The application of satellite derived bathymetry for coastline mapping

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Abstract. There is a gap in bathymetry data in shallow water due to the difficulty in measuring the depth. Meanwhile, to obtain an accurate datum-based coastline, sufficient depth and topography data are required. In the situation in which bathymetry data from the conventional method (sounding measurement) is limited, the bathymetry data resulted from Satellite Derived Bathymetry (SDB) algorithm can be an alternative solution. The SDB is estimated by correlating water depth and the spectral band of images. This research is conducted to develop a method that can be applied for coastline mapping by assessing the capability of SDB. For the integration of all input data, including land elevation and bathymetry data, a gridding method called stacked continuous curvature splines with tension is adopted. Coastline generated from the proposed method was relatively smooth and it was close to the shape of the land feature compared to coastline developed from other data sources such as the national bathymetry data and echo sounding data. From the results, we conclude that the SDB is promising in filling the gap of depth information in shallow water areas. A feasible coastline can be produced since depth information from the SDB model can increase the density of depth information required for generating a coastline model.

1. Introduction
Monitoring the coastline is essential for the planning and management of the coast. The coastline can change in various temporal scales depending on the cause of the changes. In a short time, the coastline can change, for instance, due to waves, winds, tides, and storms. Meanwhile, in longer time, the rise of sea level and land subsidence can also cause coastline changes. The frequency of monitoring of shoreline changes can vary depending on shoreline conditions. The coastline can be updated less frequently if situated in a relatively undisturbed situation. However, if the area has more significant threat from erosion and floods, it may require frequent updating [1,2].

Coastlines can be detected based on various proxies depending on the source of data. For navigation, coastline is positioned at mean lower low water (MLLW) line, while for topographic mapping, the coastline is positioned at mean high water (MHW) line [3]. The most common coastline indicators can be categorized as: a) coastal features delineated from aerial photographs or very high-resolution images; b) tidal datum-based indicators, e.g. mean sea level (MSL) or MLLW; and c) feature extracted by image processing imageries [4].

In BIG, which has a main task to provide the national coastline, coastline mapping is carried out by referring to a datum-based coastline [5]. For this purpose, to obtain an accurate coastline, a sufficient depth and topography data are required. Due to an extensive coverage and limited budget, the mapping and updating of coastlines for the entire territory of Indonesia are still incomplete. There is a lack of bathymetry data in certain areas not only due to a limited budget, but also uneasy access of the areas.
the case of very shallow waters, there is a gap in bathymetry data due to the difficulty in measuring the depth in those areas [6]. In a situation in which bathymetry data from conventional method (sounding measurement) is limited, the bathymetry data resulted from Satellite Derived Bathymetry (SDB) algorithm can be an alternative solution. SDB works by assuming that the value of the spectral reflection of remote sensing images in the optical shallow water can predict the depth of shallow waters. The SDB is estimated by correlating water depth and the spectral band of images. This research was conducted to explore an alternative method that can be applied for coastline mapping. In this case, the capability of SDB was assessed for deriving the coastline model. For the integration of all input data, including land elevation and bathymetry data, the gridding method from Hell and Jakobsson [7] was adopted.

2. Methodology

2.1. Study Area

The study area is located in the western part of the Morotai Island coastal area (Figure 1). The central point of the study area is at geographical coordinates 2° 7’ 30” N, and 128° 13’ 23” E. Morotai Island is the northernmost island in Indonesia. It is surrounded by many small islands and is one of the tourist destinations located in North Moluccas Province. The island has clear water with stunning white sandy beaches and beautiful underwater scenery with coral reef formation and seagrass [8,9].

Figure 1. The study area (red-dashed rectangle) at the western part of Morotai Island, North Moluccas Province, Indonesia. The Marine Environmental Map from BIG is used as the background.
2.2. Dataset

Datasets used in this study are described as the following:

2.2.1. Elevation and bathymetry data.

Bathymetry data from various sources (see Figure 2) were used in this experiment and described as follows:

a) National Digital Elevation Model (DEMNAS) with 0.27-arcsecond spatial resolution. It refers to the EGM2008 vertical datum [10].

b) National Bathymetry Data (BATNAS) with 6arc-second spatial resolution and it refers to the MSL datum [10].

c) Single Beam and Multi Beam Echosounder Data (SBES and MBES) provided by the Indonesia Geospatial Information Agency and was collected in October 2018. The data has undergone tidal correction. These measurement data were used for two purposes: a) as an input when performing coastline model (gridding bathymetry and topography data); and b) as an input to build and validate the SDB model in extracting bathymetry information.

d) Satellite Derived Bathymetry Data (SDB). SDB data were extracted from Sentinel 2A by using random forest (RF).

![Figure 2. Multi source of bathymetry data as input for coastline model, namely a) the national DEM; b) the national bathymetry data; and c) SBES and MBES measurement points.](image)

2.2.2. Tide gauge data.

We used hourly tides data observation from the Jailolo tide gauge station in Morotai Island. The data were recorded from 22 September 2016 to 31 December 2020 and made available from the Indonesian Geospatial Information Agency. The tide data was used in estimating the LAT position before performing the coastline model.

2.2.3. Satellite image.

For extracting bathymetry information from remote sensing data (satellite derived bathymetry), we used Sentinel 2A with four bands, namely blue (0.49 µm), green (0.56 µm), red (0.665 µm), and near-infrared (0.842 µm) parts of the spectrum [11]. The Sentinel-2A was obtained in level L2A from the ESA website, i.e., Copernicus Open Access [12]. The time acquisition of the image was 9 August 2019 with 10 m spatial resolution. The image was obtained in the format of bottom of atmosphere reflectance (BoA) and has gone through a standard radiometric and geometric correction [11].
2.3. Method

2.3.1. Performing SDB model.

For the SDB model, 80% of the SBES measurement data was selected randomly as the training data and the remaining 20% of the SBES measurement was selected for the testing data. Depth information was extracted from Sentinel-2A image by performing Random Forest (RF). We set combinations of the two parameters of RF: mtry and ntree, to obtain the highest accuracy [13]. The ntree values were tested from 50 up to 1,000 trees with intervals of 50, while the mtry values were tested from 1 up to 10 with intervals of 1. The SDB model was validated by using 5-fold cross validation [14]. For detailed information about RF, readers are advised to check references [15,16].

2.3.2. Estimating the LAT for datum-based coastlines.

Tide gauge data was analyzed by employing T-TIDE package in MATLAB [17]. The package applied least squares harmonic analysis to identify tidal component and tidal prediction by using up to 71 tidal components. The harmonic analysis application is the fitting of the chosen harmonic constituents to the sea level observation. A tidal function is fit to the sea level observation by using the following equation [18,19]:

\[ h(t) = h_0 + \sum_{i=1}^{m} f_i H_i \cos(\omega_i t + u_i - k_i^*), \]

where \( t \) is the time in serial hours, \( h(t) \) is a predicted water level at \( t \), \( h_0 \) is the mean water level, \( f_i \) is a lunar node factor for the \( i \)th constituent, \( H_i \) is a mean amplitude for the \( i \)th constituent over 18.6-year lunar node cycle, \( \omega_i \) is the frequency of the \( i \)th constituent, \( u_i \) is the nodal phase for the \( i \)th constituent, \( k_i^* \) is the phase of the \( i \)th constituent for the period origin is utilized, and \( m \) is a number of constituents.

For this study, we used four-year observation data from 22 September 2016 up to 31 December 2020. The least square method was used to fit the trend which was approximately the general patterns of the time series observation over its period [19]. The LAT was estimated over a minimum period of 20 years (during a full nodal period) using the harmonic constants that were derived from nine-year observations [20,21]. For further detailed of the harmonic method of the analysis, readers are suggested to check references [19,22].

2.3.3. Applying gridding method and extracting coastlines.

Various sources of data, including land elevation and bathymetry data were compiled to obtain the seamless digital elevation and bathymetry model by applying a gridding method. The gridding method was developed by Hell and Jakobsson [7] based on interpolation with spline tension at several resolutions determined by the source of data density. After performing the gridding method, coastlines were generated by computing the intersection line between the seamless DEBM and water level for i.e., LAT obtained from the previous step.

3. Results and Discussions

3.1. The result of the SDB model

The results of the SDB model are available in Figure 3a, while the false color composite of Sentinel 2A is in Figure 3b as a visual comparison. The depth was estimated in the SDB, and the range of the estimated depth were from less than 0 m up to more than -20 m. The land area was represented by grey pixels (in Figure 3b).
Figure 3. (a) Visualisation of SDB model produced when performing RF in the study area; and (b) false colour composite of Sentinel 2A image at the same location (red pixels are vegetation, dark blue pixels are water and grey to white pixels are very shallow water area with submerge rocks).

3.2. The LAT estimation for datum-based coastlines

The results of the tidal harmonic constituents’ analysis are plotted in Figure 4(a) consisting of the plot of tide gauge data in blue, the predicted tide level in orange and the residual of sea level in red lines. The tidal analysis results present a good agreement between water level observation (blue lines) and the predicted water level (orange line) showed by small residual values ranging from 20-30 cm. The residual also called meteorological residual is a non-tidal component remaining after the analysis eliminated the regular tides [23]. By using 71 tidal constituents produced by the T-Tide model, we estimated the LAT water level. The LAT was 0.33 m below MSL (Figure 4b).

3.3. The results of gridding method and coastline generation

Figure 5 shows the results when integrating elevation and bathymetry data with spline interpolation-based methods. We compared the result of the gridding method with other depth data from SDB (Figure 5b), raster combination of MBES and SBES data (Figure 5c) and the national bathymetry data (Figure 5d). From the figures, we can see that the national bathymetry data has less detailed information, while the SDB model seems quite noisy. In addition, the rasterization of MBES and SBES provided quite detailed depth information.

After integrating all elevation and bathymetry data, we generated the LAT coastline in Figure 6 (in yellow lines). We compared the proposed coastline with other coastlines generated from various bathymetry data such as the national bathymetry data (see Figure 6 in black lines), and magenta lines for coastlines generated by using the integration of MBES and SBES data. From the comparison in Figure 6, we can see that of the three coastlines being compared; coastlines resulted from our model presented relatively smooth coastline which was close to the shape of the land feature (red pixels).

BATNAS produced a rough coastline due to lack of detailed depth information, especially in shallow waters. Meanwhile, when the coastline was generated using MBES and SBES data, the resulting...
coastline was slightly better than coastlines obtained from BATNAS data. However, in some locations where the depth points maybe less dense, the resulting coastline was obviously shifting.

**Figure 4.** (a) The result of tidal analysis consisting of time series of hourly tide gauge data (blue line), the T-Tide prediction result (orange line) and the residual sea level (red line), the y-axis is the time of measurement and x-axis is the sea level in cm; (b) The result of tidal prediction using T-tide model (blue line) and the estimates of LAT (green line) and the HAT (in red line).

**Figure 5.** The comparison of depth data provided by gridding method (a), SDB model (b), rasterize of MBES and SBES (c) and the national bathymetry data (d).
Figure 6. The comparison of the LAT coastlines generated by various data source for instance the national bathymetry data (black line), combination of MBES and SBES data (magenta line); and (c) proposed coastline from gridding method (yellow line). False colour composite of Sentinel 2A is used as the background.

4. Conclusions
This research provides a comparative analysis of coastline models using various bathymetry data. The SDB model was successful in filling the gap of depth information in shallow water areas so that a feasible coastline was produced. In this case, depth information from the SDB model increased the density of depth data required for generating a coastline model. On the other hand, the gridding method called stacked continuous curvature splines with tension was also successful in integrating various data including land elevation and bathymetry data, as an input for the coastline model. Challenges for the improvement of the method consist of (a) experiment with other gridding method; (b) using other algorithms for SDB; and (c) using multitemporal data as input for SDB model.

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