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Performance Evaluation of the K-Means Clustering Method in Grouping Indonesian Provinces Based on Potential Disaster Impact

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Abstract

This study aims to cluster the provinces in Indonesia based on their level of potential disaster impact, which consists of hazard area, exposed population, physical losses, economic losses, and environmental damage, using the K-Means clustering algorithm and to evaluate the performance of the resulting model. The optimal number of clusters was determined using the Silhouette Coefficient and the Elbow Method with the Within-Cluster Sum of Squares (WSS) approach. The performance evaluation of the K-Means clustering was conducted using the Davies–Bouldin Index (DBI). Based on the selection of the optimal number of clusters, the Silhouette Coefficient produced the highest value at K=3, with a score of 0.699. Similarly, the Elbow Method showed a significant decrease in the mean WSS at K=3, indicating that three clusters were optimal. The performance evaluation using DBI for K=3 resulted in a score of 0.30. According to the principle of DBI evaluation, the closer the DBI value is to zero (without being negative), the better the clustering quality. Therefore, it can be concluded that the K-Means clustering algorithm successfully produced a very good clustering structure in grouping Indonesian provinces based on their potential disaster impact.

Keywords: Davies-Bouldin Index (DBI); Disaster Impact; Elbow; K-Means Clustering; Silhouette Coefficient

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1. Introduction

Indonesia is a country located in a strategically important geological position and lies at the convergence of three major tectonic plates, where tectonic activity frequently occurs. This position causes Indonesia to face substantial risks arising from such activities, namely natural disasters (Wicaksono & Susetyo, 2023). According to the World Risk Index (WRI) report in 2023, Indonesia ranked second among countries with the highest natural disaster risk index globally, with an index value of 43.50%, one level below the Philippines, which recorded an index value of 46.86% (Frege et al., 2023). Furthermore, based on Indonesia disaster information data in 2025, National Disaster Management Agency (BNPB) reported 2,606 disaster events, which were dominated by hydrometeorological disasters (98.96%) and geological disasters (1.045%). The most frequent disasters included floods, extreme weather events, forest and land fires, landslides, and droughts (BNPB, 2025).

Disaster risk does not merely refer to the probability of disaster occurrence, but also encompasses the potential losses and impacts that may result from natural disasters. According to the United Nations Office for Disaster Risk Reduction (UNDRR), disaster risk is the result of the interaction between hazard, exposure, and vulnerability within a given area. In other words, the higher the level of exposure and vulnerability to a hazard, the greater the potential losses that may occur. Thus, disaster risk is not only concerned with how frequently disasters occur, but also with the magnitude of the impacts or losses that may be generated (United Nations Office for Disaster Risk Reduction, 2022). Disaster risk assessment is an approach used to illustrate the potential negative impacts that may arise from existing disaster hazards. These potential negative impacts reflect the possible number of exposed lives, property losses, and environmental damage affected by disaster hazards (Shalih et al., 2023). Based on the BNPB report in 2025, disaster-related housing damage reached 31,469 units, damage to public facilities totaled 601 units, fatalities amounted to 361 people, 37 people were reported missing, 615 people were injured, and approximately 5.2 million people were displaced (BNPB, 2025).

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Therefore, scientific efforts are required to understand the patterns and characteristics of disaster risk across different regions in Indonesia.

One approach that can be used to understand the patterns and characteristics of disaster impact risk is clustering analysis. Clustering is one of the methods applied in data mining. Clustering analysis classifies objects such that objects with similar characteristics are grouped into the same cluster (Utami et al., 2023). K-Means is one of the most commonly used methods in cluster analysis. K-Means clustering aims to partition objects into k clusters and then assign each object to the cluster whose mean is closest to it. This algorithm is a well-known, simple, and easy-to-understand solution for data clustering problems. (Pratama et al., 2023). K-Means clustering is an important algorithm in data mining due to its ease of implementation and execution. In practice, this algorithm is frequently applied because it is relatively fast and adaptive (Luchia et al., 2022). Previous studies have extensively implemented the K-Means clustering method in disaster-related research. Dhewayani et al. (2022), in their study on clustering fire-prone areas, found that K-Means successfully performed clustering by producing optimal cluster memberships, thereby providing valuable information on the potential for forest and land fires in each region. This result was supported by a cluster evaluation using the Silhouette Coefficient, which yielded a value of 0.74. Similarly, Baldah et al. (2023), in their study on clustering natural disaster-prone areas in Indonesia, reported that the K-Means algorithm successfully grouped disaster-prone regions, with cluster validation results showing a Silhouette Coefficient value of 0.75.

These findings can assist relevant institutions in obtaining a clearer understanding of regions with similar characteristics in terms of disaster occurrence potential. However, an important consideration is that, in addition to clustering based on disaster occurrence potential, clustering based on the potential negative impacts of disasters also needs to be conducted. This approach enables more targeted disaster response, mitigation efforts, and resource allocation (Monalia & Noorratri, 2024). Therefore, this study aims to evaluate the performance of the K-Means clustering method in grouping provinces in Indonesia based on their level of potential disaster impact. The clustering process employs five main indicators that represent disaster risk dimensions, namely hazard area, exposed population, physical losses, economic losses, and environmental damage. Through this analysis, the study seeks to identify patterns of similarity in risk characteristics across regions and to determine groups of provinces with comparable levels of potential disaster impact, so that the results can serve as a basis for more focused decision-making in disaster mitigation planning and disaster risk management.

2. Material and Methods

2.1. Data and Data Sources.

The data used in this study are secondary data obtained from the official in a Risk BNPB website (https://inarisk.bnpb.go.id/irbi). In the available data source, data for four provinces located on the island of Papua were not available. Therefore, this study involved only 34 provinces included in the dataset. The research dataset is presented in Table 1. To examine data characteristics, descriptive statistical analysis was conducted using IBM SPSS Statistics software. Subsequently, clustering analysis was performed using R-Studio software.

Table 1. Descriptive Analysis

Province	Hazard Area (Ha)	Exposed Soul	Physical Losses (Billion IDR)	Economic losses (Billion IDR)	Environmental (Ha)
Gorontalo	5013549	6744213	37035441	463099.6	974600
West Kalimantan	56088504	22594497	93958.26	1075124.05	8305227
North Kalimantan	22704937	2734288	10926143	312230.25	7755056
East Kalimantan	39464506	14799440	48914557	1051517.09	12325220
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
Banten	4375744	65326965	183367257	1066058.56	84462
Aceh	23275837	29600251	156779777	1321015.48	4283699
Papua	37107060	5491715	38384129	234357.46	10529581

2.2. Optimal Cluster Determination

In this study, the selection of the optimal number of clusters was carried out by comparing the Elbow method using the Within-Cluster Sum of Squares (WSS) approach and the Silhouette Coefficient method. This comparison is necessary because K-Means is a non-hierarchical clustering algorithm that requires the number of clusters to be specified in advance. One limitation of the K-Means algorithm is that it does not automatically determine the optimal number of clusters, and there is no single universally correct method for doing so. Therefore, cross-validation between methods is required to ensure that the selected number of clusters is optimal (Baldah et al., 2023).

2.2.1. Elbow Method

The Elbow method utilizes a graph that illustrates the relationship between the number of clusters and the total Within-Cluster Sum of Squares (WSS). The optimal number of clusters is identified by comparing the WSS values for each number of clusters; as the number of clusters increases, an "elbow" shape is formed, and the WSS value decreases as the value of k becomes larger. Therefore, in analyzing the elbow plot, the optimal number of clusters is selected at the point where a significant decrease occurs, forming a sharp bend in the curve (Ikhram & Sani Mutia, 2025). The equation used to calculate the WSS value is presented in Equation (1) (Umagapi et al., 2023).

$$WSS = \sum_{k=1}^{K} \sum_{i \in C_j} \|x_i - \mu_k\|^2 \tag{1}$$

where k is the number of clusters being tested, C_j denotes the set of observations belonging to the *k*-th cluster, x_i represents the *i*-th observation, μ_k is the centroid of the *k*-th cluster, and $\|x_i - \mu_k\|^2$ denotes the squared distance between the observation x_i and the cluster centroid.

2.2.2. Silhouette Coefficient Method

The Silhouette Coefficient is a method that combines measures of cohesion and separation. Cohesion is measured by calculating the similarity of all objects within a cluster, while separation is measured by calculating the average distance between each object in a cluster and its nearest neighboring cluster (Dinh et al., 2019). Distances between data points are computed using the Euclidean distance formula. To provide information on the quality of the clustering results, silhouette values can be calculated for each cluster as well as for the entire clustering solution produced by a clustering algorithm. The silhouette value for the entire data set with *k clusters*, can be defined as *sil(k)* calculated using Equation (2), which is the average silhouette value for all clusters (Paembonan & Abduh, 2021).

$$sil(c) = sil(k) \frac{1}{|k|} \sum_{i=1}^{k} sil(c_i) \tag{2}$$

where *Sil(k)* denotes the overall silhouette value of the clustering solution, $|k|$ is the number of clusters, and $Sil(c_i)$ is the average silhouette value for cluster *i*.

The Silhouette Coefficient ranges from 0 to 1, where higher values indicate better-defined more coherent clusters. The interpretation categories for the Silhouette Coefficient are presented in Table 2 (Karo et al., 2023).

Table 2. Description of Silhouette Coefficient Values

Silhouette Coefficient	Description
$0.7 < SC \leq 1$	Strong cluster structure
$0.5 < SC \leq 0.7$	Moderate cluster structure
$0.25 < SC \leq 0.5$	Weak cluster structure
$SC \leq 0.25$	No apparent structure

2.3. K-Means Clustering.

K-Means Clustering is a clustering method that utilizes the distance between objects, where the resulting distances reflect the degree of similarity between them. This method is a non-hierarchical clustering tecnique and is advantageous due to its ability to group large datasets quickly and efficiently (Akram et al., 2024). In K-Means, data are divided into several group which each cluster contains objects that are similar to one another but distinct from objects in other clusters (Dhewayani et al., 2022). The K-means clustering algorithm follows the procedure outlined below (Meliyana et al., 2025).

(1) Determine the optimal number clusters;

(2) Initialize the centroids randomly according to the predefined number of clusters;
(3) Calculate the distance between each data point and every centroid using Equation (3);

$$d(x_i, \mu_j) = \sqrt{\sum (x_i - \mu_j)^2} \quad (3)$$

where x_i represent a data point and μ_j denotes the centroid of cluster j.
(4) Asign each data point to the nearest centroid based on the smallest distance;
(5) Update the centroid values using the new mean of all point assigned to each cluster, as shown in Equation (4);

$$\mu_j(t+1) = \frac{1}{N_{sj}} \sum_{j \epsilon sj} x_j \quad (4)$$

where $\mu_j(t+1)$ mis the update centroid for iteration $(t+1)$, and N_{sj} is the number of data points in cluster S_j.
(6) Repeat the process until the centroid values no longer change or the algorithm reaches the predetrmined maximum number iterations.

2.4. Cluster Quality Evaluation

To evaluate the quality of the clusters formed in this study, the *Davies-Bouldin Index* (DBI) metric was employed. DBI is a metric used to evaluate the quality of clustering in data analysis. Its purpose is to assess how well a clustering algorithm separates different groups of data while maintaining compactness within each cluster. A lower DBI value in dictates better clustering performance (Faturrahman et al., 2023). The formula used to calculate DBI is presented in Equation (5) (Turnip & Fitriana, 2023).

$$DB = \frac{1}{n} \sum_{i=1}^{n} max_{i \neq j} \frac{(a_1 + a_j)}{(d(c_i, c_j))} \quad (5)$$

where n is the number of clusters, a_i and a_j represent the average distance of all members within clusters i and j respectively, and $d(c_i,c_j)$ denotes the distance between the centroids of the two clusters.

3. Result and Discussion

3.1. Descriptive Analysis

To understand the characteristics of the data used in this study, a descriptive statistical analysis was conducted. The result is presented in Table 3.

Table 3. Descriptive Statistics of Research Variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Hazard Area	34	571,637	128,161,719	21,293,204.94	23,356,201.21
Exposed Soul	34	2,734,288	240,264,323	38,00,713.56	56,221,028.76
Physical Losses	34	31,234.1	123,678,418.1	123,678,418.7	1,652,204,242.7
Economic Losses	34	67,730.74	6,016,967.60	1,398,881.080	1,549,606.356
Environmental	34	461	31,711,201	4,012,934.15	6,039,191.101

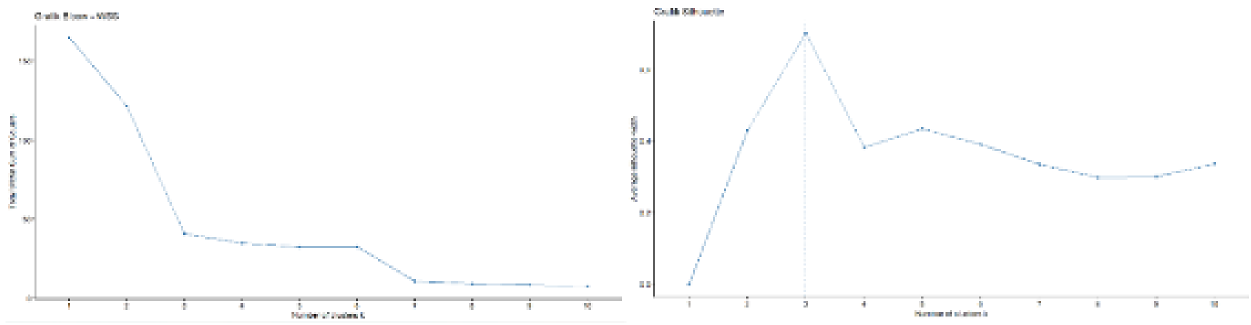
Based on the descriptive analysis presented in Table 3, it can be observed that the five variables used in this study exhibit a wide range of values across provinces. For example, for the hazard area variable, all provinces in Indonesia have areas that are potentially affected by disasters, with an average of approximately 21.9 million hectares. However, this hazard area varies substantially, as some provinces have affected areas of less than 600 thousand hectares, while others exceed 128 million hectares. This extreme disparity is clearly reflected in the standard deviation, which is much larger than the mean value. A similar pattern is also observed for the exposed population variable, where the number of people potentially affected by disasters has an average of about 38 million, but the minimum and maximum values range from 2.7 million to more than 240 million. This indicates a large disparity between densely populated provinces and those with smaller populations.

In addition, the loss variables, including physical losses, economic losses, and environmental damage, also show very pronounced differences across regions. The minimum and maximum values of these variables are separated by extremely large gaps, which causes their standard deviations to be far greater than their respective means. This condition indicates that potential disaster impacts are unevenly distributed among provinces and are highly dependent on regional characteristics and their respective levels of vulnerability.

3.2. Model Development

3.2.1. Optimal Cluster Determination

The K-Means clustering analysis was initiated by determining the optimal number of clusters to be used. In this study, the number of clusters was determined based on the Elbow method using the WSS approach and the Silhouette Coefficient method. The optimal number of clusters is presented in Figures 1(a) and 1(b).



(a) (b)

Figure 1. (a) Elbow Plot for Number of Clustes; (b) Silhouette Coefficient Plot for Number of Clusters

Based on the Elbow plot shown in Figure 1(a), the most significant decrease in the WSS value occurs at K = 3. This point, referred to as the elbow point, indicates the optimal number of clusters. This result is further supported by the Silhouette Coefficient plot in Figure 1(b), which shows that the highest Silhouette value is obtained at K = 3, with a value of 0.699. Therefore, it can be concluded that K = 3 is the optimal number of clusters to be used in the clustering analysis in this study.

3.2.2. Clustering Analysis using K-Means Method

Based on the analysis, the optimal number of clusters was determined to be three using the Elbow method and the Silhouette Coefficient. The clustering model was then constructed using the R programming language. The resulting clusters were visualized to illustrate the distribution of each cluster based on the characteristics used in the analysis. The distribution of the clustering results is presented in the scatter plot shown in Figure 2. Based on Figure 2, three distinct clusters can be clearly identified. Cluster 1 is represented by red points and contains only one province, indicating that this cluster is an outlier whose characteristics are substantially different from those of the remaining data. Cluster 2 is represented by green points and constitutes the largest cluster in the dataset. Cluster 3 is represented by blue points and forms a medium sized cluster.

Each cluster exhibits unique characteristics that distinguish it from the others. The characteristics of each cluster, based on the mean values of each variable, are presented in Table 4, while the interpretation of cluster characteristics and their respective members is provided in Table 5. The clustering results are also visualized using a thematic map, as shown in Figure 3. Based on the map, Cluster 1 consists of only one province, namely Central Papua, which is the sole member of this cluster. Cluster 2 is the largest cluster and includes all provinces on the islands of Sumatra, Kalimantan, Sulawesi, the Maluku Islands, Bali and Nusa Tenggara, most of Java Island, and one province on the island of Papua. In contrast, Cluster 3 comprises a small number of provinces located on the island of Java.

3.3. Model Evaluation

After performing the clustering analysis using the K-Means method, a model evaluation was conducted to assess the quality of the resulting data grouping. In this study, the model was evaluated using the Davies Bouldin Index. The evaluation results yielded a DBI value of 0.30 for K = 3, indicating that the resulting clusters have very good quality. The evaluation results are presented in Table 6.

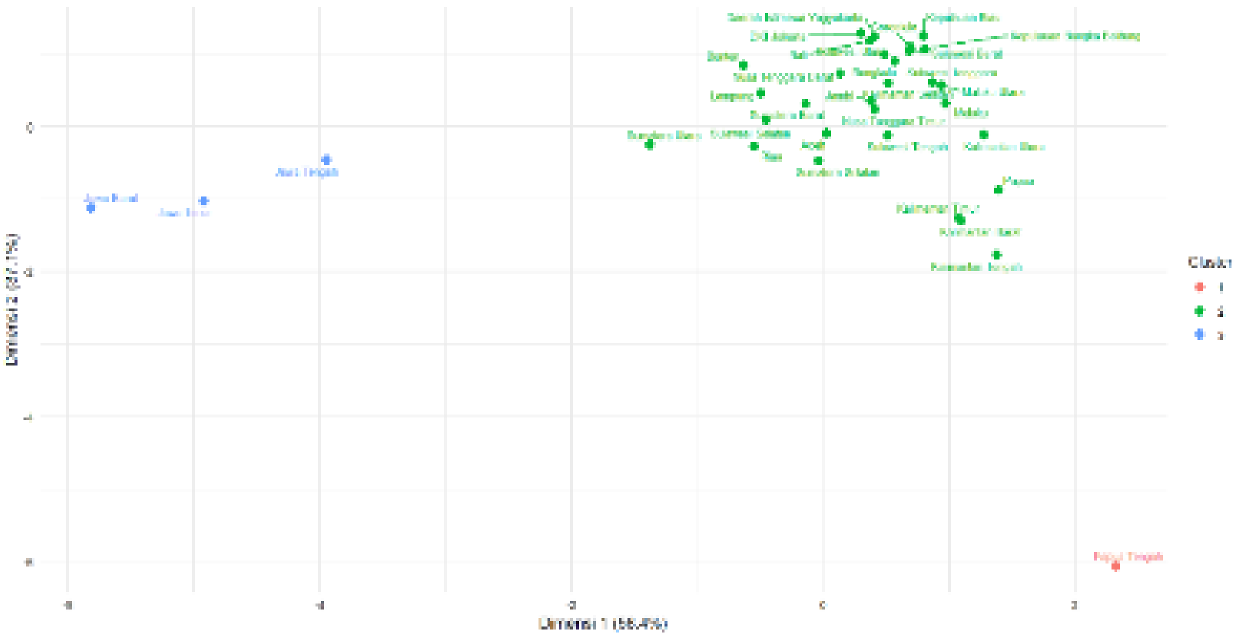


Figure 2. Cluster Distribution Scatterplot

Table 4. Average Values of Each Variable in Each Cluster

Cluster	Hazard Are (Ha)	Exposed Soul	Physical Losses (Billion IDR)	Economic Losses (Billion IDR)	Environmental (Ha)
1	12,816,719	1,795,807	11,741,529	712,132	**31,711,201**
2	**18,231,068**	2,177,183	7,554,073	1,018,602	3,442,254
3	16,291,741	**20,699,302**	**60,714,306**	**5,430,584**	486,982

Table 5. Characteristics and Members of Each Cluster

Cluster	Characteristics	Members
1	This cluster, which consists only of Central Papua Province, is an outlier relative to the other clusters. It represents a province facing disaster impact threats in the form of significant environmental damage. The primary risk in this cluster does not lie in human exposure, but rather in the high level of environmental degradation.	Central Papua
2	This cluster represents the national average condition, comprising regions with a high potential hazard area. Although economic and physical losses are not extreme, they remain cumulatively significant due to the large number of provinces included in this cluster.	Gorontalo, West Kalimantan, North Kalimantan, East Kalimantan, Banten, South Kalimantan, Yogyakarta, Maluku, Southeast Sulawesi, Jambi, West Sulawesi, South Sumatra, East Nusa Tenggara, North Sulawesi, Riau, Bangka Belitung Islands, Riau Islands, Jakarta Special Capital Region, North Maluku, Central Kalimantan, Lampung, Bengkulu, Bali, North Sumatra, West Nusa Tenggara, West Sumatra, South Sulawesi, Central Sulawesi, Aceh, Papua.

3	This cluster represents regions with systemic risk to the national economy. The combination of large economic and physical losses and a very high exposed population results in a highly significant potential for disaster related losses.	West Java, East Java, Central Java.

Figure 3. Cluster Thematic Map

Table 6. Model Evaluation Result

Number of Cluster	DBI Value
3	0.30

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4. Conclusions

Based on the results of this study, it can be concluded that the K-Means clustering method provides a very good grouping of Indonesian provinces based on their potential natural disaster impacts. The determination of the optimal number of clusters using the Elbow and Silhouette Coefficient methods consistently indicates that K = 3 is the most appropriate number of clusters. The resulting clusters reflect substantial variation in regional risk characteristics, ranging from provinces with extreme potential environmental impacts, to regions with relatively stable risk conditions representing the national average, and to provinces with very high levels of population exposure as well as significant economic and physical loss potential. The model evaluation using the Davies Bouldin Index yielded a value of 0.30, confirming that the resulting cluster structure has excellent separation and cohesion quality.

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