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Coastline Accuracy Assessment Developed By Using Multi Data Source

Nadya Oktaviani [1], Prayudha Hartanto[1], Danang Budi Susetyo[2], Ratna Sari Dewi[1] , Sandi Aditya[1], Irmadi Nahib[2], Hollanda Arief Kusuma[3*]

[1] Geospatial Information Agency (BIG), Jl. Raya Jakarta Bogor KM 46 Cibinong, Bogor 16913
[2] National Research and Innovation Agency (BRIN)
[3] Universitas Maritim Raja Ali Haji, Jl. Politeknik Senggarang, Kampus UMRAH, Tanjungpinang Kota, Tanjungpinang, Kepulauan Riau, Indonesia
*Corresponding author e-mail : hollandakusuma@umrah.ac.id

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Abstract

This research aimed to integrate a Digital Elevation Model (DEM) using four different input data scenarios to determine the accurate position of the coastline. The study used elevation data from single-beam echosounder (SBES), multi-beam echosounder (MBES), satellite derived bathymetry (SDB), and the National Digital Elevation Model (DEMNAS) to produce the DEM. The accuracy of the resulting coastline was then assessed by comparing it to a reference coastline provided by the Indonesian Geospatial Information Agency (BIG). The results showed that the specifications and quality of the input data greatly influenced the accuracy of the DEM integration results. The integration of SBES and MBES data blended well and the inclusion of bathymetry data improved the representation of deeper areas. The first scenario, which involved three datasets (SBES, bathymetry, and elevation data from DEMNAS), had the highest accuracy with 69.86% of the total area categorized as acceptable compared to the reference coastline. The results also showed that Root Mean Square Error (RMSE) values indicated the lowest accuracy of the model, but RMSE is just one metric used to evaluate the accuracy of the coastline model and other measures should also be considered. This research highlights the importance of careful examination of input data for accurate integration of DEM and the accurate assessment of coastline models.

Keywords: Coastline, Integration of multiple dataset, Accuracy, Digital Elevation Model, Root Mean Square Error

1. Introduction

The coastal zone, also referred to as the coastal area, is the transition area between land and sea (Xu et al., 2016). It encompasses many environments and landscapes, including shorelines, coastal islands, estuaries, bays, dunes, forests, and tidal waters. It is important to note that the boundary between the coastal zone and the sea is not permanent and can change daily due to tides, moon phases, seasons, storms, and river floods (Emery and Aubrey, 1991). Natural and human-made factors dynamically influence the coastal zone, so it is vital to monitor and understand the changes in this region.

(Oertel, 2005) has characterized the coastline as a dividing line between land and sea on both regional and global levels, while the shoreline encompasses all of the shore's distinctive features. Consequently, the precise location of the coastline is critical for coastal zone planning and management purposes, including land use and cover classification, coastal erosion analysis, and environmental monitoring (Stanchev et al., 2011). Additionally, information about the coastline is crucial for inventorying natural resources and identifying areas most susceptible to hazards. Nonetheless, determining the accurate position of the coastline is challenging due to its dynamic environment. Factors that affect coastline length and its accurate position include the geological structure of the coast, the scale of geographical spatial data, the type and resolution of spatial data, the map projection used, map generalization, measuring units, and horizontal and vertical data for geographical coordinates (Monmonier, 2008).

The position of coastlines has been studied and determined using a variety of methods in the literature. Traditional ground survey methods were widely used and produced accurate results (Crowell et al., 1991). However, these methods were expensive in terms of time and resources (Morton et al., 1993). Later, aerial photographs were introduced and further replaced by stereo aerial photographs (Moore, 2000). In recent times, new methods such as LIDAR-based (Bretel et al., 2013; Kim et al., 2018; Sesli and Caniberk, 2015; Soeksmantono et al., 2021; White and Wang, 2003) and satellite-based techniques, such as the water index method (Choung and Jo, 2017; Hu et al., 2012; Lan et al., 2022; Yun-Jae, 2017), band ratio techniques (Khalifeh et al., 2007; Paengwangthong, 2021; Pirasteh et al., 2005; Saied et al., 2005), and classification method (Taha and Elbeih, 2010; Tamassoki et al., 2014) have been introduced. It is crucial to determine proxies or indicators that can identify the coastline position based on the area's topography, data source, and scientific preferences to extract coastline information from any data source (Dewi, 2019).

The objective of this research is to identify coastlines by integrating multiple datasets, such as the elevation data obtained from single-beam echosounder (SBES), multi-beam echosounder (MBES), 10 m resolution satellite bathymetry, and the 0.27" spatial resolution National Digital Elevation Model (DEMNAS). Based on a geoid model, the Mean Sea Level is adopted as the tidal datum and reference level for all data. The assimilation of the data is performed using GMT Surface. The accuracy of the resulting coastline is then assessed by comparing it to the reference coastline, derived from a coastal map produced by the Indonesian Geospatial Information Agency (Badan Informasi Geospasial – BIG) in 2018.

2. Methods

This research focuses on extracting coastlines at the Tanjung Kelayang coastal area. Tanjung Kelayang is a popular marine tourism destination located on Belitung Island in the Bangka Belitung Province of Indonesia (as seen in Figure 1) with coordinates 2º34'1.2" S and 107º38'9.6" E. The seabed substrate of the area is sandy, and the tide is diurnal, with a range of approximately 2.4 m. During the dry season (June to August), the surface current flows from southeast to northwest, while during the wet season (December to February), it flows from north to southeast.

This study uses bathymetry, and topographic data adjusted to the Mean Sea Level (MSL) obtained from BIG tides prediction (Badan Informasi Geospasial, 2019). The data sources include Single-beam Echosounder (SBES) SyQwest Bathy-500MF, Multi-beam Echosounder (MBES) Teledyne Odom MB2, and shallow water bathymetry data from Satellite Derived Bathymetry (SDB). The SBES and MBES data were obtained from the Indonesia Geospatial Information Agency, while the SDB data was obtained from a previous study (Dewi et al., 2019). Dewi et al. (2019) used a random forest algorithm to extract depth information from Sentinel 2A with 500 trees and one variable at each split, resulting in a variance explained by the model of 99.54% with an RMSE value of 0.11m.

The data acquisition year can be found in Table 1. The topographic data was obtained from the 0.27 arc-second spatial resolution National Digital Elevation Model (DEMNAS) (Badan Informasi Geospasial, 2018) processed from multiple input data sources such as ALOS PALSAR, IFSAR, and TERRASAR-X with vertical datum EGM2008. The study also uses a coastline reference from a 1:25000 coastal map from the Indonesia Geospatial Information Agency (BIG) to validate the model.

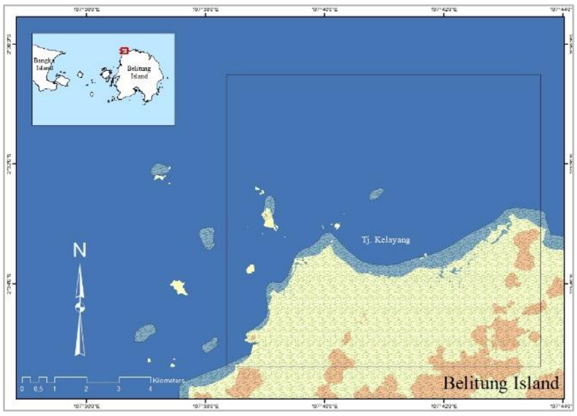

Fig 1. Study Area in Belitung Island, Bangka Belitung Province, Indonesia.

Table 1. Data acquisition date from every source

Source	Year acquisition
SBES	2018
MBES	2018
SDB	July 2019

This study utilized the continuous curvature splines in the tension interpolation method to construct a grid of multiple datasets with varying resolutions (Hell and Jakobsson, 2011). The grid represents regular-spaced spatial values created through subsampling, interpolation, and extrapolation principles in two dimensions. Interpolation estimates values using the closest sample values, known as spatial autocorrelation (DeWitt, 2022), and aims to minimize data gaps in the gridded data from different resolution sources. The outcome of constructing the grid from multiple-resolution data is an integrated Digital Elevation Model (topographic and bathymetric). This integrated DEM can then be used to extract the coastline.

This study used four datasets with different spatial resolutions and densities (Figure 2). The first dataset was recorded in 2018 and collected using a Single-beam echosounder (SBES) with a point density of 1 m and a line survey interval of 200 m. The second dataset was collected using a multibeam echosounder (MBES) with a 5 m raster grid. The third dataset was a Satellite-derived bathymetry (SDB) with 10 m spatial resolution obtained from Sentinel 2. The last dataset was the National Digital Elevation Model (DEMNAS), with a spatial resolution of 8.1 m (0.27 arc-seconds).

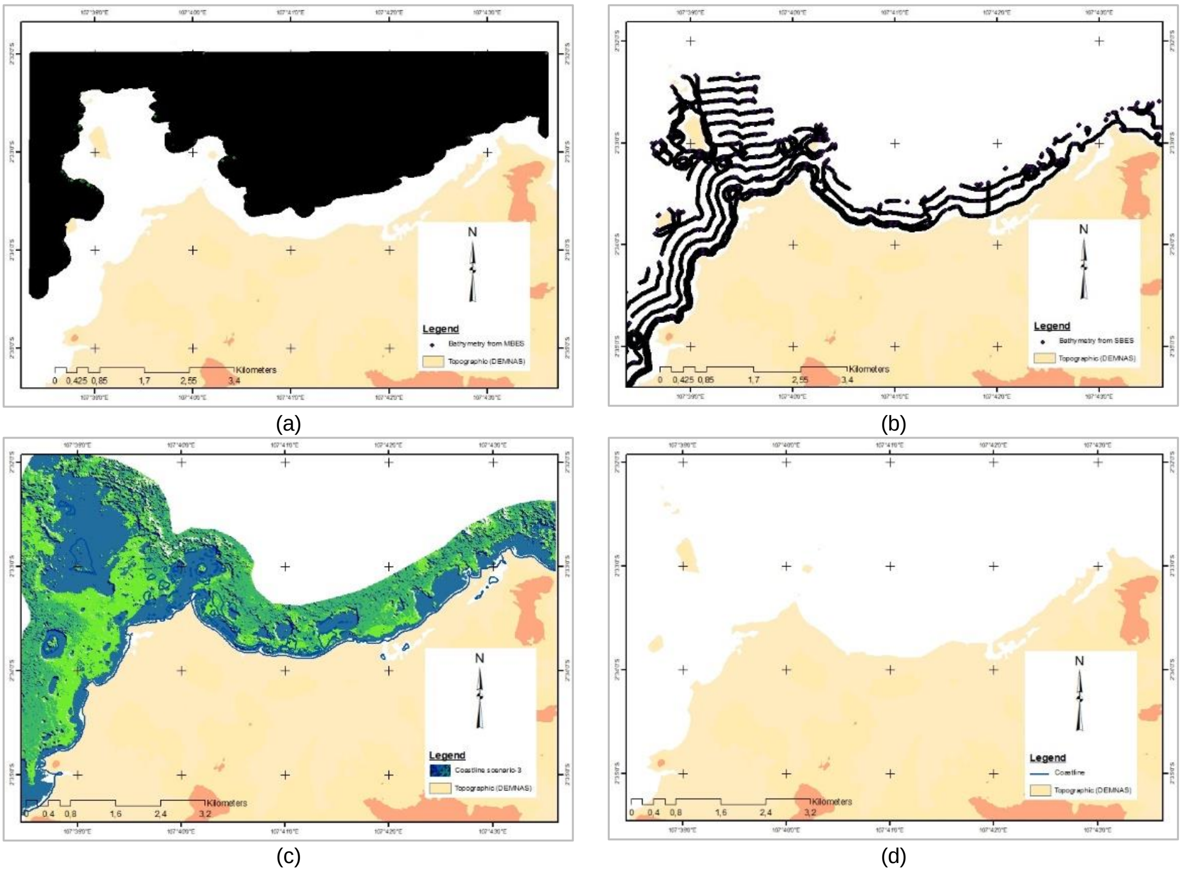

Fig 2. Input data used for this research : (a) Multibeam echosounder data, (b) Singlebeam echosounder data, (c) Satellite Derived Bathymetry Data, (d) DEMNAS

This study's entire data processing was conducted using the open-source Generic Mapping Tools (The GMT Developers, 2019). The data has a small scale but has a large coverage serving as a preliminary basis to accumulate more data. While for more detailed data, the resolution of the data is maintained until the final grid determination. The grids were first piled up using the grdstack function at GMT, with different resolutions for each dataset. Next, the surface masking function was implemented to determine the number of grid cells with limited data. Finally, the empty value was defined as "NaN" if a grid value was not met (Hell and Jakobsson, 2011). The Final result of this step is a raster file. The general workflow of generating the coastline in this study can be found in Figure 3. The illustration of grid stacking and surface masking can be seen in Figure 4.

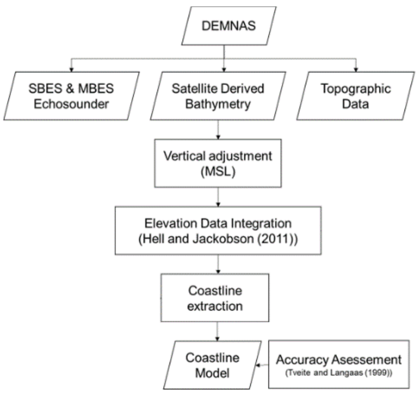

Fig 3. The general workflow of generating coastline in this study

This study employed four different scenarios in its data processing. These scenarios were determined by the input data used in the modeling. The first scenario utilized three datasets: single-beam echosounder (SBES), bathymetry data from Sentinel 2 (SDB), and topographic data from the Digital Elevation Model DEMNAS. The second scenario involved using multi-beam echosounder (MBES) data, bathymetry data from SDB, and topographic data from DEMNAS. The third scenario incorporated MBES, SBES, and topographic data from DEMNAS. Finally, the fourth scenario utilized bathymetry data from SDB, topographic data from DEMNAS, and echo-sounding data from both SBES and MBES. All scenarios can be seen in Table 2.

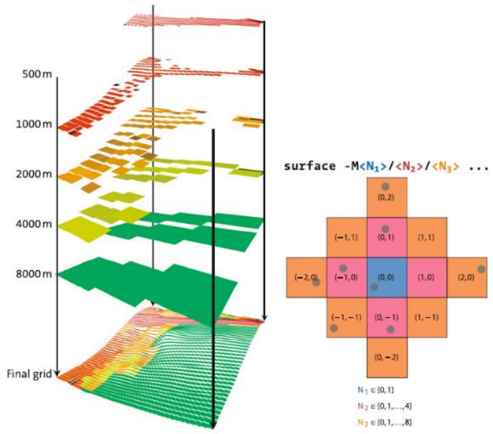

Fig 4. Ilustration of grid stacking (a) and surface masking (b). Source: (Hell and Jakobsson, 2011)

Table 2. Data used in every scenario for the modeling

Scenario	Model Data Processing
1	SBES, SDB, DEMNAS
2	MBES, SDB, DEMNAS
3	SBES, MBES, DEMNAS
4	SBES, MBES, SDB, DEMNAS

The model's accuracy was assessed using a method outlined in (Tveite, 1999). Multiple ring buffers were created in ArcGIS using the model coastlines and reference coastline from Indonesian Coastal Environment Map (LPI) as input. All experiments used ten buffer sizes ranging from 1 m to 10 m (the maximum assumed error equal to Sentinel 2A pixel size). The buffer polygons from both coastlines were intersected using the union command, and statistics were calculated. The results were visualized in a spreadsheet program. The Root Mean Square Error (RMSE) was also calculated to measure the difference between the model coastline and the reference coastline in square meters (m^2). The RMSE can be used to evaluate the accuracy of the coastline model, with a low RMSE value indicating accurate predictions and a high value indicating poor predictions (Chai and Draxler, 2014).

3. Results and Discussion

3.1 The DEM Integration Visualization

The Digital Elevation Model (DEM) integration was visualized through four different scenarios, as shown in Figure 5. The specifications and quality of the input data, such as coverage, position, and spatial detail, influence the variations in the DEM integration results. As seen in Figure 5a, integrating single-beam echosounder (SBES) and multi-beam echosounder (MBES) data provides good visualization and blends well. On the other hand, Figures 5b to 5d illustrate that MBES data provides more detailed depth information due to its 5 m raster grid resolution. Adding bathymetry data from the SDB results in representing deeper areas, as indicated by the blue pixels in Figures 5a, b, and d. Therefore, it is crucial to carefully check the input data, particularly to ensure that all input data are in the raster data format.

The results of the DEM integration shown in Figure 5 were used to generate coastlines, as shown in Figure 6. All scenarios produce similar coastlines. However, some differences are still noticeable, for example, the coastline of small islands (as seen in grid cells 2B, 3C, and 1E in Figure 6).

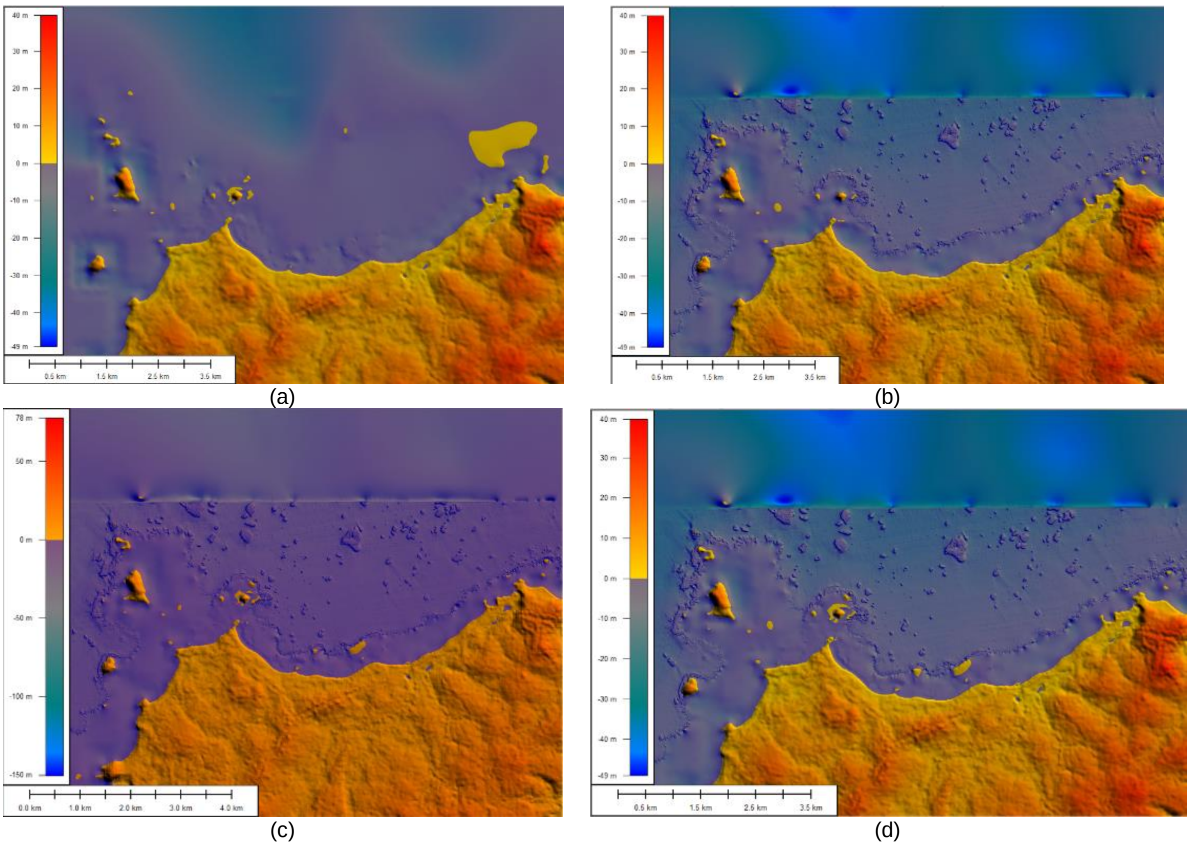

Fig 5. Visualization comparison of DEM integration results based on four input-data scenarios; a) scenario 1 using SBES, SDB, and DEMNAS; b) scenario 2 using MBES, SDB, and DEMNAS; c) scenario 3 using MBES, SBES, and DEMNAS; and d) scenario 4 using, SBES, MBES, SDB, and DEMNAS

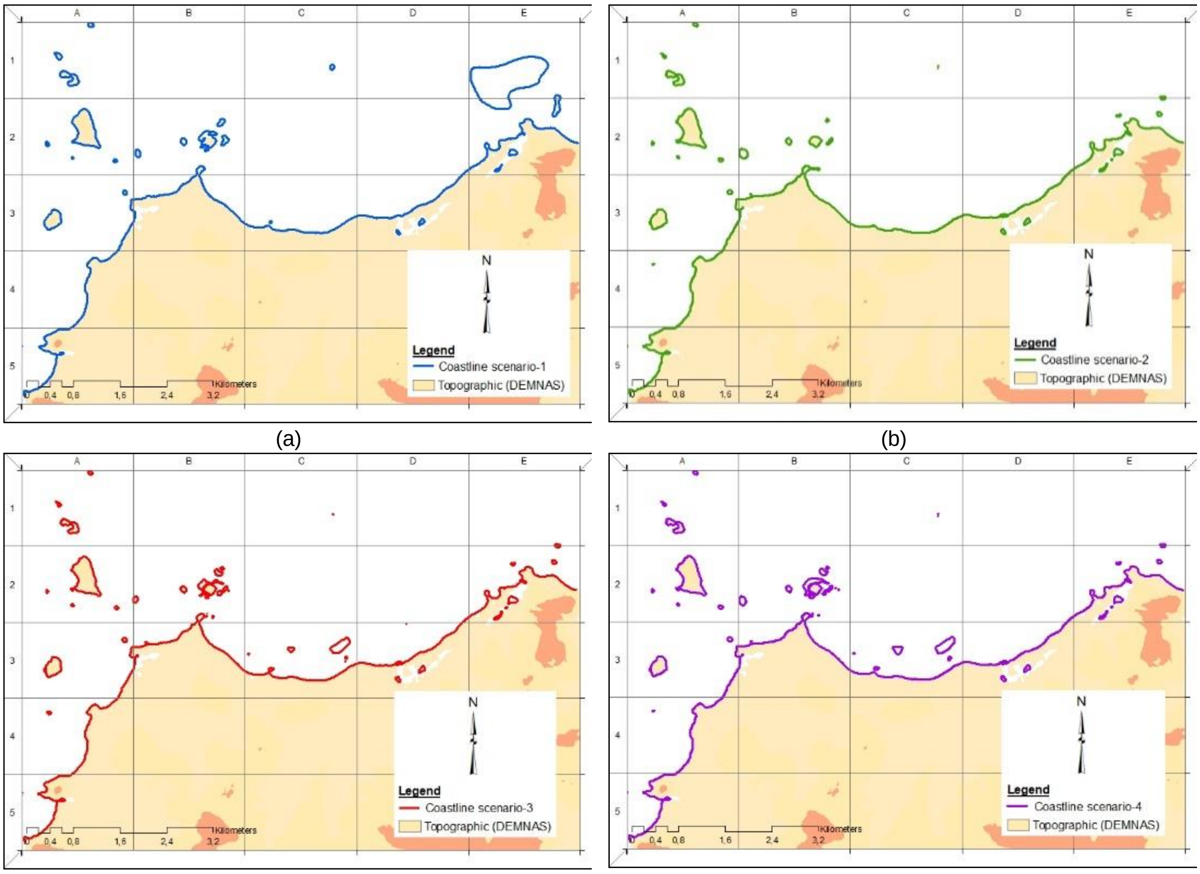

Fig 6. Visualization comparison of coastline model based on four input-data scenarios; a) scenario 1, b) scenario 2, c) scenario 3, and d) scenario 4

3.2 Accuracy Assessment of Coastline Models and Error Evaluation

The results of the accuracy assessment of the coastline models are shown in Figure 7. The accuracy is determined by comparing the buffer area generated along the coastlines with the reference coastline. The highest accuracy value is given by using the first scenario, which involves three datasets: SBES, SDB, and elevation data from DEMNAS. In the first scenario, the model obtained the largest error values for the displacement around 1 m from the reference coastline. Therefore, it implies that the model has high accuracy. Thus, 69.86% of the total area can be categorized as acceptable relative to the reference. The second and third scenarios have lower results than the first. Similar to the first scenario, the largest error value for the displacement was around 1 m from the reference coastline. However, the third scenario has the lowest accuracy of only 65.45%. The complete accuracy assessment results of this research based on four scenarios are presented in Table 3.

The Table 4 shows the Root Mean Square Error (RMSE) values of four different scenarios for the coastline models. The RMSE is a measure of the difference between the scenario results and the reference coastline. The lower the RMSE value, the more accurate the coastline model is in predicting the coastline shape and extent.

In this case, Scenario 1 has the highest RMSE value of 0.0706 m², indicating the lowest accuracy of the model. Meanwhile, Scenarios 2, 3, and 4 have RMSE values of 0.0662 m², 0.0662 m², and 0.0668 m² respectively, which are slightly higher accuracy than Scenario 1. However, it is important to note that RMSE is just one metric used to evaluate the accuracy of the coastline model, and other measures should also be considered to get a comprehensive understanding of the model's performance.

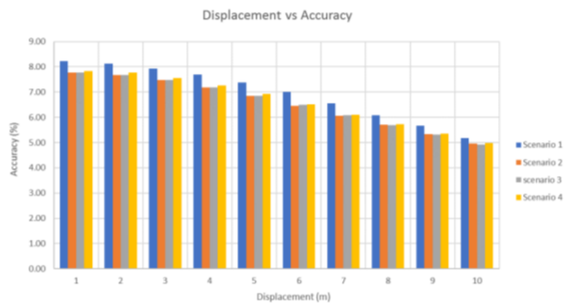

Fig 7. Accuracy test graph for each scenario relative to the reference coastline

Table 3. Assessment results of coastline models

Scenario	Accuracy (%)		
	0 - 5 m	5 - 10 m	> 10 m
1	39.37	30.49	30.14
2	36.95	28.53	34.52
3	36.96	28.49	34.55
4	37.37	28.69	33.95

Table 4.RMSE of coastline models

Scenario	RMSE (m^2)
1	0.0706
2	0.0662
3	0.0662
4	0.0668

3.3 Discussion

The results of this research aimed to integrate a Digital Elevation Model (DEM) using four different scenarios. The results showed that the specifications and quality of the input data, such as coverage, position, and spatial detail, greatly influence the variations in the DEM integration. The integration of single-beam echosounder (SBES) and multi-beam echosounder (MBES) data provided a good visualization and blended well (Ahmed, 2012). Adding bathymetry data from the SDB improved the representation of deeper areas. However, the importance of examining the input data carefully to ensure that it is in the raster data format cannot be overstated.

The results also showed that all scenarios produced similar coastlines, but some differences were noticeable in small island coastlines. The accuracy of the coastline models was assessed by comparing the buffer area generated along the coastlines with the reference coastline. However, all quality measures in this study were affected by errors generated from fragmentations and noises (Goeman et al., 2005), so more data is needed to improve the accuracy of the coastline model.

The results align with related research, suggesting that integrating multiple datasets can improve the accuracy of coastline models (Kostopoulou, 2021). However, the results also indicate that adding more data does not guarantee an improvement in accuracy, as all quality measures were affected by errors generated from fragmentations and noises.

The results showed that integrating SBES and MBES data in Scenario 1 provided good visualization and blended well. However, the inclusion of bathymetry data from the SDB did not significantly improve accuracy as measured by the assessment results and RMSE values. Further research may be necessary to identify other factors that affect coastline models' accuracy and determine the optimal methods for integrating DEM data to generate accurate coastline models.

4. Conclusion

This research aimed to integrate a Digital Elevation Model (DEM) using four different input data scenarios and to assess the accuracy of the resulting coastline models. The results showed that the specifications and quality of the input data greatly influence the variations in the DEM integration results. Integrating single-beam echosounder (SBES) and multi-beam echosounder (MBES) data blended well and including bathymetry data from the SDB improved the representation of deeper areas. The accuracy assessment results showed that the first scenario, which involved three datasets (SBES, SDB, and elevation data from DEMNAS), had the highest accuracy, with 69.86% of the total area categorized as acceptable relative to the reference coastline. However, all quality measures presented were affected by errors generated from fragmentations and noises.

The Root Mean Square Error (RMSE) values showed that Scenario 1 had the highest RMSE value, indicating the lowest accuracy of the model. However, it is important to note that RMSE is just one metric used to evaluate the coastline model's accuracy. Other measures should also be considered to understand the model's performance comprehensively.

Overall, the results of this research highlight the importance of careful examination of input data to ensure that it is in the correct format and of good quality for accurate integration of DEM and for the accurate assessment of coastline models. The results also provide valuable insights for future coastal mapping and management research.

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