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Spatiotemporal heterogeneity of $PM_{2.5}$ and its relationship with urbanization in North China from 2000 to 2017

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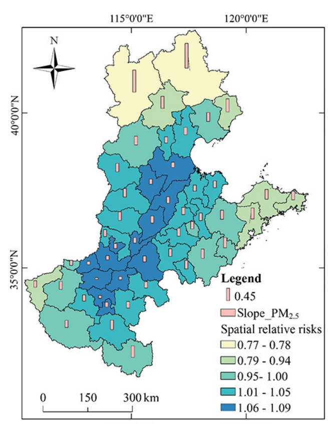
HIGHLIGHTS

- The spatiotemporal heterogeneity of $PM_{2.5}$ pollution
- The correlation between the spatial relative risks of the $PM_{2.5}$ concentrations and their temporal variation trends
- The association between urbanization or other socioeconomic factors and the $PM_{2.5}$ concentrations

GRAPHICAL ABSTRACT



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ABSTRACT

Fine particulate matter ($PM_{2.5}$) pollution is becoming an increasing global concern due to rapid urbanization and socioeconomic development, especially in North China. Although North China experiences poor air quality and high $PM_{2.5}$ concentrations, their spatial heterogeneity and relationship with the relative spatial risks of air pollution have not been explored. Therefore, in this study, the temporal variation trends (slope values) of the $PM_{2.5}$ concentrations in North China from 2000 to 2017 were first quantified using the unitary linear regression model, and the Bayesian space-time hierarchy model was introduced to characterize their spatiotemporal heterogeneity. The spatial lag model was then used to examine the determinant power of urbanization and other socioeconomic factors. Additionally, the correlation between the spatial relative risks (probability of a region becoming more/less polluted relative to the average $PM_{2.5}$ concentrations of the study area), and the temporal variation trends of the $PM_{2.5}$ concentrations were quantified using the bivariate local indicators of spatial association model. The results showed that the $PM_{2.5}$ concentrations increased during 2000–2017, and peaked in 2007 and 2013. Spatially, the cities at high risk of $PM_{2.5}$ pollution were mainly clustered in southeastern Hebei, northern Henan, and western Shandong where the slope values were low, as demonstrated by the value of Moran's *I* (−0.56). Moreover, urbanization and road density were both positively correlated with $PM_{2.5}$ pollution, while

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the proportion of tertiary industry was negatively correlated. Furthermore, a notable increasing trend was observed in some cities, such as Tianjin, Zaozhuang, Qingdao, and Xinyang. These findings can contribute to the development of effective policies from the perspective of rapid urbanization to relieve and reduce $PM_{2.5}$ pollution.

1. Introduction

In recent decades, rapid globalization and urbanization have greatly impacted environmental and socioeconomic conditions worldwide, and are closely related to air quality and human health (Wang et al., 2018a; Wang et al., 2018b; Hoek et al., 2013). $PM_{2.5}$ is classified as airborne particulate matter smaller than 2.5 μm (Prada et al., 2017), and high $PM_{2.5}$ concentrations can decrease atmospheric visibility, influence the radiation balance and negatively impact the climate (Wang and Fang, 2016), and incerease morbidity, hospitalization, and mortality due to respiratory diseases (Franchini et al., 2016), cardiovascular diseases (Peng et al., 2008), and cancer (Di Lorenzo et al., 2015).

Air pollution is aggravated by rapid urbanization and the growth of urban agglomerations, which are occurring in many countries worldwide. The level and speed of urbanization significantly differ between different countries, regions, and cities, resulting in spatiotemporal heterogeneity in the $PM_{2.5}$ concentrations. Different regions across China are under different stages of urbanization, and most cities are experiencing varying degrees of haze pollution (Wang and Fang, 2016). Furthermore, China faces the highest number of mortalities associated with air pollution worldwide (Li et al., 2018; World Health Organization, 2016). Accordingly, the association between urbanization and $PM_{2.5}$ pollution in China must be understood to aid in the development of policies to decrease air pollution and achieve sustainable development.

Most previous studies on $PM_{2.5}$ were conducted under the natural sciences field (Onat and Stakeeva, 2013; Pateraki et al., 2012). However, numerous studies have demonstrated that, in addition to natural conditions, anthropogenic social and economic activities also influence the generation and spread of $PM_{2.5}$ pollution. For example, economic development, industrial structures, soot emissions, population density, traffic intensity, foreign direct investment, and coal consumption are major emission sources of $PM_{2.5}$ (Cheng et al., 2017; Lin et al., 2014; Liu et al., 2019; Luo et al., 2018; Wu et al., 2018; Xie et al., 2020). Cities are the spatial containers of these emissions, and the urbanization process involves various socioeconomic factors that directly generate $PM_{2.5}$ pollution, thereby further affecting the $PM_{2.5}$ concentrations in the atmosphere (Zhu et al., 2019; Zhang et al., 2019). For examples, Yang et al. (2018) found that road density had a high determinant power on the $PM_{2.5}$ concentrations, and Wang et al. (2019) demonstrated that population density enhances $PM_{2.5}$ pollution. Similarly, Zhu et al. (2019) demonstrated that the $PM_{2.5}$ concentrations in urban areas were higher than those in surrounding areas, indicating that urbanization plays an important role in the $PM_{2.5}$ concentrations. Furthermore, the Ministry of Environmental Protection of China reported that, in 2015, the air qualities of Baoding, Tangshan, Hengshui, Xingtai, Handan, Langfang, Shijiazhuang, Zhengzhou, Jinan, and Shenyang were the worst (Yan et al., 2018). Excluding Shenyang, all of these cities are located in North China, where the problem of $PM_{2.5}$ pollution cannot be overlooked. Therefore, studying the temporal evolution and spatial heterogeneity of $PM_{2.5}$ pollution in North China will deepen our understanding of the characteristics of air pollution, assist in urbanization policy making, and ensure that targeted control measures are implemented.

To our best knowledge, few researchers have examined the spatiotemporal heterogeneity of $PM_{2.5}$ concentrations in North China region and quantified the correlation between the spatial relative risks and the temporal variation trends of $PM_{2.5}$ concentrations. Therefore, the aims of this study were to (1) investigate the spatiotemporal heterogeneity of $PM_{2.5}$ pollution risk from 2000 to 2017 in North China region from a regional perspective, (2) examine the correlation between the spatial relative risks and the temporal variation trends of the $PM_{2.5}$ concentrations, and (3) quantify the relationships between urbanization or other socioeconomic factors and $PM_{2.5}$ concentrations.

2. Methods

2.1. Study area

North China was taken as the study region in this work, which includes the provinces of Hebei, Henan, and Shandong, and 48 cities in total including Beijing and Tianjin (Fig. 1). There is clear socioeconomic disparity between the cities in the study area. The economies of most cities in southern Henan and southwestern Shandong are underdeveloped, while the core area of North China region comprising most of the cities in Beijing-Tianjin-Hebei, is one of the most densely populated and economically advanced regions of China. This resulted in remarkable spatiotemporal heterogeneity in both urbanization and $PM_{2.5}$ concentrations. Regional variations in urbanization may impact the spatial pattern of $PM_{2.5}$ concentrations and their temporal evolution. Accordingly, this study focused on the effects of the evolution of urbanization on the $PM_{2.5}$ concentrations in this area.

2.2. Data sources

The remotely sensed $PM_{2.5}$ concentrations data from 2000 to 2017 analyzed in this study were obtained from the Atmospheric Composition Analysis Group of Dalhousie University (http://fizz.phys.dal.ca/~atmos/martin/), which has a spatial resolution of $0.1° \times 0.1°$. The data were calculated based on the aerosol optical depth, which was retrieved from the NASA, MISR, MODIS, and SeaWiFS instruments combined with the atmospheric chemical model, and calibrated with the monitored $PM_{2.5}$ concentrations. This dataset has great accuracy as it has been corrected with global station-based observation values based on the geographically weighted regression model, with an R^2 value of 0.817 (Van Donkelaar et al., 2016), and has been used in many studies (Van Donkelaar et al., 2015; Pinault et al., 2016; Lu et al., 2018). The annual mean $PM_{2.5}$ concentrations of each city in the study area during 2000–2017 were then extracted using the zonal statistics tool in the ArcGIS10.3 software based on the average values of the raster in each city (Fig. 2).

Based on previous studies, the explanatory variables used this study for the same period were acquired from China's city and governmental economic statistical yearbooks of Beijing, Tianjin, Hebei, Henan and Shandong, which included the non-agricultural proportion of the population (UR), per capita gross domestic product (GDP), industrial output (IO), proportion of secondary industry (PS), proportion of tertiary industry (PT), and road density (RD). The UR is a traditional and commonly used proxy to represent urbanization, and has been widely discussed in many previous studies (Han et al., 2014; Shen et al., 2017; Wang et al., 2018a; Wang et al., 2018b). The road data used in this work were gathered from Open Street Map (https://www.openstreetmap.org), including multistage highways and urban roads, and the RD was then extracted using "line density" in the spatial analysis tools of ArcGIS 10.3.

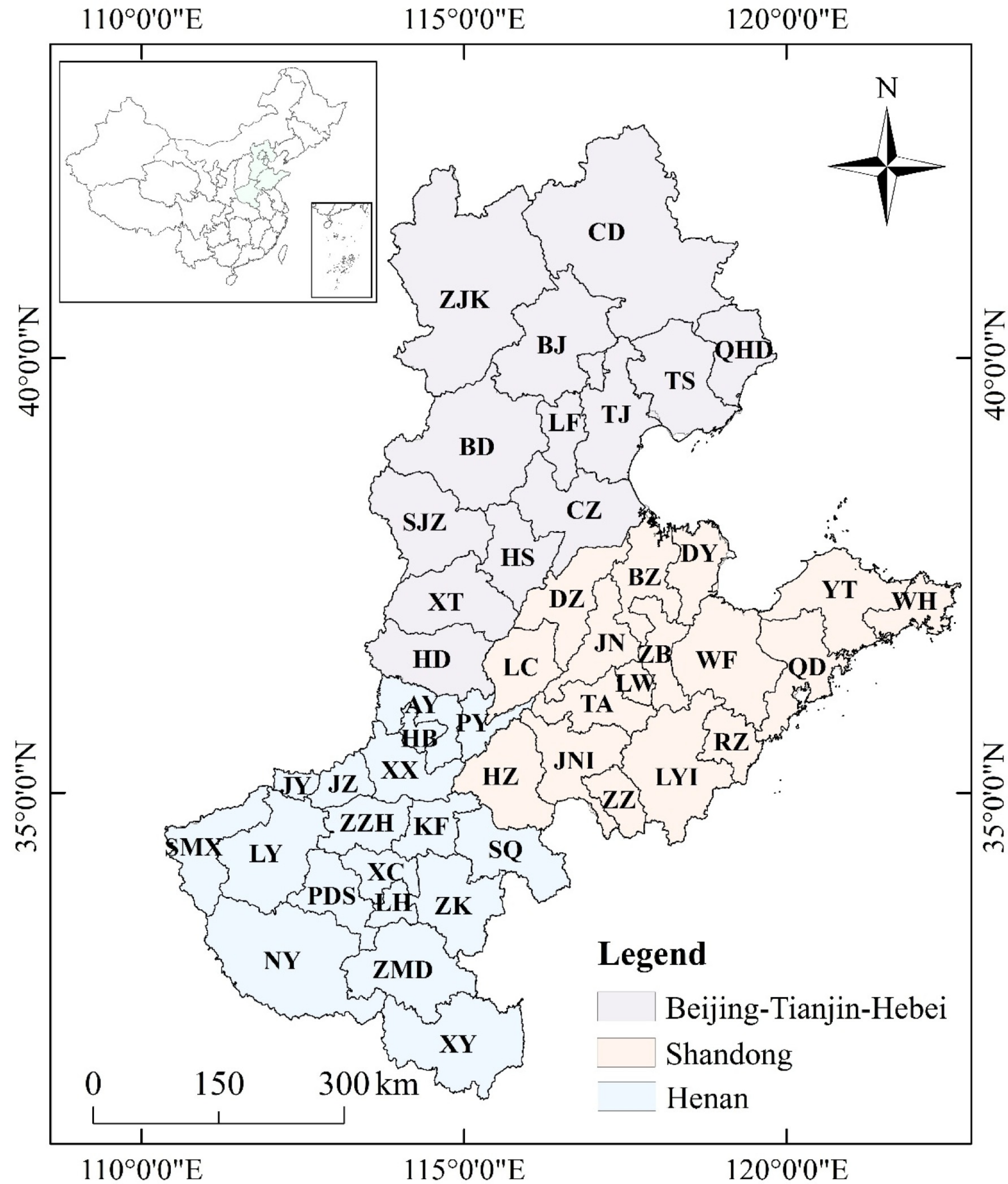

Fig. 1. Geographic location of the study area. Note: CD: Chengde city; ZJK: Zhangjiakou; BJ: Beijing; LF: Langfang; TS: Tangshan; QHD: Qinhuangdao; BD: Baoding; TJ: Tianjin; CZ: Cangzhou; SJZ: Shijiazhuang; HS: Hengshui; XT: Xingtai; HD: Handan; DZ: Dezhou; BZ: Binzhou; DY: Dongying; YT: Yantai; WH: Weihai; JN: Jinan; ZB: Zibo; WF: Weifang; QD: Qingdao; LC: Liaocheng; LW: Laiwu; TA: Taian; HZ: Heze; JNI: Jining; ZZ: Zaozhuang; LYI: Linyi; RZ: Rizhao; AY: Anyang; HB: Hebi; PY: Puyang; XX: Xinxiang; JY: Jiyuan; JZ: Jiaozuo; SMX: Sanmenxia; LY: Luoyang; ZZH: Zhengzhou; KF: Kaifeng; SQ: Shangqiu; XC: Xuchang; PDS: Pingdingshan; LH: Luohe; ZK: Zhoukou; NY: Nanyang; ZMD: Zhumadian; XY: Xinyang.

2.3. Statistical analysis

The unitary linear regression model was first used to reveal the linear relationship between the $PM_{2.5}$ concentrations and time, where the fitted coefficients (slope values) represented the temporal variation trends within the selected period. The larger the absolute value of the slope, the stronger the increasing/decreasing temporal trend (Yang et al., 2020), with positive slope values indicating an increasing trend over time. This is a common analysis method, thus, the formula can be found in previous studies (Yang et al., 2018). The Bayesian space-time hierarchy model (BSTHM) was then used to investigate the spatiotemporal heterogeneity of $PM_{2.5}$ pollution and identify high- and low-risk cities in the study area. The local indicators of spatial association (LISA) model was then introduced to determine the correlation between the spatial relative risks of $PM_{2.5}$ concentrations and their temporal variations. Finally, the spatial lag model (SLM) was used to quantify the association between urbanization or other socioeconomic factors and the $PM_{2.5}$ concentrations.

2.3.1. Bayesian spatiotemporal hierarchy model

The BSTHM (Li et al., 2014) is a novel statistical model for exploring spatial patterns and temporal evolution in data, and has been widely

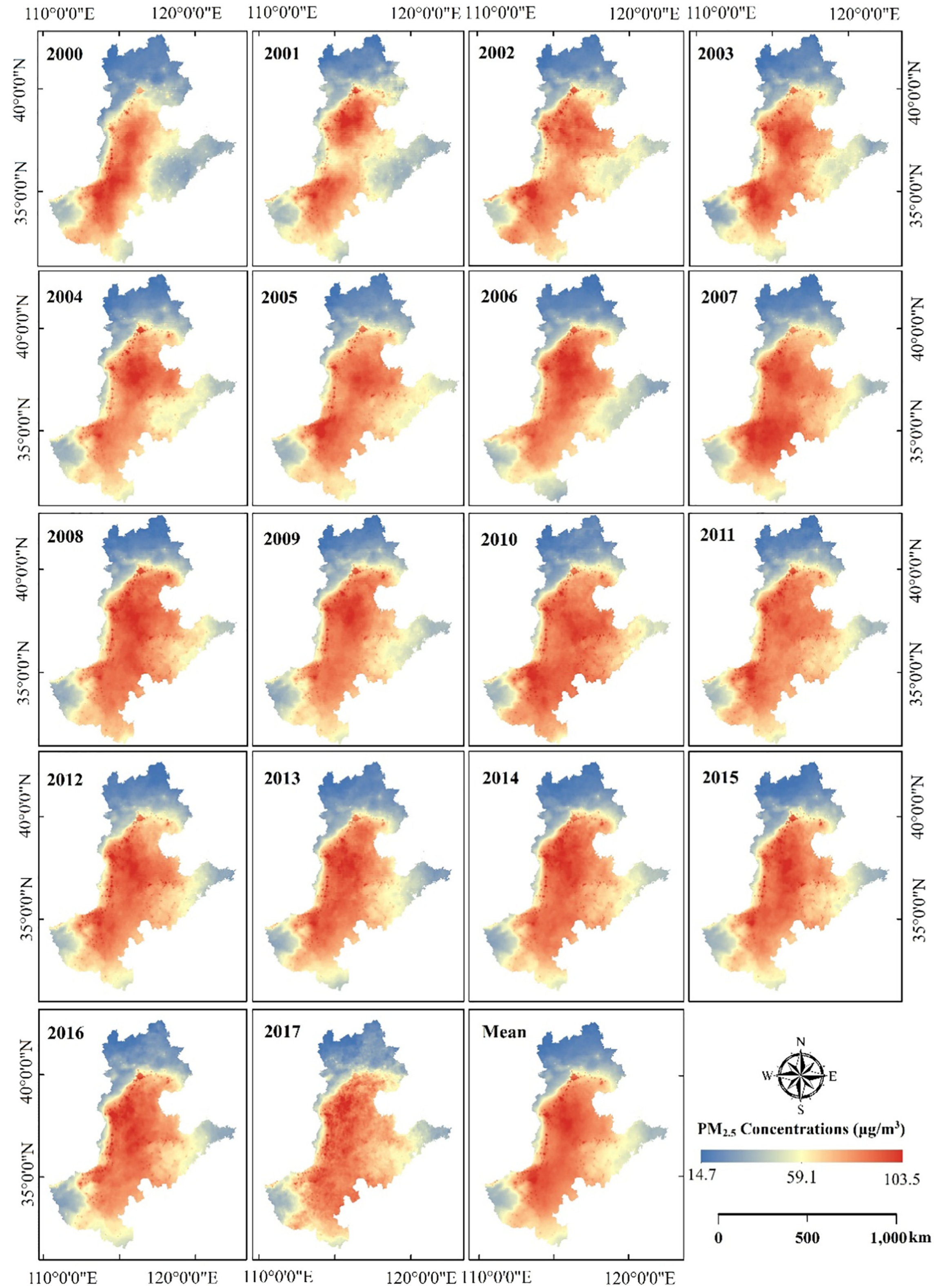

Fig. 2. Spatiotemporal distribution of the annual average $PM_{2.5}$ concentrations from 2000 to 2017 in North China.

used in epidemiology, atmospheric science, and geography (Zhang et al., 2020; Li et al., 2018; Kang et al., 2019; Zhang et al., 2018; Barboza, 2019). This method can capture the most representative spatiotemporal patterns of raw data. Additionally, it can also solve problems of sample bias and ensure accurate and stable results, and is thus more informative than traditional spatiotemporal technologies.

The $PM_{2.5}$ data from 2000 to 2017 for 48 cities were used as the spatiotemporal data in the study, and the corresponding mathematical definition was as follows:

$$y_{it} \sim N\left(u_{it}, \sigma_y^2\right) \tag{1}$$

$$\log(u_{it}) = \alpha + s_i + (b_0 t^* + v_t) + b_{1i} t^* + \varepsilon_{it} \quad (2)$$

where y_{it} is the annual average $PM_{2.5}$ concentrations of the cities i ($i = 1, 2, \ldots, 48$) in year t ($t = 1, 2, \ldots, 18$), u_{it} is the mean parameter of the raw data's likely distribution and represents the potential pollution risk, σ_y^2 is the variance of the corresponding normal distribution, and α is used to indicate the fixed effect of the pollution risk in North China during 2000–2017. The spatial term s_i describes the spatial heterogeneity of the pollution risk during the selected period. Similarly, $(b_0 t^* + v_t)$ denotes the overall temporal variations of the pollution risk, while t^* expresses the temporal span for the middle time point, and b_{1i} reveals the deviation from b_0, representing the local temporal trend. Finally, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ denotes the Gaussian noise (Gelman, 2006). All the BSTHM calculations in this study were conducted using WinBUGS 1.4, which was designed specifically for Bayesian research (Lunn et al., 2000).

2.3.2. Bivariate spatial correlation

The bivariate LISA model was developed from the spatial correlation analysis to not only quantify the local spatial correlation, but to also determine the class of spatial correlation between two studied subjects, including the spatial relative risks and temporal variation trends (Anselin et al., 2002). The local Moran's I model can be explained as follows:

$$I_{kl}^i = Z_k^i \sum_{j=l}^{n} W_{ij} Z_l^i \quad (3)$$

$$Z_k^i = \frac{x_k^i - \overline{x_k}}{\sigma_k}, Z_l^i = \frac{x_l^j - \overline{x_l}}{\sigma_l} \quad (4)$$

where the spatial weight matrix is represented by W_{ij}, and x_k^i and x_l^j are the values of variables k and l at locations i and j, respectively. σ_k and σ_l a represent the variations in x_k and x_l, respectively.

$Z_k^i$and the corresponding spatial lag WZ_l^i at location i are presented on the vertical and horizontal axes of Moran's I scatter plot, respectively (Anselin et al., 2002). The spatial correlation is then divided into four quadrants by the two-coordinate axis, with the first and third quadrants indicating positive spatial correlation, and the second and fourth quadrants representing negative spatial correlation. The quadrants were categorized as "High-High (HH)," "Low-Low (LL)," "High-Low (HL)," and "Low-High (LH)." The LISA processes were conducted using GeoDa.

2.3.3. Spatial lag model

Socioeconomic variables, such as the local economic environment, population conditions, and traffic identify, greatly influence the concentrations of $PM_{2.5}$. In this study, the SLM was used to quantify the impacts of urbanization or other socioeconomic factors on the $PM_{2.5}$ concentrations, as follows:

$$y_i = \rho \boldsymbol{W}_{y_i} + \boldsymbol{X\beta} + \boldsymbol{\varphi} \quad (5)$$

where ρ is the coefficient of the response variable being analyzed, with a value ranging from 0 to 1; if the value is closer to 1, the response variables in the adjacent spatial statistical units are more similar. The spatial adjacent matrix, signified by $\boldsymbol{W}$, indicates whether two spatial units share a common boundary; the diagonal entries of $\boldsymbol{W}$ are given a value of zero and non-diagonal entries are given a value of 1, and $\boldsymbol{\beta}$ represents the regression coefficient of the explanatory variables, which are represented by $\boldsymbol{X}$ and include all of the introduced socioeconomic factors. Finally, $\boldsymbol{\varphi}$ indicates the error term.

3. Results

3.1. Temporal characteristic of $PM_{2.5}$ concentrations in different regions

Both the temporal evolution of the average $PM_{2.5}$ concentrations and the temporal relative risks in the study area from 2000 to 2017 were calculated to determine their temporal variations (Fig. 3). Geographically, the $PM_{2.5}$ concentrations were greater in Tianjin and Henan from 2000 to 2007. In contrast, they were relatively low in Beijing and Shandong. The temporal relative risks were consistent with the average value of each city (Beijing and Tianjin)/province, with the peak values occurring in 2007 and 2013, respectively, and followed an overall increasing trend. Both temporal variations and regional differences were observed. In 2000, the mean $PM_{2.5}$ concentrations were 28.24, 42.30, 42.80, 60.59, and 38.48 μg/m^3 in Beijing, Tianjin, Hebei, Henan, and Shandong, respectively. In the Beijing-Tianjin-Hebei region, the $PM_{2.5}$ concentrations all increased until 2006, with peak values of 58.47, 84.66, and 73.50 μg/m^3, respectively, but subsequently decreased from 2007 to 2012, and have fluctuated interannually since 2013. In Henan and Shandong Provinces, the $PM_{2.5}$ concentrations clearly increased before 2007 and reached maximum levels of 84.59 and 73.13 μg/m^3, respectively, before decreasing from 2007 to 2012, with interannual fluctuations thereafter.

3.2. Spatial patterns and temporal variations in the $PM_{2.5}$ concentrations risks

The $PM_{2.5}$ pollution risk in the 48 cities from 2000 to 2017 was extracted using the BSTHM. The temporal variation trends of the $PM_{2.5}$ concentrations were then extracted for each city using unitary linear regression, as shown in Fig. 4. The risk of $PM_{2.5}$ pollution was relatively high in cities located in southeastern Hebei, northern Henan, and

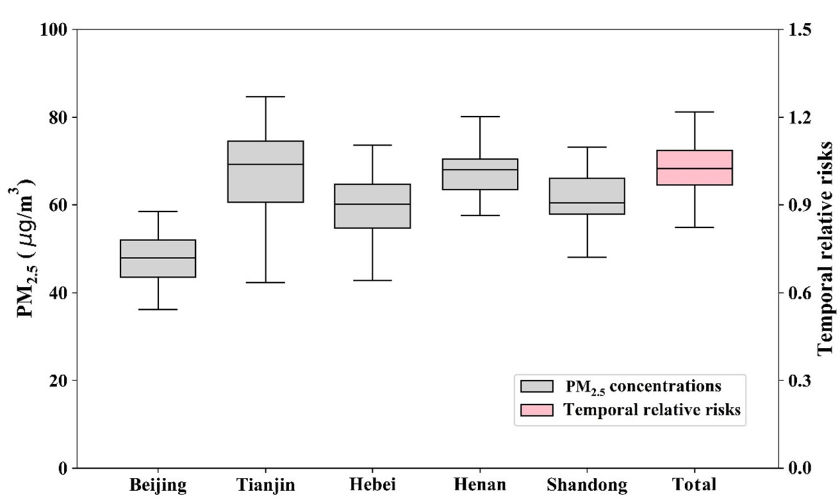

Fig. 3. The temporal relative risks (exp $(b_0 t^* + v_t)$) and temporal evolution of the $PM_{2.5}$ concentrations in different regions during 2000–2017.

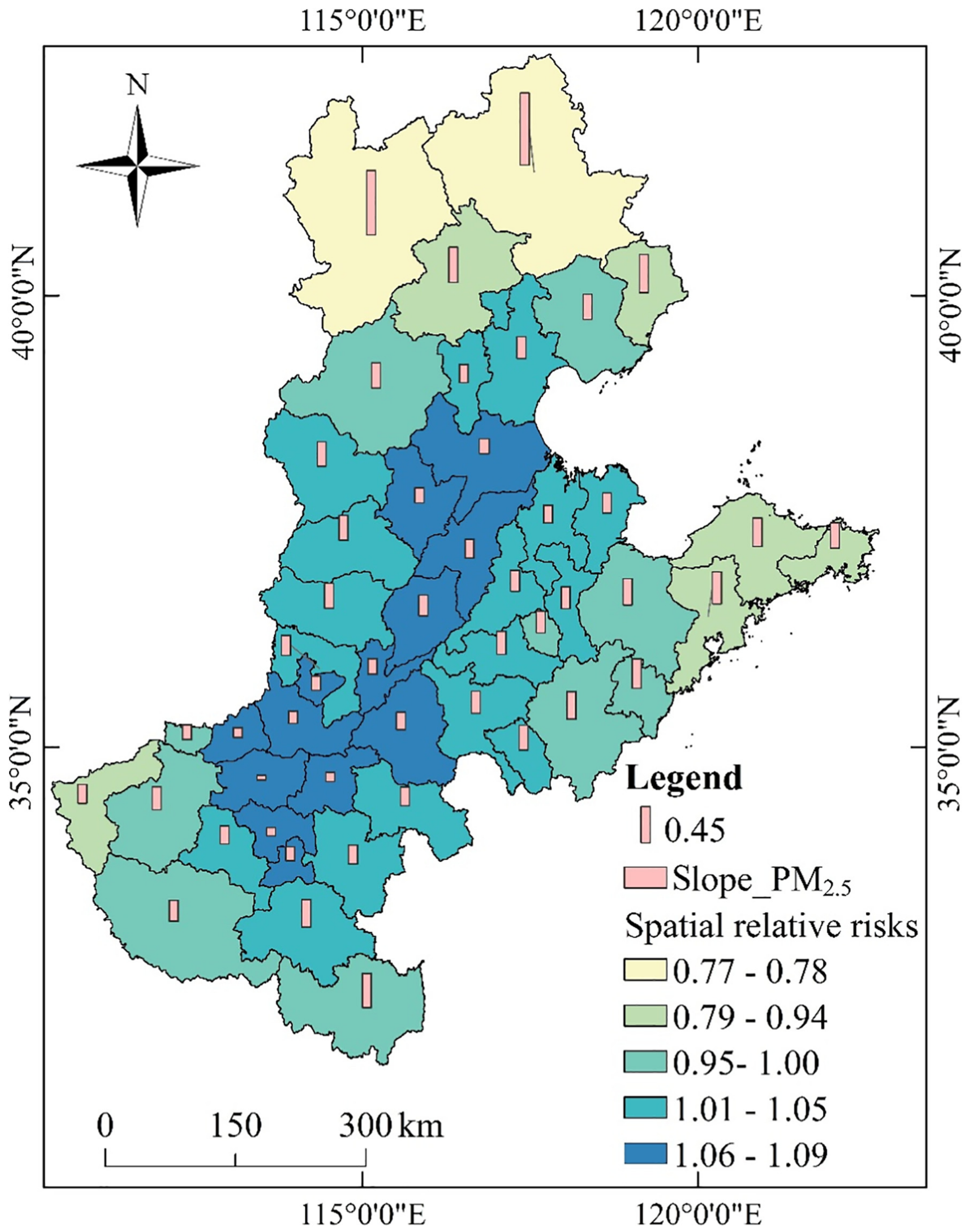

Fig. 4. Spatial relative risks ($\exp(s_i)$) and temporal variation trends (slope values) of the $PM_{2.5}$ concentrations in each city of North China. Note: All of the slope values are positive and significant at the 5% level ($p < 0.05$), indicating a significant increasing trend in which the height of the columns represents the magnitude of the slope values of each city.

western Shandong, while it was relatively low in cities located in northern Hebei, southern Henan, and eastern Shandong. Generally, the spatial heterogeneity of the $PM_{2.5}$ concentrations indicated that the risk of $PM_{2.5}$ pollution was higher in central cities than that in the peripheral cities in North China. The slope values of the $PM_{2.5}$ concentrations demonstrated that increasing trends occurred for each city as they were positive, but differed between cities. The $PM_{2.5}$ concentrations followed a significantly increasing trend in most of the cities in Hebei, particularly in Chengde and Zhangjiakou.

The LISA model was subsequently used to calculate the association between the spatial relative risks and temporal variation trends, which was then mapped to reveal the types of their spatial associations (Fig. 5). The Moran's I (-0.56) values indicated that increasing trends in higher-risk areas were lower. As shown in Fig. 5, both the spatial relative risks and slope values of the $PM_{2.5}$ concentrations were higher in Tianjin and Zaozhuang; thus, the pollution risk in these cities would likely be greater in the future than those of other cities in the study area. Moreover, the cities in northern Hebei, southern Henan, and western

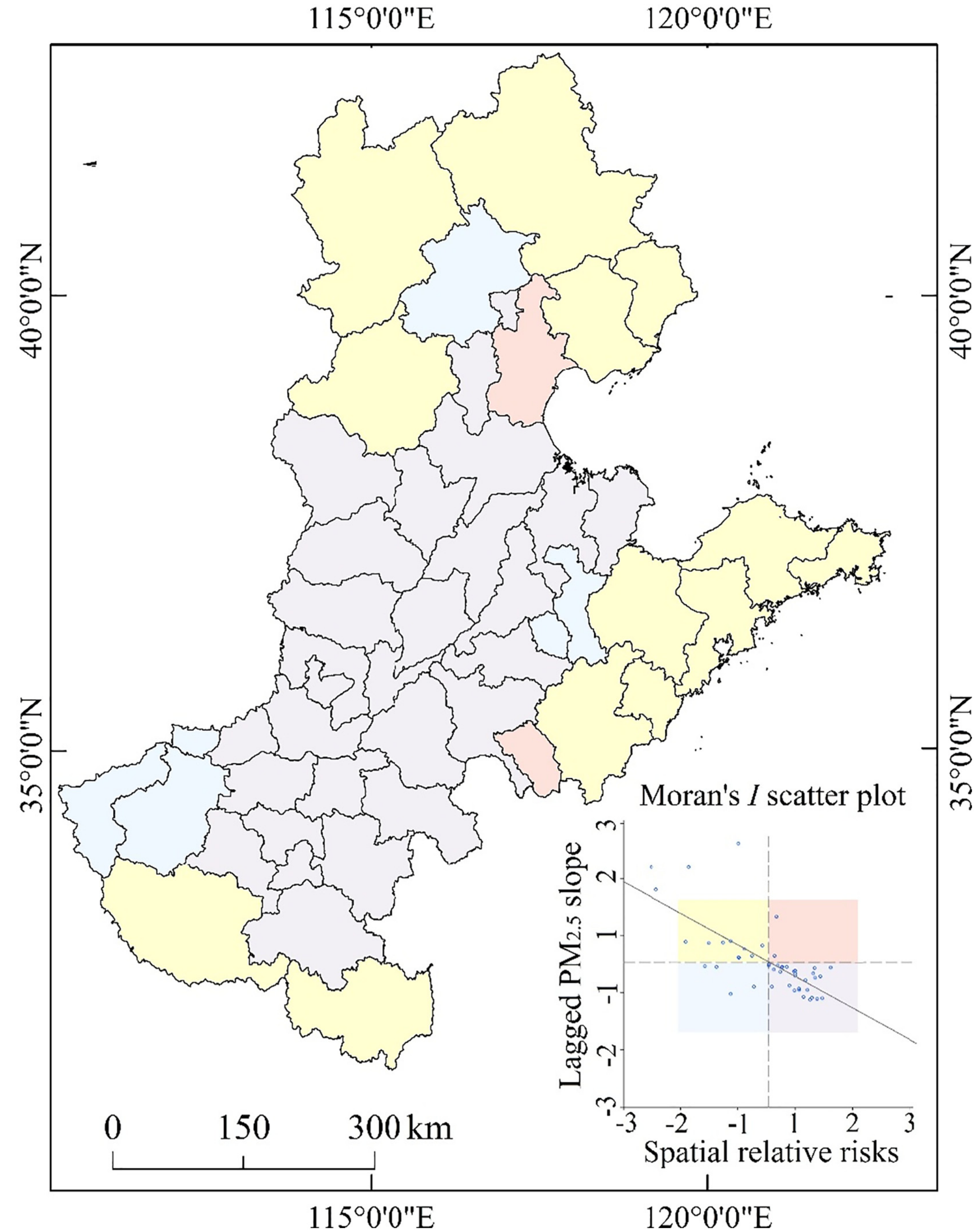

Fig. 5. The map of Moran's *I* scatter plot for the relative risks of spatial and temporal of the $PM_{2.5}$ concentrations in each city of North China.

Shandong had lower $PM_{2.5}$ pollution risk but higher increasing trends, such as Chengde, Zhangjiakou, Xinyang, and Qingdao, where $PM_{2.5}$ pollution could be more dangerous in the future than that in the other cities of the study area.

3.3. Impact factors analysis

Different socioeconomic conditions may affect the spatiotemporal heterogeneity of $PM_{2.5}$ concentrations to varying degrees. The SLM was used to quantify the associations between the $PM_{2.5}$ concentrations and urbanization or other socioeconomic variables, as shown in Table 1.

A positive relationship between urbanization, which was represented by the UR, and the $PM_{2.5}$ concentrations ($p < 0.05$) was observed, indicating that a high urbanization rate aided in increasing the $PM_{2.5}$ concentrations (Table 1). RD was also positively associated with the $PM_{2.5}$ concentrations ($p < 0.01$), thereby indicating that high traffic intensity would likely cause an increase in the $PM_{2.5}$ concentrations (Table 1).

The PT was significantly and negatively correlated with the $PM_{2.5}$ concentrations ($p < 0.01$), indicating that the $PM_{2.5}$ emissions from cities at a higher stage of social development would be suppressed (Table 1). However, the calculated coefficients for the PS, per capita GDP, and IO were not statistically significant (Table 1).

The results also demonstrated that socioeconomic factors notably influenced the spatiotemporal heterogeneity of the $PM_{2.5}$ concentrations, as a statistically significant correlation was observed between the $PM_{2.5}$ concentrations and the following socioeconomic factors: urbanization, RD, and PT ($p < 0.05$).

Table 1
The estimated coefficients of socio-economic factors in SLM.

Socio-economic variables	Coefficient	Std. error	z	p
Proportion of non-agricultural population (%)	0.43	0.19	2.26	0.02*
Road density (km/km^2)	12.55	3.06	4.10	0.00**
Proportion of tertiary industry (%)	−0.99	0.32	−3.10	0.00**
Proportion of second industry (%)	−0.34	0.27	−1.27	0.20
Per capita GDP (10^4 CNY)	-7.39×10^{-5}	9.51×10^{-5}	−0.78	0.44
Industrial output (10^4 CNY)	7.52×10^{-8}	5.69×10^{-8}	1.32	0.19

Note: **statistical significance level: 0.01; *statistical significance level: 0.05.

4. Discussion

$PM_{2.5}$, a major air pollutant, poses a significant threat to the environment and public health worldwide, and has recently attracted increasing attention (Li et al., 2019). As one of the most densely populated and economically advanced regions in China with millions of migrants the $PM_{2.5}$ concentrations in North China have increased greatly. In this study, a unitary linear regression model was used to examine the temporal variation trends of the $PM_{2.5}$ concentrations for each city in the region from 2000 to 2017. The BSTHM was then used to explore the spatiotemporal heterogeneity of the $PM_{2.5}$ concentrations, and the association between the spatial relative risks and temporal variation treads was quantified using the LISA model. Additionally, the determinant power of urbanization and other socioeconomic factors to the $PM_{2.5}$ concentrations was quantified using the SLM. The results indicated that the areas with the highest increases were mainly concentrated in the border cities of the study area, while the high-risk cities were predominantly located at the center, suggesting that the variation trends for high-risk cities were lower. Furthermore, urbanization and other socioeconomic factors played a notable role in the spatiotemporal heterogeneity of the $PM_{2.5}$ concentrations.

The temporal evolution of $PM_{2.5}$ concentrations in North China from 2000 to 2017 was examined. Both the temporal relative risks and concentrations of $PM_{2.5}$ increased across all the cities in the study area during the selected years. This may be because China experienced rapid urbanization in recent decades, especially in the study area, where industries such as steel and transportation facilities are highly concentrated (Zhao et al., 2012). Notably, these industries consume great volumes of fossil fuels and inevitably produce high emissions. Moreover, during urbanization, the effects of socioeconomic conditions, such as population concentrations, traffic intensity, and energy consumption, on the city continuously increase. Furthermore, the expansion of cities would also increase the area of surface dust formation (Lu et al., 2018; Yang et al., 2018).

Urbanization was also significantly and positively related to the $PM_{2.5}$ concentrations spatially, indicating that $PM_{2.5}$ pollution is more severe in cities undergoing rapid urbanization. Some studies have also demonstrated that urbanization is positively correlated with the $PM_{2.5}$ concentrations. For example, Lu et al. reported a positive association between urbanization and $PM_{2.5}$ concentrations (Lu et al., 2019), and Yang et al. demonstrated that rapid urbanization would promote the generation and growth of $PM_{2.5}$ pollution (Yang et al., 2018). Moreover, Lu et al., also found that urbanization enhanced the $PM_{2.5}$ concentrations (Lu et al., 2019). This may be because urban development is accompanied by increasing $PM_{2.5}$ emissions, and cities undoubtedly contain large numbers of $PM_{2.5}$ emission sources and factors that impact them, which has been corroborated in published research. For example, Lu et al. studied the correlation between $PM_{2.5}$ concentrations and land use, and reached analogous conclusions (Lu et al., 2018). Furthermore, increasing numbers of people are moving from rural to urban areas, and the continuous expansion of cities increases the urban heat island effect, which would also promote the generation and accumulation of pollution sources and exacerbate the damage to the atmospheric environment (Zhang et al., 2009). These phenomena demonstrate that the spatial heterogeneity of $PM_{2.5}$ concentrations is closely linked to differences in the level of urbanization.

In this study, PT, an inevitable result of increased productivity and social progress, was significantly and negatively related to the $PM_{2.5}$ concentrations, which was consistent with the results of previous studies. For example, Han et al. (2014) and Yu and Liu (2016) both demonstrated that environmental pollution would continuously increase to a "peak point", after which the pollution will decrease, according to the Environmental Kuznets Curve hypothesis. This may be because the tertiary industry mainly involves industries that are not directly related to $PM_{2.5}$ emissions, such as scientific research, technical services, and environmental and public facilities management. Moreover, with the rapid development of the tertiary industry, the level of socialization and specialization of industrial and agricultural production would be greatly improved, the production structures would be optimized, and the advanced scientific technologies and ideal prevention and control measures would greatly inhibit or reduce $PM_{2.5}$ emissions, thereby promoting sustainable environmental and economic development.

The results of the LISA model further confirm that the spatial relative risks of $PM_{2.5}$ pollution were negatively correlated with the temporal variation trends, indicating that cities with lower $PM_{2.5}$ pollution risk exhibited a greater increasing trend, and cities with higher $PM_{2.5}$ pollution risk exhibited a lower increasing trend. Notably, some cities, such as Tianjin and Zaozhuang, not only exhibited higher $PM_{2.5}$ pollution risk, but also presented strong increasing trends. Furthermore, Zhangjiakou, Chengde, Rizhao, Qingdao, and Nanyang exhibited relatively high growth trends, yet their risk of $PM_{2.5}$ pollution was currently low. This may be because, when the degree of development differs between regions, the pollutant emission intensity or type would also differ, and during urbanization, industries continue to move to an area's surrounding cities (Zhao et al., 2012). Therefore, these cities should receive more attention as they could become high-risk areas in the future.

Based on the above findings, we propose the following recommendations. First, industry is an important factor affecting air pollution in China (Zhu et al., 2019), and cities with high industrial activities ensure high air pollution, such as Tianjin, Zhengzhou, and Zaozhuang. Therefore, during rapid urbanization, industrial expansion should be sufficiently restricted, particularly the expansion of polluting industries. Moreover, in the future development of cities, sustainable construction should be strengthened to decrease and control the emissions and accumulation of $PM_{2.5}$ (Lu et al., 2018). Furthermore, strengthening pollution regulations, using clean energy, and improving technologies would aid in relieving the increasing $PM_{2.5}$ concentrations. Additionally, regional cooperation should be strengthened, as air pollutants spread due to their mobility. Furthermore, polluting enterprises relocate from coastal to inland cities during urbanization (Yang et al., 2020), and this should be limited to reduce air pollution issues and ensure sustainable development.

This work had some limitations. First, we considered urbanization and other socioeconomic factors as the impacting factors; however, several environmental factors, such as atmospheric humidity and air temperature, were omitted. Second, the $PM_{2.5}$ product used in the study has some biases across China, which may introduce some uncertainty (Li et al., 2017). However, this does not affect the long-term $PM_{2.5}$ concentrations trends. The dataset has good accuracy, and the cross-validated R^2 value between the estimated annual average $PM_{2.5}$ concentrations and station-based observation values in the study area was 0.75. A higher spatiotemporal resolution (such as 1 km) may be necessary if the study region is a city or a smaller unit. In the future, $PM_{2.5}$ data with higher spatiotemporal resolution and more detailed statistical units will be used to provide more accurate estimates of the $PM_{2.5}$ pollution risk.

5. Conclusions

In this study, a unitary linear regression model was used to explore the temporal variation trends in the North China region from 2000 to 2017. The BSTHM was then used to investigate the spatiotemporal heterogeneity of $PM_{2.5}$ pollution, and the correlation between its spatial relative risks and temporal variation trends was further examined using the LISA model. Finally, the determinant power of urbanization and other socioeconomic factors on $PM_{2.5}$ concentrations was quantified using the SLM. Temporally, the $PM_{2.5}$ concentrations increased during the selected period. Spatially, the relative risks were negatively related to temporal variations, while urbanization was significantly and positively linked to the $PM_{2.5}$ concentrations. Cities were found to have either high or low $PM_{2.5}$ pollution risk, but all cities exhibited a notably increasing trend, such as Tianjin, Zaozhuang, Qingdao, and Xinyang, which will experience more severe air pollution problems with rapid urbanization and should receive more attention in the near future. Therefore, it is strongly recommended that policy-makers consider these future air pollution trends when developing urban development policies.

CRediT authorship contribution statement

Xiangxue Zhang: Conceptualization, Methodology, Writing - original draft. **Xinchen Gu:** Visualization, Investigation. **Changxiu Cheng:** Writing - review & editing, Supervision. **Dongyang Yang:** Data curation, Writing - review & editing.

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.

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