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RESEARCH ARTICLE

Spatio-temporal trends and influencing factors of $PM_{2.5}$ concentrations in urban agglomerations in China between 2000 and 2016

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Abstract

An urban agglomeration (UA), similar to a megalopolis or a metropolitan area, is a region where cities and people are concentrated, and where air pollution has adversely impacted on sustainable and high quality development. Studies on the spatio-temporal trends and the factors which influence $PM_{2.5}$ concentrations may be used as a reference to support air pollution control policy for major UAs throughout the world. Nineteen UAs in China covering the years 2000–2016 were chosen as the research object, the $PM_{2.5}$ concentrations being used to reflect air pollution and being estimated from analysis of remote sensing images. The Exploratory Spatial Data Analysis method was used to study the spatio-temporal trends for $PM_{2.5}$ concentrations, and the Geodetector method was used to examine the factors influencing the $PM_{2.5}$ concentrations. The results revealed that (i) the temporal trend for the average values of the $PM_{2.5}$ concentrations in the UAs followed an inverted U-shaped curve and the inflection points of the curve occurred in 2007. (ii) The $PM_{2.5}$ concentrations in the UAs exhibited significant global spatial autocorrelation with the high–high type and the low–low type being the main categories. (iii) The rate of land urbanization and the structure of energy consumption were the main factors which influenced the $PM_{2.5}$ concentrations in the UAs.

Keywords Spatio-temporal trend · Influencing factor · $PM_{2.5}$ · Air pollution · Urban agglomeration · China

Highlights

- Spatio-temporal trends for $PM_{2.5}$ concentrations were studied using the Exploratory Spatial Data Analysis method.
- Factors which influenced $PM_{2.5}$ concentrations were examined using the Geodetector method.
- Temporal trends for the average $PM_{2.5}$ concentrations followed an inverted U-shaped curve.
- $PM_{2.5}$ concentrations exhibited significant global spatial autocorrelation, the main categories being the high–high and the low–low type categories.
- Main factors which influenced $PM_{2.5}$ concentrations were the rate of land urbanization and the structure of energy consumption.

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Introduction

With the reform and opening up of China in 1978, the country has seen rapid urbanization. The resident population in urban areas increased from 173 million in 1978 to 831 million in 2018. The rate of urbanization increased from 17.9% in 1978 to 59.6% in 2018. The level of urbanization successively surpassed low-income countries in 1980, lower middle-income countries in 1997, middle-income countries in 2009, and the world average in 2014 (Li 2018). Urbanization has become an important engine for modernization in China, because urbanization has absorbed a large proportion of the rural work force via new employment, improved the allocation efficiency of production factors, facilitated the sustained and rapid development of the national economy, and promoted profound changes in social structure and the overall progress of social undertakings. However, together with urbanization and industrialization, air pollution has increased due to extensive and inefficient development modes, adversely influenced the physical and mental health of the residents, and impacted negatively on the sustainable development and international image of China. For instance, the Beijing Tianjin Hebei urban agglomeration (UA) is a major strategic area for China's economy and reflects the competitiveness of the country (Lu 2015). However, this UA also suffers from severe air pollution (Parrish and Zhu 2009); for instance, in 2014 and 2015 the area accounted for 8 and 7 of the 10 worst cities in China for air quality, respectively. Atmospheric particulate matter that has a size diameter of less than 2.5 μm ($PM_{2.5}$) is an important category of air pollution, and it is known there are regional and a number of complex features associated with its distribution (Zhou et al. 2019). Rapid urbanization and industrialization, large-scale consumption of energy, industrial emissions, dusts originating from urban construction, and emissions from motor vehicles are the main sources of particulate matter accounting for the increase of suspended fine particles in the atmosphere of which $PM_{2.5}$ is a major concern (Liu et al. 2018a, b; Du et al. 2019). The $PM_{2.5}$, which is closely related to human activities, extends to the troposphere, and can reduce visibility and form new pollutants via participation in chemical reactions in the atmosphere. Medical studies show that $PM_{2.5}$ can seriously affect human health. On inhalation, $PM_{2.5}$ can cause respiratory and cardiovascular disease, and the immune system can be compromised such that the risk of death in exposed populations increases (Delfino et al. 2005; Laden et al. 2000, 2006; Samet et al. 2000; Samet and Chung 2018). The number of premature deaths as a result of exposure to air pollution over a long period of time is in excess of 1.25 million persons, and about 40% of the world's population is considered to be at increased health risk from air pollution (Wang et al. 2012).

As a new approach to space utilization between nearby cities, UAs have become one of the main means to promote new urbanizations in China and are a key vehicle for facilitating economic activity and competition at a global scale. The spatial organization pattern of UAs in China has been gradually evolving. There are now five national large-scale UAs, eight regional medium-scale UAs, and six regional small-scale UAs in the national UA spatial structure system (Fang et al. 2018a, b). A UA may be defined as a highly developed urbanization region with a megacity at its core and whose main purpose is to drive forward the coordinated development of the different cities (Fang et al. 2018a, b). The concept of a UA is similar to those of the megalopolis (Gottmann 1957) and megaregions (Meijers and Burger 2010). A UA is a region with a high population density and a large economy. However, because of the lack of unified environmental protection measures in the extended space structure, a conflict arises between urbanization and environmental protection. At the same time, a UA can become a zone for the collection and accumulation of $PM_{2.5}$ pollution (Liu et al. 2017). Thus, $PM_{2.5}$ pollution in UAs attracts the attention of government departments and researchers.

Literature review

Computational method for $PM_{2.5}$

In previous studies, $PM_{2.5}$ concentrations were obtained by calculating the ground observational data and by inversion of the satellite remote sensing (RS) data. Calculation of the ground observational data included consideration of the following sources: The hourly data released by the Ministry of Ecology and Environment of China as used in studies by Wang et al. (2014) on the spatial and temporal variations of $PM_{2.5}$, and including the concentrations of PM_{10}, CO, SO_2, and NO_2 in 31 major cities in China between March 2013 and February 2014. The data were collected by Fu et al. (2018) and included the spatial and temporal variations for six criteria concerning the levels of CO, SO_2, NO_2, and O_3 at 37 sites in nine major cities within Fujian Province between January 2015 and December 2016. For inversion of the satellite RS data, various sources were consulted. The $PM_{2.5}$ data for 2000 to 2015 were determined from inversion of the National Aeronautics and Space Administration (NASA) atmospheric RS images published in the study of Zhou et al. (2019), and the variability in the spatio-temporal evolution patterns for $PM_{2.5}$ in China were then evaluated. The study of Wan et al. (2019) utilized the raster dataset for the annual average variability in the global atmospheric $PM_{2.5}$ in order to analyze the spatio-temporal evolution of $PM_{2.5}$ in the Yangtze River Economic Belt at different regional scales.

The accuracy and temporal resolution of the ground observational data were higher than the data for the RS inverted images; however, the data from the monitoring stations cannot fully reflect the spatial differences of

$PM_{2.5}$ in large-scale regions. Particularly in mountainous areas with complex terrain or cities with complex land surfaces and high-density populations, estimating the effect of $PM_{2.5}$ on human health using calculated ground observational data may produce errors. Compared with the calculated ground observational data, in the case of the inverted satellite RS data, we can obtain the $PM_{2.5}$ data at a large scale and on a continuous basis. Furthermore, we can obtain the $PM_{2.5}$ in regions without ground observation stations.

Spatial heterogeneity of $PM_{2.5}$

After calculation of the $PM_{2.5}$, the spatial heterogeneity, or the spatial pattern of the $PM_{2.5}$ in various regions, was studied. Peng et al. (2016) found that the areas most polluted by $PM_{2.5}$ were south of Hebei, north of Henan, and west of Shandong provinces and the health risk in the central and eastern areas of China was the highest. Liu et al. (2018a, b) found that the spatial heterogeneity of $PM_{2.5}$ in the Beijing Tianjin Hebei UA was characterized as high in the southeast and low in the northwest. Wang et al. (2019) reported that the health risk of $PM_{2.5}$ was higher in Eastern China compared with Western China and the Hu Huanyong Line was the demarcation line; also, the rate of increase of $PM_{2.5}$ in Eastern China was higher than that of Western China. Bai et al. (2019) also judged that the Hu Huanyong Line was a demarcation line for the $PM_{2.5}$ distributions in China; moreover, the spatial heterogeneity for $PM_{2.5}$ in the Southeast was higher than that for the Northwest; the concentration of $PM_{2.5}$ in the North China Plain was found to be the highest. Zheng et al. (2019) also found that the spatial distribution of $PM_{2.5}$ in China was remarkable with high-value clusters for cities being concentrated in most parts of Shandong, Henan, Hebei, Jiangsu, Anhui, Hunan, Hubei, and eastern Sichuan, while low-value clusters for cities were encountered in Inner Mongolia, northwestern Heilongjiang, Xinjiang, Tibet, Taiwan, Hainan, Fujian, and other regions. In general for air pollution in China, the degree of pollution in the east of the country tends to be more serious than that in the west, and the developed areas have more serious pollution than the less developed areas.

The city was chosen as the basic research object for investigation of the spatial heterogeneity of the $PM_{2.5}$ distribution. A UA consists of different cities and typically is a region with severe air pollution. When selecting a UA as the research object, what will be the characteristics of the spatial heterogeneity of the $PM_{2.5}$ in such a large-scale region? As the status of UAs becomes more and more important, it is necessary to view the UA as a basic unit of space in order to study the spatial heterogeneity of $PM_{2.5}$.

Factors which influence the $PM_{2.5}$ concentrations

Research on the factors which influence the $PM_{2.5}$ concentrations may provide a reference for implementing measures to control air pollution. Lin et al. (2019) studied the effects of land use on $PM_{2.5}$ and their removal at regional spatial scales and found that forested land and industrial land had greater impact on the $PM_{2.5}$ than did other land-use types; also, industrial land and built-up land had greater effects on the $PM_{2.5}$ in winter than in summer. Fan et al. (2019) proposed that the distribution of the scale of urbanization, agglomeration, and haze pollution presented complex asymmetrical features, with the former two exhibiting a “core-periphery” distribution, while the latter had a tendency to spread. Similarly, Han et al. (2014) investigated the impact of urbanization on $PM_{2.5}$ at the prefectural level in China and demonstrated that urbanization had considerable impact on $PM_{2.5}$. Li et al. (2019) studied the impact of the urban spatial structure on air pollution in China and found positive relationships between poly-centricity, dispersion, and $PM_{2.5}$ concentrations in cities. Several researchers have studied the impact of socioeconomic factors on the $PM_{2.5}$ concentrations. Han et al. (2019) found that areas in China having $PM_{2.5}$ levels > 35 $\mu g/m^3$ increased from 39 to 42%. Huang et al. (2019) pointed out that economic density, the proportion of secondary industries, population density, and the rate of urbanization had a positive effect on the increase of $PM_{2.5}$ in the Yangtze River Economic Belt. Air pollution is considered a key research topic in environmental economics, as evidenced by the frequent use of the Environmental Kuznets Curve (EKC) (Grossman and Krueger 1995) for studying the effects of urbanization (Fang et al. 2015), population density (Hixson et al. 2012), urban form (2017), energy consumption (Yuan et al. 2015), and industrial production (Lin and Wang 2016) on air pollution. Hence, present research can be considered as a type of focused study on the factors which influence $PM_{2.5}$ concentrations in UAs.

The $PM_{2.5}$ concentrations are affected by various natural and socio-economic factors, and the main factors influencing the $PM_{2.5}$ concentrations are different in different regions. For regions with highly developed urbanization and industrialization, socioeconomic factors will be the main factors, while for remote regions, natural factors such as the meteorology and topography will be the main factors. Clearly, studies are warranted on the factors which influence the $PM_{2.5}$ concentrations in UAs.

In this study, 19 UAs in China were selected as the research object and the $PM_{2.5}$ concentrations were assessed using the inverted atmospheric RS images of NASA. The spatiotemporal trends for the $PM_{2.5}$ concentrations in the UAs were studied using the Exploratory Spatial Data Analysis method, and the factors influencing the $PM_{2.5}$ concentrations were examined using the Geodetector method. The novelty and contributions of this research include the following: A UA was chosen as the study object (rather than a city) to explore the spatio-temporal trends of $PM_{2.5}$, given that such information will enhance the knowledge base concerning air pollution in UAs. Urban agglomerations play an important role in China's economic and social development. Solving air pollution problems in UAs contributes to the sustainable development and construction of ecological civilization in China. Studying the spatio-temporal trends and influencing factors of $PM_{2.5}$ may lead to new practical ideas and countermeasures for controlling air pollution in UAs.

Research object

China has established 19 UAs as part of the *National New Urbanization Plan* (2014–2020) (http://politics.people.com.cn/n/2014/0317/c1001-24649809.html), and these 19 UAs were selected for study by Wang and Yang (2018). The same UAs were chosen as research objects in the present study (Fig. 1). Among them, the Beijing Tianjin Hebei UA, the Yangtze River Delta UA, the Pearl River Delta UA, the middle reaches of the Yangtze River UA, and the Chengdu Chongqing UA are representative of the national large-scale UAs. The South Central Liaoning UA, the Shandong Peninsula UA, the west coast of the Taiwan Strait UA, the Harbin Changchun UA, the Central Henan UA, the Guanzhong Plain UA, the Beibu Gulf UA, and the Northern slope of the Tianshan Mountains UA are the regional medium-scale UAs. The Central Shanxi UA, the Hohhot Baotou Erdos Yulin UA, the Central Yunnan UA, the Central Guizhou UA, the Lanzhou Xining UA, and the Ningxia along the Yellow River UA are representative of regional small-scale UAs. The national large-scale UAs are drivers for national economic growth delivering competitiveness and global influence. At the core of the regional medium-scale UA is a central city, and its function is to drive forward regional economic growth. The regional small-scale UAs are at an early stage of formation and cultivation, and their function is to drive forward the economic growth of the provinces and absorb people moving from rural to urban areas. The scope for each UA is referred to in the planning document for UAs as proposed by the State Council of China. Table 1 lists the cities in the 19 UAs.

Data and methods

Data sources

The research data consists of three types: (1) the $PM_{2.5}$ data are derived from inversion of RS images. The raster data for the variability in the global atmospheric $PM_{2.5}$ data (http://earthdata.nasa.gov) for the years 2000 to 2016, published by NASA and having a resolution ratio of 0.1°, were used as the basic research data. The aerosol optical depth (AOD) data inverted from the RS images have the advantages of low cost, wide regional coverage, and high precision; thus, such data are widely regarded as an index of $PM_{2.5}$. (2) The geographic data and the administrative boundaries for the UAs were derived from basic geographic data (1:4 million items) for China. (3) The socioeconomic data were derived from the *China Statistical Yearbook* (2001–2017a) and the *China Urban Statistical Yearbook* (2001–2017b).

Methodology

Spatial autocorrelation model

Global spatial autocorrelation and local spatial autocorrelation were used to study the spatial autocorrelation of $PM_{2.5}$ in the UAs. Some 223 cities in the UAs were selected as space units. The research procedures and formulae adopted were based on the work of Xue et al. (2020).

(1) Global spatial autocorrelation

The average similarity of $PM_{2.5}$ concentrations between adjacent regions may be determined by the Global Moran's I value and may be measured using Eqs. (1) to (4):

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

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{2}$$

$$Z_i = Y_i - \overline{Y} \tag{3}$$

$$Z_j = Y_j - \overline{Y} \tag{4}$$

where I denotes the index of global spatial autocorrelation, Y_i and Y_j denote the $PM_{2.5}$ concentrations of cities i and j, $\overline{Y}$ denotes the average concentration value of $PM_{2.5}$, w_{ij} denotes the spatial weight matrix, and n denotes the number of space units. If I is greater than 0, the space units have a positive spatial autocorrelation, and the larger the value is, the stronger is the spatial agglomeration of the $PM_{2.5}$ between different cities. Conversely, when I is less than 0, the $PM_{2.5}$ has a negative spatial autocorrelation, and a smaller value indicates a stronger spatial dispersion of the $PM_{2.5}$ concentrations between different cities. The significance test for the Global Moran's I value may be measured using Eq. (5):

$$Z(I) = \frac{[I - E(I)]}{\sqrt{\mathrm{Var}(I)}} \tag{5}$$

where $Z(I)$ denotes the significance of Moran's I, $E(I)$ denotes the mathematical expectation of Moran's I, and $\mathrm{Var}(I)$ denotes the variance of Moran's I.

Table 1 Cities in the 19 urban agglomerations

UA	City
Beijing Tianjin Hebei UA	Beijing, Tianjin, Tangshan, Baoding, Langfang, Qinhuangdao, Cangzhou, Zhangjiakou, Chengde, Shijiazhuang, Xingtai, Hengshui, Handan
Yangtze River Delta UA	Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou, Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng
Pearl River Delta UA	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhongshan, Dongguan, Huizhou, Zhaoqing
Middle reaches of Yangtze River UA	Wuhan, Huangshi, Ezhou, Huanggang, Xiaogan, Xianning, Xiantao, Qianjiang, Tianmen, Xiangyang, Yichang, Jingzhou, Jingmen, Changsha, Zhuzhou, Xiangtan, Yueyang, Yiyang, Changde, Hengyang, Loudi, Nanchang, Jiujiang, Jingdezhen, Yingtan, Xinyu, Yichun, Pingxiang, Shangrao, Fuzhou, Anji
Chengdu Chongqing UA	Chongqing, Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guangan, Dazhou, Yaan, Ziyang
South Central Liaoning UA	Shenyang, Dalian, Anshan, Yingkou, Fushun, Tieling, Dandong, Panjin, Benxi, Liaoyang, Fuxin, Huludao, Jinzhou
Shandong Peninsula UA	Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Binzhou, Dehou, Liaocheng, Linyi, Heze, Laiwu
West coast of Taiwan Strait UA	Fuzhou, Quanzhou, Xiamen, Zhangzhou, Putian, Ningde, Chaozhou, Jieyang, Shantou, Shanwei, Wenzhou
Harbin Changchun UA	Harbin, Daqing, Qiqihar, Suihua, Mudanjiang, Changchun, Jilin, Siping, Liaoyuan, Songyuan, Yanbian
Central Henan UA	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Xinxiang, Jiaozuo, Xuchang, Luohe, Jiyuan, Hebi, Shangqiu, Zhoukou, Jincheng, Bozhou
Guanzhong Plain UA	Xian, Baoji, Xianyang, Tongchuan, Weinan, Shangluo, Yuncheng, Linfen, Tianshui, Pingliang, Qingyang
Beibu Gulf UA	Nanning, Beihai, Qinzhou, Fangchenggang, Yulin, Chongzuo, Zhanjiang, Maoming, Yangjiang, Haikou, Danzhou, Dongfang
Northern slope of Tianshan Mountains UA	Urumqi, Karamay, Shihezi, Changji, Fukang, Kuitun, Wusu, Wujiaqu
Central Shanxi UA	Taiyuan, Yangquan, Jinzhong, Xinzhou, Changzhi, Fenyang, Xiaoyi
Hohhot Baotou Erdos Yulin UA	Hohhot, Baotou, Erdos, Yulin
Central Yunnan UA	Kunming, Qujing, Yuxi, Chuxiong
Central Guizhou UA	Guiyang, Zunyi, Anshun, Bijie
Lanzhou Xining UA	Lanzhou, Xining, Baiyin, Dingxi, Haidong, Linxia
Ningxia along the Yellow River UA	Yinchuan, Shizuishan, Wuzhong, Zhongwei

(2) Local spatial autocorrelation

Local spatial autocorrelation can reflect the level of influence of local space units to global space units and the degree of correlation of $PM_{2.5}$ values between a region and its neighbors. It can be measured using Eq. (6) as follows:

$$I' = \frac{n\left(x_i - \overline{x}\right)\sum_{j=1}^{m} W_{ij}\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}, \quad (i \neq j) \tag{6}$$

where x_i and x_j denote the $PM_{2.5}$ concentrations of cities i and j, w_{ij} denotes the spatial weight matrix, n denotes the number of space units, and m denotes the number of contiguous space units of city i. The significance test for local Moran's I can be calculated by $Z(I)$, and the formula is similar to Eq. (5). If I' is significantly positive, this indicates that there is a significant local spatial positive autocorrelation and spatial clustering. In contrast, if I' is significantly negative, this indicates that there is a significant local negative spatial autocorrelation and spatial dispersion.

The space units with a significance reaching a certain threshold (p = 0.05) can be categorized into four types of spatial autocorrelation by comparing the numerical value of $Z(I)$ and the significance of I. If I is significantly positive and $Z(I > 0$, the space unit is termed a "high–high" type and this indicates that the $PM_{2.5}$ concentrations in this space unit and in the contiguous space units are high; this type can be termed a hot spot. If I is significantly positive and $Z(I < 0$, the space unit is termed a "low–low" type and this indicates that the $PM_{2.5}$ concentrations in this space unit and contiguous space units

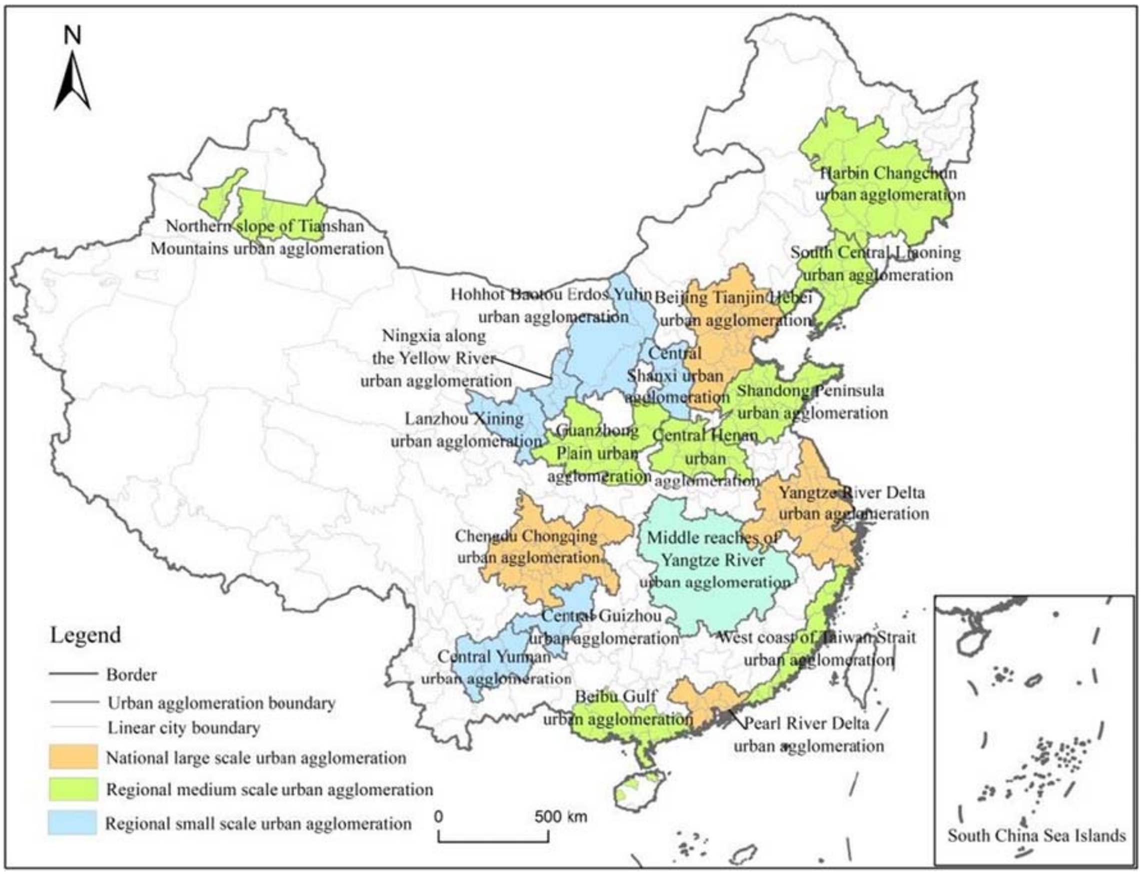

Fig. 1 The 19 urban agglomerations in China

are low; this type can be termed a cold spot. If I is significantly negative and $Z(I > 0$, the space unit is termed a "high–low" type and indicates that the high $PM_{2.5}$ space units are surrounded by low contiguous space units. If I is significantly negative and $Z(I < 0$, the space unit is termed a "low–high" type and indicates that the low $PM_{2.5}$ space units are surrounded by high contiguous space units.

Geodetector method

The spatial heterogeneity of the data set can be searched using the Geodetector method to reveal the factors influencing the research object. The core idea of the Geodetector method is as follows: If an independent variable has influence on a dependent variable, then the spatial distributions of the independent variable and the dependent variable should be similar (Wang et al. 2010). The method is applicable to not only numerical data but also determinate data, and the relationship between different factors and dependent variables can be analyzed (Wang and Xu 2017). Factor detection in this model can test whether one factor is the reason for the difference in the spatial distribution of a certain index value or not. The specific approach used is to compare the total variance of the index in the different categories with the total variance of the index for the whole study area. The research procedure and formula adopted are based on the work of Liu and Hao (2020). The model is described as follows:

$$P_{D,H} = 1 - \frac{1}{n\sigma_H^2} \sum_{i=1}^{n} n_{D,i} \sigma \frac{2}{H_{D,J}} \tag{7}$$

where $P_{D,\ H}$ indicates the explanatory power for the factor which influences the $PM_{2.5}$ concentration; D indicates the factors influencing the $PM_{2.5}$ concentrations; n and σ^2 indicate the overall sample quantity and the variance of the research region, respectively; m indicates the number of categories of factors which influence the $PM_{2.5}$ concentrations; $n_{D,\ i}$ indicates the number of the D index for category-i samples; and $P_{D,\ H}$ ranges from 0 to 1, and a larger value indicates the factor has a stronger explanatory power to change the $PM_{2.5}$ concentration.

Spatio-temporal trends of $PM_{2.5}$

Temporal characteristics of $PM_{2.5}$

The temporal trends for the $PM_{2.5}$ concentrations for the 19 UAs in 2000–2016 are illustrated in Fig. 2. The average values

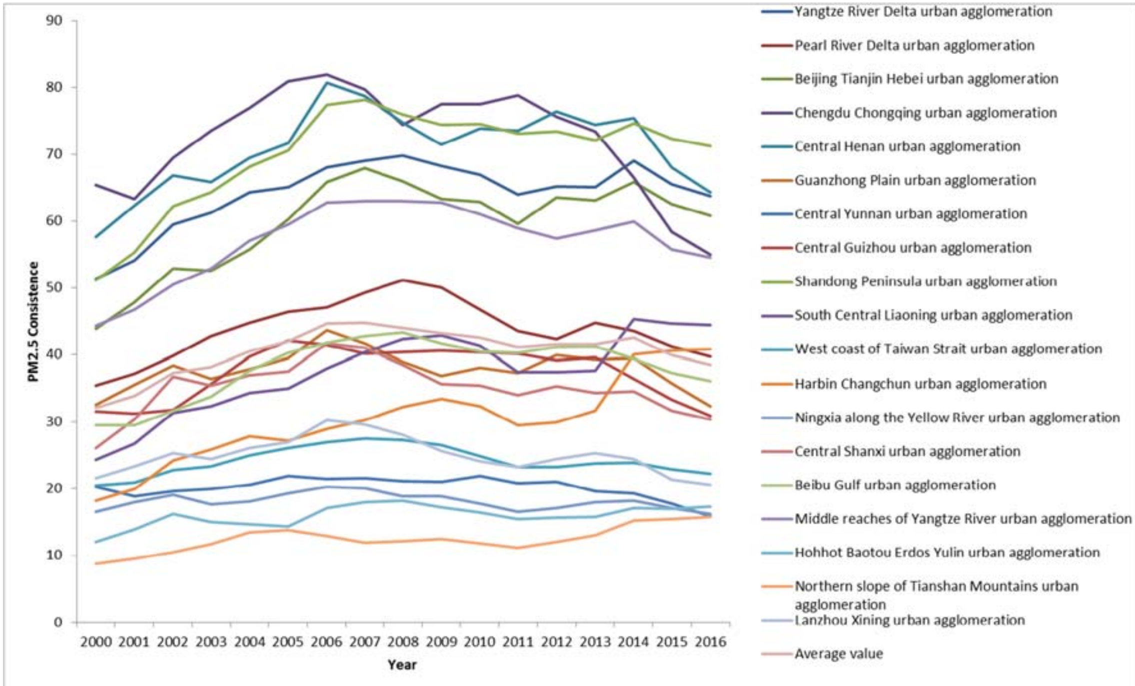

Fig. 2 Temporal trends for the $PM_{2.5}$ concentrations in the 19 urban agglomeration in China

for the $PM_{2.5}$ concentrations in the 19 UAs when plotted on a time basis gave an inverted U-shaped curve. In the period 2000–2007, the average $PM_{2.5}$ concentrations increased from 32.18 to 44.79 μg/m^3, and for 2008–2016 the values decreased from 44.04 to 37.32 μg/m^3. The $PM_{2.5}$ variability for the Yangtze River Delta UA, the Pearl River Delta UA, the Chengdu Chongqing UA, the Central Guizhou UA, the Shandong Peninsula UA, the west coast of the Taiwan Strait UA, the Central Shanxi UA, the Beibu Gulf UA, the middle reaches of the Yangtze River UA, and the Lanzhou Xining UA also exhibited inverted U-shaped curves, the inflection points corresponding to the years 2008, 2008, 2006, 2005, 2007, 2007, 2006, 2008, 2007, and 2006, respectively. Inflection points for the Beijing Tianjin Hebei UA, the Central Henan UA, and the Guanzhong Plain UA were also observed, but the $PM_{2.5}$ variabilities exhibited upward trends for some years after the inflection points. Thus, the $PM_{2.5}$ temporal profiles for these UAs exhibited N-shaped curves. The $PM_{2.5}$ values for the Central Yunnan UA, the Hohhot Baotou Erdos Yulin UA, the Ningxia along the Yellow River UA, and the Northern slope of the Tianshan Mountains UA were lower than for the other urban UAs. The $PM_{2.5}$ values for the South-Central Liaoning UA and the Harbin Changchun UA did not exhibit inflection points, the $PM_{2.5}$ values showing an increasing upward trend. In general, the $PM_{2.5}$ values for most of the UAs exhibited inflection points in the temporal profiles, reflecting significant changes and developments in the built environment and environmental protection policies. Adjustments to the industrial structure and improvements in energy efficiency also had an effect on the suppression of particulate emissions including the $PM_{2.5}$.

Spatial characteristics of $PM_{2.5}$

Global spatial autocorrelation

A spatial autocorrelation test for the $PM_{2.5}$ concentrations in the 19 UAs for 2000–2016 was performed using ArcGIS, and the results are presented in Table 2. The Global Moran's *I* values were positive, and the values passed the 5% significance test. The results reflect similarities in the spatial characteristics of the $PM_{2.5}$ concentrations for the 19 UAs; therefore, statistical analysis of hot and cold spots may be performed. The Global Moran's *I* value peaked in 2012 and then decreased year by year; thus, the spatial agglomeration of the $PM_{2.5}$ levels for the 19 UAs reached an inflection point in 2012 and appeared later than the time of the inflection point of $PM_{2.5}$. This explains the time lag effect for the spatial autocorrelation of $PM_{2.5}$. The main reason for the time lag is that once the $PM_{2.5}$ exhibits spatial agglomeration characteristics, it will be more difficult to control the air pollution, which leads to the time lag and the later appearance of the inflection point.

Local spatial autocorrelation

The results for local spatial autocorrelation analysis of the $PM_{2.5}$ concentrations for the 19 UAs in 2000, 2005, 2010, and 2016 are displayed in Fig. 3. The results for the other

Table 2 The Global Moran's I values for $PM_{2.5}$ concentrations in the 19 urban agglomerations

Year	Global Moran's I	P value
2000	0.8271	0.0276
2001	0.8225	0.0241
2002	0.8226	0.0168
2003	0.8254	0.0183
2004	0.8300	0.0191
2005	0.8286	0.0215
2006	0.8244	0.0181
2007	0.8128	0.0176
2008	0.8059	0.0164
2009	0.8092	0.0168
2010	0.8187	0.0148
2011	0.8326	0.0139
2012	0.8261	0.0154
2013	0.8149	0.0161
2014	0.8033	0.0212
2015	0.8015	0.0252
2016	0.7982	0.0308

years are presented as Supplementary material. The city-level space units in the UAs, which exhibit significant local spatial autocorrelation, can be divided into four types based on local spatial autocorrelation analysis, that is, high–high, low–low, high–low, and low–high.

The high–low type is where the $PM_{2.5}$ concentrations in one city are significantly higher than that of adjacent cities, and the spatial pattern is high in the middle and low in the peripheries. Xianyang city (Guanzhong Plain UA) in 2008, 2010, and 2015 belonged to this category. The level of $PM_{2.5}$ concentrations for the UAs in Northwest China is lower than in other UAs. Thus, once a city in this region exhibits serious pollution after a few years, the high–low category will appear.

The low–high type is where the $PM_{2.5}$ concentrations in a particular city are significantly lower than that of adjacent cities, and the spatial pattern is low in the middle and high in the peripheries. Yicheng city (Yangtze River Delta UA) in 2002–2016, Xingtai city (Beijing Tianjin Hebei UA) in 2000–2015, and Yichang city (middle reaches of Yangtze River UA) in 2000–2001, 2009–2010, and 2013–2014 belonged to this category. This situation may reflect the fact that the pollution levels in these three cities are relatively low considering their UAs as a whole.

The high–high type is where the $PM_{2.5}$ concentrations for a particular city and the adjacent cities are high, such that there are consistently high $PM_{2.5}$ concentrations. The Beijing Tianjin Hebei UA, the Yangtze River Delta UA, the Shandong Peninsula UA, and the Central Henan UA for 2000–2016 all belonged to this category. Also, the Chengdu Chongqing UA in 2000–2013 belonged to this type, while the number of UAs belonging to this type began to decrease significantly after 2014. The middle reaches of the Yangtze River UA belonged to the high–high type except for the years 2005, 2007, and 2012. It is clear that these four UAs are characterized as having large populations and large amounts of industrial emissions; thus, there is a close relationship between population agglomeration, industrialization, and air pollution.

The low–low type is where the $PM_{2.5}$ concentration in a particular city and adjacent cities are low, and where there are consistently low $PM_{2.5}$ concentrations. There was a declining trend in the number of cities of this type with 44 in 2000 and 37 in 2017. In the year 2000, the cities of this type were distributed in the Northern slope of the Tianshan Mountains UA, the Hohhot Baotou Erdos Yulin UA, the Ningxia along the Yellow River UA, the Lanzhou Xining UA, the Harbin Changchun UA, the South Central Liaoning UA, the Central Yunnan UA, and the west coast of the Taiwan Strait UA. In 2016, cities of the low–low type were distributed in the Northern slope of the Tianshan Mountains UA, the Hohhot Baotou Erdos Yulin UA, the Ningxia along the Yellow River UA, the Lanzhou Xining UA, the Central Yunnan UA, and the west coast of the Taiwan Strait UA. Except for the west coast of the Taiwan Strait UA, all other UAs are located in the central and western regions of China. It is also of interest to note that the central and western regions of the country were less polluted than the eastern regions.

Influencing factors of $PM_{2.5}$ in UAs

A UA is an area where the cities and the inhabitants are highly concentrated, and the natural conditions of the area confer certain advantageous. In this study, the influence of socioeconomic factors on the concentrations of $PM_{2.5}$ in the UAs was examined. Eight socioeconomic factors were chosen in an attempt to estimate their contributions to $PM_{2.5}$ formation in the UAs. The eight factors were economic growth, industrial structure, economic openness, the rate of population urbanization, the rate of land urbanization, technical advancement, the extent of environmental regulation, and the structure of energy consumption. The relevant data were obtained from the China Urban Statistical Yearbook (2001–2017b) and the China Energy Statistical Yearbook (2001–2017c).

Economic growth, expressed as per capita GDP, will correspond to an increase in output level per unit time, and this expansion of output may lead to an increase in industrial emissions unless new cleaner technologies are adopted (Zhang and Wang 2014). The industrial sector is a large contributor of airborne emissions (Shao et al. 2011), and the greater the proportion of secondary industries in the industrial structure, the less probability there will be of airborne emissions being

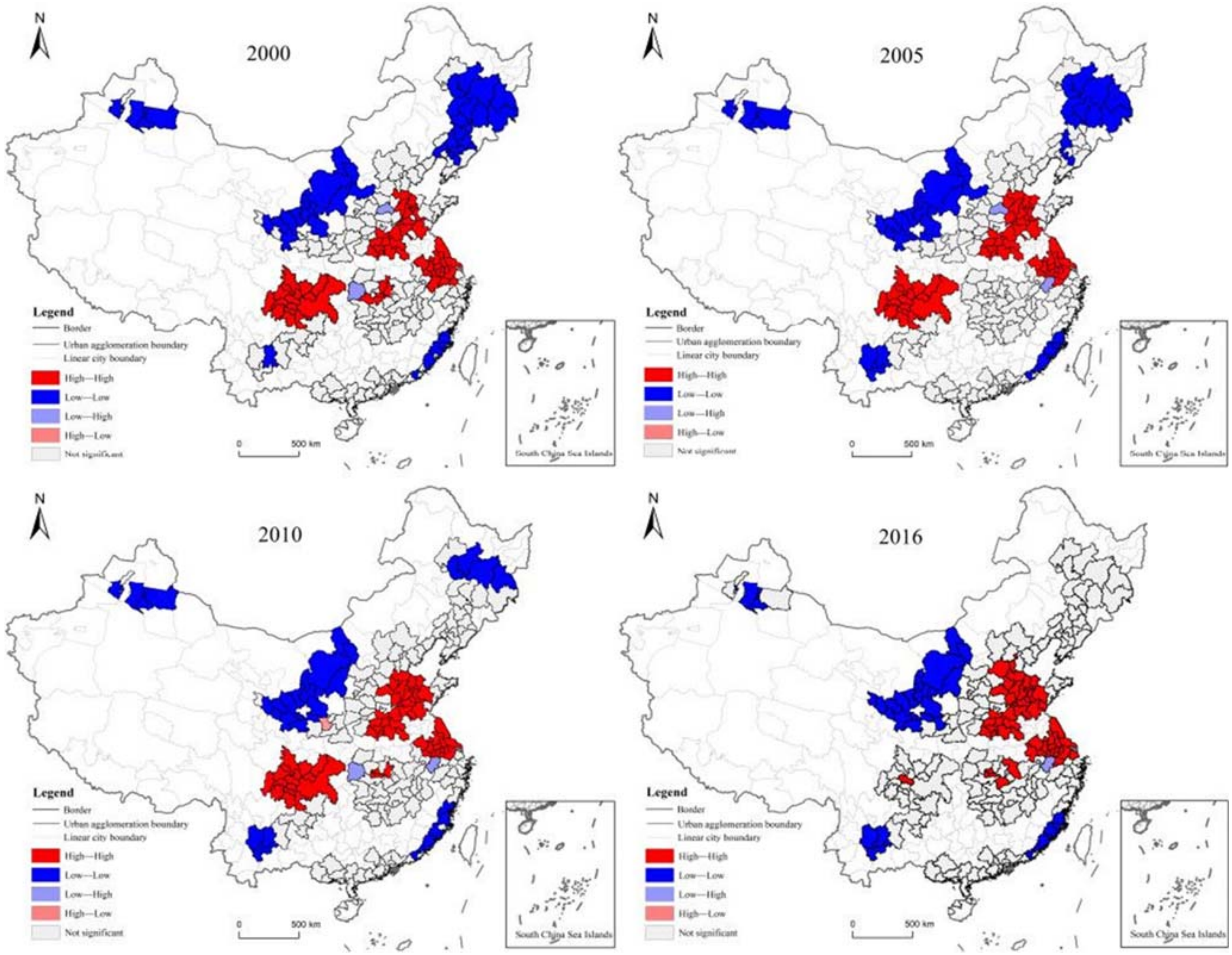

Fig. 3 Local spatial autocorrelation of $PM_{2.5}$ concentrations in 2000, 2005, 2010 and 2016

reduced. Economic openness may be expressed in terms of the amount of foreign capital utilized per 10,000 persons, and this factor has a dual impact on air pollution (He 2006; Wagner and Timmins 2009); thus, this factor should be taken as one of the factors influencing $PM_{2.5}$ concentrations. The rate of population urbanization expressed by the urban population ratio, the rate of land urbanization expressed by the proportion of built-up areas, urbanization will increase the demand for energy and resources (Perry 2013), which will have an impact on the atmospheric environment. Technical advancement expressed by the number of patents granted per 10,000 people, should not only contribute to a reduction in air pollutant emissions, but may also increase emissions of air pollutants (Shao et al. 2019); hence, the overall impact on air pollution is uncertain. The extent of environmental regulation expressed by the extent of environment-friendly municipal solid waste treatment operations, and stricter environmental regulations, will force enterprises to either opt for emissions reduction technology or relocate; hence, it is vital to restrict air pollutant emissions (Huang and Lin 2013). Finally, the structure of energy consumption expressed by the proportion of coal consumption is a critical factor, given that coal combustion represents a considerable source of air pollution. Thus, maintaining a high proportion of coal in the energy market structure is not conducive to reducing airborne emissions.

Table 3 lists the q value data for the factors influencing the $PM_{2.5}$ concentrations. According to the results, the contributions from the rate of land urbanization and the structure of energy consumption were significantly higher than the other factors, and the contribution of these two factors has continued to increase gradually over time. Therefore, the rate of land urbanization and the structure of energy consumption may be regarded as the main factors which influence $PM_{2.5}$ pollution in UAs in China. Land urbanization is a main driver for promoting the rapid development of China's urbanization, and it is growing at a faster rate than that of population urbanization. In land urbanization, China has embarked on what might be called "urban sprawl construction," a process whereby derelict land is developed and used for construction of buildings and infrastructure and for cultivation purposes. Construction

Table 3 *q* value detection results for the factors influencing $PM_{2.5}$ concentrations

Year	Economic growth	Industrial structure	Economic openness	Rate of population urbanization	Rate of land urbanization	Technical advancement	Extent of environmental regulation	Structure of energy consumption
2000	0.0072	0.0665	0.0345**	0.0387	0.2454	0.0853**	0.0072	0.3109
2001	0.0089	0.0635	0.0423**	0.0542	0.2412	0.0973**	0.0091	0.3224
2002	0.0123	0.0234	0.0315**	0.0521	0.3894	0.0652	0.0152	0.3745
2003	0.0132	0.0355	0.0379**	0.0324	0.3421	0.0523	0.0110	0.3893
2004	0.0133	0.0598	0.0399**	0.0424	0.4921	0.0342	0.0142	0.3987
2005	0.0157	0.0672	0.0489**	0.0268	0.5234	0.0432	0.0197	0.3823
2006	0.0189	0.0824	0.0499	0.0389	0.5893	0.0578	0.0174	0.4123
2007	0.0246	0.0642	0.0589**	0.0274	0.5123	0.0576	0.0187	0.4145
2008	0.0296	0.0654	0.0634**	0.0521	0.6394	0.0678	0.0219	0.4239
2009	0.0287	0.0678	0.0646**	0.0562	0.7942	0.0783**	0.0231	0.4398
2010	0.0360	0.0399	0.0787**	0.0372	0.7189	0.0624**	0.0238	0.4528
2011	0.0268	0.0462	0.0854**	0.0467	0.8989	0.0893	0.0187	0.4828
2012	0.0236	0.0569	0.0689**	0.0578	0.5341	0.0789**	0.0256	0.5212
2013	0.0220	0.0438	0.0677**	0.0356	0.9234	0.0659**	0.0278	0.5403
2014	0.0128	0.0562	0.0623**	0.0523	0.9340	0.0442**	0.0319	0.5523
2015	0.0100	0.0768	0.0486**	0.0412	0.9432	0.0372**	0.0328	0.5689
2016	0.0137	0.0653	0.0482**	0.0324	0.9674	0.0238**	0.0397	0.5810

**is significant at the 5% level; others are significant at the 1% level

land in China will continue to be made available (Jin et al. 2019), such that the country will see an increase in land for construction purposes and various industrial activities will increase and spread. Uncontrolled expansion and a disorderly spread of urban construction have resulted in an increase in air pollution in the last two decades as reported by Deng et al. (2015). The energy consumption structure in China is dominated by coal (Lin and Wang 2020); hence, UAs are associated with coal combustion and elevated concentrations of air pollutants such as SO_2, CO, CO_2, NO_X, and other toxic gases, smoke, dusts, and radioactive particles which are emitted during coal combustion.

Conclusions and policy recommendations

Conclusions

In this research, 19 UAs in China were chosen as the research areas, and the $PM_{2.5}$ concentrations were evaluated from analysis of the RS images. The Exploratory Spatial Data Analysis method was used to study the spatio-temporal trends of the $PM_{2.5}$ concentrations, and the Geodetector method was used to examine the influencing factors of $PM_{2.5}$ concentrations. Based on the temporal trends in the data, the average concentrations for $PM_{2.5}$ in the UAs exhibited an inverted U-shaped curve, the inflection point occurred in 2007. With regard to the results for the spatial distributions, the $PM_{2.5}$ in the UAs exhibited clear global spatial autocorrelation, the high–high and the low–low space unit types being the main agglomeration modes. The high–high type was a feature of the Beijing Tianjin Hebei UA, the Yangtze River Delta UA, the Shandong Peninsula UA, and the Central Henan UA, while the low–low type occurred in the Northern slope of the Tianshan Mountains UA, the Hohhot Baotou Erdos Yulin UA, the Ningxia along the Yellow River UA, the Lanzhou Xining UA, the Harbin Changchun UA, the South Central Liaoning UA, the Central Yunnan UA, and the west coast of the Taiwan Strait UA. With respect to the results for the factors influencing the $PM_{2.5}$ in the UAs, the rate of land urbanization and the structure of energy consumption were the main factors.

The contributions and scientific value of this research are reflected in the following: By exploring the spatio-temporal trends and the factors which influence the concentrations of $PM_{2.5}$ in the UAs, scenarios which simulate air pollution in the UAs have been realized such that new knowledge concerning the occurrence of air pollution in the UAs has been realized. This work also contributes to the identification and confirmation of the key socioeconomic factors which influence air pollution in the UAs and hence can aid in the rational development of appropriate pollution control measures for UAs. Of course, this study has limitations, given that only the socioeconomic factors were examined. Clearly, the $PM_{2.5}$

concentrations in UAs are also influenced by topographical and climatic conditions in addition to other external factors and future work will seek to clarify the importance of these sources relative to the socioeconomic factors examined in the present study.

Policy recommendations

Extensive and inefficient land urbanization is one of the main causes of air pollution in UAs. Therefore, judicious planning of the geographical layout of industry and people in public spaces is necessary to realize an efficient economic development model in UAs. First, UAs in China should plan to undertake urban construction at a purposeful scale and avoid a dilution of resources caused by excessive urban dispersion. Second, ecological space can play a role in improving and even purifying air quality; however, the current proportion of ecological space in UAs is low, and the proportion of construction land is high; thus, ecological construction and green space expansion should to be carried out in the UAs. Third, in the process of urbanization in China, large-scale construction of new towns and new districts will lead to rapid land urbanization, and also to the problem of the waste of resources and air pollution. Therefore, the development of new towns and new districts needs to be planned properly with approval being given to the introduction of new and higher regulatory standards with respect to the environment and the buildings infrastructure.

The coal-dominated energy consumption structure is an important source of air pollution in UAs. Moves towards the decarbonization of energy consumption would play a key role in solving air pollution problems in the UAs. First, adjustments in how the energy market operates with control of energy prices and reform of energy systems are needed. The energy prices should reflect supply and demand, the market price, and the costs for environmental regulation. Private capital should be attracted to the energy sector to realize a diversification in energy investments. The arrangements for carbon trading and quotas for carbon emissions should be optimized to achieve an internalization in the costs of environmental pollution and low carbon emissions from energy consumption. Second, measures should be taken at the technical level, to introduce new production and energy consumption technologies. Clean energy cannot replace conventional fossil fuels in the short time scale; therefore, improving production and energy consumption technologies can be seen as an effective way to reduce the sources of $PM_{2.5}$. Clean technology based on desulfurization and denitrification, and improved quality of fuels are needed especially in areas exposed to high concentrations of SO_2 and NO_X. Development and utilization of new low carbon and clean energy technologies are needed in UAs, including, for example, use of natural gas, wind, and nuclear power generation as replacements for traditional fossil fuel-based power generation.

Authors' contributions Caihong Huang analyzed the influencing factors of $PM_{2.5}$ concentrations. Kai Liu conceived and designed the research and was a major contributor in writing the manuscript. Liang Zhou analyzed and interpreted the data for $PM_{2.5}$. All authors read and approved the final manuscript.

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Data availability All data generated or analyzed during this study are included in this article.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

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