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Model-Based Approach for Clustering Regencies/Cities in The Land of Papua Based on Food Security Indicators

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ABSTRACT

The demand for food continues to increase as population growth concerns the Indonesian government, as stated in the second goal of the Sustainable Development Goals, namely zero hunger. The National Food Agency (BPN) uses the Food Security Index (IKP) to monitor food security conditions in Indonesia's district/city and provincial levels. Based on the BPN data, most districts/cities in The Land of Papua (so called Irian Province before the year 2000) are food insecure. However, the IKP has a weakness in the subjectivity of determining weights so that it can disguise the failure of a program or exaggerate a success. The model-based clustering (MBC) method can measure the food security of districts/cities in this area based on food security indicators. However, the data conditions are generally not multivariate distributed, and there are many outliers, so this study used MBC with multivariate *t* distribution because it is more robust. The best model was obtained with two clusters based on the largest Bayesian Information Criterion value. Cluster 1, located in the mountains and islands such as Nduga, Intan Jaya, Mamberamo Tengah, Puncak, and Lanny Jaya, had low food security, low indicator achievements with high poverty characteristics, many households with a portion of household expenditure on the food of more than 65%, low access to electricity and clean water, low life expectancy and average years of schooling for women, and the percentage of stunted toddlers. Meanwhile, Cluster 2, areas with high food security, had the opposite condition.

Keywords: food security, model-based clustering, multivariate *t* distribution, Land of Papua

INTRODUCTION

Food is a primary need of the community that must be met. The need for food, both in quality and quantity, is increasing as the population increases (Dyah *et al.* 2021; Kurnia *et al.* 2020). Food shortages will impact social, economic, and political instability (Amelia and Prasetyo 2022). Therefore, food security is one of the country's national resilience supporters (Dirhamsyah *et al.* 2016; Wijaya *et al*. 2022). Food issues are a national and international concern, as stated in the second goal's Sustainable Development Goals (SDGs). The two SDGs are zero hunger, including ending hunger, achieving food security, improving nutrition, and promoting sustainable agriculture (Kementerian PPN/Bappenas 2020). Food security in Indonesia is one of the national development targets as stated in the 2020-2024 National Medium-Term Development Plan (RPJMN), which is to increase the availability, access, and quality of food consumption (Kementerian PPN/Bappenas 2019).

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The Food and Agriculture Organization (FAO) defines food security as a condition when all people at one time, physically, socially, and economically, get enough, safe, and nutritious food to meet and choose food for an active and healthy life (FAO *in* Haldar and Pearlin 2023). The measurement of national food security has three pillars: availability, access, and utilization (Badan Pangan Nasional 2022). Monitoring the status of food security can be seen from a composite index. On an international scale, food security status can be seen from the Global Food Security Index (GFSI) score triggered by *the* Economist Intelligence Unit (EIU). The change in Indonesia's GFSI score from 2016 to 2021 is insignificant. Indonesia's GFSI score in 2021 reached 59.2 out of 100 points, meaning it was in the medium category and ranked 69th out of 113 countries (The (Economist Impact 2021). This shows that food security in Indonesia must be appropriately managed so that the GFSI score can continue to be improved. Headey and Martin (2016) said that food security that is not managed properly will have an impact on poverty and hunger.

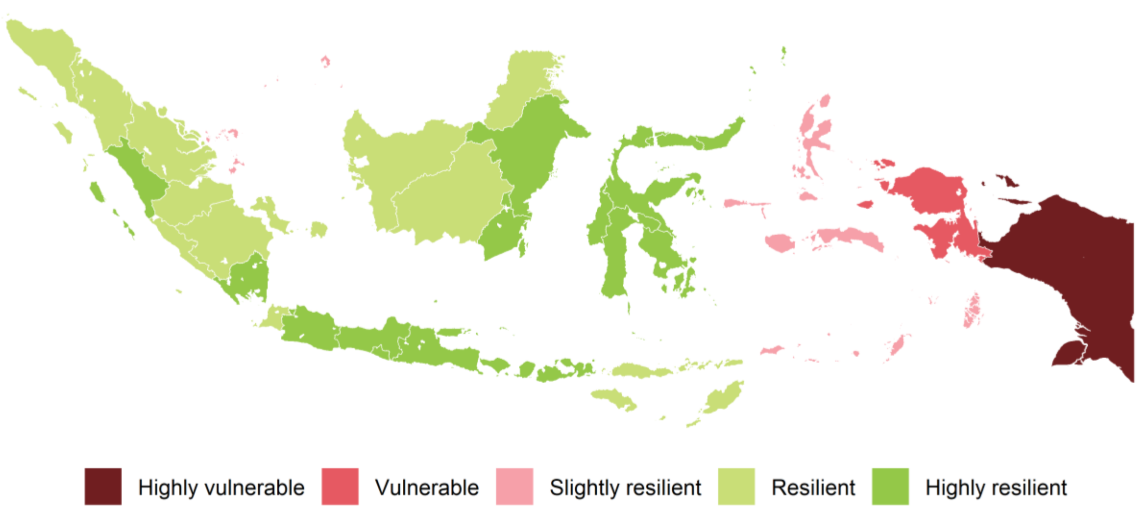
The success of government policies in realizing food security will largely depend on the approach chosen in looking at the context of food security and integrating food security policies with other national development policies, such as poverty alleviation and macroeconomic policies. Food security at the meso (regional, provincial, and district/city levels) and micro (family/individual) levels must be considered, not only macro (aggregate or national) food security. Therefore, food security must be lowered from the national level to the local region in stages/hierarchies at the provincial and district/city levels to finally, the food security of families and individuals (Salasa 2021).

Indonesia's National Food Agency (BPN) uses the Food Security Index (IKP) to monitor the food security conditions at the district/city and provincial levels in Indonesia. Figure 1 shows the map of provincial IKP in Indonesia in 2021. Regencies/cities with red gradations indicate food-vulnerable areas, while green gradations indicate food-insecure areas. Most districts/cities in the Land of Papua are in the red gradient. This means that the Land of Papua is facing food insecurity.

According to the Ministry of Agriculture in the 2022 Food Security Analysis publication, the eastern part of Indonesia generally has a lower IKP value than the western Indonesia. The IKP scores of West Papua and Papua provinces from 2019 to 2021 show improvement, although they consistently remain lower outliers. West Papua has always had a higher IKP score than Papua Provinces in average. West Papua's IKP was 46.05 in 2021, with the food insecure category. Meanwhile, Papua's IKP was 35.48 in the category of very food-vulnerable. However, Papua needs to get a priority in handling comprehensive food vulnerabilities. Papua has a large area with several regencies/cities, so it has different characteristics of food insecurity dimensions (Indahyani and Maga 2023). Thus, the characteristics of food insecurity in each region need an appropriate and targeted program.

The food security condition from region to region can be seen based on the IKP. However, a composite index can disguise the failure of a program or vice versa (Faradis and Afifah 2020). It happens if the preparation of the index needs to be more transparent or can lead to inappropriate policies due to ignoring reality that is difficult to measure (OECD 2008). The picture of each district/city using an index results from calculations from several constituent indicators. Each district/city has different conditions based on each constituent indicator, so there may be a gap, or a region may be good just because one of the indicators has an excellent value, or vice versa. In addition, preparing the 2021 IKP data uses weights sourced from expert judgment recommendations from academics and the government (Badan Pangan Nasional 2022). It creates an element of subjectivity in determining the weight of the indicator.

Limitations on composite indices lead to the need for alternative approaches to measuring food security. Cluster analysis can be carried out as a complement in measuring food security. The purpose of cluster analysis is to group a set of objects into a group or clusters with the same characteristics (Puspita 2021). Various studies on food security groupings have been performed (Aini and Kurniawan 2019). The K-Means Clustering method was based on nine indicators and simplified into three factors using confirmatory factor analysis. Adha (2022) grouped districts/cities in the Eastern Region of Indonesia (Maluku, North Maluku, Papua, and West Papua Province) based on six food indicators, namely



Source: BPN 2022.
Figure 1 Map of Food Security Index at the Provincial Level in Indonesia in 2021.

the percentage of poor people, the percentage of food expenditure per capita per month, the percentage of households without access to electricity, the average length of schooling for girls, the percentage of households without access to clean water, and the life expectancy. The grouping was carried out by the hierarchical clustering method. In addition, other research by Rahayu *et al.* (2019) analyzed Indonesia's food security using the model-based clustering multivariate normal distribution method. The result was a mapping of food security clustering in each province of Indonesia.

As described previously, the food problem in the Land of Papua is a serious problem that needs attention. Thus, grouping districts/cities based on food security indicators with the proper clustering method is necessary *to* accommodate the similarities and differences in food security characteristics across the Land of Papua. Clustering methods based on probability distributions, such as model-based clustering, are considered superior to clustering methods based on distance, correlation, or association (Agustini *in* Hamidah *et al.* 2022). This is because model-based clustering can identify uncertainties during classification (Fraley and Raftery 2011; Gormley *et al.* 2023). Therefore, this study aims to provide a general overview of food security indicators and group districts/cities in the Land of Papua based on food security indicators and identify the characteristics of each cluster formed. With this study, it is hoped that the government can consider it in determining further policies related to food security in the Land of Papua.

METHODS

Research Location

This research focuses on the Land of Papua, which refers to the part of Papua Island within Indonesian territory. This focus is due to the region's heavy reliance on food sources that are highly vulnerable. Therefore, Land of Papua is one of the regions in Indonesia that is a priority for handling food security problems. Grouping regions based on similarity in food security characteristics is important to streamline and effectively implement government programs to overcome food security problems on this territory.

The unit of analysis was all districts/cities in the Land of Papua in 2021. The two provinces in the Land of Papua, Papua and West Papua, consist of 40 districts and 2 cities. Thus, this study's analysis units/datasets amounted to 42.

Data Source

The data sources used in this study are secondary data obtained through the publication of the 2021 National Socio-Economic Survey (Susenas 2021), the 2021 Health Worker Profile, and the 2021 Indonesian Nutrition Status Survey (SSGI 2021). Susenas is a survey that is routinely held once a year by the Central Statistics Agency (BPS) to collect data related to the socio-economic conditions of the Indonesian people. Health Worker Profile is a publication issued by the Ministry of Health of the Republic of Indonesia (Kemenkes RI) that describes the number and distribution of health workers in hospitals and health centers in all districts/cities in Indonesia. Furthermore, SSGI is a national-scale survey that aims to determine the development of the nutritional status of toddlers at the national, provincial, and district/city levels. This survey results from a collaboration between the Health Research and Development Agency (Balitbangkes) of the Ministry of Health of the Republic of Indonesia and BPS.

Research Variables

The first step that can be taken to unravel problems related to food security is to identify *proxy* indicators. These indicators differ from each other but have a strong relationship. In preparing the IKP, the indicators used amounted to 9 and were grouped into three dimensions: food availability, access, and utilization (Kementerian Pertanian 2021). The indicators for preparing the IKP are adopted from those used in preparing the GFSI, which are adjusted to the availability of data and information at the district/city and provincial levels in Indonesia.

In this study, the food security indicators used in the grouping only take from two dimensions: food access and food utilization. Table 1 provides more detail on the indicators used in the study and their operational definitions.

The lack of indicators related to the dimension of food availability in this study is a limitation of the research. This is because in urban areas, the indicator data that describes this dimension, namely the ratio of normative consumption per capita to the net production of local government carbohydrate sources (rice, corn, sweet potato, cassava, and sago, as well as rice stocks), cannot really describe the condition of food availability in the region. It should be noted that food availability in urban areas is not affected by production originating from its own region but comes from trade between regions (Kementerian Pertanian 2021). In addition, there is limited data at the district level on specific sources of carbohydrates, such as sago, which is the primary source

Table 1 List of Indicators Used in the Study

Dimension	Notation	Indicator	Operational Definition
Access to Food	*pov*	Percentage of population living below the poverty line	A person is considered living below the poverty line if their per capita monthly expenditure is lower than the poverty line.
	food	Percentage of households spending more than 65% of total expenditure on food	The percentage of households with food expenditure exceeding 65% of their total household expenditure compared to all households in a region.
	elec	Percentage of households without access to electricity	The percentage of households lacking access to electricity, either from PLN (State Electricity Company) or non-PLN sources, compared to all households in a region.
Food Utilization	*school*	Average years of schooling for females aged 15 and older	The average number of years females aged 15 years and above have attended school, including all years of education up to the highest level and grade completed.
	water	Percentage of households without access to clean water	Households using unsafe water sources for drinking, such as unprotected wells, unprotected springs, surface water, rainwater, and others, located within 10 meters from a latrine.
	health	Ratio of population to healthcare personnel adjusted for population density	The ratio of the total population to the number of healthcare personnel, adjusted for population density.
	stunting	Percentage of children under five with stunted growth	Children under five years old whose height is less than -2 Standard Deviations (-2 SD) based on the height-for-age index (H/A) specific to their age and gender.
	life	Life expectancy at birth	The average estimated lifespan of a newborn, assuming no changes in mortality patterns throughout their lifetime.

Source: BPS 2021.

of carbohydrates consumed by the residents of the Land of Papua (Kementerian Pertanian 2022).

Data Analysis

This study used two types of analysis methods: the descriptive analysis method and the inference analysis. The descriptive analysis aims to describe, In general, the food security indicators and the characteristics of regional clusters formed through the inferential analysis in the Land of Papua in 2021. The analysis tools used are graphs, tables, boxplots, and thematic maps. Meanwhile, inferential analysis is used to group districts and cities in the Land of Papua based on food security indicators. Model-based clustering was selected as the clustering method for regions in the Land of Papua because it can better handle overlapping data compared to other classical clustering methods.

Model-based clustering is a clustering technique based on probability and population distribution modeled as a finite *mixture distribution* (Scrucca *et al.* 2023). *Finite mixture distribution is* a flexible tool for modeling heterogeneous data, for example, from populations consisting of several hidden homogeneous subpopulations (Lecestre 2023; Nadeb & Torabi 2022). Thus, the assumption that must be fulfilled in this model is that the subpopulations obtained from a population have a certain distribution of opportunities, and each subpopulation formed from that population has different parameters from each other (Panić, Klemenc, & Nagode 2020).

Banfield & Raftery (1993) first developed a model-based clustering framework by decomposing eigenvalues from the covariance matrix. The development of *the model-based clustering* framework is as follows:

$$\Sigma_g = \lambda_g D_g A_g D_g^T \quad (1)$$

where:

λ_g : elliptical volumes presented in scalar form

D_g : orthogonal matrix of eigenvalues which is the orientation of Σ_g

A_g : diagonal of a matrix whose elements are proportional to the eigenvalue as well as the contour of the density function.

In applying *the mixture model,* the multivariate normal *finite mixture* model is the *most widely used compared to other types of* mixture models because the calculation is easy. However, in the data with outliers, the normal multivariate finite mixture *will result in inaccurate parameter estimation and grouping* (Giordani *et al.* 2020).

A multivariate finite mixture t *model can be used* to overcome data with outliers. The model is considered a more *robust* approach to overcoming unusual observations. Remember that the *t* distribution has a slower tail than the normal distribution to cope with data that contains *outliers* (Agustini 2017; Anton & Smith 2023; Hamidah *et al.* 2022; Lee & McLachlan 2022). The *finite mixture* t multivariate model assumes that X1, X2, ..., Xp is distributed *t* multivariate with groups as much as *g*. In general, the density function of *the finite mixture* multivariate model can be described as follows:

$$f(x_i;\pi_g,\mu_g,\Sigma_g,v_g) = \sum_{g=1}^{G} \pi_g f_g(x_i;\mu_g,\Sigma_g,v_g) \qquad (2)$$

where $g = 1,2,\dots,G$; $i = 1,2,\dots,n, \sum_g^G \pi_g = 1$; and

$$f(x_i;\mu_g,\Sigma_g,v_g) = \frac{\Gamma\left(\frac{v_g+p}{2}\right)\left|\Sigma_g\right|^{1/2}}{(\pi v_g)^{p/2}\Gamma\left(\frac{v_g}{2}\right)}\left(1 + \frac{\delta(x_i,\mu_g;\Sigma_g)}{v_g}\right)^{-\left(\frac{v_g+p}{2}\right)} \qquad (3)$$

and

$\delta(x_i,\mu_g;\Sigma_g) = (x_i-\mu_g)^T \Sigma_9^{-1}(x_i-\mu_g)$: the square of the distance of Mahalanobis between and $x_{i\ and}\ \mu_g$

$\mu_g = [\mu_{1g}\ \ \mu_{2g}\ \dots\ \mu_{pg}]^T$: vector mean group of g-by $\mu_{jg} = E[X_{jg}]$

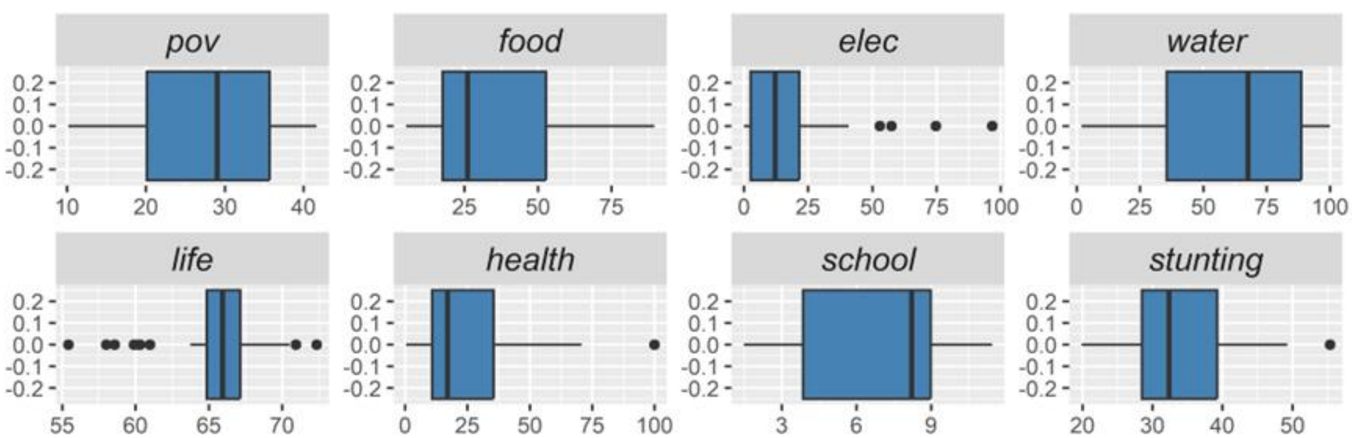
$\Sigma_g = \begin{bmatrix} \sigma_{11g} & \cdots & \sigma_{1pg} \\ \vdots & \ddots & \vdots \\ \sigma_{1pg} & \cdots & \sigma_{ppg} \end{bmatrix}$: covariant matrix of group g with

$\sigma_{jjg} = Var[X_{jg}]$; $\sigma_{jj*g} = Cov[X_{jg,}X_{j*g,}]$; $j \neq j$

v_g : degree of freedom of *g*th

If so, the t distribution will lead to a normal distribution. Thus, the parameter is considered a robust introductory parameter (Anton & Smith 2023; Hamidah *et al.* 2022). Briefly, the stages of this research are divided into several stages, which are as follows:

1. Conducting multivariate normal tests and multivariate *outlier detection* using a plot between *robust distance* and Mahalanobis *distance.* When the data is not normally distributed multivariate and has many outliers, *a based-clustering model* with a multivariate t distribution is better used (Anton & Smith 2023).
2. Selection of the *best based clustering model* in grouping districts/cities based on the maximum *Bayesian Information Criterion* (BIC) value. In this study, the selection of the best model was carried out by looking at the BIC criteria because it is the best criterion for *the mixture model* when compared to *the Akaike Information Criterion* (AIC) and *the Akaike Information Corrected Criterion* (AICc) (Dziak *et al.* 2020).The one-way manova test between *the clusters that have been obtained, this is done to find out whether the clusters formed are reliable.*
3. Cluster labeling and interpretation of the characteristics of each *cluster* that has been obtained.



Source: BPS and Kemenkes, 2021.
Figure 2 Boxplot of Food Security Indicators.

RESULTS AND DSCUSSION

Overview of Food Security in the Land of Papua in 2021

An overview of the food security indicators in the Land of Papua can be seen through the *boxplot* in Figure 2. *The boxplots* of the percentage of the population living below the poverty line (*POV*), the percentage of households without access to clean water (*water*), the life expectancy at birth (*life*), and the average length of schooling for girls over 15 years *(school*) show negative *skewness*). Thus, these indicators have more values above the average value of the related indicators. Meanwhile, *the boxplot* of the percentage of households with a proportion of spending on food is more than 65 percent to total expenditure (*food*), the percentage of households without access to electricity (*elec*), the ratio of the number of people per health worker to the level of population density (*health*), and the percentage of children under five with substandard height (*stunting*) shows the data distributed to the right (*positive skewness*. Thus, these indicators have more values than the related indicators' average value.

The boxplot in Figure 2 shows that several indicators of food security experience quite severe inequality, which is shown by a small box that contains many *outliers*. Some indicators that have severe inequality are the percentage of households without access to electricity (*elec*), the percentage of households without access to clean water (*water*), the ratio of the number of people per health worker to the level of population density (*health*).

In more detail, the districts/cities with the lowest and highest food security indicator achievements can be seen in Table 2. Based on the highest percentage of households without access to electricity is Puncak Jaya Regency, with a value of 96.76 percent, while in Jayapura City and Manokwari Regency, all households have been able to access electricity. All households in Paniai Regency, Central Mamberamo Regency, Yalimo Regency, Intan Jaya Regency, and Deiyai Regency do not have access to clean water. In contrast, in Jayapura City, only 1.93 percent of households cannot access clean water. The ratio of people per health worker to the population density level in Waropen Regency and Central Mamberamo Regency reached 100, while the lowest was in Jayapura City at 0.40.

Grouping of Districts/Cities Based on Food Security Indicators

As explained earlier in the methodology section, *model-based clustering* with a normal distribution of multivariate has the assumption that the data is normally distributed multivariate (Anton & Smith 2023; Scrucca *et al.* 2023). When the data is not normally distributed multivariate due to a large number of *outliers*, one alternative that can be used is *model-based clustering with* a multivariate t distribution, also known as *a multivariate* finite mixture t model (Agustini 2017; Anton & Smith 2023; Lee & McLachlan 2022). The multivariate normal assumption test was carried out using the *S*hapiro-Wilk multivariate normal test, which produced *a p-value* of 0.000 (less than an *alpha value* of 0.05). This shows that the assumption of multivariate normally distributed data is not met.

The next stage is the detection of *multivariate* outliers with *a distance-distance plot (*dd plot), which is a plot of the distance between the mahalanobis and *the robust* distance. Then, the value of the distance will be compared with the value of $\sqrt{\chi^2_{0,975;p}}$ as *a cut-off*, where p is the number of variables used (Iqbal *et al.* 2020; Siagian 2014). Based on this formula, the *cut-off* value in this study is 4,187. Observations that have a distance value above *the cut-off* will be included as *outliers.* Based on Figure 3, dd plot shows that the number of *outliers* in the data used is as many as 17 districts/cities or about 40 percent. The state of data that does not follow the normal distribution of multivariate and the

Table 2 Minimum and Maximum Values of Food Security Indicators in the Land of Papua in 2021

	Minimum		Maximum	
	Regencies/Cities	Value	Regencies/Cities	Value
elec	Kota Jayapura and Manokwari	0.00	Puncak Jaya	96.76
food	Kota Jayapura	5.14	Lanny Jaya	89.61
health	Kota Jayapura	0.40	Waropen and Mamberamo Tengah	100.00
life	Nduga	55.43	Mimika	72.36
pov	Merauke	10.16	Intan Jaya	41.66
school	Puncak	1.48	Kota Sorong	11.47
stunting	Kota Sorong	19.90	Pegunungan Bintang	55.40
water	Kota Jayapura	1.93	Paniai, Mamberamo Tengah, Yalimo, Intan Jaya, and Deiyai	100.00

Sumber: BPS (2021).

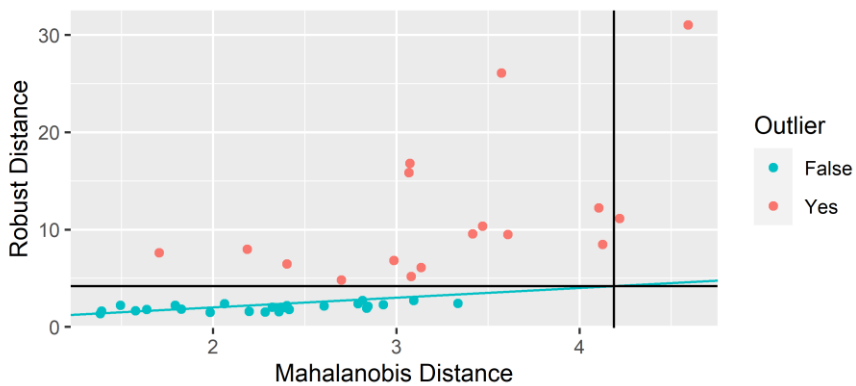
number of *outliers makes* the multivariate t distribution approach in *model-based clustering more robust.*

Model-based clustering with multivariate t distribution in this study uses the help of R software through the "*teigen*" package. In the *teigen package,* a total of 24 models can be formed; details and explanations of these models can be seen in the following literature (Andrews *et al.* 2018; Tomarchio, Bagnato, and Punzo 2022). The result of selecting the highest BIC value obtained was -860.77 in the UIUU model with the best number of *clusters* of two clusters (G=2). The formed UIUU model shows that the elliptical volume, shape, and degrees of freedom between the two *clusters* are different. In contrast, the cluster's orientation follows the axis's direction.

The average vector difference test between the two *clusters* with a one-way Manova test was carried out after obtaining the district/city cluster. The test is carried out to determine whether the cluster formed is trustworthy and can be interpreted (Agustini 2017; Siagian 2014). The one-way manova test assumes that both populations follow the normal distribution of multivariate and homogeneous variance-covariance matrix (de Melo *et al.* 2022; Pramana *et al.* 2018). The data for the two *clusters* formed in this study did not have a normal multivariate distribution, as shown in Table 3.

The homogeneity test of the variance-covariance matrix was carried out using the Box's M test. This causes the manova test with *Wilk's lambda test* statistics to be less precise. Statistics of *the Pillai's Trace test* can be performed if the assumption of the homogeneity of the variance-covariance matrix is not met (Lestari *et al.* 2018; Zhang *et al.* 2020). In addition, *Pillai's Trace* test statistics are also more *robust* against data that are not normally distributed multivariate (Ateş *et al.* 2019; Rencher 2002).

The statistical value of the *Pillai's Trace* test obtained was 0.791 with *a p-value* of 0.000 (less than 0.05), so H0 was rejected. This shows a difference in the two clusters'



Source: BPS and Kemenkes, 2021
Figure 3 *Distance-distance plot* (ddplot).

Table 3 Results of the Multivariate Normality Test Using Shapiro-Wilk on the Formed Clusters

Data	*W-statistic*	*p-value*
Cluster 1	0,771	0,000
Cluster 2	0,633	0,000

Source: BPS dan Kemenkes 2021.

Tabel 4 Food Security Status Based on the Comparison of Cluster Average Values to the 95% Confidence Interval of the Indicator Mean

Indicator	Food Security Status	
	Cluster 1	*Cluster 2*
Pov	High	Low
Food	High	Low
Elec	High	Low
Water	High	Low
Life	Low	High
Health	Medium	Medium
School	Low	High
Stunting	High	Low

Source: BPS and Kemenkes 2021.

average vector of food security indicators. Thus, *the food security clusters formed can be trusted, and the characteristics of each cluster can be interpreted.*

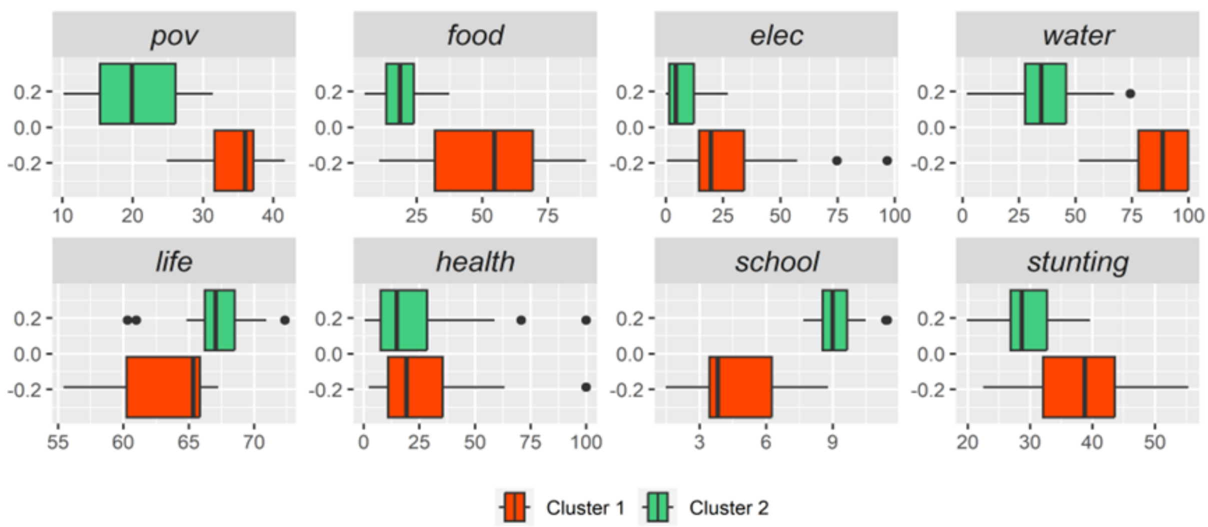
Analysis of Characteristics of Clusters Formed

The next stage is the interpretation or labeling of each formed cluster. In this study, the interpretation of the clusters formed was carried out by comparing the average value of the variables of each *cluster* with 95% of the average confidence interval (IK) of the variables, as carried out by Siagian (2014). He categorizes *clusters* with low achievement in a variable when the average value of the variable is below 95% IK; if it is at 95% IK, then the medium category and high category if the average variable is above 95% IK. The classification of food insecurity levels from the clusters formed is based on Table 4.

Based on Table 4, *cluster* 1 has poor achievements for all food security indicators except for the health variable. *Cluster* 1 has the characteristics of a high percentage of poor people (*POV*); many households have a portion of food expenditure of more than 65 percent (*food*), there are still many households that do not have access to electricity (*elec*) and clean water (*water*), life expectancy at birth (*life*) and the average length of schooling for girls over 15 years (*school*) is low, as well as a high percentage of *stunting* in children under five (*stunting*). Meanwhile, in *cluster* 2 it is very inversely proportional to *cluster* 1. This condition can also be seen through the boxplot in Figure 4, where there is a striking difference between the achievement of district/city food security indicators in *cluster* 1 and *cluster* 2. The difference that is not too noticeable is only in the health variable. Therefore, *cluster* 1 has low food security, while *cluster 2* has high food security. The full details of the members of each *cluster* can be seen in Table 5.

Pattiasina & Iswati (2019) explained that one cause of inequality in Papua is difficult access to the region. This is in line with the thematic map of the cluster results in Figure 5. Most of the districts/cities that are members of *cluster* 1 (low food security) are in mountainous areas and archipelagos. Difficult geographical conditions and unpredictable weather often cut off logistics access. Roads that are cut off are generally caused by landslides due to continuous high rainfall.

In *cluster 1* (low food security), two districts still have very low access to electricity; namely, more than 74.2 percent of households do not have access to electricity.

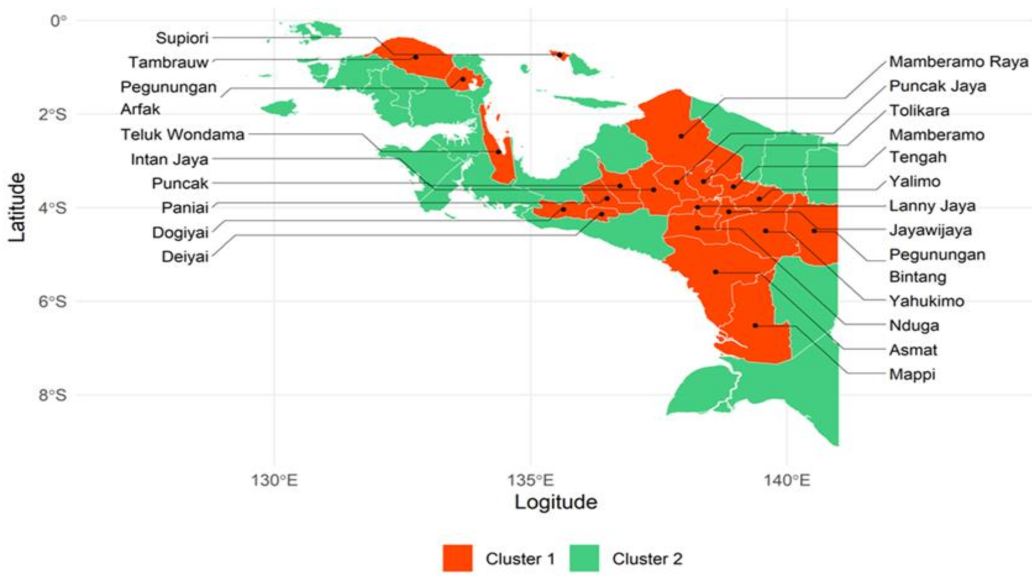


Source: BPS and Kemenkes, 2021
Figure 4 Boxplot of the Distribution of Each Food Security Indicator Variable Based on Clusters.

Table 5 List of Regencies/Cities in Each Cluster

Cluster with Low Food Security	*Cluster with High Food Security*
Asmat, Deiyai, Dogiyai, Intan Jaya, Jayawijaya, Lanny Jaya, Mamberamo Raya, Mamberamo Tengah, Mappi, Nduga, Paniai, Pegunungan Arfak, Pegunungan Bintang, Puncak, Puncak Jaya, Supiori, Tambrauw, Teluk Wondama, Tolikara, Yahukimo, Yalimo	Biak Numfor, Boven Digoel, FakFak, Jayapura, Kaimana, Keerom, Kepulauan Yapen, Kota Jayapura, Kota Sorong, Manokwari, Manokwari Selatan, Maybrat, Merauke, Mimika, Nabire, Raja Ampat, Sarmi, Sorong, Sorong Selatan, Teluk Bintuni, Waropen

Source: BPS and Kemenkes 2021.



Source: BPS and Kemenkes 2021

Figure 5 Map of Food Security Cluster Distribution in the Land of Papua in 2021.

In addition, at least 51.5 percent of households in Cluster 1 do not have access to clean water (See Figure 4). Good infrastructure development will catalyze human resource development in the Land of Papua (Mahani, 2023). Therefore, developing logistics infrastructure, particularly in remote areas, will enhance food security in the Land of Papua. Some of the districts included in *cluster* 1 with the lowest Food Security Index (IKP < 20) are Nduga, Intan Jaya, Central Mamberamo, Puncak, and Lanny Jaya Regencies.

CONCLUSION

Based on the research results, it is concluded that there is severe inequality in several indicators of food security as seen from a very high range value. The indicators that experienced severe inequality were the percentage of households without access to electricity, the percentage of households without access to clean water, and the ratio of the number of people per health worker to the level of population density.

Model-based clustering with *multivariate t* distribution produces two district/city *clusters* based on food security indicators. The model formed is UIUU, which means that the elliptical volume, shape, and degrees of freedom between the two *clusters* are different. However, the orientation of the *cluster follows* the direction of the axis. The results of the Manova test show that the clusters formed have average vector differences between *clusters* so the formation of *clusters* can be trusted.

Based on the clustering results, the districts and cities in Cluster 1 are characterized by a high percentage of poor populations. Additionally, a significant number of households allocate more than 65% of their expenditure to food. Moreover, many households in these areas still lack access to electricity and clean water, low life expectancy at birth and the average length of schooling for girls over 15 years old, as well as *a high percentage of stunting* in children under five. Meanwhile, *cluster* 2 has the opposite characteristics. Thus, *cluster* 1 is called a low food security cluster while *cluster* 2 is called a high food security cluster. Based on geographical characteristics, *cluster* 1 (low food security) has a geographical location in mountainous areas and islands. Difficult geographical conditions and uncertain weather make logistics access often cut off.

Based on the research results, the government is expected to make efforts to alleviate food insecure areas, especially in areas included in *cluster* 1 (low food security). Some of the districts included in Cluster 1 with the lowest Food Security Index (IKP < 20) are Nduga, Intan Jaya, Mamberamo Tengah, Puncak, and Lanny Jaya Regencies. Efforts that can be made are (1) the development of logistics infrastructure specifically for difficult areas, such as the construction of roads with the soil retaining wall method (DPT) to anticipate landslides due to high rainfall (2) the construction of renewable energy power plants to provide access to electricity under challenging areas (3) the management of water sources for clean water services for residents; (4) Improving access and quality of education through the provision of educational facilities and infrastructure as well as increasing the quantity and quality of educators.

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