1	18	0	22	81.82	18.18
Rubble	0	1	6	4	0	10	21	47.62	52.38
Total	29	29	30	29	29	29	175		
PA (%)	86.21	62.07	60.00	82.76	62.07	34.48		OA = 64.57%	
OE (%)	13.79	37.93	40.00	17.24	37.93	65.52		*K* = 0.57	

Table 3

Confusion matrix for classification of S2B with DII

Classification	*Field data*						*Total*	*UA (%)*	*CE (%)*
	Live coral	*Macro algae*	*Seagrass*	*Sand*	*Dead coral*	*Rubble*			
Live coral	22	1	2	0	1	0	26	84.62	15.38
Macroalgae	1	18	1	1	4	10	35	51.43	48.57
Seagrass	4	2	21	0	1	1	29	72.41	27.59
Sand	0	0	1	23	0	6	30	76.67	23.33
Dead coral	2	5	0	2	23	0	32	71.88	28.13
Rubble	0	3	5	3	0	12	23	52.17	47.83
Total	29	29	30	29	29	29	175		
PA (%)	75.86	62.07	70.00	79.31	79.31	41.38		OA = 68.00%	
OE (%)	24.14	37.93	30.00	20.69	20.69	58.62		*K* = 0.62	

The difference between the RGB composite and the DII transformation is the detail level of the information displayed. The image resulting from the DII transformation produces more detailed information on the distribution of shallow-water habitat, especially in the reef crest area to the slope. This aligns with Siregar (2010), which stated that the water column correction produced a more detailed map in a particular depth. Purwanto et al (2020) also confirmed that the correction is essential to eliminate the effect of the water column by paying attention to the blue and gbands' values used.

Figure 3 shows the result of Landsat 8 using supervised classification. The comparison maps produced results with overall accuracies lower than S2B. For example, an OA of 66% (K = 0.6) for DII transformation and 62% (K = 0.55) for RGB composite were obtained (Tables 4 and 5). On other hand, Landsat 8 has higher user and producer accuracies on macroalgae and rubble. This indicates that these classes are more likely to be correctly classified on Landsat 8.

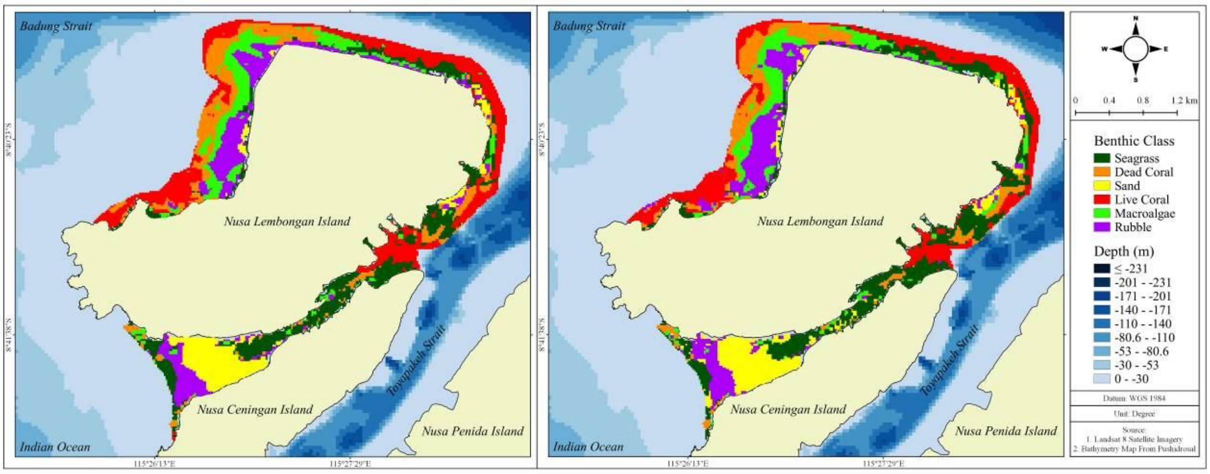


Figure 3. The result of maximum likehood classification of Landsat 8 image: a. from RGB composite, b. from DII image.

Table 4

Confusion matrix for classification of Landsat 8 without DII

Classification	*Field data*						*Total*	*UA (%)*	*CE (%)*
	Live coral	*Macro algae*	*Seagrass*	*Sand*	*Dead coral*	*Rubble*			
Live coral	26	2	10	0	1	0	39	66.67	33.33
Macroalgae	1	13	1	0	1	8	24	54.17	45.83
Seagrass	0	2	12	5	1	2	22	54.55	45.45
Sand	0	0	2	20	0	6	28	71.43	28.57
Dead coral	2	8	1	0	26	1	38	68.42	31.58
Rubble	0	4	4	4	0	12	24	50.00	50.00
Total	29	29	30	29	29	29	175		
PA (%)	89.66	44.83	40.00	68.97	89.66	41.38		OA = 62.29%	
OE (%)	10.34	55.17	60.00	31.03	10.34	58.62		*K* = 0.55	

Table 5

Confusion matrix for classification of Landsat 8 with DII

Classification	*Field data*						*Total*	*UA (%)*	*CE (%)*
	Live coral	*Macro algae*	*Seagrass*	*Sand*	*Dead coral*	*Rubble*			
Live coral	25	1	7	0	1	0	34	73.53	26.47
Macroalgae	1	15	1	0	1	7	25	60.00	40.00
Seagrass	0	0	15	6	1	2	24	62.50	37.50
Sand	0	2	1	20	0	4	27	74.07	25.93
Dead coral	3	7	1	0	26	1	38	68.42	31.58
Rubble	0	4	5	3	0	15	27	55.56	44.44
Total	29	29	30	29	29	29	175		
PA (%)	86.21	51.72	50.00	68.97	89.66	51.72		OA = 66.29%	
OE (%)	13.79	48.28	50.00	31.03	10.34	48.28		*K* = 0.60	

Compared to previous shallow-water habitat mapping using satellite imagery, the accuracy of the S2B and Landsat 8 for Nusa Lembongan is in the good category with OA > 60%, and the kappa index (K) is between 0.4 and 0.8 which falls in the medium category (Congalton & Green 2008; LIPI 2014). This result is close to Nababan et al (2021), where drones were used to map the benthic shallow-water habitats in the waters of Wangiwangi Island, Wakatobi Regency, with overall accuracy of 77.4% and 81.1% for 9 and 12 classes, respectively. Rende et al (2020) concluded that satellite mapping increases cost and time efficiency more than traditional methods. Desa (2017) mapped 11 benthic classes in the shallow-waters of Harapan and Kelapa Islands, Kepulauan Seribu using SPOT 7 imagery and obtained an OA of 66.66% for the RGB composite and 24.07% for the DII transformation. Putra & Khakhim (2014) used QuickBird imagery on Kemujan and Karimunjawa Islands, obtaining an OA with a 6 class classification scheme of 67.70% for DII transformed and 58.38% for images without water column correction.

According to previous studies, it is possible to obtain higher accuracy using Sentinel imagery with higher resolution. For example, Prawoto & Hartono (2018) mapped the benthic habitats with Sentinel-2A multi-spectral imagery in the waters of Menjangan Kecil and Menjangan Besar, Karimun Jawa Islands with an OA resulting from the DII transformation of 80.73% greater than the image without water column correction at 71.56%. The study used a four-class classification, scheme to contribute to the high accuracy value. Selamat et al (2012) stated that the more classes are displayed, the lower the accuracy of the thematic map. Another factor that can affect the level is the spatial resolution of the image used. For example, Helmi et al (2018), using GeoEye-1 images with 1.86 m spatial resolution, obtained a high OA of 83.7% in benthic diversity mapping at Parang Islands Karimunjawa National Park, Indonesia.

The distribution of each habitat class can be calculated based on the classification of the map. Tables 6 and 7 show each distribution and percentages from the S2B and Landsat 8 maps, and the total area is estimated to be 453.38 ha. The macroalgae class has the highest distribution, with an area of 98.24 ha for the S2B map with DII and 101.50 ha for the S2B composite RGB, but the Landsat 8 sensor produced a different estimation. Live coral has dominated the Nusa Lembongan shallow-water benthic in the Landsat 8 RGB composite map at 114.51 ha. In comparison, seagrass is more dominant than other classes at 103.21 ha in the Landsat 8 DII map as shown in Table 7.

Table 6

Distribution of benthic classes from Sentinel-2B (S2B)

Classification	*RGB composite*		*DII (Lyzenga)*	
	Coverage (ha)	*Percentage (%)*	*Coverage (ha)*	*Percentage (%)*
Live coral	90.03	19.86	77.02	16.99
Macroalgae	101.50	22.39	98.24	21.67
Seagrass	96.05	21.19	77.51	17.10
Sand	61.58	13.58	54.65	12.05
Dead coral	38.43	8.48	67.94	14.99
Rubble	65.79	14.51	78.02	17.21
Total	453.38	100	453.38	100

Table 7

Distribution of benthic classes from Landsat 8

Classification	*RGB composite*		*DII (Lyzenga)*	
	Coverage (ha)	*Percentage (%)*	*Coverage (ha)*	*Percentage (%)*
Live coral	114.51	25.26	99.23	21.89
Macroalgae	56.09	12.37	51.73	11.41
Seagrass	89.58	19.76	103.21	22.77
Sand	50.08	11.05	56.98	12.57
Dead coral	73.43	16.20	66.95	14.77
Rubble	69.67	15.37	75.26	16.60
Total	453.36	100	453.36	100

Conclusions. Nusa Lembongan is part of MPA in Indonesia with its complex ecosystem. Sentinel-2B (S2B) has enough accuracy for mapping shallow-water benthic distribution in the small island Nusa Lembongan, Bali, with up to 68% overall accuracy, higher than Landsat 8 image (66%). The application of the DII method using the Lyzenga transformation increased the accuracy. The difference in the pixel size of satellite images also affects the accuracy results where the S2B satellite data has higher accuracy than Landsat 8. In conclusion, S2B and Landsat 8 images can be used for shallow-water benthic mapping.

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Conflict of interest. The authors declare that there is no conflict of interest.

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