Preventive Medicine Reports 35 (2023) 102362

Contents lists available at ScienceDirect

Preventive Medicine Reports

journal homepage: www.elsevier.com/locate/pmedr

Analysis of spatial characteristics and geographic weighted regression of tuberculosis prevalence in Kashgar, China

Xiaodie Chen [a,1,2], Mawlanjan Emam [b,1,2], Li Zhang [c], Ramziya Rifhat [d], Liping Zhang [d], Yanling Zheng [d,*]

[a] College of Public Health, Xinjiang Medical University, Urumqi 830017, China
[b] Center for Disease Control and Prevention, Kashgar 844000,China
[c] First Affiliated Hospital of Xinjiang Medical University, Urumqi 830011, Xinjiang, China
[d] College of Medical Engineering and Technology, Xinjiang Medical University, Urumqi 830017, China

ARTICLE INFO

Keywords:
Tuberculosis
Moran's I
Spatial autocorrelation
Geographically weighted regression

ABSTRACT

Number of cases of tuberculosis (TB) was higher than that of the national level in Kashgar, China. This study aimed to analyze the spatial and temporal distribution of TB and the relationship between TB and social factors, which can provide a reference for the prevention and control of TB. We applied spatial autocorrelation analysis to study the distribution of tuberculosis in Kashgar. We used a geographically weighted regression (GWR) model to analyze the relationship between TB and social factors. A total of 100,330 cases of TB in Kashgar from 2016 to 2021 were analyzed. The number of TB cases in Kashgar was higher in the east, lower in the west, and most elevated in the center. The highest cumulative number of cases was found in Shache county. Global Moran's I ranged from -0.212 to -0.549, and local spatial autocorrelation analysis identified four clusters. According to our analysis, the incidence of tuberculosis was negatively correlated among the regions of Kashgar, and the related causes need to be analyzed in depth in future studies. Per capita gross domestic product (GDP), number of medical institutions per capita, and total population influenced the incidence of tuberculosis in Kashgar. Based on our findings, we suggest some effective measures to reduce the risk of TB infection, such as improving the living standard, developing the regional economy, and distributing health resources rationally.

1. Introduction

Tuberculosis (TB) is an ancient and widely spread infectious disease and is one of the three major public health problems that seriously endanger human health. It is a chronic respiratory infection caused by Mycobacterium TB and transmitted by coughing or sneezing (Center, 2021, Natarajan, 2020). Previous studies have shown that China has a high incidence of TB, accounting for 8.5% of the global incidence (WHO, 2021). Several methods are presently employed in China for TB prevention and control, including directly observed therapy, DOTS (short-term treatment strategy), and so on (Zuo et al., 2020). Although implementing the above measures has reduced the TB incidence in China, it still exceeds the global average level (Jiang H, 2021). Over 28,000 new TB cases occur each year. Xinjiang is one of the provinces in China with a high TB incidence (Jiang, 2021, Zheng, 2021). The distribution of TB in Xinjiang has significant regional differences, with its southern part having a higher incidence than other regions. Kashgar, located in the southern part of Xinjiang, is a high TB prevalence area (He, 2017, He, 2017). Even though the Kashgar region has carried out a series of initiatives to prevent and control TB, for instance, the scope of national physical examination screening was expanded, the task of TB prevention and control in Kashgar is still arduous (He, 2017, Wang et al., 2021).

Spatio-temporal characterization includes temporal and spatial analysis, which refers to data analysis with time series and spatial location attributes (absolute and relative locations). Spatial autocorrelation analysis is a crucial method for describing Spatio-temporal characteristics, including global spatial autocorrelation analysis and local spatial autocorrelation analysis. Among them, global spatial autocorrelation analysis is a common method to describe the spatial

* Corresponding author at: College of Medical Engineering and Technology, Xinjiang Medical University, Urumqi, China.
E-mail address: zhengyl_math@sina.cn (Y. Zheng).
[1] Xiaodie Chen and Mawlanjan Emam are co lead author.
[2] Xiaodie Chen and Mawlanjan Emam contributed equally to this study.

https://doi.org/10.1016/j.pmedr.2023.102362
Received 14 April 2023; Received in revised form 7 July 2023; Accepted 2 August 2023
Available online 4 August 2023

correlation of data. Local spatial autocorrelation is often used to explore the location and type of data clusters. Zhang Hao (Hao Zhang, 2022) applied a spatial autocorrelation analysis model to explore the spatial and temporal distribution characteristics of TB prevalence in Nanjing, and found that the prevalence of TB in Nanjing decreased year by year. Bi Siyu (Bie, 2021) analyzed the relative risk of TB in mainland China using a spatial autocorrelation model, and the results showed that the relative risk varied among provinces and differed in time, season, and month.

Influencing factors play an essential role in the progression of the disease. Some factors may influence the development of disease or determine the specificity of the disease and cause damage to the organism. Therefore, analyzing the influencing factors of the disease can provide scientific reference to help preventing the further development of the disease and avoid causing irreversible damage to the body (Ofori-Anyinam, 2020, Mulholland, 2019, Sapriel, 2019, Xu, 2022).

Compared with traditional linear regression, the geographically weighted regression model (GWR) model considers the geographic coordinate information of the data and incorporates them into the regression parameters, enabling relevant studies to consider changes in a geographic location more comprehensively (Dangisso, 2020). Previous studies have pointed out that TB was related to the environment, humans, and germs, where the environment refers to the social, economic, and demographic social environment (Wang, 2016). Using the GWR model, Zhang Fangyu (Wang, 2021) explored the relationship between TB disease and demographic, economic, and welfare factors in each province of China in 2015 and found that different social factors affect the incidence of TB disease in different regions. Zhongbao Zuo (Wang, 2021) applied the GWR model to analyze the spatial and temporal characteristics of TB from 2004 to 2017 and found that the autoregressive component played a decisive role in TB incidence.

We collected the number of tuberculosis cases in Kashgar region from 2016 to 2021. First, descriptive epidemiological statistical analysis was applied to analyze the epidemiological trend of the disease. Secondly, we applied global spatial autocorrelation analysis to understand the geospatial distribution of TB in Kashgar region. In addition, the spatial aggregation pattern of TB was explored using the LISA index. Finally, the influencing factors of TB in Kashgar region were discussed by building a GWR model.

2. Methods

2.1. Research area and data source

Kashgar is located in southwestern Xinjiang, China, with 12 counties in the area (Kashgar City, Shufan County, Shule County, Yinjisha County, Yupu Lake County, Gashi County, Shache County, Zepu County, Yecheng County, Mageti County, Batu County, Tashkurgan Tajik Autonomous County), with a total area of 162,000 square kilometres.

We collected data on all TB cases in Kashgar region from January 1, 2016 to December 31, 2021 from the information reporting system of the Kashgar Disease Control Center. We conducted a spatial distribution analysis using TB case data from 2016 to 2021 in Kashgar region. Indicators of influencing factors related to TB incidence, including data on natural population growth rate, gross product per capita, birth rate, number of medical institutions per capita, and total population, were collected and organized by different years and study areas from the Kashgar Statistical Yearbook 2016–2018 (Xinjiang Bureau of Statistics, 2017, Xinjiang Bureau of Statistics, 2018, Xinjiang Bureau of Statistics, 2019).

2.2. Analysis of spatial–temporal characteristics

Spatial autocorrelation is mainly applied to study the spatial correlation between geographical factors, which contains both global and local spatial autocorrelation (Assefa, 2022). In this paper, we applied Moran's I index to study the regional correlation of tuberculosis in Kashgar and explored the spatial aggregation pattern of tuberculosis in the region using LISA index.

Global spatial autocorrelation analysis is commonly applied to analyze the spatial aggregation of data. Moran's I statistic is utilized as an indicator for evaluating spatial autocorrelation, and the values range is [-1, 1] (Zhang, 2019). The closer the I value is to 1, the closer the spatial units are, the more similar the attributes are, and the overall distribution is aggregated; when the I value is closer to -1, the overall spatial distribution is dispersed; when the I value is 0, the overall distribution is random. $p<0.05$ indicates that the original hypothesis is rejected and spatial autocorrelation exists.

The global spatial autocorrelation is calculated as follows:

$$I = \frac{\sum i = 1n \sum i = 1nWij(xi - x)(xj - x)}{s2 \sum ni = 1 \sum nj = 1wij}$$

where n is the number of the counties or cities in Kashgar, x is the number of TB cases in each county or city, $\bar{x}$ is the mean value of the corresponding attribute, i and j stand for different area codes, W_{ij} denotes the spatial weight matrix, and s^2 represents the sample variance.

Local spatial autocorrelation analysis is generally applied to calculate the degree of correlation between adjacent regions. There are four main types of correlations: high-high value clustering, low-low value clustering, high-low value clustering, and low -high value clustering (Wang, 2020). To reveal the distribution of TB in Kashgar and their relationship with neighbouring counties, it is significant to detect the correlation in some regions by the local spatial autocorrelation method (Xie, 2021).

The local spatial autocorrelation is calculated as follows:

$$I_i = \frac{x_i - x}{s_i^2} \sum_{j=1, j\neq i}^{N} W_{ij}(x_i - x)s_i^2 = \frac{\sum_{j=1, j\neq i}^{N} (x_i - x)^2}{N - 1} - x^2$$

where x is the number of TB cases in each county or city, $\bar{x}$ is the mean value of the corresponding attribute, W_{ij} is the spatial weight between features i and j, N is the number of the county in Kashgar, and s^2 denotes the sample variance.

2.3. Geographically weighted regression model

Geographically weighted regression (GWR) is a spatial analysis technique commonly applied to identify areas and populations at high risk of disease and to analyze illness in time and space (Wu, 2021, Parwati, 2021). We investigated the relationship between tuberculosis and social factors using the GWR model.

The equation for the GWR model is shown below (Brunsdon, 1996, Fotheringham, 1997):

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{k=1}^{p} \beta_k(\mu_i, \nu_i)x_{ik} + \varepsilon_i(i = 1, 2, \ldots, n),$$

where, (μ_i, ν_i) is the spatial coordinate of the ith sample point, β_k is the estimated parameter of the kth explanatory factors in the ith data for the object under study, and ε_i is the random error. If β_0 held constant in space, the GWR model is a global model. y_i is the number of TB cases at the ith sample point., x_{ik} is the kth influencing factor of the ith sample point.

2.4. Trend analysis

We applied ArcGIS 10.4.1 software to map the spatial distribution trends of TB, where the x-axis direction is east, the y-axis direction is north, and the z-axis direction is the direction of the increasing number of TB cases (Parwati NM, 2021) Each geographic area unit is located in the xy-plane, and the height of the black vertical bar indicates the data point in each geographic area (which is the TB in our study cases in our study) by size and location. These points are projected onto the xz and yz planes, respectively, and the best-fit curves are made by connecting the points. The blue curve on the xz plane represents the east–west direction, and the pink curve on the yz plane represents the north–south direction. Trend analysis is to convert the points in the study area into a three-dimensional graph with certain attribute heights and to analyze the overall trend of the data set from multiple perspectives.

2.5. Data analysis procedure

The spatial visualization, mapping, and the GWR model building of the TB incidence in the Kashgar region were analyzed using Arcgis 10.4.1 software. Spatial autocorrelation analysis of the TB in Kashgar was performed using Geoda software. Differences were considered statistically significant if $P<0.05$.

3. Results

A total of 100,330 TB cases were analyzed in Kashgar from 2016 to 2021, and the number of TB cases in 2018 was 33,450 or 33.3%. During the study period, male patients with TB were significantly higher than female patients with a sex ratio of 1.17:1.The results of this study showed that the number of TB cases was low between 0 and 18 years of age, with an overall increasing trend with age after 18 years of age. Patients over 65 years of age accounted for 40% and 38% of patients between 40 and 65 years of age (see Table 1).

From January 1, 2016 to December 31, 2021, there were new cases of TB in Kashgar region every month. As seen in Fig. 1, the peak TB cases in the region vary from year to year and are generally more severe in the spring and winter. However, the situation was different in 2018. The peak of the disease onset was from August to December.

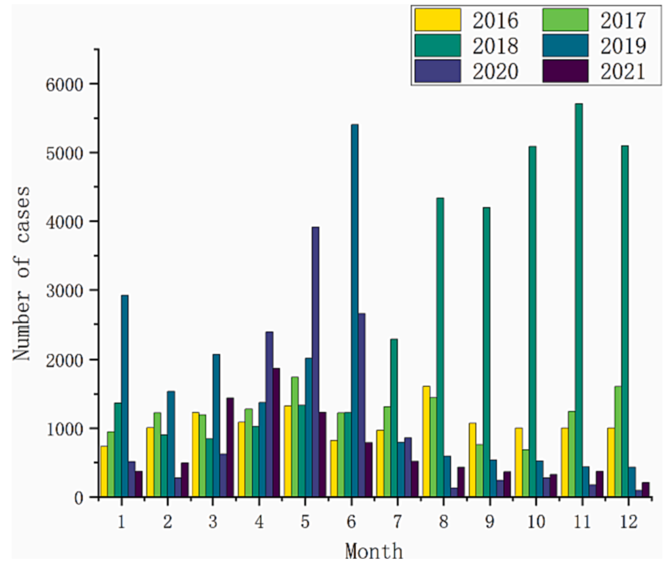

Fig. 1. Monthly graph of the number of tuberculosis cases in Kashgar from 2016 to 2021.

3.1. Spatial autocorrelation analysis

3.1.1. Global spatial autocorrelation analysis

In this study, a global spatial autocorrelation analysis was conducted on the number of TB cases in Kashgar region from 2016 to 2021. It was found that the differences in Moran's I values for TB in 2016, 2020 and 2021 were statistically significant ($p<0.05$) with values ranging from -0.212 to -0.549 (see Table 2 and Fig. 2).The results of Moran'I were based on Geoda software.

Table 2
Global spatial autocorrelation results for annual TB in Kashgar from 2016 to 2021.

Year	Moran's I	z-value	*p*	Type
2016	-0.446	-1.927	0.013	Queen
2017	-0.309	-1.349	0.085	Queen
2018	-0.337	-1.549	0.059	Queen
2019	-0.212	-0.636	0.282	Queen
2020	-0.549	-2.758	0.001	Queen
2021	-0.451	-2.407	0.003	Queen

3.1.2. Local spatial autocorrelation analysis

We identified four disease aggregation areas by local spatial autocorrelation analysis. Yecheng and Shacheng counties were in the H-L (high-low) aggregation area, indicating that the tuberculosis prevalence was more severe in this area and less severe in the surrounding areas. The L-H (low–high) aggregation area was distributed in Tashkurgan Tajik Autonomous County and Yupuhu County, indicating a significant negative correlation between these areas and the surrounding areas (see Fig. 4). Among the 12 counties in Kashgar region, the three areas with the highest cumulative number of cases were Shache County, Yinjisha County and Yecheng County (see Fig. 3).

3.1.3. Spatial distribution trend

The general trend of the distribution of the number of TB cases in 12 counties or cities in Kashgar region from 2016 to 2021 can be observed through the 3D view (see Fig. 5). The results show that TB in Kashgar region shows a clear upward trend from west to east, and TB in the central part is higher than that in the east and west, in an inverted U. In 2020 and 2021, TB in Kashgar region shows an upward trend from north to south, but a downward trend from south to north in both 2017 and 2019.

3.2. Geographically weighted regression model

Before performing geographically weighted regression modelling, we applied ordinary least squares to find the optimal model and performed a covariance test. When VIF $>$ 7.5, it indicates a co-linearity between the explanatory variables, and the variable needs to be excluded. After the test, the only explanatory variables with VIF values$<$7.5 were the number of medical facilities per capita, GDP per capita, and total population.

Therefore,in this paper, a GWR model was developed with the

Table 1
Notification cases of TB with different demographic characteristics in Kashgar from 2016 to 2021.

		2016	2017	2018	2019	2020	2021
Gender	**Male**	6194(48.1%)	7338(50.0%)	17138(51.2%)	10384(55.6%)	6521(53.5%)	4227(50.1%)
	Female	6696(51.9%)	7343(50.0%)	16312(48.8%)	8286(44.4%)	5673(46.5%)	4218(49.9%)
Age	**≤18**	159(1.2%)	172(1.2%)	21(0.1%)	380(2.0%)	260(2.1%)	226(2.7%)
	>18~40	1342(10.4%)	1569(10.7%)	3278(9.7%)	4021(21.5%)	2335(19.2%)	1269(15.0%)
	>40~65	5321(41.3%)	6086(41.5%)	10010(30.0%)	7276(39.0%)	4513(37.0%)	3139(37.2%)
	>65	6068(47.1%)	6854(46.6%)	20141(60.2%)	6993(37.5%)	5086(41.7%)	3811(45.1%)

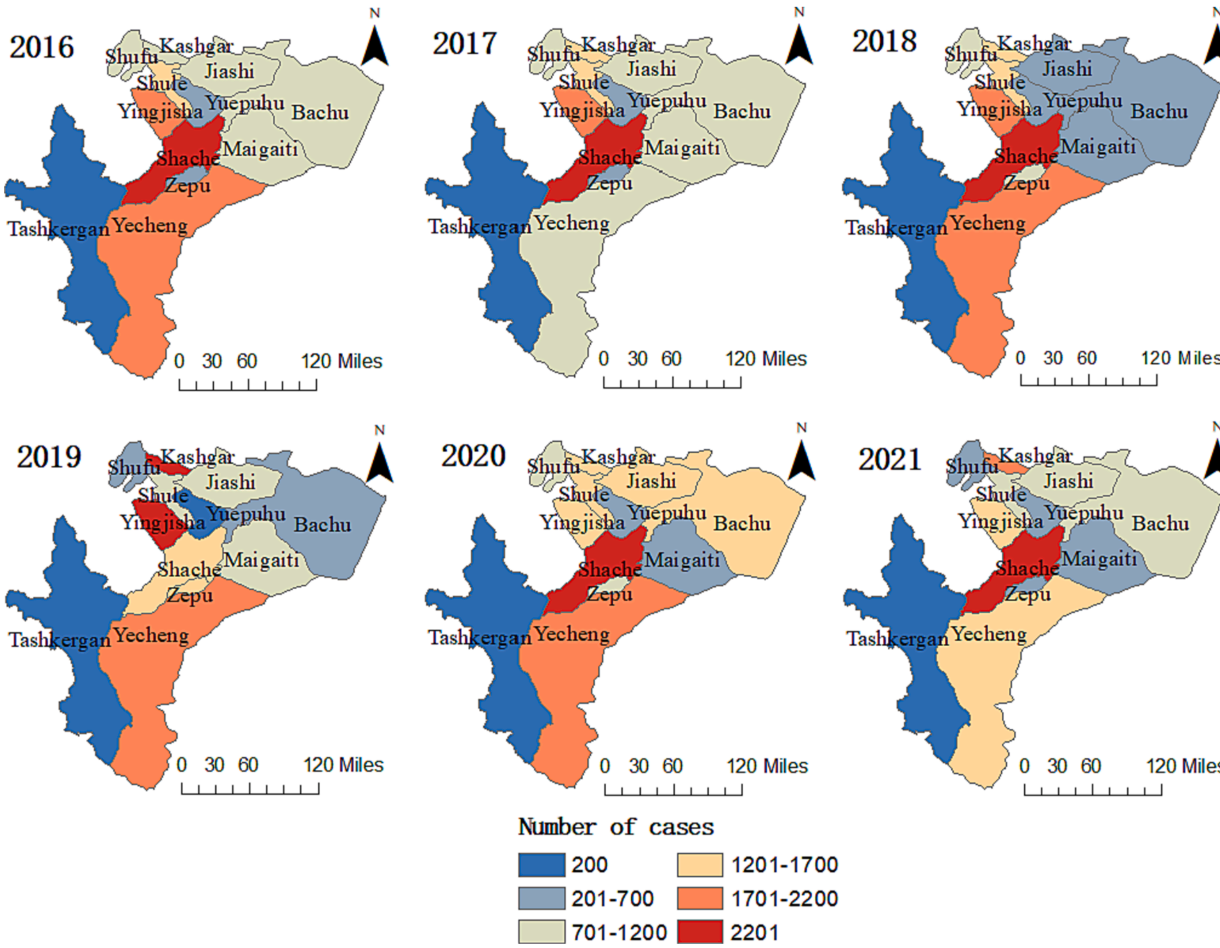

Fig. 2. The space distribution of TB at the county or city level in Kashgar, 2016–2021. The Maps were created by ArcGIS (version 10.4.1). The areas marked in red are those with higher values of the average number of TB cases, such as Shache, YeCheng, et al. The areas marked in blue are those with lower values of the average number of TB cases, such as Tashkergan, Yuepuhu, et al. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

number of TB cases as the dependent variable and the number of health care facilities per capita, GDP per capita and total population as the independent variables. The R^2 estimated by the model ranged from 0.6677 to 0.7464 (see Fig. 6), and the GWR model fit better in the southwest region compared to the northeast region.

The results showed (Figs. 7-9) that the number of health care facilities per capita and total population were positively correlated with TB, and GDP per capita was negatively correlated with TB. The distribution of medical institutions per capita and total population decreased from the southwest to the northeast. In contrast, the correlation between the number of medical institutions per capita and TB in 2017 was more pronounced in the northeast than in the southwest; GDP per capita showed an overall increasing trend from the southwest to the northeast.

4. Discussion

TB is a chronic respiratory infectious disease with complex influencing factors, including demographic, geographic, climatic, and so on (Yin et al., 2021). Kashgar is located in the southern region of Xinjiang and is an ethnic minority region. Previous studies have shown that southern Xinjiang has been a high incidence area for TB (Zheng et al., 2022). Although some measures have alleviated the prevalence of the disease, the task of TB prevention and control in Kashgar is still heavy (Wubuli, 2017).

The annual peak prevalence of TB in Kashgar varied, with a generally higher prevalence in the spring and winter months, which is consistent with the study by Jiang H (Zuo et al., 2020).The peak prevalence in 2018 was in August-December, which may be related to meteorological conditions and the new TB screening method in 2018. This result is consistent with the characteristics of respiratory infections; that is, during the summer months, the possibility of TB transmission increases due to higher temperatures, leading to faster multiplication of mycobacteria. This phenomenon can also be explained by the holiday effect (Chen, 2019), i.e., the Spring Festival and the National Day mini-holidays reduce the incidence of TB; as the holidays end, the incidence gradually increases (Zuo et al., 2020).

We found that the number of TB cases in Kashgar region showed an increasing trend from 2016 to 2018, reaching a peak in 2018 and then a decreasing trend. This may be due to the integration of TB screening into health checkups in Kashgar since 2018, which has enhanced the detection of TB cases, while the region has reduced the financial burden of medical care for patients to a certain extent, increased awareness of medical care for residents (Tusun, 2021). Meanwhile, the area began to strengthen the capacity of pathogenic testing in 2019, which led to an increase in TB incidence that year (The State Council of the people's Republic of China, 2017). Although the outbreak of COVID-19 has affected the prevention and control work of TB to some extent in recent years, Kashgar has still completed the screening of TB patients through universal health screening, reducing the impact of the external environment on the disease (Shen, 2020).

In this paper, we performed a spatial autocorrelation analysis, and the results showed a negative distribution of TB cases from 2016 to 2021

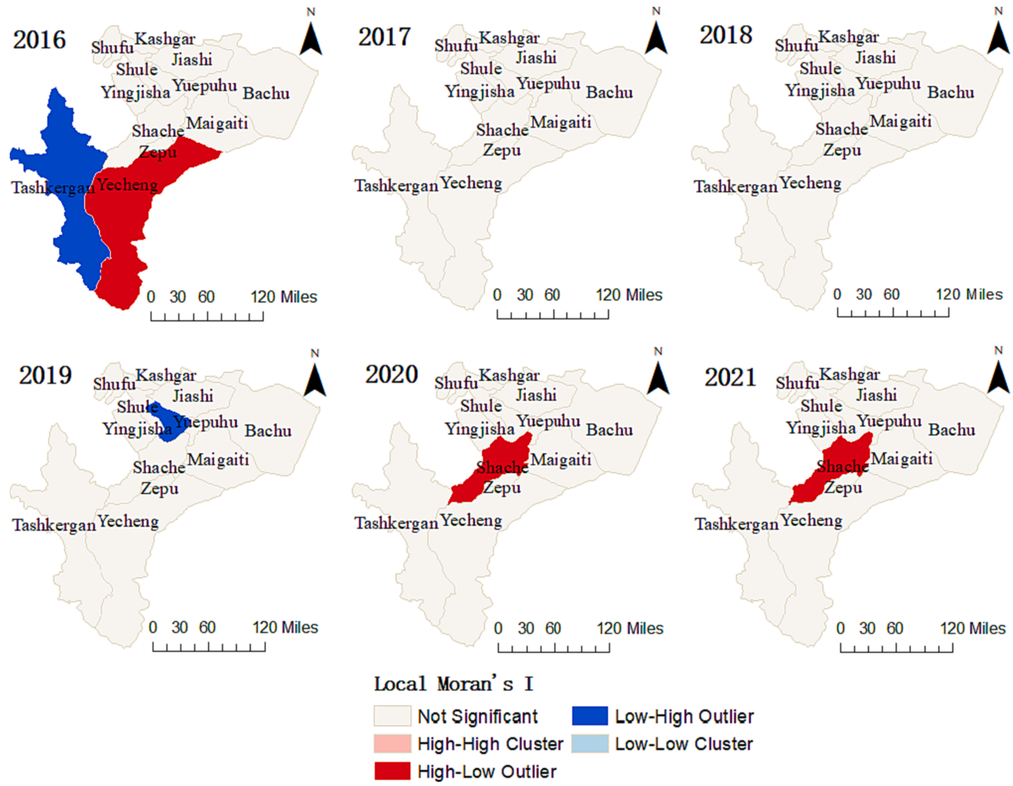

Fig. 3. Maps of local autocorrelation analysis of TB in Kashgar from 2016 to 2021. The Maps were created by ArcGIS (version 10.4.1). Different colours indicate different aggregation patterns in this area, and light grey areas indicate that aggregations are insignificant.

(Yang, 2013). In other words, high TB prevalence areas were adjacent to low prevalence areas with low aggregation and high spatial variability, which was different from previous studies. This phenomenon may be related to the different TB prevention and control measures adopted by the 12 counties. In addition, factors such as population density and level of health resource allocation may also be related to this phenomenon, and further studies are needed.

In this article, a local spatial autocorrelation model was applied for the spatial clustering of TB in the Kashgar region. Based on our analysis, we identified four aggregation areas: Yecheng county and Shache county were high-low aggregation areas, indicating that this region needs to beware of its influence on the neighbouring area with the low epidemic. This situation may be that the county is well developed and has significant clustering advantages for TB prevention, control, and treatment, hence the difference (Xie, 2021). Tashkurgan Tajik Autonomous county and Yupuhu county belong to the low–high aggregation area, indicating that these areas negatively correlate with the surrounding areas. This may be caused by the inability of the area to effectively utilize the high-quality resources of the surrounding areas (Xie, 2021), so local TB prevention and control agencies should pay attention to the impact of neighbouring areas on this aggregation area. The serious development of tuberculosis in Kashgar in 2018 indirectly affected the prevalence of tuberculosis in the surrounding areas. The geographical proximity, regional convenience, and increased population movement between counties and cities have increased the spread of TB and the prevalence of TB between counties and cities to varying degrees.

We investigated the social factors influencing the prevalence of TB in Kashgar, and first excluded factors with contributing relationships by ordinary least squares, and then developed a GWR model for 2016–2018. The results showed no covariance in GDP per capita, healthcare facilities per capita, and total population, and all were statistically significant ($P<0.05$). In particular, the number of medical institutions per capita is positively correlated with the number of TB cases in Kashgar, indicating that the level of health resource allocation has an impact on the prevalence of TB (Sun Yahong, 2022, Yi Min, 2020, Dong, 2020), that is, areas with a higher number of medical institutions are more likely to be screened for TB. In some areas of Kashgar, medical facilities are more numerous and well-equipped to provide immediate medical care if the population needs it, thus allowing for rapid treatment of the disease. In contrast, delayed disease attendance may occur in areas where the allocation of health resources is relatively poor. This situation can lead residents to prioritize areas with good levels of medical resources once they require medical care, and population movement increases the prevalence of TB in the area, which makes it easier to screen for TB in these areas than in areas with fewer health care facilities. In Kashgar, the service radius of medical institutions is large, the transportation is inconvenient, and the service quality is poor. These factors may affect patients' treatment to a certain extent (Sun Yahong, 2022).

We found that GDP per capita was indirectly and negatively associated with the number of TB cases in Kashgar, which is consistent with the findings of Wubuli A (Wubuli, 2015).The results of the GWR model showed that GDP per capita significantly influenced the prevalence of TB in northeastern Kashgar. Economic factors in TB control can be effectively utilized if regional economic development can be accelerated (Yang LJ, 2019, Li et al., 2014). In addition, demographic factors are positively correlated with TB, i.e., the more populous the region, the more severe the disease prevalence. This suggests that population accelerates the spread of TB bacteria, expands the infected population, and increases the scope of the disease.

Our study also has some limitations: (1) The occurrence of tuberculosis in Kashgar is severe. We aimed to focus on the spatial distribution of tuberculosis in Kashgar region. However, the Kashgar region contains only 12 counties or cities, resulting in a small sample size for this paper. This situation may lead to unstable results of our study (Arbona and Barro, 2020, Hong, 2020, Yin, 2022). In further studies, we will conduct further data collection and do more detailed analysis of the region, such as spatial distribution analysis of TB prevalence in township-level spatial

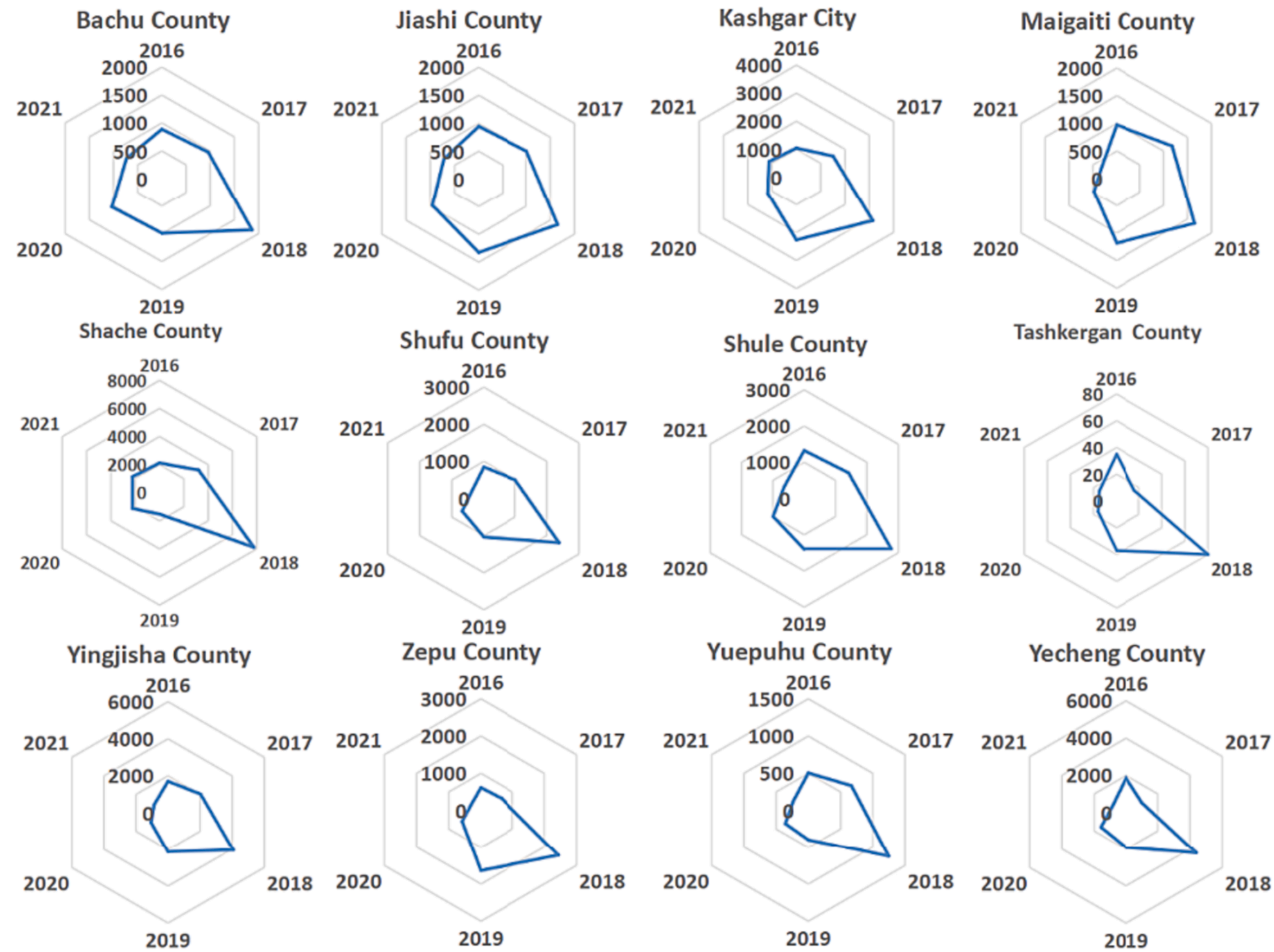

Fig. 4. Number of TB cases in 12 counties or cities in Kashgar from 2016 to 2021.

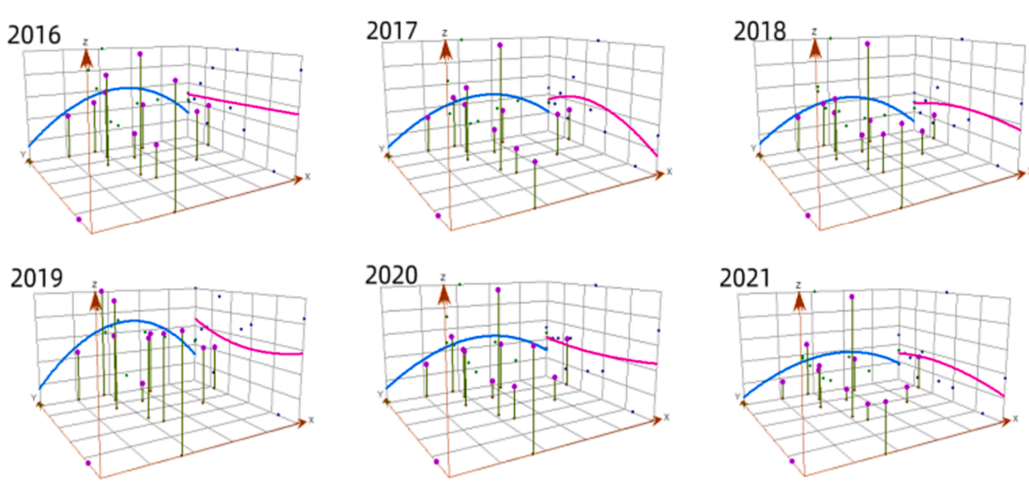

Fig. 5. Analysis of the three dimension trends of TB incidence in Kashgar from January 2016 to December 2021. The x-axis is oriented east, the y-axis is oriented the north, and The direction of the Z-axis is the direction of the increase in the number of TB cases. The blue curve on the xz plane represents the east–west direction, and the pink curve on the yz plane represents the north–south direction. The dots represent the location of the prevalence in each region in 3D space, and the length of the green line is used to describe the magnitude of the prevalence. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

units in Kashgar region, based on which we will increase the sample size of our study. (2) Due to limited data collection, we did not study more factors influencing TB disease, nor did we conduct an in-depth analysis of the spatial aggregation and evolution of the disease. We will fully consider the above factors in future studies and conduct in-depth studies on spatial autocorrelation analysis to further improve the application value of the model.

5. Conclusions

This is the first study that discusses the characteristics in detail and influencing factors of TB prevalence in Kashgar and provides some scientific references for TB prevention and control institutions in Kashgar. The study results showed that TB in the Kashgar region was highest in June and lowest in February; TB was higher in males than in females. TB in Kashgar region was negatively correlated with space. Yecheng and Shache counties were H-L agglomerations, and Tashkurgan and Yupuhu

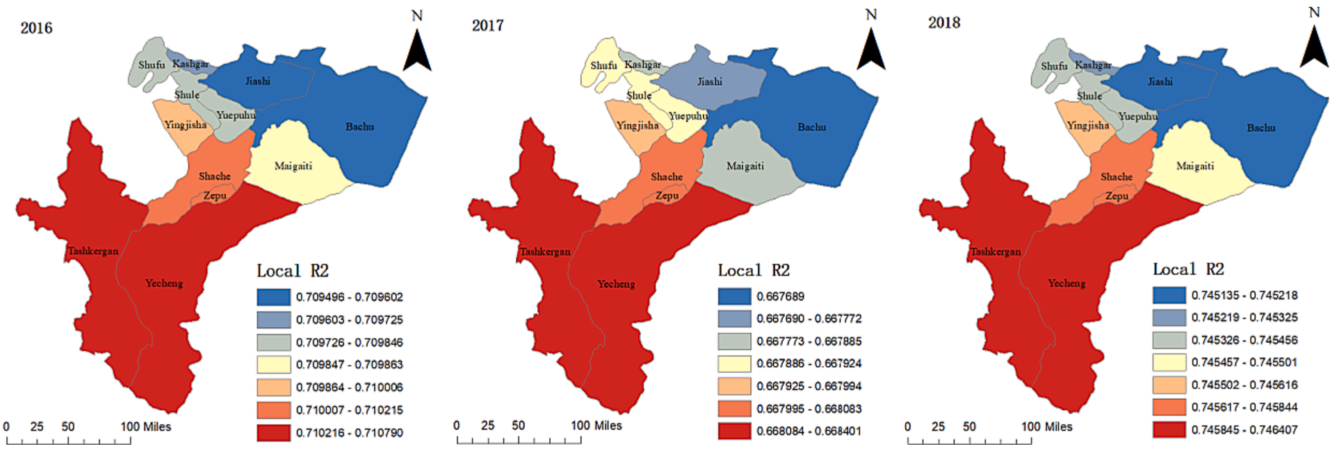

Fig. 6. Geographic distribution of R^2 values in the GWR model. Blue to red represents R^2 values from low to high. From left to right are the distribution plots for 2016,2017 and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

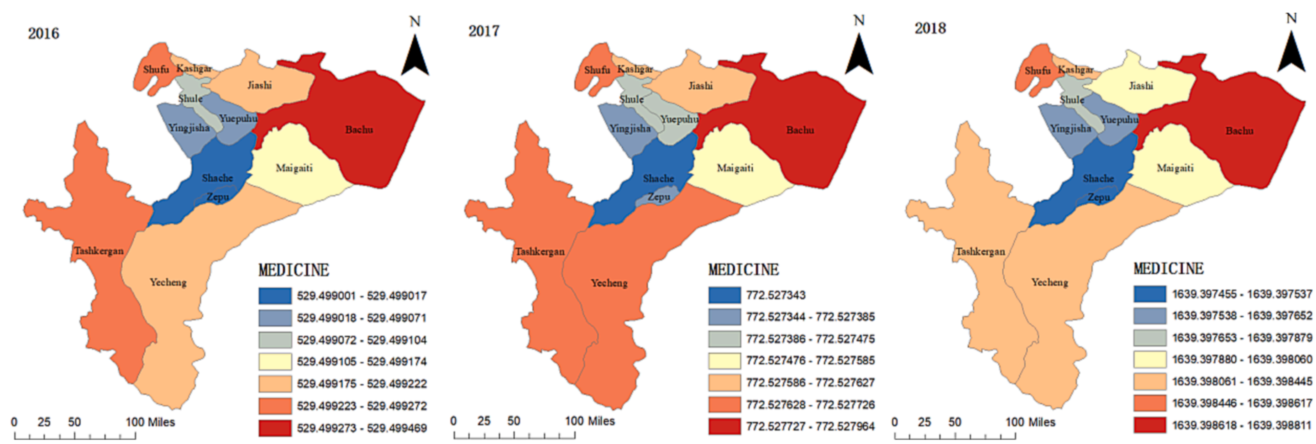

Fig. 7. Geographical distribution of the impact of the number of health care facilities per capita on TB in Kashgar, 2016–2018. The red area indicates the significant impact of the number of medical institutions per capita on TB. Conversely, the blue area indicates a small effect of the number of health care facilities per capita on TB. From left to right, the distribution is shown for 2016,2017 and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

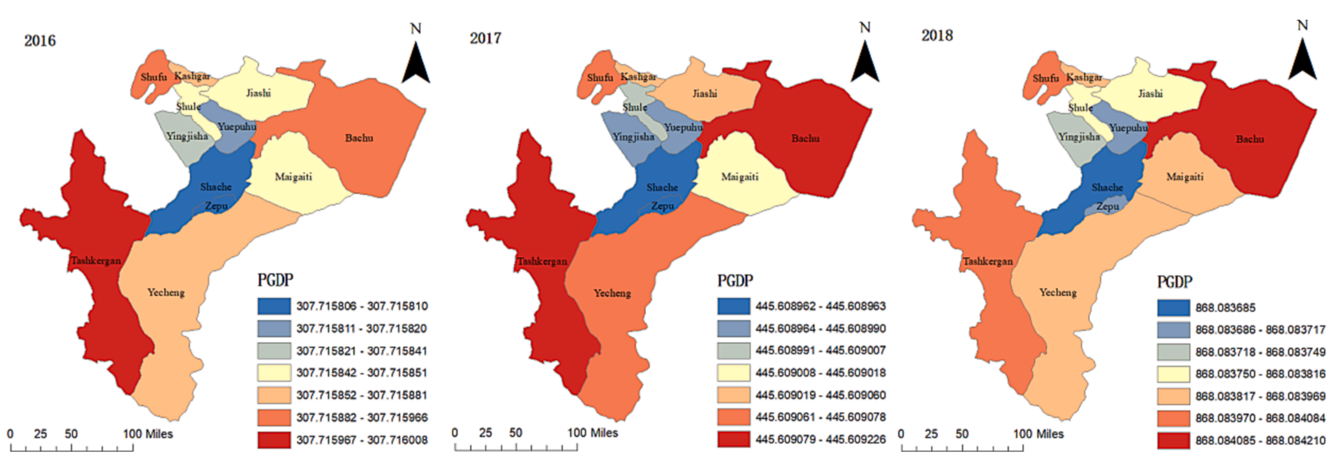

Fig. 8. Geographical distribution of the impact of GDP per capita on TB in Kashgar region, 2016–2018. The red area indicates the more pronounced impact of GDP per capita level on TB. In contrast, the blue area indicates the lesser impact of GDP per capita level on TB. From left to right, the distribution is plotted for 2016, 2017 and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

counties were L-H agglomerations; the number of medical institutions per capita and total population were positively correlated with TB prevalence, and GDP per capita was negatively correlated with TB prevalence. People should take measures to prevent TB in their daily life. Relevant departments should strengthen the publicity and education on TB and screening of crucial regions and populations, establish a sound

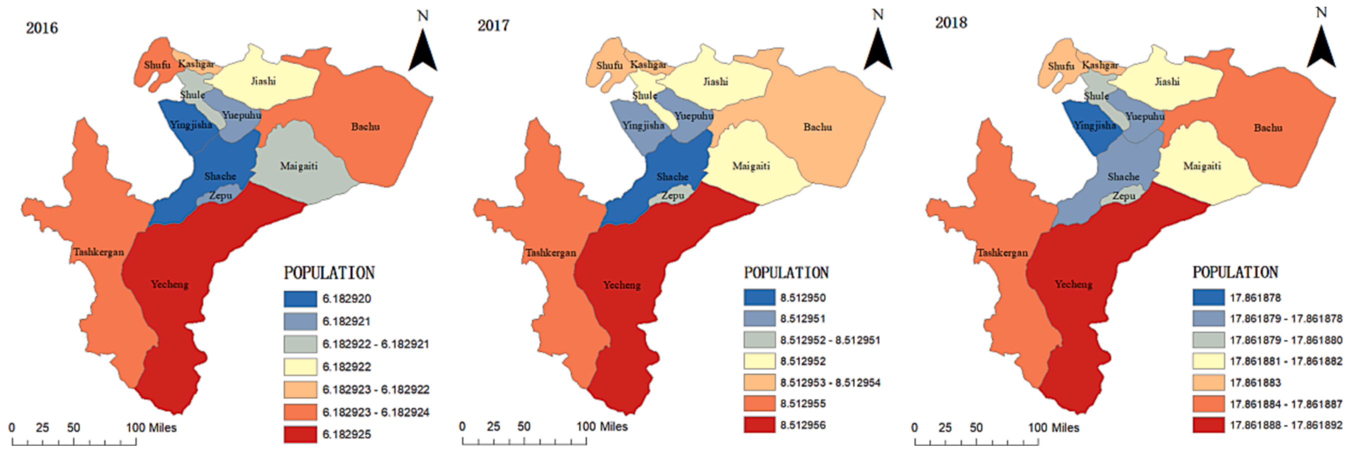

Fig. 9. Geographical distribution of the impact of total population on TB in Kashgar region, 2016–2018. The red areas indicate the impact of population size on TB, while the blue areas indicate a smaller impact on TB. From left to right, the distribution is shown for 2016,2017 and 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

social and medical security system, improve the accessibility of TB, and reduce the risk of TB by improving living standards, developing regional economies, allocating health resources rationally, and improving the quality of health services.

6. Data availability

The datasets are obtained from Center for Disease Control and Prevention of Kashgar, China, and they are available by request to the corresponding author.

7. Ethics approval

This study was approved by the Ethics Committee of Xinjiang Medical University (XJYKDXR20230605001). Patient records were anonymized and de-identified prior to analysis for this study, and all personal data were kept confidential.

Funding

This work was supported by National Natural Science Foundation of China (Grant No. 72064036,72174175,72163033,81960145,12101529); and Tianshan Excellent Youth Project of Xinjiang Uygur Autonomous Region, China (Grant No. 2020Q020).

CRediT authorship contribution statement

Xiaodie Chen: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Mawlanjan Emam:** Conceptualization, Investigation, Resources, Data curation, Visualization. **Li Zhang:** Conceptualization, Investigation, Resources, Data curation, Visualization. **Ramziya Rifhat:** Investigation, Visualization. **Liping Zhang:** Investigation, Visualization. **Yanling Zheng:** Investigation, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Arbona, S.I., Barro, A.S., 2020 Aug. Exploring the spatial determinants of late HIV diagnosis in Texas. Prev. Chronic Dis. 27 (17), E96.
Assefa, D.G., Zeleke, E.D., Bekele, D., Ejigu, D.A., Molla, W., Woldesenbet, T.T., Aynalem, A., Abebe, M., Mebratu, A., Manyazewal, T., 2022 Dec 29. Isoniazid preventive therapy for prevention of tuberculosis among people living with HIV in Ethiopia: a systematic review of implementation and impacts. Int. J. Environ. Res. Public Health 20 (1), 621.
Bie, S., Hu, X., Zhang, H., et al., 2021. Influential factors and spatial-temporal distribution of TB in mainland China. Sci. Rep. 11 (1), 6274.
Brunsdon, C., Stewart Fotheringham, A., Charlton, M., 1996. Geographically Weighted Regression: A Method For Exploring Spatial Nonstationarity. Geogr. Anal. 28, 281–289.
China Center for Disease Control and prevention, technical guidelines for TB control in China (2021 Edition). people's Health Publishing House. 2022.
Chen, J., Qiu, Y., Yang, R., et al., 2019. The characteristics of spatial-temporal distribution and cluster of TB in Yunnan Province, China, 2005–2018. BMC Public Health 19 (1), 1715.
Dangisso, M.H., Datiko, D.G., Lindtjørn, B., 2020. Identifying geographical heterogeneity of TB in southern Ethiopia: a method to identify clustering for targeted interventions. Glob. Health Action 13 (1), 1785737.
Dong, E., Liu, S., Chen, M., Wang, H., Chen, L.-W., Xu, T., Wang, T., Zhang, L., 2020. Differences in regional distribution and inequality in health-resource allocation at hospital and primary health centre levels: a longitudinal study in Shanghai, China. BMJ Open 10 (7), e035635.
Fotheringham, A.S., Charlton, M., Brunsdon, C., 1997. Two techniques for exploring non-stationarity in geographical data. Geographical Systems. 4, 59–82.
He, X., Cao, M., Mahapatra, T., et al., 2017. Burden of TB in Xinjiang between 2011 and 2015: a surveillance data-based study. PLoS One 12 (11), e0187592.
Hong, L., Huang, Y., Peng, S., Hewitt, J., 2020 Feb 5. Monitoring the trends of water-erosion desertification on the Yunnan-Guizhou Plateau, China from 1989 to 2016 using time-series Landsat images. PLoS One 15 (2), e0227498.
Jiang, H., Liu, M., Zhang, Y., et al., 2021. Changes in incidence and epidemiological characteristics of TB in Mainland China, 2005–2016. JAMA Netw. Open 4 (4), e215302.
Li, X.X., Wang, L.X., Zhang, H., et al., 2014. Spatial variations of TB prevalence co-impacted by socio-economic and geographic factors in People's Republic of China, 2010. BMC Public Health 14, 257.
Mulholland, C.V., Shockey, A.C., Aung, H.L., et al., 2019. Dispersal of mycobacterium tuberculosis driven by historical european trade in the South Pacifc. Front. Microbiol. 10, 2778.
Natarajan, A., Beena, P.M., Devnikar, A.V., Mali, S., 2020. A systemic review on tuberculosis. Indian J. Tuberc. 67 (3), 295–311.
Notice of the general office of the State Council on printing and distributing the national TB prevention and control plan during the 13th five year plan. Bulletin of the State Council of the people's Republic of China. 2017;1582(07):32-37.
Ofori-Anyinam, B., Riley, A.J., Jobarteh, T., et al., 2020. Comparative genomics shows diferences in the electron transport and carbon metabolic pathways of Mycobacterium africanum relative to Mycobacterium tuberculosis and suggests an adaptation to low oxygen tension. Tuberculosis (Edinb.) 120, 101899.
Parwati, N.M., Bakta, I.M., Januraga, P.P., Wirawan, I.M.A., 2021 Dec 15. A health belief model-based motivational interviewing for medication adherence and treatment success in pulmonary tuberculosis patients. Int. J. Environ. Res. Public Health 18 (24), 13238.
Sapriel, G., Brosch, R., Bapteste, E., 2019. Shared pathogenomic patterns characterize a new phylotype, revealing transition toward host-adaptation long before speciation of mycobacterium tuberculosis. Genome Biol. Evol. 11 (8), 2420–2438.

Shen, X., Sha, W., Liu, J.J., 2020. Impact of coronavirus disease 2019 (COVID-19) on TB control and countermeasures in China. Chin J Antituberc. 42 (6), 544–548.

Tusun, D., Abulimiti, M., Mamuti, X., et al., 2021. The epidemiological characteristics of TB - Kashgar prefecture, Xinjiang Uygur autonomous region, China, 2011–2020. China CDC Wkly. 3 (26), 557–561.

Wang, S., 2021. Analysis of TB registration and treatment outcome in Zepu County. Disease Prevention and Control Bulletin.

Wang, Q.i., Feng, H., Feng, H., Yu, Y., Li, J., Ning, E., 2021. The impacts of road traffic on urban air quality in Jinan based GWR and remote sensing. Sci. Rep. 11 (1).

Wang, W., Jin, Y.Y., Ci, Y., et al., 2016. Local spatial variations analysis of smear-positive TB in Xinjiang using geographically weighted regression model. BMC Public Health 16 (1), 1058.

Wang, Y.S., Wang, J.M., Wang, W.B., 2020. Temporal-spatial distribution of TB in China, 2004–2016. Zhonghua Liu Xing Bing Xue Za Zhi 41 (4), 526–531.

World Health Organization. Global TB report 2021, https://www. who. int/teams/global-TB-programme /tb-reports (Accessed on 14 Oct 2021).

Wu, X., Zhang, J., 2021. Exploration of spatial-temporal varying impacts on COVID-19 cumulative case in Texas using geographically weighted regression (GWR). Environ. Sci. Pollut. Res. Int. 28 (32), 43732–43746.

Wubuli, A., Xue, F., Jiang, D., et al., 2015. Socio-demographic predictors and distribution of TB (TB) in Xinjiang, China: a spatial analysis. PLoS One 10 (12), e0144010.

Wubuli, A., Li, Y., Xue, F., et al., 2017. Seasonality of active TB notification from 2005 to 2014 in Xinjiang, China. PLoS One 12 (7), e0180226.

Xie, X., Zhang, L., Sun, H., Chen, F., Zhou, C., 2021. Spatiotemporal Difference Characteristics and Influencing Factors of Tourism Urbanization in China's Major Tourist Cities. Int. J. Environ. Res. Public Health 18 (19), 10414.

Xinjiang Uygur Autonomous Region Bureau of Statistics. Xinjiang Statistical Yearbook-2017. China Statistics Press. 2017.

Xinjiang Uygur Autonomous Region Bureau of Statistics. Xinjiang Statistical Yearbook-2018. China Statistics Publishing House. 2018.

Xinjiang Uygur Autonomous Region Bureau of Statistics. Xinjiang Statistical Yearbook-2019]. China Statistical Publishing House. 2019.

Xu, A.-M., He, C.-J., Cheng, X., Abuduaini, AniKiz, Tuerxun, Z., Sha, Y.-Z., Kaisaier, A., Peng, H.-M., Zhen, Y.-H., Zhang, S.-J., Xu, J.-R., Li, L.i., Zou, X.-G., 2022. Distribution and identification of Mycobacterium tuberculosis lineage in Kashgar prefecture. BMC Infect. Dis. 22 (1).

Yahong, S., Maozai, T., Yanwu, N., et al., 2022. Spatial panel data analysis of spatial and temporal distribution characteristics and influencing factors of TB in China from 2015 to 2019. Chinese Journal of preventive medicine. 23 (06), 436–441.

Yang, J.M., Simahule, J.E.S., Tai, X.R., et al., 2013. Analysis of TB epidemiological survey conducted in 2010–20ll in Xinjiang Uygur autonomous region. Chinese Journal of AntiTB. 35, 960–964.

Yi, M., Peng, J., Zhang, L., et al., 2020. Is the allocation of medical and health resources effective? Characteristic facts from regional heterogeneity in China. Int. J. Equity Health 19 (1), 89.

Yin, J.F., Huang, R.W., Jiang, H., et al., 2021. Spatio-temporal distribution of TB and influencing factors in Beijing, 2008–2018. Zhonghua Liu Xing Bing Xue Za Zhi 42 (7), 1240–1245.

Yin, S., Liu, J., Han, Z., Yang, J., 2022 Feb 9. Relationship between urban morphology and land surface temperature-a case study of Nanjing City. PLoS One 17 (2), e0260205.

Zhang, Y., Liu, M., Wu, S.S., et al., 2019. Spatial distribution of TB and its association with meteorological factors in mainland China. BMC Infect. Dis. 19 (1), 379.

Zhang, H., Wang, W., Jingjing, S.u., et al., 2022. Temporal and spatial distribution characteristics of TB incidence in Nanjing and its relationship with gender and age. Infectious Diseases Information. 35 (02), 144–150.

Zheng, Y., Zhang, X., Wang, X., Wang, K., Cui, Y., 2021. Predictive study of tuberculosis incidence by time series method and Elman neural network in Kashgar, China. BMJ Open 11 (1), e041040.

Zheng, Y., Emam, M., Lu, D., et al., 2022;Sep. Analysis of the effect of temperature on tuberculosis incidence by distributed lag non-linear model in Kashgar city, China. Environ. Sci. Pollut. Res. Int. 12, 1–12.

Zuo, Z., Wang, M., Cui, H., et al., 2020. Spatiotemporal characteristics and the epidemiology of TB in China from 2004 to 2017 by the nationwide surveillance system. BMC Public Health 20 (1), 1284.