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Hierarchical Cluster Analysis Based on Stunting-Related Indicators in Maluku and North Maluku

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Abstract: Stunting remains one of the major public health challenges in Indonesia because it affects children's physical growth, cognitive development, and future productivity. Identifying regional characteristics based on stunting-related indicators is important to support more targeted intervention policies. This study aims to classify regions in Maluku and North Maluku Provinces based on stunting-related indicators using Hierarchical Cluster Analysis. The study employed secondary data from 21 districts/cities in 2023 obtained from the Ministry of Health of the Republic of Indonesia, the National Socio-Economic Survey (SUSENAS), Statistics Indonesia (BPS), and the National Food Agency. The variables analyzed were expected years of schooling, food security index, households with access to proper sanitation, poverty rate, access to safe drinking water, complete basic immunization coverage, and the percentage of children under two years who received breastfeeding. Prior to clustering, all variables were standardized using Z-scores. Hierarchical Cluster Analysis was performed using Ward's linkage method and Squared Euclidean Distance. The results indicated that the regions could be classified into two clusters. The agglomeration schedule and dendrogram supported a two-cluster solution, which was further confirmed by K-Means validation. The first cluster consisted of four regions characterized by higher expected years of schooling, food security, sanitation coverage, access to safe drinking water, and complete basic immunization coverage. The second cluster consisted of seventeen regions with relatively less favorable characteristics. Although the average prevalence of stunting was relatively similar between the two clusters, the results suggest that regions with comparable stunting prevalence may possess different socioeconomic, environmental, and health-related profiles. These findings provide useful information for identifying regional characteristics and may support the formulation of more targeted stunting prevention and control strategies.

2020 Mathematical Subject Classification: 62H30, 62P10.

Keywords: Hierarchical Cluster Analysis, Maluku, North Maluku, Regional Classification, Stunting-Related Indicators, Ward's Method.

1. Introduction

Child nutritional status is an important component of human development because nutritional problems experienced during early childhood may have long-term consequences for health, education, and productivity. One of the major nutritional problems that continues to receive attention is stunting, which is a condition of impaired growth resulting from chronic nutritional deficiencies over a prolonged period. Stunting not only

affects physical growth but is also associated with lower cognitive performance, reduced learning achievement, and decreased quality of human resources in the future [1-3]. Furthermore, longitudinal evidence suggests that growth failure during early childhood may influence cognitive abilities later in life, highlighting the importance of preventing stunting during critical periods of child development [4].

In Indonesia, the prevalence of stunting has shown a declining trend over the last decade. According to the National Basic Health Research (Riskesdas), the prevalence of stunting among children under five years was 37.2% in 2013 [5]. More recent data from the Indonesian Health Survey (SKI) indicated a decrease to 21.5% in 2023 [6]. Although this achievement reflects progress in national nutrition programs, stunting remains a significant public health challenge due to the persistence of regional disparities. Several regions in eastern Indonesia continue to experience relatively high stunting prevalence, suggesting that differences in socioeconomic, environmental, and health-related conditions may contribute to variations in child nutritional outcomes [7].

Previous studies have shown that stunting is influenced by a combination of socioeconomic, environmental, and health factors. Educational attainment, poverty, sanitation, and healthcare access have been reported as important determinants of child nutritional status [8]. More recent studies in Indonesia have identified social and environmental factors, including household socioeconomic conditions, access to basic sanitation, and health-related services, as significant contributors to childhood stunting [9,10]. Similarly, [11] emphasized that nutritional interventions should consider multiple risk factors simultaneously because the causes of stunting are multidimensional and interconnected. Since these indicators may vary considerably across regions, areas with similar stunting prevalence may not necessarily share the same characteristics.

To understand regional similarities based on multiple stunting-related indicators, cluster analysis can be employed as an exploratory multivariate technique. Cluster analysis groups objects into relatively homogeneous clusters according to their characteristics, allowing regions with similar profiles to be identified more effectively than through separate analyses of individual indicators. In the context of stunting, clustering can support policymakers in identifying groups of regions with comparable characteristics and designing intervention programs that are more appropriate to local conditions. [12], for example, applied the K-Means clustering method to classify health data related to stunting in Binjai City and identified distinct clusters with different health characteristics. Their findings showed that clustering techniques can effectively reveal groupings with similar profiles and provide valuable information for designing more targeted health intervention programs. These results highlight the potential of cluster analysis as a useful approach for understanding regional heterogeneity and supporting evidence-based decision-making.

Among the available clustering approaches, Hierarchical Cluster Analysis is widely used because it does not require prior information regarding cluster membership and provides a visual representation of grouping structures through a dendrogram. In particular, Ward's method is frequently applied because it minimizes within-cluster variation and tends to produce compact and homogeneous clusters. Despite the growing use of clustering techniques in health-related studies, research focusing on the classification of regions in Maluku and North Maluku based on stunting-related indicators remains limited. Most previous studies in Indonesia have focused on identifying determinants of stunting through regression or spatial analysis approaches [9], [13], while studies examining regional similarities through cluster analysis are relatively scarce. Therefore, this study aims to classify regions in Maluku and North Maluku based on stunting-related indicators using Hierarchical Cluster Analysis with Ward's method. The resulting clusters are expected to provide a clearer understanding of regional characteristics and support the formulation of more targeted stunting prevention and control strategies.

2. Research Method

2.1. Data and Variables

This study employed secondary data from 21 districts/cities in Maluku and North Maluku Provinces in 2023. The data were obtained from the Ministry of Health of the Republic of Indonesia, Statistics Indonesia (BPS), the National Socio-Economic Survey (SUSENAS), and the National Food Agency. The variables used in this study consisted of stunting prevalence (Y) and seven stunting-related indicators, namely expected years of schooling (X_1), food security index (X_2), percentage of households with access to proper sanitation (X_3), poverty rate (X_4), percentage of households with access to safe drinking water (X_5), complete basic immunization coverage (X_6), and percentage of children under two years old who received breastfeeding (X_7). The clustering process was performed using the seven stunting-related indicators (X_1 - X_7), while stunting prevalence (Y) was used as a supplementary variable to support cluster interpretation.

2.2. Hierarchical Cluster Analysis

Cluster analysis is a multivariate statistical technique used to classify objects into relatively homogeneous groups based on their characteristics while maximizing differences among groups [14]. In this study, Hierarchical Cluster Analysis was employed using Ward's linkage method and Squared Euclidean Distance.

The Squared Euclidean Distance between two observations is calculated using the following formula:

$$d_{ij}^2 = \sum_{k=1}^p (x_{ik} - x_{jk})^2 \quad (1)$$

where d_{ij}^2 represents the squared Euclidean distance between observations i and j , x_{ik} and x_{jk} are the values of the k -th variable for observations i and j , respectively, and p denotes the total number of variables included in the analysis.

Ward's method is an agglomerative clustering approach that combines clusters by minimizing the increase in within-cluster variance at each stage of the clustering process [15]. This method is widely used because it tends to produce compact and relatively homogeneous clusters [16].

2.3. Research Procedure

The analysis was conducted through the following stages:

1. Descriptive statistical analysis was performed to summarize the characteristics of the variables using the mean, standard deviation, minimum value, and maximum value [17].
2. Correlation analysis among the stunting-related indicators was conducted to examine the relationships among variables and identify potential redundancy before clustering [18].
3. All variables were standardized using Z-score transformation to eliminate the effects of different scales and variability among variables. Standardization ensures that each variable contributes equally to the distance calculation process [14].
4. Hierarchical Cluster Analysis was performed using Ward's method and Squared Euclidean Distance to classify regions according to their stunting-related characteristics [15,16].
5. The optimal number of clusters was determined based on the dendrogram and agglomeration schedule. A substantial increase in the agglomeration coefficient indicates the merging of heterogeneous clusters and may be used to identify an appropriate cluster solution [14].
6. K-Means clustering was subsequently applied using the selected number of clusters to evaluate the consistency of the clustering structure obtained from the hierarchical procedure [19].
7. Finally, the characteristics of each cluster were interpreted based on the cluster centers and the average values of the stunting-related indicators.

3. Results and Discussion

3.1. Descriptive Statistics

Descriptive statistics were used to provide an overview of the characteristics of the stunting-related indicators in Maluku and North Maluku Provinces. Table 1 presents the minimum, maximum, mean, and standard deviation values of each variable.

Table 1. Descriptive Statistics of Stunting-Related Indicators

Variable	Min	Max	Mean	SD
X1	12,33	16,07	13,47	1,01
X2	6,83	89,51	60,60	17,94
X3	65,91	98,29	84,10	10,98
X4	3,39	28,78	13,90	7,98
X5	66,47	99,44	89,39	7,49
X6	15,99	74,85	47,81	17,40
X7	82,60	100	91,99	4,25
Y	11,7	40,6	26,63	6,80

The descriptive statistics indicate substantial variation among districts/cities in Maluku and North Maluku. For example, the Food Security Index (X_2) ranged from 6.83 to 89.51, while Complete Basic Immunization Coverage (X_6) varied from 15.99% to 74.85%. In contrast, Expected Years of Schooling (X_1) showed a narrower range, from 12.33 to 16.07 years. These results indicate heterogeneity in educational, socioeconomic, environmental, and health-related conditions across regions, suggesting that the observed districts/cities may exhibit distinct regional profiles.

3.2. Data Standardization

Prior to clustering, the variables were standardized using the Z-score transformation. Although all variables were expressed as percentages, substantial differences in variability were observed among the indicators. As shown in Table 1, the standard deviations ranged from 1.01 for Expected Years of Schooling (X_1) to 17.94 for the Food Security Index (X_2) and 17.40 for Complete Basic Immunization Coverage (X_6). Such differences may cause variables with larger variances to exert a greater influence on the distance calculation process used in cluster analysis. Therefore, standardization was performed to ensure that all variables contributed equally to the clustering procedure.

Following standardization, each variable had a mean of approximately zero and a standard deviation of approximately one. The standardized variables were subsequently used in the Hierarchical Cluster Analysis and K-Means validation.

3.3. Determination of the Number of Clusters

The optimal number of clusters was determined using the agglomeration schedule and dendrogram obtained from Hierarchical Cluster Analysis with Ward's method. Table 2 presents the final stages of the agglomeration process.

Table 2. Final Stages of the Agglomeration Schedule

Stage	Coefficient	Increase
16	48.085	7.881
17	65.130	17.045
18	84.098	18.968
19	106.313	22.215
20	140.000	33.687

The agglomeration coefficients increased gradually during the clustering process. However, a substantial increase was observed between Stage 19 and Stage 20, where the coefficient increased from 106.313 to 140.000. This increase indicates that two relatively heterogeneous clusters were merged at the final stage. Therefore, the clustering process was stopped before this merger, resulting in a two-cluster solution.

The dendrogram also supports the formation of two major clusters. The largest separation among observations occurred before the final merger, indicating that a two-cluster structure adequately represents the regional characteristics associated with the analyzed indicators.

3.4. Results of Hierarchical Cluster Analysis

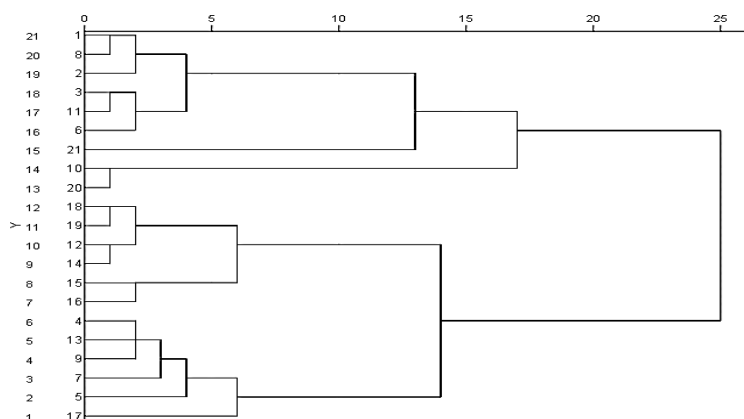


Fig. 1. Dendrogram of Hierarchical Cluster Analysis Using Ward's Method

Fig. 1 presents the dendrogram obtained from Hierarchical Cluster Analysis using Ward's method based on the standardized variables (Z-scores). The dendrogram confirms the existence of two major clusters, which is consistent with the results obtained from the agglomeration schedule. Based on the hierarchical clustering procedure, the 21 districts/cities were classified into two clusters. Cluster 1 consisted of four regions, whereas Cluster 2 consisted of seventeen regions. The membership of each cluster is presented in Table 3.

Table 3. Cluster Membership

Cluster 1	Central Maluku, Ambon City, Tual City, Ternate City.
Cluster 2	West Southeast Maluku, Southeast Maluku, Buru, Aru Islands, West Seram, East Seram, Southwest Maluku, South Buru, West Halmahera, Central Halmahera, South Halmahera, North Halmahera, East Halmahera, Sula Islands, Morotai Island, Taliabu Island, Tidore Islands City.

The clustering results indicate the presence of distinct regional profiles based on the analyzed stunting-related indicators. Regions grouped within the same cluster exhibit relatively similar characteristics, whereas regions belonging to different clusters demonstrate greater dissimilarity in terms of educational, socioeconomic, environmental, and health-related conditions. A more detailed interpretation of the cluster characteristics is presented in Section 3.6.

3.5. Validation Using K-Means Clustering

Table 4. Final Cluster Centers Based on Standardized Variables

Variable	Cluster 1	Cluster 2
X ₁	1.57339	-0.37021
X ₂	0.82205	-0.19342
X ₃	0.97228	-0.22877
X ₄	-0.26395	0.06211
X ₅	1.01349	-0.23847
X ₆	1.15986	-0.27291
X ₇	-0.17159	0.04037

To evaluate the consistency of the clustering structure obtained from Hierarchical Cluster Analysis, K-Means clustering was performed using the standardized variables and a two-cluster solution. The K-Means procedure produced two clusters consisting of four and seventeen districts/cities, respectively, which is consistent with the hierarchical clustering results. This consistency indicates that the identified clustering structure is relatively stable.

Table 4 presents the final cluster centers obtained from K-Means clustering. Since the analysis was performed using standardized variables, the reported values represent standardized cluster centers (Z-scores). Positive values indicate that the corresponding indicator is above the overall mean, whereas negative values indicate values below the overall mean.

Cluster 1 exhibited positive standardized values for Expected Years of Schooling (X₁), Food Security Index (X₂), Proper Sanitation (X₃), Access to Safe Drinking Water (X₅), and Complete Basic Immunization Coverage (X₆). Conversely, Cluster 2 showed negative standardized values for most of these indicators. These results suggest that Cluster 1 generally possesses more favorable educational, environmental, and health-related characteristics than Cluster 2.

Table 5. ANOVA Results for Cluster Differentiation

Variable	F	Sig.
X ₁	29.920	<0.001
X ₂	3.808	0.066
X ₃	5.790	0.026
X ₄	0.333	0.571
X ₅	6.461	0.020
X ₆	9.458	0.006
X ₇	0.139	0.713

To identify the indicators that contributed most strongly to cluster differentiation, an analysis of variance (ANOVA) was examined. The results are presented in Table 5. The ANOVA results indicate that Expected Years of Schooling (X₁) provided the greatest contribution to cluster separation, as reflected by the highest F-value (29.920). Complete Basic Immunization Coverage (X₆), Access to Safe Drinking Water (X₅), and Proper Sanitation (X₃) also contributed substantially to distinguishing the clusters. In contrast, Poverty Rate (X₄) and the Percentage of Children Under Two Years Old Who Received Breastfeeding (X₇) exhibited relatively small F-values, indicating a comparatively limited role in differentiating the cluster structure.

Overall, the similarity between the results obtained from Hierarchical Cluster Analysis and K-Means clustering supports the stability of the two-cluster solution. Therefore, the identified clusters can be considered a reliable representation of regional similarities based on the analyzed stunting-related indicators.

3.6. Cluster Characteristics

To facilitate the interpretation of the identified clusters, the mean values of the original variables for each cluster were examined. The results are presented in Table 6.

Table 6. Mean Values of Stunting-Related Indicators by Cluster

Variable	Cluster 1	Cluster 2
X ₁	15,06	13,09
X ₂	75,34	57,13
X ₃	94,78	81,58
X ₄	11,79	14,39
X ₅	96,99	87,60
X ₆	67,99	43,06
X ₇	91,27	92,17
Y	25,80	26,82

Table 6 shows that Cluster 1 generally exhibited more favorable conditions across most of the analyzed indicators. Regions belonging to this cluster had a higher average Expected Years of Schooling (15.06 years), compared with 13.09 years in Cluster 2. Similarly, the Food Security Index in Cluster 1 reached 75.34, substantially higher than the average value of 57.13 observed in Cluster 2.

Differences were also evident in environmental and health-related indicators. The average percentage of households with access to proper sanitation and safe drinking water in Cluster 1 reached 94.78% and 96.99%, respectively, whereas Cluster 2 recorded lower averages of 81.58% and 87.60%. In addition, Complete Basic Immunization Coverage was considerably higher in Cluster 1 (67.99%) than in Cluster 2 (43.06%). These findings suggest that regions in Cluster 1 generally have better access to basic health and environmental services.

In terms of socioeconomic conditions, Cluster 1 exhibited a lower average poverty rate (11.79%) compared with Cluster 2 (14.39%). This result is consistent with the relatively higher educational attainment and food security observed in Cluster 1. However, only a slight difference was observed in the percentage of children under two years old who received breastfeeding, with average values of 91.27% and 92.17% for Clusters 1 and 2, respectively.

Although Cluster 1 demonstrated more favorable characteristics across most indicators, the average prevalence of stunting was relatively similar between the two clusters, namely 25.80% and 26.82%. This finding indicates that regions with comparable levels of stunting prevalence may exhibit different socioeconomic, environmental, and health-related profiles. Therefore, the clustering results provide additional information that cannot be obtained solely from the analysis of stunting prevalence, highlighting the importance of considering multiple indicators simultaneously when designing intervention strategies.

The clustering results indicate that educational attainment, food security, sanitation, access to safe drinking water, and immunization coverage were important characteristics distinguishing the identified clusters. These findings are consistent with previous studies reporting that socioeconomic, environmental, and health-related factors are closely associated with child nutritional outcomes [8-10]. Regions with better educational and health conditions generally exhibited more favorable values across the analyzed indicators.

However, the average prevalence of stunting was relatively similar between the two clusters. This finding suggests that regions with comparable stunting prevalence may possess different underlying characteristics. Therefore, intervention strategies should not rely solely on prevalence figures but should also consider the specific socioeconomic, environmental, and health conditions of each region. The clustering approach provides additional insights for identifying regional similarities and may support the development of more targeted stunting reduction programs.

4. Conclusion

This study classified districts/cities in Maluku and North Maluku based on seven stunting-related indicators using Hierarchical Cluster Analysis with Ward's method and identified a stable two-cluster structure. The results of the agglomeration schedule and dendrogram indicated that a two-cluster solution was the most appropriate classification structure. The subsequent K-Means validation produced a consistent clustering pattern, supporting the stability of the identified clusters.

The cluster characteristics revealed that Expected Years of Schooling, Food Security Index, Proper Sanitation, Access to Safe Drinking Water, and Complete Basic Immunization Coverage were the indicators

that most clearly differentiated the clusters. Regions in Cluster 1 generally exhibited more favorable educational, environmental, and health-related conditions than those in Cluster 2. However, the average prevalence of stunting was relatively similar between the two clusters. This finding suggests that regions with comparable levels of stunting prevalence may possess different socioeconomic, environmental, and health-related profiles. Therefore, the use of cluster analysis provides additional insights beyond stunting prevalence alone and may support the development of more targeted and region-specific stunting prevention and control strategies.

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