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Spatiotemporal Clustering of Tuberculosis Incidence and Identification of Hotspots in Bobonaro Municipality, Timor-Leste: A Five-Year Ecological Study (2021–2025)

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Abstract

Background: Tuberculosis (TB) remains a major public health challenge in Timor-Leste, with important geographic variation in disease burden. Identifying spatial patterns at the sub-municipal level may support geographically targeted surveillance and control.

Methods: We conducted an ecological spatiotemporal study using aggregated notifications of new pulmonary TB cases from 50 sucos in Bobonaro Municipality from January 2021 through December 2025. Annual TB incidence rates were calculated per 10,000 population using annual suco population estimates. Empirical Bayes smoothing was applied to reduce instability associated with small-area populations. Global Moran's I was used to assess annual spatial autocorrelation using a first-order queen contiguity spatial-weights matrix with row standardization. Local Indicators of Spatial Association (LISA) with false discovery rate (FDR) correction were used for years with significant global spatial autocorrelation. Getis-Ord Gi_{*} analysis was used as a complementary hotspot assessment.

Results: A total of 1,440 new TB cases were notified during 2021-2025. Municipal crude incidence ranged from 18.9 to 38.6 per 10,000 population, with the highest incidence in 2023. Global Moran's I showed no statistically significant evidence of spatial autocorrelation in 2021 ($I=0.152$, $p=0.051$), 2022 ($I=0.094$, $p=0.202$), or 2025 ($I=0.123$, $p=0.102$). Significant positive spatial autocorrelation was detected in 2023 ($I=0.239$, $p=0.003$) and 2024 ($I=0.251$, $p=0.002$). LISA identified three significant Low-Low (LL) clusters in 2023 located in Lebos, Lontas, and Guda, and one Low-High (LH) spatial outlier in Male-Ubu. In 2024, one High-High (HH) cluster was identified in Bobonaro, together with three LL clusters in Gildapil, Lontas, and Deudet.

Conclusion: TB incidence in Bobonaro Municipality revealed temporal heterogeneity in spatial dependence, with significant global clustering concentrated in 2023 and 2024. Local spatial analysis can support identification of priority areas for surveillance and targeted TB-control activities. Spatial clusters should be interpreted as geographic associations in reported incidence rather than direct evidence of transmission between neighboring sucos.

Keywords: Tuberculosis; spatial autocorrelation; Moran's I; LISA; Getis-Ord Gi^{*}; GIS; Timor-Leste; Bobonaro

1. Introduction

Tuberculosis (TB), caused by *Mycobacterium tuberculosis*, remains a major global public health challenge and a leading cause of death from infectious disease. TB is transmitted predominantly through airborne spread from individuals with infectious pulmonary disease. Despite being preventable and curable, TB persistence is associated with socioeconomic inequalities, health-system constraints, delayed diagnosis, and unequal access to services [1], [2], [3], [4].

The World Health Organization (WHO) estimated 10.7 million people developed TB in 2024 (131/100,000 population), with 1.23 million deaths. Progress under the End TB Strategy remains below 2025 targets [5].

Timor-Leste, with ~1.3 million population, reports high TB burden and increasing notifications. TB is a priority under National Health Sector Strategic Plan II 2020–2030, focusing on prevention, diagnosis, treatment, and surveillance [6], [7], [8].

Bobonaro Municipality in western Timor-Leste borders Indonesia and comprises 6 administrative posts and 50 sucos. [7] Cross-border mobility and rural health access limitations provide context for examining TB geographic distribution [9].

TB has an important spatial dimension. Geographic patterns reflect population distribution, mobility, socioeconomic conditions, and service access. Geographic Information Systems (GIS) and spatial statistics identify patterns not apparent from municipal aggregates. Global Moran's I evaluate spatial autocorrelation [10], while Local Indicators of Spatial Association (LISA) identifies local clusters and outliers [11].

Spatial methods have been applied to TB in Indonesia, Nepal, Nigeria, Ethiopia and South Korea [12], [13], [14], [15], [16]. However, suco-level analysis is lacking in Timor-Leste. This gap matters because small populations produce unstable rates and targeted interventions may be more efficient. [17], [18].

This study aimed to characterize spatiotemporal distribution of notified TB incidence in Bobonaro (2021–2025) using Global Moran's I and LISA, with objectives: (1) calculate annual incidence/10,000 at suco-level; (2) assess global autocorrelation; (3) identify local clusters/outliers; (4) inform targeted surveillance and control.

2. Methods

2.1 Study design and setting

This was an ecological spatiotemporal study conducted in Bobonaro Municipality, Timor-Leste, covering January 2021 to December 2025. Bobonaro is in western Timor-Leste and borders Indonesia. The municipality covers approximately 1,380.8 km² and comprises six administrative posts and 50 sucos. The 2022 Population and Housing Census reported a population of 106,639 [19]. The municipality's cross-border mobility and limitations in rural health services provide an important setting for spatial TB surveillance [22].

2.2 Data sources

Three data sources were used. First, aggregated TB notification data for 2021–2025 were obtained from the District Tuberculosis Centre under the Bobonaro Municipal Health Service. The dataset was compiled from seven Community Health Centers and Maliana Referral Hospital. Data for the period 2021–2025 were obtained from the national TB surveillance system after completion of annual reporting and data finalization in the first quarter of 2026. The finalized dataset was extracted in July 2026.

Case definitions followed the Integrated Disease Surveillance and Response (IDSR) guidance [20] and included bacteriologically confirmed cases and clinically diagnosed cases initiated on a full TB treatment course. Available variables included year of diagnosis, suco of residence, age, sex, and clinical form.

Second, annual population projections for each suco for 2021–2025 were obtained from the General Directorate of Statistics, Timor-Leste [19]. Third, administrative boundaries for the 50 sucos were obtained in shapefile format from the National Directorate of GIS, Ministry of State Administration [21]. Spatial data were projected in WGS 1984 UTM Zone 52S.

2.3 Eligibility criteria

The analysis included new bacteriologically confirmed and clinically diagnosed TB cases with permanent residence in Bobonaro Municipality and a diagnosis date between January 2021 and December 2025. Relapse cases, cases residing outside Bobonaro, and records without suco information were excluded.

2.4 Data processing and incidence estimation

Annual crude TB incidence was calculated for each suco as:

$$IR_i = (C_i / P_i) \times 10,000$$

where C_i is the number of eligible TB cases in suco i and P_i is the corresponding annual population. Because sucos have relatively small populations, Empirical Bayes smoothing was applied to the annual incidence rates before spatial analysis using GeoDa 1.22. The smoothed incidence rates were used as the principal variables for spatial analysis [22].

2.5 Spatial data preparation

The administrative boundary dataset represents 50 unique sucos. Two sucos, Raifun and Atudara, have administrative territories that are geographically situated within or spatially embedded in the area represented by another suco. Consequently, the cartographic representation contains 52 polygon features, while the epidemiological and spatial statistical analyses were conducted using the 50 unique sucos as the analytical units. Each suco was assigned a unique identifier (ID_SUCO 1–50), and TB data were joined to the administrative boundary layer using this identifier in ArcGIS 10.8.

2.6 Spatial-weights matrix

A first-order Queen contiguity spatial-weights matrix was constructed for the 50 analytical sucos. Two sucos were considered neighbors when their polygons shared either a boundary segment or a vertex. The matrix was row-standardized and used consistently in ArcGIS 10.8, GeoDa 1.22, and R 4.3.

2.7 Global spatial autocorrelation

Global Moran's I was calculated separately for each year to assess whether smoothed TB incidence was spatially clustered, dispersed, or consistent with the null hypothesis of spatial randomness. Moran's I was calculated as:

$$I = (n/W) \times [\sum_i \sum_j w_{ij} (x_i - \bar{x}) (x_j - \bar{x})] / [\sum_i (x_i - \bar{x})^2]$$

where n is the number of analytical spatial units (50 sucos), x_i and x_j are the smoothed TB incidence values for sucos i and j , $\bar{x}$ is the mean incidence, w_{ij} is the spatial weight between sucos i and j , and W is the sum of all spatial weights. The null hypothesis was that there was no global spatial autocorrelation.

Under the null hypothesis of spatial randomness, the expected value of Moran's I was calculated as $E(I) = -\frac{1}{(n-1)}$. Where $n = 50$ sucos

With 50 analytical sucos, the expected Moran's I was $E(I) = -\frac{1}{(50-1)} = -\frac{1}{49} = -0.0204$.

Statistical significance was assessed using 999 permutations, with a significance level of $\alpha = 0.05$. Positive Moran's I values indicate positive spatial autocorrelation, whereas negative values indicate negative spatial autocorrelation.

A positive Moran's I value alone was not interpreted as evidence of statistically significant spatial clustering; statistical significance was determined from the corresponding inferential test based on the permutation distribution. Significant positive Moran's I values were interpreted as evidence of positive spatial autocorrelation, whereas non-significant values were not interpreted as evidence of spatial clustering.

2.8 Local spatial autocorrelation

For years with statistically significant global spatial autocorrelation, Local Moran's I was used to identify High-High (HH), Low-Low (LL), High-Low (HL), and Low-High (LH) patterns. HH indicates a relatively high-incidence suco surrounded by high-incidence neighbors, whereas LL indicates a relatively low-incidence suco surrounded by low-incidence neighbors. HL and LH represent spatial outliers. Local significance was evaluated at $p < 0.05$, with False Discovery Rate (FDR) correction for multiple testing.

2.9 Getis-Ord Gi* hotspot analysis

Getis-Ord Gi* hotspot analysis was performed for 2024, the year with the strongest global spatial clustering, as a complementary local hotspot assessment. Hotspot significance was evaluated at 90%, 95%, and 99% confidence levels.

2.10 Software and reproducibility

Data cleaning was performed in Microsoft Excel 2021. Spatial analysis was conducted in ArcGIS Desktop 10.8 and GeoDa 1.22. Statistical validation was performed in R 4.3 using the spdep package. The study source states that spatial-weights matrices and analysis scripts are available from the corresponding author upon reasonable request.

2.11 Ethical considerations

The study source exempted from ethical approval as it utilized secondary data from the National TB Report of Bobonaro Municipality, Timor-Leste. The research employed publicly available, de-identified surveillance data previously collected by health authorities for routine disease monitoring. No primary data collection or human subject interaction occurred, and all data were aggregated at the population level without personally identifiable information. These characteristics classify the study as exempt from institutional review board oversight under standard research ethics guidelines while maintaining full compliance with research integrity standards.

3. Results

3.1 TB incidence, 2021–2025

A total of 1,440 new TB cases were notified in Bobonaro Municipality during 2021–2025. Municipal crude incidence fluctuated between 18.9 and 38.6 per 10,000 population, with the highest incidence in 2023 (Table 1).

Table 1 Annual tuberculosis incidence and Global Moran’s I statistics across 50 sucos in Bobonaro Municipality, Timor-Leste, 2021–2025.

Year	Population	TB cases	Crude incidence /10,000
2021	104,958	198	18.9
2022	106,639	318	29.8
2023	108,345	418	38.6
2024	110,078	244	22.2
2025	111,839	262	23.4

Population for 2021 and 2023–2025 was projected from the 2022 Census baseline using the 1.6% annual growth rate specified in the source study.

3.2 Global spatial autocorrelation

Global Moran’s I demonstrated temporal variation in spatial dependence across the five-year study period. Statistically significant positive spatial autocorrelation was detected in 2023 and 2024, whereas no statistically significant evidence of global spatial autocorrelation was detected in 2021, 2022, or 2025 (Table 2)

Table 2 Global Moran’s I statistics for tuberculosis incidence across 50 sucos in Bobonaro Municipality, Timor-Leste, 2021–2025.

Year	Moran’s I	E(I)	Z-score	p-value	Interpretation
2021	0.152	−0.0204	1.946	0.051	Not significant
2022	0.094	−0.0204	1.275	0.202	Not significant
2023	0.239	−0.0204	2.923	0.003	Significant positive autocorrelation
2024	0.251	−0.0204	3.062	0.002	Significant positive autocorrelation
2025	0.123	−0.0204	1.634	0.102	Not significant

The highest observed Global Moran's I was recorded in 2024 ($I = 0.251$, $p = 0.002$), followed by 2023 ($I = 0.239$, $p = 0.003$). In 2021, the observed spatial autocorrelation approached but did not reach statistical significance ($I = 0.152$, $p = 0.051$). For all years, the expected Moran's I under spatial randomness was -0.0204 , based on the 50 analytical sucos.

3.3 Local clusters and spatial outliers

Local Moran's I (LISA) analysis was conducted for 2023 and 2024 because these years showed statistically significant global spatial autocorrelation (**Figure 1**). In 2023, three significant Low–Low (LL) clusters were identified in Lebos, Lontas, and Guda, while one significant Low–High (LH) spatial outlier was identified in Male-Ubu. In 2024, one significant High–High (HH) cluster was identified in Bobonaro, together with three significant Low–Low (LL) clusters in Gildapil, Lontas, and Deudet. No significant High–Low (HL) spatial outliers were identified in either year. The remaining 46 sucos were not statistically significant in each year.

3.4 Getis-Ord G_i^* analysis

The Getis-Ord G_i^* analysis for 2024 corroborated the Local Moran's I (LISA) findings, identifying Suco Bobonaro as a statistically significant hotspot at the 99% confidence level (Figure 2). Suco Bobonaro was also classified as a significant High–High (HH) cluster in the LISA analysis, providing concordant evidence of a localized concentration of high TB incidence.

3.5 Figures

Figure 1. Local Moran's I (LISA) cluster and spatial-outlier maps of smoothed TB incidence in Bobonaro Municipality for 2023 and 2024.

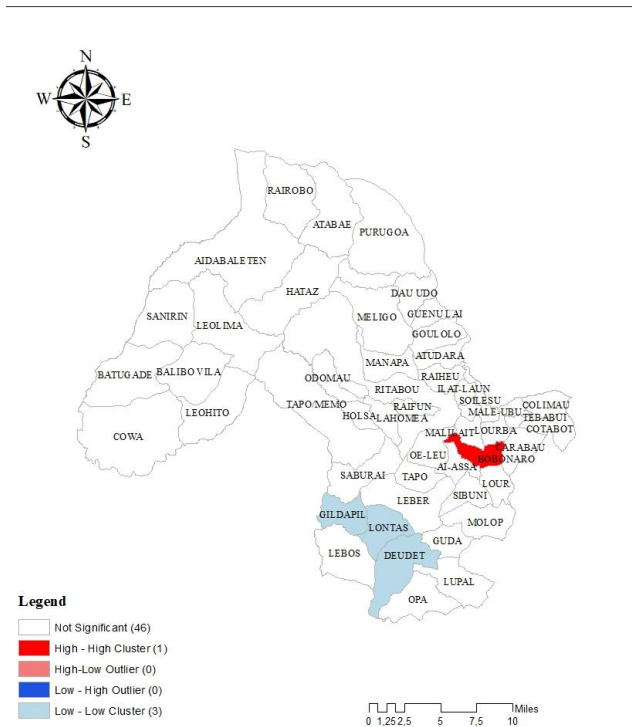
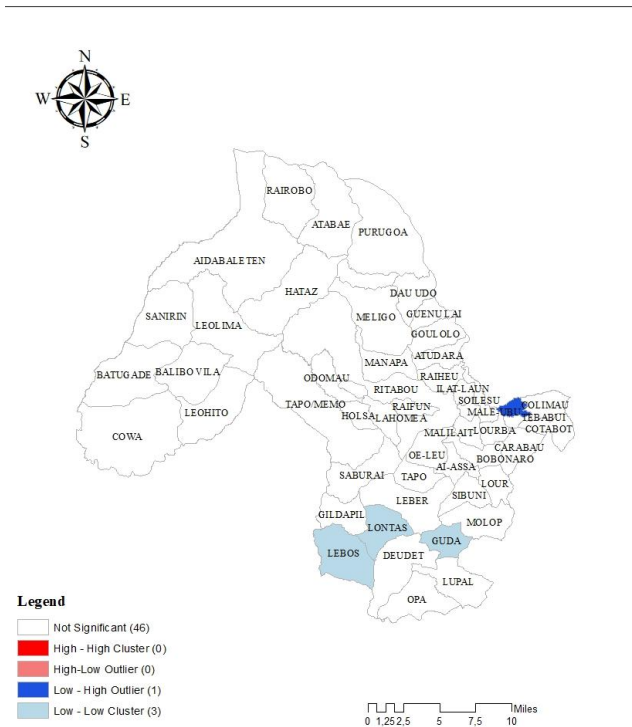
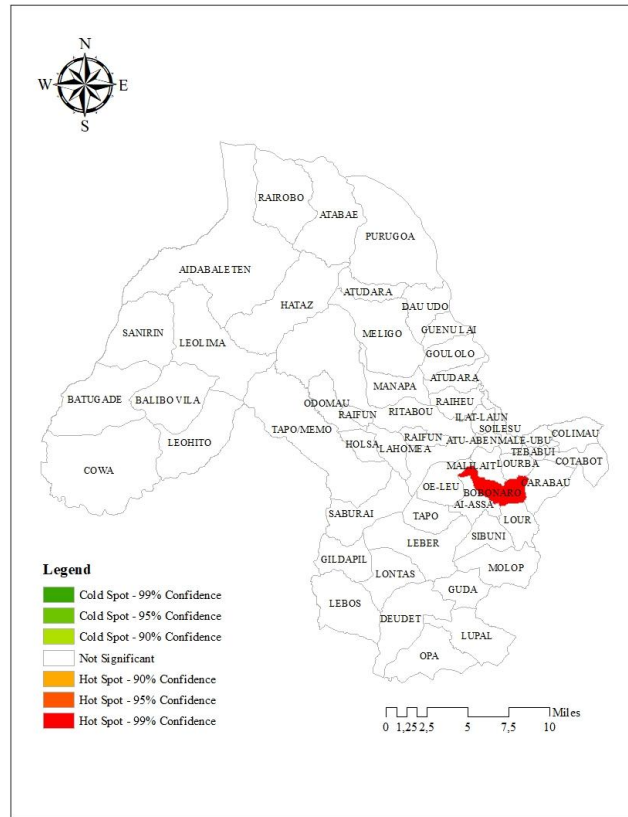


Figure 2. Getis-Ord G_i^* hotspot map of smoothed TB incidence in Bobonaro Municipality for 2024, showing 90%, 95%, and 99% confidence categories.



4. Discussion

4.1 Principal findings

This five-year ecological analysis demonstrates substantial temporal variation in the spatial distribution of notified TB incidence across Bobonaro Municipality. Our analysis revealed significant positive global spatial autocorrelation in 2023 (Moran's $I = 0.239$, $p = 0.003$) and 2024 (Moran's $I = 0.251$, $p = 0.002$), indicating that TB incidence was not randomly distributed but tended to cluster spatially across sub-municipalities. These findings indicate that spatial dependence in TB incidence was not constant throughout the study period. The results therefore support a temporally heterogeneous interpretation rather than a conclusion that TB was continuously clustered across Bobonaro. Spatial autocorrelation analysis evaluates whether observations at neighboring locations exhibit systematic similarity or dissimilarity [10]. The modest increase in Moran's I from 0.239 to 0.251 suggests stronger positive spatial association in 2024 under the specified queen-contiguity spatial-weights matrix. Local spatial statistics such as LISA can subsequently be used to identify localized pockets of spatial association and potential hotspots [11].

This spatial pattern is biologically and epidemiologically plausible, as TB distribution can be influenced by social and economic conditions, living and working environments, population movement, and access to

health services [5], [23]. However, these mechanisms were not directly measured in the present ecological study and therefore cannot be established as causal explanations for the observed spatial clustering.

The non-significant Moran's I values observed in 2021, 2022, and 2025 should not be interpreted as definitive evidence of complete spatial randomness. Rather, they indicate insufficient statistical evidence to reject the null hypothesis of no global spatial autocorrelation under the specified spatial-weights matrix [24], [25].

The observed temporal variation in spatial clustering may reflect a complex interplay of differences in active case finding, reporting completeness, healthcare access, population movement, and the localized implementation of TB control interventions. However, because these mechanisms were not directly measured in the present ecological study, they should be considered hypothesis-generating rather than causal explanations and warrant further investigation using individual-level, spatial, and programmatic data.

4.2 Interpretation of global spatial autocorrelation

The temporal variation in the global Moran's I suggests that the spatial structure of notified TB incidence changed over the study period rather than remaining stable. The significant positive autocorrelation observed in 2023 and 2024 indicates that neighboring sucos tended to exhibit similar incidence levels during these years, whereas the absence of statistically significant autocorrelation in 2021, 2022, and 2025 indicates insufficient evidence for a global spatial pattern under the specified spatial-weights matrix. These findings highlight the importance of interpreting spatial autocorrelation in relation to the study year rather than assuming a persistent spatial structure [26], [27], [28].

The stronger spatial association observed in 2024 provides justification for examining local spatial patterns in greater detail. However, global Moran's I do not identify the location or type of clusters. Therefore, LISA and Getis-Ord Gi* analyses were used to characterize localized spatial patterns and identify areas warranting further epidemiological and programmatic investigation. Changes in spatial clustering may reflect differences in case detection, reporting, healthcare access, population mobility, local transmission, or implementation of TB-control measures. Because these mechanisms were not directly measured, they should be regarded as hypotheses requiring further investigation rather than established explanations [29], [30], [31].

4.3 Local clusters and spatial outliers

LISA provides geographically explicit information that cannot be obtained from a single global statistic [32]. The identified LL clusters in 2023 and 2024 represent areas of relatively low TB incidence surrounded by neighboring areas with similarly low incidence. These areas may warrant investigation of surveillance completeness, healthcare access, program implementation, and population characteristics; however, LISA alone cannot establish that low incidence resulted from protective factors[33], [34]

The identified HH cluster in 2024 represents a suco with relatively high TB incidence surrounded by neighboring sucos with similarly high incidence. This pattern is appropriately interpreted as a high-incidence spatial cluster or hotspot for surveillance and programmatic prioritization. It should not, however, be interpreted as direct evidence of person-to-person transmission between neighboring sucos, because transmission pathways were not measured in this ecological study.[26], [35]

The identified LH outlier in 2023 represents a suco with relatively low TB incidence surrounded by neighboring sucos with higher incidence. This pattern may generate hypotheses regarding differences in case detection, healthcare access, population characteristics, or local TB-control practices. Further analytical or qualitative research would be required to determine whether any contextual or programmatic factors contribute to the observed lower incidence [31], [36].

4.4 Comparison with previous studies

The finding that TB spatial clustering varies across years is broadly consistent with previous spatial analyses conducted in different epidemiological and geographic settings, including Indonesia, Nepal, Nigeria, South Korea, and China. These studies have reported spatially heterogeneous distributions of TB, with clustering patterns varying across geographic areas and/or study periods. Such variation may reflect differences in population characteristics, healthcare access, case detection, socioeconomic conditions, and local transmission dynamics. However, direct comparisons should be made cautiously because observed spatial patterns are influenced by differences in geographic units, study periods, case definitions, population denominators, statistical methods, smoothing procedures, and spatial-weights or neighborhood specifications [37], [38], [39], [40], [41], [42].

Notwithstanding methodological heterogeneity, the consistent observation of spatially heterogeneous TB distribution across diverse settings supports the broader interpretation that TB incidence is often unevenly distributed and may exhibit localized clustering. This pattern underscores the potential value of subnational spatial analyses to inform surveillance and programmatic prioritization, while recognizing that the underlying drivers may differ across contexts and require local investigation [37], [38], [43]

4.5 Public health implications

The findings support the incorporation of spatial analysis into routine TB surveillance in Bobonaro Municipality. When statistically significant local clusters are identified, program managers may use spatial outputs as decision-support tools to prioritize active case finding, contact investigation, treatment-support activities, community education, and review of diagnostic and referral pathways. LL areas may also be examined to identify contextual or programmatic factors associated with lower reported incidence, while recognizing that low notification may also result from under-detection or incomplete reporting.

Because Bobonaro Municipality shares an international border with Indonesia, spatial surveillance may also benefit from attention to population mobility and continuity of TB care across administrative and national borders. However, geographic proximity alone should not be interpreted as evidence of cross-border transmission. Integrating surveillance data with information on population movement, referral pathways, and continuity of treatment could help identify potential gaps in cross-border TB prevention and care.

4.6 Strengths

The principal strengths of this study are the use of five consecutive years of suco-level data, population-adjusted incidence rates, Empirical Bayes smoothing to address instability in small-area estimates, a consistent spatial-weights matrix, false discovery rate correction for multiple local statistical tests, and complementary Local Indicators of Spatial Association (LISA) and Getis-Ord G_i^* analyses.

4.7 Limitations

Several limitations should be considered. First, the ecological design limits individual-level inference and is subject to ecological fallacy. Second, the analysis relies on notified cases and may therefore underestimate the true burden because of underdiagnosis, delayed diagnosis, or under-reporting. Third, socioeconomic, demographic, environmental, mobility, and healthcare-access variables were not included, limiting our ability to assess potential determinants of spatial clustering. Fourth, residence-based mapping does not necessarily represent the location of infection or transmission. Fifth, the five-year observation period may be insufficient to characterize longer-term spatial cycles or persistent changes in the spatial distribution of TB. Finally, sensitivity analyses using alternative spatial-weights specifications were not performed; therefore, the robustness of the observed spatial patterns to alternative definitions of neighborhood structure remains uncertain.

4.8 Future research

Future studies should integrate demographic, socioeconomic, environmental, healthcare-access, mobility, laboratory, and treatment data to investigate potential determinants of TB spatial heterogeneity. Spatial regression or Bayesian hierarchical models could be used to assess determinants of high-incidence areas while accounting for spatial dependence and uncertainty in small-area estimates. Prospective surveillance and population-movement data could further distinguish geographic concentration of notified cases from potential transmission pathways.

Future studies should also evaluate monthly or quarterly spatial patterns to determine whether the annual clusters identified in this study represent persistent geographic concentrations or shorter-term fluctuations in TB notification. Where feasible, molecular epidemiology could be integrated with spatial and epidemiological data to help distinguish geographic proximity from likely transmission linkages.

5. Conclusion

This five-year ecological analysis demonstrated temporal variation in the spatial dependence of reported TB incidence in Bobonaro Municipality. Significant positive global spatial autocorrelation was detected in 2023 (Moran's $I = 0.239$, $p = 0.003$) and 2024 (Moran's $I = 0.251$, $p = 0.002$), with the strongest spatial association observed in 2024, whereas no statistically significant global spatial autocorrelation was detected in 2021, 2022, or 2025. Local spatial analyses identified significant clusters and spatial outliers during years with significant global spatial autocorrelation, demonstrating geographic heterogeneity that may not be apparent from municipality-level summaries alone. These findings support the integration of GIS-based spatial surveillance into routine TB control to inform geographically targeted case-finding, surveillance, and program planning in Bobonaro Municipality. However, the observed spatial patterns represent geographic associations in reported incidence and should not be interpreted as direct evidence of transmission or causal determinants.

Declarations

Conflict of interest

The authors declare that they have no commercial or financial relationships that could be construed as potential conflicts of interest.

Consent for publication

Not applicable.

Ethics approval

This study used aggregated, de-identified secondary surveillance data and involved no direct contact with human participants. The study was conducted in accordance with applicable institutional and national requirements for the use of secondary surveillance data.

Availability of data and materials

The datasets used are available from the corresponding author on reasonable request. The data analyzed in this study were derived from routine TB surveillance records of Bobonaro Municipality. Because the dataset is subject to Timor-Leste Ministry of Health data-governance and confidentiality requirements, individual-level data are not publicly available. Aggregated data may be available from the corresponding author or relevant health authority upon reasonable request and subject to applicable permissions.

Funding Declaration

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Software

Data management and analysis were performed using Microsoft Excel 2021, ArcGIS Desktop 10.8, GeoDa 1.22, and R version 4.3 with the spdep package.

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