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Development Disparity Analysis: Clustering Regencies and Cities in Riau Province Based on Socio-Economic Indicators Using K-Means and Hierarchical Algorithms

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Abstract

Inter-regional socio-economic disparity remains a persistent challenge in regional development across Indonesia, including Riau Province. Differences in economic capacity, human development quality, poverty levels, and labor absorption indicate that development characteristics across regencies and cities are not yet uniform. This study aims to classify regencies and cities in Riau Province based on socio-economic indicators for the 2019–2023 period using K-Means and Hierarchical Clustering algorithms, as well as to compare the most suitable method for representing the data structure. Secondary data utilized in this study consist of five main macro-indicators: Gross Regional Domestic Product (GRDP) per capita, poverty rate, open unemployment rate, Human Development Index (HDI), and mean years of schooling. The research stages involve data preprocessing, Min-Max normalization, outlier detection, clustering algorithm implementation, and evaluation using the Silhouette Coefficient, Davies-Bouldin Index, and Calinski-Harabasz Score. The results demonstrate that the optimal number of clusters is two, where both algorithms yield identical evaluation values: a Silhouette Coefficient of 0.55, a Calinski-Harabasz Score of 34.45, and a Davies-Bouldin Index of 0.47. The clustering results reveal that Pekanbaru City forms a distinct, solitary cluster due to its superior macro-indicators, while the other eleven regencies and cities are grouped into the same cluster. This finding confirms a sharp socio-economic division between the provincial capital and its peripheral regions, which can simultaneously be utilized by the regional government as an empirical baseline evaluation to accelerate the achievement of SDGs Goal 1, Goal 4, and Goal 8 targets at the local level.

Keywords*: Clustering, K-Means, Hierarchical Clustering, Socio-Economic Indicators, Sdgs, Riau Province*

1. INTRODUCTION

Equitable distribution of development outcomes across regions has now become a crucial indicator of economic success, shifting the old paradigm that focused solely on high aggregate growth. In the global landscape, inter-regional socio-economic disparity frequently triggers inefficiencies in resource allocation, widens gaps in public service delivery, and hinders the inclusive achievement of Sustainable Development Goals (SDGs) targets [1], [2], [3]. This phenomenon is commonly observed in developing nations, where uniform, "one-size-fits-all" policy interventions often fail to resolve structural issues due to highly heterogeneous regional characteristics. Consequently, an objective, data-driven analytical approach is required to identify and map regional typologies to support adaptive decision-making processes.

Riau Province presents a unique yet paradoxical case study within the context of regional development in Indonesia. As one of the regions with the strongest economic activity driven by abundant natural resources and dynamic regional trade Riau's macroeconomic performance is not automatically reflected in the equitable distribution of welfare across all regencies and cities. While some areas exhibit significant acceleration in economic performance and human development quality, peripheral areas remain trapped in acute poverty, limited job market access, and low educational attainment. In this study, such spatial variability is comprehensively explored by integrating five sectoral macro-indicators: Gross Regional Domestic Product (GRDP) per capita, poverty rate, open unemployment rate, Human Development Index (HDI), and mean years of schooling. The combination of these indicators simultaneously represents the dimensions of economic capacity, social vulnerability, and human capital quality [1], [2], [4].

To extract hidden patterns from such heterogeneous multivariate data, an unsupervised learning approach using clustering techniques offers a robust methodological solution. In the data mining domain, clustering algorithms can group spatial objects based on the similarity of their intrinsic characteristics without requiring initial labels, thereby minimizing analytical subjectivity [5], [6], [3]. Numerous prior studies have utilized the K-Means algorithm to map regional poverty clusters [2] or the distribution of unemployment rates [5]. On the other hand, hierarchical clustering methods have also proven effective in presenting visual structures of regional similarities hierarchically through dendrograms, such as in HDI or social assistance analyses [3], [7]. Other spatial analysis models in Sumatra and Riau have also expanded the utilization of partitioning to map more specific regional constraints like poverty and localized unemployment rate distributions [8], [9], [10]. Furthermore, other studies in Indonesia have expanded this focus by comparing K-Means with other clustering techniques to identify household groups based on socio-economic facilities[11].

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This condition highlights the research gap and establishes the novelty of this study. This research does not merely observe a single social or economic dimension partially; instead, it integrates macroeconomic indicators and human quality of life to obtain a comprehensive, multidimensional typology of regions in Riau Province. Furthermore, this study confronts two algorithms with different mathematical philosophies: K-Means as a representation of an efficient partitioning method, and Hierarchical Clustering as a representation of a hierarchy-based method. This comparison is rigorously evaluated using three internal validity metrics the Silhouette Coefficient, Calinski-Harabasz Score, and Davies-Bouldin Index to guarantee the robustness and stability of the resulting cluster structures [6], [12], [13].

Practically, these clustering results are directly integrated with national SDGs achievement targets at the local level, specifically Goal 1 (No Poverty), Goal 4 (Quality Education), and Goal 8 (Decent Work and Economic Growth). Accordingly, this study aims to classify 12 regencies and cities in Riau Province for the 2019–2023 period, compare the performance of both algorithms, and formulate strategic policy implications. The findings of this research are expected to provide a theoretical contribution to the development of regional clustering methodologies while serving as an empirical reference for the Regional Development Planning Agency (BAPPEDA) in optimizing the allocation of local SDGs Action Plans (RAD) effectively.

2. RESEARCH METHODOLOGY

2.1 Research Design and Data Sources

This study applies a descriptive quantitative approach based on unsupervised machine learning to explore the socio-economic regional typologies. The research locus encompasses 12 regencies and cities in Riau Province, with the observation period spanning from 2019 to 2023. The primary focus of the analysis is to identify the latent similarity structures among regions. Consequently, the utilization of clustering algorithms is highly relevant since it does not require initial assumptions regarding dependent variables or predefined class labels.

The utilized secondary data were sourced from the Central Bureau of Statistics (BPS) and integrate five core macro-indicators: Gross Regional Domestic Product (GRDP) per capita (X_1), Poverty Rate (X_2), Open Unemployment Rate/TPT (X_3), Human Development Index/HDI (X_4), and Mean Years of Schooling/MYS (X_5). The determination of this variable structure is based on their capabilities to represent the main pillars of the Sustainable Development Goals (SDGs) at the local level, specifically SDGs Goal 1 (No Poverty), Goal 4 (Quality Education), and Goal 8 (Decent Work and Economic Growth).

Systematically, the research workflow is organized into six logical stages: problem identification, macro data collection, data preprocessing, implementation of the K-Means algorithm, construction of Hierarchical Clustering, and comparative evaluation along with policy interpretation.

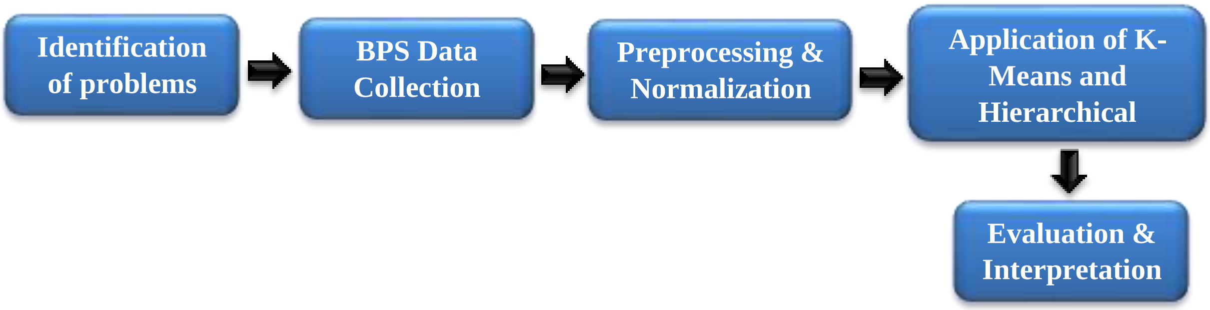

Figure 1. Research process flow.

2.2 Data Preprocessing, Algorithm Formulation, and Evaluation Metrics

Given that the indicators used possess vastly disparate dimensions and scale ranges. For instance, GRDP per capita values reach hundreds of millions of rupiah, whereas poverty and TPT operate within single-digit percentage scales the data preprocessing stage becomes highly critical. To mitigate spatial bias, where variables with larger domains dominate the distance function, data normalization is performed using the Min-Max Scaling technique to transform all values into the interval of [0, 1], using Equation (1):

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin} \qquad (1)$$

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Subsequently, outlier detection is conducted to identify extreme data variations across regencies/cities that could potentially distort the positioning of cluster centroids.

The normalized dataset is then processed using two algorithms with distinct mathematical approaches. The first algorithm is K-Means, a partitioning method that iteratively minimizes within-cluster variance by calculating the Euclidean distance of each object to its nearest centroid, utilizing the objective function in Equation (2):

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{2}$$

The second algorithm is Hierarchical Agglomerative Clustering employing Ward's linkage method, which builds the grouping hierarchy progressively (bottom-up) based on minimizing the increase in the total within-cluster sum-of-squares.

To test the robustness and determine the most optimal number of cluster partitions (k), this study does not rely on a single measure but instead combines three internal validity metrics:

a. *Silhouette Coefficient* (SC): Measures the cohesion level of an object within its cluster compared to its nearest neighboring cluster within a range of [-1, 1].
b. *Calinski-Harabasz Score* (CH): Calculates the ratio of between-cluster dispersion to within-cluster dispersion, where higher values indicate better separation.
c. *Davies-Bouldin Index* (DBI): Evaluates the degree of overlap between clusters, where values closer to zero indicate a highly well-separated cluster structure.

The combination of these three internal validity metrics is selected to ensure that the decision regarding the optimal number of clusters rests on a comprehensive mathematical foundation and is not biased toward a single evaluation metric. As the operational framework, the details of the five macro variables and their roles in supporting the analysis are presented in Table 1.

Table 1. Socio-economic indicators used in the research

Indicator	Role in Analysis	Direction of Interpretation
GRDP per capita	Describes the regional economic capacity	The higher, the better
Poverty rate	Describes welfare vulnerability	The lower, the better
OUT (Open Unemployment Rate)	Describes labor absorption capacity	The lower, the better
HDI (Human Development Index)	Represents the quality of human development	The higher, the better
MYS (Mean Years of Schooling)	Represents the educational attainment of the population	The higher, the better

Table 1 summarizes the multivariate indicators used as the basis for regional grouping. This integration of economic, educational, and social welfare data yields a cluster structure that is richer in terms of interpretation, as the profile of each region is no longer viewed partially through a single dimension.

3. RESULTS AND DISCUSSION

3.1 Cluster Validity Assessment and Optimal Partition Determination

Initial exploration of the dataset containing 12 regencies and cities in Riau Province confirms the presence of significant structural heterogeneity. Extreme variability is clearly observable between regions with high urban economic capacities, such as Pekanbaru City, and peripheral archipelagic regions, such as Kepulauan Meranti Regency, which records the highest macro poverty rate at 22.98%.

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To determine the best number of clusters, a comparative test was conducted by mapping the k values from a range of 2 to 5 for both algorithms, as presented in Table 2.

Table 2. Evaluation results of cluster numbers on K-Means and Hierarchical Clustering

Method	Number of Clusters *(k)*	Silhouette	Calinski-Harabasz	Davies-Bouldin
K-Means	2	0,55	34,45	0,47
K-Means	3	0,51	39,26	0,48
K-Means	4	0,45	55,49	0,74
K-Means	5	0,41	62,24	0,78
Hierarchical	2	0,55	34,45	0,47
Hierarchical	3	0,51	39,26	0,48
Hierarchical	4	0,47	48,94	0,57
Hierarchical	5	0,41	61,69	0,78

Based on the evaluation results in Table 2, a two-cluster partition (k = 2) consistently demonstrates the most stable empirical performance for both the K-Means and Hierarchical Clustering algorithms. The selection of k = 2 is strongly supported by the achievement of the highest Silhouette Coefficient value of 0.55 and the lowest Davies-Bouldin Index value of 0.47 across both methods. Although the Calinski-Harabasz Score tends to increase as the number of clusters grows, this rise is accompanied by a sharp decline in the Silhouette value and a substantial spike in the DBI value. This pattern signifies that adding clusters beyond two merely triggers high overlapping and obscures the structural boundaries between regional groups. Therefore, a two-cluster architecture is adopted as the foundation for the subsequent structural analysis.

3.2 Spatial Polarization: Characteristics and Composition of Cluster Members

Membership analysis demonstrates a robust spatial finding: both algorithms produce a 100% identical partition composition. This convergence between the partition-based approach (K-Means) and the hierarchical approach proves that the socio-economic data structure in Riau Province possesses a highly distinct polarization pattern, rather than being continuous or randomly distributed.

Table 3. Comparison of cluster membership for regencies/cities

Regency/City	K-Means Cluster	Hierarchical Cluster
Kuantan Singingi	2	1
Indragiri Hulu	2	1
Indragiri Hilir	2	1
Pelalawan	2	1
Siak	2	1
Kampar	2	1
Rokan Hulu	2	1
Bengkalis	2	1
Rokan Hilir	2	1
Kepulauan Meranti	2	1
Dumai	2	1
Pekanbaru	1	2

Note: The cross-labeling between Cluster 1 and Cluster 2 is purely a matter of software index assignment and does not alter the fact that the groupings are 100% identical.

The major cluster groups 11 regencies and cities en masse, namely Kuantan Singingi, Indragiri Hulu, Indragiri Hilir, Pelalawan, Siak, Kampar, Rokan Hulu, Bengkalis, Rokan Hilir, Kepulauan Meranti, and Dumai. Generally, this cluster represents the hinterland areas characterized by human development performance and educational attainment that fall below the provincial capital's average, with the HDI ranging between 67.28 and 75.66, and the Mean Years of Schooling (MYS) remaining within the corridor of 7.09 to 10.16 years. The low MYS in this cluster indicates real structural barriers to achieving SDGs Goal 4 (Quality Education) targets in coastal and supporting regencies. Furthermore,

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social vulnerability in this cluster is exacerbated by wide disparities in poverty rates, peaking in Kepulauan Meranti at 22.98%. This fact confirms the paradox of regional economic growth, where natural resource exploitation in several regencies has not automatically translated into equitable welfare distribution for local communities.

Conversely, the other group forms a solitary spatial anomaly (singleton cluster) occupied exclusively by Pekanbaru City. As a metropolitan hub and economic agglomeration center, Pekanbaru displays a highly superior macro profile compared to the other regions: its HDI reaches 82.38 (classified as very high), MYS reaches 11.94 years, GRDP per capita capacity stands at 157,385 thousand rupiahs, and it maintains the lowest poverty level at 3.16%. Interestingly, Pekanbaru also records a massive volume of open unemployment. From a regional economic geography perspective, high unemployment in a primary growth center is not an anomaly, but rather a logical consequence of urban pull factors that trigger a concentration of educated job seekers and high labor mobility from the surrounding hinterland areas.

3.3 Methodological Theoretical Discussion and Strategic Policy Implications

Methodologically, even though both algorithms yield identical membership outputs, they complement each other in strengthening the validity of the interpretation. K-Means proves superior in terms of computational efficiency and the simplicity of presenting regional taxonomies for decision-makers. However, Hierarchical Clustering provides an analytical depth that K-Means lacks through dendrogram visualization.

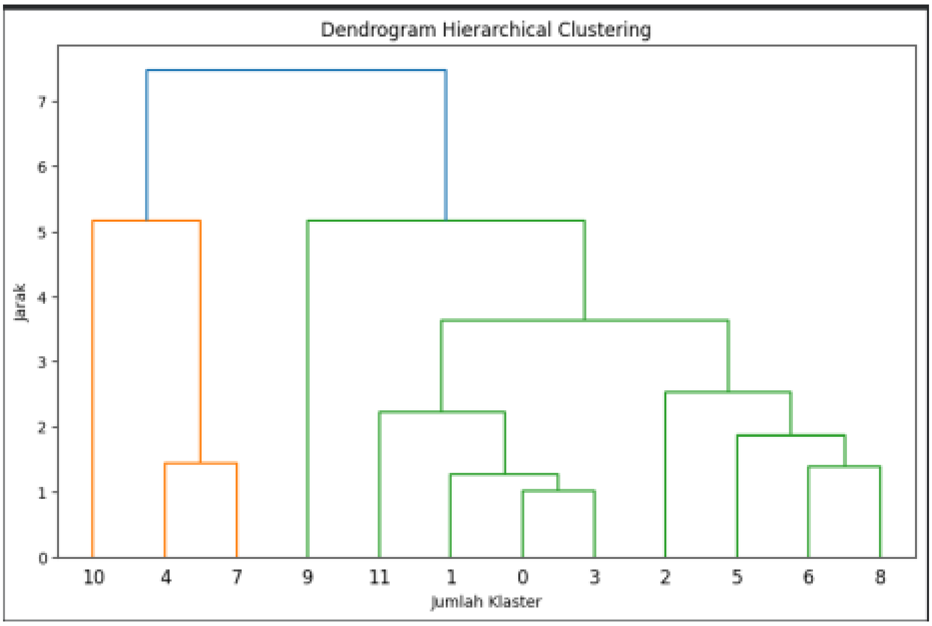

Figure 2: Dendrogram Hierarchical Clustering

Based on the dendrogram structure shown in Figure 2, it can be detected that the 11 regencies and cities in the hinterland cluster group together at a very early distance threshold. This indicates that the similarity of characteristics among these regencies is exceptionally dense. In contrast, Pekanbaru City integrates into the hierarchical branch at the very last stage with a very wide distance gap. This visualization empirically confirms that the gap between the capital city and its satellite regions in Riau Province has reached a stage of profound macro polarization [14], [15], [16].

These findings carry radical policy implications for the Regional Development Planning Agency (BAPPEDA) of Riau Province [17], [18]. Regional development planning designs can no longer adopt a generalized model or rely on single sectoral indicators. Using GRDP per capita as the sole indicator of success will mask structural poverty issues in resource-rich oil and gas regions, while focusing exclusively on poverty will overlook the unique needs of regions with metropolitan labor markets.

Consequently, government interventions must be transformed into a cluster-based intervention strategy. For the 11 regencies and cities in the hinterland group, the absolute priority of the local SDGs Action Plans (RAD) must be directed toward massive investment in basic educational infrastructure to boost MYS (SDGs Goal 4) and integrated social safety nets specifically tailored for coastal zones to alleviate macro poverty (SDGs Goal 1). Meanwhile, for Pekanbaru City, the policy focus must shift toward urban agglomeration management, formal job creation, and facilitating the transition of the educated workforce to curb the open unemployment rate (SDGs Goal 8). This model is critical for regional planning agencies to optimize development budgets based on regional taxonomies, whether driven by welfare indicators or structural infrastructure gaps [19], [20].

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4. CONCLUSION

This study has successfully mapped the socio-economic regional taxonomy in Riau Province for the 2019–2023 period using a comparative analysis of K-Means and Hierarchical Clustering algorithms. Based on the evaluation of three internal validity metrics (Silhouette Coefficient, Davies-Bouldin Index, and Calinski-Harabasz Score), a two-cluster configuration (k = 2) is proven to be the most optimal and stable data partition model for both algorithms. The 100% identical convergence of membership outputs underscores a stark spatial inequality in Riau Province, where Pekanbaru City detaches itself as a solitary cluster with superior macroeconomic and social performance, confronting 11 other regencies and cities characterized by homogeneous profiles of low mean years of schooling and high macro-poverty vulnerability in several coastal areas. Practically, these clustering results are recommended to BAPPEDA of Riau Province as an empirical evaluation instrument to optimize the allocation efficiency of local SDGs Action Plans (Goals 1, 4, and 8) based on regional characteristics for a more inclusive development paradigm.

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