Comparison of Satellite-Derived Bathymetry Algorithm Accuracy Using Sentinel-2 Multispectral Satellite Image

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Abstract

The utilization of satellite image data and image data processing techniques has become an efficient alternative to obtain bathymetric data in a broad and complicated area. This study aimed to determine the algorithm's performance in the waters of Lambasina Island. Atmospheric and radiometric correction using the Dark Object Subtraction (DOS) method for initial processing of Sentinel-2 images. The multispectral channel used, namely the blue, green, and red bands, was tested by regression using field observation data. The algorithms used to estimate bathymetry include Lyzenga, Stumpf, and Support Vector Machine (SVM). The test results of the three algorithms showed that the support vector machine algorithm was the best algorithm for estimating bathymetry after the Stumpf and Lyzenga algorithms. The correlation results of the SVM algorithm in the waters of the small Lambasina island got a correlation coefficient of determination R^2 = 0.81 and the large Lambasina waters area R^2 = 0.82. The second-best algorithm was Stumpf, with a correlation coefficient of determination of R^2 = 0.79 in the waters of the small Lambasina island and R^2 = 0.80 in the waters of the large Lambasina island. Lyzenga's algorithm got the correlation coefficient of determination R^2 = 0.78 on small Lambasina Islands and large Lambasina Islands with a determination correlation coefficient value of R^2 = 0.79.

Keywords: *bathymetry, Lyzenga, remote sensing, Stumpf, Support Vector Machine*

INTRODUCTION

Bathymetric data is an essential source of information in understanding marine environmental conditions. Bathymetry data is also a starting point for coastal area management based on seabed surface conditions. Remote sensing has an essential role in obtaining information about the condition of the marine environment, and the ability to obtain bathymetric data using wavelengths is an exciting topic in coastal observation and research (Mynett and Vojinovic, 2009; Vojinovic, 2015). The utilization of remote sensing technology applications in coastal and marine areas is one of the key elements used for research and resource and environmental management purposes (Kuffner *et al*., 2007). The ability of sunlight to penetrate the air column to a certain depth is the advantage of remote sensing for conducting studies on the column to the bottom of shallow water.

The potential use of remote sensing satellite data has been used for mapping and monitoring coastal areas (Moradi and Kabiri, 2015; Kay *et al*., 2009). In this regard, multispectral satellite imagery has been widely used to estimate depth in shallow waters (Doxani *et al*., 2012; Deng *et al*., 2008; Siregar and Selamat, 2010). Lyzenga (1978) was the first to develop a linear transformation method for estimating depth values using multispectral satellite imagery. This method can affect the variation of the base type at the specified depth value. Then Stumpf *et al*. (2003) proposed a new transformation ratio method, which has a greater ability to estimate depth values in deeper areas. Several studies have estimated shallow water depths using multispectral satellite imagery, including Landsat 8 (Vinayaraj *et al*., 2016) and Sentinel-2 (Hedley *et al*., 2018). By using Landsat-OLI data, bathymetry extraction has been carried out by several researchers (Pacheco *et al*. (2015); Jagalingam *et al*. (2015); Vinayaraj *et al*. (2016); Pushparaj and Hegde (2017). According to Manessa *et al*. (2016), the bathymetry estimation method using SPOT 6/7 data has also been carried out by several researchers Arya *et al*. (2016) and Manessa *et al*. (2016).In Indonesia, the use of the method of estimating water depth through satellite imagery by applying the method Lyzenga is Arya *et al*.

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(2016) in Teluk Belang Mamuju using SPOT 7 imagery and Subarno *et al*. (2015) using Stumpf *et al*. (2003) in Kelapa-Harapan Island using Worldview-2 imagery. Several algorithms to estimate the depth of water have been studied and developed (Misra *et al*., 2018; Vojinovic *et al*., 2013) have developed a machine learning algorithm, namely a support vector machine (SVM) for estimating water depth, and used to improve the performance of ratio transformation models.

The Sentinel-2 satellite is equipped with a multispectral channel with 13 spectral channels. Differences in wavelength and spectral resolution cause the difference in spectral response in each satellite imagery channel. Lower albedo variations in the water column will also respond differently to reflected electromagnetic waves. Generally, shallow water depth estimation uses the single band method (Lyzenga), and channel ratio (Stumpf). In this study, it is hoped that testing can improve the results of good depth estimation.

Lambasina Island is located in the waters of Bone Bay, Kolaka Regency, Southeast Sulawesi Province with different characteristics of air depth. However, no research has been conducted on aquatic ecology or bathymetry in this area. Therefore, it is essential to do research in this area. This study is conducted to compare the ability to measure the depth of bathymetry using satellite imagery in the waters of the small and large Lambasina Islands.

MATERIALS AND METHODS

The research was conducted on two islands: large and small Lambasina Islands, Kolaka Regency, Southeast Sulawesi (Figure 1). Lambasina Island is located at coordinates 121°25'4.69"E and 04°7'34.99"LS. The field survey was conducted from 21 to 25 November 2020. Bathymetry data were obtained by taking direct measurements in the field using a motorboat and a depth-measuring device in the form of a map sounder by following the prepared track to get depth data (Z) and geographic position data (X, Y). Bathymetry data were collected in the coastal areas of small Lambasina Island and large Lambasina Island. Depth measurement data using a map sounder is corrected for tides and transducer poles. Tidal data used for correction was obtained from the Geospatial Information Agency in November 2020 for 30 days. Bathymetric observation data from field noise correction were corrected with the lowest mean sea level (LLWL, *Lowest Low Water Level*).

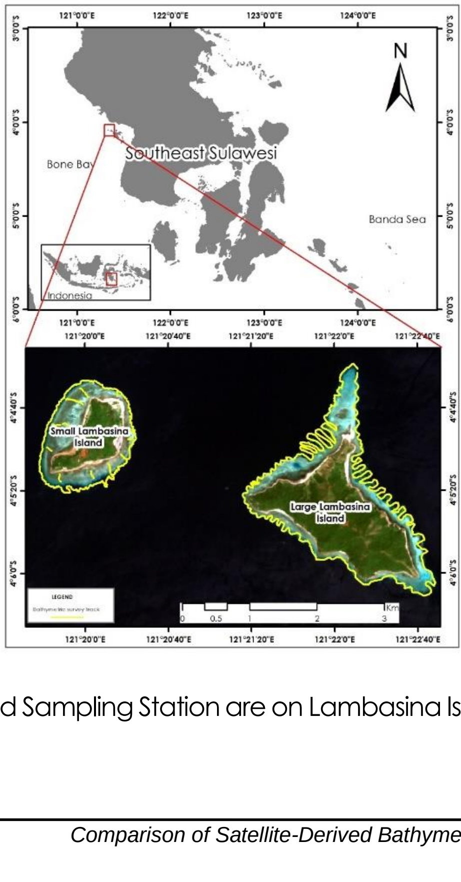


Figure 1. The Research Location and Sampling Station are on Lambasina Island, Bone Bay, Southeast Sulawesi

Table 1. Characteristics of a visible band of the Sentinel-2 image

Band	Sentinel-2	
	Wavelength (nm)	Spatial Resolution (m)
Blue	398–594	10
Green	515–605	10
Red	626–702	10
NIR	790–980	10

Image Pre-Processing

The image pre-processing process consists of atmospheric correction, radiometric correction, image cropping, and geometric correction. Atmospheric correction and radiometric correction of Sentinel-2A imagery were carried out using the Sen2Cor plugin in the SNAP 5 software. This plugin is useful for converting Sentinel-2A image data from Level-1C Top Of Atmosphere Reflectance to Level-2A Bottom of Atmosphere Reflectance. Atmospheric correction is carried out to produce more accurate surface reflectance values and potentially improve the extraction of surface parameters from satellite imagery. The atmospheric correction method used in this research is the Dark Object Subtraction (DOS) method. The DOS method assumes that an object absorbs solar energy perfectly so that the thing is zero (Ardiansyah, 2015). Geometric correction is done to correct the difference between the location coordinates of the image data and the actual location coordinates so that geometric distortions can be eliminated (Dave *et al*., 2015). A total of 30 Ground Control Point (GCP) points on each side of the island are used to make geometric corrections. Satellite imagery-2A uses the Universal Transverse Mercator (51S UTM) projection system.

Linear Transform Algorithm (Lyzenga)

The reflectance transformation of the bottom of the water using natural logarithms will linearize the effect of depth. In theory, each type of bottom water is represented by a parallel line, where the gradient is the ratio between the attenuation coefficients in each band (ki/kj). The single band algorithm used to calculate the water depth according to Lyzenga (1978, 1985) is:

$$Z = a_0 + a_1X_1 + a_iX_i \text{ ....}(1)$$

Note: Z = the depth value, a_0, a_1, a_i is the coefficient determined through regression analysis, and X_1, X_i is the reflectance value of each band/channel.

Ratio Transform Algorithm (Stumpf)

Stumpf (2003) has designed a ratio transformation method for shallow water bathymetry estimation. This model is principally based on the concept that light weakens exponentially at water depths and shows an albedo effect on the substrate, and will be minimized using two bands to obtain water depth. Thus, according to this model, different spectral bands will weaken at different depth levels. Therefore, the ratio between the two spectral bands will vary in obtaining water depth data.

$$Z = m_1 \frac{ln\ (nR_w(\lambda i))}{n\ (nR_w(\lambda j))}\ m_0 \text{.................................}(2)$$

Note: Z = bathymetry depth; m_1, m_0 = regression coefficient value; $R_w(\lambda i)$= reflectance value of band *i*; and $R_w(\lambda j)$ = reflectance value of band *j*.

Support Vector Machine (SVM)

Estimating water depth in the relationship between the ratio's value and the water depth's importance may not always depend linearly. Therefore, this study tries applying a nonlinear function (f) using machine learning to map bathymetry by refining the equation (Vojinovic *et al*., 2013).

$$Z = f\frac{ln\ (nR_w(\lambda i))}{n\ (nR_w(\lambda j))} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

The regression model used in the machine learning algorithm can be seen as follows:

$$E = \sum_{i=1}^{p} L_{si} + \lambda \parallel Pf \parallel^2 = \sum_{i=1}^{p} L_{si} + \Omega(h, I) \ldots\ldots\ldots\ldots(4)$$

In equation 4, there are two terms, the first is to minimize empirical risk, and the second is to smooth the function (Vapnik, 1998).

Where E generally refers in the literature as a function of cost or generalization error to measure the performance of a model, goodness of fit; Lsi indicates the proximity of the data, namely the number of differences in measurements and model outputs calculated in the training phase, which refers to the size of the measurement or training data; Pf indicates the capacity of the SVM, which controls the parameter to minimize E; Ω the VC function (Vapnik and Chevron) is called the confidence interval and corresponds to the smoothness of the estimate; λ represents the regulatory parameter; h dimension VC I indicates the number of support vectors.

The vector training data is mapped to a higher dimensional space using a nonlinear kernel function. The function of the kernel is to take data as input and convert it into the required format. Several kernel functions that can be applied to the SVM model include linear functions, polynomial functions, radial basis functions (RBFs), or sigmoid functions. This study uses the RBF kernel because this kernel has a good generalization system from other kernels (Girosi & Poggio, 1990).

$$K(x_i, x_i) = \exp(-\varphi \parallel x_i - x_i \parallel^2), \varphi > 0 \ldots\ldots\ldots\ldots(5)$$

Where is a gaussian function and x_i, x_i as feature vectors.

After deciding which kernel function to use, the next step is using the R-studio software (Package "e1071") to determine the best C and parameters to use in the SVM model. Parameter C affects the penalty value assigned to the prepared data. A low value of C indicates a low tolerance value in estimation error and vice versa. This parameter γ affects setting the speed of the learning process. The higher the value γ, the faster the learning process. For parameter e, the results of the support vector will decrease reducing the data. Increasing the value e can smooth data that is considered incorrect and can reduce the level of accuracy (Vojinovic *et al*., 2013; Misra *et al*., 2018; Mateo-Pérez *et al*., 2021).

Statistical Analysis

The data from the depth modeling of satellite imagery were tested statistically using the RMSE (Root mean squared error) method, and MAE (Mean absolute error) on each depth data to obtain the accuracy level of each algorithm (Mateo-Pérez *et al*., 2021).

$$RMSE = \sqrt{\sum \frac{(Z_{sat} - Z_{obs})^2}{N}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \parallel Z_{sat} - Z_{obs} \parallel \ldots\ldots\ldots\ldots\ldots(7)$$

The RMSE compares the predicted value with the observed value to measure how much error there is between the two data sets. The smaller the RMSE value, the closer to the predicted and observed values. MAE measures how far the predicted value is from a known observation. Bias to get the difference in the range of values between predictive data and observational data.

RESULTS AND DISCUSSION

The data obtained from field observations are adjusted to each pixel of the red, green, and blue bands in the Sentinel-2A satellite image, with each pixel resolution measuring 10x10 meters in the determination of training data and test data applied to each algorithm. Data from field observations by first doing data filtering to eliminate noise data by adjusting the depth point to the pixel resolution of the image data. The data obtained can be seen in the following Table 2.

Application of Water Depth Estimation Algorithm

There are many kinds of band treatment combinations for each depth estimation procedure that can be used. Several combinations of band treatments in the depth estimation procedure used have varied outputs in this study. In this study, three depth estimation methods are applied to Sentinel-2A images, namely linear transform algorithm, ratio transform, and support vector machine on Small Lambasina Islands and Large Lambasina Islands.

Linear Transform Algorithm

The linear transform algorithm developed by Lyzenga (1978, 1981, 1985) uses visible light, namely the red, green, and blue bands that have been corrected and regressed to field noise data. The optimal wavelength can be determined by measuring the spectrum at different depths and selecting the most sensitive band to bathymetry.

After testing the regression model on each visible band, the combined results of the red, green, and blue bands showed the best regression values on the two islands. Small Lambasina Island shows a correlation value of $r = 0.87$ and a determinant correlation value of $R^2 = 0.78$, and on a large Lambasina Island, it shows a correlation value of $r = 0.85$ and a determinant correlation value of $R^2 = 0.73$ (Table 3). According to Green *et al*. (2000), the red band can penetrate water to a depth of 5 m, while the blue and green bands can penetrate water to a depth of 30 m for the blue band and 15 m for the green band. Based on the value of the correlation coefficient (r) obtained, combining red, green, and blue bands is better for obtaining coefficient values for use in estimating bathymetry.

The coefficient values of the regression results are transformed into the Lyzenga model equation and applied to the Sentinel-2 image to obtain pixel-based bathymetry data. The estimation results on the small Lambasina island show a depth range of 0 to 21.5 meters; on the large Lambasina island, the value ranges from 0 to 20.4 meters (Figure 2).

The combination model of the three visible bands of Sentinel-2 imagery applied to the two islands obtained a good depth estimation value. The regression test results between the field noise depth data and the image depth data obtained the value of R^2 determination on each island, namely 0.78 on the small Lambasina Island and 0.79 on the large Lambasina Island (Figure 3). Penetration of light through the water column supported by excellent water brightness conditions allows depth estimation results using satellite imagery to get better information. The ability of visible light bands with radiation from 0.48 μm (B2) to 0.60 μm (B3) can penetrate clear and calm waters around 15-20 m (Gao, 2009) with the best detection at a depth of about 10 m (Bagheri *et al*., 1998).

Table 2. Amount of data used for depth estimation

Islands	Data Training			Data Test		
	Amount of Data	Maximum Depth (m)	Minimum Depth (m)	Amount of Data	Maximum Depth (m)	Minimum Depth (m)
Small Lambasina	420	19.7	0.4	282	18.0	1.5
Large Lambasina	912	19.23	0.8	607	15.33	0.78

The Depths (Z) are tidally corrected and reduced to mean sea level (MSL) (Pacheco *et al*. 2015).

Table 3. Regression test values on each image band of Sentinel-2A

Small Lambasina Island						
Single	r	R^2	Intercept	Slope Red	Slope Green	Slope Blue
Red	0.77	0.68	13.5703	-157.0798	-	-
Green	0.84	0.75	13.9129	-	-109.5861	-
Blue	0.81	0.71	16.8532	-	-	-166.094
Green, Red	0.83	0.73	13.5974	-151.122	-4.5274	-
Blue, Red	0.82	0.72	12.4546	-191.664	-	45.7735
Blue, Green	0.85	0.76	7.2119	-	-303.3398	328.8555
Red, Green, Blue	0.87	0.78	8.4025	-90.5413	-200.5074	261.1526
Large Lambasina Island						
Single	r	R^2	Intercept	Slope Red	Slope Green	Slope Blue
Red	0.69	0.48	13.563723	-0.0203603	-	-
Green	0.83	0.68	15.411624	-	-0.01440284	
Blue	0.76	0.58	18.638746	-	-	-0.02032344
Green, Red	0.83	0.69	15.444439	0.0056164	-0.01735347	-
Blue, Red	0.77	0.6	17.882296	-0.006136	-	-0.01577816
Blue, Green	0.84	0.71	12.299083	-	-0.02453915	0.01602235
Red, Green, Blue	0.85	0.73	11.16832	0.010334	-0.0338473	0.022154

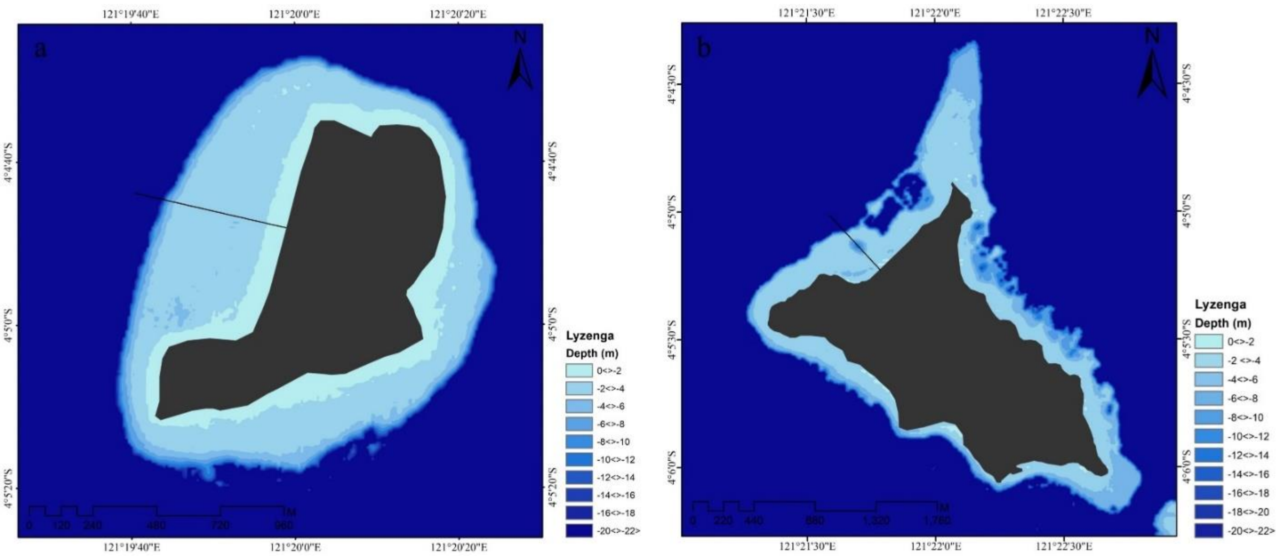


Figure 2. Lyzenga algorithm model: (a) Small Lambasina Island, (b) Large Lambasina Island

Ratio Transform Algorithm (Stumpf)

This methodology is in the form of a ratio transform algorithm or Stumpf (Figure 4) using a simple linear relationship between reflectance ratios and examines any combination of band ratios with depth data. The model test is carried out to get the best combination ratio value to get a depth value closer to the actual depth. The regression test results for each combination of ratios get a value close to 1 so that the results from a value close to 1 are used to transform data into depth data in the image. The band ratio value is the best in the combination of blue and green bands on both islands, with a correlation of r = 0.9 and a determinant correlation of R^2 = 0.8 on a small Lambasina island and a large Lambasina island with a correlation value of r = 0.87 and a determinant correlation R^2 = 0.76. Several other model test results can be seen in Table 4 and Figure 5.

The results of the correlation test between each combination of band ratios can be seen in the large Lambasina Island test that there are some significant differences in the values, especially the combination of blue/red and green/red bands only gets a correlation value (r) of 0.38 and 0.31. Penetration of the blue and green bands can penetrate clean waters at a longer distance than the red bands. Wicaksono (2010) and Nurkhayati and Khakhim (2013) and Chénier *et al*, (2018) get the results of the correlation coefficient test of the ratio of the blue band to the green band better than the combination of other band ratios.

Support Vector Machine (SVM)

The results of the ratio model regression are applied to the support vector machine (SVM) algorithm using training and test data. The SVM model is used using the R software (package 'e1071') with input data ratio B2/B3 with training data. The kernel used is the RBF kernel and is applied to SVM applications, then the best C and ε parameter values are determined, while for γ, the values are

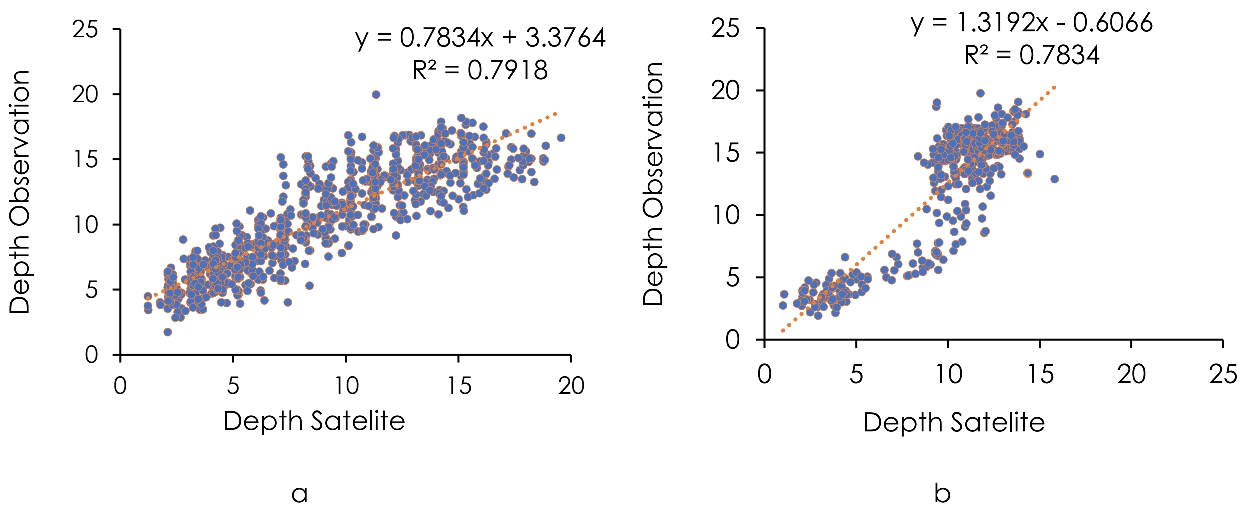


Figure 3. Regression test of field noise depth data and image estimation results of the lyzenga algorithm: (a) Regression graph of Small Lambasina, (b) Regression graph of Large Lambasina

Table 4. Test Results of the correlation coefficient

Small Lambasina Island				
Band Ratio	r	R^2	Intercept	Slope
Blue/Green	0.9	0.8	19.806	-12.418
Blue/Red	0.89	0.79	17.443	-14.936
Green/Red	0.83	0.75	15.519	-9.092
Large Lambasina Island				
Band Ratio	r	R^2	Intercept	Slope
Blue/Green	0.87	0.76	-7.392	13.583
Blue/Red	0.38	0.14	2.341	2.717
Green/Red	0.31	0.1	13.891	-2.57

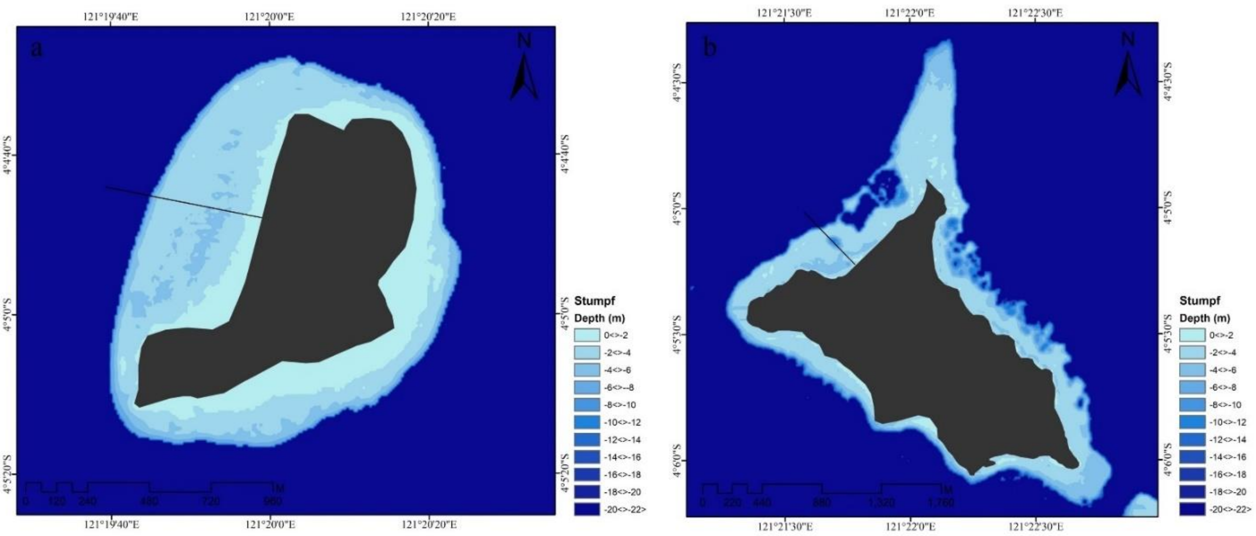
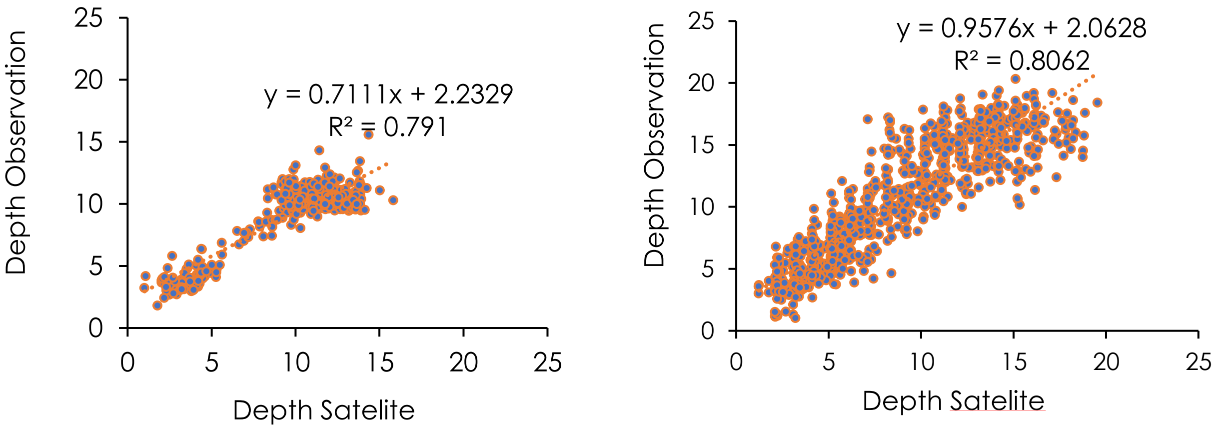


Figure 4. Model of stumpf algorithm: (a) Small Lambasina Island, (b) Large Lambasina Island



a b

Figure 5. Regression test of field noise depth data and the estimation results of the Stumpf algorithm image: (a) Regression graph of Small Lambasina, (b) Regression graph of Large Lambasina

created automatically. The Rstudio software tuning results obtained the best values of the parameters C and ε, namely 1 and 0.1, which were then used in the SVM application. According to Vojinovic *et al*, (2013) and Mateo-Pérez *et al*, (2021), the lower value of parameter C indicates a lower prediction error tolerance. The support vector in SVM is training data that lies on and outside the boundary of the decision function. The model and results of the SVM algorithm regression analysis can be seen in Figures 6 and 7.

Depth Profile Comparison of Each Model

Based on the cross-section of each model, the Lyzenga, Stumpf, Support vector machine algorithm shows that the profile of the seabed conditions is not much different, and the distance from the shoreline to the reef slope area is ±500 m. Small Lambasina Island shows a uniform appearance in the form of a reef with a depth of generally less than 5 m, with benthic habitats found in the form of coral and sand. The cross-section of the depth profile of the algorithm model on Small Lambasina Island can be seen in Figure 8.

Based on the cross-section of each algorithm model on Large Lambasina Island, Figure 9 shows that the profile of the seabed conditions is not much different, and the distance from the shoreline to the reef slope area is ±430 m on the west side of the island. Large Lambasina Island shows a reasonably diverse appearance due to the presence of gobah areas at a distance of 100 m with a depth of 5 m and a distance of 200 m with a depth of 9 m in each model. Along the transect line from point 0 to the slope area with a distance of ±430 m or marine areas in benthic habitats found are sand, coral, and coral fractures.

Bathymetric data generated by satellite image estimation has a weakness in the limited ability of wave penetration in the water column. The area of water in the electromagnetic wavelength cannot reach the bottom of the water more than 22 meters. Penetration of light that enters through the water column, its intensity will decrease exponentially with increasing depth (attenuation) (Effendi, 2003). The process of absorption and scattering by organic and inorganic particles can reduce the intensity of light penetrating the water column (Guntur *et al*., 2012).

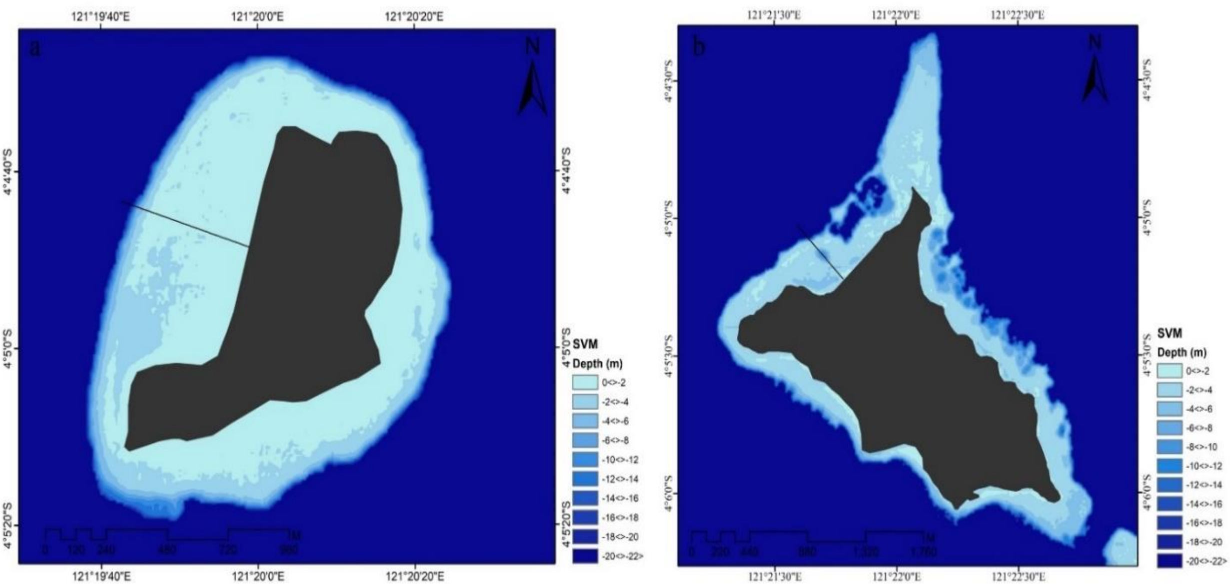


Figure 6. Model of SVM Algorithm: (a) Small Lambasina Island, (b) Large Lambasina Island

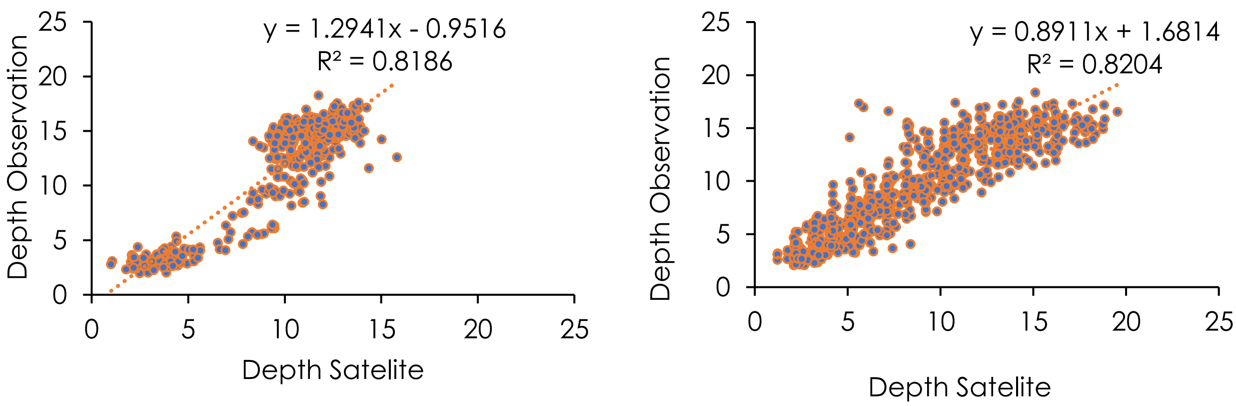


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Figure 7. Regression Test of field noise depth data and the estimation results of SVM algorithm image: (a) Regression graph of Small Lambasina, (b) Regression graph of Large Lambasina

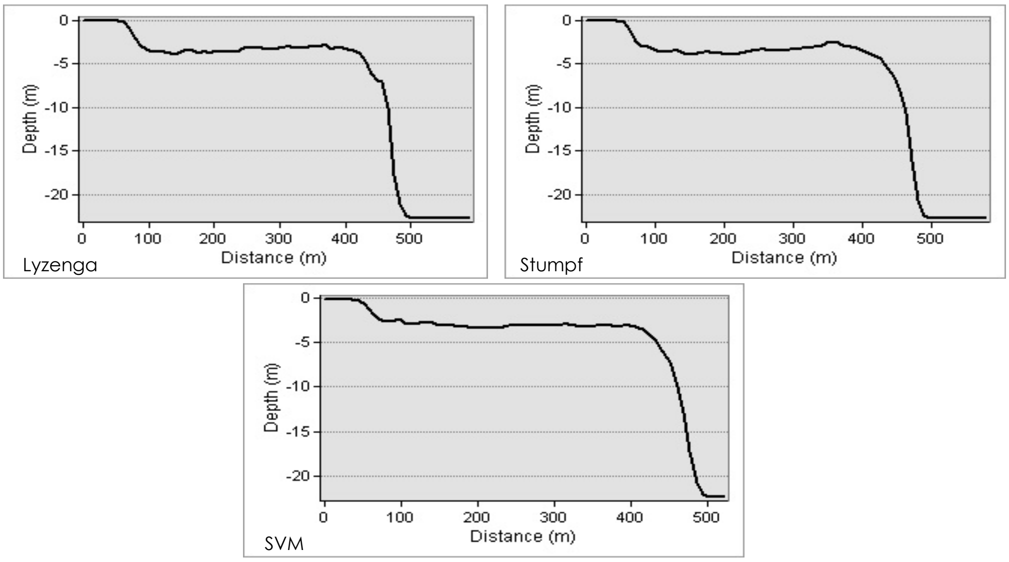

Figure 8. Cross-section of the depth profile of the algorithm model on Small Lambasina Island

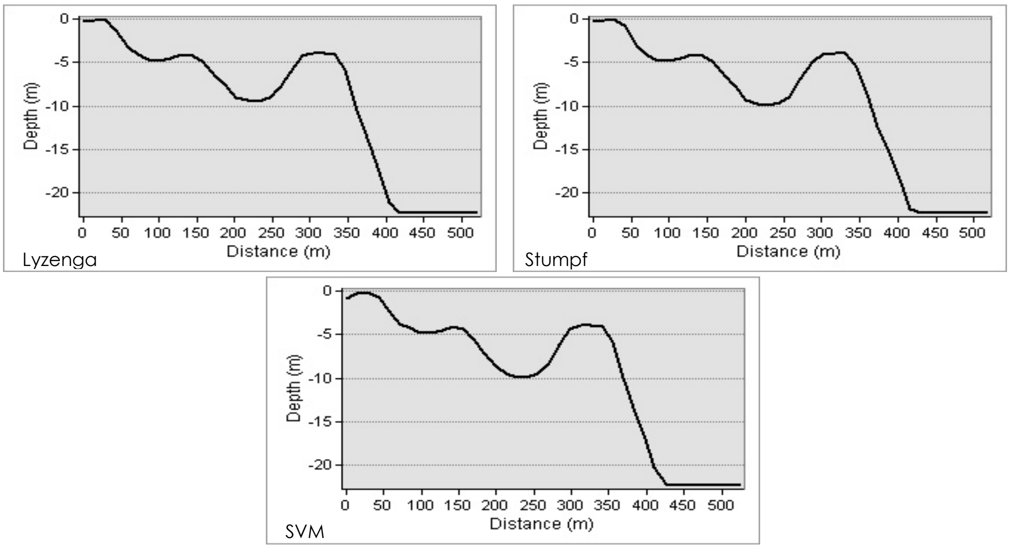

Figure 9. Cross-section of the depth profile of the algorithm model on Large Lambasina Island

Result Validation Test of Depth Estimation

Statistically, there is a sizeable improvement in the depth estimates for SVM compared to the linear and ratio models, especially regarding RMSE and MAE values. The use of the SVM model gets a pretty good value in estimating shallow water bathymetry. That is shown by getting the results of the regression test and MAE and RMSE error tests on each algorithm model. It was observed that the value of R^2 (Table 5) obtained was very strongly related to the SVM model compared to the ratio and single model. The value obtained from each island is close to 1, namely small Lambasina with $R^2 = 0.81$ and large Lambasina with $R^2 = 0.82$. The value of the coefficient of determination is between values of 0 and 1, meaning that if the value of the coefficient of determination is close to the value of 1, then the relationship between the noise depth data and the image estimation data (the dependent variable and the independent variable) has a solid relationship (Ghozali, 2016). The error test is divided into two depth data, namely the depth of 0-5, 5-10, 10-15, and 15-20 meters, so the differences in the error test are based on depth (Table 6). The results of the SVM model on the two islands get a smaller error value compared to the ratio and single model. Statistically, there is a significant improvement in the depth estimation for the SVM model compared to the single model

Table 5. Results of comparison of accuracy calculations of each model based on depth division

Small Lambasina Island									
Model	R^2	0 - 5 meter		5 - 10 meter		10 - 15 meter		15 - 20 meter	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Single (Lyzenga)	0.78	0.02	8.81	2.19	22.25	2.51	38.84	2.03	22.85
Rasio (Stumpf)	0.79	0.01	9.47	1.34	15.12	1.63	27.86	1.95	22.38
SVM	0.81	0.03	7.93	1.18	14.03	1.51	25.85	1.76	20.69
Large Lambasina Island									
Model	R^2	0 - 5 meter		5 - 10 meter		10 - 15 meter		15 - 20 meter	
		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Single (Lyzenga)	0.79	2.32	40.15	2.31	43.62	1.75	35.75	2.03	22.85
Rasio (Stumpf)	0.8	1.46	28.48	2.01	41.86	1.55	33.42	1.95	22.38
SVM	0.82	1.02	20.92	1.74	38.41	1.52	32.09	1.76	20.69

and the ratio model, especially in the RMSE and MAE values. Small Lambasina Island and large Lambasina Island along the coastline did not find any turbidity from the river, which means that the light penetration process is not disturbed in penetrating the bottom of the waters.

In Table 5, the single model algorithm has a lower coefficient of determination compared to the ratio and SVM models. That is also in line with the lower MAE and RMSE error test results compared to the ratio and SVM models, both at depths of 0-5, 5-10, 10-15, and 15-20 meters. Bathymetric mapping using satellite imagery for research purposes from a depth of 0 to 15 meters was carried out by Vojinovic *et al*. (2013) using the linear model, ratio model, and SVM getting different values. The SVM model got the lowest error test value compared to the other two models (Table 9). The advantage of the SVM model over ratio and linear models is that it can predict depth by utilizing non-linear data that shows the ability to estimate shallow water bathymetry (Mateo-Pérez *et al*., 2021).

CONCLUSION

Statistical and visual assessments obtained for two shallow water areas, namely small and large Lambasina Islands, show the ability of the SVM method to estimate the depth of clear shallow waters with image conditions free from atmospheric disturbances. The RMSE and MAE values get a reasonably low error value obtained on the small and large Lambasina islands by focusing on the level of accuracy of the lowered depth measurement. Satellite-derived bathymetry generated by this method has great potential to complement survey data more efficiently and cost-effectively because it is not limited by ships or other survey systems. In addition, the availability of high- and medium-resolution satellite data has been made available for free with a five-day recording time interval on sentinel-2 imagery, making it a very useful tool from the perspective of continuous bathymetric data monitoring. Therefore, the method can obtain fast and up-to-date depth measurement information, which can then be used as input data for numerical modeling studies to understand coastal dynamics and management better.

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