

MAPPING FOOD SECURITY DIVERSITY IN SUMATRA: A K-MEANS CLUSTERING APPROACH

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Abstract

Food security remains a strategic issue in Indonesia, particularly in Sumatra, which plays a crucial role as one of the country's major food-producing regions. Despite its substantial agricultural potential, significant disparities in food security conditions persist across provinces. This study aims to identify regional typologies of food security and socioeconomic conditions in Sumatra using the K-Means Clustering approach. The analysis employs five indicators, namely the Food Security Index (FSI), Normalized Difference Vegetation Index (NDVI), Night-Time Light (NTL), agricultural production, and poverty rate. Data from ten provinces in Sumatra during the period 2019–2024 were utilized. The optimal number of clusters was determined using the elbow method, which indicated that three clusters provided the most appropriate grouping structure. The results reveal substantial heterogeneity among provinces. Cluster 1 consists of Bengkulu, Jambi, and Riau, characterized by moderate food security, relatively high economic activity, and moderate agricultural production. Cluster 2 includes the Riau Islands and Bangka Belitung Islands, which exhibit low agricultural production but relatively stable food security and low poverty rates. Cluster 3 comprises Aceh, Lampung, West Sumatra, South Sumatra, and North Sumatra, functioning as major food-producing regions with varying socioeconomic vulnerabilities. The findings uncover a food security paradox in Sumatra, where high agricultural production does not necessarily correspond to stronger food security outcomes, while regions with limited production can maintain relatively stable food security through economic integration and food distribution networks. These results highlight the importance of adopting region-specific food security policies that consider not only production capacity but also socioeconomic and accessibility dimensions.

Keywords: Food Security, K-Means Clustering, Regional Typology, Agricultural Production, Poverty, Sumatra

INTRODUCTION

The island of Sumatra holds significant potential for supporting national food security. Its rich natural resources, vast agricultural land, and diverse ecosystems make Sumatra a key pillar of national food security. However, this significant contribution and potential do not always translate into improved food security at the provincial level. Sumatra faces food insecurity challenges, both on the supply side and on the production side. Previous research indicates that disparities in food security persist between regions in Sumatra, in terms of food availability, access, affordability, and nutritional quality. Furthermore, this negatively impacts the increased vulnerability of poor households to food insecurity.

Food security at the provincial and district levels in Indonesia is represented by the Food Security Index (FSI) and mapped using the Food Security and Vulnerability Atlas (FSVA). The index generates a composite score based on the pillars of availability, access, and utilization. Therefore, the FSI serves as an instrument for evaluating current conditions and a tool for identifying food vulnerability in a region.

According to the June 2025 National Food and Nutrition Alert Executive Report, 18 provinces were on alert status for food availability. Of these, four are on the island of Sumatra (Riau, South

Sumatra, Bengkulu, and the Riau Islands). This indicates that the Sumatra region still faces serious challenges in terms of food availability.

Table 1. Food Security Index of Sumatra Island in 2024

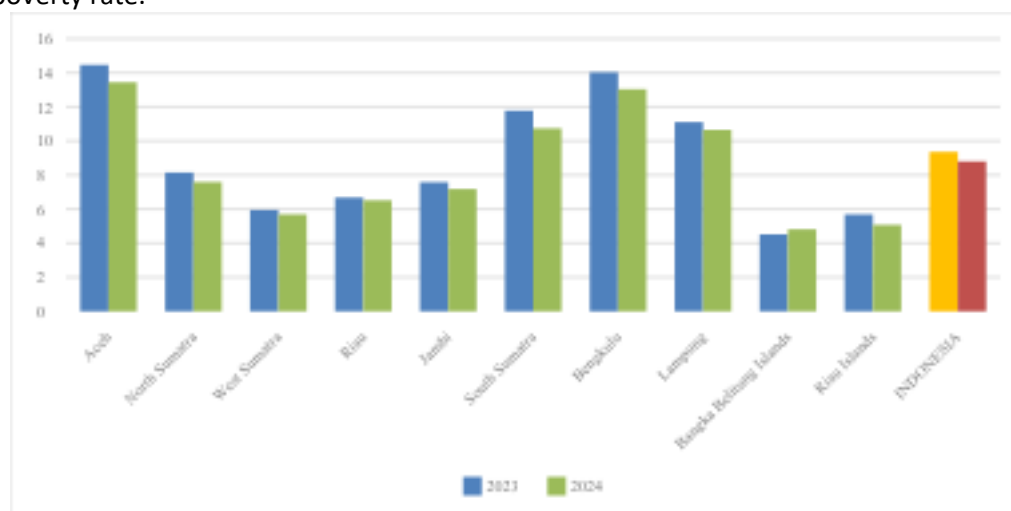
Provinces	FSI	Rank	FSI Group
Aceh	73,94	22	5
North Sumatra	77,49	15	6
West Sumatra	84,32	4	6
Riau	70,42	27	5
Jambi	74,94	20	6
South Sumatra	74,07	21	5
Bengkulu	73,39	24	5
Lampung	82,58	10	6
Bangka Belitung Islands	70,21	28	5
Riau Islands	66,29	30	5

Source: National Food Agency, 2025

Table 1 shows the Food Security Index (FSI) achievements on the island of Sumatra in 2024. Based on the data in Table 1, two provinces, West Sumatra (ranked 4th, FSI 84.32) and Lampung (ranked 10th, FSI 82.58), have FSI scores above 80 and are ranked tenth nationally. This indicates that these two provinces have superior food security compared to other provinces in Sumatra. Conversely, other provinces (Riau Islands and Bangka Belitung Islands) have moderate FSI achievements. This situation indicates disparities in food security among provinces in Sumatra. Provinces with moderate FSIs require attention because pressure from land conversion in some areas can increase food security risks.

Social and economic dimensions also play a crucial role in maintaining food security. Poverty can hinder households' access to nutritious food, while rising prices reduce purchasing power. Food security can be achieved through strong integration between development, the environment, and socioeconomic conditions.

Figure 2 shows the poverty rate on Sumatra Island in 2023 and 2024. Overall, the poverty rate has decreased, but several provinces have poverty rates above the national average. The poverty rates in Aceh (13.44%), Bengkulu (13.04%), and South Sumatra (10.74%) are above the national average. Provinces such as Aceh and Bengkulu show a combination of relatively high poverty rates with a "resilient" FSI, indicating structural vulnerabilities that require specific interventions. This situation indicates that Sumatra Island faces a double burden: a low FSI and a high poverty rate.



Source: Statistics Indonesia (BPS) 2025

Figure 1. Poverty Rate on Sumatra Island in 2023 and 2024

Food security cannot be separated from welfare, efforts to increase food security must be accompanied by more effective poverty alleviation strategies (Headey & Martin, 2016; Hjelm et al., 2016; Mahadevan & Hoang, 2016; Mukhlis et al., 2021). Poverty can be a major factor hindering household access to sufficient, nutritious food (Mahadevan & Hoang, 2016). People living below the poverty line tend to limit their consumption, resulting in low nutritional intake and vulnerability to food insecurity. In line with the concept of accessibility in food security, limited purchasing power is a barrier to achieving adequate food (Mahadevan & Hoang, 2016).

This phenomenon demonstrates that food security is not solely determined by production volume but also by other multidimensional factors. Development intensity, represented by non-economic variables such as Night-Time Light (NTL), is often associated with increased access to infrastructure, transportation networks, and food distribution capacity (Andiojaya et al., n.d.). However, unbalanced development can potentially deepen inter-regional disparities and further suppress the ability of poor communities to meet their food needs (Khoirunurrofik & D. Fitriatinnisa, 2021).

Furthermore, environmental conditions are a crucial factor in determining food security. The Normalized Difference Vegetation Index (NDVI) is an indicator that represents vegetation health (Bellón et al., 2017; Li et al., 2019). NDVI reflects a region's ability to maintain the sustainability of its ecosystem. Declining NDVI values due to land degradation or deforestation can threaten agricultural productivity, reduce land production capacity, and weaken food security (Li et al., 2019). Sumatra Island is one of the regions with the highest rates of land cover change in Indonesia, making this a crucial issue to address.

Empirically, the combination of NTL and NDVI provides analytical opportunities to uncover the mechanisms by which development interacts with land production capacity, ultimately affecting poverty and food security (Bellón et al., 2017). Several international studies have confirmed the ability of NTL and NDVI to capture development-environment trade-offs and predict aspects of well-being. However, the application of NTL and NDVI integration to FSI/FSVA in the Sumatran context is still relatively limited. This is crucial because Sumatra exhibits heterogeneous development patterns. Coastal corridors and plantation areas can exhibit high NTL while experiencing declining NDVI. Therefore, without analysis that examines spatial interactions and spillover effects between regions, food and development policies risk being misdirected.

LITERATURE REVIEW

Economic development in developing countries often faces a paradox between increasing economic activity and ecological sustainability (Setyawati, 2021). Within the capability approach framework proposed by Sen (1976), community well-being is measured not only by increasing income but also by the capacity to access basic resources such as food. Food security, in this case, is a concrete manifestation of this capability (Haini et al., 2023; Rabbitt et al., 2020). However, economic development, characterized by increased infrastructure, urbanization, and industrial activity, also has the potential to reduce environmental quality and impact the carrying capacity of food ecosystems (Olembo, 2020).

In contemporary literature, satellite imagery has become a primary approach for simultaneously measuring development dynamics and ecological conditions. Night-Time Light (NTL), or nighttime light intensity, is widely used as a proxy for economic development (Andiojaya et al., n.d.). Cross-country studies show that NTL is positively correlated with macroeconomic indicators such as Gross Regional Domestic Product (GRDP) and per capita income (Gibson et al., 2021). NTL data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor is even considered more accurate than the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), especially at the sub-national level due to its higher resolution and reduced oversaturation (Gibson et al., 2021). Similar findings were also demonstrated by Bruederle

& Hodler (2018) who confirmed that NTL can be used to map development distribution and spatial inequality in developing regions.

On the other hand, the Normalized Difference Vegetation Index (NDVI) is a commonly used indicator to measure vegetation health and crop productivity. Chen et al. (2024) in his review demonstrated that NDVI plays a crucial role in identifying the availability of vegetation that supports food systems and in detecting trade-offs between urbanization and environmental conservation. The relationship between NTL and NDVI is complex. Increases in nighttime light intensity, indicating growing economic activity, are often accompanied by decreases in NDVI values due to the conversion of vegetative land to residential or industrial areas (Chen et al., 2024).

In the context of Sumatra, this research gap becomes even more significant. Food Security and Vulnerability Atlas (FSVA) data shows that several provinces in Sumatra, such as Aceh, Bengkulu, and Lampung, still face high food security vulnerabilities, even though the NTL (National Land Use Index) shows a trend of economic growth in urban areas (Bappenas, 2022). This asynchronous increase in economic activity (NTL) and food security indicates a gap: development growth, as reflected in nighttime light intensity, does not automatically improve food security. However, in the Indonesian context, particularly in Sumatra, research using a spatial approach that combines NTL, NDVI, poverty indicators, and the food security index is still rare.

Based on this explanation, two main research gaps are clear. First, the limited literature integrating NTL and NDVI satellite indicators with socio-economic data, such as poverty and food security, in the Indonesian regional context. Second, empirical evidence in Sumatra demonstrates a disparity between economic activity growth and food security achievements that has not been adequately explained by previous research. By addressing this gap, research combining NTL (Natural Land Use Index), NDVI (Natural Land Use Index), poverty indicators, and the food security index in Sumatra will provide both theoretical and practical contributions to the formulation of sustainable development policies.

Research by Yanti et al. (2022) demonstrated that NDVI values can be used to estimate rice yields, suggesting that areas with higher NDVI tend to have better food security. Based on empirical findings, this study proposes the following hypotheses: 1) NDVI has a positive effect on the Food and Agriculture Index, 2) NTL has a negative effect on the FSI, 3) agricultural production has a positive effect on the FSI, 4) poverty rate has negative on the FSI, 5) agricultural production mediates the relationship between NDVI and the FSI, and 6) agricultural production mediates the relationship between NTL and the FSI. This series of hypotheses is expected to empirically test the complex relationships between economic development, ecological conditions, and food security in the Sumatran context.

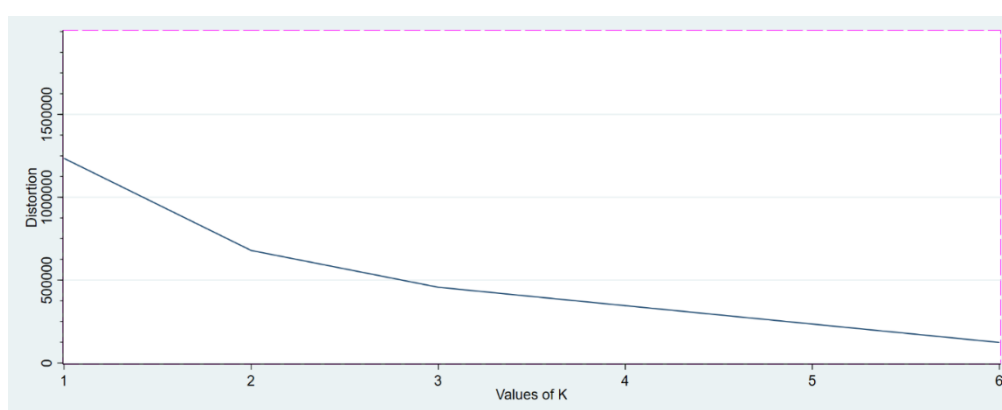
RESEARCH METHODS

This study uses secondary panel data covering ten provinces on the island of Sumatra during the 2019–2024 period. The provinces studied include Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, the Bangka Belitung Islands, and the Riau Islands. The data used comes from the National Food Agency (Bapanas), the Central Statistics Agency (BPS), and remote sensing data processing. The variables used include the Food Security Index (IKP), Normalized Difference Vegetation Index (NDVI), Night-Time Light (NTL), agricultural production, and poverty levels. IKP is used as an indicator of food security, NDVI as a proxy for vegetation condition, NTL as a proxy for economic activity, agricultural production as an indicator of food supply capacity, and poverty as an indicator of community access to food. This study uses the K-Means Clustering method to identify food security typologies and socio-economic conditions across provinces on the island of Sumatra. K-Means is a clustering method that aims to minimize variation within clusters (within-cluster variation) and maximize variation between clusters (between-cluster variation). Before the clustering process is carried out, all variables are normalized to have a comparable scale. The optimal number of clusters is determined using the elbow method by

evaluating the Within Cluster Sum of Squares (WCSS) value for various numbers of clusters. The elbow point is used as the basis for determining the most optimal number of clusters. Clustering is carried out using Euclidean distance. The analysis stages include: (1) data collection, (2) calculation of the average value of each variable during the research period, (3) data standardization, (4) determination of the optimal number of clusters using the elbow method, (5) the K-Means iteration process until a stable centroid is obtained, (6) interpretation of the characteristics of each cluster, and (7) visualization of the cluster results in the form of tables and maps.

RESULTS AND DISCUSSION

Figure 1 shows the application of the elbow method to determine the optimal number of clusters in research data. The horizontal axis represents the number of clusters (K), while the vertical axis shows the *distortion value*. (*within-cluster sum of squares*). As the number of clusters increases, the distortion value decreases because the data is divided into more homogeneous groups. However, after a certain point, the rate of decline becomes more gradual, so the curve no longer shows a significant decrease.



Source: data processed with STATA, 2025

Figure 1. *Distortion Score Elbow*

In these results, the curve shows a clear elbow point at K=3. This point indicates that three clusters is the most appropriate number, as it balances significant distortion reduction with minimal model complexity. Therefore, the choice of K=3 can be considered a valid basis for further cluster analysis, both spatially and statistically, in this study.

Table 1. *K- Means Results Clustering*

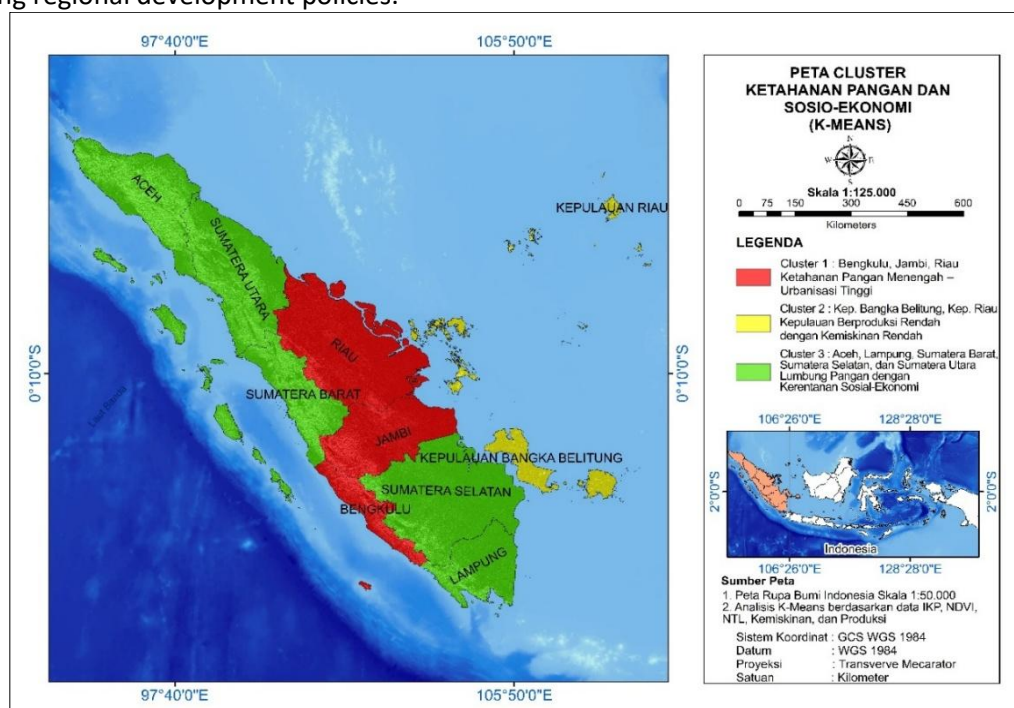
Province	Cluster	Average Value (2019-2024)				
		IKP	NDVI	ΣNTL	Poverty	Production
Bengkulu	1	69.34	0.70	0.46	14.44	283,594
Jambi	1	71.50	0.60	1.13	7.61	304,867
Riau	1	66.67	0.63	0.41	6.83	222,267
Bangka Belitung Islands	2	68.92	0.66	0.44	4.65	63,668
Riau Islands	2	63.41	0.70	0.52	5.79	666
Aceh	3	70.97	0.74	0.33	14.73	1,613,341
Lampung	3	78.25	0.71	0.36	11.74	2,589,540
West Sumatra	3	80.10	0.66	0.43	6.12	1,399,991
South Sumatra	3	70.84	0.65	0.73	12.12	2,736,026
North Sumatra	3	73.10	0.77	0.29	8.42	2,084,080

Source: data processed with STATA software, 2025

An analysis of food security and socio-economic conditions in Sumatra provinces was conducted using K-Means clustering, utilizing the IKP, NDVI, NTL, rice production, and poverty levels. The IKP reflects the level of food security on a scale of 0–100, NDVI is calculated as the total NDVI divided by the number of observation pixels to obtain the provincial spatial average, while NTL is calculated similarly as a proxy for urbanization and economic activity. Rice production is expressed in tons, and poverty is expressed as the percentage of the poor population.

Based on the elbow method, the optimal number of clusters formed is three, indicating differences in food security, production, urbanization, and socio-economic vulnerability characteristics between provinces. The formation of these three clusters allows for the identification of spatially and socio-economically homogeneous regional patterns.

Cluster 1 includes Bengkulu, Jambi, and Riau, with moderate food security (IKP 66.7–71.5), moderate to high NDVI (0.60–0.70), and relatively high NTL (0.41–1.13), indicating higher levels of urbanization. Cluster 2 consists of the Bangka Belitung Islands and the Riau Islands, characterized by low rice production ($\leq 64,000$ tons) but low poverty (4.65–5.79%), representing island regions with limited production capacity and relatively low socio-economic risks. Cluster 3 includes Aceh, Lampung, West Sumatra, South Sumatra, and North Sumatra, which act as food barns with high production (1.6–2.7 million tons), but have varying socio-economic vulnerabilities, indicated by poverty of 6.1–14.7% and low to moderate NTL (0.29–0.77), indicating limited urbanization. These results confirm the complex interrelationships between food security, production, urbanization, and socio-economic vulnerability at the provincial level, and serve as an important basis for formulating regional development policies.



Source: data processed with ArcGIS, 2025

Figure 2. Food Security and Socio-Economic Cluster Map (K-means)

The K-Means *clustering results* for food security and socio-economic conditions in Sumatra show three distinct groups of provinces, which can be better understood through the cluster distribution map (Figure 2). Spatially, Cluster 1 (Bengkulu, Jambi, Riau) is marked in red and spread across central and eastern Sumatra, reflecting medium food security with a relatively high level of urbanization, as seen from the greater NTL. Cluster 2 (Bangka Belitung Islands and Riau Islands) is colored yellow, located in the eastern archipelago of Sumatra, indicating low rice production but

low poverty, emphasizing the character of the archipelago with limited production capacity and low socio-economic risk.

Cluster 3 (Aceh, Lampung, West Sumatra, South Sumatra, and North Sumatra), in green, covers a larger area in the western and southern parts of Sumatra. This cluster acts as a food barn with high rice production but exhibits varying socioeconomic vulnerabilities. This distribution pattern indicates a geographic trend: the larger western and southern regions are centers of food production, while the central-eastern regions have medium to low food security with higher urbanization or are confined to the islands.

Overall, the cluster map reveals a link between geographic location and socioeconomic characteristics: provinces on the east coast tend to be highly urbanized or low in production, while provinces in the west and south, particularly the vast plains of Sumatra, act as food barns with high production but varying levels of poverty. This distribution underscores the importance of spatial considerations in formulating policies for food security and regional economic development.

CONCLUSION

This study aims to identify the typology of food security and socio-economic conditions of provinces in Sumatra Island using the K-Means Clustering approach by utilizing the Food Security Index (IKP), Normalized Difference Vegetation Index (NDVI), Night-Time Light (NTL), agricultural production, and poverty levels. Based on the results of the elbow method analysis, the optimal number of clusters formed is three clusters that are able to describe the heterogeneity of food security characteristics and socio-economic conditions between provinces in Sumatra. The clustering results show that Cluster 1 consisting of Bengkulu, Jambi, and Riau has the characteristics of medium food security with a relatively high level of economic activity and moderate food production capacity. Cluster 2 consisting of the Bangka Belitung Islands and the Riau Islands is characterized by a low level of food production, but has a relatively low level of poverty and a fairly stable food security condition. Meanwhile, Cluster 3 including Aceh, North Sumatra, West Sumatra, Lampung, and South Sumatra is the region with the largest food production capacity and plays a role as a regional food barn, although it still shows variations in poverty levels and socio-economic vulnerability. The research findings reveal a paradox of food security in Sumatra, where high food production does not always equate to a high level of food security in a region. Conversely, several provinces with relatively low production capacity are still able to maintain good food security through the support of economic activities, market connectivity, and interregional food distribution. This indicates that food security is not only determined by the aspect of food availability, but is also influenced by factors such as accessibility and the socio-economic conditions of the community. Overall, the research results emphasize the importance of a regional typology-based approach in understanding the dynamics of food security on the island of Sumatra. Grouping regions using the K-Means method can provide a more comprehensive picture of the characteristics of each province, thus providing a basis for developing food development strategies that are more appropriate to the conditions and needs of each region. Thus, efforts to improve food security need not only focus on increasing production, but also on strengthening food access, distribution connectivity, and improving community welfare.

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