Improvement of Seagrass Habitat Mapping Using Integration of Habitat Suitability Model and Seafloor Classification Map

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Abstract

Acoustic datasets offer considerable advantages in high-resolution seagrass habitat mapping applications. However, the nature of seafloor features for seagrass habitat on a habitat suitability model (HSM) is limited due to single-species output. Classifying the seafloor features suitable for seagrass habitat using supervised classification is propitious for explaining the potential distribution of seagrass habitat. An integrated approach is adopted between HSM and the seafloor classification map, which can simultaneously illustrate predicted seagrass habitat with suitable seafloor features. Acoustic data were acquired using a multibeam echosounder (MBES) in Redang Marine Park. Multibeam echosounder predictors, including the bathymetric map, slope, eastness, northness, and curvature, backscatter mosaic 32-bit and 8-bit, grey-level co-occurrence matrix (GLCM) texture features (homogeneity, entropy, correlation), and angular range analysis (ARA) parameters (phi and characterisation), were derived. Maximum entropy (MaxEnt) algorithm was used to produce the seagrass habitat suitability model (SHSM), while random forest (RF) algorithm was utilised to produce the seafloor classification map. As for the ground-truthing, seagrass occurrence data were used to train and test the SHSM. Improved seagrass habitat mapping information was introduced by integrating habitat suitability index, suitable seafloor features for seagrass habitat (i.e., seagrass on fine sand, seagrass on coarse sand, fine sand, and coarse sand), and suitable depth for seagrass habitat. The proposed integration approach has produced a detailed map of seascape and seagrass. The seascape seagrass map will provide decision-makers, such as the marine park authority, with helpful information for managing seagrass habitats.

Keywords: mapping, seagrass, MBES, HSM, supervised classification, integration

Introduction

Coastal waters support various human activities like tourism, fishing, aquaculture, and coastal protection. However, these activities have increasingly harmed the ocean and its inhabitants. To protect marine biodiversity, it is essential to preserve genetic, species, and ecosystem diversity, along with their habitats, ensuring the ocean's health and vitality (Lotze, 2021). Recent advancements in acoustic technology have enabled scientists to better examine the relationship between seafloor features and marine habitats. Instruments like multibeam echosounders (MBES) now provide detailed bathymetry and backscatter data, offering fine-scale insights into seafloor features (Brown et al., 2011; Fakiris et al., 2019; Lecourset et al., 2017; Lecours et al., 2015; Porskamp et al., 2022), especially for seagrass applications (Lucieer et al., 2017; Lurton et al., 2015; Vialaet et al., 2021). The complexity of these features significantly influences habitat diversity for marine life (Degraer et al., 2008; Ierodiaconouet et al., 2007; Lucieeret et al., 2013). Thus, understanding seafloor characteristics is key to comprehending marine habitats.

Multibeam echosounder is a widely used tool for comprehensive seafloor mapping (Monahan, 2019; Sen et al., 2016). Bathymetry data, which can indicate marine habitats like seagrass affected by light attenuation with depth (Becket et al., 2018; Duarte, 1995; Ralph et al., 2007), along with environmental derivatives like rugosity, aspect, and slope, help understand seagrass distribution in shallow waters. Multibeam echosounder also provides backscatter data, reflecting acoustic intensity, which infers geological and biological seafloor characteristics. High reflectivity links to coarse grains, while low reflectivity indicates fine grains (Boswarva et al., 2018; Ferrini & Flood, 2006).

Over the past decade, marine habitat mapping has undoubtedly used image analysis with habitat suitability modelling and image classification methods. Both these methods give different methodologies, analyses, and outputs. For example, HSM is used as a predictor and ground-truth data to predict species distribution (Elith & Leathwick, 2009) and illustrate the potential range for species distribution (Lissovsky et al., 2021). Meanwhile, image classification (i.e., supervised) used predictors and ground-truth data to categorise all pixels in a raster to obtain topography cover themes (Al-doski et al., 2013; Lillesand et al., 2015).

Despite these advantages, habitat suitability models produced by previous studies (Muhamad & Che Hasan, 2022; Muhamad et al., 2021) have a limitation in mapping seagrass habitats around the Redang Marine Park (RMP). Habitat suitability index (HSI) from all models only showed ranges that illustrate the potential or predicted range for species habitat (Bittner et al., 2020; Downie et al., 2013; Elith & Leathwick, 2009; Elith et al., 2011).

This study developed a new mapping strategy by combining a habitat suitability model with a seafloor classification map in Terengganu, Malaysia. The seagrass habitat map created provides a novel method for monitoring and assessing seagrass habitat distribution. By integrating these models, the study accurately reflects seagrass habitats' location and extent. Specifically, the study achieved two goals: (1) producing a seagrass habitat suitability map and seafloor classification map using machine learning and high-resolution MBES datasets, and (2) integrating these maps to enhance spatial information for the RMP area.

Materials and Methods

Ethical approval

This study did not involve any live vertebrate animals, animal handling, or animal experimentation. All analyses were conducted using machine-learning techniques applied to high-resolution multibeam echosounder (MBES) acoustic datasets and video-based seagrass occurrence data and therefore did not require approval from an Institutional Animal Care and Use Committee (IACUC).

Study area

The RMP, situated 24 nautical miles from Kuala Terengganu in Malaysia, is one of the largest archipelagos on the east coast of Peninsular Malaysia (Fig. 1). It comprises 12 islands: Redang, Pinang, Ling, Ekor Tebu, Kerengga Besar, Kerengga Kecil, Paku Besar, Paku Kecil, Chupak, Yu Kecil, Yu Besar, and Lima. Fisheries activities are prohibited around the RMP under the Fisheries (Prohibited Areas) Regulations 1983. Designated as Redang Marine Park by the Marine Park Malaysia Order 1994, the coastal waters within two nautical miles of these islands are protected. The RMP's coastal waters feature coral reefs, mangroves, and seagrass.

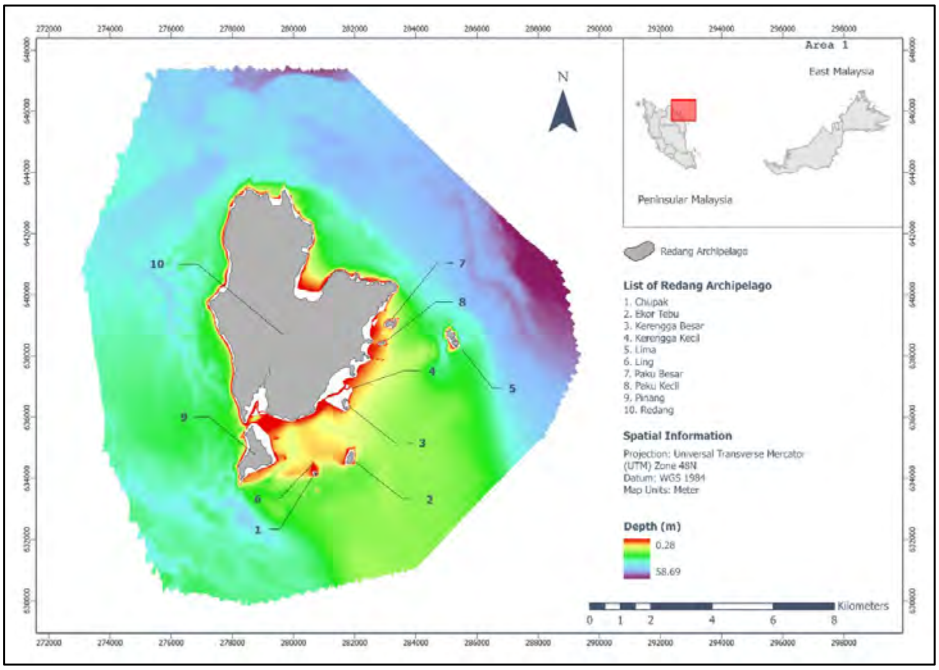

Fig. 1. Map of Redang Marine Park (RMP) bathymetry coverage, Kuala Nerus, Terengganu, Malaysia. Ten of the RMP, including Chupak, Ekor Tebu, Kerengga Besar, Kerangga Kecil, Lima, Ling, Paku Besar, Paku Kecil, Pinang, and Redang. The red box represents the overview of the RMP area within Peninsular and East Malaysia.

Multibeam echosounder survey

From April 6th to April 24th, 2019, a multibeam echosounder (MBES) survey was conducted two nautical miles from Redang Island within the RMP. Bathymetry and backscatter were collected using a Kongsberg EM2040C MBES (Kongsberg, Norway) with the seafloor information system (SIS) software (Kongsberg, Norway). The MBES operated at a high frequency (300 kHz) with a beamwidth of $1^{\circ} \times 1^{\circ}$, adjusting pulse length and ping rate based on water depth. Sound velocity profiles were recorded daily using a Valeport monitor (Teledyne, USA), and tide levels were collected every 10 min with a Valeport 740 tide gauge. A Kongsberg Seatex MRU 5 (Kongsberg, Norway) measured heave, pitch, roll, yaw, and heading, while positioning was provided by a Veripos Demodulator LID3S (Veripos, UK) in DGPS mode.

Underwater imagery sampling and secondary data

From July 8th to 10th, 2019, underwater imagery sampling was conducted along the RMP's coastal area using a GoPro Hero mounted on a steel ballast frame. Ninety-one video samples were collected through cluster sampling around targeted seagrass areas. An underwater spotlight (SeaLife Sea Dragon 2300F Auto, USA), illuminated the seafloor, and each sample's location was recorded with a GPS receiver (Hemisphere GNSS AtlasLink, USA) with 50 cm accuracy. A mobile device logged each sample's date, time, and location. Two ground-truth datasets from Sokiman et al. (2014) and Akmal et al. (2019) were used as the secondary data. These data provided seascape features information in the coastal water of the RMP. Twenty-three samples were obtained from Sokiman et al. (2014) and 12 from Akmal et al. (2019).

Bathymetry and backscatter data processing

CARIS HIPS & SIPS 10.4 (Teledyne CARIS, Canada) was used for bathymetric map production, including data integration and cleaning. Data integration combined bathymetry with supplementary data (positioning, tidal, heading, motion, latency, and sound velocity) using SIS, while cleaning involved removing outliers. Fledermaus Geocoder Toolbox (FMGT version 7.4.4b) software (Quality Positioning Services, Netherlands) processed backscatter data, correcting source level, absorption, spreading losses, and insonified areas to generate a backscatter mosaic using 400 beams and beam average. Processing also included eight corrections: transmit and receive power gain, beam pattern, angular varied gain (AVG), window size, anti-aliasing, despeckle, line blending, and mosaicking. The final bathymetric map and backscatter mosaic were gridded at a 1 m spatial resolution.

Bathymetry and backscatter predictors

Four bathymetric predictors, including bathymetry map, slope, curvature, eastness, and northness (Muhamad et al., 2021) and seven backscatter predictors, including mosaic (32-bit in decibel unit), backscatter mosaic 8-bit (grayscale), grey-level co-occurrence matrix (GLCM) texture features (correlation, entropy, and homogeneity), angular range analysis parameters (characterisation and phi). Backscatter mosaic 8-bit (grayscale unit) was rendered from backscatter data. A summary of all MBES predictors is described in Table 1.

Seagrass occurrence and seascape feature data

Underwater imagery samples were used for habitat suitability modelling and image classification. The coral point count with Excel extensions (CPCe) programme (Kohler & Gill, 2006) identified seagrass and seascape features. Seagrass was classified as either present or absent, while seascape features were identified using 50 spatially random points per location, with the most common feature designated as dominant. A secondary dataset from previous studies by Sokiman et al. (2014) and Akmal et al. (2019) was compiled with seascape feature data. Both seagrass and seascape feature data were organized in a spreadsheet and converted to shapefiles using ArcMap 10.5. Seagrass data served for habitat suitability modelling, and seascape feature data were converted into polygons for image classification.

Correlation analysis of predictors

Multibeam echosounder predictors were assessed using Pearson's correlation coefficient in the *corrplot* package in R. A correlated MBES predictor is defined as having a correlation coefficient (r) ≥ 0.5, while an uncorrelated predictor has r < 0.5 (Zuur et al., 2009). Therefore, any MBES predictors that produced a high correlation coefficient (r ≥ 0.5) between other predictors were eliminated from the modelling process, and only MBES predictors with low correlation coefficient (r <0.5) were retained for further analysis (Rowden et al., 2017; Trzcinska et al., 2020). The removal of highly correlated predictors is commonly used for habitat mapping in the marine environment (Ohlemuller et al., 2008; Porskamp et al., 2018; Porskamp et al., 2022; Rowden et al., 2017; Trzcinska et al., 2020).

Habitat suitability modelling

A MaxEnt algorithm (v3.4.1) was used to create the seagrass habitat suitability model (SHSM) with presence-only seagrass data and uncorrelated MBES predictors. The data were split 75 %–25 % for training and validation, following Briscoe et al. (2014) and Wang et al. (2017). All models used auto features to limit feature types based on ground-truth data (Blondel & Sichi, 2009; Phillips & Dudík, 2008; Wang et al., 2017).

Using twenty replicates and bootstrapping methods, the SHSM was produced. Default settings were applied for the regularised multiplier, background points,

Table 1. The list of bathymetric and backscatter predictors used in this study.

Multibeam echosounder predictors	Description	Software
1. Bathymetric map	Illustrates the seafloor depth (Jena et al., 2012)	Focal statistics (ArcGIS 10.5)
2. Slope	Steepness at each pixel of a raster surface (Burrough et al., 2015)	TASSE toolbox version 1.1
3. Eastness	Direction of the uphill or downhill slope faces (for the east and west directions)(Muhamad et al., 2021)	TASSE toolbox version 1.1
4. Northness	Direction of the uphill or downhill slope faces (for the north and south directions)(Muhamad et al., 2021)	TASSE toolbox version 1.1
5. Curvature	Convexity of a pixel of a raster surface (Walbridge et al., 2018)	TASSE toolbox version 1.1
6. Backscatter mosaic 32-bit	Acoustic intensity, in decibels (dB), scattered by the seafloor (Le Bas & Huvenne, 2009)	TASSE toolbox version 1.1
7. Backscatter mosaic 8-bit	Acoustic intensity converted to grayscale raster (0–255 units)	Focal statistics (ArcGIS 10.5)
8. Correlation, entropy, and homogeneity	Grey-level co-occurrence matrix (GLCM) texture features (Haralick et al., 1973)	ENVI 5.1
9. Characterisation and Phi	Angular range analysis ARA-parameters (Fonseca & Mayer, 2007)	FMGT 7.4.4b

iterations, and coverage thresholds (Halvorsen, 2013; Phillips & Dudík, 2008; Wang et al., 2017). The SHSM output was logistic, indicating habitat suitability from 0 (less suitable) to 1 (more suitable). Model performance was evaluated using AUC, splitting seagrass occurrence data into training and testing sets (Swets, 1988). This process was repeated 20 times, generating 20 output rasters, with the mean AUC used to assess accuracy. The final SHSM was based on the model with the highest AUC, and the contribution of each MBES predictor was calculated by its gain increase.

Supervised image classification using machine learning

This research utilised the RF machine learning algorithm with several R packages, including *caret* (Kuhn et al., 2007; Kuhn et al., 2020), *raster* (Hijmans, 2019), and *rgdal* (Bivand et al., 2015) packages to create a seafloor classification map. The process involved four stages: data input, preparation, model fitting, and image classification. Two datasets were used: seascape feature data (classified into six types) and MBES predictors, which were converted from ESRI ASCII to .tif format to reduce file size and processing time.

Integration of seagrass habitat suitability model and seafloor classification map

The integration of the seagrass habitat suitability model (SHSM) and seafloor classification map involved three steps: (1) filtering the seafloor classification map, (2) removing isolated pixels from SHSM, and (3) selecting suitable depth for seagrass habitat (Fig. 2). The first step involved removing isolated pixels from the seafloor classification map using the Majority/Minority Filter tool in QGIS Desktop 3.26.0. In ArcMap 10.5, the Extract by Attribute tool was used to extract seascape features from the seafloor classification map. Each seascape feature was saved as a separate raster layer. Only suitable seascape feature layers be used for the integration process.

The second step involved removing isolated pixels from the SHSM. The raster function in the "raster" package was used to read the seascape feature layers. Each layer's five-number summary statistics (i.e., minimum, first quartile, median, third quartile, and maximum) were computed. The boxplot charts were produced using the summary and boxplot functions in the "ggplot2" package. The isolated pixels (for lower and upper whiskers) were identified using five-number summary statistics (except median). Finally, the Reclassify and Extraction by Attribute tools were used to remove isolated pixels from SHSM.

The third stage involved removing pixel values (i.e., bathymetric depth) unsuitable for seagrass habitats from the bathymetric map. The suitable bathymetric depth was determined based on the depth of seagrass occurrences determined by previous research (Zakaria et al., 2003) and the ground-truth data. A new bathymetric map representing the suitable bathymetric depth for the seagrass habitat was

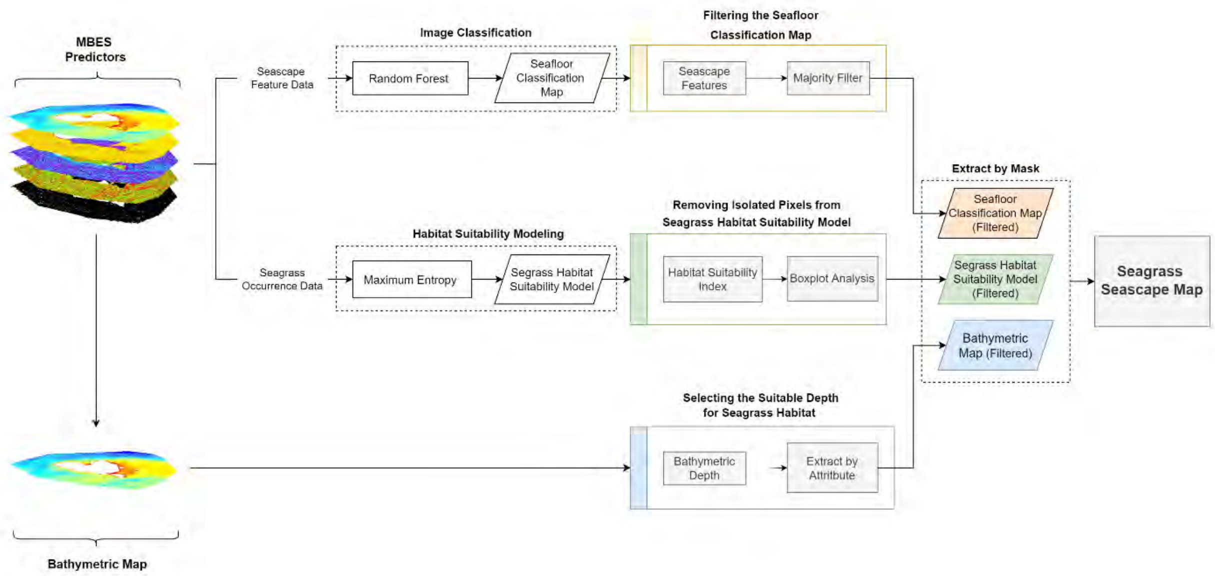

Fig. 2. The proposed integration process of seagrass habitat suitability model (SHSM) and seafloor classification map. Three main steps engage in this process, including (1) filtering the seafloor classification map, (2) removing isolated pixels from SHSM, and (3) selecting suitable depths for seagrass habitat.

extracted. The outputs from three stages, including suitable bathymetric depth, cleaned SHSM, and suitable seascape feature layers, were masked to generate the seagrass seascape map using the Extract by Mask tool in ArcMap 10.5.

Results

Predictor selection

The results found that bathymetry, slope, eastness, northness, and GLCM entropy have weak correlations, ranging from -0.01 to -0.39 (negative correlation) and ranging from 0.21 to 0.25 (positive correlation) (Fig. 3). Other MBES predictors were classified as having a strong correlation (≥0.5) with other MBES predictors. Multibeam echosounder predictors with Pearson's correlation coefficient value (*r*) less than 0.5 were retained for habitat suitability modelling and image classification processes, and vice versa, MBES predictors with Pearson's correlation coefficient value (*r*) equal to or higher than 0.5 were not retained. See Figure 3 for the correlation between MBES predictors, either strong or weak correlation.

Seagrass habitat suitability model

The result of the SHSM is depicted prediction of suitable habitats for seagrass (Fig. 4). Prediction of this model depicted that suitable habitat for seagrass (habitat suitability index higher than 0.5) was generally predicted to occur at shallow coastal water areas, especially along the near to southeast coastline of Redang Island. Some of the areas of the seagrass habitats were predicted to occur along the coastal line of small islands such as Chupak and Ling (referred at Area 1 in Fig. 4 and Ekor Tebu (referred at Area 2 in Fig. 4) islands. Some channels to the north of Pinang Island were predicted as a highly suitable area (habitat suitability index higher than 0.90) for seagrass habitat (refer to Area 3 in Fig. 4). Additionally, this model showed that the north bay area of Redang Island, Teluk Dalam (referred at Area 4 in Fig. 4), was predicted to be suitable for seagrass habitat with a habitat suitability index increased proportionally with depth. Some scattered area along the coastline at the northwest of the Redang Island were also predicted as suitable habitat for seagrass (habitat suitability model higher than 0.5). Meanwhile, the distribution patterns of unsuitable seagrass habitats predicted by this model were generally at deep coastal water areas.

Model performance and predictor importance

Both seagrass habitat suitability models (i.e., training and testing model) were assessed using training and testing datasets comprised of spatially distributed samples from seagrass occurrence data. The predictive model for seagrass performed excellently with mean AUC of 0.98 and 0.93, respectively. Predictor importance was ranked using the percentage of predictor contribution for seagrass habitat suitability model development. A more significant value for the percentage of MBES predictor contribution indicates that the MBES predictors contributed more during the model development. Predictor importance plots for the seagrass habitat suitability model are shown in Figure 5. The bathymetric map exhibited the most significant contribution for predicting seagrass habitat around the RMP. Other MBES predictors, including eastness, northness, slope, and GLCM entropy, gave less than 10 % of contribution to the development of seagrass habitat suitability model. Northness was ranked second highest with a contribution of 6.8 %, followed by GLCM entropy (4.3 %), slope (2.4 %), and eastness (1.2 %).

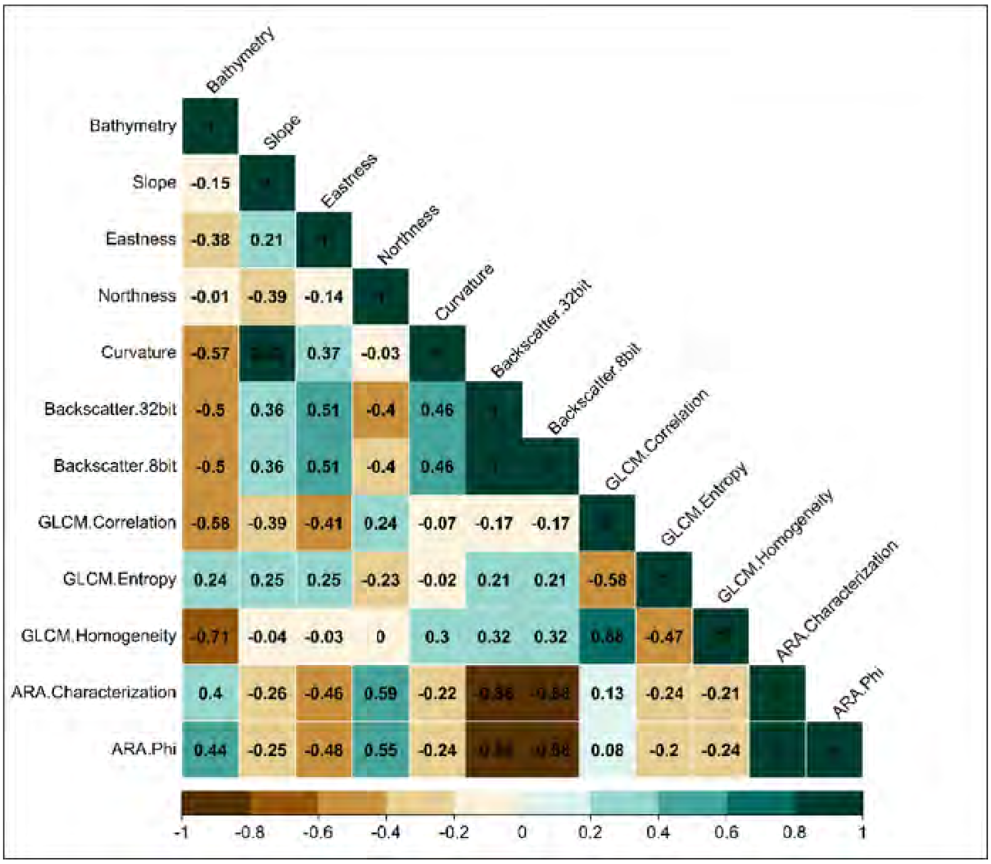

Fig. 3. A correlation matrix plot contains the multibeam echosounder (MBES) predictors for habitat suitability modelling and image classification. Colour and number represent the correlation between MBES predictors. The green colour indicated a positive correlation, and the brown colour indicated a negative correlation. Based on correlation matrix plot, bathymetry, slope, eastness, northness, and grey-level co-occurrence matrix (GLCM) entropy show low correlation among other MBES predictors and retained for habitat suitability modelling and image classification.

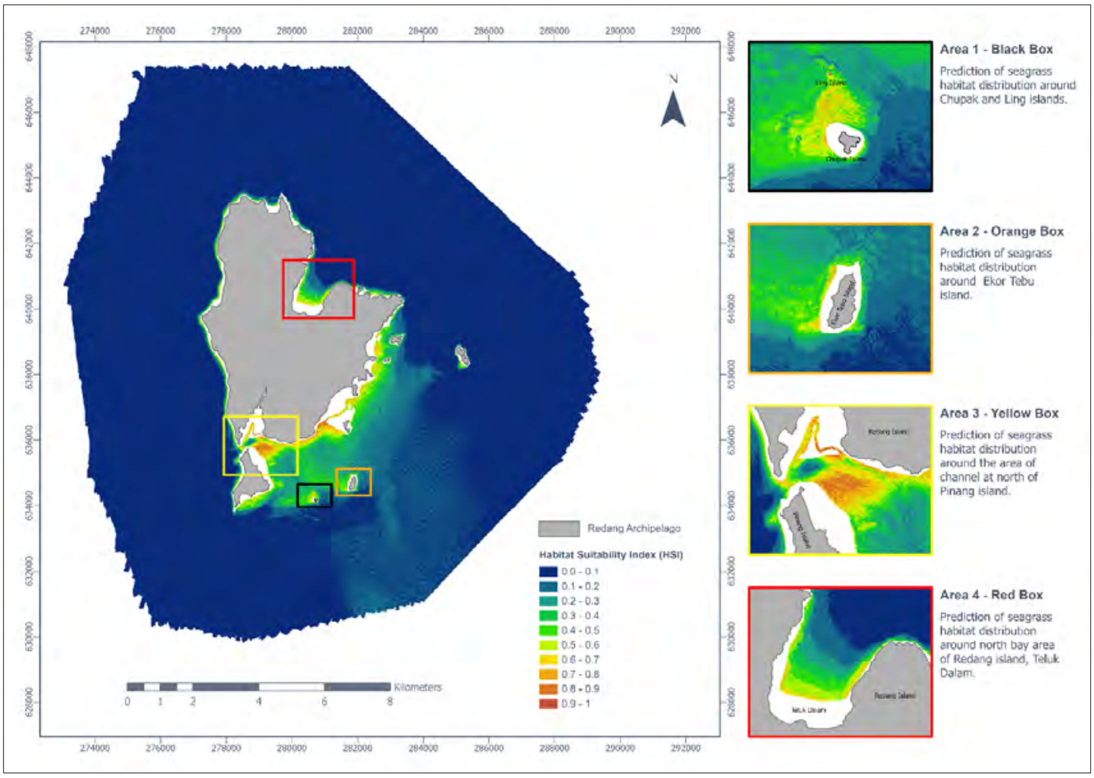

Fig. 4. Seagrass habitat suitability map around the Redang Marine Park (RMP). The habitat suitability index ranged from 0 (lowest seagrass habitat suitability index) and 1 (highest seagrass habitat suitability index). Area 1, 2, 3, and 4 are example areas for the prediction of seagrass habitat distribution around RMP.

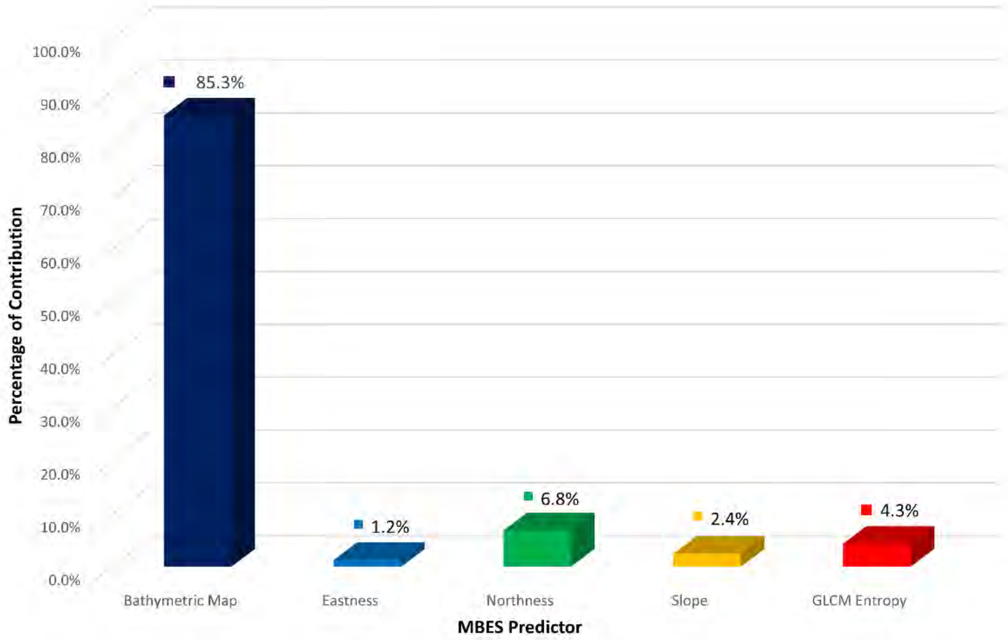

Fig. 5. The percentage of multibeam echosounder (MBES) predictor contribution to develop the seagrass habitat suitability model by the maximum entropy (MaxEnt) algorithm. These predictors were used to build the seagrass habitat suitability model.

Seafloor classification map

The results of the seafloor classification maps indicate that the RMP is characterised by fine sand, medium sand, coarse sand, coral, seagrass on fine sand, and seagrass on coarse sand (Fig. 6). The habitat classification map for the RMP shows that coarse sand dominates the deep-water area in the MBES surveyed area and the shallow-water area along the shoreline with a mean depth of 36 m. The areas covered by other classes are noticeably different. The next most extensive seascape feature by area is medium sand at a mean depth of 35 m and represents 30 % (by area) of the seafloor classification map. The minor sediment class, accounting for 1 % of the seascape feature in the study area, is fine sand scattered in the west coast area of Redang and other small islands in Area 3 in Figure 6, such as Chupak, Ling, and Ekor Tebu islands. The mean depth of this sediment class is 18 m and it can be found in Areas 1 and 2 in Figure 6. Two of the five seascape features, seagrass on fine sand and coarse sand, portrayed 0.01 % and 0.38 % (by area) of the seafloor classification map, respectively.

The seagrass habitats on fine sand were found at a mean depth of 7 meters and are distributed primarily in the south of the Redang island. Patches can also be found near Teluk Dalam in the north (Area 4 in Fig. 6). This habitat is also scattered in the eastern part of the study area, near small islands that are sheltered from the open water of the South China Sea. In contrast, seagrass habitats on coarse sand were found along the seagrass habitats on fine sand and coral. Most of this seafloor class were found associated with seagrass on fine sand in the south of the study area and also in the shallow water area of Teluk Dalam. Although seagrass on fine and coarse sand was recorded on the southern part of the RMP and is associated with the coral community, it did not share zones with other marine habitats.

Accuracy assessment, kappa statistics, specificity, sensitivity, and predictor importance

The accuracy of the seafloor classification map was calculated using a confusion matrix that compares classified images to a testing dataset (i.e., validation dataset) comprised of spatially distributed samples from seascape feature data from primary and secondary datasets. The seafloor classification map performed with excellent with an overall accuracy and kappa statistics of 97 % and 0.95, respectively (Table 2).

For the seafloor classification map, variable importance was ranked using the percentage importance (i.e., mean decrease in accuracy) (Fig. 7). During the classification process, the MBES predictor's significance was highlighted by its percentage importance's growing significance. The bathymetric map was performed exceptionally at 100 % for the seafloor classification map, followed by the slope (70.8 %), eastness (44.7 %), and northness (33.9 %). Only GLCM entropy had no contribution to the classification process.

Integration of seagrass habitat suitability model and seafloor classification map

Filtered seafloor classification map

The result of the seafloor classification map indicated that the study area contained locally isolated pixels

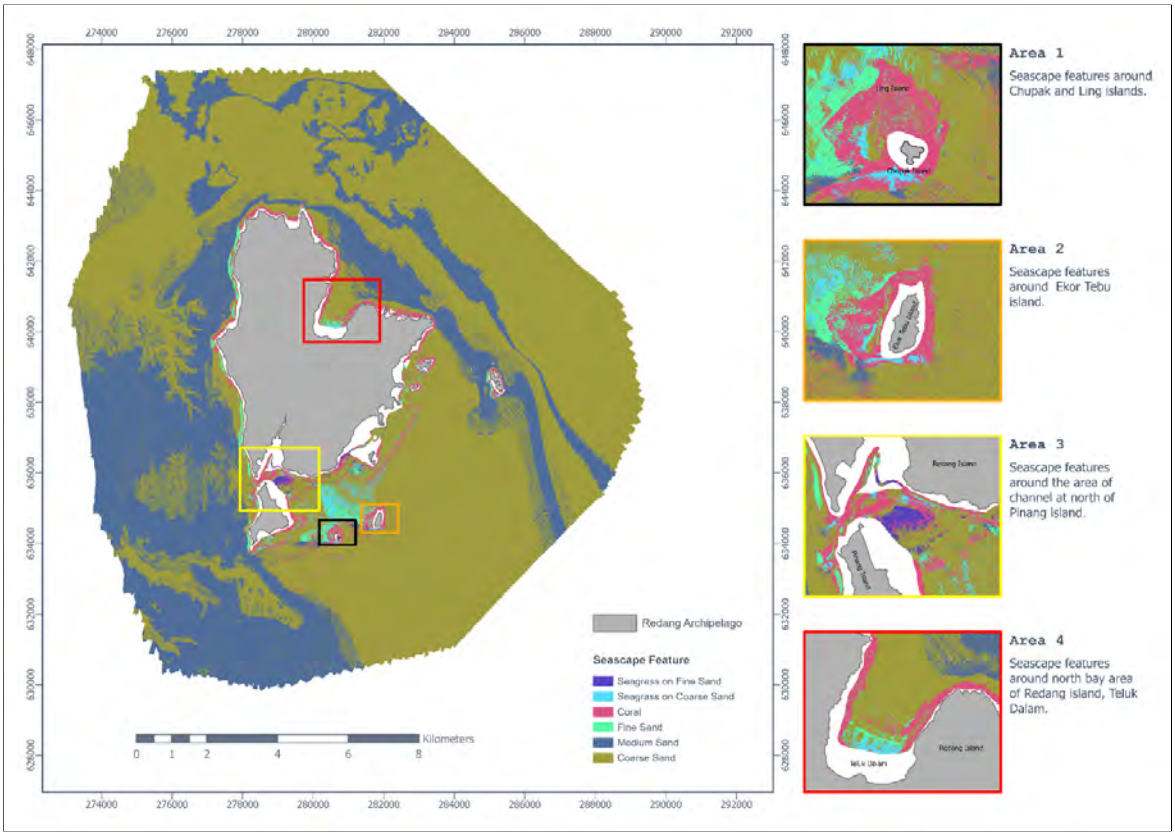

Fig. 6. Seafloor classification map around the Redang Marine Park (RMP). Six seascape classifications: fine sand, medium sand, coarse sand, coral, seagrass on fine sand, and seagrass on coarse sand. Area 1, 2, 3, and 4 are example areas for the distribution of seascape features within RMP.

Table 2. Confusion matrix for seafloor classification map. Seascape feature code as follows: coarse sand (CS), seagrass on fine sand (SFS), seagrass on coarse sand (SCS), coral (COR), fine sand (FS), and medium sand (MS).

		Training dataset						
		CS	SFS	SCS	COR	FS	MS	Sensitivity
Seafloor Classification Map	CS	623	1	5	18	4	1	95.6 %
	SFS	0	33	0	1	0	0	97.1 %
	SCS	0	0	114	1	0	0	99.1 %
	COR	5	0	0	313	2	0	97.8 %
	FS	4	0	0	1	124	2	94.7 %
	MS	2	0	0	0	0	126	98.4 %
	Specificity	98.3 %	97.1 %	95.8 %	93.7 %	95.4 %	97.7 %	
Overall accuracy = 96.6 % and Kappa statistics = 0.95								

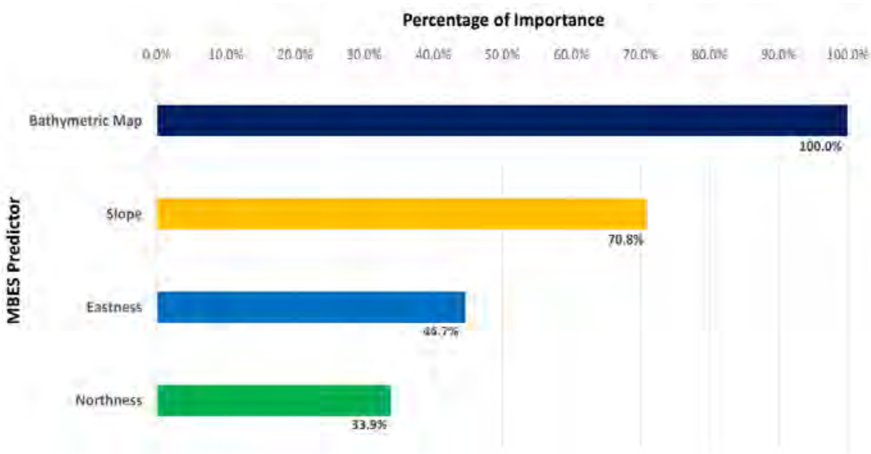

Fig. 7. Predictor importance for weak correlation predictor used to develop seafloor classification map using random forest algorithm. Percentage of importance (i.e., mean decrease in accuracy) represents the seafloor classification map decrease in accuracy when that predictor is excluded during the classification process. A larger percentage of predictor importance indicated that the predictor was more critical.

that resulted during the image classification process. The isolated pixel values were removed using the Majority Filter tool. Figure 8 shows the example area from the seafloor classification map before and after filtering. For example, isolated pixels from coral were scattered and distributed around coarse sand around Area 1 of the study area. While Area 2 contained isolated pixels from medium sand scattered around the coarse sand area. Conversely to Area 3, where isolated pixels from coarse sand were scattered around medium sand. Based on the filtered seafloor classification map, all isolated pixels from seascape features were removed during filtering process (Fig. 8).

Filtered seagrass habitat suitability model

The boxplot analysis identified isolated pixels in the seagrass habitat suitability model, which are crucial to filter out. Figure 9 illustrates the isolated pixels (circled in red) according to seascape features from the seafloor classification map. The analysis reveals that medium sand had the highest number of isolated pixels, followed by coarse sand, seagrass on fine sand, coral, fine sand, and seagrass on coarse sand (Fig. 9).

Figure 10 shows the results from SHSM and filtered SHSM within the study area. After identifying isolated pixels that resulted during habitat suitability modelling using boxplot analysis, isolated pixels were removed using Reclassify tool in ArcMap 10.5. Unlike the seafloor classification map, SHSM depicts isolated pixels initially undefined within the study area. It can be seen in Figure 10, which shows the filtered SHSM after removing a large number of isolated pixels from medium sand, coarse sand, and seagrass on coarse sand using boxplot analysis. For instance, Area 1 from Figure 10 showed that SHSM displayed a full range of habitat suitability index, which indicates this area contained low and high suitability for seagrass to inhabit this area. After the filtering, large numbers of pixels in SHSM were removed within the coarse sand area. In addition, in the bay area of Teluk Dalam (Area 2 in Fig. 10) and part of the sheltered water area, the west coast of Pinang Island (Area 3 in Fig. 10) also showed that SHSM produced isolated pixels from the coarse sand within the shallow water area.

Filtered bathymetric map

Subtidal seagrass habitats along the RMP coastline typically occur in shallow, calm areas with flat seafloor. These habitats, dependent on light for photosynthesis, are usually found at depths of 2.5 to 24.0 m. To determine suitable seagrass habitats, the SHSI and seascape features must account for this depth range. Bathymetric maps were classified into two categories: ≤24 m and >24 m. The seagrass habitat suitability model was overlaid with the bathymetric map (≤24 m) to identify optimal seagrass habitats based on depth (Bujang et al., 2006; Zakaria & Bujang, 2013; Zakaria et al., 2003).

Seagrass seascape map

Figure 11 presents a seagrass seascape map of RMP's coastal waters, integrating bathymetric depth, seascape features, and the filtered SHSM. This map, created from the SHSM, seafloor classification map, and bathymetric map, highlights seagrass habitats predominantly in the southeast. The map includes only four classes—SHSM-FS, SHSM-CS, SHSM-SCS, and SHSM-SFS—excluding SHSM-COR and SHSM-MS. SHSM-MS was omitted due to its association with fine and coarse sand only, while SHSM-CS was excluded because seagrass and coral represent different habitats.

The seagrass seascape map shows HSI variations across seascape features: SHSM-FS (0.02–0.75), SHSM-CS (0.02-0.19), SHSM-SCS (0.39–0.95), and SHSM-SFS (0.09–0.62). Coastal areas were mainly dominated by SHSM-CS, followed by SHSM-SCS, SHSM-FS, and SHSM-SFS. Although SHSM-CS was widespread in the RMP area, the map indicates that coarse sand areas are less suitable for seagrass habitats. For instance, Areas 1 and 4 were dominated by SHSM-CS, with scattered SHSM-FS and SHSM-SCS, respectively. Area 2 was dominated by SHSM-FS and SHSM-SFS, with scattered SHSM-CS and SHSM-SCS. In Area 3, SHSM-FS and SHSM-CS dominated the west coast shoreline of Redang Island. Area 5 contained all classes, with SHSM-SFS dominating the central region and patches in the north and south. In Area 6, SHSM-FS, SHSM-CS, and SHSM-SCS were the main classes, covering similar areas, with SHSM-FS found near Ling and Ekor Tebu Islands.

Discussion

Implementation of multibeam echosounder (MBES) dataset for seagrass habitat mapping

Mapping seafloor habitats is essential for managing marine databases and preserving the environment. It provides crucial decision-support tools for spatial management, including species and biodiversity management. Improving map accuracy enhances confidence for decision-makers. However, compared to terrestrial habitats, marine habitat data is often limited, prompting the development of new technologies to improve mapping accuracy (Fakiris et al., 2019; Porskamp et al., 2022). Building on previous research using MBES systems and machine learning (Che Hasan et al., 2022; Muhamad et al., 2021), this study integrated spatial data (SHSM and seafloor classification maps) to produce a seagrass seascape map, offering a more accurate description of seagrass distribution and demonstrating the value of integrating multiple spatial data for improved habitat prediction.

Contribution of multibeam echosounder (MBES) predictors

In habitat suitability modelling and supervised image

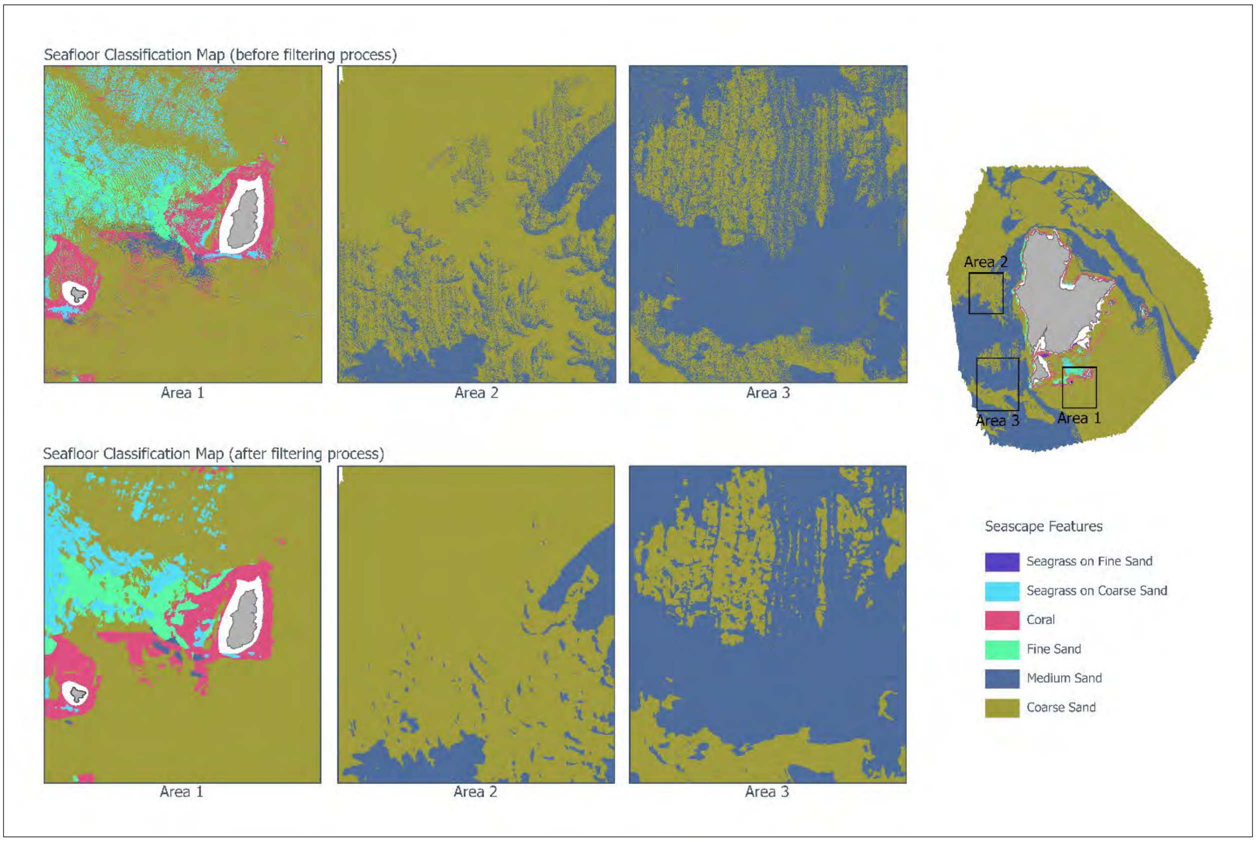

Fig. 8. Sample areas for the seafloor classification map (above) and filtered seafloor classification map (below). Three sample areas (Area 1, 2, and 3) illustrate the changes before and after the seafloor classification map filtering process.

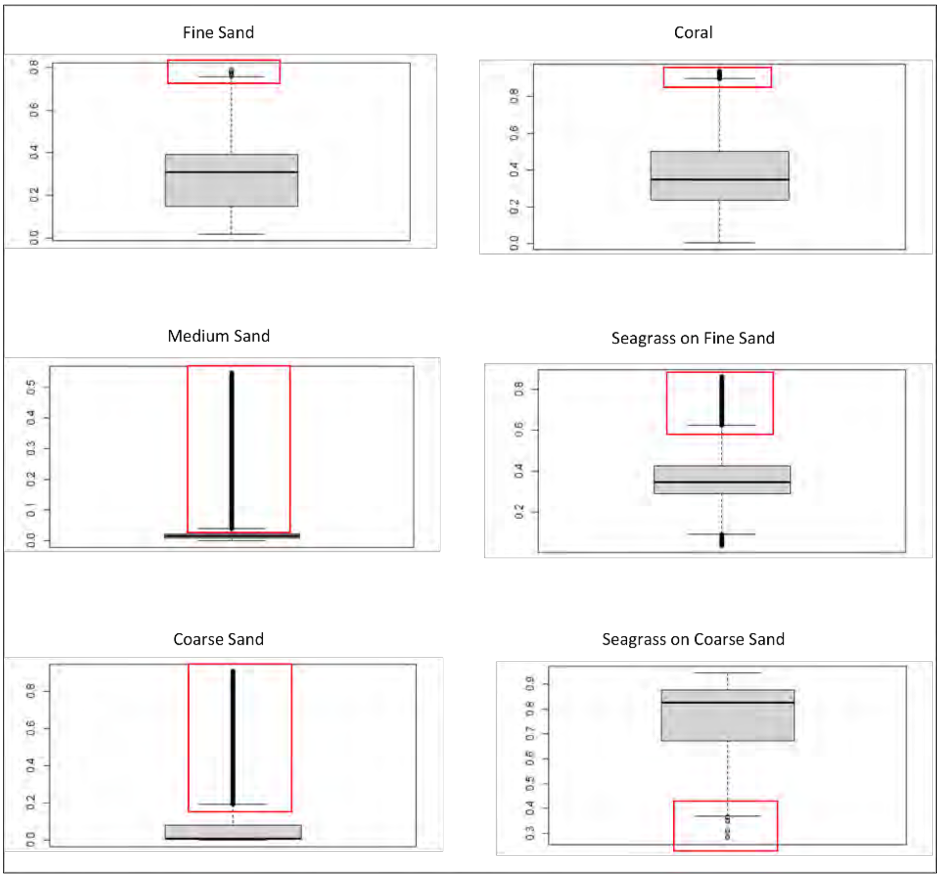

Fig. 9. Boxplot analysis for identifying the isolated pixels in the seagrass habitat suitability model (SHSM) based on the seascape features from the filtered seafloor classification map. Each seascape feature's isolated pixels (circles in the red boxes) are identified after the whiskers (two horizontal lines outside the box).

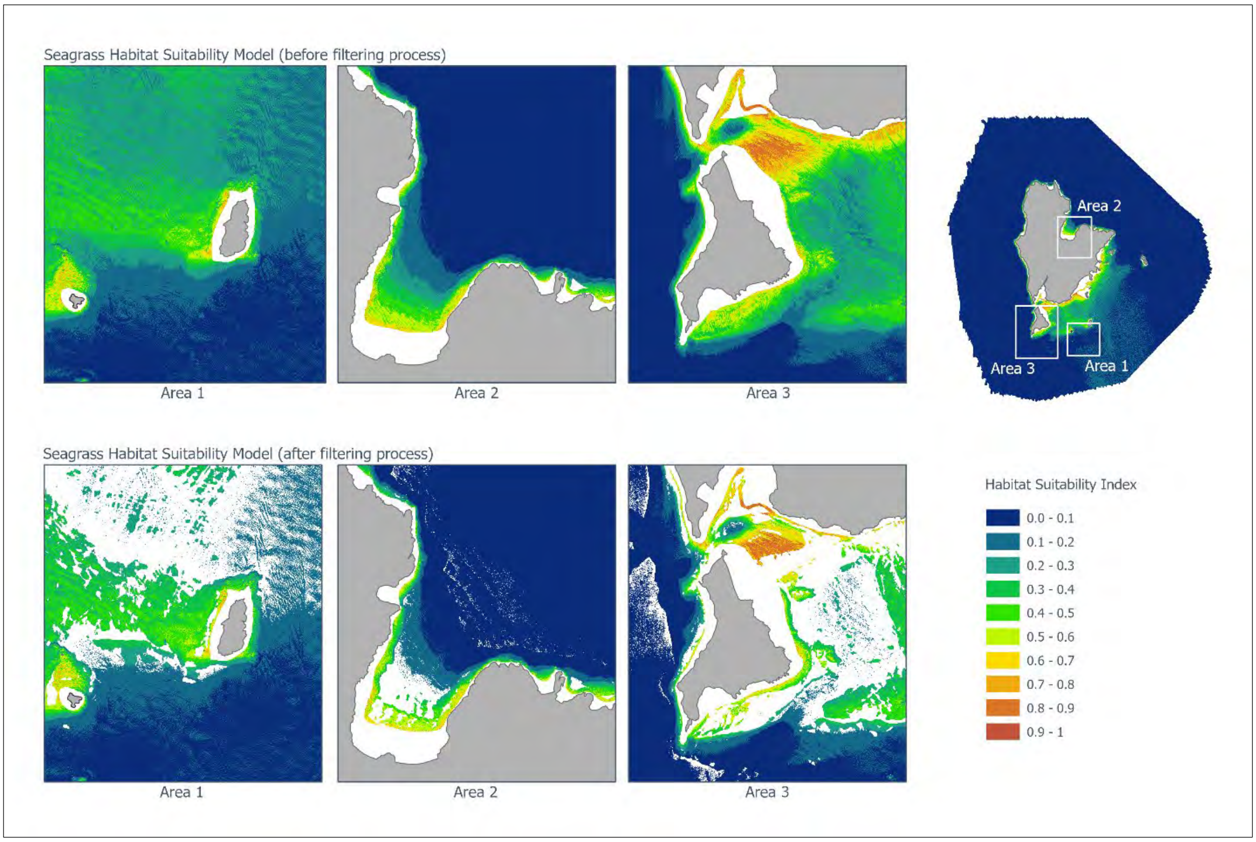

Fig. 10. Sample areas for the seafloor classification map (above) and filtered seafloor classification map (below). Three sample areas (Area 1, 2, and 3) illustrate the changes before and after the filtering process of seafloor classification map.

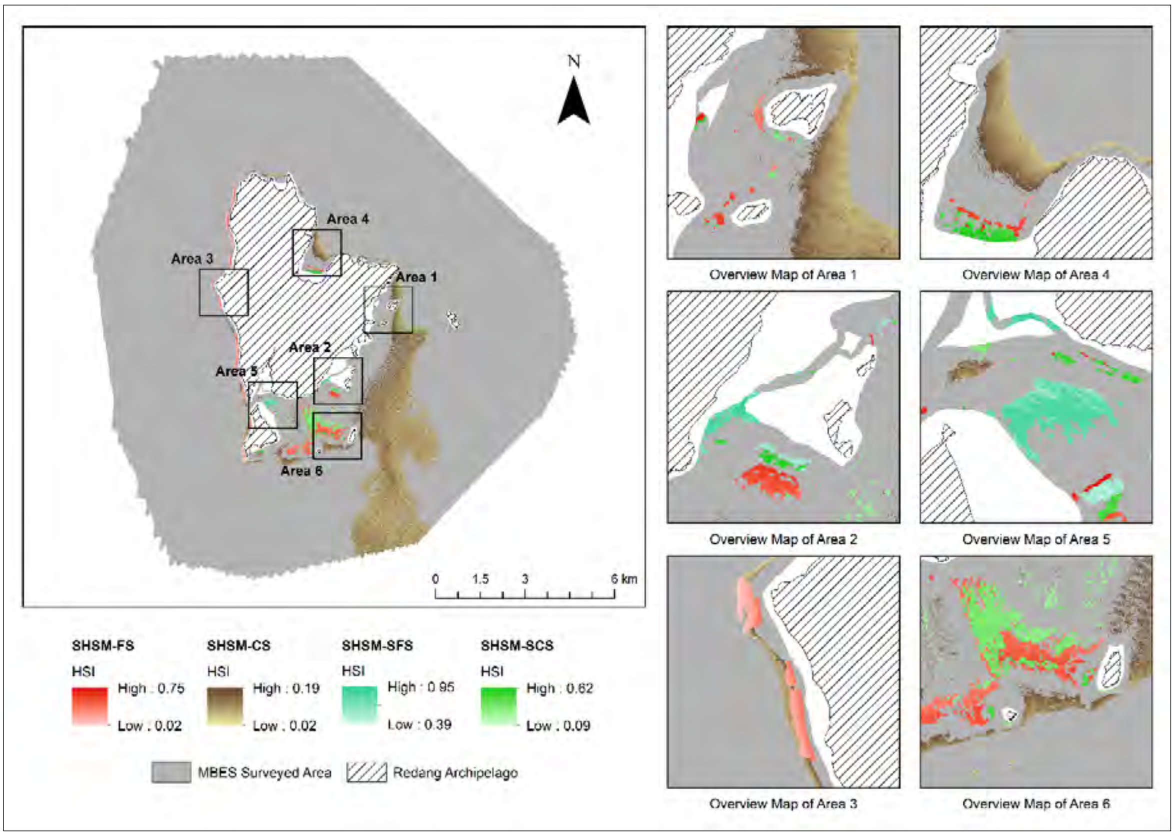

Fig. 11. The integration of seagrass habitat suitability model (SHSM), seafloor classification map, and bathymetric map at the Redang Marine Park (RMP) that produced a seagrass seascape map. Seagrass seascape map depicted by four classes of suitable habitat of seagrass, including SHSM-fine sand (SHSM-FS), SHSM-coarse sand (SHSM-CS), SHSM-seagrass on fine sand (SHSM-SFS), and SHSM-seagrass on coarse sand (SHSM-SCS).

classification, bathymetric maps were the most influential variables, while other bathymetric predictors like eastness, northness, slope, and GLCM entropy ranked lowest. These findings align with Muhamad et al. (2021) and Che Hasan et al. (2022), who observed that bathymetric maps from MBES data strongly correlate with seafloor complexity and aid in distinguishing marine habitats, particularly seagrass. The prominence of bathymetric maps as predictors likely stems from the critical role of depth variation in defining marine habitats in the RMP (Fig. 7). This depth-based delineation has been shown to enhance model performance, particularly in classifying seagrass habitats (Che Hasan et al., 2022; Muhamad et al., 2021; Zakaria et al., 2003).

The other predictors, such as eastness, northness, slope, and GLCM entropy, contributed less than 10 % to the development of the SHSM, with values between 1.2 % and 6.8 % (Fig. 5). In contrast, these predictors played a larger role (33.9 % to 70.8 %) in producing a seafloor classification map compared to the SHSM. This supports Muhamad and Che Hasan (2022) hypothesis that variable importance differs across machine learning algorithms in habitat model development. Each MBES predictor, including eastness, northness, and GLCM entropy, showed varying effects in modelling seagrass habitats and classifying marine habitats. Their limited contribution to predicting seagrass habitats is likely due to local environmental conditions such as water clarity, salinity, temperature, currents, physical exposure, sediment characteristics, and nutrients. However, in classifying marine habitats like fine sand, medium sand, coarse sand, coral, seagrass on fine sand, and seagrass on coarse sand, these predictors contributed significantly among bathymetric predictors.

Seagrass habitat suitability model

The efficiency of habitat suitability modelling using maximum entropy (MaxEnt), using underwater imagery samples and MBES dataset to produce habitat suitability map for seagrass habitat around RMP was first demonstrated by Muhamad et al. (2021). Comparison between machine learning algorithms (i.e., random forest and support vector machine) for predicting seagrass habitat have been assessed within RMP by Muhamad and Che Hasan (2022). Remarkable results from both studies (Muhamad & Che Hasan, 2022; Muhamad et al., 2021) showed that the MaxEnt algorithm produced outstanding accuracy scores, with more than 90 % AUC scores.

Based on findings, the prediction model shows suitable seagrass habitats expanding along the contiguous shoreline and all around the RMP. The model reveals that suitable seagrass habitats predominate in areas of shallow water, particularly in the southern part of the study area. Furthermore, the distribution of high HSI of predicted model has been found having good agreement with the distribution of underwater imagery samples and the results of previous research by Zakaria et al. (2003). This study demonstrated that bathymetric map being the most important MBES predictor to predict seagrass habitat and develop SHSM. The general pattern of distribution predicted by SHSM conforms to expectations from previous study (Zakaria et al., 2003) of the distribution of seagrass habitat at shallow subtidal zones in the inner bays (i.e., sheltered coastal waters), and depth is influencing the distribution of seagrass at the study area.

Habitat suitability modelling uses species' occurrences relationship with environmental conditions to predict the suitability of a location for a single species or a group of species (Rowden et al., 2017). This modelling technique in this study only illustrated HSI that indicates whether or not a seagrass is present at a location. Modelling for single species of the current study are consistent with those of Lee-Yaw, L. McCune, Pironon, and N. Sheth (2021) who agree that habitat suitability modelling do unsatisfactorily when it comes to predicting abundance of many species. Most studies of a single species found a positive correlation between abundance and predicted habitat suitability (Lee-Yaw et al., 2021). There are few studies showed that abundance and prediction of suitable habitat have negative correlations (Dallas & Hastings, 2018; Santini et al., 2018; Sporbert et al., 2020). As a result, habitat suitability modelling is not very accurate when used to predict the abundance of many species. Habitat suitability modelling for single species only predicts local occurrence, rather than other aspects of population marine species (i.e., the full demographic niche of marine species, such as corals). Given the limited ability of habitat modelling for population marine species to portray the demographics of real populations, the use of other statistical methods (e.g., unsupervised, or supervised image classification) should be assessed in population biology, such as biodiversity.

Seafloor classification map

The information on seabed substrata and faunal community structure that is provided by marine habitat mapping using image classification can be beneficial to decision-makers such as research scientists, conservation organisations, and policymakers (Ariasari et al., 2019; Bayyana et al., 2020; Benmokhtar et al., 2021; Calvert et al., 2015; Upadhyay et al., 2020; Zhafarina & Wicaksono, 2019). Recent study performed supervised classification using random forest algorithms for seafloor mapping, this technique to directly classify the distribution of seagrass habitat.

The current study used a supervised classification approach to map the distribution of seascape features around RMP. These seascape features were mapped according to various topographical features and sediment compositions. The ground-truth data were classified into several existing features that were discovered during the underwater imagery sampling. This revealed six seascape features in the study area, including fine sand, medium sand, coarse sand, coral, and seagrass on fine sand and seagrass on coarse sand. According to Montereale-Gavazzi et al. (2017), the overall accuracy (A) and kappa (K) accuracy metrics were utilised in order to assess the accuracy achieved to develop seafloor classification map. The seafloor classification map performed excellently for overall accuracy and kappa statistics. The results showed that the overall accuracy and kappa accuracy had a predictive power of RF algorithms as explained by Diesing et al. (2014) and Li et al. (2016). Furthermore, the specificity (i.e., producer accuracy) and sensitivity (i.e., user accuracy) were assessed, and each seascape feature were excellent with all six seascape features.

Seagrass seascape map

A seagrass habitat suitability model (SHSM) highlights suitable areas for seagrass and guides protection and restoration efforts, but it can't reliably predict actual seagrass habitats based only on suitable seascape features. For example, while an SHSM may show areas in the MBES survey suitable for seagrass, it often misrepresents actual habitats, potentially because it emphasizes factors with high SHSI values. In assessing RMP, six seascape features were identified, with fine sand, coarse sand, and their seagrass counterparts influencing seagrass distribution. Ground-truth surveys confirmed seagrass on fine and coarse sand, aligning with Zakaria et al. (2003). While, Ismail (1993) found seagrass in coral rubble areas, Zakaria et al. (2003) and Guannel et al. (2016) have proved that seagrass meadows and coral habitat did not share similar habitat. Therefore, actual seagrass distribution is likely more accurate when various seascape features are considered than predicted by SHSM alone.

The high spatial resolution of datasets often leads to the presence of isolated pixels (Blaschke et al., 2000; Hirayama et al., 2018; Zhai et al., 2017). A key task in data analysis is to identify and reduce these isolated pixels (Hirayama et al., 2018). Previous studies have addressed the issue of isolated pixels in the model development (Hirayama et al., 2018; Liu et al., 2014) and classification process (Parnum & Gavrilov, 2011; Shun et al., 2022; Su, 2017). Alternative statistical methods can help detect isolated pixels in habitat suitability models and classified images.

Few MBES predictors influenced seagrass presence during habitat modelling and image classification. The study found that bathymetric maps were crucial for both processes. Several studies have highlighted depth as a key factor in identifying seagrass habitats (Aoki et al., 2020; Micallef et al., 2012; Muhamad et al., 2021; Zakaria et al., 2003), with findings supported by previous researches (Aoki et al., 2020; Duarte, 1991; Zakaria et al., 2003). Seagrass is typically found in shallow waters, less than 24 m deep, and in intertidal zones (Bujang et al., 2006; Zakaria et al., 2003).

Limitations and recommendations

This study has limitations, notably insufficient MBES data in shallow waters (<5 m) due to safety and time constraints. Alternatives include tilted MBES sonar to enhance coastline coverage (Song et al., 2014), and also can maximize surveyed area and minimize data gaps during the MBES survey (Huizinga, 2014) and using USVs or ASVs for broader survey coverage in shallow areas (Lewicka et al., 2022; Nikolakopoulos et al., 2018; Specht et al., 2017). This study focuses on terrain characteristics and sediment composition (e.g., bathymetry and backscatter) to predict seagrass distribution, though other factors like light (Collier et al., 2012), temperature (Cullen-Unsworth & Unsworth, 2013; Kemp et al., 2005), and waves (Bekkby et al., 2008; Downie et al., 2013; Hossain et al., 2016; Short & Coles, 2001; Zakaria et al., 2003). Integrating these factors may enhance seagrass habitat predictions (Short & Coles, 2001; Townsend et al., 2014). The study focused on predicting seagrass habitats around RMP, offshore islands with fringing corals, where only subtidal seagrass species were found at depths of 2.5 to 24.0 m in silt-sand areas (Zakaria et al., 2003). Future research should map seagrass habitats in various coastal zones and substrate types across Peninsular and East Malaysia (Bujang et al., 2006; Zakaria et al., 2003).

Conclusion

This study aims to assess seagrass habitats using MBES datasets and machine learning. The method integrates statistical and filtering techniques to handle isolated pixels and excludes unsuitable habitats. Depth is considered crucial, as seagrass requires sunlight for photosynthesis. The results demonstrate the method's accuracy in assessing seagrass habitats around the RMP, with potential applicability to other regions in Malaysia and beyond.

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