# Spatial Epidemiology of Infectious Diseases in Indonesia: Patterns, Clusters, and Environmental Determinants

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## Abstract

Indonesia’s vast geography, high population density, and environmental diversity contribute to uneven patterns of infectious disease transmission. This study aims to explore the spatial distribution and environmental influences of seven key infectious diseases—acute respiratory infections (ARI), pneumonia, tuberculosis (TB), hepatitis, diarrhea, malaria, and filariasis—across the country's 34 provinces. We used data from the 2018 National Health Survey and the 2018 Environmental Quality Index (EQI). Spatial statistical techniques—including the Variance Mean Ratio (VMR), Moran’s *I*, Moran Scatter Plots, and Spatial Autoregressive (SAR) modeling—were applied to detect spatial clustering, spatial autocorrelation, and neighborhood effects. We also examined the role of environmental quality in shaping disease patterns. Most infectious diseases demonstrated significant spatial clustering, with Java Island and its surrounding areas showing the highest concentration. Strong spatial correlations were observed among ARI, pneumonia, TB, hepatitis, diarrhea, and filariasis. In contrast, malaria displayed a distinct, uncorrelated pattern. SAR modeling revealed positive spatial spillover effects, indicating that neighboring provinces influenced disease occurrences in the province under study. Moreover, provinces with higher EQI scores tended to have lower rates of ARI, TB, diarrhea, and other diseases—except for malaria, which followed a different pattern. The findings suggest that infectious disease patterns in Indonesia are not random but geographically clustered and environmentally influenced. Targeted health interventions that consider both spatial dynamics and environmental quality are essential for effective disease control and prevention.

## Keywords

Environmental quality; infectious diseases; Indonesia; spatial epidemiology; spatial clustering

# Introduction

Indonesia is a vast archipelagic nation covering 5,180,053 km$^2$—comprising 1,922,570 km$^2$ of land and 3,257,483 km$^2$ of marine territory—and home to more than 270 million people (BPS – Statistics Indonesia, 2022); its equatorial location (6° North–11° South and 95° East–141° West), position between the Pacific and Indian Oceans and the Asian–Australian continents, tropical climate, heterogeneous topography, and high population density collectively create favorable conditions for the persistence and transmission of infectious diseases such as acute respiratory infections (ARI), pneumonia, tuberculosis (TB), hepatitis, diarrhea, malaria, and filariasis.

A substantial body of global evidence demonstrates that the spread of infectious diseases is not random but spatially structured by environmental, demographic, and geographic factors, as shown by malaria's association with elevation and coastal proximity in Tafea Province and Tanna Island (Reid et al., 2010), persistent malaria clusters near shaded stagnant water in Pahang, Malaysia (Shahari et al., 2024; Sunaryo, 2021), hyper-localized malaria transmission in Ghana (Magna et al., 2019) and Zanzibar (Björkman et al., 2017), as well as pronounced spatial clustering of TB in urban Mexico (Zacarías-Hernández et al., 2025), high-risk Local Government Areas in Nigeria linked to household size and health service access (Daniel, 2017), marked provincial disparities in Indonesia (Puspita et al., 2021), and suburban TB–HIV clusters in Zimbabwe (Chirenda et al., 2020).

Comparable spatial dependence has been documented for diarrheal diseases in India (Dmello et al., 2022) and Ethiopia (Yitageasu et al., 2024), pneumonia and influenza in Canada (Crighton et al., 2007), ARI among children in Ethiopia (Amsalu et al., 2019; Tam et al., 2022), and hepatitis in Brazil, Germany, and other settings (Kauhl et al., 2015; Santos et al., 2017; Yamada et al., 2021), reinforcing the central role of spatial epidemiology in revealing disease clustering and guiding targeted interventions.

Environmental quality is increasingly recognized as a fundamental determinant of these patterns, operating through air pollution, water and sanitation, climate variability, and the built environment, with poor environmental conditions accounting for an estimated 12.6 million deaths globally (Prüss-Ustün et al., 2016) and empirical studies demonstrating climate-sensitive, lagged effects on TB (Wang et al., 2024), reduced infectious disease outbreaks with improved sanitation and safe water at the global scale (Martínez-Zarzoso et al., 2025), and disproportionate mortality impacts of air pollution, unsafe water, and non-optimal temperature on vulnerable populations (Liu et al., 2024). Nevertheless, most studies remain fragmented, focusing on single environmental exposures or individual diseases, prompting the need for integrated approaches such as the EQI, which combines air, water, land, built, and sociodemographic environments into a composite indicator of population-level environmental exposure (Messer et al., 2014), yet whose systematic influence across multiple infectious diseases and heterogeneous settings remains insufficiently explored.

Moreover, contemporary public health theory emphasizes that environmental risks interact dynamically with social determinants of health, including education, income, employment, access to services, health literacy (Nutbeam & Lloyd, 2021), social connection and isolation (Holt-Lunstad, 2022), climate extremes and system resilience (Ebi et al., 2021), institutional bias in health care (Vela et al., 2022), climate communication and misinformation

(Lewandowsky, 2021), and broader systems-inspired conceptual models of health disparities that highlight feedbacks, nonlinearity, and multilevel interactions (Roux, 2012).

In parallel, methodological advances—such as spatial scan statistics, Bayesian disease mapping (Lawson, 2018), GeoDetector (Ke et al., 2025), Local Indicators of Spatial Association (Chen, 2024), and spatial autocorrelation models (Pfeiffer et al., 2008)—have become essential for capturing these complex spatial dynamics. Building on this integrated environmental, social, and spatial perspective, the present study aims to examine whether environmental quality, as measured by the EQI, influences the spatial characteristics and geographic clustering of seven major infectious diseases across the Indonesian archipelago, thereby clarifying the role of overall environmental quality in shaping infectious disease distribution and providing evidence to support more responsive, data-driven, and equitable public health planning in environmentally and socially vulnerable regions of Indonesia.

These patterns underscore a critical point: infectious diseases often follow the contours of the environments and societies in which they spread. Recognizing and understanding these spatial dynamics is essential for developing more targeted, equitable, and effective public health strategies. These examples likewise reflect a broader global trend: infectious diseases are not evenly distributed, and environmental, demographic, and geographic factors often shape their spread. In this context, spatial epidemiology has emerged as a powerful discipline for analyzing, predicting, and managing disease dynamics. By applying geospatial tools and statistical models, spatial epidemiology enables researchers and policymakers to uncover hidden patterns, identify high-risk areas, and develop targeted public health interventions.

Building on this growing body of global and regional evidence, the present study aims to investigate whether environmental quality, as measured by the EQI, influences the spatial distribution of infectious diseases in Indonesia. Specifically, this study examines the spatial characteristics and geographic clustering of seven major infectious diseases across the Indonesian archipelago. By assessing whether areas with poorer environmental quality exhibit higher disease concentrations or distinct spatial patterns, this research seeks to clarify the role of EQI in shaping the distribution of infectious diseases. Understanding how these diseases cluster and spread in relation to environmental quality is expected to provide critical insights to support more responsive, data-driven public health planning—particularly in strengthening disease surveillance, targeting prevention efforts, and enhancing community awareness in environmentally vulnerable regions.

Building on this evidence, the objectives of this study are to (1) examine the spatial characteristics and geographic clustering of seven major infectious diseases across the Indonesian archipelago; (2) assess the association between environmental quality, as measured by the EQI, and the spatial distribution of these infectious diseases; and (3) identify whether areas with poorer environmental quality exhibit higher disease concentration or distinct spatial patterns, thereby providing evidence to support more targeted, equitable, and environmentally informed public health planning and disease prevention strategies in Indonesia.

# Methods

## Data sources

This study draws on data from the 2018 Indonesian Basic Health Research (Riskesdas), a nationwide survey conducted by the Ministry of Health of the Republic of Indonesia through the National Institute of Health Research and Development (NIHRD). Riskesdas is one of the most comprehensive and authoritative sources of public health data in the country and has been widely used in epidemiological studies and health policy assessments (Ministry of Health of the Republic of Indonesia, 2019).

The use of the Riskesdas 2018 data in this study is justified for several reasons. First, Riskesdas is an official nationwide survey conducted by the Ministry of Health of the Republic of Indonesia through the NIHRD, ensuring methodological rigor, reliability, and credibility. Second, the survey has extensive national coverage, with a large and representative sample across all provinces and districts, making it suitable for both national- and regional-level analyses. Third, the Riskesdas 2018 dataset is highly comprehensive, covering a wide range of public health indicators, including nutritional status, communicable and non-communicable diseases, health behaviors, and access to health services, making it a valuable resource for epidemiological and policy-related research.

Moreover, Riskesdas 2018 remains widely used as a primary reference in scientific studies and health policy assessments due to its completeness and accessibility. Although the most recent Riskesdas, conducted in 2023, is available, the full dataset is not yet widely accessible to the public; therefore, the 2018 data remain the most recent comprehensive source. Finally, Riskesdas 2018 enables consistent longitudinal or trend analysis with earlier waves, such as Riskesdas 2013, further supporting its continued relevance in current research.

The dataset covers the incidence of seven infectious diseases—ARI, pneumonia, TB, hepatitis, diarrhea, malaria, and filariasis—across all 34 provinces of Indonesia. Data were drawn from the Riskesdas 2018, with the number of respondents varying across 34 provinces in Indonesia. Aceh had 41,596 respondents; North Sumatra, 69,517; West Sumatra, 37,063; Riau, 26,778; Jambi, 21,602; South Sumatra, 33,566; Bengkulu, 17,419; Lampung, 31,462; Bangka Belitung Islands, 1,256; and Riau Islands, 11,698. Jakarta recorded 15,170 respondents; West Java 73,285; Central Java 91,161; Yogyakarta 11,319; East Java 98,566; Banten 23,262; and Bali 20,560.

Furthermore, West Nusa Tenggara had 21,308 respondents; East Nusa Tenggara, 44,782; West Kalimantan, 28,343; Central Kalimantan, 22,092; South Kalimantan, 23,915; East Kalimantan, 17,490; and North Kalimantan, 7,574. In Sulawesi, North Sulawesi recorded 25,661 respondents, Central Sulawesi 21,904, South Sulawesi 50,127, Southeast Sulawesi 22,982, Gorontalo 10,997, and West Sulawesi 10,843 respondents. Maluku had 19,019 respondents, North Maluku 15,381, West Papua 13,656, and Papua 24,625 respondents. These data were reported by the Ministry of Health of the Republic of Indonesia (2019). These figures provide the basis for spatial comparisons throughout the study. Reported cases were scaled to provincial populations using mid-year population estimates from the BPS – Statistics Indonesia (2019). To enable spatial analysis, each province was georeferenced to the latitude and longitude of its capital city, following standard practice in epidemiological research (Kienberger et al., 2013).

The environmental context was incorporated using the EQI, a composite measure developed by Indonesia's Ministry of the Environment and Forestry (KLHK). The EQI combines four sub-indices: the Water Quality Index (surface and groundwater suitability), Air Quality Index (major pollutants: $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, CO), Land Quality Index (soil erosion, land degradation, vegetation cover), and Marine Water Quality Index (for coastal provinces, assessing marine ecosystems and pollution). Together, these yield a single EQI score that reflects overall environmental health and its potential influence on disease dynamics.

According to the KLHK of the Republic of Indonesia (2018), Indonesia's national EQI averaged 67.48 (Table 1). Provinces scoring 80–100 are classified as very good, 70–79.99 as good, 60–69.99 as moderate, 50–59.99 as poor, and below 50 as very poor. This index provides a standardized benchmark for assessing ecological conditions, guiding resource allocation, and linking environmental status with public health outcomes. It highlights both regions requiring urgent intervention and those demonstrating progress in sustainable environmental management.

**Table 1:** EQI by Province in Indonesia

| No | Province | Air Quality Index | Water Quality Index | Land Cover Quality Index | Environmental Quality Index |
|---|---|---|---|---|---|
| 1 | Aceh | 88.33 | 75.71 | 75.37 | 79.36 |
| 2 | North Sumatra | 85.72 | 63.06 | 49.44 | 64.41 |
| 3 | West Sumatra | 88.37 | 83.98 | 67.46 | 78.69 |
| 4 | Riau | 89.91 | 73.68 | 48 .37 | 68.43 |
| 5 | Jambi | 88.04 | 81.21 | 50.56 | 71 |
| 6 | South Sumatra | 85.32 | 88.15 | 40.17 | 68.11 |
| 7 | Bengkulu | 91.63 | 82.08 | 55.52 | 74.32 |
| 8 | Lampung | 82.98 | 68.73 | 35.93 | 59.89 |
| 9 | Bangka Belitung Islands | 89.09 | 82.13 | 40.78 | 67.68 |
| 10 | Riau Islands | 90.83 | 57.85 | 54.75 | 66.5 |
| 11 | Jakarta | 66.57 | 51.93 | 24.14 | 45.21 |
| 12 | West Java | 72.8 | 65.77 | 38.51 | 56.98 |
| 13 | Central Java | 82.97 | 77.77 | 50.12 | 68.27 |
| 14 | Yogyakarta | 84.25 | 81.63 | 33.03 | 62.98 |
| 15 | East Java | 81.8 | 74.43 | 50.52 | 67.08 |
| 16 | Banten | 71.63 | 67.32 | 38.28 | 57 |
| 17 | Bali | 88.97 | 77.67 | 41.56 | 66.62 |
| 18 | West Nusa Tenggara | 87.17 | 74.63 | 66.56 | 75.16 |
| 19 | East Nusa Tenggara | 86.83 | 58.09 | 63.84 | 69.01 |
| 20 | West Kalimantan | 88.68 | 69.38 | 64.19 | 73.09 |
| 21 | Central Kalimantan | 87.07 | 61.15 | 78.12 | 75.71 |
| 22 | South Kalimantan | 87.75 | 75.8 | 49.29 | 68.78 |
| 23 | East Kalimantan | 83.36 | 86.19 | 87.59 | 85.9 |
| 24 | North Kalimantan | 90.95 | 81.86 | 87.59 | 86.88 |
| 25 | North Sulawesi | 91.07 | 78.5 | 60.19 | 74.95 |
| 26 | Central Sulawesi | 93.56 | 82.62 | 54.94 | 74.83 |
| 27 | South Sulawesi | 89.09 | 75.95 | 84.58 | 83.34 |
| 28 | Southeast Sulawesi | 89.85 | 86.17 | 75.91 | 83.17 |
| 29 | Gorontalo | 92.17 | 81.93 | 79.64 | 84.09 |

| No | Province | Air Quality Index | Water Quality Index | Land Cover Quality Index | Environmental Quality Index |
|---|---|---|---|---|---|
| 30 | West Sulawesi | 89.26 | 82.43 | 70.96 | 79.89 |
| 31 | Maluku | 84.99 | 67.4 | 88.78 | 81.23 |
| 32 | North Maluku | 90.77 | 88.01 | 86.54 | 88.25 |
| 33 | West Papua | 90.41 | 81.25 | 100 | 91.5 |
| 34 | Papua | 89.89 | 61.78 | 95.94 | 83.88 |
|  | Indonesia | 84.74 | 72.77 | 61.03 | 71.67 |

*Source: Ministry of Environment and Forestry of the Republic of Indonesia (2018)*

## Analyses

Provinces were classified into three groups based on infectious disease burden, using a 90% confidence interval. Provinces with case numbers below $\bar{x} - 1.692\, SD/\sqrt{34}$ were categorized as *low*, those between $\bar{x} - 1.692\, SD/\sqrt{34}$ and $\bar{x} + 1.692\, SD/\sqrt{34}$ as *moderate*, and high, respectively, with those above the upper threshold classified as *high*. Here $\bar{x}$ is the mean number of cases, *SD* the standard deviation, 34 the number of provinces, and 1.692 the *t*-value for a 90% confidence level with 33 degrees of freedom (Moore et al., 2017; Navidi & Monk, 2025; Ott & Longnecker, 2016). To examine spatial distribution, we first applied the Variance Mean Ratio (VMR), calculated as:

$$VMR = \frac{Variance}{Mean}$$

A VMR > 1 indicates clustering, VMR ≈ 1 indicates randomness, and VMR < 1 suggests a uniform distribution (Anselin, 2024; D'Angelo & Adelfio, 2025; Lawson, 2018).

Spatial dependence was then assessed using a spatial regression framework. A spatial weights matrix—constructed from geographic contiguity—captures inter-provincial relationships. The Spatial Autoregressive (SAR) model was used to evaluate spillover effects:

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \in$$

where $\boldsymbol{y}$ is the vector of case counts, $\mathbf{W}$ is the spatial weights matrix, ρ(rho) is the spatial dependence coefficient, and ∈ is the error term. A positive ρ indicates clustering of high or low values across neighbors, ρ = 0 reflects independence, and a negative ρ implies contrasting patterns between provinces.

To detect local hotspots and outliers, Moran Scatter Plots were used to plot standardized values against their spatial lags. Four quadrants describe the spatial association: High–High (hotspots), Low–Low (cold spots), Low–High (negative outliers), and High–Low (positive outliers). The slope of the fitted line corresponds to Global Moran's *I*, summarizing overall autocorrelation (Chen, 2024; Griffith, 2023; Moraga, 2024; Pebesma & Bivand, 2023) (Table 2).

**Table 2:** Description of Moran Scatter Plots

| Quadrant | Description | Interpretation |
|---|---|---|
| I | High values surrounded by high values | High-High (Hotspot) |
| II | Low values surrounded by high values | Low-High (Negative Outlier) |
| III | Low values surrounded by low values | Low-Low (Cold spot) |
| IV | High values surrounded by low values | High-Low (Positive Outlier) |

Finally, to assess environmental influences, simple linear regression was performed with infectious disease incidence as the dependent variable and the EQI as the predictor variable (Ministry of Environment and Forestry of the Republic of Indonesia, 2018). This model quantifies the association between disease burden and environmental quality, integrating factors such as air and water pollution, land conditions, and ecosystem health (Messer et al., 2014).

# Result

## Relationship between infectious diseases and regional clustering

In 2018, Indonesia reported high incidence rates of several diseases. Diarrhea recorded the highest incidence (18,216,498 cases), followed by ARI (11,807,326), pneumonia (5,421,584), TB (1,130,081), hepatitis (1,059,262), filariasis (2,154,100), and malaria (991,967). Diarrhea had the highest number of cases and the most significant interprovincial variation.

Significant positive correlations were observed among ARI, pneumonia, TB, hepatitis, diarrhea, and filariasis, suggesting that these illnesses tend to co-occur in the same provinces. For example, the number of ARI cases strongly correlates with pneumonia ($r = 0.942$), TB ($r = 0.883$), hepatitis ($r = 0.958$), diarrhea ($r = 0.962$), and filariasis ($r = 0.924$), all statistically significant at $p < .001$. Malaria, in contrast, showed no significant correlation with the other diseases, indicating a distinct spatial distribution.

To assess spatial distribution, the VMR and Moran's $I$ Index were employed. A VMR value greater than 1 indicates clustering, while Moran's $I$ with a significant $p$ value confirms spatial autocorrelation.

**Table 3:** Distribution of the Number of Infectious Disease Cases

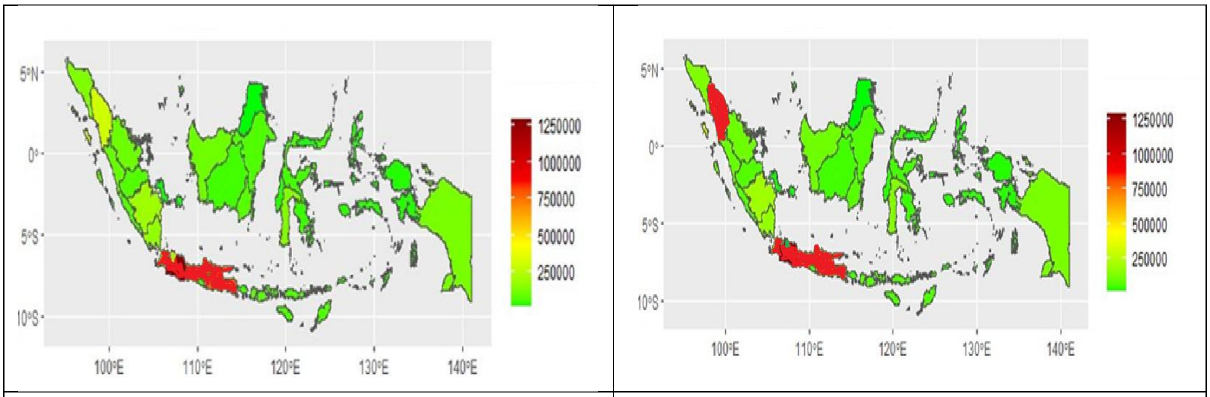
| No | Provinces | Number of Infectious Disease Cases | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **ARI** | **Pneumonia** | **TB** | **Hepatitis** | **Diarrhea** | **Malaria** | **Filariasis** |
| 1 | Aceh | 231,688 | 134,703 | 26,402 | 22,091 | 457,989 | 10,776 | 70,045 |
| 2 | North Sumatera | 414,355 | 310,766 | 44,395 | 54,754 | 1,198,670 | 29,597 | 133,186 |
| 3 | West Sumatera | 227,374 | 94,277 | 17,192 | 19,965 | 460,293 | 7,764 | 38,820 |
| 4 | Riau | 152,926 | 104,268 | 15,293 | 27,110 | 444,877 | 8,341 | 41,707 |
| 5 | Jambi | 115,334 | 68,480 | 9,731 | 14,056 | 147,772 | 9,371 | 25,229 |
| 6 | South Sumatera | 301,028 | 197,818 | 45,584 | 28,383 | 430,040 | 20,642 | 86,008 |
| 7 | Bengkulu | 177,493 | 67,806 | 8,177 | 8,575 | 177,493 | 30,712 | 17,949 |
| 8 | Lampung | 358,462 | 170,696 | 28,165 | 25,604 | 384,066 | 21,337 | 59,744 |

| No | Provinces | Number of Infectious Disease Cases | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | ARI | Pneumonia | TB | Hepatitis | Diarrhea | Malaria | Filariasis |
| 9 | Bangka Belitung Islands | 22,047 | 20,577 | 1,323 | 2,646 | 47,034 | 15,727 | 8,819 |
| 10 | Riau Islands | 87,761 | 39,262 | 6,698 | 5,774 | 90,071 | 7,390 | 32,333 |
| 11 | Jakarta | 285,563 | 232,681 | 53,940 | 50,767 | 602,855 | 4,231 | 63,458 |
| 12 | West Java | 2,329,564 | 1,288,695 | 312,261 | 223,043 | 3,667,825 | 19,826 | 495,652 |
| 13 | Central Java | 1,597,957 | 625,288 | 125,058 | 97,267 | 2,501,150 | 10,421 | 277,906 |
| 14 | Yogyakarta | 109,738 | 50,950 | 6,271 | 13,717 | 239,071 | 3,135 | 19,596 |
| 15 | East Java | 2,397,354 | 719,206 | 115,872 | 159,824 | 2,597,134 | 7,991 | 239,735 |
| 16 | Banten | 683,451 | 257,906 | 98,004 | 54,160 | 980,043 | 11,606 | 90,267 |
| 17 | Bali | 203,062 | 44,144 | 5,739 | 15,892 | 291,350 | 1,766 | 17,658 |
| 18 | West Nusa Tenggara | 141,099 | 73,163 | 16,723 | 29,265 | 438,976 | 33,968 | 31,355 |
| 19 | East Nusa Tenggara | 402,478 | 60,647 | 14,886 | 19,297 | 281,183 | 109,717 | 38,594 |
| 20 | West Kalimantan | 163,357 | 107,203 | 18,378 | 14,804 | 377,763 | 19,399 | 40,839 |
| 21 | Central Kalimantan | 166,551 | 51,040 | 10,477 | 10,745 | 123,570 | 4,835 | 24,177 |
| 22 | South Kalimantan | 98,178 | 72,566 | 17,501 | 14,086 | 239,042 | 5,122 | 34,149 |
| 23 | East Kalimantan | 139,259 | 65,965 | 12,094 | 14,292 | 186,900 | 7,329 | 25,653 |
| 24 | North Kalimantan | 14,876 | 17,710 | 3,684 | 2,338 | 46,754 | 1,133 | 5,667 |
| 25 | North Sulawesi | 52,771 | 45,232 | 9,800 | 11,811 | 135,697 | 11,811 | 12,565 |
| 26 | Central Sulawesi | 80,124 | 52,389 | 12,019 | 19,107 | 224,964 | 22,805 | 21,572 |
| 27 | South Sulawesi | 168,887 | 142,221 | 32,000 | 38,222 | 622,216 | 11,555 | 44,444 |
| 28 | Southeast Sulawesi | 75,698 | 43,256 | 11,084 | 10,544 | 151,396 | 5,948 | 35,146 |
| 29 | Gorontalo | 23,726 | 21,353 | 4,982 | 6,525 | 75,923 | 1,424 | 5,932 |
| 30 | West Sulawesi | 24,806 | 30,318 | 4,272 | 7,855 | 95,089 | 2,894 | 12,403 |
| 31 | Maluku | 100,078 | 33,955 | 6,970 | 6,076 | 96,503 | 21,624 | 32,168 |
| 32 | North Maluku Utara | 30,055 | 26,298 | 3,757 | 4,133 | 55,101 | 17,031 | 10,018 |
| 33 | West Papua | 73,950 | 28,594 | 5,226 | 4,141 | 66,062 | 85,190 | 13,804 |
| 34 | Papua | 356,276 | 122,152 | 26,127 | 22,394 | 281,627 | 409,547 | 47,503 |

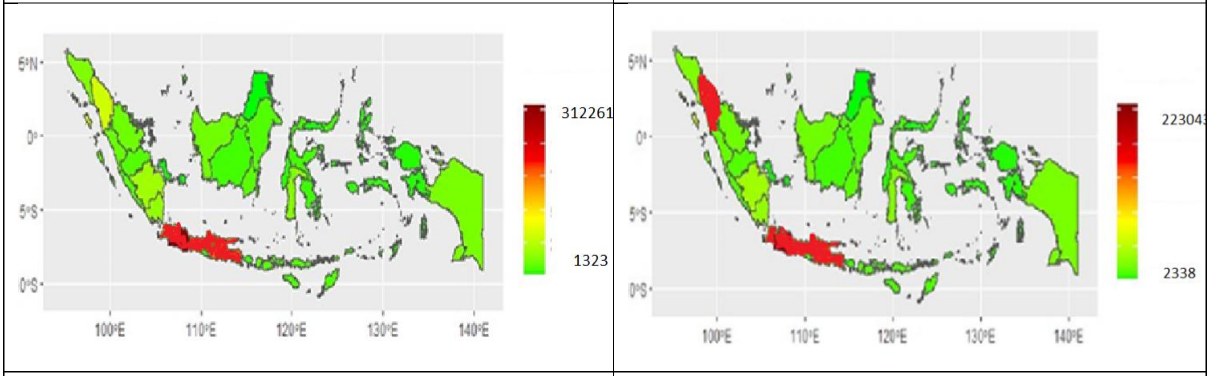
| | |
|---|---|
| 🟨 | Low |
| 🟧 | Middle |
| 🟥 | High |

The average number of ARI cases per province was 347,274, with a variance of 3.41 × $10^{11}$, yielding a VMR of 2,158,662, indicating strong clustering. Moran's $I$ was 0.0714 ($p$ = .0087), reinforcing this pattern. Based on case counts, provinces were categorized as low (< 299,079), moderate (299,079–981,524), or high (> 981,524). High-prevalence regions are concentrated in Java, including Banten, Central Java, West Java, and East Java (Table 3, Figure 1A).

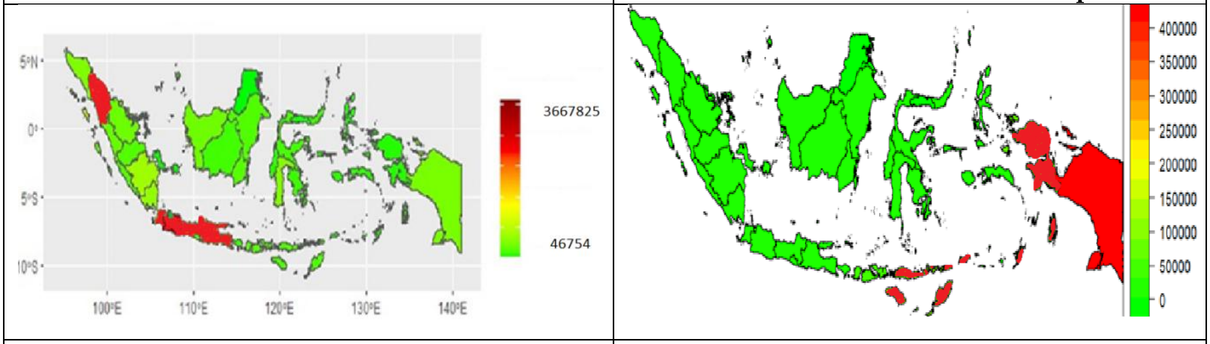
**Figure 1:** Spatial Distribution of the Number of People Suffering from Infectious Diseases



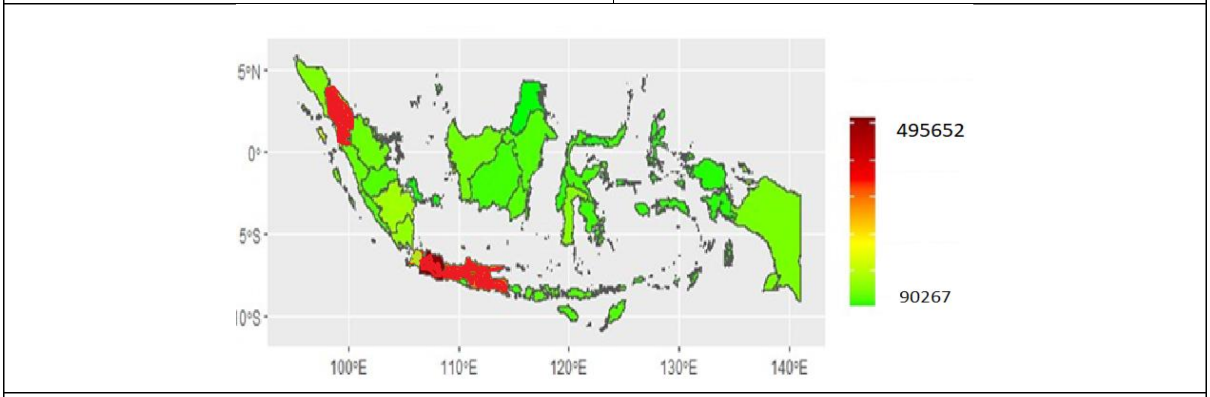
**A. Distribution of the Number of ARI** **B. Distribution of the Number of Pneumonia**



**C. Distribution of the Number of TB** **D. Distribution of the Number of Hepatitis**



**E. Distribution of the Number of Diarrhea** **F. Distribution of the Number of Malaria**



**G. Distribution of the Number of Filariasis**

Pneumonia showed a mean of 159,458 and a variance of $6.43 \times 10^{10}$ (VMR = 403,367), also indicating clustering. Moran's *I* was 0.0741 (*p* = .0073), confirming a significant spatial pattern.

Case classifications were < 85,850 (low), 85,850–233,067 (moderate), and > 233,067 (high). High case provinces include regions in Java and North Sumatra (Table 3, Figure 1B).

The map illustrates the spatial distribution of pneumonia cases in Indonesia, with color intensity indicating case counts across provinces. Areas shown in red indicate provinces with the highest pneumonia burden, while green areas represent lower case counts. On the map, Java Island stands out as the primary hotspot, particularly in provinces along Java's western and central regions, where pneumonia cases are markedly higher than in other areas. This pattern is likely influenced by high population density, urban crowding, air pollution, and greater detection and reporting capacity, facilitated by access to health services. Sumatra also shows elevated pneumonia cases in certain provinces, although the intensity is generally lower than in Java.

In contrast, eastern Indonesia (Kalimantan, Sulawesi, Maluku, and Papua) is predominantly green, indicating fewer reported pneumonia cases. This may reflect a combination of lower population density, different environmental conditions, and potential underreporting or limited access to health facilities, rather than a genuine absence of disease. Overall, the spatial pattern suggests that pneumonia cases are not evenly distributed across Indonesia but are clustered in densely populated and highly urbanized regions. This clustering highlights the importance of spatially targeted public health interventions, particularly in high-burden provinces, focusing on air quality improvement, early case detection, vaccination coverage, and strengthened primary health care services (Figure 1B)

TB recorded an average of 33,238 cases with a variance of 337,855,961 (VMR = 10,164.8). Moran's $I$ was 0.08899 ($p$ = .00264), indicating significant spatial clustering. Classification intervals were < 16,368 (low), 16,368–50,108 (moderate), and > 50,108 (high). High-prevalence provinces are primarily on Java Island, including Jakarta, Banten, Central Java, East Java, and West Java (Table 3, Figure 1C).

The mean for hepatitis was 31,155, with a variance of 208,546,511 (VMR = 6,693.84), also showing clustering. Moran's $I$ was 0.07578 ($p$ = .00656), confirming spatial autocorrelation. Case thresholds were < 17,901 (low), 17,901–44,409 (moderate), and > 44,409 (high). High numbers were noted in Java and North Sumatra (Table 3, Figure 1D).

Diarrhea had a provincial mean of 535,779 with a variance of $6.58 \times 10^{11}$, yielding a VMR of 124,678.72, which again confirms clustering. Moran's $I$ was 0.07835 ($p$ = .00553). Classifications were < 300,281 (low), 300,281–771,277 (moderate), and > 771,277 (high). High-case provinces include West Java (3,667,825), East Java (2,597,134), Central Java (2,501,150), North Sumatra (1,198,670), and Banten (980,043) (Table 3, Figure 1E).

Malaria showed an average of 29,175 with a variance of $5.01 \times 10^{9}$ (VMR = 171,773), suggesting clustering, but Moran's $I$ of 0.02944 ($p$ = .08122) indicated no statistically significant spatial pattern. Case classifications were < 8,629 (low), 8,629–49,722 (moderate), and > 49,722 (high). The provinces with the highest case counts—Papua (409,547), East Nusa Tenggara (109,717), and West Papua (85,190)—were geographically dispersed (Table 3, Figure 1F).

For filariasis, the average was 63,356, and the variance was $9.39 \times 10^{9}$ (VMR = 148,223), indicating clustering. Moran's $I$ was 0.05358 ($p$ = .02492), confirming a significant spatial pattern. To better understand disease burden across Indonesia, case counts were grouped into three categories: *low* (< 35,230 cases), *moderate* (35,230–91,482), and *high* (> 91,482). Several provinces stood out for their high case numbers—most notably West Java (495,652), followed by Central Java (277,906), East Java (239,735), North Sumatra (133,186), and Banten (90,267) (Table 3, Figure 1G).

Overall, the analysis reveals that most infectious diseases exhibit strong spatial clustering, particularly on Java, Indonesia's most populous and densely populated island. This pattern underscores the combined influence of population density, mobility, and infrastructure on disease transmission. An important exception, however, is malaria, which displays a distinctly different distribution. Unlike other diseases, malaria does not follow spatial proximity; it appears more closely linked to ecological factors, such as elevation, climate, and land use. These findings emphasize the importance of regionally tailored health strategies. Rather than a one-size-fits-all approach, interventions should be informed by disease-specific spatial patterns, with special attention to high-burden areas identified through clustering analysis (Table 3, Figures 1A–1G).

## Measuring disease transmission across provinces

To explore how infectious diseases may spread between provinces, this study used two spatial diagnostic tools: Moran's Index (*I*) and the spatial correlation between each province's case count **(y)** and the average case count in its neighboring provinces (**Wy**). Moran's *I* offers a national-level perspective on spatial autocorrelation. A positive Moran's *I* indicates that provinces with similar disease levels—whether high or low—are located near each other, suggesting geographic clustering. A negative value indicates dispersion, in which low-case neighbors surround high-case provinces. When Moran's *I* is close to zero, it shows that disease distribution lacks spatial structure and may be influenced by random or non-spatial factors.

In contrast, the **y–Wy** correlation focuses on local patterns. It examines whether that of its immediate neighbors mirrors a province's case burden. A positive correlation implies spatial spillover, in which provinces with high case counts are likely to be adjacent to those with similarly high burdens. A negative correlation, by contrast, indicates spatial divergence, in which lower-case provinces border high-case provinces. Together, these spatial diagnostics offer a powerful lens for understanding how diseases move, where they cluster, and why some areas may be more vulnerable than others. This evidence supports more responsive, place-based public health planning—especially in anticipating and containing infectious disease outbreaks.

In 2018, the spatial correlation between **y** and **Wy** was positive for most diseases, although none were statistically significant at the 5% level. Tuberculosis (TB) had the highest spatial correlation (0.316), followed by diarrhea (0.301), hepatitis (0.297), pneumonia (0.283), ARI (0.267), and filariasis (0.225). Malaria was the only disease with a negative spatial correlation (- 0.236). This suggests that, while most infectious diseases tend to cluster locally, malaria behaves differently: provinces with high malaria case counts are often surrounded by provinces with lower counts (Table 4).

**Table 4:** Spatial Correlation of the Number of Infectious Diseases

| | | **ARI** | **Pneumonia** | **TB** | **Hepatitis** | **Diarrhea** | **Malaria** | **Filariasis** |
|---|---|---|---|---|---|---|---|---|
| W_ARI | Correlation | 0.267 | | | | | | |
| | Sig | 0.127 | | | | | | |
| W_Pneumonia | Correlation | | 0.283 | | | | | |
| | Sig | | 0.104 | | | | | |

| | | ARI | Pneumonia | TB | Hepatitis | Diarrhea | Malaria | Filariasis |
|---|---|---|---|---|---|---|---|---|
| W_TB | | | | 0.316 | | | | |
| | | | | 0.068 | | | | |
| W_Hepatitis | Correlation | | | | 0.297 | | | |
| | Sig | | | | 0.089 | | | |
| W_Diarrhea | Correlation | | | | | 0.301 | | |
| | Sig | | | | | 0.083 | | |
| W-Malaria | | | | | | | -0.236 | |
| | | | | | | | 0.179 | |
| W_Filariasis | | | | | | | | 0.225 |
| | | | | | | | | 0.201 |

To further analyze the influence of neighboring provinces, spatial regression models were used for each disease. To better understand how infectious diseases interact across space, spatial regression models were used to estimate the number of cases in each province from the average number of cases in neighboring provinces (Table 5). These models help uncover not only where diseases cluster but also how the burden in one area may influence surrounding regions.

**Table 5:** Spatial Regression of the Number of Infectious Diseases with the Number of Infectious Diseases in Neighbors

| | **ARI Coef** | **t** | **Sig.** | | **Pneumonia Coef** | **t** | **Sig.** |
|---|---|---|---|---|---|---|---|
| (Constant) | 57,037.708 | 0.272 | 0.787 | (Constant) | 21,806.757 | 0.235 | 0.815 |
| W_ARI | 0.836 | 1.569 | 0.127 | W_Pneumonia | 0.863 | 1.671 | 0.104 |
| | **Diarrhea Coef** | **t** | **Sig,** | | **Malaria Coef** | **t** | **Sig,** |
| (Constant) | 54,997,532 | 0.183 | 0.856 | (Constant) | 87,068.184 | 1.985 | 0.056 |
| W_Diarrhea | 0.897 | 1.787 | 0.083 | W_Malaria | -1,984 | -1.372 | 0.179 |
| | **TB Coef** | **t** | **Sig,** | | **Hepatitis Coef** | **t** | **Sig,** |
| (Constant) | 768.417 | 0.039 | 0.969 | (Constant) | 3,002.771 | 0.169 | 0.867 |
| W_TB | 0.977 | 1.887 | 0.068 | W_Hepatitis | 0.904 | 1.757 | 0.089 |
| | **Filariasis Coef** | **t** | **Sig,** | | | | |
| (Constant) | 19,714.93 | 0.529 | 0.601 | | | | |
| W_filariasis | 0.689 | 1.305 | 0.201 | | | | |

Take TB as an example. The model estimates TB cases using the equation:

TB = 768.42 + 0.977 × neighboring TB cases. This suggests that for each additional TB case in neighboring provinces, the local case count is expected to increase by nearly one, indicating a strong spatial spillover effect. A similar trend is seen with diarrhea and hepatitis.

- Diarrhea = 54,997.53 + 0.897 × neighboring diarrhea cases
- Hepatitis = 3,002.77 + 0.904 × neighboring hepatitis cases

Both models reveal strong spatial dependence, indicating that provinces are not independent in their disease dynamics. Instead, conditions in surrounding areas play a significant role in shaping local health outcomes—highlighting the interconnected nature of disease transmission. However, malaria behaves differently. Its regression equation is: malaria = 87,068.18 − 1.984 × neighboring malaria cases. Unlike other diseases, malaria exhibits a negative spatial coefficient, indicating that areas with lower incidence often surround provinces with higher incidence. This suggests a negative spillover effect or more localized ecological drivers—such as mosquito habitats, elevation, or microclimate—that are not shared across borders.

In summary, while most infectious diseases in Indonesia tend to cluster both globally and locally—reflected in positive Moran's *I* values, and **y–Wy** correlations—malaria emerges as a notable outlier. More dispersed spatial behavior points to distinct transmission mechanisms and underscores the need for disease-specific strategies. These findings reinforce the importance of incorporating spatial thinking into public health planning, enabling more responsive, targeted, and regionally appropriate interventions.

## Comparison of provincial clustering: Number of infectious disease cases vs. their neighbors

When comparing the number of infectious disease cases in each province with its neighboring provinces, four spatial clustering patterns can be observed: provinces with high cases surrounded by high-case neighbors (high-high), high cases surrounded by low-case neighbors (high-low), low cases surrounded by high-case neighbors (low-high), and low cases surrounded by low-case neighbors (low-low). This classification is based on standardized values (Z-scores) and spatial weight matrices.

**Figure 2:** Moran Scatter Plot of Infectious Diseases

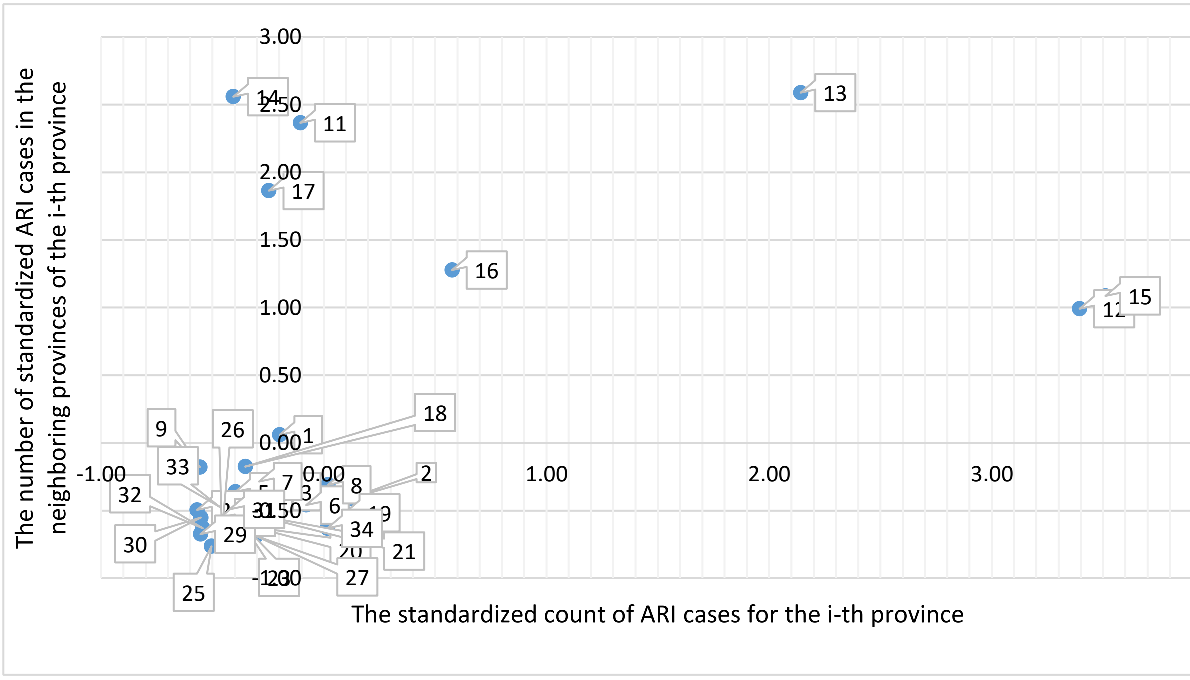


**Figure 2A. Moran Scatter Plot of ARI Cases**

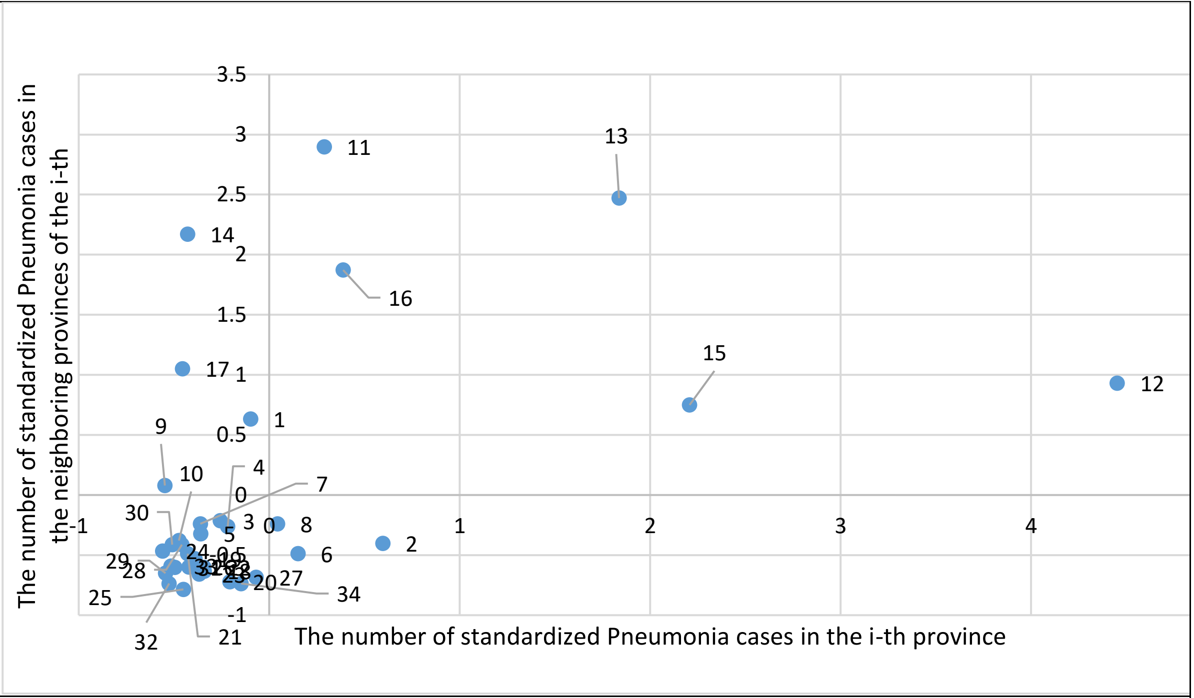


Figure 2B. Moran Scatter Plot of Pneumonia Cases

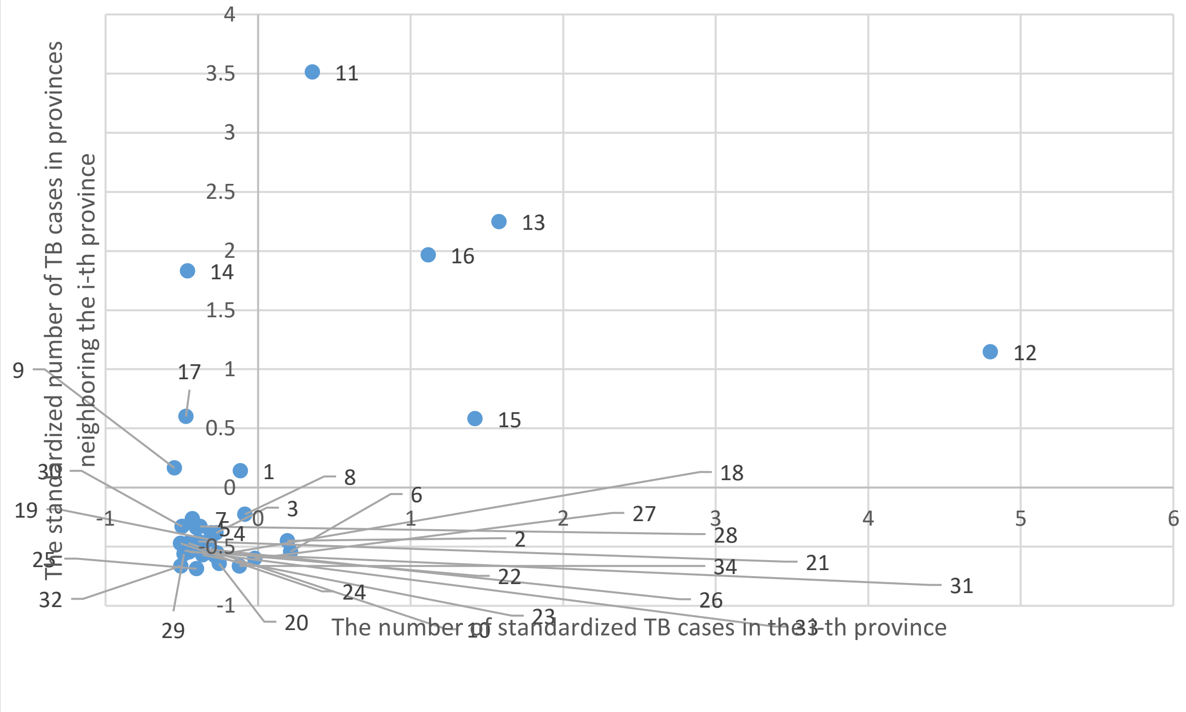


Figure 2C. Moran Scatter Plot of TB Cases

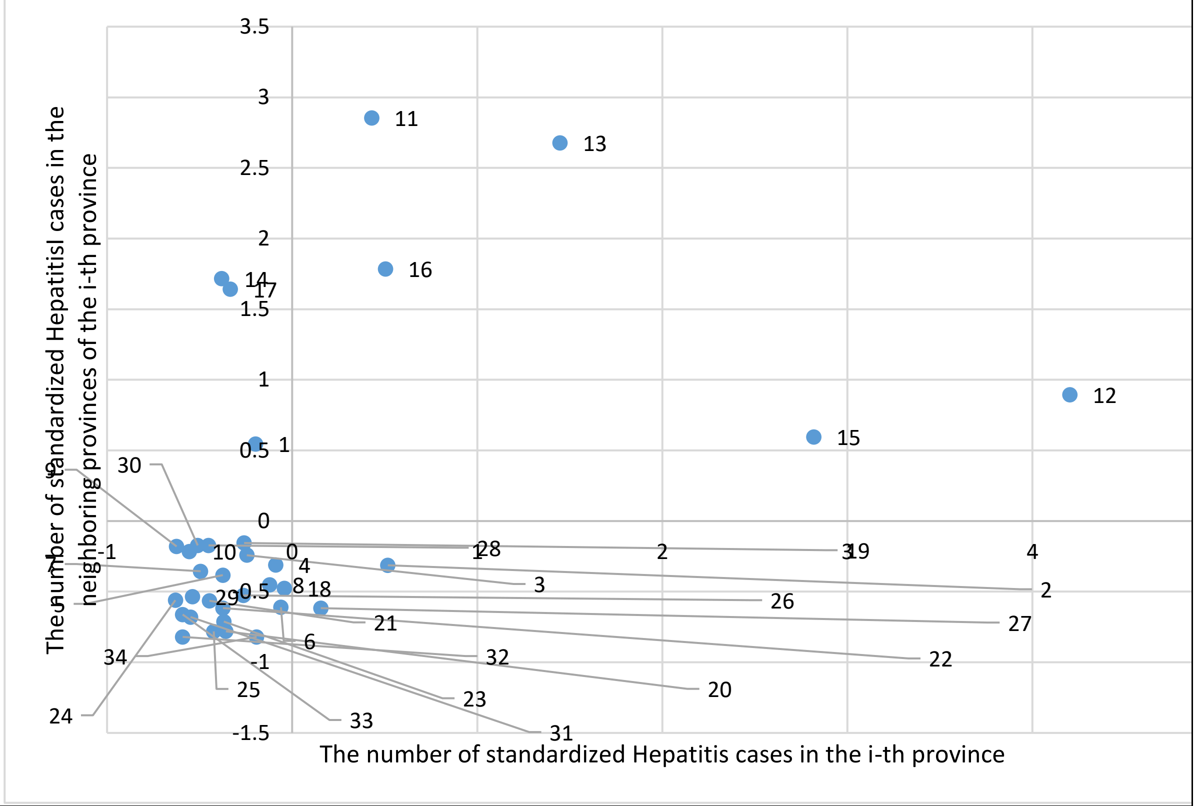


Figure 2D. Moran Scatter Plot of Hepatitis Cases

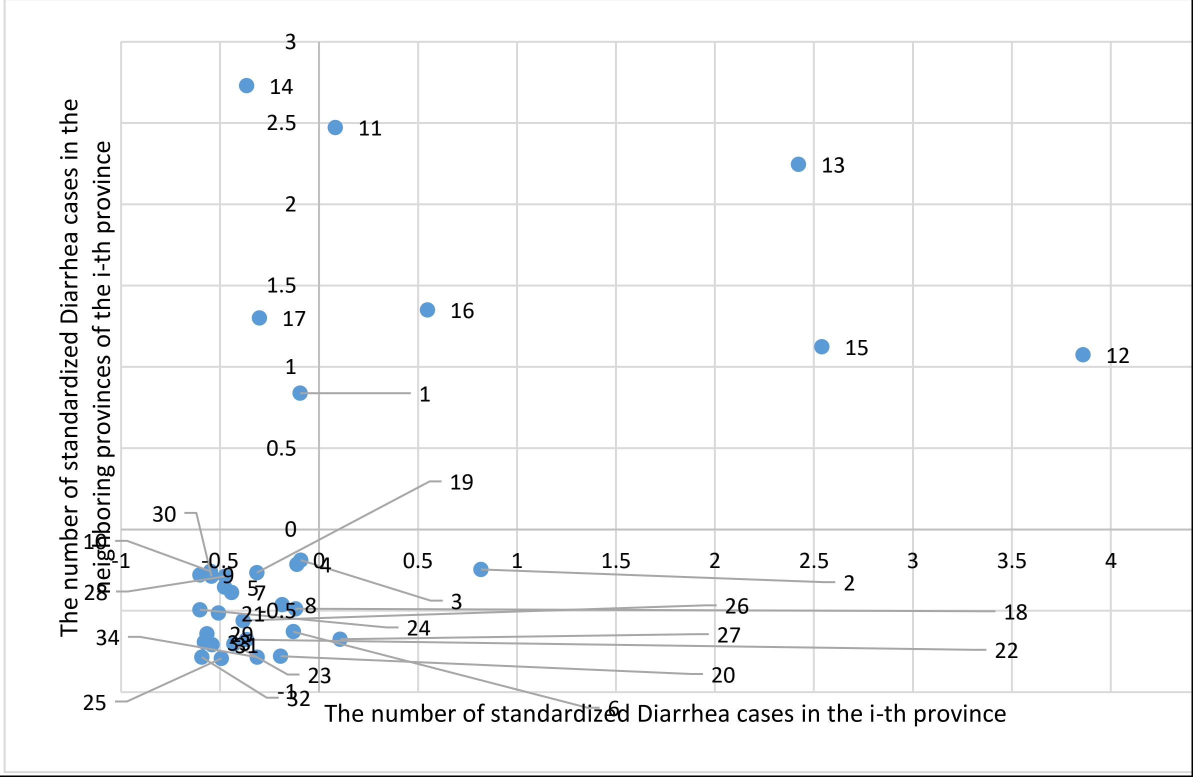


Figure 2E. Moran Scatter Plot of Diarrhea Cases

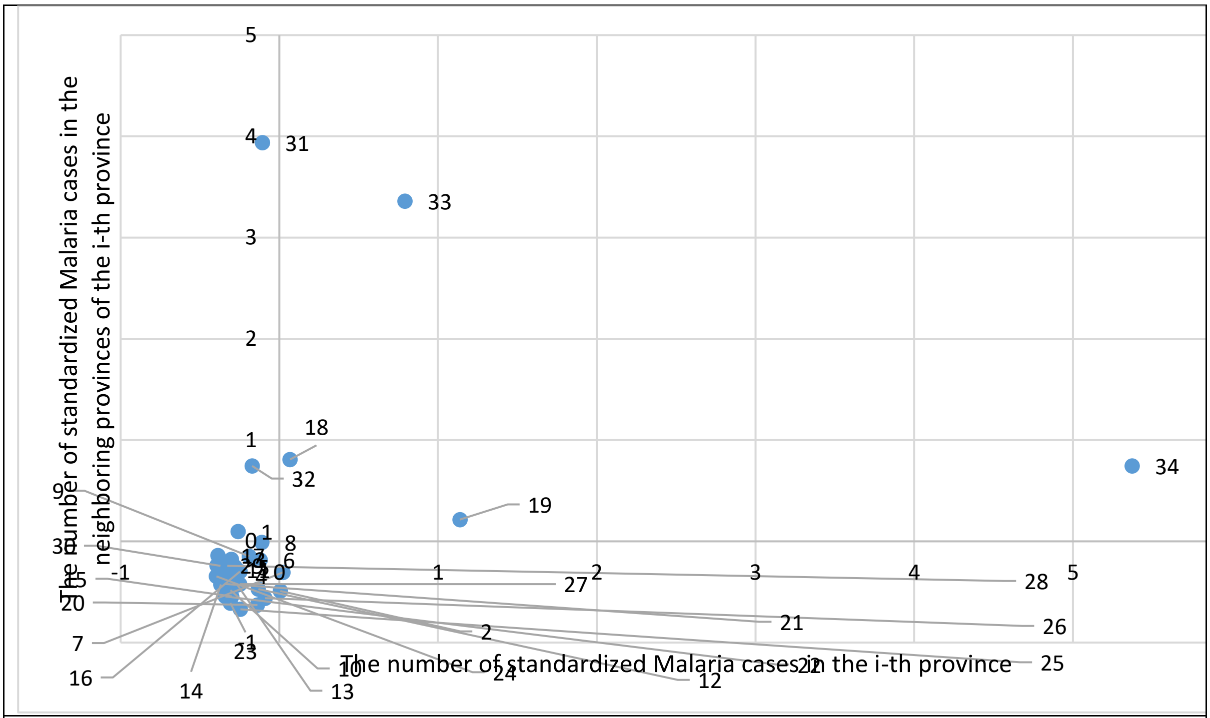


**Figure 2F. Moran Scatter Plot of Malaria Cases**

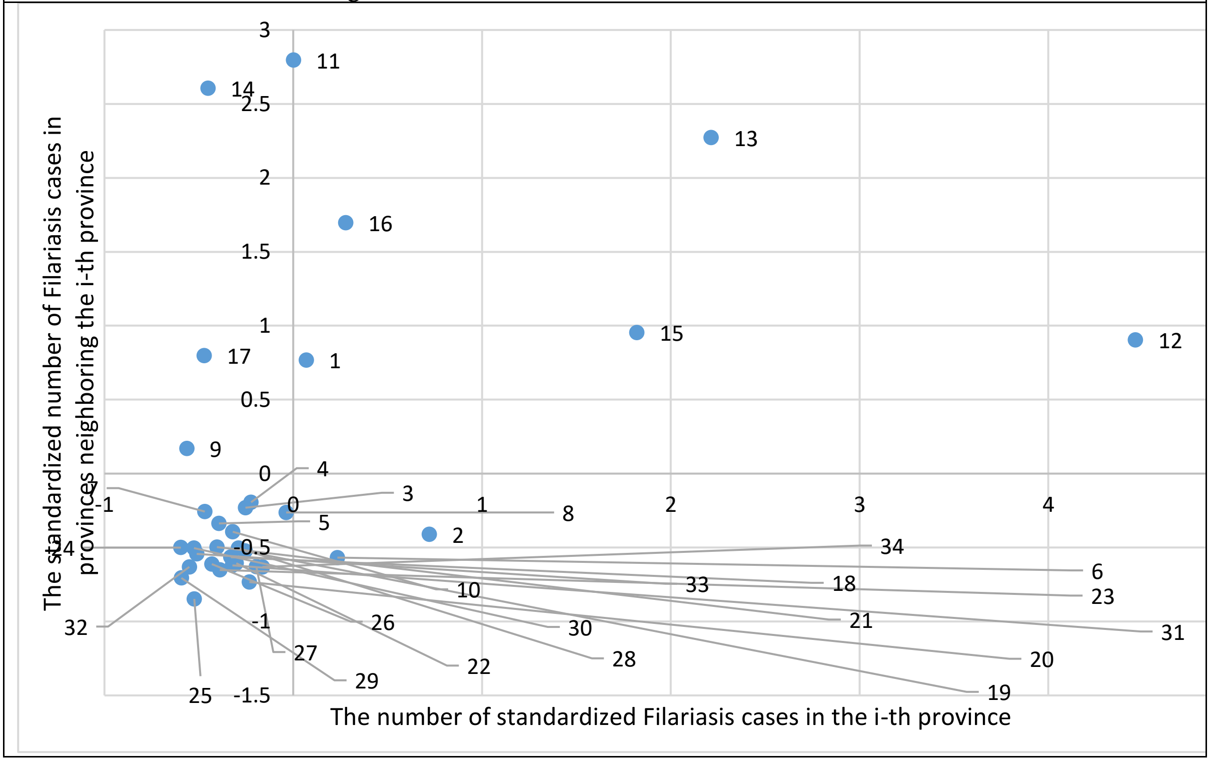


**Figure 2G. Moran Scatter Plot of Filariasis Cases**

*Note: The numbers on the map represent the names of the provinces as listed in Table 1*

In the case of ARI, provinces such as East Java, West Java, Lampung, Central Java, and Banten exhibit high ARI incidence, with surrounding provinces also exhibiting high incidence, forming high-high clusters. On the other hand, provinces like Papua, East Nusa Tenggara, and North Sumatra show high ARI cases but are surrounded by low-case provinces, forming high-low clusters. Provinces such as Jambi, Bengkulu, South Sumatra, Bali, Bangka Belitung, Jakarta, and Yogyakarta have low ARI incidence, whereas their neighbors report high numbers, forming low-high clusters. Most eastern and some western provinces, including West Papua, North Maluku, and Aceh, fall into low-low clusters (Figure 2A).

For pneumonia, East Java, South Sumatra, West Java, Lampung, Central Java, Banten, and Jakarta form high-high clusters. North Sumatra appears as a high-low cluster, while West Sumatra, Riau, Bali, and others fall into low-high clusters. Provinces such as Papua, West Papua, Maluku, and several in Sulawesi and Kalimantan are low-low clusters (Figure 2B). In TB, provinces such as South Sumatra, Jakarta, Banten, East Java, Central Java, and West Java constitute high-high clusters. North Sumatra represents a high-low pattern. Bali, Jambi, and similar provinces are low-high, while many eastern and central provinces form low-low clusters (Figure 2C).

For hepatitis, high-high clusters are found in Jakarta, Banten, Central Java, East Java, and West Java. Provinces such as South Sulawesi and North Sumatra are high but surrounded by low-case provinces (high-low), whereas areas such as Bangka Belitung, Bali, and Yogyakarta are low-high. The majority of eastern provinces and regions in Kalimantan fall into low-low clusters (Figure 2D). Regarding diarrhea, high-high clusters include East Java, West Java, Central Java, Banten, and Jakarta. North Sumatra and South Sulawesi are high-low. Provinces such as West Sumatra, South Sumatra, and others in western Indonesia are low-high, while many in eastern and central regions are low-low clusters (Figure 2E).

Unlike most other infectious diseases, malaria exhibits a distinctive spatial pattern. High-high clusters—where both the province and its neighbors report high case numbers—are found in West Nusa Tenggara and West Papua. In contrast, Papua and East Nusa Tenggara form high-low clusters, suggesting they are high-burden areas surrounded by provinces with lower case counts. Meanwhile, the islands of Java and Sumatra are primarily characterized by low-low clusters, reflecting both local and neighboring low incidence. Interestingly, several provinces, such as Jakarta, Bali, and Central Sulawesi, fall into low-high clusters, in which local case numbers are low, but adjacent provinces report higher levels (Figure 2F).

The spatial pattern of filariasis paints a different map. High-high clusters are concentrated in several densely populated and urbanized provinces, including South Sumatra, East Java, West Java, Central Java, Banten, and Jakarta. In contrast, Aceh and North Sumatra fall into high-low zones, indicating high local incidence with surrounding provinces reporting lower levels. Low-low clusters dominate Papua, Maluku, Sulawesi, and Kalimantan, while low-high groupings appear in West Sumatra, Riau, Bali, and Yogyakarta (Figure 2G). These spatial configurations highlight the non-random distribution of disease, reinforcing the importance of spatial proximity in disease dynamics. In many cases, high-case provinces are either influenced by or exert influence on their neighbors, pointing to potential transmission corridors or shared environmental and social risk factors. Understanding these patterns is vital for designing targeted and geographically sensitive health interventions (Figures 2A–2G).

## Environmental quality and disease burden

Environmental conditions are inextricably linked to public health. In Indonesia, the EQI provides a composite measure of environmental health, combining indicators of air quality, water quality, and land cover. To explore the impact of environmental conditions on disease prevalence, this study employed ANOVA regression analysis to examine the association between EQI scores and the number of infectious disease cases across provinces (Table 6).

**Table 6:** Regression of the Number of Infectious Diseases as a Function of the EQI

| ANOVA F | ANOVA Sig | B | | Std. Error | *t*-test | Sig. |
|---|---|---|---|---|---|---|
| **Regression of ARI =1,990,808.177-22,512.440*EQI+Error** | | | | | | |
| 5.939485 | 0.020545 | (Constant) | 1,990,808.177 | 680,817.822 | 2.924 | 0.006 |
| | | EQI | -22,512.440 | 9,237.366 | -2.437 | 0.021 |
| **Regression of Pneumonia =972,354.652-11,134.713*EQI+Error** | | | | | | |
| 8.154545 | 0.007482 | (Constant) | 972,354.652 | 287,383.573 | 3.383 | 0.002 |
| | | EQI | -11,134.713 | 3,899.233 | -2.856 | 0.007 |
| **Regression of TB =223,999.595-2,612.977*EQI+Error** | | | | | | |
| 8.656044 | 0.006018 | (Constant) | 223,999.595 | 65,457.380 | 3.422 | 0.002 |
| | | EQI | -2,612.977 | 888.129 | -2.942 | 0.006 |
| **Regression of Hepatitis =180,039.055-2,039.355*EQI+Error** | | | | | | |
| 8.511736 | 0.006405 | (Constant) | 180,039.055 | 51,518.881 | 3.495 | 0.001 |
| | | EQI | -2,039.355 | 699.010 | -2.917 | 0.006 |
| **Regression of Diarrhea =3,040,326.601-34,306.240*EQI+Error** | | | | | | |
| 7.425173 | 0.010338 | (Constant) | 3,040,326.601 | 927,903.053 | 3.277 | 0.003 |
| | | EQI | -34,306.240 | 12,589.829 | -2.725 | 0.010 |
| **Regression of Malaria =-76,934.958+1,453.457*EQI+Error** | | | | | | |
| 1.487182 | 0.231567 | (Constant) | -76,934.958 | 87,842.099 | -0.876 | 0.388 |
| | | EQI | 1,453.457 | 1,191.845 | 1.220 | 0.232 |
| **Regression of Filariasis =354,993.423-3,994.729*EQI+Error** | | | | | | |
| 6.978269 | 0.012658 | (Constant) | 354,993.423 | 111,454.154 | 3.185 | 0.003 |
| | | EQI | -3,994.729 | 1,512.215 | -2.642 | 0.013 |

At the 5% significance level, the regression results indicate that the EQI is a statistically significant predictor for most of the infectious diseases analyzed, and the estimated regression parameters provide insight into both the direction and magnitude of these effects. For ARI, the model is significant ($F$ = 5.939485; $p$ < .05). The estimated intercept is 1,990,808.177, representing the expected number of ARI cases when EQI equals zero. The EQI regression coefficient is -22,512.440 and statistically significant ($p$ < .05), implying that a one-unit increase in EQI is associated with an average decrease of approximately 22512 ARI cases, holding other factors constant.

For pneumonia, the regression model is also significant at the 1% level ($F$ = 8.154545; $p$ < .05). The intercept is estimated at 972,354.652, and the EQI coefficient is -11,134.713, which is statistically significant. This parameter estimate indicates that each one-unit improvement in environmental quality reduces pneumonia cases by nearly 11135 cases on average. Similarly, in TB model ($F$ = 8.656044; $p$ < .05), the intercept is 223,999.595, and the EQI coefficient is -2612.977, indicating that better environmental quality significantly reduces TB incidence, though to a smaller extent than for ARI and pneumonia.

The hepatitis results further confirm the critical role of environmental quality. The model is significant at the 1% level ($F$ = 8.511736; $p$ < .05), with an intercept of 180,039.055. The EQI coefficient is -2,039.355, which is statistically significant, indicating that a one-unit increase in EQI is associated with an average reduction of approximately 2,039 hepatitis cases. For diarrhea, the regression model remains significant ($F$ = 7.425173; $p$ < .05), and the intercept is relatively large at 3,040,326.601, reflecting the high baseline incidence. The EQI coefficient of -34,306.240 is statistically significant, suggesting that improvements in environmental quality have a particularly strong effect in reducing diarrhea cases.

In contrast, the malaria regression model is not statistically significant at the 5% level ($F$ = 1.487182; $p$ > .05). The intercept (-76,934.958) and the EQI coefficient (1,453.457) are both statistically insignificant, indicating that changes in environmental quality do not meaningfully explain variations in malaria incidence in this model. This suggests that malaria transmission is driven more by specific climatic and ecological factors than by general environmental quality.

Finally, for filariasis, the model is significant at the 5% level ($F$ = 6.978269; $p$ < .05). The intercept is estimated at 354,993.423, and the EQI coefficient is -3,994.729, which is statistically significant. This negative parameter indicates that a one-unit increase in EQI is associated with an average reduction of about -3,994 filariasis cases. Overall, the regression parameters consistently show that improvements in environmental quality significantly reduce the incidence of most infectious diseases, both statistically and substantively, except malaria, when evaluated under a strict 1% significance criterion.

These findings strongly suggest that investments in environmental management—such as improving air and water quality, reducing pollution, and enhancing land cover—can play a critical role in reducing disease prevalence. The statistical significance of these associations reinforces the idea that environmental quality is not merely a background factor, but a key determinant of public health outcomes in Indonesia

The statistical analysis found no significant association between EQI and the number of malaria cases, suggesting that ecological or vector-related factors may exert greater influence on malaria than general environmental quality. This study provides compelling evidence that improving environmental conditions—such as cleaner air, safer water, and healthier land ecosystems—can substantially reduce the spread of several major infectious diseases across Indonesia. Provinces with higher EQI scores consistently report lower incidence rates of diseases such as ARI, pneumonia, TB, hepatitis, diarrhea, and filariasis. These patterns suggest that raising environmental standards is not only an ecological goal but a powerful public health strategy, especially in areas where environmental degradation directly amplifies disease risks.

# Discussion

## Regional clustering and disease interconnectedness

This study reveals strong positive correlations among ARI, pneumonia, TB, hepatitis, diarrhea, and filariasis, which often cluster within the same provinces. These overlaps reflect shared vulnerabilities—poor sanitation, overcrowding, limited access to clean water, and inadequate access to healthcare. For example, polluted water and insufficient waste management drive diarrhea, hepatitis, and filariasis, while dense housing and poor ventilation increase the risk of ARI, pneumonia, and TB (Batura et al., 2022; Prüss-Ustün et al., 2019; World Health Organization [WHO], 2025). Poverty, malnutrition, and weak health systems amplify these risks, fueling co-infections like TB-HIV and diarrhea-hepatitis.

Malaria stands apart. As a vector-borne disease, its prevalence depends on ecological factors—rainfall, elevation, temperature, and mosquito habitat—not population density or sanitation (Gething et al., 2011; Yamba et al., 2023). Concentrated in eastern provinces like

Papua and East Nusa Tenggara, malaria reflects distinct ecological realities and targeted vector-control policies (Ministry of Health of the Republic of Indonesia, 2023).

Java, despite covering only 7% of Indonesia's land, remains a hotspot for multiple diseases due to extreme population density, pollution, flooding, and aging sanitation systems. Spatial analysis confirms this: ARI, for instance, shows a very high VMR (~2.16 million) and significant clustering (Moran's $I$ = 0.071, $p$ = .0087). These findings highlight how urban congestion and environmental degradation fuel disease, though stronger surveillance in some provinces (e.g., North Sumatra, Aceh) may also explain higher reported numbers. In sum, infectious diseases thrive where environmental stress, inequality, and weak infrastructure intersect, but strong surveillance and preparedness can shift outcomes. Policies must address both structural vulnerabilities and localized dynamics to reduce disease burden.

## Transmission across provinces

Spatial regression results confirm that infectious diseases often transcend provincial borders. TB shows the strongest spatial dependence (ρ = 0.977), consistent with airborne transmission through mobility and dense urban centers (Lönnroth et al., 2009). Hepatitis (ρ = 0.904) and diarrhea (ρ = 0.897) also demonstrate strong spatial spillovers, reflecting shared waterways and sanitation systems (Prüss-Ustün et al., 2019). Respiratory diseases such as pneumonia (ρ = 0.863) and ARI (ρ = 0.836) are associated with regional air pollution and seasonal weather patterns (Rudan et al., 2008).

Vector-borne diseases show different patterns. Filariasis exhibits moderate clustering (ρ = 0.689), which is associated with local drainage and waste conditions (de Souza & Bockarie, 2025). Malaria, uniquely, shows a negative coefficient (ρ = –1.984), with hotspots such as Papua adjacent to low-incidence provinces—likely due to ecological isolation or effective vector control (Reiner et al., 2015). These findings underscore the need for coordinated, cross-border interventions. For diseases clustered on Java (TB, ARI, diarrhea), solutions must integrate housing, sanitation, water safety, and pollution control. For malaria and filariasis, ecological and vector-specific strategies remain essential.

## Provincial disease clusters: A regional epidemiological profile

Spatial clustering analysis highlights distinct patterns:

- ARI & Pneumonia: High-high clusters dominate Java (East/West/Central Java, Banten, Lampung), reflecting shared urban and environmental pressures.
- TB: Concentrated in Java and Jakarta, with outliers like North Sumatra showing localized high-low clustering.
- Hepatitis & Diarrhea: Java again emerges as a hotspot, while peri-urban provinces (e.g., Bangka Belitung, Bali) show low-high patterns.
- Malaria: Ecologically driven, with high-high clusters in Papua and West Nusa Tenggara, contrasting with widespread low-low zones in Java, Kalimantan, and Sulawesi.
- Filariasis: Mirrors urban clustering of TB and ARI, concentrated in Java and Jakarta, with peri-urban spillovers.

Comparative insights reveal:

- Urban corridors (Java, Jakarta, Sumatra) are multi-disease hotspots driven by density, pollution, and sanitation gaps.
- High-low clusters (e.g., North Sumatra) indicate localized burdens requiring targeted support.
- Low-high provinces are at risk from surrounding clusters and need preventive vigilance.
- Eastern provinces often form low-low clusters, though underreporting cannot be ruled out.
- Malaria diverges fundamentally, requiring ecological rather than infrastructure-driven solutions.

These patterns confirm that effective interventions must be both *place-based* and *disease-specific*, balancing urban planning with ecological management.

## Environmental quality and disease burden

Environmental conditions play a critical role in determining the prevalence of infectious diseases. The regression results indicate that higher EQI scores are consistently associated with lower incidence of ARI, pneumonia, TB, hepatitis, diarrhea, and filariasis, demonstrating a robust inverse relationship between environmental quality and disease burden. Specifically, a one-unit increase in EQI is associated with an average reduction of approximately 22,512 ARI cases and nearly 11,135 pneumonia cases, highlighting the strong responsiveness of respiratory diseases to improvements in environmental conditions.

Similar negative associations are observed for other infectious diseases. In the case of tuberculosis, a one-point increase in EQI corresponds to an average decline of about 2,613 TB cases, indicating that improved environmental quality contributes to lower TB incidence. However, the magnitude of this effect is smaller than that observed for ARI and pneumonia. For hepatitis, the results indicate that each one-unit increase in EQI is associated with an average reduction of approximately 2,039 cases, underscoring the importance of environmental sanitation and safe water in preventing liver-related infectious diseases.

The impact of environmental quality is particularly pronounced for diarrheal disease, with a one-unit increase in EQI associated with an average reduction of approximately 34,306 cases, reflecting the strong dependence of diarrheal disease on water quality, sanitation, and hygiene. In addition, improvements in environmental quality are also associated with reductions in filariasis, suggesting that better waste management, drainage, and overall environmental cleanliness can limit vector breeding and disease transmission. Overall, these findings support the interpretation that environmental improvements—such as cleaner air, improved housing, safe water supply, adequate sanitation, and effective waste management—are fundamental determinants of infectious disease control. Consistent with global evidence (Prüss-Ustün et al., 2019), the results emphasize that enhancing environmental quality should be regarded not merely as an ecological objective, but as a core and effective public health strategy for reducing the burden of infectious diseases.

Malaria, however, shows no significant association with EQI, underscoring its dependence on micro-ecological rather than composite environmental conditions. Unlike other diseases, malaria transmission in Indonesia is strongly influenced by localized dynamics including vector species diversity, microclimate variability, human–non-human primate interactions, and mosquito behavioral adaptations. Recent research illustrates this complexity:

- Zoonotic transmission and vector diversity: In Southeast Sulawesi, multiple *Anopheles* species—including *An. sulawesi*—have been found to carry sporozoites of primate malaria parasites (e.g., *Plasmodium inui*), highlighting the risk of spillover in deforested landscapes (Permana et al., 2023).
- Microclimatic sensitivities: Temperature within the 25–32 °C range accelerates mosquito and parasite development, whereas precipitation effects vary across regions, shaping the spatial heterogeneity of incidence (Wang et al., 2023).
- Landscape fragmentation and deforestation: Forest edges, mining zones, and disturbed habitats often create mosquito breeding grounds, disproportionately affecting vulnerable communities near them.
- Ecological complexity beyond broad indices: Malaria's persistence is mediated by localized vector behavior, primate reservoirs, and micro-habitat suitability—factors not captured by generalized indices like the EQI.

This divergence emphasizes that while integrated environmental policies can substantially reduce the burden of most infectious diseases, malaria requires site-specific ecological interventions, such as targeted vector habitat management, insecticide-treated nets, and community-based surveillance. Recognizing malaria's ecological distinctiveness strengthens the manuscript by highlighting the limits of generalized environmental approaches and the need for tailored, locally adaptive control strategies.

# Conclusion

Infectious diseases in Indonesia exhibit apparent spatial clustering, particularly in Java and parts of Sumatra, where high urban density and shared infrastructure contribute to a high disease burden. Diseases like tuberculosis, diarrhea, hepatitis, and pneumonia display moderate spatial dependence, meaning that provinces with high case numbers often border others with similar rates. This underscores the need for coordinated public health efforts across neighboring regions. In contrast, malaria follows a different pattern. It does not cluster with other diseases and exhibits a negative spatial relationship, meaning that high malaria incidence in one province often coincides with low incidence in nearby provinces. This suggests that malaria is driven more by local ecological conditions—such as forest cover and mosquito habitat—than by regional transmission dynamics.

The identification of high-high clusters (e.g., in Java) reveals persistent disease hotspots that require integrated health strategies. In contrast, mismatched clusters (high-low or low-high) indicate risks of spillover and local outbreaks. Low-low clusters in more remote areas may reflect genuine low incidence or simply weak surveillance systems. Overall, these spatial patterns highlight the importance of combining environmental improvements—such as clean water, better housing, and sanitation—with targeted interventions for specific diseases. Addressing spatial dynamics in public health planning can lead to more effective surveillance, prevention, and control of infectious diseases across Indonesia.

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