HUMAN BIOLOGY
2024, VOL. 94, ISSUE 5
ORIGINAL ARTICLE

OPEN ACCESS

Spatio-Temporal Analysis of Tuberculosis in Eastern Qinghai Province, China, 2013-2022

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ABSTRACT

Objective: Tuberculosis (TB) represents a significant public health challenge among infectious diseases, and Qinghai Province is notable for its high TB notification rates in China. However, there is currently no detailed analysis of the temporal and spatial distribution patterns of TB at the township level. This study aims to investigate the temporal and spatial distribution characteristics of TB epidemics in Haidong City, with the goal of implementing targeted interventions to address the TB epidemic.

Methods: The study described the distribution of cases by age, sex, and occupation. Global spatial autocorrelation statistics, local spatial autocorrelation statistics, and spatiotemporal scanning techniques were employed to analyze the temporal series and spatial clustering of tuberculosis notifications in Haidong City from 2013 to 2022, identifying spatiotemporal clusters. We also utilized a spatial panel model to investigate potential associated factors.

Results: This study included a total of 9,377 cases from 2013 to 2022. The total PTB registration rate shows an increase and then decrease, starting with a significant decrease from 2018 (100.93/100,000) - 2022 (42.21/100,000). Men and individuals in farming occupations were the predominant groups among TB patients. Registered cases peaked during the spring and summer months and decreased during the fall and winter seasons. During the study period, the Moran's I global statistic ranged from 0.0312 to 0.2843, indicating spatial autocorrelation. The primary hotspots are predominantly situated in the central and southern regions. Spatiotemporal scanning identified one most likely cluster and five secondary clusters, primarily concentrated in the southern region. These findings align closely with those observed in hotspots regions, and this clustering persisted through the end of 2022.

Conclusions: TB remains a significant public health challenge in Haidong. The incidence of tuberculosis in Haidong City, Qinghai Province, exhibited a seasonal pattern, with lower rates peaking in spring and higher rates in winter. Analysis of PTB registration data indicated that hotspots were predominantly concentrated in the central and southeastern regions. The persistent presence of high-risk areas underscores the necessity for targeted prevention and control strategies.

INTRODUCTION

TB is an airborne, contagious pulmonary disease caused by Mycobacterium tuberculosis, which spreads rapidly through the atmosphere via the emission of substantial droplet amounts expelled during sneezing, coughing, and expectoration. It remains a formidable public health challenge in many developing nations. In low-and middle-income countries, TB propagate swiftly, leading to substantial morbidity and mortality Wu et al. (2023), Murray et al. (2022). According to the World Health Organization (WHO), TB in China was estimated at 7.5 million Global tuberculosis report et al. (2023). China ranks second among the 30 countries with a significant TB burden. The incidence of TB in China decreased from 96.31 cases per 100,000 people in 2005 to 45.37 cases per 100,000 people in 2021. The cumulative number of TB cases has exceeded 900,000. China has implemented measures, including the provision of free basic tuberculosis treatment Long et al. (2020), Wang et al. (2014). Despite significant improvements in TB management, their effectiveness in reducing the overall TB burden burden remains limited.

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Keywords: Tuberculosis, Spatial analysis, Space-time clusters, Haidong, China

TB prevalence in the underdeveloped western regions is approximately three times higher than in the eastern regions, underscoring substantial disparities in TB treatment accessibility across economically diverse regions Wang et al. (2014). Qinghai Province is located in the northeastern region of the Qinghai-Tibet Plateau, characterized by an inhospitable natural environment and relative scarcity of healthcare resources Wei et al. (2023). Consequently, several regions in Qinghai exhibit a significant registration rate of PTB, marked by notably high rates of delayed diagnosis and numerous registrations compared to other areas Santos et al. (2021). Despite the introduction of active case detection in regions with low registration rates, these disparities endure. The WHO has set a global goal to eliminate TB by 2035. Achieving this objective poses ongoing challenges for TB prevention and control efforts in China.

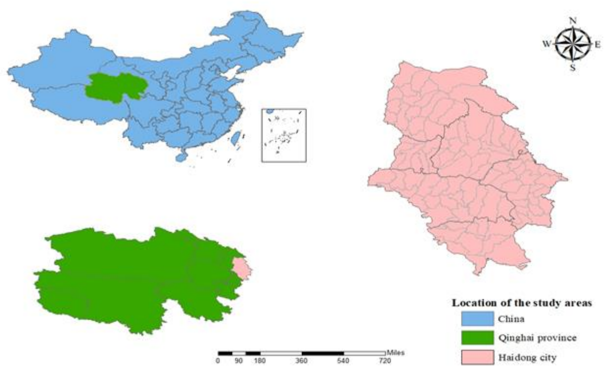
Geospatial analysis methods are indispensable for advancing our comprehension of public health concerns. Spatial epidemiology is a burgeoning subfield of epidemiology that investigates and interprets the geographical distribution patterns of diseases. Given tuberculosis's multifaceted and diverse dynamics across various scales, numerous studies have endeavored to elucidate its temporal and spatial distribution Khan et al. (2024), Shang et al. (2022), Rao et al. (2016). The tuberculosis landscape in China is characterized by complexity and spatial heterogeneity. Previous research primarily focused on the provincial, municipal, and district levels. Wang et al. (2023), Chen et al. (2019). Yet, there exists a noticeable research gap concerning the spatial and temporal clustering patterns at the township level. This study addresses this gap by employing spatial statistical analysis and spatio-temporal scanning statistics to explore the spatial distribution characteristics of tuberculosis registrations across townships in Haidong City, Qinghai Province, covering the period from 2013 to 2022. This represents the inaugural application of such methodologies within this context. This analysis comprehensively examined spatial distribution patterns, hotspots, and spatio-temporal clustering tendencies of TB cases within Haidong City over the specified period, focusing on township-level administrative divisions. This study aims to assess the impact on the notification rate and severity of TB, with the goal of laying a foundation for the development of more effective public health strategies aimed at preventing and reducing TB incidence.

METHODS

Study Area

The study was conducted in Haidong City, located in Qinghai Province, China. Geographically, Haidong spans from 100°41.5' to 103°04' east longitude and 35°25.9' to 37°05' north latitude, with two districts, four counties, and a total of 96 townships.

Figure 1: Location of the Haidong City, China. The statistical maps were created using ArcGIS software (version 10.8.0, ESRI Inc., Redlands, CA, USA)



By the end of 2023, the permanent resident population had reached 1.338 million, representing 22.52% of the province's total population. Haidong City is situated in the underdeveloped northwest region of China, where tuberculosis notification rate is higher compared to other parts of the country. With an average elevation ranging from 2200 to 3000 meters, Haidong exhibits a typical plateau and mountainous climate characterized by abundant sunshine, intense solar radiation, significant diurnal temperature fluctuations, and minimal seasonal temperature variations. The spatial distribution of climate demonstrates a clear vertical gradient, with temperatures decreasing as altitude increases.

Data Sources

The registered PTB case data for Haidong City, Qinghai Province, spanning from 2013 to 2022, were sourced from Qinghai Center for Disease Prevention and Control (Qinghai CDC) from the TB Information Management System (TBIMS) within the China Disease Prevention and Control Information System (Pandemic Reporting System) Shang et al. (2022). Specifically, data on tuberculosis diagnoses occurring between January 1, 2013, and December 31, 2022, were extracted from the primary diagnostic records. A total of 8,699 new cases were included in the analysis. Demographic information used in this study was obtained from the Qinghai Provincial Statistical Yearbook, and geographic data for Haidong City was sourced from the National Basic Geographic Information Center Rao et al. (2018). This study encompasses two districts and four counties, comprising a total of 96 township-level administrative units.

Spatial autocorrelation analysis

The spatial autocorrelation statistics are pivotal metrics for assessing the spatial distribution characteristics of disease cases and have been extensively utilized across numerous studies. Spatial autocorrelation is generally categorized into global and local types Liang et al. (2023), Peng et al. (2023). Global spatial autocorrelation evaluates the overall distribution patterns within the study region, indicating the average level of aggregation among similar variables across the area Duan et al. (2022). Local spatial autocorrelation, on the other hand, examines specific locations of clusters or hotspots Liu et al. (2021).

In this study, ArcGIS 10.8.0 software was utilized to perform spatial autocorrelation analysis and visualize the results in Haidong City. The Moran's I statistic was applied to assess the spatial correlation among neighboring observations, aiming to ascertain whether the distribution of pulmonary tuberculosis (PTB) cases in Haidong City exhibited randomness. The null hypothesis posited that TB case distribution in Haidong followed a random spatial pattern. Moran's, I range from -1 to 1, where values closer to 1 indicate a stronger spatial clustering of incidences across townships. Conversely, values approaching zero suggest a more random distribution. A significance level with a P-value less than 0.05 would indicate regional clustering of the disease. Understanding such spatial aggregation is crucial for subsequent spatial regression analyses due to its implications for disease control strategies. The Moran's I index is calculated as follows Ord et al. (1995):

$$I = \frac{n}{w} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2}$$

$$w = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$$

Where n represent the total number of spatial units and symbolize the attribute values of spatial unit i. The spatial weight value of spatial unit j is denoted by w, which is the sum of all weight values.

Spatio-Temporal Scan Analysis

The spatiotemporal scan statistic, which is based on a discrete Poisson model, utilizes a dynamically circular window to identify potential spatiotemporal clusters, which the radius denotes the spatial extent of the cluster, indicating its magnitude, while the height signifies the temporal duration of the cluster Kulldorff et al. (1997). The discrepancy between theoretical and actual cases is determined using the log-likelihood ratio (LLR) statistic as follows Wu et al. (2017):

$$LLR = \log\left(\frac{n}{E(n)}\right)^2 \left(\frac{N-n}{N-E(n)}\right)^{N-n} I$$

where n is the observed number of cases within the scan window, N is the total number of cases, E(n) is the expected number of cases within the scan window, and I is an indicator.

This study employed monthly incidence rates as cluster units and conducted spatiotemporal scanning analysis using SaTScan 10.1.3 software, with townships as the smallest spatial units. The aim was to analyze the patterns of tuberculosis incidence in Haidong City, Qinghai Province, from 2013 to 2022, focusing on spatiotemporal clustering characteristics. The log-likelihood ratio (LLR) of the data within the study area was computed using a scanning statistical approach assuming a Poisson distribution. A Monte Carlo simulation was employed to conduct statistical testing and determine P-values. The cluster with the highest LLR value and a statistically significant difference ($p < 0.05$) was identified as the primary cluster, while clusters with lower LLR values and statistical significance were considered secondary clusters Sun et al. (2021).

RESULTS

Descriptive analysis of PTB cases

This study compiled data on 9,377 confirmed tuberculosis cases spanning the period from 2013 to 2022 across 96 townships and towns in Haidong City, encompassing 2 districts and 4 counties. After excluding 678 cases of duplicate registrations, a total of 8,699 new cases were analyzed. Besides, 3 cases existed outside the Haidong city. Table 1 presents the epidemiological characteristics of PTB. Statistically significant disparities in PTB registration rate were observed between males and females ($\chi2=50.027$, P-value <0.01). Moreover, PTB registration rates were highest among citizens aged over 60 and lowest among those aged 0-14, with significant differences noted across all age groups ($\chi2=1216.436$, $P<0.01$). From an occupational standpoint, farmers represented the predominant group among tuberculosis patients, comprising nearly 90% of cases, followed by students and retirees. Temporal analysis from 2013 to 2022 revealed distinct variations in PTB distribution patterns in Haidong City. Among the patients, 49.78% tested positive for tuberculosis. Notably, this proportion exhibited an increasing trend from 2013 to 2018, followed by a decline from 2019 to 2022, as depicted in Figure 2.

Figure 2: Tuberculosis registration rate trends in Haidong City, 2013-2022.

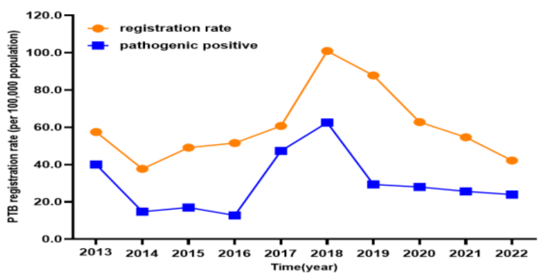


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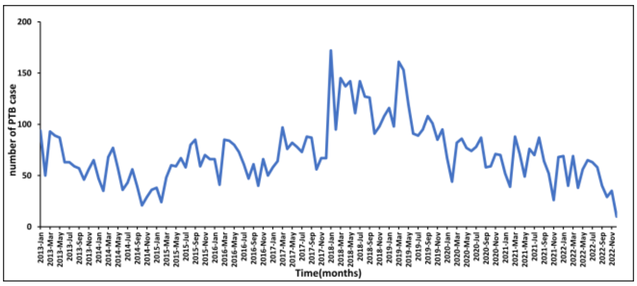
Table 1: The demographic characteristics of PTB cases in Haidong City, China, 2013 – 2022

Characteristic	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Gender										
Male	481	309	405	433	496	836	694	457	380	300
Female	341	235	309	321	397	658	617	396	362	272
Age (year)										
0-14	1	0	0	3	7	21	21	13	8	8
15-29	110	86	104	95	105	281	198	160	122	65
30-44	157	90	138	121	127	227	189	125	91	69
45-59	164	142	161	167	194	328	284	205	173	144
≥60	390	226	311	368	460	637	619	350	348	286
Occupation										
Student	29	17	29	35	47	80	60	58	39	24
Teacher	3	3	3	6	3	8	1	9	0	0
Farmer	755	500	643	697	812	1190	1030	698	642	478
Laborer	11	3	10	4	6	12	15	6	5	6
Medical staff	2	2	1	1	1	4	4	3	1	1
Retired	12	2	16	0	13	34	25	15	19	10
Others	10	17	12	11	10	166	176	64	36	53

The change in tuberculosis registration rates demonstrated statistically significant trends ($\chi 2=57.687$, P-value <0.01). Figure 3 illustrates seasonal fluctuations in tuberculosis cases, with peaks typically occurring in March and a subsequent decline from March to October. There was an upward trend from October to January, with February recording the lowest registration rates of the year.

Figure 3: Distribution of cumulative monthly pulmonary tuberculosis patient registrations in Haidong City 2013-2022.



Spatial distribution

A global spatial autocorrelation analysis of PTB registration rates in Haidong City from 2013 to 2022 was conducted, yielding findings detailed in Table 2. The global Moran's I index ranged from 0.0312 to 0.2843, with statistically significant positive values observed for all years except 2022 (P-value < 0.01 for 2013 and 2014, P-value < 0.05 for others). These results indicate significant geographical correlation and spatial heterogeneity, suggesting that PTB registration rates at the township level in Haidong City are not randomly distributed. Furthermore, consistent cutoff values were maintained to visually represent the fluctuation in registration rates among different townships over time.

The registration rates of PTB exhibited heterogeneous distribution at the township level, as illustrated in **Table 2** and **Figure 4** depicting variations across townships in Haidong City from 2013 to 2022. The average PTB registration rate at the township level was 8.30 per 100,000 population, equivalent to approximately 352.37 cases per million people. Geographically, these townships are predominantly concentrated in the southern counties, with Gongboxia Management Committee and Lijiaxia Management Committee being the only areas lacking data out of the 96 townships. Among these townships, those with the highest rates, based on population density, include Xiamen Town (352.37/100,000), Qianhe Township (328.98/100,000), Beishan Township (257.72/100,000), Gangou Township (228.60/100,000), and Fengdui Township (207.94/100,000). Conversely, Gaodian Town had the lowest rate (8.30/100,000). High registration rates were predominantly observed in the southern and central regions of Haidong City, encompassing Minhe County and Hualong County. Conversely, the northern section, including Tiny Gorge Town and Ping'an Town in Ping'an District, exhibited significantly lower rates. There were notable year-to-year variations in PTB registration rates, exemplified by Beishan Township in Minhe County, where rates surged from 129.48 per100,000 in 2013 to 840. 98 per 100,000 in 2018.

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Table 2: The Global Spatial Autocorrelation in Registration rate of PTB in Haidong, 2013–2022

Year	variance	expected index	Moran's I	Z-score	P value
2013	0.003689	-0.010526	0.1258	2.2438	0.025
2014	0.002305	-0.010526	0.09	2.0931	0.036
2015	0.002539	-0.010526	0.2071	4.3192	< 0.001
2016	0.00252	-0.010526	0.2843	5.8741	< 0.001
2017	0.002284	-0.010526	0.2308	5.0497	< 0.001
2018	0.002392	-0.010526	0.2126	4.5634	< 0.001
2019	0.002554	-0.010526	0.1399	2.9765	< 0.001
2020	0.002514	-0.010526	0.1816	3.8324	< 0.001
2021	0.002412	-0.010526	0.2383	5.0675	< 0.001
2022	0.002321	-0.010526	0.0312	0.8672	0.386

Figure 4: The registration rate of total number of PTB cases at township level in Haidong City, 2013-2022.

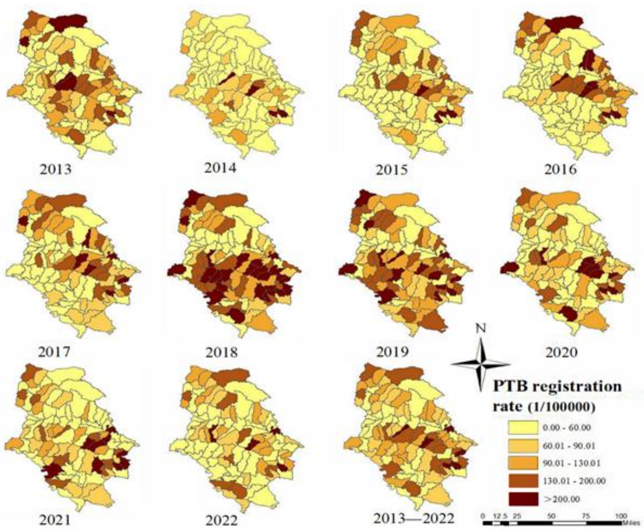
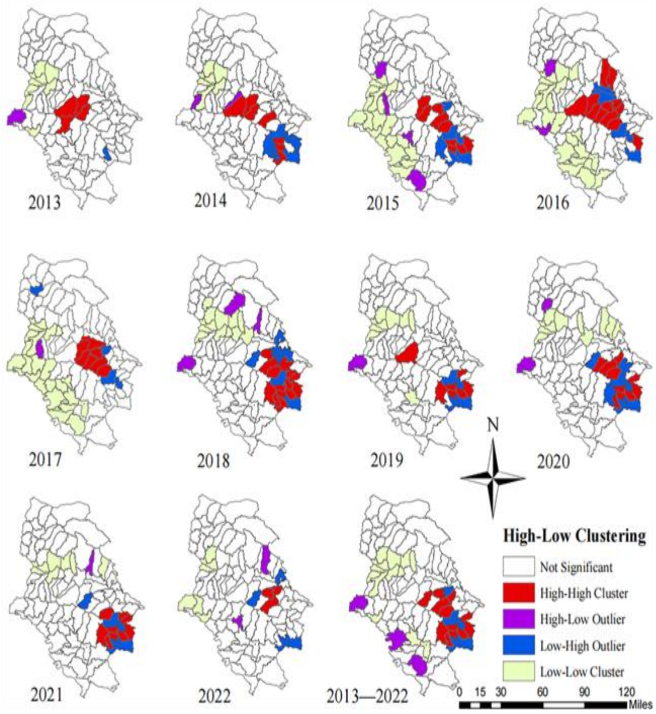


Figure 5 showed the analysis results of the local spatial autocorrelation. Hot spots, indicative of high concentrations, are predominantly situated in the southern Ledu District (including Qutan Town, Putai Township, Fengdui Township, and Zhongba Tibetan Autonomous Township), the northwestern sector of Minhe County (encompassing Xinmin Township, Songshu Township, and Xiamen Town), the southern area (Manping Town, Maying Town, Zaodao Township, Qianhe Township, and Xinger Township), as well as Taga Tibetan Township in Hualong County.

Over the years, the hot spots area around Ledu has expanded outward, with the number of townships identified as hot spots increasing from 4 in 2013 to a peak of 13 in 2018. Subsequently, post-2018, the majority of hot spots have been concentrated in Minhe County. Conversely, cold spots, indicating areas of lower prevalence, are primarily located in Ping'an District (including Ping'an Town and Xiaoxia Town), the southern section of Huzhu County (encompassing Gaozhai Town, Halazigou Township, and Hongyazigou Township), the eastern part of Hualong County, and most townships in Xunhua County. The distribution of cold spots exhibits a concentrated pattern that intensified from 8 townships in 2013 to 18 townships in 2017. However, from 2017 onwards, the prevalence of cold spots gradually decreased, becoming predominantly centered in Ping'an District, situated in the middle and western regions of Haidong City.

Figure 5: Local spatial autocorrelation of PTB registration rates in Haidong City, 2013-2022.



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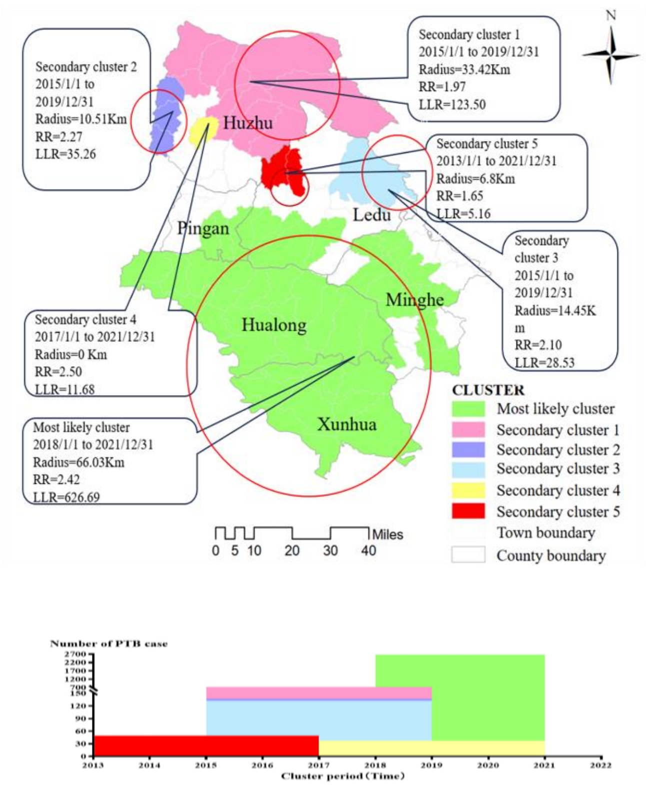
Spatiotemopral clustering analysis

We conducted a spatiotemporal scanning analysis of PTB registration rates in Haidong City from 2013 to 2022. Our findings reveal temporal and spatial aggregation of PTB registration rates. **Table 3** and **Figure 6** illustrate the primary cluster and five secondary clusters, respectively, with Figure 4 using color coding to distinguish these clusters. The largest cluster, excluding Huzhu County, is predominantly centered in the central and southern areas of Haidong City, encompassing 55 townships across Xunhua County, Hualong County, most of Minhe County, the southwest of Ledu District, and the southeast of Ping'an District. The primary clustering period was from January 1, 2018, to December 31, 2021 (LLR = 626.69, P < 0.001), during which 2,639 tuberculosis cases were identified.

Table3： Significant high-rate PTB Clusters in Haidong, China detected by SaTScan from 2013 to 2022

Clusters	Number of Clustering areas	Latitude (N)	Longitude €	Radius (km)	Time Frame (Year)	Population	Observed cases	Expected cases	RR	LLR	*P*
Most likely cluster	55	35.84	102.27	66.03	2018/1/1 to 12/31/2021	553,462	2639	1326.94	2.42	626.69	＜0.001
Secondary cluster 1	10	37.01	102.3	33.42	2015/1/1 to 12/31/2019	117,321	704	372.29	1.97	123.5	＜0.001
Secondary cluster 2	3	36.79	101.85	10.51	2015/1/1 to 12/31/2019	19,512	137	60.94	2.27	35.26	＜0.001
Secondary cluster 3	4	36.59	102.57	14.45	2015/1/1 to 2019/12/31	19,837	132	63.35	2.1	28.53	＜0.001
Secondary cluster 4	1	36.74	101.98	0	2017/1/1 to 12/31/2021	4,924	37	14.83	2.5	11.68	0.017
Secondary cluster 5	2	36.59	102.25	6.8	2013/1/1 to 12/31/2017	9137	49	29.85	1.65	5.16	0.979

Figure 6: The space-time clusters of the total PTB cases at the township level in Haidong, 2013–20122.



Importantly, our results indicate that the tuberculosis risk among these township populations is 2.42 times higher compared to populations outside these hotspot areas (relative risk, RR = 2.42). Additionally, we identified four statistically significant secondary clusters, with the largest, Cluster 1, encompassing 10 townships concentrated in Huhui County. This cluster's aggregation period was from January 1, 2015, to December 31, 2019 (LLR = 123.50, P < 0.001), and its spatial extent was relatively limited, scattered across various parts of Mutual Aid County. Furthermore, the aggregation periods across different spatial clusters varied, suggesting distinct temporal trends in tuberculosis registration rates across different regions.

These space-time clusters are distinguished in different colors. As show in the bottom panel, the height of the columns represents the total number of cases in the cluster across all the years in which cases in that cluster were registration.

DISCUSSION

This study employed GIS and Kulldorff scanning statistical analysis techniques to discern the spatial and temporal patterns of tuberculosis registration rates at the township level in Haidong City, situated on the Qinghai-Tibet Plateau in Qinghai Province, China.

The findings revealed significant spatial autocorrelation in tuberculosis registration rates in Haidong City from 2013 to 2022, as evidenced by the notable results presented in Table 2, suggesting a clustered distribution of tuberculosis cases. To our knowledge, prior studies have primarily investigated TB spread in China at provincial, municipal, and county levels, with few research focusing on the township level Liu et al. (2018), Cui et al. (2019). The substantial number of recorded tuberculosis cases in 2022, amounting to 574, poses a significant challenge to achieving the goal of tuberculosis eradication by 2035 World Health Organization et al. (2015).

Descriptive studies have identified a higher registration rate of PTB among males compared to females in Haidong City. This observation aligns with epidemiological trends observed nationally and internationally, as supported by various research findings Horton et al. (2016), Onozaki et al. (2015). The aging process is likely to exert a significant influence on the heightened occurrence of PTB in males Gao et al. (2015). PTB registration rates is notably concentrated among individuals aged over 60 years, a demographic characterized by compromised immune systems and diminished lung defenses, factors that enhance susceptibility to PTB infection Zhang et al. (2019). Additionally, the study identified farmers as the predominant occupational group in Haidong City, comprising approximately 90% of the population, consistent with national PTB registration rates.Given the city's agrarian context, challenges persist in economic development, healthcare services, and health education Jiang et al. (2021), Zhu et al. (2022). The region's lower educational attainment levels also contribute to suboptimal adherence to tuberculosis prevention and control strategies Long et al. (2020). Consequently, these findings imply a need for prioritizing older males in future tuberculosis reduction initiatives.

Our research findings in the Tibetan Plateau region corroborate earlier studies, thereby supporting our seasonal hypothesis Lai et al. (2024), Zhang et al. (2023), Alene et al. (2021). Moreover, distinct seasonal patterns are clearly discernible. The annual PTB registration rates from Haidong City consistently demonstrates a marked increase during late spring and summer, with a peak in March. Increased susceptibility to TB infection is associated with reduced exposure to ultraviolet (UV) radiation, inadequate vitamin D levels, and environmental contamination Zhang et al. (2023), Alene et al. (2021), Nie et al. (2022), Kuddus et al. (2019), Butt et al. (2021), Douglas et al. (1998). Additionally, during the Spring Festival, characterized by Lunar New Year celebrations, there is a noticeable reluctance to seek medical treatment, resulting in a significant decrease in registration TB cases, particularly in January and February Shang et al. (2022), Li et al. (2013). This observation underscores the importance of considering potential delays in diagnosis in our research efforts Li et al. (2020). Prior studies suggest that requiring prompt medical attention Kirolos et al. (2021). This phenomenon is among the primary reasons for the consistently high registration rates of PTB during the spring season.

In our study, global spatial autocorrelation analysis revealed a distinct clustering pattern in PTB registration rates within Haidong City. Advanced local spatial autocorrelation techniques further identified subtle temporal variations in PTB hotspots. Between 2013 and 2022, these hotspots predominantly emerged in areas with elevated PTB registration rates. Notably, among Haidong City's 96 townships, Xiamen Township, Qianhe Township, Beishan Township, Gangou Township, and Fengdui Township consistently reported higher tuberculosis rates over the past decade. These disparities likely arise from demographic, healthcare, sanitation, economic, and educational inequalities among the population Shang et al. (2022), Wellhoner et al. (2011). Moreover, specific environmental and meteorological factors pertinent to the Qinghai-Tibet Plateau region may also influence PTB registration rates. Haidong City faces several challenges including underdeveloped economic conditions and insufficient transportation infrastructure, which constrain financial resources and hinder professional recruitment for PTB prevention and control efforts Zhu et al. (2022). Moreover, the city's diverse population, encompassing multiple ethnic groups with diverse languages and lifestyles, complicates the implementation of targeted PTB prevention and control strategies Wang et al. (2021). Financial limitations and inadequate infection control measures frequently contribute to PTB patients discontinuing treatment, thereby perpetuating disease transmission. The analysis revealed a consistent increase in PTB hotspots in Haidong City from 2013 to 2016, reaching a peak in 2018, followed by a gradual decline in PTB registration from 2018 to 2022, indicating a recent decrease in disease burden. This observed trend likely reflects heightened governmental prioritization of tuberculosis control and prevention efforts in recent years. These efforts include the comprehensive adoption of a new tuberculosis prevention and control service model, strategic interventions, increased funding allocation, and extensive health promotion campaigns aimed at enhancing public awareness of PTB prevention and treatment Wang et al. (2020), Liang et al. (2023). The overarching goal is to advance knowledge and understanding of tuberculosis prevention in regions characterized by cold climates and high altitudes.

Through a global and local spatial analysis, the central and southeast regions of Haidong City have been identified as key areas for TB prevention and control efforts. To delve into the temporal dynamics of disease geography, spatial-temporal scanning analysis was employed to examine the impact of temporal factors on the geographic distribution of PTB within the city.

Kulldorff's retrospective scan statistics effectively integrates spatial and temporal dimensions, enabling dynamic, three-dimensional, and multi-scale cluster analysis across diverse time frames Kulldorff et al. (1997). This advanced technology allows researchers to identify spatial-temporal correlations and has found extensive application in disease cluster surveillance Xiao et al. (2017), Zhang et al. (2019), Rao et al. (2017). In our investigation, temporal windows were set at 50% of the study's duration, revealing no overlapping high-risk clusters. Comparing with distinct spatial models, the spatiotemporal scanning approach highlights the efficacy of temporal analysis, with identified clusters aligning closely with Moran's I local autocorrelation statistics, thereby validating the study's robust findings.

Utilizing scanning statistics, we identified one primary cluster and five secondary clusters in Haidong City spanning from 2013 to 2022, consistent with previous observations in Qinghai Province. The primary cluster is located in the central and southern regions of Haidong City. This phenomenon primarily arises due to the lower socioeconomic status, poorer living conditions, limited access to sanitation facilities, and heightened clustering risk among the population in the central and southern four counties of Haidong City Rao et al. (2017). These findings underscore the need for targeted tuberculosis prevention and control strategies tailored to the economic and health realities of affected regions. Fortunately, Haidong City witnessed declining TB registration rates from 2018 to 2022, attributed largely to provincial policies aimed at enhancing tuberculosis control. This study constitutes the initial comprehensive examination of township-level spatial-temporal clustering patterns in Haidong City, identifying regions most vulnerable to TB. Effective management strategies for TB control are crucial going forward.

This study was subject to some limitations. First, the system is based on passive case discovery, and this approach may miss some cases Shang et al. (2022). Fortunately, according to the survey results of the missing rate of infectious diseases, the missing rate of tuberculosis notification in Haidong City is less than 5%.

Second, we conducted spatio-temporal scan statistic to detect clusters in different space and periods of time but this method only relies on circular spatial scanning and cylinder space-time scanning, and doesn't allow for irregular space. Third, our analysis is based on the data of the national surveillance system, so there may be a small number of cases that are not captured, which may cause an underestimate of the tuberculosis epidemic in Haidong. Finally, this study did not examine additional factors that could influence TB incidence, including individual lifestyle choices, socioeconomic conditions, meteorological factors, and healthcare resource availability Couceiro et al. (2011).

CONCLUSION

Tuberculosis continues to pose a significant public health challenge in Haidong. Our findings highlight PTB's notable spatiotemporal characteristics at the townships level within the region. This study investigated the epidemiological and spatial distribution of tuberculosis in Haidong City from 2013 to 2022. Spatiotemporal scanning analysis indicated a reduction in cluster sizes, reflecting advancements in PTB control programs. Nonetheless, persistent high-risk areas necessitate targeted prevention and control measures, underscoring the study's relevance in guiding TB prevention strategies. The aim of this research is to inform the scientific formulation and enhancement of the tuberculosis prevention and control plan during the 14th Five-Year Plan in Haidong City, thereby advancing the scientific rigor of tuberculosis prevention and control efforts and providing insights for timely adjustment or improvement of prevention strategies.

DECLARATIONS

Acknowledgements

We thank all the staff at the Center for Disease Control and Prevention (CDC) in Haidong City, Qinghai Province, China, for their support.

Financial support

This work was supported by the National Natural Science Foundation of China (81860593).

Author Contributions

DY : Conceived and designed research, analyzed data, and wrote major manuscripts. SJ: Data collection and organization. YZ, XW, CZ, YR: Help with draft starters. ZW: revised the manuscript

All authors read and approved the final version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethics approval and consent to participate

In this study, TB data were collected by routine TB surveillance and control activities. Therefore, ethical consent was not essential.

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