Spatial association of socioeconomic factors and prevalence of Tuberculosis in Java Indonesia, 2021-2022

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ABSTRACT

Background: Tuberculosis (TB) remains one of the deadliest infectious diseases even in the aftermath of the COVID-19 pandemic. Although it is treatable and supported by national programs, Indonesia accounts for the second highest proportion of TB cases worldwide. Research on tuberculosis in Indonesia is generally limited to single-year studies in narrow areas at the regency level, restricting broader regional insights.

Objectives: This research aimed to identify the spatial relationship between socio-economic factors and tuberculosis prevalence in Java, Indonesia, for the years 2021 and 2022.

Methods: This cross-sectional study employed a geographical analytic approach using TB reported data across three provinces in Java, Indonesia to investigate the spread of disease and association in 2021-2022 from various sources. Spatial autocorrelation analysis relies on Moran's I values to determine associations and Local Indicator of Spatial Association (LISA) to identify which regions in Java have high or low cluster values.

Results: The prevalence rate of tuberculosis in Java from 2021 to 2022 showed an increasing trend from an average of 145 to 148 per 100,000 inhabitants, with Tegal City consistently recording the highest prevalence. Boyolali Regency had the lowest rate in 2021, while Trenggalek had the lowest rate in 2022. TB hotspot detected in Bogor, Bandung, Karawang, Bekasi, Bekasi City, Cimahi City and Depok City. Meanwhile TB coldspots were consistently detected in Wonosobo, Magelang, Wonogiri, Magelang City, Surakarta City, Salatiga City, Pacitan, Ponorogo, Trenggalek, Tulungagung, Kediri, Madiun, Magetan, Ngawi, and Madiun City. Bivariate analysis indicated a positive spatial association between population density, per capita expenditure, night-time light (NTL), regional wage, and unemployment rate.

Conclusion: There existed spatial association between socioeconomic characteristics and tuberculosis prevalence in Java from 2021 to 2022, particularly in urbanized regions. This cartographic research should serve as a guideline for TB management in Java.

Keywords: Prevalence, Socioeconomic factors, Spatial analysis, Tuberculosis

1. Introduction

Following the COVID-19 infection, tuberculosis (TB) remains one of the deadliest infectious diseases, causing the highest number of fatalities globally [1]. Although it is treatable, TB caused the loss of 1.13 million lives worldwide in 2022. Geographically, the regions with the highest percentage of TB cases in 2021 were Southeast Asia (45%), Africa (23%), and the Western Pacific (18%). Conversely, the Eastern Mediterranean (8.1%), the Americas (2.9%), and Europe (2.2%) reported the lowest percentages of TB cases [2]. Indonesia, a Southeast Asian nation, accounts for the second-highest proportion of TB cases worldwide following the COVID-19 pandemic [1]. Based on data released by the Ministry of Health Indonesia, the number of TB cases increased from 200,651 in 2021 to 670,484 in 2022, representing the highest case detection since 2012. The provinces of West Java, East Java, and Central Java recorded the highest prevalence from 2018 to 2022 [3].

TB predominantly affects people of productive age, with more than 50% of TB cases occurring in this age group in Indonesia, particularly in Java. This pattern is closely linked to socioeconomic conditions, as individuals in this age group are heavily engaged in the workforce. Socio-economic factors significantly impact TB case detection by influencing healthcare accessibility. Per capita expenditure affects living standards and access to medical services, unemployment rates shape healthcare seeking behaviour and vulnerability, while regional wage and urbanization (NTL data) influence disparities in healthcare access and disease prevalence [4-7]. Understanding the spatial dynamics of TB and socioeconomic factors will facilitate policymakers in achieving the eradication of tuberculosis by 2030. Hence, this study aimed to investigate the association between socioeconomic factors and TB prevalence in 2021-2022.

2. Methods

2.1 Study Area

This study was conducted across 100 combinations of regencies and cities in three provinces of Indonesia namely Central Java, East Java and West Java. The total area is 106,141 km², encompassing the entirety of Central Java Province, which includes 29 regencies and 6 municipalities. Additionally, East Java Province consists of 29 regencies and 9 cities, while West Java Province comprises a total of 17 regencies and 9 cities. The administrative boundary data was collected from the Indonesia Geospatial Portal (https://big.go.id).

2.2 Study Design, Population and Variables

This cross-sectional study employed a geographical analytic approach using secondary data to investigate the spread of tuberculosis across three provinces in Java, Indonesia. Prevalence of TB case in Java was obtained from the respective Provincial Health Departments, accessible through their official websites [8-10]**.** The data was then collected, cleaned, and standardized to ensure consistency across regions. The socio-economic data such as population density, per capita expenditure, unemployment rate, and regional wage, were extracted from the Central Bureau of Statistics of each province [11]. The data was initially collected at the provincial level from official sources and subsequently disaggregated to align with specific regency and city. Additionally, night-time light (NTL) were obtained from the Earth Observation Group (EOG) and extracted through Google Earth Engine [12]. The data was processed using statistical mean functions, ensuring that the calculations were disaggregated by regency and city within the study area.

2.3 Statistical Analysis

Combination of QGIS (version 3.38.0) and GeoDa (version 1.22.0.2) provides a comprehensive approach to spatial epidemiology. QGIS was primarily used for visualizing spatial data in this study. It enables the creation of detailed maps and the overlay of various data layers to offer a distinct and visually perceptible depiction of how things are arranged and organized in space [13]. Then GeoDa provides tools for conducting spatial autocorrelation analyses with Moran's I and identifying clustering patterns in the data. A univariate Moran's I value near +1 implies significant positive spatial autocorrelation (clustering), whereas a value near -1 suggests significant negative spatial autocorrelation (dispersion). A value close to 0 indicates a high degree of randomness [14]. A bivariate Moran's I analysis was conducted to investigate the spatial correlation between two variables with Local Indicator of Spatial Association (LISA). The analysis was divided into four quadrants: High-High (HH), where both variables have high values; Low-Low (LL), where both are low; High-Low (HL), where the independent variable is high but the dependent variable is low, indicating spatial outliers; and Low-High (LH), where the independent variable is low but the dependent variable is high, also marking spatial outliers [14].

We employed this, specifically Moran's I with 999 permutations, to examine clustering patterns from 2021 to 2022 combined with statistical significance level at 0.05. In this study, a 3-nearest neighbour (3k-nearest neighbour) weight matrix was used to specify that each regency is influenced by its three closest neighbours. This reflects historical administrative partitions, where each administrative region typically consists of three subunits and high daily commuting levels, with workers regularly travelling across an average of three regencies or cities, contributing to the formation of clusters for analysis.

3. Results

3.1 Spatial Distribution of TB Prevalence Rate in Java, 2021-2022

The prevalence rate of tuberculosis in Java from 2021 to 2022 showed an increasing trend from an average of 145 to 148 per 100,000 inhabitants, with Tegal City consistently recording the highest prevalence. Boyolali Regency had the lowest rate in 2021, while Trenggalek had the lowest rate in 2022. Figure 1 highlighted the spatial cluster of TB prevalence rates, showing high and low prevalence regions. High prevalence of TB was predominantly concentrated in West Java and the cities in Central and East Java (Figure 1).

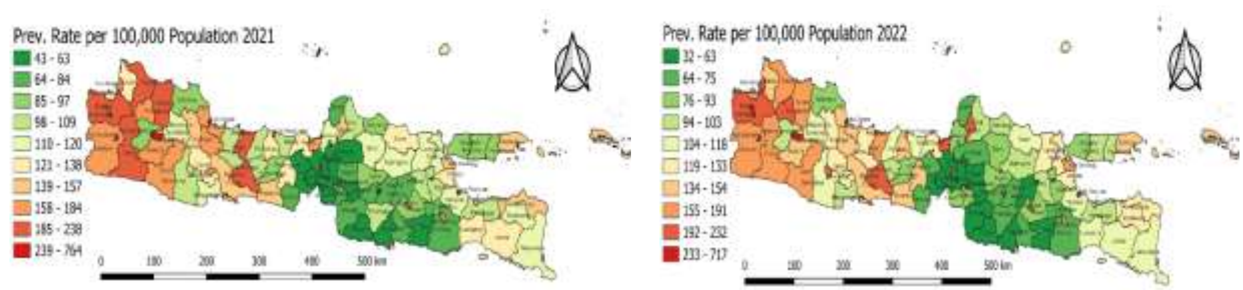


Figure 1: Tuberculosis Prevalence Rate per 100,000 Population in Java 2021-2022

3.2 Univariate Analysis of Tuberculosis Prevalence in 2021-2022

Figure 2 displayed TB prevalence's spatial distribution, clustering patterns, statistical significance, and cluster types using Moran's I values and LISA analysis. In the years 2021 and 2022, positive autocorrelation was significant at a level of <0.05, with several urban regions including Bogor, Bandung, Karawang, Bekasi, Bekasi City, Cimahi City and Depok City, consistently identified as HH clusters and becoming TB hotspots. Meanwhile, TB coldspots were consistently detected in Wonosobo, Magelang, Wonogiri, Magelang City, Surakarta City, Salatiga City, Pacitan, Ponorogo, Trenggalek, Tulungagung, Kediri, Madiun, Magetan, Ngawi, and Madiun City (Figure 2).

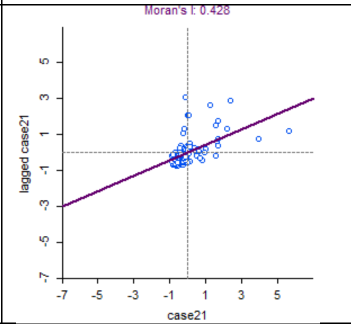
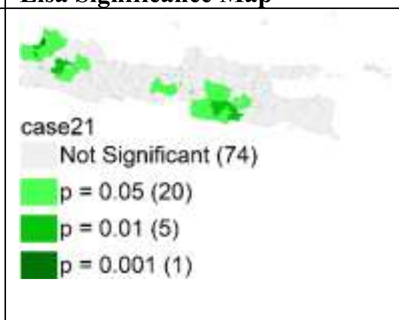
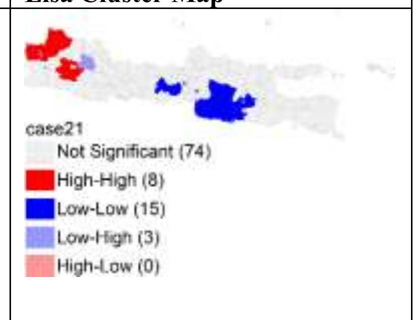
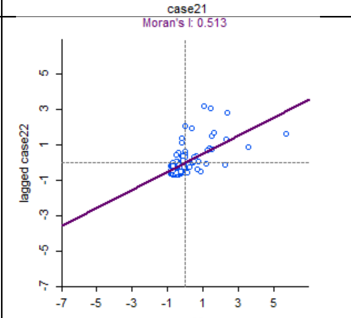
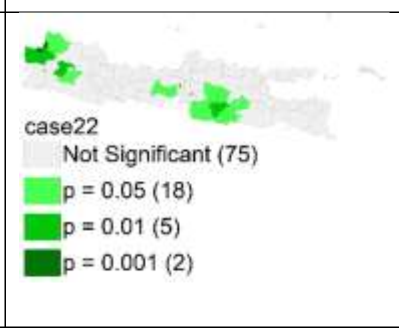
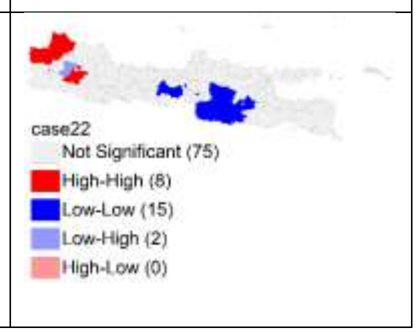
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 2: Univariate Analysis of Tuberculosis Prevalence in Java 2021-2022

3.2 Bivariate Analysis of Socio-economic Factors with Tuberculosis in Java, 2021-2022

Association of Per-capita Expenditure with Tuberculosis in Java, 2021-2022

Figure 3 showed positive spatial autocorrelation with a P-value of <0.05 in both years, with Moran's I values of 0.386 and 0.415, respectively. This figure also showed HH clusters of high tuberculosis and high expenditure in Bekasi, Bekasi City, Depok City, Sukabumi City, Bogor, and Cimahi City consistently detected throughout all the years (Figure 3).

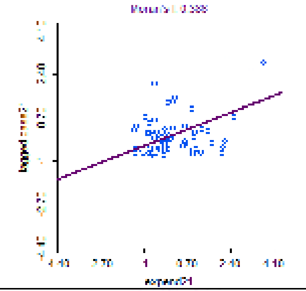
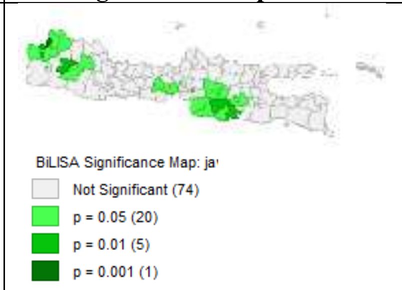
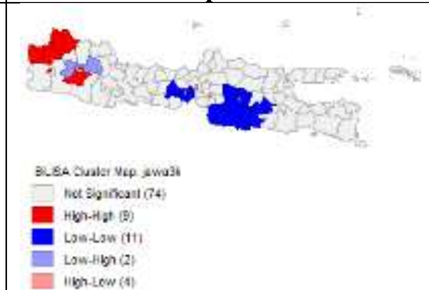
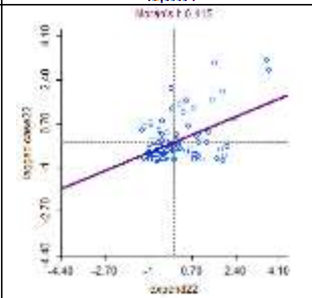
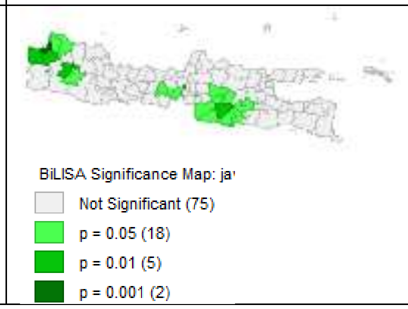
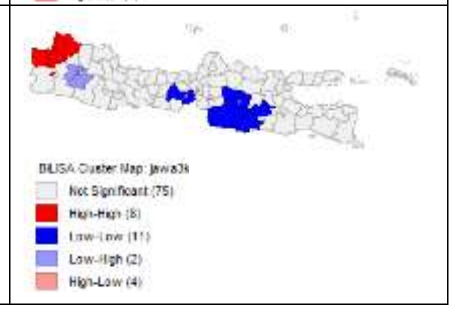
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 3: Bivariate Analysis of Tuberculosis with Per-capita Expenditure in Java, 2021-2022

Association of Unemployment Rate with Tuberculosis in Java, 2021-2022

In both years, there was positive autocorrelation between the two variables with positive values and a P-value of <0.05. Figure 4 showed that Bogor, Bogor City, Bekasi, West Bandung, Bekasi City, Depok City, and Cimahi City consistently formed HH clusters consecutively (Figure 4).

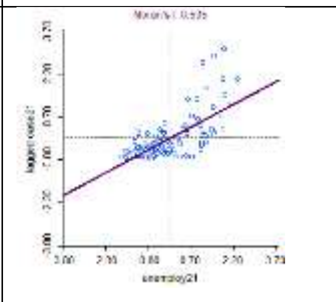
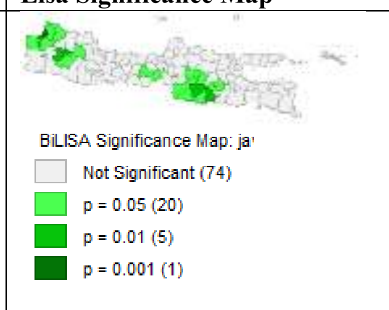
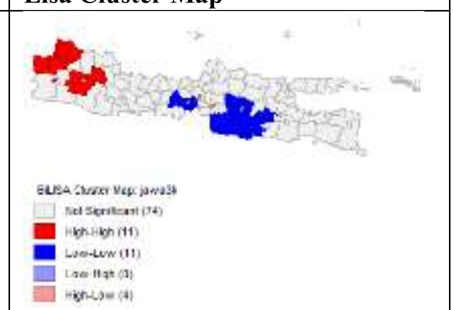
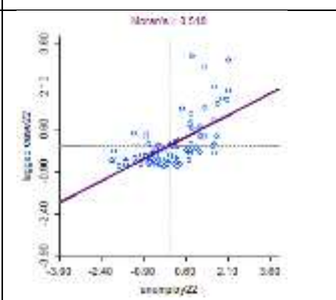
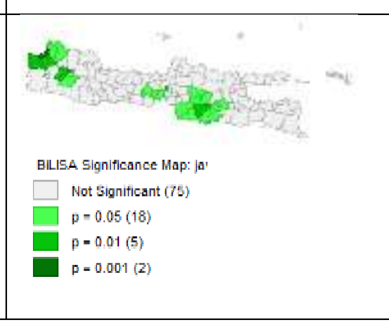
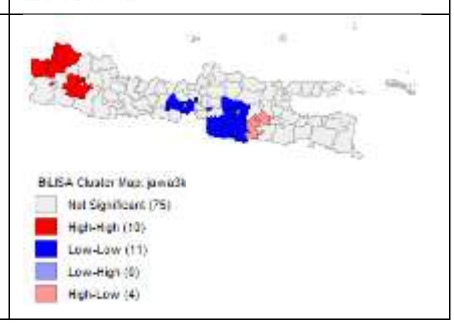
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 4: Bivariate Analysis of Tuberculosis with Unemployment Rate in Java, 2021-2022

Association of Regional Wage with Tuberculosis in Java, 2021-2022

Figure 5 illustrated the relationship between TB prevalence and regional wage through a bivariate analysis, emphasizing statistical significance and identifying cluster patterns based on the LISA framework. Bogor, Bekasi, West Bandung, Bogor City, Bekasi City, Depok City, and Cimahi City consistently appeared as HH clusters over the two years. Positive spatial autocorrelation occurred in the association of these variables with a P-value of <0.05 in both years.

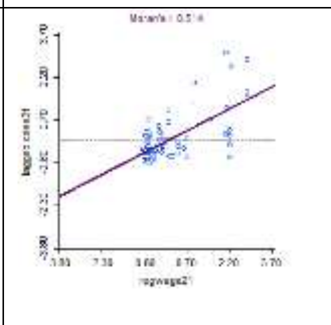
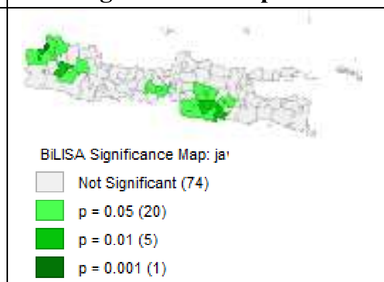
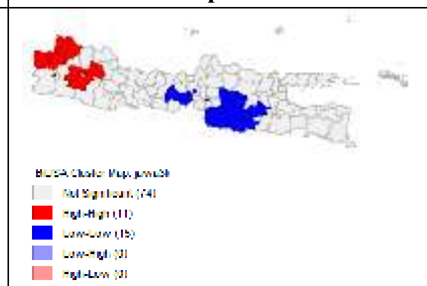
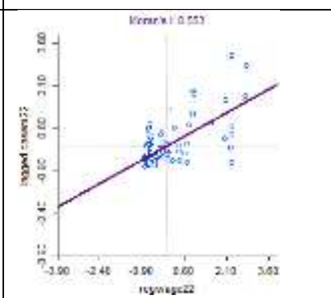
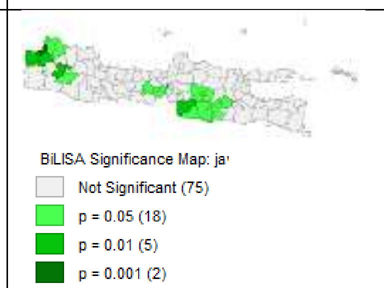
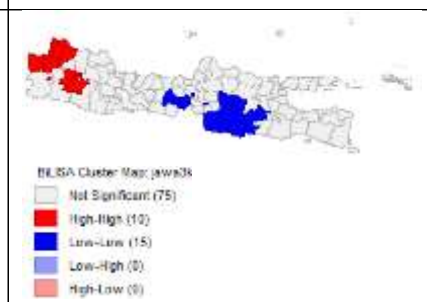
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 5. Bivariate Analysis of Tuberculosis with Regional Wage in Java, 2021-2022

Association of NTL with Tuberculosis in Java, 2021-2022

Figure 6 presented a bivariate analysis of TB prevalence and NTL, highlighting statistical significance and cluster types using the LISA framework. The spatial analysis of NTL and tuberculosis cases across Java from 2021 to 2022 revealed a significant and consistent clustering patterns with P-value <0.05 both years. Regions consistently identified as HH clusters for both years were Bekasi, Bogor City, Sukabumi City, Bekasi City, Depok City, and Cimahi City.

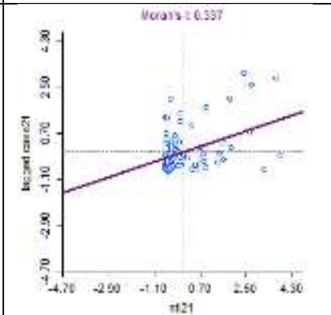
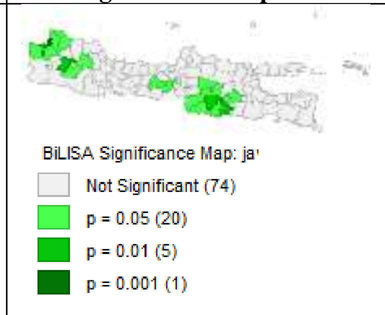
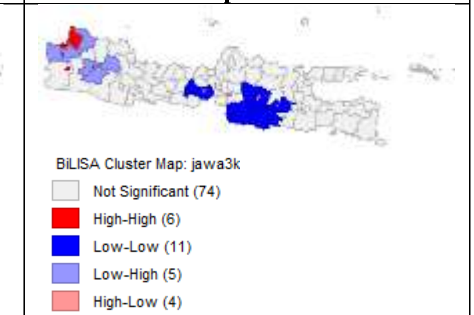
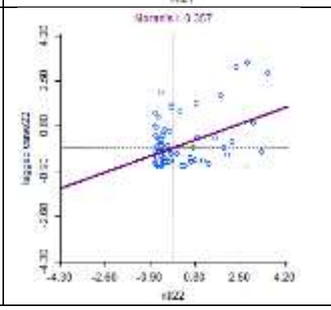
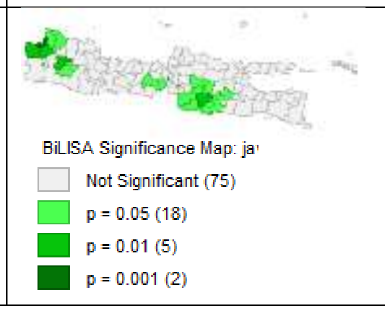
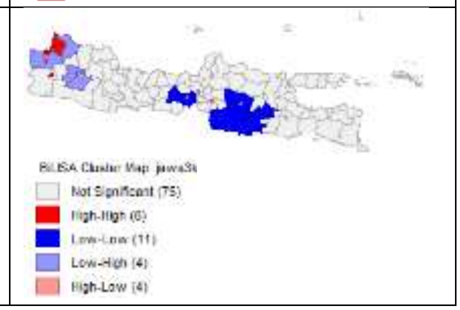
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 5: Bivariate Analysis of Tuberculosis with NTL in Java, 2021-2022

Association of Population Density with Tuberculosis in Java, 2021-2022

Population density in Java showed positive autocorrelation with a P-value of <0.05 during the years 2021-2022. The HH clusters, indicating areas with high values for both variables consistently include Bekasi, Kota Bogor, Kota Bekasi, Kota Depok, and Kota Cimahi across all two years (Figure 7).

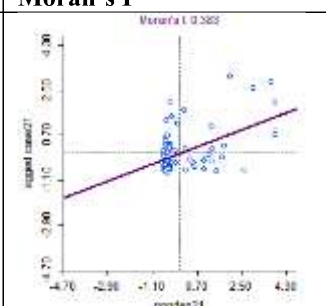
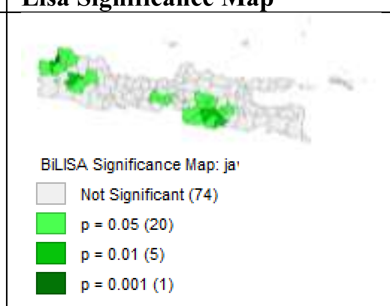
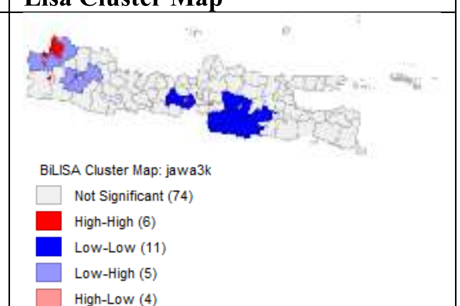
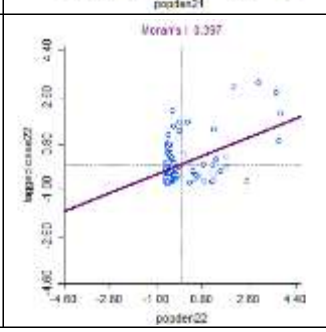
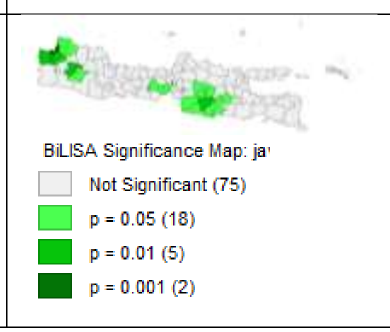
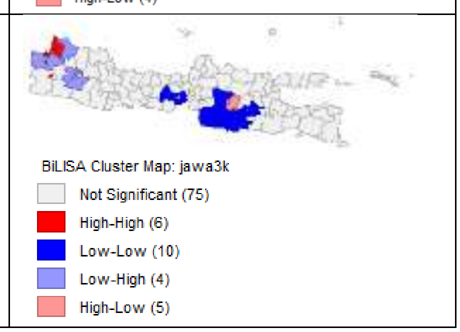
Year	Moran's I	Lisa Significance Map	Lisa Cluster Map
2021			
2022			

Figure 6: Bivariate Analysis of Tuberculosis with Population Density in Java, 2021-2022

3.3 Spatial Regression of Socioeconomic Factors and TB Prevalence

Regression analysis was conducted by comparing the Ordinary Least Squares (OLS) model as a baseline with the Spatial Lag Model (SLM) and Spatial Error Model (SEM), both of which account for spatial dependence. The Lagrange Multiplier (LM) test indicated that a lower coefficient suggests a stronger potential for significant spatial dependence. The R-squared value reflects the model's ability to explain variations in the dependent variable, with higher values indicating better explanatory power. Additionally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to assess model performance, with the lowest values identifying the most optimal model.

For both years analysed in this study, the Spatial Lag Model (SLM) proved to be the most appropriate, as it demonstrated the strongest ability to explain variability compared to other models. Consequently, this model effectively captures the interaction between variables, highlighting their spatial dependence within the dataset (Table 1).

Table 1: Regression Parameters Obtained from Ordinary Least Square Model, Spatial Lag Model and Spatial Error Model Models

Variable	2021			2022		
	OLS	SLM	SEM	OLS	SLM	SEM
Constant	520.104	528.308	903.616	330.333	500.379	864.101
Population Density	0.503***	0.387**	0.431***	-	-	-
Per-capita Expenditure	0.002**	0.002*	0.002**	-	-	-
Unemployment Rate	-	-	-	686.381***	523.97***	592.332***
NTL	-	-	-	830.013***	708.396***	791.348***
Land Use	-12808.3***	9992.5***	-11050.9***	-16658.9***	-14651.5***	-16404.5***
Lamda			0.189			0.179
Rho		0.226			0.200	
Log Likelihood	-873.719	-870.584	-872.329	-918.198	-915.519	-916.850
R-squared	0.304	0.354	0.329	0.463	0.496	0.481
AIC	1755.44	1751.17	1752.66	1844.4	1841.04	1841.7
BIC	1765.86	1764.19	1763.08	1854.82	1854.06	1852.12
Lagrange Multiplier		0.000	0.055		0.002	0.049

Note: *correlation significance at 0.05 level; ** 0.01 level; *** 0.001 level; OLS, ordinary least squares; SLM, spatial lag model; SEM, spatial error model; Constant, the regression model intercept (the expected mean value of Y when all X=0); Lagrange Multiplier, spatial dependency parameter; AIC, Akaike's information criterion; BIC, Bayesian information criterion

4. Discussion

The pattern of tuberculosis prevalence distribution in the three provinces with the highest cases in Indonesia over the past two years has formed clusters, as indicated by the increasing Moran's I value. This suggested that tuberculosis prevalence has become more spatially clustered over time, with high prevalence areas remaining concentrated in the West Java regions (near Metropolitan City Jakarta such Bogor, Bandung, Karawang, Bekasi, Bekasi City, Cimahi City, Depok City) and low prevalence areas consistently forming clusters in the Southern border areas of Central Java and East Java (Wonosobo, Magelang, Wonogiri, Magelang City, Surakarta City, Salatiga City, Pacitan, Ponorogo, Trenggalek, Tulungagung, Kediri, Madiun, Magetan, Ngawi, and Madiun City).

Population density describes the number of people living in an area. In the northwestern part of Java, the population density is quite high due to its proximity to the metropolitan area of Jakarta, which is the economic hub. This region, acting as a buffer for Jakarta, is a significant hub for urbanization and possesses the largest population of individuals of productive age in Indonesia [15]. The higher the population density, the greater the likelihood of tuberculosis spread due to interactions among residents [16]. This finding is corroborated by spatial analysis studies, locations with dense populations, population movement, transportation, and infrastructure are contributing factors to the rapid spread of TB cases [17]. According to research by *Teibo et al.* [18], TB is commonly found among impoverished populations, primarily due to inadequate living conditions. The disease is more prevalent in densely populated areas like in Nepal where accessing healthcare services is challenging [19].

The socioeconomic conditions of a region can provide economic insights into the pattern of TB case distribution. This study found a positive association between TB and per capita expenditure. Similar to findings in China, regions with higher GDP are associated with more TB cases [20]. This indicates that regions with high per capita expenditure are associated with higher TB prevalence and vice versa. This is supported by *Onyechege et al.* [21], who found that financial capability is related to higher tuberculosis prevalence. Regions with better and higher economic or urban conditions tend to have more adequate healthcare facilities, and residents have better access [22]. In another study, the incidence of registered tuberculosis cases was positively associated with urban per capita disposable, significantly showing that residents with lower expenditure would spend less on healthcare services as well [23].

As an indicator in urbanization and the economy, NTL density was a factor investigated in this study, using satellite imagery. It revealed that higher night-time illumination indicated dense urban settlements, extensive road networks, and active economic centres, suggesting improved access to public services, transportation, and healthcare. From this context, the spatial distribution of average NTL density with TB prevalence showed high clusters near the major city of Jakarta (Northwest Java). Areas with high NTL density are located in Metropolitan areas near Jakarta, resulting in very high populations and serving as industrial regions. These densely populated areas are significant determinants of TB transmission [16]. Urban regions generally exhibited higher income levels and superior access to healthcare facilities, facilitating the detection of new and relapsed tuberculosis patients more effectively than rural areas [24]. NTL does not directly contribute to an increase in tuberculosis prevalence; rather, its mechanism is associated with lifestyle alterations in urban environments characterized by sedentarism and restricted access to green spaces, alongside nutritional modifications in modern culture [25]. Diverse lifestyle patterns can result in interrupted sleep and chronic disorders [26], such as diabetes mellitus, which are strongly associated with heightened TB incidence [27] due to compromised immunity [28].

The spatial relationship of regional wage with tuberculosis prevalence has significantly positive Moran's I throughout the study. Areas with higher regional wage are part of the Greater Jakarta Metropolitan area, which experienced significant urban migration and population growth like in HH clusters, leading to areas bearing the burden of tuberculosis and notifying more case [29]. Sufficiently high minimum wages enable residents to access better healthcare [21]. While higher earnings generally improve living standards and healthcare access, studies in China showed that regions with higher GDP also report higher tuberculosis incidence [20].

This study found that the distribution of high unemployment rates with high tuberculosis cases (HH) in Java is clustered in the Western part. This area is an urbanization region with a high number of workforces, indicating that higher unemployment rates are followed by higher tuberculosis prevalence. These regions also attract urbanization as large industrial centres, leading to high unemployment due to increased competition and workforce influx [30]. The unemployment rate indirectly affects incomplete and delayed tuberculosis treatment, contributing to the recurrence of the disease [31, 32]. As shown by data, there is a high prevalence in West Java, particularly near the Jakarta Metropolitan area. According to *Przybylski et al.* [32], the unemployment rate is also a predictor of tuberculosis incidence. This is supported by research in Indonesia, which suggests that the unemployment rate may predict variations in tuberculosis incidence across provinces [33]. Unemployment individuals might lack sufficient finances, resulting in insufficient resources for obtaining healthcare services.

Based on the analysis results, Bekasi Regency, Bekasi City, Cimahi City, and Depok City exhibit high socioeconomic conditions alongside elevated TB prevalence. It is crucial to implement comprehensive intervention strategies aimed at TB eradication in these regions to effectively address the disease burden.

5. Conclusion

There existed an association between socio-economic characteristics and tuberculosis prevalence in Java from 2021 to 2022, particularly in urbanized regions. This cartographic research should serve as a guidance for TB management in Java. Effective TB control requires collaboration across economic sectors, including partnerships between industries, healthcare providers, and government agencies. This collaboration will support expanded diagnostic services, treatment accessibility, and corporate-led health initiatives aimed at addressing TB risks in densely populated regions.

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Author Contribution

ABS: Conceptualization, data curation, formal analysis, methodology, writing - original draft, writing - review and editing.

KS: Conceptualization, methodology, supervision, writing - review and editing.

Declaration

Ethical approval and consent to participate

This research has been approved by the Centre for Ethics in Human Research, Khon Kaen University, with the identification number HE672289. The analysis did not involve human subjects in the research and relied solely on secondary data.

Competing interests

We declared that we have no competing interests.

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