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Spatial analysis of tuberculosis based on geographic information systems in Sleman district, Special Region Yogyakarta

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ABSTRACT

The number of tuberculosis cases continues to rise annually, with Sleman Regency recording 2,372 cases in 2024, making it one of the highest in the Special Region of Yogyakarta Province. This study aims to analyze spatial autocorrelation and spatial relationships of tuberculosis cases in Sleman Regency in 2024 using geographic information systems (GIS) and spatial analysis. A quantitative cross-sectional design was applied to 1,406 tuberculosis cases across 86 villages. Bivariate local indicators of spatial association (LISA) analysis were performed using GeoDa software, while geographically weighted regression (GWR) in R Studio examined local environmental influences. Bivariate LISA results showed no significant spatial autocorrelation for population density, air temperature, air humidity, precipitation, and altitude (p-values: 0.173, 0.265, 0.138, 0.312, and 0.401, respectively). GWR revealed negative correlations between these variables and tuberculosis cases. Findings highlight spatial patterns and inform targeted interventions, recommending enhanced tuberculosis awareness and treatment access in low-density, high-incidence areas, along with public education on ventilation and preventive measures during colder seasons, and strengthened prevention in high-risk lowland villages.

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1. INTRODUCTION

In 2015, 193 countries declared and agreed on the Sustainable Development Goals (SDGs), which contain the dimensions of the Millennium Development Goals (MDGs), which emphasize the eradication of world poverty by 2030. The SDGs are based on 3 pillars, based on 17 points, which are broken down into 169 targets and 241 indicators that influence each other [1]. In point 3, 9 core targets are all related to health, and one of the 9 targets (point 3.3) is related to efforts to end tuberculosis. This target also includes the commitment of the World Health Organization (WHO) and United Nations SDGs, which include reductions for the tuberculosis incidence rate, the absolute number of deaths caused by tuberculosis, and the cost faced by people with tuberculosis and their households [2].

Tuberculosis is an infectious disease caused by infection with Mycobacterium tuberculosis complex, which is transmitted through the air [3]. Other studies have shown that risk factors for tuberculosis transmission result from suboptimal anti-tuberculosis treatment, socioeconomic factors, and the environment [4]. Globally, in 2023, the number of tuberculosis cases has reached 8.2 million people, indicating an increase from previous years. In that year, Indonesia became the second country contributing to tuberculosis cases (10%) after India

(26%) [2]. Based on data from the World Health Organization (WHO), in 2023, there were 281 million people in Indonesia, 1.09 million of whom had been exposed to tuberculosis.

The Special Region of Yogyakarta Province continues to face significant challenges in controlling tuberculosis. In 2024, the province ranked 26th nationally in estimated tuberculosis cases, with Sleman Regency reporting the highest burden within the province. A preliminary study conducted in January 2025 by the Sleman Regency Public Health Office revealed an increasing trend in tuberculosis cases: 933 in 2020, 978 in 2021, 1,955 in 2022, 2,509 in 2023, and 2,372 in 2024. Although the health office has utilized geographic information systems (GIS) to map tuberculosis cases on the SmartDinkes platform, the data are limited to aggregated figures at the village level. This study addresses this gap by providing a more granular spatial analysis of tuberculosis distribution in Sleman Regency, applying advanced spatial statistical methods such as local indicators of spatial association (LISA) and geographically weighted regression (GWR). By integrating these techniques, the research offers novel insights into the localized spatial patterns and environmental factors influencing tuberculosis incidence, which have not been previously explored in this region.

GIS has become an essential tool in public health, enabling the visualization, analysis, and interpretation of spatial data to improve understanding of disease patterns and guide evidence-based interventions [5]. Specifically, GIS applications enhance tuberculosis surveillance, prevention, and mapping of accessibility to health facilities [6]. Mapping the spatial distribution of tuberculosis cases allows identification of high-risk areas and supports the development of targeted control strategies, thereby facilitating informed decision-making.

2. METHOD

This study employed a quantitative method emphasizing objectivity and accuracy in measuring variables and drawing conclusions from the population sample [7]. A cross-sectional design was used, with data collected from the Sleman Regency Health Office in 2024. The total sampling included 2,372 tuberculosis cases undergoing treatment in Sleman Regency. After applying the inclusion criteria—patients residing in Sleman Regency with clearly identified residential villages—a final sample of 1,406 cases was selected. The data analyzed originated from 86 villages across the Sleman Regency area. The study analyzed several independent variables, including the population density, the air temperature, the air humidity, the precipitation, and the altitude. Population density and altitude data were obtained from the Central Statistics Agency of Sleman Regency, while air temperature, air humidity, and precipitation data were sourced from NASA satellite imagery.

Spatial autocorrelation analysis is an analysis method to determine the pattern of relationships or correlations between observation locations [8]. It includes global autocorrelation analysis and local autocorrelation analysis (LISA) [9]. This study used GeoDa software to conduct spatial autocorrelation analysis. With its user-friendly interface, GeoDa enables researchers to perform LISA bivariate analysis without requiring advanced programming skills, thereby making the interpretation of results more accessible. Index Moran's I had been used in global autocorrelation analysis with a range of [-1, 1] [10]. When the I index value approaches 1, it indicates a clustered pattern. Then, if the I index value approaches -1, it indicates a spread pattern, and the I index = 0 indicates a random pattern. This analysis used a significance level of 5% [11]. If the p-value <0.05, then the initial hypothesis is rejected, so that there is spatial autocorrelation [12]. Local autocorrelation analysis (LISA) is used to determine the degree of correlation between adjacent areas [13]. This analysis produces 4 quadrants consisting of quadrant 1 (high-high), quadrant 2 (low-high), quadrant 3 (low-low), and quadrant 4 (high-low).

The study also employed R Studio software for spatial correlation analysis using geographically weighted regression (GWR). Unlike classical regression models that produce a single global parameter estimate for the entire study area, GWR generates unique parameter estimates at each location, thus providing localized results [14]. GWR is particularly suited for spatial data because traditional regression assumptions of independent and homogenous residuals are often violated in spatial contexts; using classical regression in such cases may yield biased estimates and incorrect conclusions [15].

3. RESULTS AND DISCUSSION

3.1. Result

3.1.1. Local indicators of spatial autocorrelation (LISA) analysis

Based on the results of the bivariate LISA analysis, the Moran's I index between the number of tuberculosis cases and population density is 0.0464, with an expected value E(I) of -0.0118 as shown in Table 1. Since Moran's I value is greater than E(I), this indicates positive spatial autocorrelation or clustering in the data (Figure 1(a)). However, the significance test shows a p-value of 0.173, which is greater than the 0.05 threshold, indicating that the spatial autocorrelation between tuberculosis cases and population density is not statistically significant. Figure 1(b) illustrates two villages in quadrant I (high-high), representing locations where high numbers of tuberculosis cases are surrounded by areas of high population density. These areas are Kalitirto and Tamanmartani. Then, there are seven villages in quadrant II (low-high), representing locations where a low number of cases are surrounded by areas with low population density. These areas are Sendangtirto, Tegaltirto, Jogotirto, Sambirejo, Umbulmartani, Hargobinangun, and Umbulharjo. Furthermore, in quadrant III (low-low), there is one village, namely Sidomulyo. Quadrant III indicates an area with a low number of cases surrounded by areas with low population density. Meanwhile, there are no areas included in quadrant IV (high-low).

Based on the results of the bivariate LISA analysis, the Moran's I index between the number of tuberculosis cases and air temperature is -0.0343, with an expected value E(I) of -0.0118 (Table 1). Since Moran's I value is less than E(I), this indicates a negative spatial autocorrelation or a dispersed pattern in the data (Figure 1(c)). However, based on the significance test, the p-value is 0.265, which is greater than 0.05, indicating no statistically significant spatial autocorrelation between the number of cases and air temperature. Figure 1(d) shows two villages in quadrant I (high-high), where areas with a high number of cases are surrounded by areas with high air temperatures. These areas include Argomulyo and Umbulmartani. Then, there are two villages in quadrant II (low-high): Argomulyo and Umbulmartani. Quadrant II indicates that areas with low tuberculosis cases are surrounded by areas with high air temperatures. Furthermore, in quadrant III (Low-Low), there is one area that meets the criteria, namely Sendangarum. Quadrant III indicates an area with a low number of tuberculosis cases surrounded by areas with low air temperatures. Meanwhile, in quadrant IV (high-low), there are three villages. There are Sendangagung, Sendangrejo, and Sidorejo. Quadrant IV indicates that areas with a high number of tuberculosis cases are surrounded by areas with low air temperatures.

Based on the results of the bivariate LISA analysis, the Moran's I index between the number of tuberculosis cases and air humidity is 0.0593, with an expected value E(I) of -0.0118 (Table 1). Since Moran's I value is greater than E(I), this indicates positive spatial autocorrelation or clustering in the data (Figure 1(e)). However, the significance test shows a p-value of 0.138, which is greater than 0.05, indicating no statistically significant spatial autocorrelation between tuberculosis cases and air humidity. Figure 1(f) illustrates two villages in quadrant I (high-high), where areas with a high number of cases are surrounded by areas with high air humidity. These areas include Lumbungrejo and Tlogoadi. Meanwhile, in quadrant II (low-high), there is one village, namely Sinduadi. Quadrant II indicates that areas with a low number of tuberculosis cases are surrounded by areas with high air humidity. Furthermore, in quadrant III (low-low), there are no areas that meet this quadrant. Then, in quadrant IV (high-low), there are four villages. There are Margokaton, Kalitirto, Sumberharjo, and Gayamharjo. Quadrant IV indicates areas with a high number of tuberculosis cases surrounded by areas with low air humidity.

Based on the results of the bivariate LISA analysis, the Moran's I index between the number of tuberculosis cases and precipitation is 0.0248, with an expected value E(I) of -0.0118 (Table 1). Since Moran's I index is greater than E(I), this indicates positive spatial autocorrelation or clustering in the data (Figure 1(g)). However, the significance test shows a p-value of 0.312, which is greater than 0.05, indicating no statistically significant spatial autocorrelation between tuberculosis cases and precipitation. Figure 1(h) shows two villages in quadrant I (High-High), where areas with a high number of cases are surrounded by areas with high precipitation. These areas include Tlogoadi and Wedomartani. Meanwhile, in quadrant II (Low-High), there are five villages. There are Tamanmartani, Sendangadi, Tridadi, Triharjo, and Pandowoharjo. Quadrant II indicates that areas with a low number of tuberculosis cases are surrounded by areas with high precipitation. Furthermore, there are no areas included in quadrant III (low-low). Meanwhile, in quadrant IV (high-low), there are four villages. There are Margokaton, Kalitirto, Sumberharjo, and Gayamharjo. Quadrant IV indicates that areas with a high number of tuberculosis cases are surrounded by areas with low precipitation.

Based on the results of the bivariate LISA analysis, the Moran's I index between the number of tuberculosis cases and altitude is -0.0122, with an expected value E(I) of -0.0118 (Table 1). Since Moran's I value is slightly less than E(I), it indicates negative spatial autocorrelation or a dispersed spatial pattern (Figure 1(i)). The significance test yielded a p-value of 0.401, which is greater than 0.05, indicating no statistically significant spatial autocorrelation between tuberculosis cases and altitude. Figure 1(j) shows that no areas fall within quadrant I (high-high). Meanwhile, in quadrant II (low-high), there are 7 villages. There are Balecatur, Sidomulyo, Sidokarto, Sidoarum, Banyuraden, Tirtoadi, and Margoluwih. Quadrant II indicates that areas with a low number of tuberculosis cases are surrounded by high altitude. Furthermore, in quadrant III (low-low), there are 5 villages. There are Triharjo, Sendangadi, Umbulmartani, Selomartani, and Sambirejo. Quadrant III indicates that areas with a low number of tuberculosis cases are surrounded by low altitude. Meanwhile, there are no areas included in quadrant IV (high-low).

Table 1. The result of the bivariate LISA analysis

Variables	Moran's I	E(I)	Z-score	P-value	Classification
Population density	0.0464	-0.0118	0.9562	0.17300	Not Significant
Air temperature	-0.0343	-0.0118	-0.6061	0.26500	Not Significant
Air humidity	0.0593	-0.0118	1.1089	0.13800	Not Significant
Precipitation	0.0248	-0.0118	0.4702	0.31200	Not Significant
Altitude	-0.0122	-0.0118	-0.2880	0.40100	Not Significant

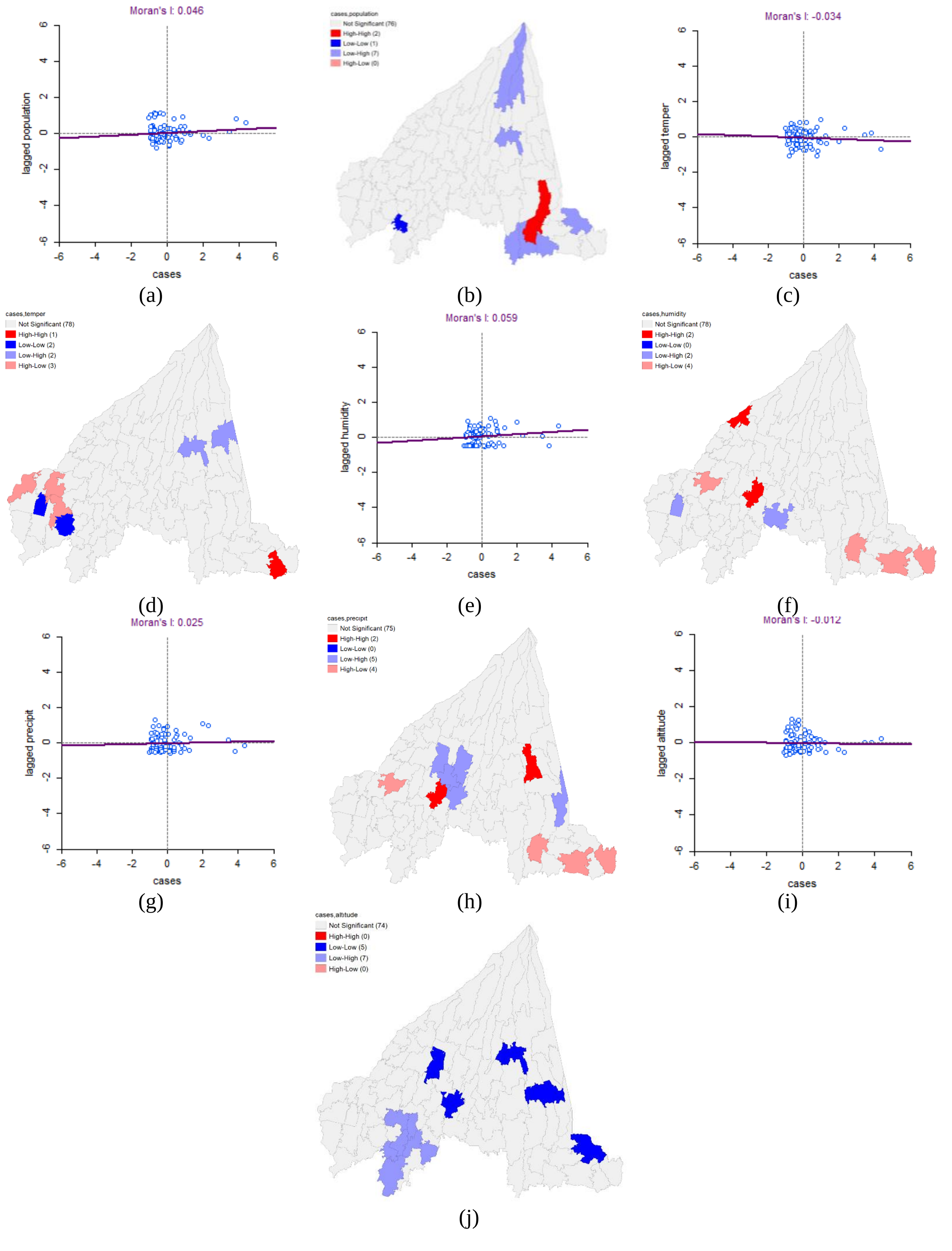

Figure 1. Scatterplots and clustering maps of population density, air temperature, air humidity, precipitation, and altitude: (a) population density scatterplot, (b) population density clustering map, (c) air temperature scatterplot, (d) air temperature clustering map, (e) air humidity scatterplot, (f) air humidity clustering map, (g) precipitation scatterplot, (h) precipitation clustering map, (i) altitude scatterplot, and (j) altitude clustering map

3.1.2. Geographically weighted regression (GWR) analysis

Spatial relationship analysis was performed using geographically weighted regression (GWR) in R Studio, starting with an ordinary least squares (OLS) test. The OLS model yielded a multiple R-squared of 0.3758 and an AICc of 676.45, while the GWR model showed a higher R-squared of 0.7482 and an AICc of

649.08. These results indicate that GWR provides a better fit for the spatial data than OLS. Local GWR coefficients between tuberculosis cases and environmental factors are presented in Table 2.

Table 2. The local GWR coefficient between tuberculosis cases and environmental factors in Sleman Regency in 2024

Variable	Min.	1st Qu.	Median	3rd Qu.	Max
Intercept	-3,501.0	-1,618.1	-769.95	-3.768	244.6836
Population density	-0.0013101	0.0008785	- 0.0024384	0.0046412	0.0151
Air temperature	-0.57189	6.702	12.384	24.406	49.0803
Air humidity	-2.2463	2.7164	6.5674	13.42	29.0272
Precipitation	-44.332	-24.844	-11.51	-6.4871	0.0160
Altitude	-0.077513	-0.013763	0.0013857	0.033011	0.3032

Table 2 shows that all environmental factors have a negative correlation with tuberculosis cases. Based on the GWR analysis, spatial relationships between tuberculosis cases and environmental factors are determined by p-values ($p < 0.05$). The results indicate that 27 villages show significant spatial relationships between tuberculosis cases and population density (Figure 2(a)), including Banyuraden, Candibinangun, Caturtunggal, Condongcatur, Donoharjo, Donokerto, Girikerto, Harjobinangun, Maguwoharjo, Minomartani, Nogotirto, Pakembinangun, Pandowoharjo, Purwobinangun, Sardonoharjo, Sariharjo, Sendangadi, Sendangtirto, Sinduadi, Sinduharjo, Sukoharjo, Tegaltirto, Trimulyo, Umbulmartani, Wedomartani, Widodomartani, and Wonokerto.

For the air temperature variable, 13 villages were found to have a spatial relationship with tuberculosis cases (Figure 2(b)). There are Bokoharjo, Jogotirto, Kalitirto, Madurejo, Maguwoharjo, Purwomartani, Selomartani, Sendangtirto, Sumberharjo, Tamanmartani, Tegaltirto, Tirtomartani, and Wedomartani. Regarding air humidity, 32 villages exhibited a spatial relationship with tuberculosis incidence (Figure 2(c)), including Bangunkerto, Banyuraden, Candibinangun, Caturtunggal, Condongcatur, Donoharjo, Donokerto, Girikerto, Hargobinangun, Harjobinangun, Maguwoharjo, Minomartani, Nogotirto, Pakembinangun, Pandowoharjo, Purwobinangun, Sardonoharjo, Sariharjo, Sendangadi, Sendangtirto, Sinduadi, Sinduharjo, Sukoharjo, Tegaltirto, Tridadi, Trihanggo, Trimulyo, Umbulmartani, Wedomartani, Widodomartani, Wonokerto, and Wukirsari.

Based on precipitation, 26 villages also showed a spatial relationship with tuberculosis cases (Figure 2(d)), namely Candibinangun, Caturtunggal, Condongcatur, Donoharjo, Donokerto, Girikerto, Harjobinangun, Maguwoharjo, Minomartani, Nogotirto, Pakembinangun, Pandowoharjo, Purwobinangun, Sardonoharjo, Sariharjo, Sendangadi, Sendangtirto, Sinduadi, Sinduharjo, Sukoharjo, Trihanggo, Trimulyo, Umbulmartani, Wedomartani, Widodomartani, and Wonokerto.

A total of 41 villages were found to have a significant spatial association between tuberculosis cases and altitude (Figure 2(e)), including Argomulyo, Bangunkerto, Banyuraden, Bimomartani, Candibinangun, Caturtunggal, Condongcatur, Donoharjo, Donokerto, Girikerto, Hargobinangun, Harjobinangun, Maguwoharjo, Minomartani, Nogotirto, Pakembinangun, Pandowoharjo, Purwobinangun, Sardonoharjo, Sariharjo, Selomartani, Sendangadi, Sendangtirto, Sidoarum, Sidomoyo, Sinduadi, Sinduharjo, Sukoharjo, Sumberadi, Tirtoadi, Tlogoadi, Tridadi, Trihanggo, Triharjo, Trimulyo, Umbulharjo, Umbulmartani, Wedomartani, Widodomartani, Wonokerto, and Wukirsari.

3.2. Discussion

3.2.1. Spatial analysis of the tuberculosis cases and population density

Based on the LISA analysis results, there was no spatial autocorrelation between the number of tuberculosis cases and population density in Sleman Regency. This may occur because some areas have a high number of cases but low population density, and vice versa. These findings are consistent with research conducted in Central Java Province in 2022, which reported a p-value of 0.449 [16]. A bivariate analysis in Kupang from 2022 to 2023 also reported p-values of 0.318 and 0.353 between tuberculosis cases and population density [17]. However, these results contrast with studies in Surakarta, northern China, Bekasi, and West Java [18]-[21]. Based on the local coefficient in GWR analysis, a negative correlation was shown, with 27 villages exhibiting a spatial relationship with the number of tuberculosis cases and population density. This means that in certain local areas, higher population density is associated with fewer reported tuberculosis cases. This may be due to the relatively adequate availability of healthcare facilities in high population density areas, along with the presence of good personal hygiene practices, which together contribute to reducing the incidence of tuberculosis [22]. Meanwhile, this result contrasts with other studies conducted in Makasar City in 2022 and Gombak, Malaysia [23], [24]. Other research has shown that population density is a factor associated with increased tuberculosis cases [25]. High population density can accelerate the spread of tuberculosis bacteria, leading to a higher number of cases [12]. Moreover, high population density can result in the formation of slum areas, where 22 studies reported that a person's chance of contracting tuberculosis is almost three times higher than the national average [26]. From this research, it is hoped that health workers will be more active in socializing tuberculosis disease and increasing access to and coordination of treatment services, especially in areas with low population density but still high tuberculosis cases, so that prevention and control can be more effective.

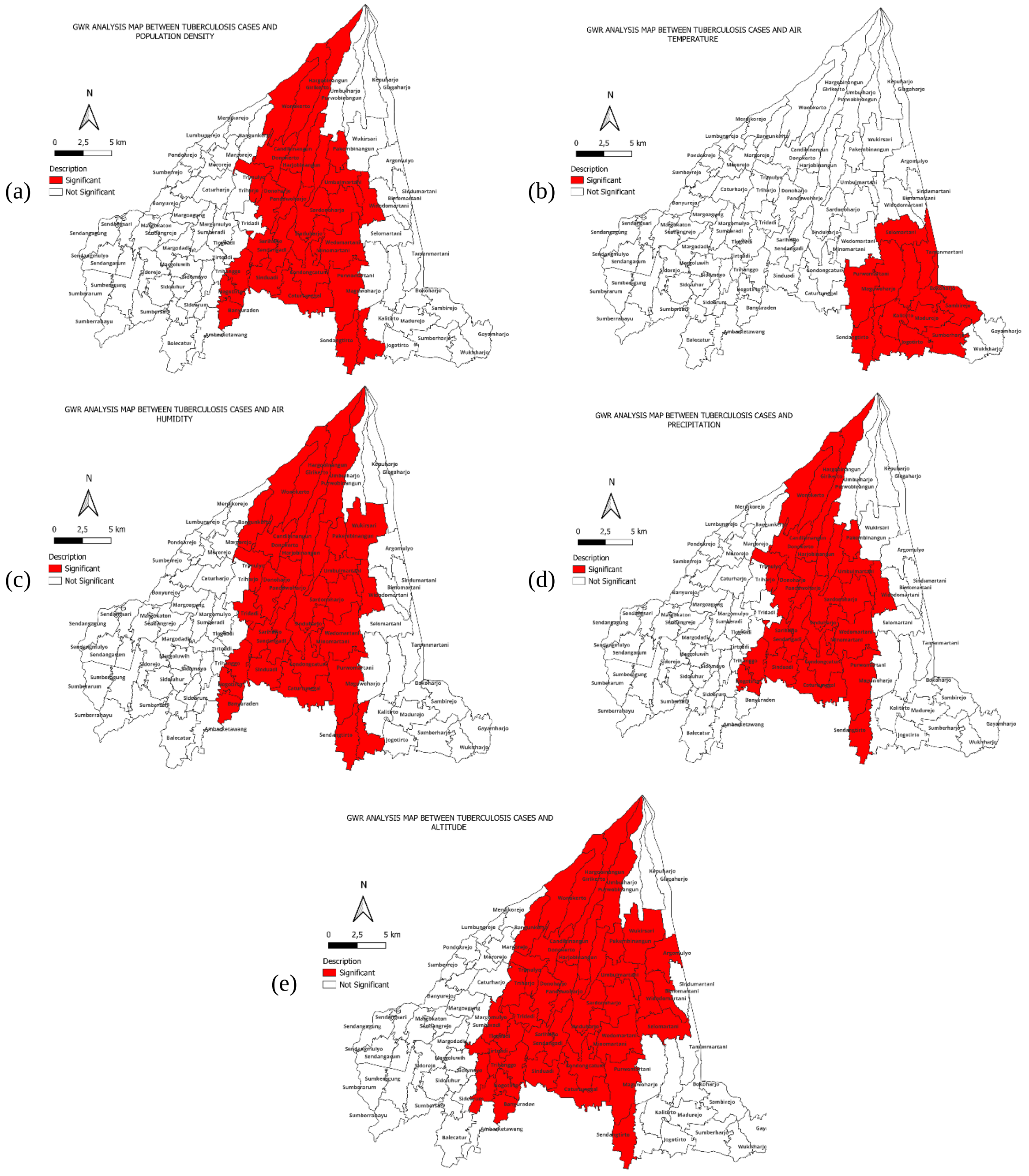

Figure 2. Geographically weighted regression map between tuberculosis cases with population density, air temperature, air humidity, precipitation, and altitude. Geographically weighted regression map of (a) population density, (b) air temperature, (c) air humidity, (d) precipitation, and (e) altitude

3.2.2. Spatial analysis of the tuberculosis cases and air temperature

Based on the LISA analysis results, no spatial autocorrelation was found between the number of tuberculosis cases and air temperature in Sleman Regency. However, these results differ from a study in Nepal during 2020-2023, where Moran's I index showed a positive spatial autocorrelation between land surface temperature and the tuberculosis prevalence [27]. Moreover, the GWR analysis revealed a negative correlation, with 13 villages exhibiting a spatial relationship with the number of tuberculosis cases and air temperature, indicating that the lower temperature increases the risks of tuberculosis cases [28]-[30]. Another study in Mozambique showed higher tuberculosis incidence in areas with colder temperatures compared to other areas [31]. Tuberculosis transmission may increase due to more indoor activities and reduced ventilation during colder weather, which facilitates transmission [32], [33]. Additionally, cold air temperatures can reduce the body's immunity, thereby increasing individual susceptibility to infection and enhancing the survival of tuberculosis bacteria in airborne droplets [34]. Further studies have reported strong associations between environmental factors, including air temperature, and tuberculosis cases [31], [35]-[37]. Environmental factors, allergic reactions in the respiratory tract, and decreased temperatures may also cause bronchoconstriction and airway narrowing, potentially damaging respiratory epithelial cells and worsening tuberculosis conditions [38]. Given the negative correlation between air temperature and tuberculosis incidence, governments can seek to increase awareness and preventative interventions, particularly during cold periods, by improving indoor ventilation and encouraging protective behaviors to reduce the risk of transmission in vulnerable populations.

3.2.3. Spatial analysis of the tuberculosis cases and air humidity

Based on the results of the bivariate analysis using LISA, there was no spatial autocorrelation between air humidity and the number of tuberculosis cases in Sleman Regency. However, GWR analysis revealed a negative correlation, with 32 villages showing significant spatial relationships. Similar findings have been reported in the southeast and northwest regions of China during 2010-2017 [39]. A study conducted in Beijing, China, also found a negative correlation between the number of tuberculosis cases and air humidity during 2004-2016 [40]. Other studies examining air humidity have reported associations between tuberculosis incidence and humidity levels [41], [42]. Low air humidity is known to increase resistance in the respiratory tract to tuberculosis bacteria, due to reduced protective mucus on the respiratory surface [30], [40]. From this condition, it is hoped that the government will enhance public education on the importance of optimal ventilation and air humidity as part of intensified interventions to prevent tuberculosis transmission.

3.2.4. Spatial analysis of the tuberculosis cases and precipitation

Based on the LISA analysis results, there was no spatial autocorrelation between the number of tuberculosis cases and precipitation in Sleman Regency. In contrast, previous studies reported positive spatial autocorrelation between tuberculosis prevalence and precipitation in Nepal (2020-2023) and China (2005-2015) [10], [27]. Meanwhile, the GWR analysis showed a negative correlation, identifying 26 villages with a spatial relationship to tuberculosis cases. This suggests that the lower precipitation in Sleman Regency is inversely related to higher tuberculosis incidence. Supporting this, a study in Khuzestan Province, Southern Iran, and China (2010-2017) found that increased average precipitation is associated with decreased tuberculosis cases [39], [41]. Additionally, areas with low annual precipitation and dry climates have a higher risk of tuberculosis spread [41]. Conversely, other research indicates that high precipitation increases air humidity, which can support tuberculosis bacteria growth [43]. During the rainy season, individuals have a 3.33 times higher risk of contracting tuberculosis due to increased indoor physical activity [44]. Thus, precipitation can create ideal conditions for the growth of tuberculosis-causing bacteria [45].

3.2.5. Spatial analysis of the tuberculosis cases and altitude

Based on the results of the bivariate LISA analysis, there was no spatial autocorrelation between the number of tuberculosis cases and altitude in Sleman Regency. However, the GWR analysis revealed a negative correlation between tuberculosis cases and altitude, with 41 villages showing a spatial relationship with tuberculosis case numbers. The altitude in Sleman Regency ranges up to less than 2500 meters above sea level, increasing toward the peak of Mount Merapi on the northern side, while the southern side has lower altitudes. Data presentation shows that moderate to high tuberculosis cases are mostly found in areas below 500 meters above sea level. Therefore, the lower the altitude in Sleman Regency, the higher the number of tuberculosis cases, indicating an inverse relationship. Lowland areas have a greater potential for tuberculosis transmission compared to highlands, as indicated by the decrease in tuberculosis cases with increasing altitude [46]. It is recommended that the government and stakeholders focus on strengthening tuberculosis prevention and control efforts in lowland areas that have a higher risk, by improving access to health services, health education on risk factors and transmission, and optimizing early detection and complete treatment programs. Additionally, specific interventions related to environmental management and enhancing vitamin D levels through adequate sunlight exposure in low-altitude areas should be considered to support the population's immune response. Furthermore, highland areas receive higher exposure to UV-B rays, which can increase vitamin D levels, enhancing immune response and reducing the risk of tuberculosis reactivation. Previous epidemiological studies in Kenya, Peru, Mexico, and Vietnam similarly revealed decreased tuberculosis death and notification rates in highland areas [47]. A comparable pattern is observed in China, where tuberculosis prevalence is higher in low-altitude and coastal regions, while mountainous and hilly areas have lower prevalence [48].

Results from the bivariate LISA analysis indicated no significant spatial autocorrelation between tuberculosis cases and the environmental and demographic variables studied. This lack of significance may suggest weak or spatially inconsistent relationships at local scales or the influence of unmeasured confounding factors. Consequently, GWR was employed to capture spatial heterogeneity and local variations in the associations between tuberculosis cases and predictors such as population density, air temperature, air humidity, precipitation, and altitude. The GWR model revealed significant negative spatial correlation across all examined variables, implying that higher values of these environmental factors were locally associated with reduced tuberculosis case counts. However, this study is limited by its reliance on secondary tuberculosis case data, which may lack granularity and timely updates. Furthermore, the environmental variables of humidity, rainfall, and temperature were aggregated on an annual basis, potentially overlooking seasonal fluctuations. To address these limitations and gain a more comprehensive understanding of the spatiotemporal dynamics influencing tuberculosis, it is recommended that future analyses incorporate data at quarterly intervals to reflect seasonality more accurately. In addition, supplementary analyses that include socioeconomic factors such as poverty levels, sanitation conditions, and health education are necessary, as these determinants may have a more substantial role in tuberculosis transmission dynamics within the study area.

4. CONCLUSION

This study aimed to investigate the spatial relationship between environmental factors and tuberculosis cases. This study found no significant spatial autocorrelation between population density, air temperature, air humidity, precipitation, and altitude with tuberculosis cases. However, all these variables showed a negative correlation with tuberculosis cases, indicating that higher values are linked to fewer cases. Advanced spatial and temporal analyses are necessary to identify hidden risk factors and local dynamics, which will clarify temporal trends and spatial variability in tuberculosis distribution. The study also highlights the need for health workers to actively promote tuberculosis awareness and enhance treatment access, especially in low-density areas with high tuberculosis cases. Given the negative correlation between air temperature and tuberculosis cases, governments should increase public awareness during colder periods by improving indoor ventilation and encouraging protective behaviors. Intensifying education on optimal ventilation and humidity is essential. Governments are advised to strengthen tuberculosis prevention in high-risk lowland villages through improved healthcare access, targeted health education, early detection, and comprehensive treatment programs.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Angga Eko Pramono	✓			✓				✓		✓		✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

ETHICAL APPROVAL

This study was conducted after obtaining a research eligibility letter (ethical clearance) from the Health Research Ethics Committee of the Yogyakarta Ministry of Health Polytechnic, numbered No.DP.04.03/e-KEPF.1/409/2025. All regulations related to research ethics and data protection have been described in the research eligibility letter. Through this letter, the confidentiality of patient data has been guaranteed and its use is limited to research purposes.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AEP], upon reasonable request.

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