Geodesy and Cartography
ISSN 2029-6991 / eISSN 2029-7009
2023 Volume 49 Issue 4: 186–194
https://doi.org/10.3846/gac.2023.18250

UDC 528.47

A COMPARISON OF DIFFERENT GIS-BASED INTERPOLATION METHODS FOR BATHYMETRIC DATA: CASE STUDY OF BAWEAN ISLAND, EAST JAVA

Danar Guruh PRATOMO*, Rizka Amelia Dwi SAFIRA, Olivia STEFANI

Department of Geomatics Engineering, Faculty of Civil Planning and Geo Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

Received 07 December 2022; accepted 22 November 2023

Abstract. The bottom surface's portrayal is crucial in many different practices. Therefore, accurate bathymetry data is required. The interpolation method is one element that influences the accuracy of a Single Beam Echosounder's depth data. IDW, Kriging, and TIN are three standard interpolation techniques. This study compares these three methods with two scenarios utilizing the spatial analysis to establish the most effective technique for producing the digital elevation model of the seafloor beneath Bawean Island. The IDW exhibits the strongest R-squared (0.9998779 in Scenario-1 and 0.9999875 in Scenario-2) and correlation (0.9998796 in Scenario-1 and 0.9999595 in Scenario-2). It indicates that IDW and bathymetric data have the closest relationships. IDW has the lowest error, as measured by the MAE value (0.02 in Scenario-1 and 0.009 in Scenario-2), followed in both cases by Kriging and TIN. Additionally, the RMSE for IDW shows the same outcome (0.045 in Scenario 1 and 0.016 in Scenario 2). In the meantime, comparing the first and second scenarios reveals that the second, which has fewer data, is preferable to the first. Since the MAE and RMSE in the first scenario are greater than those in the second, we may infer that more data leads to more significant errors.

Keywords: SBES, interpolation methods, IDW, Kriging, TIN, spatial analysis.

Introduction

Bathymetric and morphologic of bottom surfaces are helpful for knowledge regarding water quality, temperature, salinity, and the other processes in the ocean (Curtarelli et al., 2015). This way, the bathymetric data are essential to define the bottom surface. Additionally, bathymetric data is essential for assessing safe vessel navigation, often determined by surveying shallow or coastal waters. This information will be necessary for setting up shipping routes and establishing nautical charts (Hell et al., 2012). One of the bathymetry measurement tools is Single Beam Echosounder (SBES). Due to its effectiveness, affordability, and accessibility, the Single Beam Echosounder (SBES) is the most often used instrument in port, lake, and river surveys (Arseni et al., 2019). SBES aims to measure the sea depth in the vicinity of the shipping lane (Parente & Vallario, 2019). The sonar device's electrical and acoustic properties impact these readings. Acoustic factors govern underwater acoustic signals' propagation properties, including frequency, bandwidth, and signal length. The performance of the sonar may be understood and analyzed using the sonar equation. The signal or sound detection is defined as echo excess (EE) in the following equation, which is made up of the electrical characteristics of the sonar: $EE = SL - 2TL - (ND - DI) + BS - DT$ (Kartal et al., 2022), where SL is the "source level", a measurement of a sound source's power emitted, more specifically it is a measurement of its far-field radiant intensity; TL is the "transmission loss", the difference between the signal level received at the sonar and the SL, which is the inverse of the transfer function from source to receiver; NL is "noise level", the degree of undesired noise or non-acoustic noise interfering with the sonar signal; DI is the "directivity index", as a rough estimate of the array gain; BS is the "bottom backscattering strength", used for assessing an accurate mapping and categorization of the seafloor; and DT is the "detection threshold" as the space-time processor (Ainslie & Leighton, 2016; Solikin et al., 2018; Yang et al., 2018). However, there will be several sites where the SBES has not assessed the depth. Interpolation is required to complete the data. The product decides which is the most performed for the selected study area.

*Corresponding author. E-mail: *guruh@geodesy.its.ac.id*

1. Study area

The study area taken for this research is Bawean Island, East Java, Indonesia, precisely in the coastal area positioned 140 km from the north coast of Gresik Regency, as shown in Figure 1. Geographically, it is located between 5° 49′ 12.56″ S and 5° 49′ 27.94″ S and 112° 44′ 9.19″ E and 112° 44′ 24.45″ E. Hence, the projected coordinate system used for data processing is UTM Zone 49S. Bawean Island itself has two districts, including Sangkapura District and Tambak District. Each of the districts has 17 and 13 villages, respectively. Due to its neutral nautical environment, this island has become one of the most visited islands for tourists.

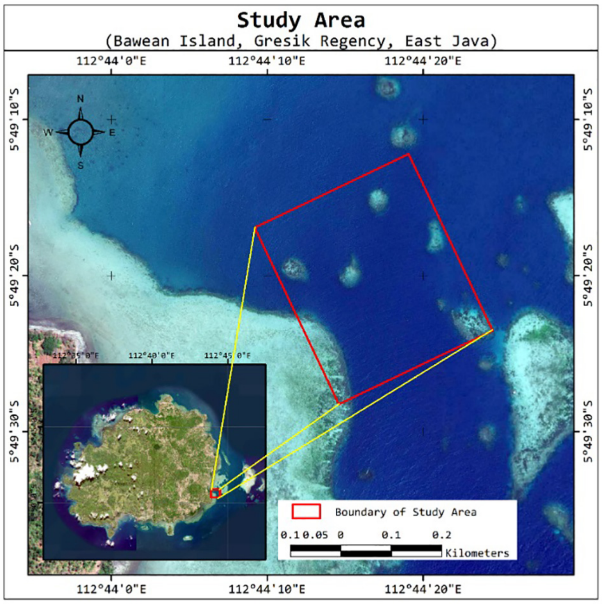

Figure 1. Study area (Bawean Island)

2. Data and methodology

The method of this study is illustrated in the flowchart depicted in Figure 2. The dataset utilized in this study is developed based on bathymetric surveying using Single Beam Echosounder (SBES) to obtain the depth information held in Bawean Island from 22nd to 26th May 2021. Eight hundred three points with corrected depth (x, y, z) are selected about the study area. The test data were divided into two scenarios to analyze the accuracy of the depth by different interpolation methods. The first scenario includes all points into interpolation, which is 803 points. At the same time, the second scenario includes 150 points in total to be interpolated. These points are randomly chosen and uniformly spread throughout the study area. The interpolated points in terms of predicted points will be compared to the corrected depth generated from SBES. With this approach, we will examine the quality assessment of each interpolation procedure represented by the value of the standard deviation, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and regression analysis depending on the different set of control points. Not simply the quality, but we also aim to compare the total area of each depth classification. We will divide the Z value into seven classes to meet this result. The interpolation methods are Inverse distance weighted (IDW), Kriging, and Triangular Irregular Network (TIN). The utilization of variation of interpolation methods seeks to know the most suitable interpolation method for the data set of the selected study area.

Meanwhile, the conclusion of the best method for this research cannot entirely be used for different data sets in other study areas because no interpolation method will assure the most promising results for all data sets. It means we should consider the characteristics of the data set to conclude which method is best (Hu, 1995). The interpolation method, or spatial interpolation, in GIS itself, is a procedure to assemble reported assumptions when values of the fields have not been measured at an exact place. Data commonly employed in spatial interpolation are elevation data, rainfall data, meteorological data, topography, and population density (Sukkuea & Heednacram, 2022). This method effectively predicts the geographic data distribution, increasing data density, designating a fierce distribution of data with a small data set coverage, and acquiring complete information of unmeasured data (Hamdy et al., 2022).

2.1. Interpolation methods

The three interpolation methods were chosen because these methods 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 Inverse Distance Weighted (IDW), Kriging, and Triangular Irregular Network (TIN) methods.

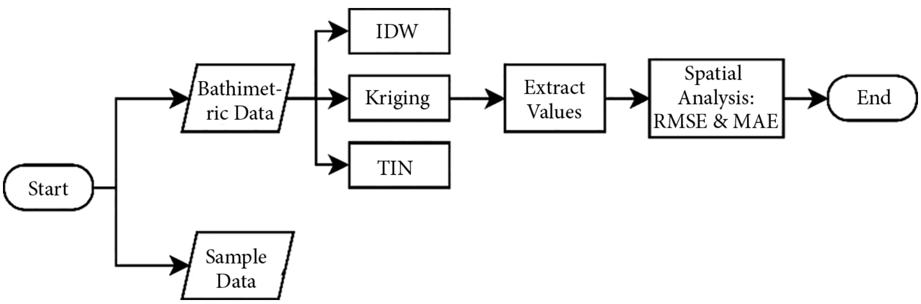

Figure 2. Flowchart of methodology

2.1.1. Inverse distance weighted (IDW)

Inverse Distance Weighted (IDW) interpolation is the simplest method. The calculation of predicted points using this method is based on the distance between the observation point and the predicted point itself. Therefore, closer to the observational point, the interpolation points will receive a more significant influence than more prominent interpolation points distanced (Liu & Yan, 2021). A weighted average of the values at the dispersed nearby sites serves as the interpolation value at each interpolation point. Each scatters point's weight is reduced as the distance from the interpolation point grows (Tasri, 2022).

Further, this interpolation performs excellently with evenly distributed points (Liu & Yan, 2021). The unknown values determined by measuring a linear combination point were given a deterministic estimate by the IDW approach (Mohammad Sham et al., 2022). Hence, the mathematical formula for generating IDW is written below.

$$z_j = \frac{\sum_{i=1}^{n} \frac{x_i}{d_{ij}^{\beta}}}{\sum_{i=1}^{n} \frac{1}{d_{ij}^{\beta}}}, \qquad (1)$$

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 (Arkoc, 2022).

2.1.2. Kriging

Kriging is an interpolation method that employs Gaussian processes in data modeling and prediction. Hence, Kriging is generally known as Gaussian Process Regression (GPR). These processes have been developed since the 1940s by D. G. Krige, the South African engineer, and involved reams of applications (Hossen et al., 2022). This approach is frequently utilized in the geochemistry, geology, soil science, and ecological fields of mining and petroleum. In addition, the primary distinction between deterministic methods and Kriging is the utilization of a statistical model, which incorporates autocorrelation. Spatial autocorrelation is the term for this association between the values of data points and their separation from one another. When a spatially associated distance or directional bias in the data is known, Kriging is the best option. A semi-variogram based on known data points will be made first to model the surface using the Kriging method (Ajvazi & Czimber, 2019). Several types of Kriging may be used, including Simple Kriging, Ordinary Kriging, Universal Kriging, and External Trend Kriging (Sukkuea & Heednacram, 2022). For the experiment, this study will employ simple Kriging. The weight values in Simple Kriging are established by reducing error variance. A variogram, which is nothing more than a function of the separation distance, is typically used in Kriging to quantify covariance (Lu et al., 2022). The empirical equation used to create the variogram is as follows:

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

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

2.1.3. Triangular irregular network (TIN)

An alternate method for representing topography is the triangulated irregular network (TIN), which divides a surface into a set of continuous, non-overlapping triangles. Each triangle node's elevation is noted, and since heights between nodes may be interpolated, a continuous surface can be created (Guo et al., 2010). The triangular irregular network (TIN) model, which predicts values in an unsampled region, is an alternative to the grid-based and geometric models. It displays the original form of objects. Numerous issues, such as creating a topographic map, object buffers, and multiplayer data, have been solved using TIN mesh (Liu & Wu, 2019).

Further, Delaunay triangulation is the name given to the triangles that the TIN technique generates. When interpolating inside triangles, it is advantageous since it offers the set of most equiangular triangles. Any triangle with no other points on a circumscribing circle that passes through its vertices is said to be a Delaunay triangle (Jones et al., 1994).

2.2. Quality assessment

The quality assessment to render the performance of different interpolation methods and the number of selected sample points is divided into two categories. In the first category, we will examine the statistical approaches using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These approaches were selected due to their effectiveness, simplicity, and widely used method in measuring the accuracy of the studies. Moreover, these two absolute error measures are employed in a broad range of fields, including geosciences, atmospheric sciences, biosciences, machine learning, data mining, time series analysis, and others. Model fitting (best parameter selection for a given model), model validation, model selection, model comparisons (among numerous competing models), and prediction evaluations are the primary uses of these metrics (Karunasingha, 2022). MAE and RMSE are respectively formulated below.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| x_i - z_j \right|; \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(x_i - z_j \right)^2}, \qquad (4)$$

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 (Sukkuea & Heednacram, 2022; Liu & Yan, 2021).

For the second quality assessment category, we will show the relationship analysis using two-dimensional scatterplots for each interpolation method's link between predicted and observed values for various sample points. The concept used in this analysis is a linear regression model that will reveal the strong relationship between predicted and observed values. It is determined by the coefficient of determination, the *p*-test, and the correlation coefficient, which will be conducted using R. Studies comparing different quantitative methods are often interpreted using linear

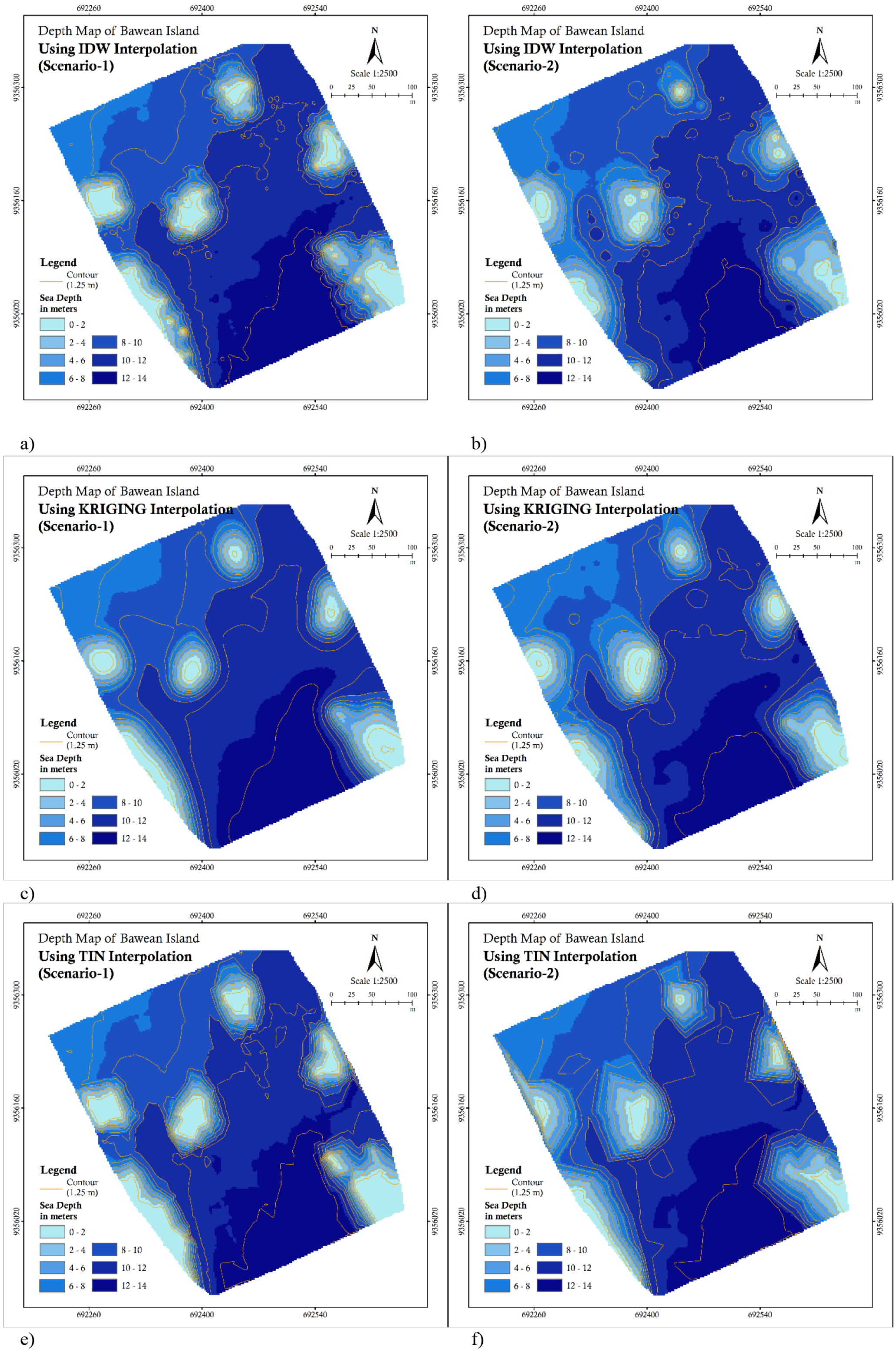

Figure 3. Depth map generation using the first scenario (left) and second scenario (right): a – IDW first scenario; b – IDW second scenario; c – Kriging first scenario; d – Kriging second scenario; e – TIN first scenario; f – TIN second scenario

regression and correlation. Their main advantage is that they are well-known, and as a result, both are used in most technique comparison studies (Twomey & Kroll, 2008).

2.3. Previous research

Several studies have compared the effectiveness of some interpolation methods to estimate bathymetric surfaces reliably. Ferreira et al. (2017) directly generated the Digital Model of Depth (DMD) using Universal Kriging (UK) and Inverse Distance Weighted (IDW) in the computational representation of bathymetric surfaces. Through the results, Universal Kriging interpolation has the superiority in efficiency in creating DMD with a basis in the bathymetric surveys data. Furthermore, Henrico (2021) has also conducted an analogous investigation to analyze and compare the effectiveness of the IDW and OK interpolation methods for determining the bathymetry of Saldanha Bay. The study interpolates sounding data using two interpolation methods: Inverse Distance Weighted (IDW) and Original Kriging (OK). The investigation reveals that IDW has emerged as the technique of chosen interpolation of Saldanha Bay bathymetry in the future, which is demonstrated by the high value of the coefficient of determination and descriptive statistics from the ANOVA test. However, the study achieved by Šiljeg et al. (2015) publicizes that the Simple Cokriging method favored the most excellent performance among the other 13 interpolated methods used, one of them included IDW, to present the seabed digital elevation model of Lake Vrana, Croatia. From various studies using the IDW and Kriging methods to interpolate depth data from bathymetric survey results, these two methods will be tested on a case study of Bawean Island depth data recognized using a Single Beam Echosounder, coupled with the TIN interpolation method. Hence, the outcomes are site-specific, and previous research has shown that there is "no consensus as to a superior or preferable strategy" (Murphy et al., 2010). Finding the best approach for interpolating the bathymetry of Bawean Island is crucial, given these inconsistent findings and the likelihood that results may be site-specific.

3. Result and discussion

The digital elevation model (DEM) of the bottom surfaces is generated from interpolation processes. These models are frequently used in hydrological studies, facility siting, and urban design (Zhang et al., 2022). By applying three interpolation methods and two scenarios representing the number of involved sample points, it produces six digital elevation models. As previously mentioned, every model will be classified into seven classes based on the minimum and maximum depth developed by each interpolation method. The interpolation maps (Figure 3) are shown with a ramp of blue hue that denotes shallow to deep seas; the darker the blue, the greater the depth. The scale used for these maps is 1:2500, which becomes the basis for determining the contour interval.

It is clear from a visual comparison of these data that IDW, Kriging, and TIN for each scenario assess and construct the continuous surface of bathymetry in explicitly identified ways. Additionally, the smoother depiction of the interpolated surface generated by the Kriging technique is seen in contrast to the more angled depth contours produced by IDW and TIN. This difference may be explained by the estimating strategy used by each interpolation method. Moreover, the area comparison is performed for a separate depth class to get a more profound explanation as shown in Figure 4. This calculation is based on the produced pixels that store elevation information from the interpolation processes.

The Table 1 shows the area percentage for each interpolation method and scenario.

It is possible to determine that the difference area in each class for each interpolation technique and scenario is relatively diverse based on the computation of the area in each depth class in Table 1. By using the value of standard deviation, the difference in the area at a depth interval of 6–8 m is the most notable, with a standard deviation value of 2.580. The depth interval between 2–4 m has the slightest significant variance in depth, with a standard deviation of 0.483. Differences in the techniques used by each method to interpolate depth points and the number

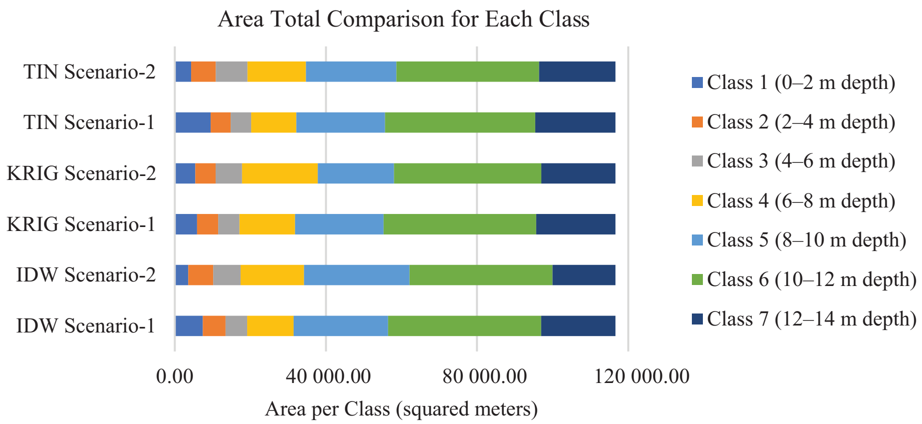

Figure 4. Area total comparison for each class of depth in square meter

Table 1. Area percentage comparison for each interpolation method and scenario

Class	Interval of Depth (m)	Scenario-1			Scenario-2			Standard Deviation
		IDW	KRIGING	TIN	IDW	KRIGING	TIN	
1	0–2	6.364	5.064	8.149	3.061	4.652	3.717	1.851
2	2–4	5.149	4.802	4.552	5.661	4.617	5.587	0.483
3	4–6	4.908	4.826	4.655	6.231	6.005	7.196	1.007
4	6–8	10.560	12.612	10.228	14.383	17.185	13.280	2.580
5	8–10	21.437	20.082	20.132	23.952	17.276	20.508	2.167
6	10–12	34.726	34.609	34.088	32.433	33.424	32.383	1.039
7	12–14	16.856	18.006	18.197	14.280	16.841	17.329	1.411

of points cause variations in the accumulated area per class. In TIN, the algorithm used is the Delaunay triangle triangulation. While the principle used in IDW is the closeness of the distance between the correct points and the predicted points so that the closer the distance is, the more it will affect the resulting elevation. Then in Kriging, the principle used is the correlation between points. In the next section, the analysis will focus on regression and statistical analysis.

3.1. Statistical testing: Mean Absolute Error and Root Mean Square Error

In the first scenario, the Digital Elevation Model (DEM) of the seabed is constructed utilizing 803 sample points and three interpolation methods. Directing to Figure 5, which delivers the produced DEM, IDW and TIN appear relatively comparable, despite some authentic dissimilarities. Meanwhile, the outcome does a smooth interpolation for Kriging. Using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for error analysis shows that IDW is the most preferable method for interpolating the selected sample points, followed by TIN and Kriging. For the second scenario, a total of 150 sample points is used to interpolate using the three cited methods. By studying the visualization of those three developed DEMs, there are differences in the color ramp that portrays the depth of the seabed. The second scenario shows that the shallower depth covers a broader area than in scenario one. Simultaneously, the visualization of IDW is identical to TIN, which has the same finding as in the first scenario. According to the value on MAE, IDW has the lowest value of error, followed by Kriging and TIN.

Moreover, the same result also occurs in the value of RMSE. The second scenario for the study case can be interpolated most accurately using IDW, followed by Kriging, which is just 3.4 cm less accurate than IDW and least accurately using TIN. The concluding MAE and RMSE values for Kriging and TIN in this second scenario discovery are partially different from those in the first scenario (Table 2).

Table 2. The summary of MAE and RMSE value as error analysis for each interpolation method and both scenarios

MAE		
	Scenario-1	Scenario-2
TIN	0.072409398	0.073927029
Kriging	0.478380284	0.032340756
IDW	0.021678711	0.009297303

RMSE		
	Scenario-1	Scenario-2
TIN	0.209980024	0.140393633
Kriging	0.924688479	0.050680085
IDW	0.044779433	0.016437696

3.2. Linear regression analysis between predicted and observed depth values

The two-dimensional scatterplots with regression lines are performed to show the relationship between predicted and observed depth values as illustrated in Figure 6.

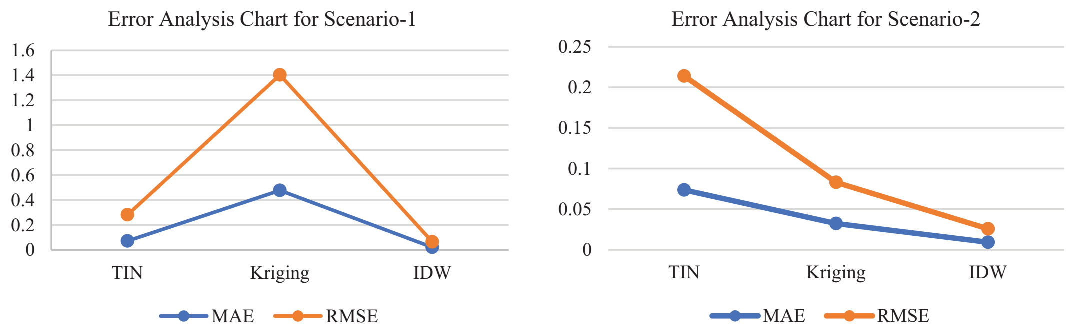

Figure 5. Error analysis of MAE and RMSE for each scenario

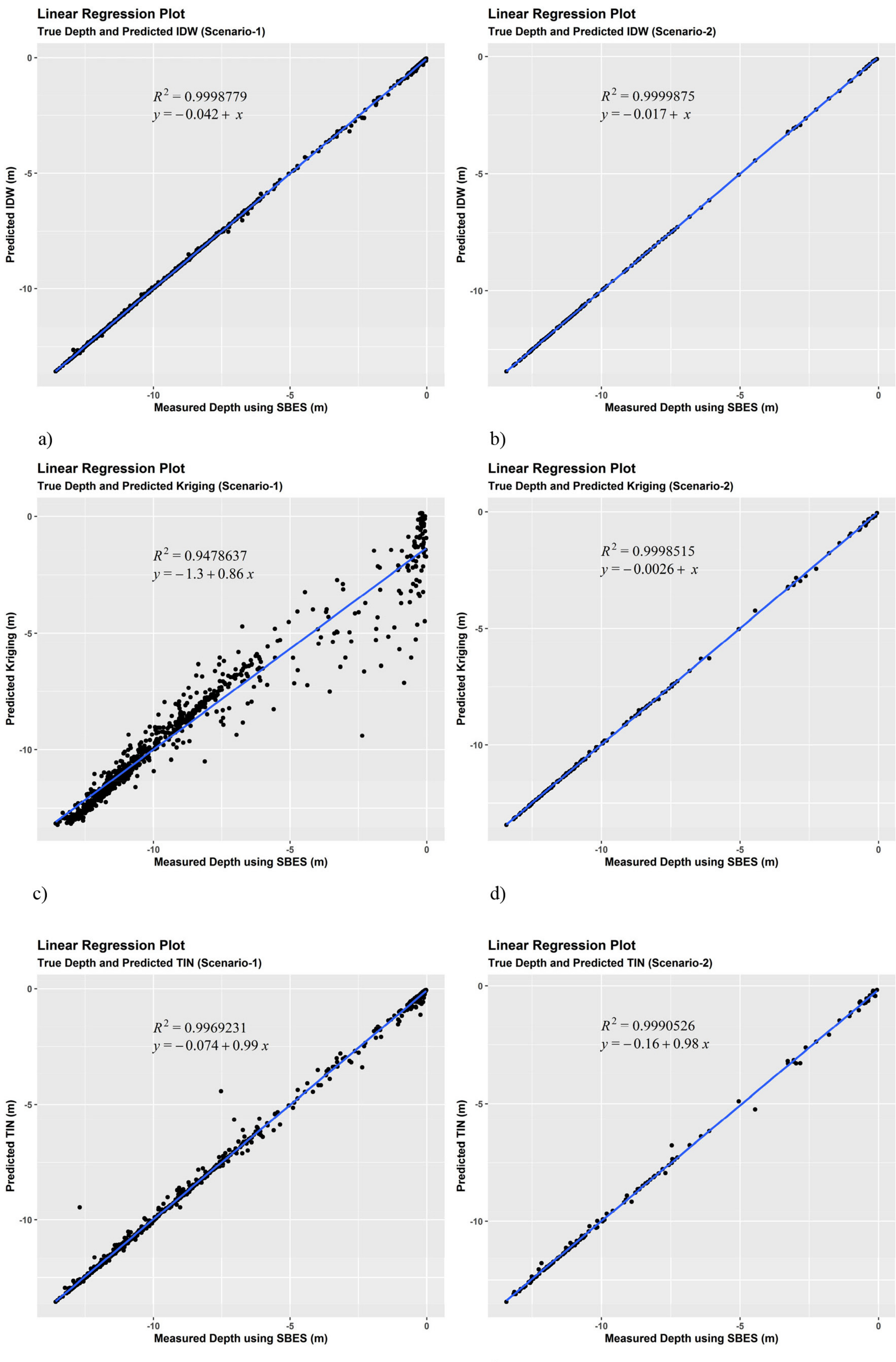

Figure 6. Linear regression plot: a – predicted IDW first scenario; b – predicted IDW second scenario; c – predicted Kriging first scenario; d – predicted Kriging second scenario; e – predicted TIN first scenario; f – predicted TIN second scenario

Table 3. R-squared and Spearman's Coefficient Correlation comparison

Analysis Approach	Scenario-1			Scenario-2		
	IDW	KRIGING	TIN	IDW	KRIGING	TIN
R-squared	0.9998779	0.9478637	0.9969231	0.9999875	0.9998515	0.9990526
Spearman's Coefficient Correlation	0.9998796	0.9864415	0.9970156	0.9999595	0.9998524	0.9990433

The findings demonstrate a substantially linear relationship in every method and scenario, as shown by the coefficient of determination *(R^2)* values of more than 0.9. However, this result is slightly different from the initial hypothesis and previous studies that mention that the more sample points, the better the interpolation results. This discovery proves there are no consistent conclusions concerning how the contributing elements affect how well the interpolation methods work. The performance of the approaches was also said to be unaffected by sample density, which was shown to be inconsequential (Henrico, 2021). Along with regression analysis, to deepen the knowledge about the relationship between observed and predicted depth values in the study area, Table 3 shows Spearman's correlation coefficient and the summary of R^2 for each interpolation method and scenario. By employing rank to determine the correlation, Spearman's correlation test offers a non-parametric measurement of the link between variables. This approach is utilized when it is impossible to maintain the assumption of a bivariate normal distribution. Spearman correlation evaluates how well the link between two variables can be explained using a monotonic function. In contrast, Pearson correlation characterizes the strength of the association between variables using a linear function. Like those of Pearson, Spearman's correlation coefficient values fall between –1 and 1, with $r > 0$ denoting a positive association, $r < 0$ denoting a negative relationship, and $r = 0$ denoting no relationship (Rebekić et al., 2015).

Conclusions

The interpolation methods are essential for the bathymetric data. Among the methods of interpolating data, IDW is the most suitable method for bathymetric data. Using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for error analysis shows that IDW is the most preferable method for interpolating the selected sample points, followed by TIN and Kriging. The IDW's result shows the highest R-squared (0.9998779 in Scenario-1 and 0.9999875 in Scenario-2) and correlation (0.9998796 in Scenario-1 and 0.9999595 in Scenario-2). It means that IDW has the closest relation in bathymetric data. According to the MAE, IDW has the lowest error value (0.02 in Scenario-1 and 0.009 in Scenario-2), followed by Kriging and TIN.

Moreover, the same result also occurs in the value of RMSE (0.045 in Scenario-1 and 0.016 in Scenario-2). Meanwhile, if we compare the first and second scenarios, it can be obtained that the second scenario is better than the first. The MAE and RMSE in the first scenario are more significant than in the second scenario, so we can conclude that the more data, the more significant error.

Acknowledgements

The authors thank the anonymous editors and reviewers for their helpful and valuable comments. Thanks are also delivered to PT. Geosolution Pratama Nusantara for approval to use and publicize the data and for its backing.

References

Ainslie, M. A., & Leighton, T. G. (2016). Sonar equations for planetary exploration. *The Journal of the Acoustical Society of America*, *140*(2), 1400–1419. https://doi.org/10.1121/1.4960786

Ajvazi, B., & Czimber, K. (2019). A comparative analysis of different dem interpolation methods in GIS: Case study of Rahovec, Kosovo. *Geodesy and Cartography*, *45*(5), 43–48. https://doi.org/10.3846/gac.2019.7921

Arkoc, O. (2022). Modeling of spatiotemporal variations of groundwater levels using different interpolation methods with the aid of GIS, case study from Ergene Basin, Turkey. *Modeling Earth Systems and Environment*, *8*(1), 967–976. https://doi.org/10.1007/s40808-021-01083-x

Arseni, M., Voiculescu, M., Georgescu, L. P., Iticescu, C., & Rosu, A. (2019). Testing different interpolation methods based on single beam echosounder river surveying. Case study: Siret River. *ISPRS International Journal of Geo-Information*, *8*(11), 507. https://doi.org/10.3390/IJGI8110507

Curtarelli, M., Leão, J., Ogashawara, I., Lorenzzetti, J., & Stech, J. (2015). Assessment of spatial interpolation methods to map the bathymetry of an Amazonian hydroelectric reservoir to aid in decision making for water management. *ISPRS International Journal of Geo-Information*, *4*(1), 220–235. https://doi.org/10.3390/ijgi4010220

Ferreira, I. O., Rodrigues, D. D., Dos Santos, G. R., & Rosa, L. M. F. (2017). Em superficies batimétricas: IDW ou krigagem? *Boletim de Ciencias Geodesicas*, *23*(3), 493–508. https://doi.org/10.1590/S1982-21702017000300033

Guo, Q., Li, W., Yu, H., & Alvarez, O. (2010). Effects of topographic variability and lidar sampling density on several DEM interpolation methods. *Photogrammetric Engineering & Remote Sensing*, *76*(6), 701–712. https://doi.org/10.14358/PERS.76.6.701

Hamdy, O., Gaber, H., Abdalzaher, M. S., & Elhadidy, M. (2022). Identifying exposure of urban area to certain seismic hazard using machine learning and GIS: A case study of Greater Cairo. *Sustainability*, *14*(17), 10722. https://doi.org/10.3390/SU141710722

Hell, B., Broman, B., Jakobsson, L., Jakobsson, M., Magnusson, Å., & Wiberg, P. (2012). The use of bathymetric data in society and science: A review from the Baltic Sea. *Ambio*, *41*(2), 138–150. https://doi.org/10.1007/s13280-011-0192-y

Henrico, I. (2021). Optimal interpolation method to predict the bathymetry of Saldanha Bay. *Transactions in GIS*, *25*(4), 1991–2009. https://doi.org/10.1111/tgis.12783

Hossen, I., Anders, M. A., Wang, L., & Adam, G. C. (2022). Data-driven RRAM device models using Kriging interpolation. *Scientific Reports*, *12*(1), 1–12. https://doi.org/10.1038/s41598-022-09556-4

Hu, J. (1995, May). *Methods of generating surfaces in environmental GIS applications* [Conference presentation]. ESRI User Conference Proceedings, San Diego. https://proceedings.esri.com/library/userconf/proc95/to100/p089.html

Jones, C. B., Kidner, D. B., & Ware, J. M. (1994). The implicit triangulated irregular network and multiscale spatial databases. *The Computer Journal*, *37*(1), 43–57. https://doi.org/10.1093/comjnl/37.1.43

Kartal, S. K., Hacıoğlu, R., Görmüş, K. S., Kutoğlu, H., & Leblebicioğlu, M. K. (2022). Modeling and analysis of sea-surface vehicle system for underwater mapping using single-beam echosounder. *Journal of Marine Science and Engineering*, *10*(10), 1349. https://doi.org/10.3390/JMSE10101349

Karunasingha, D. S. K. (2022). Root mean square error or mean absolute error? Use their ratio as well. *Information Sciences*, *585*, 609–629. https://doi.org/10.1016/j.ins.2021.11.036

Liu, H., & Wu, C. (2019). Developing a scene-based triangulated irregular network (TIN) technique for individual tree crown reconstruction with LiDAR data. *Forests*, *11*(1), 28. https://doi.org/10.3390/f11010028

Liu, Z., & Yan, T. (2021). Comparison of spatial interpolation methods based on ArcGIS. *Journal of Physics: Conference Series*, *1961*(1), 012050. https://doi.org/10.1088/1742-6596/1961/1/012050

Lu, Y., Song, W., Ro, Y., & Yoo, C. (2022). Numerical experiments applying simple kriging to intermittent and log-normal data. *Water*, *14*(9), 1364. https://doi.org/10.3390/W14091364

Mohammad Sham, N., Anual, Z. F., & Shaharudin, R. (2022). GIS based interpolation method to urinary metal concentrations in Malaysia. *Food and Chemical Toxicology*, *163*, 112949. https://doi.org/10.1016/j.fct.2022.112949

Murphy, R. R., Curriero, F. C., & Ball, W. P. (2010). Comparison of spatial interpolation methods for water quality evaluation in the Chesapeake Bay. *Journal of Environmental Engineering*, *136*(2), 160–171. https://doi.org/10.1061/(ASCE)EE.1943-7870.0000121

Parente, C., & Vallario, A. (2019). Interpolation of single beam echo sounder data for 3D bathymetric model. *International Journal of Advanced Computer Science and Applications*, *10*(10), 2019. https://doi.org/10.14569/IJACSA.2019.0101002

Rebekić, A., Lončarić, Z., Petrović, S., & Marić, S. (2015). Pearson's or spearman's correlation coefficient - which one to use? *Poljoprivreda*, *21*(2), 47–54. https://doi.org/10.18047/poljo.21.2.8

Šiljeg, A., Lozić, S., & Šiljeg, S. (2015). A comparison of interpolation methods on the basis of data obtained from a bathymetric survey of Lake Vrana, Croatia. *Hydrology and Earth System Sciences*, *19*(8), 3653–3666. https://doi.org/10.5194/hess-19-3653-2015

Solikin, S., Manik, H. M., Pujiyati, S., & Susilohadi, S. (2018). Measurement of bottom backscattering strength using single-beam echosounder. *Journal of Physics: Conference Series*, *1075*, 012036. https://doi.org/10.1088/1742-6596/1075/1/012036

Sukkuea, A., & Heednacram, A. (2022). Prediction on spatial elevation using improved kriging algorithms: An application in environmental management. *Expert Systems with Applications*, *207*, 117971. https://doi.org/10.1016/J.ESWA.2022.117971

Tasri, A. (2022). Inverse distance interpolation for used in unstructured mesh finite volume solver. *Journal of Applied Engineering Science*, *20*(2), 597–601. https://doi.org/10.5937/jaes0-34022

Twomey, P. J., & Kroll, M. H. (2008). How to use linear regression and correlation in quantitative method comparison studies. *International Journal of Clinical Practice*, *62*(4), 529–538. https://doi.org/10.1111/J.1742-1241.2008.01709.X

Yang, Y., Hui, L., Ran, X., Liu, M., Yang, L., & Zhou, Y. (2018). Application of sonar equation in the design of ocean instruments. In *Proceedings of the 2018 International Symposium on Communication Engineering & Computer Science (CECS 2018)* (pp. 186–192). Atlantis Press. https://doi.org/10.2991/cecs-18.2018.34

Zhang, Y., Yu, W., & Zhu, D. (2022). Terrain feature-aware deep learning network for digital elevation model superresolution. *ISPRS Journal of Photogrammetry and Remote Sensing*, *189*, 143–162. https://doi.org/10.1016/J.ISPRSJPRS.2022.04.028