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Bathymetric model generation in shallow waters with optical satellite images and machine learning algorithms

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Abstract

Bathymetric mapping is essential for understanding ocean dynamics, mapping ecosystems, and forecasting coastal erosion. The goal of this study is to produce bathymetric models in shallow coastal area of rarely investigated Antarctic region using machine learning methods and Sentinel-2 satellite image. Based on satellite imagery and multibeam echosounder data, two algorithms, random forest (RF) and support vector machine (SVM), were used to predict ocean depths. The accuracy criteria used to evaluate the models' performance included RMSE, MAE, and R2. With an RMSE of 1.51, an MAE of 1.04, and an R2 of 0.77, the RF model produced promising results. These metrics provided low errors and a good fit between projected and observed water depths. The SVM model also provided promising results with slightly lower performance with an RMSE of 1.58, an MAE of 1.13, and an R2 of 0.75. Overall, this study showed that above mentioned algorithms can be used as viable approach for generating bathymetric models in shallow coastal areas. These models can contribute to our understanding of underwater topography, ecosystem dynamics, and the impacts of climate change.

1. Introduction

A bathymetric model is a digital representation of the ocean floor's topography, usually in the form of a map or 3D model. Bathymetric mapping of shallow waters is useful for a variety of purposes, including navigation, resource exploration, and environmental monitoring (Vojinovic et al., 2013). Bathymetry is important in many scientific fields, including oceanography, marine biology, and climate research. It gives important information on the structure and properties of the seabed, which is necessary for understanding ocean dynamics, mapping ecosystems, and forecasting coastal erosion. However, conventional techniques for gathering bathymetric data, like using sonar or performing hydrographic surveys, can be time-consuming and expensive, particularly in environments with shallow water where the water is too shallow for ships to access (Jagalingam et al., 2015). The use of optical satellite imagery and machine learning algorithms as an alternative technique for creating bathymetric models in shallow waters has gained popularity in recent years (Duan et al, 2022; Lumban-Gaol, Ohori & Peters, 2021; Misra et al, 2018; Mudiyanselage et al, 2022; Tonion et al, 2020; Wu, Mao & Shen, 2021).

Climate change's negative impacts have become increasingly visible in recent years, with rising temperatures and extreme weather events occurring all across the world. These changes have been most noticeable in the polar areas, resulting in major heatwaves and temperature rises (Gülher & Algancı, 2023). The Antarctic Peninsula and sub-Antarctic islands have been identified as hotspots of fast warming, with record-breaking temperatures and increased snowpack melt. These concerning patterns underline the critical importance of ongoing monitoring of the environment and sea level rise in shallow coastal locations. The precise evaluation of water depths, or bathymetry, is a critical component in understanding and mitigating the consequences of climate change in these locations.

To address these issues, bathymetric models are created in the study region near the Antarctic Peninsula using satellite images and machine learning methods. This study also aims to examine the viability and precision of creating bathymetric models in shallow waters using machine learning algorithms and Sentinel-2 image. To achieve this, a Sentinel-2 image and associated multibeam echosounder (MBE) bathymetric data was gathered. The Sen2Cor atmospheric correction algorithm was applied to Sentinel-2 image to investigate

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its impact of the bathymetric model's accuracy on the Sentinel-2 satellite image that encompasses the study area.

2. Method

The proposed methodology initially starts with preprocessing of the Sentinel 2A satellite image, which includes atmospheric correction, registration and sub-setting. Then land masking was applied to imagery. As a next step random forest (RF) and support vector machine (SVM) models were trained with in-situ MBE data and resulting SDB maps were then validated with independent validation MBE data. Flowchart of the study is presented in Fig. 1.

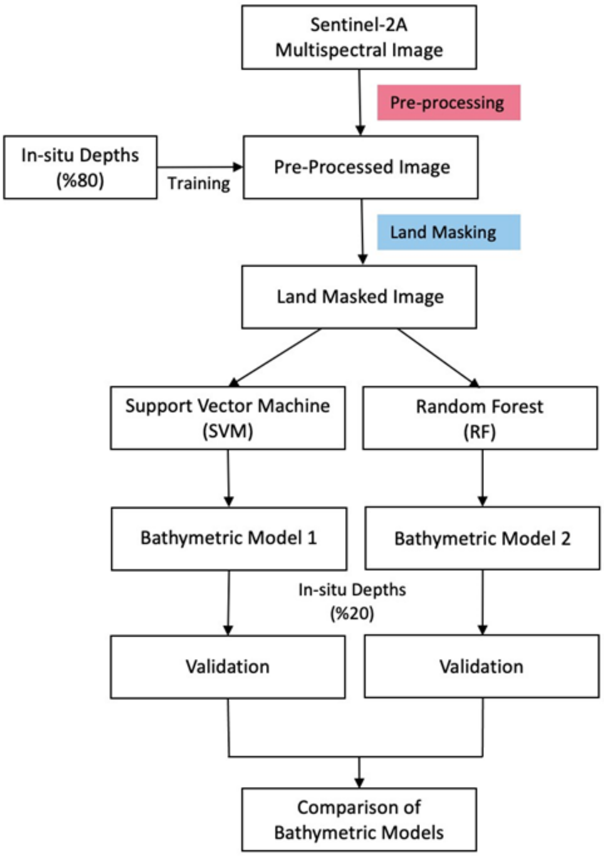

Figure 1. Flowchart of proposed methodology

2.1. Study area

This study focuses on a 22.24 km^2 study area located in Antarctica near Adelaide Island. Adelaide Island is one of the largest islands in the Marguerite Bay region, which is located on the Antarctic Peninsula's west coast. This area has a distinct arctic environment with pristine, unaffected shallow waters. Because of the varying depths and seafloor features, these waters are of particular interest for bathymetric modeling. The underwater features of the study area include complex bathymetry, channels, ridges, and submerged valleys. The chosen research area is ideal for assessing the performance of proposed bathymetric surface modeling techniques using optical satellite imagery and machine learning algorithms. Figure 2 provides the overviews of the study region.

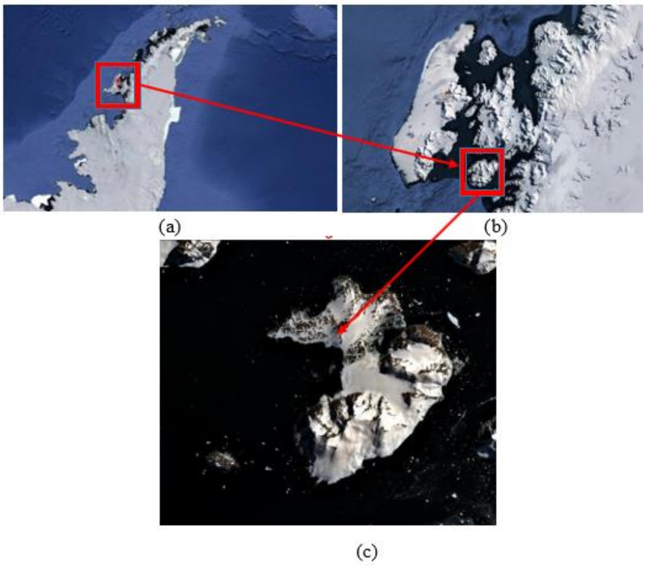

Figure 2. Study area (a), zoomed study area (b), natural color imagery of the study area derived from the Sentinel-2 satellite image (c)

2.2. Data

For SDB mapping purpose 2019 -01-24 dated Sentinel 2A image that was processed in Level 1C was used. The in situ bathymetric data was collected with an MBE with 5m horizontal spacing. A total of 18,928 bathymetry points with 0-15 m depth interval, were used to train and test machine learning algorithms. Among them, 80% (15142 points) were used to train the models, and 20% (3786 points) were used for validation.

2.3. Preprocessing and land masking

Sentinel-2 satellite image is corrected for atmospheric effects using optimized algorithms in the Sen2Cor module. It uses a set of sophisticated algorithms to calculate atmospheric scattering and absorption effects in satellite images, estimate aerosol density, and convert reflectance values into atmospherically corrected ones. A land masking technique was used on Sentinel-2 satellite imagery using the Google Earth Engine (GEE) platform to remove land masses and focus on depth analysis. Due to its inherent sensitivity to land reflectance, the near-infrared band (B8) of Sentinel-2 imagery was chosen to create the land mask. Several threshold values were experimented with and evaluated in order to determine the most accurate threshold value for detecting land pixels.

2.4. RF and SVM modeling

Both RF and SVM algorithms are used in state of regressor for this study to determine the correlative structure of surface reflectance and in situ MBE data. A parameter tuning process was carried out in order to determine the optimal parameters for the RF algorithm. The number of trees in the ensemble is a key parameter in RF, and it has a significant impact on the model's performance. The tree parameter from 10 to 1000 were experimented in this study and it was observed that the model achieved the optimum performance when the tree parameter was set to 400. The model's accuracy was evaluated using appropriate validation techniques, and it was discovered that the tree selection had a minimal impact on overall accuracy, with an approximate impact of only 0.001. SVM is interested in two hyperparameters: gamma and C. The influence of a single training example is controlled by Gamma, while C determines the trade-off between achieving a low training error and maintaining a wide margin. To find the best combination, a grid search was run over a predefined range of gamma and C values. In the grid search, the combination of gamma: 0.1 and C: 100 produced the best results. These values were chosen as the best hyperparameters for the SVM algorithm to use when creating the bathymetric model.

3. Results

After training the both algorithms, resulting SDB surfaces were assessed through RMSE, MAE and R^2 accuracy metrics by use of independent validation points (Table 1). Results showed that RF performed slightly better for the 0-15m depth range according to all metrics.

Table 1. Error metrics for the two models

Metric/Method	RF	SVM
RMSE	1.51	1.58
MAE	1.04	1.13
R^2	0.77	0.75

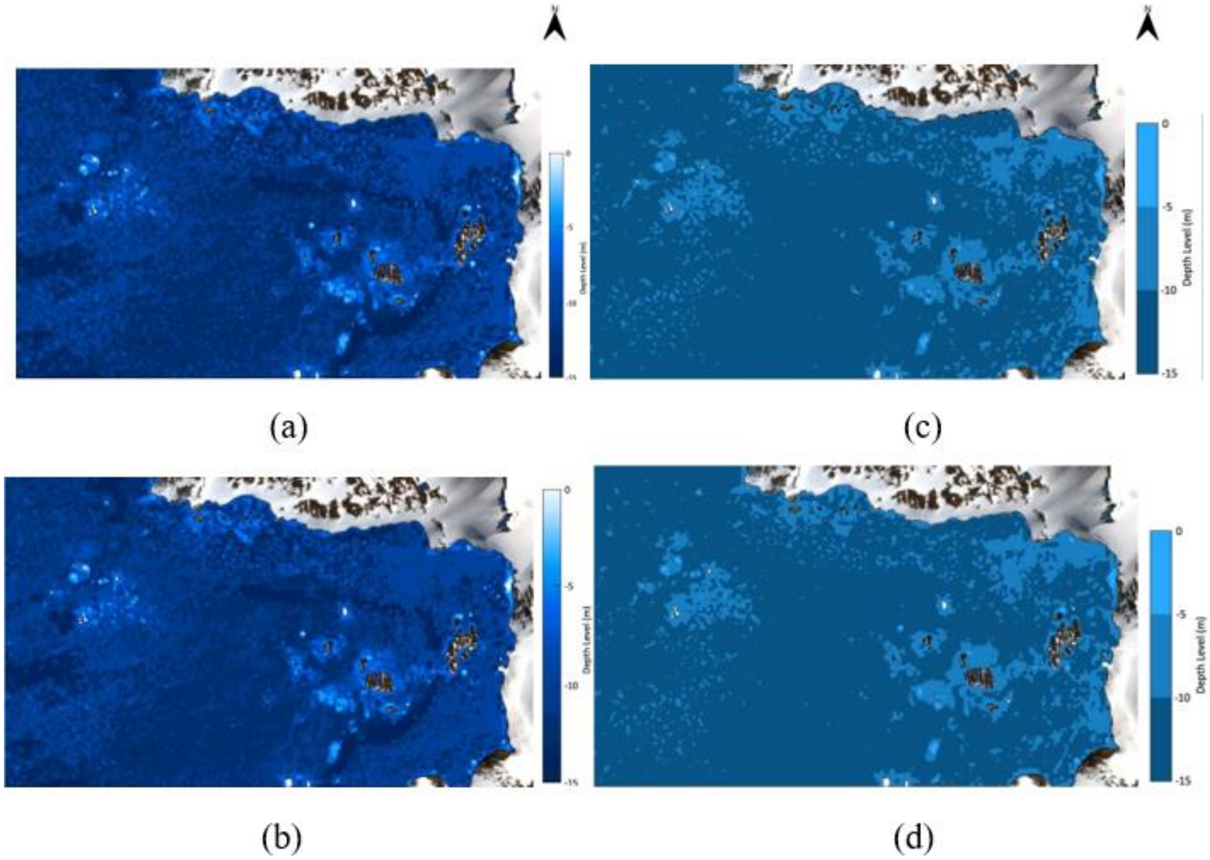

Figure 3. SDB surfaces and maps derived with RF algorithm (a, c) and SVM algorithm (b, d).

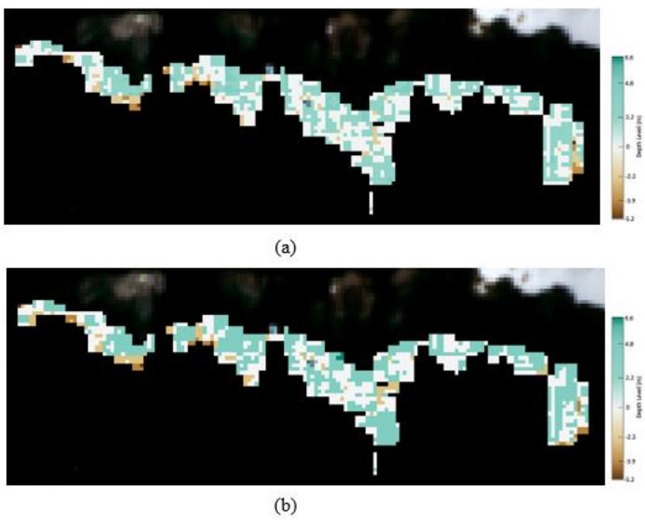

Figure 4. Reference Data–RF Difference (a), Reference Data–SVM Difference (b)

The accuracy achievement level according to MAE metric corresponds to A2/B IHO CATCOC level vertical accuracy requirements. This finding is in line with similar studies that used Sentinel 2 or better spatial resolution satellite images, however this finding is significant considering the complexity of study region and atmospheric conditions. After validating the efficient performance, SDB maps of the region were produced from surface rasters with 5m depth intervals (Figure 3).

Produced SDB maps are extracted from the same resolution grid generated from MBE point data. The difference layer is visualized for 0-15m depth range to understand the distribution of errors. This analysis provided that both algorithms showed similar error distribution with a slight overestimate of depths (Figure 4).

4. Discussion

RF model demonstrated promising performance in estimating water depths in shallow coastal areas. The RF model provided relatively low errors, with an RMSE of 1.51 and an MAE of 1.04, indicating a reasonable match between predicted and observed depths. The R^2 value of 0.77 indicates that the RF model can explain roughly 77% of the variance in water depth. These findings show the RF algorithm's ability to capture the complicated correlations between satellite images and bathymetric data. Similarly, the SVM model demonstrated bathymetric modeling capability, but with slightly more errors than the RF model. The RMSE of the SVM model was 1.58 and the MAE was 1.13, indicating a somewhat higher average difference between predicted and observed depths. The R2 value of 0.75 indicates that the SVM model can explain roughly 75% of the variance in water depth. While the SVM model has significantly lesser accuracy than the RF model, it nevertheless gives useful information for bathymetry estimate in shallow seas. The selection of these algorithms is influenced by project needs, computer resources, and the trade-offs between accuracy and computational efficiency.

In the context of bathymetric modeling, the comparison of the RF and SVM models highlights the strengths and limits of each technique. The RF model performed particularly well in estimating water depths, In the future, the findings of this study may help to a better understanding of the consequences of climate change on the arctic areas, notably in terms of sea level rise and ecosystem dynamics. Furthermore, the bathymetric models created will provide useful data for future monitoring. Using modern remote sensing techniques and machine learning algorithms, accurate bathymetric models have been created to enhance knowledge of the changing polar environment.

5. Conclusion

This study investigated the potential use of Sentinel-2 images on Antarctic region for shallow water bathymetry extraction. Overall, the integration of machine learning algorithms, particularly RF and SVM, with Sentinel-2 satellite images has shown to be a promising strategy for building bathymetric models in shallow coastal regions. This work provided how remote sensing and machine learning approaches may give excellent information on water depths, which is important for a variety of applications such as navigation, ecosystem monitoring, and climate research. Future study in this area could concentrate on improving the models by including more variables or applying more powerful machine learning techniques. Extending the investigation to larger areas or different geographic regions could also provide useful insights into the models' generalizability and performance under varying environmental conditions.

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