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Shallow water marine habitat mapping of Kaledupa Island using integrating tradisional ecological knowledge and multispectral image classification

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Abstract. Marine scientists had applied many remote sensing methods to shallow-water marine habitat mapping. However, integrating traditional ecological knowledge and remote sensing application to produce marine habitat map was still very limited. The aims of this study are to try to implement the integration of traditional ecological knowledge and multispectral image classification for shallow-water marine habitat mapping in the marine protected area (MPA) of Kaledupa Island, Wakatobi National Park (WNP). Imagery data used was Landsat 8 Operational Land Imager (2016). Fishers from Kaledupa Island visually interpreted Landsat 8 OLI multispectral image to identify sangnga (live coral), sangnga mate (dead coral), rondo (lamun), and one (sand). Their interpretations were used as input to image supervised classification with Mahalanobis and Maximum Likelihood. Then, habitat mapping with four classes could be produced. Results indicate that marine habitat mapping can be generated well by combining traditional ecological knowledge and multi-spectral image classification, Mahalanobis with the overall accuracy 71.67% and kappa statistic 0.62%; Maximum Likelihood Analysis with the overall accuracy 73.33% and kappa statistic 0.65%. This hybrid method is useful to marine scientists and coastal resource managers in producing shallow-water marine habitat map and management planning of MPA.

1. Introduction

Conservation is an attempt to maintain ecological functions of coastal habitats [13]; [25]; [8]. The success of this conservation can be estimated by monitoring shallow water marine habitats periodically to ensure good and healthy habitat conditions [16].

Methods of monitoring shallow water marine habitats continue to experience development. Conventional methods are considered ineffective for extensive study areas with a relatively short time scale. The limitations of this method are then answered with remote sensing technology [34]; [28]; [8]; [3]. In various studies, scientists have used remote sensing technology for monitoring coral reefs [22];



[17]; [5]; [18]; [33]; [39]. Similarly, seagrass monitoring using remote sensing has also been widely studied [2]; [23]; [37]; [30]; [32].

Classification of shallow water marine habitats based only on the ad hoc, geomorphological and biotic community definitions used by marine scientists [15], has been continuously modified according to the needs and development of science. In recent years, marine conservation management based on social ecological systems, remote sensing methods began to develop by combining local wisdom. This method is called a hybrid approach that integrates multispectral image classification with traditional ecological knowledge [6]; [27]; [7]; [21]. However, the application of this hybrid method is still very limited, including the management of the Wakatobi conservation area. The aims of this study are to try to implement the integration of traditional ecological knowledge and multispectral image classification for shallow-water marine habitat mapping in the marine protected area (MPA) of Kaledupa Island

2. Material and Method

2.1. Study Area

WNP is one example of a marine conservation area in Indonesia that has a purpose for the protection of coastal ecosystems. WNP has a strategic geographical and ecological location, located at the center of the world's coral (Coral Triangle). This condition is not surprising if WNP has a very high marine biodiversity [29]; [38]; [12]. The study location focused on Kaledupa Island (Figure 1).

2.2. Data and Image Pre-Processing

The imagery data used to map the shallow water marine habitat of Kaledupa Island by integrating the traditional ecological knowledge is Landsat 8 OLI (path 111, row 64), recording September 5, 2016. Pre-processing is an initial process that must be done before image classification. This research image pre-processing refers to Ardiansyah [4] which consists of calibration and correction. Calibration is the process of transforming pixel values to obtain spectral values for radiance and reflectance. According to Ardiansyah [4], the Landsat 8 OLI calibration into the reflectance value (Top of Atmosphere / TOA) is used as follows:

$$\rho\lambda' = M\rho Q_{cal} + A\rho$$

Annotation:

- $\rho\lambda'$ = TOA reflectance which has not been corrected by the sun's angle
- $M\rho$ = scale factor (band-specific multiplicative rescaling factor)
- $A\rho$ = addition factor (band-specific additive rescaling factor)
- Q_{cal} = pixel value (digital number/DN)

The next process was radiometric correction to improve image quality (Ardianyah 2015). Distortion was very possible when satellites record objects on earth caused by atmospheric disturbances. In this study radiometric correction was used with Atmospheric Correction Module, Fast Line of sight Atmospheric Analysis of Hypercubes (FLAASH). Thin cloud correction (cirrus) was not carried out because the study area was not covered by thin clouds. This radiometric calibration and correction were operated in ENVI 5.1 software.

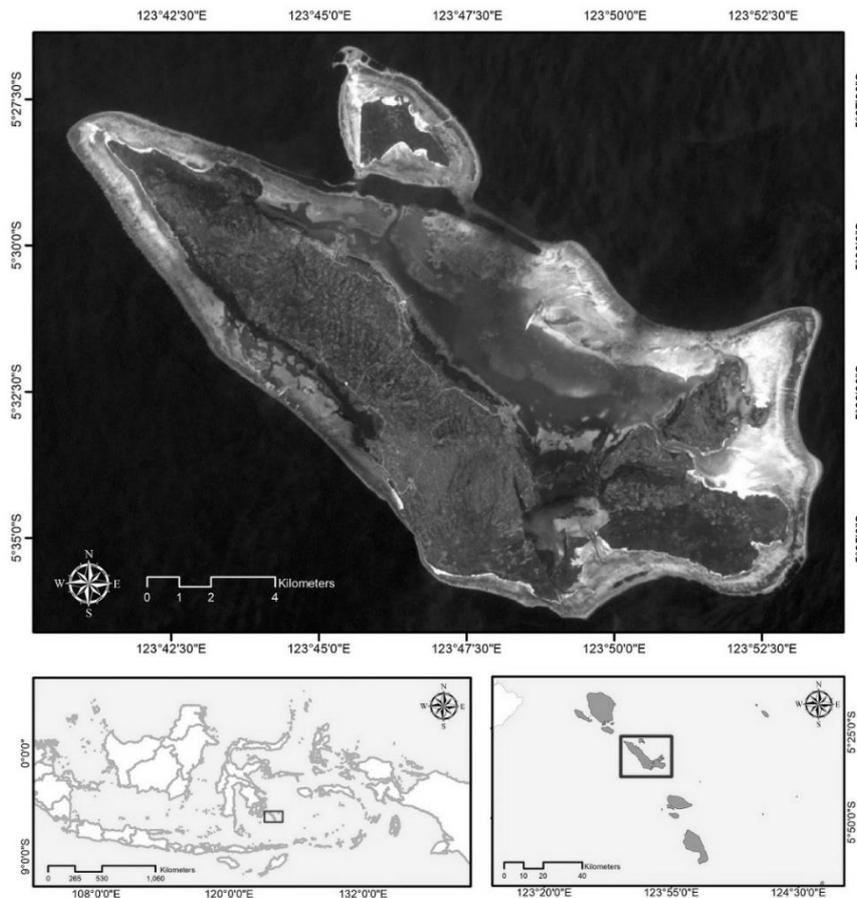


Figure 1. Kaledupa island, WNP.

While to change DN to Landsat 8 radians spectral OLI the following formula is used:

$$L\lambda = M_L Q_{cal} + A_L$$

Annotation:

- $L\lambda$ = spectral radians
- M_L = scale factor (radiance multiplicative rescaling factor)
- A_p = addition factor (radiance additive rescaling factor)
- Q_{cal} = pixel value (digital number / DN)

2.3. Reasons for Kaledupa Island Local Ecological Knowledge Integration

The Kaledupa Island communities have local knowledge of the sea and shallow water marine habitat. In addition, it is an ancestral heritage in the Buton Sultanate era, the local ecological knowledge is also obtained from everyday life that continues to interact with the sea. Some local terms in the marine management system with the space approach in Kaledupa being the legacy of the Buton Sultanate include the right to fish, wehai, bala watu, huma, tepepali, and restrictions on fishing gear by outside fishermen (Personal Communication with Hasanuddin, 2016).

Wehai was usually focused on coastal areas having bays (kolo) and there was much fish. Bala Watu was a stone fence with a height of about 1 meter, circular from the edge to the land. It was made outside the natural coral reef area, with the intention of fish catching in the area not to damage the reef. Huma was the naming of wooden pillar houses in tidal areas in the Pasi area (atoll). Meanwhile, tepepali has the area or natural resources that were prohibited from being taken or considered sacred. If anyone violate this belief, they will get some kind of curse or suffer illness.

The local community had a local term in naming the coastal habitats. For instance, sangnga (live coral), sangnga mate (dead coral), one (sand), rondo (seagrass), and akka (mangrove). The type of coral reef in Kaledupa is dominated by fringing reef, with the local name huu mbatu. In addition, there is a Kaledupa atoll (Pasi).

Some reasons for incorporating the traditional ecological knowledge of Kaledupa Island in the classification of multispectral satellite imagery to produce shallow water base habitat maps are First, the Kaledupa community has good knowledge of shallow water marine habitats based on geomorphology and abiotic substrate, as well as associated biota [14]; [11]. This is clear because in meeting their daily needs they always use coastal and marine resources. In addition, the management of the sea area has been carried out since the era of the Buton Sultane by Barata Kahedupa, where the customary territory covers the highest tidal area to the slope area of fringing reef. Second, to encourage community participation in coastal resource management. Community participation is indispensable for the success of conservation programs [14]; [11]; [26]; [1].

2.4. Participatory Image Interpretation Method

The method used to get the results of participatory image interpretation was by asking for help to local communities having ecological knowledge to provide definition, interpretation and identification of marine habitat by observing Landsat Satellite Imagery. This method was adopted and modified from research conducted by Lauer and Aswani [21]. The first step was taken in order to meet competent informants, the researchers consulted with the Non-Governmental Organization in Kaledupa Island, namely the Forum Kahedupa Toudani (Forkani). Some recommended informants were then met personally and group discussions to ask for their opinions and perspectives. Informants who were randomly selected were 10 fishermen, including 1 key respondent from Forkani. Before discussing with respondents, researchers prepared the Landsat 8 OLI Image on September 5, 2016. The image was chosen because it was clean from the cloud and could facilitate the public to interpret.

Landsat imagery was made with a combination of true colors (bands 4, 3, and 2) to enhance image visualization. This imagery was printed on A4 paper so the informant could immediately determine the points and describe the polygon of the sangnga (live coral), sangnga mate (dead coral), one (sand), and rondo (seagrass). Each respondent completed his interpretation for about 60 minutes. The results of this interpretation were then scanned into digital data as guided classification input. The data were then georeferenced by image-to-image registration. Interpretation of respondents produced 4 classes. The results of these community interpretations were then conducted a ground truth survey to validate the truth of the basic habitat of the Kaledupa Island waters.

2.5. Field survey

Field data collection in this study modified the method of Madden et al. [24]. To produce a map of shallow water marine habitat (consisting of 4 classes: live coral, dead coral, seagrass, and sand), 8 transects were made in the field survey. Each transect consists of several observation points. The distance of each observation point was 30 meters representing Landsat 8 OLI spatial resolution; supratidal, intertidal, and subtidal benthic environments; and changes in spectral color appearance on satellite imagery. The total sampling points (ground truth) are 40 training area points and 60 accuracy points. The geographical coordinates of the sampling point were selected by random stratified sampling. Location survey activities used a boat owned by Kaledupa fishermen.

2.6. Data analysis

Data analysis was carried out supervised classification using ENVI version 5.1. The accuracy test of this hybrid method used Mahalanobis and Maximum Likelihood Classification. Both of these analyzes were used to assign each pixel in the image to a different class. Iteratively, the pixel class was then combined at the thematic class level to represent the four marine habitat classes of Kaledupa Island.

The step before doing classification was water column correction. This correction was intended to sharpen the interpretation in a visual way and to produce a precise classification. Water columns had a considerable influence on obtaining quantitative information about shallow water marine habitats [20];

[28]; [31]. Water column correction in this study used Depth Invariant Index (DII) of each spectral band pair [15]; Yamano, 2013). DII was divided into several steps, as follows

Conduct training areas on homogeneous substrates in different depths. Substrate data and depth were obtained from field observations. The training area was carried out on the observation points of homogeneous objects in band pairs to obtain attenuation coefficient values.

With the help of spreadsheet data processing (Microsoft EXCEL), the training area results in each band pair were then calculated the attenuation coefficient value with the equation;

$$K_i/K_j = a + \sqrt{a^2 + 1}$$

Where:

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

and

$$\sigma_{ij} = \bar{X}_i\bar{X}_j - \bar{X}_i\bar{X}_j$$

K_i/K_j is attenuation coefficient, σ_{ii} is variance measurement X_i , σ_{jj} is variance measurement X_j and σ_{ij} is covariance X_i dan X_j

The next step, calculating the depth invariant index (DII) with the equation

$$DII_{ij} = x_i - \left[\left(\frac{K_i}{K_j} \right) * (x_j) \right]$$

The final stage of the classification process was testing the results of mapping accuracy consisting of overall accuracy (OA), producer accuracy (PA) and user accuracy (UA) [10]. OA was the overall level of truth between image and reference data where in this case was a map of the classification results. UA was calculated to predict the accuracy of classification of habitat class variation determined from field observations. PA was calculated to estimate the ability of each class resulting from image classification.

3. Results and Discussion

Supervised classification obtained from the integration of Landsat 8 OLI multi spectral classification with traditional ecological knowledge using Mahalanobis analysis had overall thematic accuracy of 71.67% and kappa statistic of 0.62. Estimating the accuracy of classification of habitat class variations determined from field observations, UA ranged from 50% to 90%. Whereas the sangnga mate (dead coral) had the lowest accuracy value (50%), while the highest was the One (sand) of 90%. Estimating the ability of each class resulting from image classification, AP ranged from 60% to 87.5%. The lowest accuracy was that of the sangnga mate (dead coral) 60% and One (Sand), while the highest accuracy was Rondo (Seagrass) of 87.50%. The mapping accuracy of the shallow water marine habitat of Kaledupa Island based on Mahalanobis analysis can be seen in Table 1.

Meanwhile, the Maximum Likelihood classification had overall thematic accuracy of 73.33% and kappa statistics of 0.65. UA ranged from 64% to 100%. Sangnga (live coral) had the lowest accuracy value (64.71%), while the highest was Rondo (seagrass) of 100%. Meanwhile, the estimation of the ability of each class resulting from image classification, AP, ranged from 50% to 100%. The lowest accuracy was Rondo (seagrass) by 50%, while the highest accuracy was Sangate (dead coral) by 100%. The mapping accuracy of the shallow water marine habitat of Kaledupa Island based on Maximum Likelihood can be seen in Table 2.

Table 1. The mapping accuracy of the shallow water marine habitat of Kaledupa Island based on Mahalanobis classification.

Classification	Reference data				Total	User accuracy
	Sangnga	Rondo	One	Sangnga mate		
Sangnga	11	1	0	1	13	84.62%
Rondo	1	14	0	4	19	73.68%
One	0	0	9	1	10	90.00%
Sangnga mate	2	1	6	9	18	50.00%
Total	14	16	15	15	60	
<i>Producer accuracy</i>	78.57%	87.50%	60%	60%		

Overall accuracy 71.67%, kappa statistic 0.62%

Table 2. The mapping accuracy of the shallow water marine habitat of Kaledupa Island based on the maximum likelihood classification.

Classification	Data Reference				Total	User accuracy
	Sangnga	Rondo	One	Sangnga mate		
Sangnga	11	3	3	0	17	64.71%
Rondo	0	8	0	0	8	100.00%
One	0	2	10	0	12	83.33%
Sangnga mate	3	3	2	15	23	65.22%
Total	14	16	15	15	60	
<i>Producer accuracy</i>	78.57%	50.00%	66.67%	100%		

Overall accuracy 73.67%, kappa statistic 0.65%

Based on the results of this hybrid method, the total area of Rondo was 5294.24 ha (49.1% of the total area); sangnga mate was 2108.44 ha (19.5%); sangnga 2039.44 ha (18.9%); and One 1345.51 ha (12.5%). The total area and percentage of cover of the shallow water marine habitat of Kaledupa Island based on participatory classification are shown in Table 3, while the map is presented in Figure 2.

Table 3. The total area and percentage of shallow water marine habitat of Kaledupa Island based on the hybrid method.

Class	Area (ha)	Coverage Percentage
Sangnga	2 039.44	18.9
Rondo	5 294.24	49.1
One	1 345.51	12.5
Sangnga mate	2 108.44	19.5
Total	10 787.63	100

The study of shallow water marine habitat mapping in Kaledupa Island by integration of traditional ecological knowledge is an accurate remote sensing method. The total accuracy obtained from this study is high, namely 71.67% (Mahalanobis) and 73.33% (Maximum Likelihood). This value is still in the recommended range of accuracy in the classification of satellite images, 60% to 90% [15]. Relatively low UA in the sangnga mate (dead coral) class indicates that the classification error is moderate. While the sangnga (live coral) and rondo (seagrass) get high accuracy and can be accounted for.

There are several reasons for the low accuracy of dead coral. First, on dead coral beds have biotic and abiotic complexity in the form of a mixture of coral, algae, moss, or sediment [7]. This diversity causes the spectral value of object reflection to be not very clear. The spectral value of dead coral states is known, but cannot be accurately distinguished through multi-spectral image classification, except

using the airborne hyperspectral images of a CASI (Compact Airborne Spectrographic Imager) sensor that is flown simultaneously [9]. Similarly, the low PA value in seagrasses from the results of Maximum likelihood analysis was due to the heterogeneity of the seagrass ecosystem.

The second reason, when taking data both direct observation at marine and during interviews (participatory image classification) with local communities, didn't categorize dead coral in detail. According to Clark et al., [9] dead coral surfaces consist of partial colony death (a transitional category between death and life, calcium 20-80% living tissue); new dead coral, about 6 months, with corallite appearance; and coral dies long, death is more than 6 months, corallite structures are moved by grazing fish and urchins. The dead coral has the same overall spectrum but the reflectance peak is not well defined. Spectrum from long dead coral is the same as the new dead coral form but the reflectance is higher at all wavelengths [9].

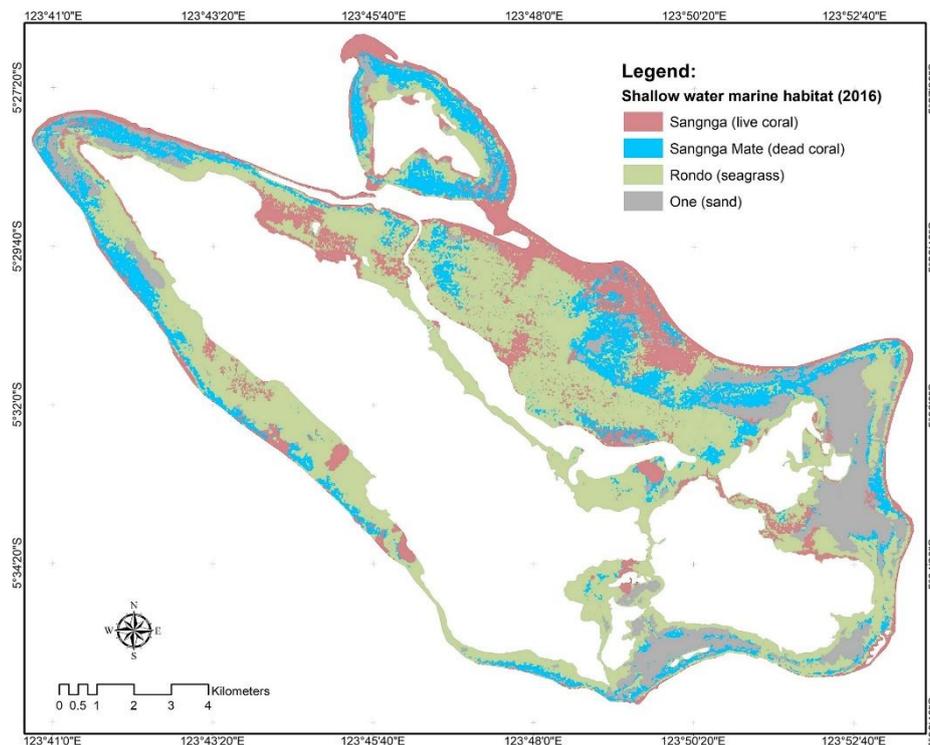


Figure 2. Map of shallow water marine habitat of Kaledupa Island based on integration traditional ecological knowledge and multispectral classification.

The results of this study thoroughly explain that the integration method of multi-spectral image classification and traditional ecological knowledge can be used by scientists to help decision makers and other stakeholders in managing coastal and marine resources. A hybrid approach like this also provides recommendations for community-based conservation management, not top-down. Remote sensing technology and local knowledge have weaknesses, so that the combination of the both can complement each other, proven to produce high accuracy values. This is as described by Lauer and Aswani [21] in his research in Lagoon Roviana, Solomon Islands. They revealed that to achieve the success of coastal management, science and technological development cannot be separated from the local wisdom of each region. At present many scientists, development practitioners and policy makers have committed to juxtapose local ecological knowledge with global knowledge. Understanding that local wisdom is an ancient culture, and having a narrow scope and inhibiting the development of modern science or technology, must be eliminated. Local wisdom has advantages that are not obtained in formal education. Local knowledge is generally derived from the experiences of the people experienced in daily life in a long time.

Scientific and local knowledge should be integrated in resource management and coastal conservation areas [36]; [21]. All knowledge systems are heterogeneous, both temporally and spatially, as well as sequences of historical changes [35]. The culture of management of the coastal resources of the Kaledupa community is a legacy of the royal / imperial period of Buton (from 1332 to 1960). The customary institution that is authorized in the Kaledupa area is Barata Kahedupa. Sara Barata Kahedupa in 2017 has formally determined the rules for the management of coastal and marine resources in the Kaledupa region. This institution carries out their roles and collaborate with WNP authority to achieve successful management of conservation areas.

Map produced from this research is one form of application of integration of local ecological knowledge with remote sensing. This method of Kaledupa Island in general increases the recognition that social and ecological systems combined with remote sensing appropriately lead to better planning and management of conservation areas. Participatory techniques will bring up the idea of adaptive planning to achieve the effectiveness of conservation area management [19] because it always adapts to the local wisdom of each region.

4. Conclusion

Shallow water marine habitat mapping can be produced by integration multispectral image classification with traditional ecological knowledge. For its supervised classification, this hybrid method may be done with Mahalanobis and Maximum Likelihood. This approach can be accounted for scientifically. Mahalanobis is proven by the value of overall accuracy of 71.67%; kappa coefficient 0.62%. Whereas the map produced from the Maximum Likelihood, the overall accuracy is 73.33%; kappa coefficient 0.65%. The accuracy values obtained from this study are higher than those of Lauer and Aswani [21] conducted in Lagoon Roviana, Solomon Island. The results of the study obtained 64.5% overall accuracy; kappa coefficient 0.53%.

The results of this study indicate that remote sensing methods that use a hybrid approach can provide useful outputs for coastal managers to assess marine resources and design conservation areas [6]; [21]; [27]. A hybrid approach, in participatory remote sensing provides great opportunities to be a relevant and effective method. This method will continue to increase in coastal resource research and management. Although not always appropriate, this method can help bridge the gap between scientists and local communities and encourage management of coastal ecosystems or ecosystems that are socially acceptable and sustainable.

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