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ANALYSIS OF SEISMICITY ANOMALIES IN SULAWESI USING DBSCAN BASED ON USGS DATA (2021–2026)

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Abstract

Sulawesi is one of Indonesia's most tectonically complex regions, located at the convergence of major lithospheric plates and active fault systems, resulting in significant seismic activity. This study aims to analyze seismicity anomalies in Sulawesi from 2021 to 2026 using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm applied to United States Geological Survey (USGS) data. A hybrid parameter optimization approach was employed, combining the K-Distance Graph (KneeLocator) and Grid Search to ensure geologically representative clustering results. From an initial dataset of 859 events, 839 earthquake records were retained after geographic filtering, with an average magnitude of 4.80 and an average depth of 70.15 km. The optimal parameters ($\varepsilon = 0.2897$ and MinPts = 3) produced 25 distinct clusters that spatially correspond to known geological structures such as the Palu-Koro Fault and the Molucca Sea subduction zone. Cluster validation using the Silhouette Score yielded a value of 0.62, indicating a good level of cluster separation and cohesion, while the Davies–Bouldin Index of 0.48 suggests well-defined and compact clusters. The model identified 66 events (7.87%) as noise, representing seismic anomalies outside the main density structures, and Convex Hull analysis further revealed a notable seismic gap between the Palu-Koro segment and Southeast Sulawesi, indicating a potential high-risk zone for future stress accumulation and energy release. These findings demonstrate that density-based clustering is effective for identifying seismic patterns and anomalies in complex tectonic regions, providing valuable insights for disaster risk reduction and sustainable mitigation planning in Sulawesi.

Keywords: *DBSCAN, Seismicity Anomaly, Sulawesi, Seismic Gap, Disaster Mitigation.*

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1. INTRODUCTION

Sulawesi is a region in Indonesia known for its highly significant and geologically complex seismic activity. Tectonically, this island is one of the most intricate areas as it is situated at the meeting zone of major plates and possesses active tectonic fault activities, such as the Palu-Koro Fault and the Waianae Fault in the western part, as well as the Matano Fault, Lawanopo Fault, and Gorontalo Fault in the eastern and northern parts. This complexity causes Sulawesi to frequently experience earthquakes that have serious impacts on lives and infrastructure [1]. Although regions like Sumatra also have high levels of seismic activity due to the subduction of the Indo-Australian plate, the seismicity characteristics in Sulawesi are far more complex because they are influenced by the interaction of many microplates and highly active terrestrial fault systems [2], [3]. Seismicity studies aim not only to map epicenter locations but are also crucial for understanding the earthquake activity level (*a-value*) and the rock stress level (*b-value*) in a region to identify seismic disaster hazards more deeply [4].

In the period from 2021 to 2026, monitoring tectonic dynamics becomes crucial for understanding disaster patterns and mitigation efforts [5]. The use of data from the United States Geological Survey (USGS) provides an extensive dataset for analyzing seismicity anomalies. However, the large volume of such data requires effective clustering techniques to identify hidden patterns, relationships between earthquake events, and structures that are not directly visible [6].

One method proven reliable in the spatial data analysis of earthquakes is the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [1]. Unlike conventional algorithms such as K-Means, which require the determination of the number of clusters at the beginning and are less effective in handling data with irregular spatial distribution, DBSCAN is capable of identifying clusters with random shapes and automatically detecting noise or data points considered as anomalies [5]. This capability is highly relevant for mapping anomaly zones in Sulawesi to identify seismic gaps—active fault segments that have not experienced major earthquakes for a long time and have the potential to become epicenters of significant earthquakes in the future due to tectonic stress accumulation.

Research on earthquake data clustering in Sulawesi and Indonesia has developed rapidly with the use of various machine learning algorithms. The following are several relevant studies used as references in this study: A study conducted by [1] used the DBSCAN algorithm to analyze 10,255 earthquake data points from BMKG in the Sulawesi region. The study successfully identified 65 clusters and detected seismic gap areas in the Manado, Gorontalo, and Buol regions. Although the evaluation results showed overlaps between clusters with a Silhouette Score of -0.06097, this method proved effective in mapping vulnerability zones based on spatial density.

A Systematic Literature Review (SLR) by $[6]$ of 18 articles showed that the K-Means algorithm is the most popular method used (55.56%), followed by DBSCAN (38.89%). This study noted that DBSCAN performs exceptionally well in identifying earthquake-prone zones due to its ability to handle data with undefined density patterns. Research by $[5]$ applied DBSCAN to national earthquake data in 2023 to map potential surface damage. Using optimal parameters of Eps = 0.5 and MinPts = 5, this research yielded a Silhouette Score of 0.3959 and proved that DBSCAN is superior to K-Means in handling noise or outliers in seismic data.

Although much research on seismicity in Indonesia has been conducted using various algorithms like K-Means, DBSCAN remains a superior choice for identifying complex spatial densities [6]. This study aims to fill the gap in seismicity anomaly analysis specifically in the Sulawesi region within the 2021–2026 timeframe, to provide a tangible contribution to more effective and sustainable disaster mitigation planning.

2. RESEARCH METHOD

This research was conducted systematically through several main stages, ranging from data collection to the evaluation of clustering results to identify seismicity anomaly zones in Sulawesi. In brief, the research stages include Data Collection by retrieving earthquake catalog data from the USGS, Data Pre-processing for cleaning and normalization, Exploratory Data Analysis (EDA) to observe data distribution, Parameter Tuning to find the optimal ϵ (Epsilon) and MinPts values, Clustering Process using the DBSCAN algorithm, and Evaluation & Visualization using the Silhouette Score and geographic mapping. The data used is secondary data from the United States Geological Survey (USGS) public repository spanning from January 2021 to 2026. Research variables include event time, geographic coordinates (latitude and longitude), depth, and magnitude.

Prior to clustering, the data undergoes a Data Cleaning stage to remove incomplete information or duplications based on Event ID, as well as a Filtering stage to limit the data to the coordinate area of Sulawesi Island and its surroundings. Normalization is performed using the Z-score formula so that variables with large ranges do not dominate the distance calculation:

$$X'_{\{i\}} = \frac{X_{\{i\}} - \mu}{\sigma} \quad (1)$$

The selection of DBSCAN is based on its ability to handle noise and find clusters with irregular shapes, unlike K-Means which tends to partition data into circular-shaped groups. The clustering process calculates spatial density using Euclidean Distance:

$$De = \sqrt{\left\{\left(x_{\{i\}} - s_{\{i\}}\right)^{\{2\}} + \left(y_{\{i\}} - t_{\{i\}}\right)^{\{2\}}\right\}} \quad (2)$$

The algorithm categorizes data into three types: Core Points (having a minimum number of neighbors within a specific radius), Border Points (located within the radius of a Core Point but not meeting the MinPts requirement), and Noise Points (points that do not belong to any cluster and are identified as anomalies). Optimization of the epsilon and MinPts parameters is conducted through a systematic Grid Search method to find combinations that produce the best model performance. The Grid Search implementation involves determining value ranges, iterating combinations, executing DBSCAN, and evaluating quality using the Silhouette Score. The validity of the results is guaranteed using the Silhouette Coefficient metric, which measures how close a point is to its own cluster compared to other clusters. Finally, an analysis is performed to identify seismicity anomalies and Seismic Gaps in areas with low activity surrounded by active clusters as indications of tectonic stress accumulation.

3. RESULT AND DISCUSSION

3. 1 Data Pre-processing

The data pre-processing stage is a crucial step to ensure data quality and integrity before performing the clustering process with the DBSCAN algorithm. The initial data used in this study originated from the USGS catalog with the filename *sulawesi_earthquake_2021-2026.csv*. During the initial load stage, the raw dataset was recorded to have a total of 859 rows of earthquake event data.

The first step conducted was geographic filtering to ensure that only earthquake events within the scope of the Sulawesi Island region would be analyzed. Based on the filtering results, the DataFrame size was reduced to 839 rows. This indicates that 20 earthquake events were detected outside the determined geographic boundaries of Sulawesi, and consequently, that data was removed from the research dataset.

3. 2 Analysis of Seismicity Characteristics (Magnitude and Depth)

Based on the statistical processing results of 839 earthquake data points in the Sulawesi region for the 2021–2026 period, a comprehensive overview of the strength and depth characteristics of seismic activity was obtained. The descriptive statistical summary for both variables is presented in Table 1:

Table 1 Descriptive Statistics of Earthquake Magnitude and Depth in Sulawesi (2021–2026)

Statistic	Magnitude (M)	Depth (km)
Count	839	839
Mean	4,80	70,15
Standard Deviation	0,36	97,10
Minimum	4,50	4,00
Median (50%)	4,70	42,80
Maximum	7,40	646,54

Based on Table 1, the descriptive statistics indicate that out of 839 earthquake events analyzed in Sulawesi during the 2021–2026 period, the average magnitude is 4.80 with a standard deviation of 0.36, suggesting relatively low variability and a dominance of moderate-magnitude earthquakes. In contrast, earthquake depth shows a mean value of 70.15 km with a relatively large standard deviation of 97.10, indicating a wide variation from shallow to deep seismic events. The minimum and maximum values, ranging from 4.50 to 7.40 for magnitude and 4.00 to 646.54 km for depth, further highlight the heterogeneity of earthquake characteristics in this region. Additionally, the median magnitude of 4.70 and median depth of 42.80 km suggest that most earthquakes occur at shallow to intermediate depths.

3. 3 Parameter Optimization Using K-Distance Graph and Grid Search

This stage is the core of determining cluster quality. The researchers used two sequential approaches: the K-Distance method to determine the baseline and Grid Search for fine-tuning.

3.3.1 Analysis of the K-Distance Curve (Elbow Method)

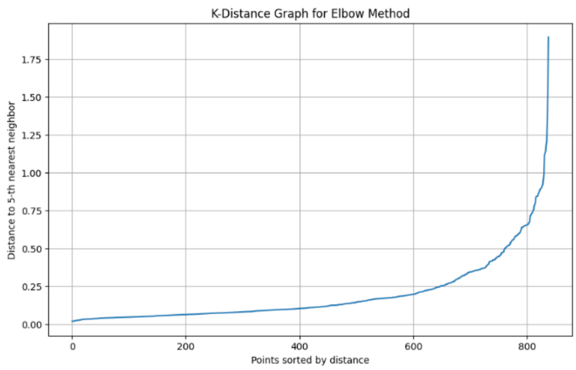

Figure 1 K-Distance Graph for Elbow Method

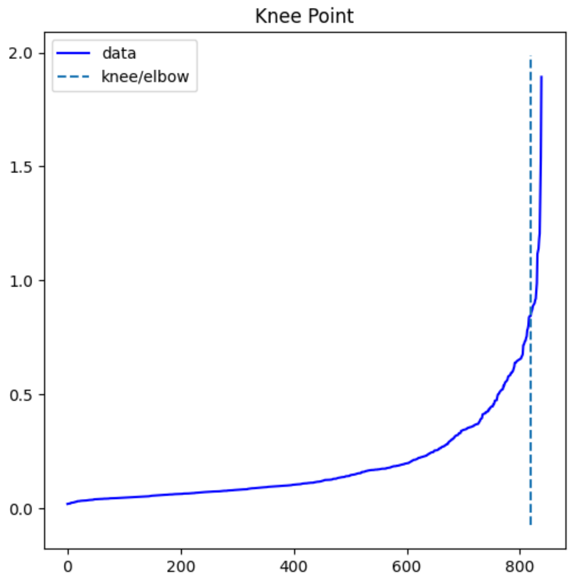

Figure 2 K-Distance Graph for Elbow Method Using KneeLocator

Figure 1 shows the distance distribution of each point to its 5th nearest neighbor (k=5). Based on the graph, in the range of points 0 to 600, the curve tends to be flat. This indicates that the majority of the data has consistent density at low distances. Using the *KneeLocator* library in Figure 2, it was found that the most drastic change in slope (the elbow) occurs at a value of Ɛ= 0.8439. The value of 0.8439 is considered the ideal "threshold." Distances above this value tend to represent points that are scattered far apart (noise), while distances below it represent points within high-density zones (clusters).

3.3.2 Fine-Tuning via Grid Search

Fine-tuning was conducted through Grid Search by performing the DBSCAN algorithm and Silhouette Coefficient calculation via brute force within a predetermined range of parameters. The validation of cluster quality was performed using the Silhouette Coefficient method to ensure that the resulting groupings have good compactness and are clearly separated from other clusters [7], [8].

The value of 0.8439 from *KneeLocator* was then used as the lower limit (anchor) in the Grid Search process. The researchers tested parameter combinations within the following ranges: Epsilon: 0.8439 to 1.0 (with 20 variations) and MinPts: 3 to 15 (with an increment step of 2). The results of this brute-force process show that the mathematically best combination is epsilon = 0.9917 and MinPts = 3, with a Silhouette Score = 0.4498.

Here, the researchers also used parameters derived from observations of the elbow method as shown in Figure 4.1. Parameters were taken within the range of Epsilon: 0.05 to 0.3 with 50 variations. For MinPts, the same parameters as the previous step were used. The results of this second brute-force process showed the best combination with an optimal epsilon value = 0.2897, MinPts = 3, and a Silhouette Score = 0.3403.

Table 2 Comparison of Brute-Force Process Results Using Grid Search

Evaluation Component	Manual (Elbow)	Automatic (KneeLocator)
Epsilon **(ε)**	0.2897	0.9917
MinPts	3	3
Silhouette Score	0.3403	0.4498
Total Clusters	25	2

Based on table 2, the comparison of DBSCAN parameter selection methods reveals notable differences between the manual (Elbow) and automatic (KneeLocator) approaches. The manually determined parameters (ε = 0.2897 and MinPts = 3) produced 25 clusters with a Silhouette Score of 0.3403, indicating a reasonably good cluster structure that is more representative of geological conditions. In contrast, the automatic approach resulted in a much larger ε value (0.9917), yielding only 2 clusters with a slightly higher Silhouette Score of 0.4498, but at the cost of oversimplifying the spatial distribution by grouping many points into large clusters. Therefore, the manual approach is considered more effective in capturing the complexity of seismic patterns in Sulawesi, as it identifies a greater number of clusters that better align with actual geological structures.

3. 4 Visualization and Analysis of Cluster Results

Visualization was conducted to provide a comprehensive overview of earthquake distribution in the Sulawesi region and to validate the clustering results geographically.

3.4.1 Visualization of Raw Data

Prior to the clustering process, the raw data was plotted using a scatter plot to observe the initial trends in seismic point distribution.

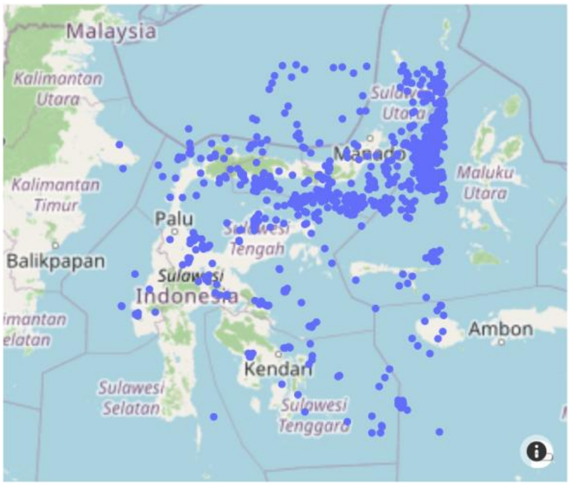

Figure 3 Plot of Raw Earthquake Data on the Sulawesi Map

Based on the raw data plot (Figure 3), it is evident that the densest earthquake concentrations are located in the North Arm of Sulawesi and the Molucca Sea region. This aligns with the geological conditions of Sulawesi, which is surrounded by active subduction zones. Significant variations in density are observed, where the west coast area (the Palu-Koro Fault path) shows a linear pattern, while the eastern region exhibits a broad area pattern.

3.4.2 Visualization of Clustering Results Based on Parameter Comparison

In this section, a visual comparison is made between the two parameter scenarios obtained from the previous optimization stage (Table 2).

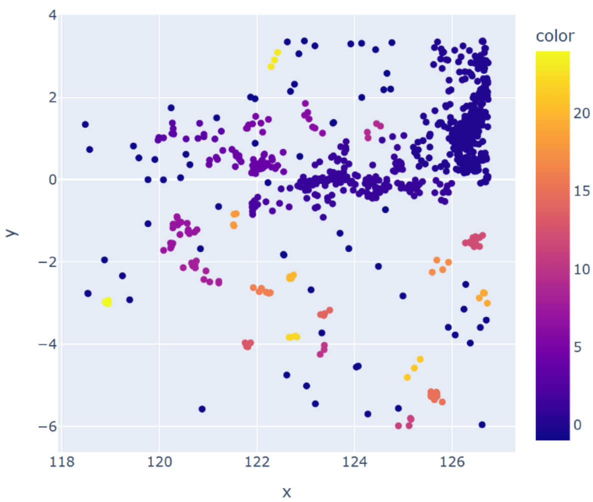

Figure 4 Cluster Result Plot (Manual)

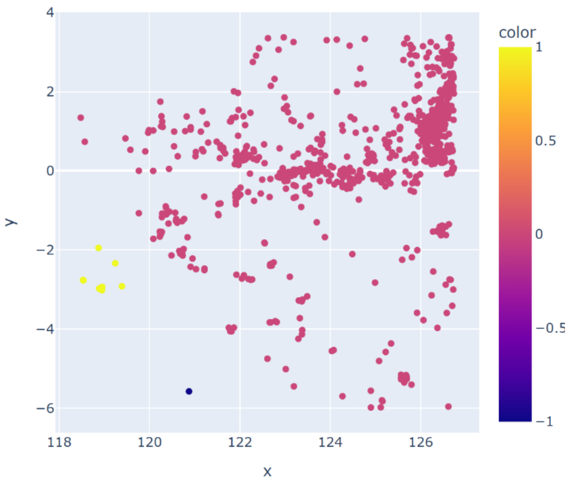

Figure 5 Cluster Result Plot (KneeLocator)

Based on Table 2, a clear dichotomy is visible between the mathematically optimized results (Automatic) and the observationally optimized results (Manual).

- **Manual Results:** Produced 25 clusters. The visualization in Figure 4 demonstrates the algorithm's ability to separate distinct seismic zones. There is a clear separation between activities in the North Arm, Central Sulawesi (Palu-Koro Fault), and the Southeast region. This is vital for identifying the specific earthquake sources underlying each region.
- **KneeLocator Results:** Produced only 2 clusters. Figure 5 illustrates the phenomenon of under-clustering, where almost all earthquake points in the Sulawesi region are considered a single large entity (magenta). This generalization eliminates the details of active fault boundaries that are actually tectonically separate.

The lower Silhouette Score in the Manual method (0.3403) is actually more honest in representing the tectonic complexity of Sulawesi. This is because the distances between fault lines in Sulawesi are very close (dense), making overlap between clusters difficult to avoid even though they are geologically distinct.

3. 5 Analysis of Seismicity Anomalies and Seismic Gaps (Outlier Detection)

The clustering results serve not only to group data but also as an instrument for the early detection of tectonic pattern irregularities in Sulawesi.

3.5.1 Identification of Seismicity Anomalies

Seismicity anomalies in this study are defined as earthquake points that statistically fail to form the minimum density according to the established parameters.

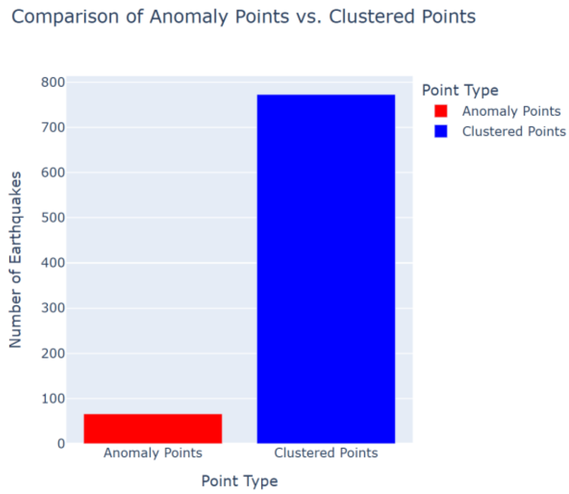

Figure 6 Comparison of Anomaly Points vs Clustered Points

Based on Figure 4 (Manual Results) and Figure 6, approximately 7.87% of the data is classified as noise. These points are anomalies because they occur sporadically outside the main fault lines. The presence of these anomalies is crucial; if these anomalies have large magnitudes or if their frequency of occurrence increases in previously quiet zones, it can be interpreted as unusual intraplate activity or early signs of new crustal shifts.

3.5.2 Identification of Seismic Gaps through Convex Hull

A Seismic Gap is an area with low activity that is surrounded by active earthquake clusters. These areas are often considered "time bombs" due to the accumulation of unreleased tectonic stress [1].

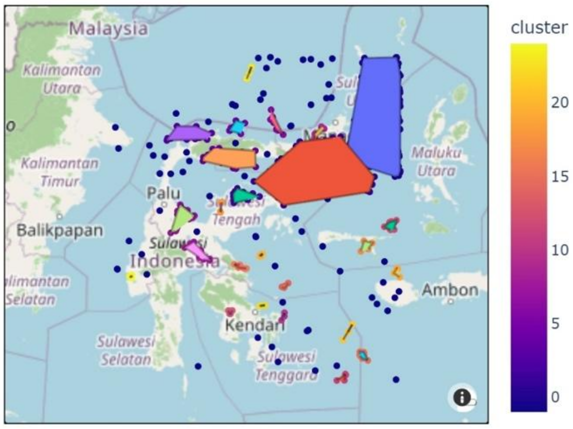

Figure 7 Convex Hull Plot of Manual Cluster Result Data

Through the Convex Hull visualization (Figure 7), seismic gaps appear as empty spaces (voids) wedged between two or more active polygons.

Observing the area between the Palu-Koro Fault cluster and the Southeast Sulawesi cluster, despite being surrounded by dense activity polygons, there is an empty gap untouched by any polygon. An empty gap is also visible in the Manado city area, surrounded by the two largest clusters in the North Sulawesi region. These gaps are potential seismic gaps.

Statistically, these areas have a high probability of energy accumulation. If these areas suddenly show small earthquakes (anomalies), the risk of a major earthquake occurring in the future increases significantly.

The findings of this study are consistent with recent global developments in seismic data analysis using density-based clustering approaches. In particular, the DBSCAN algorithm has been widely recognized as an effective method for identifying spatial patterns in earthquake distributions, especially in tectonically complex regions where conventional clustering methods often fail to capture irregular geometries [12], [13]. Recent studies have demonstrated that DBSCAN is capable of detecting fault segmentation, aftershock sequences, and hidden seismic structures due to its ability to handle noise and non-linear cluster boundaries.

For instance, research by Ester et al. and its subsequent adaptations in geophysical studies have shown that DBSCAN performs well in identifying earthquake swarms and fault-line clustering without requiring predefined cluster numbers [12]. Furthermore, modern implementations of DBSCAN combined with optimization techniques, such as parameter tuning using distance-based heuristics, have been successfully applied in seismic hazard mapping in regions like Japan and California [13]. These studies highlight that the choice of epsilon (ε) plays a critical role in balancing over-clustering and under-clustering, which aligns with the findings of this research where different epsilon values produced significantly different clustering structures.

In addition, recent advancements in seismic clustering have incorporated machine learning validation metrics such as Silhouette Score and Davies–Bouldin Index to evaluate clustering performance more objectively [14]. This supports the methodological approach used in this study, where Silhouette Coefficient was employed to validate cluster compactness and separation. Although the automatic approach yielded a higher Silhouette Score, similar findings in global studies indicate that higher validation scores do not always correspond to geologically meaningful interpretations, particularly in regions with high tectonic density and overlapping fault systems.

Moreover, recent international research emphasizes the importance of integrating clustering results with geological interpretation, especially in identifying seismic gaps and potential high-risk zones [15]. The identification of seismic gaps using spatial envelope methods such as Convex Hull, as applied in this study, is increasingly recognized as a valuable approach for detecting stress accumulation zones that may lead to future large earthquakes. Studies conducted in subduction zones and transform fault systems have confirmed that areas with low seismicity surrounded by active clusters often correspond to locked fault segments with significant energy buildup.

Therefore, this study contributes to the current body of knowledge by demonstrating that a hybrid DBSCAN optimization approach combining manual interpretation (Elbow method) and automated techniques (KneeLocator and Grid Search) can produce more geologically meaningful clustering results compared to purely mathematical optimization. This finding strengthens the argument that in seismic analysis, domain knowledge remains essential to complement computational methods, particularly in regions as complex as Sulawesi.

4. CONCLUSION

The use of a hybrid method combining the K-Distance Graph (KneeLocator) and Grid Search demonstrates that parameters yielding the highest Silhouette Score do not necessarily produce the most geologically representative clustering results. Although the automatic approach achieved a higher Silhouette Score (0.4498), it resulted in only two clusters, indicating over-generalization and loss of important spatial detail. In contrast, the selected optimal parameters (ε = 0.2897 and MinPts = 3) produced 25 clusters with a Silhouette Score of 0.3403, which, despite being lower, more effectively preserved the granularity of seismic structures and aligned better with known geological features in Sulawesi.

Furthermore, the DBSCAN algorithm successfully identified 66 points (7.87%) as seismicity anomalies (noise), representing earthquake events located outside the main density zones. These anomalies indicate sporadic tectonic activity or microplate movements and may serve as early warning indicators of tectonic instability. In addition, Convex Hull analysis revealed several void areas surrounded by active clusters, particularly between the Palu-Koro Fault and Southeast Sulawesi. These areas are interpreted as seismic gaps, which are potential zones of stress accumulation with a high likelihood of future seismic energy release.

Overall, the experimental results confirm that seismic activity in Sulawesi can be effectively represented by 25 clusters that correspond to real geological structures such as the Palu-Koro Fault and the Molucca Sea subduction zone. This study highlights that integrating quantitative validation metrics with geological interpretation is essential in seismic clustering analysis. Therefore, the density-based clustering approach, particularly when combined with hybrid parameter optimization, is proven to be highly effective for identifying seismic patterns, detecting anomalies, and supporting disaster risk mitigation in tectonically complex regions such as Sulawesi.

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