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Clustering for Mapping Food Insecurity in the Land of Papua: A Five-Year Multiyear Analysis with Spatial Interpretation (2020–2024)

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Abstract

Food insecurity in the Land of Papua remains a critical issue due to extreme geographical conditions, limited infrastructure, and unstable food distribution systems. This study aims to map food vulnerability across 42 districts/ cities in Papua island using insufficient food consumption data from 2020 to 2024. Clustering was performed using five methods—Single Linkage, Complete Linkage, Ward, K-Means, and Gaussian Mixture Model (GMM)—and evaluated using three validation indices: Silhouette, Davies—Bouldin Index (DBI), and Calinski—Harabasz Index (CHI). To obtain a balanced and comprehensive model selection, a Performance-Based Weighting (PBW) framework was applied. In this framework, the DBI was first transformed to ensure a consistent *higher-is-better* orientation, and all validation indices were normalized to the [0,1] range prior to computing variance-based weights. This normalization step mitigates potential scale dominance, particularly from the unbounded CHI metric, ensuring proportional contribution from each validation criterion in the aggregated score. Although individual validation indices exhibited varying optimal values of k, the integrated PBW evaluation consistently identifies the two-cluster configuration as the most stable and interpretable overall structure. Specifically, Complete Linkage with $k = 2$ achieved the highest combined PBW score (0.8658), reflecting strong cluster separation and consistency across validation measures. Spatial interpretation of the resulting clusters reveals that the first cluster predominantly consists of high-risk mountainous districts with persistently elevated levels of food consumption inadequacy, particularly during 2021-2022, while the second cluster represents coastal and urban regions with comparatively lower and improving prevalence in 2023-2024. These findings provide a multiyear clustering perspective with geographic insight into regional disparities in food insecurity across Papua island. Overall, this study presents a data-driven and reproducible multiyear clustering framework that integrates multiple validation criteria to enhance robustness in model selection and support evidence-based regional policy formulation.

Keywords: food insecurity; clustering; multiyear analysis; spatial interpretation; Silhouette; Davies–Bouldin Index; Calinski–Harabasz Index

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1. Introduction

Food security is one of the main foundations of human development and social stability, especially for regions with extreme geographical conditions such as the Land of Papua. Inadequate food consumption remains a crucial issue due to structural challenges, including regional isolation, dependence on external supplies, and logistical vulnerabilities that contribute to significant inequality between regions [1], [2]. Although some coastal areas, such as Merauke, Jayapura City, and Sorong City, show relatively stable conditions, many mountainous districts—including Dogiyai, Deiyai, Paniai, Tolikara, and Yahukimo—experience substantially higher levels of food insecurity with noticeable multiyear fluctuations during 2020–2024 [3], [4].

Geographically, Papua island is characterized by high mountain ranges, steep valleys, vast swamp areas, and remote coastal clusters that severely constrain land transportation. Many districts are accessible only via pioneer flights or river routes, increasing their vulnerability to supply disruptions, extreme weather conditions, and difficult operating environments [5]. These structural constraints directly affect food price stability, commodity availability, and the frequency of supply shortages, which often exceed local household capacities.

The post-COVID-19 pandemic further intensified these challenges, particularly in 2021–2022, marking a peak in food consumption insufficiency. Rising logistics costs, transportation breakdowns, and declining household incomes triggered a surge in food insecurity across rural and remote regions, especially in districts highly dependent on long and fragile supply chains [6].

In the academic landscape, food security studies in Papua island have largely relied on conventional statistical approaches that use aggregate measures such as means or medians [7], [8]. While these approaches provide general descriptive insights, they may not adequately reveal latent group structures, regional disparities, or multiyear variation patterns across districts. In particular, purely aggregate methods may overlook spatial variation between districts and evolving trends across years, both of which are important for understanding structural differences in food insecurity vulnerability.

To address this limitation, clustering methods provide an alternative data-driven approach to uncover hidden group structures among regions. However, determining the most appropriate clustering configuration remains a methodological challenge. Common validation metrics such as the Silhouette index, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI) are widely used to evaluate cluster separation quality [9], [10]. Nevertheless, each index has distinct sensitivities to cluster shape, density, and dispersion, which may lead to inconsistent model selection results when used independently.

To overcome this issue, this study introduces a Performance-Based Weighting (PBW) framework that integrates multiple validation indices into a single aggregated evaluation score. Rather than relying on a single metric, PBW assigns weights proportionally based on the variance contribution of each normalized index, thereby promoting a more balanced and robust model selection process.

This study applies the PBW framework within a multiyear (2020–2024) context using yearly indicators of food consumption inadequacy across 42 regencies/cities in the Land of Papua. The temporal dimension is incorporated through the use of annual indicators as clustering features. Meanwhile, geographic characteristics are used for contextual interpretation of the resulting clusters rather than as explicit spatial modeling components. In other words, spatial information is not embedded in the clustering algorithm through spatial weights matrices or spatial econometric models, but serves as an interpretative layer to explain the geographic distribution of clusters.

The analysis reveals notable multiyear patterns, including intensified food insecurity during 2021–2022 and relative improvements in several districts during 2023–2024. These findings provide geographically contextualized insights into regional disparities in food insecurity and offer evidence to support spatially targeted policy prioritization without employing formal spatial statistical modeling.

In summary, this study contributes methodologically by integrating multiple validation indices through the PBW framework, and substantively by applying the approach to a multiyear food insecurity dataset in Papua island. The resulting cluster-based mapping with spatial interpretation aims to support more precise, data-driven regional policy formulation at both provincial and district levels.

2. Methods

This section outlines the analytical framework of the study, including data representation and preprocessing, the clustering methods employed, the validation criteria used to assess cluster quality, and the Performance-Based Weighting (PBW) procedure for selecting the most appropriate clustering configuration.

2.1. Representation and Preprocessing

The unit of analysis in this study is each of the 42 regencies/cities in the Land of Papua (all 6 provinces)). Each region is represented by a five-dimensional feature vector, with each dimension corresponding to the prevalence of food consumption inadequacy from 2020 to 2024. No missing values were found in the dataset. Prior to clustering, the data was normalized using min-max normalization to the [0,1] range to ensure that each year contributed equally to the distance metric used in clustering.

2.2. Clustering Methods Used

This study employed five clustering methods, namely Single Linkage, Complete Linkage, Ward's Method, K-Means, and the Gaussian Mixture Model (GMM). These methods were selected to represent both hierarchical and non-hierarchical clustering approaches and to capture different perspectives on similarity and group structure in the data [11], [12], [13], [14], [15]. Since each method uses a different rule for measuring proximity between observations or clusters, their comparison provides a more comprehensive basis for identifying regional patterns of food insecurity.

2.2.1. Single Linkage

Single Linkage defines the distance between two clusters based on the closest pair of observations. The updating rule is given by

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

where $d_{(UV)W}$ denotes the distance between the newly formed cluster (UV) and cluster W, while d_{UW} and d_{VW} denote the distances from clusters U and V to cluster W, respectively. This criterion determines the distance of the new cluster using the nearest pair of points between clusters [11], [12]. As a result, Single Linkage tends to connect clusters through neighboring observations and is useful for identifying connected regional patterns in food insecurity prevalence.

2.2.2. Complete Linkage

Complete Linkage defines the distance between two clusters using the farthest pair of observations. Its updating rule is expressed as

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

where $d_{(UV)W}$ denotes the distance between the newly formed cluster (UV) and cluster W, while d_{UW} and d_{VW} denote the distances from clusters U and V to cluster W, respectively. Complete Linkage, also known as the farthest-neighbor method, determines inter-cluster proximity based on the most distant pair of observations between two clusters [11], [12]. This approach generally produces compact and well-separated clusters, making it suitable for distinguishing regions with substantial differences in food consumption inadequacy.

2.2.3. Ward's Method

Ward's Method merges clusters by minimizing the increase in within-cluster variation at each step. The corresponding distance measure is defined as

$$d_{\text{Ward}}(C_u, C_v) = \frac{n_u n_v}{n_u + n_v} \|\mu_u - \mu_v\|^2 \tag{3}$$

where n_u and n_v denote the numbers of observations in clusters C_u and C_v, respectively, while μ_u and μ_v represent their corresponding centroids. The Ward distance $d_{\text{Ward}}(C_u, C_v)$ quantifies the increase in the within-cluster sum of squares (WCSS) resulting from merging clusters C_u and C_v. By selecting the pair of clusters that produces the smallest increase in WCSS, Ward's Method tends to form compact and homogeneous clusters [16], [17]. This variance-minimization property makes the method effective for identifying well-separated groups with low internal dispersion.

2.2.4. K-Means

K-Means partitions observations into a predefined number of clusters by assigning each observation to the nearest centroid. The squared Euclidean distance used in this study is given by

$$d_{ik} = \sum_{j=1}^{m} (x_{kj} - c_{ij})^2 \tag{4}$$

where d_{ik} denotes the squared Euclidean distance between observation x_k and the centroid of cluster i, x_{kj} is the value of observation k on variable j, and c_{ij} is the coordinate of centroid i on variable j. The distance is computed across all m variables. K-Means iteratively assigns each observation to the nearest centroid and updates the centroids to minimize the total within-cluster variance [18], [19], [20]. Due to its simplicity, scalability, and strong partitioning performance, this method is widely used for identifying regional patterns in multivariate data.

2.2.5. Gaussian Mixture Model (GMM)

Unlike hard clustering methods, the Gaussian Mixture Model (GMM) represents the data as a probabilistic combination of several latent groups. The model is formulated as

$$p(x) = \sum_{i=1}^{K} \pi_i \, N(x \mid \mu_i, \Sigma_i) \tag{5}$$

where $p(x)$ denotes the overall probability density function represented as a weighted sum of K Gaussian components. Each component has mixing proportion π_i, mean vector μ_i, and covariance matrix Σ_i, which together define the density function $N(x \mid \mu_i, \Sigma_i)$. The model assumes that the data arise from a finite mixture of K underlying distributions, with each component corresponding to a latent subgroup. Because GMM assigns observations to clusters probabilistically, it is suitable for capturing overlapping structures and heterogeneous patterns of food insecurity across regions [20], [21], [22]. This flexibility is particularly useful for representing transitional characteristics between lower-risk and higher-risk districts.

2.3. Cluster Evaluation Method

To evaluate the quality of the clustering results, this study employed three widely used internal validation indices: the Silhouette Coefficient, the Davies–Bouldin Index (DBI), and the Calinski–Harabasz Index (CHI). These indices provide complementary perspectives on clustering performance by assessing both within-cluster cohesion and between-cluster separation [9], [23]. Using multiple validation criteria allows the quality of each clustering configuration to be assessed more comprehensively than relying on a single index alone.

2.3.1. Silhouette Coefficient

The Silhouette Coefficient evaluates how well each observation fits within its assigned cluster compared with other clusters. The average Silhouette value is defined as

$$\bar{S} = \frac{1}{n}\sum_{i=1}^{n}\frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{6}$$

where $a(i)$ denotes the average distance between observation i and all other observations in the same cluster, while $b(i)$ denotes the minimum average distance between observation i and observations in another cluster. The quantity $\bar{S}$ represents the average Silhouette value over all n observations. Higher Silhouette values indicate better clustering quality, as they reflect stronger within-cluster similarity and clearer separation between clusters [24].

2.3.2. Davies–Bouldin Index (DBI)

The Davies–Bouldin Index measures the average similarity between each cluster and its most similar counterpart. It is defined as

$$\mathrm{DBI} = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{S_i + S_j}{M_{ij}}\right) \tag{7}$$

where S_i and S_j represent the average intra-cluster distances for clusters i and j, respectively, while M_{ij} denotes the distance between the centroids of clusters i and j. The index computes the average of the maximum similarity ratios between each cluster and the cluster most similar to it. Lower DBI values indicate better clustering quality, since they correspond to more compact clusters with greater separation between them [9], [23].

2.3.3. Calinski–Harabasz Index (CHI)

The Calinski–Harabasz Index evaluates cluster quality by comparing between-cluster dispersion with within-cluster dispersion. It is expressed as

$$CH = \frac{BGSS/(k-1)}{WGSS/(N-k)} = \frac{BGSS}{WGSS} \times \frac{N-k}{k-1} \tag{8}$$

where $BGSS$ denotes the Between-Group Sum of Squares, which measures variation between clusters, and $WGSS$ denotes the Within-Group Sum of Squares, which measures variation within clusters. The parameter k represents the number of clusters, while N denotes the total number of observations. Higher CHI values indicate better clustering performance, as they reflect larger between-cluster variation relative to within-cluster variation [9], [23].

Taken together, these three indices provide a comprehensive basis for evaluating clustering performance. The Silhouette Coefficient emphasizes the relative assignment quality of individual observations, the Davies–Bouldin Index focuses on cluster compactness and similarity, and the Calinski–Harabasz Index evaluates the balance between between-cluster and within-cluster variation. Their combined use therefore supports a more robust assessment of the quality and stability of the clustering structures obtained in this study.

2.4. Performance-Based Weighting (PBW)

The Performance-Based Weighting (PBW) method is used to determine the most appropriate clustering model by combining three validation indices—Silhouette, DBI, and Calinski-Harabasz Index (CHI)—into a single standardized score. This approach addresses potential conflicts or inconsistencies among individual validation indices by assigning weights based on their performance variances. By integrating the indices in this way, PBW improves the robustness and stability of model selection across different clustering methods and parameter settings.

To ensure a consistent "higher-is-better" orientation, the Davies–Bouldin Index (DBI), originally a minimization metric, was first transformed into $(DBI)^* = 1/DBI$. The PBW procedure then consists of the following steps: (1) normalization of Silhouette, DBI*, and CHI to the [0,1] range using min-max scaling; (2) computation of variance-based weights from the normalized indices; and (3) weighted aggregation to obtain the final PBW score [23]:

$$w_i = \frac{\mathrm{Var}(i_{norm})}{\sum \mathrm{Var}(i_{norm})}$$

The combined scores of the three indices are calculated as:

$$Score = w_{sil} \cdot Sil_{norm} + w_{DBI^*} \cdot DBI^*_{norm} + w_{CHI} \cdot CHI_{norm}$$

Although the variance-based weights were calculated using the original scale of each index, all index values were subsequently normalized to the [0,1] range before aggregation. This normalization step ensures that differences in scale among indices—such as the larger numerical range of CHI compared to Silhouette or DBI—do not disproportionately affect the final combined score.

Notation w_i expresses the weight for the i-th index, which is determined based on the proportion of the relative variance of the index to the total variance of the entire index used. The variance of each index is denoted by $\mathrm{Var}(i_{norm})$, while $\sum \mathrm{Var}(i_{norm})$ represents the sum of variances across all normalized indices. The index values that have been normalized to a scale of [0.1] are written as $\mathrm{Sil}_{\mathrm{norm}}$, $\mathrm{DBI}^*_{\mathrm{norm}}$, and $\mathrm{CHI}_{\mathrm{norm}}$, which represent the normalized Silhouette, inverted DBI, and CHI indices, respectively. The weights of the variance calculation are written as w_{sil}, w_{DBI}, and w_{CHI}, which are used in the composition of the final score. The combined score, denoted by the score, is used as the basis for evaluating the overall performance of the clustering model being tested.

2.5. Algorithm Settings

K-Means clustering was performed using the Euclidean distance metric. Centroid initialization employed the k-means++ strategy ('plus') with 20 independent initializations (Replicates = 20) to reduce sensitivity to local minima and improve solution stability. The convergence tolerance and maximum number of iterations followed MATLAB's default settings.

For the Gaussian Mixture Model (GMM), parameter estimation was carried out using the Expectation-Maximization (EM) algorithm with 20 independent initializations (Replicates = 20) to enhance robustness against local optima. A regularization value of 10^{-6} was applied to ensure numerical stability during covariance estimation. All other parameters followed MATLAB's default configuration.

For hierarchical clustering (Single, Complete, and Ward linkage), Euclidean distance was used as the proximity metric. The full dendrogram was constructed without truncation, and clusters were formed by cutting the dendrogram at the specified number of clusters (k).

3. Results and Discussion

This section presents the clustering results of insufficient food consumption data from 42 regencies/ cities in Papua island. Five clustering methods were used: Single Linkage, Complete Linkage, Ward's Method, K-Means, and Gaussian Mixture Model (GMM). Cluster evaluation was conducted using Silhouette, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI), and the results were aggregated using the Performance-Based Weighting (PBW) method to determine the optimal clustering model. The discussion is structured to present both quantitative outcomes and contextual interpretations for policy relevance.

3.1. Overview

The analyzed dataset comprises 42 districts/cities in the Land of Papua, observed over five years (2020-2024) for the prevalence of insufficient food consumption. The data highlight the diversity of regional conditions, shaped by geographical features, accessibility, and socio-economic dynamics. In general, mountainous areas exhibit higher prevalence rates than coastal or urban areas, which tend to show lower and more stable values.

Prior to the clustering analysis, annual archetypes were evaluated to assess regional trends. The data reveal a marked contrast: some regions report prevalence as low as 17-25%, while certain mountainous districts reach 50-80%. A temporal trend is also evident, with the highest average prevalence occurring in 2021-2022, followed by a decline in 2023-2024, although this decrease is not significant for high-prevalence regions.

3.2. Average Prevalence per Cluster (2020-2024)

The average prevalence analysis per cluster was conducted to examine how regional conditions evolved between 2020 and 2024 following the clustering process. Regions were grouped into Cluster 1 and Cluster 2 based on prevalence indicators and validation results from the Silhouette, DBI, and CHI indices. The choice of a two-cluster solution is not only statistically optimal, but also contextually meaningful, as it distinguishes between regions with severe food insecurity and those with moderate or stable conditions. This dichotomy supports practical policy frameworks that differentiate between priority intervention areas and those requiring general monitoring. The average results for each cluster per year are presented in Table 1.

Table 1: Average Prevalence of Cluster 1 and Cluster 2

Year	Cluster 1	Cluster 2
2020	43.81	24.34
2021	52.62	27.99
2022	50.11	28.15
2023	50.63	26.43
2024	45.42	22.04

Table 1 depicts the division of the region into two clusters has a strong statistical basis. Cluster 1 consistently shows a much higher prevalence rate than Cluster 2, in all years of observation. This difference is not only large in terms of numbers (an average difference of around 21 percentage points), but also consistent from year to year. For example, in 2021, the prevalence of Cluster 1 reached 52.62%, while Cluster 2 was only 27.99%. Despite a general decline in 2024, the gap between clusters remained large (45.42% vs. 22.04%). This pattern indicates the existence of established structural vulnerability differences, where areas in Cluster 1 are chronic high-risk areas, while Cluster 2 reflects more stable areas with moderate to low risk. There is no apparent convergence or divergence trend, suggesting that this gap is likely to remain without targeted policy intervention.

3.3. Cluster Evaluation Based on Silhouette Score

One of the most important metrics for determining cluster quality is the Silhouette Score. A Silhouette value close to 1 indicates that the cluster is homogeneous and well separated. The following Table 2 summarizes the Silhouette values for $k = 2$ to $k = 8$ in five clustering methods:

Table 2 shows that the entire clustering method yielded the highest Silhouette value at $k = 2$. Complete Linkage and K-Means reach a maximum value of 0.7410, while Ward also gives a high result at $k = 2$ (0.7295). A fairly sharp decrease in the Silhouette value at $k \geq 3$ indicates that the formation of additional clusters tends to break down the data structure and decrease the homogeneity of the group. These findings indicate that $k = 2$ yields the highest Silhouette values for most methods, suggesting strong cluster separation at this level.

Table 2: Silhouette Value of Various Clustering Methods

Method	k Optimum (Silhouette)						
Cluster	2	3	4	5	6	7	8
Single	0.7129	0.5974	0.3862	0.2658	0.3300	0.0566	0.0650
Complete	0.7410	0.7074	0.7145	0.3951	0.3399	0.3464	0.3861
Ward	0.7295	0.4858	0.5105	0.4746	0.5043	0.4461	0.4390
K-means	0.7410	0.7074	0.5217	0.5371	0.4542	0.4119	0.4424
GMM	0.6290	0.4406	0.4561	0.2799	0.2605	0.1660	0.1313

3.4. Cluster Evaluation Based on the Davies–Bouldin Index (DBI)

To assess the quality of clustering results, the Davies–Bouldin index (DBI) is used because it is able to measure the balance between the proximity between clusters and the cohesiveness within the cluster. A lower DBI value indicates that the clusters formed are getting better, i.e., the distance between large clusters, but each cluster remains homogeneous. Evaluations were carried out on various clustering methods and multiple k-values to identify the optimal cluster configuration. By comparing the DBI values between methods, it can be seen which method produces the most efficient cluster separation. The following table provides a summary of the DBI values for each method and number of clusters, making it easier to analyze the selection of the best model.

Table 3: DBI Value of Various Clustering Methods

Method	k Optimum (DBI)						
Cluster	2	3	4	5	6	7	8
Single	0.2798	0.3963	0.5298	0.5458	0.4921	0.6989	0.6331
Complete	0.6876	0.7508	0.5461	0.9404	1.0148	1.0833	1.0557
Ward	0.7006	1.0134	0.9724	0.9806	0.8216	0.8986	0.8783
K-means	0.6876	0.7508	1.0136	0.8228	0.8965	0.9481	0.8558
GMM	0.7519	1.0656	1.0492	1.5394	1.5178	2.0075	1.6654

Table 3 shows that the entire clustering method achieved the lowest DBI value at $k = 2$, which indicates the most compact and well-separated cluster configuration. Single Linkage obtained the lowest DBI value (0.2798), but this method is generally susceptible to the "chaining" effect, so that the structure of the cluster formed is less stable. Complete Linkage, Ward, and K-Means provide more balanced DBI values and reflect more consistent cluster separation at $k = 2$. The sharp increase in DBI in $k \geq 3$ shows that the addition of the number of clusters actually reduces the quality of data separation. Although Complete Linkage achieves a slightly lower DBI value at $k = 4$, the overall pattern across methods suggests that $k = 2$ provides a stable and well-balanced configuration .

3.5. Cluster Evaluation Based on Calinski–Harabasz Index (CHI)

To complete the evaluation of cluster quality, the Calinski–Harabasz index (CHI) is used because it is able to assess how well the separation between clusters is compared to the distribution of data within the cluster. Higher CHI values indicate a clearer, well-separated cluster structure. Evaluation was carried out on various clustering methods to find out which configuration provided the optimal separation. The following table presents a comparison of the CHI values for each method and the number of clusters, making it easier to select the most stable and representative model.

Table 4 shows that Complete Linkage and K-Means produce the highest CHI value at $k = 2$, which is 67.79, which signifies a very clear and compact cluster separation. Ward also gave a fairly high CHI score (59.29), but it was still below Complete and K-Means. The much lower performance of Single Linkage and GMM shows that both methods are less suitable for this data structure. A significant decrease in CHI values at $k \geq 3$ indicates that the formation of additional

Table 4: CHI Value of Various Clustering Methods

Method Cluster	k Optimum (CHI)						
	2	3	4	5	6	7	8
Single	9.79822	12.7866	11.2542	9.0617	9.04533	7.97587	6.7263
Complete	67.7926	55.1488	41.7626	39.3462	34.5806	33.5465	33.4852
Ward	59.2932	45.4770	46.8748	41.3324	39.4428	39.4886	38.2932
K-means	67.7926	55.1488	50.4144	44.4371	41.2854	38.8724	38.3771
GMM	30.6934	41.0764	40.4154	32.0496	28.9638	25.3094	22.8799

clusters does not provide an improvement in the quality of data separation. In summary, $k = 2$ provides the highest CHI values for Complete Linkage, Ward, and K-Means. Although Single Linkage and GMM achieve higher CHI values at $k = 3$, the overall CHI pattern across methods supports $k = 2$ as a stable candidate when considering multi-method agreement.

3.6. Performance-Based Weighting (PBW)

The Performance-Based Weighting (PBW) approach was employed to obtain a more comprehensive and balanced clustering decision by integrating three validation indices—Silhouette, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI)—into a single aggregated score. To ensure a consistent "higher-is-better" orientation across all indices, the DBI was first transformed using an inverse function $(DBI)^* = (1/DBI)$. Subsequently, all indices were normalized to the [0,1] range using min-max scaling prior to weight computation. The normalization step is essential to prevent scale-induced bias, particularly due to the unbounded nature of the CHI metric. Without normalization, the relatively large magnitude of CHI values could artificially inflate its variance and disproportionately influence the resulting weights. By computing variance after normalization, the PBW framework ensures that each index contributes proportionally based on its relative discriminatory power rather than its absolute scale.

Variance-based weights were then calculated from the normalized indices and standardized proportionally to obtain the final PBW weights. Through this procedure, the aggregation process remains stable and balanced across the three validation metrics.

By integrating the weighted normalized indices, the PBW framework provides an overall evaluation that mitigates potential dominance effects and enhances the robustness of model selection compared to relying on a single validation criterion. The resulting PBW scores indicate that the Complete Linkage method with two clusters achieves the most consistent overall performance under the integrated evaluation framework. Table 5 presents the best global clustering combination based on the aggregated PBW score.

Table 5: Cluster Method Combined Score (GLOBAL)

Best GLOBAL combination (based on combined scores)		
Method	k	Score
Complete	2	0.8658

To further demonstrate the transparency of the weighting procedure, Table 6 reports the variance values computed from the normalized indices along with the resulting proportional weights used in the PBW aggregation. The results show that the weights are relatively balanced across the three indices, confirming that no single metric disproportionately dominates the final combined score.

Table 6: Variance and Final Weights of Normalized Indices (PBW)

Index	Variance (Normalized)	Weight
Silhouette	0.059479	0.384
DBI*	0.030277	0.195
CHI	0.065289	0.421

The visualization in Fig. 1 further illustrates the distinction between the two clusters. Cluster 1 exhibits a substantially higher level of Food Consumption Inadequacy compared to Cluster 2, which is consistent with the statistical patterns observed in the three validation indices and the PBW aggregation results. These findings suggest that the two-cluster configuration not only achieves numerical superiority under the integrated evaluation but also provides a meaningful and interpretable representation of the underlying data structure.

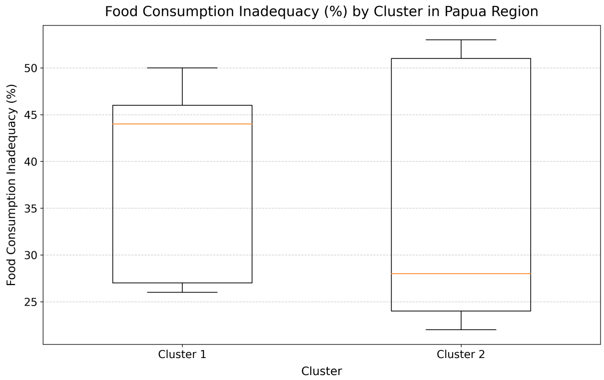

Fig. 1: Food Consumption Inadequacy (%) by Cluster in the Papua Region

Overall, the combination of global PBW scores, visual distribution patterns, and multi-index agreement supports the selection of the Complete Linkage method with two clusters as the most balanced overall configuration under the integrated evaluation framework for describing the heterogeneity of inadequate food consumption in Papua.

3.7. Spatial Map of Clustering of Papua Regency/City

Based on the results of clustering using the Complete Linkage method with the optimal number of clusters $k = 2$, two groups of regions were obtained that showed significant differences in the level of food consumption inadequacy. Validation using the three indices–Silhouette, DBI, and CHI–together with the aggregated PBW evaluation supports the selection of the two-cluster configuration as a stable and interpretable separation. The integration of cluster results and their spatial visualization in Fig. 2 provides a descriptive overview of food vulnerability patterns in Papua and West Papua Provinces, and helps to interpret how geographical, accessibility, and socioeconomic conditions are associated with risk distribution.

The first cluster consists of 14 districts/cities that show the highest level of insufficient food consumption, which is in the range of 40–80%. These areas include Dogiyai, Deiyai, Paniai, Intan Jaya, Puncak, Tolikara, Yahukimo, Pegunungan Bintang, Jayawijaya, Lanny Jaya, Mamberamo Tengah, Asmat, Mappi, and Boven Digoel. Many districts in Cluster 1 appear to be located in more remote and logistically challenged regions; however, this generalization may not apply uniformly. These districts exhibit persistent high prevalence levels, potentially linked to structural constraints such as remoteness and limited infrastructure. The spatial concentration of these characteristics suggests that the observed cluster patterns are closely related to underlying geographic and logistical conditions, which remain relatively consistent across the years.

The second cluster consists of 28 regions with a relatively lower level of food consumption inadequacy, in the range of 14–32%. Areas included in this cluster are generally located on the coast or areas with better access to land and sea transportation, including Fakfak, Kaimana, Manokwari, South Manokwari, Bintuni Bay, Wondama Bay, Raja Ampat, Sorong, South Sorong, Maybrat, Tambrauw, Sorong City, Jayapura City, Jayapura Regency, Merauke, Nabire, Supiori, Waropen, Keerom, Sarmi, Yalimo, Mamberamo Raya, and other coastal areas. Better logistics accessibility allows for a more stable food supply so that the prevalence of insufficient consumption tends to be lower and varies from year to year. In addition, several large cities such as Sorong, Manokwari, and Jayapura play a role as distribution centers that strengthen the food security of

Fig. 2: Spatial Map of Clustering of Regencies/Cities in Papua Island

the surrounding area.

Analysis of temporal trends over the period 2020–2024 confirms the existence of a consistent general pattern. The years 2021–2022 are a period when the prevalence of insufficient food consumption increased sharply, especially in districts in Cluster 1, such as Dogiyai (80.32%), Deiyai (70.33%), and Paniai (70.28%). This spike aligns with broader regional disruptions during 2021-2022, suggesting that Cluster 1 districts are more sensitive to external shocks due to their structural characteristics. In the 2023-2024 period, several areas in Cluster 2 experienced a decrease in prevalence, for example Merauke, Sorong City, and Bintuni Bay. However, despite the relative decline, areas in Cluster 1 still recorded a high prevalence rate, so they still require intensive attention.

The integration of cluster results with regional maps and yearly data provides insight into how food consumption inadequacy varies across districts and over time. While no explicit spatial or temporal model was applied, descriptive analysis of geographic and yearly trends offers valuable context for policy interpretation. The priority group includes high-risk and growing trending districts, such as Dogiyai, Deiyai, Paniai, Tolikara, and Yahukimo, which require urgent interventions in the form of buffer stocks, air-based distribution systems, and adaptive logistics reinforcement. The second priority includes high-risk areas with downward trends, such as Intan Jaya, Asmat, and the Arfak Mountains, which require supply consolidation and transportation alternatives. The third priority is low- to medium-risk areas, but the trend of insufficiency is increasing, such as Wondama Bay, Waropen, and Yalimo, which require early warning systems. Finally, the fourth priority consists of low-risk areas with a downward trend, such as Merauke, Jayapura City, and Jayapura Regency, which can be focused on strengthening local production and supply chain integration.

Overall, the spatial maps and multiyear descriptive trend analysis suggest that patterns of food vulnerability in the Land of Papua appear to reflect differences in geographical conditions, transportation accessibility, and logistical contexts.

It should be emphasized that the geographic labels such as "mountainous/ inland" and "coastal/ urban" are used as descriptive tendencies based on general regional characteristics rather than as formal geographic classifications. These terms are intended to provide contextual interpretation of the observed clustering patterns, not to define rigid spatial categories. The clustering process itself relies solely on food consumption inadequacy indicators, and no geographic variables were included as clustering inputs. Therefore, the geographic descriptions should be interpreted as qualitative contextual explanations supported by the spatial visualization in Fig. 2.

3.8. Methodological Limitations and Adaptation Conditions

This study employs the prevalence of insufficient food consumption during the 2020–2024 period as the primary indicator for clustering. While this indicator captures an important dimension of food insecurity, it remains an aggregate measure and does not encompass other relevant dimensions such as food price volatility, market accessibility, transportation infrastructure, local production capacity, or socio-political conditions. Consequently, the clustering results reflect a structural segmentation based on consumption inadequacy but do not yet represent a fully multidimensional characterization of food security.

Furthermore, the clustering procedures applied in this study rely on Euclidean distance, which assumes homogeneity in scale and sensitivity to variability across features. Although min–max normalization was implemented to standardize the data, distance-based clustering methods remain sensitive to dispersion patterns and interregional variability. As a result, the identified cluster structure may change if additional indicators are incorporated or if substantial shifts occur in the underlying value distributions. In borderline cases, small variations in indicator values may influence cluster assignment. These considerations should be interpreted as inherent methodological sensitivity rather than instability in the data itself.

Another limitation relates to the multiyear structure of the dataset. The clustering framework treats annual food consumption prevalence values as features within a unified model, capturing variation across years but not explicitly modeling temporal dependence or year-to-year transition dynamics. Thus, the observed multiyear patterns describe distributional changes rather than formal temporal causality.

From an implementation perspective, Papua island exhibits substantial geographic diversity, ranging from remote mountainous districts to relatively accessible coastal and urban areas. Differences in transportation infrastructure, logistical accessibility, institutional capacity, and exposure to extreme weather conditions imply that policy interventions derived from the clustering results may not be uniformly applicable across regions. Therefore, the findings of this study should be interpreted as an initial segmentation framework intended to support evidence-based prioritization. Effective policy formulation would require additional contextual data enrichment and district-specific adjustments.

Overall, these limitations highlight the importance of interpreting the proposed framework as a structured analytical tool for multiyear regional segmentation rather than as a comprehensive or spatially weighted modeling system. Future research may extend the framework by incorporating multidimensional indicators or integrating formal spatial analytical components where appropriate

4. Conclusions

This study evaluated several clustering methods—Single Linkage, Complete Linkage, Ward, K-Means, and Gaussian Mixture Model (GMM)—to map food insecurity in the Land of Papua based on the prevalence of inadequate food consumption across 42 districts/cities during the 2020–2024 period. The evaluation employed three widely used validation indices—Silhouette, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI)—which were integrated using a Performance-Based Weighting (PBW) framework to support a balanced and robust model selection process.

The results demonstrate that, although individual validation indices exhibit local optima at different values of k, the aggregated multi-index evaluation consistently identifies the two-cluster configuration as the most stable and interpretable overall structure. Among the tested methods, Complete Linkage with $k = 2$ achieved the highest combined PBW score, indicating balanced performance under the integrated validation framework.

From a multiyear perspective, the first cluster predominantly consists of districts with persistently higher levels of food consumption inadequacy, particularly during 2021–2022, while the second cluster includes regions with comparatively lower and more stable prevalence, with observable improvements in 2023–2024. These findings provide geographically contextualized insight into regional disparities in food insecurity across Papua island. The spatial characteristics of the districts—such as remoteness, transportation accessibility, and supply chain stability—serve as interpretative factors that help explain the observed clustering patterns.

Overall, this study presents a data-driven and reproducible multiyear clustering framework supported by integrated multi-index evaluation. By combining validation criteria through the PBW approach, the proposed framework enhances robustness in clustering model selection without relying on a single evaluation metric. The resulting cluster-based mapping with spatial interpretation offers practical insights for evidence-based regional policy formulation and prioritization of high-risk areas.

Future research may extend this framework by incorporating additional indicators–such as infrastructure development, market accessibility, and socioeconomic variables–to enable multidimensional extensions or the integration of formal spatial analytical approaches where appropriate.

CRediT Authorship Contribution Statement

Ishak S. Beno: Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Supervision. **Felix Reba**: Software, Investigation, Data Curation, Writing – Original Draft. **Alvian M. Sroyer**: Investigation, Data Curation. **Remuz M. B. Kmurawak**: Data Curation, Writing – Review & Editing. **Antonius A. P. Tama**: Investigation, Data Curation

Declaration of Generative AI and AI-assisted technologies

Generative AI and AI-assisted technologies were not used for data analysis, statistical computation, model development, or the generation of research results in this study. If any AI-assisted tool was used during manuscript preparation, it was limited to language editing and formatting assistance only, and the authors take full responsibility for the content of the manuscript.

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

The data and code supporting the findings of this study are available from the corresponding author upon reasonable request. Requests should be directed to i.s.beno@fmipa.uncen.ac.id.

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