Postprint: Analysis of Determinants of Tuberculosis Incidence in China Based on Spatiotemporal Geographically Weighted Regression Model

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Abstract

Background: Existing studies on influencing factors of pulmonary tuberculosis incidence mostly involve independent temporal or spatial regression analyses, and the research findings have limitations. Objective: To explore the temporal and spatial heterogeneity of pulmonary tuberculosis distribution in China, and analyze the temporal and spatial correlations between pulmonary tuberculosis incidence and meteorological and air quality factors, thereby providing scientific reference for formulating corresponding tuberculosis prevention and control measures. Methods: Using monthly pulmonary tuberculosis statistics by region across China from 2016-2018, with pulmonary tuberculosis incidence as the dependent variable and meteorological and air quality factors as independent variables, OLS, GWR, and GTWR models were constructed respectively after conducting multicollinearity and spatial autocorrelation tests. Model performance was evaluated and compared to select the optimal model for describing pulmonary tuberculosis incidence. Kernel density distribution maps and spatiotemporal distribution maps of fitted coefficients for each variable were plotted respectively to describe the spatiotemporal specificity of the fitted coefficients. Results: The overall pulmonary tuberculosis incidence in China is decreasing year by year, with a relatively concentrated spatial distribution. The R^2 values of the GTWR model are higher than those of OLS and GWR models, while its AICc values are lower, indicating that the GTWR model better explains the influence of independent variables on pulmonary tuberculosis incidence. Results from kernel density maps show that increased wind speed has a significant protective effect against pulmonary tuberculosis incidence in most cities; increased humidity and air pollutant concentrations significantly increase pulmonary tuberculosis incidence, with varying degrees of impact across different cities. Conclusion: Meteorological and air quality factors have significant impacts on pulmonary tuberculosis incidence, and this impact exhibits spatiotemporal specificity. Targeted disease prevention measures should be formulated for different influencing factors in different regions.

Full Text

Preamble

Analysis of Influencing Factors of Pulmonary Tuberculosis Incidence in China Based on a Geographically and Temporally Weighted Regression Model

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Abstract

Background: Most existing studies on tuberculosis influencing factors have employed independent temporal or spatial regression analyses, yielding limited results. **Objective:** To explore the temporal and spatial heterogeneity of pulmonary tuberculosis distribution in China and analyze the spatiotemporal correlations between tuberculosis incidence and meteorological and air quality factors, thereby providing scientific reference for formulating targeted tuberculosis prevention and control measures. **Methods:** Using monthly pulmonary tuberculosis statistics from 2016-2018 across Chinese regions, with tuberculosis incidence as the dependent variable and meteorological and air quality factors as independent variables, we conducted multicollinearity and spatial autocorrelation tests before constructing OLS, GWR, and GTWR models. Model goodness-of-fit was evaluated and compared to select the optimal model for describing tuberculosis incidence patterns. Kernel density distribution maps and spatiotemporal distribution maps of variable coefficients were generated to characterize their spatiotemporal specificity. **Results:** China's total tuberculosis incidence decreased annually with concentrated spatial distribution. The GTWR model achieved higher R^2 values and lower AICc values than both OLS and GWR models, indicating superior explanatory power for the influence of independent variables on tuberculosis incidence. Kernel density results showed that increased wind speed had a significant protective effect in most cities, while increased humidity and air pollutant concentrations significantly increased tuberculosis incidence with varying degrees of impact across cities. **Conclusion:** Meteorological and air quality factors significantly influence tuberculosis incidence with spatiotemporal specificity. Targeted disease prevention measures should be formulated based on different influencing factors in different regions.

Keywords: tuberculosis; GTWR; meteorological factors; air pollutants

Introduction

Pulmonary tuberculosis is a chronic respiratory infectious disease caused by *Mycobacterium tuberculosis* with strong transmissibility, representing one of the major infectious diseases threatening human health. Patients in the sputum-positive phase are infectious, with one untreated active case capable of infecting 15-20 contacts annually. According to the 2019 Global Tuberculosis Report, approximately 10 million people worldwide develop tuberculosis each year, with latent tuberculosis infection affecting about one-quarter of the global population. China reported 833,000 new cases with an incidence rate of 58 per 100,000, ranking third globally and representing a high-burden country where tuberculosis prevention and control remains critical.

With the development of geographic information technology, numerous spatial statistical methods based on spatial econometrics have been proposed, leading to widespread application of GIS and spatial statistics across various fields. The Geographically Weighted Regression (GWR) model, proposed by British scholar Fotheringham, can intuitively detect spatial non-stationarity in relationships and has been widely applied across multiple disciplines. However, GWR only incorporates spatial characteristics while ignoring temporal effects, limiting its applicability to data with prominent spatiotemporal features. Consequently, Professor Bo Huang of the University of Hong Kong proposed the Geographically and Temporally Weighted Regression (GTWR) model, which better evaluates spatiotemporal distributions and characteristics, effectively addressing spatiotemporal non-stationarity in regression models. This approach has gained extensive attention and continuous refinement through applications by numerous scholars.

Recent studies have extensively examined the spatiotemporal distribution of tuberculosis, demonstrating strong temporal and spatial characteristics. However, most existing research conducts independent temporal or spatial regression analyses, yielding limited findings. For instance, time series analysis using ARIMA models ignores spatial factors, while spatial clustering and GWR analyses cannot capture temporal characteristics. Therefore, simultaneously analyzing temporal and spatial factors using GTWR for tuberculosis incidence is essential. This study employs GTWR to explore the spatiotemporal heterogeneity of tuberculosis distribution in China and analyze correlations with meteorological and air quality factors, providing scientific reference for targeted prevention and control measures.

Methods

Data Sources

Tuberculosis incidence data were obtained from the Public Health Science Data Center (https://www.phsciencedata.cn/Share/), including monthly statistics from 2016-2018 across 31 Chinese provinces (excluding Hong Kong, Macau, and Taiwan). The selected indicator was incidence rate (cases per 100,000 population). Meteorological data (including monthly average temperature, humidity, wind speed) were sourced from Weather Post (http://www.tianqihoubao.com/). Air quality index data (including monthly average concentrations of PM2.5, PM10, SO2, NO2, CO, O3) were obtained from the Air Quality Index Historical Data website (https://www.aqistudy.cn/historydata/). All data were derived from public databases, thus not requiring ethical review.

Multicollinearity Assessment

Multicollinearity refers to precise or high correlations among explanatory variables in linear regression models, causing estimation distortion or inaccuracy. To ensure model validity, we analyzed collinearity among candidate variables using Variance Inflation Factor (VIF), a common metric for detecting multicollinearity. VIF was calculated to examine relationships between tuberculosis incidence and influencing factors, avoiding compromised regression results from high collinearity. The formula is:

$$VIF = \frac{1}{1 - R^2}$$

where R^2 is the coefficient of determination reflecting the percentage of dependent variable variation explained by the regression equation. Larger VIF values indicate greater collinearity likelihood. VIF values between 0-10 suggest no severe multicollinearity, permitting regression analysis.

Spatial Autocorrelation Analysis

Spatial econometric methods require spatial heterogeneity among sample data. Therefore, spatial autocorrelation analysis of variables was necessary before constructing GWR and GTWR models. Global Moran’ s I is commonly used for global spatial autocorrelation analysis to determine whether attribute values are spatially associated. We calculated global Moran' s I to assess spatial autocorrelation of tuberculosis incidence:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

where S_0 is the sum of all spatial weights and z_i represents the deviation of attribute value at sample point i from its mean. Moran' s I ranges from -1 to 1, with positive values indicating spatial clustering (closer to 1 means stronger clustering), negative values indicating dispersed distribution, and zero indicating random distribution without significant patterns.

Regression Model Construction

We constructed Ordinary Least Squares (OLS), GWR, and GTWR models to analyze tuberculosis incidence empirically, comparing model fit to determine whether GTWR optimally handles tuberculosis data.

The OLS model is a traditional linear regression approach that provides average or global parameter estimates but cannot capture spatial non-stationarity:

$$Y_i = \beta_0 + \sum_{k=1}^{m} \beta_k X_{ik} + \varepsilon_i$$

where Y_i is the dependent variable at point i, β_0 is the intercept, β_k is the regression coefficient for the kth independent variable, X_{ik} is the kth independent variable at point i, and ε_i is the random error.

The GWR model improves upon OLS by incorporating a spatial weight matrix to better reveal spatial structural differentiation:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i$$

where (u_i, v_i) represents the longitude and latitude coordinates of point i, $\beta_0(u_i, v_i)$ is the local intercept, and $\beta_k(u_i, v_i)$ is the local regression coefficient for the kth variable.

The GTWR model extends GWR by assigning temporal values to local sample point datasets, solving for local parameters at point i and utilizing temporal characteristics to improve estimation accuracy:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i$$

where t_i is the temporal coordinate, and (u_i, v_i, t_i) represents the spatiotemporal coordinates.

Parameter estimation for GWR and GTWR follows:

$$\hat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i) X]^{-1} X^T W(u_i, v_i, t_i) Y$$

where the spatial weight matrix W is determined by spatial bandwidth, kernel function, and distance calculation. Based on previous literature, we constructed models using minimum cross-validation (CV) values, Gaussian kernel function, and Euclidean distance. Model fit was assessed by comparing adjusted Akaike Information Criterion (AICc) and R^2 values, where higher R^2 and lower AICc indicate stronger explanatory power.

Statistical Analysis

We described GTWR model coefficients using mean, minimum, maximum, and interquartile range. Kernel density maps and spatiotemporal distribution maps were generated for each variable based on GTWR coefficients. Natural breaks classification grouped similar data while forcing "0" as a breakpoint to distinguish positive and negative coefficients. Positive coefficients indicate promoting effects, negative coefficients indicate inhibiting effects, and larger absolute values indicate stronger effects. Statistical description used R 4.1.3, while ArcGIS 10.7 performed parameter estimation and model construction.

Results

Spatiotemporal Distribution of Tuberculosis Incidence

Figure 1 [Figure 1: see original paper] displays the spatial distribution of national tuberculosis incidence from 2016-2018. Results show that China' s total tuberculosis incidence decreased annually with concentrated spatial distribution. High-incidence cities were mainly concentrated in Xinjiang, Sichuan, Tibet, Qinghai, Guizhou, and Guangxi. Xinjiang maintained the highest incidence for three consecutive years; Sichuan had high incidence in 2016 but substantial decreases in subsequent years; Tibet and Qinghai had low incidence in 2016 but substantial increases in later years. Low-incidence cities were primarily in Ningxia, Tianjin, Shanghai, Beijing, and Hainan.

Model Comparison Results

After multicollinearity and spatial autocorrelation testing (global Moran' s I = 0.376), temperature variables with strong collinearity (VIF_{Tmax} = 48.01, VIF_{Tmin} = 48.34) were excluded. OLS, GWR, and GTWR models were constructed and compared (Table 1). GTWR achieved higher R^2 and adjusted

R^2 values and lower AICc values than OLS and GWR, indicating superior explanatory power for variables influencing tuberculosis incidence and better handling of spatiotemporal data.

Spatiotemporal Characteristics of Coefficients

GTWR coefficients were described using mean, minimum, maximum, and interquartile range (Table 2). Kernel density maps (Figure 2 [Figure 2: see original paper]) revealed: wind speed showed multimodal distribution with a main peak around -0.5; humidity showed multimodal distribution with a main peak around 0.01 and all peaks positive; PM2.5 showed left-skewed distribution with a main peak around -0.01; PM10 showed unimodal distribution with a main peak around 0.005; SO2 showed multimodal distribution with a main peak around 0; NO2 showed multimodal distribution with a main peak around -0.03; CO showed right-skewed distribution with a main peak around -0.5; O3 showed multimodal distribution with a main peak around 0.02.

Spatiotemporal distribution maps (Figure 3 [Figure 3: see original paper]) showed: wind speed had lower coefficients in central and southeastern regions but higher coefficients in northeastern and western regions, significantly inhibiting incidence in Qinghai, Gansu, Hunan, and Jiangxi while promoting it in Tibet, Xinjiang, and Heilongjiang; humidity had lower coefficients in western and northern regions but higher coefficients in southeastern and southern regions, significantly promoting incidence in Hainan, Guangdong, and Guangxi; PM2.5 had lower coefficients in northeastern and central-eastern regions but higher coefficients in southwestern and western regions, significantly promoting incidence in Guangxi, Yunnan, Xinjiang, and Tibet; PM10 had lower coefficients in central and western regions but higher coefficients in southeastern and central-eastern regions, significantly promoting incidence in Zhejiang, Shanghai, and Fujian; SO2 had lower coefficients in central and northern regions but higher coefficients in western and southern regions, significantly promoting incidence in Tibet, Guangdong, and Xinjiang; NO2 had lower coefficients in northwestern and southwestern regions but higher coefficients in northeastern and central regions, significantly promoting incidence in Heilongjiang and Jilin; CO had lower coefficients in western and southwestern regions but higher coefficients in southeastern and central-western regions, significantly promoting incidence in Fujian, Qinghai, and Gansu; O3 had lower coefficients in northwestern and southern regions but higher coefficients in northeastern and southwestern regions, significantly promoting incidence in Xinjiang, Zhejiang, and Fujian.

Discussion

Prior to model construction, multicollinearity testing revealed strong collinearity in temperature variables. Previous studies also indicate cross-synergistic effects between temperature and other respiratory disease risk factors. Research by Ma et al. showed that combined high temperature and humidity severely impact children’ s respiratory health, while low temperature and humidity increase elderly respiratory disease risk. A time-series analysis of hospital outpatient data demonstrated significant interactions between temperature and pollutant concentrations, particularly under low temperature and high pollution conditions. Since multicollinearity may affect GTWR precision, temperature variables were excluded from our model.

Analysis of Kernel Density Distribution

Kernel density results show wind speed’ s main peak was negative with both positive and negative peaks, indicating protective effects in most cities but promoting effects in some. Humidity and SO2 showed positive main peaks with all peaks positive, indicating significant promoting effects on tuberculosis incidence. PM2.5, NO2, CO, and O3 showed multimodal distributions with both positive and negative peaks, indicating promoting effects in most cities. PM10 showed a unimodal distribution with a positive main peak, indicating significant promoting effects in most cities.

Analysis of Spatiotemporal Distribution

GTWR’ s significant advantage lies in its ability to reflect spatiotemporal variation in variable effects. Our spatiotemporal distribution maps reveal:

Wind speed significantly inhibited incidence in Qinghai, Gansu, Hunan, and Jiangxi while promoting it in Tibet, Sichuan, and Heilongjiang. Previous studies suggest wind speed promotes tuberculosis by reducing temperature and indirectly increasing risk. The bidirectional effects may be explained by: Tibet, Sichuan (high altitude) and northeastern China (naturally low temperatures) are more susceptible to temperature drops from wind, increasing risk and requiring 保暖 measures during windy weather. Conversely, Hunan and Jiangxi have higher average temperatures less affected by wind, and stronger winds reduce air pollutant concentrations, thereby decreasing risk.

Humidity significantly promoted incidence in Hainan, Guangdong, and Guangxi, consistent with previous findings that higher humidity increases tuberculosis risk. Higher humidity may increase airborne survival time of tuberculosis bacteria, raising infection risk. These regions should prioritize dehumidification and frequent drying of household items.

PM10 significantly promoted incidence in Zhejiang, Shanghai, and Fujian, aligning with research showing increased PM10 exposure raises tuberculosis risk. Inhalable particles can deposit in lungs, damaging alveoli and mucosa, causing chronic fibrosis, and reducing pulmonary resistance. Additionally, air pollutants can combine with airborne microorganisms, substantially increasing tuberculosis infection probability. These regions should avoid outdoor activities during high pollution periods.

Previous studies demonstrate that increased concentrations of air pollutants (PM2.5, SO2, NO2, CO, O3) significantly increase tuberculosis risk, which our results largely validate. However, some negative coefficients for these pollutants appear contradictory. These negative coefficients primarily occurred in coastal regions (Jiangsu, Shanghai, Guangdong) and high-altitude areas (Tibet, Xinjiang, Qinghai) with good air quality and low pollutant concentrations. In model construction, when analyzed alongside regions with poor air quality and other protective factors, these low-concentration pollutants may assume partial explanatory functions, resulting in negative coefficients. For most cities where pollutants promote incidence, active measures should improve air quality and reduce exposure during high-concentration periods.

This study has limitations. First, to avoid COVID-19 impacts (particularly indirect reductions in other respiratory diseases from pandemic control measures), we used 2016-2018 data, which may deviate from current pandemic-era realities. Second, strong data collinearity may have introduced bias, warranting validation with additional datasets. Third, while meteorological and air quality factors exhibit 3-5 day lag effects on tuberculosis incidence, data limitations prevented verification. Fourth, lifestyle, education, and economic factors were not included due to data unavailability. Future research will incorporate more comprehensive datasets to enhance model applicability and robustness.

Conclusion

The GTWR model constructed using 2016-2018 national data effectively demonstrated the spatiotemporal distribution of tuberculosis incidence in China and detailed significant correlations with meteorological and air quality factors and their spatiotemporal specificity. In practice, targeted prevention measures should be formulated based on regional influencing factors: high-altitude cities should emphasize 保暖 during windy weather; high-humidity cities should prioritize dehumidification; and cities with poor air quality should actively improve air quality and avoid outdoor activities during high pollution periods.

Author Contributions

ZHAO Mingyang: Conceptualization, data curation, formal analysis, original draft writing
ZHOU Qianyu: Methodology, supervision, review and editing
WANG Rongrong: Data curation
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Conflict of Interest

The authors declare no conflicts of interest.

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