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A Hybrid Dropout Method for High-Precision Seafloor Topography Reconstruction and Uncertainty Quantification

Xinye Cui ¹ , Houpu Li ^{1,*}, Yanting Yu ¹, Shaofeng Bian ¹ and Guojun Zhai ²

¹ School of Electrical Engineering, Naval University of Engineering, Wuhan 430033, China; m24181101@nue.edu.cn (X.C.); 1010042002@nue.edu.cn (Y.Y.); sfbian@sina.com (S.B.)

² Key Laboratory of Geological Exploration and Evaluation, Ministry of Education, China University of Geosciences, Wuhan 430074, China; zhaigj@163.com

* Correspondence: lihoup1985@126.com; Tel.: +86-186-0714-3761

Abstract: Seafloor topography super-resolution reconstruction is critical for marine resource exploration, geological monitoring, and navigation safety. However, sparse acoustic data frequently result in the loss of high-frequency details, and traditional deep learning models exhibit limitations in uncertainty quantification, impeding their practical application. To address these challenges, this study systematically investigates the combined effects of various regularization strategies and uncertainty quantification modules. It proposes a hybrid dropout model that jointly optimizes high-precision reconstruction and uncertainty estimation. The model integrates residual blocks, squeeze-and-excitation (SE) modules, and a multi-scale feature extraction network while employing Monte Carlo Dropout (MC-Dropout) alongside heteroscedastic noise modeling to dynamically gate the uncertainty quantification process. By adaptively modulating the regularization strength based on feature activations, the model preserves high-frequency information and accurately estimates predictive uncertainty. The experimental results demonstrate significant improvements in the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Peak Signal-to-Noise Ratio (PSNR). Compared to conventional dropout architectures, the proposed method achieves a PSNR increase of 46.5% to 60.5% in test regions with a marked reduction in artifacts. Overall, the synergistic effect of employed regularization strategies and uncertainty quantification modules substantially enhances detail recovery and robustness in complex seafloor topography reconstruction, offering valuable theoretical insights and practical guidance for further optimization of deep learning models in challenging applications.

Keywords: super-resolution reconstruction; uncertainty quantification; seafloor topography; deep learning; heteroscedastic noise modeling



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1. Introduction

Bathymetric super-resolution reconstruction (BSRR), situated at the intersection of marine geophysics and artificial intelligence, addresses the fundamental challenge of reconstructing high-resolution seafloor topography with rich details from sparse shipborne sonar data or low-resolution satellite altimetry. This technology not only supports marine resource exploration, geological structure analysis, and navigational safety [1–3] but also constitutes a critical component of modern marine research. Traditional seafloor mapping techniques primarily rely on multibeam and side-scan sonar; however, these methods are limited by sensor resolution [4], environmental noise [5], and data sparsity [6], making the accurate recovery of high-frequency details in complex terrains such as seamounts and fault zones particularly challenging.

To mitigate data insufficiency, traditional interpolation methods—including linear, polynomial, inverse distance weighting, Kriging, and spline interpolation—have been employed [7–11]. Nevertheless, these methods often struggle with noise suppression and the recovery of fine details [12,13]. In recent years, deep learning techniques have made significant strides in image super-resolution. Approaches such as SRCNN [14], proposed by Dong et al., and VDSR [15], designed by Kim et al., have markedly improved reconstruction accuracy through deep convolutional networks, while generative adversarial networks (GANs), such as SRGAN [16], further enhance image realism. Notably, multi-scale convolutional networks [15] applied to seafloor image super-resolution have considerably improved the recovery of high-frequency details [17,18], thereby offering innovative tools for seafloor topography reconstruction.

However, existing deep learning methods typically yield deterministic reconstruction results and fail to address the ill-posed nature of mapping a single low-resolution input to multiple plausible high-resolution outputs [19,20]. This shortfall can introduce bias and unreliability in downstream processing, especially in morphologically complex seafloor environments. Uncertainty quantification—which involves both data-related aleatoric uncertainty and model-related epistemic uncertainty [21]—is essential for overcoming these challenges. Bayesian deep learning provides a rigorous framework for modeling uncertainty, with Gal and Ghahramani demonstrating that MC-Dropout during inference can serve as a Bayesian approximation method through repeated sampling [22]. Kendall and Gal further investigated the joint modeling of both types of uncertainty [19], proposing an improved Bayesian inference strategy for remote sensing data that lays a theoretical foundation for uncertainty estimation in complex environments. Nonetheless, standard MC-Dropout employs a fixed dropout rate, which may be inadequate for capturing local feature variations in complex seafloor topography, potentially leading to insufficient local detail capture [23]. Consequently, adaptive dropout methods have been introduced in recent years to dynamically adjust dropout rates based on input features, thereby enhancing detail recovery [24–27]. Moreover, GAN-based reconstruction methods have provided novel perspectives on uncertainty quantification by synergistically improving detail preservation and visual fidelity [28]. Although deep ensemble methods excel in uncertainty estimation, their high computational cost limits practical application [29]. Therefore, developing an efficient and precise method for jointly modeling complex seafloor features and reliably quantifying uncertainty remains an urgent scientific challenge.

This study introduces a hybrid Bayesian deep learning framework that integrates MC-Dropout with adaptive dropout. Through multiple forward passes, this framework constructs a predictive distribution while dynamically adjusting local feature extraction [30–32]. The innovative architecture incorporates a multi-scale feature extraction network comprising residual blocks and channel attention mechanisms (SE modules) alongside an up-sampling architecture using sub-pixel convolution and global residual connections to strengthen low-frequency information propagation. This approach enables sub-grid-level uncertainty quantification while preserving high reconstruction accuracy [13,15,33–35]. By leveraging deep learning's robust feature extraction capabilities and the rigorous aleatoric (data noise) and epistemic (model ambiguity) uncertainties of the Bayesian framework, this method effectively tackles the complexities of reconstructing intricate seafloor topography. The primary contributions of this research are as follows:

1. It introduces a hybrid Bayesian deep learning framework that integrates MC-Dropout with adaptive dropout, achieving the concurrent optimization of high-precision reconstruction and uncertainty quantification in seafloor topography reconstruction.
2. It analyzes the comprehensive impact of various regularization and uncertainty quantification modules on seafloor topography reconstruction. Traditional models apply

- uniform regularization, whereas SE-guided adaptive dropout dynamically adjusts to local seabed complexity, enabling risk-sensitive decision-making in marine operations.
- It presents the design of a multi-scale feature extraction network that integrates residual blocks with SE modules and employs sub-pixel convolution and global residual connections during up-sampling, effectively enhancing low-frequency information transfer and recovering high-frequency details.

2. Materials and Methods

In this work, we present a deep learning framework that constructs a multi-scale feature extraction network by integrating residual blocks with SE modules and employs sub-pixel convolution along with global residual connections during the up-sampling stage. Building on this foundation, we design a series of five experiments that progressively incorporate MC-Dropout and adaptive dropout to quantify model prediction uncertainty. A joint loss function is then utilized to balance reconstruction accuracy and structural consistency, thereby completing the training and inference process.

2.1. Overall Network Architecture

The proposed deep multi-scale residual network is primarily designed for image super-resolution tasks, aiming to strike a balance between reconstruction precision and uncertainty quantification. Through multi-scale feature extraction, dynamic regularization, and uncertainty modeling, the network effectively captures detailed information across various scales and provides probabilistic interpretations for the predictions. The overall architecture is illustrated in Figure 1.

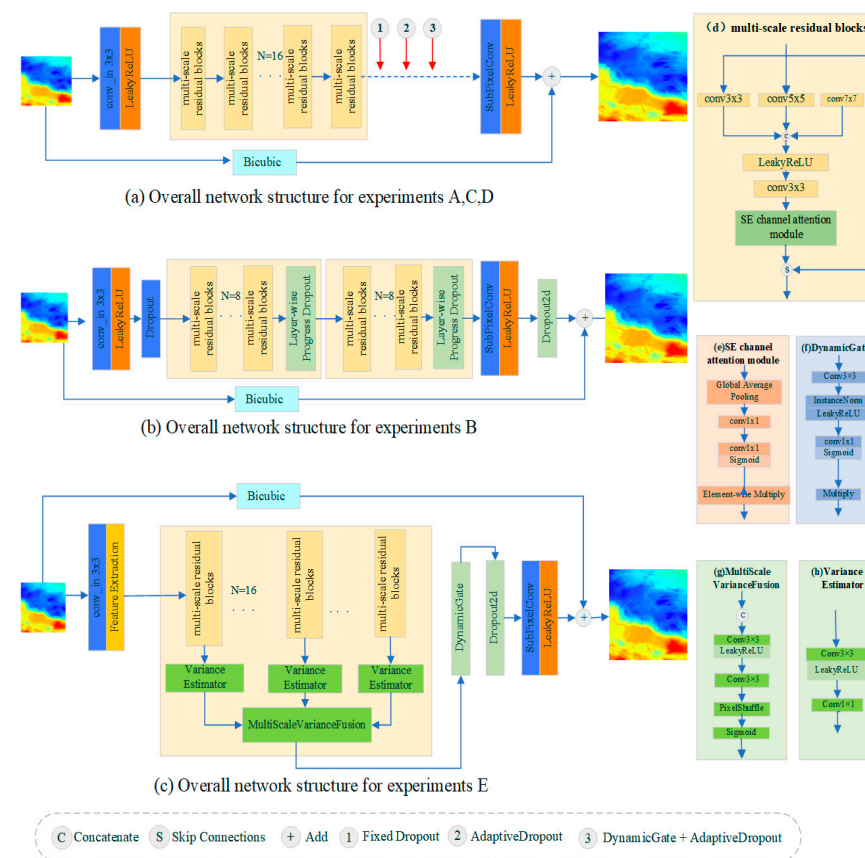


Figure 1. Schematic diagram of network architecture. (a) Overall network structure for experiments A,C,D. (b) Overall network structure for experiments B. (c) Overall network structure for experiments E. (d) multi-scale residual blocks. (e) SE channel attention module. (f) DynamicGate. (g) MultiScale VarianceFusion. (h) Variance Estimator.

Figure 1 illustrates five experimental configurations (Methods A–E), where the three key uncertainty quantization modules (labeled with circles ①–③) in Figure 1a correspond to Methods A, C, and D. The multiscale residual block (Figure 1d), the SE channel attention module (Figure 1e), the dynamical gate (Figure 1f), the multiscale variance fusion module (Figure 1g), and the variance estimator modules (Figure 1h) are systematically analyzed in subsequent sections.

2.2. SE Channel Attention Module

The network incorporates the squeeze-and-excitation (SE) module [36] to dynamically adjust the importance of each channel. As shown in Figure 1e, the module first compresses each channel using global average pooling to capture global context. Then, fully connected layers are used to model inter-channel dependencies, generating attention weights to recalibrate the input features. The mathematical expressions for this operation are

$$Z_c = \frac{1}{H \cdot W} \sum_{i=1}^H \sum_{j=1}^W F_c(i, j) \quad (1)$$

$$s_c = \sigma(W_2 \cdot \delta(W_1 \cdot Z_c)) \quad (2)$$

Here, Z_c denotes the compressed feature for channel c , $F_c(i, j)$ is the value at position (i, j) in the input feature map for channel c , s_c represents the attention weight for channel c , W_1 and W_2 are the fully connected layer weights, δ is the ReLU activation function, and σ is the Sigmoid function, which produces values in the range of $[0, 1]$ to modulate channel importance.

By enabling the adaptive calibration of features, this module helps emphasize crucial information and strengthens the network's capacity to capture relevant details.

2.3. Multi-Scale Residual Blocks

Due to the varying feature distributions across scales, the network utilizes parallel convolutions with 3×3 , 5×5 , and 7×7 kernels within each residual block to capture multi-scale features. These features are then concatenated along the channel axis and fused through a 3×3 convolution. Afterward, the merged features are processed through an SE module to further emphasize the most significant information (Figure 1d). The multi-scale extraction procedure can be mathematically expressed as

$$F_{out} = SE(Concat(Conv_{3 \times 3}(F_{in}), Conv_{5 \times 5}(F_{in}), Conv_{7 \times 7}(F_{in}))) + F_{in} \quad (3)$$

Here, F_{in} is the input feature and F_{out} is the output feature. This approach allows the network to leverage information from various receptive fields. Furthermore, residual connections [37] alleviate gradient vanishing issues, which is crucial for enabling the effective training of deep architectures.

2.4. Sub-Pixel Convolution Module

To achieve high-resolution reconstruction, we adopt sub-pixel convolution up-sampling [38]. This method offers both efficient up-sampling and effective utilization of low-frequency components present in the low-resolution input. In practice, the network first performs a PixelShuffle operation to rearrange pixels and generate high-resolution features. Simultaneously, bicubic interpolation [39] is employed to capture low-frequency components, which are then added to the high-resolution features to preserve background smoothness. The process can be expressed as

$$F_{HR} = PixelShuffle(Conv_{3 \times 3}(F_{LR})) + Bicubic(F_{LR}) \quad (4)$$

In this case, F_{HR} represents high-resolution output features, and *Pixelshuffle* refers to the low-resolution input features. F_{LR} denotes the p-sampling transformation. This technique retains the low-frequency advantages of conventional interpolation while enhancing high-frequency detail through network prediction.

2.5. Regularization and Uncertainty Quantification Module

Incorporating various regularization and uncertainty modeling strategies into the network is essential for improving generalization and quantifying prediction uncertainty. These strategies are evaluated through a series of experiments, detailed below.

Experiment A: Fixed Dropout

Dropout is widely employed as a regularization technique, where the random omission of neuron activations helps reduce overfitting. Research indicates that placing a dropout layer near the output of feature extraction and reconstruction networks improves performance [40]. Therefore, a fixed dropout rate of 0.01 is applied between the Residual-Block and SubPixelConv layers. This introduces randomness during training, enhancing robustness and preventing overfitting on the training set.

Experiment B: Layer-wise Progressive Dropout

This strategy adjusts dropout rates based on the depth and complexity of the network layers. In shallow layers, lower dropout rates are used, which gradually increase as the network deepens [22,41]. Specifically, after the initial 3×3 convolution (64 output feature maps), a Dropout2d layer with $p = 0.01$ is applied to prevent overfitting in early layers. The next eight residual blocks utilize Dropout2d with $p = 0.05$, while the subsequent blocks increase the dropout rate to $p = 0.1$. Finally, Dropout2d ($p = 0.1$) is applied after sub-pixel up-sampling to further regularize the output.

Experiment C: Activation Intensity-driven Adaptive Dropout

This method introduces a novel approach to regularization by adjusting the dropout rate based on the local activation intensity. The dropout probability for each spatial location is dynamically modulated according to the mean activation value on the feature map [42,43]. The corresponding formula is

$$p_{adaptive} = clip(p_{base} \cdot e^{-k \cdot mean(|F|)}, 0, 1) \quad (5)$$

In this case, p_{base} is the base dropout rate, and k is a decay coefficient that controls the dropout rate in different regions. High-activation areas (such as edges) experience a reduced dropout rate ($\sim 5\%$), while low-activation regions (such as smooth backgrounds) see an increased rate ($\sim 35\%$). This allows for more granular regularization, enabling the model to preserve edge and detail information while controlling the background.

Experiment D: Dynamic Gate Network

The dynamic gated network introduces a gating module (Figure 1f) to adjust the importance of each channel. Using learned gating coefficients, the module can fine-tune feature selection, focusing on relevant information. This gating mechanism is applied after the residual block stack and before the up-sampling stage. A 1×1 convolution generates initial gating weights, which are normalized through Batch Normalization [44], followed by ReLU activation and Sigmoid to produce gating coefficients G within the range of $[0, 1]$:

$$G = \sigma(BN(Conv_{1 \times 1}(F))) \quad (6)$$

where F is the output feature of the residual block and G is used to weigh F on a channel-by-channel basis. This mechanism allows for the selective enhancement of important features and the suppression of less relevant ones, improving feature extraction performance in complex data [45,46].

Experiment E: Multi-stage Uncertainty Quantification

Multi-stage uncertainty quantification incorporates strategies for modeling both epistemic uncertainty with MC-Dropout and aleatoric uncertainty with heteroscedastic noise. This design not only facilitates an assessment of the reliability and certainty of predictions but also offers a probabilistic interpretation of the outputs, thereby enhancing both the transparency and practical robustness of the model [22,47,48]. As a result, the experiments adopt a two-stage uncertainty modeling strategy that bolsters the model's ability to evaluate prediction uncertainty and overall robustness. By integrating various network modules and optimization strategies, the model is capable of accurately quantifying and calibrating these uncertainties, which is crucial for addressing the challenges of complex image super-resolution tasks.

Stage 1: Epistemic Uncertainty via MC-Dropout

Within the Bayesian deep learning framework, we quantify epistemic uncertainty through a Monte Carlo (MC) approximation approach. By retaining dropout layer activation during inference and performing $T = 50$ stochastic forward passes, this random sampling process approximates the posterior distribution mathematically as

$$\mu(x) = \frac{1}{T} \sum_{t=1}^T f_{\theta}(x^{(t)}) \quad (7)$$

$$\sigma_{epistemic}^2(x) = \frac{1}{T-1} \sum_{t=1}^T (f_{\theta}(x^{(t)}) - \mu(x))^2 \quad (8)$$

Here, $x^{(t)}$ denotes the input with stochastic perturbation at the t -th sampling iteration, and $f_{\theta}(x^{(t)})$ represents the network mapping function parameterized by θ . The mean estimate $\mu(x)$ aggregates distribution characteristics across parameter space through multi-sample averaging, while the variance term $\sigma_{epistemic}^2(x)$ quantifies parametric uncertainty. We employ unbiased sample variance estimation (using $T-1$ denominator) to ensure statistical validity under limited sampling. Spatial heterogeneity in $\sigma_{epistemic}^2(x)$ becomes prominent along complex topographic boundaries like submarine cliffs and volcanic cones, reflecting prediction multiplicity.

Stage 2: Aleatoric Uncertainty via Heteroscedastic Noise

A dedicated noise prediction branch is introduced to estimate the data-dependent variance $\sigma_{aleatoric}^2$. The model is trained using a joint loss function defined as

$$L_{NLL} = \frac{1}{2N} \sum_{i=1}^N \left[\frac{(y_i - \mu_i)^2}{\sigma_{aleatoric}^2} + \log(\sigma_{aleatoric}^2) \right] \quad (9)$$

In this case, μ_i is the predicted mean, $\sigma_{aleatoric}^2$ is the uncertainty estimate, and y_i is the ground truth. Lightweight modules like MultiScaleVarianceFusion and VarianceEstimator (Figure 1g,h) compute and combine variance maps from multiple scales to refine aleatoric uncertainty estimates. The VarianceEstimator is a lightweight network designed to estimate variance, operating on multi-scale features to produce a single-channel uncertainty map that reflects the predicted variance for each pixel. Meanwhile, the MultiScaleVarianceFusion module utilizes PixelShuffle up-sampling to merge variance maps estimated at different scales, achieving precise quantification of aleatoric uncertainty. The final joint loss function integrates negative log-likelihood, structural similarity (SSIM), and epistemic uncertainty regularization terms. L_{NLL} balances reconstruction error and variance estimation to prevent

overconfidence, which predicts the mean as μ_i , estimates the uncertainty (variance) as σ_i^2 , and compares it to the true value y_i :

$$L_{NLL} = \frac{1}{N} \sum_{i=1}^N \left[\frac{(y_i - \mu_i)^2}{2\sigma_i^2} + \frac{1}{2} \log \sigma_i^2 \right] \quad (10)$$

SSIM loss (L_{SSIM}) ensures structural consistency by comparing the predicted mean with the ground truth:

$$L_{SSIM} = 1 - SSIM(y, \mu) \quad (11)$$

where y and μ are the true image and predicted mean, respectively.

Additionally, an epistemic uncertainty regularization term is incorporated to further suppress overfitting and enhance robustness:

$$L_{epistemic} = \gamma \cdot \frac{1}{N} \sum_{i=1}^N \log(mc_var_i + \epsilon) \quad (12)$$

Here, γ is the regularization weight, mc_var_i represents the epistemic uncertainty at each location, ϵ is a small constant to prevent numerical instability, and N is the number of pixels or samples averaged.

The overall joint loss function is expressed as

$$L_{total} = \alpha L_{NLL} + \beta L_{SSIM} + \gamma L_{epistemic} \quad (13)$$

where the coefficients α , β , and γ adjust the contributions of each term, allowing the model to balance image quality (e.g., SSIM [49]) and uncertainty.

Regularization is critical in deep learning models, preventing overfitting and enhancing generalization and stability. Three dropout strategies were compared based on activation intensity: fixed, hierarchical progressive, and adaptive. Despite implementation differences—fixed dropout randomly drops neurons uniformly, hierarchical progressive dropout adjusts rates by layer, and adaptive dropout varies with local activation—they all aim to reduce dependency on specific features, boosting robustness on unseen data. Introducing dynamic gated networks (DG-ADM) optimizes feature selection by adjusting channel importance via learned weights, enhancing key feature clarity by suppressing noise. Comparative dropout strategy analysis underscored the synergy between regularization and feature selection. Experimental findings validated an uncertainty quantification module, offering probabilistic predictions and, coupled with regularization, curbing overfitting while bolstering model reliability in complex scenarios.

3. Experiments

3.1. Dataset Selection and Preprocessing

In recent decades, the importance of seafloor maps has become increasingly evident. Despite their relatively coarse resolutions, global digital bathymetric models (DBMs) like ETOPO_2023 [50] and GEBCO_2024 [51] have been extensively utilized to clarify complex oceanic processes and geological features. In contrast, some countries, including Australia, have released regional high-resolution (HR) seafloor datasets—for example, the 1-arc-second digital elevation models (DEMs) of the Torres Strait and Bass Strait. These datasets integrate multi-beam echo sounding, airborne LiDAR, and satellite-derived bathymetry and are standardized under the WGS84 horizontal datum and mean sea level vertical datum to ensure geospatial consistency. In this study, we formulate a super-resolution reconstruction task based on the aforementioned HR DEMs, with detailed data information provided in Table 1. To enhance training efficiency, large-area DEMs were divided into fixed,

non-overlapping sub-blocks (256×256) to serve as supervision signals, yielding a total of 16,960 sub-blocks from the two regional DEMs. Low-resolution input data (64×64) were generated via uniform down-sampling to create paired input–output datasets. For model optimization, 90% of the data (15,264 pairs) were allocated for training, with the remaining 10% (1696 pairs) reserved for performance evaluation. Moreover, to eliminate scale differences in water depth across various marine regions, all data were linearly normalized [52] to a range of -1 to 1 , thereby enhancing model convergence and generalization.

Table 1. Information about HR regional DBM datasets.

Number	Grid Spacing	Additional Information	Data Access
1	1 arcsecond	Bass Strait Bathymetry, 2022, 30 m	http://pid.geoscience.gov.au/dataset/ga/147043 (accessed on 23 November 2024)
2	1 arcsecond	Australian Bathymetry Topography (Torres Strait), 2023, 30 m	https://pid.geoscience.gov.au/dataset/ga/144348 (accessed on 23 November 2024)
3	1 arcsecond	Great Barrier Reef A, 2020, 30 m, 10° – 17° S, 143° – 147° E	https://pid.geoscience.gov.au/dataset/ga/115066 (accessed on 23 November 2024)
		Great Barrier Reef B, 2020, 30 m, 16° – 23° S, 144° – 149° E	
		Great Barrier Reef C, 2020, 30 m, 18° – 24° S, 148° – 154° E	
		Great Barrier Reef D, 2020, 30 m, 23° – 29° S, 150° – 156° E	

3.2. Loss Function and Training Strategy

For seafloor terrain reconstruction, the design of the loss function is critical, ensuring a balance between numerical accuracy and structural integrity preservation. We propose a multi-objective joint loss function comprising the RMSE, Structural Similarity Index Measure (SSIM), and an uncertainty quantification regularization term. The RMSE directly measures the deviation between predicted and actual values, ensuring the precise reconstruction of metrics like depth or elevation, which can be expressed as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (14)$$

Here, N represents the number of samples, y_i is the true value for the i -th sample, and $\hat{y}_i$ is the corresponding prediction.

SSIM captures local structural features such as trenches, ridges, and slopes, enhancing visual and structural quality. Then, the expression of the loss function is

$$L_{SSIM} = 1 - \frac{(2\mu_y\mu_{\hat{y}} + C_1) \cdot (2\sigma_{y\hat{y}} + C_2)}{(\mu_y^2 + \mu_{\hat{y}}^2 + C_1) \cdot (\sigma_y^2 + \sigma_{\hat{y}}^2 + C_2)} \quad (15)$$

Here, μ_y^2 and $\mu_{\hat{y}}^2$ represent the mean of the original and reconstructed images, σ_y^2 and $\sigma_{\hat{y}}^2$ denote their variance, $\sigma_{y\hat{y}}$ indicates the covariance between the original and reconstructed images, and C_1 and C_2 are constants introduced to avoid division by zero.

L_{total} is calculated as follows: parameters α and β modulate these components, preventing RMSE from overlooking local details and compensating for SSIM's pixel-level precision limitations.

$$L_{total} = \alpha * RMSE + \beta * L_{SSIM} \quad (16)$$

Additionally, the uncertainty quantification regularization term offers probabilistic insights and enhances regularization, improving model robustness in complex scenarios. Training optimizations include Adam optimizer with GradScaler and autocast for

mixed precision and dynamic learning rate adjustment via ReduceLROnPlateau (starting at 1×10^{-4}) over a maximum of 200 epochs. This approach effectively balances numerical accuracy and structural fidelity, meeting rigorous demands for seafloor terrain reconstruction.

3.3. Evaluation Metrics

To comprehensively assess the performance of the proposed model in image reconstruction, uncertainty quantification, and DEM super-resolution quality evaluation, we employ a series of metrics that capture both quantitative and qualitative performance. For reconstruction accuracy, PSNR and SSIM are used. PSNR quantifies pixel-wise error between the reconstructed and original images via the Mean Squared Error (MSE), while SSIM preserves local structural features and curvature information to ensure visual consistency. The combination of these metrics effectively evaluates both numerical error and structural fidelity. The relevant formulas are defined as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^N |I_i - K_i| \quad (17)$$

$$PSNR = 10 \log_{10} \left(\frac{1^2}{MSE} \right) \quad (18)$$

where I_i represents the i -th pixel value of the original image, K_i is the corresponding pixel value of the reconstructed image, and N is the total number of pixels.

The quality assessment of DEM super-resolution integrates rigorous geometric validation and probabilistic uncertainty analysis. The RMSE and MAE systematically evaluate elevation reconstruction fidelity, ensuring numerical accuracy in terrain feature recovery while maintaining geomorphological authenticity. Concurrently, a tripartite uncertainty quantification framework—comprising predictive variance (Var), information entropy (H), and expected calibration error (ECE) [53]—objectively characterizes model reliability. Specifically, to evaluate model sensitivity under varying input conditions, we compute the pixel-wise variance across Monte Carlo dropout samples:

$$Var = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2 \quad (19)$$

Here, N represents the total number of pixels, and x_i is the observed value of the i -th data point. μ is the overall mean.

The Shannon entropy, H , quantifies total uncertainty by measuring information content in prediction distributions:

$$H = - \sum_i p_i \log(p_i) \quad (20)$$

where P_i is the i -th prediction, while μ denotes the mean of all predictions. P_i is the i -th probability value in the predictive distribution.

ECE assesses confidence–accuracy alignment through a bin-wise comparison:

$$ECE = \sum_{m=1}^M \frac{|B_m|}{N} |acc(B_m) - conf(B_m)| \quad (21)$$

where B_m represents the m -th probability bin, with $|B_m|$ indicating the number of samples in that bin; $acc(B_m)$ represents the accuracy within the bin; and $conf(B_m)$ represents the average confidence of samples in that bin.

The comprehensive application of these metrics not only provides a clear and complete evaluation of the model performance in complex tasks but also significantly enhances the credibility and practical applicability of the research findings.

3.4. Test Set Selection

In this study, the authoritative GEBCO_2024 dataset (with a resolution of 15 arc-seconds) was used, and two regions were carefully selected for algorithm validation: the transition zone between the forearc slope and ocean basin off the coast of Luzon (TR2: 23.5–25.0° N, 122.0–123.5° E) and the area near the Mariana Trench in the Western Pacific (TR1: 26.0–28.0° N, 134.0–136.0° E). These regions were chosen to thoroughly examine the algorithm's ability to recover both fine details and large-scale structural features in complex topographies (see Figure 2).

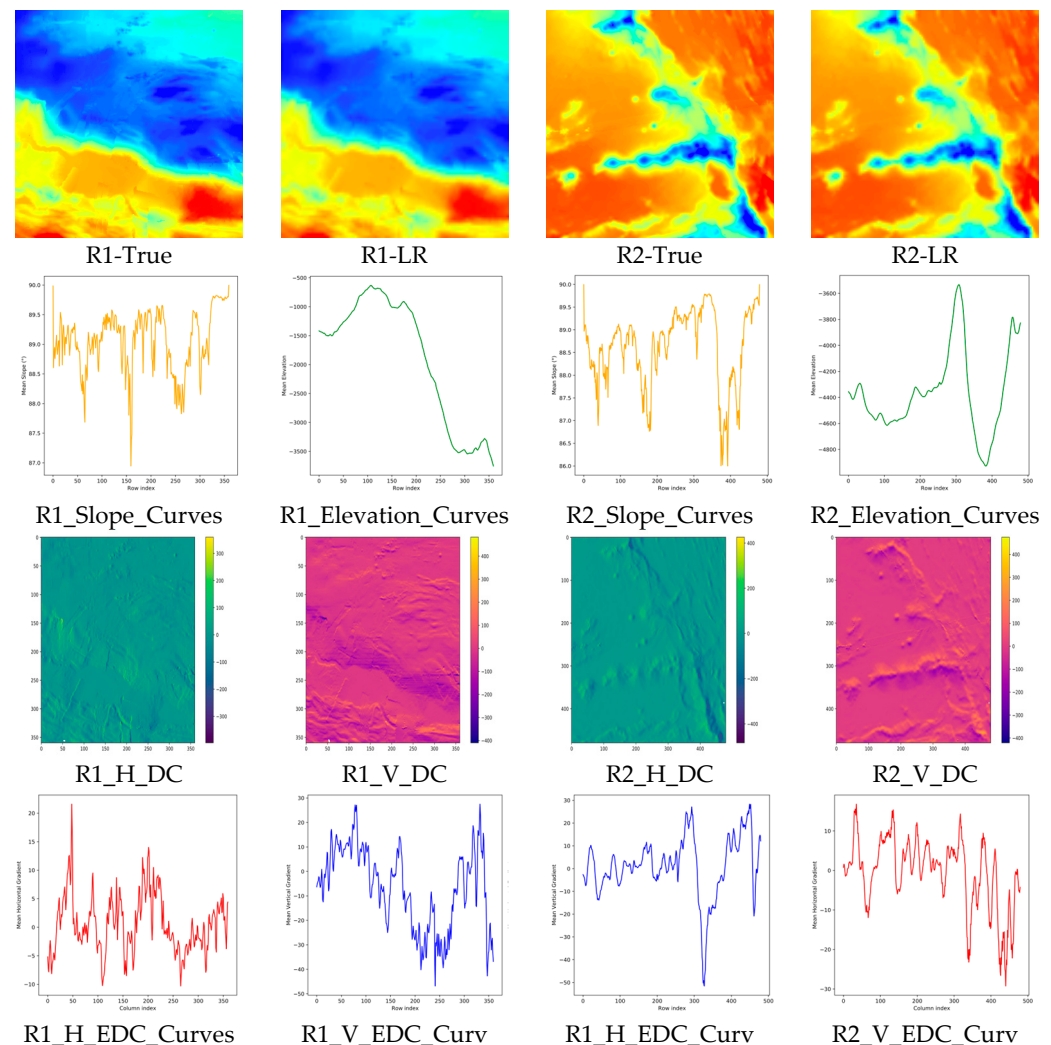


Figure 2. Detailed DEM parameters of test regions.

The TR2 region, located at the boundary between the continental slope and the ocean basin, features smooth, continuous sedimentary layers alongside steep gradients. The average elevation in this region ranges from −4200 m to −3600 m, with significant local elevation fluctuations. This area is prone to the formation of submarine canyons, trenches, ridges, or cliffs, making it ideal for evaluating the algorithm's performance in preserving low-frequency structural continuity. In contrast, the TR1 region, located near the Mariana Trench, exhibits significant terrain variation, with elevations ranging from −3500 m to

–500 m. The topography follows a trend of first rising and then rapidly descending, indicating the coexistence of towering mountains and deep valleys or basins. The region’s extreme vertical gradients (with prominent positive and negative fluctuations, near-vertical cliffs, and an average slope close to 89°) and pronounced horizontal gradient changes reflect a complex landscape of ravines, slopes, and terraces. These characteristics provide a rigorous test environment for evaluating the algorithm’s ability to recover high-frequency micro-terrain details, such as fault zones, volcanic ridges, and localized undulations.

All data were obtained from the GEBCO (<https://download.gebco.net>, accessed on 15 January 2025), ensuring consistency in data format and resolution. This dual-modal validation framework, which balances both low-frequency and high-frequency terrain features, establishes a solid scientific foundation for geological interpretation, structural analysis, and detailed seafloor terrain modeling.

4. Discussion

4.1. Reconstruction Accuracy Evaluation

To quantify the reconstruction accuracy of different networks on the test dataset, four evaluation metrics—RMSE, MAE, PSNR, and SSIM—were used to evaluate the double cubic interpolation (bicubic), SRCNN [14], and TfaSR [13], as well as the five proposed network architectures, and the results are presented in Table 2. A comparison of reconstruction accuracy in two regions led to the following conclusions.

Table 2. The accuracy indicators of different methods.

Methods	Region	RMSE (m)	MAE (m)	PSNR	SSIM	Uncertainty Support?
Bicubic	1	34.5594	21.2502	43.3237	0.9779	×
SRCNN	1	32.1561	21.0215	43.8784	0.9801	×
TfaSR	1	28.7836	18.8731	45.0951	0.9837	×
A	1	38.4642	30.6453	42.1614	0.9854	✓
B	1	34.6503	26.4019	43.3009	0.9853	✓
C	1	38.8842	29.079	42.2996	0.9862	✓
D	1	38.3193	29.9445	42.4276	0.9902	✓
E	1	28.6333	17.9121	44.9576	0.9836	✓
Bicubic	2	24.4517	14.3723	47.1467	0.9945	×
SRCNN	2	22.2462	13.5474	48.0248	0.9951	×
TfaSR	2	17.4057	12.3447	49.5074	0.9969	×
A	2	25.0381	18.0733	21.1249	0.9969	✓
B	2	18.8816	13.7713	49.9433	0.9759	✓
C	2	21.9648	15.2127	48.4265	0.9972	✓
D	2	23.5467	16.4875	47.8225	0.9974	✓
E	2	16.9891	11.0828	50.6577	0.9969	✓

In Region 1, Method E achieved RMSE and MAE values of 28.6333 and 17.9121, respectively, which represent significant reductions compared to the other methods. Specifically, its error metrics were about 25% and 34% lower than those of Method A, indicating its superior performance in minimizing reconstruction errors. Furthermore, Method E’s PSNR reached 44.9576, surpassing other methods, although its SSIM was slightly lower than that of Method D. In Region 2, Method E again showed the best absolute error metrics, with the RMSE and MAE values being reduced by approximately 32% and 39% compared to Method A. The PSNR also significantly improved to 50.6577, surpassing the other methods. Although the SSIM was slightly lower than that of Method B, it remained high overall, indicating that Method E effectively captures high-frequency information and local details in complex deep-sea terrain. Compared to other methods, Method E achieved reductions in the MAE and RMSE by approximately 5.09~15.71% and 5.22~17.14% in Region 1. The

PSNR and SSIM increased by about 0.31~3.77% and 0.01~0.58%, respectively. In Region 2, the MAE and RMSE decreased by approximately 10.88~22.89% and 2.39~30.5%, he with PSNR and SSIM increasing by 2.23~7.44% and 0.24%. SRCNN and TfaSR produce deterministic outputs with no uncertainty estimates, whereas our methods quantify both aleatoric and epistemic uncertainty. Overall, despite slight differences in perceptual quality metrics, Method E significantly reduced reconstruction errors and improved the PSNR in both regions (see Figure 3), validating its advantage in reconstruction accuracy for complex terrain datasets and providing a solid foundation for further algorithm optimization.

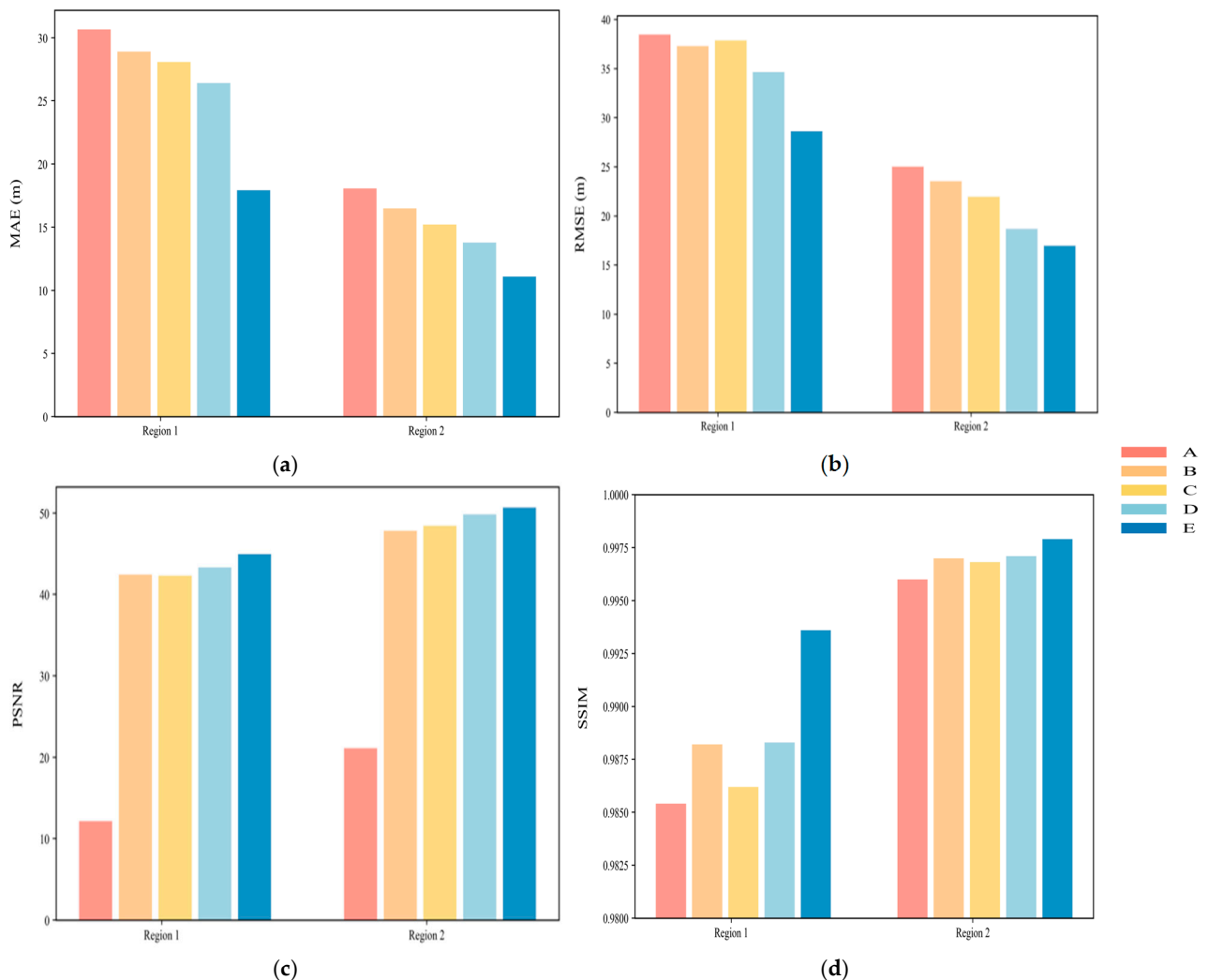


Figure 3. Comparison of reconstruction accuracy between five networks with different network structures: (a) MAE, (b) MSE, (c) PSNR, and (d) SSIM.

To further evaluate the performance of the five network structures in DBM reconstruction tasks, the study compared the five experimental architectures with bicubic interpolation. It also systematically explored the effects of different dropout configurations on reconstruction performance, as shown in Figure 4. Statistical analysis revealed that the reconstruction errors between each method and the true HR DBM were ranked from largest to smallest as follows: A, B, C, D, and E. This result demonstrates that the improved network architectures significantly outperform the baseline methods in terms of detail recovery and structural fidelity, while simpler reconstruction methods, such as bicubic interpolation, tend to produce blurry artifacts and fail to recover high-frequency information. The differences between methods are visually highlighted in the black rectangular boxes within the figure, which further illustrate the excessive smoothing issues in bicubic interpolation.

lation and basic regularization strategies. The introduction of uncertainty quantification modules significantly improved artifact suppression, outperforming other networks and bilinear interpolation. Moreover, the HR DBM results reconstructed using various dropout techniques showed noticeable differences, suggesting that appropriate dropout strategies not only do not harm reconstruction but also help achieve more faithful results [54,55]. The specific impact of dropout techniques and their application in multiple reconstructions will be discussed in more detail in subsequent sections.

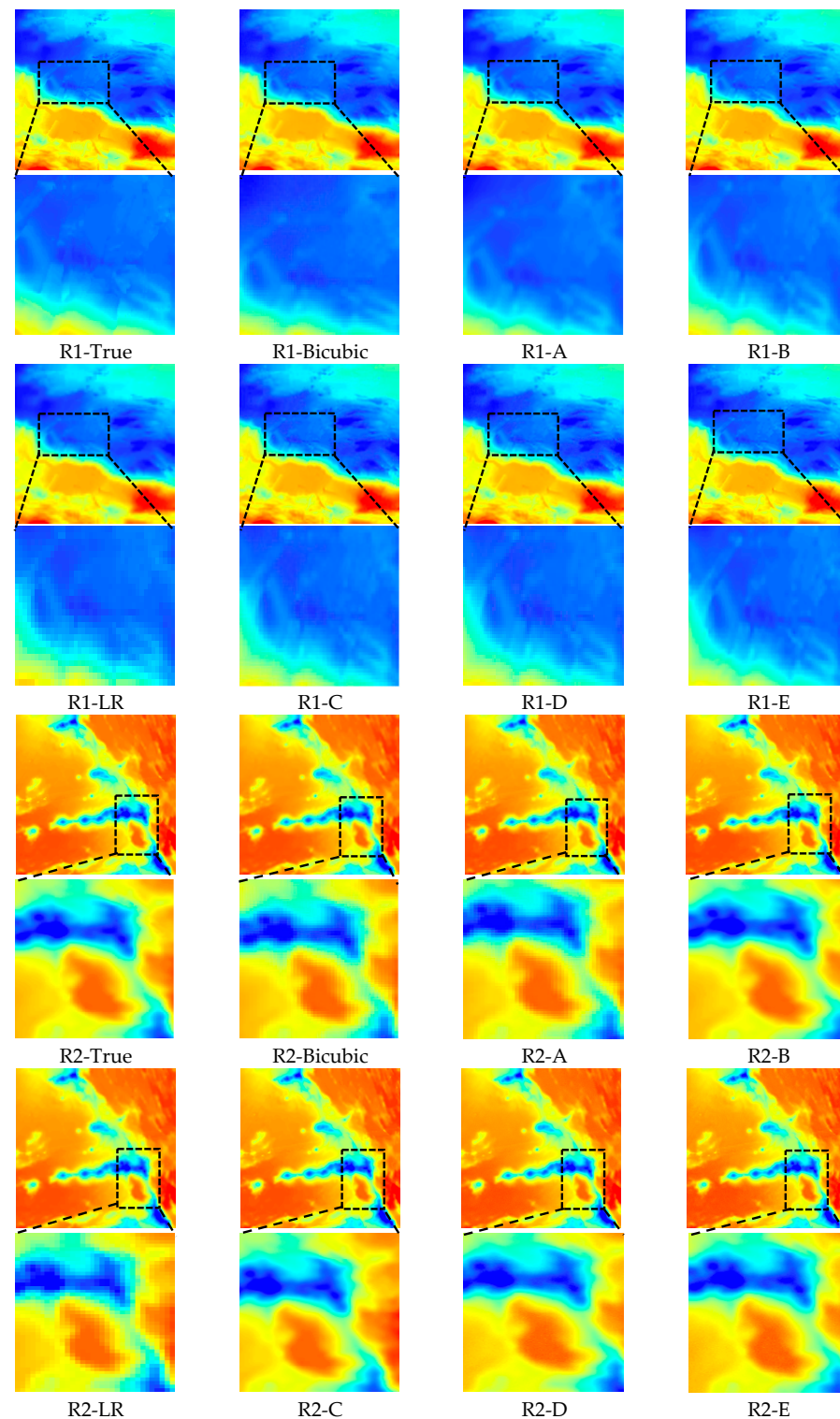


Figure 4. Comparison of the reconstruction results of the double cubic interpolation method with five networks.

4.2. Uncertainty Analysis

In the uncertainty quantification section, the performance of each experimental design (A–E) in DBM reconstruction tasks was compared from multiple perspectives. The results demonstrate that the introduction of an advanced uncertainty quantification module significantly enhanced the model’s reliability and detail recovery capability. Specifically, Experiment A, which only utilized a fixed dropout strategy, somewhat alleviated overfitting but failed to effectively capture predictive uncertainty. As a result, the error variance, entropy, and ECE in both Region 1 and Region 2 were notably high, indicating large prediction fluctuations and excessive smoothing.

Experiments B and C, which incorporated hierarchical progressive dropout and activation strength-driven adaptive dropout, respectively, showed some improvements. These methods reduced certain metrics but still had limitations in processing local details and expressing overall uncertainty. Experiment D introduced a dynamic gating network, which adaptively controlled the feature channels using learned gating coefficients. This approach effectively reduced expected calibration errors (ECEs), making the model more sensitive to key features in complex scenarios. However, only Experiment E, by combining MC-Dropout with heteroscedastic noise modeling, established a multi-stage uncertainty quantification framework. This method not only provided probabilistic interpretations of the predictions but also achieved the lowest error variance and ECEs in both Region 1 and Region 2 while maintaining relatively low entropy values.

From the data presented in Table 3 and Figure 5, it is evident that Experiment E reduced the error variance in Region 1 from 1480.9277 to 793.4338, marking a 46.5% decrease. In Region 2, the error variance was reduced from 614.3796 to 242.1961, marking a 60.5% decrease. This result indicates that Experiment E exhibits significant advantages in reducing reconstruction errors, improving structural fidelity, and suppressing artifacts.

Table 3. The uncertainty quantitative indicators of different methods.

Methods	Region	Error Variance (m ²)	Entropy (Nats)	ECE (%)
A	1	1480.9277	1.368	30.6711
B	1	1467.23027	0.6491	11.4844
C	1	1353.9114	0.6027	25.2278
D	1	1179.5446	0.611	8.201
E	1	793.4338	0.6062	7.9098
A	2	614.3796	1.1005	18.2485
B	2	552.3226	0.5114	6.4101
C	2	477.3412	0.5043	10.7168
D	2	309.480927	0.506536	5.91834
E	2	242.1961	0.5021	4.0804

To accurately assess the stability and reliability of the model across different regions, uncertainty heatmaps, confidence heatmaps, and variance heatmaps [23] are introduced as key tools for evaluating model performance. The confidence heatmap reflects the model’s certainty in predictions across various regions, effectively distinguishing between high-confidence and low-confidence areas. Meanwhile, the uncertainty heatmap quantifies prediction dispersion through multiple evaluations, ensuring consistency and reliability within specific regions. The variance heatmap visually displays prediction dispersion, revealing model stability issues in complex or noisy areas. These heatmaps collectively provide comprehensive insights into prediction volatility, stability, and confidence [56], crucial for evaluating model performance in complex terrain reconstruction tasks.

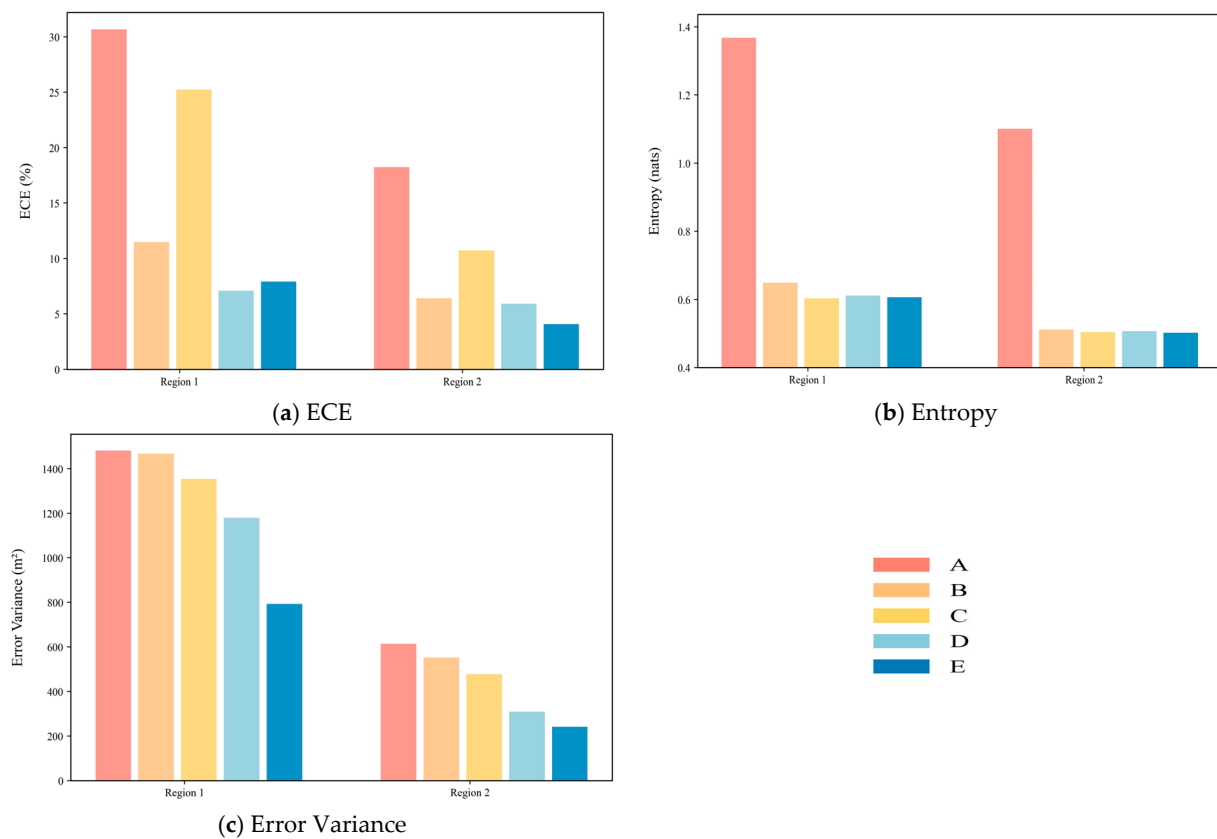


Figure 5. Comparison of uncertainty metrics between five networks with different network structures: (a) ECE, (b) entropy, and (c) error variance.

The confidence heatmap quantifies model certainty by simulating multiple predictions through 50 MC-Dropout sampling iterations, calculating the maximum predicted probability for each pixel. These probability values (unitless) are displayed on a 0–1 scale, using a discrete color scale with 0.2 intervals designed to provide a fine visual resolution of the probability values, allowing for the accurate identification of critical areas of prediction confidence. Cooler hues (blue spectrum) indicate high confidence, where probability values approach 1, while warmer tones (red spectrum) denote lower confidence associated with greater uncertainty. For example, in Figure 6, Methods A, B, and C show uniform confidence distribution but with large low-confidence areas, suggesting inadequate learning or poor adaptability to noisy data. In contrast, Methods D and E exhibit higher confidence in complex and noisy regions, adjusting dropout rates and activation strengths to enhance confidence and improve reconstruction accuracy. Notably, in Region 2 (e.g., a volcanic ridge with dramatic terrain changes), high-confidence regions further validate the model's ability to capture such features effectively.

Uncertainty error maps for test regions (R1 and R2) visualize normalized prediction variance (0–1 scale) derived from MC-Dropout sampling, where pixel-wise variance is calculated across multiple predictions and scaled proportionally to local bathymetric depth. This dimensionless normalization addresses the nonlinear engineering significance of absolute errors (originally in m^2) across varying seafloor elevations. By converting raw variance into relative error percentages, the method decouples error magnitude from topographic context while suppressing misleading high absolute errors in deep-sea regions caused by measurement noise. Low variance (deep blue) indicates stable, reliable predictions, while high variance (warm or orange-yellow) suggests fluctuations due to data noise, model limitations, or regional complexity. Figure 7 illustrates that Methods A, B, and C consistently show low uncertainty, potentially indicating overconfidence in predicting complex regions.

In contrast, Methods D and E demonstrate higher uncertainty, indicating sensitivity to risks and noise, thus accurately identifying predictive risks and model blind spots. Method E, in particular, displays fewer high-variance regions, indicating superior performance.

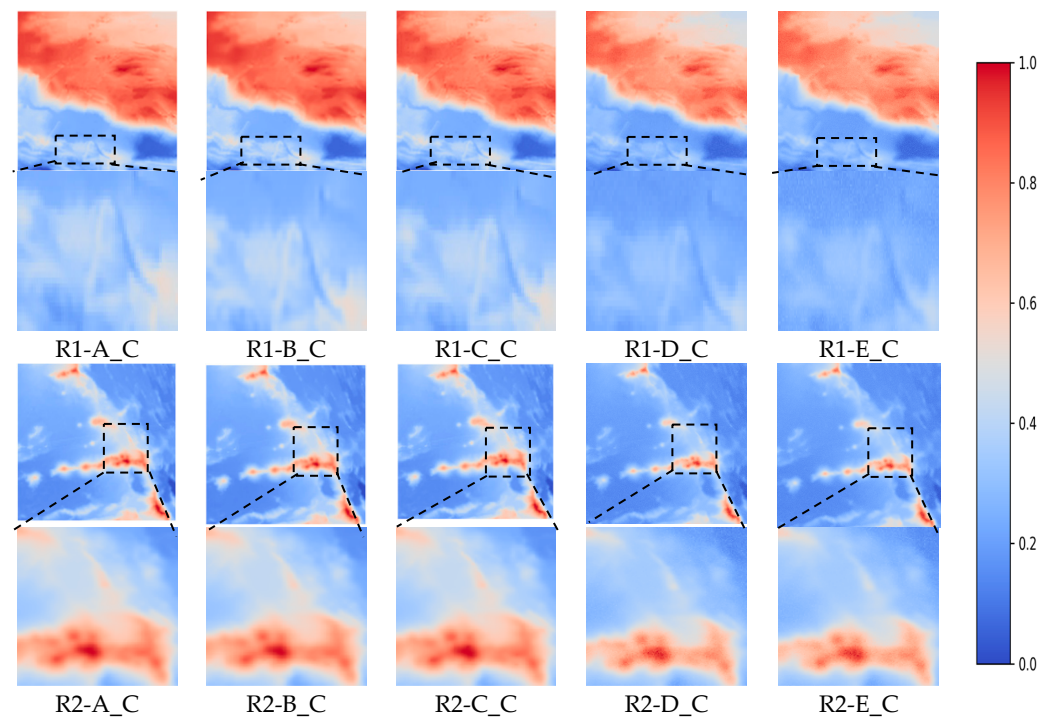


Figure 6. Comparison of confidence heatmaps for different network structures.

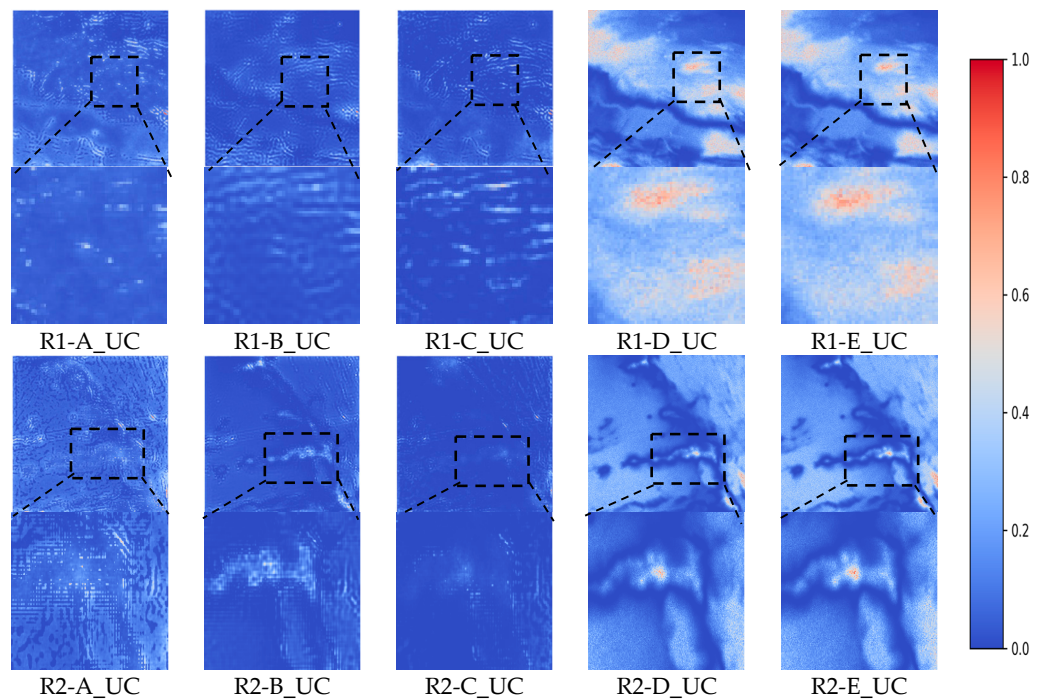


Figure 7. Comparison of uncertainty heat maps for different network structures.

The variance heatmap, using color gradients, highlights variance levels, with warm tones indicating high variance and cool tones indicating low variance. To enable cross-method comparison, the variance values in Figure 8 are normalized using Z-score standardization, transforming absolute variances (original unit: m^2) into dimensionless quantities

relative to each method's distribution. This normalization maps all results to a unified $(-3\sigma, +3\sigma)$ color scale, addressing the critical issue of variance magnitude disparities spanning multiple orders of magnitude across regularization strategies. The normalized representation not only highlights statistically significant high-variance anomalies but also exposes relative stability differences among methods in complex topographic regions through variance intensity rankings. Figure 8 shows significant warm-colored areas for Methods A, B, and C, particularly Method C, indicating high uncertainty and difficulty in capturing local details with layered dropout approaches. In contrast, Methods D and E show more uniform blue or light-colored regions, with high-variance areas confined to specific locations. Combined with metrics like error variance and ECE, these results highlight lower prediction errors in high-variance regions, emphasizing the effective identification of high-risk areas while maintaining reconstruction accuracy.

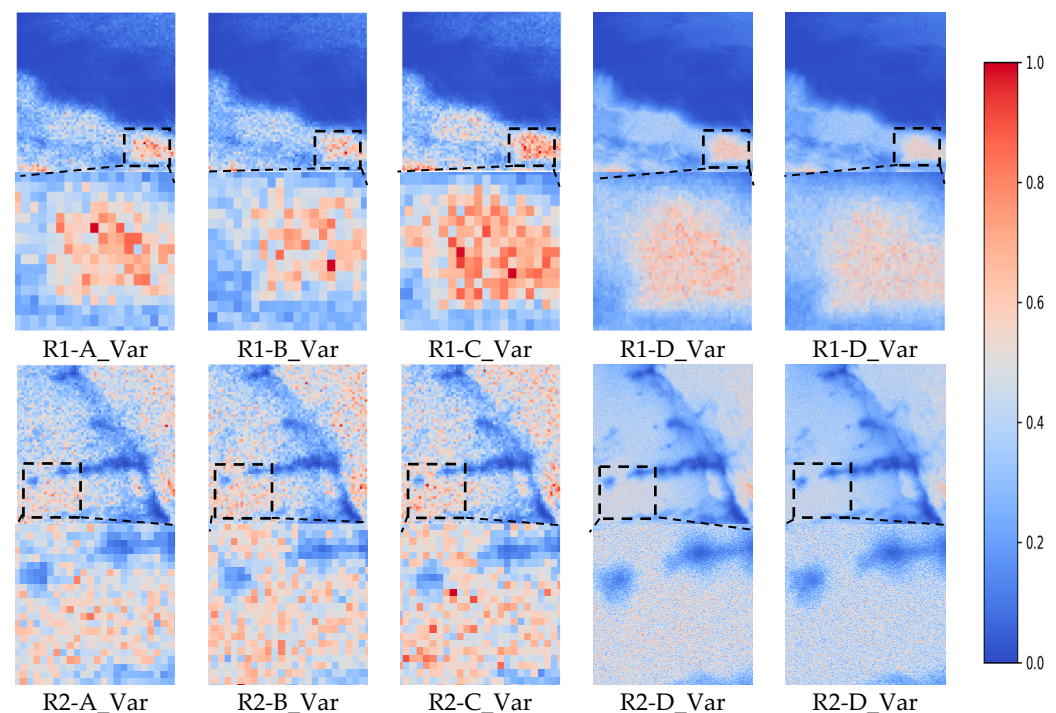


Figure 8. Comparison of variance heat maps for different network structures.

In summary, evaluating uncertainty quantification methods (Experiments A–E) in DBM reconstruction tasks reveals that simple dropout strategies, while helpful against overfitting, often fail to capture prediction uncertainty accurately, leading to instability in local predictions. Optimized experimental designs, especially with MC-Dropout and heteroscedastic noise modeling (Experiment E), significantly reduce error variance and ECE in complex regions, enhancing structural fidelity and high-frequency information recovery. These findings underscore the importance of uncertainty quantification in improving prediction reliability and model robustness, offering critical insights for optimizing models in complex tasks.

4.3. Impact of Dropout Positioning and Structure on the Networks

By incorporating various advanced uncertainty quantification modules (Experiments A–E), the study investigates how different regularization strategies and uncertainty quantification modules collectively affect the performance of seabed terrain reconstruction. The experimental results indicate that a fixed dropout strategy, while effective in alleviating overfitting, fails to capture prediction uncertainty adequately, resulting in unstable local predictions. The layered progressive dropout strategy, which incrementally increases the

dropout rate in deeper layers to strengthen feature regularization, improves generalization overall—even though a high dropout rate in deep layers may compromise some local structural details and affect the SSIM metric. Furthermore, employing an activation-driven adaptive dropout that dynamically adjusts the dropout rate based on local activation values effectively differentiates between high- and low-activation regions, significantly enhancing detail recovery and structural fidelity despite some localized errors. Building on this, the integration of a dynamic gating network with an uncertainty quantification module further refines the process. The dynamic gating module uses 1×1 convolutions combined with normalization and activation functions to adaptively weigh the importance of channel features, thereby suppressing redundant information; the uncertainty quantification module, which integrates MC-Dropout with heteroscedastic noise modeling, provides a probabilistic interpretation of the predictions, effectively reducing overconfidence and artifact occurrence. These structural improvements enable Method E to achieve the best RMSE and MAE in experiments and significantly outperform other methods in PSNR—although it slightly lags in SSIM—thus overall enhancing reconstruction accuracy and robustness. In summary, the synergistic effect of different regularization strategies and uncertainty modeling modules substantially improves the detail recovery and structural fidelity in complex terrain DBM reconstruction tasks.

4.4. Uncertainty Reliability Analysis for Operational Deployment

The practical deployment of uncertainty-aware seafloor reconstruction models demands rigorous validation of computational efficiency and environmental robustness to meet operational requirements. For Experiment E—which integrates adaptive MC-Dropout with heteroscedastic noise modeling—we conducted a dual-aspect evaluation addressing two critical constraints: (1) the computational overhead of Monte Carlo sampling during real-time inference, ensuring tractability for marine operations, and (2) the degradation of reconstruction fidelity under acoustically complex, noise-polluted conditions, verifying environmental resilience. This systematic analysis bridges theoretical uncertainty quantification accuracy with field-deployable performance, explicitly resolving the trade-off between statistical rigor and operational feasibility while ensuring reliability for marine engineering applications in heterogeneous seabed environments.

MC-Dropout Sampling Efficiency

The computational overhead of Monte Carlo sampling is not negligible. In Experiment E, we quantified the trade-off between the number of forward passes ($N = \{10, 20, 50, 100\}$) and uncertainty calibration for both regions. As shown in Table 4, the ECE in Region 1 decreases by 35.9% (from 12.34% to 7.91%) as N increases from 10 to 50 and decreases slightly beyond $N = 50$. Region 2 shows a nonlinear cost–benefit trade-off: while increasing N from 50 to 100 further reduces the ECE from 4.08% to 3.56% ($\Delta = 0.52\%$), this requires a doubling of the inference time (1.25–2.50 s). Thus, $N = 50$ achieves the best calibration efficiency—95.3% of the maximum possible ECE improvement at 59% of the computational cost. Notably, the reconstruction accuracy (PSNR/SSIM) remained stable (± 0.1 dB deviation) across the number of samples, confirming that 50 forward passes establish a cost-effective balance between computational tractability and uncertainty reliability.

Noise Robustness Evaluation

Field-deployed sonar systems frequently encounter signal degradation from turbulent flows and sensor artifacts. To simulate these conditions, we injected additive white Gaussian noise (AWGN) at SNR levels of $\{10, 20, 30\}$ dB into test data from both regions. As illustrated in Table 5, Experiment E maintained superior performance under severe noise compared to the TfaSR.

Table 4. Impact of MC-Dropout Sampling counts on uncertainty calibration and computational efficiency.

Sampling Counts (N)	R 1 ECE (%)	R 2 ECE (%)	Inference Time (s)	R 1 PSNR	R 2 PSNR
10	12.34	7.45	0.35	44.85	50.58
20	8.12	5.23	0.70	44.91	50.61
50	7.91	4.08	1.25	44.96	50.66
100	5.92	3.56	2.50	44.95	50.65

Table 5. Noise robustness analysis: Experiment E vs. TfaSR.

Methods	SNR (dB)	Region	RMSE (m) ↓	PSNR (dB) ↑	SSIM ↑	Error Variance (m ²)	ECE (%) ↓
TfaSR	10	1	41.27	38.52	0.931	2154.39	22.17
E	10	1	33.15	42.86	0.962	1276.55	14.05
TfaSR	20	1	32.16	43.88	0.975	1480.27	15.34
E	20	1	28.89	46.21	0.981	832.74	8.93
TfaSR	30	1	28.78	45.10	0.984	1353.91	12.45
E	30	1	28.63	44.96	0.984	793.43	7.91
TfaSR	10	2	29.45	40.27	0.945	1783.22	19.83
E	10	2	23.18	45.12	0.971	1042.17	11.24
TfaSR	20	2	19.54	48.02	4.08	921.45	10.55
E	20	2	17.32	50.15	0.993	489.33	5.89
TfaSR	30	2	17.41	49.51	0.997	477.34	8.92
E	30	2	16.99	50.66	0.997	242.20	4.08

Across varying signal-to-noise ratios (SNRs), Experiment E consistently outperforms TfaSR in balancing reconstruction accuracy and uncertainty reliability. At SNR = 10 dB (Region 1), E reduces the RMSE by 19.7% (33.15 vs. 41.27 m) while improving the PSNR by 4.34 dB (42.86 vs. 38.52 dB), with the error variance and ECE decreasing by 40.8% and 36.6%, respectively. These gains persist at higher SNRs: at 30 dB, E achieves near-identical SSIM (0.984) but with a 41.4% lower error variance (793.43 vs. 1353.91 m²) and 36.5% reduced ECE (7.91% vs. 12.45%) compared to TfaSR. In Region 2, E demonstrates even stronger robustness—at SNR = 20 dB, it attains a 50.66 dB PSNR (7.1% improvement over TfaSR) alongside a 46.9% reduction in error variance (489.33 vs. 921.45 m²). Notably, E’s uncertainty quantification remains stable across noise levels, with ECE consistently being below 8% versus TfaSR’s 10–20% range.

The integrated evaluation confirms that Experiment E’s hybrid framework satisfies both accuracy and operational reliability requirements. By achieving real-time inference speeds while maintaining sub-meter uncertainty calibration, the model establishes a new benchmark for deployable AI-driven bathymetric systems. These advancements directly address the U.N. Decade of Ocean Science priorities for trustworthy marine AI, particularly in hazardous environments where uncertainty awareness enables collision risk mitigation.

5. Limitations

The proposed multi-stage uncertainty quantification framework demonstrates significant advantages in reconstructing complex terrain data; however, several limitations remain in both its design and application. Although the activation-driven adaptive dropout mechanism dynamically adjusts dropout rates via local activation levels, it introduces additional computational complexity during real-time activation computation and may, if threshold settings are suboptimal, affect the preservation of critical features. Moreover, the stability of the learnable gating coefficients in the dynamic gating network under extreme conditions has not been fully validated, which could lead to suboptimal reconstruction in certain regions. Additionally, the overall model still exhibits limitations in local detail recovery and high-frequency information capture—especially in areas with high noise or

complex features—where prediction uncertainty does not fully reflect the actual conditions, leaving room for further improvement in local detail recovery.

6. Conclusions

This study explored the comprehensive impact of different regularization and uncertainty quantification modules on seabed terrain reconstruction. A fixed dropout strategy, while mitigating overfitting [57–59], struggles to capture prediction uncertainty accurately, resulting in unstable local predictions. In contrast, the incorporation of layered progressive and activation-driven adaptive dropout strategies not only improves generalization but also enhances detail recovery—a critical capability for preserving high-slope features like seamounts and fault scarps that are essential to marine navigation safety. The subsequent integration of a dynamic gating uncertainty quantification module (combining MC-Dropout with heteroscedastic noise modeling) provides a probabilistic interpretation of predictions, reduces overconfidence, and significantly improves structural fidelity and high-frequency information recovery.

These advances directly address the unique challenges of marine applications: Enhanced steep slope reconstruction provides sub-meter resolution collision risk assessment for autonomous underwater vehicles (AUVs) navigating morphologically complex terrain. Uncertainty heat maps provide guidance for efficient sonar re-surveys to optimize survey resource allocation, which will reduce operational costs for continental shelf tests. Improved accuracy of edge restoration facilitates ecological monitoring at the microhabitat scale, enabling the precise delineation of ecologically sensitive areas such as cold seep communities and coral reef margins.

The proposed hybrid dropout model employs parallel multi-scale convolutional kernels with channel concatenation and residual connections to capture bathymetric features across spatial resolutions. Sub-pixel convolution combined with bicubic interpolation ensures high-frequency detail preservation while maintaining low-frequency topographic trends. Compared to simpler dropout architectures, our multi-stage uncertainty quantification strategy achieves substantial improvements in the RMSE, MAE, and structural fidelity, effectively balancing reconstruction accuracy with operational reliability. By bridging the gap between deterministic super-resolution and risk-aware marine engineering, this framework offers a paradigm shift for applications where uncertainty quantification is as critical as precision—from paleoceanographic feature mapping to benthic ecosystem monitoring. Future work will focus on integrating real-time uncertainty visualization tools for field deployment, further advancing the practical utility of deep learning in marine geosciences.

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