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Remote Sensing Analysis of Seagrass Beds in Bontosua Island, Spermonde Archipelago

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Abstract. Research on mapping and monitoring of seagrass ecosystems using satellite imagery data is still lacking. The availability of spatial information on benthic habitat is becoming very important with the increasing awareness of environmentally based management. Various methods of analysing remote sensing information on benthic habitat have been developed and utilized, such as the application of the Lyzenga algorithm. This algorithm requires data on the variation of water depth in the coastal areas to be mapped. The purpose of this research was to study the effect of using Lyzenga algorithm on the mapping of coral reef/ seagrass ecosystem by comparing the results of seabed classification from Sentinel-2a imagery processed and without using the Lyzenga algorithm. Image classification with Lyzenga algorithm is easily recognizable with the Lyzenga index value format that has been freed from the effect of water depth. In this study, benthic cover in the shallow waters around Bontosua Island, Spermonde Archipelago-Indonesia, was classified using six habitat types: aquatic, land, sand, rubble, coral and seagrass. Seagrass habitat was further classified based on percentage cover as class 4 (76-100%), class 3 (51-75%), class 2 (26-50%) and class 1 (0-25%). Based on the analysis of Sentinel-2a data, the area with seagrass cover was estimated at 31.27 Ha. Seagrass mapping using medium-resolution satellite imagery can be helpful in providing data over a more extensive area than is likely to be possible using direct observation in the field alone.

1. Introduction

Remote sensing relying on satellite technology has the advantage of being able to record data across wide areas of the earth's surface, in detail and also repeatedly over time. Therefore, this technology has the ability to detect changes in an ecosystem [1]. Remote sensing studies of seagrass are still limited compared to studies on coral reef and mangrove ecosystems. There are strong indications that, although seagrasses can suffer from natural disturbances, impacts due to human activities are much more widespread and severe [2]. It has been estimated that Indonesian seagrass beds have shrunk in extent by 30-40% due to human activities [3].

Indonesia has 13 recorded species of seagrass, with an approximate seagrass area of 30,000 km² [4]. One of the island groups in Indonesia is the Spermonde Archipelago, of the southwest coast of Sulawesi Island. Multispecies seagrass beds with 5 seagrass species are found around Bone Batang, one of the islands in this archipelago [5], while the island of Sabangko has a seagrass ecosystem in moderate condition [6]. However there are no data on the seagrass ecosystems of many islands in the Spermonde, including the island of Bontosua. These conditions prompted the choice of this study, with Bontosua Island as the research site.



Various types of research on mapping and monitoring of aquatic ecosystems have been carried out; however, in Indonesia, especially mapping of seagrass beds, the use of satellite imagery data is still quite rare. Mapping of sea grass has only been conducted at a few locations, e.g. on the east coast of Bintan island, Riau Islands [7]; Kotania Bay and Pelitajaya, West Seram, Maluku [8]; Derawan Islands, East Kalimantan [9]; Kema, North Minahasa; Mapur Islands; Riau islands; Tual, Southeast Maluku and Rote Island, East Nusa Tenggara.

Sentinel-2a image data has a spatial resolution of 10 m with 4 bands that are used for spectral vegetation from visible light channels: near infrared, and infrared shortwave [10]. This image data has a higher spatial resolution compared to Landsat, but it is still classified as medium resolution and is considered capable of mapping basic water objects, similar to the use of Landsat TM image data which has already been used for mapping basic water objects [11]. The Lyzenga algorithm has been developed to assist in processing image data before carrying out the classification process. Research has been done on the use of the Lyzenga algorithm for the observation of basic marine objects [12]. This study was conducted using Sentinel-2a to obtain an image that provides a clearer view of the baseline image of the water features in order to be re-mapped. It was expected that this Sentinel-2a data could be processed by applying the same method (using the Lyzenga algorithm) as in previous studies by other researches using different satellite data.

2. Materials and Methods

2.1. Study area

The field component of this research was conducted from March to October 2017 in the shallow waters of Bontosua Island, Spermonde Archipelago in Pangkep District, South Sulawesi Province, Indonesia (Figure 1). The study area of approximately 63.53 Ha was located around $119^{\circ} 19' 14.63''$ E and $4^{\circ} 55' 41.22''$ S.

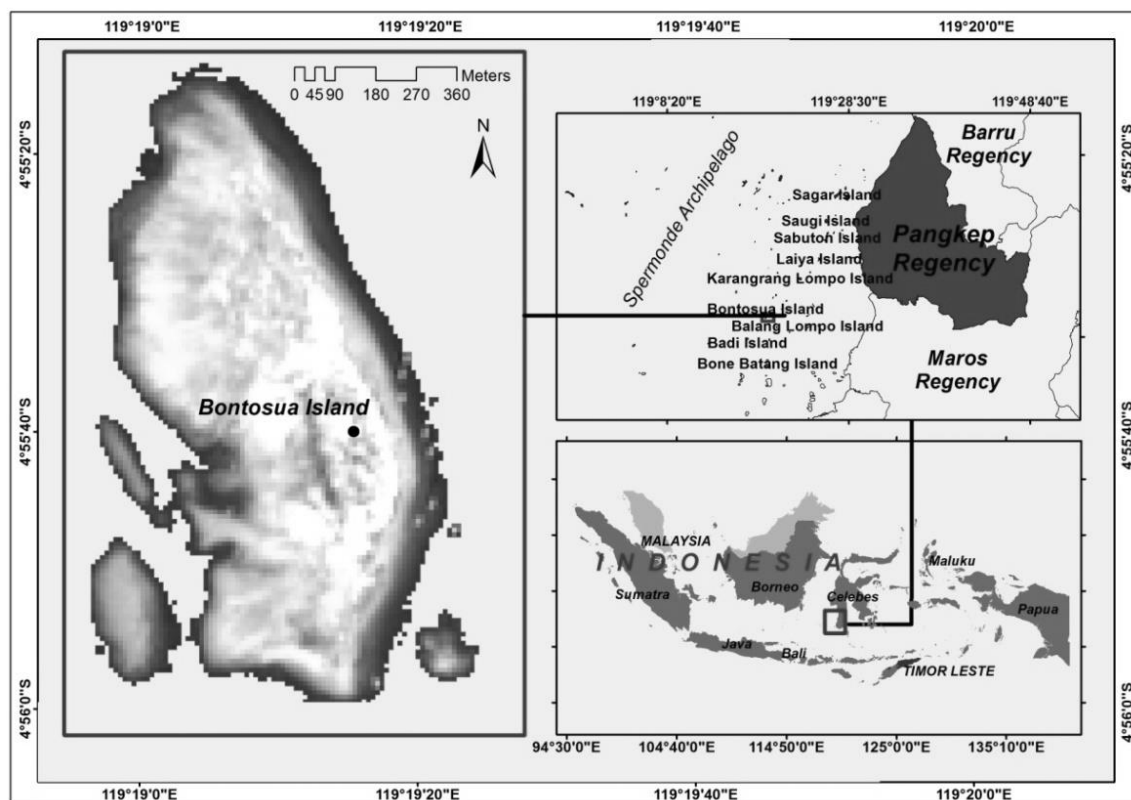


Figure 1. Map of Bontosua Island, showing the study area and sampling stations

2.2. Data collection

A Global Positioning System (GPS) was used to record the position of *in situ* measurements made along transect lines with quadrants. Visual records were made using an underwater camera, and data were collected while snorkelling. The main source of data used was a Sentinel-2A satellite image, acquisition 01 March 2017, downloaded at: <https://earthexplorer.usgs.gov/>.

2.3. Image processing

The main software used in data processing were ArcMap 10.5 (licence number 557392) and GRASS 7.2.1. Processing comprised several stages from pre-image processing and image processing, to the comparison of resulting seagrass distribution classification using algorithms with and without the Lyzenga algorithm from the Sentinel-2A medium resolution imagery (Fig. 2).

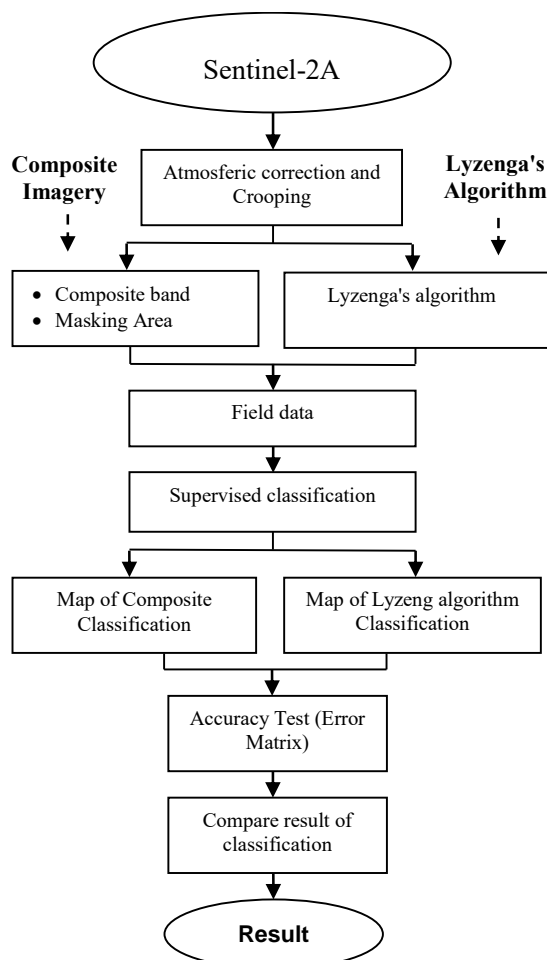


Figure 2. Flow Chart of the image processing research method and processes

Pre-processing includes atmospheric correction and image cutting. The atmospheric correction is done by using the *Dark Object Subtraction* (DOS) method, to eliminate atmospheric influence at the time of recording, so as to improve the appearance of object before to be interpreted. DOS correction is able to eliminate the radiance error resulting from atmospheric scattering (path radiance) at the time of the image recording process. The basis for this method is "that the number of pixels taken from the deep water and the Digital Number (DN) value is subtracted with each band" [13]. Atmospherically corrected radiance is given by:

$$L_i - L_{si} \quad (1)$$

where: L_i = pixel from radiance band i
 L_{si} = average value of water column light intensity in band i

Once atmospheric correction has been done, the pixel value was converted to a surface reflectance or ρ_{surface} . So the value of this reflectance then became the initial data to perform data entry into the Lyzenga algorithm. Before applying the algorithm, it is necessary to first separate the land and sea areas. Processing focused only on the shallow water areas (seagrass habitat). The next process was cropping the image to the study area, in order to minimize the area of observation and thus the size of the files to be processed. In this image Bontosua Island is located at 119° 19' 14.63" E and 4° 55' 41.22" S. The next process is image processing. The image composite used for the classification process combined 3 natural bands (RGB: 432): band 4 (red), band 3 (green) and band 2 (blue). This composite was used in the supervised classification.

The Lyzenga algorithm can be applied using the water column correction method [14] with Depth Invariant Index (DII) and finding the aquatic attenuation coefficient (k_i/k_j) by extracting the digital values in the blue channel and the green channel at the same geographical position through the creation of a training sample area in the form of a polygon. The process used 35 training sample areas in shallow water areas. Statistical calculations were then performed to obtain the value of variance and covariance for the sample area training results using the blue channel and green channel. The value of a and the attenuation coefficient ratio (k_i / k_j) were obtained based on equations (4) and (5).

$$X_i = \ln(L_i) \quad (2)$$

$$\ln(L_i) = -[(k_i/k_j) \ln(L_j)] \quad (3)$$

Where:

L_i and L_j = reflectance value of band- i and band- j

K_i/K_j = ratio of attenuation coefficients of band i and band j

While to find the value of coefficient attenuation (K_i / K_j) in (Lyzenga, 1981) [14]:

$$K_i/k_j = a + a \sqrt{a^2 + 1} \quad (4)$$

$$a = \frac{(\text{var}X_i - \text{var}X_j)}{2 \text{cov}X_iX_j} \quad (5)$$

Where:

X_i = Variance of band i

X_j = Variance of band j

X_iX_j = Covariance of band ij

The next step in image processing was the supervised classification, using the maximum likelihood algorithm. The last classification process was the accuracy test, where the classification results were validated. The results of the accuracy test from two images (composite image classification and image classification using Lyzenga algorithm) were then compared. This test is important to know how far the map can be relied on as an accurate representation of the ecosystems present. The accuracy test used was an error matrix comparing the classification with the actual class of field observations.

3. Results and Discussion

3.1. Atmospheric correction and masking

The atmospheric correction results indicated that using the DOS method changes the pixel value. The value of the pixel was previously in the form of a reflectance value and is changed to surface reflectance. The surface reflectance values are within a range between 0-1. Chavez (1977) in [13] assumes that the basis in images of several pixels of shadow and complete radians received by satellites is also caused by atmospheric scattering (radiance) [13]. This assumption is combined with the fact that very few objects on the earth's surface are truly black, so it is assumed that one percent as the minimum reflection is more accurate than zero percent.

The process of masking the boundary between land and sea areas is necessary before the classification process, in order to reduce the influence of pixels in the land area during the process of transformation and classification. The method used was to digitize the land in the image. The surrounding waters will still carry reflectance values, while the land area is left with a value of 0 (zero) so that the transformation and classification are not affected by the land area (Figure 3).



Figure 3. Image with Bontosua island land area masked

3.2. Composite classification (without Lyzenga's algorithm)

The use of colour composites with the help of NIR in 3 different bands was used to see the effect of the classification process without using the Lyzenga algorithm, the image used was the NIR-Green-Blue composite (RGB = 832). When compared with the Red-Green-Blue composite image (RGB = 432), 821 composites show a better basic appearance because NIR channels have good spectrum sensitivity in distinguishing shallow water parameters [15]. The NIR-Green-Blue composite image was further classified using the Supervised Classification-maximum likelihood method (Figure 4).

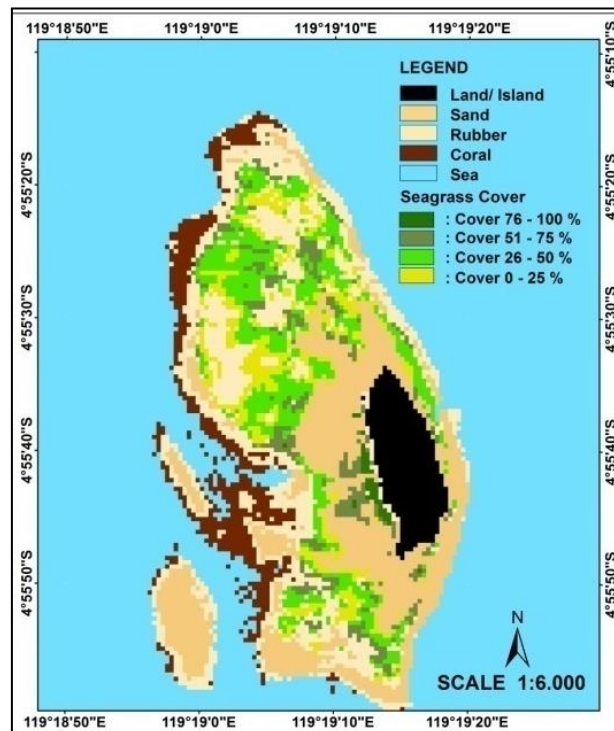


Figure 4. Composite classification of seagrass cover without Lyzenga

Four classes of seagrass cover classified were: very good (class 76-100%), good (class 51-75%), medium (class 26-50%) and poor (class 0-25%). One pixel equated to 0.01 ha, as spatial resolution of the Sentinel-2a image used is 10 x 10 m (100 m²). The results of composite classification (Table 1) found very few pixels in the very good category, with almost half of the seagrass area in the medium category. The classes were defined with reference to conditions in the field. The total seagrass area according to this classification was 19.08 ha, based on the data recorded during low tide conditions.

Table 1. Percentage of seagrass cover categories from the composite classification without Lyzenga

Class (%)	Coverage (Ha)	Coverage (%)
76-100	0.45	2.36
51-75	4.14	21.70
26-50	8.96	46.96
0-25	5.53	28.98
Total	19.08	100.00

3.3. Imagery classification using Lyzenga's algorithm

Determination of the 35 sample areas used as training sample locations was based on the distribution of differences in the depth values of shallow waters over sandy substrate. This was based on the recommendation by Lyzenga that, in order to obtain the correct linear correlation value in the process of DII [14], the training areas should have homogeneous substrate with different depths. The training was done on the natural colour image (RGB = 432), where the channels chosen to calculate the ratio were the channels with the highest water penetration, i.e. blue and green channels. Based on the training samples, the k_i/k_j value was 0.7656. The new image resulting from the application of the Lyzenga algorithm was classified using the supervised classification maximum likelihood method, with the resulting colour tones reinterpreted according to class reference (Figure 5 and Table 2).

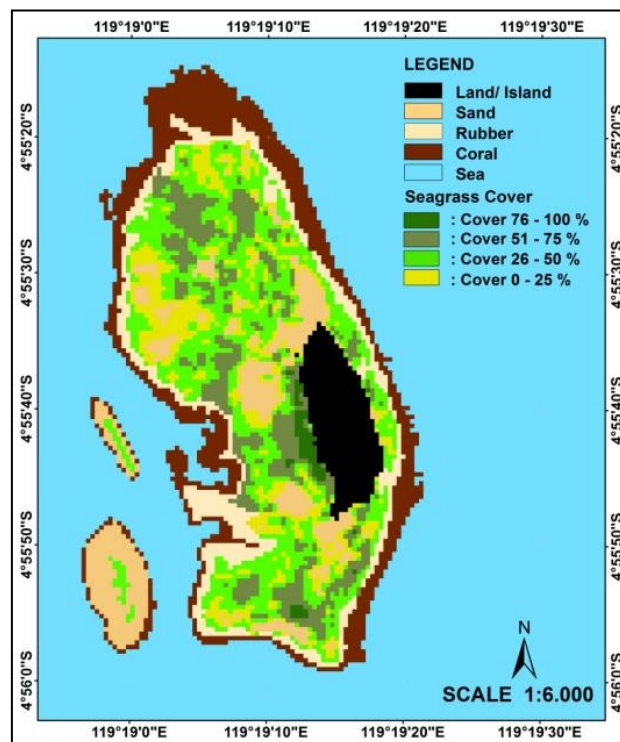


Figure 5. Classification of seagrass cover using the Lyzenga algorithm

Table 2. Percentage and extent of seagrass cover classes using the Lyzenga algorithm

Class (%)	Coverage (Ha)	Coverage (%)
76-100	0.76	2.43
51-75	8.20	26.22
26-50	15.11	48.32
0-25	31.27	23.03
Total	31.27	100.00

The overall seagrass extent based on this classification (condition at low tide) was 31.27 ha. The extent of the sand is affected by the water column correction for spectral reflection from the sand. Without this correction, seagrass around the sand can be detected as sand. The comparison with Figure 4 emphasizes that correction of water columns needs to be done to improve image quality by reducing interference in the water column [14]. Therefore, to get good baseline data on an underwater object, it is best to carry out the image processing before the classification process, by first correcting for the effects of the water column on the image data used.

3.4. Accuracy test and comparison of results

Accuracy tests carried out on the two different classification results showed that the classification with the Lyzenga algorithm achieved 88%. This shows that the classification using the Lyzenga algorithm accorded well with the data and conditions in the field. The value of 88% meets the minimum image accuracy requirements of 85% [16].

Comparison of the classification results between the composite image and image with the Lyzenga algorithm shows that the Lyzenga algorithm can improve the detection of features underwater (substrate types), in this case seagrass. The Lyzenga algorithm produced a more accurate representation of the seagrass beds with an image accuracy rate of 88%, in terms of classes of sand, seagrass and coral. However, coral reefs classified using the Lyzenga algorithm cannot be

distinguished so that all categories were entered into one class, because the reef crest and slopes around Bontosua island have less depth variation and tend to be deep. One condition for using the Lyzenga algorithm is the presence of depth variation in the study area [14].

In the composite image classification results, there were far fewer pixels where seagrasses were detected compared to the Lyzenga Algorithm image, because in shallow waters with high depth variations the water depth will produce various classes due to the effects of the water column. In this case, these effects seem to have resulted in a much higher proportion of substrate being classified as sand, including some seagrass areas. These results indicate that when the research area has relatively homogenous depths, the improvements resulting from the use of the Lyzenga algorithm will be much less marked.

4. Conclusion

Differences in the classification results obtained from image classification with and without the Lyzenga algorithm show that using the Lyzenga algorithm has an influence and can result in improved detection of some underwater features, including substrate cover by seagrasses. The classes produced from this study are classes: sand, rubble, seagrass beds and coral reefs. While the non Lyzenga classification identified approximately 19 ha of seagrass beds, the Lyzenga classification found around 31 ha, a substantial increase. However the percentage composition in terms of seagrass condition classes was similar for the two methods. This improvement in seagrass classification was not noted for coral reefs, where the depth variation was less and the average depths deeper. In further research, it is recommended to apply more in-depth pre-processing of image data before classification, and to apply the Lyzenga algorithm for supervised classification, especially for remote sensing information on benthic habitat objects such as seagrasses and corals. More specific studies are recommended to further evaluate the Bontosua Island substrate conditions, looking not only at habitat types but also sediment textures and oceanographic conditions. The extent and condition of seagrass cover on Bontosua Island, which is quite large, requires further research such as monitoring activities as well as concern for seagrass conditions on the island. It is hoped that the new information and knowledge obtained can be used for research purposes and to improve resource management.

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