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Spatial Analysis of Pulmonary Tuberculosis Risk in Surakarta, Central Java, Indonesia

Dinda Nabila Silva Diba[1)], Bhisma Murti[1)], Noor Alis Setiyadi[2)]

[1)]Masters Program in Public Health, Universitas Sebelas Maret
[2)]Faculty of Health Science, Universitas Muhammadiyah Surakarta

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ABSTRACT

Background: Pulmonary tuberculosis is an infectious disease, especially in developing countries. In 2022, the total number of tuberculosis cases in Indonesia was 677,464 cases. This study aims to conduct a spatial analysis of factors such as population size, population density, number of poor population, number of unemployed, healthy houses, and temperature to the number of pulmonary tuberculosis cases in the working area of health centers in Surakarta City in 2022.

Subjects and Method: Spatial analysis was carried out by descriptive analysis of distribution maps using QGIS, spatial cluster analysis using SaTScanTM, and autocorrelation analysis by Local Indicators of Spatial Autocorrelation (LISA) method using GeoDa. Secondary data was obtained from the public communication of the Central Statistics Agency of Surakarta and the Surakarta Health Profile in 2022. The analysis unit includes 17 working areas of health centers in Surakarta. The dependent variable is the TB cases. The independent variables were population density, number of poor people, number of unemployed, number of healthy houses, and temperature.

Results: The highest number of pulmonary TB cases were in Purwodiningratan Health Center and Sangkrah Health Center. There is the most likely cluster of pulmonary tuberculosis cases which is statistically significant in 2022 (Radius = 1.81 km; RR=17.65; p=0.003). Autocorrelation analysis showed E[I]=-0.06. There was a positive and significant spatial autocorrelation of the population (I=0.40; p=0.003), population density (I=0.33; p=0.002), number of poor people (I=0.40; p=0.002), number of unemployed (I=0.40; p=0.003), and temperature (I=0.25; p=0.009) of pulmonary TB cases in Surakarta.

Conclusion: Population number, population density, number of poor population, number of unemployed, and temperature have positive spatial autocorrelation with pulmonary TB.

Keywords: Spatial analysis, SaTScan, GeoDa, pulmonary tuberculosis

Correspondence:
Dinda Nabila Silva Diba. Master's Program in Public Health, Universitas Sebelas Maret. Jl. Ir. Sutami 36A, Surakarta 57126, Central Java, Indonesia. Email: Dinda.silva.diba@student.uns.ac.id. Mobile: 082268893633.

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BACKGROUND

Pulmonary tuberculosis is currently still a public health problem, especially in developing countries. Globally, in 2020 it is estimated that 9.9 million people suffer from pulmonary tuberculosis and Indonesia accounts for 86% of the total cases, provided that the Case Detection Rate (CDR) and Case Notification Rate (CNR) do not increase (WHO, 2021a). Most of the estimated deaths caused by pulmonary tuberculosis were recorded in four countries, namely India, Indonesia, Myanmar, and the Philippines. The number of deaths due to pulmonary tuberculosis (among HIV-negative patients) globally in 2021 was 1.4 million cases, this has increased compared to 2020, which was 1.3 million cases (Ministry of Health of the Republic of Indonesia, 2022).

In 2022, the number of all tuberculosis cases found was 677,464 cases, an increase quite high when compared to all tuberculosis cases found in 2021, which increased by 397,377 cases. The highest number of cases were reported from provinces with large populations, namely West Java Province, East Java Province, and Central Java Province. Based on data from the Indonesian Health Profile in 2022, the highest number of cases reported were from provinces with a large population, namely West Java Province (184,406 cases, IR 364.15/100,000 population), East Java Province (78,334 cases, IR 194.14/100,000 population), and Central Java Province (77,426 cases, IR 220.64/100,000 population). Pulmonary tuberculosis cases in the three provinces account for about 47% of the total number of tuberculosis cases in Indonesia. Central Java Province is the second province with the highest cases of pulmonary tuberculosis with 77,426 total cases of tuberculosis of all types (Ministry of Health of the Republic of Indonesia, 2022).

Surakarta is one of the municipalities in Central Java Province. The detection rate of pulmonary tuberculosis per 100,000 population in Surakarta City occupies the third highest position in Central Java, with details of Tegal Regency (762.10/100,000 population), Magelang Regency (507.30/100,000 population), and Surakarta City (218.50/100,000 population). The number of pulmonary tuberculosis patients in Surakarta City shows an increasing trend of cases that need to be considered. In 2019, there were 740 cases of pulmonary tuberculosis. The situation became more serious in 2020, with a significant spike to 1,026 cases. Although there was an increase in 2021, reaching 1,148 cases, 2022 was the most worrying year with the number of pulmonary tuberculosis patients reaching 2,105 cases.

The growth of the region is both administrative and ecologically, leading to the fact that health issues are always changing and vary from region to region. One of the region-based disease management methods is spatial analysis, which is a disease management method with georeferences that take into account spatial variables such as topography, urban, industrial, and rural areas (Nuraisyah et al., 2022). Spatial analysis is an analysis that analyzes and describes disease data from a geographical point of view in relation to population distribution, distribution of environmental risk factors, ecosystems, climate factors, socioeconomic risk factors, and the relationship between these variables (Achmadi, 2014). The use of geographic information systems and spatial analysis can facilitate mapping to see the distribution pattern of pulmonary tuberculosis incidence in an area, taking into account the risk factors. The spatial approach in the health sector is a new approach which means that health development is problem-oriented and prioritizes health (environmental) issues spatially (Kusumawati et al., 2016). The spatial approach of each region can be focused on tackling health problems that are considered top priorities so that resources can be used more effectively. Some of the benefits of spatial analysis in the field of health, especially epidemiology, include disease mapping, geographical correlation studies, and clustering (Elliott and Wartenberg, 2004).

This type of cluster spatial statistics can be used in identifying and investigating the geographic concentration of disease cases. This analysis involves detecting disease clusters or high-risk areas to generate hypotheses about the potential causes of the clustering. Cluster analysis is essential for understanding the spatial distribution of diseases to aid in the identification of potential risk factors and the development of targeted public health interventions. Spatial analysis of Kulldorff clusters is a commonly used and effective method to identify clusters of health problems, especially to find clusters of disease cases that have the potential to develop into outbreaks (Kulldorff, 1997). The Kulldorff method can be implemented on the SaTScan application to analyze pulmonary tuberculosis clusters, performed through statistical space-time scanning of discrete poisson probability models. The Kulldorff method is used in space-time analysis to explore spatial, temporal, and spatioral clusters of pulmonary tuberculosis.

Spatial autocorrelation is a method that can be used to determine whether disease occurrences on the earth's surface, either in the form of points or areas, show a correlation or are not in line with the surrounding area units. Anselin in 1995 introduced a method that can analyze the similarities and differences in spatial patterns and can identify hotspot and coldspot areas as well as outliers to regional units known as the LISA (Local Indicator of Spatial Autocorrelation method). The spatial effect is determined by the Moran Index (I) to analyze the spatial relationship to an event, with values ranging from -1 to 1. A high value of I means that the correlation is high, while a value of 0 indicates that there is no autocorrelation or interaction spatially. The value of I needs to be compared with the expected value, which is E [I] to see whether or not there is an autocorrelation between regions in the data. The value of $I > E[I]$ indicates that the autocorrelation value is positive (grouping pattern), the value of $I=E[I]$ indicates the absence of spatial autocorrelation and the value of $I<E[I]$ indicates that the autocorrelation value is negative and has a pattern of diffuse data. The value range of the Moran Index in the case of a standardized spatial weighting matrix is $-1 \leq I \leq 1$. A value of $-1 \leq I < 0$ indicates a negative spatial autocorrelation, while a value of $0 < I \leq 1$ indicates a positive spatial autocorrelation, a value of zero indicates non-grouping (Yuliana, 2022). In the autocorrelation analysis, four types of clustermap area division quadrants can be identified , namely quadrant I (high-high), quadrant II (low-high), quadrant III (low-low), and quadrant IV (high-low).

Factors that affect the incidence of pulmonary tuberculosis include the presence of a source of disease transmission, namely Mycobacterium tuberculosis germs, environmental risk factors (geographical and climatic conditions), population risk factors (socio-economic, age, gender, and nutritional status) and health services both in terms of facilities and health workers (Achmadi, 2014). Demographic factors such as population and population density are also risk factors for pulmonary tuberculosis cases, as explained in spatial autoregressive research for a tuberculosis case model in Central Java Province in 2019 (Zebua and Jaya, 2022). Meanwhile, other research also found that cases of pulmonary tuberculosis also spread and formed clusters significantly in population conditions that tend to be more dense (Inggarputri et al., 2023). Another demographic condition that is a risk factor for pulmonary tuberculosis is poverty, as explained in previous research that the number of poor people has a significant effect on the number of tuberculosis in Indonesia (Noventy and Suparta, 2023). Physical environmental factors that include climate and or weather such as temperature and humidity can also affect cases of pulmonary tuberculosis (Xu et al., 2020). Spatial analysis research on pulmonary tuberculosis has been carried out on an international scale (Brunton et al., 2017; Dangisso et al., 2020; Chen et al., 2023) and Indonesia (Noorcintanami et al., 2021; Putra et al., 2022; Wati and Lina, 2023), but the last research on spatial analysis of pulmonary tuberculosis in Surakarta City was conducted in 2013 (Kurniawati, 2014). Spatial analysis needs to be carried out to see the increasing distribution of pulmonary tuberculosis cases in the city of Surakarta. This study aims to conduct a spatial analysis of pulmonary tuberculosis cases in Surakarta City in 2022.

SUBJECTS AND METHOD

1. Study Design

This type of research is an ecological study. The technique used is spatial analysis, to describe the distribution of the number of pulmonary tuberculosis cases based on independent variables, identify clusters of pulmonary tuberculosis cases, and analyze the autocorrelation of independent variables to the number of pulmonary tuberculosis cases in Surakarta City in 2022.

2. Population and Sample

The population of this study is the overall case of pulmonary tuberculosis in Surakarta City recorded in the daily case report of the Surakarta City Health Office in 2022. The sample is expected to interpret conditions in the population. Referring to the research design (ecological study) with a focus on research on groups rather than individuals, the sample from this study is the entire population that meets the inclusion and exclusion criteria and is recorded in the daily report of the case. The inclusion criteria for the study subjects are to be recorded as a pulmonary tuberculosis patient in 2022 and domiciled in the Surakarta City area. The exclusion criteria of the study subjects were case data with incomplete case reporting addresses and dates, and case data originating from hospitals.

3. Study Variables

The independent variables of this study are the number of population, population density, number of poor people, number of unemployed, number of healthy houses, and temperature. The dependent variable is the number of pulmonary tuberculosis cases.

4. Operational Definition of Variables

Number of pulmonary tuberculosis cases: the cumulative confirmed cases of pulmonary tuberculosis per working area of health centers in Surakarta City in 2022.

Number of population: is the number of residents per working area of the Puskesmas in Surakarta City in 2022.

Population density: the number of people per km^2 per working area of health centers in Surakarta City in 2022.

Number of poor people: the number of poor people per working area of health centers in Surakarta City in 2022.

Number of unemployed: is the number of people who do not work per work area of health centers in Surakarta City in 2022.

Number of healthy houses: the number of heads of healthy house families per working area of health centers in Surakarta City in 2022.

Temperature: is annual average environmental temperature per working area of health centers in Surakarta City in 2022.

5. Study Instruments

Secondary data is collected using a list of secondary data records that have been compiled on a data processing application in the form of a dummy table.

6. Data Analysis

The data analysis in this study was carried out through three stages of analysis, namely descriptive analysis (presented through a map of the distribution of cases and research variables), spatial cluster analysis, and spatial autocorrelation analysis. Data analysis uses open-source applications QGIS 3.34 (ESRI, 2024), SaTScan 10.0.1 (Kulldorff, 1997), GeoDa 1.20.0.8 (Anselin, 2005), and Google Earth Pro (Google, 2021).

7. Research Ethics

Research ethics issues including informed consent, anonymity, and confidentiality, are handled with care during the research process. The approval letter for a research ethics permit was obtained from the Research Ethics Committee of the National Health Research and Development Ethics Committee (KEPPKN) of the Faculty of Health Sciences, University of Muhammadiyah Surakarta, Indonesia No. 289/KEPK-FIK/IV/2024 on April 4, 2024.

RESULTS

1. Distribution of pulmonary tuberculosis cases

Figure 1 shows in 2022, there were 285 cases of pulmonary tuberculosis spread across all health centers in Surakarta City. The lowest cases were found at the Purwosari Health Center (4 cases), and the highest cases were found at the Purwodiningratan Health Center (42 cases) and the Sangkrah Health Center (47 cases).

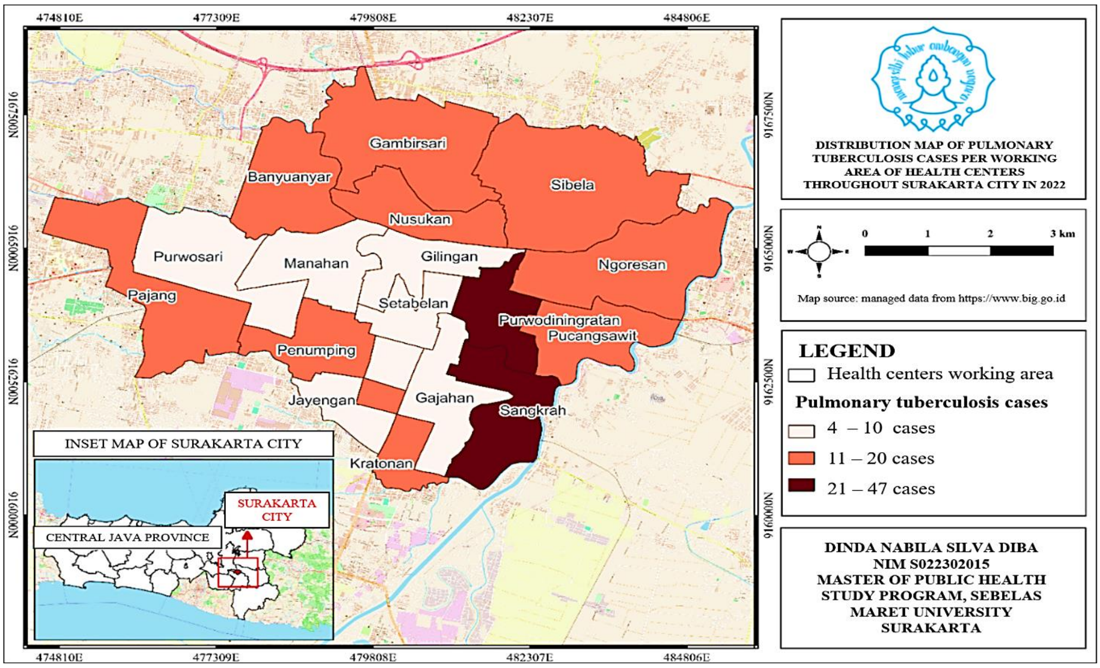

Figure 1. Distribution of pulmonary tuberculosis cases per working area of health centers throughout Surakarta, 2022

The number of pulmonary tuberculosis cases is grouped into three categories, namely regions with white (4 to 10 cases), orange (11 to 20 cases), and dark red (21 to 47 cases). The white area includes the working area of the Purwosari Health Center, Manahan Health Center, Gilingan Health Center, Setabelan Health Center, Gajahan Health Center, and Jayengan Health Center. The orange area is the area with a moderate number of cases, including the working area of the Pajang Health Center, Banyuanyar

Health Center, Penumping Health Center, Kratonan Health Center, Gambirsari Health Center, Nusukan Health Center, Sibela Health Center, Ngoresan Health Center, and Pucangsawit Health Center. The dark red area is the area with the highest number of pulmonary tuberculosis cases, including the Purwodiningratan Health Center and the Sangkrah Health Center.

Figure 2 shows that in 2022 the population of Surakarta City consists of 583,961 people. The areas with the largest population are Gambirsari Health Center (58,633 people) and Purwodiningratan Health Center (123,530 people). The Purwodiningratan Health Center is the working area with the highest number of pulmonary tuberculosis cases (21 to 47 cases) and the largest population (58,633 to 123,530 people).

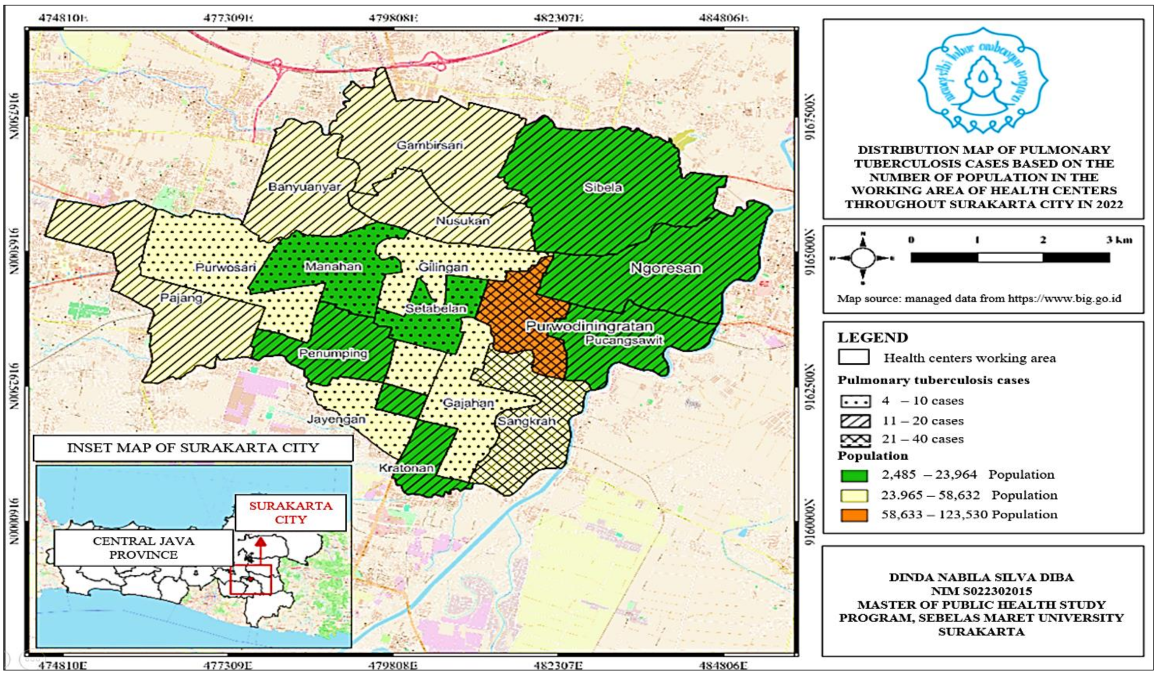

Figure 2. Distribution of pulmonary tuberculosis cases based on the number of population in the working area of health centers throughout Surakarta, 2022

Figure 3 shows that in 2022 the population density in Surakarta City with the most populated area is the Purwodiningratan Health Center (69,011,17318 people/km2), with the highest number of pulmonary tuberculosis cases. Figure 4 shows that in 2022 the number of poor people in Surakarta City is 52,396 people, with the highest poor population in the Sangkrah Health Center (6,958 people) and Purwodiningratan Health Center (9,025 people). Sangkrah Health Center is the area with the highest number of pulmonary tuberculosis cases and the highest number of poor people. Figure 5 shows the highest number of unemployed people is in the Gambirsari Health Center (12,046 people), but, the Sangkrah Health Center with 15,545 unemployed people is the area with the highest number of pulmonary tuberculosis cases.

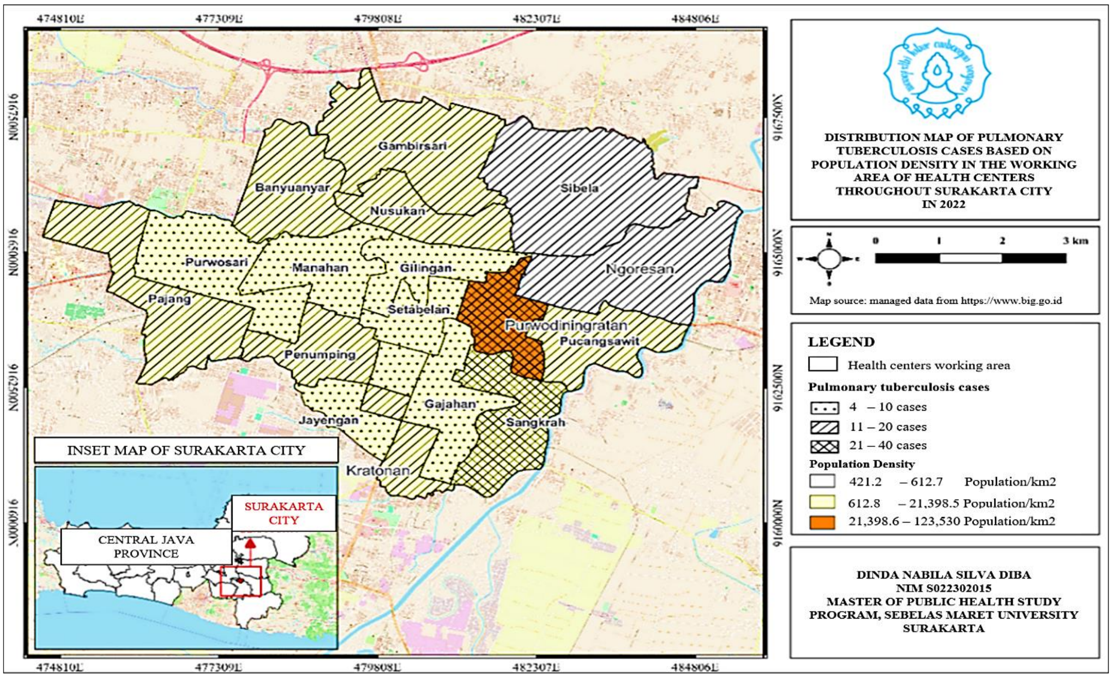

Figure 3. Distribution of pulmonary tuberculosis cases based on population density in the working area of health centers throughout Surakarta City in 2022

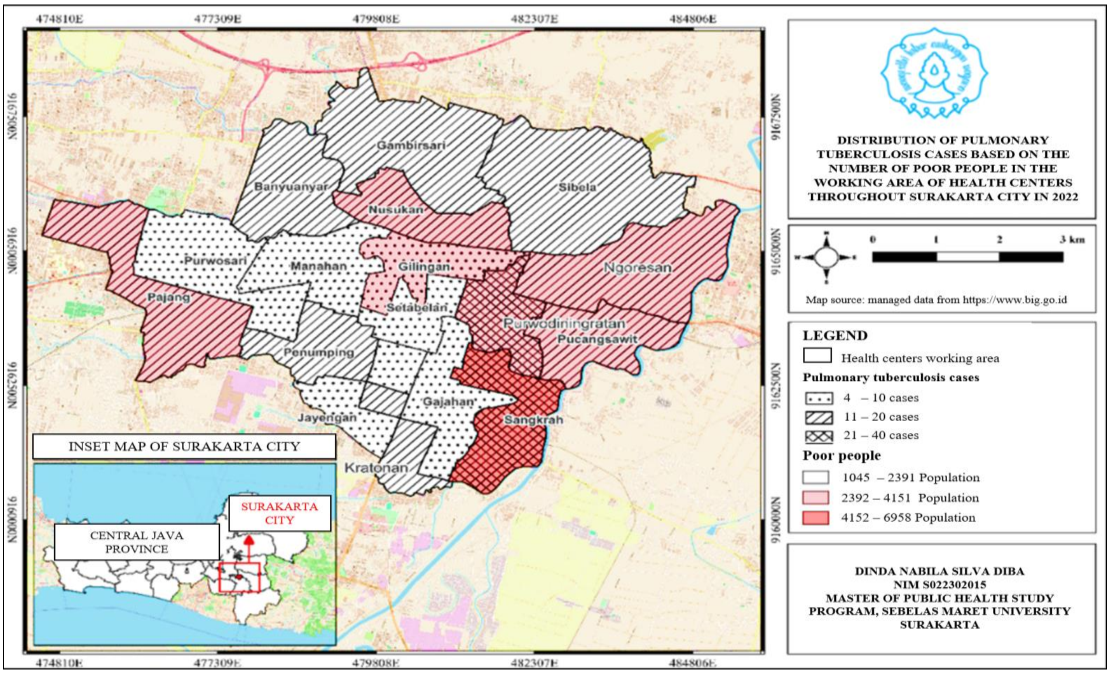

Figure 4. Distribution of pulmonary tuberculosis cases based on the number of poor people in the working area of health centers throughout Surakarta City in 2022

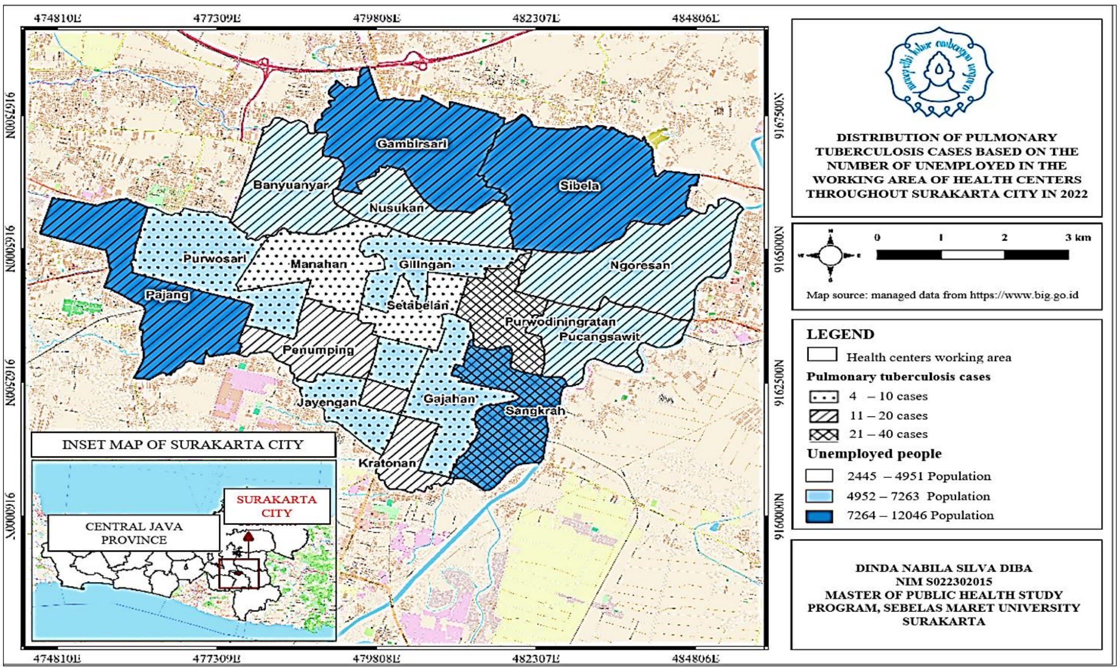

Figure 5. Distribution of pulmonary tuberculosis cases based on the number of unemployed in the work area of health centers throughout Surakarta City in 2022

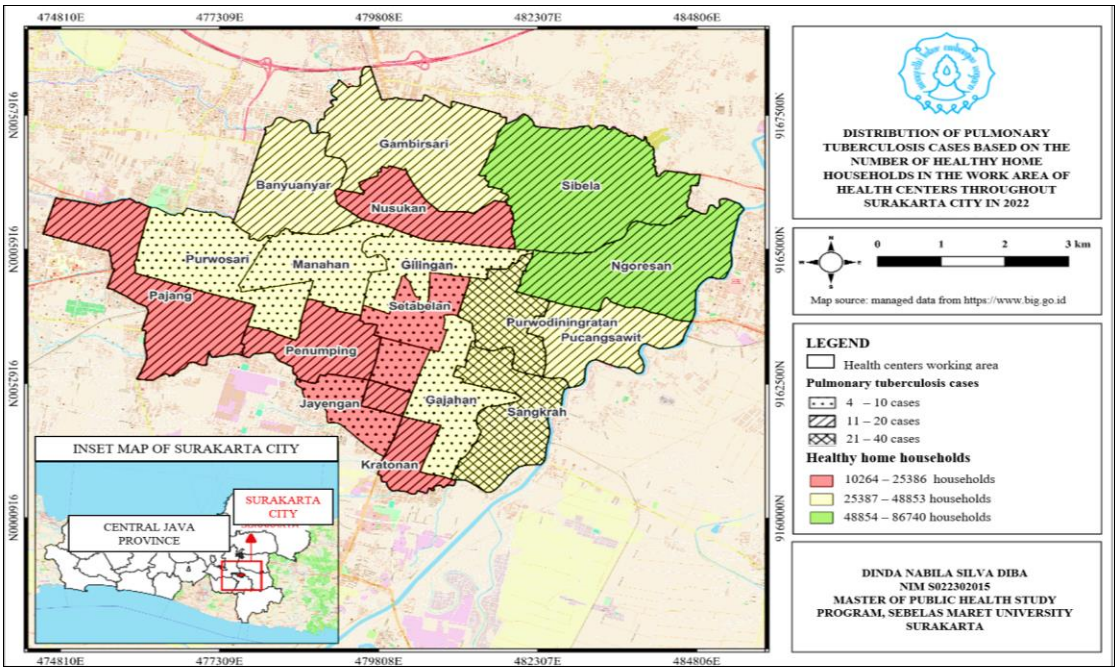

Figure 6. Distribution of pulmonary tuberculosis cases based on the number of healthy home households in the work area of health centers throughout Surakarta City in 2022

Figure 6 shows, the number of heads of families (KK) who have healthy houses is 661,192 families. Very high cases of pulmonary tuberculosis were found in areas with moderate healthy home outcomes, namely the Purwodiningratan Health

Center and the Sangkrah Health Center. Figure 7 shows that in 2022 the annual average temperature per working area of health centers in Surakarta City is 29.15°C. The areas with the highest temperatures are Purwodiningratan Health Center (30.43°C) and Sangkrah Health Center (30.48°C), with the highest number of pulmonary tuberculosis cases found. All working areas of health centers in Surakarta City have temperatures greater than 25°C and smaller than 40°C.

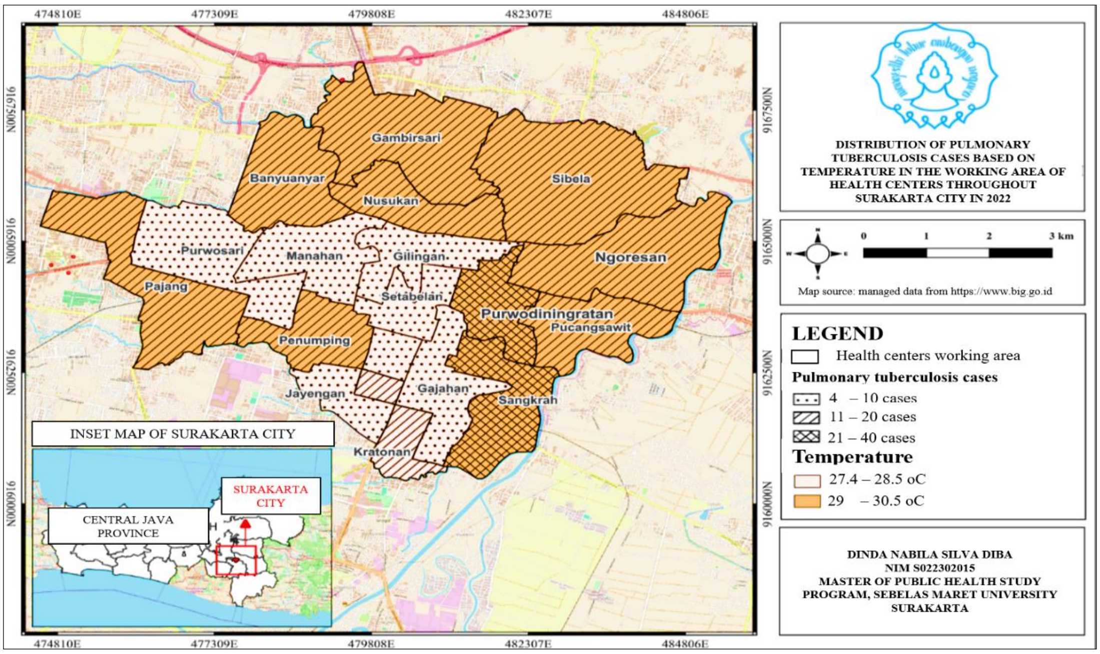

Figure 7. Distribution of pulmonary tuberculosis cases based on temperature in the working area of health centers throughout Surakarta City in 2022

2. Analysis of pulmonary tuberculosis cluster

The results of the cluster analysis of pulmonary tuberculosis cases in Surakarta City in 2022 found two clusters, namely the most likely cluster (p= 0.003) and the 1st secondary cluster (p= 0.001). The most likely cluster of pulmonary tuberculosis cases that are statistically significant compared to the surrounding area during the 2022 time period (Radius= 1.81 km; RR= 17.65; p= 0.003), with the coordinates of the cluster center -7.572051 S, 110.853370 E. The most likely location of the pulmonary tuberculosis cluster includes the working area of the Ngoresan Health Center, Purwodiningratan Health Center, Sangkrah Health Center, and Pucangsawit Health Center. These results illustrate that in 2022 if there are pulmonary tuberculosis patients in the most likely cluster area, then the population located in a radius of 1.81 km from the center of the cluster is 17.65 times more likely to contract pulmonary tuberculosis.

There was a 1st secondary cluster of pulmonary tuberculosis cases which was statistically significant compared to the surrounding area during the 2022 time period (Radius = 0km; RR= 1.79; p=0.001), with the coordinates of the center of the cluster -7.535947 S, 110.845894 E. The location of the 1st secondary cluster of pulmonary tuberculosis is in the working area of the Sibela Health Center. These results illustrate that in 2022 if there are pulmonary tuberculosis patients in the 1st secondary cluster area, then residents living in a radius of 0 km from the center of the cluster are 1.79 times more likely to contract pulmonary tuberculosis.

Table 1. Results of cluster analysis *of* pulmonary tuberculosis cases in Surakarta City in 2022

Year	Cluster Type	Coordinates (latitude, longitude)	Radius (km)	Cases (n)	People at risk
2022	Most likely cluster	-7.572051 S 110.853370 E	1.81	61	76,935
2022	1st secondary cluster	-7.535947 S 110.845894 E	0	20	2,485

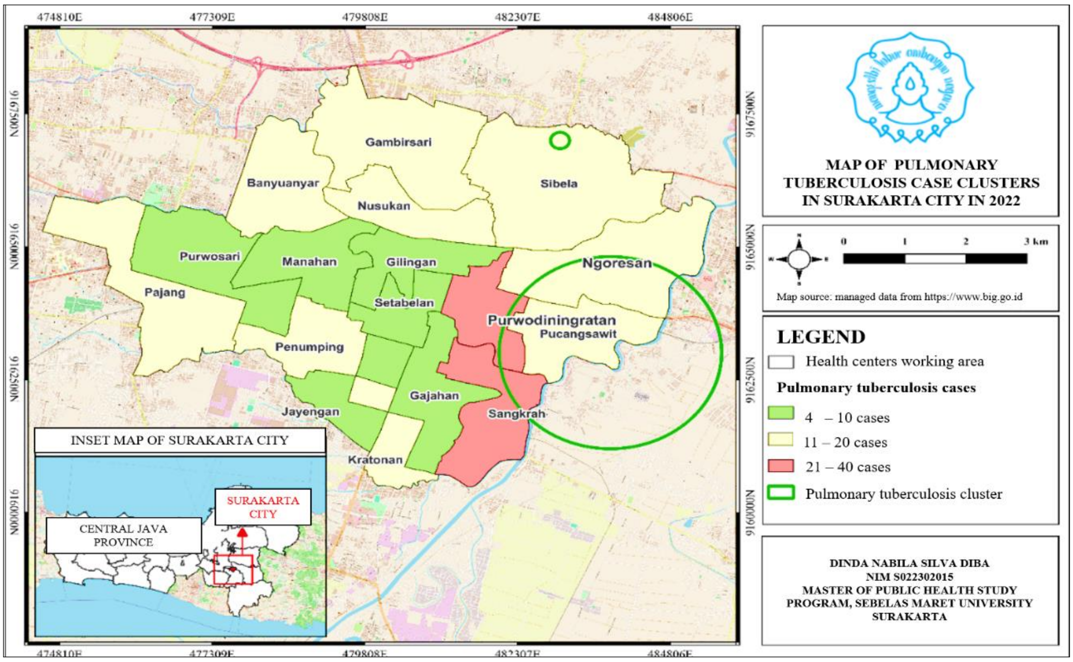

Figure 8. Map of pulmonary tuberculosis case clusters in Surakarta City in 2022

3. Spatial autocorrelation analysis

The results of the LISA cluster map of the relationship between the number of population and the number of pulmonary tuberculosis cases in Figure 10 show that in quadrant I (high-high) the area with high observation value and neighboring the health center area also has a high observation value. There are four work areas, namely Purwodiningratan Health Center, Pucangsawit Health Center, Sangkrah Health Center, and Ngoresan Health Center. In quadrant III (low-low), the area with a low observation value is surrounded by the surrounding health center area which also has a low observation value consisting of four work areas, namely the Banyuanyar Health Center, Manahan Health Center, Penumping Health Center, and Purwosari Health Center.

The results of the LISA clustermap of the relationship between population density and the number of pulmonary tuberculosis cases in Figure 11 shows that in quadrant I (high-high) there are 3 work areas, namely Purwodiningratan Health Center, Sangkrah Health Center, and Ngoresan Health Center. There is a Pucangsawit Health Center that is in quadrant II (low-high), which is an area with a low observation value neighboring the health center area that has a high observation value. In quadrant III (low-low) there are four work areas, namely Banyuanyar Health Center, Manahan Health Center, Penumping Health Center, and Purwosari Health Center.

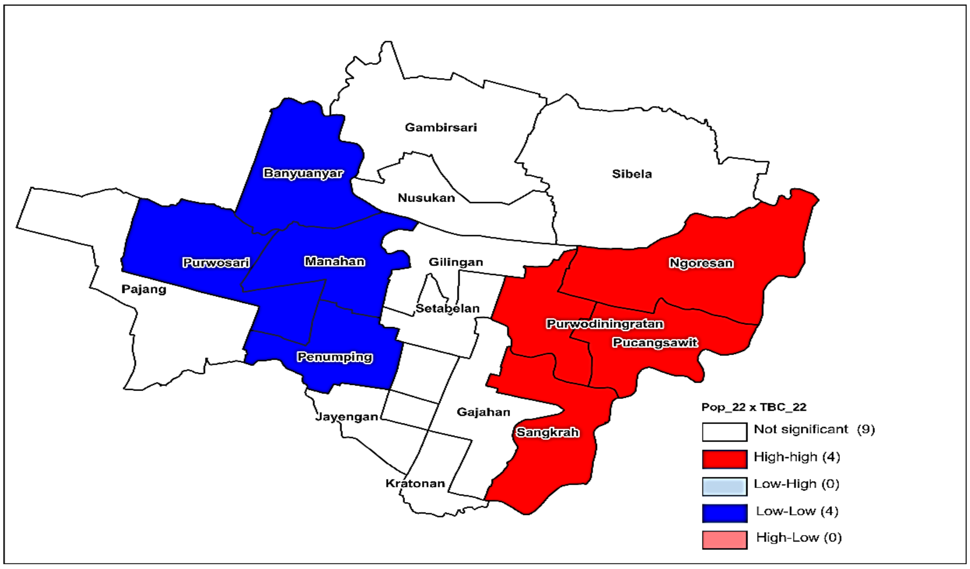

Figure 10. LISA clustermap of the population to number of pulmonary tuberculosis cases

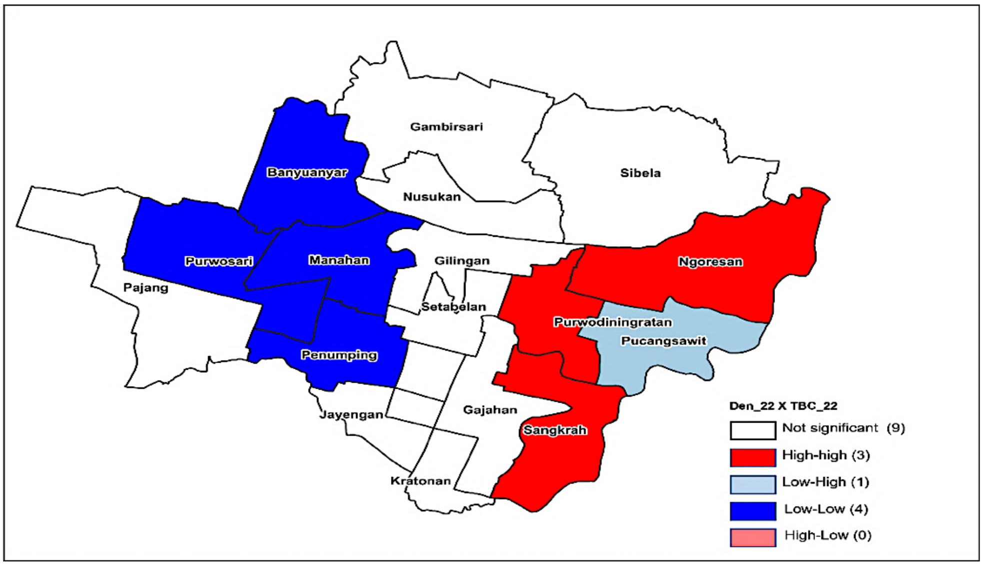

Figure 11. LISA clustermap of population density on the number of pulmonary tuberculosis cases

The results of the LISA clustermap of the relationship between the number of poor people and the number of pulmonary tuberculosis cases in Figure 12 shows that in quadrant I (high-high) there are four working areas, namely Purwodiningratan Health Center, Sangkrah Health Center, Pucangsawit Health Center, and Ngoresan Health Center. In quadrant III (low-low) there are four work areas, namely Manahan Health Center, Purwosari Health Center, Banyuanyar Health Center, and Penumping Health Center.

The LISA clustermap of the relationship between the number of unemployed and the number of pulmonary tuberculosis cases in Figure 13 shows that in quadrant I (high-high) there are four working areas, namely Purwodiningratan Health Center, Sangkrah Health Center, Pucangsawit Health Center, and Ngoresan Health Center. In quadrant III (low-low) there are 4 work areas (Manahan Health Center, Purwosari Health Center, Banyuanyar Health Center, and Penumping Health Center).

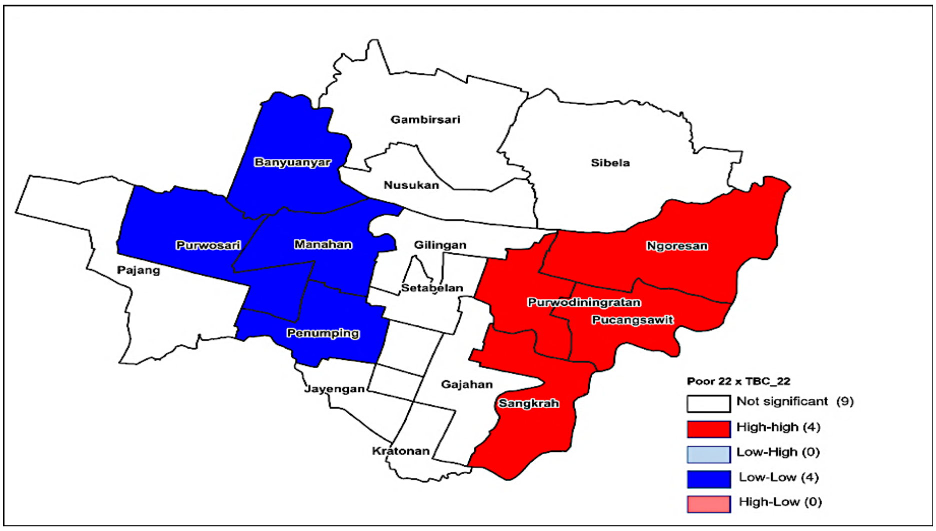

Figure 12. LISA clustermap the number of poor people to the number of cases of pulmonary tuberculosis

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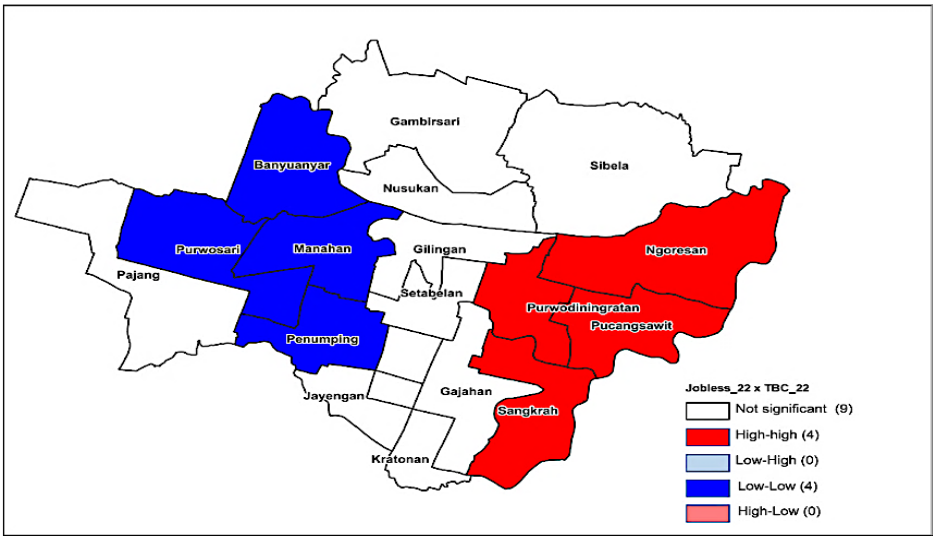

Figure 13. LISA clustermap the number of unemployed to the number of cases of pulmonary tuberculosis

The results of the LISA clustermap of the relationship between the number of healthy houses and the number of pulmonary tuberculosis cases in Figure 14 shows that there are two working areas in the first quadrant (high-high), namely the Purwodiningratan Health Center and the Sangkrah Health Center. In quadrant II (low-high) there are 2 work areas, namely the Ngoresan Health Center and the Pucangsawit Health Center.

In quadrant III (low-low) there are the working areas of the Banyuanyar Health Center and the Manahan Health Center. In Quadrant IV (low-high), which is an area with a low observation value neighboring the health center area that has a high observation value, consists of the Purwosari Health Center and the Penumping Health Center.

The distribution of tuberculosis cases and healthy homes in 2022 has a pattern that tends to be random, but there are low-high areas that need to be watched out for to prevent an increase in pulmonary tuberculosis cases, because it is a low-observation area that is around an area with high observation results.

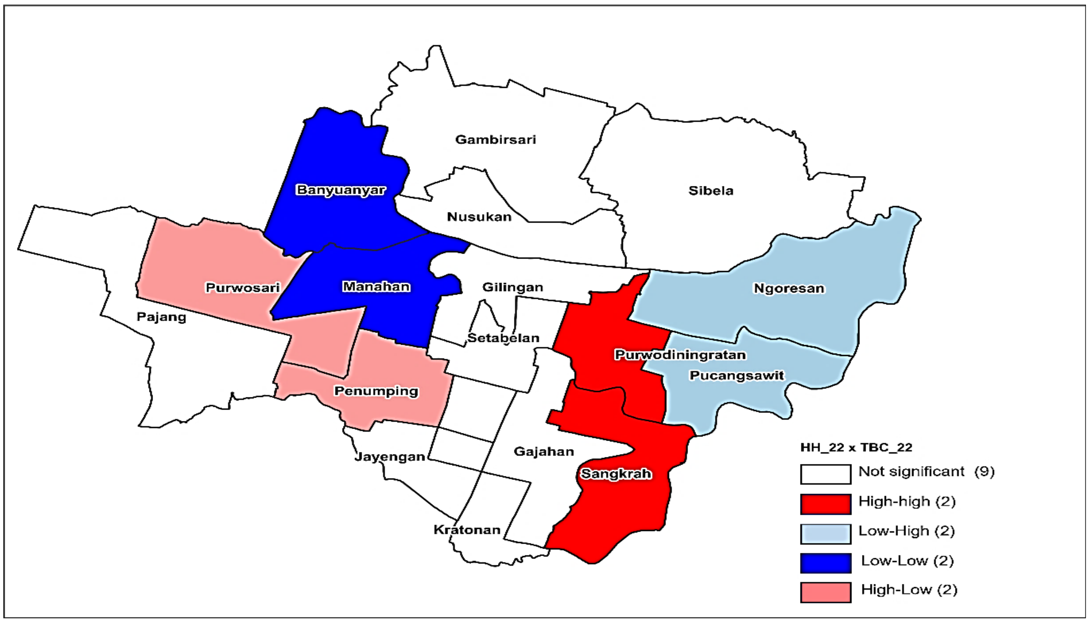

Figure 14. LISA clustermap of the number of healthy houses to the number of pulmonary tuberculosis cases

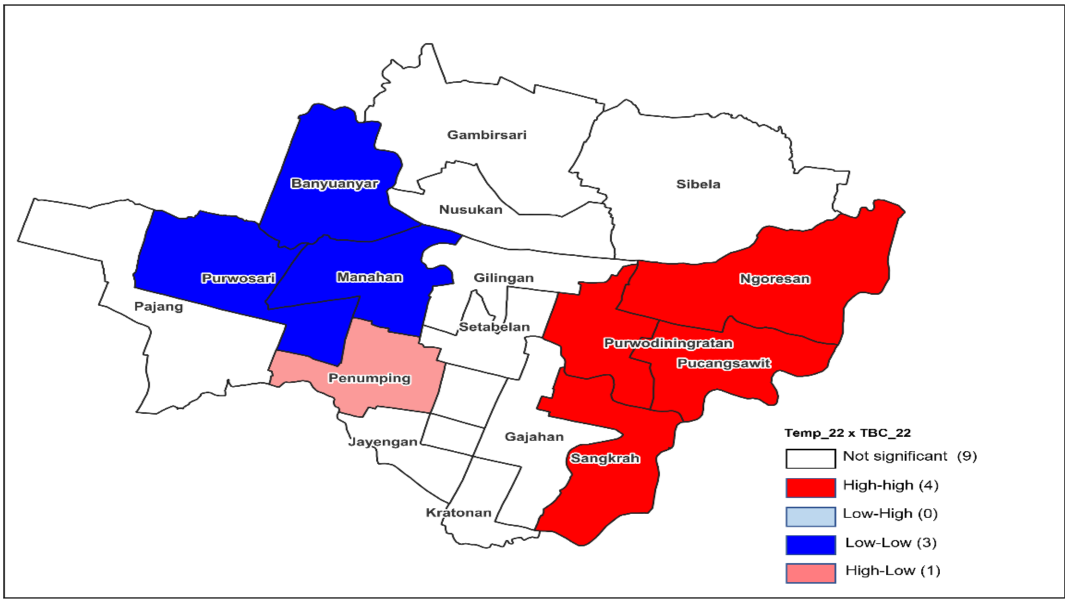

Figure 15. LISA clustermap temperature against the number of pulmonary tuberculosis cases

The results of the LISA clustermap of temperature relationship with the number of pulmonary tuberculosis cases in Figure 15 show that there are four working areas of health centers in quadrant I (high-high), namely Ngoresan, Pucangsawit, Purwodiningratan,and Sangkrah Health Centers. There are no regions in quadrant II (low-high). Meanwhile, in quadrant III (low-low) there are Purwosari, Manahan, and Banyuanyar Health Centers. Penumping Health Center is in quadrant IV (high-low).

The results of the local autocorrelation test using the Local Index Spatial Autocorrelation (LISA) obtained the expected value of the moran index or E[I]= -0.06. The variable moran index of the population (I=0.40; p=0.003), population density (I=0.33; p= 0.002), number of poor people (I=0.40; p= 0.002), number of unemployed (I=0.40; p= 0.003), and temperature (I=0.25; p=0.009) were significantly autocorrelated with the number of pulmonary tuberculosis cases. The value of the independent variable moran index is 0< I ≤1, which means that locally there is a positive spatial autocorrelation between the work areas of health centers in Surakarta City in 2022. The value of the variable moran index is greater than E[I], this shows a clustered distribution pattern between the working areas of health centers in Surakarta City. The autocorrelation between the variable of the number of healthy houses and pulmonary tuberculosis cases proved to be insignificant (I=0.01; p= 0.494).

Table 2. Results of local autocorrelation analysis using LISA

Variable	Moran Index	E[I]	p
Population	0.40	-0.06	0.003
Population density	0.33	-0.06	0.002
Number of poor people	0.40	-0.06	0.002
Number of unemployed	0.40	-0.06	0.003
Number of healthy homes	0.01	-0.06	0.494
Temperature	0.25	-0.06	0.009

DISCUSSION

The Purwodiningratan Health Center has the highest population and cases in 2022. Cases of pulmonary tuberculosis are more common in regions with high populations and poor populations (Sihaloho et al., 2019). Population growth reduces the distance between individuals, increasing the likelihood of droplet spread when people with tuberculosis speak, cough, or sneeze as when heavy use of public transportation makes droplet spread. Crowded places such as shopping malls, offices, and schools that are crowded increase the chances of droplet spreading. Lack of social distancing ability increases the risk of transmission of pulmonary tuberculosis. The results of the LISA autocorrelation analysis between population and pulmonary tuberculosis (p=0.003) showed that the hotspots were Purwodiningratan, Pucangsawit, Ngoresan, and Sangkrah Health Centers. Previous research supports that the growth of pulmonary tuberculosis and population is a significant variable (Helmy et al., 2022). The high population in hotspots is associated with high cases of tuberculosis. This autocorrelation pattern is related to the surrounding conditions, where areas with high cases affect the surrounding area through population mobilization. Dense populations increase individual interaction, making it easier to spread Mycobacterium tuberculosis bacteria through the air when coughing, sneezing, or talking.

In dense environments such as urban areas with narrow housing and poor ventilation, the risk of tuberculosis transmission increases. Unmanaged garbage, limited clean water, and dirty public facilities support the spread of infectious diseases, including tuberculosis. Large populations often include vulnerable immune groups, such as people with HIV/AIDS, who are at high risk of developing active tuberculosis. Previous research (Tabilantang et al., 2018) showed that tuberculosis cases in Manado City were found in areas with high density and poverty. LISA analysis (p=0.002) identified Purwodiningratan, Sangkrah, and Ngoresan Health Centers as hotspots. This is in line with research (Madao et al., 2024) which shows a significant population density against the prevalence of tuberculosis (p= 0.001). Previous research has also shown that population density affects pulmonary tuberculosis cases (Zebua and Yahya, 2022). Population density can affect pulmonary tuberculosis disease because in areas with high population density, people tend to live and interact in close proximity to each other. High population density is often accompanied by unhealthy environmental conditions, such as poor sanitation and inadequate ventilation. In a dense population, an infected person can easily spread the disease to many people due to more frequent and closer interactions with others. In response and prevention efforts, there is a challenge in densely populated areas where high population density can cause pressure on the health care system, which may result in limited access to quality health services for individuals infected with tuberculosis.

Tuberculosis is often referred to as a disease of the poor group because its prevalence is higher among people with low economic conditions. Based on the variable of the number of poor people, the working area of the health center that has the highest number of pulmonary tuberculosis cases with the highest number of poor people is the Sangkrah Health Center. Cases of pulmonary tuberculosis are higher in poor regions because poor areas usually have poor infrastructure, such as unsafe drinking water, ineffective sanitation, and poor ventilation, which can increase the risk of tuberculosis infection. The results of the LISA bivariate autocorrelation analysis of the number of poor people and the number of pulmonary tuberculosis (p=0.002) showed that the hotspot areas were Purwodiningratan Health Center, Pucangsawit Health Center, Ngoresan Health Center, and Sangkrah Health Center. This means that in relation to the number of pulmonary tuberculosis cases, the number of poor people in the working area of the health center that is a hotspot has the same observational nature as the Purwodiningratan Health Center, namely the number of poor people who tend to be high with high tuberculosis cases. The number of poor people in the working area of the Ngoresan Health Center and Pucangsawit Health Center is less than that of the Purwodiningratan Health Center, but its existence is neighboring areas with a higher poor population and high cases, this still makes the Ngoresan and Pucangsawit Health Centers a high-risk area for the transmission of pulmonary tuberculosis cases. The results of this study are similar to previous research, where poverty and air pollution index create a certain grouping area for pulmonary tuberculosis cases in Peru, Lima (Escobar et al., 2020).

The number of pulmonary tuberculosis cases tends to be high in poor communities due to the complex interaction between various factors that exacerbate the risk of infection and disease progression. Poor living conditions, such as population density and poor ventilation, facilitate the spread of the disease. Poverty is often accompanied by limited access to health services, leading to delays in diagnosis and treatment, so that the disease can develop and spread more easily. Poverty can also increase stress, harm the immune system, and encourage risky behaviors such as smoking. Overall, these factors create an environment where poor people are more likely to contract and develop pulmonary tuberculosis patients, as found in previous research that poverty rates affect the number of pulmonary tuberculosis cases (Sihaloho et al., 2021). Unemployment is one of the factors causing poverty, so the relationship with pulmonary tuberculosis cases tends to be similar. Previous research (Apolinário et al., 2017) showed that regions with higher cases of tuberculosis were associated with low socioeconomic conditions, a proportion of manual laborers, and a high percentage of unemployment. Previous research has found that low socioeconomic status affects the quality of the environment, access to nutrition, health facilities, and decent housing, thereby increase the risk of pulmonary tuberculosis infection (Sayidah et al., 2018). LISA analysis (p=0.003) showed hotspots in Purwodiningratan, Pucangsawit, Ngoresan, and Sangkrah Health Centers. The region has a high unemployment rate that correlates with high cases of tuberculosis.

Based on the variable number of healthy houses, no working area of the health center with the highest number of pulmonary tuberculosis cases was found with the least number of healthy houses. However, there are areas with a not-too-high number of healthy houses (29,673 to 48,853 families) but have the most cases of pulmonary tuberculosis, namely the Sangkrah Health Center and the Purwodiningratan Health Center. While the Sibela Health Center and the Ngoresan Health Center have the highest number of healthy houses, but with moderate cases (not low), therefore the distribution pattern of pulmonary tuberculosis cases based on healthy houses is random. A house that meets health standards will have a good impact on the health of its residents, and vice versa. The results of the LISA bivariate autocorrelation analysis of the number of healthy houses and the number of pulmonary tuberculosis (p= 0.494) showed that the hotspot areas of the Purwodiningratan Health Center and the Sangkrah Health Center were located. Meanwhile, the areas that are cold spots are the Banyuanyar Health Center and the Manahan Health Center. This means that in relation to the number of pulmonary tuberculosis cases, the number of healthy houses in the working areas of health centers that are hotspots and coldspots does not have a significant autocorrelation between the number of healthy houses and the number of pulmonary tuberculosis. Previous research found that the coverage of healthy homes did not have an autocorrelation with the number of pulmonary tuberculosis cases (Nahak et al., 2024).

The number of healthy homes does not have an autocorrelation with the number of pulmonary tuberculosis cases. This may be because the percentage of healthy house achievement in Surakarta City (Surakarta City Health Office, 2022) for all health center work areas has exceeded the expected achievement target, so there is no significant difference between the health center work areas. The better the coverage of healthy homes in an area, which is to reduce the risk of people becoming sick. The presence of germs that cause TB or TB sufferers at home who are in inadequate conditions will increase the number of contact with germs or sufferers, causing infection. On the other hand, home conditions met with healthy requirements will reduce the potential development of the cause of germ diseases and the onset of infectious diseases.). There have been previous studies that have stated that the coverage of healthy houses does not affect the number of pulmonary tuberculosis cases (Nariswari, 2021) because the percentage of healthy houses has increased.Healthy houses, in general, are inversely proportional to the number of pulmonary tuberculosis cases. This is because healthy households can significantly reduce the risk of pulmonary tuberculosis transmission by creating an environment that minimizes exposure to bacteria. Healthy houses, in general, are inversely proportional to the number of pulmonary tuberculosis cases. This is because healthy households can significantly reduce the risk of pulmonary tuberculosis transmission by creating an environment that minimizes exposure to bacteria. Sufficient natural light, especially sunlight, has a disinfecting effect and can help kill tuberculosis-causing bacteria in the air and surfaces of objects in the house, including on furniture that is exposed to sunlight. Access to clean water and sanitation also contributes to a stronger immune system, thereby reducing the individual's susceptibility to infection.

Based on temperature variables, the working areas of the health center that have the highest cases with an average temperature in 2022 between 29°C to 30.5°C are the Sangkrah Health Center and the Purwodiningratan Health Center. According to Gould and Brooker (2013), there is a temperature range preferred by Mycobacterium tuberculosis bacteria, namely in that temperature range there is an optimal temperature that allows the bacteria to grow quickly. Mycobacterium tuberculosis is a mesophilic bacterium that grows rapidly in the air temperature range of 25°C to 40°C, but the bacteria will grow optimally at temperatures of 31°C to 37°C. The results of the LISA bivariate autocorrelation analysis of the number of healthy houses and the number of pulmonary tuberculosis ($p= 0.009$) showed that there were hotspots consisting of the working area of the Ngoresan Health Center, Pucangsawit Health Center, Purwodiningratan Health Center, and Sangkrah Health Center. Meanwhile, the areas that are cold spots are the Manahan Health Center, Banyuanyar Health Center, and Purwosari Health Center. A hotspot can be interpreted as a grouping of areas with an autocorrelation between temperature and the number of cases is also high, and the surrounding areas have the same characteristics. Meanwhile, the coldspot area is an area with an autocorrelation between temperature and a low number of cases, with the surrounding area having the same tendency.

Mycobacterium tuberculosis grows faster in the temperature range of 25°C to 40°C because this temperature is close to the normal human body temperature, around 36.5°C to 37.5°C. As a human pathogen, M. tuberculosis has adapted to grow in a temperature range that suits the human body, as it is a natural environment in which the bacteria thrive and survive. The optimal growth of these bacteria occurs at a temperature of 31°C to 37°C because, at this temperature, environmental conditions greatly support the metabolic and reproductive processes of bacteria. At this temperature, the enzymes involved in the metabolic process of bacteria work efficiently, allowing for faster cell growth and division. In addition, this temperature is close to the temperature of the human body, where bacteria generally infect the lungs and other organs. Therefore, tuberculosis bacteria have evolved to grow and multiply optimally at those temperatures, so outside of this temperature range, bacterial growth may be stunted or even die. Temperatures that are too low or too high can inhibit enzyme activity and damage the cell structure of bacteria. An ambient temperature that is higher than a tolerable temperature will cause denaturation of proteins and other essential components so that the cell will die as well as its ambient temperature. Similarly, if the ambient temperature is below the tolerance limit, the cytoplasmic membrane will not be in liquid form, so nutrient transport will be hampered and the cell life process will be stopped. Therefore, although bacteria can grow over a wider range of temperatures, their optimal growth tends to occur at temperatures that are most similar to the temperature of the human body.

SaTScan is one of the software used for cluster analysis in epidemiology and public health research. This analysis method uses population as the most commonly used variable to detect cluster cases in an area (Sherman et al., 2014). Using spatial scan statistics, based on the number of population, one major cluster of significant pulmonary tuberculosis cases was detected in Surakarta City in 2022. The most likely cluster includes the working area of Ngoresan Health Center, Purwodiningratan Health Center, Sangkrah Health Center, and Pucangsawit Health Center. With the cluster center located in the Purwodiningratan Health Center, it is assumed that the population in the cluster has a higher risk of transmission of pulmonary tuberculosis cases due to the concentration of TB cases that occur in a certain population. Apart from the population at risk, other factors can also affect the spread of the disease such as low socioeconomic conditions, high population density, or limited access to health services. In addition, clusters can also reflect local transmission patterns, such as close contact with individuals who have been infected with tuberculosis. Cluster analysis is important in the prevention and control of tuberculosis, as it can help identify areas or populations that need extra attention in early detection, treatment, and other intervention efforts. By identifying areas at high risk of pulmonary tuberculosis transmission, specific steps can be taken to strengthen tuberculosis control programs, such as improving health service accessibility, conducting contact tracing, and improving health promotion in the region regarding the importance of tuberculosis prevention. Thus, it not only helps in understanding the pattern of disease spread, but also provides a basis for more effective actions in controlling tuberculosis transmission at the regional level in the working area of the health center in Surakarta City.

AUTHOR CONTRIBUTION

Dinda Nabila Silva Diba is the principal researcher who selects topics, conducts research, and data management, and writes manuscripts. Bhisma Murti helps to correct writing, analyze data, and provide corrections. Noor Alis Setiyadi provided input on the discussion of health phenomena in spatial analysis.

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CONFLICT OF INTEREST

There is no conflict of interest in this study.

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