

The Study of Sea Bottom Morphology and Bathymetric Mapping Using Worldview-2 Imagery

Iwan E. Setiawan

Badan Informasi Geospasial, Cibinong, Indonesia

Doddy M. Yuwono

Badan Informasi Geospasial, Cibinong, Indonesia

Vincentius P. Siregar

Institut Pertanian Bogor, Bogor, Indonesia

Gatot H. Pramono

Badan Informasi Geospasial, Cibinong, Indonesia

Abstract

Benthic habitat identification is highly associated with reef or sea bottom morphology. Penetration of multispectral bands gives benefits to identification of sea bottom morphology which could be improved by bathymetric mapping. The purpose of this study is to improve methodology of the sea bottom morphology and bathymetric mapping using Worldview-2 imagery. Sea bottom morphology mapping can also assist identification of benthic habitat in the shallow water. The approach of this study is by using several image transformations assisted by depth in situ measurement. In addition, some image classifications and transformations are also used to improve the sea bottom morphology and bathymetric mapping. The study site is around Panggang Island, Jakarta. The result of this study shows that image-based bathymetric estimation model provides best accuracy among others with varied shallow-water bottom morphology with highest R^2 of 0.711 and depth residual at 0.538 m. The result accuracy is assessed by using information from depth in situ measurement.

1. Introduction

Shallow water in tropical coastal area is a good habitat for coral reef and seagrass. In ecosystem, either coral reef or seagrass plays an important role as nursery ground for some fish species, stabilizing and protecting coastal area from destructive wave energy.

In oceanography, shallow water means an area ranges from coastline to 200 meters below the sea surface. This specific definition of shallow water is delimited by the use of light penetration and sensor technology especially in remote sensing. Based on multispectral sensor used in remote sensing technology, electromagnetic spectrum penetrates shallow water up to 20 or 30 meter below sea surface in clear water condition.

According to Nugrahadi (2010) in Guntur *et al.*, (2012), remote sensing technology is able to penetrate water column and identify shallow water objects. In other words, if there is no electromagnetic spectrum can penetrate water column, there is no information about shallow water object can be derived. Moreover, Sutanto (1992) stated that multispectral sensor, especially green and

blue band, can penetrate up to 20 meter below the sea surface in a clear water condition. It is known that electromagnetic spectrum penetration also varies and depends on water clarity conditions. Guntur *et al.* (2012) argued that higher water turbidity results in less electromagnetic spectrum penetration through water column.

In many studies, green and blue bands are the most used multispectral band in shallow water habitat mapping. One of them is Lyzenga *et al.* (2006) who used green and blue bands to extract bathymetric information of shallow water habitat.

Stumpf *et al.* (2003) developed different method to enhance bathymetric information of shallow water using bottom albedo-independent bathymetry algorithm. Calibration of relative water depth resulted by this algorithm was done by using a set of groundtruth points.

Based on several research, it is informed that spectral number detected by remote sensor is highly influenced by type of sea-bottom substrate, depth or water column, and water quality properties. Theoretically, when light or electromagnetic spectrum penetrates water column, its intensity will

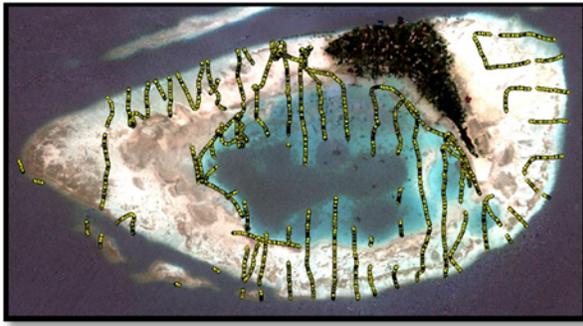


Figure 3. Worldview-2 image with sounding distribution

In addition, GPS MapSounder was also used to collect depth information for calibrating the Worldview-2 bathymetry information derived from image transformation. To calibrate depth information with real time tidal condition when image and depth information were taken, this research used real time data from BIG's tide station located on Pondok Dayung and Kolinlamil (Tanjung Priok).

2.3. Data Processing

There are several steps before Worldview-2 image can be analyzed. The first step is image pre-processing which is consisted of geometric correction, atmospheric correction, and glint removal. Second, image processing based on each depth estimation model. The first image model is image difference using band 1 vs. band 4, band 4 vs. band 6 and band 1 vs. band 5. The second is data processing using common depth-estimation algorithm developed by Lyzenga *et al.* (1978 and 2006). This algorithm is also known as depth invariant index.

Last, Worldview-2 image was processed using bottom albedo-independent bathymetry algorithm developed by Stumpf and Holderied (2003). Deeper analysis will be presented in the discussion by comparing all those image transformation/algorithm, and also compared to real depth measurement derived from GPS MapSounder.

2.3.1 Pre-processing

As mentioned above, geometric correction was done by ground control points that were collected using GPS receiver in April 2013. The margin error resulted from geometric correction is around 2 meter. Atmosphere and sea surface condition when image was taken is important to determine the degree of image correction. In this research,

Worldview-2 image atmosphere and sea surface condition is categorised as clear since there are no haze or even clouds. Sea surface condition of the image is influenced by ship activities and moderate waves causing glint effect surrounding the study area.

Atmospheric and glint removal were done at once since visual quality of the image is reasonable. The process was done only for glint removal using basically identical equation with atmospheric correction. Worldview-2 image before and after correction can be seen in Figure 4.

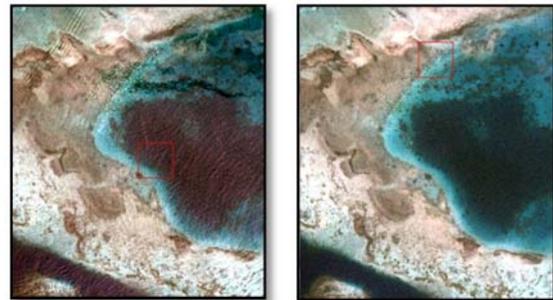


Figure 4. Image before (left) and after (right) glint removal

2.3.2 Image Difference Ratio

Image difference is commonly used in vegetation analysis to enhance or extract vegetation properties, such as chlorophyll, age, or even biomass (Gao, 2009). In vegetation remote sensing analysis, a well-known image difference is Normalized Difference Vegetation Index (NDVI). For shallow-water bottom mapping, this image difference ratio has been demonstrated by Collin *et al.* (2012). This research tried to apply the same concept of image difference to sea bottom object. Sea bottom object has higher reflectance in coastal blue and blue band while sea bottom object has lower peak reflectance in red or NIR band. The image difference ratio bands should have both higher and lower reflectance of sea bottom object. Thus, it used the combination of coastal blue and yellow band, yellow and red-edge band, and coastal blue and red band. Equation to produce image difference ratio is:

$$\text{Image difference} = \frac{(\text{band } W_i - \text{band } W_j)}{(\text{band } W_i + \text{band } W_j)}$$

in which W_i is yellow or red-edge or red band, W_j is coastal blue or yellow band.

2.3.3 Depth-estimation Algorithm

The first image algorithm assessed in this research is Lyzenga *et al.* (1978 and 2006). The basic concept of the algorithm is enhancing shallow-water bottom habitat by omitting water column effect, called water-attenuation. Lyzenga *et al.* (1978 and 2006) used green and blue band as the best band-combination in enhancing shallow-water bottom habitat. Then, image algorithm was done using the following equation:

$$Y = (\ln \text{Band1}) - (k_i/k_j * \ln \text{Band2})$$

Lyzenga *et al.* (2006) tried to overcome and calibrate the variation of water attenuation by developing more complicated equation. However, this research used a simple linear equation to calibrate the estimated depth information from Lyzenga using real depth measurement derived from GPS MapSounder. This step is considered effective because it is quick and shows the agreement between estimated and real data.

2.3.4 Bottom Albedo-independent Bathymetry Algorithm

The use of bottom albedo-independent bathymetry algorithm developed by Stumpf and Holderied (2003) is also demonstrated by Lyons *et al.* (2011). This algorithm uses a ratio of observed reflectance and two constants to derive depth information. Using real depth measurements, relative water depth derived from the algorithm was calibrated to obtain absolute water depth. Formula for calculating relative depth based on Stumpf and Holderied (2003) is:

$$Z = m1 \frac{\ln nRw(\lambda_i) - m0}{\ln nRw(\lambda_j)}$$

In which Rw is the observed reflectance of the wavelength (λ) for bands i and j , $m1$ and $m0$ are constants.

2.3.5 Real Depth Measurement

Depth measurement obtained from shallow water sounding was used for both calibration and produced shallow-water bottom surface DEM. Total points of real depth measurement is 24,844 points, 70% of which is used for calibrating the depth estimation in each model. Remaining points are used for accuracy assessment which is mainly based on R^2 calculation and residual depth data.

Using sounding data, shallow-water bottom surface derived from krigging model was created in specific grid spacing comparable to Worldview-2 pixel size and median filter which are applied in depth estimation model. This step is intentionally to

do in order to reduce horizontal error between real depth data and estimation model.

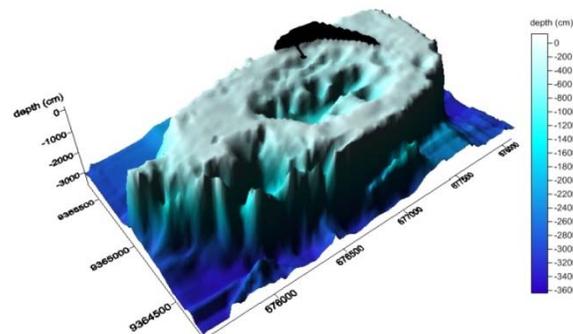


Figure 5. Krigging method was used to obtain shallow-water bottom surface DEM.

2.3.6 Median Filter

Median filter was applied to obtain fine image result or reduce high frequency noise resulting from estimation model. This research applied 4 median filters to each estimation model. The median filters used in this research are: kernel 3×3 , 5×5 , 7×7 , and 15×15 .

Result from each estimation model is expected to reduce high difference between pixel values in their neighbourhoods. Thus, pixels in neighbouring area could have approximately similar value. However, smoothing over neighbouring pixels could have smoother result and even omitting small shallow-water bottom object (ENVI, 2005).

3. Results

Each estimation model was calibrated using 70% of the real depth measurement data derived from MapSounder. From image difference ratio processing, there are three combination bands resulting three depth estimation models. The three combination bands are coastal blue vs. yellow, coastal blue vs. red, and yellow vs. red-edge. Image difference ratio band combination resulted in low R^2 of the linear model respectively: 0.568, 0.507, and 0.465. This model was run in median filter using kernel 3×3 .

Based on simple linear model above mentioned, the best band combination is between coastal blue and yellow bands. In the next step, this image difference ratio was processed using other median filters such as kernel 5×5 , 7×7 , and 15×15 . As a result, the linear model with R^2 of 0.571, 0.577, and 0.578 was produced. Chosen model with the best R^2 was used to produce bathymetric image.

However, the main purposes of this research are studying benthic habitat morphology and bathymetric mapping thus data quality should be assessed in terms of thematic and bathymetric accuracy. As we know, that median filter using

kernel 15x15 might be omitting important benthic habitat information even though it is giving best fit of the model. To meet two research purposes, all of image difference ratio results using 4 different median filters (R^2 of 0.568, 0.571, 0.577, and 0.578) were assessed.

Insignificant results were showed by depth-estimation algorithm (Lyzenga *et al.*, 1978). Based on the four different median filter processes, linear model resulted from this algorithm showed poor R^2 . This finding was contradictory with results by Lyon *et al.* (2011) who showed a good R^2 in linear model. The R^2 resulted from linear model based on each median filters respectively are: 0.0595, 0.0591, 0.0588, and 0.0586. Thus, for following processes and analyses, this algorithm will not be presented.

The last model was bottom albedo-independent bathymetry algorithm developed by Stumpf and Holderied (2003). There are two models demonstrated using this algorithm, i.e. linear and non-linear model. Worldview-2 bands used in this process are coastal blue and yellow bands. This is the best band combination used for bottom albedo-independent bathymetry algorithm as compared to blue and red banda.

Both linear and non-linear model resulting from bottom albedo-independent bathymetry algorithm have slightly similar R^2 value. However, the best fit model was generally shown by non-linear model specifically using median filter kernel 15x15. Complete R^2 resulting from linear and non-linear models is shown in the Table 1.

Table 1. R^2 resulting from linear and non-linear model

Model	3x3	5x5	7x7	15x15
Linear	0.587	0.592	0.595	0.597
Non-linear	0.670	0.684	0.693	0.700

Shallow-water bottom surface derived from krigging model used as a bathymetric reference for above mentioned estimation model was also created in various grid spacing ranges from 2 up to 30 meter. Based on visual observation of the resulted DEMs, grid spacing determines the model smoothness. Wider grid spacing produces smoother model. However, in terms of accuracy, R^2 value showed different result. Wider grid spacing produces lower R^2 value. This R^2 value is calculated as accuracy assessment using 30% of the total real depth measurement data. Moreover, DEM with narrow grid spacing showed unrealistic view compared with the wider one. In general, all of R^2 derived from krigging model to build surface DEM is very satisfying with values above 0.900.

4. Discussion and Conclusion

Sea (shallow-water) bottom morphology and bathymetric mapping could not be analyzed separately. Shallow-water bottom morphology identification needs depth information to identify the roughness of the bottom surface. Shallow-water morphology is important to address information about benthic habitat. Therefore, it needs both depth information and thematic information of the bottom surface. Accurate bathymetric and thematic information is essential for enhancing benthic habitat identification using image.

Shallow-water bottom surface derived from krigging model is a proper way to obtain accurate depth information (with all R^2 value above 0.900). However, it loses a lot of bottom surface morphological detail which is important in benthic habitat identification.

On the other hand, image-based bathymetric derived information showed moderate to poor accuracy (with R^2 value range from 0.700 to 0.500). The bathymetric accuracy is determined by R^2 and average residual depth data. The comparison of accuracy between shallow-water bottom surface derived from krigging model and image-based bathymetric derived information can be seen in Table 2.

Table 2. R^2 and average residual depth data from each selected model

Model	3.3	res	5.5	res	7.7	res	15.15	res
IDR	.579	.674	.583	.671	.586	.667	.590	.664
Lin Z	.625	.475	.606	.498	.607	.498	.607	.502
NLin Z	.714	.805	.707	.724	.710	.644	.711	.538
DEM	.998	.222	.992	.456	.996	.394	.963	1.145

in which

- IDR : image difference ratio
- Lin Z : bottom albedo-independent bathymetry algorithm (linear model)
- NLin Z : bottom albedo-independent bathymetry algorithm (non-linear model)
- DEM : krigging model to build bottom surface DEM
- res : average residual depth data

As seen on Figure 6 and 7, krigging model profile (DEM) has smooth and straight profile line. The depth difference starts to increase when reach below -2 depth. Except DEM profile, profile lines derived from image-based bathymetric data show fluctuated depth data. This is due to the estimation model which is taking into account pixel or digital number of the image. It means that image-based

bathymetric derived information provides more varied shallow-water bottom morphology. Shallow-water bottom surface derived from krigging model tends to interpolate or connect real depth information without considering pixel or digital number. Figure 8 shows the resulted bottom profiling.

Figure 9 shows the difference between shallow-water bottom surface derived from krigging model and image-based bathymetric data in representing shallow-water bottom surface morphology. DEM of shallow-water bottom surface derived from krigging model shows unrealistic surface compared to DEM of image-based bathymetric estimation model since the lack of field measurement data. This weakness could be reduced by using pixel or digital number in image-based bathymetric estimation model.

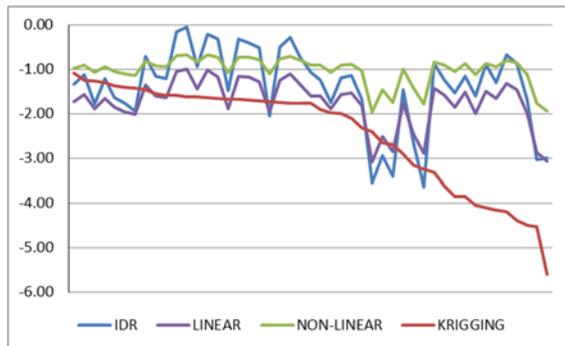


Figure 6. Line profile of each estimation model (median filter kernel 3x3)

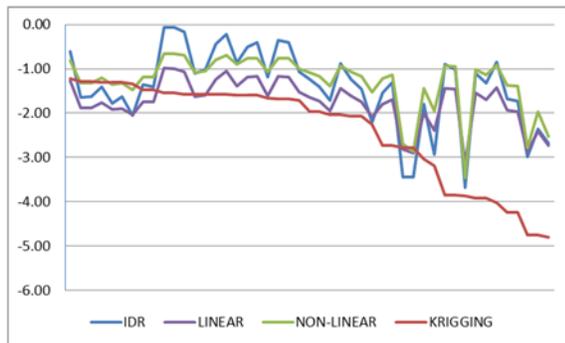


Figure 7. Line profile of each estimation model (median filter kernel 15x15)

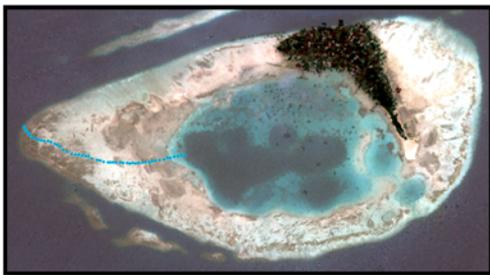


Figure 8. Blue line is a line graph for bottom profiling

As an important note, detailed shallow-water bottom surface morphology represented by image-based bathymetric data still needs to be enhanced and verified on the field. It is because the depth residual of the estimation model is still around 0.5 to 1 meter, which means that shallow-water bottom morphology illustrated by the model is not really representing real detail morphology on the field. This is an important aspect in distinguishing between coral cover and rubble. Finally, the interpreters still have to recognise those two difference morphology by its spectral reflectance (digital number).

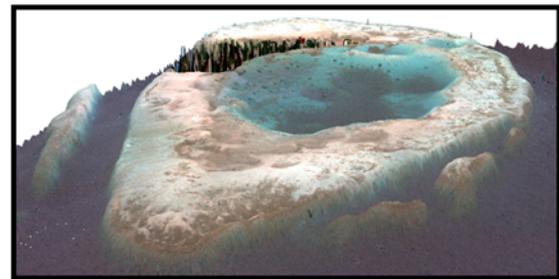
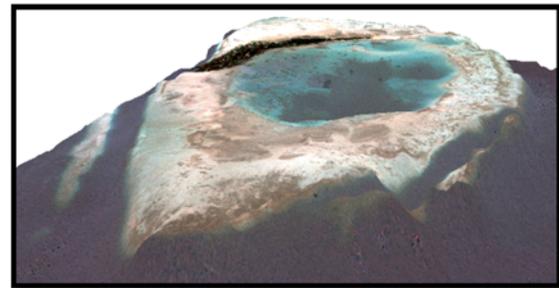


Figure 9. DEM derived from krigging model (above) and image-based bathymetric estimation model using non-linear median filter (below).

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