e-ISSN : 2597-6052

MPPKI MEDIA PUBLIKASI PROMOSI KESEHATAN INDONESIA

Research Articles Open Access

Relative Risk and Distribution Assessment of Tuberculosis Cases: A Time-Series Ecological Study in Aceh, Indonesia

Novi Reandy Sasmita[1*], Mhd Khairul[2], Mumtaz Kemal Fikri[3], Latifa Rahayu[4], Zurnila Marli Kesuma[5], Selvi Mardalena[6], Rumaisa Kruba[7], Virasakdi Chongsuvivatwong[8], M. Ischaq Nabil Asshiddiqi[9]

[1]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[2]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[3]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[4]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[5]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[6]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[7]Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia
[8]Department of Epidemiology, Faculty of Medicine, Prince of Songkla University, Hat Yai, Thailand
[9]School of Nursing, Li Ka Shing Faculty of Medicine, The University of Hong Kong, Hong Kong

***Corresponding Author:** E-mail: novireandys@usk.ac.id

ARTICLE INFO

Manuscript Received: 08 Apr, 2025
Revised: 02 May, 2025
Accepted: 05 May, 2025
Date of Publication: 05 Jun, 2025
Volume: 8
Issue: 6
DOI: 10.56338/mppki.v8i6.7264

KEYWORDS

Relative Risk;
Tuberculosis;
Standardized Morbidity Ratio;
Aceh Province;
Indonesia

ABSTRACT

Introduction: Tuberculosis (TB) remains a critical public health issue, particularly in high-incidence regions like Aceh Province, Indonesia. This study aimed to estimate the Relative Risk (RR) and analyze significant differences in the temporal distribution of TB cases across Aceh Province.

Methods: A time-series ecological study was conducted using TB case and population data from 23 districts/cities in Aceh Province between 2016 and 2022. Data were analyzed using R software, applying descriptive and inferential statistics. The Standardized Morbidity Ratio (SMR) method estimates RR and is categorized into five risk levels. The Kolmogorov-Smirnov test assessed data normality, guiding the selection of statistical tests. The Friedman and Wilcoxon Signed-Rank tests examined differences in TB case distribution trends.

Results: Significant spatial and temporal variations in TB risk were identified. Districts such as Banda Aceh (RR = 2.29–2.13) and Lhokseumawe (RR = 1.89–2.21) consistently demonstrated high RR from 2016 to 2022, reflecting persistent TB transmission. A general upward trend in TB cases was observed across districts, with significant spatial variation ($p < 0.001$), highlighting a worsening TB burden.

Conclusions: The study emphasizes the urgent need for targeted public health interventions tailored to TB's unique spatial and temporal dynamics in Aceh Province, Indonesia. Applying SMR and robust statistical analyses provides valuable insights to inform localized TB control policies and strengthen management strategies in high-burden areas.

Publisher: Fakultas Kesehatan Masyarakat Universitas Muhammadiyah Palu

INTRODUCTION

Tuberculosis (TB) is an infectious disease caused by Mycobacterium tuberculosis (M.tb). An estimated quarter of the world's population has been infected with TB. Adults account for 89% of cases, 56.5% men, and 32.5% women, while children comprise 11%. TB remains the leading cause of death after HIV/AIDS and consistently ranks among the top 20 causes of mortality worldwide. The majority of TB-related deaths occur in India, Indonesia, Myanmar, and the Philippines (1). Indonesia ranks as the second highest in TB cases globally, following India, accounting for 10% of the world's cases. In 2022, the TB incidence rate increased to 385 per 100,000 population, up from 354 per 100,000 in 2021, with a mortality rate of 49 per 100,000. By 2023, TB cases surged to 821,200 from 677,464 in 2022 (2).

In Aceh Province, one of the Provinces in Indonesia with one of the highest TB incidence rates, only 36.12% of the 10,896 TB cases reported in 2022 received standardized treatment. The pulmonary TB cure rate confirmed by bacteriology was 26.8%, while the complete treatment and success rates were 74.7% and 89.2%, respectively, with a mortality rate of 3.9%. These statistics underscore the significant challenges in managing TB in Aceh, exacerbated by limited healthcare access and high poverty rates (3,4).

Aceh Province's high TB burden is driven by intersecting challenges, including dense urban populations, limited healthcare infrastructure, persistent poverty, and low treatment adherence, which collectively exacerbate transmission and complicate control efforts (5).

In light of these conditions, estimating the Relative Risk (RR) of TB across Aceh's districts is crucial to understanding risk variations, identifying high-risk areas, evaluating the effectiveness of interventions, monitoring trends, and refining public health strategies for TB control. RR, an epidemiological metric, quantifies the risk of disease occurrence in an exposed group relative to an unexposed group (6). RR is a metric used to compare the likelihood of disease occurrence and is a critical tool for understanding and mitigating health risks. RR estimation is one of the most important issues in disease mapping. One of the several methods used to estimate RR is the Standardized Morbidity Ratios (SMR) method. SMR values can be used as an approximation of RR (7).

Recent studies estimate RR using the SMR method approach, such as those by (8), highlighting the uneven distribution of TB across Indonesia, showing that urban centers like DKI Jakarta face higher TB risks than other areas. This variation underscores the complexity of TB control efforts. Similarly, (9) identified significant differences in TB risks within Kedah, emphasizing region-specific data's importance in optimizing interventions. The absence of detailed, localized TB data in high-prevalence regions like Aceh undermines the effectiveness of targeted public health interventions.

While previous studies in Indonesia have explored spatial or temporal TB trends in isolation, few have integrated both dimensions to assess dynamic risk patterns in high-burden regions like Aceh. This study addresses this gap by combining time-series ecological design with spatial RR estimation, offering a novel framework for understanding localized TB transmission dynamics. Such dual-dimensional analysis is critical for identifying persistent high-risk areas and evaluating intervention efficacy over time, a methodological advance not yet applied in Aceh's context.To bridge this gap, it is essential to conduct a detailed analysis of spatial and temporal TB variations at the district level using precise epidemiological tools. This approach will help identify trends and variations that can enhance TB control strategies (10,11).

Based on previous methodologies, this study employs SMR methods to estimate the RR for detailed risk assessment and different tests to examine temporal trends in TB case distributions to understand the effectiveness of public health interventions and fluctuations in TB cases. This dual approach is effective in discerning both spatial and temporal patterns in disease prevalence, thereby offering a robust framework for understanding and mitigating TB risks effectively. Previous studies have established methods to assess TB risk, but there are still significant gaps in micro-level application, especially in high-burden areas such as Aceh. Many studies lack the detailed and time-specific analysis essential to identify dynamic patterns and facilitate timely interventions.

This study aims to estimate the RR and analyze whether there are significant differences in the distribution trend of TB cases in Aceh Province from 2016 to 2022. This study offers novel insights into TB's local spatial and temporal dynamics. The result of this study will support the development of tailored public health policies and enhance TB management strategies in Aceh, potentially serving as a model for other high-burden areas. The study hypothesizes significant variations in TB risk across districts and over time, contributing novel insights to TB epidemiology with implications for both policy and practice. This study contributes to the existing body of knowledge on TB distribution in high-incidence areas and provides a methodological framework that can be adapted to similar public health challenges in other regions.

METHOD

Study Design, Variables, and Data Source

This study utilized A time-series ecological study, examining data in Aceh Province as one of the highest TB incidence rates. A time-series ecological study is particularly effective for identifying and analyzing temporal trends and associations within historical data sets, making it ideal for assessing the temporal dynamics of TB cases in a defined population (12). This study will analyze TB cases and population data across 23 districts/cities in Aceh Province from 2016 to 2022. The annual secondary data will be sourced from the Aceh Health Profile Report from 2017-2023.

Software and Stage of Data Analysis

Data analysis was performed using R-4.4.2. This open-source software was chosen for its robust capabilities in handling data pre-processing and complex statistical operations (13,14). To analyze the data, the study calculated descriptive statistics. It is to provide a clear and concise summary of the data set, enabling readers to quickly understand the key characteristics and trends within the data (15,16). Furthermore, the study applied the SMR method to estimate RR. The SMR compared the case number of diseases with an expected case number obtained by applying the standard rates (17). RR classification spans five categories: $0 \leq RR < 0.5$ signifies a very low relative risk of disease spread in a region, $0.5 \leq RR < 1$ indicates low risk, $1 \leq RR < 1.5$ denotes moderate risk, $1.5 \leq RR < 2$ suggests high risk, and $RR \geq 2$ signals very high risk (18,19). The RR for the most recent year was visualized using thematic disease mapping.

The study also conducted inferential statistics beginning with normality testing using the Kolmogorov-Smirnov test. It aims to assess the normality of the data distribution and select the appropriate statistical test, either a parametric or nonparametric test (20). If the TB cases for each year are normally distributed, Analysis of Variance (ANOVA) as a parametric method would be employed, followed by a Bonferroni test as a post hoc test. If not normally distributed, the Friedman test as the nonparametric test would be used, followed by the Wilcoxon Signed-Rank test as a post-hoc test.

The synergy of spatial mapping and time-series RR estimation represents a novel advancement in TB surveillance. Unlike conventional disease mapping, this dual approach identifies not only high-risk locations but also persistent temporal hotspots, enabling precision-targeted resource allocation.

Ethical Approval

Ethical approval was not required as this study analysed aggregated, anonymized secondary data from public health reports, consistent with institutional review guidelines exempting non-human participant research.

RESULTS

Descriptive analysis provides an overview of the data being analysed (21). Table 1 highlights significant variations in TB cases across 23 districts in Aceh Province from 2016 to 2022, revealing differences in absolute numbers and population size fluctuations. North Aceh, Bireuen, and Banda Aceh reported high TB cases, with North Aceh peaking at 1,282 cases with a mean of 865. The large standard deviation indicates variability, possibly due to outbreaks or inconsistent interventions. In contrast, districts like Sabang and Bener Meriah had fewer cases with less variability. Population data in North Aceh ranged from 593,492 to 619,407, while smaller districts like Sabang ranged from 33,622 to 43,208. Expected TB cases are detailed in Table 2.

Table 1. Summary statistics on the number of TB cases and Population in Aceh Province 2016-2022

No	District/city	TB Cases					Population				
		Min	Max	*Mean*	SD	IQR	Min	Max	*Mean*	SD	IQR
1	Simeulue	80	203	158	47	66	90,291	94,876	92,684	1,518	1,613
2	Aceh Singkil	67	228	161	60	77	116,712	130,787	123,953	5,007	6,864
3	South Aceh	246	747	397	165	94	228,603	238,081	23,402	3,311	4,092
4	Southeast Aceh	58	345	164	93	72	204,468	228,308	216,450	8,585	12,041
5	East Aceh	370	813	541	159	203	411,279	436,081	425,258	8,356	9,211
6	Central Aceh	136	266	179	43	31	200,412	222,673	211,802	7,933	10,741
7	West Aceh	184	311	238	50	77	197,921	210,113	202,551	4,274	4,757
8	Aceh Besar	326	483	391	55	72	400,913	425,216	411,727	8,038	8,574
9	Pidie	463	1144	669	245	272	425,974	444,976	437,408	6,745	8,015
10	Bireuen	418	876	739	154	110	436,418	471,635	450,042	12,799	15,768
11	North Aceh	175	1,282	865	380	415	593,492	619,407	607,490	8,674	10,364
12	Southwest Aceh	18	484	227	141	81	143,312	155,046	149,431	4,033	4,798
13	Gayo Lues	105	226	176	40	41	89,500	103,131	95,856	5,344	8,504
14	Aceh Tamiang	150	573	371	144	175	282,921	301,492	292,774	6,313	7,207
15	Nagan Raya	123	373	211	87	64	158,223	173,393	166,244	5,281	6,586
16	Aceh Jaya	101	212	151	38	42	87,622	96,028	92,118	2,881	3,436
17	Bener Meriah	23	104	70	27	27	139,890	168,690	152,890	11,661	19,126
18	Pidie Jaya	65	199	137	51	76	151,472	162,771	158,153	3,903	4,328
19	Banda Aceh	379	1.108	738	251	301	252,899	270,321	259,402	6,283	7,546
20	Sabang	9	48	25	13	16	33,622	43,208	37,645	4,279	7,357
21	Langsa	241	485	342	103	177	168,820	192,630	179,857	9,240	14,479
22	Lhokseumawe	293	853	529	207	291	188,713	207,202	19,639	7,048	10,464
23	Subulussalam	72	371	191	92	50	77,084	95,199	85,152	7,456	12,241

Table 2 highlights the expected TB cases over seven years, revealing a steady increase across most districts. North Aceh, consistently reporting the highest numbers, saw cases rise from 591 in 2016 to 1,238 in 2022. Similar trends are observed in Pidie and Bireuen, with cases increasing from 424 and 442 in 2016 to 896 and 894 in 2022, respectively. Smaller districts like Sabang and Simeulue also show rising trends, though with lower absolute numbers, suggesting the need for sustained or intensified TB control measures.

Further, Table 3 presents the estimated RR values calculated using the SMR method for 2016-2022. Table 3 reveals significant temporal and spatial variations in TB risk. Over these seven years, RR values varied widely across districts. Banda Aceh consistently exhibited alarmingly high RR values, peaking at 2.291 in 2019, indicating persistent challenges in TB control due to factors such as high population density, urbanization, and inadequate public health infrastructure. Similarly, Lhokseumawe showed high RR values, with a peak of 2.30 in 2021, suggesting ongoing TB transmission issues requiring urgent public health interventions.

In contrast, districts with lower population densities displayed more variable RR values. For instance, Simeulue's RR decreased from 1.636 in 2016 to 1.051 in 2022, indicating some improvement in TB control, though the district remains at moderate risk. Aceh Singkil followed a similar trend, with RR values declining from high to moderate. These fluctuations suggest that while progress has been made, continued efforts are essential to maintain and further reduce TB risk in these areas. The SMR method for RR estimation, widely used in disease mapping, is visually represented in Figure 1.

Table 2. Expected TB cases by District/City in Aceh Province, 2016-2022

No	District/City	Years						
		2016	2017	2018	2019	2020	2021	2022
1	Simeulue	90	129	148	150	107	126	191
2	Aceh Singkil	116	169	195	200	146	173	264
3	South Aceh	228	328	377	383	268	315	478
4	Southeast Aceh	203	295	341	349	255	301	460

No	District/City	Years						
		2016	2017	2018	2019	2020	2021	2022
5	East Aceh	409	594	686	702	488	574	872
6	Central Aceh	199	289	334	342	249	294	449
7	West Aceh	197	285	330	338	229	270	409
8	Aceh Besar	399	579	669	685	468	551	835
9	Pidie	424	612	704	716	503	591	896
10	Bireuen	442	641	741	759	504	591	894
11	North Aceh	591	852	981	997	696	817	1,238
12	Southwest Aceh	143	206	238	242	174	205	312
13	Gayo Lues	89	129	149	151	115	136	208
14	Aceh Tamiang	282	406	467	475	340	400	607
15	Nagan Raya	157	228	264	269	194	229	349
16	Aceh Jaya	87	127	146	150	108	127	193
17	Bener Meriah	139	202	233	239	186	221	340
18	Pidie Jaya	151	219	254	260	183	216	328
19	Banda Aceh	254	368	425	435	292	343	519
20	Sabang	33	48	55	56	48	57	87
21	Langsa	168	243	280	285	215	254	388
22	Lhokseumawe	194	282	326	334	218	255	386
23	Subulussalam	77	111	129	131	105	125	192

In this analysis, the first step of inferential statistics before conducting a difference test is to ensure data distribution on the number of TB cases each year. The normality test results using Kolmogorov-Smirnov showed that the TB case data from 2016 to 2022 did not follow a normal distribution for each year of observation (p-value = 0.000). Based on these results, the Friedman test, a nonparametric method, was chosen to analyze the differences in the overall distribution of TB cases from 2016 to 2022. The Friedman Test results indicated a significant difference in the distribution of TB cases across the years of observation (p-value = 0.000).

Table 3. Estimated RR of TB cases in Aceh Province in 2016-2022

No	District/City	Years						
		2016	2017	2018	2019	2020	2021	2022
1	Simeulue	1.64	1.56	1.37	0.83	1.39	0.64	1.05
2	Aceh Singkil	1.34	1.35	0.92	1.04	0.65	0.39	0.74
3	South Aceh	1.08	1.01	1.02	0.98	1.05	1.32	1.56
4	Southeast Aceh	1.00	0.54	0.26	0.37	0.23	0.53	0.75
5	East Aceh	0.99	0.69	0.54	0.81	1.18	1.13	0.93
6	Central Aceh	0.80	0.47	0.52	0.53	0.76	0.50	0.59
7	West Aceh	0.94	0.74	0.69	0.92	1.13	0.68	0.71
8	Aceh Besar	0.82	0.66	0.72	0.60	0.74	0.65	0.52
9	Pidie	1.09	0.79	0.70	1.12	1.17	1.22	1.28
10	Bireuen	0.95	1.14	1.12	1.12	1.47	1.23	0.98
11	North Aceh	0.30	1.50	1.27	0.90	1.10	0.82	0.82
12	Southwest Aceh	0.13	0.71	2.04	0.83	1.33	1.20	0.84
13	Gayo Lues	2.18	1.53	1.11	1.31	0.91	1.10	1.09

No	District/City	Years						
		2016	2017	2018	2019	2020	2021	2022
14	Aceh Tamiang	0.53	0.71	1.23	0.90	0.76	1.12	0.74
15	Nagan Raya	1.02	0.77	0.68	1.06	0.63	0.79	1.07
16	Aceh Jaya	1.16	1.09	1.27	1.42	1.44	0.95	0.74
17	Bener Meriah	0.53	0.29	0.10	0.28	0.54	0.28	0.31
18	Pidie Jaya	0.70	0.74	0.70	0.77	0.36	0.39	0.49
19	Banda Aceh	2.2	2.15	1.67	2.29	1.30	1.76	2.13
20	Sabang	0.36	1.00	0.58	0.53	0.38	0.16	0.32
21	Langsa	1.43	1.05	1.60	1.44	1.16	1.20	1.25
22	Lhokseumawe	1.89	1.17	2.08	1.79	1.35	2.30	2.21
23	Subulussalam	2.40	1.83	1.03	1.33	0.69	1.62	1.93

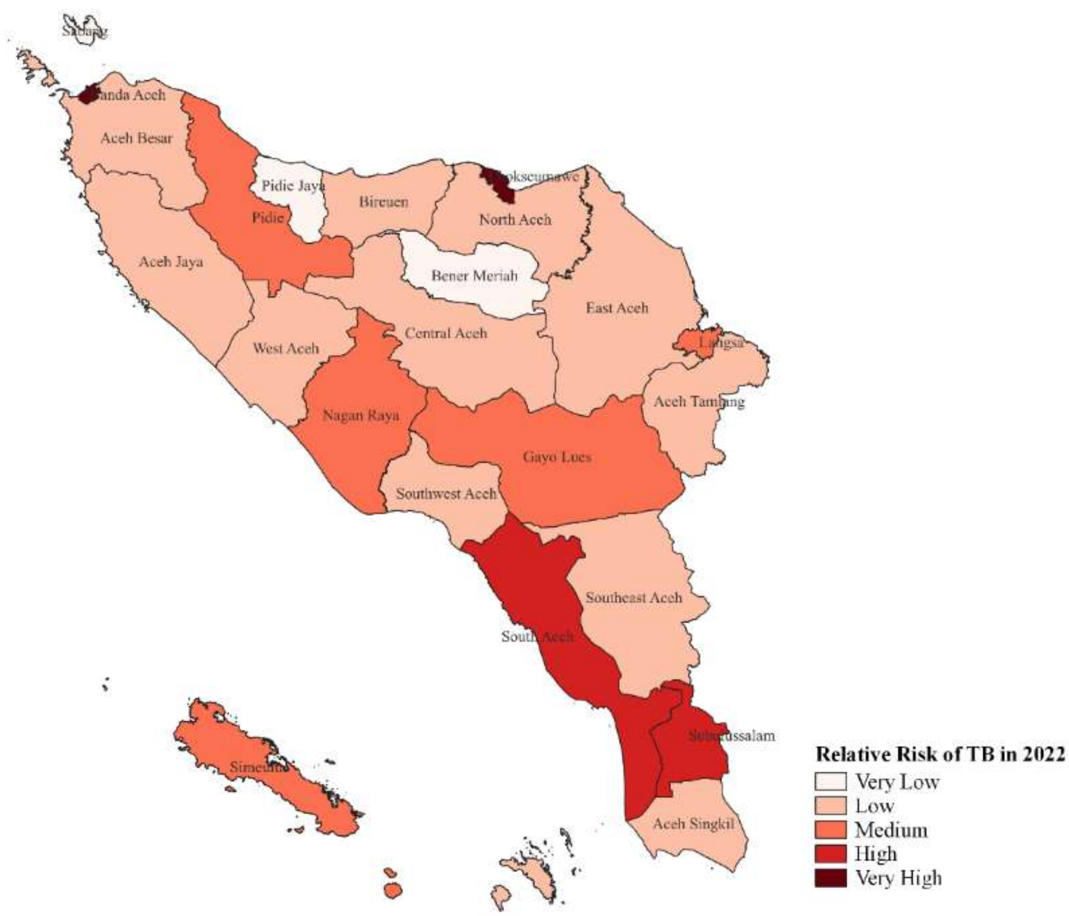

Figure 1. Disease Mapping of RR for TB cases in Aceh Province, 2022

Furthermore, the Wilcoxon Signed-Rank test was applied to identify differences in the distribution of TB cases between adjacent years. The analysis results showed significant differences in the distribution of TB cases between 2016 and 2017, 2019 and 2020, and 2020 and 2021, with p-values of 0.002, 0.000, and 0.000, respectively. In contrast, no significant differences were found between 2017 and 2018, 2018 and 2019, and 2020 and 2021, with p-values of 0.260, 0.520, and 0.073, respectively, greater than the $\alpha = 5\%$ significance level. A visualization of the results of this comparison test can be seen in Figure 2, which further explains the differences in the distribution of TB cases in Aceh Province over the period analyzed.

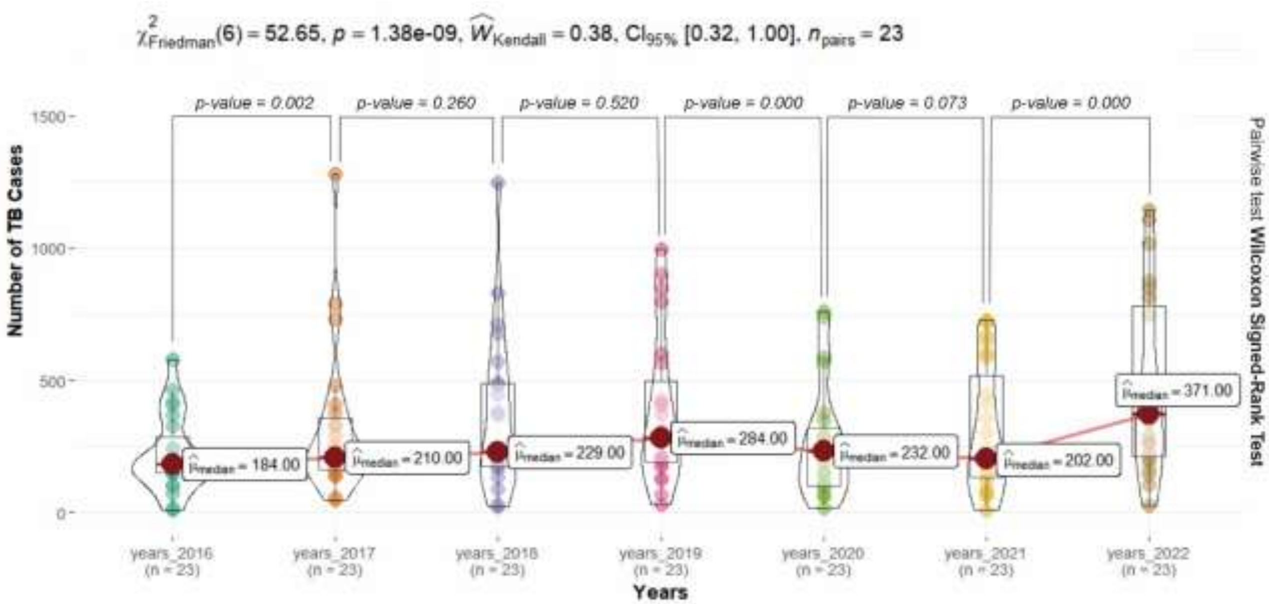

Figure 2. Visualization of the Difference Test for TB cases in Aceh Province 2016-2022

DISCUSSION

The SMR based RR estimation and disease-mapping methods contribute to knowledge on TB distribution in high-incidence areas and provide a methodological framework that can be adapted to similar public health; for instance, it can be adapted into user-friendly digital dashboards for local health authorities. Such tools, integrated with real-time data, can visualize high-risk areas and prioritize interventions, as demonstrated in similar settings (22).

Key findings revealed significant spatial and temporal variations in TB risk across the districts. Higher TB risks were consistently observed in urban centers like Banda Aceh and Lhokseumawe, underscoring the challenge of TB control in densely populated areas. The study results align with previous studies showing that urban centers exhibit higher TB risks due to factors such as high population density and mobility. These characteristics create an environment conducive to the spread of TB, making urban areas particularly vulnerable to outbreaks. High population density is a significant driver of TB transmission. The study indicates that areas with elevated population density often exhibit crowded living conditions, facilitating the spread of TB. For instance, crowded living areas, often found in urban settings, contribute to the rapid transmission of TB, especially when sanitation and nutrition are poor (23). There is a strong positive correlation between population density and TB incidence (24).

Further, mobility is another critical factor that enhances TB transmission in urban centers. The constant movement of people within and between cities can introduce new strains of M.tb, complicating control efforts. For instance, the study highlights that urban migration patterns can significantly influence TB mortality rates, particularly in informal settlements where healthcare access is limited (25). This mobility facilitates the spread of TB and complicates the epidemiological landscape, making it challenging to track and manage outbreaks effectively (26,27).

However, our study extends these findings by demonstrating that even less populated districts in Aceh show fluctuating TB risks over time, suggesting that local health interventions and socioeconomic factors also play critical roles. Low-income populations face compounded barriers, including financial constraints, distance to healthcare facilities, and low health literacy, delaying diagnosis and treatment. Poverty also correlates with malnutrition and overcrowded housing, amplifying transmission risks (28,29). The persistent high risk in specific districts indicates potential gaps in public health infrastructure and a lack of implementation of TB management strategies that need addressing (30,31). The lack of access to healthcare services in regions with TB disease can lead to delays in diagnosis and treatment, allowing the disease to spread unchecked (32). Access to healthcare services is another significant barrier to effective TB management. Individuals living in rural areas often face challenges in accessing healthcare facilities that provide TB diagnostic services, leading to increased patient delays (33). This lack of access is compounded by lower health literacy in these populations, which can result in poorer health outcomes. Similarly, the study result of (34) indicates that social and demographic factors, including living in urban slums, can further hinder timely healthcare access and contribute to delays in TB diagnosis and treatment initiation.

The study's findings are primarily generalizable to regions similar to Aceh, where a high TB burden coexists with varied access to healthcare and public health infrastructure. While the specific RR values and trends differ, the methodology and the observed impact of socioeconomic factors on TB distribution could apply to other high-burden provinces in Indonesia and similar settings globally. This study contributes to epidemiological theories by supporting the notion that TB distribution is multifactorial, influenced not just by biological factors but also by socioeconomic and environmental factors. Urban slums in districts/cities with high TB RR, e.g., Banda Aceh Lhokseumawe, lack sanitation infrastructure, fostering TB transmission. Limited education further reduces health-seeking behavior, as seen in low treatment adherence rates (35–37). It highlights the dynamic nature of TB risk, suggesting that continuous monitoring and adaptable public health strategies are crucial for effective TB control (38).

The findings highlight the need for further research into factors driving high TB risks in urban and rural settings, particularly the impact of targeted interventions and socioeconomic changes like urbanization and migration. Future studies should assess these influences to refine TB control strategies. Community-based TB control should prioritize training local health workers to conduct door-to-door screenings and education campaigns in high-risk areas. Mobile clinics offering free diagnostics and treatment and stigma-reduction programs have proven effective in similar high-burden regions. Integrating these strategies with Indonesia's existing Posyandu (community health post) network could enhance reach and sustainability. Practically, policymakers and practitioners must prioritize interventions in high-risk areas, tailoring strategy to specific regional challenges while enhancing surveillance, community engagement, and TB care accessibility (39). A localized approach is essential, with policies focused on strengthening healthcare infrastructure and integrating TB control with broader public health initiatives to address socioeconomic determinants. Further, the main limitations of this study include its reliance on secondary data in where the potential for underreporting and variability in data quality across districts could bias the RR estimates.

This study advances TB risk modelling by demonstrating how spatial-temporal integration refines epidemiological insights beyond traditional unidimensional analyses. The Aceh model, combining SMR-based RR with geospatial mapping, provides a replicable framework for LMICs grappling with heterogeneous TB burdens.

CONCLUSION

This study contributes to disease mapping methodology by demonstrating the utility of integrated spatial-temporal analysis in resource-limited settings. Our approach offers a scalable model for regional policy formulation, aligning with global TB elimination targets while addressing localized epidemiological complexities. Furthermore, this study provides critical insights into the spatial and temporal dynamics of TB disease in Aceh Province, highlighting significant intra-regional variations in TB risk. These findings reinforce the need for region-specific TB control strategies considering local health, social, and economic factors. The use of SMR for estimating RR and different tests as robust statistical analyses proved effective and could be instrumental in other epidemiological studies aiming to improve disease control and public health outcomes. The originality of this work lies in its detailed analysis of a prolonged period and its implications for improving targeted public health interventions in high-burden TB areas.

AUTHOR’S CONTRIBUTION STATEMENT

MK, MKF: Concepts, Design Data analysis, Statistical analysis, Manuscript preparation; LR, ZMK, SM, RK: Manuscript preparation and editing, Manuscript review; VC: Manuscript preparation, Manuscript editing, Manuscript review; MINA: Manuscript editing, Manuscript review; NRS: Concepts, Design, Definition of intellectual content, Data analysis, Statistical analysis, Manuscript preparation, Manuscript editing, Manuscript review.

CONFLICTS OF INTEREST

The authors have no conflicts of interest.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

This manuscript was developed without the use of Generative AI or AI-assisted technologies at any stage. The writing, idea generation, image production, graphical elements, data collection, and analysis were all conducted manually.

SOURCE OF FUNDING STATEMENTS

Research reported in this publication was supported by the Fogarty International Center and the National Institute of Allergy and Infectious Diseases, of the National Institutes of Health under Award Number D43 TW009522. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

ACKNOWLEDGMENTS

Thank you to the Aceh Provincial Health Office for their support and provision of data, which was crucial for this study.

BIBLIOGRAPHY

1. World Health Organization. Global Tuberculosis Report 2023. November. Geneva; 2023.
2. Ministry of Health Indonesia. Indonesia Health Profile 2023 [Internet]. Ministry of Health Indonesia. Jakarta; 2024. Available from: https://kemkes.go.id/app_asset/file_content_download/172231123666a86244b83fd8.51637104.pdf
3. Aceh Provincial Health Office. Aceh Health Profile 2022. Banda Aceh; 2022.
4. Sasmita NR, Phonna RA, Kesuma ZM, Kamal S, Yusya N. Spatial-Temporal Epidemiology of COVID-19 in Aceh, Indonesia: A Statistical Perspective. Unnes J Public Heal. 2024;3(2):67–79.
5. Antaria A. Tuberculosis control in Indonesia: Theory and Research. First edit. Rubbi TA, Rahnawati, editors. Vol. 7, Journal GEEJ. Malang: Literasi Nusantara Abadi Grup; 2024. 1–144 p.
6. Newman TB, Kohn MA. Evidence-Based Diagnosis. Evidence-Based Diagnosis. 2020.
7. Diah IM, Aziz N. The Comparison between Standardized Mortality Ratio, Poisson-Gamma and Stochastic Sic Model for Pneumonia Disease Mapping in Malaysia. J Inf Commun Technol [Internet]. 2022 Oct 19;21(4):549–70. Available from: https://e-journal.uum.edu.my/index.php/jict/article/view/14423
8. Puspita T, Suryatma A, Simarmata OS, Veridona G, Lestary H, Athena A, et al. Spatial variation of tuberculosis risk in Indonesia 2010-2019. Heal Sci J Indones [Internet]. 2021 Dec 16;12(2):104–10. Available from: https://ejournal2.litbang.kemkes.go.id/index.php/hsji/article/view/5467
9. Diah IM, Aziz N, Kasim MM. Tuberculosis disease mapping in Kedah using standardized morbidity ratio. AIP Conf Proc. 2017;1891:1–5.
10. Odhiambo JN, Dolan CB. Spatial and spatio-temporal epidemiological approaches to inform COVID-19 surveillance and control: a review protocol. Syst Rev [Internet]. 2022 Dec 14;11(1):1–6. Available from: https://systematicreviewsjournal.biomedcentral.com/articles/10.1186/s13643-022-02016-0
11. Guo J, Liu C, Liu F, Zhou E, Ma R, Zhang L, et al. Tuberculosis disease burden in China: a spatio-temporal clustering and prediction study. Front Public Heal [Internet]. 2025 Jan 7;12(1):1–12. Available from: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1436515/full
12. Carlos de Abreu L, Elmusharaf K, Eduardo Gomes Siqueira C. A time-series ecological study protocol to analyze trends of incidence, mortality, lethality of COVID-19 in Brazil. J Hum Growth Dev [Internet]. 2021 Dec 1;31(3):491–5. Available from: https://revistas.marilia.unesp.br/index.php/jhgd/article/view/12667

13. Sasmita NR, Ikhwan M, Suyanto S, Chongsuvivatwong V. Optimal control on a mathematical model to pattern the progression of coronavirus disease 2019 (COVID-19) in Indonesia. Glob Heal Res Policy [Internet]. 2020 Dec 5;5(1):1–38. Available from: https://ghrp.biomedcentral.com/articles/10.1186/s41256-020-00163-2
14. Saputra A, Sofyan H, Kesuma ZM, Sasmita NR, Wichaidit W, Chongsuvivatwong V. Spatial patterns of tuberculosis in Aceh Province during the COVID-19 pandemic: a geospatial autocorrelation assessment. IOP Conf Ser Earth Environ Sci [Internet]. 2024 Jun 1;1356(1):012099. Available from: https://iopscience.iop.org/article/10.1088/1755-1315/1356/1/012099
15. Earlia N, Bulqiah M, Muslem M, Karma T, Suhendra R, Maulana A, et al. Protective Effects of Acehnese Traditionally Fermented Coconut Oil (Pliek U Oil) and its Residue (Pliek U) in Ointment against UV Light Exposure: Studies on Male Wistar Rat Skin (Rattus novergicus). Sains Malaysiana [Internet]. 2021 May 31;50(5):1285–95. Available from: https://www.ukm.my/jsm/pdf_files/SM-PDF-50-5-2021/9.pdf
16. Agustia M, Noviandy TR, Maulana A, Suhendra R, Muslem M, Sasmita NR, et al. Application of Fuzzy Support Vector Regression to Predict the Kovats Retention Indices of Flavors and Fragrances. In: Proceedings of the International Conference on Electrical Engineering and Informatics. Banda: IOPScience; 2022. p. 13–8.
17. Palupi S, Chongsuvivatwong V, Surya A, Suyanto S, Kumwichar P. Cross-Risk Between Tuberculosis and COVID-19 in East Java Province, Indonesia: An Analysis of Tuberculosis and COVID-19 Surveillance Registry Period 2020–2022. Cureus [Internet]. 2023 Sep 7; Available from: https://www.cureus.com/articles/177994-cross-risk-between-tuberculosis-and-covid-19-in-east-java-province-indonesia-an-analysis-of-tuberculosis-and-covid-19-surveillance-registry-period-2020-2022
18. Awang AC, Samat NA. Leptospirosis disease mapping with standardized morbidity ratio and Poisson-Gamma model: An analysis of Leptospirosis disease in Kelantan, Malaysia. J Phys Conf Ser [Internet]. 2017 Sep;890:012168. Available from: https://iopscience.iop.org/article/10.1088/1742-6596/890/1/012168
19. Sasmita NR, Arifin M, Kesuma ZM, Rahayu L, Mardalena S, Kruba R. Spatial Estimation for Tuberculosis Relative Risk in Aceh Province, Indonesia: A Bayesian Conditional Autoregressive Approach with the Besag-York-Mollie (BYM) Model. J Appl Data Sci [Internet]. 2024 May 15;5(2):342–56. Available from: https://bright-journal.org/Journal/index.php/JADS/article/view/185
20. Azharuddin, Sasmita NR, Idroes GM, Andid R, Raihan, Fadlilah T, et al. Patient Satisfaction And Its Socio-Demographic Correlates In Zainoel Abidin Hospital, Indonesia: A Cross-Sectional Study. Unnes J Public Heal. 2023;12(2):57–67.
21. Sasaki D, Sofyan H, Sasmita NR, Affan M, Nizamuddin N. Assessing the Intermediate Function of Local Academic Institutions During the Rehabilitation and Reconstruction of Aceh, Indonesia. J Disaster Res [Internet]. 2021 Dec 1;16(8):1265–73. Available from: https://www.fujipress.jp/jdr/dr/dsstr001600081265
22. Koura KG, Hashmi S, Menon S, Gando HG, Yamodo AK, Budts A-L, et al. Leveraging Artificial Intelligence to Predict Potential TB Hotspots at the Community Level in Bangui, Republic of Central Africa. Trop Med Infect Dis [Internet]. 2025 Apr 3;10(4):93. Available from: https://www.mdpi.com/2414-6366/10/4/93
23. Gao C, Wang Y, Hu Z, Jiao H, Wang L. Study on the Associations between Meteorological Factors and the Incidence of Pulmonary Tuberculosis in Xinjiang, China. Atmosphere (Basel). 2022;13(4):1–15.
24. Rao M, Johnson A. Impact of Population Density and Elevation on Tuberculosis Spread and Transmission in Maharashtra, India. J Emerg Investig [Internet]. 2021;4(1):1–5. Available from: https://emerginginvestigators.org/articles/21-056
25. Gichuki J, Mategula D. Characterisation of tuberculosis mortality in informal settlements in Nairobi, Kenya: analysis of data between 2002 and 2016. BMC Infect Dis [Internet]. 2021 Dec 31;21(1):718. Available from: https://bmcinfectdis.biomedcentral.com/articles/10.1186/s12879-021-06464-2
26. Syarifah Khodijah, Artha Prabawa. Spatial Analysis of Risk Factors for Tuberculosis Incidence in South Jakarta City in 2022. Media Publ Promosi Kesehat Indones [Internet]. 2024 Jun 1;7(6):1518–24. Available from: https://jurnal.unismuhpalu.ac.id/index.php/MPPKI/article/view/5208
27. Teibo TKA, Andrade RL de P, Rosa RJ, Tavares RBV, Berra TZ, Arcêncio RA. Geo-spatial high-risk clusters of Tuberculosis in the global general population: a systematic review. BMC Public Health [Internet]. 2023 Aug 19;23(1):1586. Available from: https://doi.org/10.1186/s12889-023-16493-y

28. Kustanto A. The role of socioeconomic and environmental factors on the number of tuberculosis cases in Indonesia. J Ekon Pembang [Internet]. 2020 Dec 5;18(2):129–46. Available from: https://ejournal.unsri.ac.id/index.php/jep/article/view/12553
29. Mohidem NA, Hashim Z, Osman M, Shaharudin R, Muharam FM, Makeswaran P. Demographic, socio-economic and behavior as risk factors of tuberculosis in Malaysia: a systematic review of the literature. Rev Environ Health [Internet]. 2018 Dec 19;33(4):407–21. Available from: https://www.degruyter.com/document/doi/10.1515/reveh-2018-0026/html
30. Surya Hajar FD, Siregar YI, Afandi D, Nofrizal. Determinant factors that contribute to the increasing tuberculosis prevalence in Rokan Hilir, Indonesia. Casp J Environ Sci. 2023;21(1):13–34.
31. Thakur G, Thakur S, Thakur H. Status and challenges for tuberculosis control in India – Stakeholders' perspective. Indian J Tuberc [Internet]. 2021 Jul;68(3):334–9. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0019570720301980
32. Andrade HLP de, Ramos ACV, Crispim J de A, Santos Neto M, Arroyo LH, Arcêncio RA. Spatial analysis of risk areas for the development of tuberculosis and treatment outcomes. Rev Bras Enferm [Internet]. 2021;74(2):1–7. Available from: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0034-71672021000200169&tlng=en
33. Teo AKJ, Singh SR, Prem K, Hsu LY, Yi S. Duration and determinants of delayed tuberculosis diagnosis and treatment in high-burden countries: a mixed-methods systematic review and meta-analysis. Respir Res [Internet]. 2021 Dec 23;22(1):1–28. Available from: https://respiratory-research.biomedcentral.com/articles/10.1186/s12931-021-01841-6
34. Obeagu EI. Tuberculosis diagnostic and treatment delays among patients in Uganda. Heal Sci Reports [Internet]. 2023 Nov 15;6(11):1–5. Available from: https://onlinelibrary.wiley.com/doi/10.1002/hsr2.1700
35. Li X, Yang H, Wang H, Liu X. Effect of Health Education on Healthcare-Seeking Behavior of Migrant Workers in China. Int J Environ Res Public Health [Internet]. 2020 Mar 30;17(7):23–44. Available from: https://www.mdpi.com/1660-4601/17/7/2344
36. Rahayu L, Sasmita NR, Adila WF, Kesuma ZM, Kruba R. Spatial Estimation of Relative Risk for Dengue Fever in Aceh Province using Conditional Autoregressive Method. J Appl Data Sci [Internet]. 2023 Dec 1;4(4):466–79. Available from: http://bright-journal.org/Journal/index.php/JADS/article/view/141
37. Pathak D, Vasishtha G, Mohanty SK. Association of multidimensional poverty and tuberculosis in India. BMC Public Health [Internet]. 2021 Dec 11;21(1):1–12. Available from: https://bmcpublichealth.biomedcentral.com/articles/10.1186/s12889-021-12149-x
38. Jiang W, Dong D, Febriani E, Adeyi O, Fuady A, Surendran S, et al. Policy gaps in addressing market failures and intervention misalignments in tuberculosis control: prospects for improvement in China, India, and Indonesia. Lancet Reg Heal - West Pacific [Internet]. 2024 May;46:101045. Available from: https://doi.org/10.1016/j.lanwpc.2024.101045
39. MacPherson P, Shanaube K, Phiri MD, Rickman HM, Horton KC, Feasey HRA, et al. Community-based active-case finding for tuberculosis: navigating a complex minefield. BMC Glob Public Heal [Internet]. 2024 Feb 8;2(1):9. Available from: https://bmcglobalpublichealth.biomedcentral.com/articles/10.1186/s44263-024-00042-9