

Article

Normalized Satellite-Derived Bathymetry Model from Landsat 8 Single-Band Image with Underwater Topography Trend for Nearshore Shallow Waters

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Highlights

What are the main findings?

- We propose a normalized satellite-derived bathymetric (NSDB) model that innovatively integrates normalized underwater topography trends from low-resolution reference data with satellite imagery to reduce interference from water quality and seabed substrates.
- This model significantly outperforms four classic models across diverse waters (Weizhou Island, Saipan, Molokai), reducing RMSE by 20–45% and achieving R^2 values up to 0.97.

What are the implications of the main findings?

- This model provides a simple but accurate method for generating foundational nearshore bathymetric maps, overcoming accuracy limitations in challenging coastal environments.
- It represents a practical breakthrough for large-scale, cost-effective coastal bathymetric mapping with direct applications in navigation safety, coastal zone management, and geomorphic studies.



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Abstract

Satellite-derived bathymetry holds significant value for acquiring nearshore bathymetric data. However, in coastal waters, bathymetry is affected by in-water particle scattering and seafloor substrate variability, leading to spatial inconsistency between the logarithmic green band profile derived from multispectral satellite imagery and the actual water depth profile. According to the position information of interpolated points and the inverse distance square relationship with the surrounding 16 points from low-reference bathymetric data (such as the bathymetric map from GEBCO, NOAA Electronic Navigational Charts), this

model adopts a third-order inverse distance square bicubic convolution interpolation method to resample a high-resolution bathymetric map with the size of the satellite image. Normalized underwater topography trend data (derived from the low-resolution reference bathymetric map) were combined with normalized green band data to compute an averaged dataset. In this way, a linear bathymetric model was constructed. We invert this model's parameters and calculate the water depth by using the average data and reference points from reference bathymetric data. Validation tests were conducted across three test areas using independent validation bathymetric data: Weizhou Island, China (Case II waters); Saipan, Northern Mariana Islands, USA (Case I waters); and Molokai Island, Hawaii, USA (Case I waters). Each test area was studied using five error analysis methods (i.e., scatterplot, error histogram, regional bathymetric error, three check lines, and seven check points). Compared to four classic bathymetric models (i.e., single-band model, log-ratio model, ratio-log model, and multi-band model), the proposed model achieved lower root mean square errors (RMSE) of 2.08 m, 1.40 m, and 2.01 m in the three test areas, representing reductions of 35%, 43%, 45%, and 20% and overall averages of 48%, 62%, 64%, and 43%, respectively. Its goodness of fit (R^2) reached 0.87, 0.97, and 0.97, showing improvements of at least 5%, 5%, 9%, and 9% and overall averages of 17%, 77%, 84%, and 12%, respectively. The results demonstrate that the proposed model significantly improves bathymetry accuracy while maintaining algorithmic simplicity, providing a new model for acquiring nearshore foundational bathymetric maps.

Keywords: satellite-derived bathymetry (SDB); bathymetric mapping; Landsat 8; ordinary kriging difference; single-band bathymetry

1. Introduction

Nearshore bathymetric mapping is critical in many fields, including navigation safety, engineering construction, ecological conservation, resource management, and disaster prevention [1–5]. Satellite images offer advantages like broad coverage, low cost, and multi-temporal observation. While satellite-derived bathymetry (SDB) is a commonly used method [1,2,6], it tends to suffer from low accuracy [5–7].

To address this problem, researchers worldwide have developed four classic bathymetric models, i.e., the single-band model, the ratio-log model, the log-ratio model, and the multi-band model [1,2,5,8–20]. However, satellite-derived bathymetric signals comprise multiple factors, including atmospheric interference, air–water interface effects, sun glitter, and water column constituents (e.g., chlorophyll, non-chlorophyll particles, and dissolved organic matter), that reduce the signal-to-noise ratio and introduce inconsistencies between the remote sensing signal and actual water depth [21–23]. To mitigate these issues, atmospheric effects are typically corrected using radiative transfer models, such as 6S, QUAC, and ACOLITE [24–30], while the air–water interface and sun glare are addressed through subsurface-reflectance retrieval or semi-analytical modeling [6,8,22,29–32]. However, the impacts of water chlorophyll, yellow substances, non-chlorophyll particles, and seafloor reflectance remain unresolved.

Scientists have conducted extensive research on how suspended substances in water—including chlorophyll, yellow substances, and non-pigment particles—affect reflected radiation signals through absorption and scattering. The groundwork for modern aquatic optics was laid in 1971, when Brown introduced a single-band attenuation coefficient model [12]. A major breakthrough came in 1998 when Lee decomposed the absorption coefficient into four components—pure water, chlorophyll, yellow substances, and non-pigment particles—

and partitioned the backscattering coefficient into pure water and particulates, establishing a methodological framework for multi-component quantification [22]. The Quasi-Analytical Algorithm (QAA) was the first systematic method for retrieving component coefficients in deep-water environments [33]. Although Liu's Dual-Band Model Adaptation (DBMA) differentiated between clear and turbid conditions, its limited inversion accuracy ($R^2 < 0.8$) underscored the inherent limitations of single-model approaches [34–37]. The integration of the QAA and HOPE models enhanced the goodness of fit to 0.86 through depth-stratified processing, yet its regional applicability remained limited [38]. The prior-free SDB model achieved an RMSE of 1.18 m in Jinqing Island, highlighting the need for mechanism–data fusion innovations in complex aquatic systems [39,40].

To mitigate accuracy loss in satellite-derived bathymetry caused by substrate reflectance, Alexey, Petit, and Liu have made significant advances. For instance, a coral–sand–algae reflectance model has been established [41], and seagrass endmembers were added to this model [42]. The framework was further refined using a lookup table approach, forming a more complete system for quantitative substrate characterization [43]. Current methods still require improvements to address nonlinear interference and dynamic environmental variability.

To suppress noise in satellite signals of water depth, a quadratic polynomial ratio depth measurement model was proposed from multi-source active–passive images [44]. Duan developed a multi-temporal image-weighted synthesis (MIWC) model [45], while Liu leveraged terrain features and spectral information to invert shallow-water depths over coral reefs [37].

Although previous studies have explored SDB models and incorporated influencing factors, representing a vertically stratified water column and variable sediment reflectance with a single coefficient remains challenging. This limitation reduces the accuracy of recent models. To improve high-resolution bathymetric mapping from sparse point measurements, researchers have developed advanced interpolation techniques. In 2014, Chen et al. introduced fractal Brownian motion (FBM)-compensated kriging, which captures the self-similarity of underwater terrain and significantly enhances accuracy in modeling random topography [46]. The following year, Zhang et al. further improved digital elevation models (DEMs) by optimizing triangular irregular networks (TINs) and applying roughness-weighted kriging, achieving superior performance over traditional interpolation methods [47].

In 2018, Lv et al. addressed complex fractal terrains using a hybrid approach that combined modified FBM with iterated function systems (IFS), achieving superior replication of fractal properties [48]. Recent studies in 2023 further refined these approaches. Qin et al. linked interpolation errors directly to surface roughness, proposing an adaptive strategy for varying terrain conditions [49]. At the same time, Aguilar demonstrated that radial basis multifunction (RBMf) and ordinary kriging (OK) perform best in low-relief areas, whereas complex terrains require higher sampling densities (0.1024 points/m²) for reliable results. Notably, universal kriging (UK) and Gaussian Markov random fields (GMRF) produce higher vertical errors due to their sensitivity to terrain morphology and sampling density [50].

Although many interpolation methods have been developed for high-precision underwater DEM generation, the sparse spacing of input points limits their ability to capture underwater terrain, resulting in significant errors.

To address this limitation, we developed a normalized satellite-derived bathymetry (NSDB) model. This model innovatively fuses high-resolution green band satellite imagery with low-resolution topographic trends to enhance bathymetric accuracy.

This paper is structured as follows. Section 2 outlines the principles and methodology of the proposed NSDB model. Section 3 introduces the study areas, datasets, and preprocessing, including the layout of reference and validation points. Section 4 presents the experimental results, applying the NSDB model to three test sites and comparing its performance against four classic bathymetric methods. Finally, Section 5 summarizes the key conclusions.

2. Test Field and Data

To validate the proposed model across varied water conditions, three test sites with low-resolution reference bathymetric data and high-resolution reference bathymetric data were selected: Weizhou Island (China) for Case II waters with complex substrates and Saipan Island and Molokai Island (USA) for Case I waters characterized by high mineral particle content and highly variable substrates, respectively. These sites were studied to assess model performance under challenging optical and geomorphic conditions.

2.1. Three Test Areas

(1) Test area 1: As shown in Figure 1, test area 1 is located at the coastal zone west of Weizhou Island in the Beibu Gulf, Guangxi Zhuang Autonomous Region, China. This test area is a square block with geographic coordinates ranging from $21^{\circ}01'47.18''\text{N}$ to $21^{\circ}03'25.45''\text{N}$ and $109^{\circ}03'22.46''\text{E}$ to $109^{\circ}05'09.70''\text{E}$. The water area reaches $9,377,707\text{ km}^2$. Its water quality is classified as Case II. The water depth range is 0–25.7 m, with an average depth of 13.76 m. The seabed substrate shows distinct variations. The northern shore is a sandy beach extending into the sea with a light-colored bottom, i.e., sand and gravel. From a depth of about 10 m to the open sea, there is a black igneous rock base. The southern part mainly consists of black volcanic bedrock, with associated sediments including dark magnesium-rich sand, light felsic sand, and coral debris.

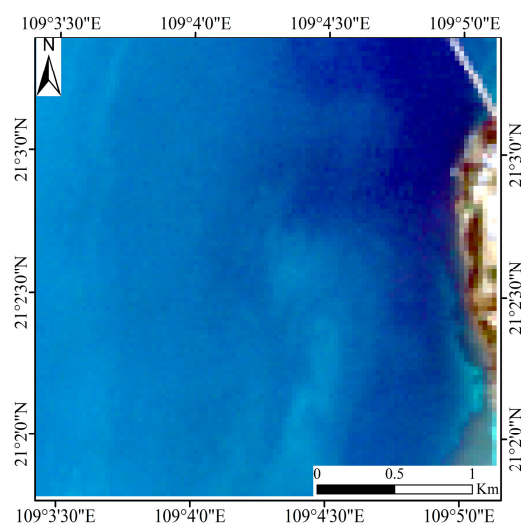


Figure 1. Weizhou Island waters.

(2) Test area 2: Test area 2 is located on the western shelf of Saipan Island (Figure 2) in the Northern Mariana Islands, USA. The test area is a rectangular block with geographic coordinates ranging from $15^{\circ}12'1.95''\text{N}$ to $15^{\circ}13'38.12''\text{N}$ and $145^{\circ}41'8.57''\text{E}$ to $145^{\circ}42'56.88''\text{E}$. The water area reaches 23.6 km^2 . Due to its distance from the mainland and the cleansing effect of strong ocean currents, the water quality is classified as Case I. The water depth range is 0–31.4 m, with an average depth of 11.64 m. The substrate consists of Cenozoic

volcanic island arc bedrock overlain by a coral reef ecosystem and calcareous bioclastic. The substrate color darkens progressively from the coastline to the offshore zone.

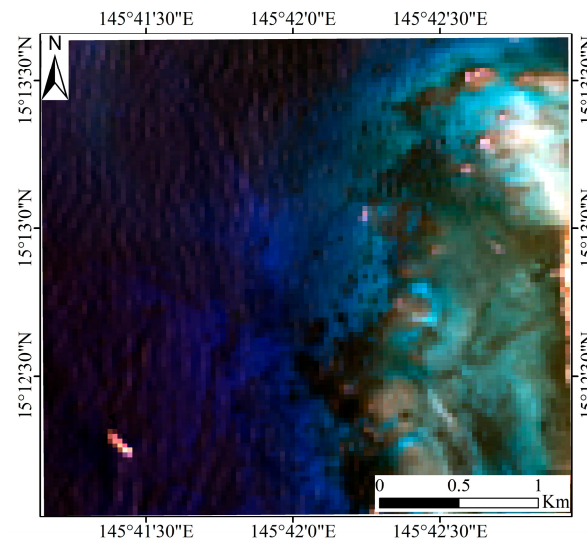


Figure 2. Saipan Island waters.

(3) Test area 3: This site is situated on the western continental shelf of Molokai Island (Figure 3), Hawaii, USA. It comprises an irregular composite block bounded by geographic coordinates $21^{\circ}10'00''\text{N}$ to $21^{\circ}10'30''\text{N}$ and $157^{\circ}10'10''\text{W}$ to $157^{\circ}14'42''\text{W}$, covering a total water area of 14.3 km^2 . This region is characterized by minimal anthropogenic disturbance, high water clarity, and Case I waters. Water depths range from 0 to 37.79 m, with a mean depth of 10.63 m. Progressing from the nearshore to the offshore zone, the benthic cover shifts sequentially from 10 to 50% coverage of emergent vegetation, coralline algae, macroalgae, and live coral to areas with 90–100% coverage of live coral.

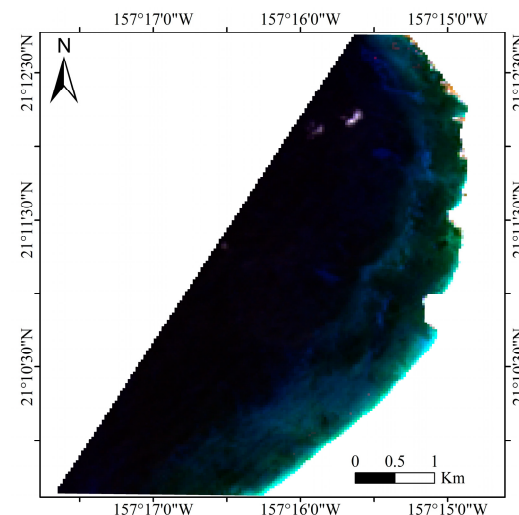


Figure 3. Molokai Island waters.

2.2. Datasets and Data Preprocessing

(1) Satellite Images and Preprocessing

Landsat 8 multispectral satellite imagery was used for the three test areas. Over Weizhou Island, Guangxi, satellite data were acquired under clear conditions, with a temperature range of $10\text{--}16\text{ }^{\circ}\text{C}$ and 4–5 Beaufort northeasterly winds. The satellite data over Saipan Island were acquired under clear skies, with temperatures ranging from $24.4\text{ }^{\circ}\text{C}$

to 29.4 °C and average northeasterly winds of 6.4 km/h. Over the island of Molokai, the satellite data were acquired under predominantly clear skies, with air temperatures ranging from 16 °C to 25 °C and an average northeasterly wind speed of 24.1 km/h. The selected images were cloud-free, with a spatial resolution of 30 m and a swath width of 185 km. Detailed image specifications are provided in Table 1.

Table 1. Satellite images of the three test areas.

Test Area	Time (GMT)	Solar Elevation Angle (°)	Solar Azimuth Angle (°)	Path	Row
Weizhou Island	2013-12-29 03:06:17	39.5	151.3°	124	45
Saipan Island	2018-8-13 00:37:33	40.2	153.4	100	49
Molokai Island	2019-12-9 20:54:22	40.4	153.4	64	45

Image preprocessing included radiometric calibration, atmospheric correction using the second simulation of the satellite signal in the Solar Spectral (6S) model, sun glitter removal, and clipping images.

(2) Bathymetry Data and Preprocessing

To ensure spatial consistency, both the low-resolution reference bathymetric data (GEBCO and NENCs) and the high-resolution reference bathymetric data (shipborne multibeam and LiDAR) were reprojected to the WGS_1984_UTM_Zone_49N coordinate system using the “Project” tool in ArcGIS 10.8 to match satellite imagery projections.

(1) Reference Bathymetric Map and Points

In test area 1, the low-resolution reference bathymetric map used for satellite-derived bathymetry came from GEBCO. Specific parameters are listed in Table 2. As shown in Figure 4a, the maximum depth of this map is 21.87 m. Seven reference points were deployed to fit the model parameters and derive the water depth.

Table 2. Parameters of the GEBCO bathymetric map.

Source	Resolution (m)	Acquisition Method	Depth Accuracy	Website
GEBCO	500	Multibeam	2–10 cm	https://www.gebco.net/ (accessed on 2 June 2025)

In test areas 2 and 3, the low-resolution reference bathymetric map used for satellite-derived bathymetry came from NENCs. Specific parameters are listed in Table 3. The maximum depth in the two test areas is 30.74 and 37.34 m. Seven evenly distributed reference points were selected to compute the model parameters and derive the water depth.

Table 3. Parameters of NENCs.

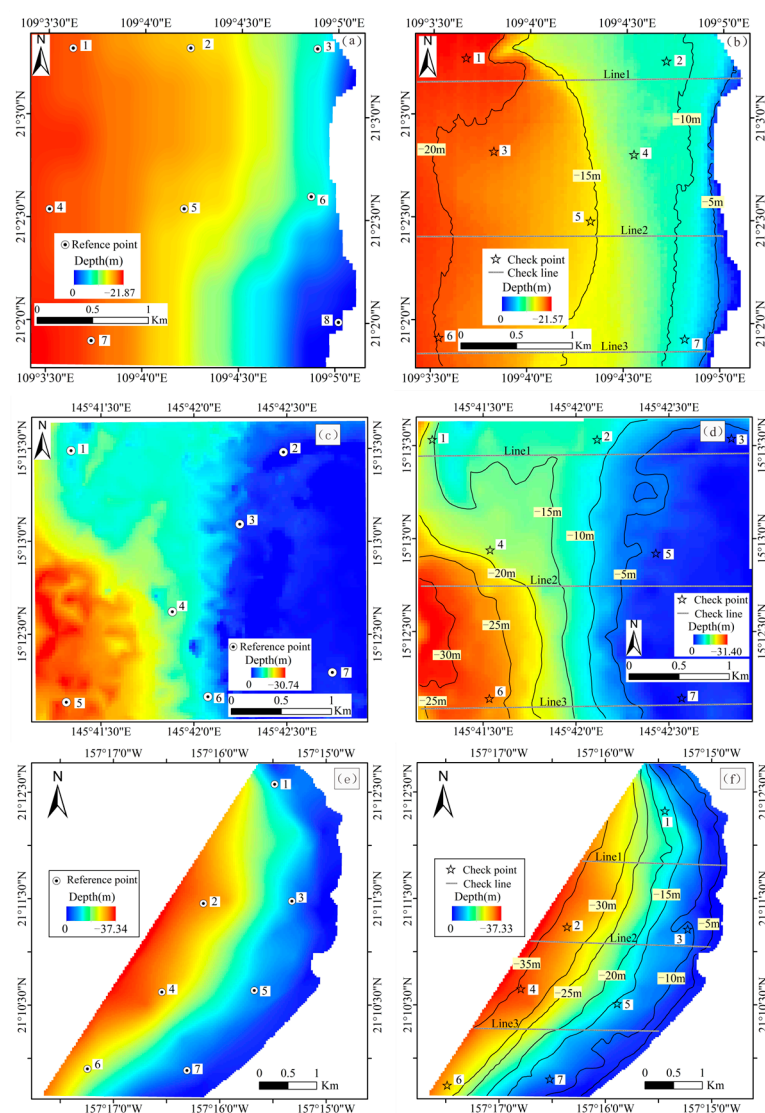
Source	Scale	Acquisition Method	Depth Accuracy	Website
NENC	1:40,000	Shipborne multibeam	<0.5 m	https://www.nauticalcharts.noaa.gov/ (accessed on 2 June 2025)

(2) Validation Bathymetric Map, Check Lines, and Check Points

To verify the effectiveness of the proposed model, we used shipborne multibeam sonar to measure the validation bathymetric map of test area 1 on 12 November 2019. The water depth ranges from 0 m to 21.57 m (see Figure 4b). Three check lines and seven check points were also deployed. The specific parameters related to water depth are shown in Table 4.

Table 4. Multibeam bathymetric parameters.

Plane Coordinates	Vertical Datum	Projection Mode	1.5° Band Projection	Scale
2000 national geodetic coordinate system	1985 National Height Datum	Gauss Kruger projection	Zone 71, central meridian 108.75°	1:5000
Plane accuracy (95% confidence)	Sounding accuracy (95% confidence)	100% seafloor scanning	System detection capability	0–20 m
2 m	0.25 m	It has to be done	Characteristics of space objects > 1 m ³	<0.3 m

**Figure 4.** Reference bathymetric map (reference points) (a,c,e) and validation bathymetric map (check points and check lines) (b,d,f) for Weizhou Island, Saipan Island, and Molokai Island.

We use the bathymetric maps of test area 2 (see Figure 4d) and 3 (see Figure 4f) from CZMIL LiDAR to verify the proposed model. The water depth ranges from 0 m to 31.4 m and 0 m to 37.33 m, respectively. We also set three check lines and seven check points. The specific parameters related to CZMIL LiDAR are listed in Table 5.

Table 5. CZMIL LiDAR parameters.

Parameter	Value
Pulse repetition frequency	10 kHz
Maximum depth single pulse	$K_d \cdot D_{\max} = 3.75\text{--}4.0$ daytime (bottom reflectivity > 15%)
Minimum depth	<0.15 m
Depth accuracy	$[0.09 + (0.013 \text{ depth})^2]\%$ m, 2σ
Horizontal accuracy	$(3.5 + 0.05 \text{ depth})$ m, 2σ
Sounding density	2 m $\times$ 2 m nominal
Scan angle	20° (fixed off-nadir, circular pattern)
Swath width	294 m nominal

(3) Tidal High Correction of Bathymetric Map

The 0.3 m, 0.66 m, and 0.01 m differences between (a) and (b), (c) and (d), and (e) and (f) in Figure 4 are attributed to tidal height variations. To align water depth data with corresponding satellite imagery, cubic spline interpolation [5] was applied separately to correct both the reference and validation bathymetric maps.

3. Normalized Satellite-Derived Bathymetry Model

3.1. Principle

The process of satellite-derived bathymetry is shown on the left of Figure 5. First, the light emitted by the sun is absorbed and scattered by atmospheric gas molecules and cloud particles. Some of the transmitted light reaches the water's surface, while other rays are reflected to satellite sensors. Another part of the light penetrates the water's surface and is absorbed and scattered by particles such as water molecules, chlorophyll, yellow substances, and non-pigment particles, reaching the bottom of the water and reflected into the water. Before reaching the water's surface, the light undergoes absorption and scattering by particles such as water molecules, chlorophyll, colored dissolved organic matter, and non-pigmented suspended solids. Light enters the atmosphere through the surface of water; it is absorbed and scattered by gas molecules and cloud particles, and then it is received by satellite sensors. Therefore, assuming constant bottom reflectance, constant surface reflectance, and invariant aquatic backscattering, the radiative transfer equation can be expressed by Equation (1) [12].

$$L_S(\Delta\lambda) = \int_{\lambda}^{\lambda+\Delta\lambda} [\rho_{bot}(\lambda)L(\lambda)e^{-(\sec\theta+\sec\phi)c(\lambda)z} + \rho_{aw}(\lambda)L(\lambda)]d\lambda + L_{SC}(\Delta\lambda) \quad (1)$$

where $L_S(\Delta\lambda)$ is the total radiance received by the sensor after atmospheric correction, $\Delta\lambda$ is the spectral bandwidth between the starting band λ and the ending band $\lambda + \Delta\lambda$, $\rho_{bot}(\lambda)$ is the bottom reflectance at wavelength λ , θ is the solar zenith angle, ϕ is the viewing zenith angle, $c(\lambda)$ is the attenuation coefficient of solar irradiance in water at wavelength λ , $L(\lambda)$ is the solar irradiance just above the water's surface at wavelength λ , $\rho_{aw}(\lambda)$ is the surface reflectance of sunlight at wavelength λ , and $L_{SC}(\Delta\lambda)$ is the water-leaving radiance due to scattering by water constituents.

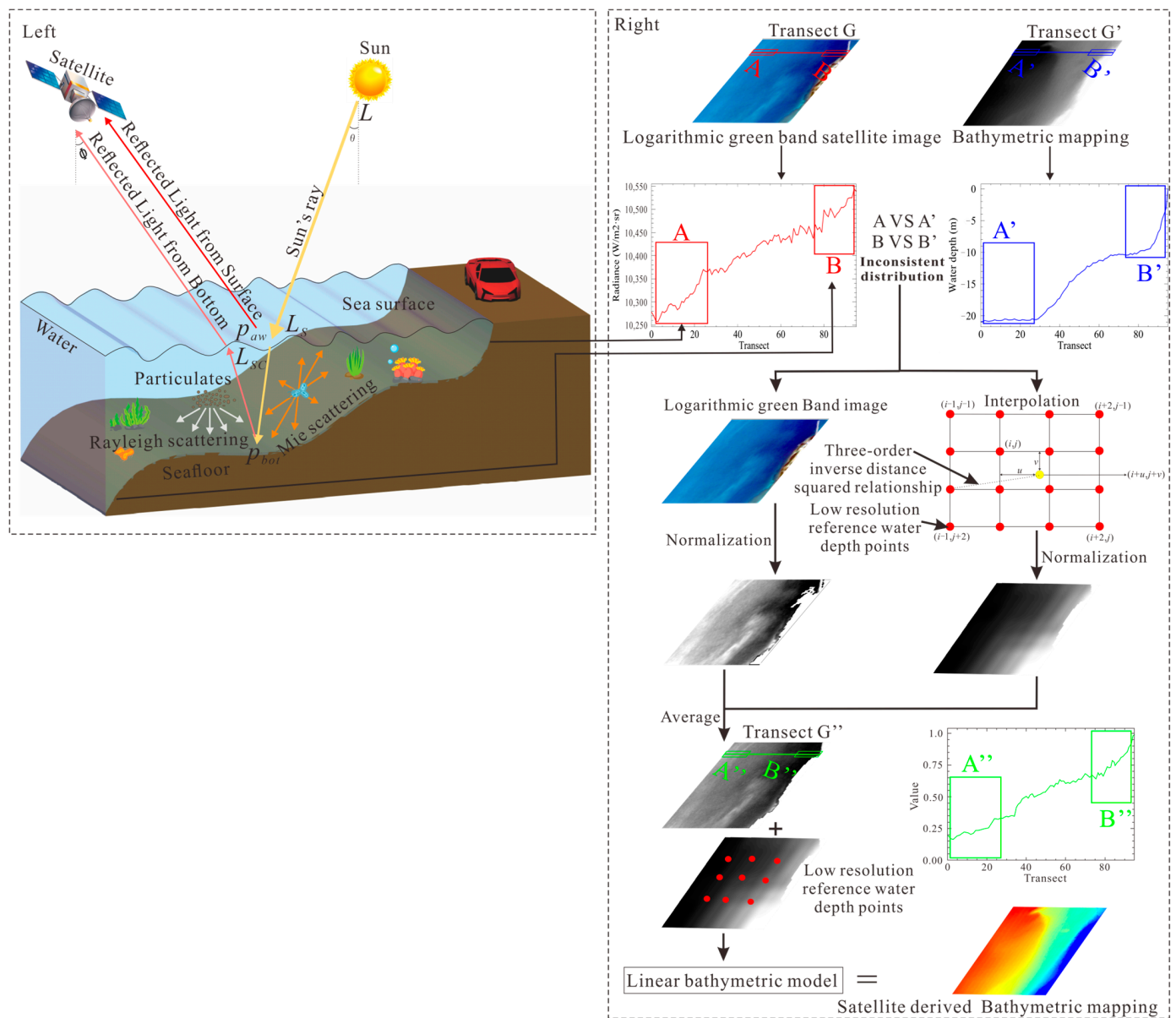


Figure 5. Optical signal transmission path and correction of satellite imagery.

In ideally calm and pure water bodies with suspended particles, radiation in the blue–green bands undergoes exponential attenuation with increasing travel distance through the water. Consequently, taking the logarithm of both sides of Equation (1) yields a linear model for water depth, as expressed by Equation (2) (λ is omitted).

$$z = - \frac{\ln \left(\frac{L_S - L_{SC} - \rho_{aw}}{\rho_{bot}} \right)}{(\sec \theta + \sec \phi)c} \quad (2)$$

Under real-world conditions, however, ρ_{bot} , ρ_{aw} , and L_{SC} in Equation (1) vary spatially and are not constants. This causes the relationship between sunlight entering the water and light received by the sensor to deviate from the strict exponential attenuation described by Beer's Law. From this, it can be inferred that due to the water surface reflection effect, suspended particles and substrate reflectance are the main sources of errors. In Case I water with stable optical properties, light radiation transmission is dominated by the selective absorption of water molecules, and the radiation attenuation coefficient shows a

corresponding relationship with water depth. However, when suspended particles (like sediment, plankton, and organic debris) are present, the light transmission mechanism changes significantly. These particles cause Mie scattering, Rayleigh scattering, and variable reflectance, leading to spatiotemporal heterogeneity of light attenuation. In turbid Case II nearshore waters, strong backscattering from suspended particles alters the light transmission gradient and disrupts the quantitative relationship between the remote sensing signal and water depth. As shown on the right of Figure 5, the distribution of Transect G in logarithmic green band satellite imagery is significantly different from that of Transect G' in bathymetric mapping. In particular, the distribution of A and B zones in Transect G and A' and B' zones in Transect G' is inconsistent.

This issue largely stems from the parameters ρ_{bot} , ρ_{aw} , and L_{SC} in Equation (1). Theoretically, these parameters are presumed to be constant. In practice, however, they exhibit significant spatial heterogeneity. A careful analysis of Equation (2) reveals that these parameters only affect the numerator on the right side of the equation, while the denominator consists of fixed parameters, establishing a proportional relationship between water depth and the numerator. This implies that, ideally, the spatial distribution of water depth should correlate with trends in satellite imagery, which is not the case in practice.

Therefore, the primary purpose of this study is to align the distribution trend of water depth with the radiance distribution of the satellite image pixels. To achieve this, as illustrated in the right panel of Figure 5, low-resolution reference bathymetric data are acquired, such as charts from GEBCO or NENCs. A third-order inverse distance squared bicubic convolution interpolation method is then applied to resample the bathymetric data to match the spatial resolution of the satellite imagery. This process ensures that each satellite image pixel is assigned a corresponding water depth value. Consequently, we can derive a normalized trend of the water depth distribution corresponding to the satellite imagery by utilizing low-resolution bathymetric data over the study area. This normalized depth trend and the normalized satellite image data are then jointly demeaned. As in the Transect G'' depicted in the right panel of Figure 5, the curve trends of A'' and B'' are more closely aligned with A' and B' in the Transect G' from bathymetric mapping. This shows that the procedure mitigates the influence of surface reflectance, water column scattering, and variable bottom reflectance on the depth signal, partially correcting errors introduced by these factors.

3.2. Model Construction

Based on the principles of suspended matter scattering illustrated in the left panel of Figure 5, the proposed model comprises the following steps (see the right panel of Figure 5).

Step 1: Interpolated underwater terrain trend

To generate bathymetric data at the resolution of the satellite imagery, the model applies a third-order inverse-distance-squared bicubic convolution interpolation to low-resolution reference data (e.g., GEBCO, NENCs). As detailed in Equation (3) and illustrated in Figure 6, this method calculates the water depth at each high-resolution pixel using a weighted average of the 16 nearest reference points. The weighting function is inversely proportional to the cube of the squared Euclidean distance, strongly prioritizing proximate data points. This ensures that the interpolated trend surface accurately preserves the underlying geomorphic structure while providing a spatially continuous foundation for integration with satellite-derived bathymetry.

$$\left\{ \begin{array}{l} D_{(i+u,j+v)} = A \times B^T \\ A = \begin{pmatrix} w_{(i-1,j-1)}, w_{(i+0,j-1)}, w_{(i+1,j-1)}, w_{(i+2,j-1)}, w_{(i-1,j+0)}, w_{(i+0,j+0)}, w_{(i+1,j+0)}, w_{(i+2,j+0)}, \\ w_{(i-1,j+1)}, w_{(i+0,j+1)}, w_{(i+1,j+1)}, w_{(i+2,j+1)}, w_{(i-1,j+2)}, w_{(i+0,j+2)}, w_{(i+1,j+2)}, w_{(i+2,j+2)} \end{pmatrix} \\ B = \begin{pmatrix} D_{(i-1,j-1)}, D_{(i-1,j+0)}, D_{(i-1,j+1)}, D_{(i-1,j+2)}, D_{(i+0,j-1)}, D_{(i+0,j+0)}, D_{(i+0,j+1)}, D_{(i+0,j+2)}, \\ D_{(i+1,j-1)}, D_{(i+1,j+0)}, D_{(i+1,j+1)}, D_{(i+1,j+2)}, D_{(i+2,j-1)}, D_{(i+2,j+0)}, D_{(i+2,j+1)}, D_{(i+2,j+2)} \end{pmatrix} \\ w_{(i+0,j+0)} = \frac{1}{16} \begin{pmatrix} 1 - \frac{\sqrt{u_{i+0}^2 + v_{j+0}^2}}{\sqrt{u_{i-1}^2 + v_{j-1}^2} + \sqrt{u_{i+0}^2 + v_{j-1}^2} + \sqrt{u_{i+1}^2 + v_{j-1}^2} + \sqrt{u_{i+2}^2 + v_{j-1}^2}} \\ \frac{1}{\sqrt{u_{i-1}^2 + v_{j+0}^2} + \sqrt{u_{i+0}^2 + v_{j+0}^2} + \sqrt{u_{i+1}^2 + v_{j+0}^2} + \sqrt{u_{i+2}^2 + v_{j+0}^2}} \\ \frac{1}{\sqrt{u_{i-1}^2 + v_{j+1}^2} + \sqrt{u_{i+0}^2 + v_{j+1}^2} + \sqrt{u_{i+1}^2 + v_{j+1}^2} + \sqrt{u_{i+2}^2 + v_{j+1}^2}} \\ \frac{1}{\sqrt{u_{i-1}^2 + v_{j+2}^2} + \sqrt{u_{i+0}^2 + v_{j+2}^2} + \sqrt{u_{i+1}^2 + v_{j+2}^2} + \sqrt{u_{i+2}^2 + v_{j+2}^2}} \end{pmatrix} \end{array} \right. \quad (3)$$

where $D_{(i+u,j+v)}$ represents the geographically referenced water depth value to be interpolated, A represents the weight vector, and B represents the vector of 16 sampling points. $w_{(i+0,j+0)}$ is the weight at point (i, j) , u_{i+0} is the distance between interpolation point (i, j) and the point to be interpolated $(i + u, j + v)$ along the x-axis direction, and v_{j+0} is the distance between interpolation point (i, j) and the point to be interpolated $(i + u, j + v)$ along the y-axis direction.

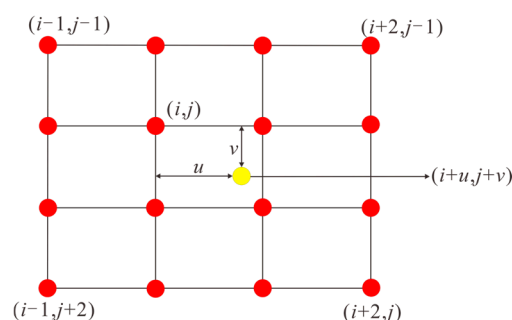


Figure 6. Principle of third-order inverse distance squared bicubic convolution interpolation.

Step 2: Normalized underwater terrain trend

We substitute low-resolution bathymetric data into the linear normalization in Equation (4) to obtain the underwater topography trend data in the $[0, 1]$ interval, denoted as D_{nij} .

$$D_{nij} = \frac{D_{ij} - \min(D_{ij})}{\max(D_{ij}) - \min(D_{ij})} \quad (4)$$

Step 3: Establish a linear relationship between water depth and the normalized green band satellite image

First, we take the logarithm of the green band satellite image using Equation (5).

$$L_{ij} = \ln(G_{ij}) \quad (5)$$

where G_{ij} is the radiant value of the i th row and the j th column of the green band of the remote sensing image, i is the number of rows of the remote sensing image, and j is the number of columns of the remote sensing image.

Then, the maximum value L_{max} and the minimum value L_{min} in L_{ij} are obtained through Equation (6):

$$L_{nij} = \frac{L_{ij} - \min(L_{ij})}{\max(L_{ij}) - \min(L_{ij})} \quad (6)$$

Step 4: Calculation of the “Average Band Image”

We use Equation (7) to calculate the “Average Band Image.”

$$B_{nij} = \frac{D_{nij} + L_{nij}}{2} \quad (7)$$

Step 5: Construction of a linear bathymetric model

$$Z = aB_{nij} + b \quad (8)$$

Step 6: Least squares method for solving the model’s parameters

First, an error function E is constructed to minimize the loss. Subsequently, partial derivatives are taken with respect to parameters a and b of E . Setting these partial derivatives to zero yields the optimal estimates for a and b .

$$\begin{cases} E = \frac{1}{n} \sum_{i=1}^n (z_i - aB_{nij} - b)^2 \\ a = \frac{\sum_{i=1}^n z_i (B_{nij} - \bar{B}_{nij})}{\sum_{i=1}^n B_{nij}^2 - \frac{1}{n} (\sum_{i=1}^n B_{nij})^2} \\ b = \frac{1}{n} \sum_{i=1}^n (z_i - aB_{nij}) \end{cases} \quad (9)$$

4. Results

We conducted experiments in test areas 1, 2, and 3. First, we used the low-resolution reference bathymetric map, i.e., the data from GEBCO and NENCs, to interpolate underwater terrain trends to the size of satellite images through Equation (3). Next, we substituted the interpolated underwater terrain trend into Equation (4) to obtain the normalized underwater terrain trend. We then substituted the green band satellite image into Equations (5) and (6) to construct a logarithmic normalized green band satellite image, followed by substituting the normalized underwater terrain trend and the logarithmic normalized green band satellite image into Equation (7) to calculate the “Average Band Image.” We then used the “Average Band Image” and Equation (8) to construct a linear bathymetric model. The sixth step involves solving the model parameters using the least squares method and reference points from the reference bathymetric map (see Figure 4a,c,e) using Equation (9). Finally, we constructed a linear bathymetric model to calculate the water’s depth.

To verify the accuracy of the proposed model, we also used single-band, ratio-log, log-ratio, and multi-band models to calculate the water depth. We also used an error scatterplot, an error histogram, regional error, check lines, and check points (see Figure 4b,d,f) to prove the effectiveness of the proposed model.

4.1. Scatterplot Analysis

To compare the performance of the proposed models, we used ENVI 5.6 to open the validation bathymetric map at the satellite flying time and the satellite-derived bathymetric map retrieved by the five models. Then, we used the scatterplot tool to plot scatter diagrams for each model in the three test areas, where the x-axis represents the true water depth at the satellite flying time, and the y-axis represents the water depth retrieved by the five models with a 5 m interval.

The first row of Figure 7, subplots (a)–(e), shows the scatterplots of the models in test area 1. Subplots (b) and (c) exhibit very poor consistency with the 1:1 line, with an R^2 of approximately 0.31. The data points are widely scattered around the 1:1 line, indicating significant divergence between the retrieved and true water depths. The RMSEs

of the ratio-log and log-ratio models exceed 6.69 m, suggesting poor performance and unsuitability for this area. This implies that these two models fail to correct for errors caused by strong scattering from abundant suspended particles and the heterogeneous bottom reflectance in Case II waters. In contrast, subplots (a) and (d) show much better agreement with the 1:1 line, with R^2 greater than 0.7. The data points are distributed closer to the 1:1 line, indicating lower divergence between the retrieved and true water depths. Their RMSEs are all below 3.2 m, demonstrating better model performance and suitability for this region. This suggests that single-band and multi-band models capture a logarithmic relationship between spectral bands and water depth. However, their accuracy is degraded by the presence of suspended particles and varying bottom reflectance. In contrast, the proposed model (see subplot(e)) incorporates topographic trends, effectively correcting the errors induced by suspended matter and bottom heterogeneity. Furthermore, as shown in Figure 7, the proposed model achieves the lowest RMSE of 2.07 m, which represents reductions of 35%, 69%, 69%, and 20% compared to single-band, ratio-log, log-ratio, and multi-band models, respectively. The proposed model also attains the highest R^2 of 0.87, representing improvements of 24%, 170%, 170%, and 9% over other models.

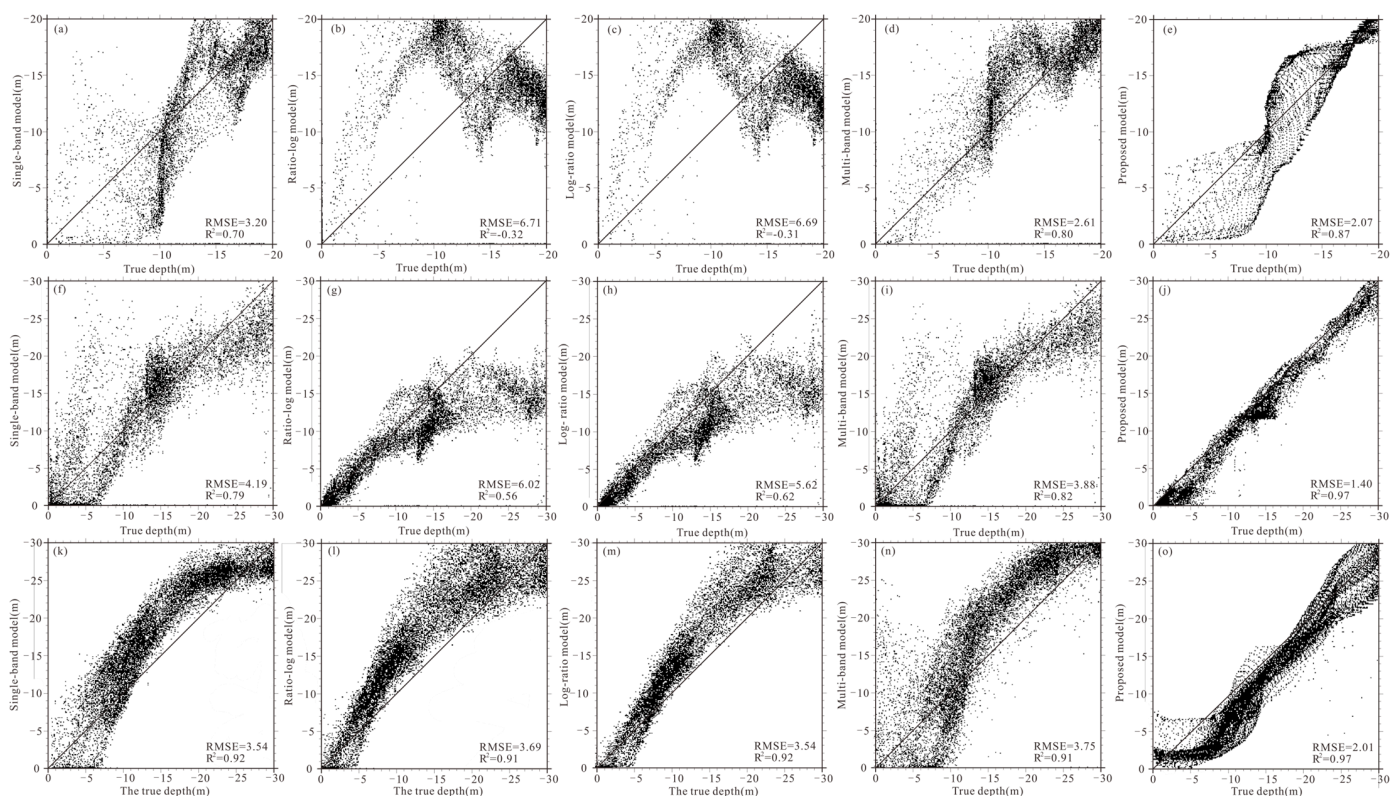


Figure 7. Validation bathymetric map vs. satellite-derived bathymetric map of Weizhou Island, Saipan Island, and Molokai Island: (a,f,k) single-band model; (b,g,l) ratio-log model; (c,h,m) log-ratio model; (d,i,n) multi-band model; (e,j,o) proposed model.

The second row of Figure 7, subplots (f)–(j), presents the scatterplots of the five models in test area 2. Subplots (f)–(i) show clear deviations from the 1:1 line, with R^2 values below 0.82. The data points are widely scattered around the 1:1 line, indicating a serious discrepancy between the retrieved and true water depths. The RMSE values of these models all exceed 3.88 m, suggesting moderate performance and unsuitability in this area. This result implies that variations in bottom types—such as sand, gravel, seagrass, and coral—cause reflectance changes that increase retrieval errors. In contrast, the scatterplot in subplot (j) shows much greater consistency with the 1:1 line, with an R^2 as high as 0.97.

The data points are densely clustered around the 1:1 line, indicating an extremely low level of dispersion between the retrieved and true water depths. The RMSE is below 1.4 m, demonstrating excellent model performance and suitability for this region. This indicates that the topographic trend incorporated in the proposed model effectively corrects the errors caused by variations in bottom reflectance. Furthermore, as shown in this figure, the proposed model achieves the lowest RMSE, which represents reductions of 66%, 75%, 77%, and 64% compared to the other models. The proposed model also attains the highest R^2 , improving by 23%, 56%, 73%, and 18% compared to the other models.

The third row of Figure 7, subplots (k)–(o), presents the scatterplots for test area 3. Subplots (k)–(n) show relatively good agreement with the 1:1 line, with all R^2 values exceeding 0.91. However, the data points remain moderately scattered from the 1:1 line, indicating a considerable discrepancy between the retrieved and true water depths. The RMSE values are all greater than 3.54 m, suggesting poor model performance and unsuitability for this region. This indicates that strong particle scattering within the water significantly affects the attenuation coefficient, resulting in reduced retrieval accuracy. In contrast, subplot (o) shows excellent consistency with the 1:1 line, with an R^2 as high as 0.97. The data points are tightly clustered around the 1:1 line, indicating a very low discrepancy between the retrieved and true water depths. The RMSE is 2.01 m, demonstrating good model performance and suitability for this area. This result shows that the topographic trend introduced in the proposed model effectively corrects the errors caused by particle scattering. Furthermore, as shown in this figure, the proposed model achieves the lowest RMSE, with reductions of 43%, 43%, 45%, and 46% compared to the other models. The proposed model also attains the highest R^2 , improving by 5%, 5%, 9%, and 9% compared to the other models.

When examined column by column, the ratio-log, log-ratio, single-band, and multi-band models show a gradual decrease in RMSE and a steady increase in R^2 from test area 1 to test area 3, corresponding to an improvement in water quality. This trend indicates that these two models are highly sensitive to water quality variations, performing well in Case I waters but poorly in Case II waters. In addition, in the shallow waters (<10 m) of test area 1, both models significantly overestimate water depth, which can be attributed to the low reflectance of basaltic substrates around Weizhou Island. In the deeper waters (>15 m) of test area 2, the retrieved depths are severely underestimated due to the high reflectance of white or light-colored carbonate sands on the seafloor. In test area 3, the retrieved water depths show a logarithmic relationship with the true depths, demonstrating that a single logarithmic transformation cannot fully linearize the relationship between satellite signals and water depth.

Single-band and multi-band models exhibit a general increase in R^2 from test area 1 to test area 3, but their RMSE values first increase and then decrease. This pattern suggests that these models are sensitive to the influence of suspended particles in the water column. Although the waters of Weizhou Island and Saipan Island are classified as Case II and Case I, the latter is home to a U.S. military base with frequent human activities that increase the concentration of suspended matter. As a result, the single-band model shows greater scatter in the retrieved depths in test area 2. Moreover, in test area 3, the single-band model still exhibits a strong logarithmic relationship with the true depths, further confirming that a single logarithmic transformation cannot linearize the relationship between satellite-derived signals and water depth.

For the proposed model, the R^2 value increases from 0.87 in test area 1 to 0.97 in test area 3, while the RMSE of 1.4 m is the smallest in test area 2, followed by 2.01 m in test area 3 and 2.07 m in test area 1. In test area 1, which is characterized by Case II water with abundant suspended particles, the retrieved depths still show some over-

and underestimation in the 0–18 m range, even after applying interpolated normalized underwater topographic trend correction. In test area 2, the interpolated topographic trend effectively corrects for errors caused by suspended particles and variations in bottom reflectance, resulting in the best RMSE and R^2 . In test area 3, the water depths within the 0–10 m range are noticeably underestimated, primarily due to the widespread presence of light-colored sandy substrates around Molokai Island, which enhances the satellite signal.

Overall, compared with the other models, the proposed model achieves significantly higher retrieval accuracy in all three test areas, reflected by improvements in both RMSE and R^2 . This demonstrates that the interpolated normalized underwater topographic trend effectively corrects errors induced by suspended particles and bottom heterogeneity, improving the accuracy of satellite-derived water depth retrievals.

4.2. Error Histogram Analysis

To evaluate the overall error and mean of the inverted water depth from the proposed model across the three study areas, we subtracted the water depths derived from the five models from the validation bathymetric map measured at the time of satellite flying to obtain the corresponding errors. Subsequently, the errors of the inverted water depth from these models were statistically analyzed using the Quick Stats tool in ENVI 5.6, and histograms were plotted to illustrate their distributions. Figure 8a–c show the error distributions of the models in test areas 1, 2, and 3.

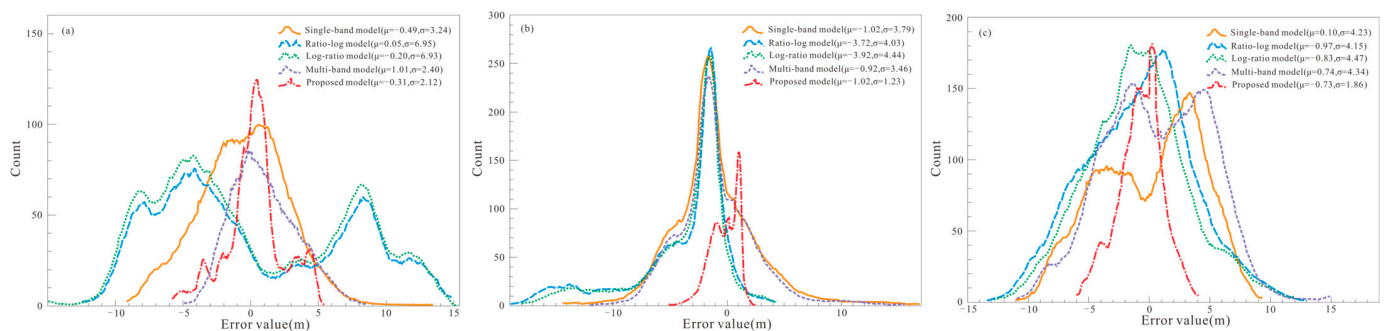


Figure 8. Error histograms of traditional models vs. the proposed model in Weizhou Island (a), Saipan Island (b), and Molokai Island (c).

As shown in Figure 8a, in test area 1, the inverted errors of the ratio-log model and the log-ratio model exhibit a tri-peaked distribution, deviating from the normal distribution. Although their mean errors are less than 0.2 m, their variances exceed 6.93 m. This indicates that these two models fail to correct the errors caused by inconsistencies in suspended particle scattering and bottom reflectance, making them unsuitable for this area. In contrast, the histograms of inversion errors from the single-band model, the multi-band model, and the proposed model display approximately normal distributions. However, their means deviate from the ideal value of 0, and their variances are greater than 2.12 m. While these three models are relatively more applicable to this region, the results also suggest that variations in bottom composition lead to shallower retrieved depths. The proposed model performs best, with the smallest absolute mean error of 0.31 m and a minimal variance of 2.12 m.

As shown in Figure 8b, in test area 2, the histograms of inverted water depth errors from the single-band, ratio-log, log-ratio, and multi-band models generally follow a normal distribution pattern, but their peaks clearly shift away from zero. The absolute mean errors of these models exceed 1.02 m, and their variances are greater than 3.46 m, indicating that variations in bottom reflectance significantly degrade their performance. The histogram of errors of the proposed model lacks the upper-left portion of the curve, but its absolute mean

error is 1.02 m, and the variance is only 1.23 m. This demonstrates that the underwater terrain trend in the proposed model effectively corrects the errors caused by variations in bottom reflectance.

As shown in Figure 8c, in test area 3, the inverted water depth error histograms of the single-band and multi-band models exhibit bimodal distributions. Although their absolute mean errors are relatively small, their variances exceed 4.23 m. The histograms of inverted water depth errors from the ratio-log and log-ratio models are roughly similar to a normal distribution. However, their absolute mean errors are greater than 0.83 m, with variances exceeding 4.15 m. This indicates that increased human activities have raised the concentration of suspended particles in the water, affecting the accuracy of inverted water depth across these four models and resulting in moderate performance in this area. In contrast, the error histogram of the proposed model conforms to a normal distribution. It has the smallest absolute mean error of 0.73 m and the lowest variance of 1.86 m. This demonstrates that incorporating the terrain trend in the proposed model effectively corrects the errors caused by scattering from suspended particles in the water.

Based on the histogram distributions and the statistical results of inverted water depth errors from the five models in test areas 1, 2, and 3, the proposed model is the best across all three regions. Its maximum absolute mean error is 1.02 m, and the largest variance is 2.12 m.

Next, we conducted a cross-comparison of the five models across the three test areas. From test area 1 to test area 3, the absolute mean error of the single-band model gradually decreases, while its variance consistently increases. This suggests that whether the water body is Case I or II, the single-band model requires further research. For the ratio-log and log-ratio models, the absolute mean error of the inverted water depth follows a “low–high–low” pattern, whereas variance shows the opposite trend of “high–low–high,” remaining above 4.03 m throughout. These results indicate that the inverted performance of these two models is relatively poor. In the case of the multi-band model, the absolute mean error continues to decrease across the three regions, but the variance keeps increasing. This demonstrates that simply increasing the number of spectral bands does not necessarily enhance the accuracy of inverted water depth. In contrast, the proposed model exhibits the lowest absolute mean errors and variances across all three test areas, effectively improving the accuracy of retrieved water depth. This confirms that incorporating the terrain trend successfully corrects the errors induced by suspended particles in the water and variations in bottom composition.

4.3. Regional Error Analysis

To more intuitively analyze the inversion errors of the proposed model, the error data from the five models were imported into ArcGIS 10.8 to generate spatial error distribution maps.

The first row of Figure 9, subfigures (a)–(e), shows the inverted water depth error maps of the models in test area 1. The areas with absolute errors less than 2 m are 4,385,954 km², 1,205,973 km², 1,272,555 km², 5,530,034 km², and 6,519,383 km², accounting for 46.77%, 12.86%, 13.57%, 58.97%, and 69.52% of the total area, respectively. As shown in subfigures (b) and (c), the ratio-log and log-ratio models achieve absolute errors below 2 m, accounting for approximately 13% of this area. Both models consistently underestimate water depth on the left side and overestimate water depth on the right, with maximum absolute errors exceeding 14.80 m. This indicates that scattering by suspended particles and variations in bottom reflectance severely affect the inversion accuracy of these two models, making them unsuitable for Case II waters. As shown in subfigure (a), the single-band model underestimates water depth in the upper-right portion of this area, primarily due to highly

reflective sandy substrates, with a maximum absolute error of 13.48 m. Subfigure (d) shows that by incorporating several additional bands, the multi-band model increases absolute errors below 2 m by 12.2% and reduces the maximum absolute error by 4.97 m in test area 1. This demonstrates that using multiple bands can correct errors caused by suspended particle scattering and variations in bottom reflectance, improving inverted water depth accuracy. As shown in subfigure (e), the proposed model slightly overestimates water depth in the upper-right region and underestimates it in the lower-right region. Nevertheless, it expands the area with absolute errors below 2 m by 22.75% and reduces the maximum absolute error by 7.65 m. While the model successfully addresses key errors from scattering and bottom variability, the results highlight its primary limitation: a need for enhanced accuracy in Case II water conditions.

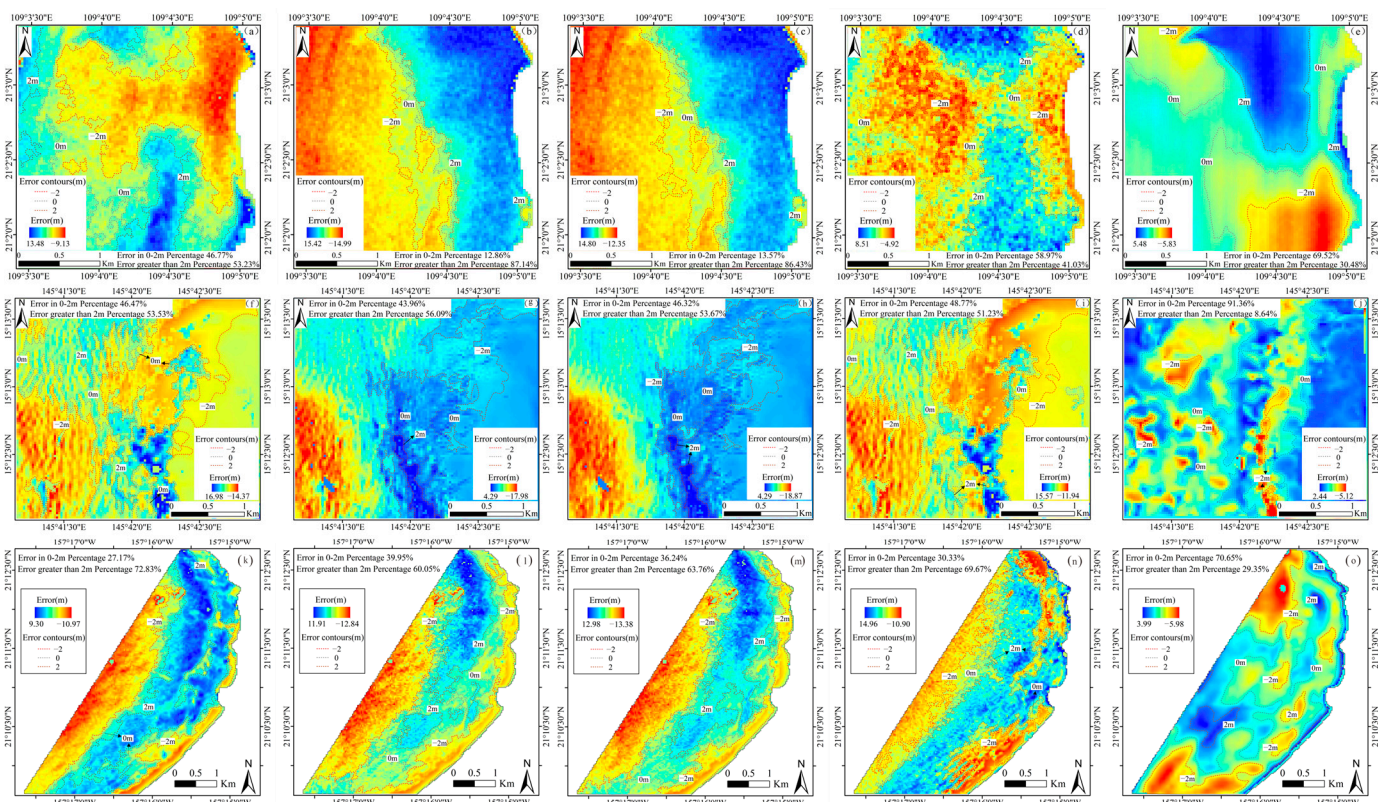


Figure 9. Bathymetric error maps of Weizhou Island, Saipan Island, and Molokai Island: (a,f,k) single-band model; (b,g,l) ratio-log model; (c,h,m) log-ratio model; (d,i,n) multi-band model; (e,j,o) proposed model.

The second row of Figure 9, subfigures (f)–(j), shows the inverted water depth error maps of the five models in test area 2. The absolute errors less than 2 m are 10.96 km², 10.37 km², 10.93 km², 11.51 km², and 21.56 km², accounting for 46.47%, 43.96%, 46.32%, 48.77%, and 91.36% of the total area, respectively. As shown in subfigures (g) and (h), the ratio-log and log-ratio models identify regions with absolute errors below 2 m that cover roughly 50% of this area. Both models continuously underestimate water depth on the left side and overestimate it on the right, with maximum absolute errors exceeding 17.98 m. This indicates that these two models fail to correct the errors caused by variations in bottom reflectance. From subfigures (f) and (i), it can be observed that the single-band and multi-band models generally overestimate water depth, which is attributed to the high reflectance of sandy substrates, with a maximum absolute error of 16.98 m. In contrast, as shown in subfigure (j), the proposed model slightly underestimates water depth only in

isolated regions. It increases the area with absolute errors below 2 m by at least 42.59% and reduces the maximum absolute error by 10.45 m.

The third row of Figure 9, subfigures (k)–(o), presents the inverted water depth error maps of the models in test area 3. The areas with absolute errors less than 2 m are 10.96 km², 10.37 km², 10.93 km², 11.51 km², and 21.56 km², accounting for 27.17%, 39.95%, 36.24%, 30.33%, and 70.65% of the total area, respectively. As shown in subfigures (k)–(n), the regions where the absolute error of inverted water depth is below 2 m are all smaller than 50% for the single-band, ratio-log, log-ratio, and multi-band models. Their maximum absolute errors all exceed 10.90 m, with significant overestimation of the mid-depth regions and underestimation of the shallow and deep regions. This indicates that these four models fail to correct errors caused by suspended sediment scattering. In contrast, as illustrated in subfigure (o), the proposed model slightly underestimates or overestimates water depth only in small areas, but it expands the area with absolute errors less than 2 m by at least 30.70% and reduces the maximum absolute error by 4.99 m. This demonstrates that the proposed model can effectively correct most of the errors induced by suspended particle scattering in the water column.

In examining the columns, from test area 1 to test area 3, absolute inverted water depth errors less than 2 m for the single-band and multi-band models gradually decrease, indicating that these models perform better in environments with higher concentrations of suspended particles. In contrast, the ratio-log and log-ratio models show poorer performance in Case II waters with abundant suspended matter but perform well in clearer Case I waters. However, the proposed model maintains absolute errors of inverted water depth below 2 m, exceeding 69.55% across all three test areas.

4.4. Check Line Error Analysis

To further validate the performance of the proposed model, the Arbitrary Profile (Transect) tool in ENVI 5.6 was used to plot the inverted water depth error profiles of the five models along check lines in each test area. In Figure 4a, check lines 1, 2, and 3 in test area 1 correspond to subfigures (a), (b), and (c) in Figure 10. In Figure 4b, check lines 1, 2, and 3 in test area 2 correspond to subfigures (d), (e), and (f) in Figure 10. In Figure 4c, check lines 1, 2, and 3 in test area 3 correspond to subfigures (h), (i), and (j) in Figure 10. Based on the dispersion of the proposed model's inversion errors, profiles of regions with absolute errors less than 2 m were drawn along the check lines.

In test area 1, the single-band and multi-band models show a decreasing trend in inverted water depth errors from left to right, with the maximum error around 5 m. This suggests that water depth is overestimated on the left, closely estimated in the middle, and underestimated on the right. From left to right, the ratio-log and log-ratio models exhibit errors ranging from −10 m to 10 m, indicating that these models are not suitable for Case II waters. The proposed model shows relatively smooth inverted errors along the first check line, with a peak in the middle due to high bottom reflectance (underestimating water depth) and an increasing error on the third check line due to low bottom reflectance (overestimating water depth). Along the first check line, the absolute errors less than 2 m for the five models are approximately 36.84%, 8.42%, 8.96%, 33.33%, and 93.33%. In the check line, these values are approximately 41.75%, 9.47%, 13.68%, 75.43%, and 96.49%. For the third check line, the percentages are approximately 24.56%, 2.63%, 2.63%, 31.58%, and 49.12%.

In test area 2, the single-band and multi-band models exhibit a pattern of inverted water depth errors that first increase, then decrease, then increase again, and finally decrease from left to right. This suggests that water depth is overestimated in the middle, while the depths on both sides are closer to the true values. The ratio-log and log-ratio models show

relatively large errors in the left half in this area. The maximum error along the first check line reaches 5 m, while for the second and third check lines, the maximum error is around 18 m, indicating that these two models are not well-suited for this region. In contrast, the proposed model exhibits relatively smooth inverted errors across all three inspection lines, with most errors remaining within 2 m. Along the first check line, the percentages of absolute errors less than 2 m for the single-band, ratio-log, log-ratio, multi-band, and proposed models are approximately 12.86%, 37.14%, 36.30%, 22.67%, and 97.14%. In the second check line, these values are approximately 48.57%, 65.71%, 64.24%, 49.14%, and 91.43%. For the third check line, the values are approximately 45.71%, 48.57%, 47.39%, 42.63%, and 95.71%.



Figure 10. Verification of single-band model, ratio-log model, log-ratio model, multi-band model, and proposed model using check lines 1, 2, and 3 for Weizhou Island (a–c); Saipan Island (d–f); and Molokai Island (g–i).

In test area 3, the single-band, ratio-log, log-ratio, and multi-band models exhibit a pattern of inverted water depth errors that decrease, then increase, then decrease, and then increase again from left to right. This indicates that the mid-depth regions are overestimated while the shallow and deep regions are underestimated. The maximum inversion error reaches up to 10 m, suggesting that these four models are not well-suited to Case I water. In contrast, the proposed model shows a relatively smooth, wave-like error distribution along all three check lines, with most errors within 2 m. Along the first check line, the proportions of absolute water depth inversion errors less than 2 m for the single-band, ratio-log, log-ratio, multi-band, and proposed models are approximately 14.43%, 17.14%, 18.00%, 27.14%, and 92.85%. In the second check line, these proportions are approximately 7.43%, 10.28%,

13.71%, 14.57%, and 55.15%. For the third check line, the values are approximately 25.43%, 22.29%, 26.29%, 21.43%, and 88.57%.

The absolute error of the check line of the proposed model in test areas 1, 2, and 3 is concentrated in the range of $-2\text{ m}\sim 2\text{ m}$, accounting for an average of 79.33%, 91.67%, and 87.17%. Accordingly, the proposed model has the smallest check line error and the best results in all test areas.

4.5. Check Point Error Analysis

(1) Test Area 1: Weizhou Island, China

Table 1 lists the multibeam bathymetric map and model-retrieved depths at seven check points for Weizhou Island. According to Table 6, we calculated the maximum absolute error, mean absolute error, and RMSE for the single-band, log-ratio, ratio-log, multi-band, and proposed models (see Table 7). Table 7 shows that the proposed model achieves optimal values for all three metrics: maximum absolute error (3.35 m), mean absolute error (1.39 m), and RMSE (1.73 m). As shown in Table 8, compared to the single-band model, the log-ratio model, the ratio-log model, and the multi-band model, the proposed model achieves reduction rates of 53.97% for the maximum absolute error, 50% for the mean absolute error, and 26.86% for RMSE.

Table 6. Check point data for Weizhou Island.

ID	True Depth (m)	Single-Band Model (m)	Ratio-Log Model (m)	Log-Ratio Model (m)	Multi-Band Model (m)	Proposed Model (m)
1	−20.91	−21.63	−10.03	−10.08	−19.45	−19.84
2	−10.18	−6.51	−23.79	−24.09	−14.76	−12.38
3	−19.27	−16.68	−13	−13.1	−16.6	−19.22
4	−11.16	−7.56	−19.44	−19.27	−12.64	−14.51
5	−15.45	−16.11	−12.59	−12.66	−15.95	−15.02
6	−19.85	−24	−13.52	−13.73	−24.19	−21.22
7	−3.08	−8.82	−12.54	−12.51	−9.58	−1.83

Table 7. Comparison of traditional models at check points for Weizhou Island.

Model	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band model	5.74	3.02	3.46
Ratio-log model	13.61	8.24	8.86
Log-ratio model	13.91	8.19	8.85
Multi-band model	4.58	3.08	3.66
Proposed model	3.35	1.39	1.73

Table 8. Error reduction rates of the proposed model vs. traditional models.

Model	Error Reduction Rates		
	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band model	41.64%	53.97%	50%
Ratio-log model	75.39%	83.13%	80.47%
Log-ratio model	75.92%	83.03%	80.45%
Multi-band model	26.86%	54.87%	52.73%

(2) Test Area 2: Saipan Island waters, USA

Table 9 lists the LiDAR bathymetric map and model-retrieved depths at seven check points for Saipan Island. According to Table 9, we calculated the maximum absolute error,

mean absolute error, and RMSE for the single-band, log-ratio, ratio-log, multi-band, and proposed models (see Table 10). Table 10 shows that the proposed model achieves optimal values for all three metrics: maximum absolute error (1.57 m), mean absolute error (0.93 m), and RMSE (0.99 m). As shown in Table 11, compared to the single-band, log-ratio, ratio-log, and multi-band models, the proposed model achieves reduction rates of 39.8% for the maximum absolute error, 29.5% for the mean absolute error, and 31.7% for RMSE.

Table 9. Check point data for Saipan Island.

ID	True Depth (m)	Single-Band Model (m)	Ratio-Log Model (m)	Log-Ratio Model (m)	Multi-Band Model (m)	Proposed Model (m)
1	−15.56	−13.76	−10.47	−10.5	−14.7	−17.13
2	−13.33	−14.51	−6.40	−6.51	−14.39	−12.44
3	−2.61	0.00	0.00	0.00	0.00	−3.21
4	−17.25	−18.26	−11.34	−10.99	−18.36	−16.52
5	−2.43	−3.61	−0.3	−0.54	−3.12	−2.07
6	−27.29	−25.69	−17.43	−15.76	−26.03	−26.13
7	−1.47	−2.65	0.00	0.00	−3.14	−2.64

Table 10. Comparison of traditional models at check points for Saipan Island.

Model	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band model	2.61	1.51	1.60
Ratio-log model	9.86	4.85	5.60
Log-ratio model	11.53	5.09	6.06
Multi-band model	2.61	1.32	1.45
Proposed model	1.57	0.93	0.99

Table 11. Error reduction rates of the proposed model vs. traditional models.

Model	Error Reduction Rates		
	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band Model	39.8%	38.4%	38.1%
Ratio-log Model	84.1%	80.8%	82.3%
Log-ratio Model	86.3%	81.7%	83.6%
Multi-band Model	39.8%	29.5%	31.7%

(3) Test Area 3: Molokai Island, USA

Table 12 lists the LiDAR bathymetric map and model-retrieved depths at seven check points for Molokai Island. According to Table 12, we calculated the maximum absolute error, mean absolute error, and RMSE for the single-band, log-ratio, ratio-log, multi-band, and proposed models (see Table 13). Table 13 shows that the proposed model achieves optimal values for all three metrics: maximum absolute error (4.33 m), mean absolute error (1.61 m), and RMSE (2.09 m). As shown in Table 14, compared to the single-band, log-ratio, ratio-log, and multi-band models, the proposed model achieves reduction rates of 10.2% for the maximum absolute error, 43.3% for the mean absolute error, and 30.6% for RMSE.

According to the check point analysis, the proposed model achieves the best results for the maximum absolute error, the average absolute error, and RMSE across test areas 1, 2, and 3, with an average of 3.08, 1.31, and 1.60 and reduction rates of 34.33%, 40.93%, and 29.72%. Accordingly, the proposed model has the smallest inversion error and the best results for all check points across the three test areas. In particular, the proposed model demonstrates superior accuracy compared to the single-band model, with RMSE

improvements of 35% (Weizhou Island), 66% (Saipan Island), and 43% (Molokai Island). Corresponding R^2 increases are 24.28%, 23%, and 5%. On average, it reduces RMSE by 48% and enhances R^2 by 17.43%.

Table 12. Check point data for Molokai Island.

ID	True Depth (m)	Single-Band Model (m)	Ratio-Log Model (m)	Log-Ratio Model (m)	Multi-Band Model (m)	Proposed Model (m)
1	−17.35	−25.77	−27.69	−27.69	−19.71	−16.89
2	−33.24	−26.84	−26.7	−26.23	−30.68	−33.23
3	−10.9	−16.33	−11.07	−11.92	−13.67	−9.83
4	−33.82	−27.98	−28.18	−27.31	−31.95	−36.15
5	−14.04	−18.82	−17.16	−18.43	−18.86	−15.22
6	−31.97	−28.94	−31.94	−30.71	−30	−30.06
7	−14.36	−17.86	−14.6	−15.72	−17.94	−10.03

Table 13. Comparison of traditional models at check points for Molokai Island.

Model	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band model	8.42	5.34	5.60
Ratio-log model	10.34	3.72	5.23
Log-ratio model	10.34	4.55	5.63
Multi-band model	4.82	2.84	3.01
Proposed model	4.33	1.61	2.09

Table 14. Error reduction rates of the proposed model vs. traditional models.

Model	Error Reduction Rates		
	Maximum Absolute Error	Mean Absolute Error	RMSE
Single-band model	48.6%	69.8%	62.6%
Ratio-log model	58.1%	56.7%	60.0%
Log-ratio model	58.1%	64.6%	62.8%
Multi-band model	10.2%	43.3%	30.6%

5. Discussion

5.1. Interpretation of Results: Confronting the Core Challenge in SDB

The central challenge in satellite-derived bathymetry (SDB) lies in decoupling the water depth signal from the confounding effects of water column optics and variable bottom albedo. This study directly addresses this by the proposed model, i.e., NSDB model, which integrates a prior low-resolution reference bathymetric data into the SDB. The results robustly validate this approach: the NSDB model achieved an average improvement of 48% in RMSE and 17.43% in R^2 over the single-band model across diverse sites. Crucially, the most significant gains were observed where traditional models fail most, as in the turbid Case II waters of Weizhou Island, where RMSE and R^2 were reduced at least 20% and 9%, respectively. This model confirms that the interpolated normalized topographic trend acts not as a simple offset, but as a reference information, effectively resolving an ill-posed inversion parameter problem caused by optical heterogeneity. This finding demonstrates that widely available global bathymetric data can be leveraged for practical, large-scale accuracy enhancement.

5.2. Methodological Contribution: A Physically Interpretable Alternative

The methodological contribution of this work is twofold. First, it introduces a corrective fusion framework that is both transparent and grounded in radiative transfer principles. Unlike purely data-driven machine learning (ML) models (i.e., the Adaptive-Geographically Weighted Regression Model [51], the spatially distributed support vector machine [52–56], Random Forest [57], Subspace K-Nearest Neighbor [58], Bagged Tree [58], eXtreme Gradient Boosting (XGBoost) [59], the Light Gradient Boosting Machine (LightGBM) [59], Categorical Boosting [60], and Gradient Boosting [61]), which often function as “black boxes” and require extensive, location-specific training data, the NSDB model offers inherent interpretability. Its parameters and the constraint mechanism have clear physical meanings, facilitating error analysis and trust in operational settings, particularly in data-sparse regions. Second, it reasserts the value of physics-based semi-empirical models in an era dominated by ML. While ML can achieve high accuracy in controlled datasets, our model demonstrates that fusing physical principles with strategic data integration provides superior generalizability across different optical water types (Cases I and II) without retraining the model. This represents a critical trade-off, prioritizing robustness and operational efficiency over peak performance in a single, well-sampled domain.

5.3. Limitations and Scope for Operational Application

The performance and applicability of the NSDB model are bounded by several factors. First, the accuracy of the model is inherently dependent on the quality and resolution of the input low-resolution reference bathymetric data. This dependence means that the required interpolation (Equation (3)) and normalization (Equation (4)) procedures inevitably introduce smoothing and potential errors, particularly in areas of complex terrain. Second, while accuracy is markedly improved, the residual errors (i.e., mean absolute errors of 0.93–1.61 m at check points) indicate that the proposed model, in its current iteration, may not yet meet the most stringent standards for applications like nautical charting under the International Hydrographic Organization’s highest orders. The most significant limitation is the boundary of validation. The proposed model’s efficacy has been proven in standard coastal waters but remains untested in optically extreme environments such as highly turbid estuaries, inland lakes rich in dissolved organic matter (CDOM), or sediment-laden rivers. Its performance in these complex aquatic systems, which are critical for comprehensive environmental monitoring, is an open question and the primary constraint on its universal deployment.

5.4. Future Research Directions

To transcend these limitations and build upon this work, we propose the following focused research trajectories:

Validation in Complex Inland and Coastal Waters: Extending rigorous testing to environments like rivers, reservoirs, and algal bloom-affected coastal zones is essential to fully map the model’s operational envelope and guide potential algorithmic adaptations.

Enhanced Prior Data Fusion: The interpolation uncertainty from coarse trends must be reduced. A promising path is the synergistic fusion of multi-source prior data, such as blending GEBCO with sparse but high-accuracy bathymetric points from satellite LiDAR (e.g., ICESat-2) or airborne bathymetry LiDAR (e.g., GQ-23, YellowScan Navigator, RIEGL VQ-840-G) within a geostatistical framework.

Development of Hybrid Active-Passive Systems: To bridge the gap towards engineering-grade bathymetry (e.g., 1:1000 scale), future work should develop robust data fusion algorithms. These would integrate the continuous, moderate-accuracy NSDB maps with

discrete, high-accuracy measurements from shipborne sonar or airborne lidar, optimizing the strengths of each sensor type.

Open-Source Implementation and Benchmarking: Releasing the NSDB processing workflow as an open-source toolkit (e.g., a Python package or QGIS plugin) would foster community adoption, independent validation, and collaborative improvement, accelerating methodological progress and application in global coastal management.

6. Conclusions

Traditional satellite-derived bathymetry (SDB) models are prone to significant errors due to variable optical conditions, such as water column scattering and diverse bottom reflectance. This study presents a novel normalized satellite-derived bathymetry (NSDB) model that addresses this limitation by integrating an interpolated low-resolution topographic trend into a single-band inversion framework. This fusion method effectively corrects for complex optical interference by spatially constraining depth retrieval with prior geomorphic information.

Validation across three Case II water regions—Weizhou Island (China), Saipan Island, and Molokai Island (USA)—demonstrates that the NSDB model reduces RMSE by at least 35%, 43%, 45%, and 20% compared to the single-band, ratio-log, log-ratio, and multi-band models, respectively, while increasing R^2 by at least 5%, 5%, 9%, and 9%. These results confirm that the model significantly enhances SDB accuracy, even with sparse in situ depth data. Although most errors fall within 0–2 m, the current accuracy does not yet meet the stringent standards required for 1:1000-scale engineering bathymetry.

The core methodological contribution of this work lies in the corrective fusion of low-resolution topographic trends, which enhances robustness against optical variability and advances the operational viability of satellite-derived bathymetry. Future work will evaluate the model's performance in more complex aquatic environments—such as nearshore zones, rivers, lakes, and reservoirs—and explore its integration into hybrid bathymetric systems combining green band imaging and active-passive LiDAR to achieve high-precision, large-scale underwater mapping.

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