BATHYMETRY ESTIMATION USING MACHINE LEARNING AND TUNING DENSITY CONTRAST IN THE YAMATO BASIN OF THE EAST SEA (SEA OF JAPAN)

Kwang Bae Kim[1], Ji Sung Kim[2] and Hong Sik Yun[3*]
[1]Research Professor, Department of Civil, Architectural and Environmental System Engineering, Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon, Gyeonggi-do, 16419, Republic of Korea
Email:kbkim929@skku.edu

[2]Postgraduate Researcher, School of Geography, Faculty of Environment, University of Leeds, Woodhouse Lane, Leeds, United Kingdom, LS2 9JT
Email: gyjki@leeds.ac.uk

[3]Professor, Interdisciplinary Program in Crisis, Disaster and Risk Management, Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon, Gyeonggi-do, 16419, Republic of Korea
Email: yoonhs@skku.edu

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ABSTRACT: The purpose of this study is to evaluate the accuracy of bathymetry predicted by the gravity-geologic method (GGM) using depth and gravity anomalies estimated using the optimized machine learning model determined from machine learning techniques around the Yamato basin in the East Sea. In this study, the optimized model using machine learning techniques was applied to estimate bathymetry using gravity-geologic method (GGM) from a tuning density contrast between seawater and the seafloor bedrock determined by downward continuation method using satellite altimetry-derived gravity anomalies. Bathymetry estimated using machine learning technique was assessed the accuracy in comparison with shipborne depth measurement obtained by the National Centers for Environmental Information (NCEI, https://www.ncei.noaa.gov), the National Oceanic and Atmospheric Administration (NOAA, http://www.noaa.gov). As a result, the GGM bathymetry predicted by the optimized machine learning model using a tuning density contrast of 13.63 g/cm^3 in comparison with that using a density contrast of 1.67 g/cm^3 shows the improvement of 67.40% in the RMSE at shipborne locations of the NECI.

1. INTRODUCTION

Because bathymetry is important data in the exploration of marine resources, marine construction, and global environment monitoring, relevant research is continuously being conducted to estimate accurate bathymetry as technology advances. Among them, bathymetry using machine learning has been proven to have superior performance compared to conventional methods. In particular, the accuracy of machine learning-based regression models has been proven to be significant in estimating dense seafloor topography from non-grid irregular data (Alevizos, 2020). Following this trend, studies have been conducted to estimate seafloor terrain using machine learning-based regression analysis. More specifically, artificial neural networks (ANN) (Al Najar et al., 2021; Dickens & Armstrong, 2019), support vector machines (SVM) (Eugenio et al., 2022; Moran et al., 2022; Susa, 2022), and decision trees (Alevizos, 2020), ensemble (Kim et al., 2023), gaussian progress regression (GPR) (Zhou et al., 2023), etc. are being used.

The East Sea (Sea of Japan) is a mature back-arc basin behind Japan island arcs in the northwestern Pacific. As shown in Fig. 1, the sea comprises three sub-basins such as the Japan, Yamato, and Ulleung basins. A Yamato basin located in the northern half of the East Sea (Sea of Japan) is the shallow (< 3000m) back-arc basin, similarly to the Ulleung basin in comparison with the relatively deep (> 3000m) and large back-arc basin such as the Japan basin (Jolivet et al., 1994).

This study aims to evaluate the accuracy of bathymetry, which is estimated using the optimized machine learning model and the gravity-geologic method (GGM) with a tuning density contrast, in comparison with the shipborne bathymetry in the Yamato basin in the East Sea.

2. BATHYMETRY ESTIMATION USING MACHINE LEARNING

In this study, we predicted bathymetry using the optimized machine learning model in the Yamato basin in the East Sea, which was selected as the study area (136.7-139.7°E, 38.9-41.4°N) denoted by the red box in Fig. 1(a). The bathymetry as a background from ETOPO1 (Amante and Eakins, 2009) is shown in Fig. 1(a). The water depth in the

Yamato basin in the East Sea is less than 3000 m. Figure 1(b) shows 108,056 shipborne measurement (including depth and gravity anomalies) locations, provided by the National Centers for Environmental Information (NCEI, https://www.ncei.noaa.gov), the National Oceanic and Atmospheric Administration (NOAA, http://www.noaa.gov) used for both shipborne depth estimation and shipborne gravity anomalies estimation using the optimized machine learning model. The 1 arc-minute satellite altimetry-derived free-air gravity anomalies obtained from Scripps Institution of Oceanography are superimposed as a background in Fig. 1(b). As shown in Fig. 1(b), the minimum, maximum, mean, and standard deviation of satellite altimetry-derived free-air gravity anomalies are -24.7, 91.9, 17.5, and 15.8 mGal, respectively.

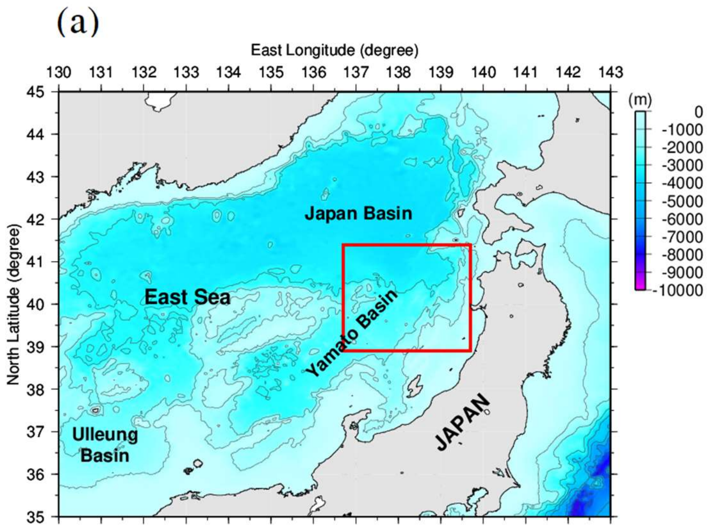

Figure 1. (a) Location map. (b) The shipborne measurements from the NECI and satellite altimetry-derived gravity anomalies (Sandwell et al., 2014) in the study area

In estimating the bathymetry of the Yamato Basin, it is reasonable to compare the performance of ANN, SVM, decision trees, ensemble, GPR, etc. and then estimate the bathymetry using the most appropriate method. The exponential GPR model shows better performance in comparison with other techniques in machine learning. The coefficient of determination (R^2) in the exponential GPR model is close to 1.00, and the root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE) are reduced compared with those of other techniques in shipborne depth and gravity anomaly estimation using machine learning. When the observed and estimated values of depth and gravity anomaly, which are represented by the black dots in Fig. 1(b), overlap, it can be seen that there is some difference between the observed and estimated values in the depth data and the gravity anomaly data, as shown in Fig. 2. The differences between the observed and estimated values of depth and gravity anomaly at 108,056 shipborne locations of the NCEI were summarized in Table 1.

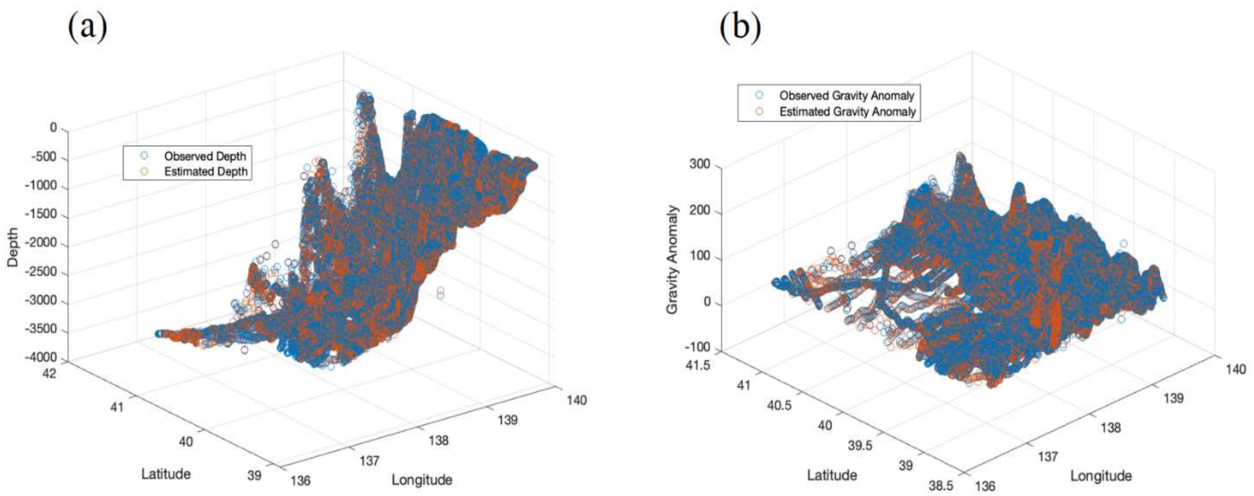

Figure 2. (a) Comparison of depth between observed and estimated values. (b) Comparison of gravity anomaly between observed and estimated values

Table 1. Statistics of the differences between the observed and estimated values of depth and gravity anomaly at 108,056 shipborne locations of the NCEI

	Min	Max	Mean	Std dev
Depth (m)	-1375.93	323.29	-0.03	7.83
Gravity anomaly (mGal)	-172.24	182.20	-0.00	2.35

In this study, the two bathymetry grid data, GGM_(1.67) and GGM_(13.63), applied to GGM with a density contrast of 1.67 g/cm^3 between seawater (1.03 g/cm^3) and the seafloor bedrock (2.70 g/cm^3) and a tuning density contrast of 13.63 g/cm^3, which was estimated by the downward continuation method (Kim et al., 2010), were generated using the depth and gravity anomalies predicted with the exponential GPR model of machine learning.

To evaluate the accuracy of the GGM_(1.67) and GGM_(13.63) grid data predicted using the exponential GPR model of machine learning, the bathymetry grid data were interpolated into the 108,056 shipborne locations (black dots) of the NCEI, as shown in Fig. 1(b). The depth differences between GGM_(1.67) and NCEI and between GGM_(13.63) and NCEI at 108,056 shipborne depth locations of the NCEI were summarized in Table 2.

Table 2. Statistics of depth differences on the NCEI shipborne locations between GGM_(1.67) and NCEI and between GGM_(13.63) and NCEI

	Min (m)	Max (m)	Mean (m)	Std dev (m)	RMSE (m)
GGM_(1.67)	-2797.4	882.0	-21.6	120.8	122.7
GGM_(13.63)	-1372.6	826.9	-3.4	39.8	40.0

From Table 1, the RMSE of the depth differences between GGM_(13.63) and NCEI is smaller than that of the depth differences between GGM_(1.67) and NCEI. These results may indicate that the GGM_(13.63) grid data predicted using the exponential GPR model of machine learning can generate accurately bathymetry in the Yamato basin in the East Sea.

3. CONCLUSION

In this study, we estimated the bathymetry in the Yamato basin in the East Sea by applying GGM with a tuning density of 13.63 g/cm^3 to depth and gravity anomalies predicted using the exponential GPR model of machine learning. As a result, the GGM bathymetry using a tuning density contrast of 13.63 g/cm^3 in comparison with that using a density contrast of 1.67 g/cm^3 shows the improvement of 67.40% in the RMSE at 108,056 shipborne locations of the NECI.

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