Theta: Journal of Statistics vol. 1, no. 1, pp. 27-34, 2025

Theta: Journal of Statistics

Journal homepage: www.jurnal.untirta.ac.id/index.php/tjs

Analysis of the Spatial Distribution Pattern of Poverty Percentage in Central Java in 2024 Using the Spatial Autocorrelation Approach

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INFORMATION

Article information:
Submitted: 16 February 2025
Revised: 26 March 2025
Accepted: 31 March 2025
Available Online: 31 March 2025

Keywords:
Spatial Autocorrelation; Moran's I; Local Indicators of Spatial Association; Inverse Distance Weight; Regional Disparities;

ABSTRACT

Poverty remains a critical socio-economic issue in Central Java, Indonesia, exhibiting significant regional disparities. This study aims to analyze the spatial distribution pattern of poverty rates in Central Java in 2024 using a spatial autocorrelation approach with an inverse distance weight matrix. Secondary data from the Central Bureau of Statistics (BPS) of Central Java is utilized, covering poverty percentages across regencies and cities. The analysis method involves Moran's I to assess global spatial autocorrelation and Local Indicators of Spatial Association (LISA) to identify local spatial clusters. The findings indicate a positive Moran's I value, suggesting a significant spatial dependence in poverty distribution. Several high-poverty clusters are identified in specific regions, confirming spatial concentration patterns. The study highlights that regional proximity influences poverty rates, where areas with high poverty tend to be surrounded by regions with similar conditions. These results provide empirical evidence for policymakers to design targeted poverty alleviation programs based on spatial characteristics. The study concludes that understanding spatial autocorrelation in poverty distribution is crucial for formulating effective regional development policies and reducing socio-economic disparities.

INTRODUCTION

Poverty is a complex and multidimensional socio-economic issue. In Indonesia, particularly in Central Java Province, the poverty rate remains a significant challenge. Central Java exhibits notable variations in poverty levels, with 19 regencies having poverty rates above 10%, while 7 regencies and 6 cities have poverty rates below 10%. Kebumen Regency has the highest poverty rate at 17.59% [1]. This phenomenon suggests the possible existence of a spatial distribution pattern of poverty that requires further investigation. Spatial analysis in Central Java has previously shown that certain regencies, such as Cilacap and Brebes, are consistently identified as high-poverty areas [2]. Spatial analysis, particularly using the spatial autocorrelation approach, serves as an effective tool for identifying and understanding this

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DOI: http://dx.doi.org/10.62870/tjs.v1i1.31320

distribution pattern. The spatial autocorrelation through Moran's I index can be used to enhance the understanding of spatial patterns and improve spatial analysis tools [3].

The spatial autocorrelation approach allows researchers to measure the degree of correlation between a variable's value in one location and its neighboring locations [4]. In the context of poverty, this method can identify whether there is a clustering pattern of high or low poverty levels. This approach employs spatial weighting, specifically inverse distance weighting, where greater weight is assigned to closer regions and lesser weight to farther regions. This concept aligns with the spatial theory that states everything is related to everything else, but closer things have a stronger influence than those further away [5]. This approach enables more accurate analysis in capturing spatial effects from one region to its surroundings. A study by Apriani applied spatial autocorrelation to identify poverty level patterns in Sumatra, showing a positive Moran's I index value, indicating clustering patterns based on poverty levels [6]. Similarly, a study by Almismary in 2024 used Moran's I and LISA (Local Indicator of Spatial Autocorrelation) to analyze the spatial distribution of poverty in Aceh Province, revealing that several regencies/cities exhibit significant spatial autocorrelation [7]. This method provides in-depth insights into the spatial distribution of poverty and the factors influencing it.

Although numerous studies have been conducted on spatial poverty patterns in various Indonesian provinces, research specifically analyzing the spatial distribution of poverty percentages in Central Java's regencies and cities using spatial autocorrelation remains limited and the data used is quite old so it is less relevant to current conditions. Therefore, this study aims to fill this gap by applying spatial autocorrelation analysis to Central Java's 2024 poverty data. The findings are expected to provide a more comprehensive understanding of poverty's spatial distribution in the province, ultimately serving as a foundation for formulating more effective and targeted poverty alleviation policies.

RESEARCH METHODS

This study utilizes secondary data obtained from the official publications of the Central Bureau of Statistics (BPS) of Central Java Province for the year 2024 [8]. The data includes the percentage of poverty in 35 districts/cities in Central Java which are the main variables in this analysis. Additionally, the study incorporates geographic coordinate data for each region to support the spatial analysis of poverty distribution patterns. To analyze the spatial distribution of poverty, this study applies the spatial autocorrelation method using Moran's I Index and the Local Indicator of Spatial Association (LISA), which were processed using R Studio software.

Moran's I Index

Moran's I is used to measure global spatial autocorrelation, determining whether regions with high poverty levels tend to be adjacent to other high-poverty regions, and vice versa. A positive and significant Moran's I value indicates clustering (spatial dependence), while a negative value suggests dispersion (no spatial correlation). According to Anselin, Moran's I Index is a global spatial statistical technique used to identify the presence or absence of spatial autocorrelation among locations [9]. Hotspot analysis, such as Getis-Ord G, was not conducted in this study because other methods, including Moran's I, Moran Scatter Plot, and LISA, already provide a comprehensive understanding of spatial patterns, both globally and locally. The Moran's I formula is expressed as follows:

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S_0(n\sum_{i=1}^{N}(x_i-\bar{x})^2)} \tag{1}$$

where:

I : Moran's I Index

n : Number of locations

x_i : Value of the variable at location-i

x_j : Value of the variable at location-j
$\bar{x}$: Mean value of the variable
W_{ij} : Spatial weight matrix (Inverse Distance Weighting)
S_0 : Sum of spatial weight elements

When neighboring regions have similar values, Moran's I is positive (indicating clustering). Conversely, if neighboring regions exhibit dissimilar values, Moran's I becomes negative (indicating dispersion). The significance of spatial autocorrelation is tested by comparing the observed Moran's I value with its expected value. The null hypothesis (H_0) assumes no spatial autocorrelation, while the alternative hypothesis (H_1) suggests the presence of spatial autocorrelation [10].

Local Indicator of Spatial Autocorrelation (LISA)

In addition to global analysis, this study applies local spatial analysis using LISA, which identifies specific clusters of poverty at a localized level. LISA evaluates spatial correlation in individual areas rather than across the entire dataset [11], [12]. According to Yuriantari et al. (2017), LISA for each region is calculated as:

$$L_i = \frac{x_i - \bar{x}}{m_2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{2}$$

with $m_2 = \sum_{j=1}^{n} \frac{(x_i - \bar{x})^2}{n}$

LISA classifies areas into four spatial categories:

1. High-High (HH) : Areas with high poverty levels surrounded by other high-poverty regions.
2. Low-Low (LL) : Areas with low poverty levels surrounded by low-poverty regions.
3. High-Low (HL) : High-poverty areas surrounded by low-poverty regions (spatial outliers).
4. Low-High (LH) : Low-poverty areas surrounded by high-poverty regions [13].

In this study, the spatial weighting used is Inverse Distance Weighting, where closer regions exert greater influence in the analysis. This approach allows for a more accurate depiction of poverty distribution patterns in Central Java. The results from Moran's I and LISA are expected to serve as a basis for spatially-informed policymaking to address poverty effectively.

RESULTS AND DISCUSSION

Spatial Distribution of Poverty Percentages

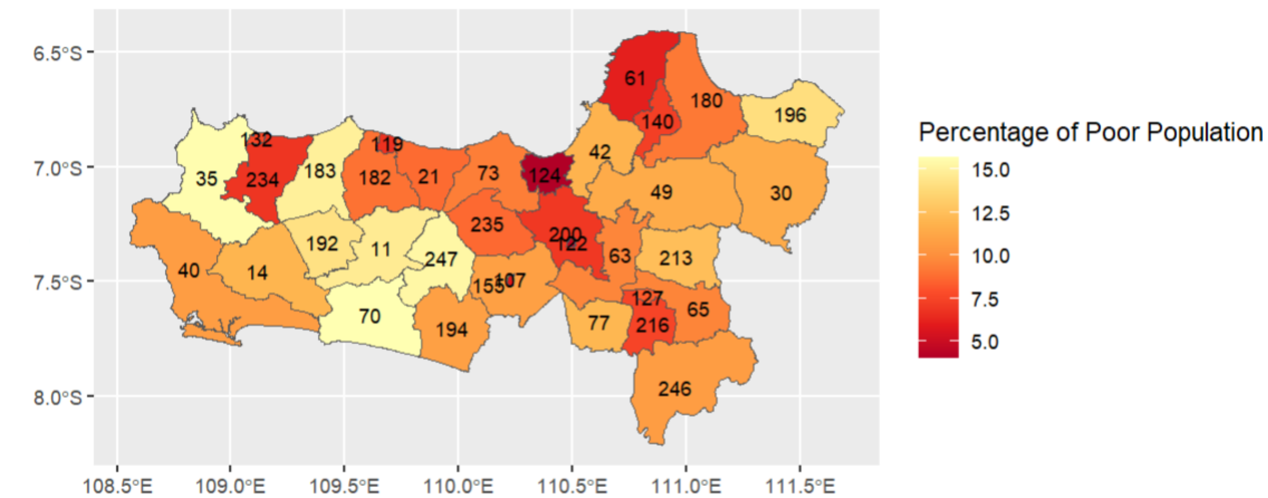

Figure 1. Distribution of the Percentage of Poor Population in Central Java in 2024

Figure 1 illustrates the spatial distribution of poverty percentages in Central Java for 2024. The color gradient represents poverty levels, where lighter shades indicate higher poverty rates, while darker shades indicate lower poverty rates. From the map, it is evident that some areas in the northern and eastern parts of Central Java exhibit higher poverty levels, as shown by the yellow to light orange colors. In contrast, areas in the western and central parts of the province display lower poverty rates, marked by darker red tones.

This spatial pattern indicates variations in poverty levels across regions, suggesting the presence of regional disparities influenced by geographical, economic, and social factors. Clusters of high-poverty areas are observed in Kebumen, Wonosobo, Banjarnegara, Purbalingga, and Pemalang, which may indicate structural and economic challenges in these regions. Conversely, lower-poverty regions, such as Semarang and Salatiga, reflect better economic conditions and infrastructure development. By applying spatial autocorrelation analysis, we can better understand the interdependence between regions and how poverty spreads spatially. This insight is essential for developing targeted policies that address poverty clusters effectively.

Spatial Autocorrelation Analysis Using Moran's I

The positive Moran's I value (0.0382) indicates a significant spatial autocorrelation, suggesting that regions with high poverty levels tend to be near other high-poverty regions. Similarly, regions with low poverty levels are clustered together, confirming the existence of spatial clustering patterns.

Table 1. Moran Index Values Based on Inverse Distance Weighting (IDW)

Moran Indeks	P-Value
0,0382	0,0323

A study by Adha and Basuki (2020) analyzed poverty across regencies and cities in Central Java and found a Moran's I value of 0,303 (p-value = 0,002), reinforcing the finding that poverty in Central Java does not occur randomly but forms distinct clusters [14]. Similarly, a study by Apriani (2022) on interregional poverty in Sumatra also found a positive Moran's I value, confirming spatial dependence on poverty distribution [6]. These findings emphasize the importance of considering spatial factors in poverty analysis, as neglecting them could lead to ineffective policy implementation. Policymakers should take into account these spatial relationships when designing poverty alleviation programs to ensure interventions are directed toward areas with high concentrations of poverty.

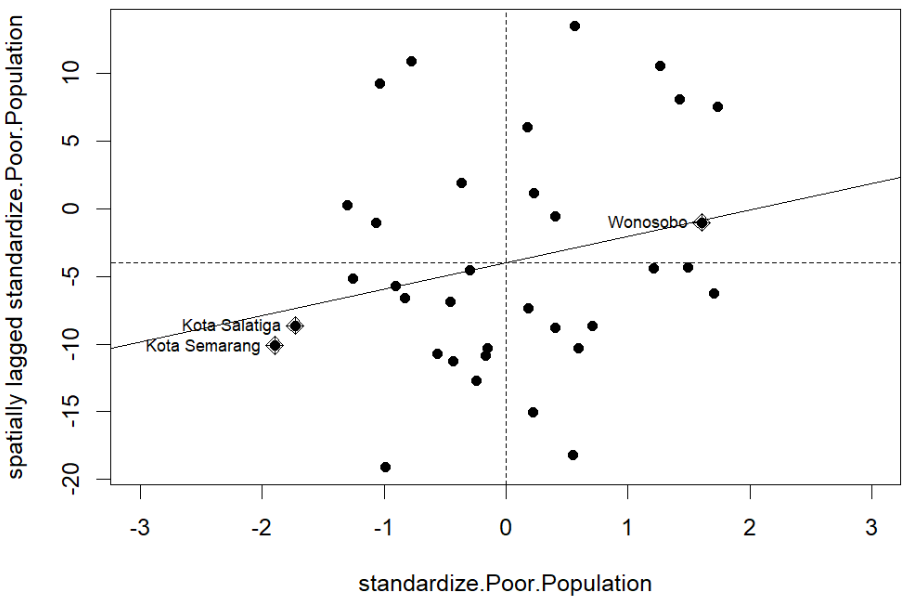

Figure 2. Moran Scatterplot on the Percentage of Poor Population

Moran's scatterplot is used to see the characteristics of each province and the general clustering tendencies. Moran's scatterplot consists of four quadrants for each calculated unit of analysis, indicating four possible clusterings. The relationship between each province and each other is depicted in Figure 4. This relationship is arranged based on the Moran index of each province.

Figure 2 shows that Salatiga City and Semarang City are in Quadrant III (bottom left side), indicating that both cities are areas with a low percentage of poor people surrounded by areas with a low percentage of poor people as well. Conversely, Wonosobo Regency is in Quadrant I (top right side), indicating that Wonosobo Regency is an area with a high percentage of poor people surrounded by areas with a high percentage of poor people as well.

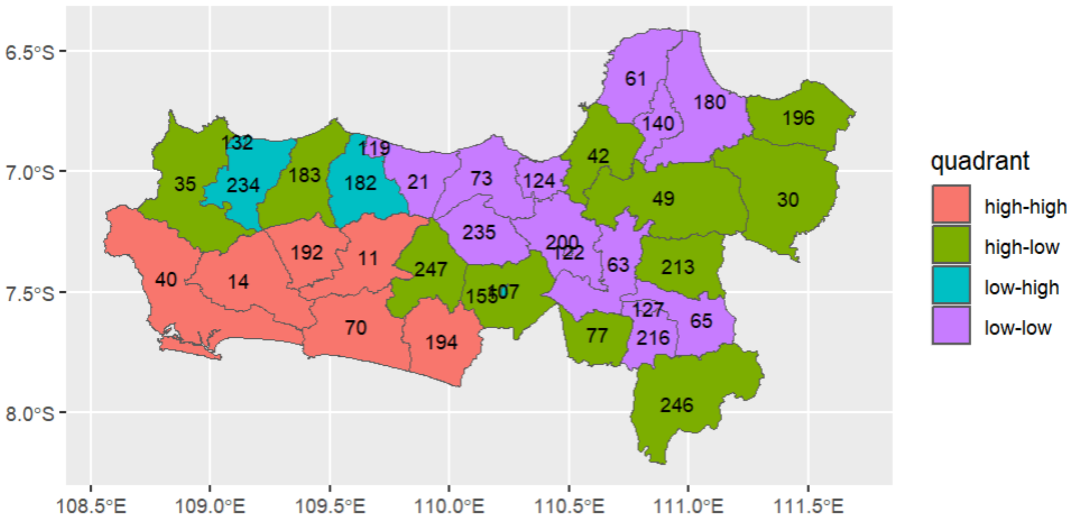

Figure 3. Local Moran Percentage of Poor Population by Quadrant

In Figure 3, there are groups of regions that fall into 4 quadrants. The regions that fall into quadrant 1 (High-High) are represented by the color red. The regions that fall into Quadrant 1 are Cilacap, Banyumas, Purbalingga, Banjarnegara, Kebumen, and Purworejo. This indicates that these regions are regions with a high percentage of poor people and are surrounded by areas with a high percentage of poverty as well. The regions that fall into Quadrant 1 need the government's attention to follow up immediately by providing special policies so that poverty is reduced. In addition, there needs to be new innovations by the local government to open up employment opportunities. Next, the regions in quadrant 2 (High-Low) are shown in green. The regions that fall into quadrant 2 are Blora, Brebes, Demak, Grobogan, Klaten, Magelang, Pemalang, Rembang, Sragen, Wonogiri, and Wonosobo. This indicates that these regions are regions with a high percentage of poor people but are surrounded by areas with a low percentage of poverty. The areas that fall into Quadrant 2 are expected to be able to follow the example of their neighboring areas in poverty alleviation.

The last important discussion is in quadrant 3 (Low-High) which is shown in blue. The areas that fall into quadrant 3 are Magelang City, Tegal City, Pekalongan, and Tegal. These areas are areas with low poverty rates but are surrounded by areas with high poverty rates. These areas are expected to provide high employment opportunities and local government policies that can help alleviate poverty for their neighboring areas.

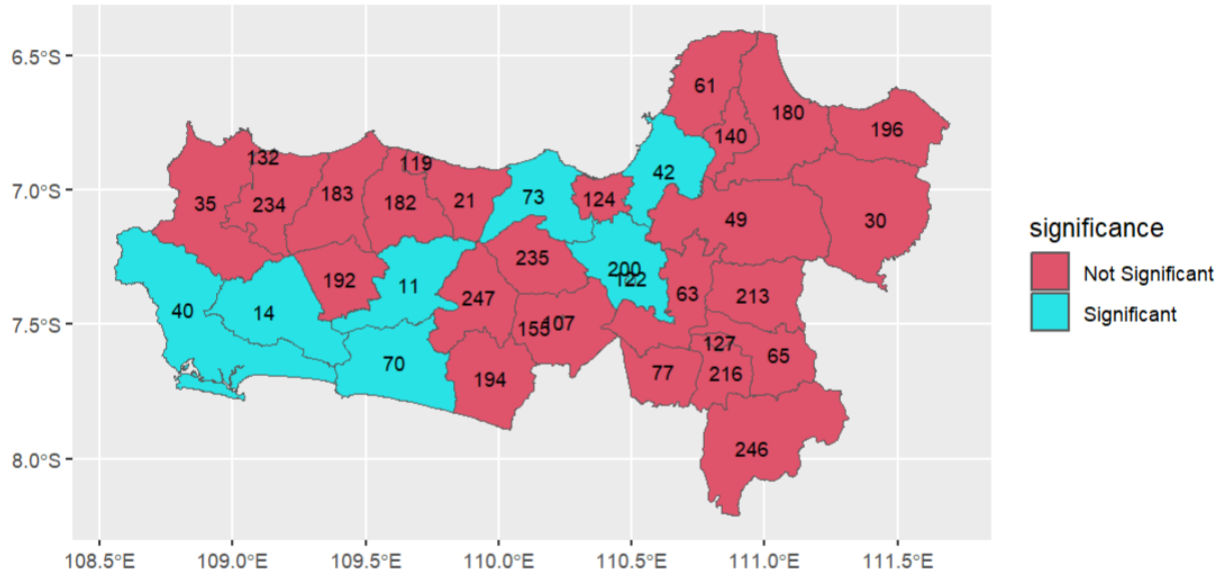

Figure 4. Local Moran Significance of the Percentage of Poor Population

Figure 4 explains the areas with local moran significance on the percentage of poor people. The results of the local Moran significance test (Statistics Local Moran) are used to identify local patterns of spatial autocorrelation that can help in understanding spatial relationships and interpreting geographic phenomena [15]. The areas with significant Local Moran's values are Banjarnegara, Banyumas, Cilacap, Demak, Kebumen, Kendal, Salatiga City, and Semarang. This means that there is a significant spatial relationship between an area and its surrounding areas on the level of poor people. In other words, if there is a change in the poverty rate in these areas, it will significantly affect neighboring areas. Neighboring areas can reduce poverty levels through shared resources and collaborative efforts by facilitating regional cooperation to collectively address poverty [16].

This analysis supports that of Sari (2024), who found patterns of poverty in Central Java with positive spatial autocorrelation values using the Moran Index [17]. There are a few distinctions, though, including the fact that the data used in this study is the most recent, with poverty-level data from 2024; additionally, the spatial weighting employed in this study is based on inverse distance, whereas prior studies continue to use data from 2022 and employ contiguity weighting based on neighbors. Additionally, the major quadrant 2 (High-High) area in this study only comprised four regions—Cilacap, Banyumas, Purbalingga, Banjarnegara, Kebumen, and Purworejo—instead of the six regions included in prior studies. Purbalingga and Purworejo are two distinct regions, and none of them significantly affected the poverty levels in the neighboring areas in this study.

CONCLUSION

The study findings indicate that the distribution of poverty in Central Java regencies/cities in 2024 exhibits a significant spatial pattern, as evidenced by a positive Moran's I value. These findings suggest that regions with high poverty levels tend to cluster together, while regions with low poverty levels exhibit similar spatial patterns. The application of spatial autocorrelation with inverse distance weighting has provided a more precise understanding of poverty distribution, facilitating the development of more region-based policies.

Given these spatial patterns, local governments can formulate more effective poverty alleviation strategies by considering interregional linkages. Spatially-based policy interventions, such as infrastructure development, improved access to education and healthcare, and local economic empowerment, should be concentrated in regions with high and clustered poverty levels. This study also recommends further analysis incorporating additional socio-economic variables to deepen the understanding of key factors influencing poverty distribution.

ACKNOWLEDGMENT

The author extends gratitude to the Central Bureau of Statistics (BPS) of Central Java Province for providing the secondary data that forms the foundation of this research. Appreciation is also expressed to Universitas Sultan Ageng Tirtayasa, particularly the Department of Statistics, for academic support and research facilities. Additionally, sincere thanks are given to colleagues and other contributors who provided valuable insights during the analysis and writing process. It is hoped that this research will contribute to the development of spatially-based poverty alleviation policies in Central Java and serve as a reference for future studies.

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