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Research Article

Seabed Geoacoustic Analysis Using Scientific Single Beam Echosounder

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Abstract

Hydroacoustic technology was able to quantify the seabed substrate and can be estimated accurately and near real time on the acoustic characters of each substrate. The purpose of the research was to identify the geoacoustic characteristics and spatial mapping of the seabed sediment in Lancang Island. Acoustic data was acquired using a Simrad EK-15 Single Beam Echosounder instrument operating at 200 kHz. Sediment samples were taken using an Ekman grab to validate the acoustic data. The results of this study indicated that the acoustic backscatter values of the seabed substrate based on the surface backscattering strength value and sediment particle size at fourteen sampling stations are -28.03 decibels to -20.02 decibels divided into 9 sediment type groups, namely medium and very coarse sand mixture; medium sand; medium, fine and coarse sand mixture; medium and fine sand mixture; fine and medium sand mixture; medium and very fine sand mixture; very fine and medium sand mixture; fine and very fine sand mixture; and fine sand. The accuracy level of k-Nearest Neighbour and Random Forest computational used has very good accuracy of 98.21 % and 96.43 % and Naevi Bayes has a lower accuracy of 58.93 %. The identified geoacoustic characteristics included the mean grain size, sound speed, density, acoustic impedance, and reflection coefficient. Faster, more effective, and efficient computational processes with high accuracy of k-Nearest Neighbour and Random Forest were models the best alternative to be used as geoacoustic computational models of seafloor sediment.

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1. Introduction

The seabed is a vital area for ecological study due to its complex geomorphological features, which influence marine habitats and coastal structures (Liu *et al*., 2013). In addition, it can provide information about various things that are inter-connected between abiotic and biotic (Pujiyati *et al*., 2010). The geomorphology of the seabed and its constituent material composition is an important physical variable in the formation of the distribution of habitats on the seabed (Lu *et al*., 2010). The composition of seabed substrates can be identified through geoacoustic properties such as acoustic impedance, density, and sound speed, which are key indicators of sediment type (Chaytor *et al*., 2022; Wang *et al*., 2023). Seabed geoacoustics is a physical property of seabed substrates in terms of the characteristics of acoustic values owned, such as acoustic impedance, density, sound speed and mean grain size (Bae *et al*., 2014; Walree *et al*., 2006). These physical properties can be known through in-situ detection and measurement as well as on a laboratory scale through acoustic methods and computational techniques (Jackson and Richardson, 2007).

Measuring geoacoustic characteristics of seabed substrates requires advanced technologies that overcome the limitations of conventional electromagnetic methods, such as by providing real-time, high-resolution data (Zou *et al*., 2015). These weaknesses can be overcome by using hydroacoustic technology (Ballard *et al*., 2020). This technology is able to detect and measure seabed substrates and can estimate accurately and in near real time the geoacoustic characteristics possessed by each type of seabed substrate sediment (Chotiros, 2017).

Determination of seabed sediment type through hydroacoustic technology is obtained from the backscattering strength value possessed by each sediment through the measurement results of hydroacoustic instruments (Sternlicht and Moustier, 2003), such as single beam echosounder (SBES). The working principle of this SBES acoustic system is that every acoustic pulse emitted will produce an acoustic footprint beam in a position just below the ship's body (Lurton, 2002). The backscattering strength value derived from the acoustic beam provides much information related to the characteristics of the seabed surface (Dall'Osto and Tang, 2022). The SBES system determines seabed substrate types by analyzing the initial reflection of acoustic pulses, which provides insight into the seafloor's acoustic properties (Manik, 2012). Information on the geoacoustic characteristics of seabed substrate types is important to know in the process of making coastal or offshore buildings that require a solid foundation on the seabed (Li *et al*., 2019; Zhang *et al*., 2017). SBES acoustic technology is one solution to analyze the geoacoustic characteristics of seabed substrates (Kim *et al*., 2018; Walree *et al*., 2006). Main grain size mapping with single beam echosounder (Walree *et al*., 2006).

Current research on seafloor sediment classification relies heavily on ground truth data to validate acoustic measurements, ensuring the accuracy of sediment type identification. This certainly requires a lot of time for data collection in the field so it results in more energy and costs incurred. Machine learning and deep learning computational engineering approaches have also been widely used to overcome these things (Yusuf *et al*., 2020; Solikin, 2020; Farihah *et al*., 2020; Frederick *et al*., 2020). However, it is still limited to the comparison of several computational methods for sediment calcification only.

This study introduced a novel application of machine learning for geoacoustic quantification, aiming to significantly reduce field survey time and improve the accuracy of sediment classification through automated analysis. In this method in the future, is hoped that it will not take a long time to survey and map the seabed. Researchers only need to conduct surveys that are not too extensive and sampling stations are few so that this becomes more effective and efficient.

This study aimed to advance the field of marine acoustic by using machine learning to map seabed sediment efficiently, with potential applications in coastal engineering and environmental monitoring. The contribution of this study lies in its innovative approach to combining hydroacoustic measurements with machine learning for efficient seabed classification. This method has the potential to revolutionize marine surveys and provide valuable insights for coastal engineering and environmental monitoring also provide spatial information about the geoacoustic characteristics of the seabed in the waters of Lancang Island, Seribu Islands.

2. Materials and Methods

2.1 Materials

The materials used in this study included a map of the research location, ArcGIS 10.5, Echoview 4.0, Microsoft Office 2016, Gradistat 8.0, Matlab 18a, and Phyton 3.8. The equipment used is a fishing boat measuring long, wide, deep (9,50 m; 1,62 m; 0,70 m) and tonnage weight 1 GT, Single Beam Echosounder (SBES) Simrad EK-15 Frequency 200 kHz, GPS MapSounder 585, Conductivity Temperature Depth (CTD) 650, Ekman Grab size 20 cm x 20 cm, and Dell laptop 14 inch processor core i7-4710 HQU, RAM 16 GB, *64-bit Windows OS.*

2.1.1 Ethical approval

This study does not require ethical approval because it does not use experimental animals.

2.2 Methods

The research was conducted in January 2020. Field data collection location in the Lancang Island seawaters, Seribu Islands (Figure 1). Data processing and analysis were carried out at the Underwater Acoustics Laboratory and Oceanography Laboratory, Department of Marine Science and Technology, Faculty of Fisheries and Marine Sciences, IPB University.

Supporting parameters in the calibration process show that the temperature and salinity of the waters at the calibration site ranged from 29.60-30.14ºC and 30.92 psu – 31.16 psu with an average of 29.72ºC and 31.14 psu. This oceanographic phenomenon was closely related to the results of measuring the speed of propagation of sound waves in seawater, which ranges from 1551.30 ms^{-1} – 1552.25 ms^{-1} with an average

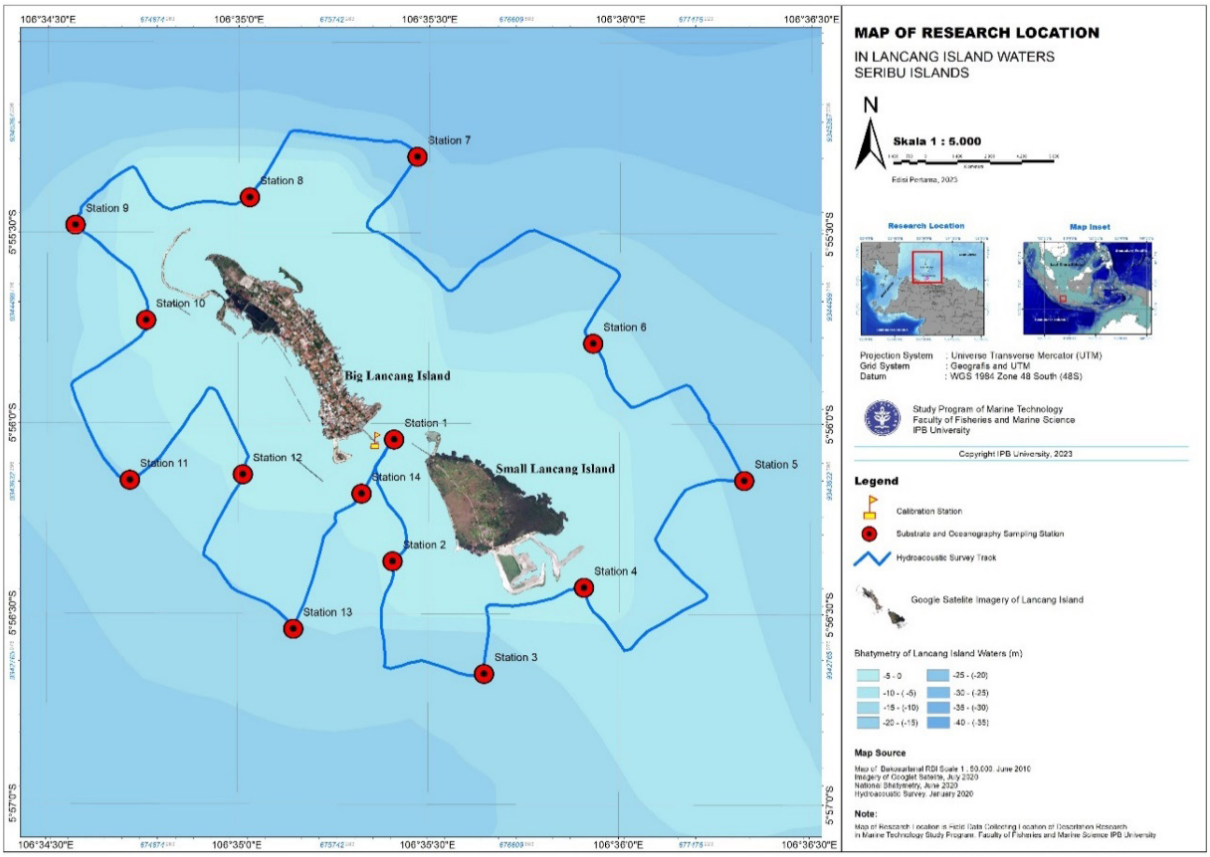

Figure 1. Map of the research location (data processing of research results, 2023).

2.2.1 Data acquisition

Before carrying out data acquisition, calibration of all equipment used was carried out with the aim of ensuring that all system configurations were functioning properly. The calibration process uses the sphere ball method. The process of recording acoustic data of SBES Simrad EK-15 using fishing boat vehicles on the survey column based on (Indonesia National Standard 7646, 2010) concerning hydrographic and oceanographic surveys using SBES. The calibration of Simrad EK15 with an operating frequency of 200 kHz showed that the Target Strength (TS) value of the sphere ball was -47.60 dB. Based on the calculation of the manufacturer of -45.96 dB. This shows that the calibrated TS value with the factory TS value of the 35 mm diameter sphere ball has a difference of -1.64 dB. This difference was used for subsequent correction of measurement results. The calibration results of Simrad EK-15 and CTD 650 are shown in Table 1.

of 1551.50 ms^{-1}. Based on measurements of oceanographic parameters and sound speed in the sea, an absorption coefficient of 0.08 dB/m was obtained. The condition of the sea waters when calibrated in the afternoon is shady and sunny.

Table 1. Result of Simrad EK-15 and CTD 650 calibration.

Parameters	Value
Depth of sea	2.3 m
Depth of transducer	0.7 m
Depth of sphere ball calibration	1.7 m
Sphere ball calibration diameter size	35 mm
Target strength of sphere ball calibration	-47.60 dB
Temperature	29.72 ºC
Salinity	31.14 psu
Sound Speed	1551.50 ms^{-1}

The survey design used longitudinally and transversely parallel patterns with a length of 14 km, as shown in Figure 1. In addition to acoustic data collection, oceanographic data collection, and sediment sampling were also carried out in fourteen sampling stations. Sediment sampling method using Ekman grab. Seabed substrate mapping uses geographic information system (GIS) methods from the results of quantification and geoacoustic computing of seabed substrates along the research survey strip.

2.2.2 Data processing

2.2.2.1 Acoustic bottom backscattering

The SBES data has an initial format extension *.raw. Furthermore, the processing process was carried out using Echoview software which is displayed in the form of an echogram. Data processing in this software is to make several echogram settings which include determining the maximum and minimum thresholds of the substrate. The echogram display was set specifically for the seabed, the target area is set to the Elementary Sampling Distance Unit (ESDU) every 100 pings with a thickness of 20 cm as an estimate of the sediment thickness reached by grab sampling and in accordance with the provisions greater than acoustic resolution (Lurton, 2002).

2.2.2.2 Identification of seabed sediment types

The technique used to identify the type of seabed sediment is through the distribution of amplitude values in existing sampling data (Anderson *et al*., 2008). Each sampling result spatially has a coordinate point at the time of data collection at each station. The results of processing backscatter data in the form of coordinate points, beams, depth, and amplitude values have been carried out before, then matching coordinate points in each sampling result is carried out. Sediment samples at each station were identified according to grain size based on the (Buscombe and Brams, 2018).

2.3 Analysis Data

Data analysis included oceanographic analysis, sediment analysis, acoustic backscattering analysis, and seabed geoacoustics analysis at each sampling station and along the survey line.

2.3.1 Oceanographic analysis

Oceanographic analysis at each sampling station includes temperature, salinity, and depth as components of the function to obtain a vertical profile of the speed of sound waves in the seawater column. According to (Zhang *et al*., 2017) that to obtain the value of the speed of sound in the seawater column using the following equation:

$$C = 1448{,}96 + 4{,}951T - 5{,}304 \times 10^{-2}T^2 + 2{,}374 \times 10^{-4} T^3 + 1{,}340\ (S\text{-}35) + 1{,}63 \times 10^{-2}D + 1{,}675 \times 10^{-7} D^2 - 1{,}025 \times 10^{-2}T\,(S\text{-}35) - (7{,}139 \times 10^{-13}TD) \quad \text{....(Eq 1)}$$

Where: C is sound speed (ms^{-1}); T is temperature (*ºC*); S is salinity (*psu*) and D is sea depth (m).

2.3.2 Seabed sediment analysis

Analysis of sediment texture sampling results was used to validate measurement data. Determination of sediment texture using a stepped sieve method that can separate sediment grains based on grain size fractions. Determination of sediment type based on (Bucombe and Brams, 2018) and computational models of k-Nearest Neighbors (k-NN), Random Forest (RF), and Naevi Bayes (NB). The k-NN model is an approach to finding cases by calculating the closeness between new cases and old cases based on matching weights from a number of existing features (Kusrini and Luthfi, 2009). The RF model is an algorithm used in classifying large amounts of data through tree pooling (Zailani and Hanun, 2020). The NB model is a classification method using probability and statistical methods. This method predicts future opportunities based on previous experience (Xhemali *et al.,* 2009). Test the accuracy of the ability of the three models to classify sediment types using the Confusion Matrix (CM). Confusion Matrix is a table that has four combinations of predicted values and actual values (Prasetyo, 2013).

2.3.3 Seabed geoacoustic analysis

Goacoustic parameters (surface backscattering, mean grain size, sound speed, sediment density, acoustic impedance, reflection coefficient) calculations of seabed acoustic backscattering analysis from SBES measurements were obtained through sonar equations, including the conversion of amplitude values into backscatter data (Lurton, 2002) and *SV* numerical models to obtain *SS* values through the equation from (Manik, 2012):

$$SV_b = SS - 10\log (c\tau/2) \quad \text{.......................... (Eq 2)}$$

Where SS is surface backscattering strength (dB); SV_b is volume backscattering strength of sea bottom (dB); c is sound speed (ms^{-1}); τ is pulse width (mm).

Geoacoustic analysis of the seabed was carried out through several equation models as follows: The mean grain size in micrometers and *phi* can be calculated based on the equations of (Chotiros, 2017).

$$M_G = exp\frac{lnP_{16} + lnP_{50} + lnP_{84}}{3}$$

and

$$M_Z = \frac{\phi_{16} + \phi_{50} + \phi_{84}}{3} \text{ ....(Eq3)}$$

Where M_G and M_z are mean grain size in micrometers (μm) and phi (ϕ); P_x and ϕ_x are the grain diameter in meters and phi at the cumulative percentile value of *x*. The cumulative percentile value of P_x and ϕ_x is the percentage of the number of values below P_x and ϕ_x.

Sound speed and sediment density were calculated through the equation from (Anderson *et al*., 2008):

$C_s = 1952 - 86{,}3M_z + 4{,}14M_z^2$ dan $\rho_s = 2380 - 172{,}5M_z + 6{,}89M_z^2$ ……..…………………..…….……......(Eq 4)

Where M_z is mean grain size (ϕ); c_s is sound speed in sediment (ms^{-1}); and ρ_s is sediment density (kgm^{-3}).

Acoustic impedance sediments were calculated through the equation (Lurton, 2002):

$Z_s = \rho_s \times C_s$ ……………………………………(Eq 5)

Furthermore, from equations (3), (4), and (5) can be obtained the reflection coefficients of the process of propagation of acoustic waves from two different mediums (water column and sediment) through the equation (Lurton, 2002):

R = (Zs-Zw) / (Zs+Zw)...................................(Eq 6)

Where *R* is reflection coefficient; Z_s is sediment acoustic impedance (kgm^{-3} ms^{-1}); and Z_w is acoustic impedance of seawater (kgm^{-3} ms^{-1}).

3. Results and Discussion

3.1 Results

3.1.1 Oceanographic conditions and speed sound at the sampling station

The results of measuring temperature and salinity parameters (Figures 2a and 2b) at each sampling station vertically showed that the pattern of temperature and salinity changes ranged from 28-30ºC and 29 psu – 32.5 psu. The measured depth of water ranges from 2.1 m – 25 m. High temperatures are generally in shallower water areas and on the surface. This is due to the high intensity of sunlight at sea level. Conversely, in deeper parts of the water, the intensity of the sun has decreased, so the temperature value decreases as the depth of the sea increases. In contrast to salinity, at sea level, the salinity value is smaller than in deeper parts of the water. Vertically, salinity values increase as ocean depth increases. The phenomenon of the marine environment is a functional component in calculating the propagation sound speed waves in the sea (Zhang *et al*., 2017).

Based on the measured temperature, salinity, and depth values at each sampling station, a vertical profile of the sound speed is obtained (Figure 2c). Changes in the sound speed values at all stations ranged from 1550,8 ms^{-1} – 1552,4 ms^{-1}. The pattern of change in the sound speed waves decreases with increasing ocean depth. The propagation of sound speed waves in water is influenced by patterns of changes in depth, temperature, and salinity. The value of the sound speed decreases with increasing depth (Lurton, 2002).

3.1.2 Acoustic backscatter of seabed

The acoustic backscatter value obtained from

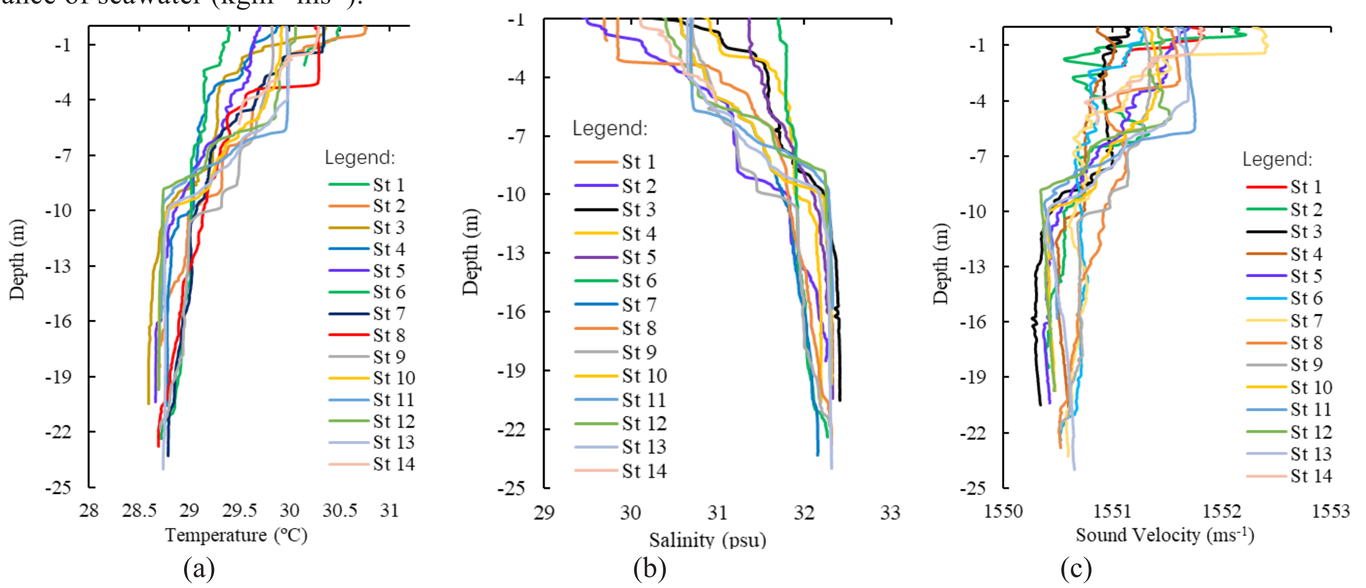

Figure 2. Vertical Profile (a) temperature, (b) salinity and (c) sound speed at the sampling station (data processing of research results, 2023).

SS through equation (2) is the result of calculating the maximum SV value. The results of waveform analysis of seabed echo and sediment analysis can be identified substrate types at each sampling station there are 9 groups, namely medium and very coarse sand mixture; medium sand; medium, fine and coarse sand mixture; medium and fine sand mixture; fine and medium sand mixture; medium and very fine sand mixture; very fine and medium sand mixture; fine and very fine sand mixture; and fine sand (Table 2). The mean grain size of substrate particle diameters on the Wentworth scale and seabed substrates was grouped based on Shepard's classification (Manik *et al.,* 2006). There were 11 sediment fractions based on the (Bucombe and Brams, 2018), namely gravel, very coarse sand, coarse sand, medium sand, fine sand, very fine sand, coarse silt, medium silt, fine silt, coarse clay, and fine clay. The results of this study showed that the seabed acoustic scattering values of all sediment type groups identified at the sampling station ranged from -28.03 dB to -20.02 dB belonging to the substrate type of the sand group. tics instrument SIMRAD EY60 120 kHz frequency and recorded by ER60 software. According to (Pujiyati, 2008) the acoustic backscattering value of sand was -20.00 dB and silt of -35.91 dB, the research location in the Sunda Strait. Acoustic data collected were using split beam hydroacoustic instruments SIMRAD EY60 and EK60 120 KHz. The hydroacoustic data of sea bottom substrates and grab sampling results were classified based on Principal Component Analysis (PCA) and Cluster Analysis. According to (Hamuna *et al*., 2018) found medium and coarse sand were are -28.02 dB to -27.36 dB, while fine sand was -28.12 dB to -28.40 dB with the research location in the Yos Sudarso Bay, Jayapura City. Acoustic data collected were using single beam echosounder SIMRAD EK15 120 kHz. Substrate sample used for data validation using sediment grab. The difference in acoustic backscattering values measured on the same substrate from several studies is due to several factors, such as the type of instrument and frequency used as well as

Table 2. Seabed substrate type classification based on particle mean diameter size, weight composition and SS value at each sampling station.

Substarate Type	Sampling Station	Particle Size (µm)	Particle Size (φ)	Very Coarse Sand (%)	Coarse Sand (%)	Medium Sand (%)	Fine Sand (%)	Very Fine Sand (%)	Other (%)	SS (dB)
I	8	490.10	1.46	24.10	13.67	37.18	11.58	3.42	10.04	-20.02
II	3	281.63	1.83	10.86	0.38	64.67	7.30	15.02	1.78	-21.08
	4	258.60	1.95	13.84	0.48	60.89	0.92	22.49	1.38	-22.10
III	12	309.30	1.69	8.78	20.18	29.44	22.78	17.73	1.09	-21.49
IV	6	257.60	1.96	6.76	5.20	42.12	32.40	12.85	0.66	-24.47
	13	255.10	2.97	9.22	0.22	45.68	26.12	16.00	2.76	-22.90
V	1	246.82	2.02	11.09	5.40	26.18	37.65	18.73	0.95	-26.67
VI	7	300.80	1.73	11.04	9.13	45.84	4.72	26.34	2.93	-23.17
	10	221.80	2.17	6.65	1.08	49.62	9.04	33.28	0.34	-24.55
VII	9	205.10	2.29	9.63	4.77	31.56	9.48	42.86	1.70	-27.26
	11	116.50	2.59	6.92	9.07	28.80	1.02	54.06	0.12	-27.42
VIII	5	165.60	2.59	2.33	0.30	21.45	41.32	34.58	0.02	-25.92
IX	2	100.55	3.31	0.98	0.96	6.99	9.17	81.80	0.11	-27.78
	14	140.70	2.83	2.73	2.44	20.67	9.77	64.36	0.02	-28.03

Source: Data processing of research results (2023)
Description:
I: medium and very coarse sand mixture; II: medium sand; III: medium, fine and coarse sand mixture; IV: medium and fine sand mixture; V: fine and medium sand mixture; VI: medium and very fine sand mixture; VII: very fine and medium sand mixture; VII: fine and very fine sand mixture; IX: fine sand.

Some other previous research results obtained seabed acoustic backscattering values such as (Manik *et al*., 2006) obtained that the sand was bottom of SS value was -18.30 dB and the silt bottom was -29.00 dB. Acoustic data collected were using hydroacous- the condition of the waters that are the location of the study. According to Chakraborty *et al.* (2007), the use of acoustic instruments with two different frequencies on the same water bottom measurement gives different acoustic reflection values, low frequencies produce higher acoustic reflections and vice versa high frequencies will produce lower acoustic reflections. Moreover, the morphology of the waters bottom such as the shape of the relief is also very influential on the penetration of acoustic waves emitted at different frequencies (Jackson and Richardson, 2007).

on sediment sampling results. Sound speed, density, and acoustic impedance in sediment layers are the results of measurements based on models developed by (Anderson *et al*., 2008). The value of the reflection coefficient of the process of propagation of sound waves from the water column to the sediment layer is the result of calculations from the equation of (Lurton, 2002).

Table 3. The accuracy rate of the k-Nearest Neighbors (k-NN), Random Forest (RF) and Naive Bayes (NB) computational models.

Models	Amount of Data		Train Data	Test Data	Accuracy	
	Labeled	Unlabeled			Train Data	Test Data
k-NN	560	858	504	56	94.42 %	98.21 %
RF	560	858	504	56	95.02 %	96.43 %
NB	560	858	504	56	65.74 %	58.93 %

Table 4. Performance validation rate of Random Forest, k-Nearest Neighbor and Naevie Bayes computational models.

Models	Accuracy	Precision	Recall	F1-Score
k-NN	0.98	0.98	0.98	0.98
RF	0.96	0.97	0.96	0.96
NB	0.59	0.60	0.59	0.57

Sediment type determination techniques were also carried out using k-Nearest Neighbors (k-NN), Random Forest (RF), and Naive Bayes (NB) computational models. These three models use SBES data of 141,800 pings consisting of data mean grain size, sound speed, density, impedance, reflection coefficient, and intensity values of seabed acoustic backscattering with ESDU per 100 pings, so that 1,418 points of data were obtained. The data has been identified as many as 560 points and those that have not been identified as many as 858 points. Furthermore, to find out the unidentified data, training data was carried out by 90% of the data that has been identified and 10% for testing data. The three models RF, k-NN, and NB have the ability to identify sediment types in the process of training and testing data with different levels of accuracy as shown in Table 3. Through this computational model, besides the sand substrate as well, silt type substrate types were also identified in the survey line area with acoustic backscattering values of -38.99 dB to -29.01 dB.

3.1.3 Geoacoustic characteristics of seabed substrates

The results of this study showed that the geoacoustic characteristics of each type of sediment identified at each sampling station and survey area include the mean grain size diameter (*Mz*), sound speed (*C*), density (ρ), acoustic impedance (*Z*) and reflection coefficient (*R*) as shown in Table 5. The mean grain size diameter is measured in micrometers and *phi* based

The results of acoustic bottom backscattering measurements provided information on the physical characteristics possessed by each seabed substrate (Sternlicht and de Moustier, 2003). Acoustic backscattering of each type of seabed substrate sediment measured is one of the geoacoustic characteristics information possessed by each of these sediments (Wang *et al*., 2023). There were discrepancies in the strength of acoustic signals reflected by seabed substrates in different sediments. The greater the reflected value resulted, the greater the substrate particle size, conversely, the smaller the returned reflection value, the smaller the particle size of the substrate (Snellen *et al*., 2011). According to (Pujiyati *et al*., 2010) the conditions of the physical characteristics of the seabed such as the size of sediment grains and the shape of relief can affect the process of backscattering acoustic signals. (Manik, 2012) also mentioned that the grain size of the bottom of the water greatly affects the value of acoustic scattering, where the substrate type with a large grain size produces greater acoustic backscatter energy compared to the smaller grain size. The phys ical properties of the seabed which are composed of various elements ranging from rough rock layers to fine clays over layers that have different compositions, provide different acoustic scattering values (Kim *et al*., 2011).

Table 5. Geoacoustic characteristics of seabed substrate types in sampling station and reference.

Substrate Type	Station	Parameters						
		SS (dB)	Diameters		Sound Speed [C (ms^{-1})]	Density [p (kgm^{-3})]	Impedance [Z (kgm^{-3} ms^{-1})]	R
			µm	ϕ				
Fine and Medium Sand Mixture	1	-26.67	246.82	2.02	1,794.67	2,059.88	3,696,810.01	0.40
Very Fine Sand	2	-27.78	100.55	3.31	1,711.47	1,884.00	3,224,398.23	0.34
Medium Sand	3	-21.08	281.63	1.83	1,808.07	2,087.68	3,774,663.64	0.41
Medium Sand	4	-22.10	258.58	1.95	1,799.36	2,069.63	3,724,015.63	0.40
Fine and Very Fine Sand Mixture	5	-25.92	165.61	2.59	1,755.98	1,978.87	3,474,871.95	0.37
Medium and Fine Sand Mixture	6	-24.47	257.57	1.96	1,798.97	2,068.81	3,721,720.73	0.40
Medium and Very Fine Sand Mixture	7	-23.17	300.85	1.73	1,814.88	2,101.76	3,814,454.18	0.41
Medium and Very Coarse Sand Mixture	8	-20.02	490.07	1.46	1,834.75	2,142.68	3,931,273.98	0.43
Very Fine and Medium Sand Mixture	9	-27.26	205.09	2.29	1,776.37	2,021.72	3,591,326.57	0.39
Medium and Very Fine Sand Mixture	10	-24.55	221.76	2.17	1,784.02	2,037.70	3,635,295.69	0.39
Very Fine and Medium Sand Mixture	11	-27.42	166.49	2.59	1,756.48	1,979.93	3,477,708.66	0.37
Medium, Fine and Coarse Sand Mixture	12	-21.49	309.28	1.69	1,817.76	2,107.70	3,831,300.59	0.42
Medium and Fine Sand Mixture	13	-22.90	255.13	1.97	1,798.01	2,066.82	3,716,151.74	0.40
Very Fine Sand	14	-28.03	140.71	2.83	1,740.98	1,947.12	3,389,888.75	0.36
Silt	Ref	-29.01	120.4	3.80	1,694.97	1,848.29	3,132,811.69	0.33

R: Reflection Coefficient

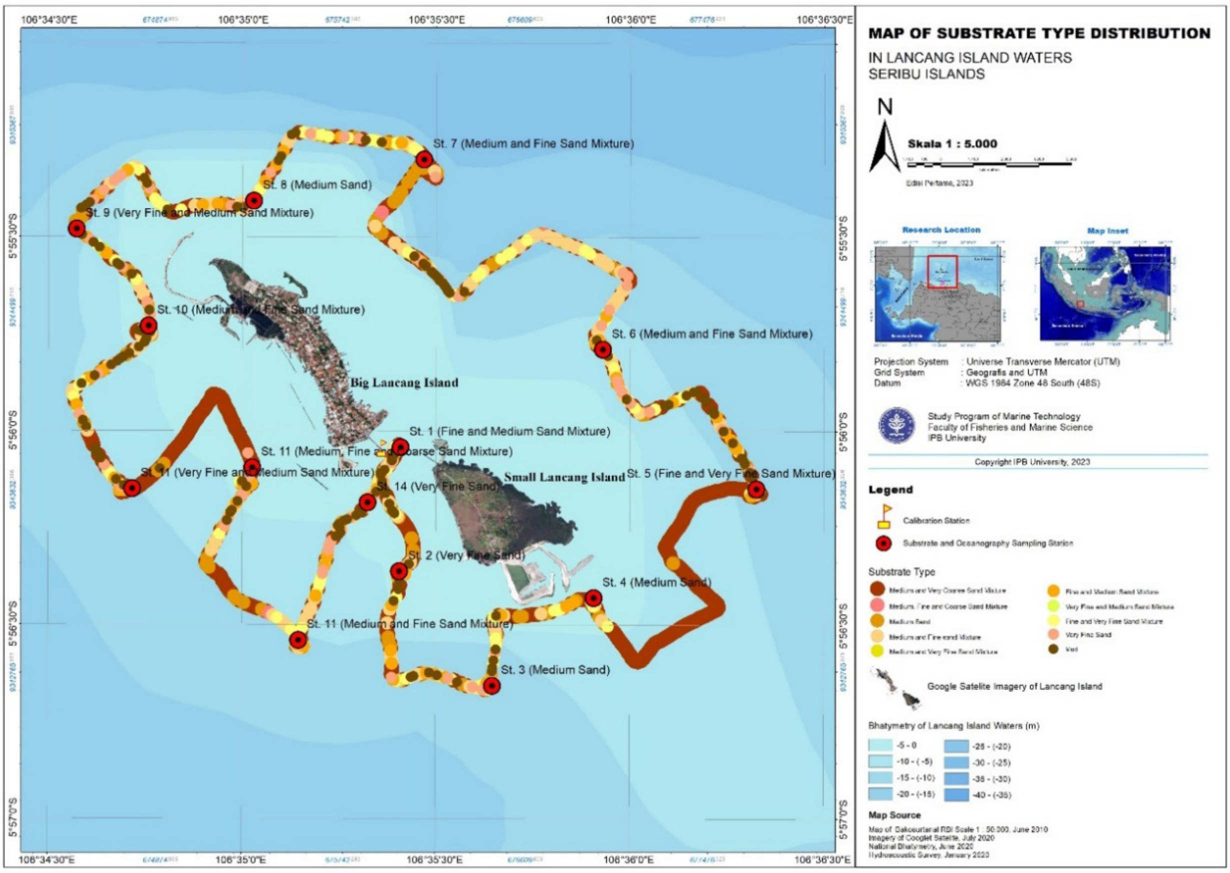

Figure 3. Map of seabed substrate type distribution in research survey area (data processing of research results, 2023).

Geoacoustic characteristics identified based on sediment physical characteristics from the classification results at each sampling station were used to determine the distribution of sediment types along the survey area (Figure 3). Spatially, the distribution of sediment types in the study area showed that mixed types of medium and coarse sand are scattered in the southern and western waters of Lancang Island. Fine sand, very fine sand, and a mixture of both spread in the eastern and northern areas of the waters of Lancang Island. Water depth in the study can affect the spatial distribution of seafloor substrate types. Differences in water depth due to unequal topography of the seabed can affect the spatial distribution of seabed substrate types (Pujiyati *et al*., 2010).

3.2 Discussion

Based on the measured temperature, salinity, and depth values at each sampling station, a vertical profile of the sound speed is obtained (Figure 2c). Changes in the sound speed values at all stations ranged from 1550,8 ms-1 – 1552,4 ms-1. The pattern of change in the sound speed waves decreases with increasing ocean depth. The propagation of sound speed waves in water is influenced by patterns of changes in depth, temperature, and salinity. The value of the sound speed decreases with increasing depth (Lurton, 2002).

The rate of accuracy of the models in defining the type of sediment that has not been identified from the results of training and testing data was carried out in the pro forma model evaluation using a confusion matrix. This evaluation technique shows that the three models used have different levels of accuracy (Table 4), which were 0.98 for k-Nearest Neighbors, 0.96 for Random Forest, and 0.59 for Naive Bayes. The high rate of accuracy in the k-NN and RF models indicates that they are accurate in correctly classifying sediment types (Hamilton, 1980). The accuracy rate of the NB model has a smaller value than the k-NN and RF models. Therefore, among these three models that are good to use to identify seabed sediment types are k-NN and RF.

Precision showed that the model was able to determine objects that have not been identified according to the actuality. Recall is a measure of the model's ability to determine objects well. Recall is a measure of the model's ability to determine objects well. High recall means that the class is well recognized, and the majority of sampling can be detected by the model (Prasetyo, 2013). F1-Score is the harmonic mean of precision and recall.

The Lancang Island seawater is an area included in the Seribu Islands cluster in the south. The island consists of small Lancang Island and large Lancang Island. These two islands have almost the same characteristics of the bottom of the waters. The waters of large Lancang Island are much influenced by human activities that carry out development in coastal areas such as piers, settlements, land and sea boundary walls in the south, and tourist buildings in the form of resorts in the south. This area also experienced a very strong influence from Java Island activities, especially in the Jakarta and Tangerang areas through runoff. This runoff generally brings various dissolved materials into the aquatic environment which can cause the mixing of seabed sediments with material that is bottom from land.

4. Conclusion

The conclusion of this study was the seabed acoustic backscatter results of scientific single beam echosounder measurements validated with ground truth results and references can be used to quantify seabed geoacoustic properties. Geoacoustic properties of the seabed were identified based on the type of substrate found in all sampling stations and acoustic survey areas, including the mean grain size diameter, sound speed, density, acoustic impedance, and reflection coefficient. Faster, more effective, and efficient computational processes with a high level of accuracy make of k-Nearest Neighbour and Random Forest models were the best alternative to be used as geoacoustic computational models of seafloor substrates. Spatially, the distribution of seabed substrate types resulting from the quantification of hydroacoustic technology and computational models in the waters of Lancang Island, Seribu Islands is dominated by sand substrate. The suggestion from this study is that it is necessary to carry out a laboratory test approach supported by adequate equipment to be able to obtain a comprehensive geoacoustic value of seabed substrate type.

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Authors' Contributions

All authors have contributed to the final manuscript. The contribution of each author is as follows, Els; collected the data, data processing and analysis, and drafted the manuscript. Hmm, Tok and Sri; devised the main conceptual ideas and critical revision of the article. All authors discussed the results and contributed to the final manuscript.

Conflict of Interest

The authors confirm that there are no conflicts of interest in writing this publication.

Declaration of Artificial Intelligence (AI)

The authors affirm that no artificial intelligence (AI) tools, services, or technologies were employed in the creation, editing, or refinement of this manuscript. All content presented is the result of the independent intellectual efforts of the author(s), ensuring originality and integrity.

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