ORIGINAL RESEARCH ARTICLE

Spatio-Temporal Patterns of Tuberculosis in Makassar, South Sulawesi Indonesia

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ABSTRACT

Background: Tuberculosis (TB) remains a major global health challenge, with Indonesia ranking among the top three countries with the highest TB burden in 2019. Information about the distribution of the tuberculosis (TB) incidence rate over time and space is necessary for the effective control of the disease. This study aimed to examine the spatio-temporal trends of tuberculosis (TB) incidence rates in Makassar, South Sulawesi.

Methods: This Ecological study utilized aggregated TB cases data in Makassar City, from the Indonesian National Tuberculosis Information System (SITB). between January-December 2022 (3977 patients). Kulldorff's space-time scan statistic, implemented using SaTScan, was applied to identify clusters of TB. In addition, Anselin's Local Moran's I, conducted in GeoDa, was utilized to further characterize tuberculosis hotspots and cold spots.

Results: The greatest Tuberculosis incidence rate was recorded in middle west area in Makassar during 2022. Kulldorf's space-time scan statistic identified the most probable cluster in 60 villages in the mid-western region of Makassar from July to December 2022, with a relative risk (RR) of 1.50 (p-value <0.001) and secondary cluster (16 villages) was identified in the southern region of Makassar, with a RR of 1.41 (p = 0.0015). Some high-trend TB statistically significant clusters were found in the same places.

Conclusions: The TB cluster was located at Middle west Makassar. Prioritizing these clusters for resource allocation could lead to more successful control and prevention of TB. Future studies should examine socioeconomic and environmental determinants to better explain TB clustering and guide comprehensive interventions.

Keywords: Tuberculosis, Spatial Analysis, Hotspot analysis, Spatio-temporal

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Introduction

Tuberculosis (TB) remains a significant global health concern, posing a major challenge to public health systems worldwide. The World Health Organization (WHO) reports that the present tuberculosis endemic is concerning., with an estimated 10 million new cases of TB reported, leading to 1.4 million TB-related deaths. In addition, the burden of multi-drug-resistant TB was estimated to affect 3.3% of new cases.[1,2] in the persistent threat of TB necessitates a deeper understanding of its spatio-temporal patterns to develop effective control and prevention strategies.[3]

In the context of Indonesia, TB poses a significant burden on public health. Indonesia ranks third among the world's highest TB-burden countries, with an estimated incidence rate of 845,000 in 2020, with 357,199 new cases reported and 13,947 deaths. However, the number of reported cases remains far below the incidence estimated by WHO. Challenges persist in diagnosing and treating the disease, with 28% of tuberculosis cases remaining undiagnosed and only 34% receiving successful treatment.[4] The country's population diversity, urbanization, and socioeconomic disparities contribute to the complex dynamics of TB transmission and its spatial distribution.[5-7]

South Sulawesi, specifically the city of Makassar, represents an important area for TB research due to its high population density and its role as a regional economic and transportation hub. Despite efforts to control TB in the region, the incidence of TB still High it was 27 per 10,000 population.[8,9] It is essential to comprehend the spatio-temporal patterns of tuberculosis in Makassar in order to identify high-risk areas., predicting disease trends, and implementing targeted interventions.[10]

Previous research has explored the social determinants of TB, highlighting factors such as poverty, malnutrition, overcrowding, and limited access to healthcare as significant contributors to TB transmission and prevalence.[11-13] However, there remains a research gap in understanding the spatio-temporal patterns of TB and investigated how these factors intersect with spatial dynamics at village level in urban setting in Makassar city.

Integrating geographical information systems (GIS) and epidemiological methods, this research will enhance our understanding of the spatial distribution of TB cases, identify high-risk areas, and explore the drivers of transmission.[14,15] It was hypothesized that TB clusters would be concentrated in urban regions with high population density.

Methodology

Study Design: An Ecological study was performed to investigate the dynamics of the spatio-temporal TB clusters in Makassar 2022. The study population included all smear-positive TB patients who were registered at The Indonesia national tuberculosis information system, Sistem Informasi Tuberkulosis (SITB) between January-December 2022, yielding a total of 3,977 cases. A total sampling was adopted to maximize statistical power, avoid potential selection bias, and ensure comprehensive cluster detection.

Study Setting: This study encompasses all of Makassar City, which is divided into 15 sub-districts with 153 villages. Minor islands were left out from sample due to their small population size (less than 1% of city's total population) and geographic isolation from the mainland. The sample included all study population with an accurate address, who had not moved to another place and who were still alive.

Geographical distribution of TB Incidence: Figure 1 presents descriptive data and references for the variables employed in the analysis. The annual tuberculosis incidence rate for administrative village-level entities is utilized as the dependent variable. The annual incidence rate is determined by dividing the number of new TB cases by the population size of each geographical unit from the statistics Makassar database. The equation is as follows:

$$\text{Incidence Rate} = \frac{\text{Total new disease cases during given period}}{\text{Total population at risk during the same period}} \times 10{,}000$$

The annual incidence was subsequently depicted in a panel of choropleth maps that were generated using Quantum GIS (QGIS 3.28).

Spatio-Temporal analysis: Spatial scan statistic of Kulldorff was applied in space-time cluster analysis to identify TB cluster locations. The analysis has been widely used in epidemiological studies of TB.[16,17] In this study, we specified a maximum spatial scanning window of 50% of the population at risk and a maximum temporal window of 50% of the study period. The analysis employed a space-time permutation model, which is appropriate for detecting clusters without requiring population-at-risk data. for the purpose of preventative and control measures. The hotspot analysis, which measures the presence of spatial autocorrelation, was used to evaluate these TB-risk areas in more detail. They were then analyzed with the space-time permutation model using the SaTScan™ version 10.[18]

Autocorrelation Analysis: The spatial autocorrelation technique is employed to gauge the level of interconnectedness among geographic data within a specific area and other similar data sets. This method encompasses two distinct categories: global spatial autocorrelation, which assesses the extent of spatial aggregation and correlation, and for detect High-high clusters groups, Low-low clusters, and spatial outliers (High-low and Low-high) was using Anselin's Local Moran's I (ALMI). A queen contiguity spatial weights matrix was applied in the analysis to define neighbourhood relationships between areas. Statistical significance for Local Moran's I was tested using

999 random permutations. All analyses were conducted using GeoDa software version 1.20.[19,20]

Ethical Considerations: Ethical clearance was obtained from the Faculty of Public Health of Hasanuddin University Health Research Ethical Committee No: 3604/UN4.14.1/TP.01.02/2023. All data used in this study were anonymized and aggregated prior to analysis to ensure the protection of patient privacy.

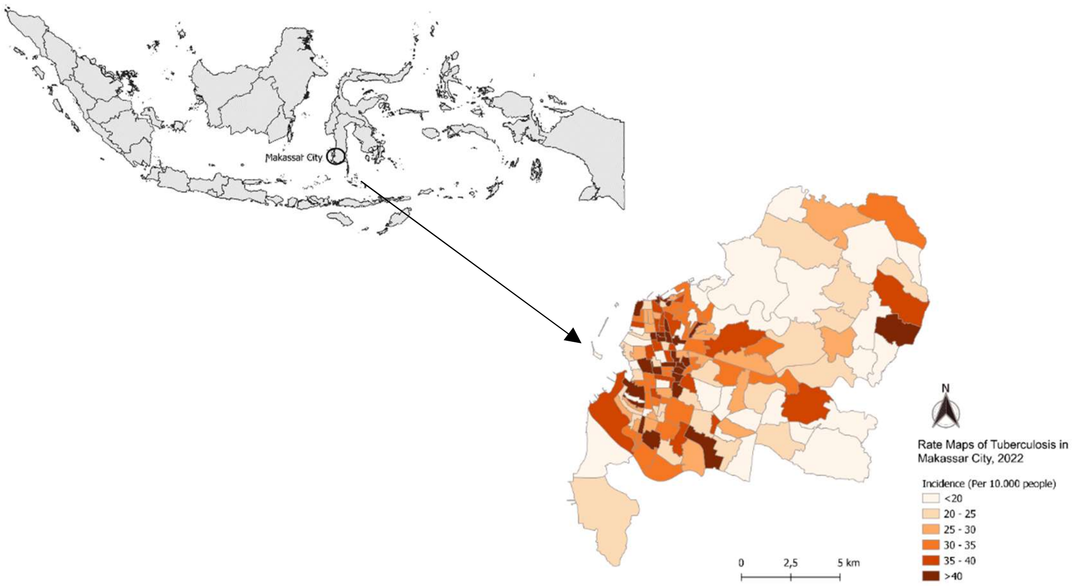

Figure 1: Distribution of TB Incidence in Makassar by Village

RESULTS

Spatio-Temporal Analysis: A total of 3,977 TB cases was reported in Makassar during 2022 with IR of 28.04 per 10,000 population. Figure 2 illustrates the identification of two statistically significant space-time clusters of Tuberculosis. A radius of less than three kilometres around the two groups. Between July and December 2022, the largest cluster (most likely cluster) was found in the middle-west of Makassar, with a relative risk of (RR) 1.50 (p<0.001) with LLR of 38.72, indicating it was the strongest cluster. This cluster had 60 contiguous villages in 8 sub-districts in Makassar (Ujung Pandang, Wajo, Makassar, Bontoala, Tallo, Panakukang, Rappocini and Mariso). The secondary cluster was located in the south of Makassar and had a relative risk of 1.41 (p=0.0015) with LLR of 15.10. The cluster occurred between August and December 2022. The second cluster had 16 contigous villages. The location in Tamalate, Mamajang and Rappocini sub-district (Table 1).

Autocorrelation analysis: The Global Moran's I statistic for tuberculosis incidence in Makassar in 2022 was 0.185 (p = 0.001), indicating a statistically significant positive spatial autocorrelation. The Anselin Local Moran's I analysis further identified 14 statistically significant hotspots (p < 0.05) located in the central-western region of Makassar. In addition, one high-low outlier (p<0.05) was observed in Antang Village, Manggala sub-district. The village has high TB cases but is surrounded by areas that have low cases (See Figure 3).

The spatio-temporal analysis of tuberculosis cases in Makassar uncovered significant discoveries. The middle-west region of Makassar had the highest TB incidence, indicating a greater burden of tuberculosis in that area compared to other regions[21,22] . Furthermore, two significant space-time clusters of tuberculosis were identified in Makassar City. The first cluster was located in the middle-west region and the second cluster in the south of Makassar. These clusters had higher relative risks, indicating a higher likelihood of TB cases occurring within those areas.

Overlay Population Density and Cluster Area: Figure 4 show spatial overlay between TB cluster areas and population density. Population density data were obtained from Statistics Indonesia [23]. The findings of this research have revealed a notable pattern, areas with elevated population density tend to exhibit a greater concentration of TB cases.

Table 1: Significant space time cluster of Tuberculosis incidence in Makassar City, South Sulawesi 2022

Period	Villages (number)	Lenght of Radius	Observed Cases	Expected Cases	RR	LLR	P value
July-December 2022	60	2.24 km	618	435.19	1.50	38.72	<0.001
August-December 2022	16	2.15 km	311	226.40	1.41	15.10	0.0015

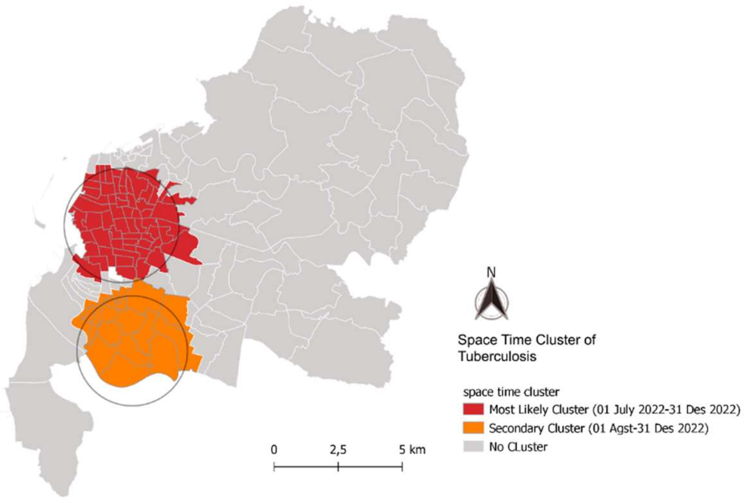

Figure 2: Space time cluster of Tuberculosis Incidence in Makassar City, South Sulawesi, 2022

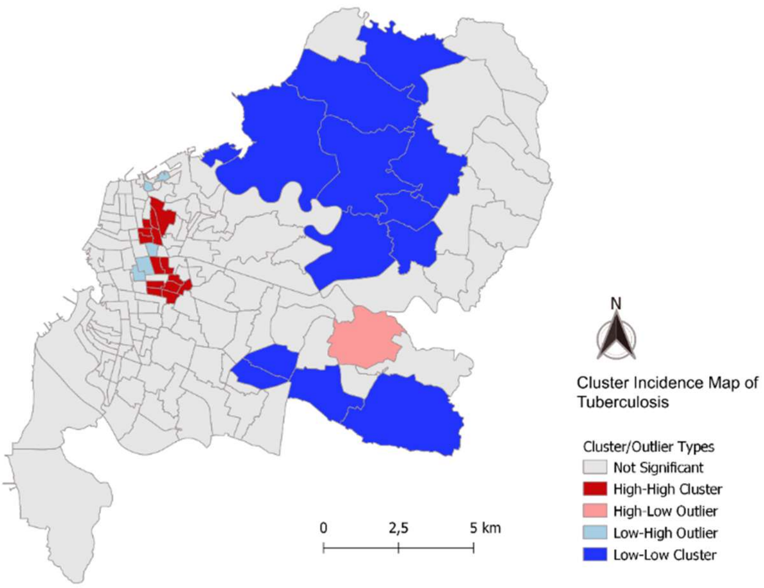

Figure 3: Cluster Incidence Map of Tuberculosis Incidence in Makassar City, South Sulawesi, 2022

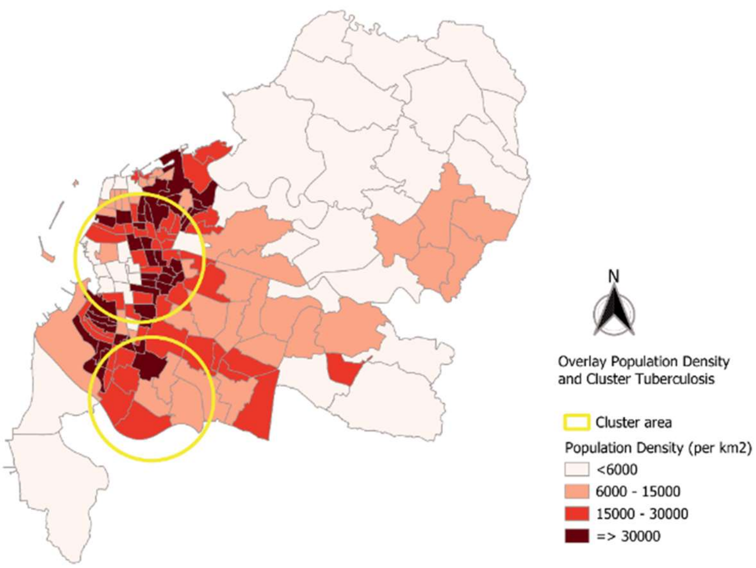

Figure 4: Overlay cluster of Tuberculosis with Population Density in Makassar City, South Sulawesi, 2022

The results of simple linear regression show that there is an effect of population density on the increase in Tuberculosis incidence in Makassar City with an R-Squared value of 0.040 or 4.0% with p-value (<0.001). This shows that population density contributes 4% to the increase in TB incidence, and the rest is likely caused by other factors. This observation is consistent with the known transmission dynamics of TB, where prolonged close contact between individuals increases the likelihood of infection, and crowded living conditions.

Discussion

This study applied spatial and space-time analysis to identify and understand the geographic and temporal distribution of tuberculosis (TB) cases in Makassar City during 2022. The results revealed the presence of two statistically significant space-time clusters: a primary cluster located in the central-western region and a secondary cluster in the southern part of the city. These clusters suggest the presence of localized TB transmission, possibly influenced by environmental or sociodemographic factors.[13,24] The high relative risk observed in both clusters, underlines the urgent need for geographically targeted public health interventions in these high-burden areas.

The spatial autocorrelation analysis further supported the clustering findings, with fourteen villages in the central-western part of Makassar identified as significant hotspots. This spatial concentration indicates that TB cases are not randomly distributed but are geographically correlated, likely driven by shared risk factors such as overcrowded living conditions, inadequate ventilation, or poor access to healthcare services. Moreover, the identification of a high-low spatial outlier in Antang village suggests that there may be unique, localized drivers of TB that deviate from broader trends, warranting further micro-level investigation. Similar patterns of spatial clustering have been documented in urban settings in other countries, such as in Thailand, Korea, and Zimbabwe, where TB hotspots were associated with population growth rate and socioeconomic deprivation.[25-27] However, unlike the studies in Thailand and Zimbabwe, this research did not incorporate direct measures of socioeconomic deprivation, limiting comparison on this dimension.

The overlay analysis between TB cluster areas and population density further demonstrated that high-density neighbourhoods tend to exhibit higher TB incidence. Although the simple linear regression yielded a low R-squared value (4.0%), indicating a weak overall correlation, the spatial co-location of high-density zones and TB clusters suggests that population density may still act as an enabling factor for transmission. This aligns with previous research in Brazil and Guinea-Bissau[28,29], which found that high-density environments contribute to increased TB risk through mechanisms such as sustained close contact and poor housing conditions.

However, the limited variance explained by population density alone underscores the multifactorial nature of TB transmission. clustering analysis did not account for potential covariates, such as socioeconomic status or healthcare access, which may confound the observed patterns. Second, the use of aggregated data at the village level introduces the possibility of ecological fallacy, where associations observed at the group level may not reflect individual-level risk. Lastly, while spatial and temporal clustering suggests possible local transmission, this study did not include molecular epidemiology to confirm transmission pathways. This calls for future research to incorporate more comprehensive multivariate spatial models such as Geographically Weighted Regression (GWR) or Bayesian spatial models, to better understand the complex interplay of determinants of TB in Urban area.[30-32]

In summary, this study highlights the value of spatial and spatio-temporal analyses in detecting high-risk areas for TB and informing geographically targeted public health strategies in Makassar, South Sulawesi Indonesia. The findings emphasize the need for intensified TB control efforts in identified hotspot regions, as well as further investigation into local contextual factors influencing disease transmission. Integration of spatial evidence into routine surveillance and urban health planning could enhance the effectiveness of TB control programs in Makassar and similar urban settings.

Conclusion

This study highlights the spatial concentration of tuberculosis (TB) in Makassar, particularly in the Middle West region where population density is highest. The presence of statistically significant clusters suggests persistent local transmission that requires immediate public health attention. Beyond identifying these high-risk zones, the findings underscore the need for context-specific interventions. Authorities should prioritize active case finding in the 60 clustered villages, strengthen contact tracing, and integrate community-based screening with primary health care services. In parallel, addressing structural factors such as overcrowding, poor housing conditions, and limited access to timely diagnosis will be essential to reduce transmission. Incorporating spatial evidence into TB control planning provides an opportunity to allocate resources more efficiently and enhance the impact of ongoing elimination efforts.

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Availability of Data: Data used in this study were obtained from The Indonesia national tuberculosis information system (SITB) by the Indonesian government Ministry of Health Republik Indonesia under permission.

Declaration of Non-use of Generative AI Tools: This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

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