



# Exposing Indonesia's Spatial Epidemiology of Pulmonary Tuberculosis: Geographic Pattern Analysis and Cluster Identification, 2000-2023

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**Abstract:** Pulmonary tuberculosis (PTB) remains a major public health challenge in Indonesia, with substantial geographical disparities in disease burden across regions. Understanding the spatial structure of PTB distribution is essential for designing effective and geographically targeted control strategies. This study aims to examine the spatial epidemiological patterns of PTB in Indonesia from 2000 to 2023 using a Geographic Information System (GIS) based approach. Secondary data on annually reported PTB cases at the provincial level were obtained from official national sources and analyzed using spatial autocorrelation techniques. Global Moran's Index was applied to assess overall spatial dependence, while Local Indicators of Spatial Association (LISA) were used to identify statistically significant local clusters of PTB cases. Spatial analyses were conducted within a GIS environment to visualize national and regional distribution patterns. The results reveal a persistent, statistically significant, clustered spatial pattern of PTB throughout the study period. Global Moran's I value consistently indicates positive spatial autocorrelation, confirming that the PTB distribution is not random. LISA analysis identifies stable High-High clusters

concentrated in the densely populated provinces of Java and enduring Low-Low clusters predominantly located in Papua and parts of eastern Indonesia. These findings demonstrate pronounced regional contrasts in PTB burden over time. In conclusion, PTB transmission in Indonesia exhibits strong spatial dependence shaped by regional connectivity and structural disparities, and integrating spatial analysis into national tuberculosis control programs can support more targeted, equitable, and effective public health interventions.

**Keywords:** Pulmonary Tuberculosis, Spatial Epidemiology, Geographic Information System, Spatial Autocorrelation, Indonesia

## Introduction

Pulmonary tuberculosis (PTB) continues to pose a significant threat to worldwide public health, especially in low- and middle-income nations ([Bai & Ameyaw, 2024](#)). The Global Tuberculosis Report 2023 indicates that Indonesia ranks second globally, behind India, in the total number of tuberculosis (TB) cases ([World Health Organization, 2023](#)). Despite various national control initiatives and efforts to eradicate TB, the disease continues to show a complex and uneven distribution throughout Indonesia ([Kementerian Kesehatan Republik Indonesia, 2023](#)). This condition signifies that the traditional national aggregate-

based methodology inadequately captures the spatial dynamics of the disease, necessitating an analysis that incorporates geographical dimensions to enhance the surveillance system, pinpoint priority areas, and facilitate location-specific intervention planning ([Iskandar et al., 2023](#); [Kak et al., 2020](#); [Surendra et al., 2023](#)).

Beyond its descriptive role, spatial epidemiology serves as a critical strategic tool for public health decision-making ([Lin & Wen, 2022](#); [Shaweno et al., 2018](#)). By identifying regions with high or persistent TB burden, spatial analysis enables evidence-based prioritization of interventions, optimal allocation of health resources, and coordinated planning across administrative and regional boundaries ([Elliott & Wartenberg, 2004](#); [Ostfeld et al., 2005](#)). Such a framework is particularly valuable in a resource-constrained setting, allowing health authorities to focus efforts where they are most needed while mitigating disparities in service coverage and program effectiveness ([Aturinde, 2020](#); [Cuboia et al., 2024](#)).

Researchers can investigate how geographic variables influence disease distribution using the analytical framework provided by spatial epidemiology ([Lin & Wen, 2022](#)). To identify clusters, highlight spatial autocorrelation, and visualize disease transmission patterns more thoroughly, this method integrates geographical data with epidemiological research ([Elliott & Wartenberg, 2004](#); [Ostfeld et al., 2005](#)). Due to its ability to combine comprehensive spatial analysis with extensive disease case data, Geographic Information Systems (GIS) are an essential tool in health geography research ([Aturinde, 2020](#); [Beyers et al., 1996](#); [Rosli et al., 2018](#)).

Importantly, the spatial epidemiological approach facilitates a deeper understanding of regional inequalities in TB burden, the role of population mobility in disease spread, and the influence of structural and socio-environmental factors on transmission dynamics ([Brown et al., 2022](#); [Lienhardt et al., 2005](#); [Lin & Wen, 2022](#)). In a geographically diverse country such as Indonesia, patterns of urbanization, interprovincial migration, transportation networks, and socioeconomic disparities can significantly shape the spread of TB ([Fahdhienie et al., 2024](#); [Iskandar et al., 2023](#); [Kak et al., 2020](#)). By accounting for these spatial dimensions, policymakers can identify higher-risk areas, detect emerging hotspots, and design interventions that reflect both the epidemiological realities and the underlying regional structures that influence disease transmission ([Alfaqeeh et al., 2025](#); [Lestari et al., 2023](#); [Surendra et al., 2023](#)).

In addition to identifying significant local clusters known as hot spots and cold spots, spatial statistical techniques such as Moran's Index and Local Indicators of Spatial Association (LISA) have been widely used to evaluate whether disease distribution is random or forms specific patterns ([Anselin, 1995](#); [Mao et al., 2019](#); [Zhang et al., 2023](#)). Both methodologies provide a solid quantitative basis for understanding the geographical

pattern of disease dissemination and play a significant role in supporting evidence-based decision-making in public health ([Rosli et al., 2018](#); [Shaweno et al., 2018](#)).

TB cases are not randomly distributed, but rather form geographical patterns centered in specific locations, according to several studies conducted in China and Malaysia ([Mohidem et al., 2021](#); [Rosli et al., 2018](#); [Sun et al., 2015](#); [Yu et al., 2020](#)). Similar studies remain rare in Indonesia and often focus on the provincial or regional level over short observation periods ([Fahdhienie et al., 2024](#); [Laferani et al., 2023](#); [Saifudin et al., 2024](#)). Because long-term national studies are relatively uncommon, the spatial patterns of PTB in Indonesia have not been adequately recorded ([Lestari et al., 2023](#); [Puspita et al., 2021](#)). Therefore, long-term spatial analysis is essential for a deeper, more contextual understanding of disease distribution patterns, given the large area, demographic variations, and topographical differences across regions.

This study aims to explore the spatial dynamics of PTB in Indonesia by systematically analyzing how case distribution develops and forms clusters across provinces. Focusing on the period from 2000 to 2023, this study presents a longitudinal overview of spatial patterns on a national scale, enabling the identification of persistent and emerging geographical trends over time. Using Moran's Index and LISA within a GIS-based analytical framework, this study aims to describe the spatial distribution of PTB cases and explicitly identify clusters characteristic of high- and low-burden regions.

By situating these spatial clusters within the broader context of regional inequalities, population mobility, and structural determinants, this analysis provides actionable insights for public health planning. The findings are intended to inform the development of targeted, adaptive TB control strategies grounded in empirical evidence that address geographic disparities and anticipate shifts in disease dynamics, thereby supporting a more effective and equitable TB control program at both provincial and national levels.

## Methods

### A. Research Design

This study used a descriptive geographical analysis methodology in conjunction with a spatial epidemiology strategy ([Lin & Wen, 2022](#); [Ostfeld et al., 2005](#); [Shaweno et al., 2018](#)). This technique was applied to systematically examine PTB case clusters and spatial distribution patterns across all Indonesian provinces between 2000 and 2023. Rather than testing causal relationships, the main objective of this study was to examine the geographical distribution of PTB within provincial administrative districts, providing insights into regional variations and potential high-risk areas for targeted interventions.

The degree to which PTB instances displayed spatial autocorrelation, a statistical relationship between the value at one location and values at geographically neighboring locations, was evaluated using spatial analysis ([Purnama et al., 2022](#); [Sadeq & Bourkadi, 2018](#); [Zhang et al., 2023](#)). Therefore, this study aims to assess whether the provincial-level distribution of PTB cases in Indonesia exhibits dispersed, random, or clustered spatial patterns. Understanding these spatial structures is essential for identifying priority areas for intervention, informing resource allocation, and guiding regional TB control strategies, particularly in resource-limited settings ([Inggarputri et al., 2023](#); [Pamadi et al., 2023](#); [Wardani et al., 2013](#)).

To improve clarity, transparency, and reproducibility, the analytical workflow of this study was organized into sequential stages and illustrated in a flowchart (**Figure 1**). This flowchart visually summarizes the full process, including data acquisition, preprocessing and harmonization, global spatial analysis using Moran's Index, local cluster detection using LISA and integration of all outputs within a GIS environment for national-scale visualization.



**Figure 1.** Analytical Workflow of the Study

By structuring the analysis in this way, readers can easily follow the methodological progression and understand how epidemiological data and spatial statistical techniques were integrated to identify PTB hotspots, cold spots, and emerging spatial patterns across Indonesian provinces. This approach also ensures that results are directly linked to actionable insights for geographically targeted public health interventions.

## B. Data Sources

To validate and normalize the spatial data, this study used secondary datasets from three authoritative government sources:

1. Ministry of Health of the Republic of Indonesia, providing annual counts of PTB cases for all provinces from 2000 to 2023.
2. Central Statistics Agency (BPS), supplying provincial administrative boundaries, population statistics, and area measurements.
3. Geospatial Information Agency (BIG), providing shapefiles of provincial boundaries, which served as the base maps for spatial mapping and GIS analysis.

To ensure data consistency and reliability, attribute data (PTB case counts) and geographic data (provincial boundaries) were carefully harmonized through a structured data alignment procedure. This included cross-checking the uniformity of coordinate systems, standardizing regional nomenclature, and reconciling administrative boundary changes effective through 2023.

Additional quality control measures included verification of PTB counts against official reports, correction of discrepancies between datasets, and validation of spatial data integrity to prevent misalignment in subsequent spatial analyses. These steps were essential to maintain the accuracy of the GIS-based mapping and spatial statistical results.

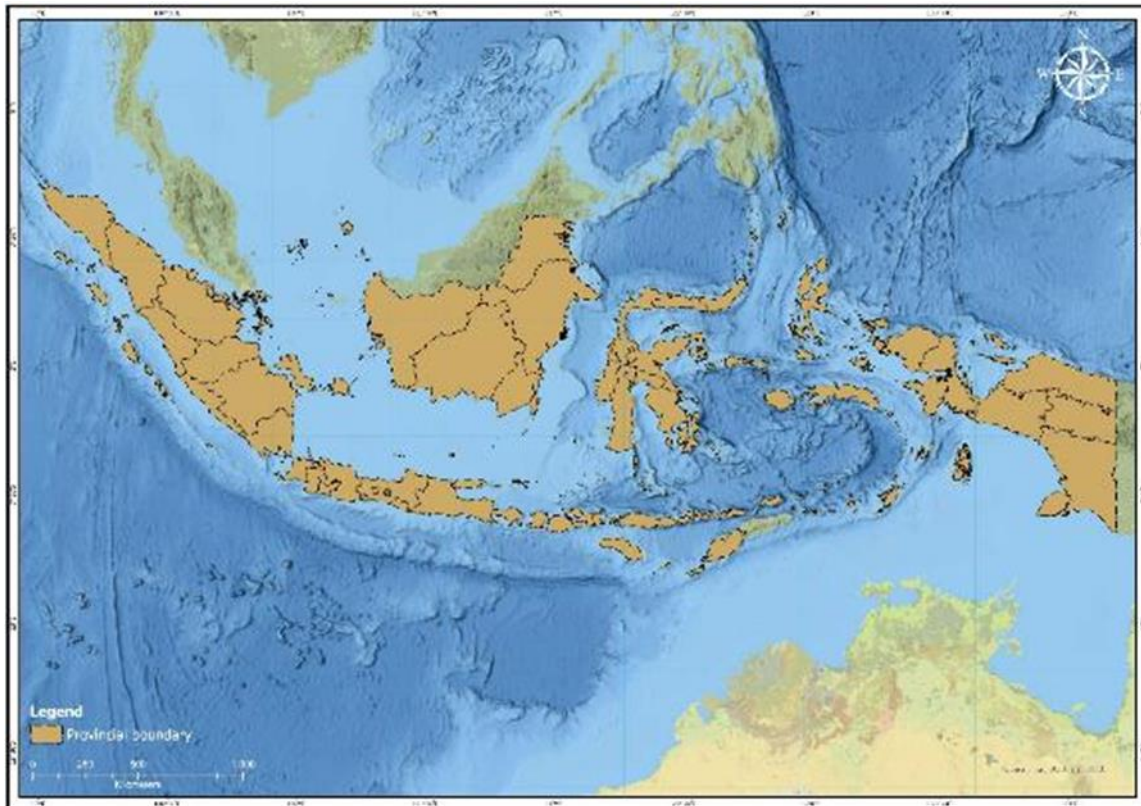
Within the overall analytical workflow (**Figure 1**), this stage represents the data acquisition and preprocessing phase. It encompasses the compilation of datasets, the harmonization of administrative boundaries, the verification of compatibility between spatial and attribute data, and the preparation of cleaned, analysis-ready datasets. This structured approach ensures that all subsequent spatial analyses are based on high-quality, reliable, and fully synchronized data, providing a robust foundation for mapping PTB distribution and detecting clusters at the provincial level.

## C. Unit of Analysis

The province, Indonesia's primary administrative tier, was employed as the unit of analysis in this study. Both methodological and practical considerations guided this selection. First, temporal consistency was ensured, as provincial-level PTB data are available continuously and comprehensively for the entire study period (2000-2023), enabling a longitudinal analysis of spatial trends and temporal changes. Second, policy relevance was a key factor, as health planning, resource allocation, and program implementation in Indonesia are predominantly organized at provincial and national levels.

A total of 38 provinces, defined under the 2023 administrative configuration, were included in the analysis (**Figure 2**). This choice allows for standardized comparisons across regions while reflecting the administrative units where TB control interventions and

resource deployment occur ([Kanchar & Swaminathan, 2019](#); [Kementerian Kesehatan Republik Indonesia, 2023, 2024](#)).



**Figure 2.** Study Area Map of Indonesia

Analyzing PTB distribution at the provincial level enables the detection of regional variations, identification of persistent and emerging hotspots, and evaluation of spatial autocorrelation patterns in a manner that is both methodologically rigorous and directly applicable to public health decision-making. This scale also facilitates integration with GIS-based mapping and spatial statistical analyses, providing a clear link between empirical findings and actionable strategies for cross-regional TB control.

By using the province as the analytical unit, the study captures both macro-level spatial structures and micro-level variations within Indonesia's diverse geographic and demographic landscape, thereby enhancing the interpretive value and practical relevance of the results.

#### **D. Research Variables**

The primary variable in this study was the annual number of PTB cases officially reported by the Ministry of Health for each province between 2000 and 2023. This is a discrete quantitative variable representing the total number of reported cases, without standardization to incidence per 100,000 population. Each province polygon in the GIS

environment was assigned this value as a spatial attribute, enabling spatial analyses that link epidemiological data to geographic locations.

Spatial autocorrelation analyses were conducted using these values to assess the geographic severity of disease, thereby capturing differences in PTB distribution across provinces. Variations in case numbers were further examined in relation to neighboring provinces to identify clustering patterns, which reflect potential geographic or socio-environmental connections influencing the spread of PTB.

By detecting these patterns, the study can identify provinces with consistently high caseloads, areas at risk of underreporting, and emerging hotspots ([Mao et al., 2019](#); [Pradana & Santosa, 2019](#); [Sun et al., 2015](#)). This information is crucial for guiding geographically targeted interventions, optimizing resource allocation, and supporting evidence-based public health strategies ([de Abreu e Silva et al., 2016](#); [Lan et al., 2025](#); [Puspita et al., 2021](#); [Rosli et al., 2018](#)).

Furthermore, examining temporal trends in these variables enables detection of changes in spatial distribution over the 24-year study period, which is essential for understanding the dynamics of PTB transmission and informing the national TB control strategy. Integrating spatial and temporal patterns provides a comprehensive understanding of both persistent high-burden areas and newly emerging clusters, enhancing the effectiveness of surveillance and intervention planning.

## E. Data Analysis Techniques

Spatial autocorrelation analysis was employed to examine the distribution of PTB cases across provinces, providing a quantitative assessment of clustering, dispersion, or randomness ([Nanque et al., 2023](#); [Shaweno et al., 2018](#); [Zhang et al., 2023](#)). This approach enables the identification of geographical correlation patterns based on both the magnitude and spatial arrangement of PTB incidence ([Alavi et al., 2023](#); [Pamadi et al., 2023](#)).

Two complementary analytical methods were applied to capture both global and local spatial patterns:

1. Global Moran's Index, used to measure the overall degree of spatial autocorrelation across all provinces. Positive values indicate a tendency for clustering, whereas negative values suggest a dispersed or random spatial structure ([Bai & Ameyaw, 2024](#); [Mahara et al., 2018](#); [Moran, 1950](#)).
2. Local Indicators of Spatial Association (LISA), applied to detect and map statistically significant local clusters, including hotspots (areas with high values adjacent to high-value neighbors) and cold spots (areas with low values surrounded by low-value neighbors) ([Madao et al., 2024](#); [Mao et al., 2019](#); [Sadeq & Bourkadi, 2018](#)).

As illustrated in the analytical flowchart (Figure X), the spatial analysis phase was organized in a sequential and transparent workflow:

- Step 1: computation of Global Moran's Index to evaluate overall spatial dependence, providing a macro-level understanding of clustering patterns;
- Step 2: LISA-based local cluster detection to identify statistically significant spatial concentrations and potential hotspots or cold spots;
- Step 3: integration of outputs into a GIS environment to generate national-scale spatial maps that visualize both global and local cluster patterns.

The GIS-based visualization allowed simultaneous examination of spatial and temporal variations, capturing changes in PTB burden across provinces over the 24-year study period. By overlaying the results of Moran's Index and LISA on provincial maps, the study provides a clear representation of both persistent and emerging clusters and regions that may be affected by underreporting ([Anselin, 1995](#); [Moran, 1950](#); [Wei et al., 2016](#)).

This mapping framework not only facilitates the interpretation of spatial patterns but also provides a rigorous empirical basis for geographically targeted public health interventions ([Mohidem et al., 2021](#); [World Health Organization, 2023](#)). Policymakers can use these results to identify high-risk provinces, prioritize resource allocation, and design evidence-based TB control strategies that account for regional heterogeneity and temporal dynamics ([Iskandar et al., 2023](#); [Kak et al., 2020](#); [Madao et al., 2024](#)).

## Results and Discussion

### A. Global Spatial Autocorrelation Analysis of Pulmonary Tuberculosis Cases in Indonesia from 2000 to 2023

The spatial distribution of PTB cases in Indonesia from 2000 to 2023 exhibits a persistent, clustered pattern, as revealed by the global spatial autocorrelation analysis using Moran's I (**Table 1**). Throughout the 24 years, all Moran's I coefficients were positive, ranging from 0.189 to 0.392, indicating statistically significant positive spatial autocorrelation. This finding demonstrates that provinces with high PTB case counts are more likely to be adjacent to other high-burden provinces. In contrast, provinces with lower incidence tend to cluster with similarly low-prevalence neighbors ([Mao et al., 2019](#); [Mohidem et al., 2021](#); [Sun et al., 2015](#); [Zhang et al., 2023](#)). Such clustering confirms that the distribution of PTB cases is not random but reflects an underlying spatial structure shaped by geographic proximity, demographic characteristics, and regional interconnectedness ([Noviyani et al., 2021](#); [Wei et al., 2016](#); [Wubuli et al., 2015](#)).

The observed pattern aligns with theoretical frameworks in spatial epidemiology, which posit that infectious disease diffusion is often influenced by social interaction

networks, population mobility, environmental similarity, and the spatial arrangement of communities ([Elliott & Wartenberg, 2004](#); [Lin & Wen, 2022](#); [Ostfeld et al., 2005](#)). This theoretical foundation underscores that disease spread is not uniform across space but is concentrated in areas where populations interact more frequently or share similar environmental conditions ([Inggaputri et al., 2023](#); [Nurjana et al., 2023](#)).

Empirical studies conducted in Indonesian settings further corroborate these results. Research by [Inggaputri et al. \(2023\)](#), [Madao et al. \(2024\)](#), and [Pamadi et al. \(2023\)](#) identified persistent TB clusters at both district and provincial levels, highlighting that PTB transmission tends to be spatially aggregated rather than dispersed evenly across regions. Additionally, analyses by [Iskandar et al. \(2023\)](#) and [Noviyani et al. \(2021\)](#) emphasize that Java's densely populated provinces consistently function as hotspots, where high population density, intense interregional mobility, and urbanization intensify spatial dependence in disease incidence. These findings illustrate that structural and demographic factors are key determinants of PTB clustering in Indonesia.

**Table 1.** Global Moran's Index of Pulmonary Tuberculosis Cases in Indonesia from 2000 to 2023

Year	Moran's I	Global Interpretation	Pattern
2000	0.344	Positive Spatial Autocorrelation	<i>Clustered</i>
2001	0.290	Positive Spatial Autocorrelation	<i>Clustered</i>
2002	0.286	Positive Spatial Autocorrelation	<i>Clustered</i>
2003	0.189	Positive Spatial Autocorrelation	<i>Clustered</i>
2004	0.279	Positive Spatial Autocorrelation	<i>Clustered</i>
2005	0.352	Positive Spatial Autocorrelation	<i>Clustered</i>
2006	0.221	Positive Spatial Autocorrelation	<i>Clustered</i>
2007	0.392	Positive Spatial Autocorrelation	<i>Clustered</i>
2008	0.382	Positive Spatial Autocorrelation	<i>Clustered</i>
2009	0.367	Positive Spatial Autocorrelation	<i>Clustered</i>
2010	0.369	Positive Spatial Autocorrelation	<i>Clustered</i>
2011	0.364	Positive Spatial Autocorrelation	<i>Clustered</i>
2012	0.360	Positive Spatial Autocorrelation	<i>Clustered</i>
2013	0.344	Positive Spatial Autocorrelation	<i>Clustered</i>
2014	0.219	Positive Spatial Autocorrelation	<i>Clustered</i>
2015	0.263	Positive Spatial Autocorrelation	<i>Clustered</i>
2016	0.272	Positive Spatial Autocorrelation	<i>Clustered</i>
2017	0.307	Positive Spatial Autocorrelation	<i>Clustered</i>
2018	0.301	Positive Spatial Autocorrelation	<i>Clustered</i>
2019	0.300	Positive Spatial Autocorrelation	<i>Clustered</i>
2020	0.306	Positive Spatial Autocorrelation	<i>Clustered</i>
2021	0.321	Positive Spatial Autocorrelation	<i>Clustered</i>
2022	0.310	Positive Spatial Autocorrelation	<i>Clustered</i>
2023	0.305	Positive Spatial Autocorrelation	<i>Clustered</i>

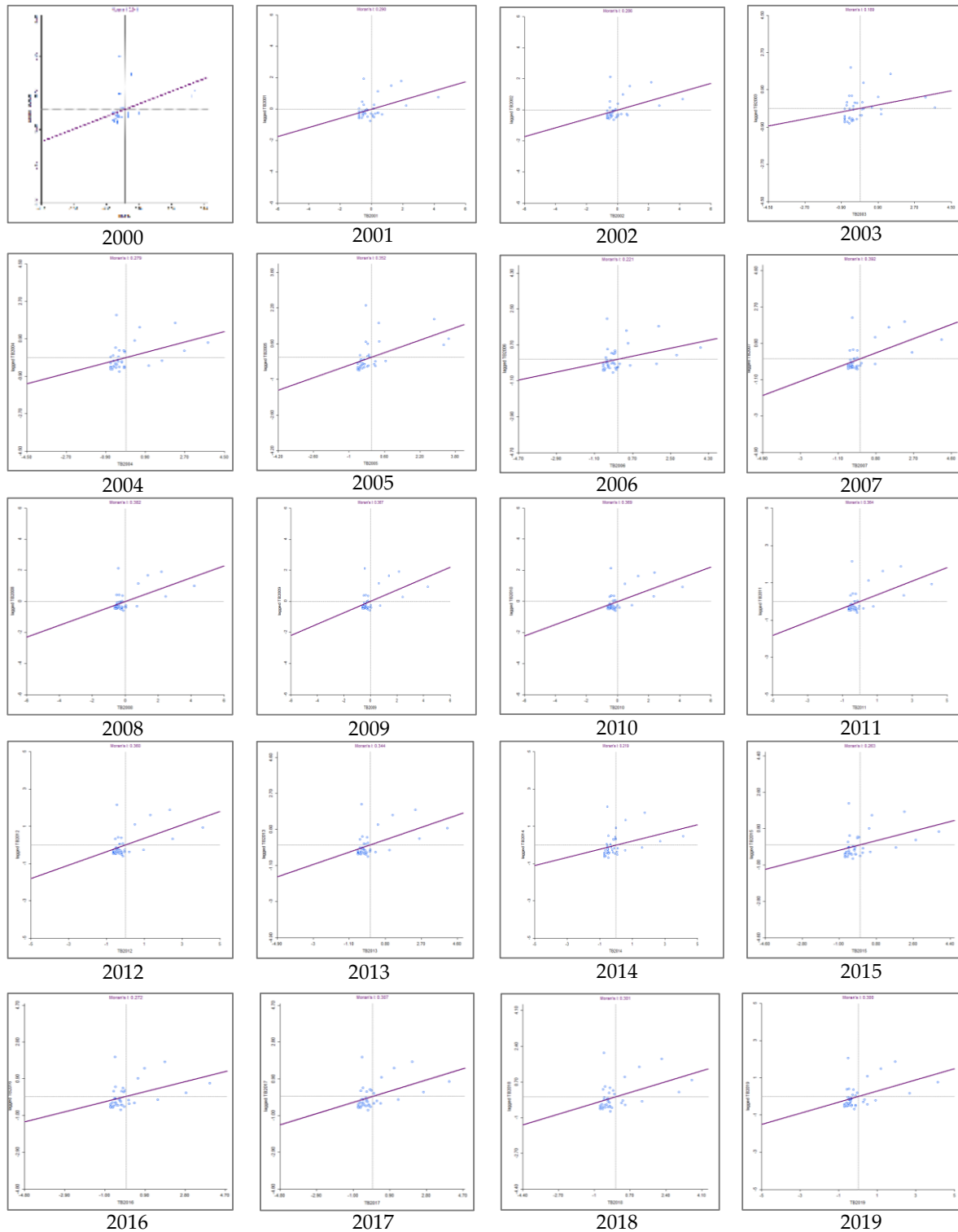
Over the two-decade period, Moran's I coefficients fluctuated, indicating a moderately variable but relatively stable pattern of spatial dependence. During the early years of observation (2000-2004), coefficients ranged from 0.189 to 0.344, suggesting weaker clustering at the national scale, possibly reflecting lower surveillance sensitivity or initial variations in TB reporting and control measures. The middle period (2005-2013) showed more pronounced and stable autocorrelation values, predominantly between 0.34 and 0.39, indicating strengthened clustering of PTB cases across provinces. Despite a temporary decline to 0.219 in 2014, the coefficients subsequently stabilized in the 0.26-0.32 range from 2015 onwards. These temporal variations may reflect dynamic changes in the effectiveness of TB control programs, regional demographic shifts, improvements in case detection, and differing implementation of public health interventions across provinces ([Bhatia et al., 2023](#); [Kak et al., 2020](#); [Surendra et al., 2023](#)).

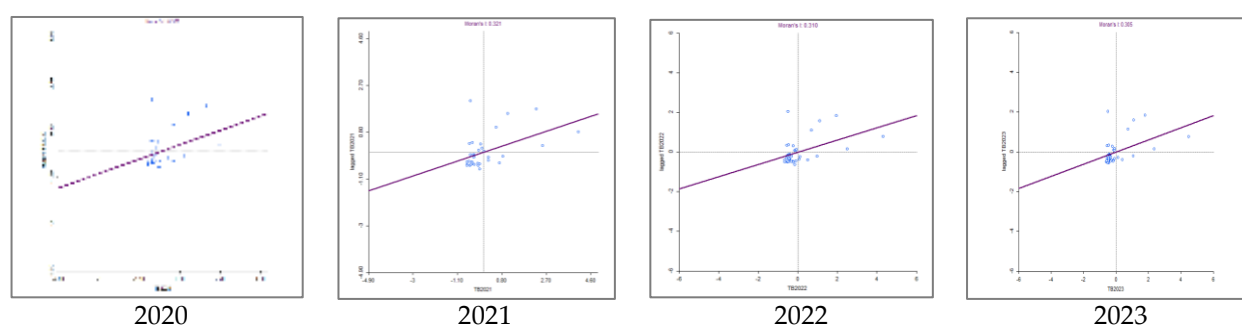
The interpretation of Moran's I coefficients is reinforced by visual examination of Moran's Scatterplots (**Figure 3**). Data points are predominantly concentrated in the high-high and low-low quadrants, confirming the presence of pronounced clusters of both high-incidence and low-incidence provinces. The high-high clusters indicate regions where PTB cases are elevated and surrounded by similarly high-burden neighbors, while low-low clusters highlight provinces with persistently low PTB incidence. This graphical evidence aligns with the positive Moran's I values observed across all years, validating the presence of consistent spatial autocorrelation.

Analyzing these results from a public health perspective, the findings emphasize the central role of geographic proximity in PTB transmission ([Kementerian Kesehatan Republik Indonesia, 2023](#); [World Health Organization, 2023](#)). Provinces that are close to one another tend to exhibit similar risk profiles due to shared socioeconomic, demographic, and environmental characteristics, such as urbanization levels, population density, access to healthcare, and interprovincial mobility patterns ([Bai & Ameyaw, 2024](#); [Brown et al., 2022](#); [Lin & Wen, 2022](#)).

The implications for TB control are substantial. Control strategies should move beyond uniform, national-level approaches and adopt spatially informed interventions that explicitly consider the geographic clustering of cases. These strategies may include strengthening cross-jurisdictional collaboration, implementing cluster-based or hotspot-focused interventions, enhancing surveillance systems to detect emerging spatial patterns, and allocating resources preferentially to high-burden provinces and their neighboring regions ([Lan et al., 2025](#); [Rosli et al., 2018](#); [Wardani et al., 2013](#)). Such spatially targeted approaches can improve the efficiency and effectiveness of TB control programs, reduce transmission within and across provinces, and optimize the utilization of public health resources.

In summary, global spatial autocorrelation analysis confirms that PTB cases in Indonesia are significantly clustered at the provincial level, with high-burden provinces tending to form contiguous clusters over time. Understanding these spatial patterns provides an empirical foundation for designing evidence-based, geographically targeted TB control interventions and underscores the importance of accounting for spatial dependencies in national and regional public health strategies.





**Figure 3.** Moran's Scatterplot Visualization of Spatial Patterns of Pulmonary Tuberculosis Cases in Indonesia from 2000 to 2023

### B. Local Spatial Autocorrelation Analysis of Pulmonary Tuberculosis Cases in Indonesia from 2000 to 2023

The spatial configuration of PTB cases in Indonesia from 2000 to 2023 is characterized by the persistence of two dominant, geographically stable cluster formations, as illustrated in **Figure 4**.

The first major cluster comprises High-High (HH) or hotspot areas, primarily concentrated on the island of Java, including the provinces of DKI Jakarta, West Java, Central Java, and Banten. These provinces consistently exhibit elevated PTB case counts and are surrounded by neighboring provinces with similarly high burdens, forming robust spatial clusters over the entire observation period. The sustained presence of this hotspot reflects the interplay of multiple epidemiologically relevant factors, including demographic concentration, rapid urban expansion, labor-driven mobility, and dense social interaction networks, all of which amplify the potential for disease transmission ([Fahdhienie et al., 2024](#); [Puspita et al., 2021](#); [Surendra et al., 2023](#)). Empirical evidence supports that urbanization, population density, and interprovincial connectivity increase vulnerability to infectious disease spread by facilitating frequent human contact and movement ([Brown et al., 2022](#); [Kak et al., 2020](#); [Madao et al., 2024](#)).

Conversely, the second major cluster comprises Low-Low (LL) or coldspot areas, predominantly located in the eastern part of Indonesia. LL clusters consistently appear in the provinces of Papua, including Central Papua, Papua Pegunungan, Southwest Papua, and West Papua, and intermittently extend to regions in eastern Kalimantan and Maluku. These LL clusters do not necessarily indicate a low absolute disease burden, but rather relatively lower reported PTB case numbers than in neighboring areas. Several structural factors likely contribute to these patterns, including geographical remoteness, limited accessibility to health facilities, shortages of trained healthcare personnel, and variation in case-finding capacity ([Alfageeh et al., 2025](#); [Kementerian Kesehatan Republik Indonesia, 2023](#); [Purnama et al., 2022](#)). Previous studies similarly emphasize that under-reporting in

remote and underserved regions can obscure the true magnitude of PTB transmission, suggesting that spatial coldspots may partially reflect limitations in surveillance and reporting ([Kementerian Kesehatan Republik Indonesia, 2020](#); [Lestari et al., 2023](#); [Nurjana et al., 2023](#)).

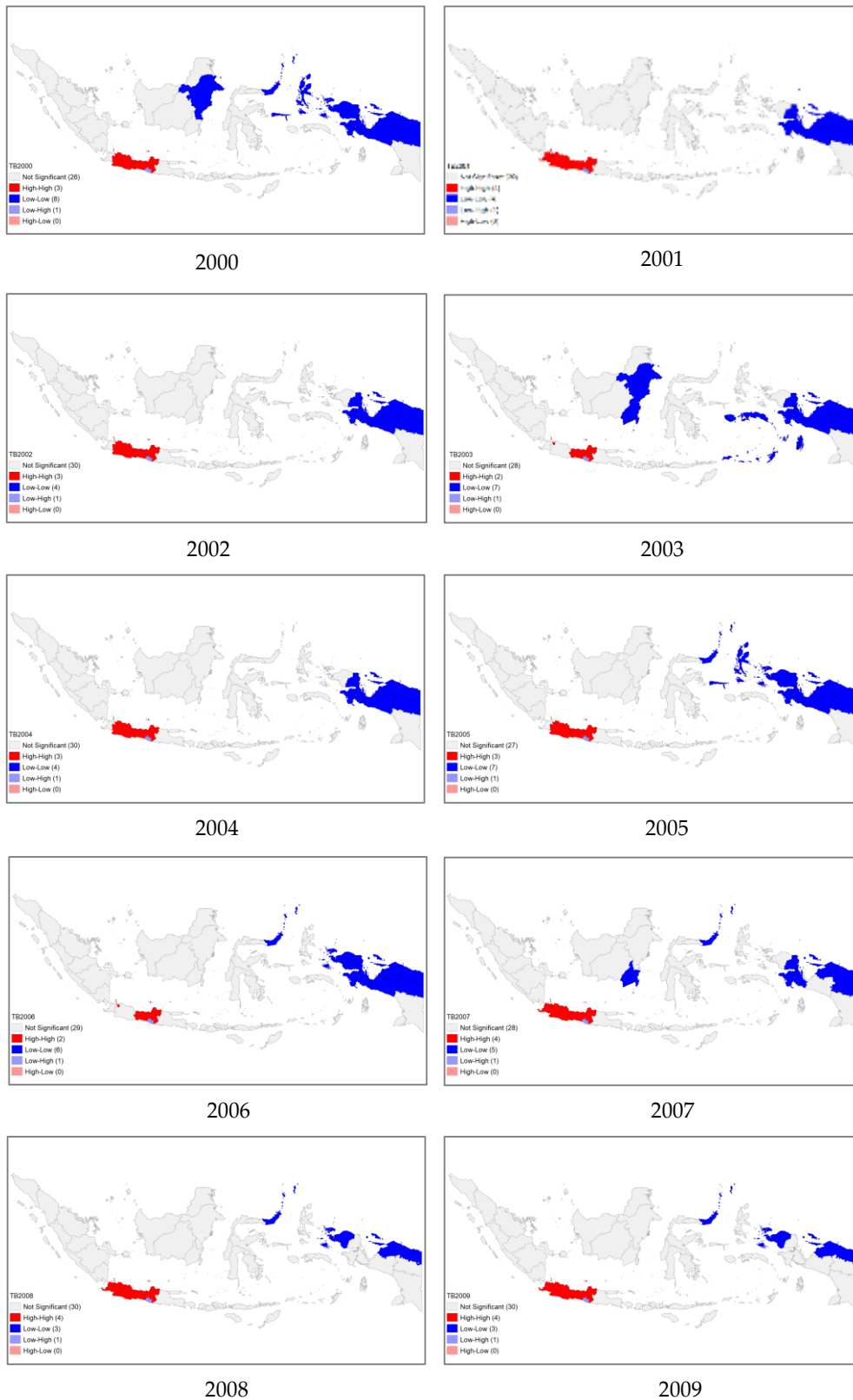
Beyond these two major clusters, several provinces demonstrate spatial outlier patterns, classified as Low-High (LH) and High-Low (HL). LH patterns denote provinces with relatively low PTB cases surrounded by high-prevalence neighbors, whereas HL patterns indicate the inverse configuration ([Anselin, 1995](#); [Madao et al., 2024](#); [Wubuli et al., 2015](#)). Yogyakarta, for example, consistently appears as an LH outlier, likely reflecting effective local health system performance, strong case detection policies, or other localized interventions that reduce PTB incidence relative to surrounding high-burden regions ([Kementerian Kesehatan Republik Indonesia, 2023, 2024](#); [Pamadi et al., 2023](#)). In contrast, North Sulawesi sporadically appears as an HL outlier, suggesting temporary deviations from regional spatial trends due to localized outbreaks or reporting variability. These spatial outliers highlight localized epidemiological, administrative, or socioeconomic dynamics that differ from broader national patterns and warrant targeted investigation ([Mahara et al., 2018](#); [Mohidem et al., 2021](#); [Wang et al., 2021](#)).

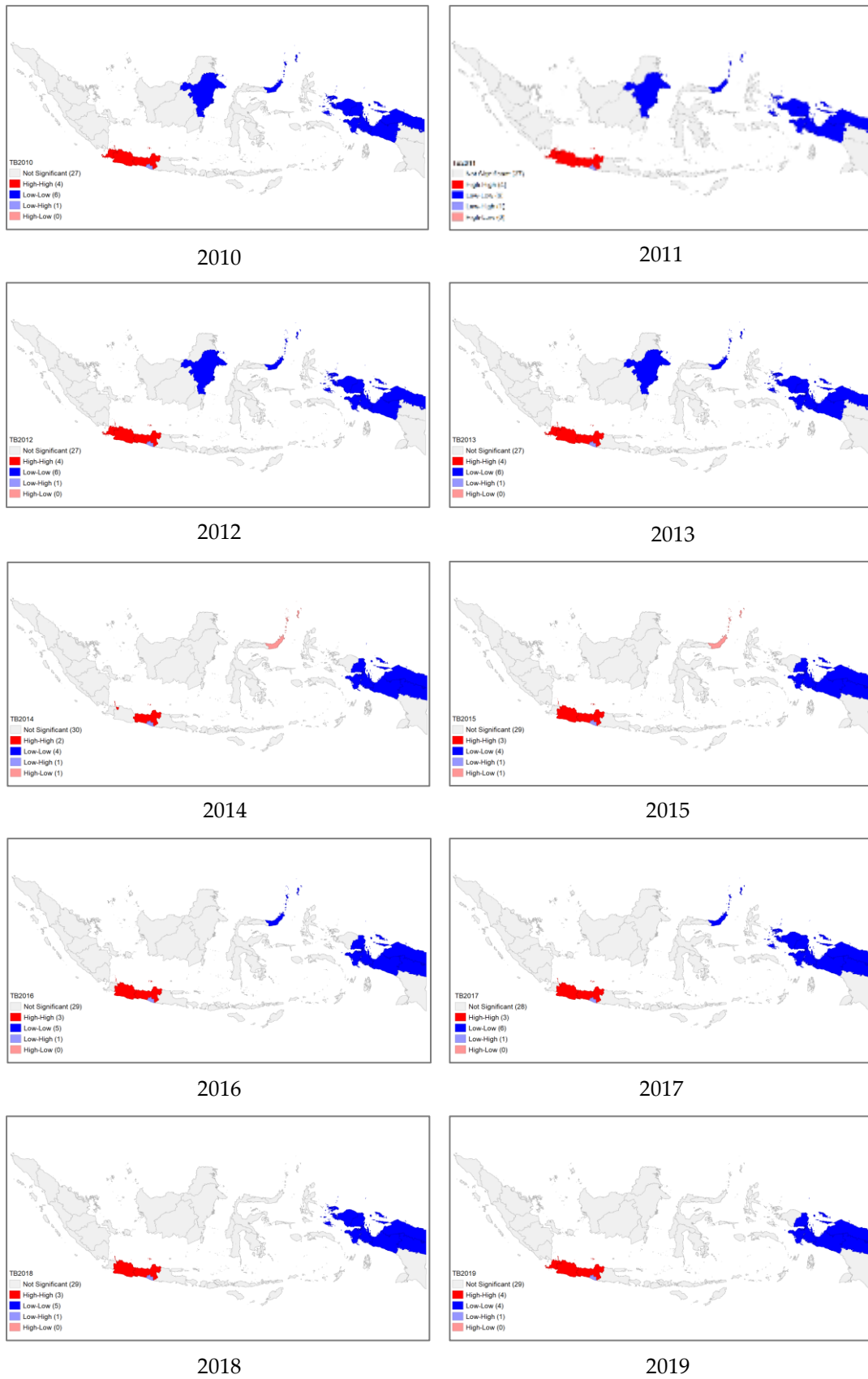
Taken together, the spatial distribution of PTB in Indonesia over the 24 years reveals a dual-core structure, with stable LL clusters in Papua and enduring HH clusters in Java. This configuration illustrates the critical role of structural disparities, including differences in healthcare access, demographic pressures, population mobility, and environmental conditions in shaping the geography of PTB transmission ([Fahdhienie et al., 2024](#); [Iskandar et al., 2023](#); [Kak et al., 2020](#); [Lestari et al., 2023](#); [Surendra et al., 2023](#)). The findings are consistent with the principle of spatial dependency, which posits that neighboring regions often exhibit correlated epidemiological outcomes due to shared risk environments and interconnected population dynamics ([Lan et al., 2025](#); [Lin & Wen, 2022](#); [Zhang et al., 2023](#)).

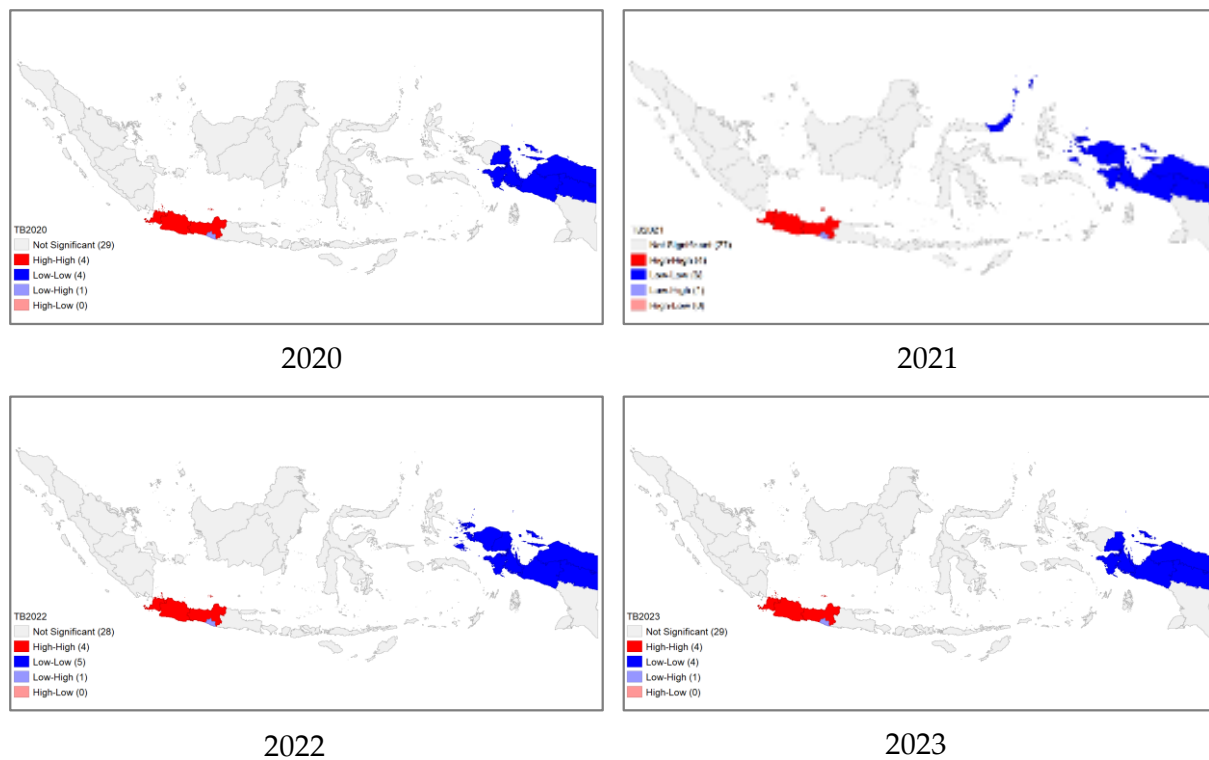
From a public health perspective, the persistence of these spatial configurations indicates that PTB transmission is influenced not only by local determinants but also by broader systemic and structural dynamics operating across provincial boundaries ([Aturinde, 2020](#); [Cuboia et al., 2024](#); [Lin & Wen, 2022](#)). The enduring nature of hotspot and coldspot clusters suggests that interventions that focus solely on clinical management or individual-level risk mitigation may be insufficient without complementary strategies to address regional inequalities in health infrastructure, surveillance capacity, and mobility networks ([Garcia et al., 2009](#); [Kanchar & Swaminathan, 2019](#); [Onozaki & Raviglione, 2010](#)).

Integrating spatial indicators into routine TB monitoring systems can facilitate the early detection of emerging clusters and support the development of anticipatory, geographically tailored public health policies ([John, 2019](#); [World Health Organization, 2014](#),

2023). Such an approach is essential for achieving sustained reductions in PTB transmission and for ensuring that national TB control efforts remain responsive to the complex spatial realities underpinning disease distribution (Alfaqeeh et al., 2025; Iskandar et al., 2023; Surendra et al., 2023).







**Figure 4.** Map of Pulmonary Tuberculosis Case Clusters in Indonesia from 2000 to 2023

## Conclusion

This study demonstrates that the geographical distribution of PTB in Indonesia from 2000 to 2023 exhibits persistent, statistically significant spatial clustering. The results of Moran's I analysis confirm that PTB distribution is not random, but reflects enduring spatial dependence shaped by demographic concentration, human mobility patterns, and interregional connectivity. High-High clusters consistently emerged in the densely populated provinces of Java, whereas Low-Low clusters predominated in the Papua region and parts of eastern Indonesia. These dual-core cluster formations underscore the role of structural disparities, including population density, health service capacity, and geographic accessibility, in driving regional variations in PTB burden.

Spatial outliers identified within the Low-High and High-Low categories further reveal localized deviations that may result from differences in surveillance quality, health service delivery, or contextual epidemiological factors. Taken together, these findings demonstrate that PTB transmission in Indonesia is strongly influenced by spatial proximity and shared environmental, demographic, and socioeconomic conditions, underscoring the need for geographically differentiated public health strategies.

Despite the strengths of this longitudinal and nationwide spatial analysis, several limitations should be acknowledged. First, the study relied on officially reported PTB case

counts, which may be affected by underreporting, delayed reporting, or variability in diagnostic practices across provinces, particularly in remote or underserved regions. Second, the analysis was conducted at the provincial level, which may mask finer-scale heterogeneity at district or subdistrict levels. Third, potential confounding factors, such as local variations in HIV prevalence, socioeconomic status, and population mobility, were not directly incorporated into the spatial models, which may partially explain the observed clustering patterns.

Based on these findings and limitations, several recommendations for future research and policy emerge:

1. Strengthening TB surveillance systems to improve data completeness and timeliness, particularly in geographically remote or underserved provinces.
2. Conducting finer-scale spatial analyses at district or subdistrict levels to capture local heterogeneity and identify micro-hotspots.
3. Integrating additional epidemiological, socioeconomic, and environmental covariates into spatial models to better understand drivers of PTB transmission.
4. Implementing geographically targeted interventions, such as prioritizing hotspot provinces in Java for intensified case detection and enhancing healthcare access in historically under-reported regions of Papua and eastern Indonesia.
5. Promoting cross-regional coordination in TB control programs to address interprovincial connectivity and mobility-driven transmission dynamics.

In conclusion, this study emphasizes the value of spatial epidemiological approaches for informing evidence-based, geographically tailored TB control strategies in Indonesia. By accounting for spatial clustering, regional disparities, and local deviations, public health authorities can design interventions that are both equitable and effective, ultimately contributing to a sustained reduction in PTB transmission nationwide.

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