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RESEARCH ARTICLE

Mapping Food Security in Indonesia: Geographic Clusters and Regional Disparities

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Abstract Food security has become a global issue, and represents the first of the Sustainable Development Goals, which is zero hunger. Many countries, including Indonesia, have set food security as the central policy on their development agenda. There has been some research into food security issues, but primarily this has no spatial context. This research identifies spatial clusters—high-high, low-low, high-low, and low-high—across four food security measures: the Food Security and Vulnerability Atlas, the Dietary Diversity Score, the Food Variety Score, and the Calorie Intake. It explores 514 districts in Indonesia for 2019 using Exploratory Spatial Data Analysis (ESDA, Global Moran's I) and Local Indicators of Spatial Association (LISA). The data for measuring food security come from SUSENAS (the National Socio-Economic Survey), Statistics of Indonesia and the National Food Agency. The research reveals the presence of regional food security in Indonesia. Eastern Indonesia faces challenges from food insecurity issues. The LISA result shows that there are low-low clusters in eastern Indonesia because of geographical isolation, poor economic performance, and a lack of infrastructure. Conversely, high clusters in western Indonesia, especially in Java Island, benefit from favorable agricultural conditions, a robust infrastructure, and diverse food markets. High-low clusters highlight that there are urban centers with better food access amidst less secure areas, while low-high clusters face economic and logistical challenges despite being near food-secure regions. This local analysis offers nuanced insights beyond the results of a standard ESDA, emphasizing the need for tailored policies to address regional disparities. Future research should explore the determinants of food security using spatial and non-spatial econometric approaches and should apply convergence analysis to identify the factors driving prosperous regions, providing benchmarks for enhancing food security across all districts.

1. Introduction

Food security has become a global issue that represents the first of the Sustainable Development Goals, namely zero hunger. Many countries have set food security as the primary aim of their development agendas. In 2012 the government of Indonesia issued Act No 18 Year of 2012 about Food, which is a guide for delivering food policy in Indonesia. The purpose of this Act is stated in Article 3: "Food implementation is carried out to meet basic human needs that provide benefits in a fair, equitable, and sustainable manner based on Food Sovereignty, Food Independence, and Food Security".

As regards the implementation of the Act, the National Food Agency (NFA) is the government body that has the task of carrying out government duties in the food sector in order to maintain food security in Indonesia, through the coordination, formulation, and determination of policies for food availability, the stabilization of food supplies and prices, food insecurity and nutrition, the diversification of food consumption, and food safety (Presidential Regulation (Perpres) Number 66 of 2021 Concerning the National Food Agency, 2021).

The NFA uses the Food Security and Vulnerability Atlas (FSVA) to monitor food security in each district in Indonesia. The indicators used for the FSVA employ the framework of food and nutrition security as the basis for analysis. Food security has three pillars—availability, access and utilization—and integrates important nutrition and vulnerability considerations (Ministry of Agriculture Indonesia; World Food Programme, 2015).

The FSVA is a thematic map that depicts a geographical visualization of areas susceptible to food insecurity. It categorizes the food security index values into six categories: very vulnerable, vulnerable, mild weak, mild resistant, resistant, and very resistant (Badan Pangan Nasional, 2023).

In the FSVA, as mentioned above, the concept of food security rests on three main pillars: availability, access, and utilization. Food availability pertains to the physical presence of food in a specific area, including through domestic production, government reserves, and external sources like imports and aid. Food access refers to a household's ability to obtain sufficient nutritious food. Food security can be achieved through various means, including self-production, purchases, bartering, or receiving aid. It is important to note that even if food is available in an area, specific households might face physical, economic, or social barriers preventing them from acquiring adequate quantities or an adequate variety of food

(Ministry of Agriculture Indonesia; World Food Programme, 2015).

Lastly, food utilization represents how households use the food they can access and how individuals absorb nutrients. This pillar encompasses various factors such as food storage and preparation methods, water safety, hygiene practices, feeding habits (especially for those with special dietary needs), fair food distribution within households, and the overall health status of family members. Interestingly, because of the significant role played by women in enhancing their family's nutritional intake, particularly for young children, the mother's education level is often used to indicate a household's food utilization (Ministry of Agriculture Indonesia; World Food Programme, 2015).

Besides the FSVA measurement, there are other measurements that could be used to monitor food security: calorie intake, the food variety score (FVS), and the dietary diversity score (DDS). The calorie intake measurement refers to the number of calories in the daily diet. At the global level, the average calorie needs vary by country according to its age and gender distribution, but the consensus is that a globally average diet should provide 2,100 kcal per capita per day (FAO, et al., 2020).

The FVS is measured as the number of items eaten by any household member on the previous day from a list of 104 food items (Hatløy, et al., 2000). The more diverse the food consumed by a household or individual, the more secure they are. In addition, the DDS is used, which measures how many of several food groups were consumed by a household or individual on the previous day (Hatløy et al., 2000). The essential difference between the FVS and the DDS measurements is the categorization of the food basket. The FVS uses items, while the DDS uses food groups.

Food security is still unequal in Indonesia. In general, the western region of Indonesia, especially the island of Java, is more food-secure than the eastern region. Figure 1 shows a darker color in the western region of Indonesia, which means that this region is more food-secure. For example, using the FSVA figures, all districts/cities on the island of Papua, except the city of Merauke, have an FSVA index of less than 5. This illustrates that most regencies/cities on the island of Papua have a very vulnerable (priority) or vulnerable (second priority) FSVA status (Badan Pangan Nasional, 2023).

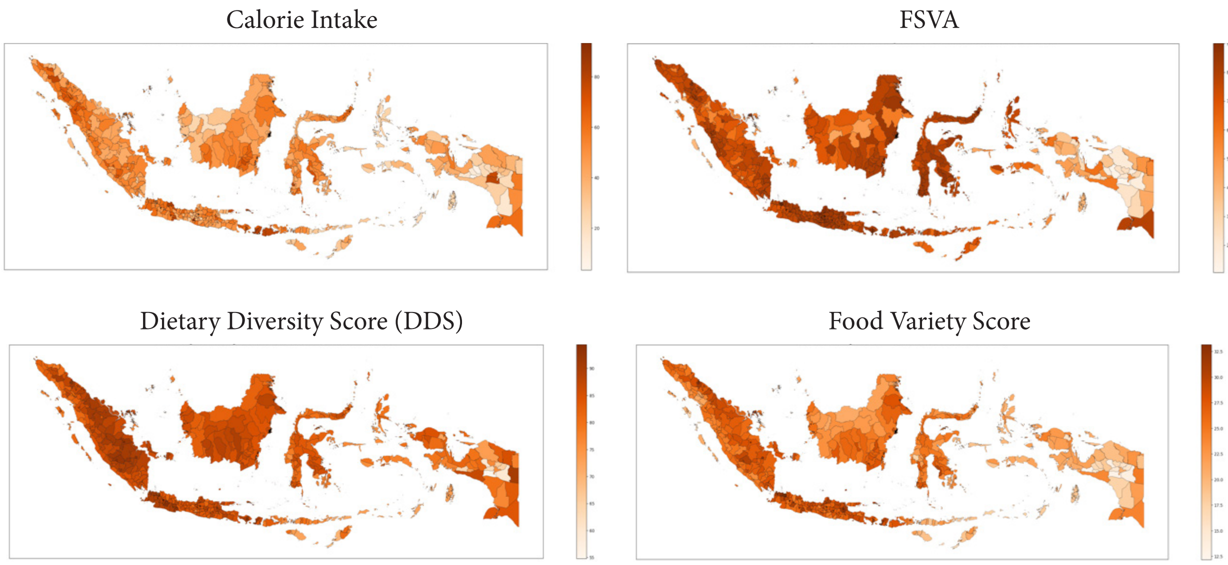
Some of the existing research on food security in Indonesia uses cross-sectional data or data panels (Aguilera & Jatmiko, 2023; Amrullah, et al., 2023; Herlina et al., 2020; Kadir, et al., 2023; Nugroho et al., 2022; Vidyarini, et al., 2021; Widada, et al., 2017; Yuliana, 2018). However, it does not describe the spatial aspect. The inclusion of spatial elements in research with cross-sectional data or data panels is beneficial for researchers and policymakers because it provides detailed nuances for each region.

Furthermore, there are several reasons why it is essential to understand the location patterns for the different food security measurements. First, identifying spatial clusters for food insecurity allows for a more efficient allocation of resources and targeted policy interventions. Second, different measurements capture different aspects of food security, and analyzing their spatial patterns provides a more comprehensive view of the issue. Third, a comparison of spatial patterns over time can help to evaluate the effectiveness of food security interventions and policies. Fourth, understanding the spatial patterns of food security can provide information for related sectors such as agriculture, health, and economic development. This study explores 514 districts in Indonesia for 2019 using ESDA. The data used come from Statistics of Indonesia and the NFA.

2. Methods

The study employs ESDA, specifically Global Moran's I, and Local Indicators of Spatial Association (LISA). ESDA uses a number of visual and numerical methods to analyze spatial data, and these methods can be categorized into two primary types. The first type use classical non-spatial descriptive statistics that are dynamically connected to GIS maps and spatial objects. The second type focus on identifying spatial interactions, relationships, and patterns by utilizing a spatial weights matrix, hypothesis testing, and various metrics (Grekousis, 2020).

Furthermore, ESDA describes and summarizes spatial data distributions, identifies spatial outliers and clusters, and examines spatial autocorrelations to explore spatial relationships through Global Moran's I and LISA analysis.



Source: Statistics of Indonesia and National Food Agency, 2019, processed

Figure 1. Food Security Map 2019

Specifically, Global Moran's I measures spatial autocorrelation, determining whether the pattern of a variable is clustered, dispersed, or random across a geographic area. Furthermore, LISA identifies local clusters and spatial outliers, offering a more detailed insight into spatial patterns at a regional level (Grekousis, 2020).

The ESDA method has two main steps, namely global investigation and local exploration. Calculating Moran's I represents the global investigation. This investigation measures the similarities and dissimilarities between observations across space. The formula for Global Moran's I (Moran, 1950) is written below:

$$I = \left(\frac{n}{\sum_i \sum_j w_{ij}}\right) x \left(\frac{\sum_i \sum_j w_{ij}(y_i-\mu)(y_j-\mu)}{\sum_i (y_j-\mu)^2}\right) \quad \text{....................(1)}$$

where the w_{ij} represent the elements of the spatial weight matrix W between two districts i and j, μ is the mean of y , and i,j = 1,…, n.

Global Moran's I is a statistic used to measure the global spatial autocorrelation of a dataset, not simply the local spatial pattern. Spatial autocorrelation refers to the degree to which similar values are clustered together in a spatial distribution. Moran's I helps to determine whether the observed spatial pattern is clustered, dispersed, or random. The value of Moran's I ranges from -1 to +1, with a value near -1 indicating dispersion and a value close to +1 indicating the presence of clustering (Grekousis, 2020).

Knowing the local measurements aids policymakers in making region-specific decisions and adds nuance to spatial analysis. LISA identifies local clusters and spatial outliers, unlike Global Moran's I, which provides a single summary statistic. LISA detects local patterns, identifies "hot spots," and assesses the influence of individual locations on the global statistics, revealing spatial relationships not visible in the global analysis. The formula for LISA (Anselin, 1995) is:

$$I_i = \; z_i \sum_j w_{ij} z_j I_i = \; z_i \sum_j w_{ij} z_j \quad \text{....................................(2)}$$

where the w_{ij} represent the elements of the spatial weight matrix W between two districts i and j, and z_i and z_j are standardized numbers for observations i and j.

LISA outputs are often shown using cluster and significance maps. A cluster map reveals four categories: high-high clusters (high values surrounded by high values), low-low clusters (low values surrounded by low values), and spatial outliers (high-low and low-high clusters). High-low clusters have high values surrounded by low values, and low-high clusters have low values surrounded by high values. This helps to identify local patterns and spatial relationships (Anselin, 1995).

The research included 514 districts in Indonesia in 2019 and applied the weight spatial matrix to calculate the Global Moran's I and apply LISA. In research that uses spatial analysis, the researcher should first identify the neighbors in which the contiguity matrix is commonly used. This contiguity is based on districts across Indonesia, and the method works in continental areas but not in regions where there are islands separated by sea. The challenge is to deal with the islands that make up Indonesia.

Previous literature has utilized the Thiessen polygon method to deal with the geographical characteristics of Indonesia. The Thiessen polygon method creates a tessellation (a way to divide an area into regular subareas) that encloses all locations that are closer to the central point than to any other point (Anselin, 2020).

The boundary of a Thiessen polygon is artificial, based on the central point of each district. Research by Miranti and Mendez (2023) and Santos-Marquez et al. (2022) utilized Thiessen polygons to create proximity at the district level. Other research conducted by Mendez and Siregar (2023) used Thiessen polygons to analyze the space-time dynamics of the administration of two levels of unemployment by simultaneously accounting for their serial persistence, spatial dependence, and common factors. Figure 2 displays Thiessen polygons and their borders at the district level in Indonesia. After the Thiessen polygons have been constructed, the researcher defines the neighborhood of each district. The research uses a queen contiguity matrix to represent the neighbors for each district.

The food security measurements are based on data from Statistics of Indonesia and the National Food Agency data. The first measurement uses the food security and vulnerability atlas (FSVA) with its index measurement. The FSVA is a thematic map that gives a geographical visualization of areas susceptible to food insecurity. The design of the FSVA is based on three aspects of food security, namely food availability, affordability/

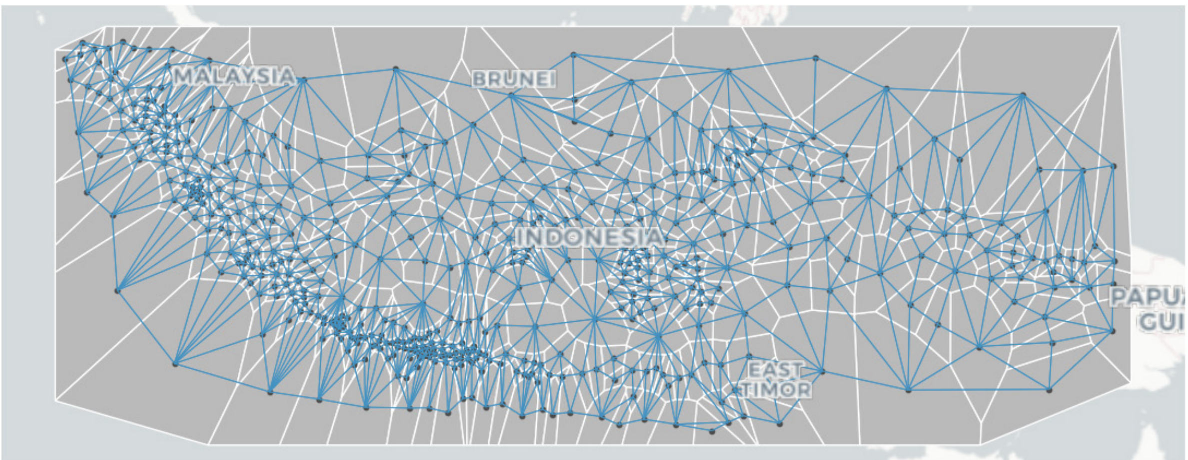


Figure 2. Centroid, Thiessen Polygon and Spatial Connectivity (Queen Matrix) at District Level in Indonesia 2019

access, and utilization (Badan Pangan Nasional, 2023). The FSVA categorizes the scores for the food security index into six categories: very vulnerable, vulnerable, slightly vulnerable, slightly resistant, resistant, and very resistant.

The second measurement is calorie intake, which measures how many calories are consumed daily. In Indonesia, the suggested calorie intake is based on the calories consumed in one day. In 2013, the Government of Indonesia issued the Regulation of Ministry of Health Republic of Indonesia No 75 Year 2013 about Nutrition Standard (2013) which states a minimum requirement for daily food of 2,150 kcal/person/day and for daily protein of 57 grams/person/day. The threshold was changed in 2019, when the caloric intake threshold was cut to 2,100 kcal/person/day (Regulation of Ministry of Health Republic of Indonesia No 28 Year 2019 about Nutrition Standard, 2019). Households or persons whose calorie intake is below the threshold are deemed to have experienced food insecurity.

The third measurement is the food variety score (FVS). The FVS is defined as the number of food items, on a list of 104 food items, eaten by any household member on the previous day (Hatløy, et al., 2000). In the original research, all the food items were given an equal weight. The households were divided into tertiles, to give a high, a medium and a low FVS, where a high was for more than 18 items, a medium score for between 14 and 18 and a low score for between 4 and 13 items. Because this study only had limited data, it counted the percentage of food items consumed by the household directly. The maximum percentage was 100 per cent, which would mean that the household consumed all the food items on the SUSENAS list (182 food items).

The last food security measurement that was used in this study is the dietary diversity score (DDS), which means the number of food groups represented in what was consumed by the household on the previous day (Hatløy et al., 2000). The DDS was generated from the same list as the FVS. Different definitions of DDS have been suggested in recent years, with variations in the number of food groups to include and their composition and in the dietary assessment methods used. The number and composition of the food groups are often different since they reflect the aim of a specific study; therefore, there is no consensus regarding the ideal number of food groups in a DDS.

There are challenges to the application of the DDS, because of the differences in food in different cultures. A DDS developed for one culture will not necessarily be the same as one used in another, but the theory and approach for developing the score can be used across cultures (Hodgson, et al., 1994). This study used 13 food groups because of the data available in the SUSENAS data, which aligns with the study by Hatløy, et al. (2000). The food groups are grains, tubers, fish, shrimp or shellfish, meat, egg or milk, vegetables, nuts, fruits, oil and coconuts, beverages, seasonings, other foods, and prepared food. In this research, the DDS was expressed as a percentage. The higher the percentage, the greater the food security. The assumption is that a household will first secure stable food and then move into tertiary food. In the research of Hatløy, et al. (2000), the DDS was divided into tertiles, which gave three categories: high for a score of 3 to 8, medium for a score of 6 or 7 and low for a score of 2 to 4.

3. Results and Discussion

This results and discussion section will be divided into three main parts: a statistical description of the data, the Global Moran's I analysis, and the LISA analysis. Descriptive statistics (distribution of data, range) are essential for understanding the data: they help to quantify the extent of variation and allow for comparisons between different datasets.

The output for the first analysis is presented in Table 2, which provides descriptive statistics on the food security

Table 1. Variables and Data Sources

Variable	Source
Food Security and Vulnerability Atlas (FSVA)	National Food Agency
Calorie Intake	SUSENAS 2019a, Central Bureau of Statistics
Food Variety Score (FVS)	SUSENAS 2019a, Central Bureau of Statistics
Dietary Diversity Score (DDS)	SUSENAS 2019a, Central Bureau of Statistics

Source: Statistics of Indonesia and National Food Agency

Table 2. Descriptive Statistics for Food Security Measurements

Description	Food Security Vulnerability Atlas	Food Variety Score (FVS)	Dietary Diversity Score (DDS)	Calorie Intake
Observations	514	514	514	514
Mean	71.23	25.46	83.57	48.97
Std	14.38	3.69	5.35	13.00
Min	10.56	12.18	54.81	3.38
Max	90.05	33.18	94.43	93.4
25%	67.04	23.33	80.97	41.51
50%	75.39	26	84.42	49.68
75%	80.65	27.91	87.08	57.25

Source: Statistics of Indonesia and National Food Agency, 2019 measurements. The data shows that the FSVA ranges from 10.56 to 90.05, with a standard deviation of 14.38 and a mean of 71.23. The standard deviation of the calorie intake is the highest among the food security measurements constructed from household surveys. The value is 13, whereas the standard deviations for the DDS and FVS are 5.35 and 3.69, respectively. In other words, the calorie intake scores are more spread out, indicating greater variability.

The second analysis calculates the Global Moran's I statistic. Figure 3 presents the Global Moran's I values for the four variables related to food security in Indonesia.

Overall, the Global Moran's I value for all the variables and the significant p-values indicate spatial clustering in food security and nutritional metrics across Indonesia. The highest degree of spatial autocorrelation is the food variety score, with a value for Moran's I of 0.92 and a p-value of 0.001, suggesting a high degree of spatial clustering in the food variety score. On the other hand, the calorie intake variable has the lowest value for the Global Moran's I, at 0.79.

A Global Moran's I scatter plot only informs us that there is spatial autocorrelation, but does not specify the location of that autocorrelation. Local indicators for spatial autocorrelation can identify and analyze local spatial patterns within a dataset, whereas global measures like the Global Moran's I cannot achieve this through the decomposition of global indicators into the contributions of individual observations. The decomposition allows the study to detect local clusters, hot spots, cold spots, and spatial outliers (Anselin, 1995). This localized analysis is essential for understanding the spatial heterogeneity and pinpointing areas that exhibit significant spatial autocorrelation. It is valuable as it allows policymakers to deliver the policy more specifically in smaller areas. As a result, the policy outcome will get good results with minimum resources.

Based on the LISA cluster map in Figure 4, regions with a low-low cluster appear mainly in eastern Indonesia for all the food security measurements. The low-low clusters (blue areas) have low food variety scores and are surrounded by other regions with low scores. This indicates areas where food insecurity arises from limited food variety that is due to geographical isolation, a lack of infrastructure, or economic challenges affecting food access and diversity.

Research by Amrullah et al. (2019) highlights that households in rural or backward regions are more likely to experience food insecurity, which is the result of geographical isolation. In addition, Akbar et al. (2023) revealed that living in an isolated location, especially in an underdeveloped non-urban region, can contribute to food insecurity. The problems with geographical access may hinder access to markets, resources, and infrastructure, impacting food availability and affordability (Thow et al., 2019).

Geographical isolation leads to a lack of infrastructure because of the difficulty of establishing access in a complex geographical region. Eastern Indonesia is an underdeveloped region with challenging geographical conditions, such as in Papua, which means that investment in infrastructure such as roads and ports is rare. Research by Wahyuni et al. (2022) found that, in 2014, only 26.39 per cent of the area of Papua and West Papua had paved roads and only 39.4 per cent had all-season road access. In the next six years, these percentages

Figure 3. Moran's I Scatter Plot on Food Security at District Level in Indonesia 2019

did not increase significantly, rising to 29.59 per cent of rural areas with paved roads and 39.32 per cent with all-season road access.

In contrast, the high-high clusters (red areas) are primarily located in the western part of Indonesia. These regions have high food security and are surrounded by other regions with similarly high scores. In addition, this clustering suggests areas where food security is consistently high, which may be due to favorable agricultural conditions, diverse food markets, effective distribution systems and a high wealth level. For instance, Java Island has a high cluster presence for all food security measurements.

Java Island has good infrastructure, such as roads, for effective distribution systems (Wahyuni et al., 2022). Java Island also has a long history, under the Dutch colonial government, of a focus on establishing infrastructure, such as building roads, railways, telegraphs, bridges, and irrigation systems. This policy encouraged Java to produce more profitable commodities for the European market (Rinardi, 2020). Java Island also has good soil for planting, compared to outer Java Island, because of its volcanic mountains (Anda & Dahlgren, 2020; Purwanto et al., 2020). In addition, Western Indonesia, especially Java Island, has diverse food markets because of its wealth. The western part of Indonesia has higher socio-economic characteristics than eastern Indonesia.

As for the other areas, high-low (orange) areas are outliers that represent regions with high food security scores surrounded by areas with food insecurity (low scores for food security). These outliers might be urban centers or regions with better access to food that stand out from their surroundings in terms of food access. High-low areas could be used as the starting point for policymakers to enhance their policy on food access equity. In other words, high-low areas could help the government to spotlight areas that they should prioritize.

For instance, Merauke City in Papua Province is a high-low area in three of the food security measures (the food variety score does not show this result). The government could quickly identify why the Mappi and Boven Digoel Districts (on the north side of Merauke) include low-low clusters by comparing the determinants of food security in the two areas. The government could then deliver specific policies to enhance particular determinants to raise the food security level in Mappi and Boven Digoel.

Like high-low regions, the outliers in low-high (light blue) areas could help policymakers to decide what to do. Low-high outliers could be areas facing specific challenges, such as economic constraints or logistical issues, preventing them from benefiting from the food security achievements of their surrounding regions.

Local analysis of the clusters using the four food security measures provides greater nuances than the ESDA standard, which focuses on a single food security measurement. Researchers can also identify areas that fall into low-low clusters from the perspective of the four food security measurements. As a result, it can be determined which areas should be prioritized for development by applying different approaches simultaneously.

Furthermore, the districts mentioned in Table 3 are in a low-low cluster for all four food security measurements. This indicates that these regions have consistently low scores across all the indicators, suggesting significant challenges and systemic issues in food security. These may include limited agricultural productivity, inadequate supply chains, and socio-economic barriers that prevent access to a diverse and sufficient diet. By focusing on these areas, policymakers can work towards improving food security and reducing the disparities highlighted in these regions by the LISA map.

For example, West Southeast Maluku is included in the low-low cluster for all food security measurements. The government must improve people's purchasing power so that they can meet the recommended calorie intake. In line with that, improving logistics, based on sea transportation into the region, is necessary to provide different foods. West Southeast Maluku (the Tanimbar Islands District) is located in the middle of the Arufu Sea.

Different policies need to be applied to low-low regions in mainland areas, such as Paniai District. This district is in the middle of West Papua Province, which has no sea (it is a landlocked district). The policies that need to be implemented in this area differ from those in the West Southeast Maluku

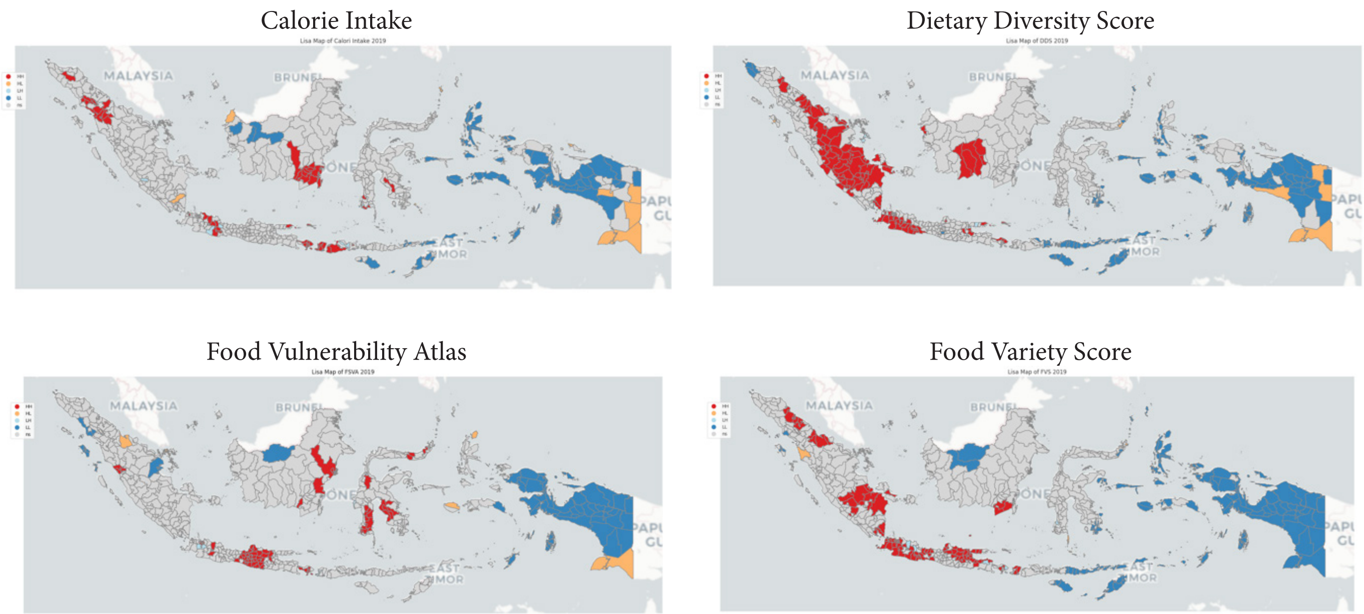


Figure 4. LISA Map of Food Security in Indonesia 2019

Table 3. Regions with Similarity (Low-Low Clusters) in Food Securities Measurements

District ID	District	Food Variety Score	Dietary Diversity Score	Calorie Intake	Food Security and Vulnerability Atlas
8101	West Southeast Maluku	0.006	0.006	0.001	0.017
8102	Southeast Maluku	0.004	0.006	0.002	0.002
8105	Aru Islands	0.001	0.007	0.001	0.001
8107	Seram Bagian Timur	0.009	0.027	0.005	0.004
8172	Tual City	0.003	0.007	0.004	0.01
9101	Fakfak	0.014	0.038	0.015	0.002
9102	Kaimana	0.001	0.005	0.002	0.001
9404	Nabire	0.001	0.004	0.001	0.001
9410	Paniai	0.001	0.002	0.001	0.001
9415	Asmat	0.001	0.001	0.014	0.001
9419	Sarmi	0.001	0.003	0.021	0.001
9420	Keerom	0.001	0.004	0.044	0.001
9426	Waropen	0.001	0.038	0.003	0.001
9428	Mamberamo Raya	0.001	0.004	0.001	0.001
9431	Central Mamberamo	0.003	0.009	0.01	0.001
9432	Yalimo	0.001	0.002	0.002	0.001
9433	Puncak	0.001	0.001	0.001	0.001
9434	Dogiyai	0.001	0.026	0.001	0.001
9436	Deiyai	0.001	0.001	0.002	0.001

Source: Author's analysis of data from Statistics of Indonesia and National Food Agency.

district. Repairing roads or improving access to pioneer logging can be a solution to encourage the distribution of varied foodstuffs.

4. Conclusion

This research identifies high-high, low-low, low-high and high-low clusters for four different food security measurements: food security and vulnerability atlas (FSVA), dietary diversity score (DDS), food variety score (FVS), and calorie intake. There are low-low regions for all food measurements in eastern Indonesia. The potential determinants are geographical isolation, economic performance, and infrastructure (connectivity and irrigation).

On the other hand, high-high clusters, which are predominantly located in the western part of Indonesia and particularly on Java Island, indicate regions with consistently high food security. This is likely due to favorable agricultural conditions, diverse food markets, effective distribution systems, and higher wealth levels. Java Island benefits from robust infrastructure, such as well-developed roads and irrigation systems, facilitating efficient food distribution. Additionally, volcanic mountains contribute to its fertile soil, enhancing agricultural productivity compared to other regions.

Furthermore, high-low clusters are outliers in which areas with low scores surround regions with high food security scores. These areas, often urban centers with better food access, highlight disparities and can guide policymakers in addressing food access equity. In addition, low-high clusters indicate regions that, despite being surrounded by food-secure areas, face challenges such as economic or logistical issues. These clusters provide valuable insights for targeted policy interventions to improve food security in less advantaged areas.

Local analysis using the four food security measures provides greater nuance than standard ESDA, identifying areas in low-low clusters across all four indicators. Regions like West Southeast Maluku and Paniai District face systemic food security challenges, including low agricultural productivity and socio-economic barriers. West Southeast Maluku requires better sea-based logistics and improved purchasing power to meet the inhabitants' calorie needs, while Paniai District, being landlocked, needs a better road infrastructure to facilitate food distribution. Tailored policies for each area can help address these disparities and improve overall food security.

Further research should include investigating the determinants of each food security measurement using spatial and non-spatial econometric approaches. Secondly, a convergence approach could be applied to address how the region could quickly achieve food security. A club convergence analysis would help policymakers and researchers to identify the factors that have enabled some regions to achieve food security. Such areas could be used as benchmarks to help other districts to achieve food security.

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