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Population and Housing Density as Determinants of Tuberculosis Distribution: Evidence from Spatial and Statistical Analysis

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ABSTRACT

Tuberculosis remains a major public health problem in Indonesia, influenced by environmental and demographic factors such as population density and housing density. This study aims to analyze the statistical relationship between population density, housing density, and tuberculosis cases in Rancaekek Subdistrict, Bandung Regency, in 2024. A quantitative cross-sectional correlational design was applied using village-level data (n = 14 villages). Population density data were obtained from the Central Bureau of Statistics, housing density was derived from Google Earth image digitization, and tuberculosis case data were collected from public health centers. Pearson correlation analysis was performed using SPSS, and Geographic Information Systems (GIS) were used for spatial visualization. The results show a very strong and significant positive correlation between population density and tuberculosis cases ($r = 0.976$, $p < 0.001$) and between housing density and tuberculosis cases ($r = 0.981$, $p < 0.001$). Spatial visualization confirms that areas with higher density tend to have higher tuberculosis incidence. These findings indicate that population density and housing density are important determinants of tuberculosis distribution at the village level. The integration of statistical analysis and spatial visualization provides useful evidence to support targeted public health interventions.

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1. INTRODUCTION

Tuberculosis (TB) remains one of the leading causes of morbidity and mortality in developing countries (WHO, 2023). According to the World Health Organization, TB continues to be a major global health burden, with millions of new cases reported annually and Indonesia ranking among the countries with the highest number of cases (WHO, 2025). The persistence of TB is influenced not only by medical factors but also by environmental and demographic conditions that shape transmission dynamics (Nurbaya and Erminawati, 2025).

Population density and housing density are widely recognized as key determinants in TB epidemiology. High population density intensifies social interaction, thereby facilitating the airborne transmission of Mycobacterium tuberculosis (Kemenkes, 2024). Similarly, high housing density is often associated with overcrowding, inadequate ventilation, and suboptimal sanitation, which further elevate the risk of TB transmission (Supit et al., 2025; Sitompul et al., 2024). Previous studies have shown that the spatial distribution of TB cases tends to follow population density patterns, with statistically significant correlations observed in several regions (Supit et al., 2025).

West Java Province is one of the regions experiencing rapid population growth and increasing housing density due to urbanization and industrial development (Badan Pusat Statistik, 2024). This growth has contributed to higher population concentration in urban and peri-urban areas and has been associated with increased tuberculosis incidence (WHO, 2025). Rancaekek Subdistrict, as part of Bandung Regency, represents a rapidly developing area characterized by heterogeneous population distribution, high mobility, and diverse settlement patterns (Sari et al., 2022; Rohman et al., 2024). In rapidly developing areas, uneven population distribution and high mobility can contribute to spatial disparities in disease incidence, including tuberculosis, due to variations in environmental exposure and access to health services (Yang et al., 2022). In 2024, population density in this area reached 4,050 people/km², accompanied by a considerable number of tuberculosis cases, indicating a potential relationship between demographic and environmental factors and disease occurrence.

Modern epidemiological studies emphasize the importance of statistical methods to objectively measure the strength and significance of relationships between variables (Mutasodirin et al., 2021). Techniques such as correlation analysis are widely used to evaluate associations between environmental factors and disease incidence, while Geographic Information Systems (GIS) are applied to visualize spatial distribution patterns (Mahawati et al., 2023; Razak et al., 2025). However, many previous studies primarily rely on descriptive or spatial approaches without conducting rigorous statistical testing to quantify these relationships (Aslam, 2024). Although spatial mapping is useful for illustrating disease distribution, it cannot independently confirm whether observed patterns reflect statistically significant relationships or are influenced by random variation (Mahawati et al., 2023).

In addition, most existing research has been conducted at broader regional or provincial scales, which may not capture local variations in transmission dynamics (Dudáš, 2024). Village-level analysis is essential because tuberculosis transmission is strongly influenced by localized environmental and demographic characteristics, including housing concentration, population clustering, and patterns of social interaction (WHO, 2023) . Despite its importance, studies that utilize recent, fine-scale data at the village level remain limited.

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Therefore, this study addresses these gaps by integrating statistical correlation analysis with GIS-based spatial visualization using recent village-level data. This approach provides both quantitative measurement and spatial interpretation of the relationship between population density, housing density, and tuberculosis cases. By combining these methods, this study offers a more comprehensive and localized understanding of TB distribution and contributes to evidence-based public health decision-making.

This research aims to analyze the statistical relationship between population density, housing density, and tuberculosis cases in Rancaekek Subdistrict, Bandung Regency. The findings are expected to contribute to the development of spatial epidemiology studies and support targeted tuberculosis control strategies at the local level.

2. METHODS

This study employs a quantitative correlational approach to analyze the relationships among population density, housing density, and tuberculosis cases in Rancaekek Subdistrict, Bandung Regency, in 2024. A cross-sectional research design was applied, in which all data were collected within the same time period. The quantitative approach was selected to obtain objective, measurable results through statistical analysis, while spatial analysis using Geographic Information Systems (GIS) served as a supporting tool to strengthen the interpretation of the findings.

The research was conducted in Rancaekek Subdistrict, Bandung Regency, which comprises 13 villages and 1 urban village, covering a total area of 46.49 km². The unit of analysis in this study is the village/urban village, resulting in a total of 14 observational units (n = 14).

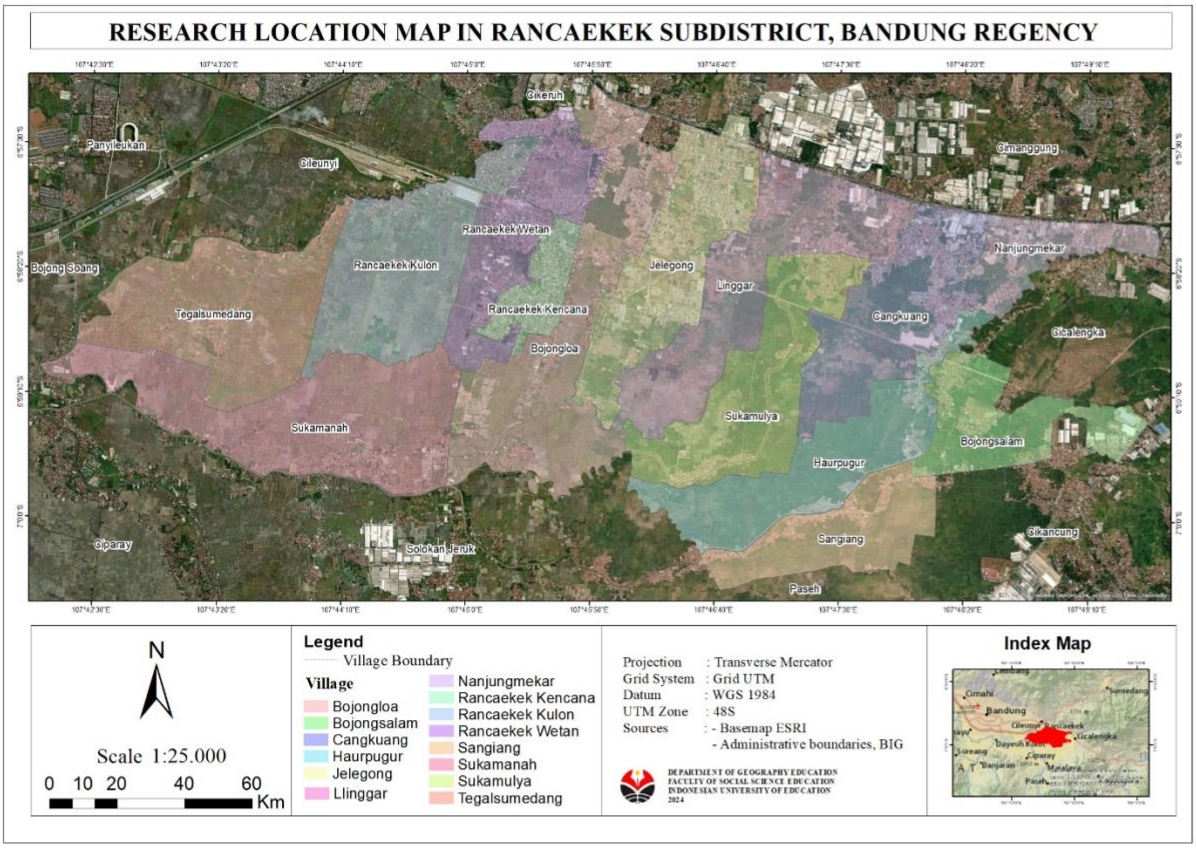

Figure 1. Research Location Map

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This study uses secondary data obtained from official institutions. Population and area data for each village were sourced from the Central Bureau of Statistics (Badan Pusat Statistik Kabupaten Bandung, 2024). Tuberculosis case data for 2024 were obtained from the Bandung Regency Health Office (Dinas Kesehatan Kabupaten Bandung, 2024). Administrative boundary data were obtained from Badan Informasi Geospasial.

In addition, housing data were derived from Google Earth imagery via digitization. This process involved interpreting high-resolution satellite imagery, digitizing individual building units within village boundaries, and calculating housing density by dividing the number of residential units by each village's area.

Pearson correlation analysis was used to examine the relationships among population density, housing density, and tuberculosis cases across the 14 villages. Each village represents one observation unit in the analysis. The variables used in this study are presented in Table 1.

Table 1. Research Variable

Variable	Type	Description
Tuberculosis case (Y)	Dependent	Number of confirmed TB cases per village in 2024
Population density (X_1)	Independent	Number of inhabitants per km²
Housing density (X_2)	Independent	Number of housing units per km²

Source: Author's Analysis.

2.1 Population Density

Population density data were obtained from Badan Pusat Statistik, Kecamatan Rancaekek. Population density was calculated as the number of inhabitants per square kilometer (people/km²) for each village and used as one of the independent variables in the statistical analysis. All data were processed and analyzed using the Statistical Package for the Social Sciences (SPSS).

Table 2. Population Density in Rancaekek Subdistrict

No	Village	Population Density (People/km²)
1	Bojongloa	5.019
2	Bojongsalam	3.659
3	Cangkuang	2.390
4	Haurpugur	2.234
5	Jelegong	5.029
6	Linggar	3.325
7	Nanjungmekar	8.515
8	Rancaekek Kencana	20.463
9	Rancaekek Kulon	4.520
10	Rancaekek Wetan	10.749
11	Sangiang	2.863
12	Sukamanah	1.841
13	Sukamulya	2.646
14	Tegalsumedang	1.175

Source: Badan Pusat Statistik, Kecamatan Rancaekek.

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Population density data were subsequently transformed into spatial data and visualized using Geographic Information Systems (GIS). To support spatial analysis, population density values were classified into three categories low, medium, and high using a scoring method adapted using a scoring-based classification method adapted from GIS-based risk classification approaches (Rahman et al., 2021; Ahmed, 2024). The classification thresholds are based on percentage ranges derived from the relative distribution of density values in the study area.

Table 3. Population Density Classification

Population Density (People/km²)	Classification	Score
≥ 70,16%	High	3
40,08% – 70,15%	Medium	2
≤ 40,07%	Low	1

Source: Rahman et al., 2021, with modifications.

2.2 Housing Density

Housing density was derived from Google Earth satellite imagery via digitization. Building units within each village boundary were manually identified and digitized using GIS software, based on administrative boundary shapefiles (SHP) obtained from Badan Informasi Geospasial.

The digitization process involved the following steps: (1) Interpreting high-resolution Google Earth imagery; (2) Digitizing individual residential buildings within village boundaries; (3) Calculating the total number of housing units in each village; and (4) Dividing the total number of housing units by the village area to obtain housing density (units/km²). The resulting housing density values were used as an independent variable in the statistical analysis to examine their relationship with tuberculosis cases.

For spatial analysis, housing density values were classified into three categories low, medium, and high using a scoring method. Housing density classification refers to urban density standards (UN-Habitat, 2020). The classification thresholds are defined as follows **(Table 4)**:

Table 4. Housing Density Classification

Housing Density (units/km²)	Classification	Score
≥ 80%	High	3
60% – 70 %	Medium	2
≤ 50%	Low	1

Source: UN-Habitat, 2020.

2.3 Tuberculosis Cases

Tuberculosis (TB) case data were obtained from public health centers (Puskesmas) in Rancaekek Subdistrict for the year 2024, under the administration of the Bandung Regency Health Office (Dinas Kesehatan Kabupaten Bandung, 2024). The data represent the number of confirmed TB cases recorded in each village. All TB case data were aggregated at the village level to ensure consistency with the unit of analysis (n = 14 villages). Prior to analysis, the data were cleaned, verified, and organized using Microsoft Excel to ensure accuracy and

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completeness. The number of confirmed TB cases per village was used as the dependent variable (Y) in the statistical analysis to examine its relationship with population density and housing density.

2.4 Pearson's Correlation

Correlation analysis was preceded by a normality test on all research variables as a prerequisite for using Pearson's correlation. Pearson correlation is widely used to measure the strength and direction of the relationship between variables (Schober et al., 2021; Jabnabillah and Margina, 2022). The normality test was performed using the Shapiro–Wilk method because the data used in this study is < 50 data. The basis for decision making can be done based on probability (Asymptotic Significant), namely if the significance value $Sig. > 0{,}05$ and are distributed abnormally if the significance value $Sig. < 0{,}05$. Pearson correlation analysis was used to analyze the relationship in this study. Pearson correlation requires interval or ratio data and assumes normally distributed variables (Schober et al., 2021).

Since all variables met the normality assumption, Pearson correlation analysis was applied to examine the relationship between:

- Population density (X_1) and tuberculosis cases (Y)
- Housing density (X_2) and tuberculosis cases (Y)

The Pearson correlation coefficient (r) was used to measure the strength and direction of the linear relationship between variables. The coefficient ranges from -1 to +1, where values closer to ±1 indicate stronger relationships, while values closer to 0 indicate weaker relationships. A positive value indicates a direct (parallel) relationship, whereas a negative value indicates an inverse relationship.

Pearson's correlation coefficient (r) is defined as:

$$r = \frac{n\sum XY - (\sum X)(\sum Y)}{\sqrt{[n\sum X^2 - (\sum X)^2][n\sum XY^2 - (\sum X)^2]}}$$

where:

r = pearson correlation coefficient

n = number of observations (villages)

X = independent variable (population density or housing density)

Y = dependent variable (tuberculosis cases)

$\sum XY$ = sum of the product of paired scores

$\sum X$ = sum of values of each variable (X)

$\sum Y$ = sum of values of each variable (Y)

$\sum X^2$ = sum of squared values (X)

$\sum Y^2$ = sum of squared values (Y)

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Hypothesis testing was conducted using the Statistical Package for the Social Sciences (SPSS). The hypotheses were formulated as follows:

H_0 There is no significant relationship between population density, housing density, and tuberculosis cases.

H_1 There is a significant relationship between population density, housing density, and tuberculosis cases.

The decision rule was based on the significance value (p-value), where:

- $p < 0.05$ indicates a statistically significant relationship
- $p \geq 0.05$ indicates no statistically significant relationship

The strength of the correlation was interpreted based on the Pearson correlation coefficient values, as shown in **Table 5**.

Table 5. Interpretation of Correlation Coefficient

r	**Correlation Strength**
0	No correlation
0.00 – 0.25	Very weak
0.25 – 0.50	Moderate
0.50 – 0.75	Strong
0.75 – 0.99	Very strong
1	Perfect

Source: Schober et al., 2021.

2.5 Data and Spatial Analysis

The data used in this study consisted of population data obtained from the Central Bureau of Statistics (BPS), housing data derived from Google Earth imagery through building interpretation and digitization, and tuberculosis (TB) case data obtained from Dinkes Kabupaten Bandung (Dinkes Kabupaten Bandung, 2024).

Population density was calculated by dividing the total population by the area of each village, resulting in units of people per square kilometer (people/km²). Housing density was calculated by dividing the number of residential buildings by the village area, resulting in units of housing units per square kilometer (units/km²). Tuberculosis case data were aggregated at the village level and used as the dependent variable in the analysis.

Statistical analysis was conducted using Pearson correlation to assess the strength and direction of the relationships among population density, housing density, and tuberculosis cases. The correlation coefficient (r) was used to quantify the relationship, while the significance value (p-value) was used to determine statistical significance. All statistical analyses were performed using SPSS software.

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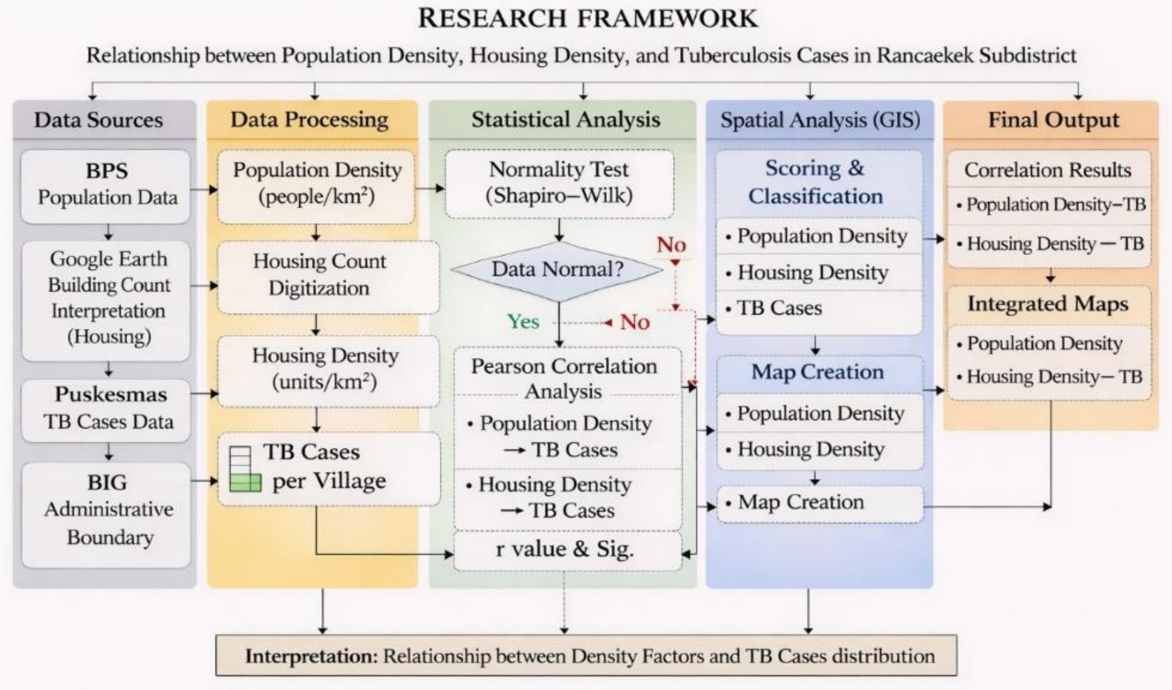

Figure 2. Research Framework

In addition to statistical analysis, spatial analysis was conducted using Geographic Information Systems (GIS) to visualize the distribution of population density, housing density, and tuberculosis cases. GIS-based spatial analysis has been widely used in epidemiological studies to identify disease clusters and analyze spatial relationships between environmental factors and disease incidence (Wang et al., 2022). The variables were classified into categories using a scoring method and presented as thematic maps. These maps were then overlaid with tuberculosis case data to identify spatial patterns and support the interpretation of statistical results. The integration of statistical and spatial analyses provided both quantitative and geographic insights into the relationships among population density, housing density, and tuberculosis cases.

2.6 Study Limitation

This study is subject to limitations due to the relatively small sample size (n = 14 villages), which may affect the stability and generalizability of the statistical results, particularly the correlation coefficients. Therefore, the findings should be interpreted with caution. This limitation is further discussed in the Results and Discussion section and explicitly acknowledged in the conclusion.

3. RESULTS AND DISCUSSION

3.1 Normality Test

Prior to the correlation analysis, a normality test was conducted to ensure that the data met the assumption of normal distribution. Since the sample size in this study was fewer than 50 (n = 14), the Shapiro–Wilk test was used, as it is considered more appropriate for small sample sizes (Schober et al., 2021).

Table 6. Results of Normality Test (Shapiro–Wilk and Kolmogorov–Smirnov)

Variable	Kolmogorov–Smirnov Statistic	df	Sig.	Shapiro–Wilk Statistic	df	Sig.
Population Density (X_1)	0.160	14	0.200	0.964	14	0.768
Housing Density (X_2)	0.193	14	0.167	0.893	14	0.089
Tuberculosis Cases (Y)	0.197	14	0.145	0.915	14	0.188

Source: Author's analysis using SPSS.

The results of the Shapiro–Wilk test indicate that all variables are normally distributed, with significance values greater than 0.05: population density ($p = 0.768$), housing density ($p = 0.089$), and tuberculosis cases ($p = 0.188$). Therefore, the null hypothesis of normal distribution cannot be rejected, indicating that the data satisfy the assumption of normality.

The Kolmogorov–Smirnov test also yielded p-values above 0.05 for all variables (population density $p = 0.200$; housing density $p = 0.167$; tuberculosis cases $p = 0.145$), further supporting the conclusion that the data are normally distributed.

Since the assumption of normality is fulfilled, Pearson correlation analysis is considered statistically appropriate for examining the relationships among variables in this study (Mutasodirin et al., 2021).

3.2 Correlation between Population Density and Tuberculosis Cases

The analysis indicates a very strong and statistically significant positive correlation between population density and tuberculosis cases ($r = 0.976$, $p < 0.001$). This result suggests that areas with higher population density tend to have more TB cases. Based on the correlation interpretation guidelines, this coefficient falls within the "very strong" category (0.75–0.99) (Schober et al., 2021).

Table 7. Pearson Correlation Matrix between Population Density, Housing Density, and Tuberculosis Cases

Variable	Population Density (X_1)	Housing Density (X_2)	Tuberculosis Cases (Y)
Population Density (X_1)	1	0.973**	0.976**
Housing Density (X_2)	0.973**	1	0.981**
Tuberculosis Cases (Y)	0.976**	0.981**	1

Source: Author's analysis using SPSS.

**Note: **Correlation is significant at the 0.01 level ($p < 0.01$)

This finding is consistent with previous studies that highlight the role of population density in shaping TB transmission dynamics (WHO, 2025; Mohidem et al., 2021). Higher population concentration increases the intensity of social interaction, which contributes to the spread of infectious diseases.

However, the correlation coefficient obtained in this study is extremely high ($r > 0.97$) and should therefore be interpreted with caution. This result may be influenced by several factors, including the relatively small sample size ($n = 14$), potential clustering effects at the village level, and limited variability in the dataset. These conditions may inflate correlation coefficients, resulting in stronger observed relationships.

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3.3 Correlation between Housing Density and Tuberculosis Cases

A very strong and statistically significant positive correlation was found between housing density and tuberculosis cases (r = 0.981, p < 0.001). This indicates that areas with higher housing density tend to have more TB cases. Based on correlation interpretation guidelines, this coefficient falls within the "very strong" category (0.75–0.99) (Schober et al., 2021; Janse et al., 2021).

This finding is consistent with previous studies that emphasize the importance of residential environmental conditions in TB transmission (Supit et al., 2025; WHO, 2025). Compared to population density, housing density shows a slightly higher correlation coefficient, suggesting that housing conditions such as overcrowding, limited ventilation, and close proximity between residents may represent a more direct environmental risk factor influencing tuberculosis incidence.

However, as with the results for population density, the very high correlation (r > 0.97) should be interpreted with caution. This may be influenced by the relatively small sample size (n = 14), potential spatial clustering at the village level, and limited variability in the dataset. These factors may inflate correlation coefficients and lead to stronger observed relationships.

3.4 Correlation between Population Density and Housing Density

The results show a very strong and statistically significant positive correlation between population density and housing density (r = 0.973, p < 0.001). This indicates that villages with higher population density also tend to have higher housing density.

This finding suggests that both variables represent closely related structural characteristics of settlement patterns, in which increases in population concentration are generally accompanied by higher housing density. Such conditions reflect spatial clustering in residential development.

However, the strong intercorrelation between these independent variables may indicate potential multicollinearity if both are included simultaneously in multivariate models. This issue should be considered in future research, and additional diagnostic tests, such as the Variance Inflation Factor (VIF), are recommended to assess the extent of multicollinearity.

3.5 Spatial Analysis of Population Density and Tuberculosis Cases

Spatial analysis using Geographic Information Systems (GIS) was conducted to visualize the distribution of population density and its relationship with tuberculosis cases in Rancaekek Subdistrict. The population density map was generated using a scoring-based classification method, categorizing villages into low, medium, and high density levels.

High population density areas are concentrated in villages such as Rancaekek Kencana, Rancaekek Wetan, Jelegong, and Nanjungmekar, while moderate density is observed in Bojongloa, Bojongsalam, Linggar, Sangiang, and Rancaekek Kulon. Low-density areas include Haurpugur, Cangkuang, Sukamulya, Sukamanah, and Tegalsumedang.

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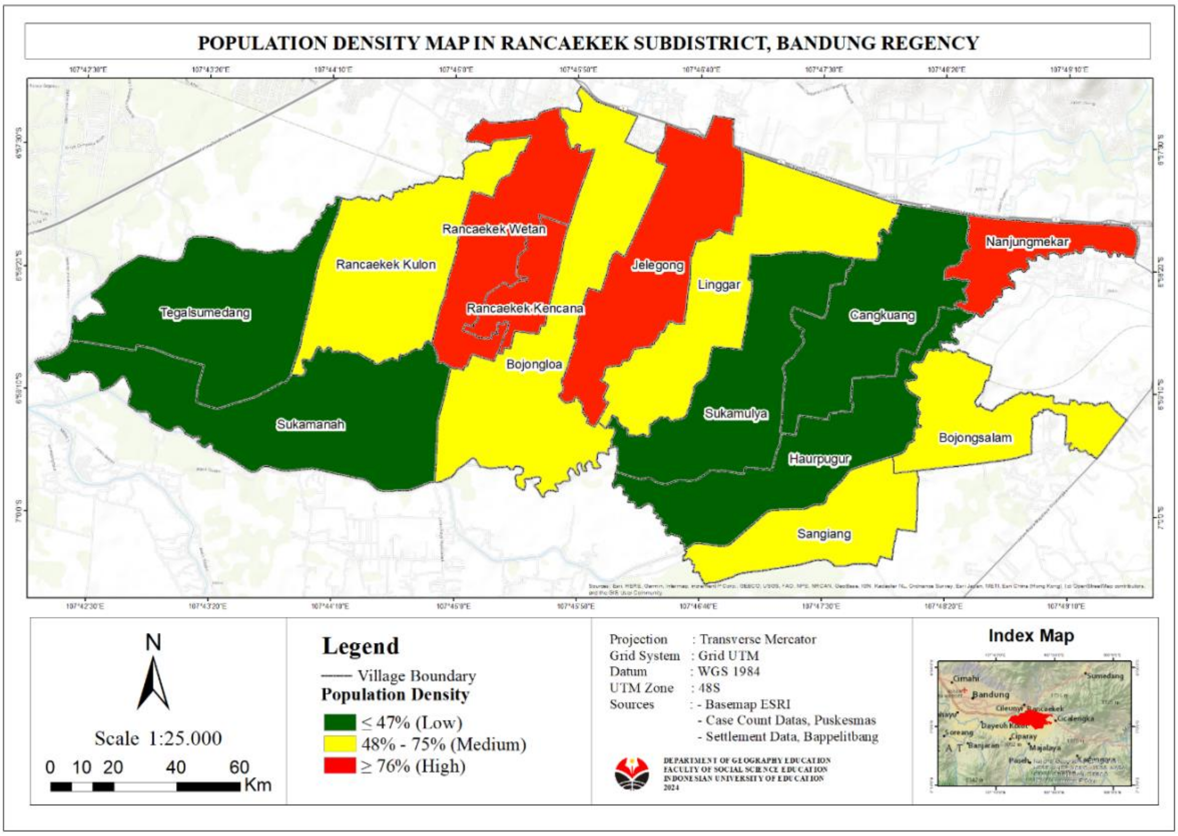

Figure 3. Population Density Map

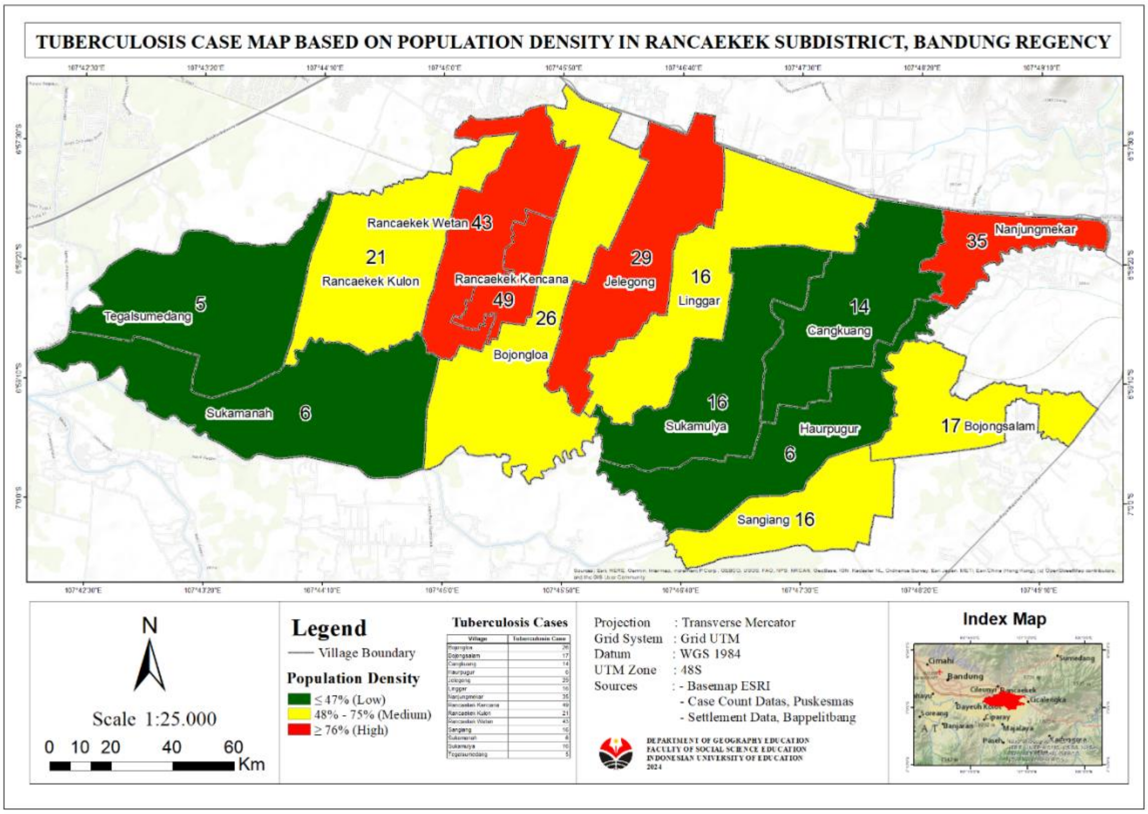

Figure 4. Tuberculosis Case Map Based on Population Density

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The spatial overlay of population density and tuberculosis cases shows a consistent pattern: high density areas tend to exhibit higher TB case counts. For example, villages classified as high-density, such as Rancaekek Kencana and Rancaekek Wetan, also record the highest numbers of tuberculosis cases. In contrast, villages with lower population density generally show fewer cases.

Table 8. Classification of Population Density by Village and Tuberculosis Cases

Population Density	Village	Tuberculosis Cases
≥ 70,16% (Low)	Cangkuang	14
	Haurpugur	6
	Sukamulya	16
	Sukamanah	6
	Tegalsumedang	5
40,08% – 70,15% (Medium)	Bojongloa	26
	Bojongsalam	17
	Linggar	16
	Sangiang	16
	Rancaekek Kulon	21
≥ 70,16% (High)	Nanjungmekar	35
	Rancaekek Kencana	49
	Rancaekek Wetan	43
	Jelegong	29

Source: Author's Analysis.

This spatial pattern supports the statistical findings presented earlier, indicating a strong association between population density and tuberculosis cases. Similar patterns have been reported in previous studies, where areas with higher population concentration tend to exhibit higher tuberculosis incidence (Mutasodirin et al., 2021; Mohidem et al., 2021). Furthermore, the observed spatial relationship is consistent with global epidemiological evidence emphasizing the role of population density in influencing TB distribution (WHO, 2025).

Overall, the spatial distribution highlights that population concentration plays an important role in shaping local disease patterns. The integration of spatial visualization with statistical analysis provides stronger evidence that areas with higher population density tend to have a greater tuberculosis burden density (Supit et al., 2025).

3.6 Spatial Analysis of Housing Density and Tuberculosis Cases

Spatial analysis using Geographic Information Systems (GIS) was conducted to visualize the distribution of housing density and its relationship with tuberculosis cases in Rancaekek Subdistrict. The housing density map was derived from Google Earth imagery via digitization and classified into low, medium, and high categories using a scoring method.

High housing density areas are concentrated in villages such as Rancaekek Kencana, Rancaekek Wetan, and Nanjungmekar. Moderate density is observed in Bojongloa and Jelegong, while low-density areas include Linggar, Sangiang, Bojongsalam, Haurpugur, Cangkuang, Sukamulya, Sukamanah, Rancaekek Kulon, and Tegalsumedang.

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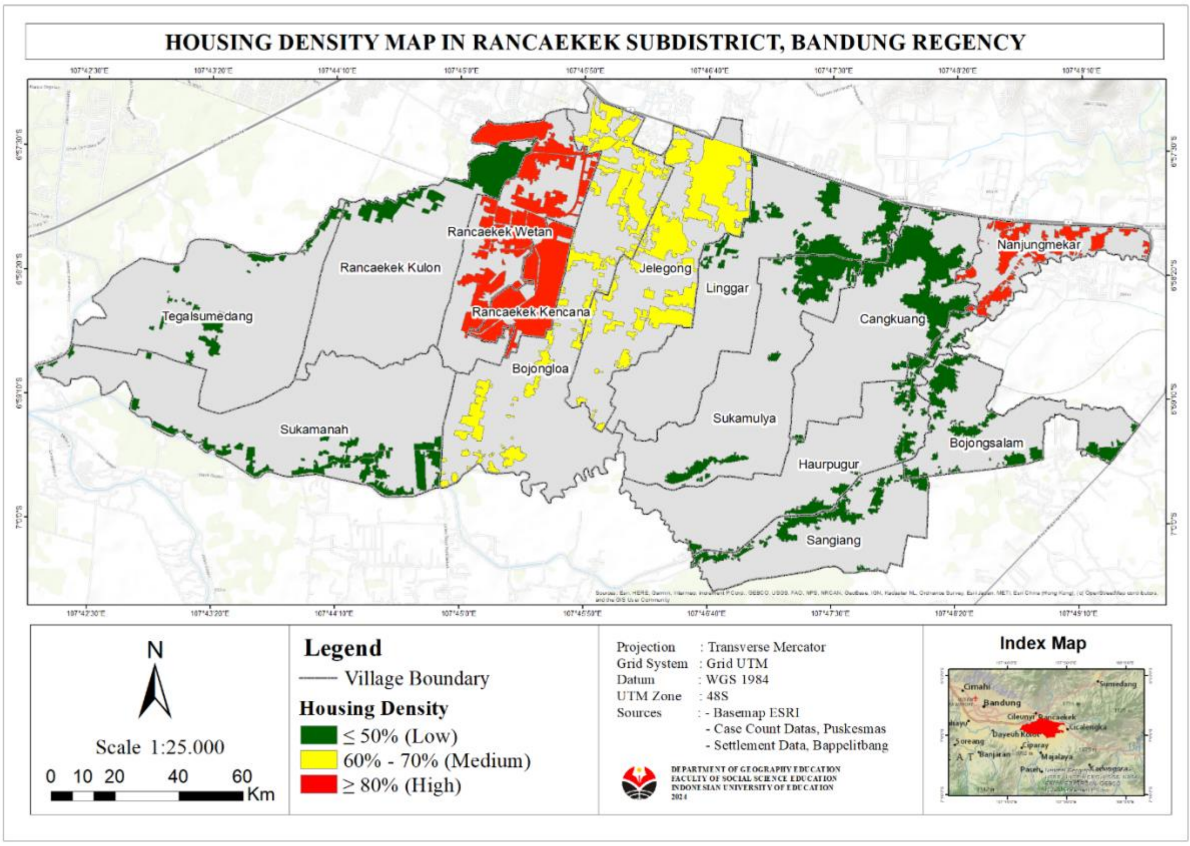

Figure 5. Housing Density Map

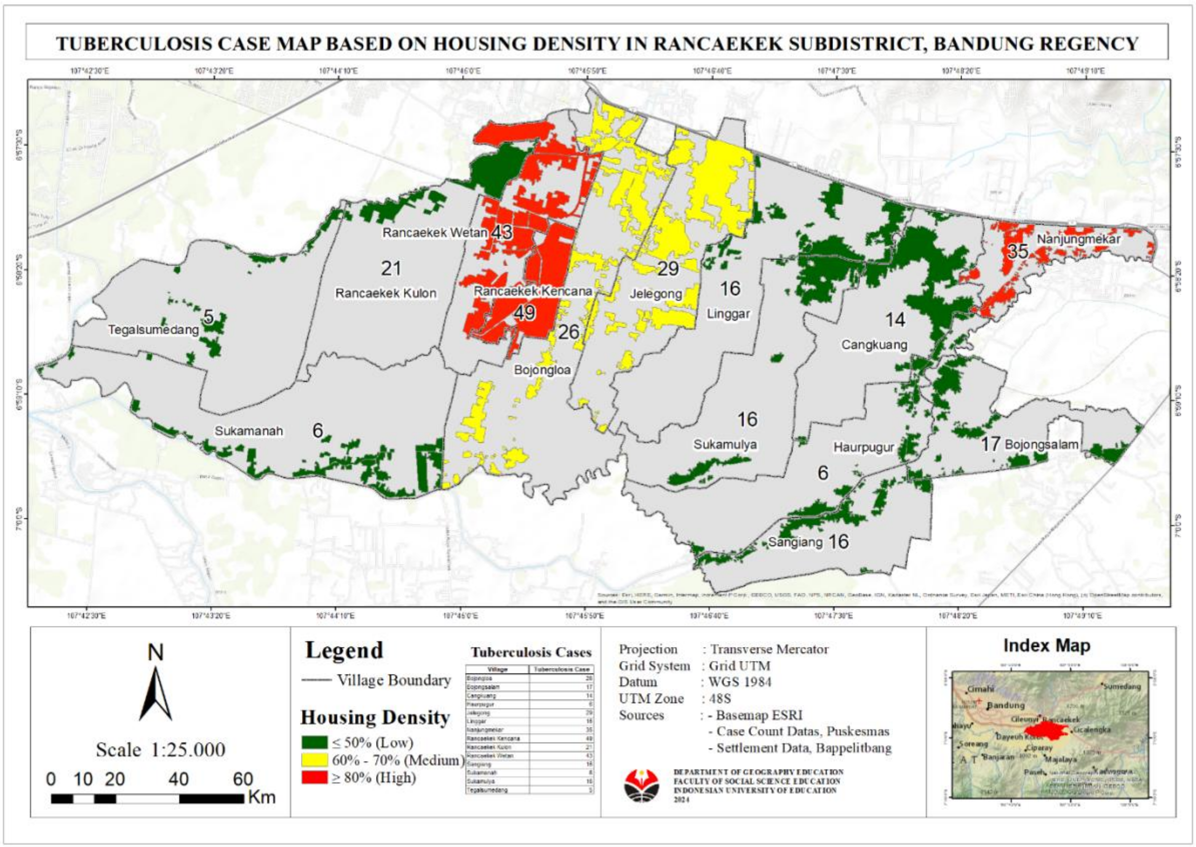

Figure 6. Tuberculosis Case Map Based on Housing Density

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The spatial overlay of housing density and tuberculosis cases shows a consistent pattern: areas with higher housing density tend to have higher TB case counts. Villages classified as high density, such as Rancaekek Kencana and Rancaekek Wetan, also record the highest numbers of tuberculosis cases, indicating spatial clustering.

Table 9. Classification of Housing Density by Village and Tuberculosis Cases

Population Density	Village	Tuberculosis Cases
≥ 80% (Low)	Bojongsalam	17
	Cangkuang	14
	Haurpugur	6
	Linggar	16
	Rancaekek Kulon	21
	Sangiang	16
	Sukamulya	16
	Sukamanah	6
	Tegalsumedang	5
60% – 70% (Medium)	Bojongloa	26
	Jelegong	29
≥ 50% (High)	Nanjungmekar	35
	Rancaekek Kencana	49
	Rancaekek Wetan	43

Source: Author's Analysis.

The spatial overlay of housing density and tuberculosis cases shows a consistent pattern in wh This spatial pattern supports the statistical findings presented earlier, indicating a strong association between housing density and tuberculosis incidence. Similar spatial relationships have been identified in previous studies, in which densely built residential areas tend to exhibit higher concentrations of tuberculosis (Mutasodirin et al., 2021; Supit et al., 2025).

The clustering of tuberculosis cases in high-density settlements suggests that residential environmental conditions play a crucial role in shaping disease distribution. Studies have shown that overcrowded housing, limited ventilation, and suboptimal environmental quality contribute significantly to the spread of tuberculosis (Mahawati et al., 2023; WHO, 2025). These conditions are commonly found in areas with high housing density, reinforcing the observed spatial patterns.

Overall, the integration of spatial visualization and statistical analysis strengthens the evidence that housing density is an important determinant of tuberculosis distribution. The spatial approach also provides practical insights for identifying high-risk areas and supports targeted public health interventions for tuberculosis control (Supit et al., 2025).

4. CONCLUSIONS

This study demonstrates that population and housing densities have strong, statistically significant relationships with tuberculosis cases in Rancaekek Subdistrict in 2024. Population density shows a very strong positive correlation with tuberculosis cases ($r = 0.976$, $p < 0.001$), while housing density exhibits an even slightly higher correlation ($r = 0.981$, $p < 0.001$), indicating that both demographic and residential factors play important roles in influencing tuberculosis incidence.

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In addition, the strong correlation between population density and housing density ($r = 0.973$, $p < 0.001$) reflects closely related settlement characteristics and spatial clustering patterns. Spatial analysis using GIS further supports these findings, showing that villages with higher population density, such as Rancaekek Kencana, Rancaekek Wetan, and Nanjungmekar, consistently have higher tuberculosis case counts.

These findings highlight that population density and housing density are key determinants of tuberculosis distribution at the village level. The integration of statistical correlation and spatial analysis provides a more comprehensive understanding of disease patterns and offers valuable insights for identifying high-risk areas and supporting targeted public health interventions.

However, this study has several limitations. The relatively small sample size ($n = 14$) may affect the stability of statistical estimates and potentially inflate correlation coefficients. In addition, the cross-sectional design limits the ability to infer causal relationships between variables. Therefore, the findings should be interpreted as indicative of strong associations rather than causation.

Future studies are recommended to incorporate larger datasets, additional socioeconomic and environmental variables, and more advanced spatial or multivariate statistical approaches to provide more robust and comprehensive evidence for tuberculosis control strategies.

5. RECOMMENDATIONS

Based on the findings, it is recommended that the Bandung Regency Health Office and public health centers prioritize tuberculosis control programs in villages with high population and housing density. These efforts may include intensified active case finding, routine screening, and GIS-based spatial surveillance to support targeted and evidence-based interventions.

Local governments and spatial planning authorities are also encouraged to integrate public health considerations into settlement development policies. This includes regulating residential density, improving housing ventilation, and enhancing environmental sanitation to reduce overcrowding and minimize the risk of tuberculosis transmission in rapidly developing areas.

For future research, it is recommended to apply more advanced analytical approaches, such as multivariate regression and spatial statistical methods (e.g., Geographically Weighted Regression/GWR), and to incorporate additional socioeconomic and environmental variables. Expanding the dataset and applying longitudinal study designs would further improve the robustness and generalizability of findings in spatial epidemiological studies.

6. REFERENCES

Ahmed, R., Jarin, N. Z., & Rahman, O. (2024). Spatiotemporal Dynamics of Flood Exposure in Bangladesh: A GIS and Remote Sensing Based Approach. In *Flood Risk Management: Assessment and Strategy* (pp. 1-22). Singapore: Springer Nature Singapore.

Aslam, M. (2024). Analysis of imprecise measurement data utilizing z-test for correlation. *Journal of Big Data*, *11*(1). https://doi.org/10.1186/s40537-023-00873-7

Badan Pusat Statistik. (2024). *Kecamatan Rancaekek Dalam Angka 2024*. *14*.

Dinkes Kabupaten Bandung. (2024). Profil Kesehatan Dinas Kesehatan Kabupaten Bandung Tahun 2024. Bandung: Dinas Kesehatan Kabupaten Bandung

Dudáš, A. (2024). Graphical representation of data prediction potential: correlation graphs and correlation chains. *Visual Computer*, *40*(10), 6969–6982. https://doi.org/10.1007/s00371-023-03240-y

Jabnabillah, F., and Margina, N. (2022). … Korelasi Pearson Dalam Menentukan Hubungan Antara Motivasi Belajar Dengan Kemandirian Belajar Pada Pembelajaran Daring. *Jurnal Sintak*, *1*, 14–18. https://journal.iteba.ac.id/index.php/jurnalsintak/article/view/23%0Ahttps://journal.iteba.ac.id/index.php/jurnalsintak/article/download/23/23

Janse, R. J., Hoekstra, T., Jager, K. J., Zoccali, C., Tripepi, G., Dekker, F. W., & Van Diepen, M. (2021). Conducting correlation analysis: important limitations and pitfalls. *Clinical kidney journal*, *14*(11), 2332-2337.

Kemenkes. (2024). *Indonesia Masuki Periode Aging Population*.

Mahawati, E., Surjati, E., Saputra, M. K. F., Sudasman, F. H., and Pertiwi, I. (2023). Hubungan Lingkungan Fisik Rumah Dengan Kejadian Tuberkulosis Paru. *The Indonesian Journal of Infectious Diseases*, *9*(1), 1–12. https://doi.org/10.32667/ijid.v9i1.169

Mohidem, N. A., Osman, M., Hashim, Z., Muharam, F. M., Elias, S. M., and Shaharudin, R. (2021). Association of sociodemographic and environmental factors with spatial distribution of tuberculosis cases in Gombak, Selangor, Malaysia. In *PLoS ONE* (Vol. 16, Issue 6 June 2021). https://doi.org/10.1371/journal.pone.0252146

Mutasodirin, M. A., Rizqullah, R. D., Setiyoko, A., and Arymurthy, A. M. (2021). Settlement Mapping for Population Density Modelling in Disease Risk Spatial Analysis. *Proceedings - IWBIS 2021: 6th International Workshop on Big Data and Information Security*, 73–80. https://doi.org/10.1109/IWBIS53353.2021.9631853

Nurbaya, and Erminawati, J. 1. (2025). Association Between Housing Density and Pulmonary Tuberculosis Prevalence in a Coal Mining Area of South Kalimantan, Indonesia. *Global Health and Environmental Perspectives*, 3047–0617. https://riverstudies.id/index.php/ghephttps://scholar.google.com/citations?view_op=list_worksandhl=idanduser=ntlDXPIAAAAJ

Rahman, M. T., et al. (2021). GIS-based risk assessment using classification methods. *Environmental Monitoring and Assessment*.

Razak, R., Rahmadina, F., & Santiyah, S. (2025). Faktor kondisi fisik lingkungan rumah terhadap kasus tuberkulosis di Indonesia: Systematic review. *Jurnal Ilmiah Kesehatan*, *17*(1), 130-142.

Rohman, H., & Nurrochman, A. (2024). Development of a WEBGIS-Mapping Information System of Tuberculosis (MISS TB) For Plotting Tuberculosis Cases: A Case Study in Sleman District, Yogyakarta Province, Indonesia. *Procedia of Engineering and Life Science*, *6*, 246-257.

DOI: https://doi.org/10.17509/gea.v26i1,%20April.97831
p-ISSN 1412-0313 e- ISSN 2549-7529

Rohman, H., Enjang, H. K., & Kusuma, O. N. (2024). Pemetaan Persebaran dan Trendline Kasus Tuberkulosis Di Wilayah Gunungkidul. *Jurnal Ilmu Kesehatan Bhakti Setya Medika*, *9*(1).

Sari, A. D. L., Rohman, H., and ... (2022). Analisis Informasi Kesehatan Melalui Pemetaan Penyakit Tuberkulosis Pada Masa Pandemi Covid-19. *Jurnal Amanah …*, *4*(1), 20–27. http://ojs.stikesamanahpadang.ac.id/index.php/JAK/article/view/140

Schober, P., Boer, C., and Schwarte, L. A. (2021). Correlation coefficients: appropriate use and interpretation. Anesthesia and Analgesia.

Sitompul, I. S., & Ashar, T. (2024). Analisis spasial persebaran dan faktor risiko tuberkulosis paru di wilayah kerja Puskesmas Hutabaginda Kecamatan Tarutung Kabupaten Tapanuli Utara tahun 2022. *TROPHICO*, *4*(2), 76-85.

Supit, N., Ratag, B. T., and Nelwan, J. E. (2025). Analisis Spasial Penyakit Tuberkulosis Di Kabupaten Minahasa Utara Tahun 2021-2024. *Prepotif : Jurnal Kesehatan Masyarakat*, *9*(2), 5571–5583. https://doi.org/10.31004/prepotif.v9i2.48059.

UN-Habitat. (2020). *World Cities Report 2020: The value of sustainable urbanization*. United Nations Human Settlements Programme.

Wang, L., Zhang, H., Ruan, Y., Chin, D. P., Xia, Y., Cheng, S., and Chen, M. (2022). Tuberculosis spatial clustering and environmental determinants analysis. *International Journal of Environmental Research and Public Health*, 19(3), 1456. https://doi.org/10.3390/ijerph19031456.

World Health Organization. (2023). *Global tuberculosis report 2023*. Geneva: WHO.

WHO. (2025). *Top findings and messages in the 2025 report*. *2025*, 2025.

Yang, K., LeJeune, J., Alsdorf, D., Lu, B., and Shum, C. K. (2022). Global distribution and environmental risk factors of tuberculosis. *Scientific Reports*, 12, 12345.

DOI: https://doi.org/10.17509/gea.v26i1,%20April.97831
p-ISSN 1412-0313 e- ISSN 2549-7529