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Spatial Variability of $PM_{2.5}$ Pollution in Imbalanced Natural and Socioeconomic Processes: Evidence from the Beijing-Tianjin-Hebei Region of China

WANG Yixu, SUN Shuo, XU Wentian, FU Xuecheng, YAO Lei

(*College of Geography and Environment*, *Shandong Normal University*, *Jinan* 250358, *China*)

Abstract: Accurately identifying and quantifying the factors influencing $PM_{2.5}$ pollution is of great significance for the prevention and control of pollution. However, the redundancy among potential factors of $PM_{2.5}$ may be overlooked. Meanwhile, the inconsistent spatial distribution of the natural and socioeconomic conditions brings unique implications for the cities within a region, which may lead to an uncertain understanding of the relationship between pollution and environmental factors. This study focused on the Beijing-Tianjin-Hebei (BTH) Region, China, which presents complex and varied background conditions. Potential impact factors on $PM_{2.5}$ were firstly screened by combining systematic cluster analysis with a random forest recursive feature elimination algorithm. Then, the representative multi-factor responsible for $PM_{2.5}$ pollution in the region during the key period of 2014–2018 (when the strict national air pollution control policy was implemented). The results showed that the key driving factors of $PM_{2.5}$ pollution in the BTH cities are different, indicating that the uniqueness of a city will have an impact on the leading causes of pollution. Further discussion shows that air control policy provides an effective way to improve air quality. This study aims to deepen the understanding of the risk drivers of air pollution within the BTH Region. In the future, it is recommended that more attention should be paid to the specific differences between the cities when formulating $PM_{2.5}$ concentration control measures.

Keywords: $PM_{2.5}$; Beijing-Tianjin-Hebei Region; multi-factor screening; driving heterogeneity

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1 Introduction

Since the reform and opening-up of China, industrialization and urbanization have developed very rapidly, bringing about a sustained economic growth. However, due to a lack of comprehensive and predictable urban planning in most cities, resource and environmental costs have been ignored in the process of urban development (Gu et al., 2021). Meanwhile, increased population and construction land as well as the high energy consumption have intensified the contradiction between China's economic development and environmental protection. This leads to huge environmental cost and serious regional environmental pollution in China, among which, the problem of air pollution is particularly prominent. According to the *Ecology and Environment Statement of China* in 2018, the days with $PM_{2.5}$ as the primary pollutant accounted for 60% of the severe pol-

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Corresponding author: YAO Lei. E-mail: alex_yaolei@126.com

lution incidents. Thus, $PM_{2.5}$ become as the major concern of air pollution in China (Ministry of Ecology and Environment of the People's Republic of China, 2019). $PM_{2.5}$ is characterized by a small particle size, high activity, the ability to carry a large number of toxic substances (such as heavy metals and viruses) and a long transportation distance. High-concentration $PM_{2.5}$ not only poses a serious threat to the atmospheric environment, but also hinders the construction of urban ecological civilizations, impedes sustainable socioeconomic development, and increases the mortality rate of exposed people (Kampa and Castanas, 2008; Pui et al., 2014; Lelieveld et al., 2015; Yang et al., 2021). Previous study showed that, for every 10 mg/m^3 increase in fine particulate matter, the risk of death from all causes, cardiopulmonary disease, and lung cancer increased by 4%, 6%, and 8%, respectively (Pope et al., 2002). The negative effects or economic losses caused by such pollutants are not estimable (Mu and Zhang, 2013; Chen et al., 2020). Therefore, $PM_{2.5}$ pollution problem in China needs to be addressed urgently (Zhou et al., 2018; Gu et al., 2021).

In order to control the sources of fine particulate matter pollution and improve the air quality in China, since 2012, the Chinese government has adopted a series of air pollution prevention and control measures. However, the air pollution situation remains serious. There is no doubt that research on the potential drivers is particularly necessary to control regional $PM_{2.5}$ pollution. In past studies, scholars have mainly focused on both the natural and socioeconomic factors. Regarding natural factors, scholars have indicated that the accumulations, diffusions, distributions, and variations of $PM_{2.5}$ are significantly affected by vegetation on the ground, topography, and meteorological factors (Lu et al., 2017; Bei et al., 2020; Xu C et al., 2020a; Xu G Y et al., 2020b). In addition, urbanization in terms of socioeconomic development has become the factor that significantly impact local air pollution, either positively or negatively (Lu et al., 2019; Zhao et al., 2019; Xu G Y et al., 2020; Zhang et al., 2020b). In the Beijing-Tianjin-Hebei (BTH) Region, Bei et al. (2020) pointed out that natural conditions such as wind, temperature, and relative humidity perform as important role in the variation of $PM_{2.5}$. Huang et al. (2018) reported that $PM_{2.5}$ pollution is closely related to population density, urbanization rate, total energy consumption, industrial pollutant discharge, *etc*. Meanwhile, considering the city as a complex social-ecological system (Zhao et al., 2021), scholars tended to explore the potential influencers of urban $PM_{2.5}$ pollution from both the natural and socioeconomic perspectives (Liu et al., 2017; Wen et al., 2018). For example, Wu et al. (2021) reported that the temperature and population density are the key driving factors in Chinese urban agglomerations. A more comprehensive index system is very important to understand $PM_{2.5}$ pollution. However, previous studies directly introduce the potential factors into the driving analysis model based on relevant studies (Lu et al., 2017; Zhao et al., 2021). Due to the similarities and complexities among the indicators, inappropriate factors may be brought into the analysis model (Yan et al., 2021b). Therefore, it is necessary to screen the indicators to avoid duplication and redundancy and to ensure a more representative index system to evaluate the causes of $PM_{2.5}$ pollution.

In recent years, scholars have systematically discussed the driving mechanisms of $PM_{2.5}$ pollution at local, regional and national scales, taking into account various indicators (Wang and Fang, 2016; Zhao et al., 2019; Shi et al., 2020; Wu et al., 2020). Most of these studies have taken the study area (such as urban agglomeration) as a unit to reveal the overall regularity. The heterogeneity of natural conditions, population and industrial structures among cities in a region has often been ignored. However, this heterogeneity, in essence, brings about different characteristics of each region (or city) in terms of natural, urbanization, and pollution conditions. Does this further lead to different key drivers affecting different cities? Some studies have considered the unbalanced distribution of factors in different regions, and then discussed the differences in driving factors across countries or urban agglomerations. For example, the population density and economic development level of underdeveloped cities in China showed opposite correlation with $PM_{2.5}$ pollution (Gu et al., 2021). However, less attention has been paid to the pollution-driven relationships between different cities within the same region. For example, many studies only focused on the large city in the BTH Region (Li et al., 2020b; Zhang et al., 2020a). Compared with the large cities in the region, the relatively underdeveloped cities have received less policy, public and academic attention. Therefore, it is necessary to pay attention to the differences in $PM_{2.5}$ pollution response to multiple factors on a detailed spatial scale.

Based on the above background, this study chose the

Beijing-Tianjin-Hebei Region, China as the case study region, where the $PM_{2.5}$ pollution situation is severe and the natural and socioeconomic conditions in the region are unbalanced. Moreover, the BTH Region is a key concern area by the China's environmental policies, such as the *Air Pollution Prevention and Control Action Plan* issued in September 2013 and the *Blue Sky Protection Campaign* launched in 2018, thus it is necessary to understand the extent of $PM_{2.5}$ pollution during the policy implementation period (Ministry of Ecology and Environment of the People's Republic of China, 2013; Wang et al., 2019). The ground $PM_{2.5}$ monitoring data and a representative index system was used to characterize urban air pollution and its influencing factors. The research objectives are as follows: 1) to identify the characteristics of the annual average $PM_{2.5}$ pollution in the study area from 2014 to 2018; 2) to quantify the specific impact of natural and socioeconomic factors on air pollution; and 3) to explore the influence of objective differences in urban natural and socioeconomic conditions on $PM_{2.5}$ pollution driving factors from the perspective of multi-city comparisons within urban agglomeration. The results of this study will help to deepen our scientific understanding of the atmospheric environmental effects of different natural and urbanization conditions, and could provide certain theoretical support for precise pollution prevention and control.

2 Materials and Methodology

2.1 Study area

The Beijing-Tianjin-Hebei Region (BTH) Region is located in North China (36°03′N–42°40′N, 113°27′E–119°50′E) (Fig. 1). The region is an important political and economic area in North China and includes Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, and Hengshui. In the long course of its development, the BTH Region has accumulated a large population and substantial economic resources. Its urbanization rate increased from 43.0% in 2005 to 59.6% in 2018 (The People's Government of Hebei Province, 2019). The rapid development in the BTH Region has been accompanied by high energy consumption and pollutant emissions. Complex terrain and meteorological conditions additionally impede the dispersion of pollutants. Therefore, the BTH Region has become one of the areas with the worst $PM_{2.5}$ pollution in China (Wang et

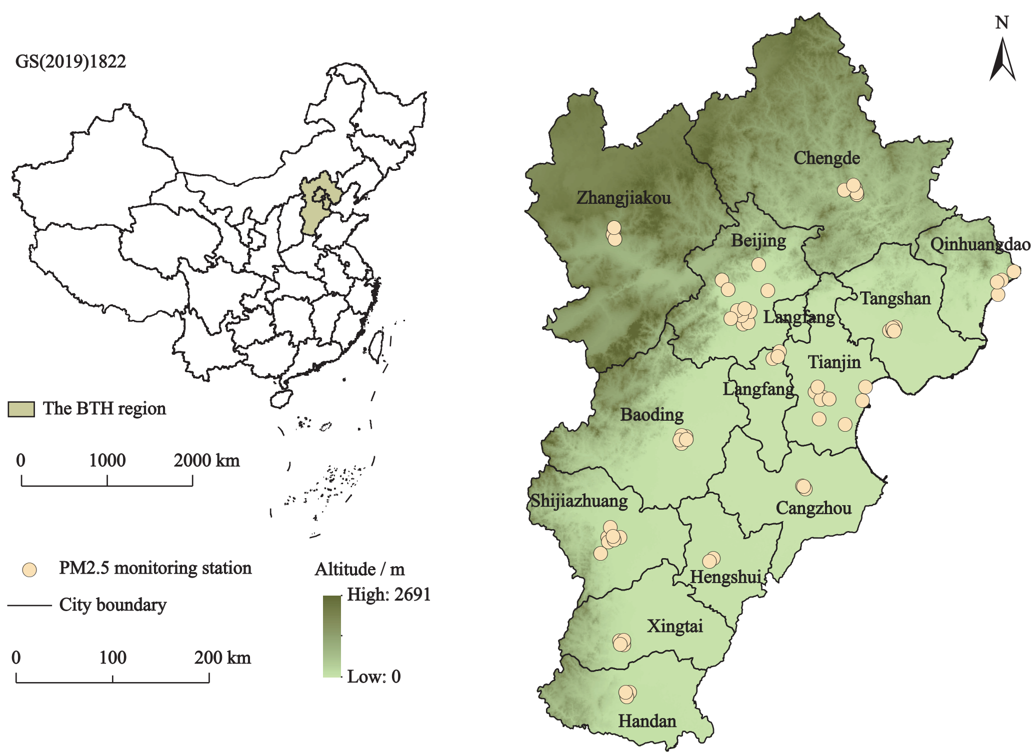

Fig. 1 The location of Beijing-Tianjin-Hebei Region (BTH) and $PM_{2.5}$ monitoring stations

al., 2019; Guo et al., 2021), which suffers enormous environmental pressure and serious threaten on local health. This pollution problem is the focus of much attention. Moreover, there are significant differences in natural and socioeconomic conditions in the cities of the BTH Region. This regional heterogeneity makes it possible to explore the potential differences in the driving forces of the $PM_{2.5}$ pollution in the study region.

2.2 Collection of $PM_{2.5}$ concentration data

In this study, we used ground recorded hourly $PM_{2.5}$ concentration data from the China's National Environmental Monitoring Station. The detailed data were downloaded from the National Urban Air Quality Real-time Publishing Platform (https://air.cnemc.cn:18007/). We collected $PM_{2.5}$ data from 1 January 2014 to 31 December 2018, and the collection range covered 69 monitoring stations in the BTH Region (Fig. 1).

2.3 Statistical analysis and visualization of $PM_{2.5}$

To investigate the dynamics of $PM_{2.5}$ pollution in the BTH Region from 2014 to 2018, we first used statistical methods to summarize the annual average concentration of $PM_{2.5}$ in each city. Thereafter, according to the annual average concentration limit of $PM_{2.5}$ (35 μg/m^3) specified in China's Ambient Air Quality Standard (GB3095-2012), the pollution conditions were divided into six categories with equal concentration interval (i.e., less than 35 μg/m^3, 35–55 μg/m^3, 55–75 μg/m^3, 75–95 μg/m^3, 95–115 μg/m^3, and more than 115 μg/m^3). Cities with similar $PM_{2.5}$ concentrations were classified and visualized using the manual classification method in ArcGIS. Moreover, the $PM_{2.5}$ pollution in the BTH Region was further defined as level I (P-Ⅰ), II (P-Ⅱ) or III (P-Ⅲ) (Table 1). Different grades represent different pollution levels, and the higher level represents more severe $PM_{2.5}$ pollution.

Table 1 $PM_{2.5}$ concentration grouping and pollution types in the Beijing-Tianjin-Hebei Region, China

Range / (μg/m^3)	Pollution levels
0–35	P-Ⅰ
35–55	P-Ⅱ
55–75	
75–95	P-Ⅲ
95–115	
>115	

2.4 Analysis of $PM_{2.5}$ pollution drivers

2.4.1 Collection and screening of impact indicators

$PM_{2.5}$ pollution is the result of the comprehensive effects of natural conditions, economic development, population, city size, transportation and other factors (Wang et al., 2021a; Yan et al., 2021a). According to previous studies on $PM_{2.5}$ pollution, the driving factors are divided into natural and socioeconomic factors. Based on the principle of integrity and availability of panel data, six natural indicators (X_1) were selected and 24 variables (Table 2) were collected from four socioeconomic perspectives (economy (X_2), traffic (X_3), population and city (X_4), and pollutant emission (X_5)). However, there are inevitably similarities and redundancies among various socioeconomic indicators that may affect the driving results. Therefore, it is necessary to introduce the initially selected 24 variables into the subsequent indicator screening model to ensure that the socioeconomic indicators that eventually entered the $PM_{2.5}$ pollution driving analysis model are representative and non-redundant.

The combination of the systematic cluster analysis method and the random forest recursive feature elimination (RF-RFE) algorithm supports the screening of important and representative factors were adopted in this study (Li et al., 2021). First, the systematic cluster analysis method was used to group and classify 24 socioeconomic factors according to their distance or similarity to ensure that indicators in the same cluster remain similar and that there are great differences between indicators in different clusters. Then, a sequential backward selection algorithm based on the random forest and the principle of the maximum interval, namely random forest recursive feature elimination (RF-RFE), was used to rank the importance of each index. Finally, the results of the above two steps were combined to select the most representative socioeconomic indicators in each different cluster category.

2.4.2 Multiple factor regression analysis

Based on the indicator screening results, stepwise regression models were established to explore the response of $PM_{2.5}$ pollution to natural and socioeconomic factors. Stepwise regression is an effective method for identifying indicators that have a significant impact on dependent variables and is widely used in multiple quantitative regression analysis (Li et al., 2020a; Zhu et al., 2020; Wang et al., 2021b). In this research, $PM_{2.5}$

Table 2 Indicators of potential influential factors of $PM_{2.5}$ polution

Theme	Indicators	Unit	Description	Reference
Natural (X_1)	Altitude (X_{11})	m	Indicates elevation changes in the study area	Liu et al., 2019; Wang et al., 2019; Bei et al., 2020; Halim et al., 2020
	Normalized difference vegetation index, NDVI (X_{12})		Represents vegetation coverage and intensity	
	Precipitation (X_{13})	mm	Meteorology information	
	Wind velocity (X_{14})	m/s		
	Air temperature (X_{15})	°C		
	Relative humidity (X_{16})	%		
Economy (X_2)	The proportion of secondary industry (X_{21})	%	Indicates the intensity of industrial development	Han et al., 2014; Ding et al., 2019; Du et al., 2019; Zhao et al., 2019; Liu et al., 2020; Yan et al., 2020; Wu et al., 2021
	The proportion of tertiary industry (X_{22})	%	Indicates the intensity of service industry	
	Per capita disposable income (X_{23})	Yuan (RMB)	Indicates the living standard of regional residents	
	Gross domestic product, GDP (X_{24})	100 million yuan	Reflects the level of economic development	
	Number of industrial enterprise (X_{25})	Count	Reflects the development of industries above the designated size	
	Foreign investment (X_{26})	USD 10000	Reflects the ability to attract foreign investment	
	Research and development internal outlay (X_{27})	10000 yuan	Reflects the scientific and technological development level of the city	
	Number of patent authorizations (X_{28})	Piece		
	Sown area (X_{29})	1000 ha	Reflects the agricultural development intensity	
	Floor space of buildings (X_{210})	10000 m^2	Reflects the activity intensity of the construction industry by the floor space under construction	
Traffic (X_3)	Area of city paved roads (X_{31})	10000 m^2	Reflects the total area of City Paved Roads	Lu et al., 2017; Harrison et al., 2021; Wu et al., 2021
	Public passenger transport (X_{32})	10000 person-times	Reflects traffic activity with the total number of public transported passengers	
	Highway passenger traffic (X_{33})	10000 persons	Reflects traffic activity with the total number of transported passengers on highways	
	Highway freight traffic (X_{34})	10000 t	Reflects traffic activity with the weight of transported goods on highways	
Population and City (X_4)	Population (X_{41})	10000 persons	Reflects the total regional population	Han et al., 2014, 2018; Zhao et al., 2019; Xu et al., 2020a; 2020b
	The proportion of urban population (X_{42})	%	Indicator of the population urbanization rate	
	Population density (X_{43})	Person/km^2	Reflects the intensity of human activity	
	Night light index, NLI (X_{44})		Indicates the level of urbanization	
	Build-up area (X_{45})	km	Reflects the process of urban expansion	
	Area of green land (X_{46})	ha	Reflects the areas used for greening	
	Electricity consumption (X_{47})	10000 kWh	Reflects the total energy consumption of the city	
	Liquefied petroleum gas supply (X_{48})	t		
Pollutant emission (X_5)	Volume of industrial Sulphur dioxide emission (X_{51})	t	Indicates the pollutant emissions associated with $PM_{2.5}$ pollution	Lu et al., 2017; Wang et al., 2021a
	Volume of industrial soot (dust) emission (X_{52})	t		

Notes: The natural (X_1) indicators were provided by the Resources and Environmental Sciences and Data Center, Chinese Academy of Sciences (http://www.resdc.cn/Default.aspx). The NLI (X_{44}) data are from the National Centers for Environmental Information in the United States with a spatial resolution of 500 m. Other statistical data were obtained from the *China City Statis*tical Yearbook (https://navi.cnki.net/knavi/yearbooks/YZGCA/detail), the *Beijing Statistical Yearbook* (http://tjj.beijing.gov.cn/tjsj_31433/), the *Tianjin Statistical Yearbook* (https://stats.tj.gov.cn/tjsj_52032/tjnj/) and the *Hebei Economic Yearbook* (http://www.hetj.gov.cn/hetj/tjsj/jjnj/)

concentration values at each monitoring station were used as response variables, various natural and socio-economic indicators of the cities where the stations are located were used as response variables. The optimal model was selected based on the goodness of fit (R^2), and the probability of factor selection in the model was set to 0.05. Thereafter, standardized coefficients were used to compare the direction and magnitude of the interaction between the selected indicators and $PM_{2.5}$ pollution, and the differences and contribution intensity of the key driving factors in each city within the BTH Region were evaluated. The greater the absolute value of the factor standardization coefficient in the model, the greater the relative contribution of the factor to pollution.

3 Results

3.1 Characteristics of $PM_{2.5}$ pollution in the BTH Region

It can be seen from Fig. 2 that the $PM_{2.5}$ concentrations in the 13 cities in the BTH Region present a spatial pattern of high concentrations in the southwest and low concentrations in the north. The air quality of Zhangjiakou and Chengde was good, and the two cities reached the lowest $PM_{2.5}$ pollution level (P-Ⅰ) in 2017 and 2018. The cities with the highest pollution level (P-Ⅲ) were mainly distributed in Baoding, Shijiazhuang, Hengshui, Xingtai, and Handan in the southwest. In addition, the difference in air pollution between the north and south weakened, and the range of high concentration pollution in the whole region gradually contracted to the southwest. Furthermore, we found that the $PM_{2.5}$ concentration in the BTH Region showed a declining trend from 2014 (94.24 μg/m^3, P-Ⅲ) to 2018 (54.94 μg/m^3, P-Ⅱ) (Fig. 2). Additionally, all the cities in the BTH Region with P-Ⅲ levels were transformed to lower P-Ⅱ level (2014–2018). Moreover, Baoding had the largest decrease (48.17%), followed by Xingtai (47.08%), Langfang (46.62%), and Shijiazhuang (44.27%), while Hengshui (42.41%), Chengde (41.76%),

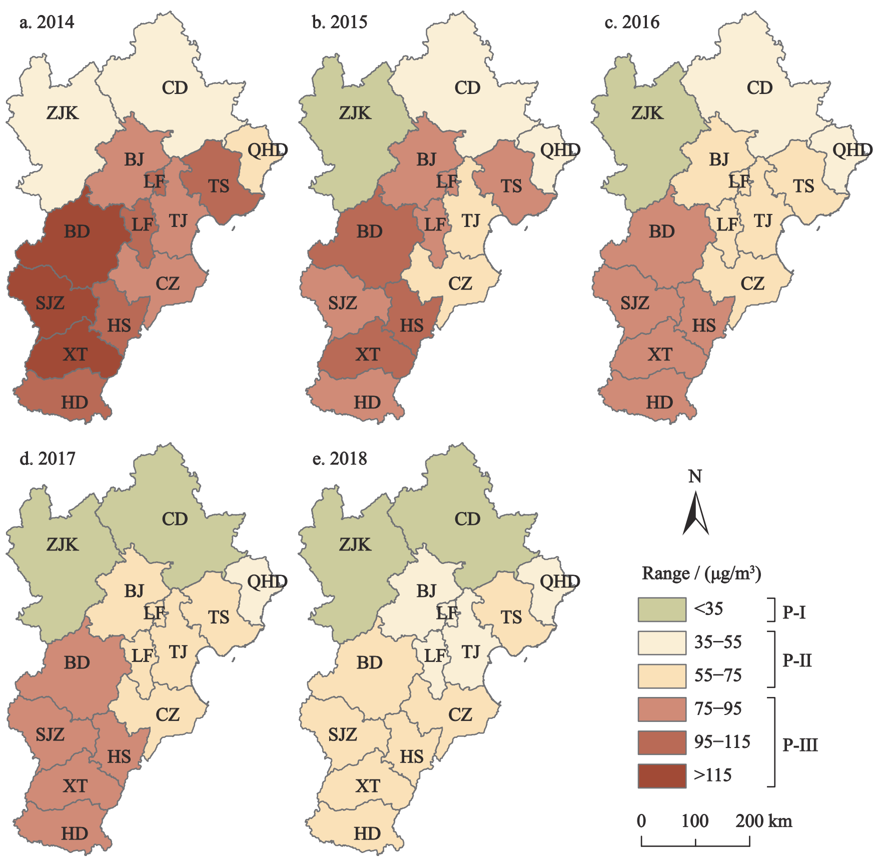

Fig. 2 $PM_{2.5}$ pollution in the Beijing-Tianjin-Hebei Region from 2014 to 2018. BJ: Beijing. TJ: Tianjin. SJZ: Shijiazhuang. TS: Tangshan. QHD: Qinhuangdao. HD: Handan. XT: Xingtai. BD: Baoding. ZJK: Zhangjiakou. CD: Chengde. CZ: Cangzhou. LF: Langfang. HS: Hengshui. P-Ⅰ, P-Ⅱ and P-Ⅲ: $PM_{2.5}$ pollution levels

Beijing (41.48%), Tangshan (40.46%), Tianjin (40.00%), Handan (39.23%), Cangzhou (34.26%), Qinhuangdao (33.87%), and Zhangjiakou had the lowest decrease (10.53%).

3.2 Factors associated with the annual $PM_{2.5}$ in the BTH Region

The results of cluster analysis showed that when the distance of classification was defined as seven, we obtained six groups of indicators with the same number as the natural indicators (Fig. 3). Table 3 showed the results of the RF-RFE method for ranking the indicators. Combined with the above analysis, the six indicators belonging to different clustering categories and ranking the highest in this category were selected, that is, the proportion of secondary industry (X_{21}), the proportion of tertiary industry (X_{22}), sown area (X_{29}), highway passenger traffic (X_{33}), population density (X_{43}), and volume of industrial soot (dust) emission (X_{52}) were selected as representative indicators to discuss the impact of socioeconomic factors on $PM_{2.5}$ pollution.

The stepwise regression results showed that the annual average $PM_{2.5}$ concentrations were significantly correlated with the natural and socioeconomic indicators for the whole BTH Region and each city ($P < 0.05$, except for Zhangjiakou) (Table 4). However, there were significant differences in the main factors affecting $PM_{2.5}$ pollution in different cities. For the BTH Region,

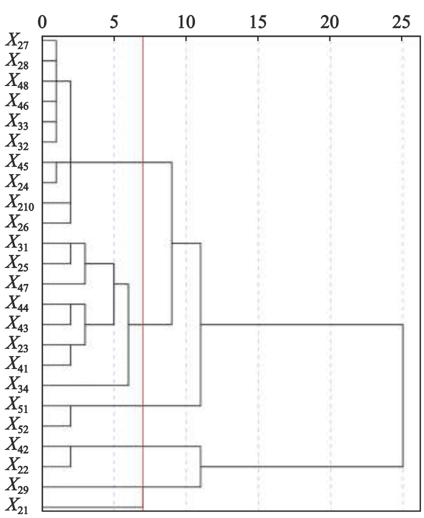

Fig. 3 The systematic clustering result of socioeconomic indicators in the Beijing-Tianjin-Hebei Region from 2014 to 2018. The horizontal axis is the classified distance of cluster analysis. All the indicators were processed by deviation standardization

Table 3 The ranking results of socioeconomic indicators using the RF-RFE method in the Beijing-Tianjin-Hebei Region from 2014 to 2018

Indicators	Rank	Indicators	Rank	Indicators	Rank
X_{21}	1	X_{210}	9	X_{41}	17
X_{43}	2	X_{34}	10	X_{24}	18
X_{25}	3	X_{28}	11	X_{46}	19
X_{33}	4	X_{23}	12	X_{45}	20
X_{47}	5	X_{27}	13	X_{31}	21
X_{44}	6	X_{26}	14	X_{51}	22
X_{29}	7	X_{52}	15	X_{42}	23
X_{22}	8	X_{48}	16	X_{32}	24

the proportion of tertiary industry (X_{22}) was the most important negative driving factor, while population density (X_{43}) was the most important positive driving factor. The proportion of secondary industry (X_{21}) was the second most negative important factor. Moreover, precipitation (X_{13}) was the least important factor, and the effects of the NDVI (X_{12}) and volume of industrial soot (dust) emission (X_{52}) were not important. For individual cities, population density (X_{43}) was the most important (negative) affecting factor in Tangshan, Xingtai, Baoding and Cangzhou. The proportion of secondary industry (X_{21}) was the most important (positive) factor in Qinhuangdao and Handan, and the influence direction of these two indicators on each city was opposite to that of the whole region. Sown area (X_{29}) and highway passenger traffic (X_{33}) were the key (positive) driving factors for Beijing and Langfang, respectively. Volume of industrial soot (dust) emission (X_{52}) was the key (positive) factor in Tianjin and Chengde. The proportion of tertiary industry (X_{22}) was the most important (negative) factor in Hengshui. NDVI (X_{12}) was the key factor in Shijiazhuang, which had a negative effect. In contrast, the NDVI (X_{12}) positively affected $PM_{2.5}$ pollution in Cangzhou, although it was not the most important factor.

4 Discussion

4.1 Relationship between $PM_{2.5}$ concentrations and multiple factors in the BTH Region

This study discussed the relationship between the natural and socioeconomic factors and the annual average $PM_{2.5}$ concentrations in the BTH Region, indicating that $PM_{2.5}$ pollution is affected by multiple factors (Table 4).

Table 4 The stepwise multiple regression models for $PM_{2.5}$ pollution in the Beijing-Tianjin-Hebei Region from 2014 to 2018 based on multiple natural and socioeconomic factors

City	Standardization Coefficient												R^2
	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{21}	X_{22}	X_{29}	X_{33}	X_{43}	X_{52}	
BTH	−0.253**		−0.082**	−0.384**	−0.363**	−0.394**	−1.683**	−3.473**	0.365**	0.581**	1.839**		0.839
BJ						0.130**			0.847**				0.849
TJ									0.280**			0.719**	0.834
SJZ		−1.068**			−0.348*								0.722
TS				−0.493**							−0.522**		0.956
QHD							0.850**						0.722
HD							0.534**				−0.483**		0.933
XT						−0.346**					−1.211**		0.951
BD				−0.459**							−0.531**		0.947
ZJK													
CD												0.911**	0.829
CZ		0.859**									−1.672**		0.915
LF		−0.129**								0.940**			0.976
HS								−0.775**		0.285**			0.983

Notes: * $P < 0.05$, ** $P < 0.01$. BJ: Beijing. TJ: Tianjin. SJZ: Shijiazhuang. TS: Tangshan. QHD: Qinhuangdao. HD: Handan. XT: Xingtai. BD: Baoding. ZJK: Zhangjiakou. CD: Chengde. CZ: Cangzhou. LF: Langfang. HS: Hengshui

In the whole BTH Region, the proportion of tertiary industry (X_{22}) had the most important negative driving effect on $PM_{2.5}$ pollution. The tertiary industry mainly involves industries such as scientific research, information, services industry, and public facility management, which have no direct relationship with the source emissions of air pollution. Furthermore, as tertiary industry development, the adoption of advanced science and technology to improve the specialization level of industrial and agricultural production has become an effective means to alleviate $PM_{2.5}$ pollution (Zhang et al., 2020b). Population density (X_{43}) was the most important positive driver. With the rapid development of urbanization, the continuous agglomeration of the urban population will inevitably lead to more intensive production and daily living needs (Liu et al., 2020). For example, the increase in production and daily living activities such as transportation and urban construction, will be accompanied by indirect energy consumption and air pollutant emissions (Lou et al., 2016). In our study, this is also demonstrated by the positive driving relationship between the traffic (X_3) indicators and $PM_{2.5}$ pollution. In addition to socioeconomic indicators, the impact of natural conditions on regional $PM_{2.5}$ pollution is also important. For example, the topography in the BTH Region is high in the north and low in the south, while the distribution of $PM_{2.5}$ pollution is low in the north and high in the south. To some extent, the negative effect of altitude on $PM_{2.5}$ pollution may be due to the high mountains in the north blocking the air pollutants from the south (Wang et al., 2019).

Further investigation at the city scale revealed that there are substantial differences in the key drivers of $PM_{2.5}$ pollution in different cities. This may be because the cities have different natural conditions and socioeconomic development levels. For example, in Beijing and Tianjin, the economic development level is far more advanced than in other cities in the BTH Region, but the urban economic structure of these cities is completely opposite. Beijing completed the industrial transformation earlier (Tian et al., 2010). However, Tianjin is a traditional industrial city with the secondary industry accounting for more than 40% of its industrial structure. Pollutant emission (X_5) has a great impact on the urban environment.

Similarly, although Qinhuangdao and Chengde are both new industrial cities, their key drivers are different. In Qinhuangdao, the four pillar industries are equipment manufacturing, food processing, glass production and metal smelting (Qinhuangdao Municipal People's

Government, 2019). Equipment manufacturing and metal smelting, which have a high energy consumption, take up a prominent proportion of these industries. Therefore, these energy-intensive industrial activities have a significant impact on the $PM_{2.5}$ pollution in Qinhuangdao. In Chengde, where the industrial energy consumption is also great, the key contributor to air pollution is volume of industrial soot (dust) emission (X_{52}), not the secondary industry. According to the *Statistical Bulletin of Chengde in 2018* (Chengde Municipal People's Government, 2019), iron ore mining and ferrous metal smelting and rolling industry, accounted for 47.5% of the industries above the designated size of the city. In the iron ore mining industry, each production process creates a large amount of air particulate matter, such as the dust emission by the transport of mineral raw materials and ore crushing and sieving classification. This will increase the environmental pressure in Chengde. Therefore, the government needs to pay attention to the targeted industrial adjustment to improve $PM_{2.5}$ pollution, such as the reasonable planning and protection of mineral resources in Chengde and strengthening the supervision and management of the iron ore mining and dressing industry.

In Shijiazhuang, NDVI (X_{12}), which can represent vegetation coverage, has a significant positive effect on air quality. This relationship between urban greening and air pollution has been confirmed in other national and regional studies (Xu et al., 2019; 2020a). Shijiazhuang is the second city in the BTH Region to win the title of National Forest City (Hebei Forestry, 2015). This means that the city has a strict supervision system for urban forest construction, under which the urban green vegetation area continuously increases. Vegetation can not only fix the soil, thus reducing the generation of $PM_{2.5}$, but also capture, retain and filter part of the dust pollution, so that the particulate matter in the air will stay in the vegetation zone (Wang et al., 2019; Xu et al., 2020a). This means that urban greening will eventually ease the air pollution pressure, therefore, in other cities, governments should encourage attention to the concept of the Ecological City or the Garden City.

4.2 Differences in $PM_{2.5}$ drivers between the BTH Region and single city

The regression results showed that, when exploring the relationship between various factors and $PM_{2.5}$ pollution from the perspective of the BTH Region and individual city, the results were notably different in the significance or impact direction of factors. Moreover, such differences may be caused by different research scales (Wang et al., 2021b; Xu et al., 2022). Taking urban agglomerations as a whole may weaken the influence of the unique characteristics of individual cities on pollution, as well as highlight the comprehensive characteristics of the impact on air pollution in the whole region.

For example, as mentioned above, due to the unique industrial characteristics of Tianjin and Chengde, soot emission has become the main driving factor impacting pollution in those cities, which is different from that of the BTH Region. In addition, although the highway passenger volume (X_{33}) was not significant in many cities, it can not be denied that X_{33} is a significant factor affecting $PM_{2.5}$ pollution in the BTH Region. In some cities, traffic (X_3) factors were relatively unimportant due to strong traffic control policies. Furthermore, the transformation of the industrial structure and the closure of heavily polluting enterprises in the BTH Region in recent years may help to explain the negative driving effect of the proportion of secondary industry (X_{21}) on BTH pollution, whereas it was positive in a few cities experiencing rapid development in high energy consuming industries (such as Qinhuangdao and Handan). Similarly, population density (X_{43}) had a negative effect on pollution in Tangshan, Handan, Xingtai, Baoding and Cangzhou, in contrary to the BTH Region as a whole. Therefore, should we revisit the specific impact of human activities on pollution? In fact, a highly concentrated population will not only bring greater daily living needs and emissions, but will also improve the urban environment in anyways, such as the provision of central heating and centralized disposal of waste (Stone, 2008; Shen et al., 2017).

4.3 The role of the clean air policies of the BTH Region

Although the above analysis shows that both the natural and socioeconomic indicators have substantial influence on urban pollution, previous studies found that the regional transmission caused by natural factors such as topography and meteorological conditions is also an important factor affecting the spatial pattern of $PM_{2.5}$ pollution in the BTH Region (Zhang et al., 2018). In addition, meteorological conditions have made little contribution to the improvement of annual average air pollution as there has been little change in recent years (Fan et al., 2020). Combining the above conclusions with the fact that air quality in the BTH Region improved significantly from 2014 to 2018, we have to ask whether the air quality improvement is ultimately caused by socioeconomic development. However, we found that the declining levels of $PM_{2.5}$ concentration were similar among some cities with deeply varied situations of socioeconomic development. For example, Beijing, which has the highest proportion of tertiary industry (more than 75%), has a similar decreasing degree in $PM_{2.5}$ pollution (41.48%) with Tangshan (40.46%), and Tangshan has a lower proportion of tertiary industry (less than 40%). It is likely that the strict clean air policies and emission restriction measures in recent years have significantly mitigated the air pollution in the BTH Region. This view has been validated in other studies (Cai et al., 2017). Environmental policies can reduce $PM_{2.5}$ emissions through industrial governance, technological innovation, vehicle emissions control, and other means. For example, policy restrictions on high energy consuming industries indirectly increased the proportion of tertiary industry in the BTH Region, resulting in regional pollution reduction. The negative correlation between the proportion of tertiary industry (X_{22}) and pollution in our study also proves this finding. Furthermore, Xiao et al. (2020) have confirmed that clean air policies can modify the relationship between the air pollution and economic growth (i.e., improve air quality without affecting the level of economic development). If stricter emission restriction policies were adopted, $PM_{2.5}$ pollution will be further remitted in the future (Li et al., 2019; Yue et al., 2020). Moreover, although the implementation of policies provides a possible way to effectively alleviate air pollution, the annual average $PM_{2.5}$ concentration in the BTH Region (P-Ⅱ) is still higher than the Chinese environmental quality class Ⅱ standard. The $PM_{2.5}$ pollution situation is still a major problem, thus stronger pollution control measures are further needed and the formulation of specific measures should also be concerned.

4.4 Implications and limitations of this study

This study constructed a unique index system for $PM_{2.5}$ pollution impact factor analysis, distinguishing it from other studies. Other research has directly determined the potential driving factors of $PM_{2.5}$ on the basis of previous similar studies (Lu et al., 2017; Zhao et al., 2021), which may be difficult to avoid the redundancy of factors. Whereas this study further screening of potential influencing factors meant that the indicators that finally entered the driving analysis model were more representative. This attempt can provide more abundant and reliable information for understanding the factors influencing $PM_{2.5}$ pollution. Moreover, this study points out that, due to differences in natural and socioeconomic conditions of the study region, each city has its dominant factors affecting $PM_{2.5}$ pollution. Most of the previous relevant studies on the whole region have ignored the refining difference characteristics driving $PM_{2.5}$ pollution within the region, bringing uncertainty to the formulation of further control measures. Our emphasis on such regional heterogeneity can provide a reference for deeper understanding of the driving differences of air pollution. At the same time, based on such differences in driving factors, the different regions should be taken into account when setting expected $PM_{2.5}$ targets. For example, the current targets for air pollution regulation in the BTH Region may be difficult to meet for cities in the Hebei Province. Strict regulations in the region have forced Hebei Province to restrict pillar industries (such as the steel and coal industries) in order to achieve the required $PM_{2.5}$ limit at the cost of slower GDP growth (Xu et al., 2020a). In future studies, specific discussions on urban pollution within the region should be strengthened so as to aid the government to propose targeted measures for regional air pollution control. It should also be noted that policies based on measures such as industrial restructuring may result in huge economic and social costs in the long run, such as unemployment (Wang et al., 2018; Li et al., 2019). In the future, measures such as strengthening urban infrastructure construction, promoting technological innovation and clean energy may be important means to ensure the sustainability of air pollution control.

There are still some limitations to this study. Firstly, the spatial distribution of $PM_{2.5}$ monitoring stations is relatively concentrated, to a certain extent, which can not accurately reflect the pollution status of the whole city. This may affect the accuracy of subsequent evaluation results. Secondly, as this study focuses on the discussion of pollution differences within an urban agglomeration, we failed to further enrich the spatial correlation research due to the limitation of the number and space interval of cities within a single urban agglomeration. Third, although reliable results of the pollution driving analysis can be obtained (Table 4, $R^2 > 0.7$), the accuracy of the model fit may still be limited by the amount of data for a short time span. In future studies, using data with wider spatial coverage and longer time series could help us obtain a higher simulation accuracy, as well as the richer pollution characteristics of $PM_{2.5}$ and the heterogeneity characteristics of the driving factors. Moreover, it must be pointed out that some relevant studies in the northern China support the significant effect of the heating in winter on the $PM_{2.5}$ pollution level, but this is not considered in this study due to limited statistical data acquisition (Wen et al., 2018). Although we selected representative natural and socioeconomic indicators for driving analysis, the complex coupling relationships among the meteorological conditions, urbanization, industrialization, economic development, and air pollution are not included in this study. A deeper understanding of these coupling relationships would be of great significance to the formulation of pollution prevention and control policies.

5 Conclusions

Based on the $PM_{2.5}$ monitoring stations data and natural and socioeconomic indicators, this study analyzed the spatial and temporal variation characteristics of $PM_{2.5}$ pollution in the BTH Region, China from 2014 to 2018. Furthermore, we explored the potential heterogeneity of $PM_{2.5}$ pollution drivers within the study area from the perspective of urban spatial differences. The main conclusions are as follows:

(1) From 2014 to 2018, $PM_{2.5}$ pollution in the BTH Region showed a spatial distribution pattern of low in the north and high in the south, and the air quality for all cities had an obvious improvement.

(2) The key driving factors of $PM_{2.5}$ pollution varied in different study cities. In the BTH Region, economy (X_2) is the most important driver of pollution. In terms of specific cities, natural (X_1) and traffic (X_3) were the key driving factors of $PM_{2.5}$ pollution in Shijiazhuang and Langfang, respectively. Economy (X_2) was the most important driver for Beijing, Qinhuangdao, Handan and Hengshui. Tangshan, Xingtai, Baoding and Cangzhou were most affected by population and city (X_4). The most important influencing factor for Tianjin and Chengde was pollutant emission (X_5).

(3) Cities with large differences in socioeconomic development had a similar decline degree of $PM_{2.5}$ pollution during the policy implementation period. Environmental policies have contributed to improving the pollution situation in the BTH Region.

The significance of this study is to emphasize the driving heterogeneity of imbalanced background conditions on $PM_{2.5}$ pollution by focusing on cities within urban agglomeration. At the same time, identifying the differences arising from the unique characteristics of different cities can facilitate the development of more targeted policies to further control air pollution in the region.

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