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Unveiling Regional Disparities in Indonesia: Clustering Provinces by Development Indicators

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Abstract. Indonesia's pursuit of sustainable development—integrating economic, social, and environmental dimensions—remains challenged by persistent regional disparities. In 2022, only four of seven national priority indicators were achieved, while 21 provinces failed to meet more than three targets. To capture these disparities more precisely, this study applies hierarchical and non-hierarchical clustering to classify 34 provinces based on seven development indicators. The comparative approach enhances robustness: hierarchical clustering reveals inter-provincial linkages, while non-hierarchical clustering improves internal consistency. Validation tests identify Ward's method as optimal, yielding four distinct clusters. Cluster 1 includes four eastern provinces with multidimensional inequality—high stunting (31.43%), early marriage (10.37%), and low literacy (36.44%). Cluster 2 comprises 20 provinces with structural stagnation, marked by persistent stunting (24.80%) and reliance on primary sectors. Cluster 3 consists of seven industrial provinces with strong economic performance (manufacturing 33.59% of GDP) and improving social indicators. Cluster 4 includes three service-based provinces excelling in social outcomes—lowest stunting (13.07%) and highest literacy (78.46%)—but facing environmental challenges. These findings highlight the urgency of region-specific, evidence-based policy interventions to promote equitable and sustainable development.
Keyword: Cluster Analysis, Early Marriage, Human Capital, Regional Disparities, Stunting.

1. Introduction

Contemporary development demands not only economic growth but also a balanced integration of social, economic, and environmental dimensions. The concept of sustainable development has been reinforced to emphasize the need for a holistic approach that integrates these three pillars. Focusing solely on economic growth often results in environmental degradation due to finite natural resources, underscoring the urgent need for a paradigm shift toward sustainable development [1].

The global commitment to sustainable development was strengthened through the adoption of the Sustainable Development Goals (SDGs) by the United Nations in 2015, comprising 17 goals and 169 targets to be achieved by 2030. This agenda urges nations, including Indonesia, to align their development policies with principles of inclusivity, equity, and environmental sustainability. To implement this agenda, Indonesia has integrated the SDGs into the National Medium-Term Development Plan (RPJMN) IV 2020–2024 by establishing seven national priority programs (NPP) as the framework for development. These programs are operationalized through the annual Government Work Plan (RKP) and evaluated using indicators aligned with the four pillars of the SDGs: economic, social, environmental, and legal and governance aspects. In 2022, national data indicated that only four of the seven NPP indicators met their targets, highlighting significant challenges in achieving comprehensive progress.The successful implementation of policies hinges on multiple factors, including strategic planning, institutional capacity, and resource availability [2]. Harmonizing global targets with local policies is equally critical to ensure the achievement of development goals [3]. Regional development in Indonesia reflects the nation's diverse social, economic, and geographical conditions, which often complicates policy alignment across provinces. These regional variations directly influence the performance of NPP, resulting in disparities in achieving their indicators across provinces.

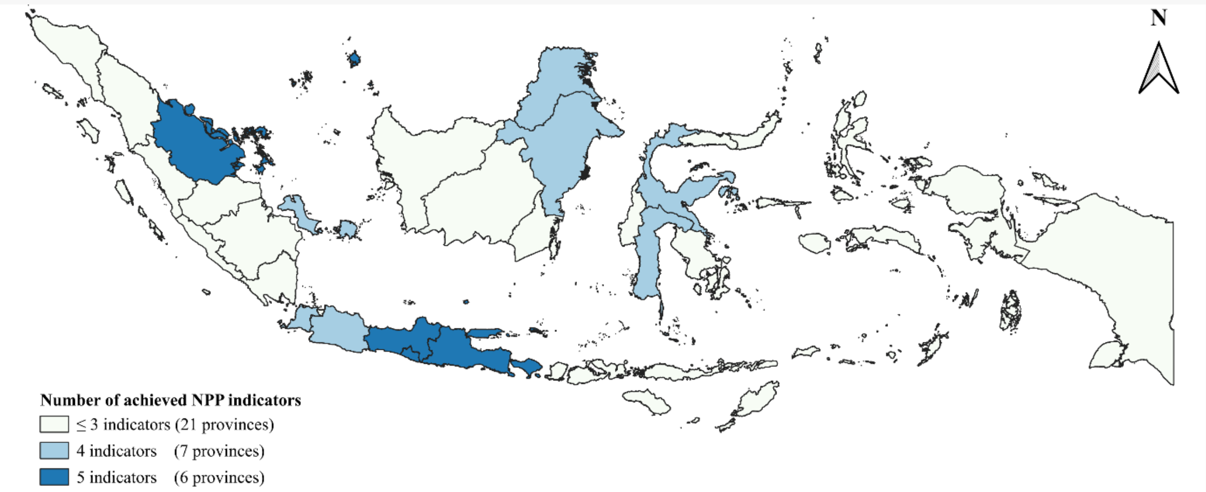

Figure 1. Distribution of provinces by number of achieved NPP indicators, Indonesia, 2022

Based on Figure 1, which uses data from the Indonesia SDGs Database 2022, the color differences on the map reflect variations in NPP indicator achievement across Indonesian provinces. Of the 34 provinces, only six—Bali, Yogyakarta Special Region, Central Java, East Java, Riau Islands, and Riau—achieved five indicators, representing the highest level of alignment with NPP targets. Hereafter, Yogyakarta Special Region will be referred to as Yogyakarta. Seven provinces met the targets for four indicators, while the remaining 21 achieved three or fewer. A noticeable disparity is evident between western and eastern Indonesia in meeting these targets, indicating uneven progress in NPP implementation, as highlighted in previous studies on regional inequality in Indonesia [4]. This disparity is largely attributed to structural challenges, including limited infrastructure and human resource capacity in many provinces. Such inequalities pose risks to the achievement of national aggregate targets and may further exacerbate regional disparities [5].

The concept of Satuan Wilayah Pembangunan (SWP), or Regional Development Units, is relevant as an established framework for regional planning in Indonesia. SWP groups provinces or districts administratively and geographically based on their resource potential and development needs, such as clusters of districts within a province (e.g., in East Java) or sub-city divisions with distinct functions (e.g., in Ambon City). While SWP focuses on resource potential and geographic proximity to guide development planning, this study's clustering based on national priority program indicators offers a performance-driven perspective, capturing variations in policy outcomes across provinces. This approach is compelling because it reveals patterns of achievement that may not align with SWP's resource-based groupings, providing insights into underperforming regions and informing targeted policy interventions to address disparities in SDG-related outcomes. Unlike SWP, which is static and resource-focused, clustering based on performance indicators enables a dynamic assessment of development progress, highlighting gaps that require prioritized action to enhance national and regional development equity.

To ensure a robust and reliable classification of provinces, this study compares hierarchical and non-hierarchical clustering techniques. Each method offers distinct advantages: hierarchical clustering captures inter-provincial linkages and structural relationships, while non-hierarchical clustering enhances internal consistency and flexibility in group formation. By evaluating both approaches, the study identifies the most effective clustering strategy for revealing meaningful patterns in regional development performance.

2. Research Methods

2.1. Cluster Analysis

Cluster analysis is a multivariate statistical technique that groups data based on their similarity, typically measured by distances between objects. As an unsupervised method, it treats all variables equally without distinguishing between independent and dependent variables [6]. Objects that are closer together, as measured by a proximity metric, exhibit greater similarity than those farther apart. The Euclidean distance is commonly used as a proximity measure, although other metrics, such as Manhattan or Minkowski distances, may also be applied depending on the data characteristics. Cluster analysis is broadly categorized into hierarchical and non-hierarchical methods, with the latter including techniques like k-means clustering [6]. The initial step involves defining a proximity measure to assess similarity between objects, followed by selecting an appropriate clustering method. Prior to clustering, data should be standardized to ensure consistent scales, and extreme outliers should be addressed to avoid skewed results [7].

Hierarchical Cluster Analysis

Hierarchical clustering methods are divided into two main approaches: agglomerative, which iteratively merges individual objects into larger clusters, and divisive, which starts with a single cluster and splits it into smaller ones [6]. The agglomerative approach, being more computationally efficient, is commonly used and forms the basis for this study. This research employs four agglomerative hierarchical clustering techniques: single linkage, complete linkage, average linkage, and Ward's method.

The agglomerative hierarchical clustering algorithm operates in the following steps: (1) treat each object as a single cluster initially, computing the proximity matrix of distances between all pairs of objects; (2) merge the two closest clusters based on the chosen linkage method; (3) update the proximity matrix to reflect the distances between the new merged cluster and the remaining clusters; and (4) repeat steps 2 and 3 until all objects are merged into a single cluster or the desired number of clusters is achieved, resulting in a dendrogram for visualization [6].

Single linkage, also known as the nearest neighbor method, merges clusters based on the minimum distance between any pair of objects in different clusters [6]. The formula is

$$d_{(UV)W} = \min \{d_{UW}, d_{VW}\} \tag{1}$$

where $d_{(UV)W}$ is the distance between the merged cluster UV and cluster W, d_{UW} is the distance between clusters U and W, and d_{VW} is the distance between clusters V and W.

Complete linkage, or the farthest neighbor method, merges clusters based on the maximum distance between any pair of objects in different clusters, emphasizing heterogeneity between clusters [6]. The formula is:

$$d_{(UV)W} = \max \{d_{UW}, d_{VW}\}. \tag{2}$$

Average linkage merges clusters based on the average distance between all pairs of objects across two clusters [6]. The formula is

$$d_{(UV)W} = \frac{\sum_i \sum_j d_{ij}}{N_{(UV)} N_W} \tag{3}$$

where d_{ij} is the distance between object i in cluster UV and object j in cluster W, and N_{UV} and N_W are the number of objects in clusters UV and W, respectively, with i and j representing provinces in this study.

Ward's method minimizes the within-cluster variance by merging clusters that result in the smallest increase in the Error Sum of Squares (ESS) [6]. The formula is

$$ESS = \sum_{i=1}^{N}(x_i - \bar{x})^T(x_i - \bar{x}) \tag{4}$$

where ESS represents the within-cluster variance, x_i is the data vector for the i-th object, and $\bar{x}$ is the mean vector of the cluster, and N is the number of objects in the cluster. When merging clusters, the increase in ESS is minimized.

After applying these hierarchical clustering methods, the best method will be selected by evaluating the strength of the clustering structure using the Agglomerative Coefficient, which measures the degree of clustering hierarchy for each method, with values closer to 1 indicating stronger clustering structure [7].

Nonhierarchical Cluster Analysis

Nonhierarchical clustering methods represent an approach in cluster analysis that enables the simultaneous grouping of objects without the hierarchical stages characteristic of hierarchical methods. These methods are particularly useful for partitioning objects into a predefined number of clusters or determining the number of clusters as part of the clustering process [6]. This research utilizes two nonhierarchical clustering techniques: K-means and K-medoids.

K-means algorithm partitions partitions a set of N objects into K clusters by assigning each object to the cluster with the nearest centroid, which is the mean of all objects in that cluster. K-means uses the centroid (mean) rather than an actual data point, making it sensitive to outliers but computationally efficient [6]. The goal is to minimize the total within-cluster sum of squares by finding the optimal set of centroids. The objective function is to minimize the sum of squared Euclidean distances from each object to the centroid of its assigned cluster, calculated as

$$W = \sum_{k=1}^{K}\sum_{i=1}^{n_k} \quad (x_{i,k} - \mu_k)^2 \tag{5}$$

where W is the total within-cluster sum of squares across all clusters, K is the total number of clusters, n_k is the number of objects in the k-th cluster C_k, x_{ik} is the i-th object in the k-th cluster C_k, μ_k is the centroid (mean) of the k-th cluster C_k, $(x_{i,k} - \mu_k)^2$ is the squared Euclidean distance between object $x_{i,k}$ and centroid μ_k.

The algorithm operates in the following steps: (1) randomly select K initial centroids from the dataset; (2) assign each object to the cluster with the closest centroid based on Euclidean distance; (3) recalculate the centroid of each cluster as the mean of all objects in that cluster; and (4) repeat steps 2 and 3 until the centroids no longer change or a predefined number of iterations is reached, achieving convergence [6].

K-medoids algorithm partitions a set of N objects into k clusters by selecting actual data points as medoids, which serve as the most representative objects for their respective clusters. Unlike K-means, which uses the mean (centroid) of the cluster, K-medoids selects an existing data point as the medoid, making it more robust to outliers and noise in the data [8]. The goal is to minimize the total dissimilarity within all clusters by finding the optimal set of medoids. The objective function is to minimize the sum of distances from each object to the medoid of its assigned cluster, calculated as

$$TC = \sum_{k=1}^{K}\sum_{i=1}^{n_k} \quad d\,(x_{i,k}, m_k) \tag{6}$$

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where TC is the total cost or dissimilarity across all clusters, K is the total number of clusters, n_k is the number of objects in the k-th cluster C_k, x_{ik} is the i-th object in the k-th cluster C_k, m_k is the medoid of the k-th cluster C_k, and $d(x_{ik}, m_k)$ is the distance (typically Euclidean or Manhattan) between object x_{ik} and medoid m_k.

The algorithm operates in the following steps: (1) randomly select K initial medoids from the dataset; (2) assign each object to the cluster with the closest medoid based on the chosen distance metric; (3) for each cluster, evaluate whether swapping the current medoid with another object in the cluster reduces the total cost; and (4) repeat steps 2 and 3 until no further swaps decrease the total cost, achieving convergence [8].

Selecting the optimal number of clusters is a critical initial step in nonhierarchical clustering methods, as these techniques require specifying the number of clusters in advance. This determination ensures that the resulting clusters effectively separate the objects based on their inherent structure. Two commonly used methods for identifying the optimal number of clusters are the elbow method, which examines the point of diminishing returns in within-cluster variance, and the silhouette method, which assesses cluster cohesion and separation [7].

Cluster Result Validation

Validation of clustering results is essential to confirm that the partitioning accurately reflects the underlying data structure and produces meaningful groupings. Several internal validity indices can be employed to evaluate and select the optimal number of clusters in both hierarchical and nonhierarchical methods, including the silhouette index, Dunn index, and Davies-Bouldin index [7]. Optimal clustering is indicated by higher values for the silhouette and Dunn indices, which signify better separation and compactness, and by lower values for the Davies-Bouldin index, which reflects reduced overlap between clusters.

The silhouette index measures how similar an object is to its own cluster compared to other clusters, providing a value between -1 and 1 for each object, with higher average scores indicating stronger clustering [9]. For a data point i, the silhouette coefficient $s(i)$ is calculated as

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{7}$$

where $a(i)$ is the average distance from i to other points in its cluster (cohesion), and $b(i)$ is the minimum average distance from i to points in any other cluster (separation). The global silhouette score is the average $s(i)$ across all data points.

The Dunn index evaluates cluster validity by maximizing inter-cluster separation while minimizing intra-cluster diameter, with higher values denoting well-separated and compact clusters [10]. The formula is

$$D = \frac{\min_{1 \le i < j \le k} d(C_i, C_j)}{\max_{1 \le l \le k} \operatorname{diam}(C_l)} \tag{8}$$

Where $d(C_i, C_j)$ is the minimum distance between any two points in clusters C_i and C_j (inter-cluster distance), and $\operatorname{diam}(C_l)$ is the maximum distance between any two points in cluster C_l (intra-cluster diameter).

The Davies-Bouldin index assesses clustering quality by quantifying the average similarity ratio between each cluster and its most similar neighbor, with lower values indicating better partitioning [11]. The formula is

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{j \ne i} \left[\frac{s_i + s_j}{d_{ij}} \right] \tag{9}$$

where k is the number of clusters, s_i and s_j are the average distances from points in clusters i and j to their respective centroids (dispersion), and d_{ij} is the distance between the centroids of clusters i and j.

2.2. Data

This study utilizes secondary quantitative data for 2022, consisting of National Priority Program (NPP) indicators from the 2022 Government Work Plan and aligned with the 2020–2024 National Medium-Term Development Plan and specific SDG indicators. The unit of analysis consists of 34 provinces across Indonesia, with data sourced from official platforms, including the Indonesia SDGs Database, the BPS-Statistics Indonesia website, and the Satu Data Indonesia portal. The year 2022 was selected because it is the most recent year for which complete and consistent data are available across all provinces for the selected indicators. A detailed description of all indicators used in the analysis is provided in Table 1.

Table 1. Description of indicators.

Indicator	Description
Manufacturing value added to GDP	Contribution of the manufacturing industry to national economic growth, expressed as a percentage of GDP.
Proportion of women aged 20–24 who married or cohabited before age 18	Prevalence of child marriage among women aged 20–24, reflecting social and gender equality.
Prevalence of stunting among children under five	Proportion of children under five with stunted growth, indicating national health, human capital quality, and long-term economic potential.
Community literacy development index	Index measuring the availability and quality of literacy support facilities, such as libraries and reading programs.
Percentage of households with access to adequate and affordable housing	Proportion of households living in homes meeting quality and affordability standards, reflecting housing quality and community well-being.
Water quality index	Index assessing the suitability of water for community needs, with higher values indicating better environmental compliance.
Index of democratic institutional capacity	Index evaluating the effectiveness of state institutions in supporting democratic functions and governance.

3. Result and Discussion

3.1. Overview of NPP Indicator Achievement Across Provinces

The indicator manufacturing value added to GDP exhibits significant disparities across Indonesia's 34 provinces, ranging from 1.21% in East Nusa Tenggara to 42.98% in West Java. The national average for this indicator is 20.47%. As shown in Figure 2, only 11 provinces—West Java, Riau Islands, Banten, Central Java, Central Sulawesi, Riau, West Papua, East Java, North Maluku, Bangka Belitung Islands, and East Kalimantan—meet the national target, while the remaining 23 provinces fall short.

For the proportion of women aged 20–24 who married or cohabited before age 18, the values range from 2.07% in Jakarta to 16.23% in West Nusa Tenggara, with a national average of 8.06%. Figure 3 indicates that 23 provinces have achieved the national target, while 11 provinces have not, demonstrating stronger performance compared to the manufacturing indicator.

The prevalence of stunting among children under five shows a substantial range of 27.3%, from the lowest to the highest prevalence across provinces, with a national average of 21.6%. Figure 4 shows that only seven provinces, primarily in Sumatra and parts of Java, meet the national target in 2022, indicating the lowest achievement among the indicators discussed.

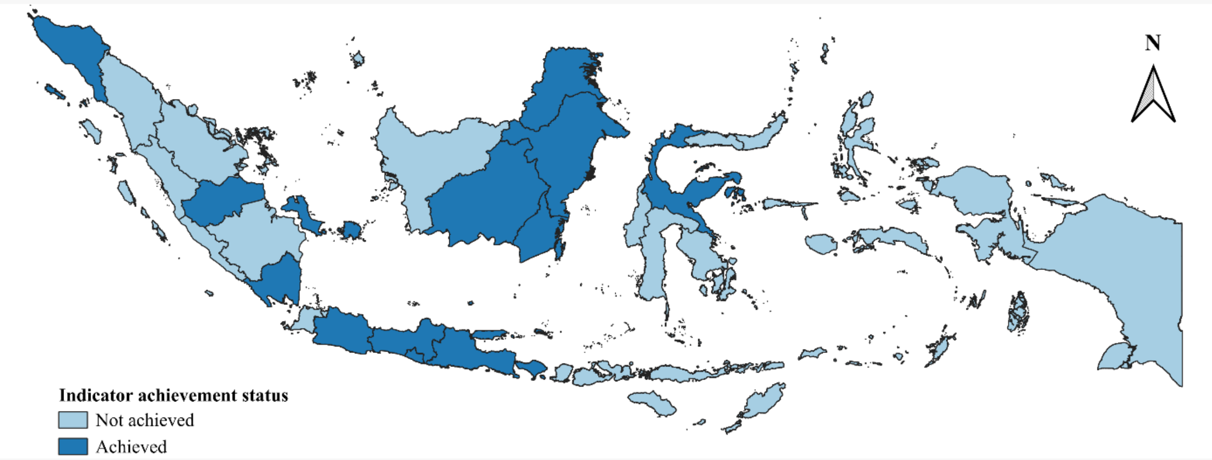


Figure 2. Provincial achievement status for NPP indicator: Manufacturing value added to GDP.

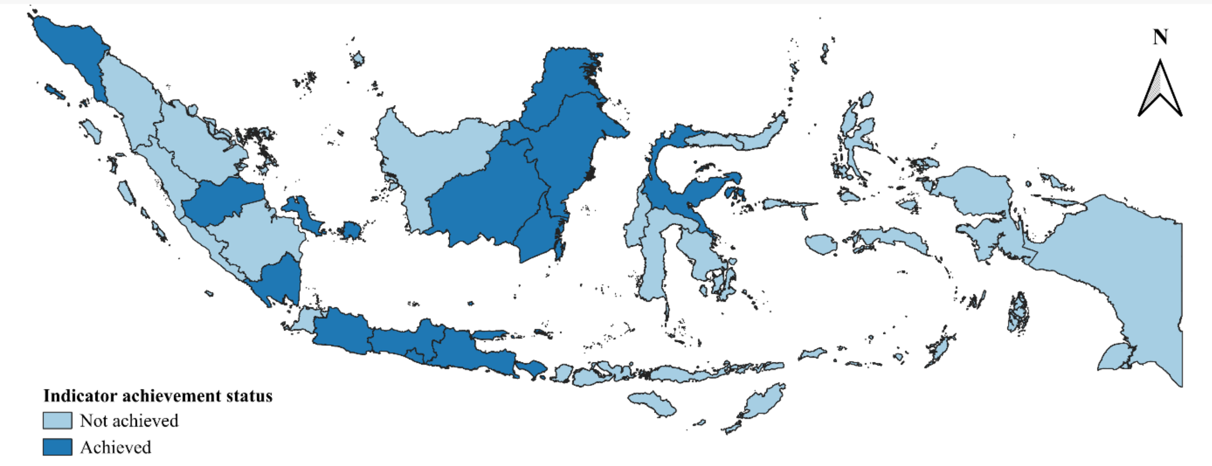


Figure 3. Provincial achievement status for NPP indicator: Proportion of women aged 20–24 who married or cohabited before age 18.

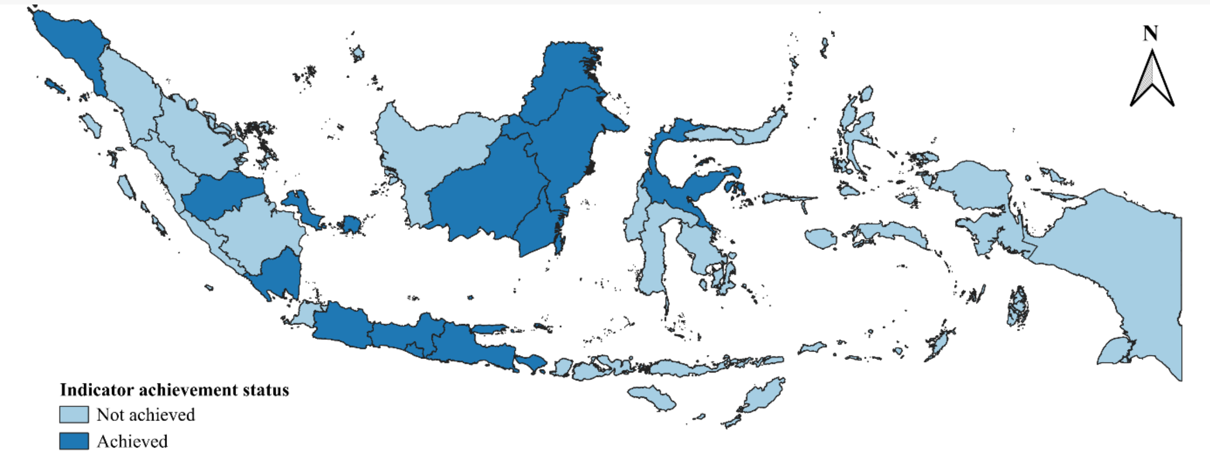


Figure 4. Provincial achievement status for NPP indicator: Prevalence of stunting among children under five.

The community literacy development index reveals a wide disparity of 63.61 points, with Yogyakarta achieving the highest score, significantly above the national average of 64.48, and Papua recording the lowest at 20.02. Figure 5 shows that most provinces in Western Indonesia meet the national target, while eastern provinces, including Papua, East Nusa Tenggara, and Maluku, exhibit lower performance, reflecting disparities in educational facilities and access to literacy resources.

The percentage of households with access to adequate and affordable housing has a national average of 60.06%, with Yogyakarta at 84.94% and Papua at 27.28%, indicating a significant disparity. Figure 6 reveals that 13 provinces meet the national target, while 21 provinces do not, with central and eastern provinces facing greater challenges in housing provision.

Figure 5. Provincial achievement status for NPP indicator: Community Literacy Development Index.

Figure 6. Provincial achievement status for NPP indicator: Percentage of households with access to adequate and affordable housing.

The Water quality index averages 53.88 nationally, ranging from 39.31 in Yogyakarta to 62 in West Papua. Figure 7 shows that 17 provinces, mostly in eastern and central regions, meet the national target, while western provinces such as Jakarta, Yogyakarta, and West Java fall short. The index of democratic institutional capacity displays varied performance, with a national average of 78.22, ranging from 50.47 in North Maluku to 85.05 in Bangka Belitung Islands. Figure 8 indicates that 14 provinces meet the national target, while 20 do not, with relatively balanced distribution across islands except for lower performance in Maluku and Papua.

Figure 7. Provincial achievement status for NPP indicator: Water Quality Index.

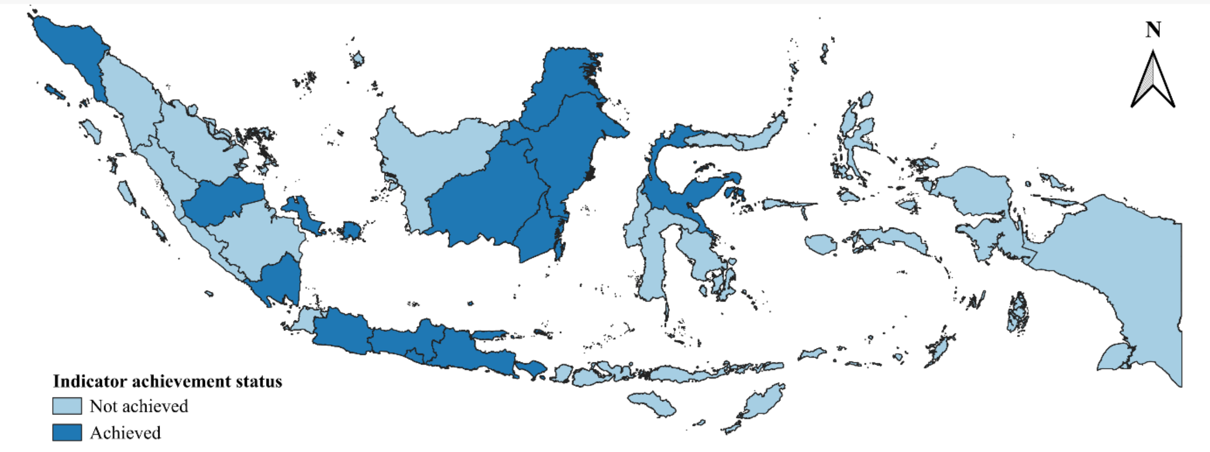


Figure 8. Provincial achievement status for NPP indicator: Index of Democratic Institutional Capacity.

3.2. Cluster Analysis Process

The cluster analysis process begins with data standardization to ensure that all indicators are on a comparable scale, accounting for differences in measurement units. Subsequently, the assumptions underlying cluster analysis are evaluated. A key assumption is the absence of high multicollinearity among variables to ensure distinct contributions to clustering. In this study, the assumption of a representative sample is not applicable, as the data encompass all 34 provinces in Indonesia, constituting population data rather than a sample.

Table 2. Correlation matrix of NPP indicators.

Indicator	X_1	X_2	X_3	X_4	X_5	X_6	X_7
X_1	1						
X_2	-0.031	1					
X_3	-0.318	0.439	1				
X_4	0.184	-0.188	-0.548	1			
X_5	-0.021	-0.010	-0.271	0.376	1		
X_6	0.154	0.173	0.267	-0.419	-0.069	1	
X_7	0.095	-0.195	-0.399	0.495	0.099	-0.095	1

Multicollinearity testing among variables in this study was conducted using a correlation matrix. The correlation matrix in Table 2 reveals several noteworthy patterns among the seven NPP indicators manufacturing value added to GDP (X_1), proportion of women aged 20–24 who married or cohabited before age 18 (X_2), prevalence of stunting among children under five (X_3), community literacy development index (X_4), percentage of households with access to adequate and affordable housing (X_5), water quality index (X_6), index of democratic institutional capacity (X_7). All pairwise correlations are below 0.8 in absolute value, suggesting no substantial multicollinearity that would confound the cluster analysis. This threshold is commonly used to indicate acceptable independence among variables [7]. Given these results, the seven indicators meet the assumptions for cluster analysis and can proceed to the subsequent stages of hierarchical and non-hierarchical clustering.

The cluster analysis begins with hierarchical methods. Dendrograms are presented for each hierarchical clustering technique: single linkage, complete linkage, average linkage, and Ward's method. Figure 9 displays the dendrograms resulting from these methods. The dendrogram for the single linkage method (Figure 9a) shows suboptimal results, as one observation forms a cluster by itself, leading to imbalanced clusters. Similar issues are observed in the average linkage method (Figure 9c), where isolated clusters reduce the overall cohesion. In contrast, the complete linkage method (Figure 9b) and Ward's method (Figure 9d) produce more balanced and proportional cluster divisions, with Ward's method demonstrating particularly compact clusters.

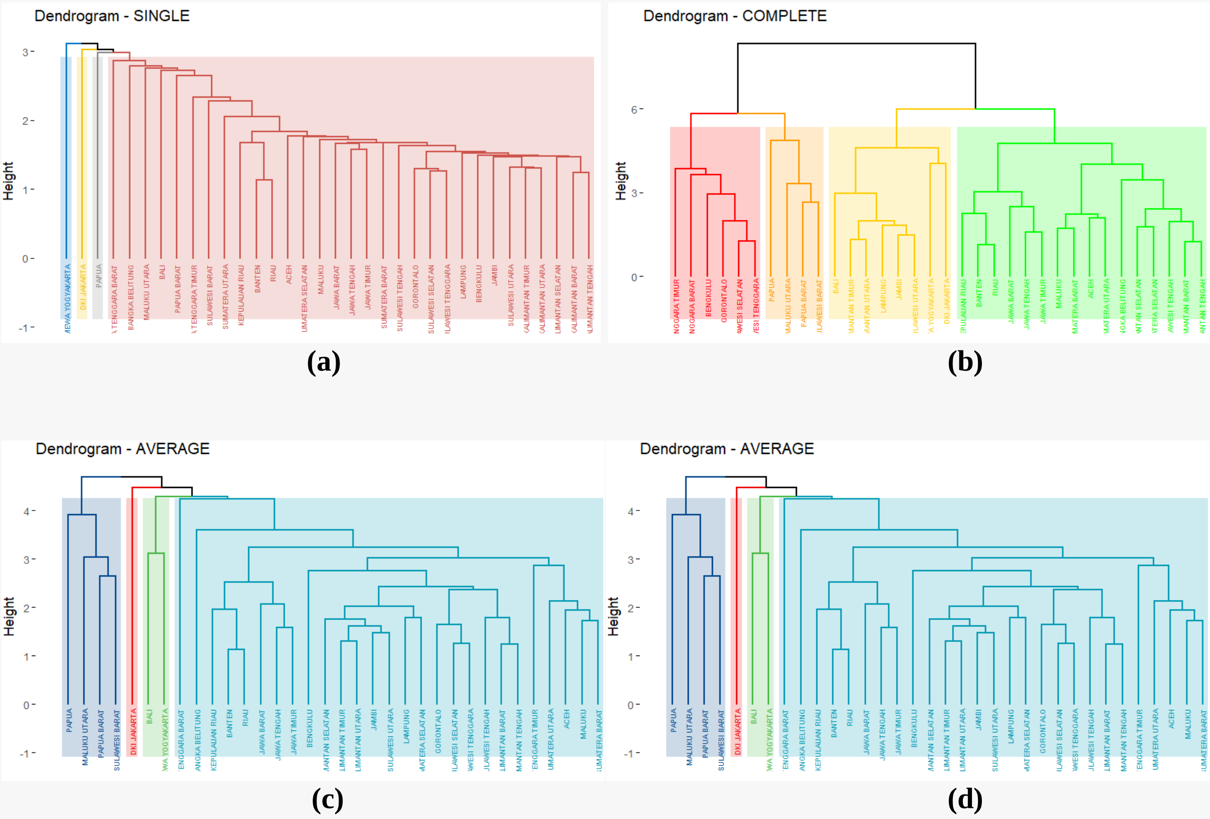


Figure 9. Dendrograms for hierarchical clustering of provincial NPP indicators: a) Single linkage, (b) Complete linkage, (c) Average linkage, (d) Ward's method.

Following dendrogram formation, the Agglomerative Coefficient (AC) is calculated to assess the strength of the clustering structure and identify the optimal hierarchical method. The AC values are as follows.

Table 3. Agglomerative coefficients for hierarchical clustering methods.

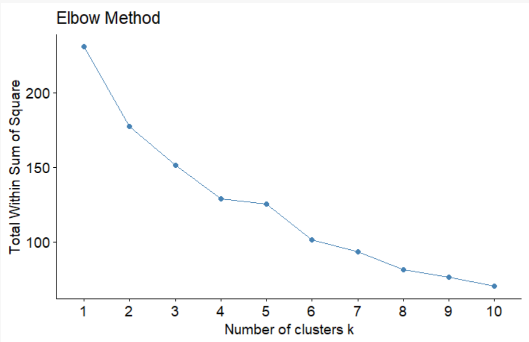
Method	Agglomerative coefficient
Single linkage	0.403
Complete linkage	0.731
Average linkage	0.544
Ward's method	0.768

As shown in Table 3, Ward's method yields the highest AC value of 0.768, indicating the strongest and most cohesive clustering structure. This suggests that Ward's method minimizes within-cluster variance effectively, making it suitable for further analysis [7]. Therefore, Ward's method is selected for comparison with nonhierarchical methods.

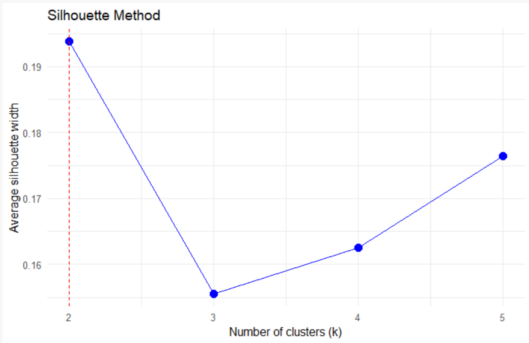
Table 4. Cluster validity metrics for Ward's hierarchical clustering method.

Method	k	Silhouette index	DB index	Dunn index
Ward's method	3	0.176	1.744	0.280
	4	0.179	1.443	0.308

Cluster validity is assessed to ensure maximum homogeneity within clusters and heterogeneity between clusters, using the silhouette index, Davies-Bouldin (DB) index, and Dunn index. Table 4 indicates that Ward's method with four clusters outperforms the three-cluster configuration, as it achieves a higher silhouette index (0.179 vs. 0.176), a lower DB index (1.443 vs. 1.744), and a higher Dunn index (0.308 vs. 0.280), reflecting better cluster separation and cohesion [7]. Thus, Ward's method with four clusters is selected as the optimal hierarchical approach for grouping the 34 provinces and is compared with nonhierarchical methods.



(a)



(b)

Figure 10. Cluster number determination for K-means clustering of provincial NPP indicators: (a) Elbow method, (b) Silhouette method.

Nonhierarchical clustering is performed using K-means and K-medoids, with the number of clusters determined by the elbow and silhouette methods. Based on Figure 10, the elbow and silhouette methods suggest varying optimal cluster numbers for K-means. To ensure a robust comparison, the data are grouped into two, three, and four clusters. Figure 11 demonstrates that K-means produces distinct clusters with no overlapping observations across all configurations, indicating effective separation of provinces based on NPP indicators [6].

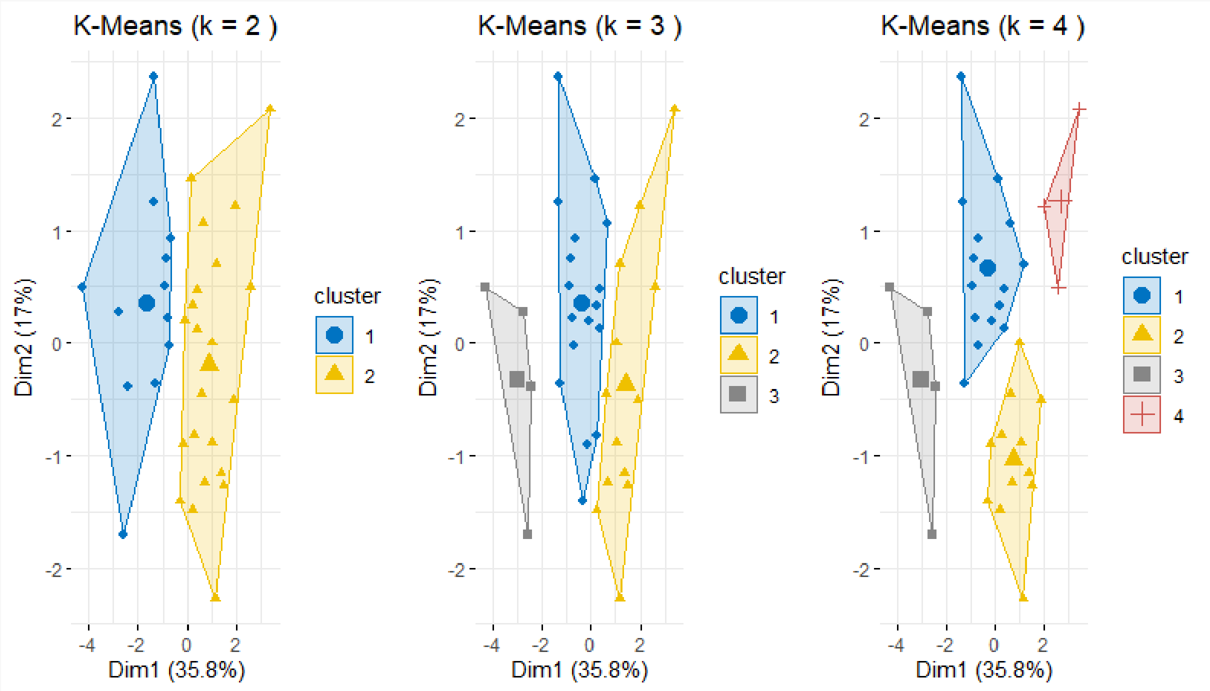
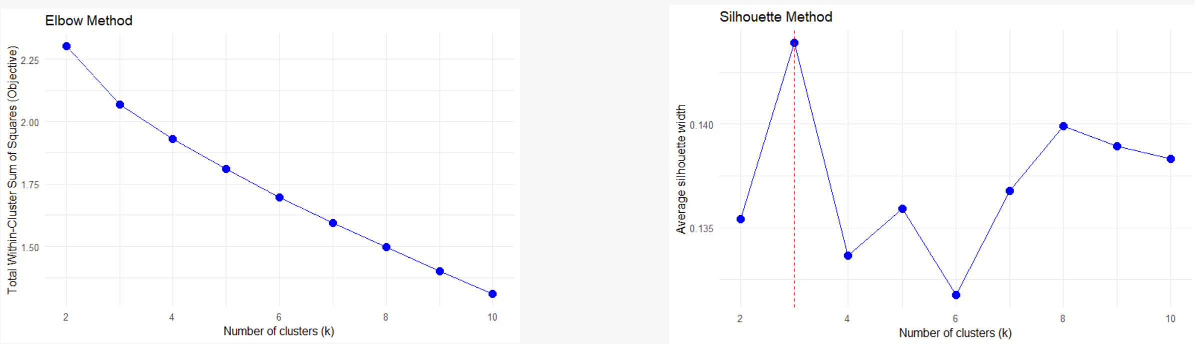


Figure 11. K-means cluster visualizations for provincial NPP indicators

Figure 12 indicates that both the elbow and silhouette methods suggest three clusters for K-medoids. However, to facilitate comparison with K-means and hierarchical methods, groupings with two, three, and four clusters are evaluated. Figure 13 reveals that K-medoids produces overlapping observations, particularly in the three- and four-cluster configurations, suggesting less effective separation compared to K-means [9, 12, 13]. This overlap may be attributed to K-medoids' sensitivity to the initial selection of medoids and its challenges in handling the complex, non-spherical structure of the NPP indicator dataset, which includes diverse socio-economic profiles across provinces.



(a) **(b)**

Figure 12. Cluster number determination for K-medoids clustering of provincial NPP indicators (a) Elbow method, (b) Silhouette method

Cluster validity is evaluated for nonhierarchical methods to determine the optimal configuration. Table 5 shows that K-means with four clusters achieves the best balance among nonhierarchical methods, with a silhouette index of 0.163, the lowest DB index (1.534), and the highest Dunn index

(0.267), indicating reasonable cohesion and separation [7]. This configuration is selected for comparison with Ward's method.

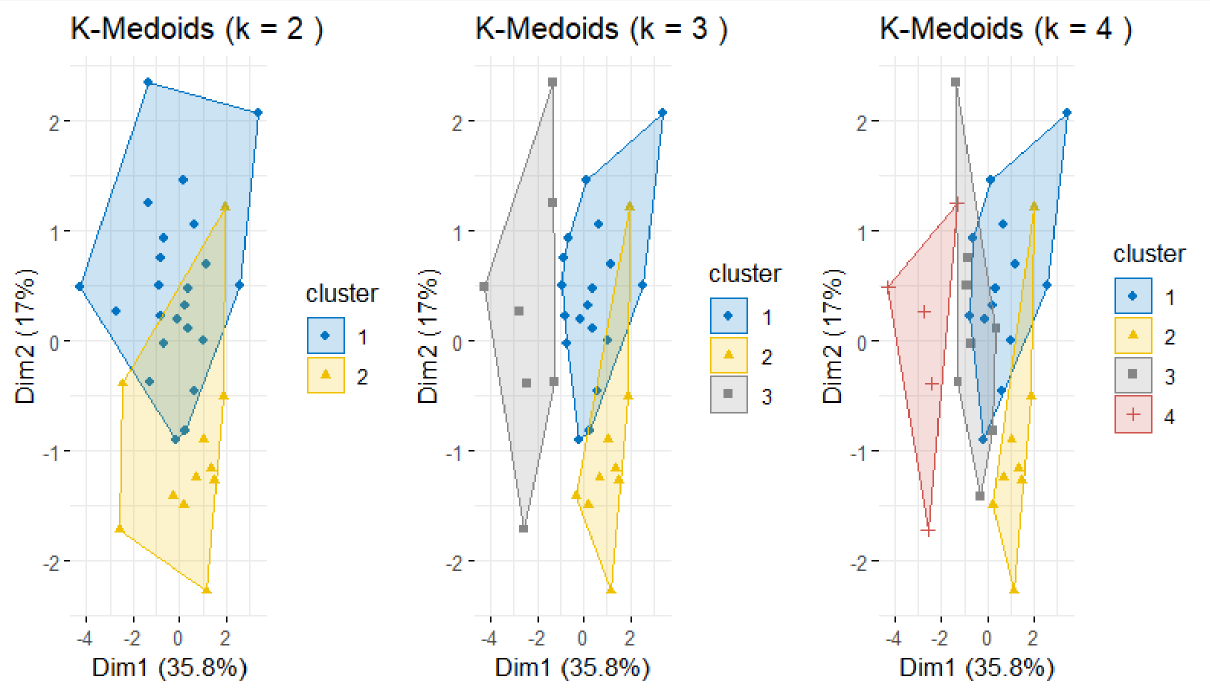


Figure 13. K-medoids cluster visualizations for provincial NPP indicators.

The optimal clustering method is determined by comparing Ward's method and K-means, both with four clusters. Table 6 demonstrates that Ward's method with four clusters outperforms K-means across all validity indices, with a higher silhouette index (0.179 vs. 0.163), a lower DB index (1.443 vs. 1.534), and a higher Dunn index (0.308 vs. 0.267). These results align with findings in the literature, which suggest that Ward's method often produces more compact and well-separated clusters in hierarchical structures compared to K-Means, particularly for socio-economic datasets [14]. Consequently, Ward's method with four clusters is identified as the optimal approach for grouping the 34 provinces based on the 2022 NPP indicators.

Table 5. Cluster validity metrics for nonhierarchical clustering methods.

Method	*k*	Silhouette index	DB index	Dunn index
K-means	2	0.194	1.759	0.210
	3	0.155	1.763	0.217
	4	0.163	1.534	0.267
K-medoids	2	0.135	2.550	0.196
	3	0.144	1.856	0.225
	4	0.134	1.729	0.241

Table 6. Comparison of optimal clustering methods for provincial NPP indicators.

Method	*k*	Silhouette index	DB index	Dunn index
Ward’s method	4	0.179	1.443	0.308

K-means	4	0.163	1.534	0.267

3.3. Cluster Results and Characterization
The clustering results using Ward's method with four clusters are summarized in Table 7, listing the provincial members of each cluster. Cluster 1 comprises 4 provinces, Cluster 2 includes 20 provinces, Cluster 3 consists of 7 provinces, and Cluster 4 has 3 provinces. Cluster 2 has the largest membership, representing a majority of provinces with similar developmental profiles. To characterize the clusters, profiles are constructed by calculating the mean value of each NPP indicator within each cluster, enabling analysis of the distinct socio-economic and developmental traits of the grouped provinces. The clustering results presented in Table 7 are also visualized in the thematic map shown in Figure 14, providing a spatial overview of the cluster distribution across Indonesia.

Table 7. Provincial cluster membership using Ward's method (k=4).

Cluster	Provincial member	Total
1	North Maluku, Papua, West Papua, West Sulawesi	4
2	Aceh, Bengkulu, Gorontalo, Jambi, West Kalimantan, South Kalimantan, Central Kalimantan, North Kalimantan, Maluku, West Nusa Tenggara, East Nusa Tenggara, South Sulawesi, Southeast Sulawesi, North Sulawesi, West Sumatra, East Kalimantan, Lampung, Central Sulawesi, South Sumatra, North Sumatra	20
3	Banten, West Java, Central Java, East Java, Bangka Belitung Islands, Riau Islands, Riau	7
4	Bali, Yogyakarta, Jakarta	3

Cluster 1, consisting of four provinces in Eastern Indonesia (North Maluku, Papua, West Papua, and West Sulawesi), exhibits the weakest performance across multiple indicators. High rates of stunting (31.43%), early marriage (10.365%), and low literacy levels (36.44%) reflect interconnected challenges, including limited access to healthcare and education, which perpetuate human capital deficits [15]. Recent studies highlight that economic growth alone cannot reduce child undernutrition in regions like Papua without targeted interventions in nutrition and sanitation [13]. Despite these challenges, Cluster 1 has the highest water quality index (57.29%), likely due to minimal industrialization and urbanization, preserving environmental quality [16]. Notably, the manufacturing value added to GDP (17.23%) exceeds that of Clusters 2 and 4, indicating reliance on large-scale extractive industries, such as mining, which fail to translate into local welfare improvements due to limited economic multipliers [17]. Characterized as a "*region of multidimensional inequality*," Cluster 1 requires comprehensive policies to leverage natural resources for social and economic gains. This multidimensional inequality refers to the simultaneous presence of disparities across several aspects of well-being—health, education, and economic structure—observed at the provincial level.

Table 8. Cluster profiles based on mean NPP indicator values.

Indicator	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Manufacturing value added to GDP	17.23	11.80	33.59	9.98
Proportion of women aged 20–24 who married or cohabited before age 18	10.37	9.34	7.37	2.84
Prevalence of stunting among children under five	31.43	24.80	18.73	13.07
Community literacy development index	36.44	65.64	71.19	78.46

Percentage of households with access to adequate and affordable housing	50.47	62.15	56.37	67.62
Water quality index	57.29	54.40	53.61	44.66
Index of democratic institutional capacity	61.44	74.24	77.24	77.72

Cluster 2, encompassing 20 provinces across western and eastern Indonesia, shows limited industrialization with the third-lowest manufacturing value added to GDP (11.80%), relying heavily on primary sectors like agriculture and fisheries. Persistent challenges include high rates of early marriage (9.34%), stunting (24.80%), and moderate literacy levels (65.64%), though these are improvements over Cluster 1. Geographic barriers and cultural norms, particularly in remote areas like Nusa Tenggara, exacerbate social issues such as early marriage and stunting, as traditional practices and limited access to services hinder progress [18]. The democratic institutional capacity index (74.24) suggests weaker governance, hindering effective policy implementation. However, Cluster 2 has the second-highest percentage of households with adequate housing (62.15%), driven by higher rural home ownership rates [19, 20]. Termed a "*region of structural development stagnation*," this cluster needs targeted poverty alleviation, food security, and economic diversification initiatives to address its developmental gaps.

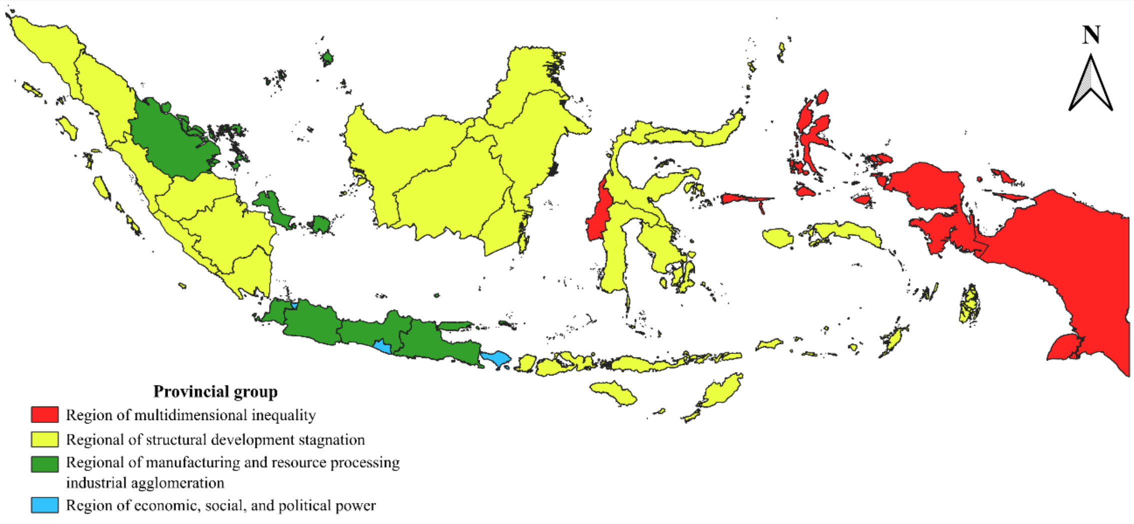


Figure 14. Geographic distribution of provincial clusters.

Cluster 3, comprising seven provinces (Banten, West Java, Central Java, East Java, Bangka Belitung Islands, Riau Islands, and Riau), is a hub of industrial activity with the highest manufacturing value added to GDP (33.59%). This economic strength correlates with better outcomes in stunting (18.73%), early marriage (7.37%), and literacy (71.19%), as industrial growth supports improved income and access to health and education services [21]. Strong democratic institutional capacity (77.24) reflects effective governance in these industrialized regions. However, the water quality index (53.61%) is moderate, as industrial activities often degrade water resources without sufficient environmental mitigation [16]. Named a "*region of manufacturing and resource processing industrial agglomeration*," Cluster 3 serves as Indonesia's economic engine but requires sustainable environmental policies to balance growth with ecological preservation.

Cluster 4, with three provinces (Bali, Yogyakarta, and Jakarta), excels in social indicators, achieving the lowest early marriage rate (2.84%), stunting prevalence (13.07%), and highest literacy (78.46%) and democratic capacity (77.72%). These outcomes are driven by robust service sectors, including tourism in Bali, education in Yogyakarta, and finance in Jakarta, fostering high human capital [22]. The highest percentage of households with adequate housing (67.62%) masks affordability challenges in Jakarta, where high rental costs burden low-income groups [20, 23]. Conversely, the lowest water quality index (44.66%) reflects pressures from urbanization and population density [16]. With a low manufacturing value added to GDP (9.980%), this cluster indicates economic maturity focused on services. Designated a "*region of economic, social, and political power*," Cluster 4 is Indonesia's developmental core but needs targeted interventions to address environmental degradation.

4. Conclusion

This study evaluates the achievement of national priority program indicators and classifies Indonesia's 34 provinces using hierarchical and non-hierarchical cluster analysis, revealing persistent development disparities in 2022. Ward's method with four clusters emerged as the optimal approach, outperforming K-Means in validity metrics, and identified distinct developmental profiles: Cluster 1, characterized by multidimensional inequality in eastern provinces; Cluster 2, marked by structural stagnation in transitional regions; Cluster 3, defined by industrial agglomeration in central economic hubs; and Cluster 4, distinguished by socio-political strength in service-oriented centers. These findings highlight significant socio-economic and environmental gaps, particularly between western and eastern Indonesia, driven by factors such as limited infrastructure, cultural norms, and industrialization impacts. To address these disparities, policymakers should implement cluster-specific strategies: enhancing infrastructure and human capital in Cluster 1 to tackle multidimensional inequality; promoting poverty alleviation, food security, and economic diversification in Cluster 2 to overcome structural stagnation; advancing sustainable industrialization in Cluster 3 to balance economic growth with environmental preservation; and improving environmental policies in Cluster 4 to address water quality challenges amid urban pressures. Future research should leverage longitudinal data to monitor cluster evolution and evaluate the effectiveness of targeted interventions, ensuring equitable development across Indonesia. To support more nuanced policy design, future studies could also incorporate regency/municipality-level data to capture intra-provincial disparities, apply spatial econometric techniques to assess geographic spillover effects, and explore the role of governance quality and local innovation in shaping development outcomes.

References

[1] S. A. Alisjahbana dan E. Murningtyas, "Tujuan Pembangunan Berkelanjutan di Indonesia : Konsep, target dan strategi implementasi," Unpad Press, Bandung, 2018.

[2] B. I. Sirat, "Analisis Faktor-Faktor Penentu Keberhasilan Implementasi Government to Government Electronic Government (G2G E-Gov) di Indonesia Studi Kasus: Komandan SIKD," 2013.

[3] Infid, "Perkembangan Pelaksanaan Sustainable Development Goals di Indonesia September 2015-September 2016," 2016.

[4] I. S. Mokoginta, "Regional Disparities in Indonesia," Institute of Research and Community Services, Parahyangan Catholic University, Bandung, 2018.

[5] W. Nurdina, "Infrastructure and Income Inequality in Indonesia: 2009-2017," The Journal of Indonesia Sustainable Development Planning, vol. II, no. 2, pp. 129-144, 2021.

[6] A. R. Johnson and W. D. Wichern, Applied Multivariate Statistical Analysis, 5th ed., New Jersey: Prentice Hall, 2002.

[7] F. J. Hair, C. W. Black, J. B. Babin and E. R. Anderson, Multivariate Data Analysis, Andover, Hampshire: Annabel Ainscow, 2019.

[8] L. Kaufman and P. J. Rousseeuw, Finding Groups in Data An Introduction to Cluster Analysis, New Jersey: John Wiley & Sons, 1990.

[9] P. J. Rousseeuw, "Silhouettes : a graphical aid to the interpretation and validation of cluster analysis," Journal of Computational and Applied Mathematics, pp. 53-65, 1987.

[10] J. C. Dunn, "Well-Separated Clusters and Optimal Fuzzy Partitions," Journal of Cybernetics, vol. IV, no. 1, pp. 95-104, 1974.

[11] D. L. Davies and D. W. Bouldin, "A Cluster Separation Measure," IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 224-227, 1979.

[12] A. K. Jain, "Data Clustering: 50 Years Beyond K-means," Pattern Recognition Letters, pp. 3-4, 2008.

[13] J. Han, M. Kamber and J. Pei, Data Mining : Concept and techniques, Waltham: Morgan Kaufmann, 2012.

[14] B. S. Everitt, S. Landau, M. Leese and D. Stahl, Cluster Analysis, Chichester: Wiley, 2011.

[15] S. Biadgilign, A. Shumetie and H. Yesigat, "Does Economic Growth Reduce Childhood Undernutrition in Ethiopia?," PLOS ONE, vol. 11, no. 8, 2016.

[16] A. A. Lubis and Z. Zen, "Analisis Dampak Sektor Industri Manufaktur, Kemiskinan dan Belanja Pemerintahan bidang Lingkungan terhadap Kualitas Air di Indonesia," QE Journal, vol. IV, no. 2, pp. 100-110, 2015.

[17] B. P. Resosudarmo and F. Jotzo, "Working with nature against poverty: Development, Resources and the Enviroment in Eastern Indonesia," Institute of Southeast Asian Studies, 2009.

[18] B. Suratman, M. Arif and S. Purnama, "Family Challenges in the Indonesia-Malaysia Border Areas: Early Marriage, Child Violence, and Stunting in Sambas Regency," Golden Age Jurnal Ilmiah Tumbuh Kembang Anak Usia Dini, vol. IX, no. 3, pp. 375-384, 2024.

[19] Badan Pusat Statistik, "Tabel Statistik : Persentase Rumah Tangga yang Memiliki Akses Terhadap Hunian Yang Layak Menurut Provinsi (Persen), 2022," 2022. [Online]. Available: https://www.bps.go.id/id/statistics-table/2/MTI0MSMy/persentase-rumah-tangga-yang-memiliki-akses-terhadap-hunian-yang-layak-dan-terjangkau-menurut-provinsi.html.

[20] D. Hartono, T. Irawan, Khoirunurrifik, R. Partama, N. W. Mujahid and D. Setiadestriati, "Determinant factors of urban housing preferences among low-income people in Greater Jakarta," International Journal od Housing Market and Analysis, vol. 15, no. 5, pp. 1072-1087, 2022.

[21] S. Vollmer, K. Hartthen, M. Subramanyam and J. Finlay, "Association between economic growth and early childhood undernutrition: Evidence from 121 Demographic and Health Surveys from 36 low-income and middle-income countries," The Lancet Global Health, vol. II, no. 4, pp. 225-234, 2014.

[22] Badan Pusat Statistik, "Tabel Statistik: Tingkat Penyelesaian Pendidikan Menurut Jenjang Pendidikan dan Provinsi," 2022. [Online]. Available: https://www.bps.go.id/id/statistics-table/2/MTk4MCMy/tingkat-penyelesaian-pendidikan-menurut-jenjang-pendidikan-dan-provinsi.html.

[23] Badan Pusat Statistik, "Tabel Statistik : Persentase Rumah Tangga menurut Provinsi, Klasifikasi Desa, dan Status Kepemilikan Bangunan Tempat Tinggal yang Ditempati Milik Sendiri," 2022. [Online]. Available: https://www.bps.go.id/id/statistics-table/2/ODM2IzI=/persentase-rumah-tangga-menurut-provinsi--tipe-daerah-dan-status-kepemilikan-rumah-milik-sendiri--persen-.html.