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SPATIAL PATTERNS OF INCOME INEQUALITY AND POVERTY IN CENTRAL JAVA PROVINCE: A MORAN'S I AND LISA APPROACH

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ABSTRACT

Income inequality and poverty remain regional development challenges, as they exhibit distinct spatial characteristics across regions. This study aims to analyze the distribution and spatial autocorrelation of income inequality and poverty in 35 districts/cities in Central Java Province, Indonesia, in 2025. Secondary Data on the Gini ratio and the percentage of the poor population were obtained from the Indonesian Statistics. Spatial analysis was done using thematic mapping, Queen Contiguity spatial weight matrix, Global Moran's I, and Local Indicators of Spatial Association (LISA). The results showed that the Gini ratio had a relatively weak positive spatial autocorrelation (Moran's I = 0.181; $z = 1.855$; pseudo $p = 0.043$), while poverty also showed a slightly higher positive spatial autocorrelation but remained relatively weak (Moran's I = 0.237; $z = 2.246$; pseudo $p = 0.021$). LISA's analysis shows that there are low–Low Gini ratio clusters in Jepara, Pati, and Kudus, while high–High poverty clusters are found in Banjarnegara, Banyumas, Cilacap, Purbalingga, Purworejo, and Kebumen. These findings suggest that the spatial pattern of poverty is broader than income inequality, while the two indicators represent different dimensions of well-being. The results of the study confirmed the importance of spatial perspective in formulating more contextual regional development policies.

Keywords: income inequality, poverty, spatial analysis, Lisa, Central Java

INTRODUCTION

Regional development is fundamentally aimed at improving community welfare, yet development outcomes are not always evenly distributed across regions. Areas with strong economic activity do not necessarily exhibit low poverty and equitable income distribution. Conversely, relatively low income inequality does not automatically indicate higher welfare because income may be distributed more evenly at a generally low level. Poverty and income inequality, therefore, represent two closely related but conceptually distinct dimensions of regional welfare. Poverty reflects limitations in individuals' or households' ability to meet basic needs, whereas income inequality reflects differences in the distribution of income among population groups. Consequently, regions with similar

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levels of economic development may exhibit different combinations of poverty and income inequality.

Central Java Province provides an important case for examining these differences because its 35 regencies and municipalities display heterogeneous socioeconomic characteristics. Variations in economic structure, urbanization, accessibility, infrastructure, labor-market conditions, and employment opportunities contribute to different welfare outcomes across regions. Some areas have developed as centers of industry, trade, and services, while others remain more dependent on lower-productivity economic activities. These structural differences allow one region to experience relatively low poverty but high income inequality, while another may face relatively high poverty with a more even income distribution.

Differences in regional welfare conditions also need to be understood spatially because socioeconomic outcomes in one region may be associated with conditions in surrounding regions. Labor mobility, trade flows, transportation networks, investment, access to markets, and the provision of public services create linkages across administrative boundaries. Conventional inequality measures are limited in explaining this geographical dimension because they generally do not account for spatial dependence and economic interconnections among neighboring regions (Panzer & Postiglione, 2020). Therefore, treating each regency or municipality as an independent observation may obscure spatial relationships that influence poverty and income distribution.

A spatial perspective is particularly relevant because poverty and income inequality may not follow identical geographical processes. Poverty can stem from shared regional disadvantages, including inadequate infrastructure, limited market access, limited employment opportunities, low productivity, and unequal access to public services. When neighboring regions face similar structural constraints, poverty may become spatially clustered. Liu et al. (2023) demonstrate that regional poverty exhibits spatial dependence and that geographical factors contribute significantly to its spatial distribution. Evidence from Indonesia also shows that poverty displays spatial dependence across districts and that neighboring conditions are associated with the dynamics of regional poverty convergence (Miranti, 2021).

Income inequality, however, reflects the internal distribution of economic opportunities and returns within a region and may therefore be influenced by somewhat different mechanisms. Differences in sectoral composition, urbanization, labor-market segmentation, skill premiums, employment structures, and the concentration of productive activities can generate unequal income distributions even in economically developed areas. Peters (2012) shows that spatial income inequality varies according to economic structure and employment composition, while Khan and Siddique (2021) find that the magnitude and form of spatial income inequality vary across geographical scales. Studies in Indonesia likewise indicate that regional income disparities exhibit spatial

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dependence and that neighboring economic conditions can influence income dynamics across districts (Purwaningsih & Suseno, 2023; Santos-Marquez et al., 2021).

The conceptual framework of this study, therefore, distinguishes the mechanisms underlying the spatial distribution of poverty and income inequality. Spatial poverty is more closely associated with shared regional disadvantages and interregional linkages that may transmit socioeconomic vulnerability across neighboring areas. Income inequality is more closely associated with the internal distribution of economic opportunities, returns, and productive resources within each region. As a result, neighboring regions may exhibit similar levels of poverty without necessarily exhibiting similar levels of income inequality, while regions with relatively low poverty may still experience substantial inequality. This distinction provides a theoretical basis for examining the two indicators simultaneously rather than assuming that they generate identical spatial configurations.

Empirical studies provide substantial evidence that poverty frequently exhibits spatial clustering. Miranti (2021) identifies spatial dependence and regional polarization in poverty across Indonesian districts. More recent evidence from West Java also shows significant positive spatial autocorrelation and local poverty clusters using Global Moran's I and Local Indicators of Spatial Association, or LISA (Lillah & Wijyaningrum, 2025). Research on Java Island likewise identifies geographically concentrated poverty gaps and spatial relationships across regencies and municipalities (Sayekti & Taher, 2025). Maulana & Fauzan (2024) further demonstrate the relevance of spatial dependence in explaining poverty variation in East Java using different spatial-weight specifications, while Jati et al. (2024) identify spatial effects in poverty patterns at the regency level. These findings indicate that poverty should not be viewed solely as an isolated local condition because neighboring socioeconomic conditions may also matter.

Evidence concerning income inequality also confirms the importance of geographical relationships, although the resulting spatial patterns are not necessarily the same as those observed for poverty. Santos-Marquez et al. (2021) find significant spatial effects in regional income disparities across Indonesian regions, while Purwaningsih & Suseno (2023) identify spatial autocorrelation between regional economic performance and income inequality in Java. These studies suggest that inequality may also exhibit spatial dependence, but its magnitude, location, and clustering structure can differ from those of poverty because the two indicators represent different dimensions of welfare.

Previous research has also examined the joint relationship between poverty and income inequality. Joshi & Gebremedhin (2012), for example, analyze the spatial relationship between poverty and income inequality at the county level in the Appalachian region and find that the relationship between the two indicators is region-specific. Nevertheless, such studies primarily focus on the relationship or determinants linking poverty and inequality rather than directly comparing whether both indicators generate overlapping or divergent global and local spatial configurations under an identical spatial

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specification. Likewise, Indonesian studies have predominantly examined poverty clustering, spatial poverty determinants, regional income disparities, or income inequality as separate analytical subjects (Lillah & Wijayaningrum, 2025; Maulana & Fauzan, 2024; Miranti, 2021; Purwaningsih & Suseno, 2023; Santos-Marquez et al., 2021; Sayekti & Taher, 2025).

This limitation constitutes the main research gap addressed by the present study. There remains limited empirical evidence on whether areas characterized by high poverty also form clusters of high income inequality when both indicators are evaluated using the same territorial units, observation period, and spatial-weight structure. A direct comparison within an identical analytical framework enables identification of three spatial configurations: overlap between poverty and inequality clusters, spatial concentration in only one indicator, or divergence between the two indicators. These distinctions are not as clear when poverty and income inequality are examined separately or when different spatial units and neighborhood definitions are applied.

This distinction is also important from a policy perspective because poverty clusters and inequality clusters may require different forms of regional intervention. Areas characterized by spatially concentrated poverty may require coordinated policies for basic services, infrastructure, job creation, accessibility, and interregional connectivity. Areas characterized primarily by high income inequality may instead require greater attention to the distribution of employment opportunities, productive resources, human-capital returns, and access to economic opportunities. Regions simultaneously characterized by high poverty and high income inequality may face a more complex set of welfare disadvantages and therefore require integrated regional interventions.

Based on this rationale, this study analyzes the spatial patterns of poverty and income inequality across 35 regencies and municipalities in Central Java Province, Indonesia, in 2025. Spatial relationships among regions are specified using a first-order Queen Contiguity spatial-weight matrix. Global Moran's I is employed to assess the presence and strength of global spatial association, while Local Indicators of Spatial Association are used to identify statistically significant local clusters and spatial outliers. Both welfare indicators are examined using the same territorial units, observation year, and spatial-weight structure, thereby allowing a direct and internally consistent comparison of their geographical configurations.

The contribution of this study lies not merely in applying Global Moran's I and LISA, which have been widely used in previous spatial research, but in simultaneously comparing poverty and income inequality under an identical spatial specification. This approach provides empirical evidence on whether the two welfare indicators coincide spatially, partially overlap, or exhibit distinct geographical patterns. It also enables the identification of regencies and municipalities that simultaneously experience local concentrations of both high poverty and high income inequality. By distinguishing these

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spatial configurations, the study contributes to a more nuanced understanding of regional welfare disparities and provides evidence to support spatially targeted regional development policies.

METHODS

2.1. Research Design and Data

This study uses a quantitative approach with exploratory spatial analysis. The units of analysis include all 35 regencies/cities in Central Java Province, comprising 29 regencies and 6 cities. All administrative areas were analyzed, so the study did not use sampling techniques.

The data used are secondary data from 2025, sourced from the Central Statistics Agency. Income inequality is measured using the Gini Ratio, while poverty is measured as the percentage of the population living below the poverty line. Both indicators are analyzed separately using the same territorial units, observation period, and neighborhood structure to enable direct comparison of spatial patterns.

Statistical data for regencies/cities were integrated with the administrative boundary map of Central Java Province in shapefile format. Data processing, map preparation, and spatial autocorrelation testing were conducted using GeoDa software.

2.2. Weight Matrix and Spatial Mapping

The spatial relationships between the districts and cities were defined using a first-order Queen contiguity weighting matrix. Two regions were considered contiguous if their boundaries met at a corner or along an edge. The Dama Contiguity was chosen because it captures broader geographical connectivity than the Tower Contiguity, which only considers regions that share an advantage. This specification is also consistent with previous research that used Queen contiguity to analyze socio-economic indicators and poverty at the regional level (Farida et al., 2024; Maulana & Fauzan, 2024). To ensure that the contribution of the neighboring regions remained proportional despite discrepancies in the number of neighbors, the row-wise weights were standardized. Each city or district had at least one adjacent area, indicating that there were no isolated spatial units; however, the number of neighbors varied across regions, with Boyolali Regency and Semarang Regency having the highest counts.

The distributions of the Gini ratio and poverty were examined with maps of natural breaks, percentiles, and quantiles before analyzing the spatial autocorrelation. These maps were used to show variations in values and the relative positions of districts and cities. Sets of categories with similar values across neighboring areas were not considered spatial groupings, since such groupings must be statistically confirmed using Moran's Global I.

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To assess robustness, the Moran Global I was also calculated using tower contiguity as an alternative specification of the spatial weights. The findings from the Contiguity of Dama and Torre revealed consistent patterns of spatial autocorrelation and statistical significance for both poverty and the Gini ratio. Consequently, the identified spatial patterns proved robust when comparing the two contiguity-based spatial weight specifications.

2.3.Spatial Autocorrelation Analysis

Spatial autocorrelation is examined both locally and globally. This work covers 35 districts or cities in the province of Central Java. To examine the spatial autocorrelation patterns of the Gini ratio and the percentage of inhabitants living in poverty, Moran's global I was used. When the value is positive, regions with similar characteristics tend to cluster together; if the value is negative, regions with different characteristics tend to cluster together. A significance test was performed using 999 permutations at a 5% significance level. With 35 units of analysis, the value of Moran's I is estimated to be -0.0294. The significance of the results is evaluated using the simulated p-value and the z-score from the permutation distribution.

The Moran Scatter Diagram, which contrasts an area's indicator values with the weighted average of nearby areas' figures, is added to the global analysis of the Moran I index. The region is divided into four quadrants: Low-Low (LL), High-High (HH), Low-High (LH), and High-Low (HL). Likewise, the local Moran I, or the Local Spatial Association (LISA) indicator, is used to detect spatial clusters and outliers. HL and LH represent spatial outliers, while HH and LL refer to spatial groups. Only areas with a significant local Moran's I in $\alpha = 0.05$ are considered anomalous groups or values. Then, the results of the poverty relationship and the Gini analysis were compared to observe if there were similarities or differences in the spatial arrangement of both indicators.

RESULTS AND DISCUSSION

3.1.Characteristics of Income Inequality and Poverty

Descriptive statistical analysis is conducted to provide an initial overview of income inequality and poverty characteristics in 35 regencies/cities in Central Java Province in 2025. The presentation of descriptive statistics is necessary to show the tendencies in average values, data dispersion, and the range of variation for each indicator before spatial analysis is performed. This information serves as a basis for understanding whether differences in conditions between regions occur only in the magnitude of indicator values or also exhibit certain geographical patterns, which will be discussed in the subsequent analysis.

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Table 1. Descriptive Statistics of Income Inequality and Poverty in Central Java Province in 2025

Variable	Number of Observations	Average	Median	Minimum	Maximum	Standard Deviation
Gini Ratio	35	0,345	0,340	0,277	0,441	0,037
Poverty (%)	35	9,19	8,71	3,80	14,15	2,82

Table 1 shows that income inequality and poverty have different characteristics among regencies/cities in Central Java Province. The Gini Ratio has an average of 0.345 and a median of 0.340, while the poverty rate has an average of 9.19 percent and a median of 8.71 percent. The median values, which are relatively close to the average for both indicators, indicate that, in general, the data distribution does not experience extreme deviations. Nevertheless, the range of minimum and maximum values demonstrates a fairly significant variation in socio-economic conditions across regions.

The variation in the Gini Ratio is narrower than that in poverty levels. The Gini Ratio ranges from 0.277 to 0.441 with a standard deviation of 0.037, whereas poverty levels have a much wider range, from 3.80 percent to 14.15 percent with a standard deviation of 2.82. This condition indicates that poverty disparities among regencies/cities remain greater than income inequality disparities. In other words, the level of public welfare in Central Java still shows more pronounced differences compared to income distribution in each region.

The difference in the characteristics of the two indicators is also reflected in the regions that occupy the highest and lowest values. Magelang City has the highest Gini Ratio at 0.441, while Demak Regency recorded the lowest value at 0.277. Conversely, the highest poverty rate is in Brebes Regency at 14.15 percent, while Semarang City has the lowest poverty rate at 3.80 percent. These differences indicate that areas with high income inequality are not necessarily areas with high poverty rates, and vice versa.

The phenomenon illustrates that income inequality and poverty represent two different dimensions of welfare. For example, the city of Magelang maintains a relatively low poverty rate despite having the highest income inequality in Central Java. This condition indicates that most of the population is above the poverty line, yet the benefits of economic growth have not been evenly distributed among community groups. Conversely, Brebes Regency has the highest poverty rate with a relatively low Gini Ratio. The low inequality in this context does not indicate a higher level of welfare; rather, it suggests that most of the population still has relatively low incomes, making income distribution appear more even.

These findings reinforce the view that poverty and inequality cannot be used interchangeably as indicators of development success. Poverty refers to the proportion of

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the population that is unable to meet basic needs, whereas the Gini Ratio measures how income is distributed within a region. Therefore, a reduction in poverty does not always coincide with a decrease in income inequality, just as an increase in income equality does not necessarily indicate an overall improvement in societal welfare. The dynamics of poverty across Indonesia's regencies are influenced by regional differences, resulting in varying rates of poverty reduction (Miranti, 2021). In addition, regional inequality can be understood more comprehensively by incorporating spatial dimensions because aggregate indicators often fail to capture the interregional relationships through which neighboring regions influence one another (Panzer & Postiglione, 2020).

The statistical characteristics in Table 1 provide an initial indication that income inequality and poverty are unlikely to follow the same geographical pattern. The relatively large variation in poverty indicators suggests the presence of areas with high poverty levels, whereas the narrower distribution of the Gini Ratio indicates that income inequality is likely influenced by each region's economic characteristics. These indicators cannot be explained solely by descriptive statistics; thus, spatial analysis is required to understand their geographic distribution and whether there is a tendency toward regional clustering.

3.2.Spatial Distribution of Income Inequality and Poverty

Spatial mapping is used to show the location of regencies/cities with low, medium, and high values. Maps not only serve as visualizations but also help identify whether areas with similar characteristics are adjacent or dispersed. The Natural Breaks classification is used so that class formation follows the natural grouping in the data.

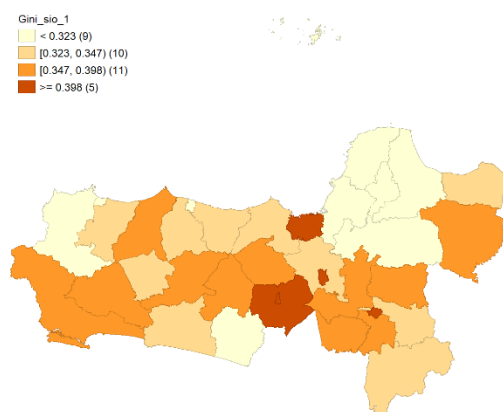


Figure 1. Map of Natural Breaks of the Gini Ratio of Regencies/Cities in Central Java Province in 2025

The map in Figure 1 shows that income inequality is not evenly distributed across the Central Java Province. Areas with the highest Gini Ratios are concentrated in Magelang City, Salatiga City, Semarang City, Surakarta City, and Magelang Regency. Conversely, Demak Regency, Purworejo, Kudus, Jepara, Tegal City, Pekalongan City, and Brebes are among those with relatively low inequality levels. This pattern indicates

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that income inequality is more prevalent in urban areas and economic growth centers than in areas dominated by agriculture or traditional economic sectors.

The concentration of inequality in urban areas indicates that economic growth is not always accompanied by an equitable distribution of income. Large cities have a more complex economic structure, with a dominance of the service, trade, industry, education, and government sectors, which can generate high incomes for certain segments of the population. However, informal workers and low-productivity sectors still receive economic benefits to a more limited extent. As a result, economic growth increases average welfare but also widens the income gap in the population.

This phenomenon is clearly evident in Magelang City, which has a relatively low poverty rate but the highest Gini coefficient in Central Java. This condition shows that poverty reduction does not necessarily imply an equitable distribution of income. The processing industry, construction, and wholesale and retail trade are the predominant sectors in Magelang's economy, with GDP figures at constant prices of 1,224, 66, and 1,213, respectively. 78 and 1,151. 36, respectively. Together, the three business sectors contribute about 44.1% of Magelang City's GRDP. The dominance of these sectors indicates a varied urban economic structure, with diverse patterns of business activity and employment. It may happen that a low proportion of the poor population occurs at the same time as a relatively high inequality in income distribution, due to differences in productivity and income specific to each economic activity. Thus, the placement of Magelang in a high Gini ratio category does not contradict the low level of poverty, since these two indicators reflect different dimensions of well-being.

These findings are consistent with previous studies indicating that regions with more advanced economic activity tend to experience higher income inequality because the gains from economic growth are not shared equally across all segments of society (Santos-Marquez et al., 2021). They also support the argument that regional inequality is better understood through a spatial perspective, since regions with higher levels of economic development do not necessarily exhibit a more equitable distribution of income (Panzera & Postiglione, 2020).

The pattern of poverty distribution shows a different geographical configuration from that of income inequality. Areas with the highest poverty rates are concentrated in the regencies of Brebes, Banjarnegara, Wonosobo, Pemalang, Rembang, Kebumen, and Purbalingga. Conversely, the cities of Semarang, Salatiga, Magelang, Pekalongan, as well as the regencies of Semarang, Kudus, Jepara, and Tegal, fall into the group with relatively low poverty levels. This distribution indicates that poverty is more prevalent in regency areas compared to the main cities in Central Java Province.

This pattern reflects differences in economic capacity between regions. Most districts with high poverty rates still rely on the agricultural sector, small-scale micro-enterprises, and economic activities with relatively low productivity. Limited formal employment opportunities, low economic diversification, and limited access to growth

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centers cause community income to increase more slowly than in urban areas. In contrast, large cities benefit from the concentration of trade, services, industry, education, and investment, enabling them to create broader employment opportunities and reduce the number of residents living in poverty.

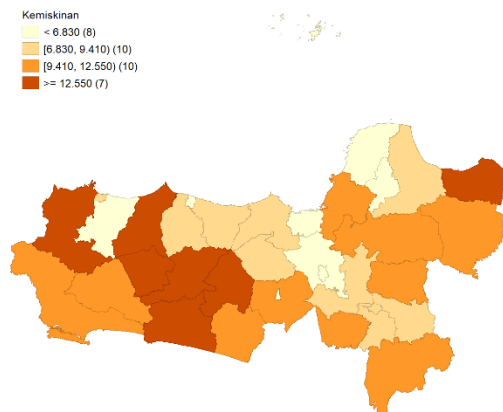


Figure 2. Natural Breaks Map of Poverty Levels in Regencies/Cities in Central Java Province in 2025

The comparison between Figure 1 and Figure 2 shows that the center of income inequality does not coincide with the center of poverty. Magelang City, Semarang City, Salatiga City, and Surakarta City have high income inequality, yet their poverty levels are relatively low. Conversely, Brebes Regency has the highest poverty rate but falls into the group with a relatively low Gini Ratio. These findings indicate that a more equitable distribution of income does not necessarily lead to higher levels of public welfare. In some regions, low inequality occurs precisely because the majority of the population is at relatively low incomes.

This phenomenon shows that poverty and inequality develop through different mechanisms. Inequality is more related to how the benefits of economic growth are distributed within a region, whereas poverty is more influenced by a region's ability to create economic opportunities and raise its population's income. Therefore, the success of development cannot be evaluated solely through either of these indicators, as each reflects different aspects of welfare.

The results of this study reinforce prior evidence that poverty dynamics across Indonesian regencies remain uneven due to differences in regional economic characteristics (Miranti, 2021). They further suggest that disparities in regional development continue to shape socio-economic conditions across Indonesia, resulting in persistent poverty in some areas despite relatively rapid economic growth elsewhere (Jati et al., 2024).

The spatial distribution of both indicators provides initial evidence that geographic characteristics help shape welfare patterns in Central Java Province.

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Nevertheless, thematic maps only show the locations of areas with high or low values and cannot confirm whether these areas are truly spatially related or merely adjacent by chance. Therefore, the analysis needs to continue using Global Moran's I to test for spatial autocorrelation and determine whether regencies/cities with similar characteristics tend to form statistically clustered patterns or are randomly dispersed.

3.3.Global Spatial Autocorrelation

The thematic map cannot yet confirm whether the observed patterns truly indicate spatial relationships. Global Moran's I is used to test whether regencies/cities with similar levels of inequality or poverty tend to be close to each other. Positive values indicate a tendency toward clustering, negative values indicate dispersion, while values approaching zero indicate a pattern that is increasingly random.

Table 2. Global Moran's I Results

Variable	Moran's I	Expected Moran's I	Standard Dev	z-value	p-value	Spatial Tendency
Gini Ratio	0,237	-0,029	0,118	2,246	0,021	Positive spatial autocorrelation
Poverty	0,181	-0,029	0,116	1,855	0,043	Positive spatial autocorrelation

The Global value of Moran's I in Table 2 indicates that income inequality and poverty exhibit positive and significant spatial autocorrelation. The values of Moran's I for the Gini ratio and poverty are 0.181 and 0.237, with pseudo p-values of 0.043 and 0.021, respectively. Although statistically significant, the coefficients for both indicators are relatively small, so the resulting spatial relationship remains weak and does not yet show strong grouping at the level of Central Java. This condition indicates that a district/city's characteristics are related to those of neighboring regions, but the relationship is not strong enough to imply that the characteristics of a region fully follow those of the surrounding region.

The value Moran's I Gini Ratio of 0.181 indicates a relatively weak positive spatial autocorrelation. The coefficient indicates the tendency for districts/cities with a relatively high level of inequality to be adjacent to areas with a relatively high or relatively low level of inequality. However, the low coefficient value indicates that the trend has not yet formed a strong inequality grouping. Thus, the distribution of inequality in Central Java remains related to the internal characteristics of each region, as well as to the spatial relationships with the surrounding area.

This condition is associated with differences in the economic structure between regions. Income inequality can be influenced by the composition of economic sectors, the

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degree of urbanization, the quality of human resources, the structure of the labor market, and the distribution of economic opportunities within a region. Cities with developed sectors of services, trade, education, and industry can have social groups with diverse income levels. In contrast, districts that are still dominated by the primary sector can have a different income structure, even though overall welfare levels are relatively low. These differences in characteristics can cause adjacent regions to have different levels of inequality, so the spatial relationships formed are not very strong.

These results support the argument that regional inequality is influenced not only by geographical proximity but also by differences in regional economic structures. As a result, neighboring areas may experience different levels of inequality because economic activities, productivity, and income distribution evolve through distinct development processes (Panzera & Postiglione, 2020).

In contrast to the Gini ratio, the poverty rate has a Moran's I of 0.237 with a pseudo p-value of 0.021, indicating a positive spatial autocorrelation that is higher than that of the Gini ratio. Nevertheless, the value still indicates a relatively weak strength of spatial relationships. These results indicate a tendency for districts/cities with relatively high poverty rates to be adjacent to other districts/cities with similar characteristics. Conversely, areas with relatively low poverty levels also tend to be adjacent to other areas with relatively low poverty levels. However, this trend cannot be interpreted as a strong grouping of poverty at the level of Central Java.

The findings indicate that poverty is not only related to a region's internal characteristics but also to the surrounding economic environment. Districts located in areas with limited infrastructure access, low connectivity, weak economic productivity, and limited employment opportunities may face similar welfare challenges. These conditions can produce spatial linkages between regions, although their strength is relatively limited.

The findings indicate that poverty has a more tangible regional dimension compared to income inequality. The condition of poverty is influenced not only by a region's internal characteristics but also by its surrounding economic environment. Regencies located in areas with limited infrastructure access, low connectivity, weak economic productivity, and limited employment opportunities tend to face similar welfare problems. As a result, poverty is more likely to form clusters of neighboring regions compared to income inequality.

These findings support previous evidence that poverty across districts in Indonesia exhibits a spatial pattern, indicating that poverty reduction does not occur independently within each region because socio-economic conditions are influenced by interactions with neighboring areas through economic linkages, population mobility, and access to regional growth centers (Miranti, 2021).

To provide a more detailed illustration of the spatial relationships, the results of Global Moran's I are visualized using a Moran Scatterplot, as shown in Figures 3 and 4.

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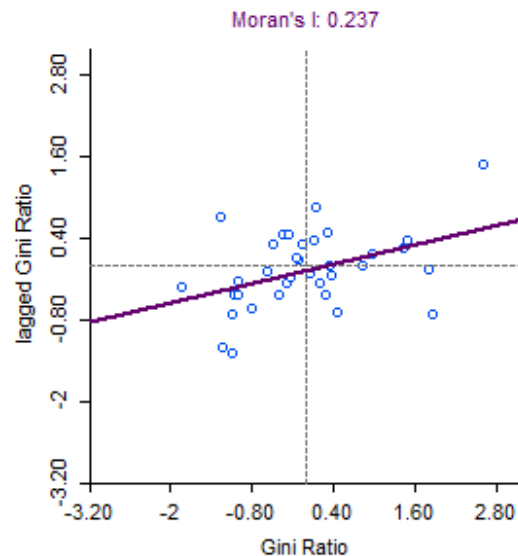


Figure 3. Moran Scatterplot of the Gini Ratio of Regencies/Cities in Central Java Province in 2025

The Moran Scatterplot of the Gini Ratio shows that most regencies/cities cluster around the center of the diagram. This distribution is consistent with the relatively small value of Moran's I, indicating that spatial relationships among regions are not strongly clustered. Nevertheless, there are still some regions in the High–High, Low–High, and High–Low quadrants, indicating local spatial relationships. These findings suggest that although the global pattern is relatively weak, several regencies/cities still exhibit characteristics that differ from those of the surrounding areas.

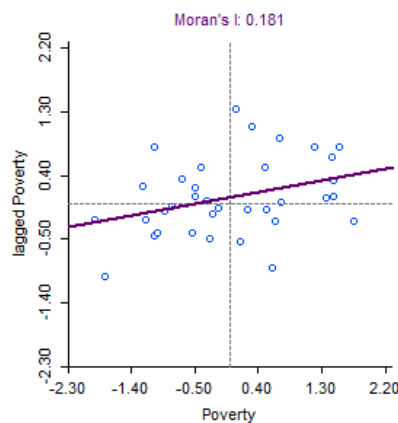


Figure 4. Moran Scatterplot of Poverty Rates of Regencies/Cities in Central Java Province in 2025

The distribution of points on the Moran Scatterplot of poverty shows a slightly more concentrated pattern than the Gini Ratio. Several regencies are located in the High–High quadrant, indicating that areas with high poverty levels tend to be adjacent to other areas with high poverty levels. Although their number is not large, the presence of these

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points reinforces the results of Global Moran's I, indicating that poverty has a clearer spatial association than income inequality.

The difference in patterns between the two scatterplots suggests that poverty and inequality develop through distinct spatial mechanisms. Income inequality more closely reflects variations in income distribution within each regency/city, whereas poverty is more influenced by regional characteristics that transcend administrative boundaries. These differences are an important reason why global analysis alone is insufficient to fully explain spatial relationships. Moran's I value only provides an average measure of the relationships across the entire area, so the presence of clusters or outliers in certain locations can still be obscured by a relatively weak global pattern.

The Local Indicators of Spatial Association (LISA) approach is necessary to identify locations that truly form spatial clusters or outliers. This analysis enables the identification of areas that are centers of poverty or inequality concentration, while also distinguishing them from regions that differ from their surroundings. Thus, the subsequent discussion not only explains whether spatial autocorrelation exists but also specifically identifies which regencies/cities are centers of clustering or spatial deviation in Central Java Province.

3.4. Local Spatial Clusters

Global Moran's I indicates that income inequality and poverty in Central Java Province exhibit positive spatial autocorrelation, although the strength is relatively weak. This value reflects the provincial-level spatial relationship tendencies, but it is not yet able to show the locations of regencies/cities that act as clustering centers or areas with characteristics different from their surroundings. To obtain more detailed information, the analysis is continued using Local Indicators of Spatial Association (LISA). Local Indicators of Spatial Association (LISA) enable the identification of each area's contribution to global spatial autocorrelation, thereby facilitating the detection of spatial clusters and spatial outliers (Lillah & Wijyaningrum, 2025).

Table 3. Classification of Local Spatial Clusters of Income Inequality and Poverty in Regencies/Cities in Central Java Province in 2025

Indicator	High–High	Low–Low	High–Low	Low–High
Gini Ratio	None	Jepara, Pati, Kudus	None	None
Poverty	Cilacap, Banyumas, Purbalingga, Purworejo, Kebumen, Banjarnegara	None	Demak	Tegal

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Based on Table 3, income inequality forms a more limited spatial cluster compared to poverty. In the GINI ratio indicator, there are low–Low (LL) clusters in Jepara, Pati, and Kudus regencies, while the high–High (HH), High–Low (HL), and Low–High (LH) categories are not found. Meanwhile, poverty forms a cluster of High–High (HH), which includes Cilacap, Banyumas, Purbalingga, Purworejo, Kebumen, and Banjarnegara, while Demak belongs to the category of High–Low (HL), and Tegal belongs to the category of Low–High (LH). The pattern shows that spatial clustering of poverty is more common than income inequality, with relatively high poverty rates concentrated in some parts of Central Java.

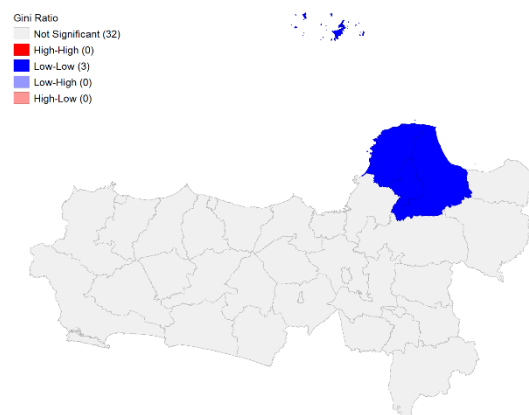


Figure 5. LISA Cluster Map of Gini Ratio of Regencies/Cities in Central Java Province in 2025

Based on Figure 5, the pattern of local autocorrelation of income inequality was found only in a small part of the region. Low-Low clusters are found in Jepara, Pati, and Kudus regencies, indicating that the three regions have relatively low inequality and are located in areas with similar inequality characteristics. Meanwhile, no regions are included in the categories High-High (High-High), High-Low (High-Low), or Low-High (Low-High). Most regions, namely 32 districts/cities, did not show significant local autocorrelation. The pattern shows that the spatial clustering of income inequality in Central Java remains limited and has not yet formed a broad cluster. This finding is in line with Moran's I Global results that show positive but relatively weak spatial autocorrelation, so that variations in income inequality reflect differences in the economic characteristics of individual regions more than strong spatial clustering patterns. Differences in economic structure, level of urbanization, business sector composition, and the distribution of economic opportunities across regions can cause adjacent districts/cities to experience different levels of inequality (Panzera & Postiglione, 2020).

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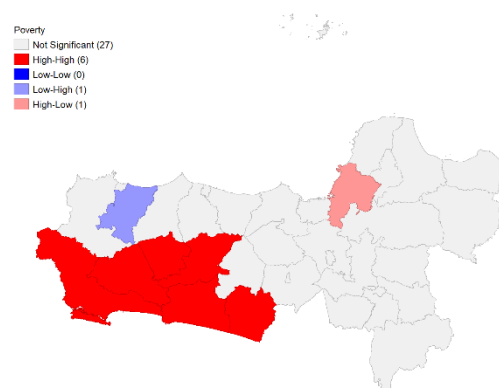


Figure 6. LISA Cluster Map of Poverty Levels by Regency/City in Central Java Province in 2025

In contrast to income inequality, Figure 6 shows that poverty forms a more pronounced local grouping pattern. High-High clusters are formed in the districts of Banjarnegara, Banyumas, Cilacap, Purbalingga, Purworejo, and Kebumen which are geographically located in adjacent areas. The pattern shows that these regions have relatively high levels of poverty and are in the vicinity of areas with similar poverty characteristics. In contrast, Demak belongs to the category of high-Low (High-Low), while Tegal belongs to the category of low-High (Low-High). These conditions indicate the existence of local characteristics that distinguish the poverty level of the two regions from the surrounding areas. This finding supports previous evidence that poverty has a spatial dimension, so the development conditions of a region are related to the economic conditions of the surrounding In contrast to income inequality, Figure 6 shows that poverty forms a more pronounced local grouping pattern. High-High clusters are formed in the districts of Banjarnegara, Banyumas, Cilacap, Purbalingga, Purworejo, and Kebumen, which are geographically adjacent. The pattern shows that these regions have relatively high poverty levels and are in close proximity to areas with similar poverty characteristics. In contrast, Demak belongs to the category of high-Low (High-Low), while Tegal belongs to the category of low-High (Low-High). These conditions indicate the presence of local characteristics that distinguish the poverty levels of the two regions from those of the surrounding areas. This finding supports previous evidence that poverty has a spatial dimension, such that a region's development conditions are related to the economic conditions of the surrounding region (Miranti, 2021).

Demak Regency, which belongs to the high-low category, shows a relatively high poverty level compared to the surrounding area, while Tegal Regency, which belongs to the low-high category, has a relatively low poverty level despite being in an area with a relatively high poverty level. Meanwhile, most of the other districts/cities, namely 27 regions, did not exhibit significant local autocorrelation. The pattern shows that poverty clustering is not evenly distributed throughout Central Java but is more concentrated in certain regions. The existence of a large, wide cluster also shows that areas with high

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poverty levels tend to be adjacent to other areas with similar conditions, so the characteristics of the surrounding area become an aspect that needs to be considered in understanding poverty patterns.

The comparison between Figure 5 and Figure 6 shows that the pattern of local autocorrelation of poverty is more extensive than that of income inequality. In income inequality, only Jepara, Pati, and Kudus districts are included in the low-low cluster, while in poverty, six districts are in the high-high cluster, and each region is in the high-low and low-high categories. The difference indicates that the spatial pattern of poverty is not identical to that of income inequality. Poverty tends to exhibit more pronounced local clustering, whereas income inequality shows more limited local patterns. These findings suggest that the spatial characteristics of poverty and income inequality need to be understood differently because they represent socioeconomic dimensions that are not entirely the same.

3.5.Comparative Spatial Pattern of Income Inequality and Poverty

Analysis of descriptive statistics, thematic maps, Global Moran's I, and LISA showed that income inequality and poverty in Central Java Province have different spatial characteristics. The differences were seen both in the degree of variation of the data and in regional clustering patterns. Income inequality shows a relatively weak spatial relationship, with few local clusters, whereas poverty shows a more pronounced tendency to cluster across several adjacent districts. This finding shows that the two indicators exhibit different spatial patterns, so they need to be understood in terms of their respective characteristics.

In terms of indicators of income inequality, most districts/cities do not form significant local spatial relationships with surrounding areas. The low Global value of Moran's I and the limited number of local clusters indicate that income inequality has a relatively weak spatial linkage. Differences in economic structure, the level of urbanization, the composition of the business sector, and the capacity of regions to create diverse economic opportunities can be among the internal characteristics that distinguish conditions of inequality between regions. Previous literature suggests that differences in economic characteristics across regions may contribute to spatial variation in inequality (Panzer & Postiglione, 2020). However, these factors were not tested empirically in this study, so they cannot be considered determinants of spatial inequality patterns. Thus, the study's results more precisely show that geographical proximity is not the only factor driving variations in income inequality between regions.

In contrast, poverty shows more consistent spatial patterns. High-High clusters were formed in Banjarnegara, Banyumas, Cilacap, Purbalingga, Purworejo, and Kebumen, indicating that areas with relatively high poverty tend to cluster around areas with similar poverty characteristics. The pattern can be related to the similarity of socio-economic characteristics between adjacent regions. Factors such as economic structure,

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productivity, employment opportunities, and access to centers of economic activity can help explain such patterns. However, since these variables were not directly tested, this study cannot confirm the contribution of each factor to the formation of poverty clusters. Findings that can be confirmed are the existence of local spatial linkages in some areas with relatively high poverty rates. This is in line with the findings of Miranti (2021) which show that poverty in Indonesia has a territorial dimension and is related to the characteristics of the surrounding area.

The comparison of the two indicators also shows that a high level of poverty is not always accompanied by high income inequality. Banyumas and Banjarnegara regencies are examples of areas that are included in high poverty clusters, but are not included in the same local cluster on income inequality indicators. In contrast, the city of Magelang has a relatively high level of income inequality, while the poverty rate is relatively low. This condition shows that the uneven distribution of income is not always synonymous with a high proportion of the poor. Both indicators describe different socioeconomic dimensions, so a region can have relatively low poverty levels yet still exhibit relatively high income inequality.

Another finding is the position of Cilacap Regency and Kebumen Regency, both of which are included in the high-Poverty Indicators cluster. These conditions indicate that the two districts have relatively high poverty rates and are in close proximity to areas with similar poverty characteristics. However, on the Gini ratio indicator, the two regions do not form high clusters. Therefore, the existence of Cilacap and Kebumen in the poverty cluster cannot be directly interpreted as a spatial grouping of income inequality. These differences show that poverty and income inequality have spatial configurations that are not entirely the same. Thus, it is necessary to examine a region's socioeconomic characteristics more specifically when describing the spatial patterns of each indicator.

The results of this study reinforce the view that spatial analysis provides more comprehensive information than conventional statistical analysis. Descriptive statistics only show the magnitude of differences in values between regions, whereas spatial approaches can reveal geographical relationships that form grouping patterns and identify regions with characteristics that differ from those of the surrounding area. Identifying local spatial autocorrelation is important because aggregate regional indicators often fail to capture the complexity of interregional relationships (Lillah & Wijayaningrum, 2025). The findings of this study are also consistent with previous studies showing that poverty in Indonesia has a territorial dimension and that regional disparities are related to local economic characteristics and spatial relationships between regions (Miranti, 2021; Panzera & Postiglione, 2020). In the context of this study, these results indicate spatial linkages but do not provide evidence of a causal effect of specific economic characteristics on poverty and income inequality.

The results showed that the development approach in Central Java province needs to account for the spatial characteristics of each region. Regions that form poverty clusters

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can be a concern in the formulation of policies that consider interregional links, such as strengthening regional connectivity, increasing local economic productivity, and expanding employment opportunities. Meanwhile, regions with relatively high levels of income inequality can pose a concern for efforts to expand the equitable distribution of the benefits of economic growth by increasing access to Education, Workforce Skills Development, and expanding economic opportunities. The recommendation is an implication of the spatial patterns found, not the result of direct testing of each factor's influence. By taking into account different spatial characteristics, development policies are expected to be designed more contextually to address poverty and income equity in a sustainable manner.

CONCLUSION

This study shows that income inequality and poverty in Central Java Province in 2025 have different spatial characteristics. Income inequality showed relatively weak positive spatial autocorrelation with limited local clusters, while poverty showed positive spatial autocorrelation with broader local grouping patterns, especially in the areas of Banjarnegara, Banyumas, Cilacap, Purbalingga, Purworejo, and Kebumen. The findings show that the spatial linkage of poverty across districts/cities is more visible than income inequality during the study period.

LISA's analysis showed that Cilacap and Kebumen districts were included in the high cluster for the poverty indicator but not for the income inequality indicator. Meanwhile, the city of Magelang showed a relatively high level of income inequality with a relatively low poverty rate. These differences indicate that poverty and income inequality reflect distinct socioeconomic dimensions and therefore cannot be used interchangeably as indicators of regional development conditions. This result also confirms the importance of a spatial approach in identifying grouping patterns and characteristic differences between regions that cannot be seen only through descriptive analysis.

However, this study has limitations because it only uses data from one year, namely 2025. Therefore, the identified spatial patterns can reflect the short-term conditions in the observation year, but have not been able to describe the changes and spatial dynamics of income inequality and poverty over time. This study also cannot explain whether the spatial patterns observed are consistent over the long term or change in response to shifts in the region's socio-economic conditions. Subsequent studies may use multi-year data or spatial-temporal approaches to identify changes in autocorrelation patterns and cluster persistence between periods. In addition, future research can conduct a spatial regression analysis by including variables such as economic structure, education, employment opportunities, urbanization, and infrastructure to examine factors that shape spatial patterns of poverty and income inequality.

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