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Hierarchical Cluster Analysis Based on Waste Sources in Indonesia in 2022

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Abstract **-** Waste, as a result of human activities, is a complex issue that requires appropriate solutions. With the increasing volume of waste, waste management in Indonesia has become a major challenge. The research examined the waste problem in Indonesia, focusing on analyzing and grouping 311 regencies/cities based on waste sources in 2022. The research also aimed to provide an in-depth understanding of waste characteristics in each region as a basis for designing more effective waste management policies at the regional level. The research applied hierarchical clustering, combining Ward's method with Euclidean distance analysis. The analysis shows 14 significant clusters with different waste composition characteristics. Interpretation of the cluster results identifies areas with low to high levels of waste. Clusters 1 to 4 have relatively little waste composition, while clusters 5 to 14 have increasing waste levels, with cluster 14 being an area with very high waste levels. The research results are expected to serve as a basis for the government to formulate more targeted and adaptive policies for handling waste in the future. The implications include improving waste management systems, recycling programs, and community education. By understanding the waste composition of each region, the government can implement solutions that suit its needs. The research provides an overview of the waste problem at the regional level in Indonesia and can be the basis for developing more effective policies. In future research, it is recommended to use more accurate and complete waste data in each regency/city for more in-depth results.

Keywords**:** hierarchical cluster, waste sources, waste management

I. INTRODUCTION

Waste is a product from households or industries generated from people's daily activities. In simple terms, waste can be defined as unwanted residual material that is discarded after a process is completed or ends. Therefore, waste is a concept related to human activities and is a consequence of human activities as stated in Law No. 32 of 2009 concerning Environmental Protection and Management - article 1 paragraph (20).

The volume of waste generated by the community continues to increase every day. Indonesia ranks second as the largest waste contributor after China (Wardhana et al., 2019). Metropolitan cities (population of 1 million) and large cities (population of 500 thousand to 1 million) have a daily average of 1,300 tons and 480 tons of waste per day, respectively (Indarmawan, 2020). The number of waste piles in Indonesia increases linearly as the population grows (Yunita et al., 2021).

Waste management in Indonesia presents a significant challenge, with many current practices still relying on unsustainable methods like open dumping and landfills. A substantial amount of waste is deposited daily in these sites, leading to excessive accumulation and severe strain on landfill capacities (Rifai et al., 2023). Although intensive research has been conducted to analyze the sanitation situation in Indonesia (Fasya et al., 2022), an urgent shift towards a transformative waste management approach is needed to prioritize environmental sustainability and public health.

Recent research has employed a two-stage clustering method that combines hierarchical and non-hierarchical clustering techniques to categorize

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Indonesian provinces based on environmental quality. This approach helps to identify priority areas needing waste management improvements (Suharyono & Digdowiseiso, 2021). In addition, another previous research has employed similar methods, recommending waste management technologies, particularly in the pulp and paper industry, to support a circular economy. These technologies provide both environmental and economic benefits, aligning with Sustainable Development Goals (SDGs) such as responsible consumption and climate action (Rapati et al., 2023).

The waste problem is a serious challenge for every regency/city in Indonesia. Waste, coming from various sources such as households, offices, markets, commerce, public facilities, areas, and other types, is a complex issue that requires the right solution. Hence, the research aims to analyze and classify 311 regencies/cities in Indonesia based on waste sources in 2022 to solve the problem. The data used include the composition of waste in various regions, focusing on household, office, market, commercial, public facility, regional, and other types of waste. Through this analysis, it is expected to gain an in-depth understanding of the waste characteristics in each region, which can be the basis for designing more effective waste management policies at the regional level. The importance of this categorization lies in identifying unique patterns in the waste composition of each regencies/cities so the government can design more targeted strategies.

Clustering analysis is a statistical technique used to group objects based on similar characteristics (Ronchi et al., 2021). Clusters are formed interactively, and objects can be moved to another cluster at the end of the process, guaranteeing a more homogeneous formation (Chen et al., 2024). Clustering is done by first analyzing a small portion of the data to determine the cluster (De Sá et al., 2024). There are two main methods for clustering. The first method is hierarchical, which includes five approaches: single relationship, average relationship, complete relationship, neighborhood method, and centroid method (Torence et al., 2023). Hierarchical clustering involves recursively grouping data into successive clusters, which are calculated based on an Euclidean distance matrix (Artanti et al., 2024). The second method is non-hierarchical (Gagolewski et al., 2023).

Various researchers have applied the hierarchical method in different fields and scenarios. For example, it is used in the fields of rheumatology, hydrology, water resource management, and building energy performance evaluation (Alter et al., 2024; Choi et al., 2024; Mavaluru et al., 2024; Mehta et al., 2023; Yu & Hou, 2022). In addition, hierarchical clustering with other agglomerative techniques has been explored in research using methods such as bisecting K-means, Nearest Neighbor Chains, complete linkage splitting, average linkage under Gaussian Kernel, Dynamic Time Warping, and dispersion metrics (Crake et al., 2023; Elderfield et al., 2024; Kumar et al., 2022; Li et al., 2024; Sadeghi et al., 2024; Soleimani et al., 2024).

The research also emphasizes the utilization of the hierarchical clustering method, using Ward's method as the basis for the final clustering. Through the use of this method, it is expected to find clusters that represent similarities in waste characteristics between regencies/cities. In turn, it can support more targeted and adaptive policymaking and is expected to provide a more in-depth view of the level, type, and distribution of waste in Indonesia, as well as a basis for improving the waste management system in the future.

Thus, the research not only provides a more comprehensive picture of the waste problem at the regional level in Indonesia but is also expected to contribute to the formulation of more effective and sustainable policies in dealing with waste in the future. The research will classifies regencies/cities in Indonesia and compare cluster results using single hierarchical linkage, complete linkage, average linkage, and Ward's method using Euclidean distance. The research is expected to be a reference for the Indonesian government in considering making policies/regulations related to waste in Indonesia.

II. METHODS

The research is conducted by studying literature. At this stage, the literature study is carried out by looking for reference materials in the form of books, journals, final assignments, theses, and the Internet in accordance with the discussed issues. Then, data collection uses secondary data from the official website of the Sistem Informasi Pengelolaan Sampah Nasional (SIPSN) (National Waste Management Information System) from the Ministry of Environment and Forestry. The data represent the waste composition in each regency/city in Indonesia in 2022.

Next, the research establishes the research variables. These variables are V1 to V7. V1 is the cumulative amount of household waste in Indonesia from each regency and city. V2 is the cumulative amount of office waste in Indonesia from each regency and city. V3 is the cumulative amount of market waste in Indonesia from each regency and city. V4 is the cumulative amount of trade waste in Indonesia from each regency and city. V5 is the cumulative amount of public facility waste in Indonesia from each regency and city. V6 is the cumulative amount of regional waste in Indonesia from each regency and city. Last, V7 is the cumulative amount of other waste in Indonesia from each regency and city.

The following process involves grouping regencies using the single linkage, complete linkage, average linkage, and Ward's method on the Euclidean distance matrix. This process forms clusters that represent patterns of similarity between regions. The optimal number of clusters is determined using the Silhouette method.

Cluster analysis is a study or analysis to classify objects based on similar characteristics in statistical analysis (Torence et al., 2023). In the grouping process, cluster analysis uses a distance measure. The distance measure can explain the proximity between data to explain the simple group structure of complex data. In Equation (1), Euclidean distance is to find the distance between objects. It has (x, y) as the distance between x and y, i as each data, z as the total data, xik as the center of the cluster data, and yjk as the data in each jkth data (Charikar et al., 2019).

$$d(x, y) = \sqrt{\sum_{i=1}^{z}(x_{ik} - y_{jk})^2} \tag{1}$$

A hierarchical cluster is a method of grouping objects to determine the grouping structure of these objects. In hierarchical clusters, there are two methods, namely agglomerative and divisive. The following is the procedure for the Agglomerative method (Muradi et al., 2016). First, clustering starts with N groups, where each group consists of one object. Then, it calculates the proximity distance for each group. Second, it calculates the minimum distance using Equation (2). The C_i and C_j are combined to form a new group. Third, it updates the distance between groups after merging. Fourth, repeating the second and third steps for all elements in 1 group is done.

$$D(C_i, C_j) = \min_{1 \le m, l \le N, m \ne 1} D(C_m, C_l) \tag{2}$$

In the agglomerative method, there are several linkage methods, such as single linkage, complete linkage, average linkage, and Ward's method. The single linkage method uses the minimum distance rule between clusters. It can look at the distance between two clusters and choose the closest distance between clusters to determine the distance of the single linkage method (Mohbey & Thakur, 2013). If there are two groups (U, V) and W, the formula used to determine the distance between the two is in Equation (3). The value of d_{UW} and d_{VW} is the smallest distance between cluster U and W and cluster V and W (Johnshon & Wichern, 2007).

$$d_{(UV)W} = \min\{d_{UW}, d_{VW}\} \tag{3}$$

Complete linkage is a method of grouping two objects with the farthest distance. Grouping the complete linkage method begins by determining the object that has the closest distance and combining these objects by looking at the far or maximum distance (Großwendt & Röglin, 2017). Hence, Equation (4) has d_{UW} as the greatest distance between clusters U and W, while d_{VW} is the greatest distance between clusters V and W.

$$d_{(UV)W} = \max\{d_{UW}, d_{VW}\} \tag{4}$$

The average linkage method is a hierarchical cluster method that groups objects based on the average distance between them (Reinaldi et al., 2021). The distance within each cluster is computed using Equation (5), which illustrates the placement of object k in cluster W, with d_i representing the distance between objects i. Then, N_W and $N_{(UV)}$ denote the number of objects in clusters W and UV, respectively.

$$d_{(uv)w} = \frac{\sum_i \sum_k d_{ik}}{N_{(UV)} N_W} \tag{5}$$

Ward's method tries to minimize the variation between objects contained in one cluster (Eszergár-Kiss & Caesar, 2017). The distance between two clusters in Ward's method is the sum of the squares between two groups for all variables. The measure used is the Sum of Square Error (SSE). Equation (6) is the distance equation used to determine the distance with Ward's method.

$$I_{ij} = \frac{1}{2} d^2(x_i, x_j) \tag{6}$$

The results are presented through a table visualizing the clustering, with interpretation based on the waste composition in each regency/city. Cluster validity is evaluated with the Silhouette coefficient, which gives an idea of the clustering quality with a value between -1 and 1. Then, cluster results are interpreted by analyzing the waste composition in each cluster, providing conclusions regarding patterns or characteristics that emerge from the clustering results. The research method is expected to make a significant contribution to processing waste composition data in Indonesia.

III. RESULTS AND DISCUSSIONS

The researchers conduct clustering to identify regencies/cities with similar waste characteristics. The researchers compute the distance measure matrix using the centroid method and Euclidean distance. The hierarchical clustering technique is employed, with the number of clusters determined using the Silhouette method, formulated as in Equation (1).

The preliminary analysis examines waste sources across 311 districts/cities in Indonesia. The data used consist of statistical information on waste composition in 2022, encompassing various sources such as households (V1), offices (V2), markets (V3), commercial establishments (V4), public facilities (V5), regional areas (V6), and other categories of waste (V7). The initial findings from the SIPSN data indicate that in 2022, Banyumas Regency generated the highest amount of household waste (V1) at 99,999.99 tons, along with office waste (V2) at 9,627 tons, public facility waste (V5) at 19,491 tons, and other waste (V7) at 9,747 tons. In the same year, Klungkung Regency recorded the largest amount of market waste (V3) at 66,575 tons, while North Minahasa Regency reported the highest volume of regional waste (V6) at 15,003 tons.

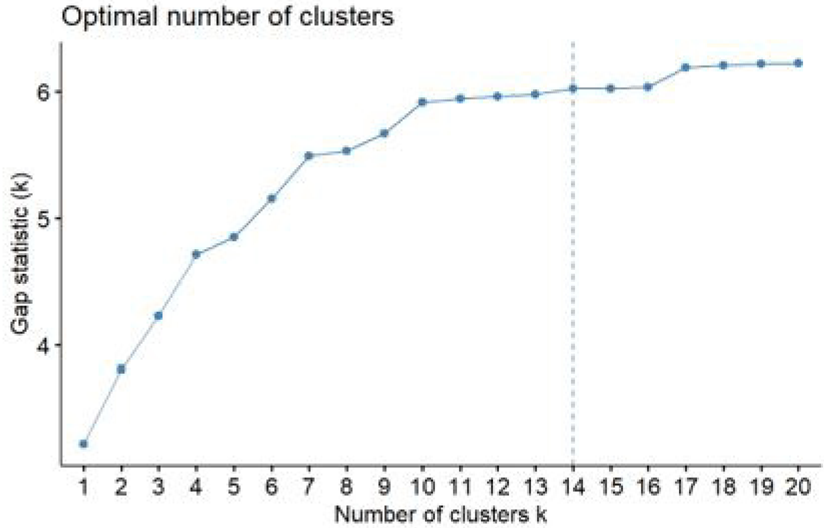

Figure 1 Results of the Optimal Number of Clusters

The next step is to analyze the hierarchical method using Euclidean distance. Clustering begins by determining the object with the closest distance based on the Euclidean distance matrix and updating the distance using the distance calculation of each hierarchical method used. So, a new cluster is obtained and repeated until the desired number of clusters is obtained. The research uses the Silhouette method to determine the number of clusters. The Silhouette method is used to determine the best number of clusters. The higher the average value of the silhouette is, the better the quality will be. Based on the analysis with the help of RStudio, the optimal number of clusters is 14. The optimal cluster results are shown in Figure 1.

Table 1 Silhouette Coefficient Result Values

No	Method	Silhouette Coefficient Value
1.	Average linkage	0.9937973
2.	Single linkage	0.9922318
3.	Complete linkage	0.9936943
4.	Ward's Method	0.9959429

The clustering results are grouped into 14 clusters using the hierarchical single linkage, complete linkage, average linkage, and Ward's method. Since the researchers do not know in advance which method will produce the best clusters, the researchers can use the linkage method to perform hierarchical clustering using several different methods. Table 1 shows the agglomerative coefficient of each method, which is a metric that measures cluster strength. The closer this value is to 1, the stronger the cluster will be. Ward's method yields the highest agglomerative coefficient (0.9959429) among these. It indicates its effectiveness in generating cohesive clusters. Hence, Ward's method is used for final hierarchical clustering.

The clustering results can be seen in Table 2. Based on the source of waste by type in regencies/cities in Indonesia, it can be concluded that clusters 1 to 4 have a small waste composition. Meanwhile, clusters 5 to 14 have an increasing waste composition, with cluster 14 having a very large waste composition.

Based on the results in Table 2, the first cluster consists of South Aceh Regency, Southeast Aceh Regency, East Aceh Regency, West Aceh Regency, Pidie Regency, Simeulue Regency, and 194 other regencies/cities. The second cluster has Banda Aceh City, Pematang Siantar City, Bengkalis Regency, Way Kanan Regency, Sumedang Regency, Wonosobo Regency, and 22 other regencies/cities. The third cluster comprises 41 regencies/cities, including Tebing Tinggi City, Pesisir Selatan Regency, Tanah Datar Regency, South Solok Regency, Payakumbuh City, Pariaman City, and 35 other regencies/cities.

The fourth cluster includes two regencies/cities: Medan City and Bekasi City. The fifth cluster consists of six regencies/cities: Palembang City, Karawang Regency, Semarang City, Malang Regency, Tangerang City, and South Tangerang City. Cluster six consists of seven regencies/cities: Deli Serdang Regency, Padang City, Indramayu Regency, Bekasi Regency, Cilacap Regency, Mojokerto Regency, and Bogor City.

The seventh cluster has seven regencies/cities, including Simalungun, Rokan Hilir, Sragen, Kudus, Lumajang, Nganjuk, and Tuban. Then, the eighth cluster consists of 13 regencies/cities: Tanggamus Regency, Ciamis Regency, Temanggung Regency, Tulungagung Regency, Pamekasan Regency, Malang City, and seven other regencies/cities. The ninth cluster consists only of the Rembang Regency. The tenth cluster has Batu City. The eleventh cluster consists only of Kuningan Regency. Similarly, the twelfth cluster twelve only has the Klungkung Regency, and the thirteenth cluster includes only the North Minahasa Regency. Last, cluster fourteen only has Banyumas Regency.

With the results of this analysis, it can provide valuable insights into waste management across Indonesia. Clusters with smaller waste compositions (e.g., clusters 1−4) may require different strategies compared to those with larger compositions (clusters 5−14). These findings can inform targeted policy interventions to address specific waste management challenges in different regions. It is hoped that it can be used as a consideration for the government to make policies in each regency/city to pay attention to the condition of waste in each region to improve the state of waste piles and minimize the level of waste emergencies due to overloaded waste in Indonesia.

Table 2 Cluster Results with Ward Method

Cluster	Regency/ City
1.	Aceh Selatan Regency, Aceh Tenggara Regency, Aceh Timur Regency, Aceh Barat Regency, Pidie Regency, Simeulue Regency, and 194 regencies/cities
2.	Banda Aceh City, Pematang Siantar City, Bengkalis Regency, Way Kanan Regency, Sumedang Regency, Wonosobo Regency, and 22 regencies/cities
3.	Tebing Tinggi City, Pesisir Selatan Regency, Tanah Datar Regency, Solok Selatan Regency, Payakumbuh City, Pariaman City, and 35 regencies/cities
4.	Medan City, and Bekasi City
5.	Palembang City, Karawang Regency, Semarang City, Malang Regency, Tangerang City, and South Tangerang City
6.	Deli Serdang Regency, Padang City, Indramayu Regency, Bekasi Regency, Cilacap Regency, Mojokerto Regency, and Bogor City
7.	Simalungun Regency, Rokan Hilir Regency, Sragen Regency, Kudus Regency, Lumajang Regency, Nganjuk Regency, and Tuban Regency
8.	Tanggamus Regency, Ciamis Regency, Temanggung Regency, Tulungagung Regency, Pamekasan Regency, Malang City, and 7 regencies /cities
9.	Rembang Regency
10.	Batu City
11.	Kuningan Regency
12.	Klungkung Regency
13.	North Minahasa Regency
14.	Banyumas Regency

IV. CONCLUSIONS

The analysis of waste across 311 regencies/cities in Indonesia in 2022 yields significant implications for waste management policies. Banyumas Regency emerges with the highest level of household waste, Klungkung Regency with market waste, and North Minahasa Regency with regional waste. Hierarchical clustering, employing Ward's method, delineates 14 optimal clusters. This choice is justified by the highest agglomerative coefficient value of 0.9959429. The resulting clusters exhibit varying waste compositions, with clusters 1 to 4 indicating minimal waste composition and clusters 5 to 14 depicting escalating compositions, with cluster 14 exhibiting a notably high waste composition.

The interpretation of cluster characteristics underscores the uniqueness of waste compositions within each cluster. For instance, the first cluster comprises regions with relatively low waste levels. Meanwhile, cluster 14 includes Banyumas Regency, characterized by significantly high waste levels.

This cluster analysis provides a foundation for tailoring policy design in waste management at the local level. By comprehending the distinctive waste compositions of each region, governments can implement targeted solutions, including enhanced waste management systems, recycling initiatives, and community education programs. Overall, this analysis offers a nuanced understanding of regional waste challenges in Indonesia, guiding the formulation of effective policies for the future.

Nonetheless, the research has certain limitations. The analysis is based on secondary data obtained from SIPSN, which may not fully capture real-time fluctuations in waste composition and volume across various regions. Variability in data reporting completeness and accuracy across districts and cities may affect the precision of the clustering outcomes. Furthermore, as the dataset is continually updated, even within the same year, researchers conducting similar analyses at different points may observe variations in results due to changes in the data. Additionally, the exclusive use of hierarchical clustering in the research constrains the exploration of non-hierarchical methods. It may offer alternative perspectives on regional waste management needs. Future research will benefit from utilizing a more comprehensive and up-to-date dataset and exploring alternative clustering methodologies to corroborate and extend the research findings.

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