COASTAL HABITATS MAPPING USING ALOS AVNIR-2 SATELLITE DATA

Nadiah N.Y.[a], Ibrahim M.[a], Samsudin A.[a], and Komatsu T.[b]

[a] Department of Remote Sensing, Faculty of Geoinformation and Real Estate,
Universiti Teknologi Malaysia, 81310 Johor Bahru, Malaysia
Tel: +6016-7151410. Email: nnadiah247@yahoo.com
Tel: +607-5530906. Email: mism@utm.my
Tel: +607-5530662. Email: sam@utm.my

[b] Atmosphere and Ocean Research Institute, University of Tokyo, Tokyo 164-8639, Japan
Tel: +81-(0)4-7136-6222. Email: komatsu@aori.u-tokyo.ac.jp

KEY WORDS: Remote Sensing, Depth Invariant Index, Bottom Reflectance Index, Sibu Island

ABSTRACT: Remote sensing provides information about the distribution of coastal habitat types such as coral reef, seaweed and seagrass up to a certain depth depending on the capability of the sensor itself. A study was carried out in Sibu Island, Malaysia to classify different coastal habitats based on ALOS AVNIR-2 satellite data acquired on 29 July 2008. Sibu Island was selected due to the obvious annihilation of the seaweed, seagrass and coral reef. Two methods namely depth invariant index and bottom reflectance index were applied in order to extract different types of coastal habitat. The depth invariant index method used the relationship between bottom surface reflectance and the radiance measured by the satellite. However, bottom reflectance index method used the combination of water depth and attenuation coefficient. The sea truth data that was acquired on 18 August 2008 was obtained to verify whether particular coastal habitats exist. A direct observation by diving was carried out to determine the various coastal habitats. Density slicing of different index ranges was made for both methods. A direct comparison of overall accuracy and Tau coefficient between both methods revealed that bottom reflectance index method provides accurate mapping with an accuracy of 66% and Tau coefficient of 0.57 while depth invariant index gives 62% accuracy and 0.52 Tau coefficient. Although depth invariant index method provides lower accuracy, it is still a very useful method for the classification of seagrass, as it allows small patch of seagrass distribution to be mapped.

1. INTRODUCTION

The coastal zones cover the boundary of land and water. These zones are very significant to the ecosystem of the marine environment and it comprises sandy beaches, rocky shores, seagrass, seaweed, coral reef and others. Remote sensing has long been used as a tool to study coastal habitats and it has proven its potential in identifying different types of habitats. Satellite images have been widely used and have gained more popularity since they provide large area coverage and are less time consuming. Numerous studies had been made to study and map the marine habitats using various techniques utilizing a variety of satellite images (Lyzenga, 1981; Mumby et al., 1997; Levings et al., 1999; Hashim et al., 2001; Sagawa et al., 2008 and Kakuta et al., 2010). The results depend on the quality of satellite images, spectral and spatial resolution of the satellite sensor, techniques used and water quality of the study area itself. In order to improve accuracy, researchers proposed variety of techniques and algorithms to identify the existence and distribution of coastal habitats (Lyzenga, 1981; Vanderstraete et al., 2004 and Sagawa et al., 2010).

Sagawa et al. (2010) mapped seagrass beds over Funakoshi Bay, Japan and Mahares, Tunisia using depth invariant index and proposed a new method called bottom reflectance index using IKONOS imagery. The bottom reflectance index had been developed since the depth invariant index is efficient for high clarity waters (Jerlov water type I to II) but not for low clarity water (Jerlov water type II to III). The depth invariant index used ratios of attenuation coefficients between bands while bottom reflectance index combines the water depth and attenuation coefficient. The results show that the accuracy over Mahares using depth invariant index was 54% while the accuracy for bottom reflectance index was 90%. The accuracy over Funakoshi Bay using depth invariant index was 61.7% whereas the accuracy using bottom reflectance index was 83.3%. The results showed that bottom reflectance index gives better accuracy than depth invariant index for low clarity water.

In this paper, both techniques have been used over Sibu Island, Johor using ALOS AVNIR-2 imagery. The results obtained were validated based on sea truth that was carried out on 18 August 2008. In order to determine the best technique; overall accuracy, kappa coefficient and tau coefficient were computed.

2. STUDY AREA

The study was carried out in Sibu Island, Johor (Figure 1). Sibu Island is located at latitude of 2^{o} 12’ North and 104^{o} 5’ East. This area was selected due to the obvious annihilation of the seaweed, seagrass and coral reef.

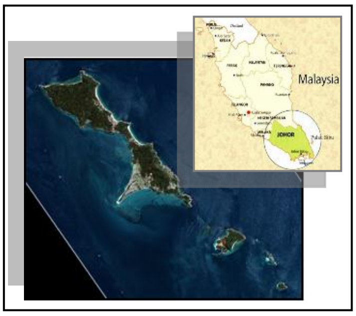


Figure 1: Location of the study area of Sibu Island, Malaysia

3. DATA AND METHODOLOGY

This section presents the data sources and materials used which includes satellite data and ancillary data. The methodology used is also described in detail.

3.1 Satellite and Ancillary Data

The AVNIR-2 (Advanced Visible and Near Infrared Radiometer type 2) data from ALOS (Advanced Land Observing Satellite) was acquired on 29 July 2008 at 11.54 am (local time). The ALOS AVNIR-2 multispectral image has four bands (blue, green, red and near-infrared), each with 10 m spatial resolution.

The ancillary data utilized were observed sea truth data, topographic map and hydrographic chart. The sea truth was done on 18 August to obtain the ground coordinates of the ground control points, sea truth points and location of boundary points for different marine habitats. On the other hand, topographic map was used to extract geographical coordinates to carry out geometric correction of the satellite image. Finally, hydrographic chart was used to obtain water depth and types of marine habitats.

3.2 Methodology

The methodology of this study is illustrated in Figure 2. Similar pre-processing of the image was applied separately for the two different techniques i.e. depth invariant index and bottom reflectance index. Both results were classified by density slicing and supervised classification.

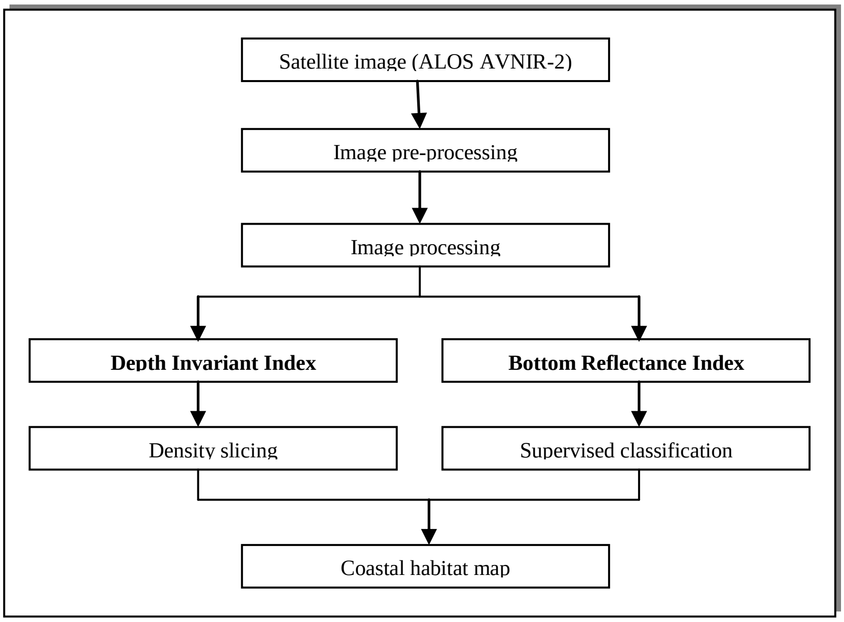


Figure 2: Methodology of both techniques

3.2.1 Depth Invariant Index

In this method, according to Lyzenga (1981) the technique for identifying sea bottom type information relies upon the fact that bottom reflected radiance is nearly a linear function of the bottom reflectance and an exponential function of the water depth. Hence, the measured radiances are transformed according to the following equation below,

$$X_i = \mathrm{Ln}\,(L_i - L_{si})$$
$$X_j = \mathrm{Ln}\,(L_j - L_{sj}) \qquad \text{(Equation 1)}$$

where,

L_i and L_j = the measured radiance in band i and band j
L_{si} and L_{sj} = the deep water radiance in band i and band j
X_i and X_j = bottom reflected radiance in band i and band j

In this study, two visible bands were used which are band 1 (0.42-0.50 μm) and band 3 (0.61-0.69 μm). This is because the bottom recognition processing is determined by a trade-off between depth of penetration and sensitivity to reflectance changes. The sensitivity to changes in bottom reflectance is largest for bands having the greatest difference in attenuation coefficients. In this case, band 1 has maximum depth penetration while band 3 has a good compromise between sensitivity to reflectance changes and penetration depth. A graph of X_i versus X_j was plotted in order to obtain the slope of K_i and K_j, where K_i and K_j are the attenuation coefficient of water in bands i and j respectively. This graph will give a linear relationship for each bottom type. By calculating the total displacement, a change in bottom reflectance can be identified although the water depth is unknown. The depth invariant index is given below,

$$Y_i = \frac{[\,K_j \ln (L_i - L_{si}) - K_i \ln (L_j - L_{sj})]}{\sqrt{(K_i^2 + K_j^2)}} \qquad \text{(Equation 2)}$$

where,

Y_i = depth invariant index
K_i and K_j = the attenuation coefficients for band i and band j.

3.2.2 Bottom Reflectance Index

Sagawa et al. (2010) proposed an alternative radiometric correction to enhance mapping precision called bottom reflectance index. This index is linearly related to bottom reflectance. This index enables to compare not only the difference in reflectance ratios between bands but also the difference in absolute reflectance for each band. The bottom reflectance index is presented by the following equation below,

$$BRI = \frac{(\,L_i - L_{si}\,)}{(\exp(\,-K_i g Z\,))} \qquad \text{(Equation 3)}$$

where,

L_i = measured radiance in band i
L_{si} = deep-water radiance in band i
K_i = attenuation coefficient for band i
g = geometric factor to account for the path length through the water
Z = water depth (m)

In this technique, depth data should be combined with attenuation coefficients. The attenuation coefficient value for each band was obtained by computing an exponential graph between radiance value and water depth. In order to calculate this index, water depth was obtained from a hydrographic chart published by the National Hydrographic Centre while *g* can be calculated from sun and satellite zenith angles obtained from header file of satellite scene. For this method, only band 1 (0.42 μm – 0.5 μm), and band 2 (0.52 μm – 0.60 μm) were used. Since band 1 has short wavelength, it penetrates depths better than other bands while the function of band 2 is quite similar to band 1 but it is not as good as band 1. These two bands were selected because this technique depends on depth and these two bands are reliable for depth penetration.

4. RESULTS

This section presents the results of coastal habitat mapping from ALOS AVNIR-2 satellite data using depth invariant index and bottom reflectance index techniques.

4.1 Depth Invariant Index

This sub-section shows the results of depth invariant index technique over Sibu Island. The graph of measured radiance of band 1 and band 3 were plotted in order to calculate the ratio of attenuation coefficient. The slope of the graph represents the ratio of attenuation coefficient and this value was used to calculate the depth invariant index image (Figure 3). Figure 4 shows the depth invariant index image. Density slicing was applied to the image to represent different types of marine habitat as shown in Figure 6(a). The related error matrix is displayed in Table 1(a) and it shows 62% correctly classified pixels.

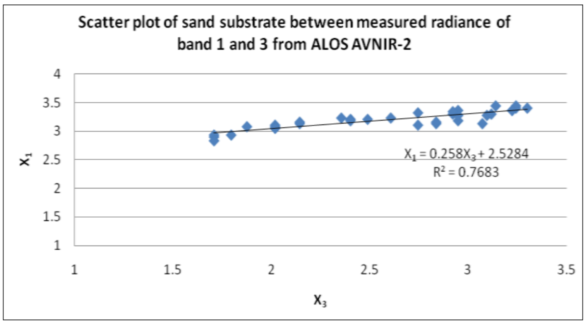
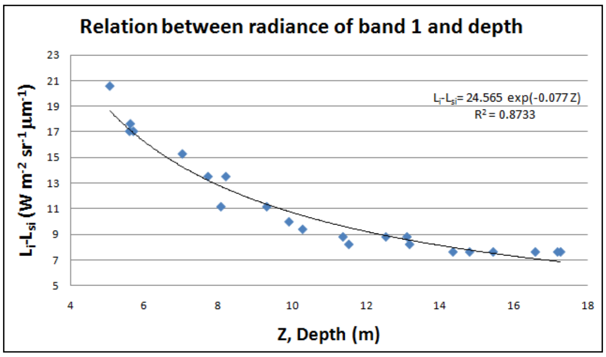


Figure 3: Graph of X_1 versus X_3

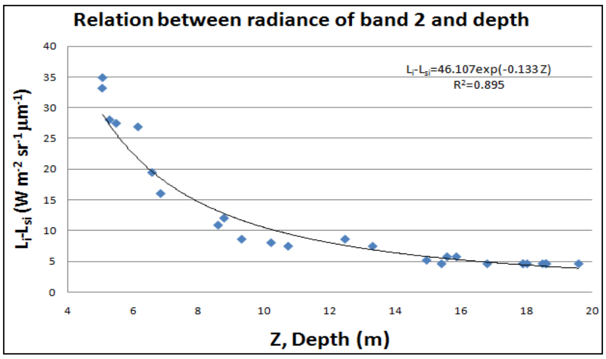
Figure 4: Depth invariant index image

4.2 Bottom Reflectance Index

The depth used to derive bottom reflectance index itself is not accurate without consideration of tidal height. The tidal height at the time of the satellite pass over the study area at 11.54 am was 2 m. After obtaining the K_i value (Figure 5(a) and (b)), bottom reflectance index was computed for bands 1 and 2 separately. A supervised classification based on maximum likelihood method was performed in order to classify marine habitats as shown in Figure 6(b). The accuracy of this result is shown in Table 1(b) and indicates higher accuracy (66%) than the previous technique.

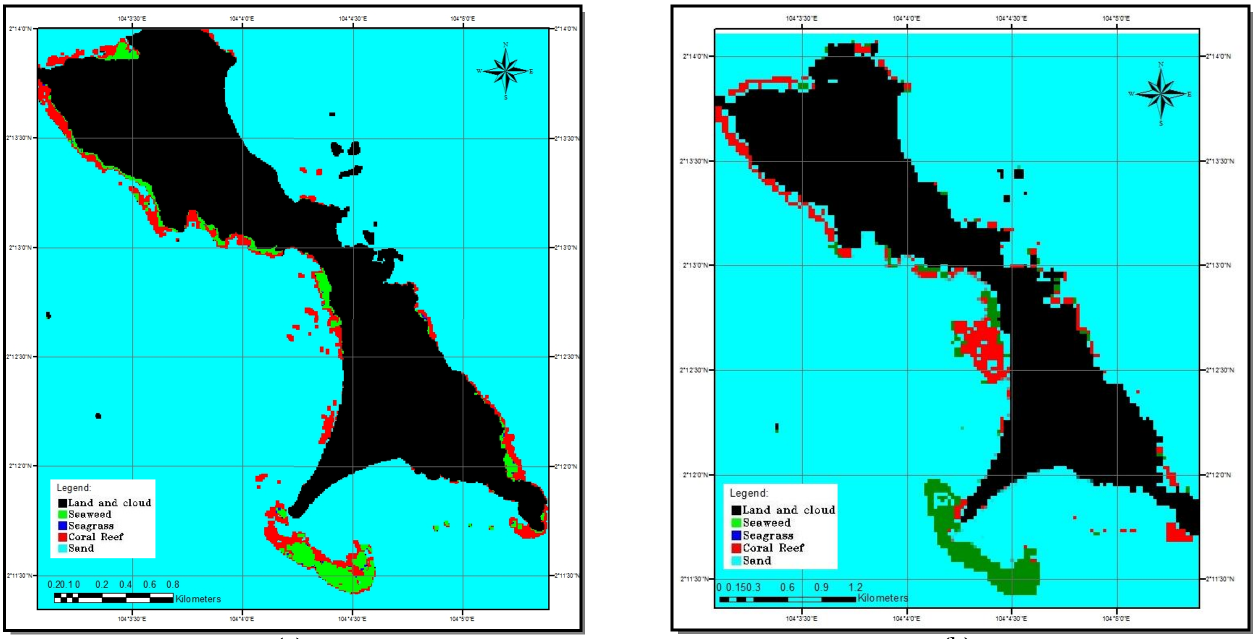


(a) Blue



(b) Green

Figure 5: Relation between radiance and depth for (a) blue and (b) green bands for ALOS AVNIR-2 satellite data



(a) (b)

Figure 6: Maps derived from ALOS AVNIR-2 imagery of Sibu Island. Black areas indicate land and cloud that have been masked out. The maps were obtained by applying two different techniques which are (a) depth invariant index and (b) bottom reflectance index.

Table 1: Error matrices for satellite image classification using (a) depth invariant index and (b) bottom reflectance index

(a)

		Classification					User Accuracy
		Seaweed	Seagrass	Coral	Sand	Total	
Sea Truth	Seaweed	49	1	19	37	106	71%
	Seagrass	0	0	0	6	6	0%
	Coral	10	0	65	39	114	71%
	Sand	10	0	8	100	118	55%
	Total	69	1	92	182	344	
Producer Accuracy		46%	0%	57%	85%		
Overall Accuracy			62%				
Kappa Coefficient			0.43				
Tau Coefficient			0.52				

(b)

		Classification					User Accuracy
Sea Truth		Seaweed	Seagrass	Coral	Sand	Total	
	Seaweed	76	0	13	17	106	80%
	Seagrass	0	0	4	2	6	0%
	Coral	15	0	59	40	114	60%
	Sand	4	0	23	91	118	61%
	Total	95	0	99	150	344	
Producer Accuracy		72%	0%	52%	77%		
Overall Accuracy			66%				
Kappa Coefficient			0.49				
Tau Coefficient			0.57				

5. DISCUSSION

Accurate classification was possible using ALOS AVNIR-2 data by using depth invariant index or bottom reflectance index. The overall accuracy, kappa coefficient and tau coefficient for bottom reflectance index method improved as water depth information was taken into account. The tau coefficient value was higher than kappa coefficient for both techniques which implies that kappa coefficient underestimated classification accuracy.

Sagawa et al. (2010) succeeded in getting better results and higher accuracy when using bottom reflectance index method (83.3% for Funakoshi Bay and 90% for Mahares) compared to depth invariant index (61.7% for Funakoshi Bay and 54% for Mahares) when using IKONOS imagery. In the Sibu Island study, the accuracy of bottom reflectance index is also higher than depth invariant index. The water transparency of Sibu Island is not so clear and gives better results when applying bottom reflectance index. The depth invariant index technique gives slightly less accuracy since the water is not so clear.

Although the depth invariant index gives slightly lower accuracy, it still enables small areas of seagrass to be mapped eventhough the error matrix shows 0% accuracy for seagrass. This is due to lack of sea truth measurements for seagrass areas. More sea truth measurements are required to verify these pixels. Figure 7 shows the distribution of seagrass patches at the southern part of the island using depth invariant index technique. The bottom reflectance index technique was not able to distinguish seagrass habitat in this study area.

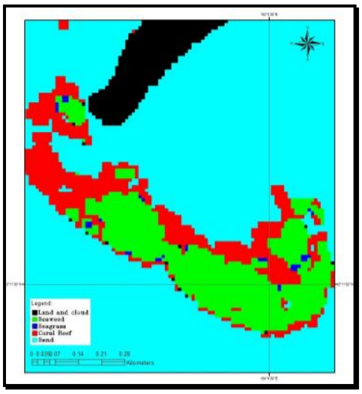


Figure 7: The result of depth invariant index method focusing at the southern part of Sibu Island with distribution of seagrass habitat (blue colour)

6. CONCLUSION

In this study the coastal habitats over Sibu Island was mapped with ALOS AVNIR-2 using two different techniques. In particular, the results that were derived from depth invariant index and bottom reflectance index are very encouraging. The overall accuracies attained are 62% and 66% respectively. Since the water clarity is slightly low, the bottom reflectance index technique is giving higher accuracy than depth invariant index technique. The existing sea truth data is not sufficient to make a conclusive decision. It can be improved if more sea truth was carried out to verify the distribution of each habitat accurately. Both techniques might also give better results by using higher spectral and spatial resolution satellite data.

REFERENCES

Hashim M., Rahman R. A., Muhammad M. and Rasib A. W., 2001. Spectral Characteristics of Seagrass with Landsat TM in Northern Sabah Coastline, Malaysia. Proceedings of 22nd Asian Conference on Remote Sensing, 5-9 November 2001, Singapore.

Kakuta S., Hiramatsu T., Numata Y., Yamano H. and Aramaki M., 2010. Satellite-Based Mapping of Coral Reefs in East Asia, Micronesia and Melanesia Regions. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, Volume XXXVIII, Part 8, Kyoto, Japan.

Levings C. D., North M. S., Piercey G. E., Jamieson G. and Smiley B., 1999. Mapping Nearshore and Intertidal Marine Habitats with Remote Sensing and GPS: The Importance of Spatial and Temporal Scales. OCEANS apos; 99 MTS/IEEE, 3, 1249 – 1255.

Lyzenga D.R., 1981. Remote Sensing of Bottom Reflectance and Water Attenuation Parameters in Shallow Water Using Aircraft and Landsat Data. International Journal of Remote Sensing, 2 (1), 71-82.

Mumby P. J., Green E. P., Edwards A. J. and Clark C. D., 1997. Measurement of Seagrass Standing Crop Using Satellite and Digital Airborne Remote Sensing. Marine Ecology, 159, 51-60.

Sagawa T., Boisnier E., Komatsu T., Mustapha K.B., Hattour A., Kosaka N. and Miyazaki S., 2010. Using Bottom Surface Reflectance to Map Coastal Marine Areas: A New Remote Sensing Method. International Journal of Remote Sensing, 31:12, 3051-3064.

Sagawa T., Mikami A., Komatsu T., Kosaka N., Kosako A., Miyazaki S. and Takahashi M., 2008. Mapping Seagrass Beds Using IKONOS Satellite Image and Side Scan Sonar Measurements: A Japanese Case Study. International Journal of Remote Sensing, 29, 281-291.

Vanderstraete T., Goossens R. and Ghaboir T. K., 2004. Coral Reef Habitat Mapping in the Red Sea (Hurghada, Egypt) Based on Remote Sensing. EARSel eProceedings, 3 (2).