

Benthic Habitat Mapping by Combining Lyzenga's Optical Model and Relative Water Depth Model in Lintea Island, Southeast Sulawesi

M Hafizt^{1*}, M D M Manessa², N S Adi³, B Prayudha¹

¹Research Center for Oceanography LIPI, Indonesia

²Geodesy Department, Pakuan University, Indonesia

³Research Centre for Coastal and Maritime Resources, The Ministry of Maritime Affairs and Fisheries, Indonesia

muhammadhafizt@gmail.com

Abstract. Benthic habitat mapping using satellite data is one challenging task for practitioners and academician as benthic objects are covered by light-attenuating water column obscuring object discrimination. One common method to reduce this water-column effect is by using depth-invariant index (DII) image. However, the application of the correction in shallow coastal areas is challenging as a dark object such as seagrass could have a very low pixel value, preventing its reliable identification and classification. This limitation can be solved by specifically applying a classification process to areas with different water depth levels. The water depth level can be extracted from satellite imagery using Relative Water Depth Index (RWDI). This study proposed a new approach to improve the mapping accuracy, particularly for benthic dark objects by combining the DII of Lyzenga's water column correction method and the RWDI of Stump's method. This research was conducted in Lintea Island which has a high variation of benthic cover using Sentinel-2A imagery. To assess the effectiveness of the proposed new approach for benthic habitat mapping two different classification procedures are implemented. The first procedure is the commonly applied method in benthic habitat mapping where DII image is used as input data to all coastal area for image classification process regardless of depth variation. The second procedure is the proposed new approach where its initial step begins with the separation of the study area into shallow and deep waters using the RWDI image. Shallow area was then classified using the sunglint-corrected image as input data and the deep area was classified using DII image as input data. The final classification maps of those two areas were merged as a single benthic habitat map. A confusion matrix was then applied to evaluate the mapping accuracy of the final map. The result shows that the new proposed mapping approach can be used to map all benthic objects in all depth ranges and shows a better accuracy compared to that of classification map produced using only with DII.

Keywords: Lyzenga, benthic habitat, mapping, Sentinel-2A, water depth

1. Introduction

Lyzenga, through his published work in 1978, was one of the pioneers introducing benthic habitat mapping technique using multispectral remote sensing data [1]. Since the targeted object in benthic



habitat mapping is located underwater Lyzenga [1] proposed a model to reduce the effect of light attenuation in the water column called as the depth-invariant index (henceforth named “DII”) which can be used to improve the accuracy of benthic classification. Using the model deeper objects of benthic habitat becomes more discernible and the accuracy of benthic habitat map is improved [2].

In 1985, the Lyzenga’s technique [1] was tested on a commercial multispectral image of Landsat MSS [3]. Since then a number of publications [2–18] have tested the technique on various types of shallow water environment using various imageries with overall satisfactory accuracies. However, several publications found that the Lyzenga’s model still has a few weaknesses. Manessa et al. [9] reveal that the Lyzenga method is sensitive to a complex shallow water environment and is not capable to completely remove the light attenuation effect, especially in the bands with longer wavelengths. Also, the DII method becomes less effective with increasing depth, or in other word, the Lyzenga’s model is not working in deep areas [10]. Moreover, Hafizt & Danoedoro [11] and Hafizt et al. [12] found that when the Lyzenga’s model is applied to shallow or over exposed area, pixel values on the DII image sometimes show negative values due to poor sample selection which causes the pixels become unclassified. It would be a problem if the unclassified class is fully covered by seagrass which is exposed at low tide condition, meaning that the information of seagrass cover could be lost.

This study aims to optimize information in benthic habitat mapping using satellite imagery by proposing a new approach combining Lyzenga’s water column correction and relative water depth index model. Based on the review of the previous studies, the approach presented here attempts to apply different techniques to different water type in term of its depth variation for classifying benthic habitat and then combine the final benthic habitat maps. The approach is to optimize the use of the DII technique for deeper water and the use of sun-glint corrected image for shallower water.

This study uses Sentinel 2A image which has blue band image that is an important requirement in benthic habitat mapping. Moreover, the Sentinel 2A image is classified as a high-resolution image that suitable to map benthic habitat cover in the study area which has a high variation of benthic habitat cover. This study was conducted in Lintea Island, part of Wakatobi Islands, Southeast Sulawesi. In addition to propose a new approach to produce a more accurate benthic habitat map, the result of this study is also expected to increase the insights of academics and practitioners about coral mapping using Sentinel image.

2. Method

2.1. Image data and Study Area

Sentinel 2A level 1C satellite imagery of study area was acquired on August 17, 2016. Level 1C means the satellite imagery has been corrected at Top-of-Atmosphere reflectance in cartography geometry [4]. The study was utilized imagery of 10-meter spatial resolution that consist of three visible bands (B2: blue band, B3: green band, B4: red band) as well as one near infrared band (B8: NIR band) which are needed for image corrections. The study area, Lintea Island, is located in the north part of Wakatobi Islands, Southeast Sulawesi. Figure 1 shows the satellite imagery of study area in natural colour composite.

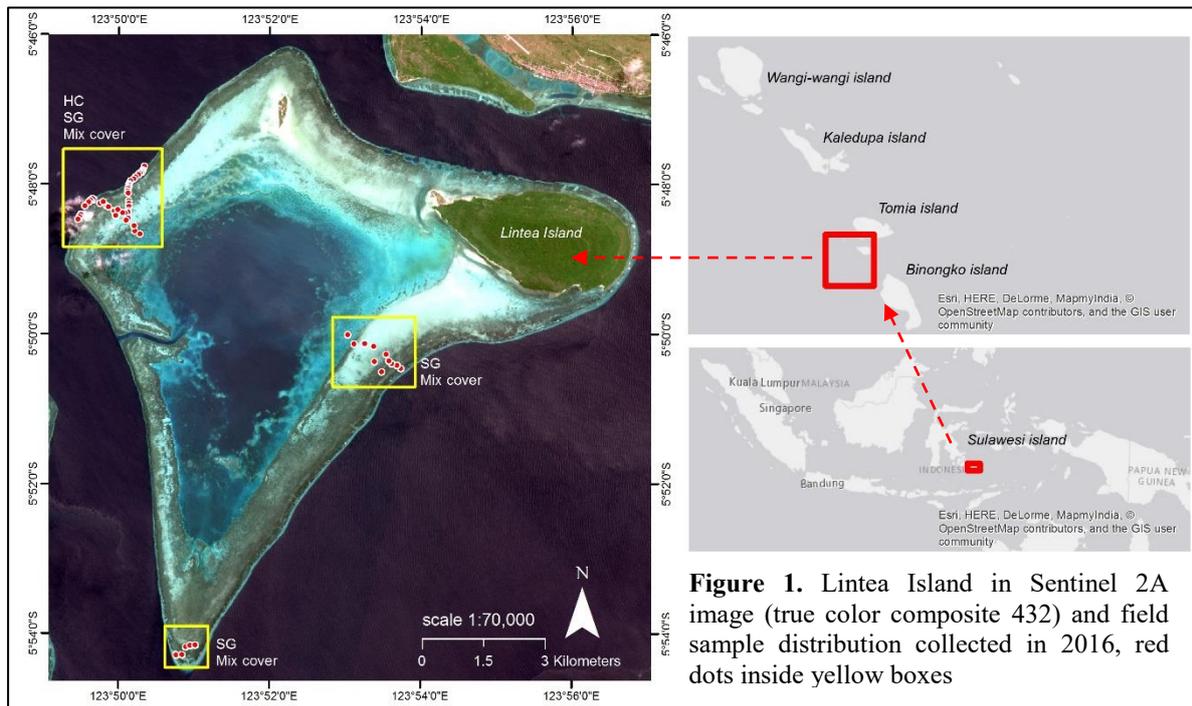


Figure 1. Lintea Island in Sentinel 2A image (true color composite 432) and field sample distribution collected in 2016, red dots inside yellow boxes

2.2. Image processing

Image processing consist of image correction, modeling and classification, the image correction itself consists of sunglint and water column corrections. Sunglint correction is useful for reducing glint effect on water surface due to sunlight reflection. We used an equation developed by Hedley at.al. [13,14] which uses deep water pixels as dark object to create offset value and use it on his equation for sunglint removal. Selecting dark object for creating offset values is similar concept to atmospheric correction using Dark Object Correction [15] method, therefore atmospheric correction is not applied to avoid double offset values creating negative values in shallower area. The sunglint equation applied to Sentinel 2A bands can be seen in Table 1.

Table 1. The equations for correcting sunglint effect, created from 131510 samples Region of Interest (ROI) in visible bands and Near-Infrared band with determination coefficient (R^2) relatively high.

Visible Bands	Determination coefficient (R^2)	Equation of sunglint correction
Blue band (B2)	0.8688	$B2-(1.0241*(B8-115))$
Green band (B3)	0.8773	$B3-(1.0851*(B8-115))$
Red band (B4)	0.8630	$B4-(0.9186*(B8-115))$

The result of sunglint correction then becomes input data for water column correction step. The aim of this correction is to reduce water column attenuation effects causing misclassification in the image classification process and would decrease the accuracy level of benthic habitat map. The water column correction is performed using Depth Invariant Index (DII) model [16], modified by Lyzenga et.al. [17]. The method used pixel values of sand samples on different depth to calculate several parameters required to create DII equation, namely variance of each visible bands, covariance between visible bands, attenuation coefficient (a) and attenuation ratio (ki/kj). The parameters of DII can be seen in Table 2.

Table 2. Parameters of the DII model, created from 739 samples ROI where the variance values of blue, green and red band are 0.027999, 0.072238, and 0.081889 respectively.

Band combination	covariance	attenuation coefficient (a)	attenuation ratio (K _i /k _j)	DII equations
Blue and green	0.044200	-0.500445	0.617788	(alog(B2))-(0.6178*(alog(B3)))
Blue and red	0.044109	-0.610872	0.560949	(alog(B2))-(0.5610*(alog(B4)))
Green and red	0.067810	-0.071161	0.931368	(alog(B3))-(0.9314*(alog(B4)))

Image modelling is performed to generate depth information from the image which is used to develop benthic habitat map. We use Relative Water Depth Index (RWDI) model developed by Stumpf et.al [18]. The model is available in image processing software and applied to Sentinel 2A image. The model output is an image showing depth information in indexed values for each pixel. The depth image is then classified as shallow and deep areas based on index value and is used as input data for classification process.

The corrected images (sunglint and DII images) were used as input data in the classification process using ISO-DATA method. The method is categorized as unsupervised classification approach meaning that spectral classes are generated automatically by computer. Our role is only determining minimum and maximum classes and number of iteration. We applied two models for the classification step for the first model (Model 1) we classified all pixels of the entire reef area using DII image as input data. For the second model (Model 2) we first classified the reef areas into shallow and deep reef areas. The shallow area is then classified using sunglint image and deep area is classified using the DII image. The accuracy level of our proposed model is assessed using confusion matrix table for its overall, producer and user accuracies [19]. The steps of image processing method which are used on each model in this research can be seen in Table 3.

Table 3. The steps of image processing method which are used on each model in this research

Treatment descriptions	Model 1	Model 2 (shallow area)	Model 2 (deep area)	Relative Water Depth Index Model (RWDI)
Using Sentinel 2A, level 1C	*	*	*	*
Atmospheric correction (software automatically)				*
Sunglint correction	*	*	*	
Water column correction	*	*	*	
Density slice image				*
ISO-DATA classification	*	*	*	
Accuracy assessment	*	*	*	

2.3. Sampling method

Sea truth for validating the resulting benthic habitat map is conducted using photo transect method developed by Roelfsema et.al. [20]. The samples are photos of bottom cover and its georeferenced information on each photo. All objects on the photos were then classified into benthic habitat classes according to previous research [21–24]. We used the field sample data to calculate the accuracy level of benthic habitat map and to validate the image classification result. Information on the accuracy level, calculated using confusion matrix table [22,25,26], is needed to measure the improvement of our proposed model presented here (Table 4).

Table 4. Confusion matrix table for calculating overall accuracy of benthic habitat map, user and producer accuracy

Cells	Ground truth sample						
	A	B	C	D	E	F	G
1	Object classes	Class 1	Class 2	Class 3	total	<i>user accuracy (%)</i>	<i>error commission</i>
Classification result	2	Class 1			=B2+C2+D2	=(B2/E2)*100	=100-F2
	3	Class 2			=B3+C3+D3	=(C3/E3)*100	=100-F3
	4	Class 3			=B4+C4+D4	=(D4/E4)*100	=100-F4
	5	Total	=B2+B3+B4	=C2+C3+C4	=D2+D3+D4	=E2+E3+E4	
6	<i>producer accuracy (%)</i>	=(B2/B5)*100	=(C3/C5)*100	=(D4/D5)*100	<i>Overall accuracy (%)</i>	=((B2+C3+D4)/E5)*100	
7	<i>error omission</i>	=100-B6	=100-C6	=100-D6			

3. Result and Discussion

3.1. Samples for sea truth

The samples used in this research are 56 samples in total, consisting of field samples collected in 2016 and additional samples collected through the image by interpretation. We added more samples because the reef area is too shallow and it is difficult to reach the inner area. We added samples which are easier to be recognized from image data i.e. sand (SD) and seagrass (SG Hi and SG Sp). In general, all samples can be classified into four classes in the field, abbreviated as HC, SG, SD, and Mix Cover. Using georeferenced photos obtained from the photo transect all classed can be detailed into subclasses (Table 5). The dominant class is hard coral (15 samples), whereas the other classes are almost equal in number, about 7 samples in average. The samples collected are sufficient to calculate the accuracy level of benthic habitat map.

Table 5. Detailed classes of field samples (sea truth classes)

General classes	Detail Classes	Information	Number of classes
HC	HC	Hard coral/healthy coral	15
	SG HI	seagrass high density	8
SG	SG SP	Seagrass sparse density, only mix with carbonate sand	7
SD	SD	Sand (carbonate sand)	6
	MIX SG BS	Mix cover seagrass and bare substratum (rubble and rock)	7
MIX Cover	MIX HC AL	Mix cover hard coral and algae (green algae or brown algae)	6
	MIX HC BS	Mix cover hard coral and bare substratum (sand, rubble, rock)	7
Total			56

3.2. Image Processing

The Image processing step is begun with image correction consisting of sunglint and water column correction (DII). The results of both corrections are shown in Figure 2, where the applied corrections transform the visualization of the image from its original image to sunglint image and finally to DII image. The sunglint correction reduces the glint effects on surface water, sharpens the contrast features on reef area, and eliminates land area. Moreover, after water column correction is applied deep area is clearly exposed but it fails in the shallow area. The unexpected result is found in shallow water area as where negative pixels values are observed after the water column correction is applied. This is due to higher pixel values for longer wavelength bands causing negative values in the DII image (Table 2). Since, Lyzenga [1] assumed that reflected radiance/reflectance in water area is exponentially linear with depth and the attenuation coefficient, then in shallow depth the attenuation effect is relatively small compared with deep area and also the attenuation coefficient is larger in longer wavelength [9].

This fact became the reason why in shallow area the longer wavelength bands (i.e. green and red band) will have higher value compared with the deep area. To solve this issue, shallow and deep area are separated using the RWDI model which generates depth information in index values and can be used to classify benthic object according to its depth zones.

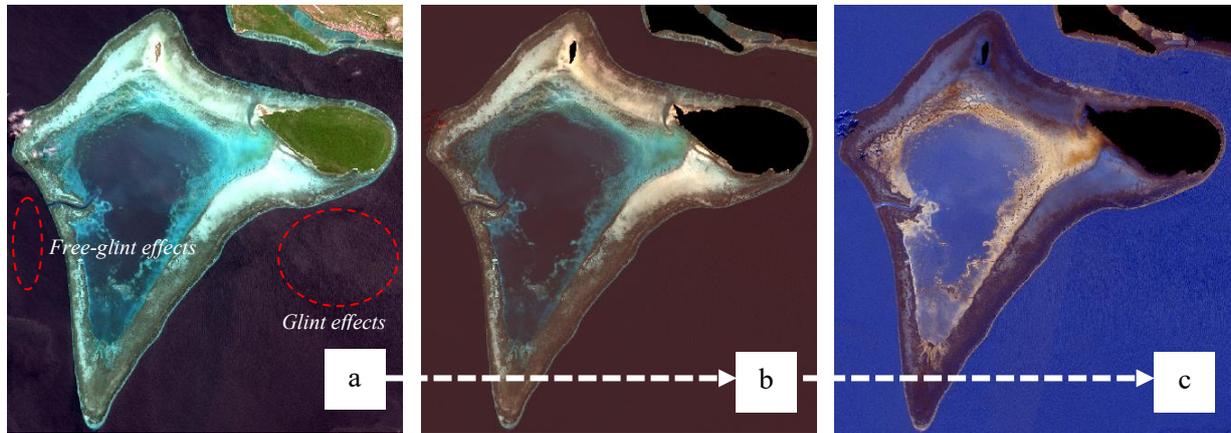


Figure 2. Transformation of image visualization, begin with original image (a) then become sunglint corrected image (b) and continue become DII image (c) as a final result in correction process

The RWDI image result can be seen in Figure 3a where the output image is a single band displayed in grayscale representing the depth of waters in index values. Slicing index values of RWDI image is implemented to obtain shallow and deep area (Figure 3b) where small and high values of the index show shallow and deep areas, respectively. Shallow area is in the range of 0.0725 to 0.15 (cyan color) and deep area is in the range of 0.01 to 0.0725 (blue color). Moreover, seagrass is classified as a personal class because the area can be delineated using index value 0 to 0.01 (green color). The classified areas convert into masker imageries which used in classification process afterwards.

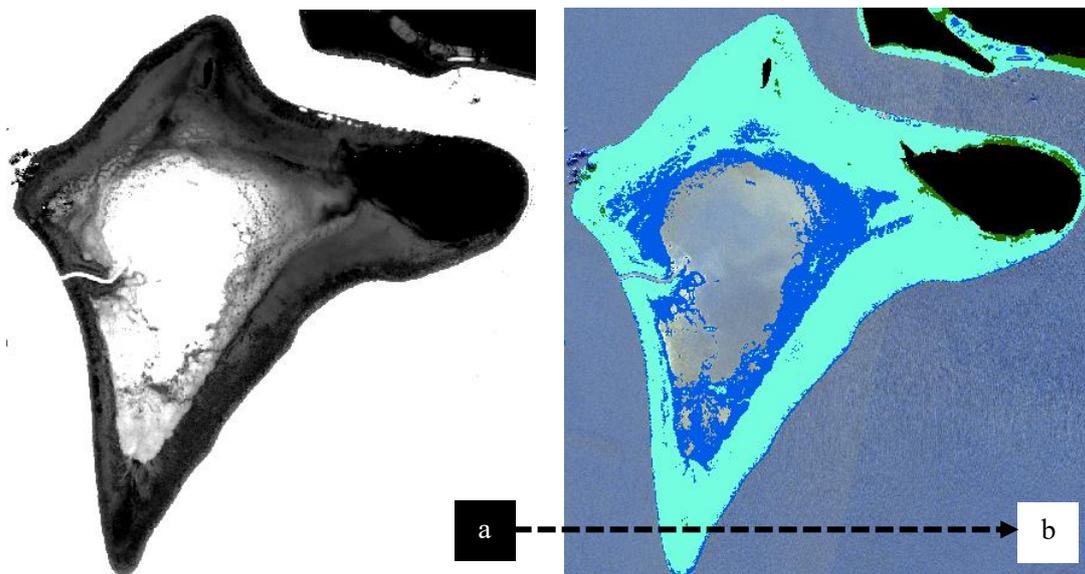


Figure 3. The greyscale band which is result of RWDI model (a) than convert into depth zones (b) using density slice classification, shallow area: cyan, deep area: blue, and seagrass area: green.

3.3. Image classification

The important part of the proposed new mapping approach is in the classification process, where the two classifications models are used, as described in section 2.2. Figure 4 shows the classification result of model 1 (without depth data) and compared with the model 2 (the proposed new approach) whereas the number class of the classification results are 7 and 17 classes respectively. More detailed classes in Model 2 is caused we used two images (sunglint and DII) in two different area (Shallow and Deep). The shallow area using sunglint image produced 10 classes and deep area which was used DII image produced 7 classes then combined the all class into total 17 classes of benthic habitat map.

The classes in Model 1 and Model 2 are spectral classes (Figure 4) which were validated according to benthic habitat classes which has created from sea truth samples (Table 5). The seven classes in Model 1 almost named according to the classes in Table 5, however not detailed to Mix cover classes (only Mix SG BS). It is obviously different to Model 2 which very detailed to carbonate sand cover (SD), hard coral cover (HC) and Mix Cover which can represented Table 4 classes. The classes in Model 2 then generalized into seven classes of sea truth (Table 5) in order to be assessed the accuracy level.

Although the benthic habitat classes created from sea truth samples was only seven classes, the variation of benthic habitat cover on the field was more than that (17 classes). The un-matching class between the sea truth classes and model 2 classes happened because the limitation in identifying benthic cover from photo samples or thoroughly on the field. So that, we must take more sample on the field to validate the undefined classes of Model 2 map to make more detailed benthic habitat map.

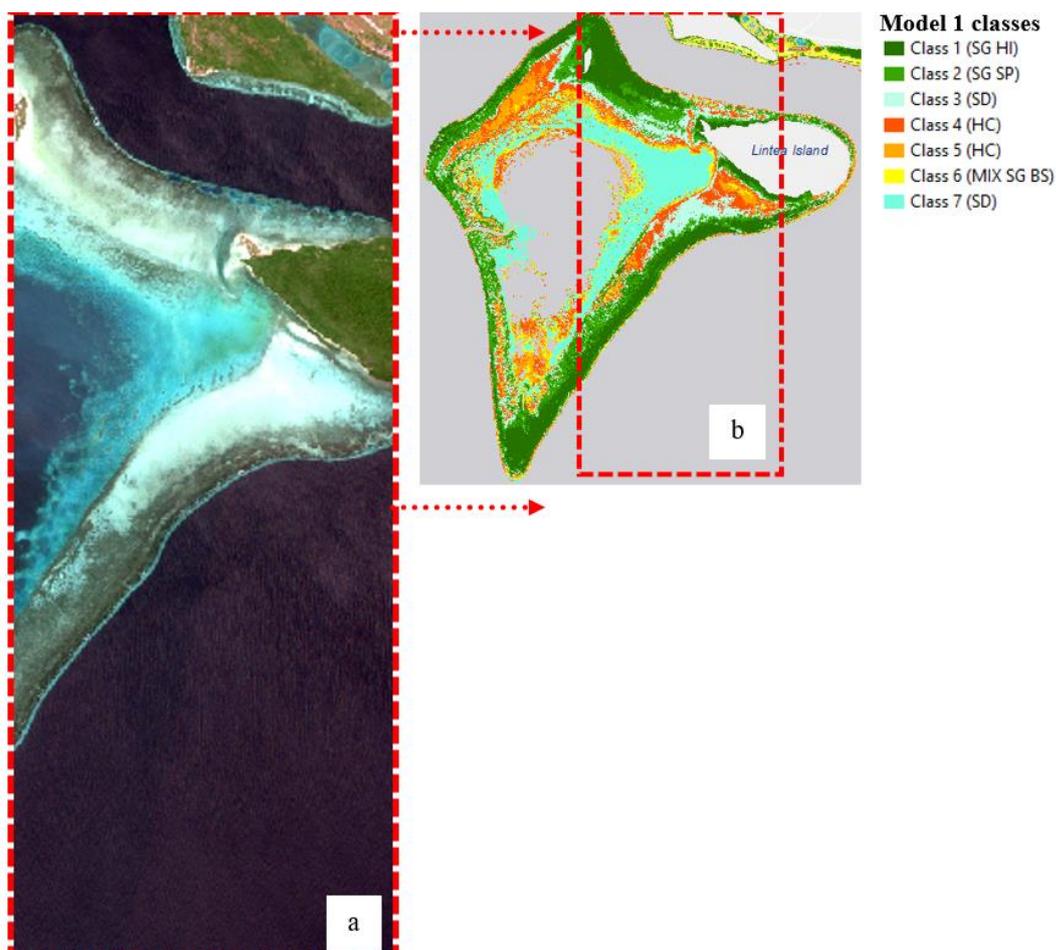


Figure 4. Classification results, original image of Sentinel 2A image (a), Model 1 classification result (b), Model 2 classification result (c) where S and D initial means Shallow and Deep Zone.

3.4. Result analysis

Based on benthic habitat sample distribution of both models, model 2 shows a better accuracy, because the shallow water area shows dominance with sand and mixed sand with other objects (mixed cover), this fact fit the image visual appearance. Moreover, coral cover class in model 2 is concentrated in slope area, a transition zone from shallow to deep area which is naturally covered by coral reef. On the other hand, model 1 shows that most of shallow area is covered by wide area of high dense seagrass and coral reef. Interestingly, based on image visualization the sand shows as the dominant object, while the image classification result shows the opposite fact.



Figure 5. Overall accuracy three different input image on classification process

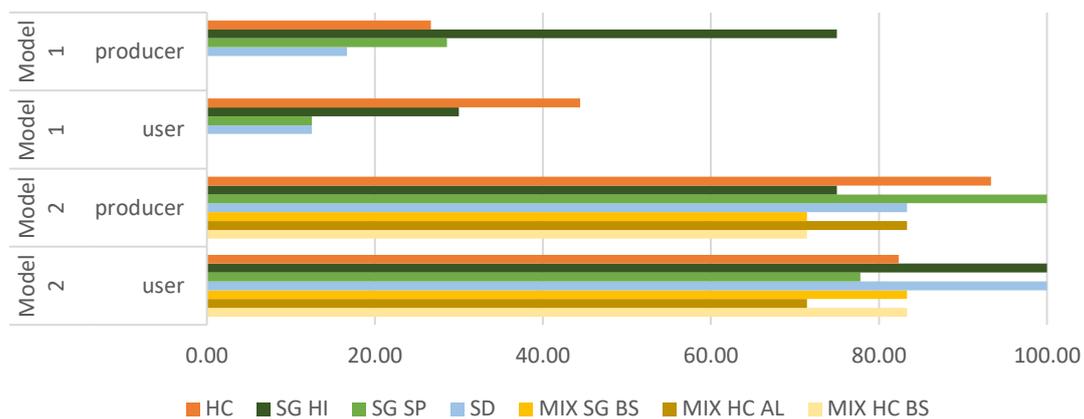


Figure 6. Accuracy assessments for two evaluated models. model 1: DII image as input, and model 2: Combination of DII and RDWII image as input

The confusion matrix shows the accuracy comparison of both methods in more detail and is summarized as Figure 5 and 6. The accuracies of the two models are compared and evaluated. The result shows that the proposed new approach (model 2) shows superiority (83.93 % overall accuracy) over model 1 (23.21 % overall accuracy). The cause of low accuracy in model 2 is due to misclassification of classified image, mix classes samples on shallow area classified as seagrass cover, so that the mix classes (Mix SG BS, Mix HC AL, and Mix HC BS) is zero producer and user accuracy. Meanwhile, the high accuracy in model 2 is due to all classes obtained from ISODATA classification is able to accommodate the classification scheme created from sea truth sample (Table 5). Figure 6 shows that all benthic classes of Model 2 have high producer and user accuracy (more than 60%), that qualifies the limit of benthic habitat mapping standard [27].

4. Conclusions

This paper introduces a new approach of benthic habitat mapping by combining the result of water column correction (DII image) and water relative index extraction (RDWII image) using Sentinel 2 image of Lintea Island. Since shallow water area is under exposure after the water column correction, this study proposed (model 2) to separately classify the target mapping area in each depth zone as shallow and deep water. By adding the depth information (model 2), the accuracy of the final benthic

habitat map was found to improve, with overall accuracy of 83% or almost three time higher compared with model 1 model (common model), respectively. The new approach also has another improvement: benthic objects can be classified into more detailed classes. The improvement is due to smaller area coverage for classification process enabling the identification and clustering of high pixel variation in smaller area (shallow and deep water), as shown in this study. The proposed new method is applicable in practice, as the depth information is extracted from the same image, meaning that no extra data such as in situ depth data are needed.

Acknowledgment

Field data in this study provided from Reef Health Monitoring activity in the year of 2015 - 2017. The activity conducted by Research Center for Oceanography, Indonesian Institute of Sciences as a part of COREMAP-CTI projects funded by World Bank. The authors also would like to thank Ir. Suyarso for contributing the data.

References

- [1] Lyzenga D R 1978 Passive remote sensing techniques for mapping water depth and bottom features. *Appl. Opt.* **17** 379–83
- [2] Wicaksono P 2010 *Integrated Model of Water Column Correction Technique for Improving Satellite-Based Benthic Habitat Mapping. A Case Study on Part of Karimunjawa Islands, Indonesia* (Gadjah Mada University)
- [3] Mumby P J, Green E P, Edwards A J and Clark C D Coral reef habitat mapping: how much detail can remote sensing provide?
- [4] John R, Vinluan N, Don J and De Alban T Evaluation of LANDSAT 7 ETM+ Data for Coastal Habitat Assessment in Support of Fisheries Management
- [5] Andréfouët S, Kramer P, Torres-Pulliza D, Joyce K E, Hochberg E J, Garza-Pérez R, Mumby P J, Riegl B, Yamano H, White W H, Zubia M, Brock J C, Phinn S R, Naseer A, Hatcher B G and Muller-Karger F E 2003 Multi-Site Evaluation of IKONOS Data for Classification of Tropical Coral Reef Environments *Remote Sens. Environ.* **88** 128–43
- [6] Philipson P and Lindell T 2003 Can Coral Reefs be Monitored from Space? *AMBIO A J. Hum. Environ.* **32** 586–93
- [7] Vanderstraete T, Goossens R and Ghabour T K 2004 Coral Reef Habitat Mapping in The Red Sea (Hurghada, Egypt) Based on Remote Sensing *EARSeL eProceedings 3*
- [8] Marlina N 2004 *The Application of QuickBird and Multi-temporal Landsat TM Data for Coral Reef Habitat Mapping. Case Study: Derawan Island, East Kalimantan, Indonesia* (The Netherlands: ITC)
- [9] Manessa M D M, Haidar M, Budhiman S, Winarso G, Kanno A, Sagawa T and Sekine M 2016 Evaluating The Performance of Lyzenga's Water Column Correction in Case-1 Coral Reef Water Using a Simulated Worldview-2 *IOP Conf. Ser. Earth Environ. Sci.* **47**
- [10] Jensen J 2007 *Remote Sensing of The Environment: an Earth Resource Perspective* (United States of America: Pearson Prentice Hall)
- [11] Hafizt M, Danoedoro P and Prayudha B 2016 Study of Shallow Water Ecosystem Based on Spatial Using Worldview-2 Imagery (Case Study: Kemujan Island, Karimunjawa Islands) *Seminar Nasional Penginderaan Jauh* (Depok, Indonesia)
- [12] Hafizt M, Iswari M Y and Prayudha B 2017 Assessment of Landsat-8 Classification Method for Benthic Habitat Mapping in Padaido Islands, Papua *Oseanologi dan Limnol. di Indones.* **2** 1–13
- [13] Kay S, Hedley J D and Lavender S 2009 Sun Glint Correction of High and Low Spatial Resolution Images of Aquatic Scenes: a Review of Methods for Visible and Near-Infrared Wavelengths *Remote Sens.* **1** 697–730
- [14] Anggoro A, Siregar V P and Agus S B 2016 The Effect of Sunlight on Benthic Habitats Mapping in Pari Island Using Worldview-2 Imagery *Procedia Environmental Sciences* vol

- 33pp 487–95
- [15] Wicaksono P and Hafizt M 2013 The Effectiveness of Various Dark Targets for Dark Subtract Atmospheric Correction Method: Case Study on Vegetation Index for Mangrove Carbon Stock Mapping *Asian Conf. Remote Sens.*
- [16] Green E, Mumby P, Edwards A and Clark C 2000 *Remote Sensing Handbook for Tropical Coastal Management* ed A J Edwards (Paris: The United Nations Educational, Scientific and Cultural Organization)
- [17] Lyzenga D R 1981 Remote Sensing of Bottom Reflectance And Water Attenuation Parameters in Shallow Water Using Aircraft and Landsat Data
- [18] Stumpf R P, Holderied K, Spring S and Sinclair M 2003 Determination of Water Depth with High-Resolution Satellite Imagery Over Variable Bottom Types *Limnol. Oceanogr.* **48** 547–56
- [19] Danoedoro P 2012 *Pengantar Penginderaan Jauh Digital* (Yogyakarta: Andi Offset)
- [20] Roelfsema C and Phinn S 2009 *A Manual for Conducting Georeferenced Photo Transects Surveys to Assess the Benthos of Coral Reef and Seagrass Habitats* (Brisbane: Centre for Remote Sensing & Spatial Information Science School of Geography, Planning & Environmental Management University of Queensland)
- [21] Goodman J, Purkis S and Phinn S 2013 *Coral Reef Remote Sensing: A Guide for Mapping, Monitoring and Management* (London: Springer)
- [22] Phinn S, Roelfsema C and Mumby P 2012 Multi-Scale, Object-Based Image Analysis for Mapping Geomorphic and Ecological Zones on Coral Reefs *Int. J. Remote Sens.* **33** 3768–97
- [23] Leon J, Phinn S, Woodroffe C, Hamylton S, Roelfsema C and Saunders M 2012 Data Fusion for Mapping Coral Reef Geomorphic Zones: Possibilities and Limitations *GEOBIA* (Rio de Janeiro) p 261
- [24] Hedley J, Roelfsema C, Koetz B and Phinn S 2012 Capability of The Sentinel 2 Mission for Tropical Coral Reef Mapping and Coral Bleaching Detection *Remote Sens. Environ.* **120** 145–55
- [25] USGS 2015 *LANDSAT 8 (L8) DATA USERS HANDBOOK* ed J 2015 (Department of the Interior U.S. Geological Survey)
- [26] Jensen J R 2005 *Introductory Digital Image Processing: A Remote Sensing Perspective* (Prentice Hall)
- [27] Peraturan Kepala Badan Informasi Geospasial Nomor 8 Tahun 2014 and BIG 2014 *Pedoman Teknis Pengumpulan dan Pengolahan Data Geospasial Habitat Dasar Perairan Laut Dangkal* ed B I Geospasial (Jakarta)