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Support Vector Machine Classification Method for Predicting Jakarta Bay Bottom Sediment Type using Multibeam Echosounder Data

Steven Solikin[1], Henry Munandar Manik[2]*, Sri Pujiyati[2] and Susilohadi[3]

[1]Graduate School of Marine Technology, PMDSU Batch II, IPB University, IPB Dramaga Campus, Bogor 16680, Indonesia
[2]Department of Marine Science and Technology, Faculty of Fisheries and Marine Science, IPB University, IPB Dramaga Campus, Bogor 16680, Indonesia
[3]Centre for Research and Development of Marine Geology, Ministry of Energy and Mineral Resources, Jl. Dr. Djunjunan No. 236 Pasteur, Bandung, Indonesia

ABSTRACT

The need for accurate seafloor maps is increasing along with the increase in marine activities, such as dredging, construction of buildings on the coast and offshore, and navigation of ships to prevent shipwrecks while sailing. The hydroacoustic technology used in this study is the multibeam echosounder system (MBES), which is the most advance acoustic instrument today. MBES can sweep very large areas in a short time, so that the survey costs can be reduced. The aim of this research was firstly to classify the seabed sediment in G-Island, Jakarta Bay using supervised classification technique. Secondly, to analyze the acoustic characteristic of the seabed sediment and compare it with the physical characteristic of the sediment.This research was conducted on October 31st to November 5th 2016 in the waters of G-Island, Jakarta Bay. In this study, supervised classification techniques were applied. The supervised classification techniques used in this research was Support Vector Machine (SVM). SVM produces classifications with 5 main classes, namely clay, fine silt, medium silt, coarse silt and fine sand. The overall accuracy value of the SVM method was 80.25% with the Kappa coefficient value of 0.2031 which is categorized into the fair class in its classification.

Keywords: Jakarta Bay, multibeam echosounder, supervised classification, support vector machine

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E-mail addresses:
steven_solikin@apps.ipb.ac.id (Steven Solikin)
henrymanik@ipb.ac.id (Henry Munandar Manik)
sripujiyati@yahoo.com (Sri Pujiyati)
s.susilohadi@mgi.esdm.go.id (Susilohadi)
* Corresponding author

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INTRODUCTION

The seabed is a habitat for various types of marine life, either fish or other benthic miofauna (Parnum et al., 2004). On the seafloor there are also various chemical, physical and biological processes, such as sediment transport and biological pump mechanics. Behind the benefits of the seabed, research on the seabed is more complex than the application of other hydroacoustic technologies (Lurton, 2002). Various problems such as rough surface of the seabed, absorption in sediments is greater than in the water column, and the presence of scatterers of other acoustic signals on the surface and in the sediments makes the study of the seabed becomes more difficult, but also more interesting to do.

One of the hydroacoustic technologies instrument that always used for seabed research is multibeam echosounder. Multibeam echosounder (MBES) is an acoustic equipment that is intensively used in water-based mapping, mainly because this technology has more capabilities, especially its broad coverage and high resolution for bathymetry data acquisition (Anderson et al., 2008) when compared with equipment such as singlebeam echosounder, side scan sonar or Light Detection And Ranging (LiDAR). Seabed mapping becomes very important because it provides detailed and accurate information about the topography of the seafloor. This information is very much needed in various aquatic applications such as making navigation maps to ensure the safety of ship traffic and searching for sinking vessels.

The MBES technology is an extension of the singlebeam echosounder (SBES) technology which only transmits one beam vertically to the bottom of the water, while the multibeam is able to transmit hundreds of beams to the bottom and its beam pattern widens and transversely to the hull (Lurton, 2010). Each beam that is emitted will get a point of depth so that if the depth points are connected it will form a topographic profile. There are two types of datasets produced by multibeam echosounder, bathymetry and backscatter data.

Information about the seabed can be used extensively, both by oceanographers to study habitat for benthic animals (Friedlaner & Perrish, 1998), as well as by industry players, even the military (Sternlicht & Moustier, 2003). Along with the increasing exploitation of marine resources, effective management of the marine environment is very important to note. Therefore, information about accurate seabed is needed to answer this challenge. Information about the bottom of the water can be obtained using MBES.

Various methods of seabed classification using MBES data to obtain benthic habitat information have been developed in the last two decades (Fonseca & Mayer, 2007). Generally there are three types of MBES data sets that are used as input in the classification process: backscatter mosaics, backscatter angular responses, and bathymetry (Manik, 2011). Backscatter is the key on determining sea surface conditions (Huang et al., 2013). The backscatter intensity obtained from the receiver provides preliminary information on the type of sediment at a spatially observed location (Huang et al., 2014; Fonseca et al., 2009).

The aim of this research was firstly to classify the seabed sediment in G-Island, Jakarta Bay using supervised classification technique. The supervised classification technique used in this research was Support Vector Machine (SVM) that is based on machine learning. Secondly, to analyze the acoustic characteristic of the seabed sediment and compare it with the physical characteristic of the sediment.

METHODS

Acoustic Data Acquisition

This research began with the data acquisition stage using the MBES acoustic instrument in the waters of Jakarta Bay. Data that can be obtained from the MBES instrument are bathymetry data and backscatter data (Marsh & Brown, 2009). Data acquisition was conducted on October 31st to November 5th 2016. Bathymetry data became the base map in the making of the Jakarta Bay seabed sediment classification map, while backscatter data were analyzed for further comparison with the sediment sample data and the output results are classification of Jakarta Bay sediments.

The survey was done using a public vessel with dimensions of 12 x 2.5 metres. Technical specifications of the survey was explained as the distance between the lanes ranges from ±100 metres with the number of main survey lines used for this research is

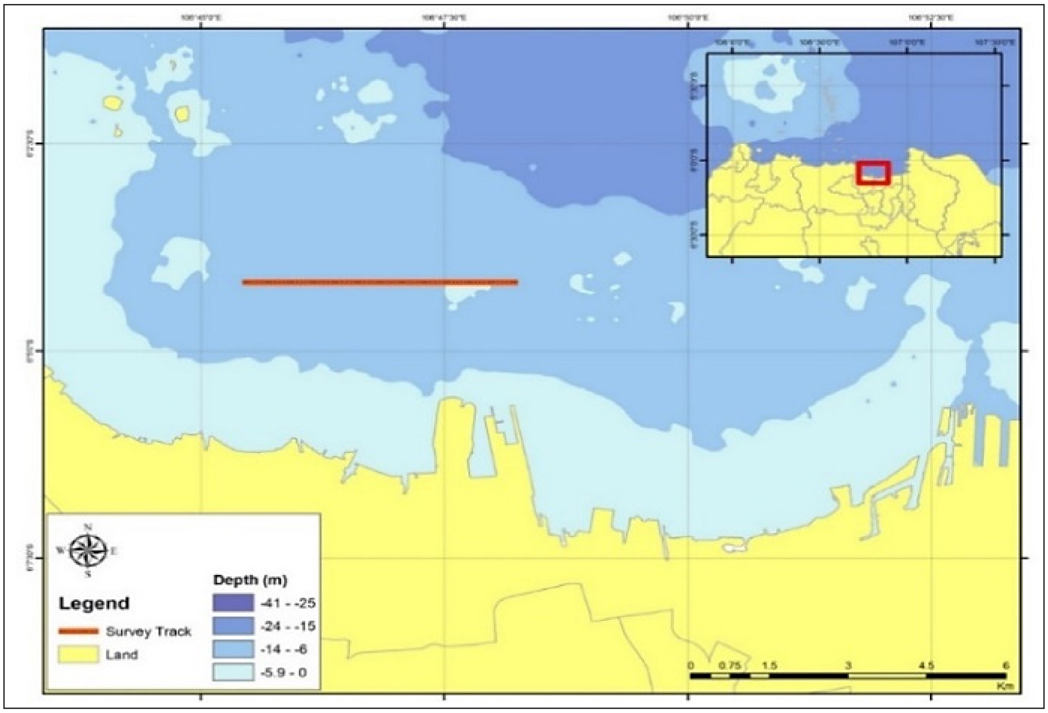

Figure 1. Location of survey area in the waters of G-Island, Jakarta Bay
The red line shows the data acquisition lane using the MBES instrument.

30 lanes of main and 3 lanes of cross. Figure 1 shows the map of the survey location in Jakarta Bay.

The MBES instrument used to obtain bathymetry and backscatter data was SIMRAD Kongsberg EM 2040 with the output frequency of 300 kHz. The frequency of 300 kHz can be used in shallow waters and waters with medium depth (<450 m). The MBES data obtained were data that had been corrected for vessel movement, bow aberration, and GPS delay correction using the Teledyne TSS DMS-05 motion sensor which has an accuracy of slant and bobbing of 0.05°. Determination of the positioning position used Veripos DGPS which had a horizontal accuracy of 0.13 metres and a vertical accuracy of 0.32 metres at a 95% confidence level. The assistance software used as a navigation guide was Automatic Data Logging (ADL) Hydro-Pro, and software for data acquisition using the Seafloor Information System (SIS).

Seabed Sediment Sample Data Acquisition

In addition to the MBES data, sediment samples were taken as validation material for the classification of sediments based on the geoacoustic properties of the sediments. Sediment samples were taken as many as 7 samples that were randomly distributed in the survey area. Sediment samples were taken using a grab sampler. Sediment samples taken are sediment samples on the bottom surface of the water only because of the limitations of the grab sampler to penetrate the sediment layer. Sediment samples obtained, placed in plastic samples and then analyzed the grain size in the laboratory.

In addition to sediment sample data, secondary data to determine sediment types in Jakarta Bay waters were also obtained from the Hydrography and Oceanography Center, Indonesia Navy based on 2016 data. This secondary data was juxtaposed with primary sediment sample data to add validation to the MBES data obtained. The type of ground truth sediments obtained through the 2016 Hydrography and Oceanography Center, Indonesia Navy data show that the Jakarta Bay waters are dominated by clay (Table 1).

Table 1
Number of points and sediment types in Jakarta Bay

No.	Sediment type	Number of points
1	Clay	3276
2	Clayey sand	14
3	Coarse silt	62
4	Fine silt	25
5	Medium silt	16
6	Sandy clay	15
7	Sandy mud	10
8	Sandy silt	89
9	Silty clay	13
10	Very fine sand	1

Data processing analysis of sediment samples was carried out using the wet sieve method using a multilevel sieve to separate the size of the sediment grains based on the grain size fraction. The fractions are determined based on Shephard's triangle (Shepard, 1954) where each fraction was divided into:

1. Gravel (gravel) fraction: a combination of rock and gravel material
2. Sand fraction (sand): a combination of fine sand to coarse sand material
3. Mud fraction: a combination of clay and silt material

Bathymetry Data Quality

The bathymetry data obtained by MBES must be in accordance with standards set by the International Hydrographic Organization (IHO). Therefore, quality control (QC) is needed in the form of bathymetry data correction. The accuracy requirements for bathymetry measurements were set into 4 levels (order) based on the S-44 IHO (2008).

Table 2
List of minimum standards for bathymetry surveys

Order	Special	1a	1b	2
Area	Areas where under-keel clearance is critical	Areas shallower than 100 metres where under-keel clearance is less critical but features of concern to surface shipping may exist	Areas shallower than 100 metres where under-keel clearance is not considered to be an issue for the type of surface shipping expected to transit the area	Areas generally deeper than 100 metres where a general description of the seafloor is considered adequate
Horizontal accuracy	2 m	5 m + 5% depth	20 m + 5% depth	150 m + 5% depth
Depth accuracy	a = 0.25 m b = 0.0075	a = 0.5 m b = 0.013	a = 1.0 m b = 0.023	same with order 2

This correction is related to the level of accuracy of the data in providing information about the actual depth value in the observed area, and to determine the quality of the data to be classified into the hydrographic order. This correction was done by comparing the value of depth at the point of intersection (cross check) between the transverse lane and the longitudinal lane, so that the deviation of depth will be obtained. The error limit at each point of correction of water depth must not exceed the fault tolerance limit set by IHO (2008). All uncertainties in calculating the vertical uncertainty should be combined statistically to obtain a total vertical uncertainty (TVU). The maximum allowable TVU for specific depth is presented in Equation [1].

$$\sigma = \pm\sqrt{a^2 - (b\ x\ d)^2} \qquad [1]$$

where:

σ : maximum allowable TVU for a specific depth (m)

a : represent the depth error constant (m)

b : a coefficient which represents a replacement factor for depth error

d : depth (m)

b x d : represents that portion of uncertainty that varies with depth

Support Vector Machine Classification

Classification technique that was used in this study was supervised classification which was the machine learning (computer based) technique. The machine learning which was now being developed and applied was Support Vector Machine (SVM). This method is rooted in statistical learning theory and works very well on high dimensional data sets. In SVM, a selected amount of data will contribute to form the model used in the classification to be studied. In addition, SVM only stores a small portion of the training data to be used at the time of prediction. The data that contribute is called the support vector, therefore the method is called SVM (Prasetyo, 2014).

The basic idea of SVM is to maximize hyperplane (decision boundary). Hyperplane which is the best separator between two classes can be found by measuring the hyperplane's margin and finding its maximum point. Margin is the distance between the hyperplane and the closest data from each class. The closest data is referred to as a support vector. Hyperplane with maximum margins provides better generalization to the classification method.

Model and Data Correlation

Accuracy level analysis between classification models and field data was performed using Kappa coefficient statistical analysis. The Kappa coefficient was developed by Cohen (1960). The Kappa coefficient was introduced for remote sensing research in the early 1980s (Congalton & Mead, 1983; Congalton, 1991) and had been an excellent test to be used to analyze the accuracy of object classification results.

In general, the Kappa coefficient can be used to measure the degree of agreement of two assessors in classifying objects into groups, as well as to measure alternative agreements of new methods with existing methods. The equation to get the Kappa coefficient is expressed in Equation [2]:

$$\kappa = \frac{N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+} X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+} X_{+i}} \qquad [2]$$

where
κ : Kappa coefficient;
N : number of observations;
X_{ii} : observation in i^{th} row i^{th} column;
X_{i+} : marginal total in i^{th} row;
X_{+i} : marginal total in i^{th} column.
A simpler equation is shown in Equation [3]:

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \qquad [3]$$

where
$p_0 = \frac{\sum X_{ii}}{N}$ = accuracy of the agreement observed,
$p_e = \frac{\sum X_{i+} X_{+i}}{N^2}$ = estimation of chance of agreement.

Class results from the Kappa coefficient value classification are divided into 5 classes; poor, fair, moderate, good, and very good (Altman, 1991). Kappa coefficient value distribution classes can be interpreted as in Table 3.

Table 3
Classification of the level of agreement between the Kappa coefficient values

κ VALUE	(STRENGTH OF AGREEMENT)
< 0.20	POOR
0.21 – 0.40	FAIR
0.41 – 0.60	MODERATE
0.61 – 0.80	GOOD
0.81 – 1.00	VERY GOOD

RESULTS AND DISCUSSION

Seabed Topography

Acquisition of sound velocity data at the study site using the AMD Oceanography CTD instrument which was carried out every day before the rating survey was conducted. The value of sound velocity (sound velocity profile, SVP) varied every day. Figure 2 shows the daily sound speed profile for 5 days from November 1st to 5th.

The results of SVP measurements at the study site ranged from 1542.5 ms^{-1} to 1544.5 ms^{-1} with a maximum depth of 12 m. This sound speed value would be a correction factor for the acoustic waves that were transmitted and received by the MBES instrument. Tidal data acquisition was carried out using the Thalimedes instrument at Pantai Mutiara dock. Figure 3 shows the tidal graph at the study site from October 31st to November 5th, 2016.

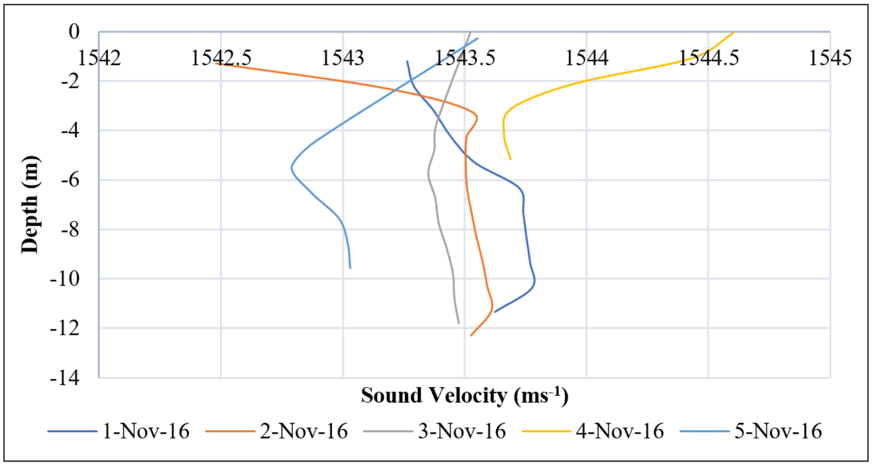

Figure 2. Sound velocity profile at the study site on November 1st to 5th, 2016

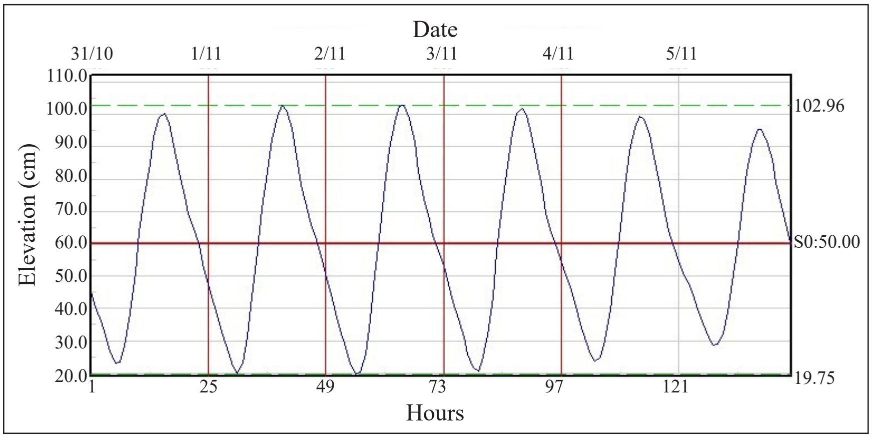

Figure 3. Tidal charts at the study site on October 31st to November 5th, 2016

The tidal graph at the study site shows the lowest tidal value is 19.75 cm and the highest tide is 102.96 cm on November 2nd, 2016. Tidal type at the study site is included in the type of daily tidal (diurnal). These results are in accordance with research conducted by Indriani et al. (2010) which showed that the type of tides in the waters of Jakarta Bay was a single daily tide. Tidal correction is needed in the processing of bathymetry data generated by MBES to get the true depth value. Tidal corrections carried out in this study used the mean sea level (MSL) value as a benchmark. The MSL value is the middle value of the tidal graph, so that all bathymetry data obtained later be reduced or added to the MSL value obtained in this study. The MSL value was computed from tidal analysis by calculating the trend of the tidal graph. MSL value obtained in this study was 60 cm.

After the data was corrected by tidal values, bathymetry profiles could be generated. Bathymetry profiles or topographic forms of the seabed surface were obtained from MBES data which had been corrected by vessel motion, position, tides, and sound velocity profiles. The bathymetry profile at the study site is shown in Figure 4.

The bathymetry profile in the study site based on the corrected MBES data showed a depth value between 9.75 m to 17.10 m. The bathymetry profile obtained showed the water in Jakarta Bay were shallow. The shallower area is in area A, while the deepest area in the study area is in area B. In area B a basin is suspected to be a pipe planting area.

The level of precision and accuracy of bathymetry data in this study was maintained in accordance with 2008 IHO standards. According to the IHO (2008) statute, the bathymetry data quality control results from MBES are validated with reference surfaces as locations for checking data quality. The reference surface in this case was the cross depth obtained from cross lane data. The method used was to compare bathymetry data from MBES results

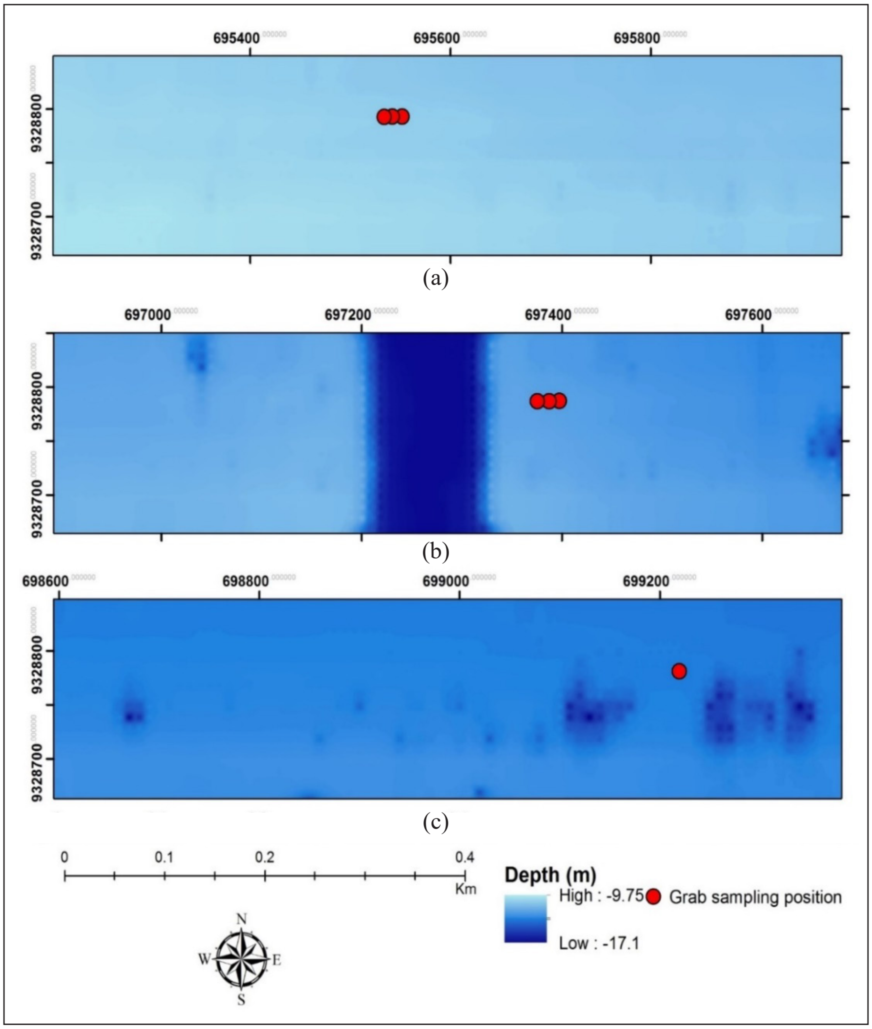

Figure 4. Bathymetry profile in study site

in the main lane with the cross lane (cross). This method aims to find fault tolerance limits. Calculation of bathymetry data quality aims to determine the value of the deviation in the same position at different times. Table 4 shows the position of the correction point, the error value and the calculation of the maximum allowable TVU.

Table 4
Bathymetry data quality on cross lanes

Longitude	Latitude	MB depth	Cross depth	Average depth	Difference	Maximum allowable TVU
-6.106	106.777	6.171	6.056	6.114	0.115	0.2500
-6.097	106.798	3.729	3.840	3.785	0.111	0.2500
-6.074	106.756	9.515	9.470	9.493	0.045	0.2500
-6.076	106.777	9.784	9.654	9.719	0.130	0.2500
-6.073	106.786	8.856	8.827	8.8415	0.029	0.2500
-6.072	106.787	11.641	11.375	11.508	0.266	0.2500
-6.070	106.761	10.434	10.360	10.397	0.074	0.2500
-6.069	106.781	13.822	12.262	13.042	1.560	0.2503
-6.071	106.794	19.045	18.323	18.684	0.722	0.2501
-6.075	106.786	11.343	10.499	10.921	0.844	0.2501
-6.073	106.765	8.941	8.479	8.71	0.462	0.2500
-6.071	106.757	14.269	13.268	13.7685	1.001	0.2501

The intersection point between the main lane and the cross lane at this study site consists of 12 points. The maximum measured error value is 1.56 meters and the minimum measured error value is 0.03 meters. By using Equation [1] an error tolerance limit value (σ) of 0.25 meters is obtained. Based on the results of manual calculations, the depth error tolerance limit between the main lane with the cross lane, it can be said that all the bathymetry data error values at the correction point are within the error tolerance limits for the measurement of water depths in the special order hydrographic survey classification.

Support Vector Machine Classification

The bottom sediments of G-Island waters, Jakarta Bay, had been classified using supervised classification techniques. The Support Vector Machine method was applied in this supervised classification technique. As many as 3.8 million points were extracted from the MBES raw data. Each point contained information about the location (latitude and longitude) and the value of backscatter intensity obtained from the MBES data.

Due to some software limitations in the classification process, 3.8 million points were reduced to approximately 40 thousand points. Reduction of the data was done by eliminating data with the same coordinates, so it would not affect the accuracy results of the classification. Of the 40 thousand data points, 20% of the data was used as training data sets, or around 8 thousand points. From these 8 thousand points, another 20% of data was taken for class accuracy testing and obtained 5 main classes in the classification using this SVM method, namely clay, coarse silt, medium silt, fine silt, and very fine sand.

The backscatter value obtained from this MBES data using the SVM method ranged from -56 dB to -14 dB. The distribution of the backscatter intensity distribution from the MBES data is shown in Figure 5.

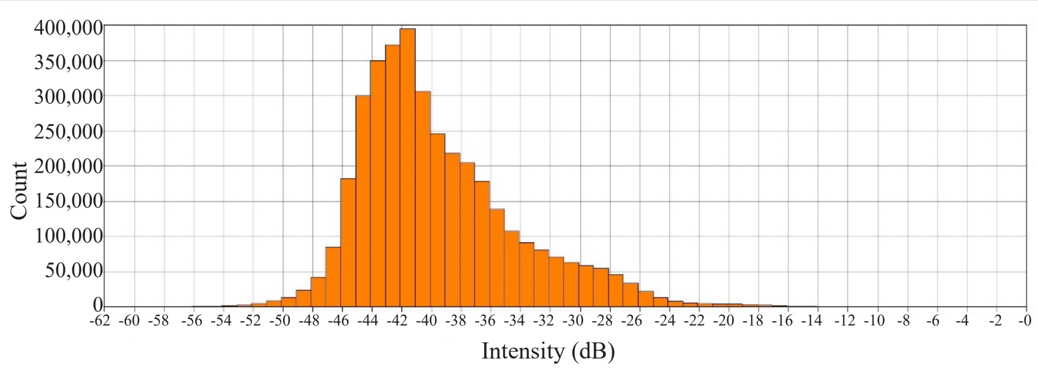

Figure 5. Frequency distribution versus backscatter intensity of MBES data using SVM method

The distribution of the most intensity values is in the range of -43 dB to -42 dB with a frequency of nearly 400 thousand points. With the highest frequency distribution in the range of -40 dB, it can be said that sediments in G-Island waters are dominated by fine sediments (De Falco et al, 2010). The results of the G-Island waters sediment type classification are shown in Figure 6.

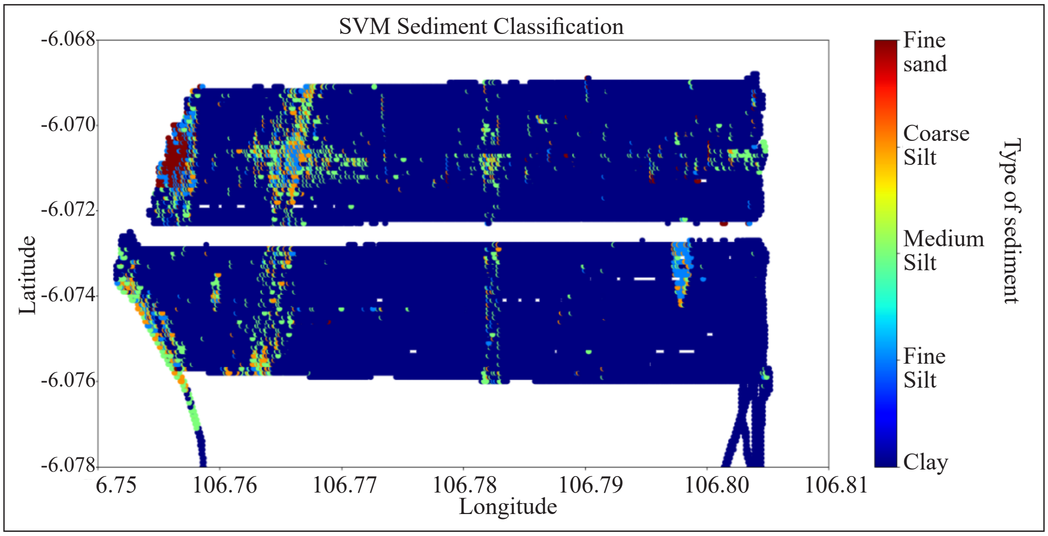

Figure 6. Classification of G-Island sediments using the SVM method

From Figure 6 we can see the spatial distribution of sediment types in the G-Island waters. From the results obtained, it appears that the type of sediment in the G-Island waters is dominated by the type of clay sediment from the classification processing results using the SVM method. Clay sediments are marked in dark blue, fine silt sediments are marked in bright blue, medium silt sediments are marked in green, coarse silt sediments are marked in orange, and fine sand is marked in red. Figure 7 shows the overlapping results between the results of the classification using the SVM method with Google Earth imagery.

From the overlapping results (Figure 7), it can be seen that the type of sediment close to the reclamation island, G-Island, the type of sediment tends to be larger and coarser. This can be caused by material or sediment originating from the reclaimed island. However, the type of sediment that dominated in the G-Island waters was still clay. The distribution of clay sediment reached 90% in these waters when referring to ground truth data.

Although the SVM method has succeeded in classifying sediment types with results similar to ground truth data, there are still some shortcomings in this method, including the inability of this method to produce classes according to ground truth. There are four classes that have not been successfully classified by this method; sandy silt, sandy clay, sandy mud, silty clay, and clayey sand. Another drawback is that there are still misclassifications of this method, such as errors in determining class. Sediments which should be categorized as silt are classified as clay by this method.

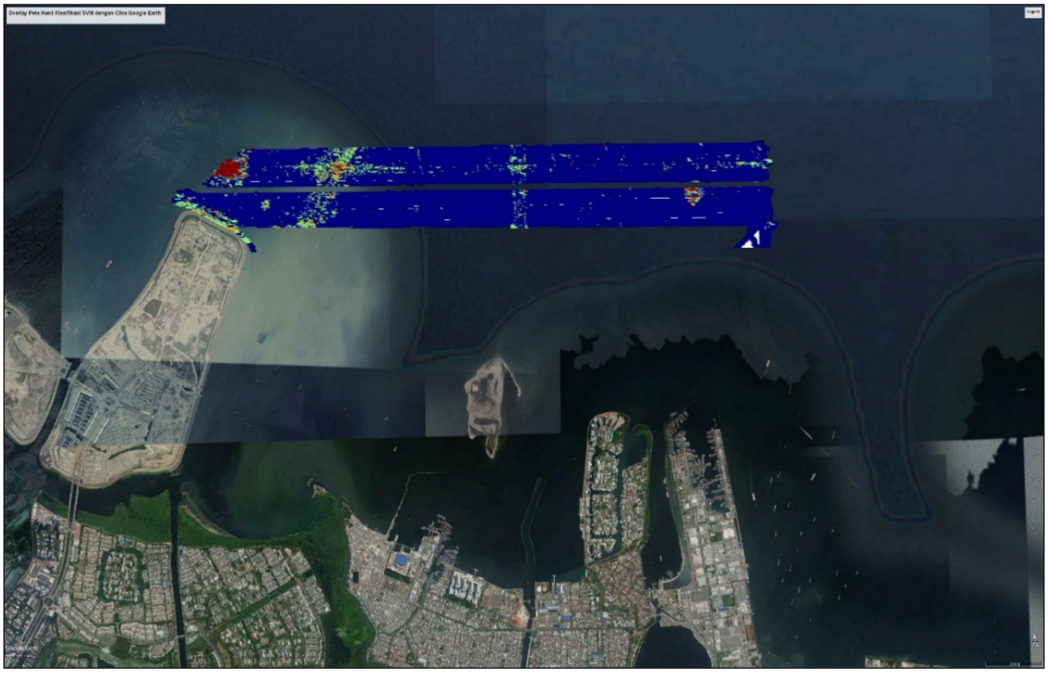

Figure 7. Overlapping between Google Earth imagery and the results of the SVM classification in the G-Island waters

SVM Accuracy Test

Supervised classification techniques also need to do an accuracy test to find out how accurate the classification model is made and how it fits with ground truth data. The accuracy test used in this method is the Kappa coefficient test.

The overall accuracy value for the SVM method generated from the Kappa test is 0.8025 with an agreement of chance value of 0.7522 at a 95% confidence interval. The accuracy value of 0.8025 is quite large for classification, which means 80.25% of the data has been successfully classified correctly by this method.

The Kappa coefficient value obtained in this study is 0.2031. This value is classified into fair class of the strength of agreement variable. These results are similar to studies conducted by Stephens and Diesing (2014) which show that the accuracy and Kappa coefficient values of the SVM method are worth 0.78 and 0.39. Testing the accuracy of this method also calculates the values of producers's accuracy and user's accuracy.

Producer's accuracy is classification accuracy which is seen from the point of view of the producer. This shows how often class results are displayed spatially correctly or the probability of a benthic habitat in an area is classified correctly, while user's accuracy is the classification accuracy seen from the point of view of the map user, not the maker. User accuracy indicates how often the class on the map can represent the real situation. Table 5 shows the classes obtained from the results of the SVM classification and the values of the producer's and user's accuracy of those classes.

Table 5
The value of producer's accuracy and user's accuracy of the classes classified by the SVM method

Class	Number of points that correctly classified	References points	Classification points	User's accuracy (%)	Producer's accuracy (%)
Clay	2796	3276	2839	98.49	85.35
Fine Silt	2	25	295	0.68	8.00
Medium Silt	3	15	238	1.26	20.00
Coarse Silt	23	62	143	16.08	37.10
Very Fine Sand	1	1	5	20.00	100.00

From Table 5 it can be explained that the value of producer's accuracy and user's accuracy will not be the same. In the case of the SVM method in this study, for example, the value of producer's accuracy for the clay class is 85.35%, while the value of user's accuracy is 98.49%. This shows that 85.35% of the clay class has been correctly identified as "clay", and as many as 98.49% of the points identified as "clay" are the actual classifications for clay. As many as 1.51% of the points are misclassified into the other four classes. These results are of course categorized as having a large enough accuracy value. This is due to the dominant class in the study area is the clay class.

In the coarse silt class, the value of the producer's accuracy for the coarse silt class is 37.10%, while the value of the user's accuracy is 16.08%. This shows that 37.10% of the coarse silt class was correctly identified as "coarse silt", and only 16.08% of the points identified as "coarse silt" were the actual classifications for coarse silt. 83.92% of the points are categorized incorrectly in other classes (clay, fine silt, medium silt, and fine sand).

CONCLUSIONS

The aims of this study was to test the supervised classification technique for their ability to predict substrate type using MBES and ground truth data. We have shown that satisfactory results can be obtained from using legacy data. The value of backscatter intensity obtained from the supervised classification techniques, is ranged from -54 dB to -14 dB using SVM classification. The basic sediment types of Jakarta Bay waters can be mapped into 5 main classes (clay, fine silt, medium silt, coarse silt, and very fine sand). The SVM method produces an accuracy level of 80.25% with a Kappa coefficient of 0.2031.

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