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Comparative analysis of interpolation methods commonly used in bathymetric data generation

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Abstract

This research paper aims to provide a comparative analysis of interpolation methods for estimating bathymetric data. Accurate measurement of bathymetry is crucial for a variety of applications, including navigation, oceanography, and coastal management. However, due to the high cost and difficulty of acquiring bathymetric data, gaps in measurements are common. Interpolation methods are widely used to fill these gaps and estimate the depths of water at unsampled locations. In this study, we analyze the most commonly used interpolation methods, including linear, inverse distance weighting, kriging, triangulated irregular network, moving least squares, piecewise cubic Hermite interpolating polynomial, and spline interpolation. We compare and evaluate the performance of these methods using both simulated and real-world datasets. Additionally, we provide a systematic analysis of the strengths and weaknesses of each method in terms of their accuracy in estimating bathymetry. The goal of this paper is to offer a comprehensive overview of interpolation methods for bathymetric data and to assist researchers and practitioners in selecting the most suitable method for a given task and dataset.

Keywords: Bathymetry; Bathymetric Data Generation; Interpolation; Bay of Bengal

1. Introduction

Bathymetry is the study of the depths and shapes of oceans, lakes, and other water bodies. Bathymetric data refers to information about the depth of a body of water, typically collected using specialized instruments such as sonar or laser-based systems. This data can be collected at various scales, ranging from small bodies of water to large oceans, and is often gathered as part of survey or mapping projects. It is used to generate maps of underwater topography, which serve various purposes, including navigation, resource exploration, oceanography, earth science research, and environmental monitoring [1]. However, there are several challenges and limitations associated with obtaining and using bathymetric data, which can restrict the types of analyses and applications possible. These challenges include cost, data quality, resolution, and format. To address these issues, several approaches can be employed, such as data sharing and collaboration, data standardization, improved measurement technologies, advanced data processing and interpolation techniques, and public-private partnerships [2]. Overall, addressing the challenges associated with bathymetric data will require collaborative efforts from various stakeholders, including government agencies, research institutions, and private companies.

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Interpolation techniques are a valuable approach for addressing some of the challenges associated with bathymetric data, particularly in improving its resolution and accuracy [3]. These methods estimate bathymetric values at unsampled locations, effectively reconstructing a complete surface from sparse measurements. They can generate a continuous surface from irregularly spaced data points, which is useful for creating maps or visualizations of the underwater landscape or for further data analysis. Interpolation also helps fill gaps in the data, enabling depth estimation at locations where direct measurements are unavailable. Additionally, these techniques can smooth out noise or errors in the data, resulting in more accurate and reliable depth estimates [4]. Overall, interpolation techniques are a powerful tool for enhancing the quality and utility of bathymetric data, especially when the data is collected at low resolution or contains gaps. These methods range from simple techniques, such as linear interpolation, to more advanced approaches, including kriging and moving least squares. The choice of an appropriate interpolation method depends on factors such as dataset characteristics, desired accuracy, and computational efficiency. It is essential to carefully evaluate the strengths and limitations of different techniques to select the one best suited to specific needs. Therefore, this paper discusses and compares various interpolation techniques suitable for bathymetric data. The methods explored include linear, inverse distance weighting (IDW), kriging, triangulated irregular networks (TIN), moving least squares (MLS), piecewise cubic Hermite interpolation (PCHIP), and spline interpolation. Using both simulated and real-world datasets, this research evaluates the performance of these methods based on their accuracy, and suitability for different types of bathymetric data. By systematically examining the strengths and limitations of each method, this study aims to guide researchers and practitioners in selecting the most appropriate interpolation technique for their specific needs. The findings of this paper contribute to a deeper understanding of interpolation methodologies, enhancing the accuracy and utility of bathymetric data in various scientific and practical applications.

The subsequent sections of this paper are structured as follows: Section 2 describes the study area. This section also delves into the source data and interpolation points where interpolation is to be performed. Section 3 and its corresponding subsections expound upon the methodology, providing a brief description of the interpolation methods. Section 4, along with its subsections, engages in a detailed discussion of the model's simulated outcomes, the accuracy of the interpolation methods, sensitivity analysis, and guidelines for researchers and practitioners in selecting the most appropriate interpolation technique for their specific needs. Section 5 presents the overarching conclusions derived from our investigation.

2. Study Area and Data Preparation

2.1. Study Area

The study area for this research spans from 21°N to 23°N latitude and 90°E to 92°E longitude in the Bay of Bengal (BOB). It is part of the coast of Bangladesh, a region characterized by significant geographical and geological complexity (see **Fig. 1**). The area encompasses both coastal and offshore zones, including the dynamic Ganges-Brahmaputra Delta. This region lies at the interface of two contrasting geographical landscapes, the ocean and the hills, creating a highly complex and diverse environment. Understanding these features is crucial for navigation, environmental conservation, and sustainable development in the region. The Himalayas and Kashi-Jaintia hills, situated to the north and east of the country, respectively, contribute to inland flooding through monsoon rains and the melting of snow and ice. These processes feed numerous rivers, which cause riverbank erosion, sedimentation, and river migration [5]. On the other hand, the BOB is the source of various natural disasters, including tropical cyclones and associated storm surges, floods, salinity intrusion, and coastal erosion. Among these, tropical cyclones and their associated surges are particularly devastating for the coast of Bangladesh. From the above description, it is evident that the coastal belt of Bangladesh is one of the world's most vulnerable regions. Additionally, two other critical factors influencing surge levels in the region are its shallow bathymetry and the presence of numerous islands of varying shapes. The bathymetry of this region is predominantly shallow, shaped by extensive sediment deposition from the Ganges and Brahmaputra rivers. These river systems transport and deposit massive amounts of sediment, forming a gently sloping seabed that extends into the BOB. The interaction of fluvial, marine, and tectonic processes further contributes to the region's dynamic nature, making accurate bathymetric measurements a significant challenge. Given the complexities and data gaps inherent in this region, interpolation methods play a crucial role in bathymetric analysis. The sparsity of direct measurements, driven by the high cost and logistical challenges of marine surveys, necessitates robust interpolation techniques to estimate depths at unsampled locations. These methods are particularly relevant in the study area, where sedimentation patterns and tidal influences create a constantly evolving seafloor.

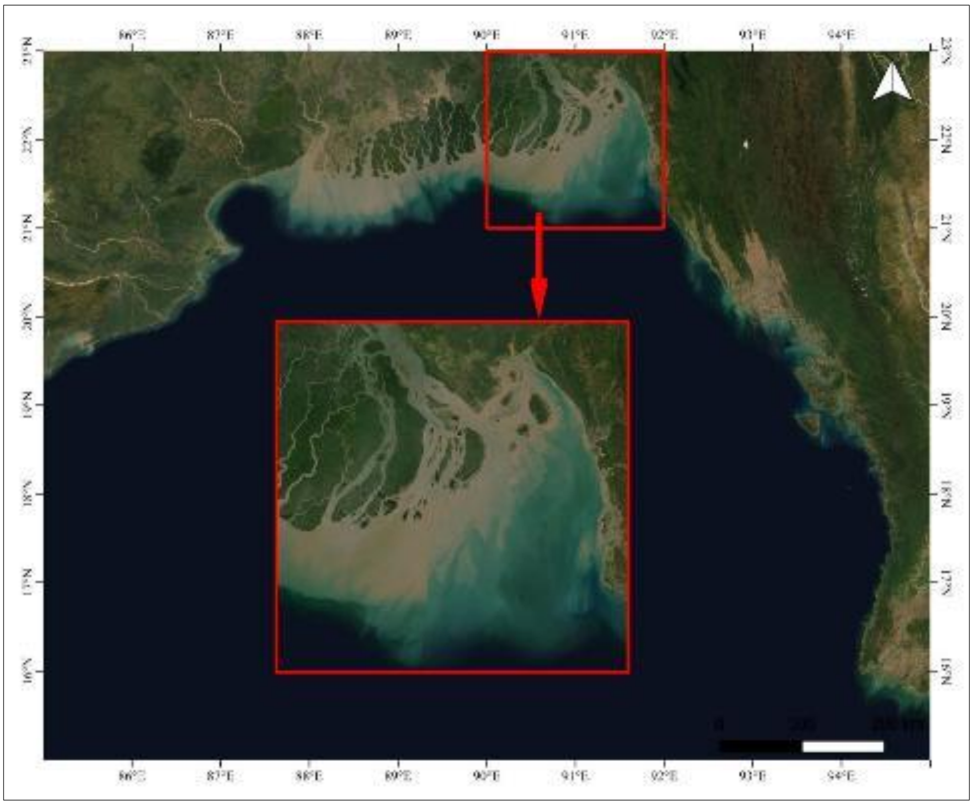


Figure 1 The study area spanning from 21°N to 23°N latitude and 90°E to 92°E longitude in the BOB

2.2. Source Data and Interpolation Points

The General Bathymetric Chart of the Oceans (GEBCO) data sets are among the most widely utilized global bathymetric resources [6]. Managed through an international collaboration of organizations and experts, GEBCO provides freely available, high-quality bathymetric data aimed at mapping the seafloor's shape and depth on a global scale. These data sets are compiled from a combination of direct measurements from ship-based surveys, satellite-derived altimetry for estimating seafloor features in areas lacking direct data, and contributions from national and international agencies, private organizations, and academic institutions. The GEBCO_2024 Grid offers a global bathymetric grid with a resolution of 15 arc-seconds (~500 meters), representing ocean floor depths relative to sea level. The dataset provides latitude and longitude coordinates in decimal degrees for every grid point. Depth measurements are given in meters, with negative values indicating depths below sea level. For the purposes of our study, the depth values were converted to positive values to simplify processing and analysis. To assess the performance of various interpolation methods, the original GEBCO dataset was systematically reduced to a coarser grid resolution of 30 arc-seconds (~1000 m). This was accomplished by skipping every second row and column in the original dataset. The resulting coarser grid simulates the presence of gaps in bathymetric data, reflecting real-world scenarios where data acquisition is incomplete or irregular due to logistical or environmental constraints. The skipped data points from the original 15 arc-second resolution were retained as ground truth for validating and comparing the accuracy of different interpolation techniques. The coarser 30 arc second grid retains sufficient information to preserve the general bathymetric features of the study area while creating a challenging test scenario for interpolation algorithms.

The study area, covering 21°N to 23°N latitude and 90°E to 92°E longitude, was divided into equally spaced [600,600] grid points. These points were used as interpolation points for various interpolation methods. The [600,600] grid resolution was selected to ensure adequate coverage of the study area while aligning with the scale of the original GEBCO dataset. This resolution also allowed for sufficient gaps in the data to test how the interpolation methods perform in filling these gaps and generating a smooth bathymetric surface. As described earlier, the study area includes both land and water regions, making it necessary to discretize and approximate the boundary between land and sea. Discretization was essential to convert the continuous surface of the study area into a manageable grid format for computational purposes. Bathymetric data inherently focuses on water depths, meaning points falling on land are not relevant for depth interpolation. Without discretization and boundary approximation, identifying grid points as either land or sea would be ambiguous, potentially reducing the accuracy of interpolation. Several methods exist for approximating complex geometric domains, among which the stair-step representation is the simplest and most effective [7]. This algorithm is particularly well-suited for handling the complex transitions between land and sea in regions like the Ganges-Brahmaputra Delta, where sediment deposition, tidal influences, and dynamic coastal processes create irregular boundaries. In this study, we also employed the stair-step representation algorithm to approximate the domain. By applying this algorithm, grid points were classified as either land or water, ensuring that interpolation methods were applied only to relevant water-covered points. This approximation improved the reliability of the generated bathymetric surfaces and provided a robust basis for comparing the performance of different interpolation methods. The approximated domain is shown in **Fig. 2**.

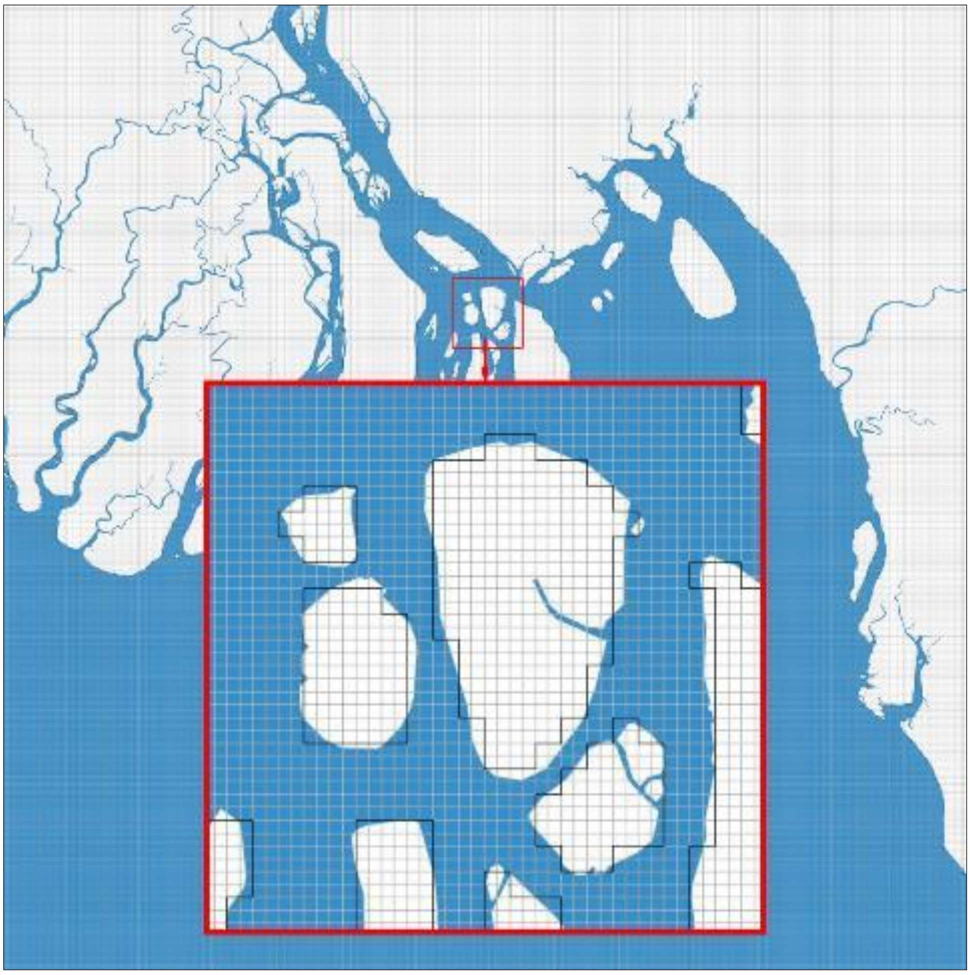


Figure 2 The approximated domain after stair step representation

3. Methodology

The study area is complex, characterized by numerous wide and narrow rivers interconnected with the BOB. The region includes both water bodies and adjacent landmasses, where the land's elevation above sea level strongly influences the performance of interpolation methods. To address this, we tested the interpolation methods in two distinct ways to assess their robustness and accuracy under varying conditions. First (Approach 1), the interpolation methods were tested without making any adjustments to the elevation values. This scenario reflected real-world conditions, where interpolation must handle the natural variability of both land and sea elevations. This approach allowed us to observe how each interpolation method performs when confronted with the complexities of mixed terrain, including abrupt transitions between land and water. Second (Approach 2), the depth values above sea level (land elevations) were set to zero. This approach aimed to minimize the influence of land heights on the interpolation process, allowing the methods to focus solely on estimating bathymetry for the water-covered regions. By reducing the variability introduced by land elevations, this setup provided a controlled environment for evaluating the interpolation techniques in areas where bathymetric data gaps exist. These two experimental setups provided a comprehensive framework to compare and evaluate interpolation methods under both controlled and natural conditions. By analyzing the outcomes, we aimed to identify the strengths and limitations of each method in handling the unique challenges posed by the study area's bathymetric and topographic complexity.

3.1. Interpolation methods

In this study, we have chosen seven interpolation methods that are often used in interpolating spatial data. Until now, interpolation methods have been very diverse. These methods are used depending on the case study. However, this study only focused on the interpolation methods stated earlier. A brief description of them is given below.

3.1.1. Linear Interpolation

Linear interpolation is a straightforward and widely used method for estimating values between two known data points. It assumes that the change between the two points follows a linear relationship and calculates the unknown value based on this assumption. This technique is particularly useful when dealing with evenly spaced data or when a simple approximation is sufficient. Linear interpolation works by drawing a straight line between two adjacent data points and determining the value at the desired location along this line. The method is computationally efficient and easy to implement, making it a popular choice for applications in fields such as engineering, computer graphics, and data analysis. However, it is important to note that linear interpolation may not accurately capture complex patterns or nonlinear relationships in the data, as it relies solely on the assumption of a straight-line relationship between points. Despite this limitation, it remains a valuable tool for quick estimations and smooth transitions between known values. For given two known points (x_0, y_0) and (x_1, y_1), the linearly interpolated value y at a point x (where $x_0 \leq x \leq x_1$) is calculated as:

$$y = y_0 + \frac{(x - x_0)}{(x_1 - x_0)}(y_1 - y_0)$$

3.1.2. IDW Interpolation

IDW interpolation is one of the simplest and most straightforward methods for spatial interpolation. This technique predicts values at unknown points based on the distances between the observed data points and the target prediction point. Specifically, the closer an observation point is to the prediction point, the greater its influence on the interpolated value compared to more distant observation points [8]. The method calculates the interpolation value at each target point as a weighted average of the values from nearby scattered data points. The weight assigned to each observed point decreases as its distance from the prediction point increases [9]. IDW interpolation performs particularly well when the data points are evenly distributed across the study area [8]. The method provides a deterministic estimate of unknown values by computing a linear combination of the observed values, with weights inversely proportional to their distances from the prediction point [10]. The mathematical formula for IDW interpolation is as follows:

$$z_j = \frac{\sum \frac{x_i}{d_{ij}^{\beta}}}{\sum \frac{1}{d_{ij}^{\beta}}}$$

where z_j – the value of unknown or interpolated points, n – the total number of sample points, x_i – the ith value of known or observation points, d_{ij} – the difference between the known and unknown values, and β – the weighting power [11].

3.1.3. Kriging Interpolation

Kriging is an advanced interpolation technique that utilizes Gaussian processes for data modeling and prediction, making it widely recognized as Gaussian Process Regression. Unlike deterministic interpolation methods, Kriging incorporates a statistical model that accounts for spatial autocorrelation. Spatial autocorrelation refers to the relationship between the values of data points and their spatial separation. This method is especially effective when there is a known spatial dependence, such as a distance or directional bias in the data. To model a surface using Kriging, a semi-variogram is first constructed based on the known data points [12]. There are several variants of Kriging, including Simple Kriging, Ordinary Kriging, Universal Kriging, and External Trend Kriging [13]. For this study, Simple Kriging will be employed. In Simple Kriging, weight values are determined by minimizing the error variance. The method relies on a variogram, which is a function of the separation distance, to quantify spatial covariance [11]. The empirical equation used to construct the variogram is as follows:

$$\gamma(d_{ij}) = \frac{1}{2n}\sum_{i=1}^{n}\left[x_i - (x_i + d_{ij})\right]^2$$

where $\gamma\left(d_{ij}\right)$ – the function of the h-variogram, n – the total number of sample points, and x_i – the ith value of known or observation points.

3.1.4. TIN Interpolation

Another effective approach for representing topography is the TIN, which models a surface by dividing it into a series of continuous, non-overlapping triangles. Each node of these triangles is assigned an elevation value, and the elevation between nodes can be interpolated to create a continuous surface [14]. The TIN model serves as an alternative to grid-based and geometric models, providing a way to predict values in unsampled regions while preserving the original shape of the terrain or objects. It has been widely used to address various challenges, such as generating topographic maps, creating object buffers, and managing multi-layer data [15]. The triangles generated by the TIN method are known as Delaunay triangulations. This approach is particularly advantageous for interpolation within triangles because it produces the most equiangular set of triangles possible. A Delaunay triangle is defined as one in which no other points lie on the circumscribed circle that passes through its three vertices [16]. This property ensures optimal geometric properties for interpolation and surface representation.

3.1.5. MLS Interpolation

The MLS method was introduced by Lancaster and Salkauskas for smoothing and interpolating data [17]. The core idea of the method is to use a weighted least squares formulation for an arbitrary fixed point and then extend this process across the entire parameter domain. For each point in the domain, a weighted least squares fit is computed and evaluated individually. The global function $f(x)$ is derived from a set of local functions $f_x(x)$, which are obtained by minimizing the following expression:

$$f(x) = f_x(x), \min_{f_x \in \prod_m^d} \sum_i \theta(\|x - x_i\|)\|f_x(x_i - f_i)\|^2$$

Instead of constructing a global approximation directly, the MLS method continuously constructs and evaluates a local polynomial fit over the entire domain, resulting in the MLS fit function. The weighting function plays a critical role in this process: when the distance between points is very small, the weights approach infinity near the input data points. This forces the MLS fit function to interpolate the prescribed function values at these points.

3.1.6. PCHIP Interpolation

The PCHIP is a widely used interpolation method designed to preserve the shape of the data and avoid overshooting or oscillating behavior, which is common in other interpolation techniques like cubic splines. PCHIP constructs a piecewise cubic polynomial that interpolates the data points while ensuring that the interpolant is monotonic in intervals where the data is monotonic. This makes it particularly suitable for applications where preserving the original trend and shape of the data is critical, such as in scientific visualization, engineering, and data analysis [18]. The method works by defining a cubic polynomial for each interval between consecutive data points. Unlike standard cubic splines, PCHIP uses a carefully chosen set of slopes (derivatives) at the data points to ensure that the interpolant does not introduce extrema (maxima or minima) that are not present in the original data. These slopes are computed based on the shape of the data, ensuring that the interpolant remains smooth and visually pleasing while adhering to the monotonicity constraints. For each interval $[x_i, x_{i+1}]$, the cubic Hermite polynomial $H_i(x)$ is defined as:

$$H_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3$$

where a_i – the function value at x_i, b_i – the slope at x_i, c_i and d_i – the coefficients determined by the function values and slope at x_i and x_{i+1}.

3.1.7. Spline Interpolation

Spline interpolation is a powerful and widely used method for constructing smooth curves that pass through a given set of data points. Unlike simpler interpolation methods like linear interpolation, spline interpolation uses piecewise polynomials achieve a high degree of smoothness and flexibility. This makes it particularly useful in applications where smoothness and continuity are critical, such as computer graphics, numerical analysis, and engineering design [19]. The key idea behind spline interpolation is to divide the domain into smaller intervals and fit a polynomial to each interval, ensuring that the resulting curve is continuous and smooth at the points where the intervals meet. The most common type of spline interpolation is cubic spline interpolation, which uses third-degree polynomials and ensures that the interpolant has continuous first and second derivatives. For a set of data points (x_i, f_i) a cubic spline $S(x)$ is defined as a piecewise function:

$$S(x) = \begin{cases} S_0(x), & x_0 \le x < x_1 \\ \vdots \\ S_{n-1}(x), & x_{n-1} \le x \le x_n \end{cases}$$

Each $S_i(x)$ is a cubic polynomial of the form:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3$$

4. Results and Discussion

4.1. Evaluation Metrics

To assess the performance of various interpolation methods, we evaluated the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the total number of water-covered interpolated points where depth values were above sea level (negative points). The RMSE and MAE indicate overall accuracy, while the total negative points highlight cases where the interpolation method incorrectly predicted land elevations in the sea. RMSE and MAE are respectively formulated below.

$$RMSE = \sqrt{\frac{1}{n}\sum\left(x_i - z_j\right)^2},$$

$$MAE = \frac{1}{n}\sum\left|x_i - z_j\right|,$$

where z_j – the value of unknown or interpolated points, n – the total number of sample points, and x_i – the ith value of known or observation points [8,13].

4.2. Comparison of Interpolation Methods

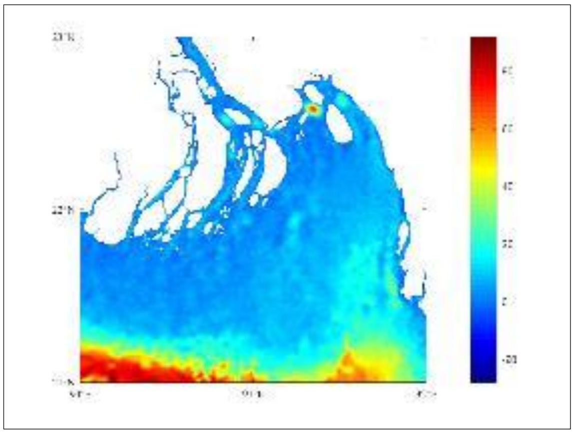
To evaluate interpolation performance, we implemented the first approach, where no adjustments were made to the elevation values. The results are summarized in **Table 1**.

Table 1 Performance comparison of interpolation methods (Approach 1)

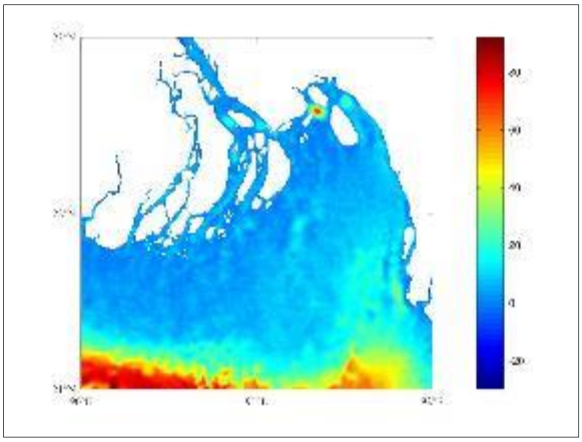
Method	RMSE	MAE	Total Negative Points
Linear	3.09	1.07	8,290
IDW	3.08	1.15	8,096
Kriging	3.05	0.89	10,182
TIN	3.31	1.04	9,594
MLS	18.36	11.67	51,942
PCHIP	3.00	1.14	8,177
Spline	3.85	1.27	8,492

From the RMSE and MAE values, Kriging performed the best in terms of overall error, achieving the lowest MAE (0.89) and a competitive RMSE (3.05). PCHIP and IDW also showed relatively lower RMSE and MAE values, making them reliable choices for bathymetric interpolation. In contrast, Moving Least Squares (MLS) performed the worst, with an exceptionally high RMSE (18.36) and MAE (11.67), indicating that it produced significantly higher overall errors in comparison to other methods. The high values of both RMSE and MAE suggest that MLS generated large discrepancies between the estimated and true depth values, making it unreliable for bathymetric applications in this study area. Additionally, MLS generated a substantial number of false land points in water, which indicates that the interpolation method misclassified water areas as land. In comparison, Inverse Distance Weighting (IDW) produced the fewest false land points, suggesting that it handled the land-water transition more effectively. Kriging and PCHIP also showed relatively reliable performance, with lower RMSE and MAE values, but IDW emerged as a more dependable method when it comes to reducing misclassification errors, particularly in the boundary regions between land and water. On the other hand, MLS's poor performance underscores the importance of choosing an interpolation method that not only minimizes error but also avoids misclassifying land and water regions. The evaluated depth values obtained using the interpolation methods under Approach 1 are presented in **Fig. 3**.

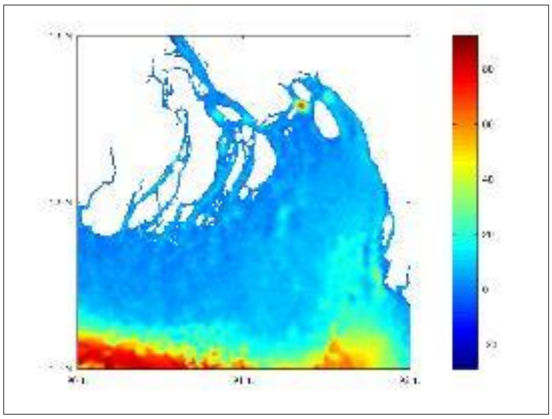
4.3. Comparison of Interpolation Methods (Approach 2)



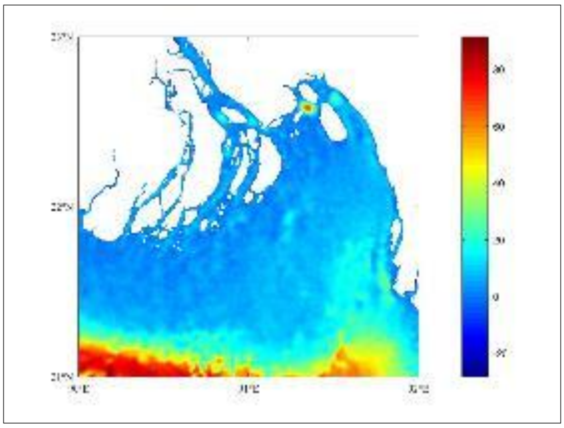
a) Linear



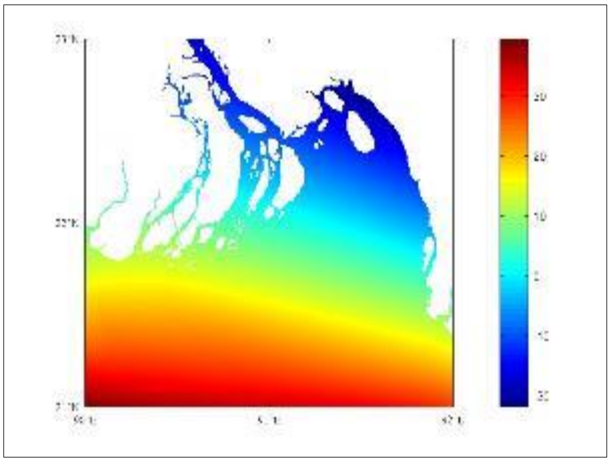
b) IDW



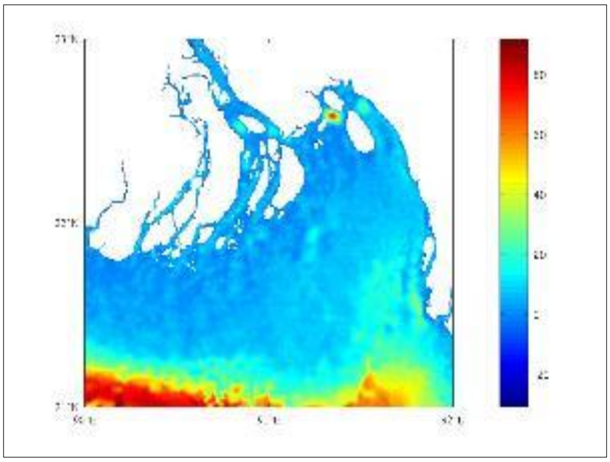
c) Kriging



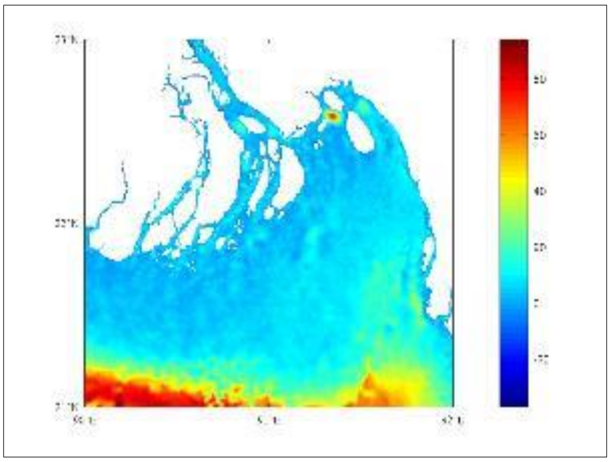
d) TIN



e) MLS



f) PCHIP



g) Spline

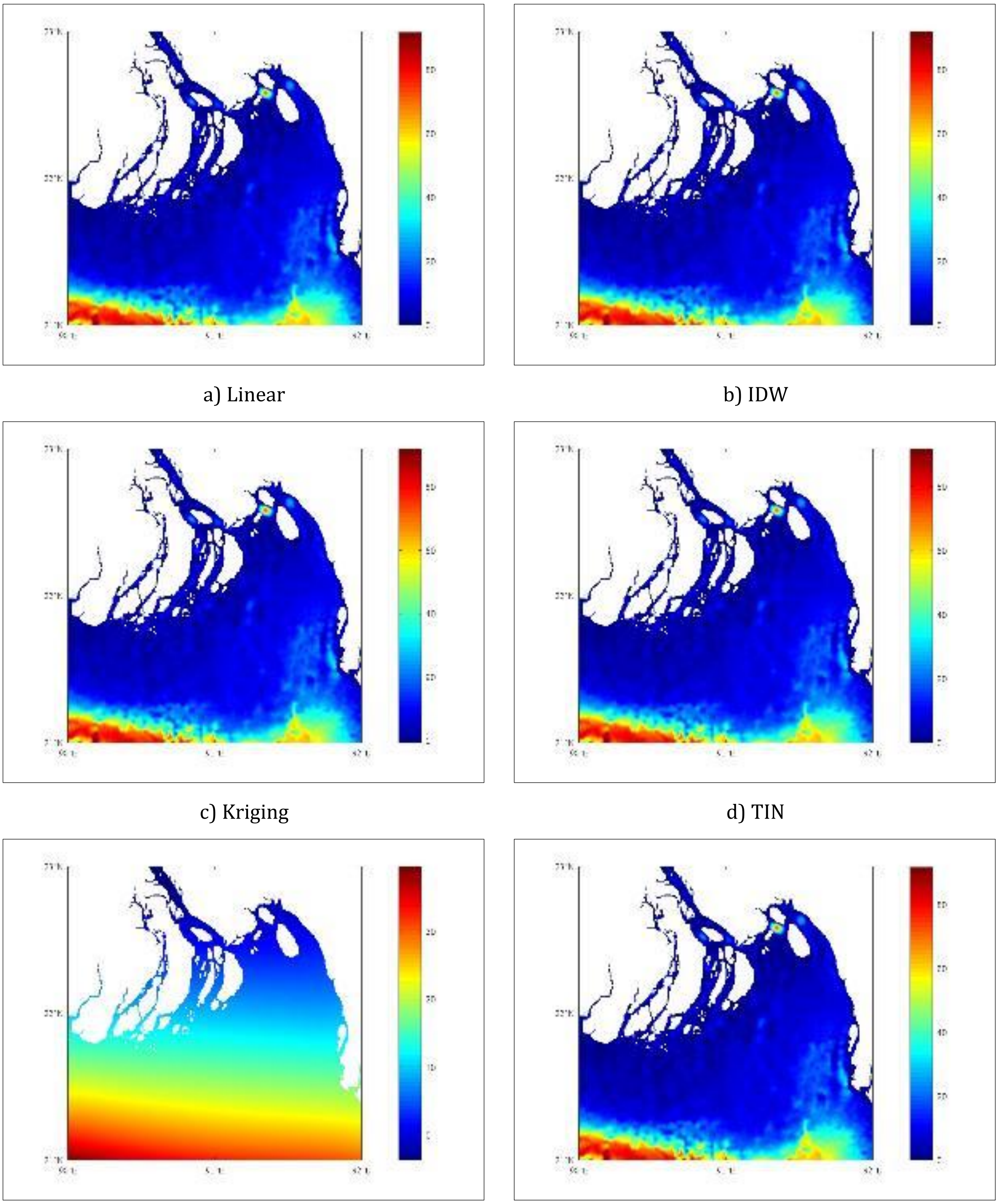
Figure 3 The evaluated depth values obtained using the interpolation methods under Approach 1

To further evaluate interpolation performance, we implemented a second approach where land elevations above sea level were set to zero. The results are summarized in **Table 2**. By setting land elevations above sea level to zero in Approach 2, we observed a substantial reduction in both RMSE and MAE for most interpolation methods. These metrics are critical for assessing interpolation performance, where RMSE measures the overall magnitude of errors (including larger discrepancies) and MAE quantifies the average absolute error. Linear, PCHIP, IDW, and TIN all exhibited relatively low RMSE and MAE values, indicating that these methods performed well in minimizing interpolation errors and provided reliable depth estimates. Notably, none of these methods generated false land points in water, demonstrating their effectiveness in managing the land-water boundary and preventing misclassification. This is a significant improvement compared to Approach 1, where more false land points were observed. Kriging, despite its lower RMSE (0.46) and MAE (0.15), still had a noticeable number of false land points in water (5,171 misclassified points). Although

Table 2 Performance comparison of interpolation methods (Approach 2)

Method	RMSE	MAE	Total Negative Points
Linear	0.61	0.28	0
IDW	0.67	0.34	0
Kriging	0.46	0.15	5,171
TIN	0.57	0.23	37
MLS	9.61	6.72	9,238
PCHIP	0.67	0.34	0
Spline	0.67	0.27	1,715

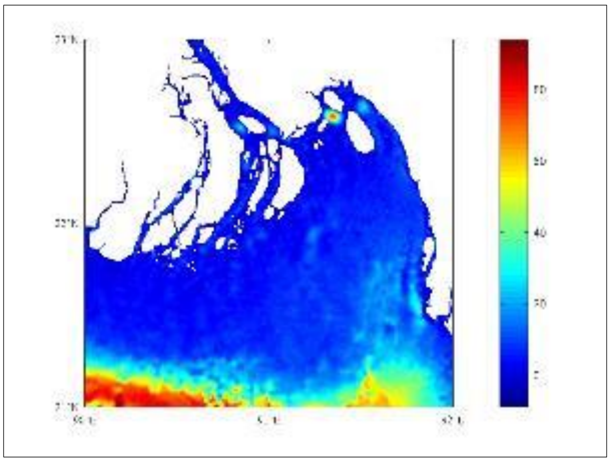
Kriging achieved the best overall error metrics, the misclassification of water as land suggests that this method remains sensitive to the topography, even when land elevation values are adjusted. This result highlights a trade-off: Kriging can minimize overall error but may still struggle in accurately distinguishing between land and water in certain regions. The Moving Least Squares (MLS) method exhibited the highest RMSE (9.61) and MAE (6.72) values, signifying that it was the least accurate of all the methods evaluated. Additionally, it produced a large number of false land points (9,238), further underscoring the limitations of this method in handling bathymetric data. The high RMSE and MAE values suggest that MLS fails to capture the true depth values effectively, particularly in areas where the land-water transition is critical. Interestingly, spline interpolation, while showing an MAE (0.27) similar to TIN and IDW, still generated a significant number of false land points (1,715). This indicates that, despite its relatively low average error (MAE), the method is more prone to misclassifying land and water regions compared to other methods like IDW and TIN, which produced no false land points. In summary, the results indicate that reducing land elevation to zero improved interpolation accuracy across most methods, particularly in terms of RMSE and MAE. However, methods like Kriging and Spline demonstrated trade-offs: while their overall error values were low, they still misclassified land and water points, emphasizing the sensitivity of interpolation methods to topographical constraints. The MLS method, on the other hand, continued to perform poorly with high error metrics and a significant number of false land points, confirming its unsuitability for bathymetric applications in this study. The evaluated depth values obtained using the interpolation methods under Approach 2 are presented in **Fig. 4**.



a) Linear b) IDW

c) Kriging d) TIN

e) MLS f) PCHIP



g) Spline

Figure 4 The evaluated depth values obtained using the interpolation methods under Approach 2

4.4. Effect of Land Elevation on Interpolation

Given the complexity of the study area, where multiple wide and narrow rivers connect to the BOB, land elevation above sea level has a significant influence on interpolation methods. To evaluate this effect, we tested two approaches: the first used raw elevation values without modification, while the second set land elevations above sea level to zero before interpolation. The results from the first approach indicated that certain methods, particularly Kriging and MLS, were more prone to introducing artificial land elevations in sea regions. In contrast, the second approach aimed to reduce the influence of land elevation on interpolation accuracy by ensuring that only water-covered areas were considered for depth estimation.

4.5. Implications for Bathymetric Interpolation

The findings of this study highlight the importance of selecting an interpolation method based on the specific characteristics of the study area. The presence of rivers, complex coastal boundaries, and varying sedimentation patterns strongly influences interpolation performance, making it essential to consider both accuracy and the potential for land-sea misclassification when choosing an interpolation technique. Future research may explore hybrid approaches that combine the strengths of multiple interpolation methods or investigate modifications to Kriging and MLS to improve their ability to distinguish between land and water regions.

4.6. Recommendations for Further Research

Further studies should explore hybrid interpolation techniques that integrate Kriging's accuracy with the robustness of IDW to enhance bathymetric estimation. Additionally, testing higher-resolution datasets could provide insights into the scalability and applicability of interpolation methods in more detailed bathymetric modeling. The impact of preprocessing techniques, such as land-sea boundary smoothing, should also be evaluated to determine their effectiveness in improving interpolation accuracy. These advancements would contribute to more accurate and reliable bathymetric data generation, which is essential for applications such as coastal management, marine navigation, and oceanographic modeling.

5. Conclusion

This study evaluated multiple interpolation methods for bathymetric data in a complex coastal environment. The results demonstrated that PCHIP and IDW were the most reliable interpolation techniques, achieving a balance between accuracy and correct land-sea classification. Kriging produced the lowest MAE but struggled with land-sea boundary misclassification, highlighting its sensitivity to elevation variations. The Moving Least Squares (MLS) method was found to be unsuitable for bathymetric interpolation due to high error rates. A key finding was that reducing the influence of land elevation by setting land heights above sea level to zero significantly improved interpolation accuracy. The two tested approaches showed that interpolation performance is strongly influenced by land-sea boundary conditions, making careful preprocessing an essential step in bathymetric modeling. Overall, the study emphasizes the importance of selecting interpolation techniques that align with the geographical complexity of the study area. Future research should focus on refining interpolation algorithms to improve land-sea boundary handling and exploring hybrid approaches for enhanced bathymetric accuracy.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that there is no conflict of interest.

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