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Spatial Analysis of Earthquake Intensity Distribution in Java Using the Interpolation Method (2022–2024)

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ABSTRACT

Java, situated in the Pacific Ring of Fire, is one of the most seismically active regions in the world, with frequent earthquakes posing significant risks to its dense population and critical infrastructure. This study aimed to analyze the spatial distribution and intensity patterns of earthquakes in Java from 2022 to 2024 using data from the Meteorology, Climatology, and Geophysics Agency (Badan Meteorologi, Klimatologi, dan Geofisika, BMKG). Spatial interpolation techniques—inverse distance weighted (IDW), nearest neighbor, and Thiessen polygon—were applied to evaluate their effectiveness in mapping earthquake intensity patterns. The dataset included the earthquake magnitude, location, and occurrence time, with performance evaluated using mean absolute percentage error (MAPE) and mean absolute error (MAE). Results showed that the nearest neighbor method achieved the highest accuracy (MAPE of 12.27%, MAE of 0.37), followed by IDW, while the Thiessen polygon method demonstrated limited suitability for continuous seismic phenomena. These findings underscore the importance of selecting appropriate interpolation methods for seismic risk mapping, providing actionable insights for disaster preparedness and urban planning in Java.

1. Introduction

Earthquakes are a significant global issue, posing substantial risks to human lives, infrastructure, and economies. The increasing frequency and intensity of seismic events have heightened the need for comprehensive research [1]. Globally, earthquakes account for a significant portion of natural disasters, often leading to catastrophic outcomes in highly populated regions [2]. While advances in geospatial technologies and data analysis methods have enhanced the understanding of seismic patterns, many regions, particularly in developing countries, remain under-researched. Java, as part of the Indonesian archipelago, lies within the Pacific Ring of Fire, making it one of the most seismically active regions in the world [3]. The island's location near the subduction zone between the Indo-Australian and Eurasian tectonic plates results in frequent and intense seismic activities. Home to over 150 million people and serving as Indonesia's economic center, Java represents a critical case study for earthquake research due to its high population density, infrastructure concentration, and economic significance. Recent earthquakes in the region have highlighted the urgent need for localized studies that can inform urban planning, disaster response, and infrastructure resilience [4].

Understanding the spatial distribution and intensity of earthquakes is crucial for mitigating risks and enhancing disaster preparedness. Accurate spatial data enables better urban planning, efficient resource allocation, and improved disaster response. However, despite its seismic activity and regional significance, research on Java faces several challenges. Java's high seismic activity is primarily due to its location near active tectonic boundaries, leading to frequent earthquakes. Despite this, detailed spatial studies on the island remain limited, hindering a comprehensive understanding of seismic patterns. The island's vulnerability is further compounded by its dense population and critical infrastructure, which amplify the impact of seismic events, making precise spatial data essential for developing effective mitigation strategies. Additionally, there is a noticeable gap in the comparison of various spatial interpolation methods for mapping earthquake intensity, which restricts the ability to generate robust insights. Furthermore, while modern geospatial techniques have proven effective in other regions, their integration into earthquake research on Java remains underutilized, preventing the application of more advanced and accurate methods for disaster preparedness and management.

Several studies have attempted to analyze seismic activity in Indonesia using geospatial techniques, yet comprehensive spatial interpolation analyses remain scarce. Prior research has predominantly focused on historical earthquake trends and seismic hazard assessments [5], [6], but comparative evaluations of different interpolation techniques—particularly in high-risk zones like Java are lacking. Studies on spatial interpolation in earthquake research have been conducted in other regions, such as China [7] and Turkey [8], demonstrating the effectiveness of inverse distance weighted (IDW), nearest neighbor, and Thiessen polygon methods. However, similar systematic comparisons for Java remain underexplored. Moreover, while global seismic hazard models provide macro-level insights [9], they often fail to capture localized variations in earthquake intensity at a finer spatial scale, which is crucial for urban planning and disaster response. Thus, the absence of a rigorous evaluation of spatial interpolation methods for Java's earthquake intensity mapping represents a critical research gap.

This study contributes to the field by conducting a comparative analysis of three spatial interpolation methods (IDW, nearest neighbor, and Thiessen polygon) specifically for Java, an island with high seismic activities but limited research on optimal spatial interpolation techniques. Unlike previous studies that focus solely on hazard zoning, this research evaluates the accuracy of different interpolation methods using performance metrics such as mean absolute percentage error (MAPE) and mean absolute error (MAE) to determine the most reliable technique for earthquake intensity mapping. This study integrated recent seismic data from the past three years, ensuring relevance for contemporary disaster mitigation strategies. By identifying the most effective interpolation approach, the findings offer practical recommendations for urban planning, emergency response, and infrastructure resilience in Java. This research not only fills a critical methodological gap but also enhances data-driven decision-making for earthquake preparedness in Indonesia's most densely populated region.

2. Method

2.1. Data Source and Preprocessing

The earthquake data obtained from the Earthquake Repository of the Meteorology, Climatology, and Geophysics Agency (Badan Meteorologi, Klimatologi, dan Geofisika, BMKG) and used in this study span a three-year period (2022–2024). Several key attributes were used in the model: magnitude, location (latitude and longitude), and occurrence time. Magnitude measures the strength of an earthquake based on the Richter scale, which is used to categorize the severity and potential impact of the earthquake. Location (latitude and longitude) indicates the earthquake's epicenter, which is crucial for mapping the spatial distribution of earthquake events and for interpolation analysis. Occurrence time records when the earthquake happened, allowing the identification of temporal patterns and seismic trends over the study period. These data were used to analyze the spatial distribution of earthquakes by applying interpolation methods, including IDW, nearest neighbor, and Thiessen polygons, to generate estimates of earthquake distribution in the study area. Before being fed into the model, data preprocessing was performed, including coordinate normalization, duplicate data removal, and validation of time and location consistency, to ensure data quality and enhance analysis accuracy. The interpolation results were then evaluated to compare the effectiveness of each method in representing the earthquake distribution patterns.

2.2. Interpolation Methods

This study implemented three spatial interpolation techniques to analyze and visualize the spatial distribution of earthquake events.

2.2.1. Thiessen Polygon (Voronoi Diagram)

The Thiessen polygon method, also known as the Voronoi diagram, is a spatial interpolation technique used to assign values to a defined region based on the nearest known data point. This method ensures that any location within a given polygon inherits the value of the nearest measured point. While it is computationally simple and widely used in meteorology and hydrology, it does not account for variations within each polygon, which can lead to inaccuracies in areas with sparse or irregular data distribution. The mathematical formulation for Thiessen polygon interpolation is expressed as in (1).

$$Z(x) = Z(x_i) \; if \; x \in P_i \tag{1}$$

where P_i is the Thiessen polygon surrounding point x_i and $Z(x_i)$ is the value at points x_i .

Recent research has evaluated the effectiveness of the Thiessen polygon method in comparison with other interpolation techniques. A study on precipitation data interpolation found that while Thiessen polygons provide a straightforward way to allocate values, they often fail to capture spatial variability effectively in complex terrains [10]. Additionally, a comparative study on interpolation methods for gridded rainfall data concluded that Thiessen polygons are suitable for rapid calculations but are less accurate than geostatistical approaches like kriging, which better handle spatial heterogeneity [11].

2.2.2. Nearest Neighbor

Nearest neighbor method assigns the value of the nearest data point to each grid cell. It captures local variations better than Thiessen polygon. The formula for nearest neighbor interpolation is presented in (2).

$$Z\,(x) = Z(x_{nearest}) \tag{2}$$

where $Z(x_{nearest})$ is the value of the nearest observation point [4].

2.2.3. Inverse Distance Weighting (IDW)

IDW calculates values for unknown points by weighting the influence of nearby points inversely proportional to their distance. This method accounts for spatial proximity and provides smoother results. The formula for IDW interpolation is in (3) [10]:

$$Z\,(x) = \frac{\sum_{i=1}^{n} w_i \, . \, z(x_i)}{\sum_{i=1}^{n} w_i} \tag{3}$$

where $Z\,(x)$ is the estimated value at location x, $Z(x_i)$ is the observed value at location (x_i) , (w) is the weight assigned to the observation, which is inversely proportional to the distance between x and (x_i) .

$$w_i = \frac{1}{d\,(x,x_i)p} \tag{4}$$

where $d\,(x, x_i)$ is the Euclidean distance between (x, x_i) and p is the power parameter (typically $p = 2$.

2.3. Evaluation Metrics

2.3.1. Mean Absolute Percentage Error (MAPE)

Two commonly used error metrics, MAPE and MAE, were employed **t**o assess the performance of the interpolation methods

MAPE is a widely used metric for evaluating predictive models, particularly in time series forecasting and regression analysis. MAPE measures the percentage difference between predicted and actual values, providing an indication of relative accuracy. It is calculated using (5).

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i|}{A_i} \right| \text{ x } 100 \quad (5)$$

where A_i is the actual value, F_i is the predicted value, and n is the number of observations. A lower MAPE value indicates better predictive performance. Generally, a MAPE value below 10% is considered highly accurate, while values between 10% and 20% are acceptable for most applications [12].

Despite its widespread usage, MAPE has certain limitations. It tends to produce biased results when actual values are close to zero, leading to inflated error values. Additionally, MAPE is more suitable for models where the scale of values does not vary significantly across the dataset [13], [14].

2.3.2. Mean Absolute Error (MAE)

MAE is a widely used metric that measures the average magnitude of errors between predicted and actual values, without considering the direction of the errors. It is defined in (6).

$$\text{MAPE} = \frac{1}{n} \sum_{i}^{n} |A_i - F_i| \quad (6)$$

where A_i is the actual value, F_i is the predicted value, and n is the number of observations. Unlike mean squared error (MSE), MAE provides an interpretable measure of model performance in the same unit as the original data, making it particularly useful in applications where absolute error magnitude is more meaningful than squared errors. A lower MAE value signifies better model accuracy.

The evaluation of MAE depends on the scale and range of the dataset. Generally, a lower MAE relative to the data range indicates better predictive performance. In geospatial applications, for instance, an MAE value below 1% of the spatial range is often considered acceptable [15], [16]. Both MAE and MAPE should be interpreted in the context of the study, considering factors such as data variability, scale, and application-specific tolerances. The choice between MAE and other error metrics depends on the specific objectives of the analysis and the sensitivity to large errors in the dataset.

2.4. Process of the Earthquake Data Interpolation and Analysis

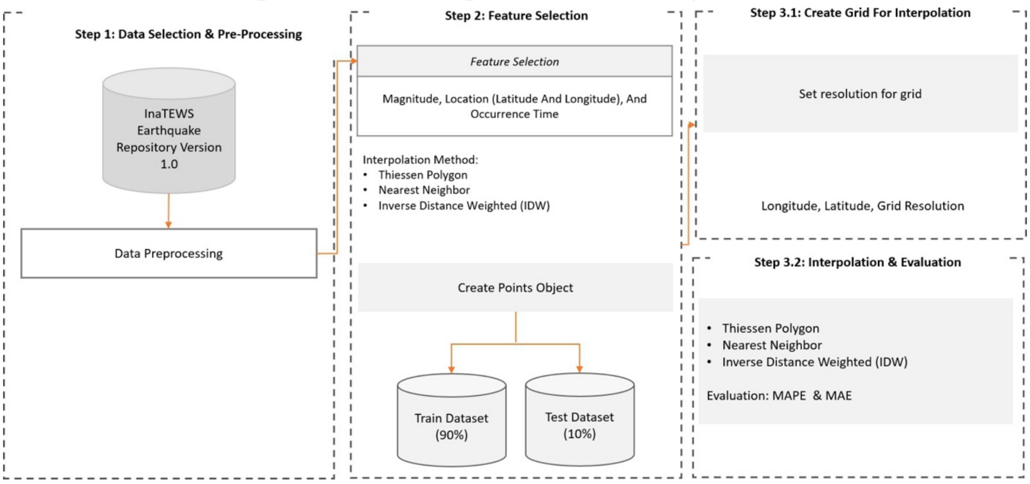

Fig. 1 Process diagram of the study.

Fig. 1 illustrates the step-by-step workflow of the study, which includes data selection and preprocessing, feature selection, grid creation for interpolation, and the evaluation of interpolation methods. This systematic approach ensures accurate spatial interpolation and validation using metrics such as MAPE and MAE.

3. Results and Discussion

The distribution of earthquakes in Java in 2022–2024 showed that the majority of earthquakes occurred in the southern region, following the subduction zone pattern between the Indo-Australian and the Eurasian plate. These earthquakes predominantly had magnitudes of 4.0 or more, which are marked with red dots. Meanwhile, earthquakes with smaller to medium magnitudes (scale of 2–4) are marked in yellow. The concentration of large-magnitude earthquakes in the southern region indicates high tectonic activity due to the active subduction zone in this area. This zone is where the Indo-Australian plate is subducting beneath the Eurasian plate, generating frequent and intense seismic activity. In contrast, while several earthquakes were observed in the northern region, they were relatively less frequent and often had smaller magnitudes. These earthquakes are likely associated with local fault systems or other minor tectonic processes rather than the primary subduction activity. The visual representation of the spatial distribution and magnitude of earthquakes across Java from 2022 to 2024 is displayed in Fig. 2.

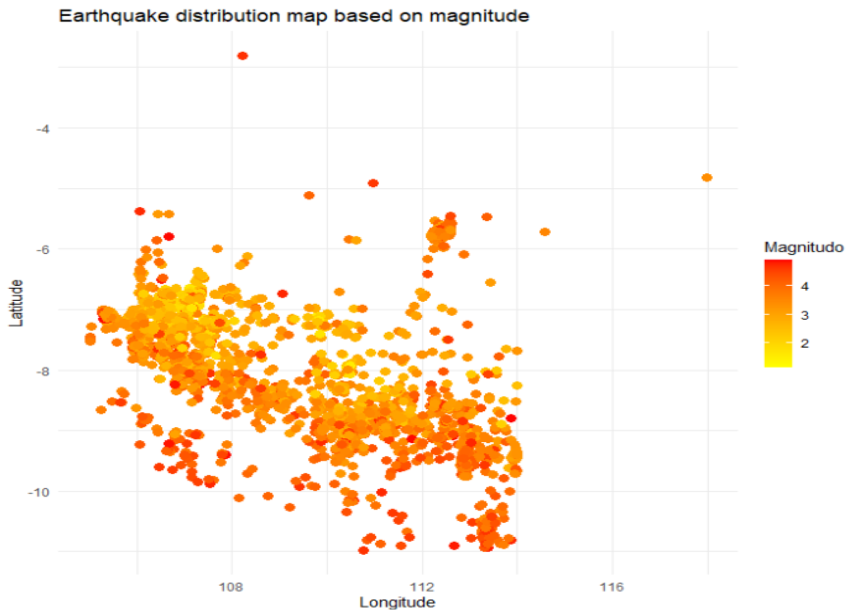

Fig. 2 Distribution of earthquakes in Java in 2022–2024.

The red dots in Fig. 2 indicate high-magnitude earthquakes (≥4.0), which are predominantly clustered along the southern margin of Java. This distribution aligns with the presence of the Sunda megathrust, a major subduction zone where the Indo-Australian plate converges with the Eurasian plate. The concentration of high-magnitude seismic events in this region highlights the significant tectonic stress accumulation and the associated seismic hazards, necessitating targeted mitigation strategies [14]. Meanwhile, the yellow dots, representing moderate to low-magnitude earthquakes (2.0–4.0), exhibit a more scattered distribution but remain closely associated with tectonic fault lines. Their presence suggests that even minor tectonic movements contribute to Java's overall seismic activity, reinforcing the need for continuous seismic monitoring [15].

Additionally, the northern region of Java exhibits a comparatively sparse distribution of seismic events, with both red and yellow dots appearing less frequently. This pattern reflects the contrasting tectonic environments across the island. While the southern margin is dominated by subduction-driven seismicity, the northern region's seismic activity is more likely influenced by local fault systems and sedimentary basin dynamics [16]. These differences underscore the importance of considering regional tectonic characteristics when assessing earthquake risks and formulating

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infrastructure resilience strategies. Trend of earthquake magnitudes from 2022, 2023, and 2024 is presented in Fig. 3.

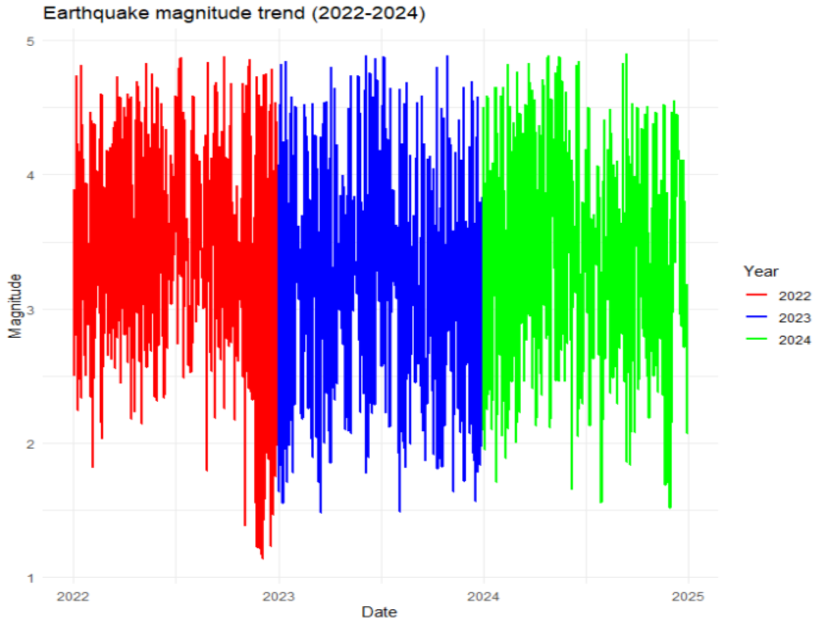

Fig. 3 Distribution of earthquakes per year.

In Fig. 3, the x-axis shows the time of occurrence, and the y-axis shows the magnitude of the earthquake. This visualization depicts the magnitude fluctuations that have occurred continuously over the last three years. There are variations in magnitude from low to high, with the magnitude range mostly between 1 to 5. Overall, the graph shows a relatively consistent frequency of earthquake events throughout the period, with no significant seasonal patterns visible. However, there are several higher-magnitude peaks scattered randomly. This trend indicates that earthquakes over the last three-year period have shown varying levels of severity, but do not show a clear increasing or decreasing trend in the magnitude of the seismicity that occurred. Table 1 presents the distribution of earthquakes per year.

Table 1. Distribution of Earthquakes per Year

Year	Count	Average Magnitude
2022	1256	3.07
2023	936	3.13
2024	868	3.35

Based on the results presented in Table 1, the distribution of earthquakes per year shows a decrease in the number of earthquakes, with 1256 earthquakes recorded in 2022, 936 earthquakes in 2023, and 868 earthquakes in 2024. However, even though the frequency decreased, the average magnitude of earthquakes increased, specifically to 3.07 in 2022, 3.13 in 2023, and 3.35 in 2024CDCD. This indicates that although the number of earthquakes decreases, the strength of the earthquakes that occur becomes greater from year to year.

The decline in the number of recorded earthquakes could be attributed to several factors. One possibility is the natural cycle of seismic activity, where certain regions may experience fluctuating periods of high and low seismicity. Another contributing factor could be stressing redistribution within the tectonic plates. As energy is released through large magnitude earthquakes, the accumulated stress in specific fault zones may temporarily decrease, resulting in fewer smaller earthquakes. Additionally, variations in tectonic processes, such as changes in subduction rate or local fault activity, could also influence the observed trend. While the frequency has decreased, the increase in average magnitude suggests that the tectonic stress is being released in fewer but stronger

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events, highlighting the need for continued monitoring and preparedness. Fig. 4 shows the IDW interpolation of earthquake magnitudes for the years 2022, 2023, and 2024.

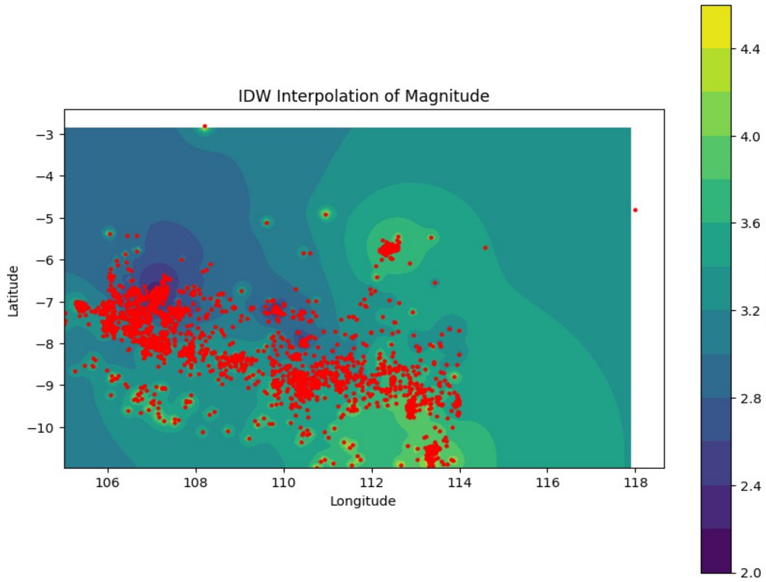

Fig. 4 IDW interpolation of earthquake magnitudes.

In Fig. 4, the x-axis represents longitude, while the y-axis represents latitude. The red points on the map denote the specific locations where earthquakes occurred, and their density indicates areas of higher seismic activity. These red points are overlaid onto a gradient buffer zone, which is color-coded to reflect the interpolated magnitudes of the earthquakes. The color gradient in the buffer zone transitions from darker shades (representing lower magnitudes, around 2.0) to brighter, more intense shades (indicating higher magnitudes, up to 4.4). This differentiation in colors allows for the identification of spatial patterns in seismic intensity. Regions with yellow and green hues signify zones where higher magnitudes are likely concentrated, while darker blue areas suggest regions with lower magnitudes or reduced seismic activity. This visualization provides an overview of the spatial distribution of earthquake magnitudes. Areas with clusters of red points surrounded by brighter colors highlight regions of frequent and intense seismic activity. This suggests that these zones may require heightened attention for monitoring and mitigation efforts. Meanwhile, regions with fewer red points and darker buffer zones might be considered less active seismically. Fig. 5 shows the interpolation of the earthquake distribution pattern on the island of Java using the nearest neighbor method.

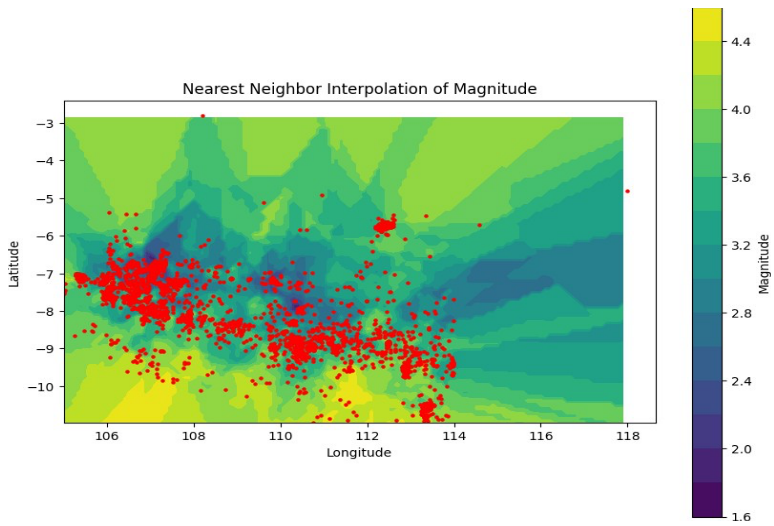

Fig. 5 Nearest neighbor interpolation of earthquake magnitudes.

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Based on Fig. 5, the nearest neighbor method produces visualizations with clearer magnitude zone boundaries than other interpolation methods, reflecting interpolation results that directly connect nearby observation data. Bright yellow areas indicate zones with high earthquake magnitudes, while green to blue areas indicate lower magnitudes. The concentration of red dots in the yellow and green zones indicates areas with significant earthquake activity, which require more attention for risk mitigation. This visualization makes it easier to identify spatial patterns of earthquake magnitude with accuracy that is relevant for geospatial analysis needs. Fig. 6 displays the interpolation of the earthquake distribution pattern in Java using the Thiessen polygon method.

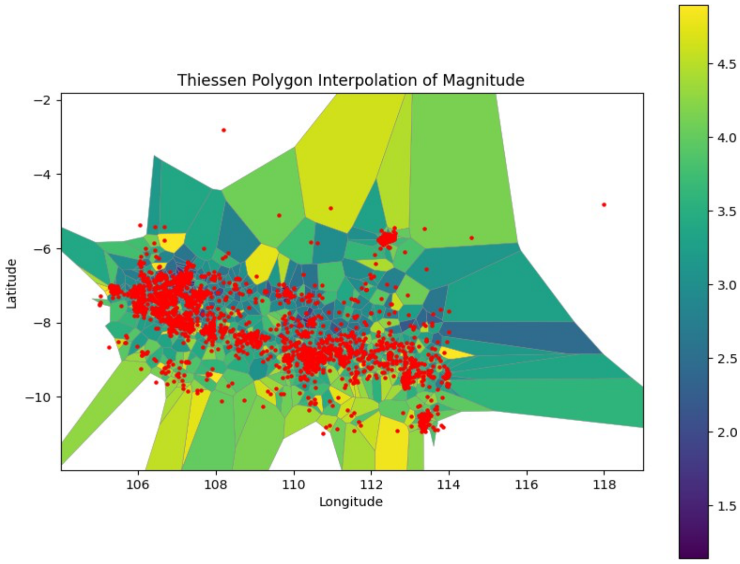

Fig. 6 Thiessen polygon interpolation of earthquake magnitudes.

Similar to the nearest neighbor method, the Thiessen polygon method (Fig. 6) also shows that the interpolation results have area boundaries that are not smooth and that the boundaries are quite sharp, making this method less realistic for natural phenomena which are usually continuous. Earthquake points that are too far from observation make interpolation less accurate so that it is only suitable for earthquake patterns for limited areas. Table 2 shows the evaluation results of the accuracy of three interpolation methods based on MAPE and MAE.

Table 2. Accuracy Prediction Model of the Interpolation Method

Interpolation Method	MAPE (%)	MAE
Inverse distance weighted (IDW)	12.37	0.38
Nearest neighbor	12.27	0.37
Thiessen polygon	15.29	0.47

Based on these results in Table 2, the IDW and nearest neighbor methods are proven to be quite ideal for measuring earthquake interpolation patterns during the 2022, 2023, and 2024 periods. Both methods exhibited low MAPE and MAE values, at 12.37% and 0.38 for IDW, and 12.27% and 0.37 for the nearest neighbor, respectively. These low error values indicate that the predictions produced by these two methods are closer to the actual values compared to the other methods.

On the other hand, the Thiessen polygon method yielded a MAPE of 15.29% and an MAE of 0.47, indicating lower prediction accuracy. This is due to the approach used by this method, which divided the study area into discrete zones without considering the continuous distribution pattern, making it less suitable for datasets such as earthquakes.

For quantitative analyses focused on prediction accuracy, the nearest neighbor method is the best choice. Its ability to produce precise predictions makes it superior for tasks requiring accurate numerical estimates. However, for visualization purposes, particularly in representing smoother and more detailed interpolation patterns, the IDW method can better depict spatial variations, albeit with a slight compromise in accuracy. Conversely, the Thiessen Polygon method is better suited for datasets with noncontinuous distribution patterns. This method partitions the area into exclusive zones based on the nearest data points, making it less ideal for representing continuous distribution patterns like earthquakes.

Overall, the choice of interpolation method depends on the purpose of the analysis. If prediction accuracy is the main priority, the nearest neighbor method is recommended. Although less optimal for earthquake data, the Thiessen Polygon method may still be useful in contexts where it aligns with the distribution patterns of the dataset.

4. Conclusion

The IDW method has demonstrated superior visual interpolation capabilities, producing smoother and more realistic spatial distributions compared to the nearest neighbor and Thiessen Polygon methods. The rigid and sharp boundaries characteristic of the latter two approaches limits their effectiveness in representing continuous geospatial patterns. In particular, the Thiessen Polygon method is not well-suited for seismic phenomena, where earthquake distributions exhibit gradual spatial variations.

However, quantitative evaluations have indicated that the nearest neighbor method slightly outperformed IDW in terms of predictive accuracy, as assessed using MAPE and MAE metrics. This suggests that while IDW excels in generating intuitive spatial representations, the nearest neighbor may provide marginally better numerical estimations under certain conditions. Given these findings, IDW remains a highly effective approach for interpolating earthquake datasets across Java for the years 2022, 2023, and 2024. Its ability to capture continuous spatial variations makes it particularly valuable for seismic hazard assessments and geospatial analyses in tectonically active regions.

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