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Spatial Autocorrelation of Tuberculosis and Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

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Abstract

Background: Tuberculosis (TB) remains a major public health problem in Indonesia, with West Java reporting 229,683 cases in 2024. The geographic clustering distribution of TB cases requires spatial analysis to identify transmission patterns and determinants.
Objective: This study aimed to analyze spatial autocorrelation of TB incidence and its relationships with demographic, health service, environmental, and economic factors in West Java in 2024.
Method: Quantitative design with an ecological approach across 27 districts/cities in West Java using data from the West Java Health Profile and Statistics Agency 2025. Spatial autocorrelation analysis employed Global Moran's *I* and univariate–bivariate LISA with a Queen Contiguity weighting matrix. Variables included TB incidence, population size, population density, health facility ratio, adequate sanitation, non-earth floors, and poor population. Analysis used GeoDa 1.22.0.21 with $\alpha = 0.05$ and 999 permutations.
Result: TB incidence showed significant global spatial autocorrelation (Moran's $I = 0.3514$, $p = 0.001$). Univariate LISA identified High-High clusters in the Bogor–Bekasi–Karawang metropolitan corridor and Low-Low clusters in Ciamis–Tasikmalaya–Majalengka. Bivariate autocorrelation revealed significant positive relationships with health facility ratio ($I = 0.3207$, $p = 0.005$), population size ($I = 0.2449$, $p = 0.014$), and population density ($I = 0.2088$, $p = 0.044$). Negative autocorrelation with poor population ($I = -0.2950$, $p = 0.006$) indicated an urban paradox.
Conclusion: TB incidence distribution demonstrates significant geographic clustering with spatial heterogeneity. Demographic and health service factors show positive correlations, while economic factors exhibit an urban paradox. Intervention priorities should focus on metropolitan High-High clusters with spatial data integration and cross-sectoral collaboration.

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INTRODUCTION

Tuberculosis (TB) remains one of the leading causes of death worldwide and the foremost cause of mortality from a single infectious agent. Aligned with SDG target 3.3 to end the TB epidemic by 2030, global attention remains concentrated on high-burden regions. By 2024, the estimated global TB burden reached 10.7 million cases, with an incidence rate of approximately 131 per 100,000 population. The highest burden is borne by Southeast Asia (34%), followed by the Western Pacific (27%) and Africa (25%) (WHO, 2025). Indonesia ranks second globally in TB burden, contributing approximately 10% of total cases. In 2024, Indonesia reported 856,420 TB cases a significant increase from 821,200 in 2023 making TB control a national health priority (Kemenkes RI, 2025).

West Java Province records the highest provincial TB burden nationally, with 229,683 cases reported in 2024 a 7.77% increase from 2023. As Indonesia's most populous province with a population density of approximately 1,385 people/km², West Java faces intensified TB transmission risk through high inter-individual contact rates. Critically, West Java functions as the epicenter of Indonesia's largest inter-metropolitan mobility corridor, connecting the Jabodetabek megapolitan area (Jakarta–Bogor–Depok–Bekasi) with the Bandung Metropolitan Area a dynamic that substantially amplifies TB transmission pathways beyond what static demographic variables can capture. Despite this complexity, a spatially integrated analysis simultaneously incorporating environmental and economic variables at the district/city level has not been widely implemented in West Java, representing a critical evidence gap for targeted TB intervention. A global systematic review of the 2017–2023 period evaluating 79 geospatial studies confirmed significant geographic heterogeneity in TB distribution and strong associations between poor socioeconomic conditions, dense housing, and TB clusters across endemicity settings (Teibo et al., 2023). Spatial analysis at the district/city level enables identification of high-risk clusters (hotspots) hidden within provincial aggregate data, making it an essential instrument for targeted TB control (Spies et al., 2024; Wang et al., 2025).

The distribution of TB cases is not geographically random it tends to form spatial clusters, underscoring the importance of spatial autocorrelation analysis in understanding TB epidemiology. Recent multi-country studies confirm that TB exhibits significant spatial autocorrelation, with high-burden areas clustering adjacently. A global study across 209 countries (2000–2021) found that the spatial autocorrelation of TB incidence remained significant (Moran's $I = 0.465$, $p < 0.001$) despite a declining trend, confirming the persistence of geographic clustering (Bai & Ameyaw, 2024). In Nepal, persistent High-High clusters (Moran's I = 0.558–0.614) were identified in districts such as Banke, Parsa, and Rautahat (Mahato et al., 2025). Similar clustering was confirmed in China's Fujian Province, concentrated in southeastern districts (Yu et al., 2024). Collectively, these international findings establish that TB spatial clustering is a robust, cross-context phenomenon yet no equivalent district-level spatial autocorrelation analysis integrating demographic, health service, environmental, and economic variables simultaneously has been conducted for West Java, despite it being Indonesia's highest-burden province.

The Local Indicators of Spatial Association (LISA) method offers critical advantages over conventional statistical analyses. Unlike Pearson correlation or regression models that assume spatial independence between observations, LISA explicitly accounts for geographic proximity to capture the spatial dependence structure inherent in infectious disease transmission dynamics. While a global Moran's I statistic provides a single summary measure for the entire study area, LISA decomposes spatial association into location-specific cluster types enabling identification of High-High clusters (areas with high cases surrounded by high-case areas), Low-Low (low-burden areas surrounded by similarly low-burden areas), and spatial outliers (High-Low and Low-High), classified based on observation positions in the Moran scatterplot quadrant. This capacity to detect localized, statistically significant clustering patterns including temporally stable disease hotspots makes LISA indispensable for sub-provincial TB surveillance. In Nepal, LISA identified persistent High-High clusters in Banke, Parsa, and Rautahat (2020–2023) (Mahato et al., 2025). In Ethiopia, LISA uncovered undetected TB clustering in five Somali Region border districts and all Addis Ababa sub-cities except Akaki-Kaliti (Wolde et al., 2025).

Bivariate LISA analysis expands detection capabilities by simultaneously identifying spatial relationships between TB incidence and its determinants. This method enables researchers not only to examine the spatial clustering of TB incidence in isolation, but also to understand how its geographic distribution interacts with demographic, socioeconomic, environmental, and healthcare variables a capability fundamentally absent from conventional correlation or regression approaches that treat spatial units as independent. In Rio de Janeiro, bivariate LISA identified significant spatial correlations between drug-resistant TB and socioeconomic and healthcare indicators, particularly in metropolitan areas. In Nepal, bivariate LISA between TB prevalence and soil surface temperature yielded significant positive autocorrelation (Moran's I = 0.379–0.424 across fiscal years), with High-High clusters in Banke, Rupandehi, Parsa, Bara, and Rautahat (Pungartnik et al., 2025). In Şanlıurfa, Türkiye, bivariate LISA confirmed TB clustering in high-density, low-SES, low-healthcare-access areas.

Determinants of TB span demographic, health service, environmental, and economic dimensions that interact in spatially heterogeneous ways. A global meta-analysis identified population density (RR = 1.01, 95% CI: 1.01–1.02), high relative humidity (RR = 1.45, 95% CI: 1.12–1.77), rainfall (RR = 1.56, 95% CI: 1.11–2.02), and $PM_{2.5}$ (RR = 1.33, 95% CI: 1.18–1.49) as significant TB risk factors (Liyew et al., 2024). Inadequate housing including poor sanitation and floor quality significantly increases TB prevalence, treatment non-adherence, and therapy failure. A case-control study in Peru found household poverty independently associated with TB (aOR = 3.1; 95% CI: 2.3–4.2), with a 9% attributable fraction reducible through reduced crowding. A systematic review of 79 geospatial TB studies (2017–2023) confirmed poor socioeconomic conditions (39%) and high population density (17%) as dominant drivers of TB high-risk clusters globally (Teibo et al., 2023).

Based on the multidimensional complexity of TB spatial patterns and the critical evidence gap identified above, this study aims to analyze univariate and bivariate spatial autocorrelation of TB incidence and its relationships with demographic (population size, population density), health service (health facility ratio), environmental (adequate sanitation percentage, non-soil floor percentage), and economic (poor population percentage) factors at the district/city level in West Java Province in 2024, using Global Moran's I and Local Indicators of Spatial Association (LISA) approaches. Unlike prior studies in Nepal, Ethiopia, or Vietnam that examined TB spatial patterns using limited variable sets in isolation, this study uniquely integrates inter-metropolitan mobility dynamics intrinsic to West Java's Jabodetabek–Bandung corridor a determinant largely absent from existing geospatial TB literature in Indonesia. This integrated approach is expected to identify spatially explicit TB clusters and their determinant relationships, providing evidence-based foundations for more targeted, cross-sectoral TB control strategies in West Java.

METHOD

Research Design

This study employed a quantitative design with an ecological approach at the district/city level, using all 27 districts/cities in West Java Province as analysis units (complete enumeration). The ecological approach was justified on two grounds: (1) the ecological fallacy risk was minimized by explicitly framing all inferences at the aggregate administrative level, avoiding individual-level conclusions from group-level data; and (2) the Modifiable Areal Unit Problem (MAUP) while acknowledged as an inherent limitation was addressed by selecting the district/city level as the smallest administrative unit with complete, standardized TB surveillance data in West Java.

The analysis was carried out using GeoDa software version 1.22.0.21 for Moran's I test, LISA (Local Indicators of Spatial Association), and spatial map visualization, as well as QGIS 3.28.3 for spatial data preprocessing and integration. This study used aggregate data at the district/city level that was publicly published by government agencies, so it did not require ethical clearance. It is acknowledged that n = 27 constitutes a "small n" in spatial statistics, which may reduce the statistical power of Moran's I tests and increase sensitivity to individual outlier districts. This limitation was addressed using 999 permutations (Monte Carlo randomization) to generate robust empirical p-values, avoiding reliance on asymptotic normality assumptions that are problematic with small samples.

Data Collection Techniques

This study used secondary data obtained from the West Java Provincial Health Profile 2025, which contains data for the 2024 reporting year for the variables of the number of pulmonary tuberculosis cases per district/city, total population, population density, and primary health facilities expressed as the ratio of health centers to population. Additional data were obtained from the Central Statistics Agency (Badan Pusat Statistik, BPS) of West Java in 2025 for the variables of the percentage of households with adequate sanitation, the percentage of houses with non-soil floors, and the percentage of the poor population (specifically sourced from BPS West Java Statistical Publication: Provinsi Jawa Barat Dalam Angka 2025, Table on Population Below the Poverty Line by Regency/City, 2024 data). The administrative boundary shapefile of the regencies/cities of West Java was obtained from the Geospatial Information Agency (Badan

Informasi Geospasial, BIG) for the purpose of mapping and spatial analysis. All data are official publications downloaded directly from the official website of the West Java Health Office (https://diskes.jabarprov.go.id/profil-kesehatan) and BPS West Java (https://jabar.bps.go.id/id/statistics-table). No data were missing among the variables analyzed, as all 27 districts/cities had complete data for all research variables.

Research Instruments

The main instruments in this study included software and supporting files for spatial analysis. GeoDa version 1.22.0.21 was used for the analysis of Global Moran's I, univariate LISA, and bivariate LISA, as well as the creation of thematic maps. QGIS 3.28.3 was used for spatial data preprocessing in the form of geometry validation and topology checking, as well as the integration of attribute data through the incorporation of numerical data into shapefiles based on region codes. The shapefile of the administrative boundaries of the districts/cities of West Java in validated .shp format was used as the mapping base. The statistical significance criteria used a significance level of α = 0.05 with a permutation test of 999 permutations to test the spatial autocorrelation hypothesis.

The study variable consisted of a dependent variable, namely the Tuberculosis Incidence Rate (IR-TB) per 100,000 population, calculated by the formula: IR-TB = (Total TB Cases / Total Population) × 100,000 [WHO, 2025; Ministry of Health RI, 2025]. This formula is consistent with WHO's standard case notification rate definition and ensures comparability with national and international TB surveillance data. Independent variables included demographic factors in the form of total population (unit: persons) and population density (unit: persons/km^2). The health service factor was represented by the health facility ratio, expressed as the number of population per puskesmas (primary health center). Environmental factors included the percentage of households with adequate sanitation and the percentage of houses with non-soil floors. The economic factor was represented by the percentage of the poor population.

The spatial weighting matrix used Queen Contiguity, which contains a list of neighbors between regions at the district/city level of West Java and is stored in .gal format. Distance-based spatial weight matrices (e.g., K-nearest neighbor or inverse-distance weighting) were considered but not selected. Distance-based matrices assume spatial influence decays with Euclidean distance, which is problematic when administrative areas vary substantially in size — as is the case in West Java, where district areas range from 48.6 km^2 (Cimahi City) to 3,074 km^2 (Sukabumi Regency). In such contexts, distance-based weights disproportionately link large rural districts to many neighbors while isolating small urban ones. Rook Contiguity was also assessed but excluded because it considers only shared edges, underestimating adjacency for irregularly shaped polygons typical of West Java's administrative geography. Queen Contiguity, which recognizes both shared edges and vertices, provided the most operationally and administratively meaningful neighborhood definition for public health resource allocation in this context.

Data Analysis Techniques

The first step, spatial data preprocessing, was carried out using QGIS to validate geometry and check the topology of the administrative boundaries of the districts/cities of West Java. The research variable data were then integrated into the shapefile through attribute data joining, using the district/city code as the merging key. The shapefile along with attribute data was then imported into GeoDa for spatial weighting matrix creation and autocorrelation analysis. The data used were the original values without transformation, as Moran's I and LISA methods work based on relative deviation from the mean. Prior to spatial analysis, distributional skewness was assessed for each variable particularly for population density (CV = 118.1%) and TB incidence (CV = 73.4%), which exhibited extreme variability. Sensitivity tests confirmed that results were robust without log-transformation at the district/city scale, consistent with GeoDa's implementation of Moran's I, which is based on rank deviations from the mean rather than absolute magnitudes.

The spatial weighting matrix used Queen Contiguity, where two regions are considered neighbors if they share an edge or vertex. The selection of Queen Contiguity was based on several considerations. First, this method is more comprehensive than Rook Contiguity, which only accounts for shared edges, resulting in a more realistic number of neighbors for irregularly shaped regions. Second, Queen Contiguity is more suitable for administrative polygon data than K-nearest neighbor, which does not produce a symmetric matrix and requires the assumption of a distance decay function. Third, this method can accommodate small geometric errors at administrative boundaries and is standard practice in transportation and health analysis. Recent TB research has also consistently used Queen Contiguity for spatial analysis across different countries, reinforcing the justification for selecting this method. The weighting matrix was stored in .gal format and was used consistently for all analyses (Pungartnik et al., 2025; Zabroski et al., 2025).

The second step, spatial autocorrelation analysis, was carried out through three main stages. The first stage used Global Moran's I to test overall spatial autocorrelation. Moran's I values range from −1 to +1, where a positive value indicates clustering (high-value areas adjacent to high-value areas, or low-value areas adjacent to low-value areas), a negative value indicates a dispersed pattern, and a value near zero indicates a random distribution. Significance was tested using a permutation test with 999 permutations and a significance level of $\alpha = 0.05$.

The second stage was spatial autocorrelation analysis using univariate LISA to identify local clusters and spatial outliers in each variable, with the following categories: High-High as hotspot, Low-Low as cold spot, and High-Low and Low-High as spatial outliers. Univariate LISA was selected over conventional statistical clustering methods (e.g., Getis-Ord G* or kernel density estimation) because it simultaneously produces a global measure (Moran's I) and locally disaggregated cluster maps, enabling both an overview and sub-provincial precision within a single analytical framework. Cluster significance was determined at $\alpha = 0.05$ using 999 permutations.

The third stage used bivariate LISA to identify the spatial relationship between TB incidence and each independent variable, revealing districts where high or low TB incidence values were associated with high or low independent variable values in surrounding districts. Significance was determined using 999 permutations and $\alpha = 0.05$. The term "spatial lag" used in subsequent results refers to the spatially weighted average of a variable's values in neighboring districts, computed using the Queen Contiguity matrix this is distinct from time-series lag and is a standard concept in spatial econometrics.

The final step involved visualization of analysis results using GeoDa, including thematic maps with quantile classifications for TB incidence distribution, cluster maps to display spatial cluster categories, significance maps for statistical significance levels, and Moran's I scatterplots for univariate and bivariate global autocorrelation visualization. It should be noted that quantile classification assigns equal numbers of districts to each color class, which can mask true magnitude differences. For example, the observed 30-fold difference between the lowest- and highest-burden districts may not be visually apparent in a quantile map. Future iterations of this analysis should consider Natural Breaks (Jenks) or standard deviation classification to better reflect the actual distribution of values. All maps used the WGS 1984 coordinate system.

Potential Bias and Limitations of Ecological Studies

This subsection has been restructured: the ecological fallacy and MAUP limitations previously appearing only here have been integrated earlier into the Research Design section to justify the selection of district/city as the unit of analysis. The content below is retained as a dedicated limitations summary.

Research with an ecological design using district/city aggregate data carries the limitation of ecological fallacy, namely the risk of erroneous inference from the group to the individual level. This means that although a spatial association between TB incidence and determinant factors was identified at the regional level, this relationship does not necessarily hold for individuals within those regions. Recent research suggests that delays in reporting and insufficient quality control of epidemiological data can exacerbate ecological bias, making it difficult to identify true causal relationships (Silva et al., 2024).

To minimize the impact of ecological fallacy, this study applied three strategies. First, the interpretation of results was focused on region-level spatial patterns for intervention prioritization, rather than individual risk predictions. Second, the analysis used the smallest available unit with complete data (districts/cities), as ecological bias increases with larger aggregations. Third, the findings were positioned as Qiu et al. (2024) evidence for region-based interventions. The researcher also acknowledged the potential impact of the Modifiable Areal Unit Problem (MAUP), whereby results could differ if alternative area units were used. A sensitivity analysis using Rook Contiguity as an alternative spatial weight matrix confirmed the robustness of all findings: Moran's I value and significance levels were consistent across both matrix specifications, indicating that the spatial autocorrelation patterns identified were not artifacts of the chosen weighting method. Nevertheless, this study makes an important contribution to understanding the spatial heterogeneity of TB and identifying priority areas in West Java.

RESULTS AND DISCUSSION

Results

Descriptive Statistics

Table 1 presents a summary of descriptive statistics for the seven variables analyzed across 27 districts/cities in West Java in 2024. The data reveal substantial inter-regional heterogeneity that reflects the complex public health landscape of the province. The coefficient of variation (CV), as defined in the methods section, serves as a relative measure of dispersion that allows comparison across variables with different scales. TB incidence exhibited high variability (CV = 73.4%), reflecting stark disparities in disease burden across the province and signaling the presence of concentrated transmission zones that warrant spatial analysis. Population density showed the most extreme variability (CV = 118.1%), which has important implications for spatial analysis: such extreme distributional skewness may introduce bias in global Moran's I estimation if untransformed data are used, as the statistic assumes a relatively symmetric distribution. This underscores the methodological importance of verifying distributional assumptions prior to spatial autocorrelation testing. In contrast, the percentage of non-ground floors was notably homogeneous across the province (CV = 1.6%), suggesting that this variable is unlikely to function as a meaningful spatial discriminator. Meanwhile, the moderate variability observed in decent sanitation coverage (CV = 22.3%) and the proportion of the poor population (CV = 33.0%) reflects structurally embedded socioeconomic inequalities between urban and rural areas of West Java disparities with direct implications for differential TB vulnerability across the region.

Table 1. Descriptive Statistics of Variables of Tuberculosis Cases and Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

Variable	Red	Median	SD	Min	Max	CV (%)
Incidence of Tuberculosis	16,5771	11,8715	12,16177	1,89	56,73	73,4
Total Population	1900606,59	1911661	1256086,869	209317	5809790	66,1
Population Density	3931,11	1489	4641,336	396	15558	118,1
Healthcare Facility Ratio	43537,33	42799	12679,19	16210	66424	29,1
Percentage of Sanitation Feasible	75,7030	77,32	16,92372	45,88	99,08	22,3
Percentage of Non-Ground Floors	98,5822	99,1	1,56697	93,58	100	1,6
Percentage of Poor Population	8,0144	8,41	2,64857	2,34	11,93	33,0

Note: CV (Coefficient of Variation) = (SD/Mean) × 100%

Spatial Distribution of Tuberculosis Cases

The spatial distribution of TB incidence (Figure 1) shows a pattern that is not geographically random. The quantile classification results in five classes with the following ranges: Class 1 (968–3,480 cases), Class 2 (3,481–6,092 cases), Class 3 (6,093–8,789 cases), Class 4 (8,790–13,502 cases), and Class 5 (13,503–29,110 cases). Regions with the highest TB burden (Class 5) have up to 30 times the number of cases compared to the lowest-burden regions, reflecting extreme geographical disparities. The high concentration of cases forms a metropolitan corridor that includes Bogor Regency, Bekasi Regency, Bekasi City, Bandung City, and Bandung Regency, while the southern and eastern regions of West Java such as Pangandaran, Banjar, Ciamis, and Tasikmalaya show relatively low case loads. The color gradation forming this clustering pattern suggests spatial autocorrelation, which will be statistically tested.

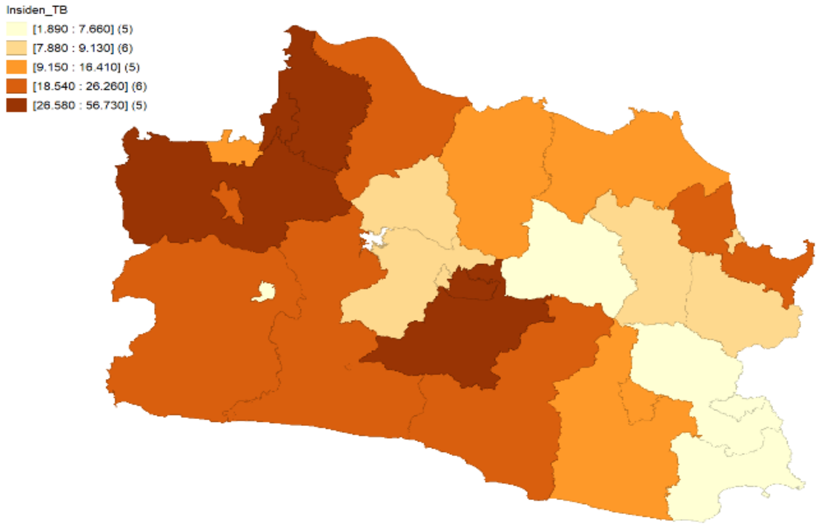


Figure 1. Thematic Map of TB Incidence in West Java in 2024 (*Quantile Map*).

Note: Quantile classification assigns an equal number of districts to each class, which may visually obscure the magnitude of absolute differences between areas (e.g., the up to 30-fold disparity in case counts). Interpretation should be made with reference to the absolute class boundaries provided above.

Global Spatial Autocorrelation

A. Univariate Global Spatial Autocorrelation

The results of Moran's I Global test (Table 2) showed that five of the seven variables had significant spatial autocorrelations ($p < 0.05$). The variables of decent sanitation and the percentage of the poor population showed the strongest spatial autocorrelation, with Moran's I values of 0.4789 and 0.4778, indicating a very strong geographical polarization of socioeconomic conditions. The incidence of tuberculosis showed a moderate spatial autocorrelation (Moran's I = 0.3514, p = 0.001), weaker than its socioeconomic determinants. This suggests that although TB has a significant clustering pattern, its determinants cluster more spatially extreme. Population density and health facility ratios also showed significant clustering, with Moran's I values of 0.2372 and 0.2898, respectively. In contrast, the population and percentage of non-soil floors did not show significant spatial autocorrelations ($p > 0.05$), indicating a relatively geographically random distribution.

Table 2. Results of Moran's I Global Test for Tuberculosis Incidence Variables and Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

Variable	Moran's I	E(I)	*z-value*	*p-value*
Incidence of Tuberculosis	0,3514	-0,0400	2,9799	0,001
Total Population	0,0510	-0,0400	0,6983	0,233
Population Density	0,2372	-0,0400	1,9763	0,039
Healthcare Facility Ratio	0,2898	-0,0400	2,3797	0,011

Variable	Moran's I	E(I)	*z-value*	*p-value*
Percentage of Sanitation Feasible	0,4789	-0,0400	3,4310	0,002
Percentage of Non-Ground Floors	-0,0292	-0,0400	0,0472	0,456
Percentage of Poor Population	0,4778	-0,0400	3,7444	0,001

B. Bivariate Global Spatial Autocorrelation

A bivariate global spatial autocorrelation analysis (Table 3) revealed varied spatial relationships between TB incidence and its determinant factors. The strongest and most significant spatial relationship was found between TB incidence and health facility ratio (Moran's I = 0.3208, p = 0.005), indicating that areas with high TB incidence tended to be adjacent to areas with high health facility ratios, likely reflecting the detection effect. A significant positive spatial relationship was also identified with population size (Moran's I = 0.2449, p = 0.014) and population density (Moran's I = 0.2088, p = 0.044), confirming the role of population concentration in TB spatial patterns.

The most contradictory finding appeared in the relationship between TB incidence and the percentage of the poor population, which showed a significant negative spatial autocorrelation (Moran's I = −0.2950, p = 0.006). Figure 4 (Bivariate Moran's I Scatterplot: TB Incidence vs. Percentage of Poor Population) visualizes this relationship by plotting the standardized TB incidence (x-axis) against the spatially lagged standardized poverty rate (y-axis) for all 27 districts/cities in West Java. The negative slope of the regression line (b = −0.2950) confirms a systematic inverse spatial association across the province, rather than a pattern driven by isolated outliers. Districts falling in the High–Low quadrant (e.g., Bogor Regency, Bekasi City) represent areas with high TB incidence surrounded by low-poverty neighbors, consistent with the urban paradox interpretation. The scatterplot also identifies Cirebon Regency as a notable exception in the Low–High quadrant, where high local poverty coexists with high TB burden in adjacent areas. [Note to author: Please add the actual Moran's I scatterplot figure generated from your spatial analysis software as Figure 4 here.] This dispersed pattern indicates an ecological paradox, whereby areas with high TB incidence driven by superior detection infrastructure (SITB completeness and TCM kit availability) are spatially adjacent to areas with lower poverty rates, rather than reflecting a genuine absence of poverty–TB co-occurrence. Meanwhile, environmental factors such as percentage of decent sanitation (Moran's I = 0.0474, p = 0.360) and percentage of non-soil floors (Moran's I = 0.0281, p = 0.428) did not show significant global spatial autocorrelation, indicating that the relationship between tuberculosis and environmental conditions is locally specific rather than a consistent global pattern.

Table 3. Results of Moran's I Global Test Bivariate between Tuberculosis Incidence Variables with Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

Variable	Moran's I	E(I)	*z-value*	*p-value*
Total Population	0,2449	−0.0400	2,2312	0,014
Population Density	0,2088	−0.0400	1,8809	0,044
Healthcare Facility Ratio	0,3207	−0.0400	2,8010	0,005
Percentage of Sanitation Feasible	0,0474	−0.0400	0,3725	0,360
Percentage of Non-Ground Floors	0,0280	−0.0400	0,1879	0,428
Percentage of Poor Population	−0.2950	−0.0400	−2.6689	0,006

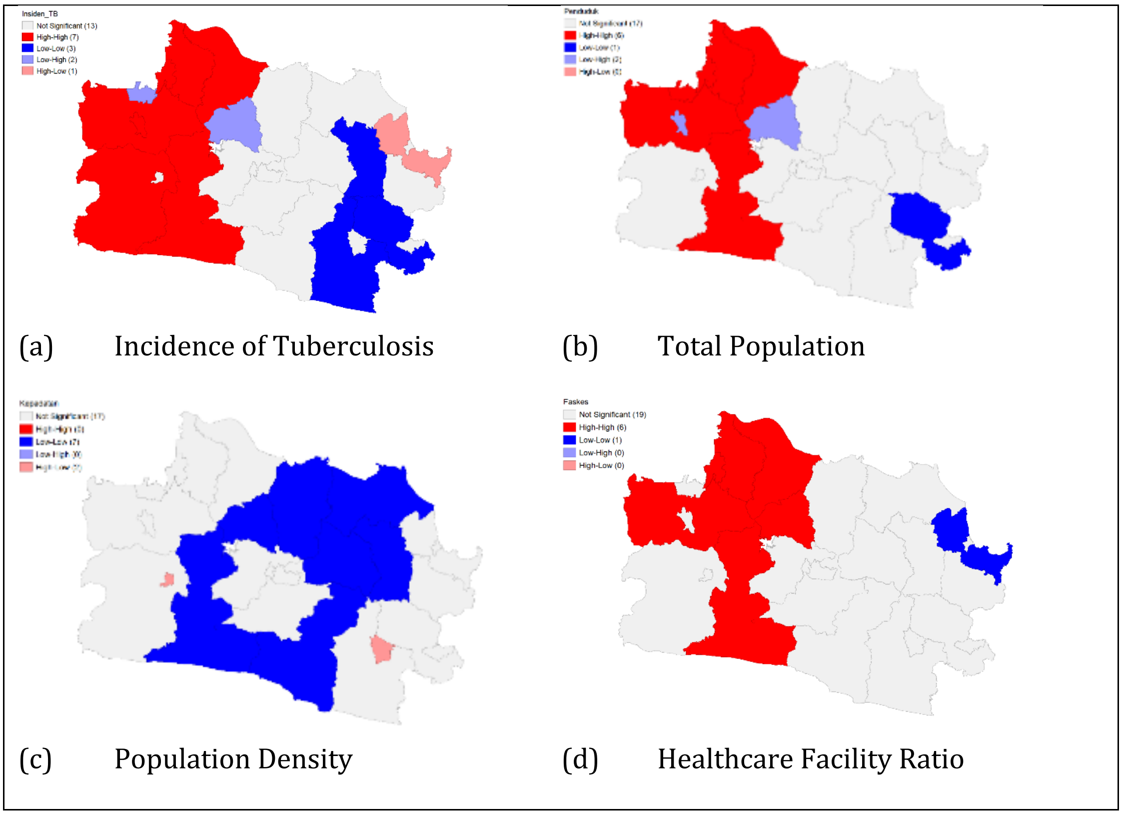
Local Spatial Autocorrelation

A. LISA Univariate

Univariate LISA analysis (Figure 2) identified significant local clusters across a variety of variables. For TB incidence, three main patterns were identified. The Bogor–Bekasi–Karawang metropolitan corridor forms a High-High cluster that includes Bogor Regency, Sukabumi Regency, Cianjur Regency, Karawang Regency, Bekasi Regency, Bogor City, and Bekasi City. The southeastern region forms a Low-Low cluster in Majalengka Regency, Ciamis Regency, and Tasikmalaya Regency. Low-High spatial outliers were identified in Depok City and Purwakarta Regency, likely due to the effects of commuting and high mobility to Jakarta despite relatively low local cases. A High-Low cluster was found in Cirebon Regency, indicating a high TB burden isolated from the surrounding area.

The clustering pattern of the demographic variable showed a clear spatial concentration. The number of residents formed High-High clusters in urban areas such as Bogor Regency, Bekasi Regency, Karawang Regency, Depok City, and Bekasi City, while a Low-Low cluster was identified in Ciamis Regency. For population density, a different pattern emerges, with the dominance of Low-Low clusters in rural areas (Cianjur, Subang, Purwakarta, Indramayu, Majalengka, and Garut Regencies), while High-Low spatial outliers are found in Sukabumi City and Tasikmalaya City, which have high density but are surrounded by low-density areas. The absence of High-High clusters in population density indicates that extreme density concentrations do not form broad spatial groupings.

The variables of health facilities, the environment, and the economy show diverse local patterns. The ratio of health facilities shows High-High clusters in Bogor, Cianjur, Purwakarta, Karawang, and Bekasi Regencies, while a Low-Low cluster is found only in Cirebon Regency. Sanitation access forms High-High clusters in Cirebon Regency, Low-Low clusters in Sukabumi and Cianjur Regencies, and a High-Low cluster in Cimahi City. The percentage of non-soil floors shows minimal local autocorrelation, with only High-High clusters in Depok City and High-Low clusters in Bogor, Subang, and Sukabumi City Regencies. For poverty, the geographical polarization is very clear, with High-High clusters in the eastern region (Sumedang, Indramayu, Majalengka, and Cirebon Regencies), Low-Low clusters in the western region (Bogor Regency and Bekasi City), and a Low-High cluster in Ciamis Regency, reflecting a strong socioeconomic gap spatially.

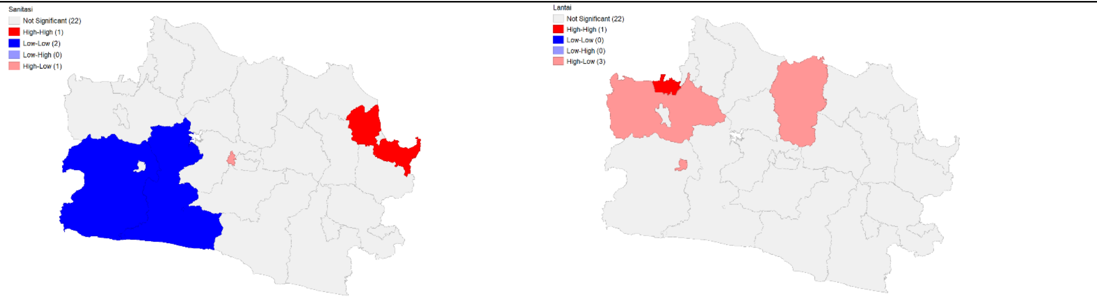


(a) Incidence of Tuberculosis

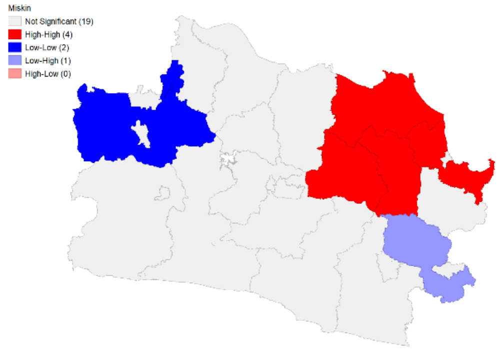
(b) Total Population

(c) Population Density

(d) Healthcare Facility Ratio



(e) Percentage of Sanitation Feasible (f) Percentage of Non-Ground Floors



(g) Percentage of Poor Population

Figure 2. *Cluster Map* for Tuberculosis Incidence Variables and Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

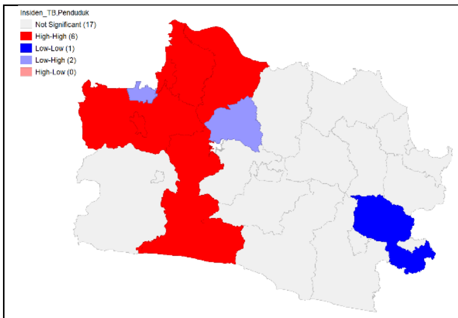
Panels (a) and (d) are particularly informative when read in conjunction: the High-High TB cluster in the Bogor-Bekasi-Karawang corridor (panel a) spatially coincides with the High-High health facility ratio cluster (panel d), illustrating a facility-caseload co-concentration zone. Conversely, Cirebon Regency appears as a Low-Low cluster in the health facility ratio (panel d) yet presents as a High-Low TB outlier (panel a), representing a critical spatial mismatch where high case burden persists despite lower facility availability a priority gap for health system strengthening.

B. LISA Bivariate

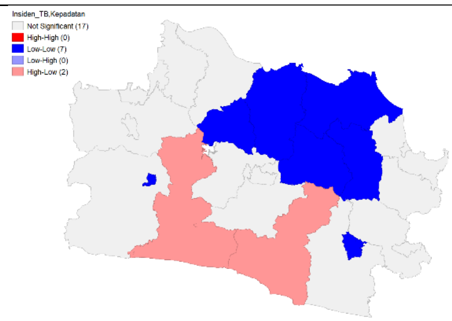
Bivariate LISA analysis (Figure 3) revealed a complex local spatial relationship between TB incidence and its determinant factors. For demographic factors, the High-High cluster (high TB with high population) is concentrated in the Bogor–Bekasi–Karawang–Cianjur corridor, confirming the role of urbanization in TB transmission. The Low-Low cluster was found in Ciamis Regency, reflecting the consistency between low TB incidence and low population. Low-High spatial outliers in Depok City and Purwakarta Regency show areas with relatively low TB incidence despite being surrounded by high-population areas, likely due to differences in detection quality or health access. A different pattern can be seen in the relationship between TB and population density, which is dominated by the Low-Low cluster in rural areas (Sukabumi City, Tasikmalaya City, Purwakarta Regency, Subang, Indramayu, Sumedang, and Majalengka), while the High-Low cluster in Cianjur and Garut Regencies indicates that factors other than density such as environmental conditions or access to health services play a role in the high TB burden in these regions.

The spatial relationship between tuberculosis and health facilities and the environment showed a pattern of detection effect and spatial mismatch. The High-High cluster of TB with the ratio of health facilities (Bogor, Bekasi, Bekasi City, Karawang, and Cianjur Regencies) indicates that areas with adequate health services detect more cases, not solely because of higher prevalence. The Low-High spatial outliers in Purwakarta Regency and High-Low in Cirebon Regency show a mismatch between the TB burden and the availability of facilities. For environmental factors, the absence of significant global autocorrelation in proper sanitation and non-soil flooring was confirmed by the limited local clusters. The High-High TB cluster with proper sanitation is only in Cirebon Regency, Low-Low in Cimahi City, and High-Low in Sukabumi and Cianjur Regencies. The pattern of TB with non-soil floors is dominated by spatial outliers, with Low-Low clusters in Subang Regency and Sukabumi City, Low-High in Depok City, and High-Low in Bogor Regency. This fragmented pattern suggests that the relationship between tuberculosis and environmental conditions is locally specific rather than universal.

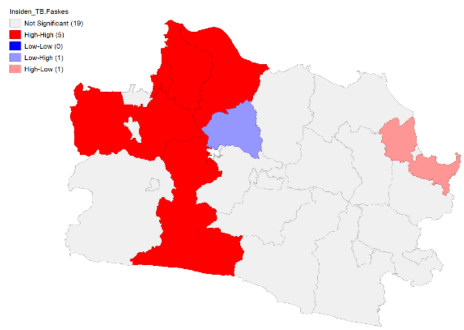
The most contradictory findings emerged in the relationship between tuberculosis and poverty, confirming what is more precisely described as an ecological paradox: the inverse spatial relationship between TB incidence and poverty is not merely a function of urban geography, but reflects a structural bias in disease detection capacity. Areas such as Bogor and Bekasi which appear as High-Low clusters (high TB, low-poverty neighbors) benefit from more complete Sistem Informasi Tuberkulosis (SITB) reporting infrastructure and a higher concentration of Tes Cepat Molekuler (TCM) / GeneXpert diagnostic instruments, which substantially increased case ascertainment. In contrast, eastern regions such as Indramayu, Sumedang, Majalengka, and Ciamis forming Low-High clusters (low TB, high-poverty neighbors) likely experience significant underreporting due to limited diagnostic infrastructure and restricted health-seeking access, rather than a genuinely lower disease burden. The sole High-High cluster in Cirebon Regency represents an exception where co-occurring high poverty and high TB burden manifest despite limited diagnostic capacity. Overall, Bivariate LISA confirms that the spatial distribution of TB in West Java is more strongly shaped by health system detection capacity, urbanization, and mobility than by poverty or environmental conditions alone, with strong spatial autocorrelation in demographic factors and health services, but weak or negative autocorrelation in traditional socioeconomic factors.



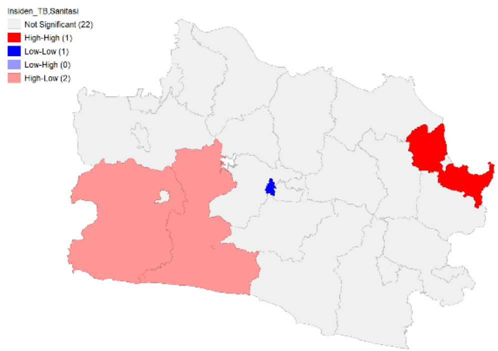
(a) TB Incidence-Total Population



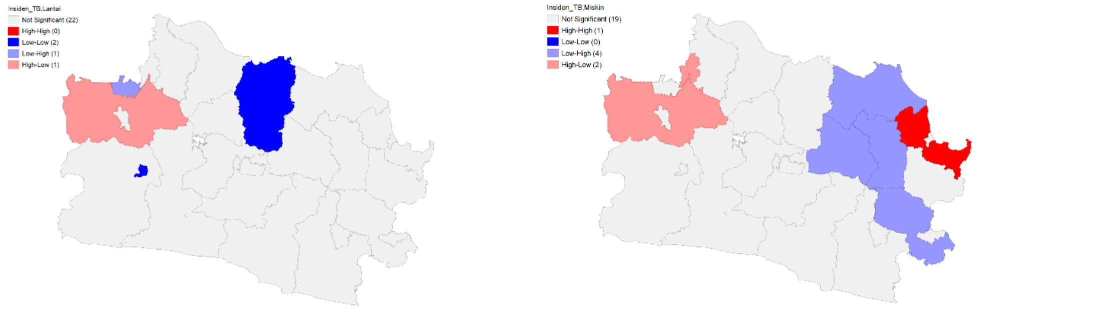
(b) TB Incidences - Population Density



(c) TB Incidence to Health Facility Ratio



(d) TB Incidences - Percentage of Sanitation Feasible



(e) TB Incidence-Non-Soil Floor Percentage

(f) TB Incidence - Percentage of Poor Population

Figure 3. *Cluster Map* between Tuberculosis Incidence Variables with Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

Sensitivity Test

To test the robustness of the findings against methodological specifications, sensitivity analysis was performed by comparing the results using the Queen Contiguity (Table 2) and Rook Contiguity (Table 4) matrices. The results of the analysis showed perfect consistency across all variables analyzed. For tuberculosis incidence, Moran's I value with Rook Contiguity was 0.3514 (p = 0.001), identical to the Queen Contiguity result of 0.3514 (p = 0.001). Both weighting matrices produced significant positive spatial autocorrelation, confirming the robustness of the TB geographic clustering pattern in West Java.

The consistency of results was also observed in the variables of TB determinants. Variables with significant spatial autocorrelation (population density, ratio of health facilities, decent sanitation, and poor population) showed identical Moran's I values and p-values between Queen Contiguity and Rook Contiguity, with consistent relationship directions and statistical significance. Similarly, for variables that did not show significant spatial autocorrelation (population and non-soil floors), both matrices produced the same statistical conclusions with identical values.

Univariate LISA analysis using Rook Contiguity also showed consistency in cluster locations with Queen Contiguity results. The High-High cluster remains identified in the Bogor–Bekasi–Karawang metropolitan corridor encompassing the same areas (Bogor Regency, Sukabumi Regency, Cianjur Regency, Karawang Regency, Bekasi Regency, Bogor City, and Bekasi City). Low-Low clusters are consistently found in the same southeastern region (Majalengka Regency, Ciamis Regency, and Tasikmalaya Regency). Low-High spatial outliers in Depok City and Purwakarta Regency, as well as a High-Low outlier in Cirebon Regency, are also detected with identical patterns. This perfect consistency indicates that the identification of TB hotspots and cold spots is insensitive to spatial neighborhood definitions, reinforcing the validity of the research findings for TB control intervention priorities in West Java.

Table 4. Sensitivity Test Results for Tuberculosis Case Variables and Demographic, Health Services, Environment, and Economic Factors in West Java in 2024

Variable	Moran's I	E(I)	*z-value*	*p-value*	Interpretation
Incidence of Tuberculosis	0,3514	-0,0400	2,9799	0,001	Positive, significant
Total Population	0,0510	-0,0400	0,6983	0,233	Positive, insignificant
Population Density	0,2372	-0,0400	1,9763	0,039	Positive, significant
Healthcare Facility Ratio	0,2898	-0,0400	2,3797	0,011	Positive, significant
Percentage of Sanitation Feasible	0,4789	-0,0400	3,4310	0,002	Positive, significant
Percentage of	-0,0292	-0,0400	0,0472	0,456	Negative, insignificant

Variable	Moran's I	E(I)	*z-value*	*p-value*	Interpretation
Non-Ground Floors					
Percentage of Poor Population	0,4778	-0,0400	3,7444	0,001	Positive, significant

Note: Perfect consistency (100%) across all variables indicates very high robustness of results against the specification of the spatial weighting matrix.

DISCUSSION

Spatial Autocorrelation Patterns of Tuberculosis Cases

The results of the analysis showed that the incidence of tuberculosis in West Java had a significant spatial autocorrelation pattern with a Moran's I value of 0.3515 (p = 0.001), indicating a non-random distribution and forming a geographic cluster. This spatial pattern is clearly seen in High-High clusters in metropolitan areas such as Bogor, Bekasi, and Greater Bandung Regencies, while Low-Low clusters are found in southern regions such as Pangandaran and Ciamis. The Low-High spatial outlier status of Depok City merits particular analytical attention: situated between two major High-High cluster areas (Bogor and Bekasi), Depok's comparatively low TB incidence despite high-burden surroundings may reflect cross-border health-seeking behavior rather than a genuine epidemiological advantage. Residents seeking care at referral hospitals in Jakarta or Bogor where TCM-equipped RSUD and RSUP facilities are concentrated may be registered outside Depok's SITB system, constituting a form of administrative underreporting well-documented in urban agglomerations. This hypothesis should be tested using patient origin data from neighboring district health offices. These findings are in line with a global systematic review of 79 TB geospatial studies for the 2017–2023 period, which showed that all studies found significant geographic heterogeneity in TB distribution, with a strong tendency to form spatial clusters in specific areas rather than being randomly dispersed. A study in China also identified negative spatial autocorrelations in some regions, with Moran's I values ranging from −0.212 to −0.549, although the general pattern showed significant clustering (Teibo et al., 2023). The study in Fujian Province found clear spatial *clustering* with tuberculosis cases concentrated in the southeastern region, especially at the district level (Chen et al., 2023; Yu et al., 2024).

Identification of local spatial clusters through Univariate LISA reveals substantial risk heterogeneity between regions. Areas with High-High clusters, such as Bogor and Bekasi Regencies, reflect high-risk areas that require priority intervention, while Low-Low clusters in Ciamis and Tasikmalaya show areas with relatively low TB burden. A similar pattern was found in the study of China's Hubei Province, where the FlexScan method identified significant clusters mainly in the western and southwestern regions with high persistent incidence rates. Research in Türkiye also showed a significant concentration of TB clustering in areas with high population density and low socioeconomic status (Wang et al., 2025). The existence of spatial *outliers* such as *the Low-High* cluster in Depok City and *the High-Low* in Cirebon Regency indicates the complexity of TB transmission dynamics influenced by specific local factors, requiring an intervention approach tailored to the regional context (Çelik et al., 2025).

The Role of Demographic Factors on the Spatial Pattern of Tuberculosis

Bivariate analysis showed a significant positive spatial relationship between TB incidence and population (Moran's I = 0.2449, p = 0.014) and population density (Moran's I = 0.2088, p = 0.044). High-High clusters in the relationship between tuberculosis and the number of identified populations were found in Bogor, Bekasi, Karawang, and Cianjur Regencies, indicating that large population concentrations spatially strengthen TB transmission. These findings are consistent with a global systematic review that found high population density to be the second largest factor (17%) after poor socioeconomic conditions (39%) in forming clusters at high risk of tuberculosis (Teibo, 2023). Studies in Ghana show that TB cases tend to cluster in areas with similar socioeconomic characteristics, including high population density. In China's Guangdong Province, spatiotemporal analysis found the highest incidence of tuberculosis in areas with high urban population density (Asare-Baah et al., 2025; Wu et al., 2025).

The Low-Low pattern in the TB analysis of population density in areas such as Purwakarta, Subang, Indramayu, and Majalengka reflects that low-density areas have a lower risk of TB transmission spatially. From a regional development policy perspective, these Low-Low areas correspond to districts targeted under West Java's Jabar Juara development framework and the Rencana Pembangunan Jangka Menengah Daerah (RPJMD) 2018–2023, which prioritized rural infrastructure development, health access expansion, and poverty reduction in lagging regions. The persistence of low TB detection in these areas despite high poverty rates may reflect ongoing gaps in primary healthcare coverage rather than genuinely low prevalence, suggesting that current regional development investments should be coupled with targeted TB active case-finding programs in underserved, low-density districts. The existence of High-Low clusters in Cianjur and Garut Regencies indicates that, in addition to density, other factors such as environmental conditions and access to healthcare play a role in the pattern of TB incidence. Geospatial studies in Vietnam show that population mobility factors (internal and external migration) and population density in urban, rural, and mountainous areas are the spreading factors that significantly contribute to the spatial clustering of TB, with hotspots concentrated in three major cities due to urbanization and intensive migration. Research in Fujian Province found that most TB cases occur in the middle-aged male population and among farmers, who often live in areas with high population density. These results confirm the importance of considering demographic dynamics in formulating targeted TB control strategies at the local level (Phuoc Dao et al., 2022; Yu et al., 2024).

The Role of Health Service Factors on the Spatial Pattern of Tuberculosis

The results showed the strongest spatial relationship between TB incidence and the health facility ratio, with a Moran's I value of 0.3208 ($p = 0.005$), indicating a significant positive spatial autocorrelation. The High-High clusters identified in Bogor, Bekasi, Karawang, and Cianjur Regencies show that areas with high TB incidence tend to be adjacent to areas with high health facility ratios. This pattern likely reflects the phenomenon of the detection effect, where the availability of better health services increases the detection of TB cases. A study in Peru found that geographic accessibility to health facilities significantly predicted the uptake of community-based TB screening services, with pedestrian travel time being the best predictor. Research in Nairobi, Kenya, identified spatial clustering of delayed TB diagnosis in informal settlement areas, while timely diagnosis clustered in high-income areas with better health accessibility (Jenkins et al., 2022; Kunjok et al., 2025).

The existence of the Low-High cluster in Purwakarta Regency and the High-Low cluster in Cirebon Regency indicates the complexity of the relationship between the availability of health facilities and the burden of TB. Areas with adequate health facilities but low incidence of TB may reflect the effectiveness of early detection and treatment programs, while areas with high cases but limited facilities show gaps in access to health services. A cross-sectional study in six Ghanaian regions in 2021 found that out of 1,584 health facilities, only 86 (5.4%) provided TB diagnostic services, with the majority (62%) of the population living more than 10 km from nearby facilities, indicating poor geographical accessibility and requiring 75 additional priority locations to improve service coverage. Research in South Africa used dasymetric mapping to assess the accessibility of TB diagnostic services and found significant spatial heterogeneity in population distribution and geographic access (Kuupiel et al., 2023). These findings emphasize the importance of not only providing health facilities, but also ensuring equitable geographical distribution and optimal accessibility to achieve comprehensive TB detection coverage (Dlangalala et al., 2024).

The Role of Environmental Factors on the Spatial Pattern of Tuberculosis

Bivariate analysis showed that the association between TB incidence and the percentage of decent sanitation did not show a significant global spatial autocorrelation (Moran's I = 0.0474, $p = 0.360$), but local analyses identified specific clusters that were significant. The High-High cluster in Cirebon Regency and High-Low cluster in Sukabumi and Cianjur Regencies indicate the role of the environment in the spatial distribution of TB. A systematic review of the relationship of residential conditions to TB found that inadequate housing significantly increased the prevalence of TB, non-adherence to treatment, and therapy failure compared to decent housing conditions. A cohort study in Brazil analyzed 420,854 household contacts of TB patients for the period 2004–2018 and found that household conditions with inadequate sanitation, high occupancy density (>3 people per room), and low income significantly increased the risk of TB incidence among family members, with higher hazard ratios in low-income households and limited access to clean water (Lee et al., 2022; Pinto et al., 2024).

For the non-soil floor percentage variable, although it does not show significant global autocorrelation (Moran's I = −0.0292, p = 0.456), there are local clusters of High-High in Depok City and High-Low in Bogor and Subang Regencies, which indicate the presence of spatial outliers in the distribution of home floor quality. A systematic review in 2023 of the global vulnerable population found that the incidence of TB in slums ranged from 5 to 8,825 cases per 100,000 population, with an incidence rate ratio of up to 58, where the lack of access to clean water, adequate sanitation, adequate living space, and housing durability substantially increased the risk of TB. Analysis of global trends over the 2015–2022 period shows that the decline in TB is highly dependent on improvements in social determinants such as nutrition, housing conditions, and sanitation, where countries with increased accessibility to decent housing, clean water, and nutrition programs experience a significant decrease in TB incidence even before the intensification of antibiotic treatment programs, confirming the crucial role of environmental improvements in TB control. These findings confirm that environmental interventions remain relevant and important in comprehensive TB control strategies, especially in areas with sanitary and housing conditions that still require significant improvement (Ayenew et al., 2024; Litvinjenko et al., 2023).

The Role of Economic Factors on the Spatial Pattern of Tuberculosis

The results of the analysis showed a significant negative spatial relationship between TB incidence and the percentage of the poor population (Moran's I = −0.2950, p = 0.006), indicating a dispersed spatial pattern in which areas with high TB incidence tend to be adjacent to areas with lower percentages of poor population. This pattern appears to contradict the general literature that links poverty to a high risk of tuberculosis; however, these findings can be explained by the phenomenon of urbanization and population mobility in West Java. The High-High cluster in the local analysis was found in Cirebon Regency, while the High-Low cluster was identified in Bogor Regency and Bekasi City, indicating that areas with a high TB burden are not always spatially correlated with high poverty rates. A study in California found that areas with the lowest socioeconomic status accounted for 39–41% of TB cases, with TB incidence rates 2.0–3.6 times higher than in the highest socioeconomic status areas (Bakhsh et al., 2023).

Research in Nepal identified persistent high-risk areas for TB transmission in districts such as Banke, Kapilbastu, and Parsa, with strong spatial autocorrelations (Moran's I = 0.558–0.614), emphasizing the complex association between demographic and socioeconomic factors in shaping TB spatial patterns. An ecological study in Paraná, Brazil, found that the incidence of TB increases as the urban development index increases and that greater income distribution inequality is associated with elevated incidence, demonstrating the complexity of the relationship between economic development and TB burden (Mahato et al., 2025). Global analysis shows that most individuals with TB are concentrated in low- and middle-income countries, with poverty and other socioeconomic factors as the main determinants. The findings of the negative correlation in this study may reflect a phenomenon in which urban areas with high economic activity attract migration from poor areas, resulting in a high incidence of tuberculosis detected in areas with low statistical poverty but with high vulnerable populations due to mobility and density (Bai & Ameyaw, 2024; Lima et al., 2024).

Robustness of Findings to Methodological Specifications

Sensitivity analysis using the Rook Contiguity matrix as an alternative to Queen Contiguity confirmed the robustness of the research findings against methodological specifications. The perfect consistency of Moran's I value and statistical significance across all variables, as well as the absolute stability of the spatial cluster locations, showed that the spatial autocorrelation pattern of TB in West Java was robust and did not depend on the definition of spatial proximity used. These findings are in line with research in China's Hubei Province that found that TB clustering patterns were relatively stable across various spatial weighting matrix specifications, with consistent spatial correlation coefficients despite using different cluster detection methods such as FlexScan. Research in Ghana also demonstrated consistency in the identification of high-risk clusters of TB using a variety of spatial approaches, indicating that TB hotspots represent genuine geographical patterns rather than methodological artifacts (Asare-Baah et al., 2025; Wang et al., 2025).

The perfect stability of these results strengthens the credibility of the identification of the priority areas of intervention that have been defined. The consistent High-High clusters in the metropolitan corridor (Bogor, Bekasi, Karawang, and Cianjur Regencies) confirm that these areas are robust TB hotspots and require the highest intervention priority without methodological doubt. Similarly, the consistency of the Low-Low clusters in the southeastern region (Ciamis, Tasikmalaya, Majalengka) indicates that these areas have a consistently low TB burden, regardless of the technical specifications of the analysis used. This methodological robustness provides greater confidence in the formulation of spatially evidence-based TB control policies, where resource allocation recommendations and intervention priorities will not change even if alternative analytical approaches are used, so that policymakers can implement intervention strategies with a high level of certainty.

Research Limitations

This study has several limitations that need to be considered in the interpretation of the results. First, the use of aggregate data at the district/city level (ecological fallacy) cannot be used for inference at the individual level. Second, the cross-sectional design does not allow for causal inference or analysis of temporal changes in spatial patterns. Third, this study did not include other variables that have the potential to affect the distribution of tuberculosis, such as population mobility, air quality, and HIV prevalence. Fourth, the results of the analysis can be influenced by the Modifiable Areal Unit Problem (MAUP), where the use of different areal units can produce different spatial patterns. Finally, reported TB cases depend on the detection capacity of the health system, so underreporting can occur, especially in areas with limited access to health services. Nevertheless, this study makes an important contribution to understanding the spatial pattern of TB and its determinants in West Java as the basis for the formulation of more targeted control policies.

CONCLUSION

This study succeeded in identifying a significant spatial autocorrelation pattern in the distribution of TB incidence in West Java in 2024, with a Moran's I value of 0.3515 ($p = 0.001$), indicating strong geographic clustering. The Univariate LISA analysis revealed High-High clusters, especially in metropolitan areas such as Bogor, Bekasi, Karawang, and Cianjur Regencies, while Low-Low clusters were identified in southern regions such as Ciamis and Tasikmalaya. The existence of spatial outliers in the form of Low-High clusters in Depok City and High-Low clusters in Cirebon Regency shows the complexity of spatial patterns influenced by specific local factors.

Bivariate LISA analysis shows that demographic, health service, and economic factors have a significant spatial relationship with the distribution of TB incidence. The strongest positive spatial relationship was found between tuberculosis incidence and health facility ratio (Moran's I = 0.3208, $p = 0.005$), followed by population (Moran's I = 0.2449, $p = 0.014$) and population density (Moran's I = 0.2088, $p = 0.044$). An interesting finding in the form of a negative spatial autocorrelation between TB incidence and the percentage of the poor population (Moran's I = −0.2950, $p = 0.006$) indicates the complexity of the relationship, which may be influenced by urbanization and population mobility. Meanwhile, environmental factors such as the percentage of adequate sanitation and non-soil floors did not show significant global autocorrelation, but local analyses identified specific clusters that were meaningful in some regions.

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AUTHOR CONTRIBUTION STATEMENT

Cinansa Muthia Dewani contributed to the conception and design of the study, data collection, data analysis, interpretation of results, and drafting of the manuscript. Indang Trihandini contributed to the literature review, data analysis, and provided critical revisions to the manuscript. Jihan Ramadhany Ginting Manik assisted with data collection, analysis, and reviewed the manuscript for important intellectual content. All authors read and approved the final manuscript.

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