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# Spatial Analysis of Food Security Index and Its Factor to Support Program Priority Area in Central Java, Indonesia

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**Abstract.** Food security Index (FSI) is a global issue influenced by ecological and socio-economic factors. Food security is a condition in which humans can meet their food needs. Therefore, it is necessary to identify the conditions of food security and the factors that can influence it as a first step in overcoming food insecurity. The study area of this research is Central Java. This study uses spatial autocorrelation method. This method can determine patterns or correlations between study locations using Moran's I and LISA. This method also provides information related to the relationship between poverty distribution characteristics between locations in Central Java. This study also analyzes the Food Security Index (FSI) in Central Java Province by integrating drought parameters (Normalized Difference Drought Index), poverty levels, food expenditure, and open unemployment rates. The results of the analysis show a correlation between ecological conditions and FSI achievements. These results confirm that the FSI level in the study area does not only depend on natural resources but is also influenced by socioeconomic factors. Thus, the results of this analysis may be beneficial as recommendations for policymakers through a spatial-based approach to provide strategies for improving food security, especially in Central Java.

**Keyword:** Food Security Index (FSI), Poverty, Central Java, Moran's I, LISA

## 1. Introduction

Poverty and food security remain interrelated issues that pose major challenges in various regions of Indonesia, including the province of Central Java. Poverty is defined as the inability from an economic perspective to meet basic food and non-food needs as measured by expenditure [4]. The problem of poverty is caused by many factors, including the number of unemployed people, which is increasing every year without a corresponding increase in job opportunities, wages that are not in line with living needs, and the low quality of life of the community [14]. Meanwhile, food security is a condition in which food is available for the country and its people, reflected in the availability of sufficient food, both in terms of quantity and quality, that is safe, diverse, nutritious, evenly distributed, and affordable, and does not conflict with the religion, beliefs, and culture of the community, so that people can live healthy, active, and productive lives in a sustainable manner [20].

The Province of Central Java, in 2024, was recorded to have a percentage of poor people of 10.47% or around 3,704.33 thousand people [3]. This figure is also reinforced by data on the percentage of poverty by province by BPS in 2024, which states that the poverty rate of the province of Central Java is ranked 18th in Indonesia. Poverty and food security are often associated with a causal relationship. Poverty will increase food vulnerability and also hidden hunger, which has a contribution to nutritional imbalances in the body which can lead to decreased work productivity and low income [6]. This is in line with which states that low income will result in a decrease in people's purchasing power to obtain nutritious and sufficient food, and hinder people's access to health facilities [13]. Thus, the condition of low community food security is a form of consequence of poverty which at the same time worsens the condition of poverty itself. However, the relationship that occurs in the province of Central Java is a different case. According to *Badan Pangan Nasional* (BPN) in 2024, the value of The Food Security Index (*Indeks Ketahanan Pangan*, IKP) of the province of Central Java is included in group 6, which means ‘Highly Secure’ [2]. The statistical data from Badan Pusat Statistik (BPS) in the same year reveal that despite this strong food security status, Central Java still recorded a poverty rate of 10.47%, ranking 18$^{th}$ nationally [3].

Spatial statistics use various techniques to be able to analyze spatial data collected at study locations that have been determined by spatial coordinates [16]. Understanding the spatial characteristics of poverty and food security is crucial, as these phenomena are not evenly distributed across regions but instead demonstrate geographic clustering and interdependence shaped by socio-economic and environmental factors. To analyze such spatial variations, this research utilizes spatial statistical methods, which serve as analytical frameworks for understanding the interactions between poverty and food security indicators within geographically defined areas [16]. The use of spatial statistical approaches in poverty and food security analysis holds substantial importance, as poverty rates commonly exhibit spatial autocorrelation. This means that areas with high poverty levels tend to be located near other regions sharing similar socio-economic conditions, forming recognizable spatial groupings and spillover effects. Such spatial dependence indicates that poverty in a given area cannot be accurately analyzed without considering the influence of its neighboring territories. Recent empirical research in Indonesia supports this perspective, showing that factors such as educational attainment, unemployment, and income inequality affect poverty not only within specific administrative boundaries but also through their spatial interactions with adjacent regions [17]. For example, Noviyanti et al. (2022) revealed that poverty determinants among Indonesian provinces are spatially interlinked, underscoring the necessity for local development strategies that reflect regional interdependencies [17]. Likewise, Nashwari (2021) demonstrated using a Geographically Weighted Regression model that global analytical approaches tend to mask local variations in poverty drivers, highlighting the value of spatially adaptive techniques for capturing regional diversity [11]. Consequently, incorporating spatial statistical methods into poverty assessment allows for a deeper understanding of inequality patterns, enhances the detection of poverty concentration zones, and aids in designing targeted, context-specific policy measures for sustainable poverty alleviation. This type of commonly used data comes from earth science, defense, cartography, biology, ecology, hydrology, epidemiology, sociology and forth. One of the main concepts in spatial statistics is spatial correlation, which in this study used Global Moran index (Moran’s I) and Local indicator of spatial association (LISA). The Global Moran Index is data that shows the value of spatial autocorrelation as an application of the first law of geography [8]. This index will provide an overview of global spatial patterns according to the scope and distribution of spatial data with the end result is a summary of statistical analysis that describes global spatial patterns [10]. The Moran’s I value is in the interval between -1 and 1 (-1 indicates perfect negative autocorrelation and 1 indicates perfect positive autocorrelation) [12]. While the Local Indicator of Spatial Association (LISA) is a local index to evaluate the tendency of spatial clustering locally and shows several forms of spatial relationships [5].

The phenomenon of spatial interconnection between poverty and food security has attracted the attention of several previous studies in Indonesia. The several earlier studies, which used a quantitative descriptive method to assess the degree of food identification indicators and ascertain each sub-district's food security status [14]. According to the study's findings, Madiun Regency's food needs were satisfactorily satisfied and came under the non-urgent. A subsequent study utilized a similar quantitative descriptive method to examine household food security and its determining factors in Jelobo Village, Klaten Regency [15]. The study's theme and methods were identical. The results indicated that the household food security status in Jelobo Village was classified as moderately food- secure. However, both studies shared limitations in that they did not employ correlation or regression-based statistical analyses and relied primarily on interview-based data collection and mapping approaches. This current study addresses the limitations of prior research on similar topics by introducing a novel spatial- quantitative approach that integrates spatial autocorrelation analysis (Moran's I and LISA) to identify clustering patterns and outliers of food security at the regency/city level in West Java Province—an approach not previously implemented in similar studies. This study applies an integrated spatial–quantitative approach that combines Moran’s I and Local Indicators of Spatial Association (LISA) analyses to identify clustering patterns and spatial outliers of food security at the regency/city level in West Java Province. This method allows for a comprehensive understanding of spatial dependencies and variations across regions. Additionally, the study utilizes secondary data obtained from the Badan Pusat Statistik (BPS) [4].

This study intends to analyze the distribution patterns of poverty and food security in Central Java Province, along with the main and supporting variables that may contribute to these issues. This study aims to analyze the spatial distribution patterns of food security index (FSI) in Central Java Province by examining the main variables influencing variations across regions. The aspects that make up the FSI complement each other to provide a comprehensive picture of the community's food security. Central Java currently still faces a number of complex problems related to food security. Geographically, Central Java has a diverse landscape, which can lead to disparities in food security due to other factors such as social and economic factors. The variation in social and economic characteristics in Central Java can be analyzed to determine the factors that influence the FSI, considering that Central Java has 29 regencies and 6 cities. The methods employed include Moran’s I and the Local Indicator of Spatial Association (LISA) to identify spatial patterns and illustrate relationships among areas based on their food security levels. Moran’s I is applied to measure global spatial autocorrelation, while LISA evaluates local spatial autocorrelation and detects clusters of areas with similar characteristics. The integration of these two methods provides a more comprehensive understanding of the spatial dynamics of food security, enabling the results to serve as a foundation for formulating priority policies to strengthen food security in Central Java Province.

## 2. Method

This research was conducted using a spatial-based quantitative descriptive approach to see the relationship between food security and poverty levels in the province of Central Java. The spatial approach was chosen because food security and poverty are not only determined by socio-economic factors, but also by inter-regional interactions. The Central Java province (Figure 1) was selected as the study area because it has a relatively high poverty rate as well as considerable spatial variation, making it relevant to examine the relationship between poverty and food security. According to statistical data published by BPS, Central Java is the province with the highest number of poor people and is ranked second in Java with a percentage of poor people of 10.47% or around 3,704.33 thousand people [4]. This condition indicates the existence of pockets of vulnerability that are important to analyze further. In terms of economic role, Central Java is the center of national food production, but food distribution and access are still uneven. Although food availability is relatively sufficient, challenges arise in terms of affordability and utilization, especially in areas with high poverty rates [19]. This makes Central Java an interesting case study as it shows the contradiction between food potential and socio-economic problems.

The food security index is constructed from several components that indicate the availability, utilization, and stability of food (Table 1). These components are derived from other more focused variables. There are several main components in the FSI, 1) Food availability, which indicates whether food is sufficiently available in a region, with derivative variables such as agricultural land productivity and rice production; 2) Access to food, which indicates the community's ability to obtain food, with derivative variables such as poverty rate, unemployment rate, and per capita income. 3) Stability, which indicates the consistency of food availability, access, and utilization over time, with derivative variables that can be seen from resilience to disasters, one of which is drought.

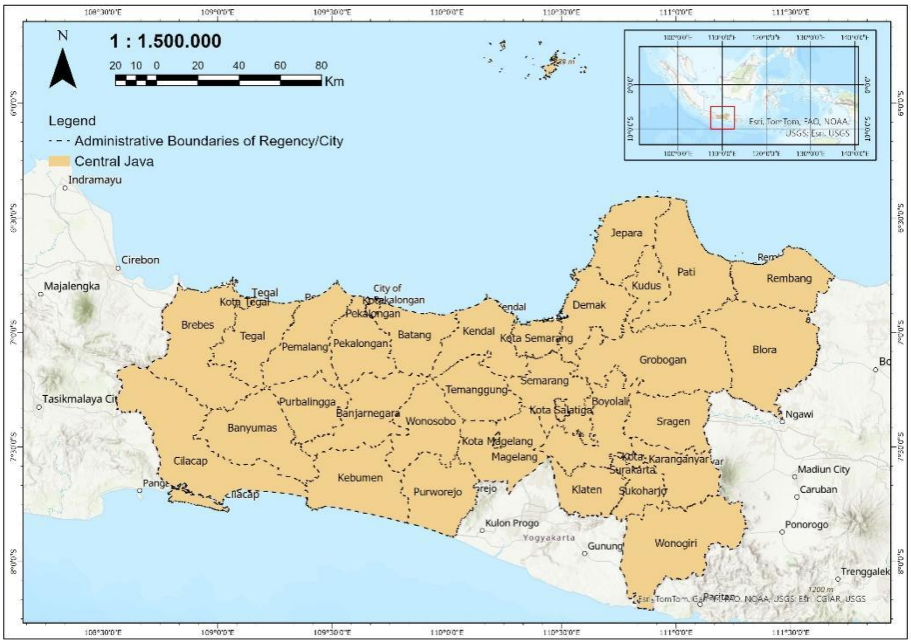


**Figure 1**. Administration Map of Central Java

The main data in the study were obtained from official government institutions. Information on the poverty rate was sourced from the Badan Pusat Statistik (BPS) of the province of Central Java in 2024, while data on food security was taken from the Food Security Index (FSI) published by the Badan Pangan Nasional (BPN) in 2024. In addition, other supporting data such as the unemployment rate, population, and socio-economic indicators were used in addition, which were also obtained from BPS publications. For spatial analysis purposes, data on the administrative boundaries of districts/municipalities in the province of Central Java were obtained from Badan Informasi Geospasial (BIG) in shapefile form. Data collection was conducted by compiling secondary data downloaded from the official websites of BPS, BPN, and the BIG portal. All data was then adjusted to be uniform in the unit of analysis (district/city) and research period (year 2024).

**Table 1**. The type of data that used in this study

| Data | Type | Scale/Level of Administration | Years | Source |
|---|---|---|---|---|
| Administration Map of Central Java | vektor (.shp) | 1 : 250.000 | 2019 - 2022 | (BIG,2020) |
| Number of Pverty Data in Central Java | Tabular | City/Regency | 2024 | (BPS, 2024) |
| Number of Rice Productivity in Central Java | Tabular | City/Regency | 2024 | (BPS, 2024) |
| Food Security Index Data in Central Java | Tabular | City/Regency | 2024 | (BPN, 2024) |
| Percapita Income Data in Central Java | Tabular | City/Regency | 2024 | (BPS, 2024) |

The Moran's Index is by far the most used tool for spatial autocorrelation. The result of calculating the Moran Index can take on values between -1 and 1. Positive spatial autocorrelation is represented by a value of 1, and negative spatial autocorrelation is represented by a value of -1. On the other hand, a value of 0 for the Moran index indicates the absence of any spatial autocorrelation [10]. Global spatial autocorrelation or Global Moran's Index is a tool for calculating global spatial autocorrelation, thereby revealing clustered or random spatial relationships [8]. Spatial autocorrelation calculated using Moran's Index with a cross-product weight matrix W, as shown in the following formula:

$$I = \frac{n \sum_i \sum_j W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{(\sum_{i \neq j} W_{ij}) \sum_i (X_i - \bar{X})^2} \tag{1}$$

where I is the value of Moran's I statistic, n is the number of locations (or spatial unit), $Xi$is the value at location i, $Xj$is the value at location j, $X$ is the mean of the variable across all locations,, and $Wij$is the weight element between location i and j[18].

The result of calculating the Moran Index can take on values between -1 and 1. Positive spatial autocorrelation is represented by a value of 1, and negative spatial autocorrelation is represented by a value of -1. On the other hand, a value of 0 for the Moran index indicates the absence of any spatial autocorrelation [9]. The significance of the Moran's Index can be assessed under a normality assumption. The Significance test for Moran's I is conducted using a normal approximation with the following specifications:

i. Hypothesis

H0: I = 0 (no spatial autocorrelation)

H1: I ≠ 0 (spatial autocorrelation exist)

ii. Significance Level (α)

iii. Test Statistic

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \approx N(0,1) \qquad (2)$$

with expectation value:

$$E(I) = -\frac{1}{n-1} \qquad (3)$$

with variance under the normality assumption[18]:

$$Var(I) = \frac{n^2\,(n-1)\,S_1 - n\,(n-1)S_2 - 2S_0^2}{(n+1)(n-1)^2\,S_0^2} \qquad (4)$$

with:

$$S_0 = \sum_{i \neq j} W_{ij} \quad , \quad S_1 = \frac{1}{2}\sum_{i \neq j}(W_{ij} + W_{ij})^2 \quad ,$$
$$S_2 = \sum_k\left(\sum_j W_{kj} + \sum_i W_{ik}\right)^2 \qquad (5)$$

iv. Criteria Region:

Based on a two-tailed test, the null hypothesis ($H_0$) will be rejected if $|Z(I)| > Z_{\left(1-\frac{\alpha}{2}\right)}$ [18].

This study also uses Local Indicators of Spatial Autocorrelation (LISA) to identify spatial linkage patterns at the district/city level [5]. LISA, breaks down the Global Moran's I statistic to identify significant spatial patterns and relationships at the local level for each specific location [1]. In this study, LISA is used to identify regions that are categorized as high-high (high poverty adjacent to poor regions), low- low (low poverty adjacent to low regions), or outliers such as high-low and low-high. The combination of these two methods provides a more comprehensive understanding. The Moran's I helps to see the general trend of the pattern, while LISA highlights specific areas that are the center of poverty concentration or areas that deviate from their surroundings. Thus, the results of the study can be used as a basis for formulating poverty reduction policies that are more targeted while supporting efforts to improve food security. Specifically, this research can be used as a basis for formulating food security and poverty reduction policies by identifying High-High clusters (hotspots) of food insecurity and poverty level, which enables the local government to efficiently prioritize resource allocation to the most vulnerable locations. Furthermore, the findings offer strong evidence to encourage the development of integrated programs and policies among relevant agencies. Simultaneously, this analysis also highlights hidden pockets of poverty (spatial outliers) often overlooked by general policies, thus allowing for the formulation of precise micro-policies to address specific issues within Central Java province.

## 3. Results and Discussion

The distribution of Food Security Index (FSI) values in the study area is concentrated in the eastern region (Figure 2). Red on the map indicates high FSI values, while brighter colors such as orange and yellow indicate lower FSI values. The majority of FSI values are between 82 and 87 and 77 and 82. This value is a composite value of resilience that involves a series of indicators. There are nine indicators used in the preparation of the FSI, which are derived from three aspects of food security, which is availability, affordability, and utilization of food. There are seven regions with the highest FSI values, namely Sukoharjo Regency, Karanganyar Regency, Pati Regency, Demak Regency, Semarang City, Salatiga City, and Magelang City.  Meanwhile, the regions with low FSI values are indicated by the colors found in 6 regencies/cities, namely Temanggung Regency, Wonosobo Regency, Banjarnegara Regency, Purbalingga Regency, Brebes Regency, and Pekalongan City. The majority of these regions with low FSI values tend to be areas located around mountains with poor access to food.

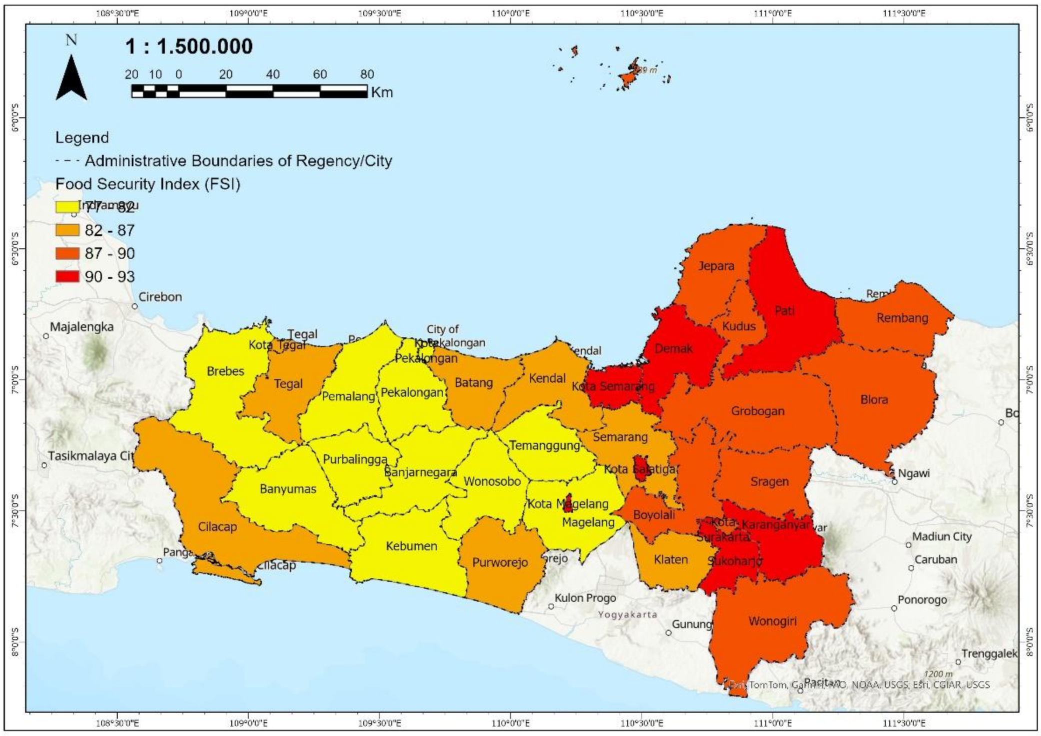


**Figure 2**. Food Security Index in Central Java 2024

The distribution of the poor population is visually concentrated in the western region (Figure 3). The red color on the map indicates a high level of poverty, while the yellow color indicates a low level of poverty. The poor population in Central Java is mostly between 43,280,000 and 102,570,000 people. The regions with high population numbers are Brebes, Pemalang, Banyumas Cilacap, and Kebumen Regencies. Meanwhile, the regions with low population numbers are urban areas such as Surakarta, Salatiga, Pekalongan, and Tegal. This is because these regions tend to be much smaller  than other regions. When compared with the distribution of the poor population, there is a correlation between the



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IKP value and the poor population, where the poor population tends to have a low FSI value. Brebes, Banyumas, and Kebumen Regencies have a high poor population with a low FSI value. Conversely, areas with a low poor population tend to have a high FSI value. This shows that poverty is one of the factors affecting food security.

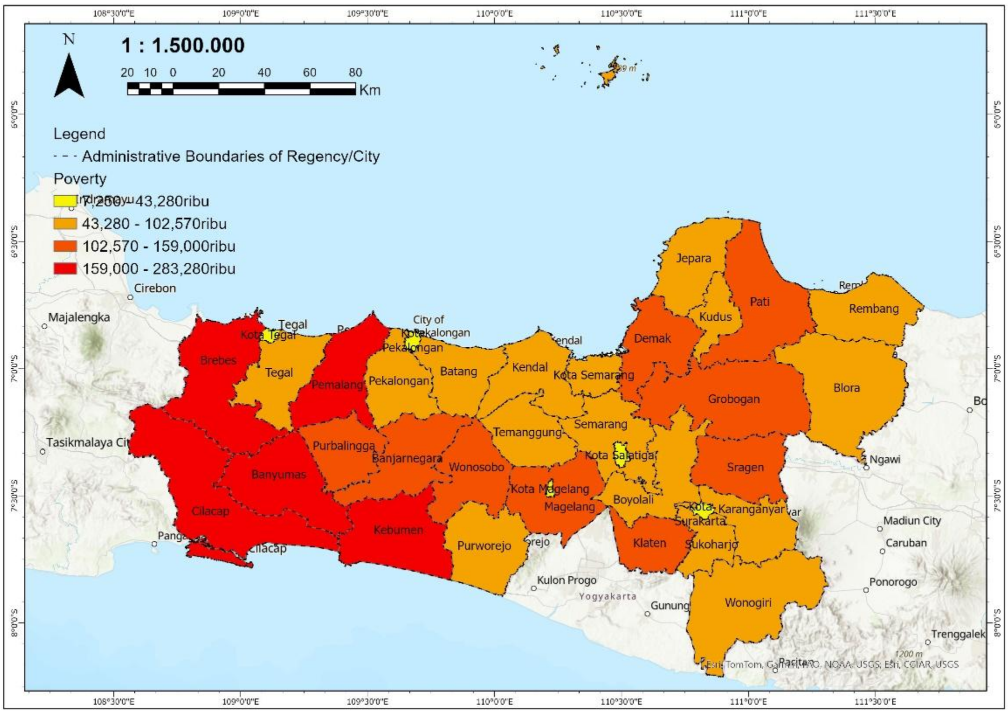


**Figure 3.** Number of Poverty in Central Java 2024

When looking at several variables related to access to food, it is clear that food issues cannot be viewed from one perspective alone. The graph in Figure 4 shows that there are several regions that have good and adequate food availability, but low purchasing power due to high poverty rates. In the graph, areas that tend to have low poverty rates show a high percentage of food expenditure, such as Tegal, Pekalongan, Purworejo, and Temanggung. This indicates that these areas are relatively prosperous. Low poverty rates indicate that the majority of the population is able to meet their basic needs. This requires controlling staple food prices by strengthening local markets, ensuring equitable distribution, and increasing food diversification. In contrast, urban areas tend to highlight the main problem of unemployment. This illustrates the lack of job opportunities despite the increasing needs of the community.

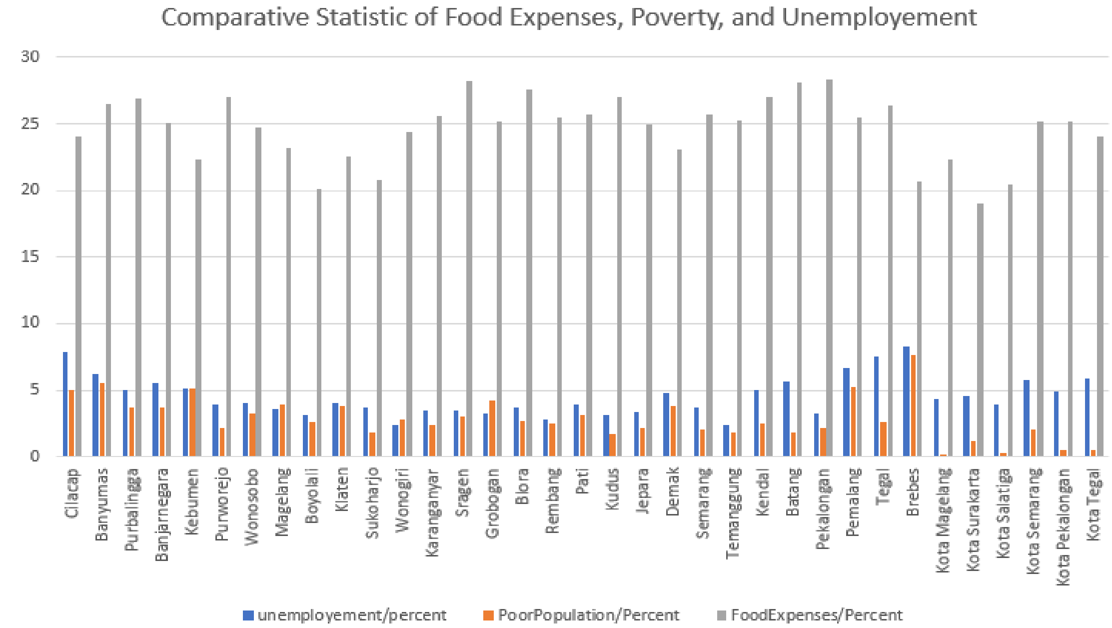


**Figure 4.** Statistic Comparative Data of Food Expenses, Poverty, and Unemployment

Local Moran's I is beneficial to determine whether the distribution of poverty in Central Java has a specific pattern, such as random, clustered, or scattered. The Moran's I in Figure 5 do not show any significant clustered or scattered spatial patterns. This can be seen in the z-score values, which range from -1.65 to +1.65 with a p-value above 0.05, indicating that the distribution of poverty in Central Java is random. This shows that poverty is not concentrated in certain areas or spread evenly. The results of Moran's analysis show statistically insignificant values ($p > 0.05$), which means that, globally, the distribution of poverty in Central Java does not form a specific social pattern and tends to be random. This means that there is no strong tendency for areas with high poverty rates to be close to each other or for areas with low poverty rates to form clusters at the provincial level.

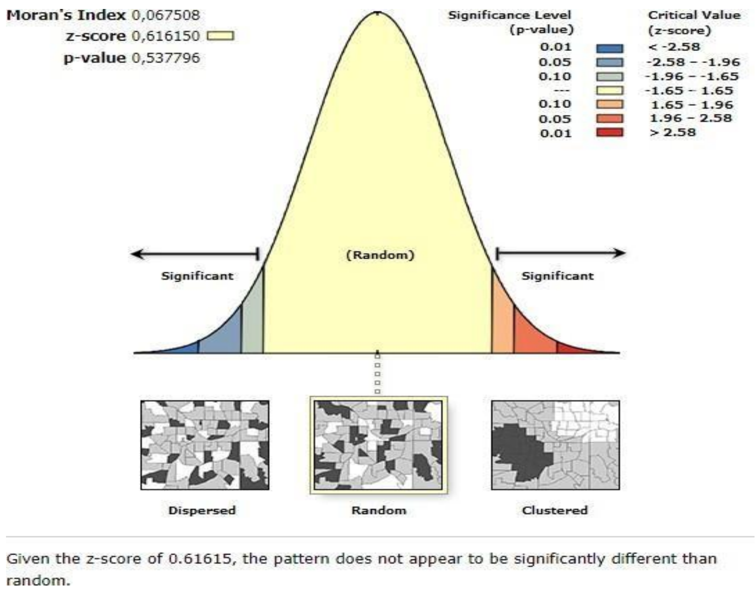


**Figure 5**. Report of Moran's Index

The LISA analysis results show that there are areas that exhibit High-Low-Low and High-High cluster patterns (Figure 6). The High-Low cluster shows areas of high poverty surrounded by areas of low poverty, indicating an anomaly that warrants attention. The High-High cluster shows areas with high poverty levels clustered with their neighbors, which also have high poverty levels. The Low-Low cluster shows areas with low poverty levels clustered with their neighbors, which also have low poverty levels. There is a graph showing a histogram of the distribution of the poor population per district/city in Central Java Province. The X-axis shows the number of poor people, and the Y-axis shows the number of districts/cities in Central Java. The blue line is the mean (average) number of poor people, which is 105.84 thousand. There are several regencies/cities with a much higher number of poor people (>200 thousand). Although the number is small, these areas pull the mean to the right, resulting in a mean value that is greater than the median. The gray line shows the standard deviation, which is quite large at 59 thousand people. This indicates a significant difference between regions with low poverty rates and regions with high poverty rates.

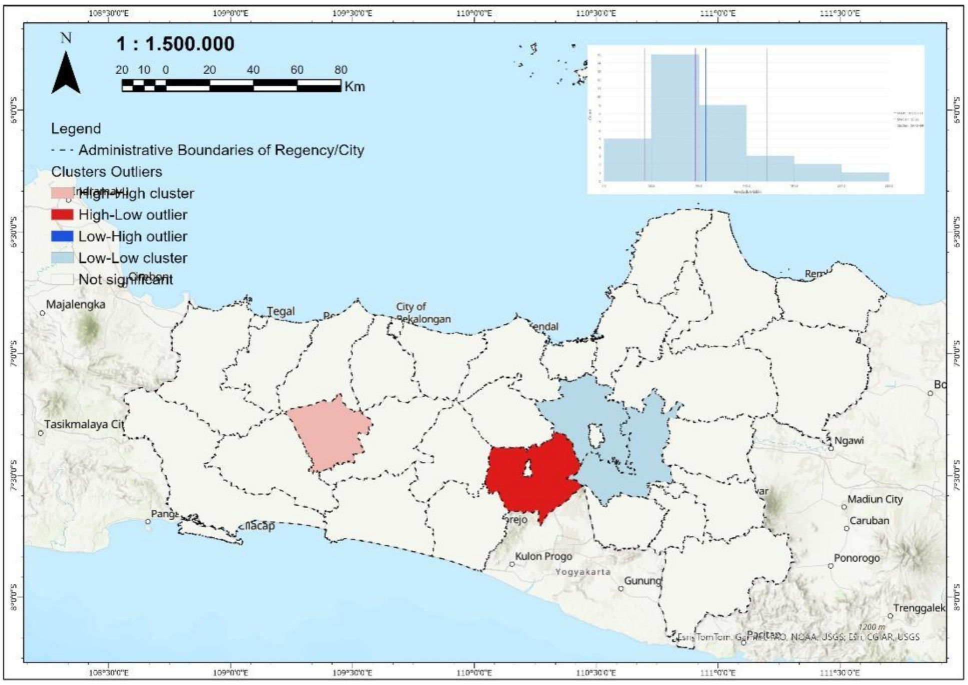


**Figure 6.** Poverty Cluster Map in Central Java 2024

In addition to socio-economic aspects, one of the variables that affecting food stability is the level of drought, which is used to assess the impact of the FSI. Figure 7 shows the level of drought based on a comparison of vegetation moisture with the availability of water on the soil surface. However, the NDDI value in this region tends to be low because, among other things, this region has a fairly high poverty rate and limited economic access, which is certainly a problem for areas around the mountains. Visually, this map is dominated by red to orange colors, which means that areas with these colors have relatively high levels of drought, while green colors indicate wet areas with good vegetation conditions. It can be seen that areas with high levels of drought are located in the regions around Pati, Grobokan, Blora, and Rembang Regencies. When viewed in their original form, these regions are areas where the majority of land use is dominated by agriculture. This is because the majority of agricultural land is rain-fed, so agricultural productivity is highly dependent on seasonal rainfall. This region shows high vulnerability to drought, which can be caused by several factors. However, this region also has a high FSI score because Grobongan and Pati Regencies in Central Java are known as food barns, meaning that these regions produce abundant harvests and generate food surpluses. This surplus covers the vulnerability during the dry season, resulting in a high average FSI score. In addition, the region has access to active agricultural passers and fairly good food distribution channels, and many people in this region do not depend on rice fields but also on the trade, livestock, and migrant labor sectors.

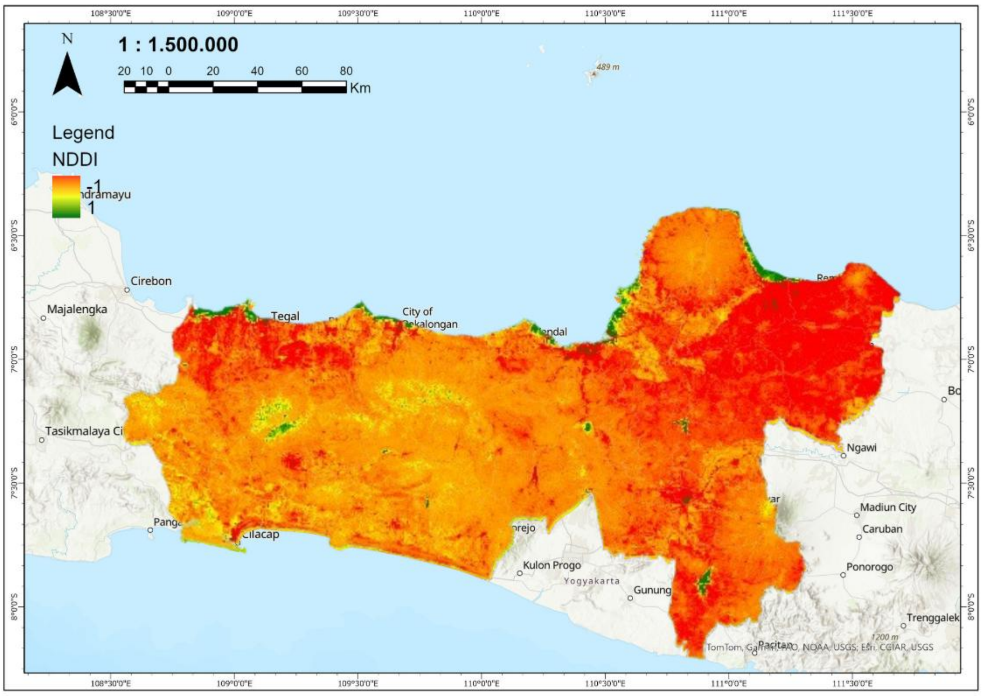


**Figure 7.** Normalized Different Drought Index Map in Central Java

## 4. Conclusion

The integration of poverty, food expenditure, and unemployment affects the FSI value through certain components in terms of access, use, and stability. Areas with poor scores in these three parameters will have a weak FSI and should be prioritized for government intervention. Conversely, areas that are poor, under control, and have diverse food consumption will record a better FSI.

However, it is not always the case that ecological conditions correlate with high or low FSI. This proves that the FSI is multidimensional, so policy improvements must take into account the integration of all parameters. Based on the results, it shows that most cities in Central Java have an average number of poverties, but there is considerable inequality because some areas have very low numbers.

The East Central Java region has a high NDDI value, which means it is vulnerable to drought. However, the FSI is relatively high because it is supported by excessive food production. This certain area still needs to be assessed in detail, especially in terms of providing irrigation infrastructure, water conservation, and diversifying basic products against more droughts to prevent food insecurity during the dry season. Central Java has a low NDDI, indicating available water and fertile soil, but a very low FSI. The main reasons are high population density and unequal access to food due to local poverty. Therefore, attention should be focused on controlling land use change, increasing human purchasing power, and stabilizing food prices. Enhancing land use regulation can stop the transformation of productive farmland into non-agricultural zones. Simultaneously, boosting employment through agro-



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industrial projects, rural business ventures, and microcredit programs can raise community income and purchasing power. These methods enhance food availability while also fostering growth in the local economy. Strategies for market stabilization are essential to ensure food remains affordable for at risk groups. Creating local food stockpiles, introducing price surveillance mechanism, and offering focused subsidies for necessary goods can reduce variations that jeopardize access to food. Combining these policies with drought adaptation strategies like water-efficient irrigation systems, watershed management, and crop variety will strengthen enduring food resilience. These collective efforts guarantee that food security in Central Java is maintained via a balanced strategy that takes into account ecological, economic, and social aspects.

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