SEAGRASS HABITAT SUITABILITY MAP AT MERAMBONG SHOAL, JOHOR: A PRELIMINARY STUDY USING MULTIBEAM ECHOSOUNDER AND MAXENT MODELLING

M. A. H. Muhamad [1] and R. Che Hasan [1,2]

[1] Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Wilayah Persekutuan Kuala Lumpur, Malaysia - muhammadabdulhakim1991@gmail.com

[2] Center for Coastal and Ocean Engineering (COEI), Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Wilayah Persekutuan Kuala Lumpur, Malaysia - rozaimi.kl@utm.my

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ABSTRACT:

In recent years, there has been an increasing interest to use high-resolution multibeam dataset and Species Distribution Modelling (SDM) for seagrass habitat suitability model. This requires a specific variable derived from multibeam data and *in-situ* seagrass occurrence samples. The purpose of this study was (1) to derive variables from multibeam bathymetry data to be used in seagrass habitat suitability model, (2) to produce seagrass habitat suitability model using Maximum Entropy (MaxEnt), and (3) to quantify the contribution of each variable for predicting seagrass habitat suitability map. The study area was located at Merambong Shoal, covering an area of 0.04 km², situated along Johor Strait. First, twelve (12) variables were derived from bathymetry data collected from multibeam echosounder using Benthic Terrain Modeller (BTM) tool. Secondly, all variables and seagrass occurrence samples were integrated in MaxEnt to produce seagrass habitat suitability map. The results showed that the Area Under Curve (AUC) values based on training and test data were 0.88 and 0.65, respectively. The northwest region of survey area indicated higher habitat suitability of seagrass, while the southeast region of survey area indicated lower suitability. Bathymetry mean found to be the most contributed variables among others. The spatial distribution of seagrass from modelling technique agreed with the previous studies and they are found to be distributed at depths ranging from 2.2 to 3.4 meters whilst less suitable with increasing of water depth. This study concludes that seagrass habitat suitability map with high-resolution pixel size (0.5 meter) can be produced at Merambong Shoal using acoustic data from multibeam echosounder coupled with MaxEnt and underwater video observations.

1. INTRODUCTION

1.1 Seagrass

Seagrass species are the most valuable ecosystem in the world (Costanza et al., 1997). Seagrass provides a variety of ecosystem functions and services to the marine ecosystem such as food sources and habitats for others benthos (Pu and Bell, 2017). Seagrass has been recognised as an important species for health and nutrients of estuarine system, reducing currents and erosion phenomena, and providing habitats for fish and shellfish species (Zimmerman, 2003).

Nevertheless, this species experiencing reduction worldwide in recent year (Duarte, 2002) due to human activity which causes physical damage and water quality deterioration. Marine biodiversity around the globe has being degraded and collapse as a result of anthropogenic activities (Jackson et al., 2001; Halpern et al., 2008). Preservation and conservation of seagrass habitats are important to sustain coastal ecosystem health. Thus, it is accountable and become a priority to any agencies, coastal management and bodies to monitor seagrass habitats (Pu et al., 2010). Therefore, seagrass distribution mapping is important task to address these issues.

Various Species Distribution Model (SDM) methods have been used to produce habitat suitability models at fine-scale by using Multibeam Echosounder (MBES) data (Monk et al., 2010; Zapata-Ramírez et al., 2014; Guinotte and Davies, 2014; Ross et al., 2015) SDMs are used to predict the geographic range of a species given presence occurrence data and derivatives assumed to influence its distribution (Wilson et al., 2011; Peterson et al., 2011; Solhjouy Fard et al., 2013). Maximum Entropy (MaxEnt) (Phillips et al., 2004b) is one of the methods that is widely used to predict the species distribution. MaxEnt has proven as a powerful modelling algorithm to predict the species distribution (Rebelo and Jones, 2010; Elith et al., 2011; Sardà-Palomera et al., 2012; Garcia et al., 2013; Marcer et al., 2013; Qin et al., 2017; Hashim et al., 2017).

To produce habitat suitability model for seagrass, SDM needs variables such as bathymetry from MBES. Most of these variables are derived to capture the seafloor morphology and proxy to habitat distributions (Diesing et al., 2014; Che Hasan et al., 2014; Subarno et al., 2016; Boswarva et al., 2018; Ierodiaconou et al., 2018). One of the tools is Benthic Terrain Modeller (BTM) to classify benthic environment especially seafloor geomorphology features (Walbridge et al., 2018). Specifically, BTM allow users to derive various bathymetry derivatives from MBES bathymetry and each of the derivative represent unique features, most likely related to the population of particular species.

The objectives of this study are; (1) to derive bathymetric derivatives from MBES bathymetry data, (2) to produce seagrass habitat suitability map using Maximum Entropy (MaxEnt) combined with MBES data, and (3) to determine the most important variables for predicting seagrass habitats distribution.

2. METHODS

2.1 Study Area

The study area encompassed 0.04 kilometres square, off Merambong shoal, located at the south western coast of Straits of Johor in the Pontian district, Johor, Malaysia (Figure 1). Seagrass habitats in this area have diverse species assemblage completely adapted to an assortment of submerged life such as vertebrates (fishes), invertebrates (shrimps and starfish) and seaweeds (Sabri et al., 2013b). Seagrass also acts as the primary food source for species as vulnerable dugongs or sea cows (*Dugong dugon*), seahorses (*Hippocampus spp.*) and endangered green turtles (*Chelonia mydas*) (Bujang et al., 2006; Hearne et al., 2019).

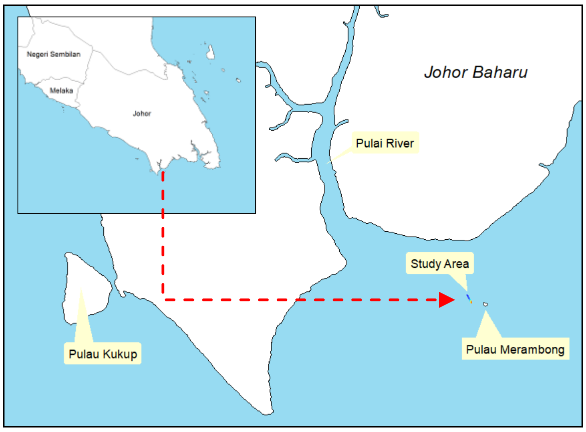

Figure 1. Location of study area.

2.2 Bathymetry Data

The bathymetry data collection was conducted from 4 April 2016 until 17 April 2016 using a side-mounted WASSP WMB-3250 Multibeam Echosounder (MBES) system which is designed to operate at shallow water environment. The MBES was integrated with a Fugro ‘‘Starfix G2+’’ Differential GPS system for positioning system and navigation purposes. The patch test calibration was conducted for heave, pitch, roll and yaw corrections. Real-time navigation, data-logging, quality control and display were provided by the QINSy software. The Minos Sound Velocity Profiler was used to measure the actual speed of sound propagated in the water column and correction for the actual depth.

The raw MBES bathymetry data was processed in Qimera, and HIPS and SIPS to obtain gridded bathymetry. The cleaning and filtering process were applied to the raw MBES bathymetry data to eliminate systematic and random errors such as roll, pitch, and heading errors, positioning errors, height errors, and latency. The spikes and noises from the raw MBES bathymetry data were removed in order to have high quality of gridded bathymetry. The outcome of the acoustic data processing was gridded bathymetry and then was exported as a raster format for subsequent process. The spatial resolution of gridded bathymetry was 0.5 meters.

2.3 Seagrass Occurrence Data

The seagrass occurrence data have been recorded across MBES surveyed area around Merambong Shoal using GoPro Hero 4. The GoPro Hero 4 was mounted on a customised cage as a ballast to provide video evidence (Figures 2 & 3). The recorded video data was classified according to seagrass occurrences based on dropping locations. The samples were georeferenced using coordinate recorded by Fugro ‘‘Starfix G2+’’ Differential GPS system. The final seagrass occurrence data includes five (5) presence and four (4) absence points (Table 1). In this study, MaxEnt requires presence-only data to produce seagrass habitat suitability model and therefore absence data was not used.

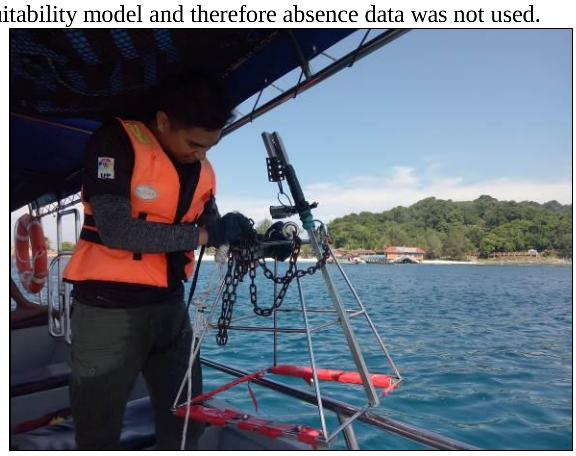

Figure 2. Visual *in-situ* sampling using GoPro Hero 4 mounted on a customize cage.

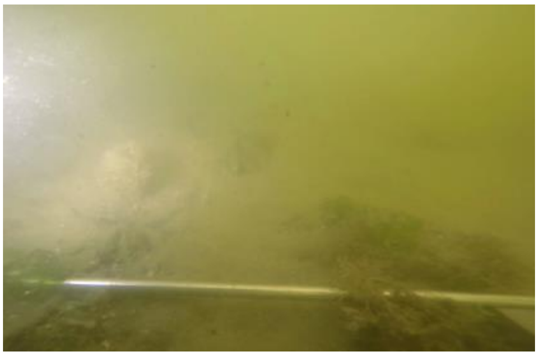

Figure 3. Sample image recorded by GoPro Hero 4.

ID	Seagrass Occurrence	Depth (meter)
X1	**Presence**	**3.25**
X3	Absence	4.55
X4	Absence	5.26
X5	**Presence**	**3.33**
GS2	**Presence**	**2.40**
GS5	**Presence**	**3.33**
GS8	**Presence**	**2.76**
GS10	Absence	3.88
GS13	Absence	5.26

Table 1. The *in-situ* samples used in this study.

2.4 Sediment Data

Sediment types play a significant role in determining the suitability of seagrass habitat. Sediment sampling has been conducted across MBES surveyed area around Merambong Shoal using Van Veen Grab sampler. The samples were georeferenced using coordinate recorded by Fugro ‘‘Starfix G2+’’ Differential GPS system. All sediment samples were analysed using Particle Size Analysis to determine sediment types. The final sediment samples data were recorded with sediment composite percentage for each sample point (Table 2).

ID	Clay	Silt	Sand	Gravel
X1	17	30	**46**	7
X3	14		**78**	8
X4	12	18	**70**	0
X5	8		**78**	14
GS2	9	20	**66**	5
GS5	9		**85**	6
GS8	6	20	**58**	16
GS10	12		**85**	3
GS13	11		**80**	9

Table 2. The sediment samples used in this study and their composite percentage (%). The bold values highlighted the percentage % of sand are the highest amongst other samples.

2.5 Derived Variables

Seabed geomorphology features are important for marine biodiversity. In this study, fourteen (14) variables (Table 3) were derived from gridded bathymetry using Benthic Terrain Modeller (BTM) tool (Walbridge et al., 2018); bathymetry variance, bathymetry standard deviation, bathymetry mean, curvature, profile curvature, plan curvature, aspect, sine of aspect, cosine of aspect, slope, Vector Ruggedness Measure (VRM), Benthic Position Index (BPI) zone (broad and fine scale BOI), based on previous studies (Micallef et al., 2012; Hasan et al., 2014; Diesing et al., 2014; Subarno et al., 2016; Ierodiaconou et al., 2018). Each variable is potentially important to define the distribution of seagrass. All variables were in raster format to achieve a set of co-located variables and produced high-resolution of seagrass habitat suitability model.

No.	Variables	Description
1	Bathymetry	Bathymetry provides information of water depth.
2	Bathymetry Mean	Bathymetry mean is a transformation from bathymetry using mean calculation.
3	Bathymetry Standard Deviation	Bathymetry standard deviation is a transformation from bathymetry using standard deviation calculation.
4	Bathymetry Variance	Bathymetry variance is a transformation from bathymetry using variance calculation.
5	Broad scale BPI	Classifies the bathymetry into several classes of surficial characteristics (broad scale). (Inner radius = 100, Outer Radius = 1000, Scale factor = 500)
6	Fine scale BPI	Classifies the bathymetry into several classes of surficial characteristics (fine scale). (Inner radius = 75, Outer Radius = 750, Scale factor = 375)
7	Curvature	Curvature is a second-order derivative from bathymetric data that displayed the shape of curvature of the slope that using basic terrain parameters described by Evans (1980).
8	Profile Curvature	Profile curvature is the curvature of the surface in the direction of slope.
9	Plan Curvature	Plan curvature is the curvature of the surface perpendicular to the slope direction.
10	Aspect	Aspect is defined as a raster surface with maximum rate of change in the slope from each cell along with direction.
11	Sine of Aspect	Sine of aspect is a transformation of aspect to measure of “northness” downslope direction
12	Vector Ruggedness Measure (VRM)	Vector Ruggedness Measure (VRM) is defined as terrain ruggedness with a surface to planar area ratio.
13	Slope	Calculate the rate of maximum change in depth from each cell of a bathymetry in degree units.

Table 3. The variables used in this study

2.6 Seagrass Habitat Suitability Model

Maximum Entropy (MaxEnt) model was used to produce seagrass habitat suitability model. MaxEnt is a machine learning method that compares the geographical conditions encountered at known presence species location, most commonly derived from GIS layers (Phillips et al., 2004a; Phillips et al., 2004b; Phillips et al., 2006; Elith et al., 2011; Downie et al., 2013). The seagrass habitat suitability model was built using MaxEnt Version 3.4.1 available (Phillips et al., 2017). First, the seagrass occurrence data and variables were simultaneously applied to this model. Twelve (12) variables were treated as continuous variables; bathymetry, bathymetry variance, bathymetry standard deviation, bathymetry mean, curvature, profile curvature, plan curvature, aspect, sine of aspect, cosine of aspect, slope, and Vector Ruggedness Measure (VRM) The two (2) of bathymetric variables were treated as categorial variables; broad scale BPI, and fine scale BPI.

The regularised multiplier, maximum number of background points, maximum iterations, and coverage threshold were set as default settings since these settings has been proven to achieve good modelling performance (Phillips and Dudík, 2008). To obtain a stable model, this study has used ten (10) replicate bootstrap procedures for the final models. Each of the replicates used a randomly selected seagrass presence-only data. The seagrass presence-only data were separated into training data and test data (75% and 25% of the data, respectively) (Briscoe et al., 2014; Wang et al., 2017). A set of seagrass occurrence data that contained five (5) drop locations within the surveyed area was used. The MaxEnt model was validated using test dataset consisting of one (1) presence data for test set. The output format is logistic, as this format can be portrayed in logistic habitat suitability index ranging from the lowest “0” to the highest “1”.

2.7 Evaluation of Model Performance

For evaluating model performance, the test data set was used to evaluate the seagrass habitat suitability model. This study applied the threshold independent measure, which is Area Under the Curve (AUC) (Swets, 1988), to test the discriminative potential, i.e. the potential of the model to distinguish between suitable seagrass habitat areas and less suitable seagrass habitat area. The AUC is calculated based on the specificity and sensitivity of the predictive model. The specificity and sensitivity indicated the success rate for classifying suitable or less suitable seagrass habitat, respectively. The AUC value of 1 indicates perfect model performance to discriminated the seagrass habitat suitability while a value of 0.5 indicates that the model is poor discrimination than random model (Fielding and Bell, 1997; Pearce and Ferrier, 2000; Downie et al., 2013). According to Hosmer Jr et al. (2013), AUC values over 0.9 indicate excellent, 0.8 to 0.9 indicate very good, 0.7 to 0.8 as satisfactory and below 0.7 represent poor discriminative ability.

MaxEnt also produced Jackknife test used to derive variable importance, expressed as AUC for seagrass habitat suitability model that used all the derived variables. Furthermore, response curves from variables for the seagrass habitat suitability model was used to examine the characteristic of seafloor geomorphology and seagrass occurrence, measured by their probabilities to predict suitability of seagrass habitat.

3. RESULTS

Figure 4 shows the high-resolution bathymetry map representing water depth at study area, overlaid with the distribution of points of seagrass occurrence Seagrass at this area are distributed at depth ranging from 2.2 to 3.4 meters. Comparison between seagrass occurrences and sediment types are shown in Table 2. Sediment types based on presence-absence seagrass occurrences were dominated by sand, followed by silt, clay, and gravel.

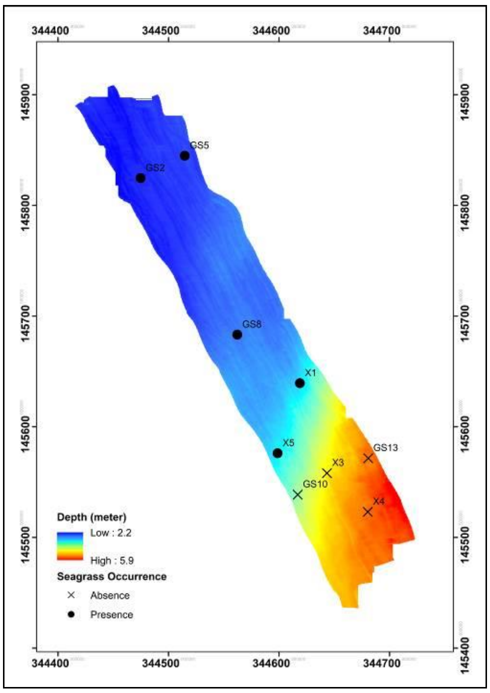

Figure 4 . Bathymetry map and seagrass occurrences.

The MaxEnt model was successful in predicting the habitat distribution of seagrass and obtained satisfactory result, with seagrass habitat suitability values ranging from 0.714 to 0.002 (Figure 5). The high value indicated suitable area for seagrass with low value indicated less suitable.

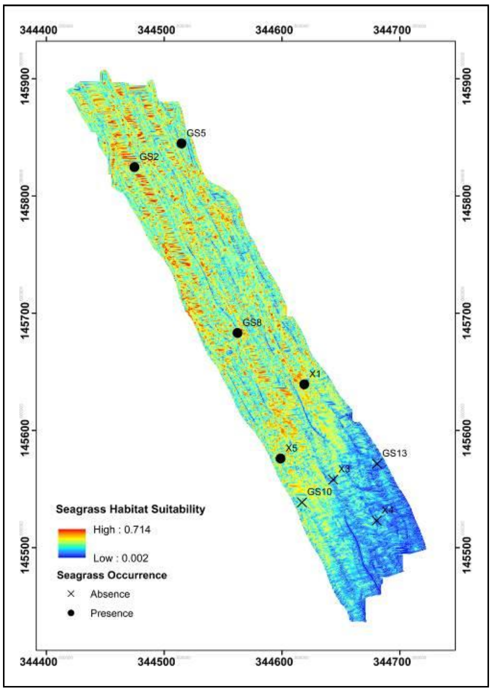

Figure 5. Seagrass habitat suitability model produced by MaxEnt model.

The MaxEnt model was successful in predicting the seagrass for both dataset, training and test dataset. The MaxEnt model generated two (2) ROC curves, displaying AUC values, for seagrass based on training data and test dataset (Figure 6). The AUC values based on the training and test data set were 0.88 and 0.65, respectively which is higher than 0.50 of a random model. Overall, the performances of the models were good for predicting seagrass habitat distribution in training, except for the test dataset.

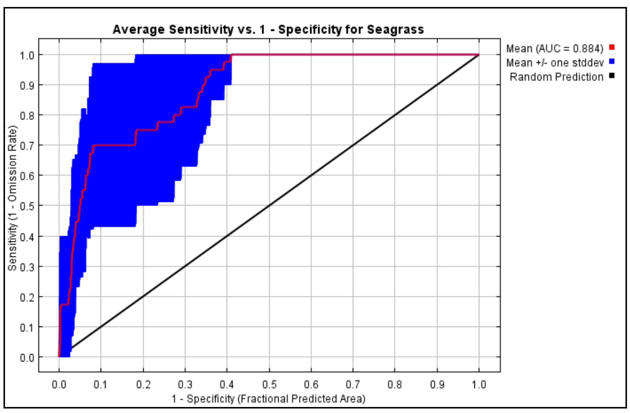

Figure 6. Seagrass habitat suitability model produced by MaxEnt model.

Bathymetry mean was considered as a variable with the highest percent contributions (18.7%) to the seagrass habitat suitability model (Table 4). This was followed by cosine of aspect, Vector

Ruggedness Measure (VRM), curvature, and sine of aspect. When each of the variable was used alone, the result shows that all variables received AUC values more than 0.5 except sine of aspect and cosine of aspect when used in isolation in Jackknife test (Figure 7).

Variable	Percent of
Bathymetry Mean	18.7
Cosine of Aspect	16.3
Vector Ruggedness Measure (VRM)	15.7
Curvature	15.0
Sine of Aspect	13.7

Table 4. The variables with high percent contributions (>10%).

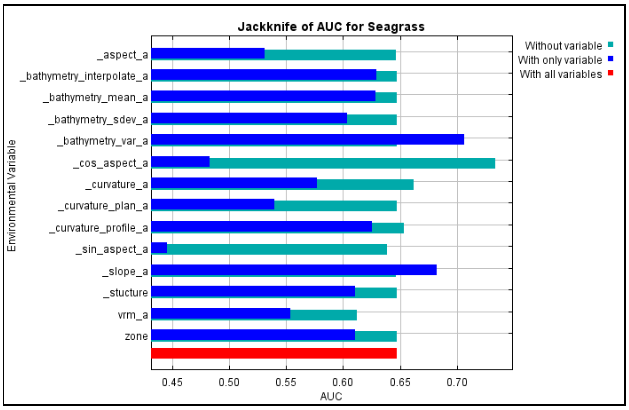

Figure 7. The Jackknife test for variable importance, expressed as AUC for seagrass habitat suitability model using each variable.

Figures 8 to 12 show the response of logistic probability of seagrass occurrence of each variables that have large percent of contribution (>10%) in predicting seagrass habitat for this model. The red lines on these figures indicated mean response and blue shaded show the standard deviation. It can be seen from these responses that the seagrass model derived in this area were distributed at 3.0 meter water depths, cosine of aspect at 0.6, almost zero ruggedness and curvature, and 0.8 sine of aspect.

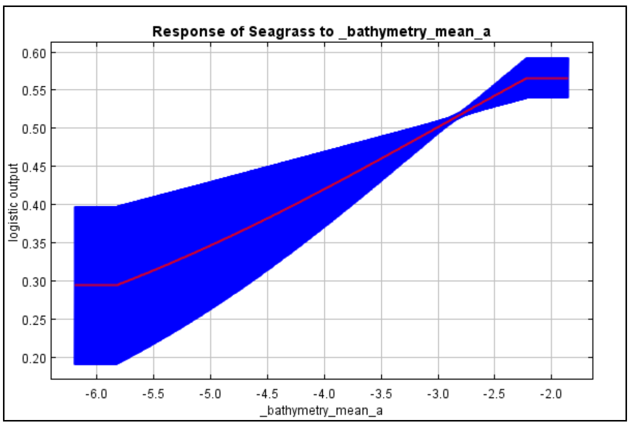

Figure 8. Response curves of mean bathymetry for the seagrass habitat suitability model.

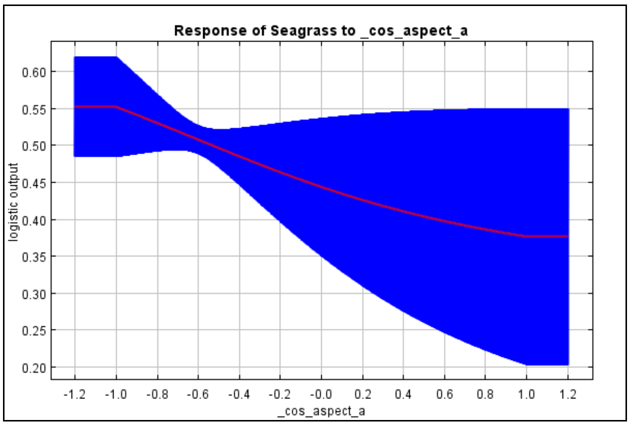

Figure 9. Response curves of cosine of aspect for the seagrass habitat suitability model.

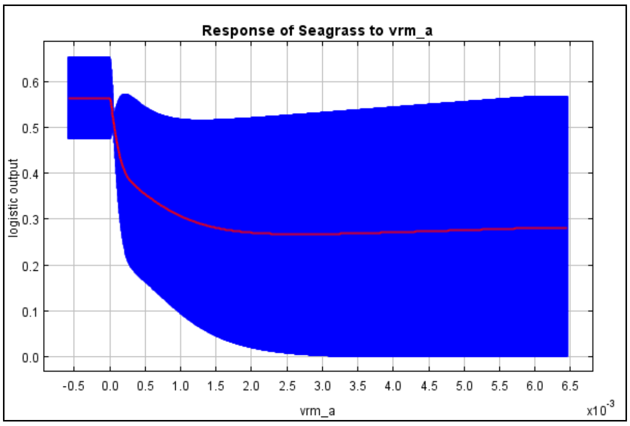

Figure 10. Response curves of Vector Ruggedness Measure (VRM) for the seagrass habitat suitability model.

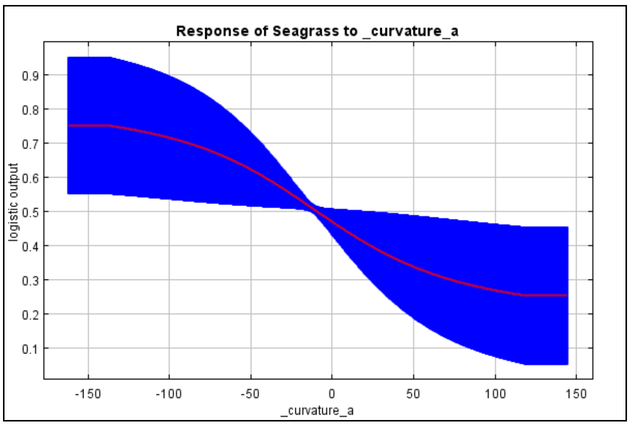

Figure 11. Response curves of curvature for the seagrass habitat suitability model.

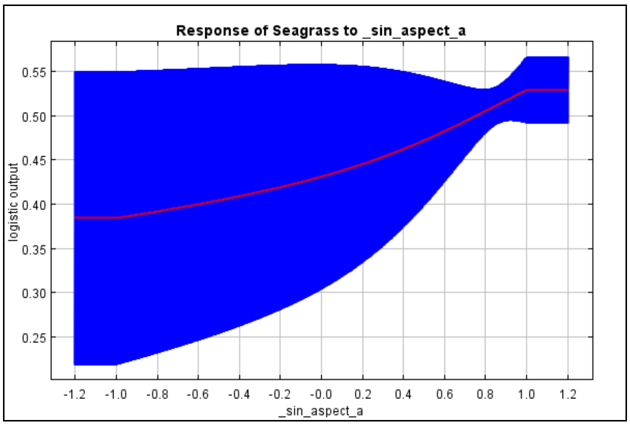

Figure 12. Response curves of sine of aspect for the seagrass habitat suitability model.

4. DISCUSSION

This study is among the first attempt to predict the suitable habitat of the seagrass in Malaysia using acoustic data from MBES. The results from this study demonstrated that the distribution of seagrass can be successfully modelled using MaxEnt model, with seagrass presence-only data and variables derived from MBES. The training model was slightly better than test model, in term of AUC (0.88 and 0.65). One of the factors is mainly because the seagrass occurrence data (i.e. presence-only) was too small for training and test dataset. In this preliminary study, only nine (9) samples were acquired with five (5) presence data and four (4) absence data. As MaxEnt can only use presence data to run the model, therefore the model might suffer from insufficient presence-only data. MaxEnt has been shown to perform well when sample sizes remain small (Elith* et al., 2006), but larger sample sizes may lead the tendency of predictive power become high (Pearson et al., 2007; Wan et al., 2019). It is suggested that other modelling techniques be tested where both presence and absence data can be incorporated, simultaneously.

Seagrass habitat in this study are distributed at depth ranging from 2.2 to 3.4 meters. This is supported by the previous studies with similar depths, ranging from 2 to 2.7 meters (Bujang et al., 2006; Kassim et al., 2009) and 2 to 3 meters (Kassim et al., 2009; Hashim et al., 2014). In addition, the model also shows that seagrass is less suitable with depth ranging from 3.5 to 5.9 meters. This could be due to the rate of light penetration through water column. Seagrass requires plenty of sun light to grow. Changes to this factor could contribute to the declination of seagrass population (Waycott et al., 2005). Sabri et al. (2013a) have shown in their study that light or water depth could be the factors that limit the distribution of seagrass. Although seagrass may be widely distributed in the study area, the results also indicated a few areas where seagrass habitats are less suitable. These areas are characterised as deep areas which light penetration is low and turbidity is high, intruded the photosynthesis reaction (Zakaria and Bujang, 2011).

Seafloor geology, particular topography is known to influence the population of seagrass (Brown et al., 2004; Micallef et al., 2012). The complex physical environment is also important as it influences the diversity of habitats for marine lives (Ierodiaconou et al., 2007; Degraer et al., 2008; Lucieer et al., 2013). In this study, bathymetry mean found to be more important than the rests because computing mean from bathymetry map has filtered and smoothed the original bathymetry map. The other variables which are derived from the bathymetry were less important because the area is quite flat and does not include large seafloor topographic variations. It can be explained from the sediment analysis that the area is a sandy environment, which make it suitable for seagrass habitats. As this study only concern with bathymetric data from MBES, future study should also include backscatter data (i.e. hardness and softness) of the seafloor to improve modelling results.

5. CONCLUSION

This study used acoustic data from MBES and MaxEnt modelling approach to predict suitable seagrass habitat in Merambong Shoal. The suitable habitat for seagrass was associated with the bathymetry depths ranging from 2.2 to 3.4 meters. Consequently, this study concluded that predictive modelling is a valuable tool to predict the distribution of seagrass. The modelling technique used in this study is also useful to quantity the contribution of each variable to the model. As this is a preliminary study to construct seagrass habitat suitability map in this area, a further investigation is needed in the future to include larger area and increase number of sampling points. Accurate seagrass suitability map is crucial to study, conserve and monitor seagrass habitats in our coastal waters from anthropogenic activities and climate change.

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REFERENCES

Boswarva, K., Butters, A., Fox, C. J., Howe, J. A., & Narayanaswamy, B. (2018). Improving marine habitat mapping using high-resolution acoustic data; a predictive habitat map for the Firth of Lorn, Scotland. *Continental Shelf Research, 168*, 39-47. doi:https://doi.org/10.1016/j.csr.2018.09.005

Briscoe, D. K., Hiatt, S., Lewison, R., & Hines, E. (2014). Modeling habitat and bycatch risk for dugongs in Sabah, Malaysia. *Endangered Species Research, 24*(3), 237-247.

Brown, C. J., Hewer, A. J., Meadows, W. J., Limpenny, D. S., Cooper, K. M., & Rees, H. L. (2004). Mapping seabed biotopes at hastings shingle bank, eastern English Channel. Part 1. Assessment using sidescan sonar. *Journal of the Marine Biological Association of the United Kingdom, 84*(3), 481-488.

Bujang, J., Zakaria, M., & Arshad, A. (2006). Distribution and significance of seagrass ecosystems in Malaysia. *Aquatic Ecosystem Health & Management, 9*(2), 203-214. doi:10.1080/14634980600705576

Che Hasan, R. C., Ierodiaconou, D., Laurenson, L., & Schimel, A. (2014). Integrating multibeam backscatter angular response, mosaic and bathymetry data for benthic habitat mapping. *Plos one, 9*(5), e97339.

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., . . . Paruelo, J. (1997). The value of the world's ecosystem services and natural capital. *nature, 387*(6630), 253.
Degraer, S., Verfaillie, E., Willems, W., Adriaens, E., Vincx,

M., & Van Lancker, V. (2008). Habitat suitability modelling as a mapping tool for macrobenthic communities: an example from the Belgian part of the North Sea. *Continental Shelf Research, 28*(3), 369-379.

Diesing, M., Green, S. L., Stephens, D., Lark, R. M., Stewart, H. A., & Dove, D. (2014). Mapping seabed sediments: Comparison of manual, geostatistical, object-based image analysis and machine learning approaches. *Continental Shelf Research, 84*, 107-119.

Downie, A.-L., von Numers, M., & Boström, C. (2013). Influence of model selection on the predicted distribution of the seagrass Zostera marina. *Estuarine, Coastal and Shelf Science, 121-122*, 8-19. doi:https://doi.org/10.1016/j.ecss.2012.12.020

Duarte, C. M. (2002). The future of seagrass meadows. *Environmental conservation, 29*(2), 192-206.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, *17*(1), 43-57.

Elith*, J., H. Graham*, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., . . . Lehmann, A. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography, 29*(2), 129-151.

Fielding, A. H., & Bell, J. F. (1997). A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental conservation, 24*(1), 38-49.

Garcia, K., Lasco, R., Ines, A., Lyon, B., & Pulhin, F. (2013). Predicting geographic distribution and habitat suitability due to climate change of selected threatened forest tree species in the Philippines. *Applied Geography, 44*, 12-22.

Guinotte, J., & Davies, A. (2014). *Predicted Deep-Sea Coral Habitat Suitability for the US West Coast* (Vol. 9).

Halpern, B. S., Walbridge, S., Selkoe, K. A., Kappel, C. V., Micheli, F., D'agrosa, C., . . . Fox, H. E. (2008). A global map of human impact on marine ecosystems. *science, 319*(5865), 948-952.

Hashim, M., Ito, S., Numata, S., Hosaka, T., Hossain, M. S., Misbari, S., Yahya, N.N., Ahmad, S. (2017). Using fisher knowledge, mapping population, habitat suitability and risk for the conservation of dugongs in Johor Straits of Malaysia. *Marine Policy, 78*, 18-25. doi:http://doi.org/10.1016/j.marpol.2017.01.002

Hashim, M., Yahya, N. N., Ahmad, S., Komatsu, T., Misbari, S., & Reba, M. (2014). Determination of seagrass biomass at Merambong Shoal in Straits of Johor using satellite remote sensing technique. *Malay. Nat. J, 66*, 20-37.

Hearne, E. L., Johnson, R. A., Gulick, A. G., Candelmo, A., Bolten, A. B., & Bjorndal, K. A. (2019). Effects of green turtle grazing on seagrass and macroalgae diversity vary spatially among seagrass meadows. *Aquatic Botany, 152*, 10-15. doi:https://doi.org/10.1016/j.aquabot.2018.09.005

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398): John Wiley & Sons.

Ierodiaconou, D., Laurenson, L., Burq, S., & Reston, M. (2007). Marine benthic habitat mapping using Multibeam data, georeferencedvideo and image classification techniques in Victoria, Australia. *Journal of Spatial Science*, *52*(1), 93-104.

Ierodiaconou, D., Schimel, A. C., Kennedy, D., Monk, J., Gaylard, G., Young, M., . . . Rattray, A. (2018). Combining pixel and object based image analysis of ultra-high resolution multibeam bathymetry and backscatter for habitat mapping in shallow marine waters. *Marine Geophysical Research, 39*(1-2), 271-288.

Jackson, J. B., Kirby, M. X., Berger, W. H., Bjorndal, K. A., Botsford, L. W., Bourque, B. J., . . . Estes, J. A. (2001). Historical overfishing and the recent collapse of coastal ecosystems. *science, 293*(5530), 629-637.

Kassim, Z., Diyana, F., & Suhaili, A. (2009). *Benthic Community of the Sungai Pulai Seagrass Bed, Malaysia* (Vol. 28).

Lucieer, V., Hill, N. A., Barrett, N. S., & Nichol, S. (2013). Do marine substrates 'look'and 'sound'the same? Supervised classification of multibeam acoustic data using autonomous underwater vehicle images. *Estuarine, Coastal and Shelf Science, 117*, 94-106.

Marcer, A., Sáez, L., Molowny-Horas, R., Pons, X., & Pino, J. (2013). Using species distribution modelling to disentangle realised versus potential distributions for rare species conservation. *Biological Conservation, 166*, 221-230.

Micallef, A., Le Bas, T. P., Huvenne, V. A. I., Blondel, P., Hühnerbach, V., & Deidun, A. (2012). A multi-method approach for benthic habitat mapping of shallow coastal areas with high-resolution multibeam data. *Continental Shelf Research, 39-40*, 14-26. doi:https://doi.org/10.1016/j.csr.2012.03.008

Monk, J., Ierodiaconou, D., Versace, V., Bellgrove, A., Harvey, E., Rattray, A., . . . P. Quinn, G. (2010). *Habitat suitability for marine fishes using presence-only modelling and multibeam sonar* (Vol. 420).

Pearce, J., & Ferrier, S. (2000). An evaluation of alternative algorithms for fitting species distribution models using logistic regression. *Ecological Modelling, 128*(2-3), 127-147.

Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography, 34*(1), 102-117.

Peterson, A. T., Soberón, J., Pearson, R. G., Anderson, R. P., Martínez-Meyer, E., Nakamura, M., & Araújo, M. B. (2011). *Ecological niches and geographic distributions (MPB-49)* (Vol. 56): Princeton University Press.

Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: an open-source release of Maxent. *Ecography, 40*(7), 887-893. doi:10.1111/ecog.03049

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3), 231-259. doi:https://doi.org/10.1016/j.ecolmodel.2005.03.026

Phillips, S. J., & Dudík, M. (2008). *Modeling of species distributions with MAXENT: new extensions and a comprehensive evaluation* (Vol. 31).

Phillips, S. J., Dudík, M., & Schapire, R. (2004a). *A maximum entropy approach to species distribution modeling.* Paper presented at the Proceedings of the twenty-first international conference on Machine learning.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2004b). *A maximum entropy approach to species distribution modeling.* Paper presented at the Proceedings of the twenty-first international conference on Machine learning.

Pu, R., & Bell, S. (2017). Mapping seagrass coverage and spatial patterns with high spatial resolution IKONOS imagery. *International Journal of Applied Earth Observation and Geoinformation, 54*, 145-158. doi:http://dx.doi.org/10.1016/j.jag.2016.09.011

Pu, R., Bell, S., Levy, K. H., & Meyer, C. (2010, 25-30 July 2010). *Mapping detailed seagrass habitats using satellite imagery.* Paper presented at the 2010 IEEE International Geoscience and Remote Sensing Symposium.

Qin, A., Liu, B., Guo, Q., Bussmann, R. W., Ma, F., Jian, Z., . . . Pei, S. (2017). Maxent modeling for predicting impacts of climate change on the potential distribution of Thuja sutchuenensis Franch., an extremely endangered conifer from southwestern China. *Global Ecology and Conservation, 10*, 139-146. doi:https://doi.org/10.1016/j.gecco.2017.02.004

Rebelo, H., & Jones, G. (2010). Ground validation of presence- only modelling with rare species: a case study on barbastelles Barbastella barbastellus (Chiroptera: Vespertilionidae). *Journal of Applied Ecology, 47*(2), 410-420.

Ross, L. K., Ross, R. E., Stewart, H. A., & Howell, K. L. (2015). The influence of data resolution on predicted distribution and estimates of extent of current protection of three 'listed'deep-sea habitats. *Plos one, 10*(10), e0140061.

Sabri, S., Said, M., Azman, S., & Goto, M. (2013a). *Seagrass at south western coast of johor* (Vol. 8).

Sabri, S., Said, M., Azman, S., & Goto, M. (2013b). Seagrass at south western coast of johor. *Journal of Sustainability Science and Management, 8*, 73-79.

Sardà-Palomera, F., Brotons, L., Villero, D., Sierdsema, H., Newson, S. E., & Jiguet, F. (2012). Mapping from heterogeneous biodiversity monitoring data sources. *Biodiversity and conservation, 21*(11), 2927-2948.

Solhjouy Fard, S., Sarafrazi, A., Moeini, M., & Ahadiyat, A. (2013). *Predicting Habitat Distribution of Five Heteropteran Pest Species in Iran* (Vol. 13).

Subarno, T., Siregar, V. P., Agus, S. B., & Sunuddin, A. (2016). Modelling Complex Terrain of Reef Geomorphological Structures in Harapan-kelapa Island, Kepulauan Seribu. *Procedia Environmental Sciences, 33*, 478-486. doi:https://doi.org/10.1016/j.proenv.2016.03.100

Swets, J. A. (1988). Measuring the accuracy of diagnostic systems. *science, 240*(4857), 1285-1293.

Walbridge, S., Slocum, N., Pobuda, M., & Wright, D. J. (2018). Unified Geomorphological Analysis Workflows with Benthic Terrain Modeler. *Geosciences, 8*(3), 94.

Wan, J.-Z., Wang, C.-J., & Yu, F.-H. (2019). Effects of occurrence record number, environmental variable number, and spatial scales on MaxEnt distribution modelling for invasive plants. *Biologia*, 1-10.

Wang, B., Xu, Y., & Ran, J. (2017). *Predicting suitable habitat of the Chinese monal (Lophophorus lhuysii) using ecological niche modeling in the Qionglai Mountains, China* (Vol. 5).

Waycott, M., Longstaff, B. J., & Mellors, J. (2005). Seagrass population dynamics and water quality in the Great Barrier Reef region: a review and future research directions. *Marine Pollution Bulletin, 51*(1-4), 343-350.

Wilson, C. D., Roberts, D., & Reid, N. (2011). Applying species distribution modelling to identify areas of high conservation value for endangered species: A case study using Margaritifera margaritifera (L.). *Biological Conservation, 144*(2), 821-829.

Zakaria, M. H., & Bujang, J. S. (2011). Disturbances in seagrasses ecosystem in Malaysia. *Seagrasses: resource status and trends in Indonesia, Japan, Malaysia, Thailand and Vietnam. Seizando-Shoten, Tokyo*, 67-78.

Zapata-Ramírez, P. A., Huete-Stauffer, C., Coppo, S., & Cerrano, C. (2014). *Using MaxEnt to understand and predict the distribution of coralligenous environments*.

Zimmerman, R. C. (2003). A biooptical model of irradiance distribution and photosynthesis in seagrass canopies. *Limnology and oceanography, 48*(1part2), 568-585.

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