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Spatial Distribution of New Pulmonary Tuberculosis Incidence in Northeastern, Thailand

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Abstract

Pulmonary tuberculosis (PTB) represents a formidable global public health challenge in Southeast Asia including Thailand. It is among the 30 countries with the highest burden of tuberculosis disease in the world, contributed by the increasing prevalence of new cases of pulmonary tuberculosis (NPTB) in northeastern Thailand (NE). This research aims to describe the distribution pattern and spatial relationship of the incidence of NPTB, especially in the NE. Based on data from the National Tuberculosis Information Project (NTIP) from 2017 to 2021, covering 322 districts in NE region, this study used a spatial analysis method. The findings revealed a total of 91,914 NPTB cases identified over a 5-year period, with a significantly higher prevalence found in males, and almost half of the cases occur in people over 60 years of age. Global spatial autocorrelation analysis revealed different cluster incidence patterns of NPTB incidence across the study area. The pattern of NPTB was clustered. The research used Getic-Ord G_i* techniques to analyze hot spots by analyzing high-risk groups within various districts, especially in Khon Kaen and Sisaket provinces. In addition, spatial-temporal cluster grouping analysis also highlighted that December is the key month for cluster formation, with 2020 recording the highest number of NPTB clusters within 5 years. These findings offer valuable insights for relevant agencies in formulating guidelines, comprehensive protection, and tracking, including PTB surveillance at the regional and national levels.

Keywords: Infectious situation; Respiratory disease; Tuberculosis; Spatial distribution; Infectious disease

1. Introduction

Tuberculosis (TB), caused by *Mycobacterium tuberculosis*, spreads through airborne transmission via respiratory excretions like coughing, sneezing, and droplet dissemination (Alene *et al.,* 2021). TB ranks as the second leading cause of mortality following coronavirus disease (COVID-19) in terms of fatalities attributed to a single infection. In 2022, there was a concerning surge in TB cases, totaling 7.5 million new cases worldwide, the highest since 1995.

TB-related mortality is projected to reach approximately 1.3 million in 2022. The global incidence rate remains high at 133 cases per 100,000 individuals, indicating a significant prevalence of TB (WHO, 2023). TB remains a substantial health crisis in Southeast Asia (Falefi *et al.,* 2023; Chen *et al.,* 2021).

Thailand, located in Southeast Asia, is one of 30 countries, including Indonesia, Myanmar, and the Philippines, with the highest burden of TB in the world (WHO, 2023).

The incidence rate of new and relapse TB in Thailand is approximately 150 cases per 100,000 people (Division of Tuberculosis, 2022). From 2016 to 2020, treatment registrations for new and relapse TB cases steadily rose, with approximately 81,268 cases recorded in 2020, marking a 1.16 times increase. In 2016, regional classification in Thailand revealed a high incidence of TB patients in the NE region (Division of Tuberculosis,2022). From 2019 -2023, the rate of over 150 tuberculosis cases per 100,000 population was mainly seen in the central and lower NE regions (Division of Tuberculosis, 2023). During 2012-2013, tuberculosis prevalence was the highest in the NE at 321.2 cases per 100,000 population, exceeding rates in the central, northern, and southern areas, which were 220.8, 143.6, and 106.9 cases per 100,000 population, respectively (Department of Disease, 2017). In 2021, the highest number of new and relapse tuberculosis cases was reported in ten provinces of Thailand. Notably, 50 percent of these cases were concentrated in the NE, particularly in Khon Kaen, Nakhon Ratchasima, Sisaket, Ubon Ratchathani, and Surin (Division of Tuberculosis, 2021).

The rising incidence of tuberculosis in the Northeast has driven the research team's interest in investigating the nature of the disease in this region. Geographic Information Systems (GIS) and spatial analysis are crucial for health planning and clarifying spatial-temporal relationships in disease occurrence and surveillance (Murad & Khashoggi, 2020). Spatial scan statistics and Global Moran's I analysis are accurate and popular, making them suitable for tuberculosis prevention planning in developing countries (Rosli *et al.,* 2018). Spatial analysis has been extensively utilized in Thailand for studying tuberculosis and other communicable diseases (Hassarangsee *et al.,* 2015; Chinpong *et al.,* 2022; Punyapornwithaya *et al.,* 2020; Luenam & Puttanapong, 2019). The objective of this study is to analyze the distribution pattern and spatial relationship of Pulmonary tuberculosis (PTB) incidence in the northeastern Thailand (NE). The anticipated findings are expected to substantially enhance policymaking, surveillance models, and monitoring of PTB in the area.

2. Methodology

2.1 Study area

The research team identified the study area as the NE, covering an approximate area of 168,854 square kilometers, which represents one-third of the country's total landmass. This area between latitude 14°7' to 18°27' north and longitude 100°54' to 105°37' east, encompassing a total of 322 districts spread across 20 provinces, namely Kalasin, Khon Kaen, Nakhon Phanom, Maha Sarakham, Mukdahan, Roi Et, Sakon Nakhon, Nong Khai, Nong Bua Lamphu, Udon Thani, Loei, Chaiyaphum, Nakhon Ratchasima, Buriram, Yasothon, Sisaket, Surin, Amnat Charoen, Ubon Ratchathani, and Bueng Kan. The climate in this region exhibits three distinct seasons: summer from February to May, the rainy season from May to October, and winter from November to February (Figure 1).

2.2 Study design and Data collection

This research employs geographic epidemiological methods to analyze the characteristics, trends, and spatial relationships of PTB incidence in the NE. The study collected data on new cases of pulmonary tuberculosis (NPTB) patients from January 2017 to December 2021. The data came from the National Tuberculosis Information Project (NTIP), which is recorded by the Ministry of Public Health. The research team collected data monthly. The research subjects were selected based on the following sample inclusion criteria: being diagnosed with PTB and properly recorded in the NTIP. Exclusion criteria encompassed individuals without Thai nationality and those with recurrent cases of relapse tuberculosis. The data collected was analyzed using GIS and spatial analysis methods to identify the distribution pattern and spatial relationships of NPTB incidence in the study area.
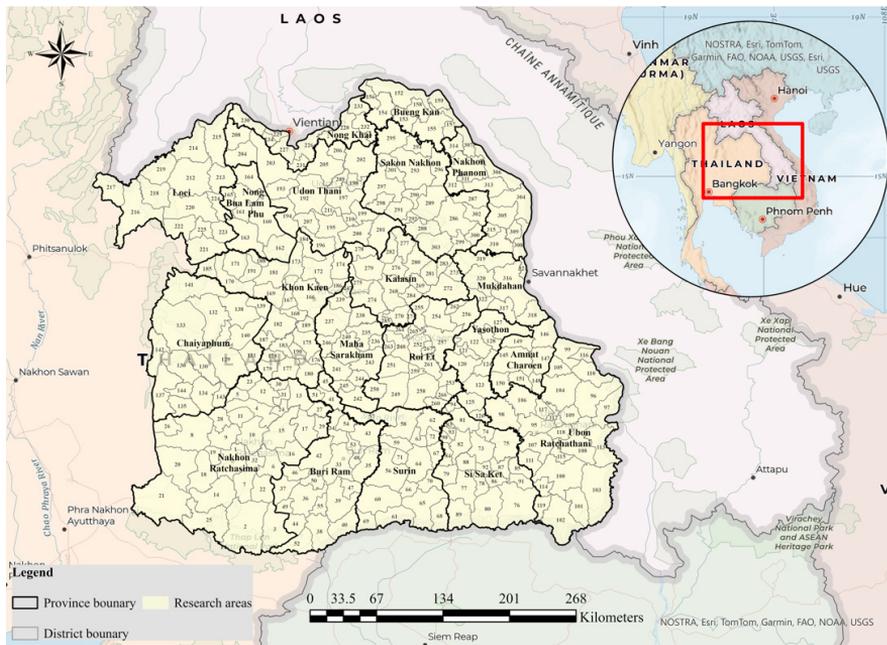
Figure 1. Map of the study area indicated the 20 provinces (322 districts) of NE.

2.3 Statistical analysis

The research team utilized ArcGIS Pro version 3.2 for data analysis to investigate patterns of NPTB incidence. They also conducted a comprehensive examination of spatial autocorrelation using the Global Moran's I statistical method, which is commonly employed to detect spatial distribution patterns of diseases and evaluate the magnitude and direction of spatial autocorrelation. The Moran's I value ranges between -1 and 1. A value of I < 0 indicates negative spatial autocorrelation or a dispersed pattern, while a value of I > 0 indicates positive spatial autocorrelation or a clustered pattern. A value of I = 0 suggests a random pattern. The significance of Moran's I was assessed using the Z-score (Z < -1.96 or Z > +1.96) and the P-value (p < 0.05)(Zhang *et al.,* 2023).The Local Indicator of Spatial Association (LISA) was used to assess the degree of local spatial autocorrelation, identifying areas as hot or cold spots. In this study, Statistical significance was assessed by using the Z-score through the application of the Getis-Ord G_i^* method. Hot spots were defined by Z-scores > 1.96 at a 95% confidence level (p-value < 0.05). Conversely, a Z-score < -1.96 indicated cold spots. Areas with Z-scores between -1.96

and +1.96 were considered not statistically significant (Gwitira *et al.,* 2021). Additionally, the research team adopted SatScan version 10.1.2 software to perform a space-time permutation model analysis (Kulldorff, 2022). Space-time scanning statistics are based on the Poisson distribution model to identify the spatial and temporal clustering of diseases. The significance of the detected clusters was determined by comparing the log-likelihood ratio (LLR) and relative risk (RR). RR was evaluated to assess the risk of diseases in the clusters under the null hypothesis of equal risk inside and outside the area (Fatima *et al.,* 2024). The highest LLR was identified as the most likely cluster, while other clusters with statistically significant LLR were defined as potential secondary clusters (p-value < 0.05). In this analysis, the p-value of LLR was assessed using 999 replications of the Monte-Carlo method, with the maximum spatial size of the clusters set at 50% of the total population at risk and the maximum temporal size at 50% of the study period (Kiani *et al.,* 2021).

2.4 Research ethical consideration

This research was approved by the Khon Kaen University Ethics Committee for Human

Research (KKUEC) based on the Declaration of Helsinki and Guideline for Good Clinical Practice, 16 October 2023, HE662221.

3. Results and Discussion

3.1 General information on NPTB registered in NTIP.

Between 2017 and 2021, a total of 91,914 NPTB cases were recorded, signaling a downward trajectory. The research findings revealed that around two-thirds of these patients were male, with the highest proportion belonging to the 60-year-old and above age bracket (Table 1). These observations on the sex ratio of NPTB are consistent with findings from similar studies conducted in various countries, particularly within the Greater Mekong Subregion (GMS), which shares cultural and lifestyle similarities with Thailand (Hoaihongthong & Kwiecien, 2022). Notable examples include the Lao People's Democratic Republic (Iem *et al.,* 2019), the Republic of the Union of Myanmar (Aye *et al.,* 2018), and the Socialist Republic of Vietnam (Hoa *et al.,* 2018). Globally, the male-to-female ratio of TB cases is approximately 1.7 (Male: Female) (Hertz & Schneider, 2019), ranging from 1.2 to 4.9 (Dutta & Schneider, 2020). Similarly, our research noted a male-to-female ratio of NPTB at about 2.3. The factors

contributing to the disparity in TB infection rates between genders remain unclear (Hertz & Schneider, 2019). Nonetheless, scholars have proposed that lifestyle habits, such as higher rates of smoking and alcohol consumption among men (Peer *et al.,* 2023), might play a role. Additionally, the heightened susceptibility of men to bacterial infections compared to women could be a significant factor in the observed gender-based disparity in illness (Dias *et al.,* 2022).

This study revealed that individuals aged 60 years and older were the demographic most affected by PTB, comprising almost half of all reported cases, in contrast to other age groups. These findings align with prior research conducted by various researchers. These findings are consistent with many researchers (Ko *et al.,* 2016; Vo *et al.,* 2020; Charoensakulchai *et al.,* 2020). Some studies have found that approximately 39% of tuberculosis patients in the Republic of the Union of Myanmar are within the age group of 15-44 years (Aye *et al.,* 2018). Conversely, in the Kingdom of Cambodia, the majority of tuberculosis patients are aged 50-59 years (Ma *et al.,* 2022). These differences may arise from the varying demographic structures of each country. For instance, Japan and the Republic of Korea, being aging societies, exhibit higher tuberculosis rates among the elderly

Table 1. Demographic characteristics of NPTB cases in NE from, 2017-2021

Characteristics	Number of NPTB patients				
	2017	2018	2019	2020	2021
Total	19,063	18,813	18,421	18,371	17,246
Sex					
Male	13,230	12,926	12,641	12,730	12,088
	(69.40)	(68.71)	(68.62)	(69.29)	(70.09)
Female	5,833	5,887	5,780	5,641	5,158
	(30.60)	(31.29)	(31.38)	(30.71)	(29.91)
Age(year)					
< 25	889	907	846	817	713
	(4.66)	(4.82)	(4.59)	(4.44)	(4.13)
25-44	4,355	3,995	3,781	3,567	3,495
	(22.84)	(21.24)	(20.53)	(19.42)	(20.27)
45-59	5,823	5,792	5,851	5,750	5,449
	(30.55)	(30.79)	(31.76)	(31.30)	(31.60)
≥ 60	7,996	8,119	7,943	8,237	7,589
	(41.95)	(43.16)	(43.12)	(44.84)	(44.00)

Note: in the parenthesis represented %

compared to other age groups (Morishita *et al.,* 2020). This consistently underscores the heightened susceptibility of the elderly to tuberculosis infection (Dong *et al.,* 2022). This vulnerability can be attributed to multiple factors, including compromised immune function, DNA degradation, and decreased cellular activity (Li *et al.,* 2021), making the elderly more susceptible to infections. Moreover, age-related physiological changes, such as reduced lung function and the presence of comorbidities like obesity, cancer, and chronic respiratory conditions (Olmo-Fontánez & Turner, 2022), have been linked to a rise in TB cases among older adults (Evangelista *et al.,* 2020), exacerbating their susceptibility. This issue is particularly concerning for countries experiencing demographic shifts toward aging populations, particularly Thailand, where the elderly population is rapidly growing. Projections indicate that Thailand's elderly population will increase from 13 percent of the total population in 2010 to around 33 percent by 2040 (Ratmanee & Tongkumchum, 2023). Consequently, given the evolving demographic structure and health challenges older adults face, regulatory bodies must proactively prepare to address and monitor these changing circumstances.

Over the 5-year study period, the NPTB cases exhibited fluctuations, with a peak observed in March 2021, totaling 1,897 cases, and a nadir in July 2021, with 1,225 cases documented. Concerning NPTB incidence rates, March 2021 recorded the highest rate at 8.3 cases per 100,000 population, while December 2019 marked the lowest rate at 5.1 cases per 100,000 population (Figure 2). The lowest and highest average incidence rates for NPTB were 5.1 and 8.3 per 100,000 population, respectively. These findings reveal a consistent trend wherein NPTB incidence peaks in March, corresponding to the summer season, and declines to its lowest point in December, aligning with the winter season. Similar seasonal patterns have been noted in various regions, including the People's Republic of China (Zhang *et al.,* 2023), and Vietnam (Bonell *et al.,* 2020). While the precise mechanisms driving these seasonal variations remain uncertain (Taylan *et al.,* 2023), hypotheses propose that weaker immune systems and vitamin D deficiency during winter months (Charles *et al.,* 2021), coupled with reduced ventilation in confined spaces, may contribute to heightened TB transmission during this period (Taylan et al., 2023). Typically, TB has an incubation period of 3-6 months (Cui *et al.,* 2019), with symptoms often appearing in summer, hence the elevated incidence observed during warmer months compared to winter. Notably, the fact that March coincides with International TB Day, marked by public health campaigns and TB screening initiatives in Thailand, potentially explains the surge in reported cases during this period which is consistent with observations by Zhang, regarding festival-related activities on International TB Day (Zhang *et al.,* 2020). Implementing similar public health measures targeting winter months could potentially aid in disease prevention and control within communities.
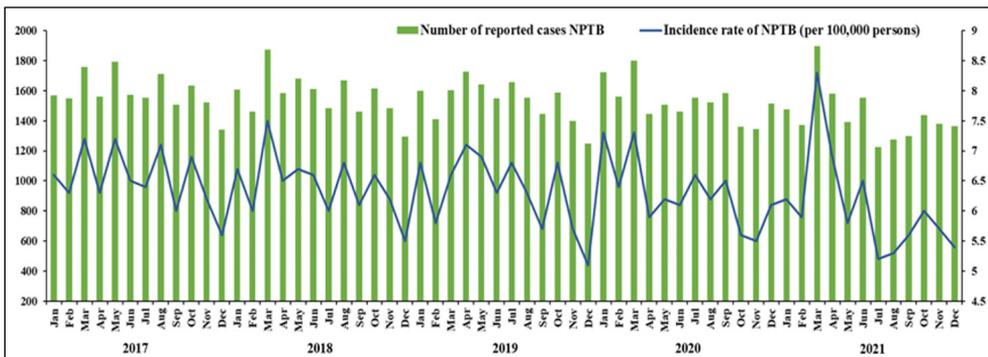

Figure 2. Monthly reported number of NPTB and Incidence rate in NE, 2017-2021

3.2 Incidence rate of NPTB cases.

The results depicted in Figure 3 show that between 2017 and 2021, regions experiencing notably high incidences of NPTB (> 10 per 100,000 population) were mainly concentrated in Khon Kaen and Sisaket provinces. Specifically, elevated NPTB occurrence rates were noted in Muang districts of several provinces, including Nakhon Ratchasima, Surin, and Ubon Ratchathani. On the other hand, certain districts within Khon Kaen Province, such as Khok Pho Chai, Non-Sila, Wiang Kao, and Don Chan District in Kalasin Province, recorded no instances of NPTB during the study duration. However, when adjusting the Standardized Morbidity Ratio (SMR) by using the mid-year population of each district to compare NPTB incidence disparities across districts, Ban Haed District in Khon Kaen Province displayed the highest SMR value, followed by Lamduan District in Surin Province and Yang Chum Noi District in Sisaket Province (Figure 4).

3.3 Spatial Autocorrelation Analysis of NPTB Incidence.

The findings of the Spatial Autocorrelation analysis of NPTB unveiled a positive and statistically significant I value (P-values < 0.05), signifying spatial clustering. This implies that districts with similar NPTB incidences tend to be spatially adjacent. The trend analysis of I values from 2017 to 2021 illustrates a steady rise, suggesting a continuous clustering of NPTB cases within the study area (Table 2).

3.4 Hot Spot Analysis of NPTB Incidence.

The findings resulting from the Hot Spot analysis employing the Local G-statistics technique (Figure 5) demonstrated that, during the period spanning from 2017 to 2020, regions with heightened risks of NPTB incidence were primarily located in the central part of the NE, encompassing various districts of Khon Kaen Province, including Mueang Khon Kaen, Ban Fang, and Ban Haed, as well as districts within Maha Sarakham Province, such as Kosum Phisai, Kantharawichai, and Chom Chom, among others. Furthermore, the analysis identified another high-risk area in the southeastern region of the research area, covering numerous districts within Sisaket Province, such as Mueang Sisaket, Yang Chum Noi, Kanthararom, and Uthumphon Phisai, among others. Conversely, cold spot areas were concentrated in the southwestern
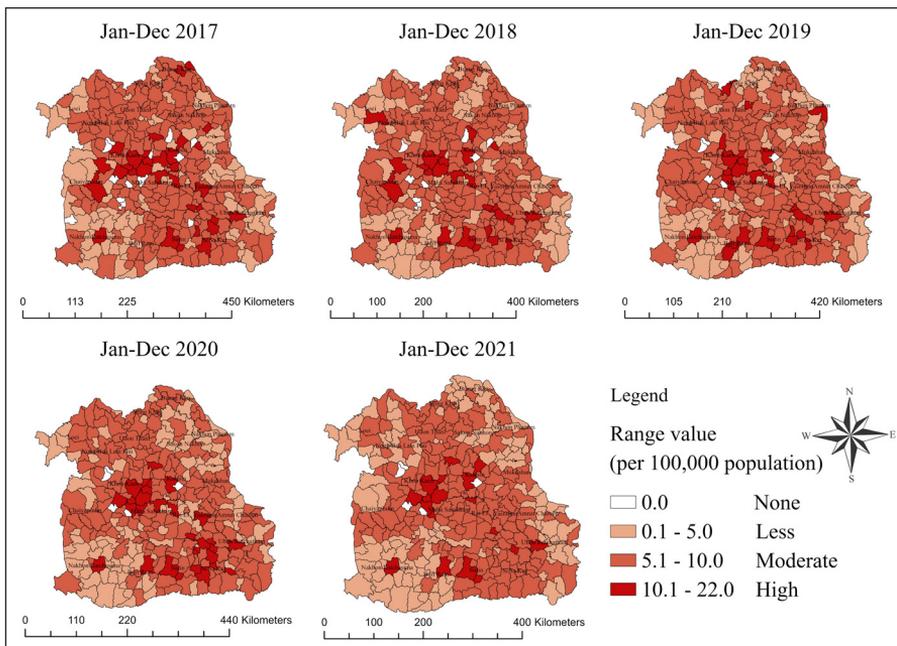

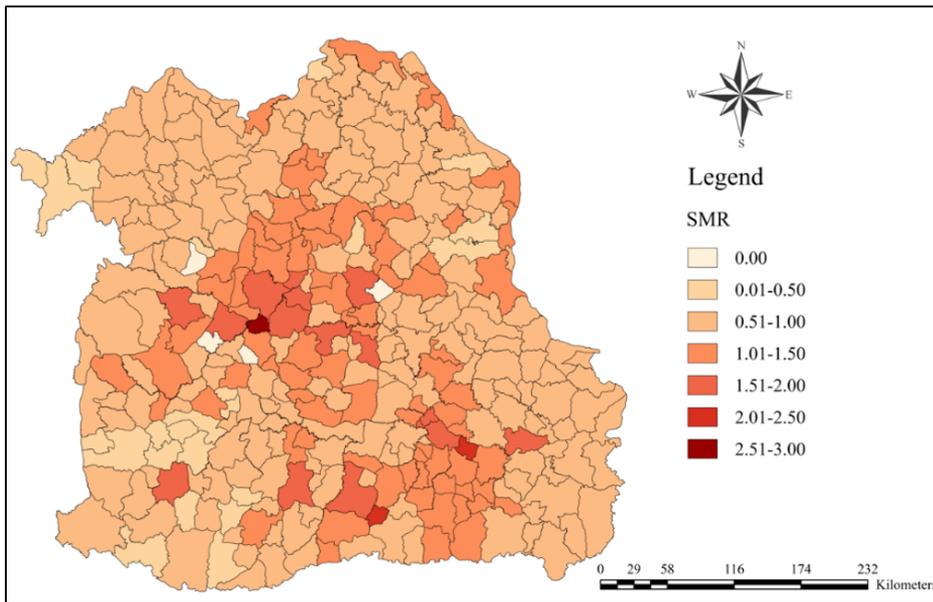**Figure 3.** Incidence map of NPTB in each district in NE, 2017-2021

Figure 4. SMR map of NPTB in NE, 2017-2021

Table 2. Global spatial autocorrelation analysis for NPTB Incidence of NE, 2017-2021

Year	Moran's I	Z-Score	P-value	Pattern
2017	0.096	3.553	< 0.001	Clustered
2018	0.149	5.472	< 0.001	Clustered
2019	0.208	7.591	< 0.001	Clustered
2020	0.306	11.117	< 0.001	Clustered
2021	0.331	11.998	< 0.001	Clustered

district of Nakhon Ratchasima Province, including Kong, Dan Khut Thot, Prathai, and Non-Daeng. Notably, between 2020 and 2021, there was a rise in low-risk areas in the northeastern sector of the study area, encompassing districts within Sakon Nakhon and Nakhon Phanom provinces.

The study findings indicate that most areas at high risk are clustered within the urban districts of each province, rather than in rural regions. This pattern is consistent with research conducted across diverse locations such as Zimbabwe (Chirenda *et al.,* 2020), and Uganda (Aturinde *et al.,* 2019), which consistently demonstrates that urban locales experience a higher prevalence of TB compared to rural areas. Urban settings inherently accommodate larger and denser populations, often characterized by crowded living conditions within households and neighboring areas (Wardani & Wahono, 2020), significantly amplifying the risk of PTB transmission. Moreover, the dynamics of

urbanization, marked by increased population mobility and social interactions, contribute to the rapid dissemination of TB within urban environments (Chirenda *et al.,* 2020). This heightened population density acts as a key factor contributing to the identification of these areas as TB hot spots.

When examining the broader scope of high-risk regions, two primary clusters become apparent: the area encompassing Khon Kaen Province and the region consisting of Sisaket Province. Within the Khon Kaen Province cluster, researchers have identified several significant factors that could contribute to the increased incidence of NPTB beyond the influence of urbanization. Particularly, it is noteworthy that the HIV/AIDS situation in Khon Kaen Province, characterized by consistently high rates of new infections from 2019 to 2022, mirrors trends observed in populous provinces of Thailand such as Bangkok, and Chonburi (Ministry of Public health, 2023). A systematic review and

meta-analysis underscored a crucial finding: individuals living with HIV are more likely to develop TB (Qi *et al.,* 2023). This correlation might indirectly contribute to the heightened risk of TB within Khon Kaen Province.

The second group primarily comprises districts within Sisaket Province, such as Mueang Sisaket, Nam Kliang, and Prang Ku, among others. These findings align with a study conducted by Hassarangsee, which investigated the spatial distribution of TB in Sisaket Province between 2004 and 2008 (Hassarangsee *et al.,* 2015). It is worth noting that Sisaket and Surin provinces share borders with Cambodia. Reports from Cambodia in 2014, indicated that around 60 percent of the population had latent TB. Additionally, it was found that TB rates are significantly elevated among Cambodian migrant workers living in Thailand (Prem *et al.,* 2019), which was also corroborated by Chinpong's study, which observed a high incidence of TB among foreign workers situated along the Cambodian border (Chinpong *et al.,* 2022). Consequently, the high-risk areas in Sisaket Province may be influenced by factors associated with foreign workers in the region. This trend is consistent with research from various countries, including Ethiopia (Alene *et al.,* 2019), and Iran (Kiani *et al.,* 2021), indicating that foreign workers play a substantial role in the TB burden. Hence, relevant authorities must establish comprehensive surveillance, control, and screening measures targeting foreign workers to mitigate risks and prevent the spread of PTB across different areas.

For the five-year research period, regions with low risk, denoted as Cold spots, were identified across several districts in Nakhon Ratchasima Province, including Phiman, Dan Khun Thot, and Phra Thongkham. Despite being the largest province in the NE, Nakhon Ratchasima has a relatively lower population density compared to provinces such as Khon Kaen and Mahasarakham, with an average population density of around 129 people per square meter from 2019 to 2021 (Ministry of Interior, 2021). Additionally, when considering the Gross Provincial Product (GPP) per capita, which reflects the province's economic productivity, Nakhon Ratchasima reported a GPP value of approximately 3,656.47 USD per capita in 2021, the highest in the NE (Office of the National Economic and Social Development Council, 2023). Academic studies indicate that poverty contributes to the risk of TB (Wardani & Wahono, 2020). However, despite its low population density and relatively high per capita income, Nakhon Ratchasima province is categorized as a low-risk area. Nonetheless, utilizing the Local G-Statistics technique enables comparison with neighboring districts to detect data clustering. Examination of NPTB incidence in Nakhon Ratchasima revealed predominantly low incidence rates across most districts, except for Mueang Nakhon Ratchasima District, which exhibited higher NPTB incidence rates. Thus, the overall research findings for this area indicate a low-risk profile.

3.5 Spatial-temporal clustering analysis by SatScan.

An investigation into the occurrence of NPTB employed a spatial-temporal clustering methodology using the space-time permutation model from 2017 to 2021. The analysis identified a total of eight statistically significant clusters (p < 0.05), predominantly occurring in December and spanning 119 districts across 13 provinces, including Roi Et, Mukdahan, Yasothon, Kalasin, Buriram, Nakhon Ratchasima, Bueng Kan, Khon Kaen, Maha Sarakham, Surin, Udon Thani, Sakon Nakhon, and Nakhon Phanom. The most likely cluster was detected in December 2021, encompassing 27 districts in four provinces: Roi Et, Mukdahan, Yasothon, and Kalasin. The analysis results indicated that the risk of NPTB in this area was 1.20 times higher than outside the clusters (RR = 1.20, LLR = 21.59, p-value < 0.001). The 1st secondary cluster emerged in Buriram and Nakhon Ratchasima provinces, while the 2nd secondary cluster appeared in Bueng Kan Province. The 3rd secondary cluster arose in Khon Kaen and Maha Sarakham provinces, and the 4th secondary cluster in Nakhon Ratchasima province. The 5th secondary cluster was detected in Roi Et, Maha Sarakham, and Surin provinces. The 6th secondary cluster occurred in Udon Thani, Sakon Nakhon,

and Kalasin provinces, and the final secondary cluster emerged in Sakon Nakhon and Nakhon Phanom provinces (Table 3).

The analysis of the spatial distribution pattern of NPTB incidence demonstrates a clustered arrangement, characterized by a peak in NPTB cases occurring in March and the lowest incidence recorded in December. Regions with low NPTB risk, referred to as Cold spots, are predominantly situated within Nakhon Ratchasima province, while areas with high NPTB risk, termed Hot spots, are concentrated in Khon Kaen

and Sisaket provinces. The research team suggests that the heightened risk in these areas may be attributed to various factors, including the influx of foreign workers from neighboring countries, which is a significant concern. Additionally, the prevalence of HIV/AIDS contributes to the increased risk of PTB. Nevertheless, the incidence of TB is influenced by a range of factors, such as low levels of education, unfavorable economic conditions (Rao *et al.,* 2016), air pollution, and meteorological factors, among others (Ge *et al.,* 2016).
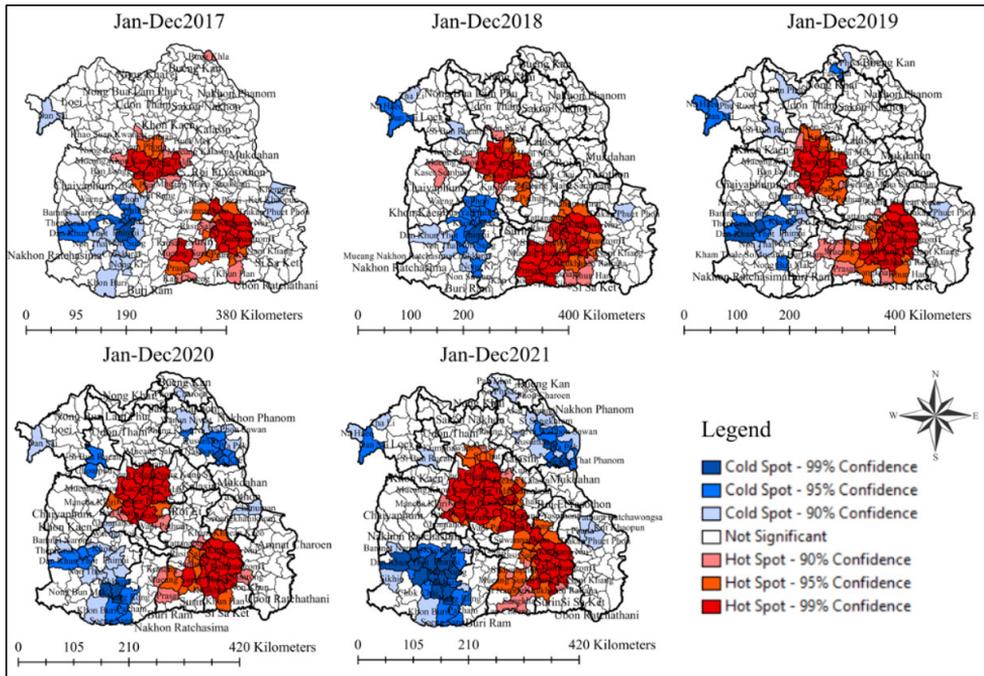

Figure 5. Spatial clusters of NPTB Incidence at the district level using the Getis-Ord G_i^* statistics

Table 3. NPTB case clusters based on spatial-temporal analysis in NE, 2017-2021

Area	Cluster type	Coordinates	Radius (km.)	Time frame	Number of cases	Expected cases	RR	LLR	P-value
1	Most likely	16.388333 N, 104.156667 E	63.53	1-31/12/2021	1,316	1,093.14	1.20	21.59	< 0.001
2	1st secondary	14.850360 N, 102.687996 E	59.67	1-31/12/2019	1,583	1,349.00	1.17	19.52	< 0.001
3	2nd secondary	18.219967 N, 103.756379 E	38.51	31/12/2017 - 31/01/2018	347	251.99	1.38	16.06	< 0.001
4	3rd secondary	16.438333 N, 102.838889 E	53.57	1-31/12/2020	2,224	1,989.52	1.12	13.61	< 0.001
5	4th secondary	15.662778 N, 102.527222 E	13.98	1/12/2020 - 31/12/2021	45	19.76	2.28	11.80	< 0.001
6	5th secondary	15.656944 N, 103.580571 E	44.27	1-31/12/2021	809	686.92	1.18	10.34	0.002
7	6th secondary	17.286667 N, 103.223333 E	49.86	1-31/12/2021	1,208	1,063.31	1.14	9.54	0.004
8	7th secondary	17.056111 N, 104.455278 E	25.37	31/12/2017 – 31/12/2018	366	292.17	1.25	8.66	0.015

RR: Relative risk, LLR; Log-likelihood ratio.

The research team conducted an investigation in the NE, known for its high prevalence of NPTB cases. Spatial tools were employed to analyze the incidence pattern of NPTB at the district level, aiming to offer comprehensive insights into the regional incidence trend. However, the study has limitations. Firstly, it depends on secondary data, which could be susceptible to under-reporting or collection biases. Moreover, the study lacks adequate individual-level information about patients, such as occupation data, which could have enhanced the understanding of the personal factors linked to the risk of PTB.

4. Conclusion

This study aims to examine the spatial distribution pattern of NPTB incidence in the NE spanning from 2017 to 2021. Through analysis, it is observed that NPTB incidence reaches its peak in March, while the lowest rates are recorded in December. Spatially, the distribution pattern of NPTB incidence demonstrates clustering with high-risk areas predominantly situated in the central and southeastern regions of the studied area, whereas the southwestern part is categorized as a low-risk area. These findings hold significance for pertinent agencies as they can guide the formulation of preventive guidelines and monitoring strategies aimed at managing PTB within both the studied area and the nation as a whole.

Acknowledgment

Conflicts of Interest

The authors declare no competing interests.

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