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BATHYMETRY AND BATHYMETRIC DIFFERENCES MBES MULTIFREQUENCY FOR SEAFLOOR SEDIMENT MAPPING

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ABSTRACT: Seafloor sediments have a significant role in the planning and development of coastal areas, especially port areas. Acoustic technology developing today, especially multifrequency Multibeam Echosounder (MBES), is expected to measure seafloor sediment and detect the type and distribution of seafloor sediments. The question posed in this study is how to improve the accuracy of sediment classification using multifrequency MBES. This study uses deep neural networks to classify seafloor sediments in the study area with input bathymetric and bathymetric differences and 74 in situ sediment samples (silt, clayey sand, silty sand, and sandy silt). Sediment classification results show that clayey sand dominates the sediment distribution in the Central and Eastern regions. On the other hand, sandy silt predominates in the western area (harbor pond). Classification of seafloor sediments in the study area has an accuracy of 41.9% (average) and a kappa coefficient of 21.9% (fair). The implication of the study is that bathymetric and bathymetric differences from multifrequency MBES produce a low sediment classification accuracy value of below 50%. Therefore, it needs to be re-evaluated in relation to bathymetric and bathymetric differences and the amount and distribution of sediment sample data needed to improve its accuracy.

Keywords: Coastal areas, Overall accuracy, Kappa coefficient, Deep neural network, Acoustic

1. INTRODUCTION

Coastal zones are unique areas at the interface of land and sea [1] and are dynamic and change spatiotemporal. There are strong interactions between land and sea in coastal areas such as beaches, swamps, mangroves, coral reefs, etc. The transition from land to sea creates highly diverse and productive ecosystems. Coastal areas have very high economic value. Coastal areas also are rich in biodiversity and function as places for exchange between countries, islands, and regions.

Activities in coastal areas require marine maps to support economic and environmental activities on the coast. Nautical charts are important to marine data and information, depicting the configuration of the seafloor and coastlines [2]. A nautical chart contains geographic information from the sea and coastal areas, which includes bathymetry, seafloor sediments, coastlines, navigation hazards, natural and artificial navigation aids, tides, currents, man-made structures such as ports, buildings, jetties, and bridges [3]. Apart from that, the characteristics of seafloor sediments must be included in a nautical chart [4].

The characteristics of seafloor sediments play a significant role in the planning and development of marine and coastal areas, such as safety transportation and navigation, marine structures constructions (pipelines, cables, platforms, harbors), and the marine environment (habitats, waste treatment, sedimentation). Seafloor sediment maps are usually obtained by in situ data (grab and core samplers), optical (camera and video), and acoustic methods (sonar) [5]. The acoustic methods commonly used to classify seafloor sediments are single beam echosounder (SBES), side scan sonar (SSS), and multibeam echosounder (MBES).

Over the past five years, technological developments have been used to classify seafloor sediments using multifrequency MBES, where a survey directly captures multifrequency based on ping by ping [6,7]. Multifrequency MBES data comes with bathymetric and backscatter data for each frequency. The bathymetric data for each frequency can be adjusted to obtain the sediment thickness (depth difference) between the frequencies.

Recent developments in MBES technology can produce bathymetric, backscatter, and water column data in one survey [8,9]. Researchers often use backscatter data to classify seafloor sediments in single frequency [10-14] and multifrequency [6,7,15-17]. In addition, some researchers use bathymetric and backscatter data [18-20] and bathymetric and backscatter features [14,21-24]. Currently, there are no studies that use bathymetric data and bathymetric differences for sediment classification.

According to many researchers, including [25], further investigation of the depth difference parameters between frequencies is recommended to ensure accurate interpretation and classification of multifrequency data. Therefore, this study aims to examine the types of seafloor sediments in coastal waters using the depth and depth differences of multifrequency MBES. A positive correlation between depth difference (sediment thickness) and seafloor sediment should exist.

2. RESEARCH SIGNIFICANCE

Seafloor sediment classification has a vital role in port area management. This study utilizes the bathymetric multifrequency MBES to classify seabed sediments. The method used in this study is a deep neural network with input data in the form of bathymetric and bathymetric difference data from multifrequency MBES. In situ sediment sample data are used as validation. Although the results of this study are not satisfactory because the accuracy of the classification of seabed sediments is still below 50%, this is a breakthrough in terms of the classification of seabed sediments with bathymetric data.

3. DATA AND METHODOLOGY

3.1 Research Location

PT Gresik Jasatama has operated since 2005 as Gresik's first inland port. This port integrates large-scale modern facilities with transshipment services, making it one of the fastest operating ports in East Java. The port of Gresik Jasatama (GJT port) is an essential national object and a key force in the national economy. The company operates around the clock while applying innovations to maintain the nation's and its stakeholders' trust. It is committed to the nation's prosperity and being the most trusted and environmentally responsible company.

GJT port is located on the north coast of Gresik Regency, East Java, in the West Shipping Channel of Surabaya. It currently covers 8.3 hectares of reclaimed land, with five fully operational berths, at the end of 2016 [26]. Fig.1 shows the survey area represented by the yellow rectangle located in Gresik, East Java, Indonesia.

3.2 Multibeam Echosounder Survey and Processing

The MBES survey was conducted on Wednesday, January 4, 2023, covering an area of approximately 41 hectares. The depth of the study ar ea is less than 25 m LWS. The reliefs of the area studied are simple, with the usual harbor and coastline. The seafloor is covered with various landforms, and sediments, including clay, mud, sand, and gravel. The study of the acoustic properties of sediments has dramatically benefited from using seafloor sediments. Collect depth measurement data using R2Sonic 2020 multifrequency MBES. This survey uses five frequency modes: 400, 350, 300, 250, and 200 kHz. The 2020 MBES R2Sonic is a ping by ping based multifrequency, which means the system can capture frequency-to-frequency depth measurement data in a single survey.

Fig.1 Area Survey Location at Gresik Jasatama Port, East Java, Indonesia

During the adjustment survey, the MBES converter was installed on the side of the ship (side-mounted). The GNSS differential horizontal and directional positioning is linked directly to the CORS station. The survey also included a sound velocity profiler to measure the speed of sound waves in the water layer at the survey's beginning, middle, and end. Data from the Sound Velocity Profiler (SVP) was corrected for the velocity of the sound waves emitted by the MBES. The data acquisition system is automatically adjusted, including transmit power, gain, and pulse length. The inertial motion unit (IMU) sensor measures the ship's attitude, such as roll, pitch, and yaw. In addition, tidal observation was also made around this location to adjust the benchmark to the chart datum, lower water spring (LWS). The parameters and specifications of MBES R2Sonic 2020. Table 1 shows the parameters and specifications of MBES R2Sonic 2020, which were used in this survey.

Table 1 Parameter and spesification R2Sonic 2020 MBES [9]

Beam width (Ω_{tx} and Ω_{rx})	4° x 4° at 200kHz; 1.8° x 1.8° at 450kHz;
Selectable Swath sector	10° to 130° User selectable in real-time
Pulse type	Shape CW
Number of soundings	Up to 1024 soundings per ping
Frequency	200 – 450 kHz
Sounding Pattern	Equiangular Equidistant single
Nominal pulse Length τ_n	15 s – 1 ms

MBES raw bathymetric measurements were processed using Eiva NaviModel software. Post-processing includes corrections for sound signal loss during transmission, encoder effects, and system-implemented model removal. A patch test is calibrated for latency and the ship's attitude, such as yaw, roll, and pitch. Configure the SVP aims to achieve a sound speed profile at each depth layer. SVP value to correct the sound wave generated by the MBES transducer. Tidal data is obtained by converting readings from tidal observations into chart datum that refers to the low water spring (LWS). Raw bathymetric measurement is performed by frequency separation into five frequencies: 200 kHz, 250 kHz, 300 kHz, 350 kHz, and 400 kHz. After receiving the patch test calibration value, the sound speed profile, and the vertical reference, these can be imported into the depth data as a bathymetric map. Finally, the bathymetric of each frequency is matched to obtain the difference in depth between the frequencies.

3.3 Seafloor Sediment Samples

This study collected up to 74 seafloor sediment samples in the study area (GJT port) using the Van Veen type. Van Veen in situ sampling is suitable for bulk sampling a wide range of materials, from soft, fine-grained materials to sandy materials [27]. Sampling points are based on a predefined initial schedule evenly distributed throughout the survey area. Due to current and other factors, the final sampling location can be seen in Fig.2.

Fig.2 Seafloor sediment sample distribution in the survey area (blue dots)

Locate the sampling points using a Global Navigation Satellite System Real Time Kinematic (GNSS RTK) linked to the nearest Continue Operating Reference Station (CORS) station, which has an accuracy of less than 10 cm [28]. Samples are taken to a professional laboratory for screening and sieve analysis. A sieve analysis [29] is a procedure used to examine and measure the size of particles in a material sample. It usually involves sieving the sample through a series of sieves, each with a different mesh size, to allow the passage of particles of different sizes. The proportions of particles of different sizes can then be measured and compared, helping to assess sample quality. The result is the percentage composition of each gravel, sand, clay, and mud type.

4. RESULT AND DISCUSSION

4.1 Bathymetric Map

Fig.3 describes the bathymetric map for each frequency in the survey area. The depth of the survey area ranges from 2.4 m to 25.5 m. The area near the port (port pool) in the west has a depth of less than 8.2 m, the middle of the survey area has a depth of 8.2 to 19.7 m, and the eastern part of the study area, which is the western shipping channel of Surabaya has a depth of more than 19.7 m from the Lower Water Spring (LWS). In general, and visually in the image, depth at each frequency is almost like depth at one frequency with depth at another. Although theoretically, lower frequencies will have deeper depths compared to higher frequencies. High-frequency waves travel a shorter distance because of their longer cycles, meaning more energy is dissipated into heat more quickly. Their small wavelength makes them useful for detecting objects since they reflect them.

4.2 Bathymetric Difference Inter Frequencies

The bathymetric data of each frequency (200 kHz, 250 kHz, 300 kHz, 350 kHz, and 400 kHz) are subtracted from each other such as h200 – h250, h200 – h300, and others. A map of bathymetry between frequencies can be seen in Fig.4. The difference in bathymetry between frequencies is -10 cm to 10 cm, except for the difference in bathymetric results between frequency depths of 300 kHz, 350 kHz, and 400 kHz, which range from -5 cm to 5 cm.

Several spots have a bathymetric difference between 10 cm to 40 cm, and tiny spots of more than 1 m in the western area (blue), which can be caused by the noise that occurs and significant errors in this area. According to [30], bathymetric differences between frequencies have a less significant impact on the calculation of dredging volume.

4.3 Deep Neural Network Classifier

The Deep Neural Network (DNN) is a deep learning Artificial Neural Network (ANN) model [31], which consists of a multi-layer perceptron with many hidden layers, the weights of which are fully connected and often initialized using unlabeled or labeled pre-training techniques. The main purpose of a neural network is to take a set of inputs, perform increasingly complex calculations on them, and provide an output to solve real-world problems such as classification. The DNN model is widely used in signal and image processing due to its advantages, such as its simple and easy-to-understand structure [32].

Apart from that, another definition based on [21] states that a DNN is a network model with an input layer structure, an output layer, and several hidden layers connected to each layer. The significance of the specific layers and neurons in DNN structure is to perform feature extraction, identifying and separating relevant information from input data needed to make predictions and decisions. Fig.5 shows the DNN structure diagram used in this case, with the input layer having 15 neurons (five bathymetric and ten bathymetric differences), the hidden layers' corresponding weights and biases, and four neurons (four sediment types) as the output layer.

An activation function is needed to determine whether the neuron should be active or not based on the weighted sum of the input. The activation function is a function that is used to process information from input with calculations. Several activation functions can be used in deep learning networks, but in this case, the ReLu activation function is used to process the hidden layer, and softmax activation functions are used to process the output layer. The Deep Neural Network model created with various predetermined parameters is then carried out in a calculation process using previously prepared input data.

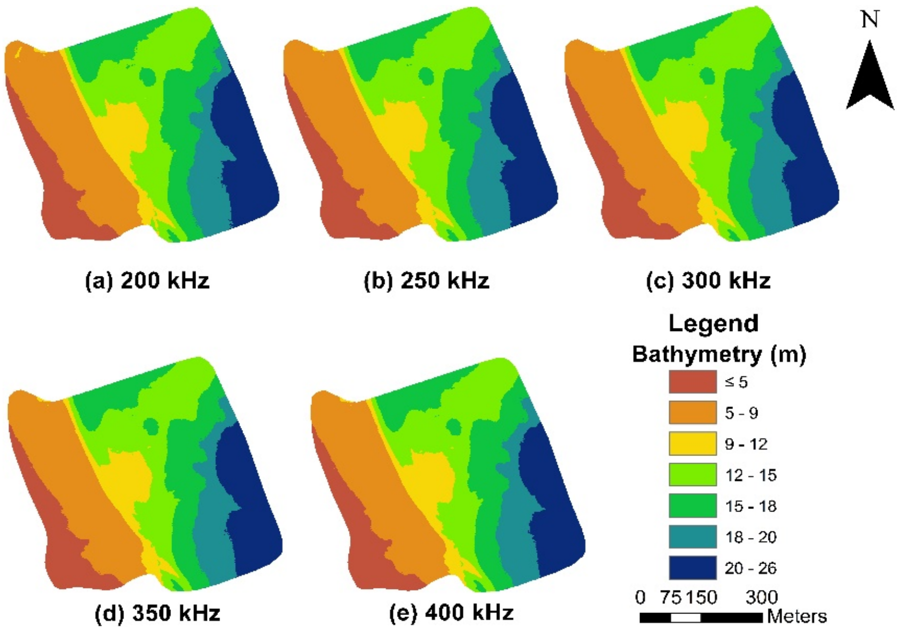

Fig.3 Bathymetric Map for each frequency (a) 200 kHz (b) 250 kHz (c) 300 kHz (d) 350 kHz (e) 400 kHz

In this study, 74 input data were used, corresponding to the number of types of sediment samples that had been obtained. From the 74 types of sediment sample data, other variables were added in the form of bathymetry data and bathymetry differences. The 74-input data were divided into training data (70%), which is used to measure model performance during training, and validation data (30%), which is used to measure model performance during training and assist in parameter tuning. In this study, the training data got an accuracy of 62.9%, while the validation data got an accuracy of 50%.

4.4 Seafloor Classification and Classification Accuracy

Fig.6 shows the results of seafloor sediment classification using a deep neural network (DNN) with bathymetric and bathymetric differences in frequency data input. In general, the bottom sediment in the study area is dominated by clayey sand and followed by silty sand. Silty Sand spreads near the coast and a small part to the east (APBS channel). The distribution of the Clayey Sand classification dominates the area of the port channel. A small part of the area is silt, and very little is Sandy Silt.

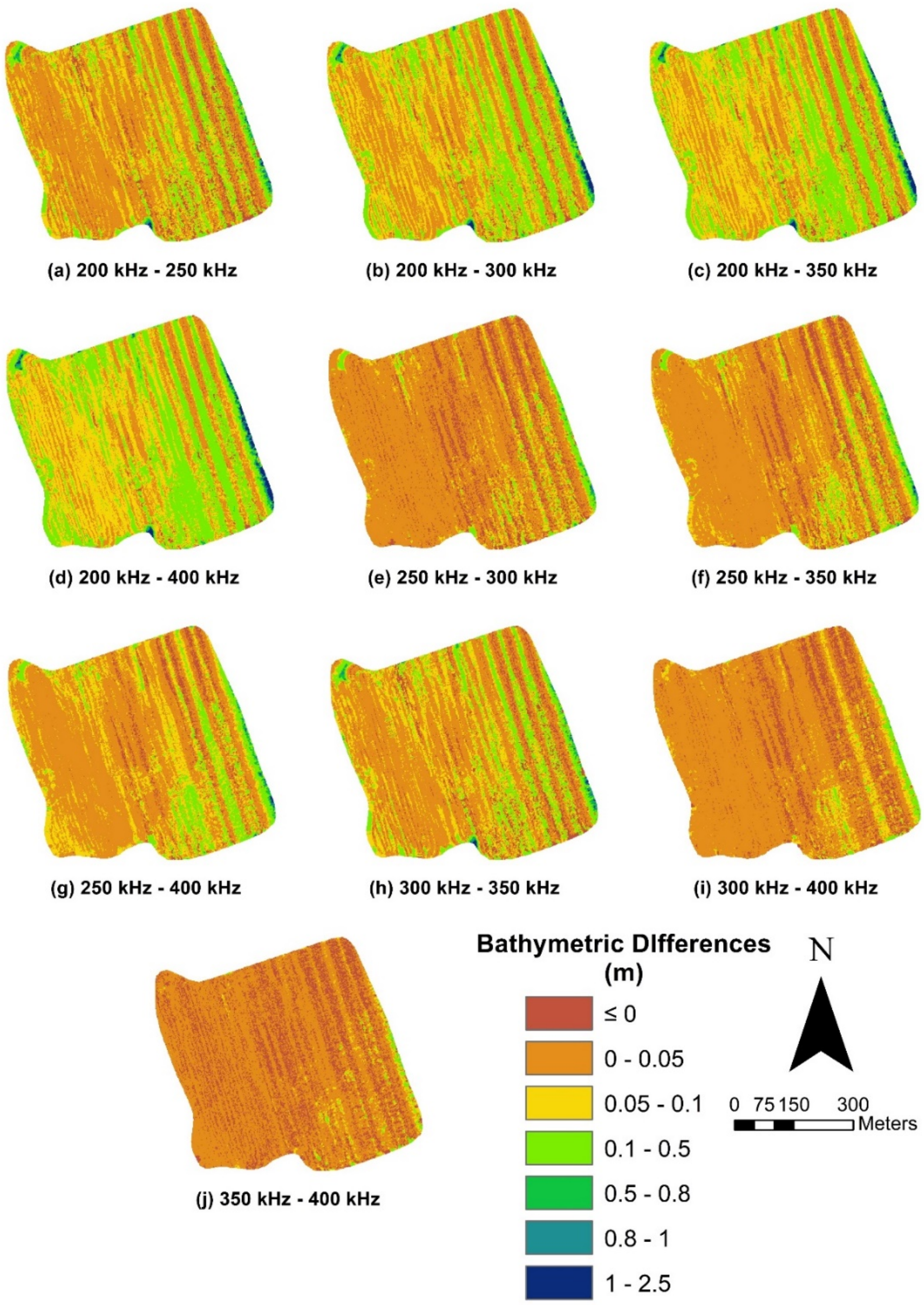

Fig.4 Bathymetric differences inter-frequencies

Table 2 presents estimates of sediment classification accuracy using the confusion matrix, which is used for classification because errors can occur when classifying a map based on selected pixels that do not match the in-situ data. Data in Table 2 can be used to calculate Overall Accuracy (OA), Producer's accuracy (PA), User's Accuracy (UA), and Kappa coefficient. OA describes the proportions mapped correctly out of all the reference locations. OA is often expressed as a percentage, with an accuracy of 100 being a level of perfect classification where all reference locations have been correctly classified. At the same time, PA is the accuracy of a map from the cartographer's perspective. It is the frequency with which actual topographic features are accurately represented on a classified map or the probability that a given land cover of a ground area is so classified. In comparison, UA is the accuracy from the perspective of the map user. User accuracy indicates how often the layer on the map will be present at the scene.

In this study, OA, the seafloor sediment classification, is only 41.9%. Landis and Koch [33] consider 0-0.20 (slight), 0.21-0.40 (fair), 0.41-0.60 (moderate), 0.61-0.80 (severe), and 0.81-1 (almost perfect). Thus, the sediment classification in this case is included in the moderate category (0.41 – 0.60). The user and producer accuracy for any given class is often different. In this case, the PA for the silt class was 25.9%, while the UA was 47%. It means that although 25.9% of the reference silt areas have been correctly identified as silt, only 47% of the areas identified as silt in the classification were silt.

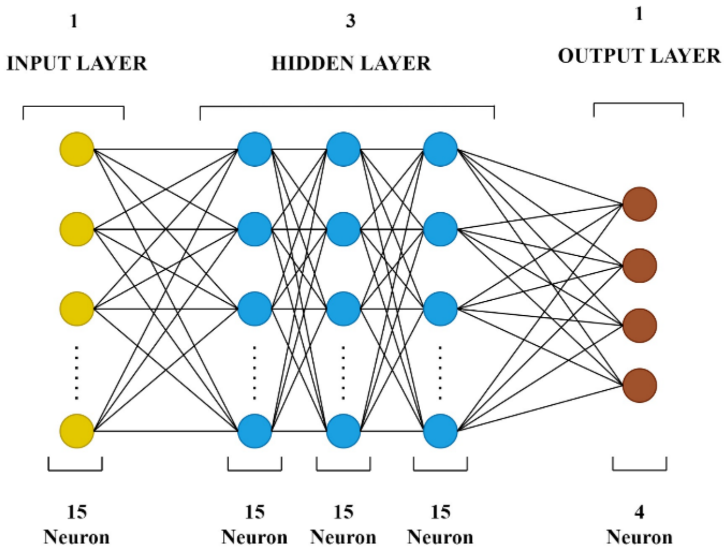

Fig.5 Deep Neural Network classifier model

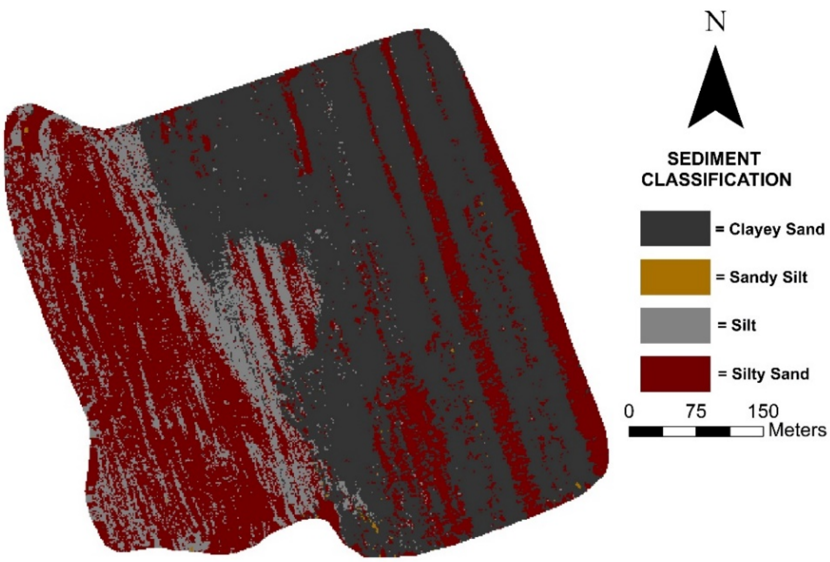

Fig.6 Seafloor Sediment Classification Map

Table 2 Matrix Confusion between in situ and classified data

		In situ Data				
		Silt	Sandy Silt	Clayey Sand	Silty Sand	Total
Classified Data	Silt	7	1	4	3	15
	Sandy Silt	0	1	0	0	1
	Clayey Sand	3	5	13	1	22
	Silty Sand	17	4	5	10	36
	Total	27	11	22	14	74

Analyzing the accuracy and error metrics is better for evaluating classification and results. Often, very high accuracy for certain classes, while others may have poor accuracy. The information is important to evaluate the appropriateness of the seafloor sediment classified map.

Classifiers built and evaluated on datasets of different class distributions can be compared more reliably using the Kappa statistic [34] to evaluate the predictive performance of classifiers. The Kappa coefficient is generated from a statistical test to evaluate classification accuracy. Essentially, the Kappa coefficient evaluates classification performance to just assign random values. The Coefficient of Kappa has a value between -1 and 1. Zero value indicates that the classification is no better than random classification. Negative numbers indicate that the classification is significantly worse than chance. A value of 1 indicates that the classification is significantly better than random classification. In this area survey, seafloor sediment classification had a kappa of only 21.9%. According to Landis and Koch [33], this result is included in the Fair category (0.21 – 0.40).

The results of seabed sediment mapping using DNN, in this case, have a smaller accuracy value compared to other studies that have been conducted by other researchers, such as Zhu et al. [21] and Cui et al. [22]. As mentioned above, the main input of this study is bathymetric data and bathymetric differences between frequencies from multifrequency MBES data, while according to [21,22], using input data in the form of backscatter data and backscatter features which correlate very strongly with seabed sediment types.

5. CONCLUSION

Multifrequency MBES survey data in Gresik Jasa Tama port waters produced water depths for each frequency ranging from 2.4 m LWS to 25.5 m LWS. The bathymetric difference between frequencies (200 kHz, 250 kHz, 300 kHz, 350 kHz, and 400 kHz) shows a depth difference of ± 10 cm.

The seafloor sediment classification results show that clayey sand dominates sediment distribution in the central and east areas. In contrast, silty sand dominates in the western area (harbor pond), with little silt-type sediment and very little or no sandy silt sediment.

The classification of seafloor sediments in the survey area with DNN with bathymetric inputs and bathymetric differences has an accuracy of 41.9% (moderate) and a kappa coefficient of 21.9% (fair).

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