

Agglomerative Spatial Clustering Analysis for Mapping Crime Risk Zone Clusters

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Abstract

Public safety and order are essential to social and economic life, especially in densely populated urban areas. High crime rates can reduce quality of life and public trust. This study aims to map crime risk zones in Indonesia using the Agglomerative Clustering method, integrating socio-economic and demographic variables. The method was selected for its ability to group data based on similar characteristics, enabling the identification of high-risk areas. The analysis resulted in four distinct clusters representing the spatial distribution of crime risk across Indonesia. One cluster includes provinces with similar crime patterns, while the others show marked differences—particularly Jakarta, which exhibits unique criminal characteristics. This clustering reveals underlying patterns that are often obscured in aggregate data. The study offers practical insights to support data-driven policymaking in crime prevention and public safety planning. The findings are expected to assist policymakers and law enforcement in designing more targeted, effective, and resource-efficient strategies to address crime.

Keywords—spatial mapping, agglomerative clustering, crime risk zones, socio-economic analysis, crime prevention

1 Introduction

Public safety and order are fundamental aspects of daily life that influence various sectors, from economics to socio-cultural aspects [1], [2], [3], [4]. In the context of increasingly dense and complex urban environments, the challenge of maintaining security has become more significant. High crime rates in a region lead to increased vulnerability to criminal acts in that area [5], which not only harms society materially but also negatively impacts the sense of security and quality of life [4], [6] (see Figure 1). Therefore, a deep understanding of crime distribution patterns is crucial [7], [8] for designing effective prevention and mitigation strategies.

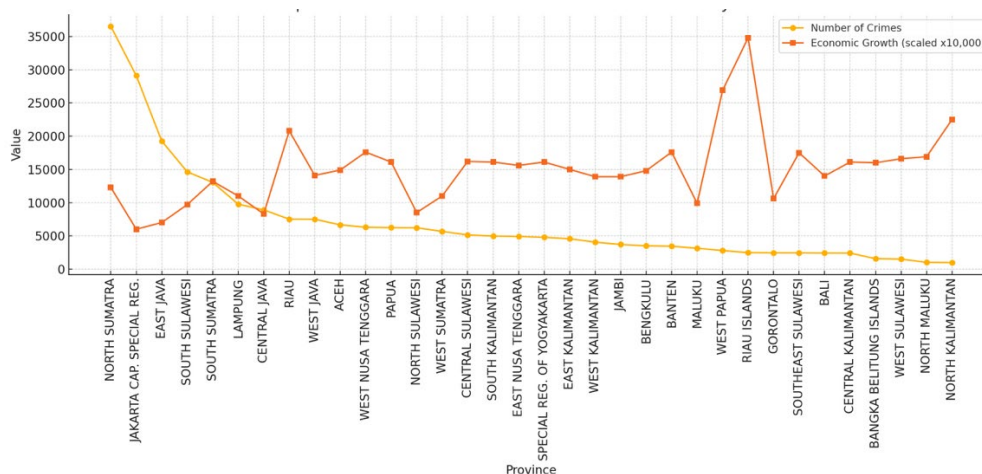


Figure 1. Comparison Of Economic Growth And Number Of Crimes By Province

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This study focuses on spatial mapping of crime risk zones using the Agglomerative Clustering method. This method was chosen because of its ability to group data based on similar characteristics [9], [10], [11], [12], [13], making it easier to identify high-risk areas. This cluster-based spatial mapping is expected to provide a clearer picture of crime distribution in a given region [14], [15], which, in turn, can be used to develop more targeted prevention strategies. The urgency of this research cannot be overlooked, given the increasing incidence of crime in many large cities in Indonesia, which tends to fluctuate [16], [17]. With a growing population, rapid urbanization, and inadequate socio-economic conditions, crime patterns have become more dynamic and complex [18], [19]. The government and law enforcement agencies need more advanced tools and methods to map and understand these patterns in order to enhance the effectiveness of their operations in preventing and addressing criminal acts.

The primary objective of this study is to develop a spatial mapping model of crime risk zones based on Agglomerative Clustering. Specifically, this study aims to (1) identify factors that influence the distribution of criminal acts in a region, (2) cluster regions based on crime risk levels, and (3) visualize the mapping results in the form of a risk map that is easy to understand and use by policymakers and law enforcement agencies. The expected benefits of this study include increased effectiveness in resource allocation for crime prevention, improved prediction capabilities for identifying high-risk areas, and support for data-driven public policy planning. With accurate mapping, it is hoped that preventive measures can be more targeted and efficient. The contribution of this study is expected to be felt by various stakeholders, particularly local governments, law enforcement agencies, and the general public. For local governments, the results of this study can be used as a basis for planning development that considers security aspects. For law enforcement agencies, these results can serve as a tool to prioritize and develop operational strategies. Meanwhile, for the general public, this research can raise awareness and vigilance regarding crime risks in their surrounding environment. The main novelty of this research lies in the application of the Agglomerative Clustering method for crime risk mapping, which has not been widely applied in Indonesia. The use of this method is expected to provide a new perspective in crime data analysis, given its advantage in clustering complex data. Additionally, this study integrates various socio-economic and demographic variables in the analysis model, enabling a more comprehensive identification of risk patterns.

Research on spatial mapping and crime risk analysis has been widely conducted using various methodological approaches. One commonly used method is Geographic Information Systems (GIS), which allows visualization and analysis of crime data based on geographic locations. GIS enables the integration of various types of spatial and attribute data, providing in-depth insights into crime distribution patterns [20], [21], [22]. With the development of technology and methodologies, clustering approaches such as K-means and Agglomerative Clustering have started to be applied in crime spatial analysis [23], [24], [25]. K-means clustering, which groups data based on Euclidean distance, has been used in several studies to identify crime hotspots [23], [25], [26], [27]. However, this method has limitations, particularly in handling non-circular cluster shapes, sensitivity to outliers, and sensitivity to the randomly chosen initial points [28], [29], [30], [31]. In contrast, Agglomerative Clustering, a hierarchical method, offers a different approach by building a dendrogram to iteratively identify clusters based on the closest similarity [32], [33], [34]. This method is more flexible in handling complex cluster shapes, yet is easier to understand [35] and more robust to variations in data [36], [37], [38], [39].

A study by [40] shows that crime hotspot mapping can enhance police intervention effectiveness by identifying areas with high crime concentration. They found that hotspot mapping methods, including the use of kernel density estimation (KDE), can help plan police patrols and allocate resources more efficiently. However, this approach also has limitations in addressing data with complex spatial variation. Another study by [41] discusses spatial crime analysis techniques, including the use of GIS, statistical techniques, and crime mapping tools. They emphasize the importance of combining quantitative and qualitative methods in understanding the local context of crime and applying more effective prevention strategies. In recent research, the use of data mining and machine learning has also gained attention. Several studies, such as those conducted by [15], [23], [25], [26], [27], have applied clustering methods to crime data to uncover hidden patterns that cannot be identified through traditional methods. The results show that clustering algorithms can help identify crime risk zones more accurately and effectively. Although various methods have been applied, the novelty of this study lies in the integration of Agglomerative Clustering with a broader set of socio-economic and demographic variables. For instance, studies by [16], [19], [42], and [43] reveal that factors such as unemployment rates, population density, and area accessibility have significant correlations with crime distribution. The integration of these variables is expected to provide a more comprehensive understanding of the factors influencing crime patterns. Furthermore, this study aims to fill the gap in the literature by focusing on the

Indonesian context, where similar studies remain limited. The use of local data and analysis tailored to the specific conditions of the region is expected to make a meaningful contribution to the literature and practice of crime spatial mapping in Indonesia.

By referencing various previous studies, this research not only seeks to apply existing methods but also aims to develop a more holistic and adaptive approach to local conditions. Therefore, this study is expected to provide new and deeper insights into crime risk mapping, as well as support the development of more effective public policies for crime prevention.

2 Research methods

This research adopts a quantitative approach with the application of the Agglomerative Clustering method for spatial mapping of crime risk zones. The first step in this methodology involves collecting crime data, including the location and frequency of criminal incidents. Additionally, demographic, geographic, and socio-economic data from the Central Statistics Agency (BPS) and relevant institutions are also gathered to complement the analysis. Newman in [44] states that crime can occur due to various factors, such as economic, social, governmental, and other physical factors. This aligns with research conducted by [42]. Therefore, demographic, geographic, and socio-economic data are also utilized in this study.

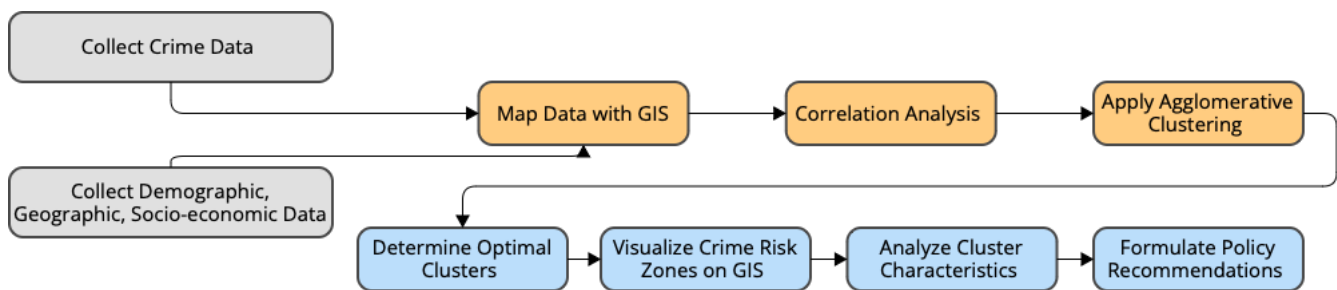


Figure 2. Research Method Workflow for Crime Risk Mapping

The demographic data includes population size, population growth rate, educational levels ranging from primary school to higher education, and marital status (including marriage and divorce statuses). The geographic data encompasses location (geographical coordinates), building density, accessibility, area type, and distance to security centers. Socio-economic data includes unemployment rate, average income, poverty level, access to healthcare services, economic activities, and property ownership. These data are then mapped using Geographic Information Systems (GIS) to generate an initial visualization of crime distribution.

After the data has been collected and mapped, the next step is to conduct correlation analysis to identify the factors influencing the spread of criminal acts in each province of Indonesia. Following that, the Agglomerative Clustering method is applied. This process begins by calculating the distance between each data point using an appropriate distance metric, such as Euclidean distance. Then, the clustering process starts by iteratively merging pairs of data points that are closest to each other until all data points are combined into a single large cluster. The result of this process is a dendrogram that illustrates the cluster hierarchy. By cutting the dendrogram at the optimal level, crime risk zones can be identified. The resulting clusters are then visualized again in GIS to generate a crime risk zone map.

To facilitate the clustering and visualization process, this study uses Orange Data Mining software version 3.35, a visual programming tool that supports reproducible workflows. Specifically, the analysis utilizes the "Unsupervised" widget category—particularly the Hierarchical Clustering widget—to conduct the clustering, and the "Geo" widget to integrate geographic coordinates for mapping purposes. The combination of these tools enables an intuitive and transparent analysis pipeline, ensuring both analytical rigor and ease of interpretation. This map is further analyzed to identify the characteristics of each crime risk zone, which can be used as a basis for policy recommendations and crime prevention strategies. Figure 2 illustrates the systematic steps in a quantitative research approach for mapping crime risk zones using the Agglomerative Clustering method. It begins with the collection of crime and supporting data, followed by initial GIS-based mapping, correlation analysis, and clustering to identify crime-prone areas. The final visualization supports data-driven policy formulation and crime prevention strategies.

3 Results and Discussion

3.1. Factors Influencing the Distribution of Criminal Acts in a Region

To understand the factors that influence the distribution of criminal acts in each province, correlation analysis was conducted on the sixteen variables (see Figure 3). Based on the correlation analysis, it is evident that population density and population size have a significant positive relationship with the number of criminal acts. In line with research conducted by [16] and [45], the higher the population density and the larger the population in a region, the higher the number of criminal acts that occur. This phenomenon can be explained by the increased social interactions in densely populated areas, which in turn raise the potential for conflict and criminal behavior. Areas with large populations may also face challenges in maintaining security and order, as the number of people to be managed is greater.

Furthermore, variables such as marital status and the number of divorces also show a positive correlation with the number of criminal acts, in line with the findings of [46] and [47]. This may indicate that household dynamics and family issues play a role in increasing crime rates. A high number of divorces, for example, could be an indicator of family instability, which may contribute to criminal behavior. Family problems often lead to stress and tension, which can escalate into criminal actions.

On the other hand, economic growth rate and homeownership show a negative correlation with the number of criminal acts. This suggests that areas with good economic growth and higher homeownership rates tend to have lower crime rates. A strong economy is typically followed by improved well-being and quality of life, which can reduce the incidence of criminal acts. This is consistent with the studies conducted by [4], [48], and [49], which state that socio-economic conditions, especially poverty levels, tend to influence the occurrence of criminal acts. Homeownership also reflects social and economic stability, contributing to a safer environment [50]. Longitude shows a negative correlation with crime rates, indicating that provinces located further east tend to have lower crime rates. This could be related to demographic, social, and economic differences across geographical regions in Indonesia.

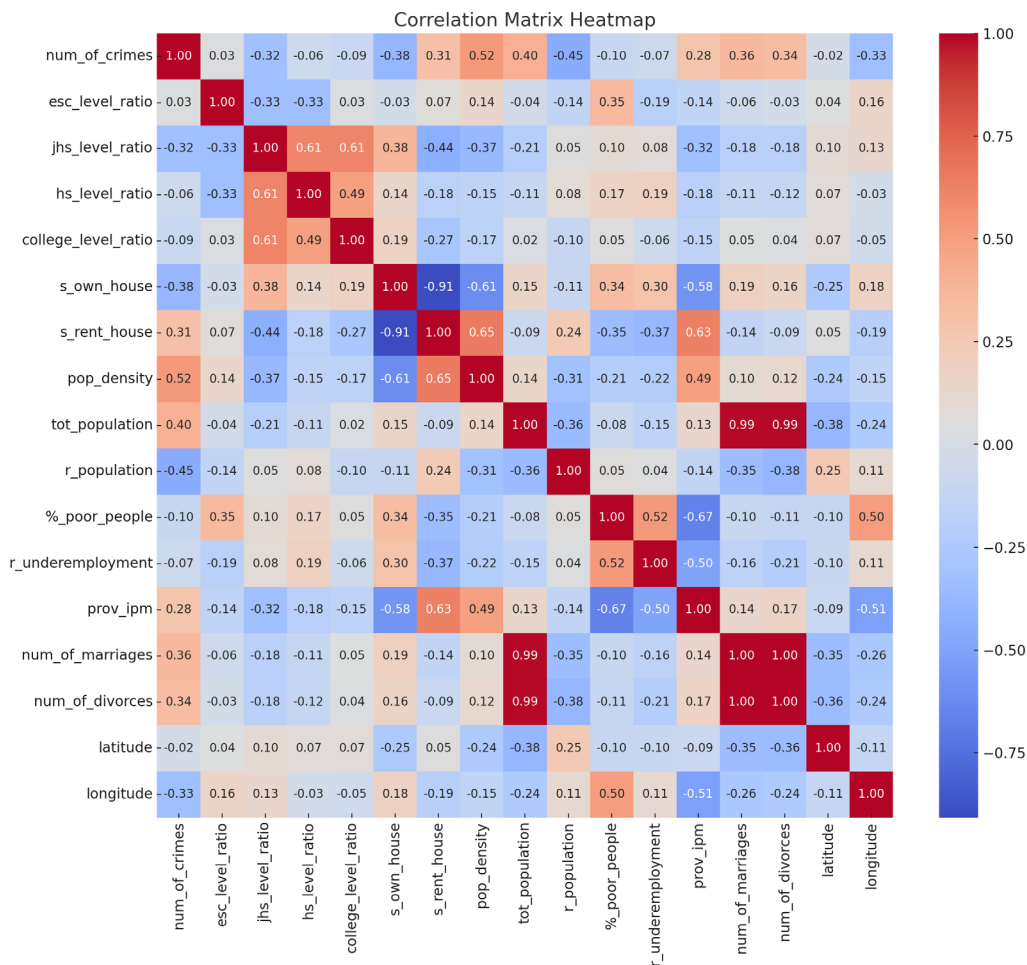


Figure 3. Correlation Matrix of All Variables

Several education-related variables, such as junior high school graduation rates (*jhs_level_ratio*) and college graduation rates (*college_level_ratio*), show a negative correlation with crime rates. This suggests that higher education may act as a protective factor, reducing individuals' tendency to engage in criminal activities. The Human Development Index (*prov_ipm*) shows a moderate positive correlation with crime rates. This may seem counterintuitive, but it could be because regions with higher HDI have better crime reporting and more effective law enforcement, resulting in the recording of more crimes that actually occur. Looking at this correlation in the context of the correlation matrix, it can be seen that population density has a correlation of 0.518 with the number of criminal acts, while population size has a correlation of 0.405. Marital status and the number of divorces each have correlations of 0.356 and 0.336, respectively. Meanwhile, economic growth rate and homeownership have negative correlations of -0.451 and -0.381 with the number of criminal acts. These positive correlations suggest that an increase in these variables is associated with a rise in the number of criminal acts. Conversely, negative correlations suggest that an increase in economic growth rate and homeownership is associated with a reduction in criminal acts. This provides a comprehensive view of the factors that influence crime levels in a region and could serve as a foundation for more effective public policies.

Overall, these findings highlight the importance of considering socio-economic factors in crime prevention efforts. Demographic and social factors such as population density, housing status, and education levels play a crucial role in influencing crime rates across provinces. Areas with high population density require special strategies to manage social interactions and prevent conflicts. On the other hand, strengthening the economy and increasing homeownership may be strategic steps in creating a safer and more stable environment.

3.2. Hierarchical Clusters of Crime Risk Levels

Figure 2 shows the results of hierarchical clustering analysis based on crime data from various provinces in Indonesia. In this dendrogram, the vertical axis represents the names of the provinces, while the horizontal axis shows the distance or dissimilarity between clusters, representing differences in crime levels among provinces. This dendrogram identifies four main clusters: Cluster 1 (C1), Cluster 2 (C2), Cluster 3 (C3), and Cluster 4 (C4).

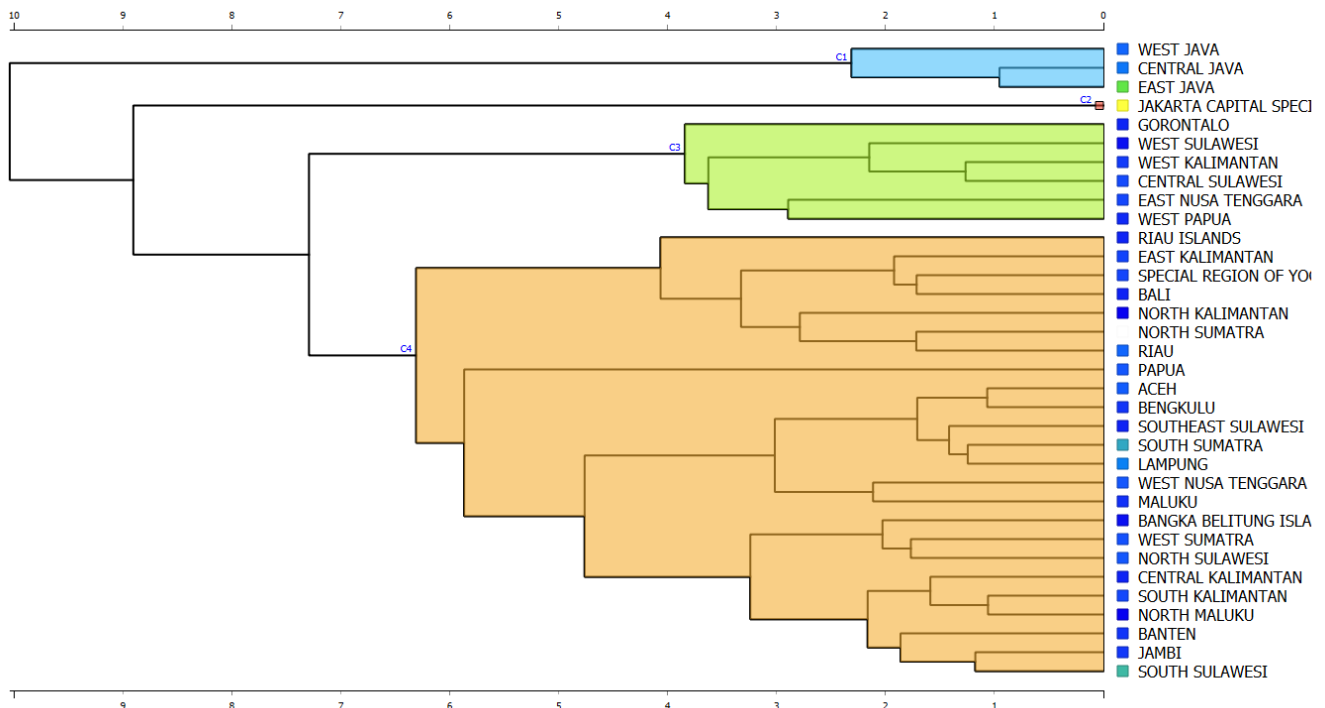


Figure 4. Crime Risk Zone Dendrogram Based on Demographic, Geographic, and Socio-economic Indicators

Cluster 1 (C1) includes West Java, Central Java, and East Java. Specifically, for West Java, the clustering analysis shows that this province has a significantly different crime pattern compared to the other two provinces in the same cluster. Meanwhile, Central Java and East Java appear to have crime patterns similar to those of West Java, which is why they are grouped into the same cluster. In Cluster 2 (C2), only the Special Capital Region of Jakarta is included. This province has a crime pattern and characteristics that are significantly different from the other provinces, which

is why it forms a separate, single cluster. Cluster 3 (C3) includes six provinces, indicating that these provinces share similar crime patterns and characteristics. However, analysis of the clustering results shows that Gorontalo has a significantly different crime level compared to the other five provinces: West Sulawesi, West Kalimantan, Central Sulawesi, East Nusa Tenggara, and West Papua. Cluster 4 (C4) contains more provinces, reflecting the similar crime characteristics across these regions. A total of eight provinces are included in C4, indicating similar crime characteristics in each province. The clustering analysis also shows that Riau Islands has a distinct crime pattern compared to the other twenty-nine provinces. The crime characteristics of Riau Islands act as an umbrella for the crime patterns of several other provinces, such as a combination of Special Region of Yogyakarta, Bali, and East Kalimantan, as well as a combination of North Kalimantan, North Sumatra, and Riau. The characteristics of other provinces can be seen more clearly in Figure 4.

Table 1. Silhouette Index for Agglomerative Clustering

Linkage	Number of Group Cluster	Silhouette Index Average
Single	2	0.8927
	3	0.8446
	4	-0.2575
Average	2	0.8446
	3	0.8446
	4	-0.2575
Weighted	2	0.8927
	3	0.8446
	4	-0.0533
Complete	2	0.8927
	3	0.6217
	4	-0.0786
Ward	2	0.8927
	3	0.6621
	4	0.04517

Table 1 shows the Silhouette Index Average values for different linkage methods and the number of clusters, providing important insights into the quality of the clusters formed. Of all the linkage methods analyzed (Single, Average, Weighted, Complete, and Ward), two clusters consistently show the highest silhouette values, with a value of 0.8927 for the Single, Weighted, Complete, and Ward methods. A silhouette value close to 1 indicates that objects within the cluster are very similar to each other and clearly separated from objects in other clusters, signaling very good and valid clusters. However, when the number of clusters is increased to three, the average silhouette value consistently decreases across all methods. In the Single, Average, and Weighted methods, the silhouette value becomes 0.8446, which still suggests good clustering but indicates a decrease in quality compared to two clusters. In the Complete and Ward methods, the silhouette values decrease further, to 0.6217 and 0.6621, respectively. This decline suggests that increasing the number of clusters to three results in some objects being less suited to their clusters or closer to objects from other clusters, reducing the clarity and validity of the formed clusters. In response to the clustering evaluation, it is important to highlight that the silhouette index values for the four-cluster configuration yielded negative results across several linkage methods, particularly Single, Average, and Complete. Negative silhouette values indicate that many data points are likely assigned to the wrong cluster, as they exhibit higher similarity to points in other clusters than to those within their own. This phenomenon may stem from overfitting, where the algorithm attempts to over-segment the data despite insufficient separation between inherent patterns. Furthermore, the use of heterogeneous socio-economic, demographic, and geographic variables may introduce noise that disrupts the cohesion of clusters when the number of groups is unnecessarily increased.

To ensure cluster validity, various linkage methods were compared. The results consistently demonstrate that the two-cluster solution produces the highest average silhouette index, reaching 0.8927 under the Single, Weighted, Complete, and Ward linkage methods. These values, approaching 1, indicate strong intra-cluster similarity and inter-cluster dissimilarity—hallmarks of high-quality clustering. While the three-cluster configuration remains acceptable (average silhouette $\approx$ 0.8446 for most methods), its interpretive clarity is reduced. In contrast, the four-cluster solution presents poor cohesion and separability, confirming the risk of misclassification.

Based on this analysis, the Weighted linkage method with two clusters was selected for further discussion. This choice is supported by its superior and stable performance, as well as its ability to maintain a balance between cluster separation and interpretability. By avoiding over-segmentation, the final model ensures a more accurate and actionable representation of crime pattern distributions across Indonesian provinces.

3.3. Visualizing the Results in the Form of a Risk Map that is Easy to Understand and Use by Policymakers and Law Enforcement

The risk map shown in Figure 5 presents a visualization of the provincial clusters based on the groups formed in the previous clustering step. The spatial map displayed shows the mapping of crime risk zones across Indonesia based on the clustering analysis. Cluster 1 (C1) includes West Java, Central Java, and East Java. The clustering analysis shows that while these three provinces belong to the same group, West Java has a significantly different crime pattern compared to Central Java and East Java. Meanwhile, Central Java and East Java have crime patterns that are quite similar to West Java, thus classifying them in the same group. This indicates that there are differences in the dynamics of crime in each province, even though they are geographically close.

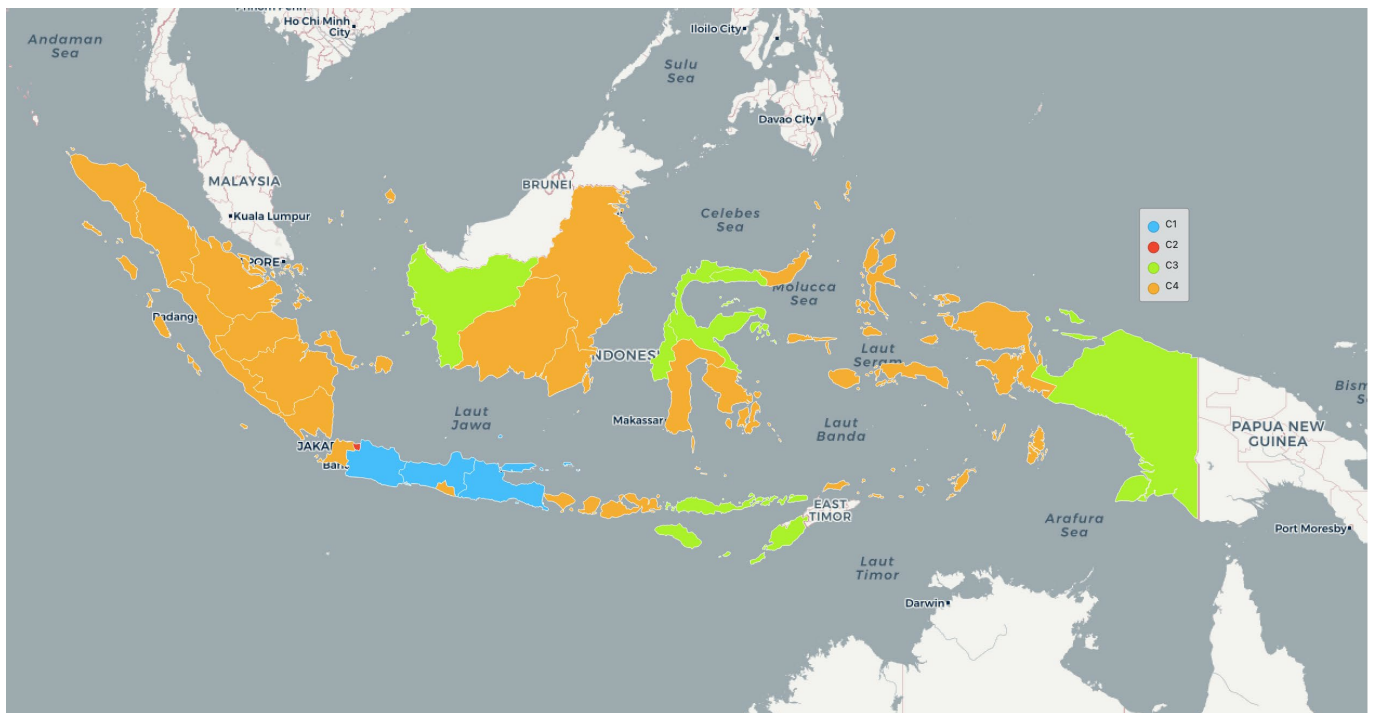


Figure 5. Crime Risk Map Based on Hierarchical Clustering Results

In Cluster 2 (C2), only the Special Capital Region of Jakarta is included. Jakarta has a crime pattern and characteristics that are vastly different from other provinces, which is why it is clustered separately. This significant difference is likely due to specific factors that only apply in the capital city, such as higher population density, rapid urbanization, and unique socio-economic factors. As a result, Jakarta exhibits a more complex and distinctive crime pattern compared to other regions in Indonesia.

Meanwhile, Cluster 3 (C3) includes six provinces showing similar crime characteristics. These six provinces are Gorontalo, West Sulawesi, West Kalimantan, Central Sulawesi, East Nusa Tenggara, and West Papua. While they are clustered together, further analysis shows that Gorontalo has a significantly different crime rate compared to the other provinces in this cluster. Finally, Cluster 4 (C4) consists of eight provinces showing similar crime characteristics. Riau Islands has a very distinct and even more specific pattern compared to other provinces. The crime characteristics of Riau Islands serve as an umbrella encompassing the combined crime characteristics of other provinces, such as a combination of Special Region of Yogyakarta, Bali, East Kalimantan, and a combination of North Kalimantan, North Sumatra, and Riau.

Figure 6 illustrates the comparative analysis of socio-economic indicators across different cluster groups. The data reveal that crime rates and the percentage of poor people vary significantly among clusters, indicating disparities

in social conditions. Additionally, clusters differ in economic growth, underemployment rates, and higher education attainment, suggesting that these socio-economic variables play a key role in differentiating regional characteristics. These findings highlight the importance of targeted policies tailored to the specific needs and profiles of each cluster.

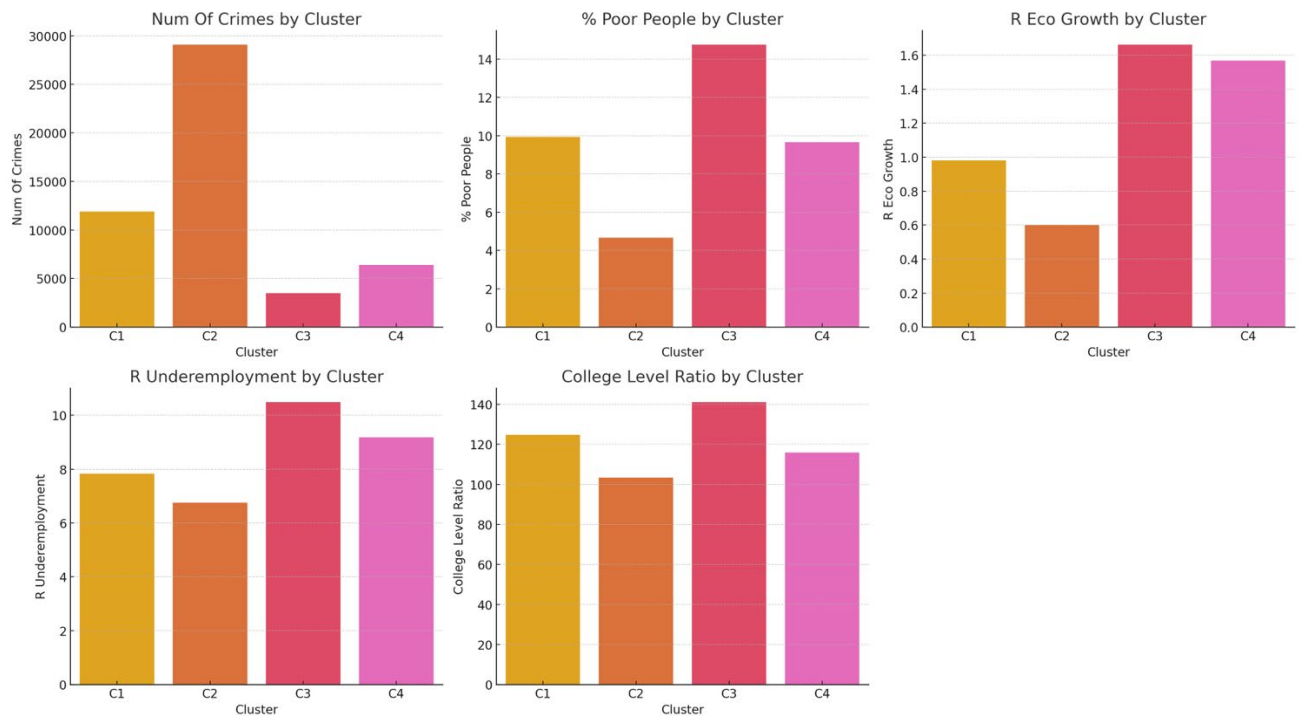


Figure 6. Comparison of socio-economic indicators across clusters

4 Conclusion

The conclusions of this study indicate that the application of Agglomerative Clustering for spatial mapping of crime risk zones in Indonesia successfully identified and grouped provinces based on shared crime patterns. Through cluster analysis, it was found that West Java, Central Java, and East Java, although in the same cluster, exhibited different characteristics, with West Java having a more distinct crime pattern than the other two provinces. Meanwhile, Jakarta formed a separate cluster with a very different crime pattern, likely due to high population density, rapid urbanization, and unique socio-economic factors. On the other hand, Clusters 3 and 4, which contain several provinces, showed similar crime patterns, although small differences were evident, such as Gorontalo having a significantly different crime rate compared to the other provinces in that cluster.

Overall, the results of this study contribute significantly to understanding the distribution of crime risks in Indonesia and can be used as a foundation for designing more effective and data-driven crime prevention policies and strategies. By utilizing the Agglomerative Clustering method, which integrates various socio-economic and demographic variables, this research provides deeper insights into the factors influencing crime levels in different regions. The resulting crime risk map can serve as a tool for policymakers, law enforcement agencies, and other stakeholders to allocate resources more efficiently and formulate public policies that are more responsive to local needs, with the hope of improving the effectiveness of crime prevention and mitigation efforts in Indonesia.

5 Suggestion

While this study provides valuable insights into crime risk mapping using Agglomerative Clustering, there are several areas that can be explored in future research to address certain limitations. First, while demographic, geographic, and socio-economic factors were integrated into the analysis, there could be a deeper exploration of additional variables, such as psychological and cultural factors, that may influence crime rates. Future studies could investigate how regional cultural practices and local attitudes toward law enforcement contribute to crime dynamics. Additionally, the current study relies on secondary data sources, which may have limitations in terms of data accuracy, consistency, and completeness. Further research could explore the use of primary data collection methods, such as surveys or interviews with local communities, law enforcement officers, and policymakers, to gather more nuanced insights into crime factors. Another potential avenue for future research is the use of other clustering

methods, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) or Self-Organizing Maps (SOM), to compare how these methods perform in terms of clustering accuracy and ability to handle complex crime patterns.

Moreover, future studies could focus on the temporal aspect of crime distribution. By integrating time-series data, researchers could analyze how crime patterns evolve over time and explore seasonal variations, enabling the development of dynamic crime prevention strategies that adapt to changing conditions. Lastly, while this study focused on crime risk mapping at the provincial level, future research could expand the analysis to a finer spatial resolution, such as at the district or neighborhood level, to provide a more granular understanding of crime distribution within urban areas. By addressing these areas, future research can provide more comprehensive and actionable insights for crime prevention and public safety policy.

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