The Spatial Pattern of COVID-19 Incidence in Relation to Poverty Across Central Java Province

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Abstract. The COVID-19 outbreak has negative effects not only on public health but also on socioeconomic circumstances, leading to reduced income, unemployment, and an escalation in poverty. The study explores the spatially varying relationships between COVID-19 incidence and poverty in Central Java Province and analyzes the spatial correlation of COVID-19 with poverty. The Central Statistical Agency has provided supplementary data for the calculations. The research method is observational with Moran's Index technique, including Univariate Moran's I and Bivariate Moran's I using GeoDa software. The results showed that the distribution pattern of COVID-19 and poverty in Central Java Province was clustered. The spatial autocorrelation is positive; the value of I = 0.070; 0.211 is greater than E(I) = -0.029. The spatial correlation of COVID-19 with poverty shows a negative value, meaning that the number of confirmed cases of COVID-19 in the observation districts does not have a similar value to poverty around them. Most observed districts are in quadrants II and III. COVID-19 vaccination to hinder the propagate of the virus should prioritize regencies in quadrants II and III. Healthy residents will help increase the economy, and The growth of the Central Java region in terms of reducing poverty has been significantly influenced by the slowly improving economy.

Keywords: Spatial Pattern · Moran's Index · COVID-19 · Poverty

1 Introduction

This COVID-19 disease has, directly and indirectly, impacted all people's lives (Singh & Singh, 2020). More cases of COVID-19 continue to run rampant, causing a lockdown rule because the COVID-19 virus had quickly spread anywhere. Lockdown is detrimental to economic sectors in all regions that implement this policy because stopping community activities can cause all macro and micro businesses to be hampered, which will be challenging to restore (Adam et al., 2020). Social restrictions are also implemented as an attempt to hinder the spread of the virus transmission. Limited social distance impacts the economic aspect (Khalifa et al., 2021).

H. Z. Hadibasyir and V. N. Fikriyah (Eds.): ICGDM 2022, ASSEHR 755, pp. 450–463, 2023.
https://doi.org/10.2991/978-2-38476-066-4_29

The COVID-19 pandemic simultaneously caused health and economic crises (Susskind & Vines, 2020; Hitt et al., 2021). The health crisis occurred because many people were infected with COVID-19, so the level of human health declined and even resulted in death (Omer et al., 2020). The economic crisis was caused by the lockdown, which is one way to deal with the transmit of COVID-19.

The COVID-19 outbreak impacts an economic crisis (Ozili, 2021) that affects socioeconomic conditions such as a decline in per capita income, unemployment, and poverty levels. (Chernyshov & Usmanov, 2020). Companies that fire some employees because they are unable to pay employee salaries make that person have to change professions until the impact on the unemployment rate increases. Restricted community activities cause significant effects on the industry, tourism, and international transportation, constricting the world economy (Chang et al., 2020). This impact also affected the price of necessities, which increased significantly. This condition creates additional problems for all communities or consumers to meet their food needs. Behind the expensive food prices, it turns out that there are people who deliberately increase the price of goods to increase their income quickly (Mohiuddin, 2020).

COVID-19, which is spreading globally, affects poverty globally as well, which is a danger to development efforts because it is influenced by the crisis that emphasizes the lack of income and consumption with aspects of human welfare (Ranasinghe et al., 2021). The economy during the COVID-19 outbreak looks terrible, impacting income and poverty (Han et al., 2020). COVID-19 affects the macro and micro economy, which has a negative impact on GDP and employment, which has the potential to lead to an increase in the incidence of poverty (Deyshapriya, 2020).

The Indonesia Government has taken several initiatives to manage and deal with the COVID-19 outbreak. This step is a disaster mitigation effort to lessen the consequence of the COVID-19 disaster (Pragholapati, 2020). The government made these efforts to overcome the rising poverty rate. The percentage of Indonesia's poverty increased to 10.19% in 2020 from 9.22% in 2019, the percentage of the population. Regions in Indonesia experiencing a surge in the number of poor people are no exception for Central Java Province. In 2020, 11.84% of the population was classified as poor, which increased by 1.26% in 2019 (BPS, 2021). Hence this study aimed to analyze the spatial arrangement of COVID-19 incidence and the poverty rate and the geographical correlation of COVID-19 incidence with the poverty rate across Central Java Province.

2 Methods

2.1 Research Location and Data Sources

The study area is situated in the Central Java Province, which comprises 35 districts. Figure 1 displays the map of the study location.

This study uses data on valid event of COVID-19 and the poverty rate across Central Java Province in 2020. Data regarding verified instances of COVID-19 was collected during the initial stages of the COVID-19 outbreak, namely March 2020, until the end of December 2020. The pandemic period was sourced from the official website of the COVID-19 tactical force for each Regency and City in Central Java Province. In Central Java, there have been 93,353 valid cases of COVID-19 (see Fig. 2).

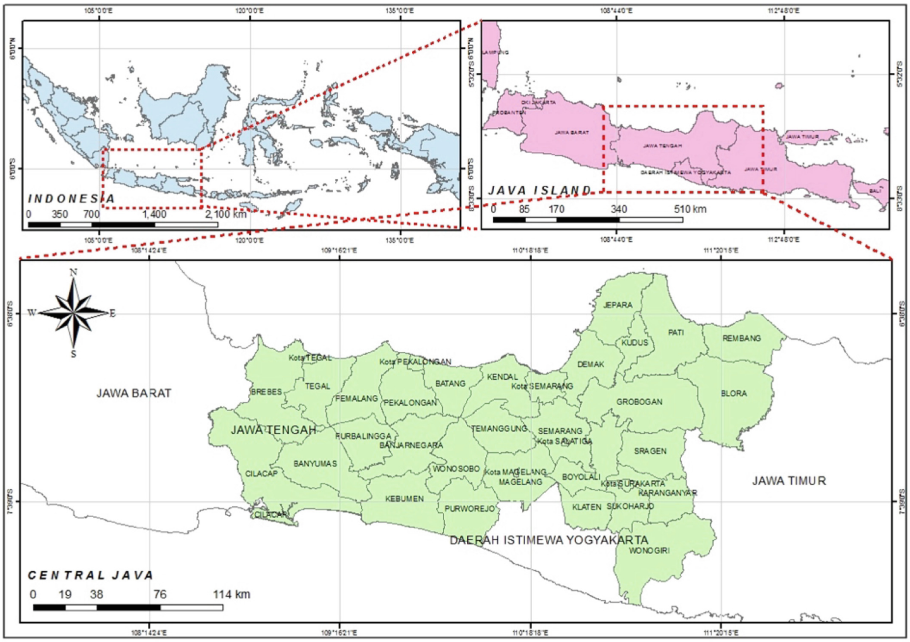

Fig. 1. The research location.

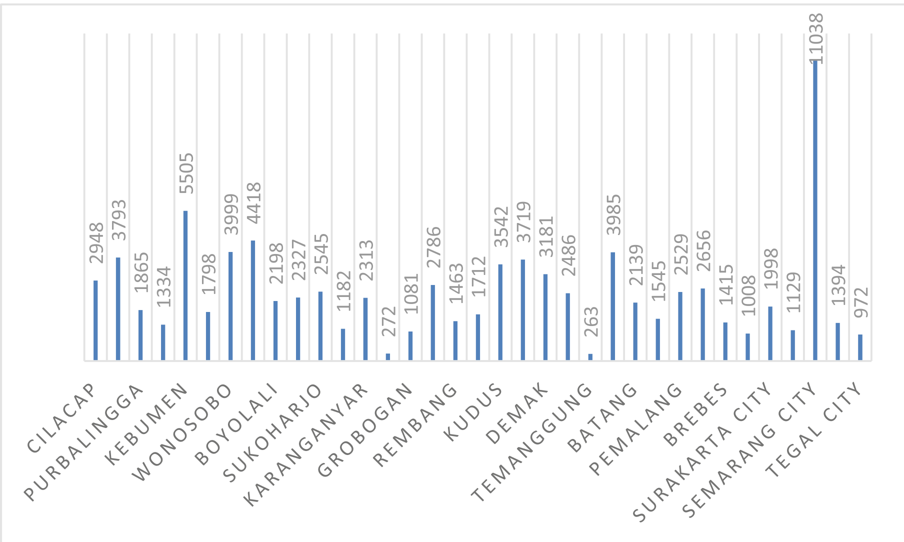

Fig. 2. The number of COVID-19 confirmed cases across Central Java Province in 2020.

The poverty rate in Central Java from 2016 to 2019 fell significantly, but during the pandemic period in 2020 and 2021, it increased compared to previous years (Central

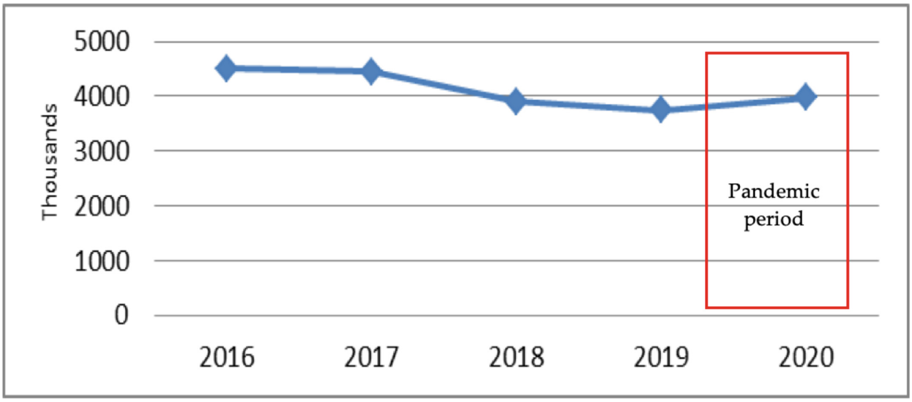

Fig. 3. The poverty rate in Central Java Province 2016–2020.

Statistics Agency, 2020). The number of poor people in 2016 was 4,506,890 people, and in 2019 it dropped significantly, amounting to 3,743,230 people. However, in 2020 the number of financially struggling masses increased to 3,980,900 people. This trend shows that the increase in poor people coincides with the COVID-19 outbreak (Fig. 3).

2.2 Data Processing and Analysis

The data is processed using GeoDa software in the form of Moran's Index statistics which produce spatial correlation coefficients. Moran's Index is a statistical test to calculate global autocorrelation and spatial correlation values (Amin et al., 2021). The spatial weighting matrix is carried out to find out the closest neighbours of the research area in the form of the Queen Contiguity method; namely, the calculated sides and angles that intersect are used to determine the observation location.

The first step was a spatial autocorrelation test using Univariate Moran's I to investigate the arrangement pattern of valid cases of COVID-19 and the number of poor people. If the value of the Moran's I test is negative, it indicates that there is a negative autocorrelation. Conversely, if there is a positive autocorrelation, the value of the Moran's I test will be positive. For the determination of the distribution pattern, Moran's Index value results are between -1 and 1. The range of values for the Moran's I test can be used to represent the presence and direction of spatial autocorrelation. If the value falls between -1 and 0, it indicates a negative spatial autocorrelation. On the other hand, if the value is between 0 and 1, it represents a positive spatial autocorrelation. Identify the pattern using the criteria if the value of $I > E(I)$ = clustered pattern, if $I < E(I)$ = spread pattern and if $I = E(I)$ = unevenly spread pattern. The value of E(I) is the expected value of I, which is formulated as follows (Bivand, 2009).

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

Note: n = the number of regions (Regencies/Cities in one Province).

Then a spatial correlation test was carried out with the number of confirmed cases of COVID-19 with the number of poor people using Bivariate Moran's I. The value of the Moran's I test was positive, so there was a positive spatial correlation globally. The value of Moran's I test is negative, so there is no global spatial correlation. Moran's Scatterplot is a way to determine spatial autocorrelation in units. This scatterplot utilizes the Moran's I statistic, which displays the correlation between the observed values at a specific location and the average values of observations in nearby areas (Faiz et al., 2013).

The Moran's Scatterplot is divided into four quadrants. The first quadrant, positioned at the top right, is referred to as the High-High quadrant. This quadrant illustrates areas where high observed values are found alongside other areas with high observed values. Quadrant II (Low-High), positioned at the top left, shows locations with low observed values encircled by areas with high observed values. Quadrant III (Low-Low) is located at the bottom left of the diagram and represents locations with low observed values that are surrounded by areas with high observed values. Quadrant IV (High-Low) is positioned at the bottom right and depicts locations with high observed values that are surrounded by areas with low observed values.

To determine the spatial pattern of distribution and correlation of the number of confirmed COVID-19 cases and the poverty variable, the Moran's I test was conducted using GeoDa Software. This involved performing both the Univariate Moran's I test and the Bivariate Moran's I test. The resulting output of the Moran's I test was in the form of a Moran's index value. The spatial distribution pattern is known based on comparing the values I and E(I). The Moran Index value is obtained from data processing on the GeoDa Software.

3 Results

3.1 Spatial Patterns of COVID-19 Incidents Across Central Java Province

Central Java Province has 35 districts, so the number of n is 35. The result of the Univariate Moran's I test for the variable number of valid cases of COVID-19 is a value of I of 0.070 (see Fig. 3) which indicates a positive spatial autocorrelation with a clustered distribution pattern. Positive spatial autocorrelation means that the number of con-firmed cases of COVID-19 in districts/cities in Central Java Province has similar values in the surrounding areas. The spatial pattern of the distribution of valid cases of COVID-19 shows clusters because the value of I = 0.070 is greater than the value of E(I) = -0.029.

Based on Fig. 4, the areas within quadrant I exhibit a high number of COVID-19 incidents, and their surrounding areas also have high numbers of COVID-19 incidents. The districts included in quadrant I are Cilacap, Demak, Jepara, Kebumen, Kendal, Semarang City, and Wonosobo. Areas included in quadrant II mean that the area has a low number of COVID-19 incidences. However, the surrounding area has a high COVID-19 incidence. The districts in quadrant II include Banjarnegara, Klaten, Purworejo, Semarang, Temanggung, and Magelang City. Quadrant III includes areas with a low number of confirmed COVID-19 cases, and these areas are surrounded by other areas that also have low numbers of confirmed COVID-19 cases. The districts enclosed in quadrant III include

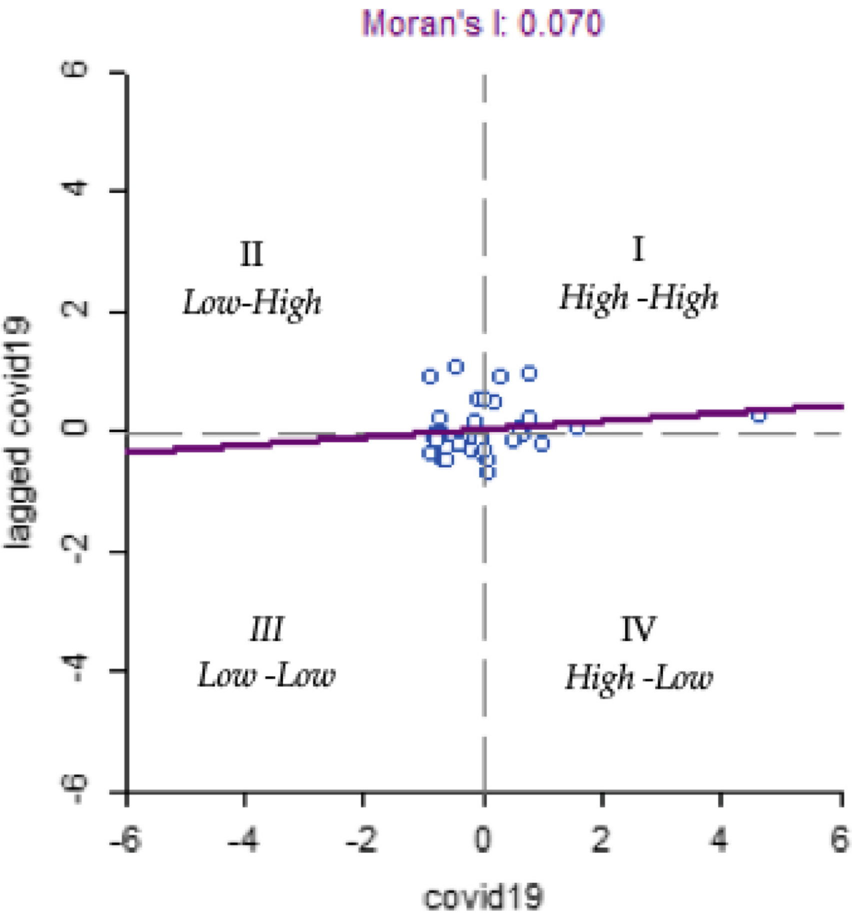

Fig. 4. Univariate Moran's Scatterplot of the COVID-19 incidence in Central Java Province.

Batang, Brebes, Grobogan, Boyolali, Karanganyar, Pati, Pekalongan, Pemalang, Purbalingga, Rembang, Sukoharjo, Tegal, Wonogiri, Pekalongan City, Salatiga City, Surakarta City. Meanwhile, the area in quadrant IV shows that the area has a high number of COVID-19 confirmations, but the surrounding area has a low COVID-19 confirmation. The districts included in quadrant IV are Banyumas, Blora, Kudus, Magelang, and Sragen. Based on Moran's scatterplot test for the number of confirmed COVID-19 variables, most areas in Central Java Province are in quadrants I and III. The data on the number of confirmed cases of COVID-19 in Central Java Province is visualized with a map using GeoDa software which is classified based on the Natural Breaks Map method, which can be seen in Fig. 5.

The distribution of confirmed COVID-19 cases in Central Java Province is illustrated in Fig. 5, with colour gradations indicating the distribution level. The darker the colour gradation, the higher the number of confirmed COVID-19 cases. The area with a dark gradation is Semarang City, indicating that the number of confirmed COVID-19

Fig. 5. Map of the Distribution of the Number of Confirmed COVID-19 Cases in Central Java Province 2020 (grouped using the Natural Breaks Map method).

cases in Semarang City has very high number of cases. Meanwhile, the areas with the low number of confirmed cases of COVID-19 are Brebes, Pekalongan, Banjarnegara, Wonogiri, Grobogan, Rembang, Pati, and Pekalongan City.

3.2 Spatial Patterns of Poverty Distribution in Central Java Province

The Univariate Moran's Scatterplot test on the poverty variable (see Fig. 5) shows that Moran's index value (I = 0.211) is greater than the expected value (E(I) = -0.029. Based on these results, it can be seen that the pattern of the distribution of poverty in Central Java Province is positive. A positive Moran's index value for poverty in Central Java Province indicates a positive spatial autocorrelation, which means that the poverty value in all districts within the province is similar to that of the surrounding areas.

In the Moran's Scatterplot Fig. 6, regions included in quadrant I have a high poverty rate, and the surrounding areas also have a high poverty rate. The regencies in quadrant I include Banjarnegara, Banyumas, Brebes, Cilacap, Kebumen, Pemalang, Purbalingga, Sragen, Tegal, and Wonosobo. Regions included in quadrant II have a low poverty rate, but the surrounding area has a high poverty rate. The regencies in quadrant II include Blora, Boyolali, Magelang City, Kudus, Pekalongan, Purworejo, Rembang, Temanggung, and Tegal City. Regions included in quadrant III have low poverty rates, and the surrounding areas also have low poverty rates. The regencies in quadrant III include Batang, Jepara, Karanganyar, Kendal, Semarang, Sukoharjo, Wonogiri, Pekalongan City, Salatiga City, Semarang City, and Surakarta City. Regions included in quadrant IV have

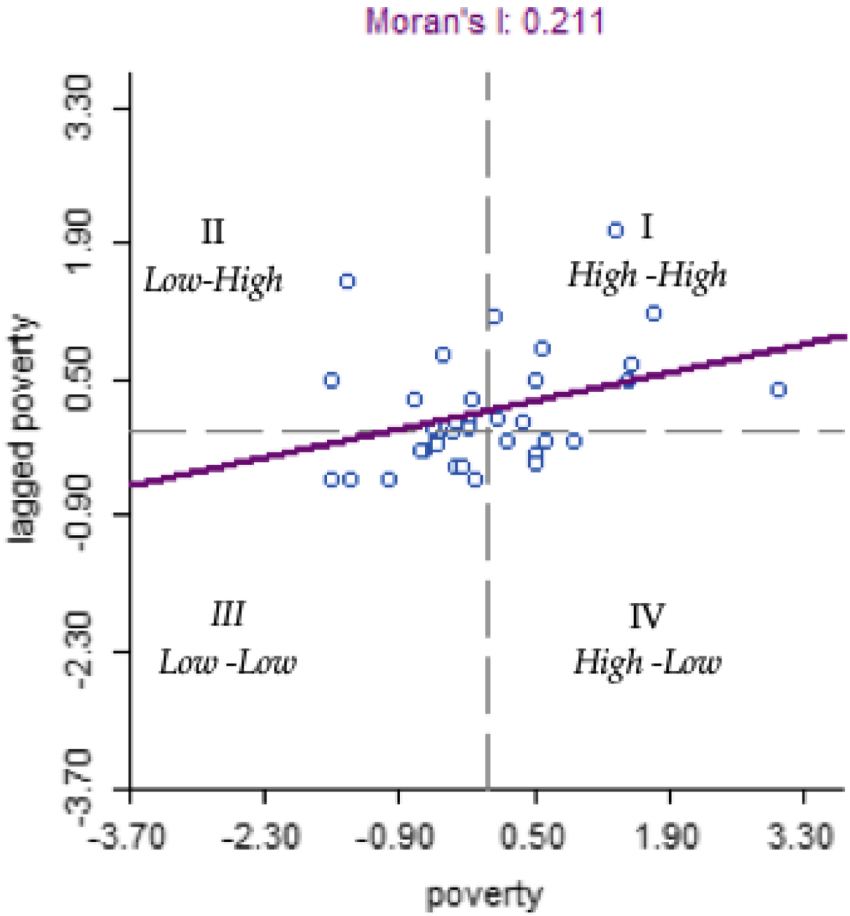

Fig. 6. Univariate Moran's Scatterplot of the Poverty in Central Java Province.

a high poverty rate, but the surrounding areas have a low poverty rate. The regencies in quadrant IV include Demak, Grobogan, Klaten, Magelang, and Pati. Based on Moran's scatterplot test for the poverty level variable, most districts in Central Java Province are in quadrants I and III. The distribution of the poverty rate is visualized using a map using GeoDa software which is classified based on the Natural Breaks Map method, can be seen in Fig. 7.

Figure 7 shows a map of the distribution of poverty levels in Central Java Province, with colour gradations showing the distribution classification. The darker the colour gradation, the higher the poverty level. Areas with a dark gradation are the Regencies of Brebes, Banyumas, Pemalang, Cilacap, and Kebumen, indicating that these areas have a very high poverty classification. Meanwhile, the areas with low poverty classification are Tegal City, Pekalongan City, Magelang City, Surakarta City, and Salatiga City.

Fig. 7. Map of the Distribution of poverty rate in Central Java Province 2020 (grouped using the Natural Breaks Map method).

3.3 Spatial Pattern of COVID-19 Incidence in Relation with Poverty Across Central Java Province

The Bivariate Moran's I test showed that the result was a value of I = -0.011 (see Fig. 7), which means the spatial correlation of the number of confirmed COVID-19 cases with poverty in Central Java Province is negative.

Moran's Scatterplot shows regions in quadrant I with a high number of confirmed COVID-19 cases, and the surrounding area also has a high poverty rate. The regencies in quadrant I are Banyumas, Blora, Cilacap, Kebumen, Kudus, Wonosobo, and Sragen. Regions in quadrant II have a low number of confirmed COVID-19 cases, but the surrounding areas have a high poverty rate. The regencies in quadrant II are Banjarnegara, Brebes, Boyolali, Pekalongan, Pemalang, Purbalingga, Purworejo, Rembang, Tegal, Temanggung, Magelang City, Tegal City. The region in quadrant III is an area that has a low number of confirmed cases of COVID-19, and its surroundings also have a low poverty rate. The regencies in quadrant III are Batang, Grobogan, Karanganyar, Klaten, Pati, Semarang, Sukoharjo, Wonogiri, Pekalongan City, Salatiga City, and Surakarta City. Regions in quadrant IV have a high number of confirmed COVID-19 cases, but the surrounding areas have low poverty rates. The regencies in quadrant IV are Demak, Kendal, Semarang City, Magelang, and Jepara. Moran's bivariate results show that most districts in Central Java Province are in quadrants II and III. Moran's Bivariate test results are visualized on a map using GeoDa software, as shown in Fig. 9.

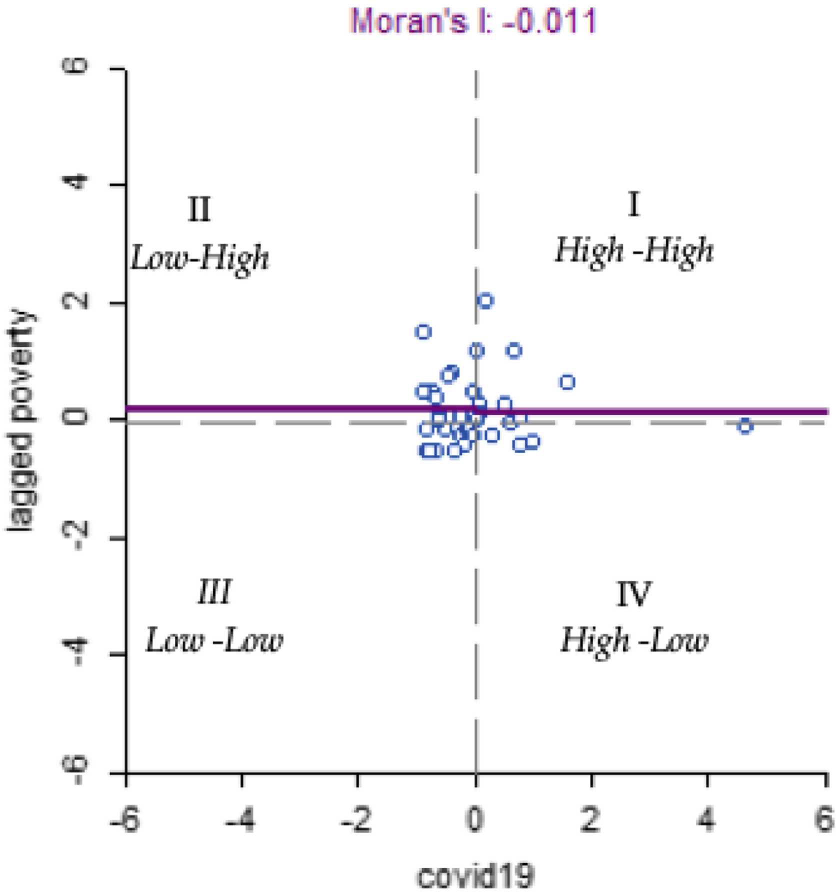

Fig. 8. Bivariate Moran's Scatterplot of COVID-19 Incidence and the Poverty in Central Java Province.

Figure 8 shows the districts included in quadrant I, indicated by a red colour gradation; quadrant II, indicated by a light blue colour gradation; quadrant III, indicated by a blue colour gradation; and quadrant IV, indicated by a pink colour gradation. Based on the Bivariate Moran's I test results, the global spatial correlation of the number of confirmed cases of COVID-19 with the poverty rate across Central Java Province is negative. Meanwhile, when viewed from the unit, most districts are in quadrants II and III.

4 Discussion

Economic inequality due to differences in regional geographical conditions can be found in various regions, which is still experienced by regions of Indonesia in general (Sari et al., 2022). This study exhibits the clustering of the distribution patterns of the number of verified COVID-19 cases and poverty, as well as the positive spatial autocorrelation

Fig. 9. Map of the spatial correlation of COVID-19 incidents with poverty rates across Central Java Province.

for each variable. Districts in Central Java Province have a high (low) number of confirmed cases of COVID-19; therefore, the surrounding areas also have a similar number of confirmed COVID-19 cases with a high (low) value. For example, Semarang City, which has the highest number of confirmed COVID-19 cases, the closest neighbour of Kendal Regency, also has a high number of confirmed COVID-19 cases. Semarang City is the center of economic activities, such as working outdoors and indoors causes the coronavirus to spread quickly. People who work outdoors are more likely to get COVID-19 (Olivia et al., 2020). In addition, population density also affects the COVID-19 virus, which can spread easily and quickly (Zhang & Schwartz, 2020) because a dense population in Semarang City creates crowds that make people ignore social distancing then the COVID-19 virus can spread quickly.

Research on the relationship between COVID-19 with spatial-temporal and poverty has been widely carried out from 2020 to 2022 (Jumadi et al., 2022). Districts in Central Java Province with high poverty in their surrounding areas also have similar high poverty values, and vice versa. For example, in Banyumas Regency, which has high poverty, the surrounding areas such as Cilacap, Kebumen, Brebes, and Pemalang Regencies also have high poverty values. A similar phenomenon also occurs in Brazil. Spatially the District of Sao Paulo shows the highest incidence of COVID-19, surrounded by areas of households living in high slums (Ferreira, 2020). The results of this study also show a similar phenomenon because slum areas are the residences of the majority of the poor.

The COVID-19 pandemic, which affects slow economic activity, has increased the number of poor people (Ningrum et al., 2020). However, the results of this study indicate that spatially COVID-19 incidence and poverty rates have a different relationship. The Bivariate Moran's Scatterplot of the two variables is negative, which means that the spatial correlation between COVID-19 incidence and poverty rate is negative, which means that areas with high confirmed cases of COVID-19 do not necessarily mean that their surrounding areas have a high poverty rate.

The value of the number of confirmed cases of COVID-19 in the districts in Central Java Province does not have a similar value to the surrounding poverty. These results overcome the increase in poverty in Central Java Province. There is a need for equitable social assistance for the poor because assistance can help residents to open new businesses (Nicola et al., 2020). A COVID-19 vaccination is also needed to prevent the spread of the COVID-19 virus because a healthy population will help in efforts to improve the economy. Slowly the recovering economy became the main factor in the development of the Central Java region in eradicating poverty (Hidayah & Amin, 2021). Support from the government and all residents of Central Java Province is needed to restore economic conditions.

5 Conclusion

The study shows that the spatial pattern of the number of confirmed COVID-19 cases and the poverty rate in Central Java is clustered. The spatial correlation of the number of confirmed cases of COVID-19 with the poverty rate in Central Java is negative. Based on the results of Moran's univariate index shows that the spatial pattern of the number of confirmed COVID-19 cases in Central Java Province is clustered, and the spatial pattern of poverty levels in Central Java Province is clustered. Because the result of Moran's index value is greater than the expected value of E(I), clustering means that there is a spatial autocorrelation, namely sub-districts that have a high number of confirmed cases of COVID-19, surrounded by areas with a high number of confirmed cases of COVID-19 as well. Districts with high poverty rates surround sub-districts with high poverty rates.

The pattern of distribution of the number of confirmed COVID-19 cases and the distribution pattern of poverty in Central Java Province is clustered. It shows that the spatial autocorrelation for each variable is positive. However, globally, the spatial correlation between the number of COVID-19 confirmations with poverty in Central Java Province is negative. So, to deal with the increase in poverty in Central Java Province, it is necessary to overcome the covid-19 virus through a comprehensive vaccination program in all areas of Central Java Province. Therefore, a healthy Central Java community will revive economic activity so that the poor will decrease.

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