

A Spatial Epidemiological Study of Tuberculosis Incidence in Indonesia

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ABSTRACT

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Tuberculosis (TB) remains a major public health challenge in Indonesia, with an uneven distribution of cases across provinces. While previous studies have examined spatial patterns of TB, limited attention has been given to simultaneously addressing spatial dependence and spatial heterogeneity in TB distribution. This study aims to analyse the spatial distribution of TB cases across 38 provinces in Indonesia in 2024 and to identify their determinants using an integrated spatial modelling framework. The study employs secondary provincial-level data consisting of demographic, socioeconomic, health, and environmental indicators. The analysis includes descriptive statistics, Global Moran's I, and Local Indicators of Spatial Association (LISA) to detect spatial autocorrelation, followed by spatial regression models including Ordinary Least Squares (OLS), Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). To further capture spatial heterogeneity, Geographically Weighted Regression (GWR) was also applied. The results reveal substantial disparities in TB cases across provinces in Indonesia. The OLS model identifies population density and the number of community health centers (Puskesmas) as significant determinants of TB cases. Moran's I results confirm significant positive spatial autocorrelation, indicating that provinces with high TB cases tend to cluster geographically. Spatial regression analysis shows that the SDM provides the best model performance, with the lowest AIC value (19.84) compared to OLS (36.82), SAR (37.84), and SEM (36.21), as well as a significant spillover effect of population density from neighboring provinces (coefficient = 0.55, $p < 0.01$), suggesting the presence of both direct and spillover spatial effects between provinces. In addition, GWR results demonstrate spatial heterogeneity, indicating that the influence of explanatory variables varies across regions. These findings highlight that TB cases in Indonesia are influenced by both spatial dependence and spatial heterogeneity. Therefore, TB control policies should adopt spatially targeted approaches that consider regional characteristics to improve the effectiveness of public health interventions.



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A. INTRODUCTION

Tuberculosis (TB) is a chronic infectious disease caused by *Mycobacterium tuberculosis* and remains a major global public health problem (World Health Organization, 2024). Indonesia ranks second among countries with the highest TB burden worldwide, with approximately 1,060,000 cases annually (Kementerian Kesehatan Indonesia, 2024). The increasing number of

TB cases highlights the need for more effective and targeted control strategies (Kementerian Kesehatan Indonesia, 2024; Kementerian Kesehatan Indonesia, 2025).

Previous studies have shown that TB incidence is influenced by environmental, behavioral, and socioeconomic factors such as sanitation, housing conditions, smoking habits, and economic status (Lee et al., 2022; Singh et al., 2025). In addition, TB transmission is closely related to spatial interactions between regions, making spatial approaches important for identifying clustering patterns and spatial dependence (Fatima et al., 2022; Rao et al., 2016; Zhang et al., 2019).

Several studies have reported significant spatial clustering of TB incidence using Moran's I, LISA, and spatial regression methods (Kibuuka et al., 2021; Mahato et al., 2025; Xue et al., 2023). Spatial regression models such as SAR have also demonstrated the influence of socioeconomic and environmental factors while accounting for spatial dependence between neighboring regions (Moyo et al., 2021; Wang et al., 2019; Zebua & Jaya, 2022). However, global spatial models assume constant relationships across regions, whereas Indonesia has substantial geographic and socioeconomic diversity that may lead to spatial heterogeneity (Zhu et al., 2026). Therefore, Geographically Weighted Regression (GWR) is applied to capture local variations in TB determinants across regions (Wang & Zhang, 2025).

Despite this growing body of literature, most spatial studies on TB in Indonesia have applied either global spatial dependence models (e.g., Moran's I, LISA, SAR, SEM) or local heterogeneity models (e.g., GWR) separately, and have largely focused on a single province or a limited set of districts (Fahdhienie & Sitepu, 2022; Zebua & Jaya, 2022), so that the simultaneous spatial dependence and heterogeneity of TB at the national, cross-provincial level remain underexplored. This represents an important research gap, because relying on a global model alone may mask important local variations in TB determinants, while relying on GWR alone may overlook spillover effects of TB risk factors from neighboring provinces. Combining global spatial regression models (OLS, SAR, SEM, SDM) with GWR within a single, integrated analytical framework therefore allows this study to capture both the overall spatial dependence and spillover effects between provinces and the province-specific heterogeneity in the influence of TB determinants, providing a more comprehensive evidence base for spatially targeted TB control policy in Indonesia (Wang & Zhang, 2025; Zhu et al., 2026).

This study aims to analyze the spatial distribution of tuberculosis incidence in Indonesia and identify the factors influencing its prevalence using spatial analysis methods, particularly Geographically Weighted Regression (GWR). The findings are expected to support more targeted public health policies in Indonesia.

B. METHODS

1. Research Design

This study used a quantitative cross-sectional design with GIS-based spatial analysis of TB incidence across 38 Indonesian provinces in 2024, reflecting the well-documented geographic clustering and spatial interaction patterns of TB transmission (Fahdhienie & Sitepu, 2022; Wang et al., 2019).

2. Study Area

The study covered all 38 provinces in Indonesia. TB incidence data (2024) were obtained from Kementerian Kesehatan Indonesia; socioeconomic and environmental variables from the Central Bureau of Statistics (BPS); and administrative boundary shapefiles from the Geospatial Information Agency (BIG).

3. Data Sources

All data were sourced from official Indonesian government institutions, as detailed in Section 2.2 above.

4. Variables

The dependent variable was the total number of tuberculosis (TB) cases in Indonesia at the provincial level in 2024. Independent variables included population density, poverty rate, smoking prevalence, access to safe drinking water, access to adequate sanitation, number of healthcare facilities (Puskesmas), health complaints, population growth rate, mean years of schooling, and unmet need for healthcare services. These variables have been widely associated with TB incidence in spatial epidemiological studies (Lee et al., 2022; Singh et al., 2025; Wang et al., 2019).

These variables were selected based on established theoretical and empirical relevance to TB transmission and detection: population density and growth rate reflect demographic transmission risk (Bussi & Gutierrez, 2019; Wang et al., 2019); poverty rate, years of schooling, and unmet healthcare need capture socioeconomic determinants of exposure and access (Lee et al., 2022; Singh et al., 2025); water and sanitation access represent environmental and housing conditions (Lee et al., 2022); smoking prevalence and health complaints represent behavioral susceptibility factors (Patra et al., 2015); and the number of Puskesmas reflects healthcare infrastructure affecting TB detection (Paisal & Laksono, 2025).

5. Data Analysis Techniques

a. Descriptive Analysis

Descriptive analysis was conducted to describe TB distribution across provinces, summarize statistical characteristics, and identify initial spatial patterns using thematic maps.

b. Spatial Weight Matrix

The spatial weight matrix was constructed using the Queen contiguity method, where provinces sharing either a common boundary or vertex were considered neighbors. This approach captures broader spatial interaction among adjacent regions and is commonly used in spatial epidemiological studies. The matrix was row-standardized to ensure comparability across regions Geospatial Health Data (Mahato et al., 2025).

c. Global Spatial Autocorrelation (Moran's I)

Global spatial autocorrelation was analyzed using Moran's I statistic to determine whether TB incidence exhibits clustering, dispersion, or random patterns. Moran's I is formulated as follows in Equation (1).

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

where w_{ij} represents spatial weights and x_i is the observed value at location i . Moran's I is widely used in spatial epidemiology studies, including tuberculosis analysis (Mahato et al., 2025; Xue et al., 2023).

d. Local Spatial Analysis (LISA)

Local Indicators of Spatial Association (LISA) were used to identify local spatial clusters:

- 1) High-High (hotspots),
- 2) Low-Low clusters,
- 3) High-Low,
- 4) Low-High areas.

LISA provides detailed insight into local spatial patterns and is commonly used in TB studies (Kibuuka et al., 2021; Wolde et al., 2024).

e. Spatial Regression Analysis

1) Ordinary Least Squares (OLS)

The baseline model is Ordinary Least Squares (OLS), expressed in Equation (2) as follows.

$$y = X\beta + \varepsilon \quad (2)$$

Before model estimation, classical assumption tests including normality, multicollinearity, heteroscedasticity, and autocorrelation tests were conducted. However, OLS assumes independence between observations, which is often violated in spatial data (Moraga, 2019).

2) Spatial Regression Models

To account for spatial dependence, Spatial Autoregressive (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) were applied:

$$y = \rho W y + X\beta + \varepsilon \quad (3)$$

$$y = X\beta + u, u = \lambda W u + \varepsilon \quad (4)$$

$$y = \rho W y + X\beta + W X \theta + \varepsilon \quad (5)$$

These models are widely used to capture spatial interactions among neighboring regions in tuberculosis studies (Moyo et al., 2021; Wang et al., 2019; Zebua & Jaya, 2022).

3) Geographically Weighted Regression (GWR)

To capture spatial heterogeneity, Geographically Weighted Regression (GWR) is applied. The GWR model is defined as follows in Equation (5).

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (6)$$

where (u_i, v_i) represents the spatial coordinates of location i , and $\beta_k(u_i, v_i)$ are location-specific parameters. GWR allows regression coefficients to vary across

space, enabling a more detailed understanding of local relationships between TB incidence and explanatory variables (Wang & Zhang, 2025).

f. Model Selection

Model selection followed a stepwise procedure: (1) estimate and refine OLS, retaining significant predictors; (2) confirm spatial autocorrelation via Moran's I and LISA; (3) estimate SAR, SEM, and SDM using the same predictors; (4) apply GWR to assess spatial heterogeneity; and (5) select the best model based on lowest AIC, Adjusted R^2 , and residual diagnostics.

C. RESULT AND DISCUSSION

1. Descriptive Analysis

The descriptive statistics of tuberculosis (TB) and explanatory variables across 38 provinces in Indonesia are presented in Table 1.

Table 1. Descriptive Statistics of Variables

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Total TB Cases	1.400	22.977	42.877	123.247	124.049	938.662
Access to Safe Drinking Water	30,64	82,22	89,02	87	94,65	99,96
Population Density	5	39,5	100	678,2	251,8	16.165,00
Population Health Complaints	8,85	20,23	23,87	23,74	28,86	38,87
Number of Community Health Centers	52	108	208	270,5	301,8	1.110,00
Percentage of Poor Population	3,8	5,782	9,57	10,665	12,61	29,66
Smoking Prevalence	19,22	25,05	28	27,4	29,75	33,84
Population Growth Rate	0,31	1,17	1,365	1,296	1,472	1,93
Average Years of Schooling	5,1	8,785	9,34	9,292	9,93	11,49
Access to Proper Sanitation	12,61	79,38	83,36	81,14	87,18	96,83
Unmet Need for Health Services	1,39	4,112	4,83	4,87	5,657	8,24

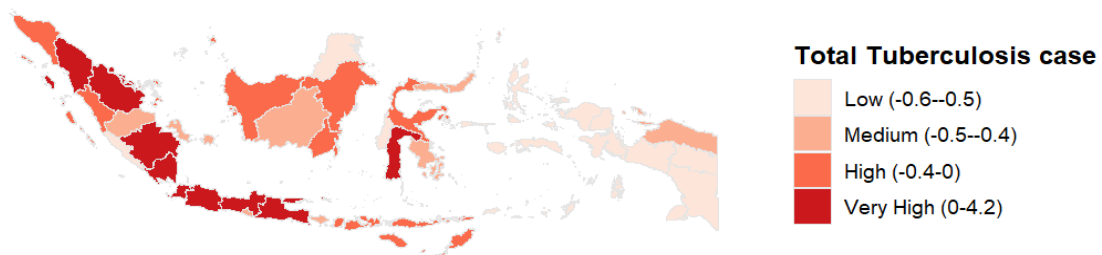
Based on Table 1, descriptive statistics indicate substantial disparities among provinces in Indonesia, particularly in population density, healthcare facilities, and socioeconomic conditions. The TB Case Notification Rate (CNR) ranges from 104 to 872 cases per 100,000 population, reflecting unequal disease burden across regions. In addition, low minimum values for access to safe drinking water and sanitation indicate persistent infrastructure inequality. These findings suggest that TB incidence is closely associated with both health and socioeconomic conditions across provinces.

2. Spatial Distribution of TB Cases

The spatial distribution of total tuberculosis (TB) cases across Indonesia in 2024 is illustrated in Figure 1.

Distribution of Tuberculosis case

Indonesia by Province (2024)



Source: Kementerian Kesehatan RI (2024)

Figure 1. Map of Total Tuberculosis Cases by Province

Figure 1 reveals that higher TB concentrations are predominantly in western Indonesia, particularly Java Island, while eastern regions show low to medium levels, providing a preliminary basis for spatial autocorrelation analysis.

3. Spatial Weight Matrix

Table 2 summarizes the spatial neighbor structure derived from Queen contiguity.

Table 2. Summary of Spatial Neighbor Structure

Characteristics	Value
Number of Regions	38
Number of Nonzero Links	128
Percentage of Nonzero Weights	8,86
Average Number of Neighbors	3,37
Type of Relationship	Non-symmetric
Most Connected Region	Province 5 (6 neighbors)
Least Connected Region	Provinces 1 and 25 (1 neighbor)

The spatial weight matrix revealed 128 spatial links with an average of 3.37 neighbors per province. Province 5 exhibited the highest connectivity, while Provinces 1 and 25 had the lowest. Row-standardized weights were used to ensure comparability across provinces, providing an appropriate spatial structure for subsequent spatial econometric analyses.

4. Ordinary Least Squares (OLS) Regression

The initial regression analysis using OLS is presented in Table 3.

Table 3. Initial OLS Regression Results

Variable	Coefficient	Std. Error	p-value	Remark
Intercept	$2,420 \times 10^{-16}$	0,059	1	Not significant
Access to Safe Drinking Water	0,108	0,114	0,3536	Not significant
Population Density	0,291	0,084	0,0019	Significant
Population Health Complaints	0,09	0,123	0,47	Not significant
Number of Community Health Centers	0,847	0,073	0	Significant
Percentage of Poor Population	-0,126	0,1	0,2166	Not significant
Smoking Prevalence	0,126	0,086	0,1553	Not significant
Population Growth Rate	0,031	0,088	0,7257	Not significant
Average Years of Schooling	-0,051	0,118	0,6685	Not significant
Access to Proper Sanitation	-0,129	0,177	0,4716	Not significant
Unmet Need for Health Services	-0,213	0,107	0,0551	Not significant

Population density and Puskesmas count have statistically significant positive effects on total TB cases ($p < 0.05$), reflecting transmission risk and case detection capacity respectively. The unmet need for health services shows a marginally significant negative relationship; all other variables are not significant.

Table 4. Final OLS Regression Results

Variable	Coefficient	Std. Error	p-value	Remark
Intercept	$1,238 \times 10^{-16}$	0,06	1	Not significant
Population Density	0,314	0,061	0	Significant
Number of Community Health Centers	0,898	0,061	0	Significant

The final OLS model identifies population density and the number of Puskesmas as significant predictors of TB cases. The standardized coefficient of the number of Puskesmas (0.898) is substantially larger than that of population density (0.314), indicating that healthcare accessibility and case detection capacity contribute more strongly to the recorded number of TB cases. This finding suggests that provinces with more Puskesmas tend to report higher TB cases primarily due to improved case detection rather than increased disease occurrence, consistent with the “detection effect” reported in previous studies (Akkerman et al., 2023; Wolde et al., 2024). Meanwhile, the positive effect of population density highlights the importance of strengthening TB control measures in densely populated areas, where transmission risk is inherently higher. Classical assumption tests were then performed to assess the model, with results presented in Table 5.

Table 5. Classical Assumption Tests

Classical Assumption Test	Testing Method	Statistic Value	p-value	Decision Criteria	Conclusion
Heteroskedasticity	Studentized Breusch–Pagan Test	BP = 10,571 (df = 2)	0,0051	p-value > 0,05	Heteroskedasticity detected
Multicollinearity	Variance Inflation Factor (VIF)	VIF = 1,004	–	VIF < 10	No multicollinearity detected
Autocorrelation	Durbin–Watson Test	DW = 1,8705	0,3246	p-value > 0,05	No autocorrelation detected

The model is free from multicollinearity (VIF = 1.004) and autocorrelation (DW p = 0.325), but the Breusch–Pagan test detects heteroskedasticity (p = 0.005), motivating the use of spatial regression models.

5. Global Spatial Autocorrelation (Moran's I)

The results of Moran's I test are presented in Table 6.

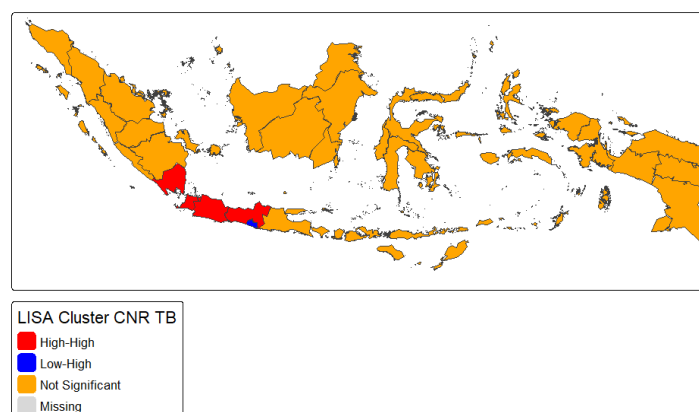
Table 6. Moran's I Test Results

Test Statistic	Value
Moran's I	0,3962
Expected Value E(I)	–0,0270
Variance	0,0123
Z-Statistic	3,8169
p-value	0,00007
Alternative Hypothesis	Positive autocorrelation (greater)

The Moran's I value of 0,3962 indicates positive spatial autocorrelation, meaning that provinces with high numbers of TB cases tend to be located near provinces with similarly high cases. The result is statistically significant (p-value < 0,05), confirming that the spatial distribution of TB cases is not random and exhibits spatial clustering patterns across provinces.

6. Local Spatial Analysis (LISA)

Peta LISA CNR Tuberkulosis Provinsi Indonesia

**Figure 2.** LISA Cluster Map

Based on Figure 2, the LISA analysis identifies significant local spatial clustering of TB cases in Indonesia. High–High clusters are concentrated mainly in several provinces on Java Island, indicating provinces with high TB cases surrounded by neighboring provinces with similarly high cases. In contrast, Low–High clusters indicate provinces with relatively low TB cases located near provinces with higher TB cases. Most provinces are classified as not significant, suggesting that local spatial autocorrelation is not uniformly distributed across Indonesia.

7. Spatial Regression Analysis

a. Spatial Lag Model (SAR)

Table 7. SAR Model Results

Variable	Coefficient	Standard Error	z-value	Sig.
Constant	–0,007	0,057	–0,117	0,907
Population Density	0,281	0,062	4,554	0,000 **
Number of Community Health Centers	0,874	0,062	14,013	0,000 **
Rho (ρ)	0,082	0,08	1,032	0,302

Table 7 shows that population density and Puskesmas remain significant ($p < 0.01$), but the spatial lag coefficient ($\rho = 0.082$, $p = 0.302$) is not significant, indicating weak province-to-province spatial diffusion in the SAR model.

b. Spatial Error Model (SEM)

Table 8. SEM Model Results

Variable	Coefficient	Standard Error	z-value	Sig.
Constant	–0,003	0,088	–0,031	0,976
Population Density	0,229	0,057	4,031	0,000 **
Number of Community Health Centers	0,885	0,059	15,049	0,000 **
Lambda (λ)	0,387	0,161	2,398	0,017 *

Based on Table 8, the SEM model shows that population density and the number of community health centers (Puskesmas) remain positive and statistically significant in explaining the total number of TB cases ($p\text{-value} < 0,01$). The significant spatial error coefficient ($\lambda = 0,387$) indicates the presence of spatial dependence in the error component, suggesting that unobserved spatial factors may also influence TB cases across provinces.

c. Spatial Durbin Model (SDM)

Table 9. SDM Results

Variable	Coefficient	Standard Error	z-value	Sig.
Constant	0,032	0,043	0,737	0,461
Population Density	0,295	0,053	5,563	0,000 **
Number of Community Health Centers	0,811	0,049	16,597	0,000 **
Spatial Lag of Population Density	0,55	0,142	3,869	0,000 **

Variable	Coefficient	Standard Error	z-value	Sig.
Spatial Lag of Community Health Centers	-0,127	0,165	-0,770	0,441
Rho (ρ)	0,003	0,191	0,018	0,985

Table 9 shows that the SDM retains significant direct effects for population density and Puskesmas, and adds a significant spillover effect of population density from neighboring provinces (coefficient = 0.55, $p < 0.001$), indicating that a province's TB burden is also influenced by the density of surrounding provinces. The overall spatial lag ($\rho = 0.003$, $p = 0.985$) remains non-significant.

8. Geographically Weighted Regression (GWR)

GWR was applied using the final OLS specification to allow regression coefficients to vary across locations. Results are summarized in Table 10.

Table 10. Summary of GWR Coefficient Estimates

Variable	Min	Q1	Median	Q3	Max
Intercept	-0,0424	-0,0326	0,0079	0,0128	0,0152
Population Density	0,3111	0,3128	0,313	0,3213	0,3228
Number of Community Health Centers	0,8097	0,8561	0,9178	0,9256	0,9345

The GWR results reveal spatial heterogeneity in the relationships between population density, the number of community health centers (Puskesmas), and TB cases across provinces. Compared with the global OLS model, GWR produced a slightly lower AIC and a higher R^2 value (0.8794), indicating a modest improvement in model fit. This suggests that local spatial variation contributes to explaining differences in TB distribution, although its effect remains limited. The spatial variation of local coefficients is illustrated in Figure 3 and Figure 4.

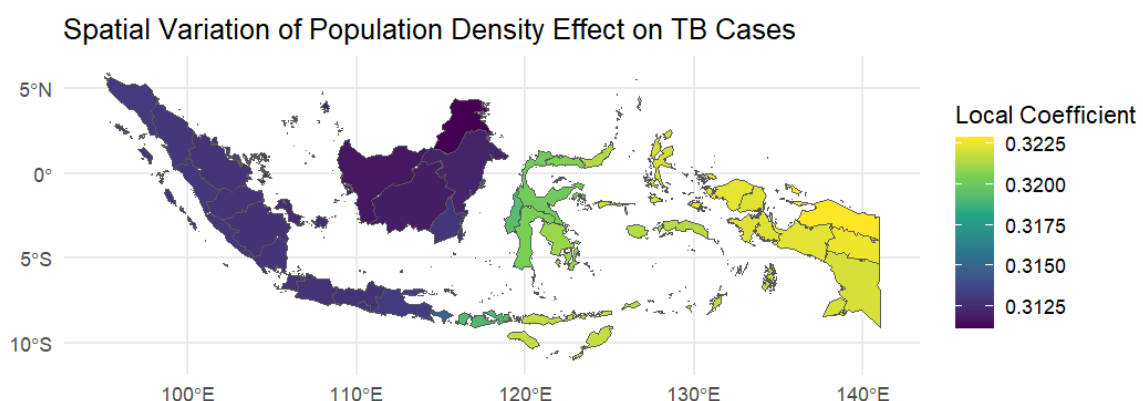


Figure 3. Spatial Variation of Population Density Effect on TB Cases

Figure 3 shows that all local coefficients of population density are positive (range: 0.3111–0.3228), confirming a consistent positive effect across all provinces. However, the effect is stronger in densely populated Java Island provinces and comparatively weaker in eastern Indonesia, demonstrating spatial heterogeneity in magnitude while direction remains uniform.

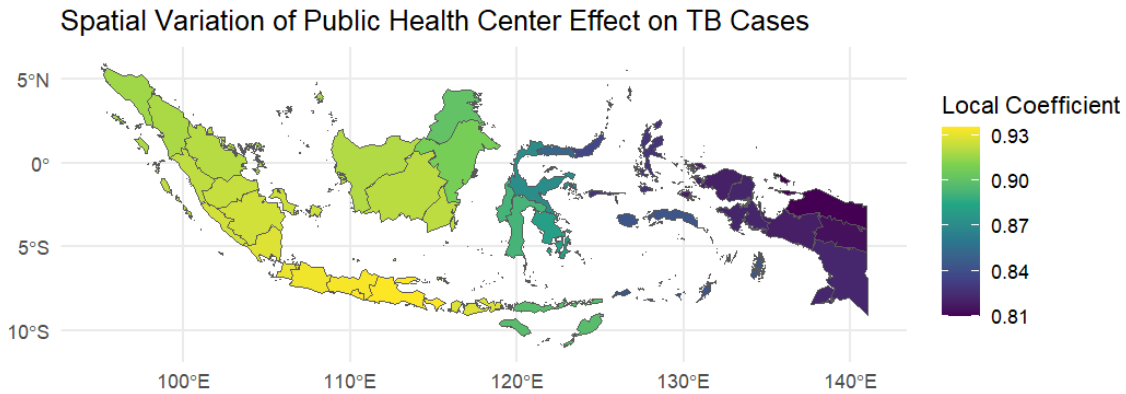


Figure 4. Spatial Variation of Public Health Center Effect on TB Cases

Figure 4 shows that the coefficients of Puskesmas remain positive across all provinces, ranging from 0.8097 to 0.9345. The variation reflects differences in the strength of the relationship rather than differences in its direction, indicating spatial heterogeneity in healthcare-related TB case detection.

9. Model Comparison and Discussion

To evaluate the overall performance of the models, a comparison of global and spatial regression approaches is presented in Table 11.

Table 11. Model Comparison

Model	AIC	R ²	Adj. R ²	Residual SE (σ)	Description
OLS	36,82	0,8716	0,8643	0,3684	Baseline global model
SAR	37,84	0,8784*	0,8714*	0,3487	Spatial lag model
SEM	36,21	0,8893*	0,8830*	0,3328	Spatial error model
SDM	19,84	0,9317*	0,9234*	0,2613	Spatial Durbin model
GWR	30,50 (AIC) / 38,45 (AICc)	0,8794	0,8621	0,3658	Local spatial model

Table 11 shows that the Spatial Durbin Model (SDM) outperformed all competing models, yielding the lowest AIC (19.84), the highest R² (0.9317), and the smallest residual standard error (0.2613). These results indicate that SDM provides the best fit for explaining TB cases across Indonesian provinces. The superior performance of SDM suggests that TB distribution is influenced not only by local factors but also by spatial spillover effects from neighboring provinces. Although GWR identified spatial heterogeneity, the relatively small variation in local coefficients indicates that spatial dependence plays a more dominant role. Therefore, SDM was selected as the most appropriate model for this study.

D. CONCLUSION AND SUGGESTIONS

This study identified significant spatial variation in TB cases across Indonesia's 38 provinces. Population density and the number of Puskesmas were consistently significant determinants across all models; the substantially larger Puskesmas coefficient primarily reflects enhanced case detection (detection effect) rather than higher transmission. Moran's I and LISA confirmed positive spatial autocorrelation with High-High clusters concentrated on Java Island. The SDM performed best (AIC = 19.84) and revealed a significant spillover effect of

population density from neighboring provinces (coefficient = 0.55, $p < 0.001$). GWR confirmed that both effects, while consistently positive, varied in magnitude across provinces. Overall, TB distribution in Indonesia reflects combined cross-provincial spatial dependence and province-specific heterogeneity, underscoring the need for spatially targeted interventions.

TB control should prioritize hotspot provinces on Java Island through active case finding, contact investigation, and improved ventilation in crowded settings. Under-detecting provinces with limited Puskesmas coverage relative to population should expand primary healthcare infrastructure and TB diagnostic capacity (e.g., GeneXpert placement, active community screening). Given the significant spillover effect of population density, neighboring provinces—especially within the Java–Greater Jakarta corridor—should coordinate cross-border surveillance and referral systems. For provinces where the Puskesmas effect is weaker, local barriers to healthcare access should be investigated and locally tailored outreach strategies developed. Future research should apply spatial panel data or machine learning approaches with multi-year data to capture temporal TB dynamics and evaluate intervention impact.

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