Shallow Water Bathymetry Retrieval in the Guangxi Beibu Gulf, China, Using Optical Remote Sensing and Electronic Nautical Charts

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Abstract

The rapid and accurate acquisition of nearshore bathymetry is crucial for coastal economic development, safe navigation, and marine ecological protection. This study focuses on the shallow coastal waters of Beihai and Fangchenggang in the Guangxi Beibu Gulf, China. Utilizing Landsat-9 multispectral imagery and Electronic Nautical Chart (ENC) data, three empirical Satellite-Derived Bathymetry (SDB) algorithms—single-band linear regression, dual-band ratio, and multi-band combined regression—were formulated and comparatively analyzed. Furthermore, a depth-stratified inversion approach was introduced to evaluate its impact on retrieval accuracy across different depth zones. Experimental results demonstrated that the multi-band combined regression model yielded the highest inversion accuracy in both study areas. For the unzoned global inversion, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were 1.38 m and 1.76 m in Beihai, and 1.86 m and 2.46 m in Fangchenggang, respectively. Notably, following the implementation of the depth-stratified inversion strategy, the weighted average errors were substantially reduced. In the Beihai region, the MAE and RMSE decreased by 0.64 m and 0.80 m, respectively, while in Fangchenggang, they witnessed significant reductions of 1.68 m and 1.92 m. The findings confirm that the depth-stratified multi-band combined regression model provides superior performance and robustness for nearshore bathymetric mapping.

1. Introduction

Bathymetric surveying is of vital importance to coastal region development, aquatic environmental protection, marine transportation, island exploitation, and marine life conservation. Common underwater detection techniques include single-beam echo sounders (SBES), multi-beam echo sounders (MBES), and Airborne LiDAR Bathymetry (ALB). While shipborne acoustic surveys are highly accurate, they are often restricted by extremely shallow waters, and are time-consuming and labor-intensive (Shang et al., 2019). With the rapid development of remote sensing technology, its advantages of broad spatial coverage and simple data acquisition have gradually made it a crucial technique in this field (Zhang et al., 2023).

A large number of models and methods have been proposed globally for shallow-water bathymetry, primarily focusing on Spectrally Derived Bathymetry (SDB). Additionally, other advanced shallow-water surveying techniques, such as multimedia photogrammetry and Airborne LiDAR Bathymetry (ALB), have also been widely applied. SDB methods are mainly based on three fundamental frameworks: statistical correlation models, theoretical analytical models, and semi-theoretical and semi-empirical models. Among these, empirical SDB approaches are heavily built upon foundational theories. Notable examples include the widely used linear multi-band model proposed by Lyzenga (1978, 1981), which effectively accounts for bottom reflectance variations, and the dual-band log-ratio model introduced by Stumpf et al. (2003), which is particularly robust against varying bottom albedo and water column turbidity. Theoretical analytical models feature high precision and transferability. Chen et al. (2012) extracted depth distribution information by introducing the optical thickness of the water body into a physical remote sensing model, which greatly improved accuracy. However, this model does not consider the spatial variations of bottom substrates, leading to certain errors in practical applications. Statistical correlation models have fewer parameters and strong applicability, yielding numerous achievements. For example, Leng et al. (2020) introduced a new framework combining a GRU deep learning model for deep turbid sea area extraction, which broadened the application range of traditional optical inversion models with excellent overall results. However, training this model requires sufficient samples and presents regional limitations.

In recent years, an increasing number of scholars have applied semi-theoretical and semi-empirical models to bathymetry inversion research. Zhang (2016) proposed a multi-dimensional remote sensing inversion fusion method based on a voting mechanism. Experiments show that the results of multi-band combined regression models are generally better than those of single-band models. This is because single-band optical imagery is highly susceptible to environmental noises, such as sea surface wind-induced waves and complex bottom reflectance. Consequently, combining multiple spectral bands is considered an effective strategy to mitigate these environmental uncertainties. Zhang et al. (2018) proposed establishing dual-band and multi-band inversion models using multi-measurement point data of the same pixel. Although this method achieves high accuracy, its errors increase due to sediment content and proximity to land. Li et al. (2022) compared the inversion effects of multi-band regression, logarithmic band ratio, SVM, and BP neural network models, concluding that the multi-band regression model offers higher accuracy and efficiency, despite having more error sources and complex elimination operations. Zhu et al. (2021) proposed a geographically weighted regression model based on principal component analysis, which effectively reduces data space non-stationarity, but is limited to specific water types. Wu et al. (2016) utilized the dual-band ratio method to retrieve depths within 20 m, demonstrating good applicability but susceptibility to wave-breaking zones within 5 m.

To objectively analyze the actual inversion differences among these models, this study selects Beihai and Fangchenggang in the Guangxi Zhuang Autonomous Region as study areas. Using Landsat-9 imagery and ENC data, we construct a single-band linear regression model, a dual-band ratio model, and a multi-band combined regression model to conduct comparative bathymetry inversion experiments. Building upon this, the study areas are partitioned into different depth zones for stratified inversion, followed by a comparative analysis of the accuracy before and after zoning. This research provides valuable reference for the application of typical semi-empirical models in shallow-water bathymetry.

2. Research area and data processing

2.1 Overview of the research area

The research areas comprise the northwestern coastal region of Beihai City (Figure 1(a)) and the southern coastal region of Fangchenggang City (Figure 2(b)) in the Guangxi Beibu Gulf, China. Beihai and Fangchenggang, located in the northeastern and southern Guangxi Beibu Gulf, China, present highly complex coastal configurations. Beihai's 500.13 km coastline provides expansive tidal flats and gentle gradients ideal for SDB, while Fangchenggang's 580 km coastline is notably more intricate and tortuous. These contrasting coastal morphologies contribute to significant spatial variations in bottom reflectance and water optical properties, which are essential for validating the robustness of our depth-stratified inversion models.

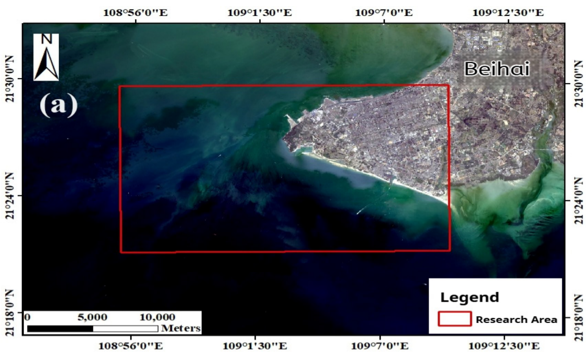

Figure 1. (a) Beihai City research area

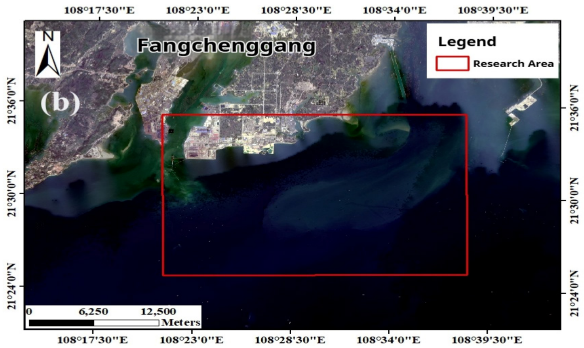

Figure 2. (b) Fangchenggang City research area

2.2 Research Data

The study utilized Landsat-9 Operational Land Imager 2 (OLI-2) multispectral satellite remote sensing images with a spatial resolution of 30 m. The visible bands (Coastal Aerosol, Blue, Green, and Red) were specifically selected due to their water penetration capabilities. Furthermore, the selected coastal regions in the Guangxi Beibu Gulf, China, are characterized by moderate turbidity and complex bottom types (such as mud, sand, and localized reefs), adding important context to the optical inversion. The images for Beihai and Fangchenggang were acquired at 3:11 AM on December 21, 2022, and 3:11 AM on March 8, 2022, respectively. The images cover the entire study area with low cloud cover and good quality, facilitating the depth inversion research. Due to the difficulty in obtaining in-situ measured data, this experiment obtained electronic charts using SAS.Planet software to collect actual depth data. The electronic nautical chart (ENC) was utilized to extract actual water depth data. It is important to note that ENC soundings involve specific hydrographic considerations; the data are typically referenced to a vertical datum such as the local Lowest Astronomical Tide (LAT). Therefore, strict tidal corrections were performed using local tidal gauge data to align the satellite image acquisition time with the ENC vertical datum. This ensures that the evaluated MAE/RMSE values reflect the actual SDB performance rather than reference dataset uncertainties. The ENCs for the Beihai and Fangchenggang areas contain detailed information such as depth values, ports, anchorages, and obstacles.

2.3 Data Preprocessing

Preprocessing operations such as radiometric calibration, atmospheric correction (utilizing the FLAASH algorithm to retrieve accurate surface reflectance), geometric correction, and tidal correction were performed on the Landsat-9 multispectral satellite remote sensing data. Tidal correction was carried out because the water depths in the ENC were not the actual depths at the time of satellite acquisition. Initially, the Modified Normalized Difference Water Index (MNDWI) was used for water extraction. The water-land separated images were then used to register the ENC data, and the depth points were vectorized. Given the modest sample size and to prevent potential overfitting (especially for the multi-band regression approach), the extracted water depth points were strictly divided into an independent calibration dataset (for model training) and a validation dataset (for accuracy testing) at a ratio of 2:1. This clear distinction ensures the reliability of the independent validation results. Finally, the obtained tide height data was used for tidal level correction.

3. Methodology and Accuracy Assessment

3.1 Selecting inversion factors and constructing inversion models

The visible bands (Bands 1 to 4) of the Landsat-9 imagery were initially selected as candidate factors for bathymetry inversion. Correlation coefficients were first calculated between each band and the observed water depths at the modeling points. Subsequently, we computed the correlation coefficients for both the raw band reflectances and their log-transformed values against the ENC water depth data in the Beihai and Fangchenggang study areas. Bands or band ratios exhibiting higher absolute correlation coefficients were identified to construct the inversion models.

Finally, the model selection strategies were established as follows: the single-band linear regression model utilized the single band with the highest correlation coefficient; the dual-band ratio model employed the log-transformed band ratio with the highest correlation coefficient; and the multi-band combined regression model utilized the top four transformed bands with the highest correlation coefficients as the primary inversion factors.

Based on established SDB theories, the generic forms of the three applied models are formulated as follows:
(1) The single-band linear regression model is expressed as:

$$Z = n \cdot ln\left(b_i\right) + m \tag{1}$$

(2) Dual-band ratio model:

$$Z = n \cdot \frac{\ln\left(b_i\right)}{\ln\left(b_j\right)} + m \tag{2}$$

(3) Multi-band combined regression model:

$$Z = n + m\sum_{i=1}^{N} \ln\left(b_i\right) \tag{3}$$

Where Z represents the derived water depth, n and m are the linear regression coefficients, and b_i and b_j denote the reflectance values of the corresponding bands in the remote sensing imagery.

3.2 Stratified inversion of water depth

The water depths in both the Beihai and Fangchenggang research areas are within 20 m. Using the contour lines marked on the ENC, the depth areas were partitioned into three zones: 0–7 m, 7–12 m, and 12–20 m. Subsequently, using the modeling points within these different depth zones, the reflectances of the corresponding points were extracted, and localized inversion models were constructed using MATLAB software.

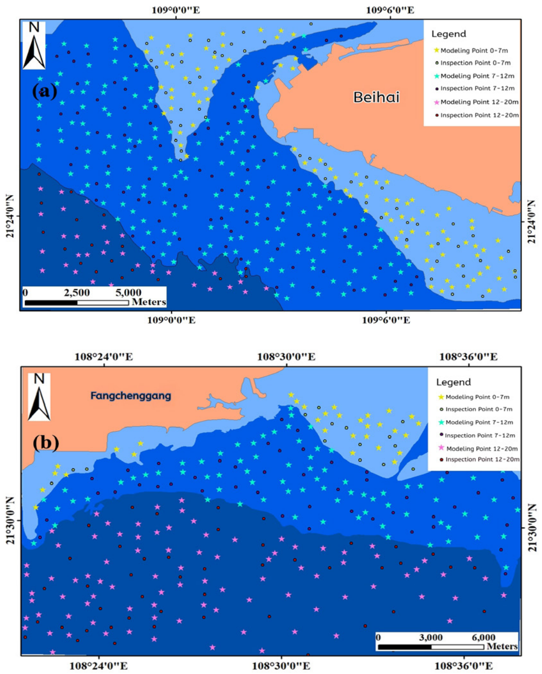

Figure 3. (a) distribution of modeling points and test points in the Beihai research area, (b) distribution of modeling points and test points in the Fangchenggang research area

3.3 Accuracy Assessment

To quantitatively evaluate the quality of the inversion, this research employs a multi-metric evaluation framework consisting of three primary accuracy indicators: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The selection of this combined set of metrics aims to provide a comprehensive assessment of the model's reliability from different statistical perspectives. Specifically, a higher (R^2), value indicates a superior goodness-of-fit and a higher proportion of variance explained by the model, signifying a better overall inversion effect. Conversely, smaller values of RMSE and MAE are indicative of reduced prediction residuals and higher absolute inversion accuracy. By integrating these indicators, the stability and predictive power of the proposed models can be rigorously validated, ensuring that potential outliers and systemic errors are adequately accounted for during the performance assessment phase.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(\bar{y} - y_i\right)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{5}$$

Where $\hat{y}_i$ represents the inverted water depth, y_i is the tide-corrected water depth from the electronic nautical chart (ENC), and n is the number of measured water depth test samples.

4. Result Analysis

4.1 Inversion accuracy analysis

Based on the calibration dataset, the specific empirical coefficients for the three inversion models were derived. The actual formulas for both the Beihai and Fangchenggang research areas are summarized in Table 1.

Research Area	Model Type	Derived Empirical Formula
Beihai	Single-band	Z = 15.6243 * ln(B3) - 31.7355
	Dual-band	*Z* = 54.5891 * ln(B4)/ln(B3) + 71.8296
	Multi-band	*Z* = 4.4751 * ln(B3) +7.8736 * ln(B4)/ln(B3) - 9.6743 * ln(B2) +45.967*ln(B3)/ln(B1) - 78.6927
Fangchenggang	Single-band	Z = -42.1472 * ln(B3)-101.908
	Dual-band	Z = 152.0759 * ln(B3)/ln(B1)-124.587
	Multi-band	Z = 3888.164 * ln (B3)/ln (B1)-35.2313 * ln(B3) ln(B2)-3359.33 * ln(B4)/ln(B1) +2943.562 * ln(B4)/ln(B3)-3365.91

Table 1. Empirical formulas and actual coefficients for the three inversion models.

To evaluate the inversion quality, the Beihai research area used 150 test points for the inversion accuracy test, and the Fangchenggang research area used 100 test points. The inversion accuracies of the three established water depth inversion models are shown in Table 2.

Research Area	Inversion model	Accuracy evaluation		
		R2	MAE (m)	RMSE (m)
Beihai	Single-band linear regression	0.4302	1.5312	1.8912
	Two-band ratio	0.4309	1.4355	1.8839
	Multi-band combined regression	0.5026	1.3843	1.7611
Fangchenggang	Single-band linear regression	0.2650	2.8221	3.2934
	Two-band ratio	0.5657	1.9483	2.5317
	Multi-band combined regression	0.5900	1.8609	2.4599

Table 2. Inversion Accuracy Table for each inversion model

The accuracy of the water depth values retrieved by the three models gradually improved in the sequence of the single-band linear regression model, the dual-band ratio model, and the multi-band combined regression model. The multi-band combined regression model exhibited the highest inversion accuracy in both areas. In Beihai, the evaluation yielded R^2 = 0.5026, MAE = 1.3843 m, and RMSE = 1.7611 m, in Fangchenggang, it yielded R^2 = 0.5900, MAE = 1.8609 m, and RMSE = 2.4599 m. Overall, the inversion accuracy in Beihai is slightly better than in Fangchenggang. In Beihai, both MAE and RMSE were less than 2 m; in Fangchenggang, MAE was less than 3 m and RMSE was less than 3.5 m. The depth accuracy obtained by the single-band model was generally poor.

Furthermore, when comparing these indicators with other models in the literature, it is worth noting that state-of-the-art physics-based inversion models or deep learning approaches can achieve relative errors in the 5% region. In contrast, our empirical multi-band model exhibited an RMSE of roughly 1.3-2.5 m (representing an 8-12% error at a 20 m maximum depth). However, compared to those complex models, the proposed empirical approach offers superior computational efficiency, straightforward implementation, and requires fewer parameter inputs, making it highly advantageous for rapid, large-scale reconnaissance mapping tasks.

4.2 Visual Analysis

To analyze the inversion quality of the three models at different water depths, scatter plots comparing inverted water depth values with ENC water depth values were generated (Figure 4), with the ENC depth on the horizontal axis and the inverted depth on the vertical axis.

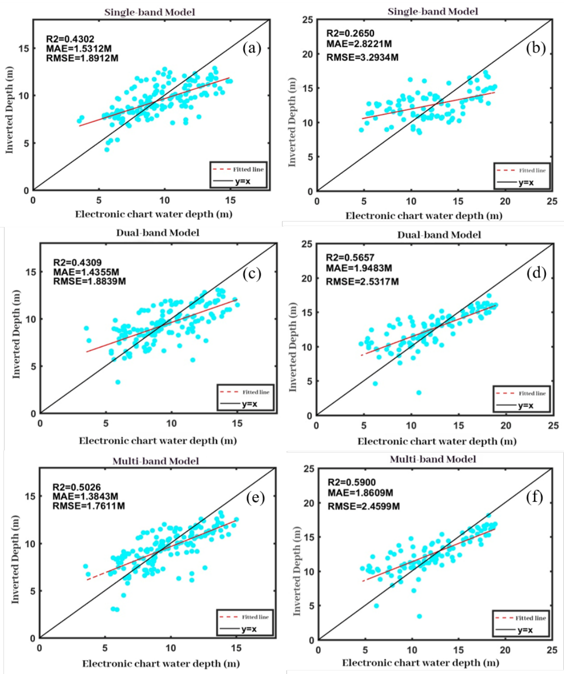

Figure 4. Scatter plots comparing inverted depths versus chart depths for different models a) Beihai single-band linear regression model, b) Fangchenggang single-band linear regression model, c) Beihai dual-band ratio model, d) Fangchenggang dual-band ratio model, e) Beihai multi-band combined regression model, f) Fangchenggang multi-band combined regression model.

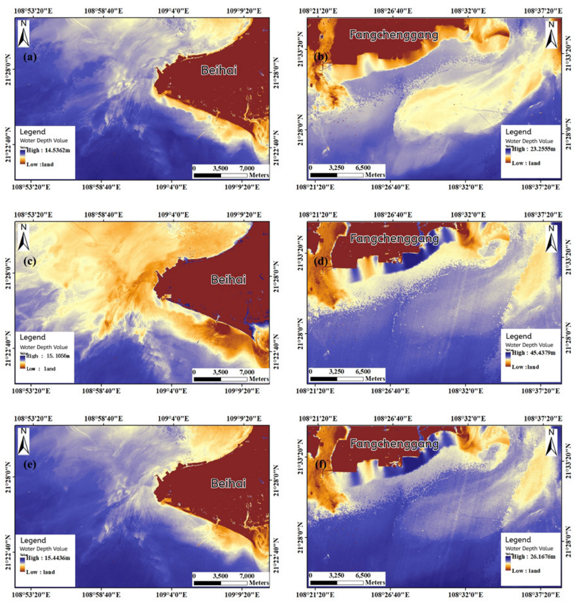

Figure 5. Bathymetric inversion results using single-band, dual-band, and multi-band models for the Beihai and Fangchenggang research areas a) Beihai single-band linear regression inversion, b) Fangchenggang single-band linear regression inversion, c) Beihai two-band ratio inversion, d) Fangchenggang two-band ratio inversion, e) Beihai multi-band combined regression inversion, f) Fangchenggang multi-band combined regression inversion

The single-band linear regression model demonstrated unsatisfactory inversion performance across both the Beihai and Fangchenggang research areas. Specifically, in the Beihai area, this model consistently overestimated water depths within the 5-7 m range relative to the ENC reference data. The two-band ratio model exhibited superior accuracy compared to the single-band model, with inversion results converging more closely toward the 1:1 reference line. The multi-band combined regression model outperformed both preceding models, achieving the highest retrieval quality. Notably, this model demonstrated optimal performance within the 7-12 m depth range for the Beihai study area and the 13-16 m range for the Fangchenggang area.

By comparing the scatter plots across the two research areas, it is evident that none of the models perform well when the water depth is greater than 13 m, where the depth obtained by inversion is consistently less than the depth on the chart.

4.3 Stratified inversion analysis

Since performance varies substantially with depth, depth-binned metrics were calculated to provide additional insight into the vertical stability and reliability of the proposed inversion algorithms. The study areas were partitioned into three distinct depth zones (0–7 m, 7–12 m, and 12–20 m) based on the electronic chart contours. The weighted average accuracy of the depth-zoned inversion was calculated for both research areas and compared with the accuracies of the unzoned models to rigorously quantify the precision enhancement yielded by this localized zonation strategy. The results are shown in Table 3.

Research Area	Model	Partition inversion accuracy (m)		Unpartitioned inversion accuracy (m)	
		MAE	RMSE	MAE	RMSE
Beihai	Single band linear regression	0.8898	1.0881	1.5312	1.8912
	Two-band ratio	0.8296	1.0327	1.4355	1.8839
	Multi-band combined regression	0.8025	1.0538	1.3843	1.7611
Fangchenggang	Single-band linear regression	1.1433	1.3771	2.8221	3.2934
	Dual-band ratio	1.1029	1.2989	1.9483	2.5317
	Multi-band combined regression	1.0110	1.2286	1.8609	2.4599

Table 3. Comparison of Accuracy Before and after partition inversion

After depth zoning, the inversion accuracies of all three models improved to some extent in both areas. Specifically, compared to the global unzoned inversion, the depth-stratified approach demonstrated a significant accuracy improvement. For instance, the MAE and RMSE of the single-band model in the Fangchenggang research area were substantially reduced by 1.6788 m and 1.9163 m, respectively. This comparison strongly highlights the necessity of considering depth-dependent local contexts in empirical SDB work. The single-band linear regression model saw the greatest improvement in Beihai as well, with MAE and RMSE dropping by 0.6414 m and 0.8031 m, respectively.

When generating the stratified inversion raster images (Figure 6), the depth values post-stratification showed a high degree of agreement with the ENC data, though some po or transitions were observed at the boundaries of different depth zones. Although the multi-band model in Fangchenggang still exhibited excessive inverted depths in the nearshore part, the overall quality of the results significantly improved compared to the unstratified approach. Overall, stratified depth inversion reduces errors caused by variations in underwater sediments, water quality types, and suspended matter within specific depth ranges.

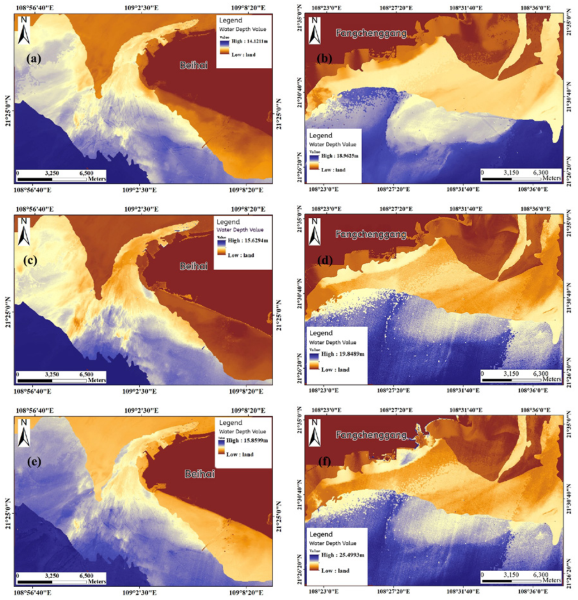

Figure 6. Water depth inversion results after depth-stratified partitioning for the three models in both research areas a) Beihai single-band linear regression inversion, b) Fangchenggang single-band linear regression inversion c) Beihai dual-band ratio inversion, d) Fangchenggang dual-band ratio inversion, e) Beihai multi-band combined regression inversion, f) Fangchenggang multi-band combined regression inversion

5. Conclusions

In this paper, using Landsat-9 imagery and electronic nautical chart (ENC) data, comparative bathymetry inversion experiments were conducted in the shallow waters of the Guangxi Beibu Gulf, China, by constructing single-band linear regression, dual-band ratio, and multi-band combined regression models. Based on this, comparative experiments between global inversion and depth-stratified inversion were carried out. The results show:

The multi-band combined regression model consistently achieved the highest inversion accuracy in both study areas. The inversion accuracy for the Beihai research area was evaluated as $R^2 = 0.5026$, MAE = 1.3843 m, and RMSE = 1.7611 m, for the Fangchenggang research area, the evaluation yielded $R^2 = 0.5900$, MAE = 1.8609 m, and RMSE = 2.4599 m.

Influenced by site-specific factors such as water quality and location, the inversion performance of the same model varied across different regions. For example, the multi-band combined regression model exhibited optimal performance in the 7-12 m depth range for Beihai and the 13-16 m range for Fangchenggang. A similar depth-dependent performance pattern was observed for the single-band and dual-band models.

The depth-stratified inversion approach effectively improved the retrieval accuracy for all three models. Specifically, in the Beihai research area, the MAE and RMSE were improved by 0.6414 m and 0.8031 m, respectively; in the Fangchenggang research area, the MAE and RMSE improved by 1.6788 m and 1.9163 m, respectively. These results confirm that depth-stratified inversion is a more practical strategy for shallow-water bathymetry.

The findings verify the practicality of the multi-band combined regression model for satellite-derived bathymetry. Although the current model shows promising results, it is important to note that with a 30 m pixel resolution and RMSE values of approximately 1.7-2.5 m, this method is best suited for rapid, reconnaissance-level shallow-water mapping and environmental monitoring. Future work will aim to validate this model using multi-temporal imagery across broader geographic regions to reduce site-specific contingencies and enhance the model's robustness.

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