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Analysis of the Factors Influencing Urban Size on Air Concentrations of Particulate Matter $PM_{2.5}$ and PM_{10} in China

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Abstract In the construction of resilient cities, regional air pollution prevention plays a pivotal role. Building on the previous research experience, the relationship between air pollution concentration and urban size exhibits a sublinear allometric growth pattern. To identify effective strategies for mitigating particulate matter air pollution, this study quantitatively explored 6 variables influencing urbanization in China's cities and established an allometry model. Empirical analysis was conducted using data from 293 prefecture-level cities and 1,827 county-level cities to examine the relationship between annual concentrations of fine particulate matter $PM_{2.5}$ and PM_{10} in the atmosphere. ① The findings of this study provided partial validation for the Kuznets curve and demonstrated a reverse 'U'-shaped association between urbanization and levels of $PM_{2.5}$ and PM_{10} pollution. ② By partitioning the Hu Huanyong line, this study identified the spatial distribution pattern of $PM_{2.5}$ and PM_{10}. In central and western regions, as urban size expands, inhalable particle concentrations tended to increase further; whereas in the southeast region, inhalable particle concentrations gradually decreased and stabilized after a certain threshold of urban scale expansion was reached. Among the factors influencing urban size, green coverage within built-up areas exerted the most significant impact on both $PM_{2.5}$ and PM_{10} concentrations, followed by the extent of built-up areas and the scale of secondary industries. This study presented an effective strategy for reconciling conflicts between urban expansion and air pollution management, while concurrently promoting resilient cities characterized by high levels of modernization and superior quality.

Keywords Urban size, Allometry, The Kuznets curve, $PM_{2.5}$ and PM_{10}, Urban resilience
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1 Introduction

Rapid urbanization has imposed substantial challenges on the environment. From 1978 to 2022, the Chinese urbanization rate has surged by 3.6 times, housing over 800 million people in towns and cities of varying sizes as of 2018. In the next 2 decades, China is projected to construct 300 cities with a population of over 1 million. Rapid urbanization significantly impacts human health and the local living environment. The relentless expansion of cities, population growth, and industrial development exert immense pressure on the ecological ecosystem[1], with air pollution posing a more severe challenge than other factors. In recent years, the severity of China's central and eastern atmospheric compound pollution has intensified, particularly in urban agglomeration areas such as the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta, where frequent heavy haze episodes occur. According to the *Report on the State of China's Ecological Environment*, in 2018, among the 338 prefecture-level cities in China, $PM_{2.5}$, fine particulate matter, was the primary pollutant with heavy or higher pollution levels for 60% of the total number of days. The air quality guidelines established by the World Health Organization (WHO) indicate that prolonged exposure to $PM_{2.5}$ air pollutants is associated with increased mortality rates in humans, particularly among individuals suffering from cardiopulmonary diseases and lung cancer. Moreover, since 2001, the United States Environmental Protection Agency has incorporated both $PM_{2.5}$ and PM_{10} as particulate matter (PM) pollutants into their regulatory criteria for controlling air pollution[2]. Air pollutants seriously threaten health and impede high-quality economic development to some extent[3-4]. Therefore, it is crucial to comprehensively analyze the influence factors of different urban sizes on the concentration of inhalable particulate matter during the rapid urbanization in China and to discover the overall pattern of change in geographic regions, which will have a positive effect on the construction of "resilient cities" with high levels of modernization and quality, and provide an empirical basis for the mechanism of urban environmental governance and the enhancement of population agglomeration scale effects. It also provides empirical evidence for urban environmental governance mechanisms and planning strategies, such as enhancing the scale effect of population agglomeration.

2 Literature review

The concept of "allometry" has its roots in the 1920s and 1930s, with Huxley first mentioning it in his book *The Problem of Relative Growth in 1932 and his thesis Constant Differential Growth Ratios and Their Significance* in 1924[5]. In biology, Kleiber's law refers to the law of anisotropic scaling between metabolism and organism size[6]. Recent studies by Hilbers, a biologist, have put forward a systematic assessment framework for evaluating wildlife's extinction risk. By examining the correlation between various wildlife statistical parameters and animal body size within the context of anisometric growth, this framework serves as a guiding principle for wildlife conservation efforts[7]. Subsequently, the application of heterochronous growth laws in the abiotic field has gradually emerged. Initially, geographer Narol and biologist Bertalanffy collaborated to integrate the law of anisotropic growth, initially derived from biology and ecology, into the field of geography[8].

Urbanization represents a crucial domain for examining the law of heterogeneous growth. Heteroscedastic growth has been employed to delineate the correlation between an urban system and its largest city within a specific geographical region[9]. In the realm of urban research on hetero-speed relationships, the scale relationship and hetero-speed laws between urban area and population size were initially identified[10] and

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garnered significant attention. Many researchers are now focusing on the correlation between the hetero-speed growth of urban socio-economic indicators and urban population. Schlapfer et al. discovered a super-linear relationship between people's communication activity records and urban population size[11]. Precisely within the realm of conventional biology in China, researchers have investigated the application of heterozygous scaling. Shi et al. established a model founded on the heterozygous growth relationship and resource limitation, delving into forest biomass estimation derived from individual and regional tree height estimations[12]. Moreover, Li et al. analyzed the alterations in the heterozygous growth relationship amidst urban development in China and the underlying factors[13]. In recent years, an increasing number of scholars have focused on the study of the heterogeneous velocity growth of urban scales. For instance, Lan et al.examined the correlation between the fractal dimension of the urban road network and the urban scale in Hong Kong from 1971 to 2011[14]. The researchers discovered a positive anisotropic growth relationship between the structural fractal dimension and indicators such as population, carbon dioxide emissions, GDP, merchandise imports, and exports. Additionally, an inverse anisotropic growth relationship was observed between arable land and agricultural land. Their findings suggest that the structural fractal dimension exhibits an anisotropic growth relationship with city size, potentially indicating diverse relationships, thereby laying the foundation for further urban development research.

The majority of current researches concerning heterogeneous growth in urbanization is focused on whether the human-land relationship aligns with the heterogeneous growth model and identifies the factors contributing to disparate coefficients of heterogeneous growth across diverse regions. However, the existing literature on air quality in urbanization predominantly investigates the correlation between urban form and air quality determinants, as well as the mechanism of influence. Building upon these findings, this study rigorously examines the relationship between different urban sizes and their corresponding annual average concentrations of atmospheric particulate matter $PM_{2.5}$ and PM_{10} in 293 prefectural-level cities and 1,827 county-level cities across China in 2018. It integrates the principles of anisotropic growth with the spatial distribution characteristics of air pollutants in Chinese cities and the effects of anisotropic growth coefficients. By analyzing the main influencing factors and their respective laws impacting the anisotropic growth coefficients of air quality indices, this research provides empirical evidence for the effective management of urban air pollution and the rational planning of urban agglomeration scale and other strategic policies.

3 Date sources and methods

3.1 Data sources and description

The size of a city is influenced by multiple factors, including its economic level, population size, natural conditions, and geographical environment. In 2013, Chun categorized the overall scale of cities into six categories: population size, spatial scale, economic scale, capital scale, labor force scale, and market scale[15]. This thesis combines Chao's City Scale−Environment Quality model established in 2009[16] to develop a stochastic model for assessing the particulate matter $PM_{2.5}$ and PM_{10} of cities of different sizes. The variables considered include the Green rate of built-up area (grba), Urban population (up), Surface area of roads in the built area (srba), Gross Domestic Product (gdp), Urban built-up area (uba), and Industrial and manufacturing area (indu) as shown in Table 1. To address the heteroscedasticity phenomenon, the data units of indicators with a similar nature are standardized and logarithmized using base 10 logarithm transformation (lg). Finally, based on different significance levels, the significant explanatory variables for the fixed model are selected using the stepwise regression method to avoid multicollinearity problems while eliminating insignificant variables.

The data on Green rate of built-up area, Surface area of road in built area, GDP, Urban built-up area, Industrial and manufacturing area in Table 1 are derived from the *2018 Urban Construction Statistical Yearbook*[17] published by the National Bureau of Statistics, as well as statistical yearbooks from various provinces and statistical bulletins on national economic and social development.

The determination of a city's population size is rooted in the number of its urban permanent residents. This study utilizes the fundamental data gathered from the *2018 Statistical Yearbook of Population and Employment*, along with the official websites of each city, encompassing the built-up area and urban resident population statistics of 293 prefectural-level cities and 1,827 county-level cities (excluding Hong Kong, Macao, and Taiwan). Due to the suboptimal administrative functions of counties, a portion of county-level cities lacks in reliable official data.

The distribution characteristics of the Green rate of built-up area, Urban population, Urban built-up area, and Industrial and manufacturing area in China in 2018 are shown in Fig.1 below. According to the simulation analysis conducted using ArcGIS software, Fig.1 clearly demonstrates discernible disparities in the variables influencing urban scale in China during 2018 along the Hu Huanyong Line. A distinct pattern of aggregation characterized by a "southeast high and northwest low" configuration has unequivocally emerged along this line.

The annual average concentration data of $PM_{2.5}$ and PM_{10} employed in this study are derived from the Data Center of the Ministry of Environmental Protection of the People's Republic of China (MEP) and the China Air Quality Online Monitoring and Analysis Platform (CAQAMP), a monitoring website that has established 1,499 monitoring sites in 367 cities nationwide and provides real-time data updates every 24 hours. The thesis calculates the annual averages of $PM_{2.5}$ and PM_{10} concentrations from January 2018 to December 2018 as the primary analysis data, the spatial distribution characteristics of annual average concentrations of $PM_{2.5}$ and PM_{10} are depicted in Fig.2 below.

3.2 Allometry model

The law of heteroscedastic scaling describes the functional relationship between 2 physical quantities that scale with each other over a significant interval[18]. An example is the power law behavior, where the change in one quantity is the power of the other. The spatially self-similar distribution of urban attributes (specific patterns recurring on different spatial time scales) reflects the logic of growth and agglomeration patterns inherent in cities[19].

In the dynamic development of any dynamically changing organism or integrated system,

Table 1 Variables selection of imfluencing factors of Urban size

Explaining variable	Variable Name	Unit	Symbol	Model 1	Model 2
Urban size	Green rate of built-up area	%	grba	grba- PMn	lggrba
	Urban population	10,000	up	up- PMn	lgup
	Surface area of road in built area	10 km²	srba	srba- PMn	lgsrba
	GDP	100 million	gdp	gdp- PMn	lggdp
	Urban built-up area	km²	uba	uba- PMn	lguba
	Industrial and manufacturing area	km²	indu	indu- PMn	lgindu

there are 2 dynamic rates of subjective and local indicators: uniform and non-uniform. In the objective world, from a unit to a country, the phenomenon of an anisotropic rate of development is more common. The law of heterogeneous scaling of the city is expressed as follows.

$$Y = C \times N^B \quad (1)$$

Y–dependent variable (annual average concentrations of $PM_{2.5}$ and PM_{10})

N–independent variable (urban population)

C–constant

B–scaling exponent, B>1 indicates conformity to a super-linear heteroscedastic relationship, B<1 indicates a sublinear heteroscedastic scaling, and B≈1 is a linear relationship.

In most cases, it is difficult to directly observe the anisotropic growth relationship on the scatter plot of Eq.(1). To facilitate the analysis, it is common to convert Eq.(1) to Eq.(2) by taking logarithms on both sides simultaneously:

$$\log Y = \log C + B \times \log N \quad (2)$$

From Eq.(2), it can be seen that it is easier to observe by fitting a linear function to the urban population size (N) and PM concentration (Y) after taking logarithms. If $\log Y$ and $\log N$ are linearly correlated, then the scaling index B between Y and N can be derived to analyze the quantitative scaling relationship further.

4 Data analysis

4.1 Characteristics of the spatial distribution of $PM_{2.5}$ and PM_{10} in China

Changes in atmospheric particulate matter $PM_{2.5}$ and PM_{10} concentrations have traditionally been associated with fossil fuel combustion, transportation emissions, and climatic conditions. The population size is considered one of the primary drivers[20]. With a gradual decrease in dust and sand emissions[21], as well as reduced influence from climate and topography, human activities have become the main contributing factor to air pollution formation. In comprehensive studies on air pollution issues, urban population factors exhibit higher representativeness compared to industrial structure factors[22-23]. Therefore, the disparity in distribution patterns of these two types of atmospheric particulate matter primarily arises from variations in pollutant emission sources and differences in the intensity of human activities across cities.

4.1.1 The spatial distribution of delicate particulate matter $PM_{2.5}$ levels. The spatial distribution of the annual average concentration of fine particulate matter $PM_{2.5}$ in 2018 was characterized by apparent regional agglomeration (Fig.2). Taking the secondary attainment value of the annual average concentration of air quality in China (35 μg/m^3) as the standard, the cities exceeding this standard accounted for 52% of the total number of cities. Among them, the areas with $PM_{2.5}$ annual average concentrations exceeding 104 μg/m^3 are Laiwu City in Shandong Province and Hotan Region in Xinjiang Province; the areas with concentrations between 104 μg /m^3 and 72 μg/m^3 are Anyang City in Henan Province and Kashgar Region in Xinjiang Province; and the areas with concentrations between 72 μg/m^3 and 53 μg/m^3 are located in the southern part of Shanxi Province, the southwestern part of Hebei Province, the northern part of Henan Province, the western part of Shandong Province, the northern part of Anhui Province, and the northwestern Jiangsu province. The annual average $PM_{2.5}$ concentration in cities across the country was 36.81 μg/m^3 in 2018, falling short of China's secondary standard for annual average air quality concentration (35 μg/m^3). The highest concentration in the Hotan region of Xinjiang reached 107.83 μg/m^3, 10.7 times higher than the WHO annual average attainment concentration (10 μg/m^3). The lowest $PM_{2.5}$ concentration was in the Ali region of Tibet, with a concentration of 6.08 μg/m^3. To summarize, there was an explicit regional clustering of the distribution of $PM_{2.5}$ concentrations in Chinese cities in 2018, with an overall presentation of "high in the north and low in the south, high in the center, and low in the southeast".

4.1.2 The spatial distribution of coarse particulate matter PM_{10} levels. The annual average PM_{10} concentration in cities across China in 2018 was 65.61 μg /m^3. However, it has reached the secondary standard of China's annual average air quality concentration (70 μg /m^3), higher than the WHO's annual average urban compliance concentration (40 μg /m^3). The lowest city was Linzhi, Tibet (12.25 μg/m^3), and the highest was Hotan, Xinjiang (325.33 μg/m^3). PM_{10} concentrations between 326 μg/m^3 and 127 μg/m^3 were found in western Xinjiang and Laiwu, Shandong Province, and those between 127 μg/m^3 and 98 μg/m^3 were mainly located in northern Xinjiang; the spatial distribution of PM_{10} concentrations in 2018 was characterized by obvious regional agglomeration, with an overall presentation of "high in the north and low in the south, high in the northwest and low in the southeast" (Fig.2).

According to Fig.2, the average annual concentrations of $PM_{2.5}$ and PM_{10} in 2018 exhibits a comparable spatial distribution pattern concerning urban size as an influencing factor. Notably, the Hu Huanyong line distinctly demarcates the disparity in the average annual concentration distributions of $PM_{2.5}$ and PM_{10} between the eastern and western regions. The central region, which is affected by the Hu Huanyu line, exhibits high levels of air pollution, gradually decreasing in the southeast (this observation also supports the Kuznets curve theory that suggests a decline in air pollution levels with increasing urbanization up to a certain extent). In the northwestern regions of Inner Mongolia and Xinjiang, where energy consumption has experienced rapid growth in recent years, accelerated urbanization has exacerbated air pollution.

4.2 Relationship between urban size and $PM_{2.5}$ and PM_{10} concentrations

4.2.1 Curve Drawing and Weight Analysis. Six variables listed in Table 1 are selected as core explanatory factors to represent the extent of urban development, while the annual average concentrations of $PM_{2.5}$ and PM_{10} utilized as indicators for assessing air pollution levels. The curve relationship in Model 1 is summarized, with the corresponding results depicted in Fig.3 and Fig.4.

According to the linear fitting results, it is evident that as the scope of relevant influencing factors expands, there is a gradual increase in the annual average concentration of $PM_{2.5}$. In other words, the progressive worsening of air pollution levels represented by $PM_{2.5}$ can be attributed to the continuous enhancement of infrastructure construction, significant improvement in living standards, and the gradual advancement of urbanization accompanied by rapid economic development. The findings of this study provide empirical support for a segment of the Kuznets environmental hypothesis[24-25], which posits an inverted 'U-shaped' relationship between environmental pollution and economic development. Our results indicate that as economies progress, there is an intensification in the level of environmental pollution. However, in the latter phase of this inverted 'U', as economic growth continues to advance, there is a gradual decline in environmental pollution levels. Despite minor deviations, Fig.3 and 4 illustrate that with expanding urban influencing factors, their impact on $PM_{2.5}$ and PM_{10} concentrations weakens over time and eventually reaches a stable state.

In the context of linear regression, this study further investigates the impact weights of six factors influencing urban size on the concentrations of $PM_{2.5}$ and PM_{10} using SPSS software. As illustrated in the Fig.6 pie chart, the Greening rate of built-up area in developed areas demonstrates the highest weight ratio of influence on both $PM_{2.5}$ and PM_{10}, followed by

Industrial and manufacturing area size. Moreover, a noticeable level of influence is observed from the Urban built-up area.

According to the previous analysis, this study aims to investigate influential factors with higher weight and better linear fitting degrees. In ArcGIS, the spatial distribution patterns of the following 4 factors in the country are further analyzed, as depicted in Fig.6.

4.2.2 Data analysis based on the allometry model. By employing the Allometry model in conjunction with Table 3 and Fig.7, this study reveals a sublinear heteroscedastic scaling relationship between 6 influencing factors of urban scale in China during 2018 and the annual

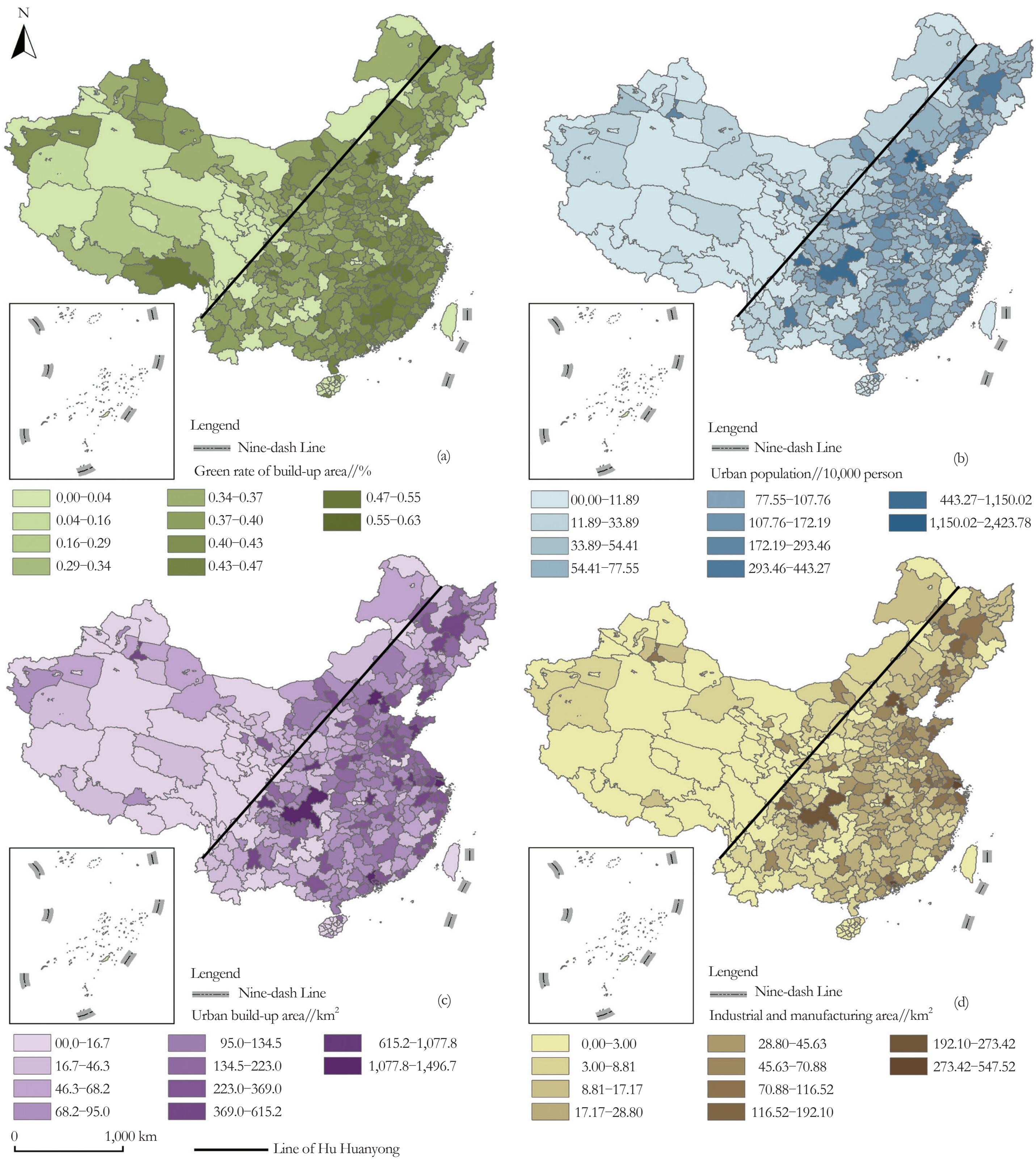
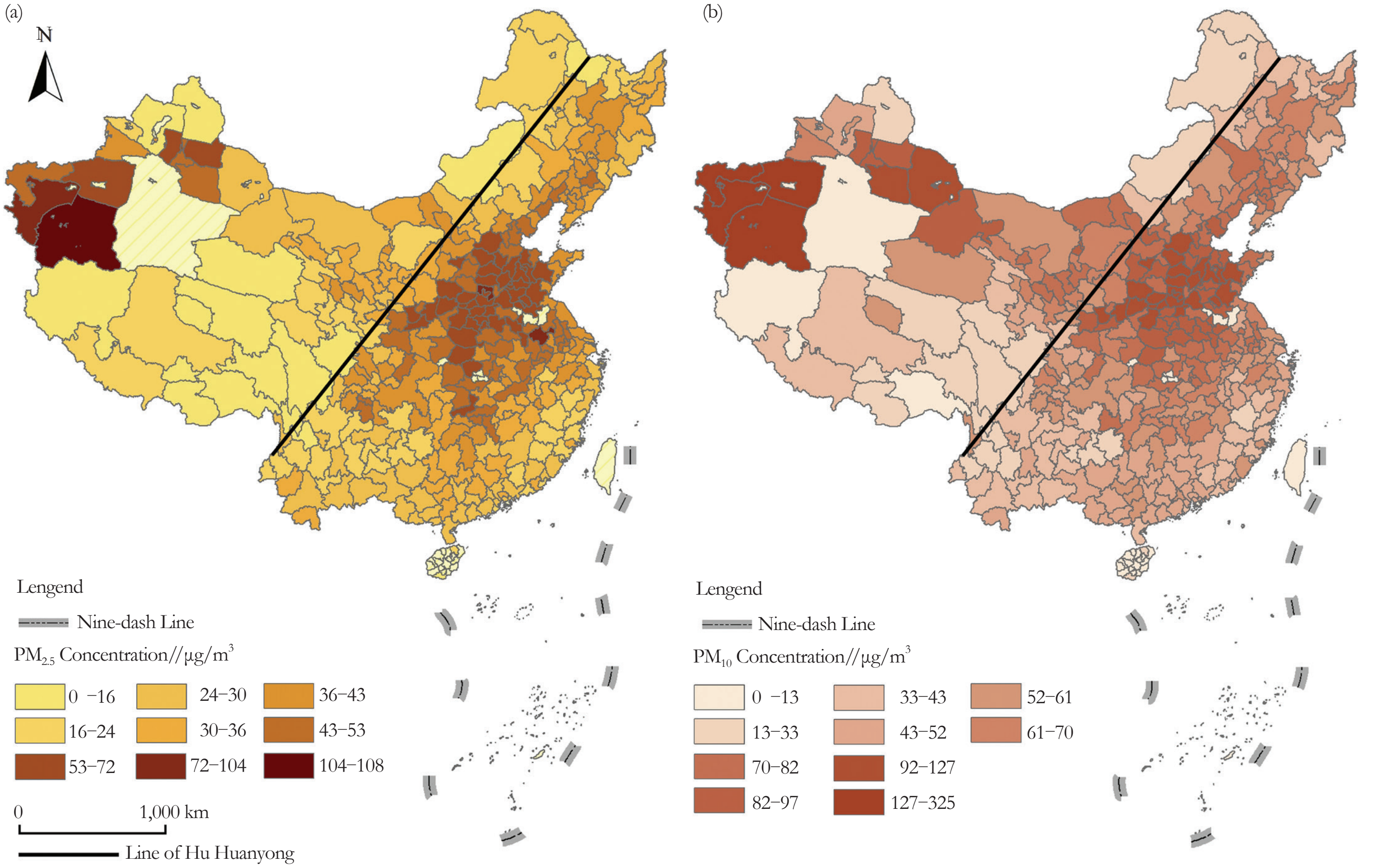


Fig.1 Spatial distribution characteristics of influencing factors of urban size in China in 2018

average concentrations of $PM_{2.5}$ and PM_{10} (Fig.7). The logarithmic functions determine that the scaling exponent B for the corresponding concentrations of $PM_{2.5}$ and PM_{10} is less than 1, indicating a sublinear association. These findings demonstrate that as urban size expands, there is an increase in the concentrations of $PM_{2.5}$ and PM_{10} within respective cities; however, the growth rate of urban size surpasses that



Note: (a) Annual average $PM_{2.5}$ concentration distribution; (b) Annual average PM_{10} concentration distribution

Fig.2 Annual average $PM_{2.5}$ and PM_{10} concentration distribution of cities in China in 2018

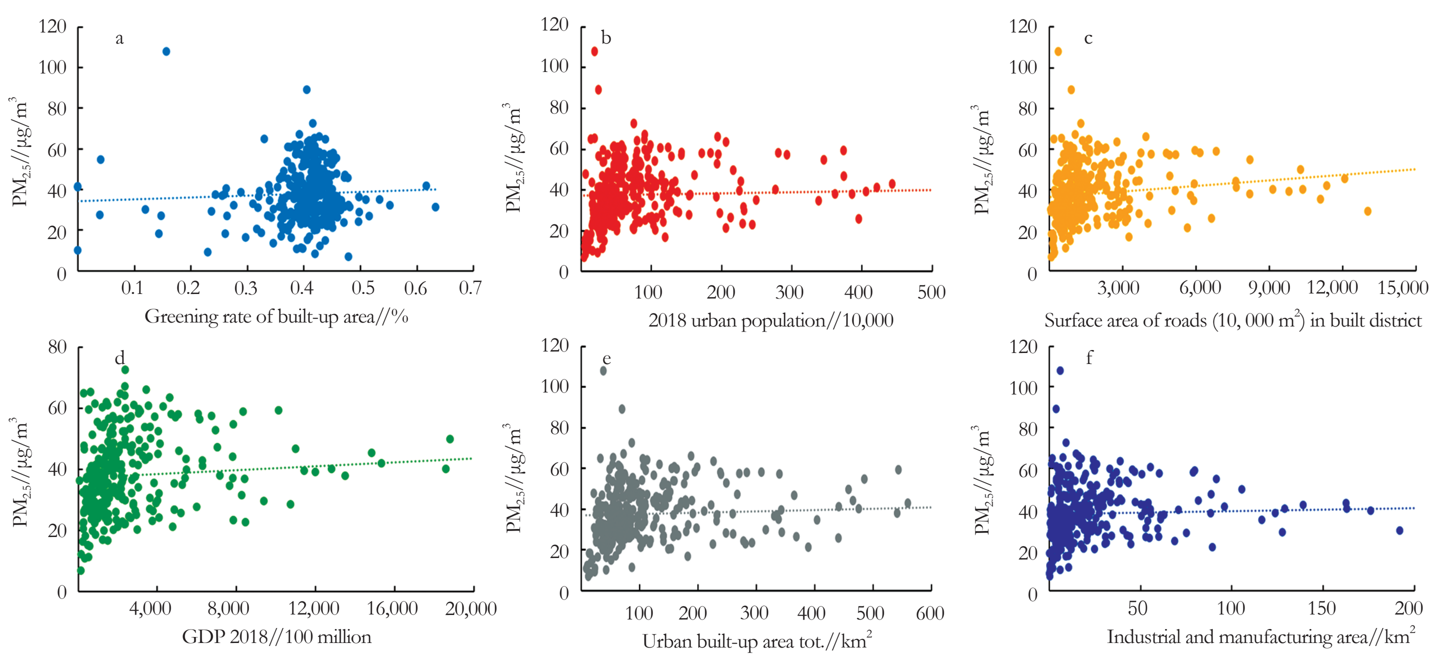


Fig.3 The variables influencing urban size and their linear relationship with the annual average $PM_{2.5}$ concentration in China in 2018

observed for $PM_{2.5}$ and PM_{10} concentration.

Based on the analysis presented in Table 3, it can be observed that the allometric model exhibits a low goodness of fit (R^2), indicating inadequate fitting performance of the equation. In other words, only a subset of cities adheres to the allometric sublinear growth law. Further optimization of data independent variables revealed that optimized cities mostly located west of Hu Huanyong Line exhibited $P<0.05$ within a 95% confidence interval. This finding further confirms that once a certain level is reached in the urbanization process, most cities no longer exert a significant impact on air environmental quality.

5 Discussion and conclusions

5.1 Discussion

In 2018, the concentration distribution of $PM_{2.5}$ and PM_{10} in Chinese cities exhibited distinct regional agglomeration characteristics. The spatial distribution of $PM_{2.5}$ and PM_{10} concentrations was demarcated by the Hu Huanyong line, with generally higher levels observed in the western and central regions compared to the southeastern regions. Notably, coastal areas with lower concentrations of $PM_{2.5}$ and PM_{10} demonstrated a higher degree of urbanization, accompanied by more developed influencing factors related to relevant variables. Humidity and rainfall in southern coastal areas played a role in reducing dust particles and purifying the air quality. The winter heating practices prevalent in northern China heavily rely on coal combustion, which contributes to elevated concentrations of various pollutants within central Chinese cities. Specifically, for effective prevention and control measures targeting $PM_{2.5}$ pollution, attention should be directed towards Laiwu City in Shandong Province, Anyang City in Henan Province, as well as Hotan and Kashgar regions in Xinjiang along with other central regions exhibiting high levels of pollution indicators. Regarding efforts focused on mitigating PM10 pollution risks, priority areas include concentrated interventions within the northern Xinjiang region alongside southern Shanxi Province, western Hebei Province, Shandong Province as well and northern Henan Province. It is crucial to emphasize comprehensive assessments encompassing regional energy consumption patterns while considering industrial structure dynamics alongside transportation emissions management strategies coupled with industrial emission controls[26-28]. Promoting interregional collaborative remediation initiatives aimed at addressing air pollution challenges can effectively enhance inhalable particulate matter (PM) air quality standards while ensuring sustained long-term decline trends for both $PM_{2.5}$ and PM_{10} concentrations between different geographical zones.

Based on the aforementioned findings,

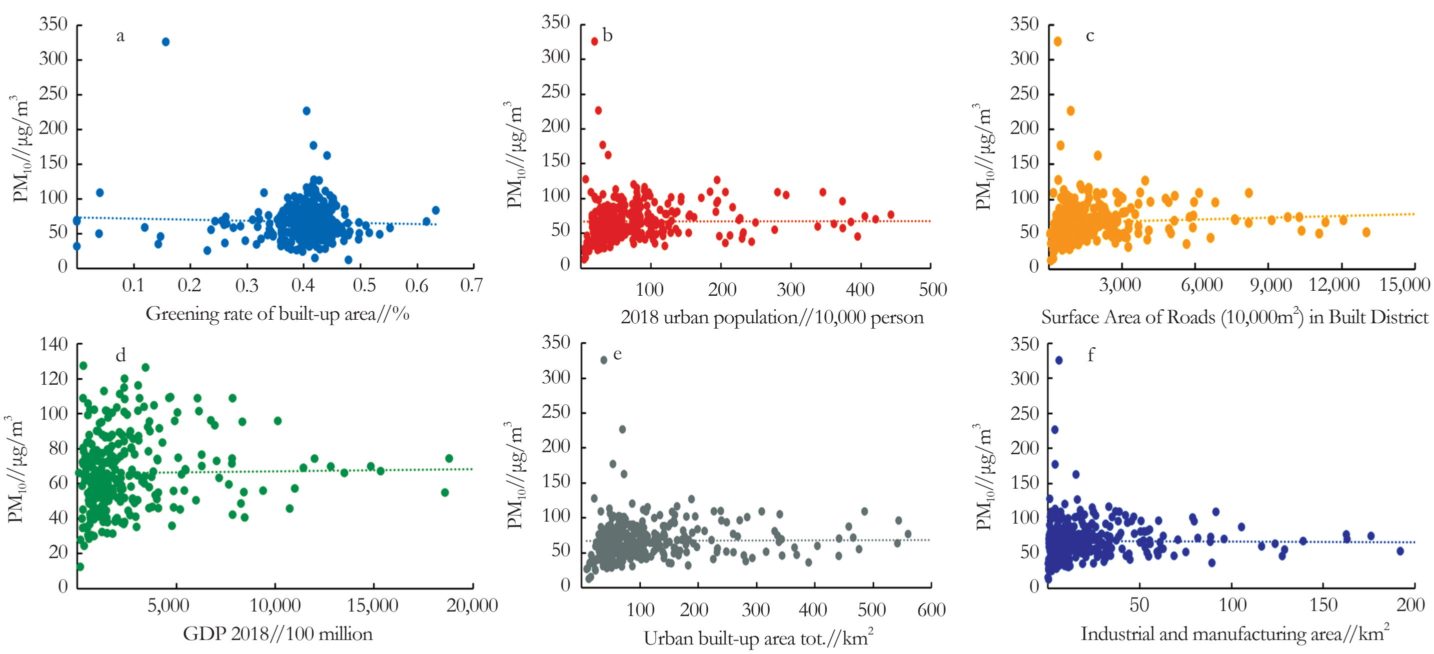


Fig.4 The variables influencing urban size and their linear relationship with annual average PM_{10} concentration in China in 2018

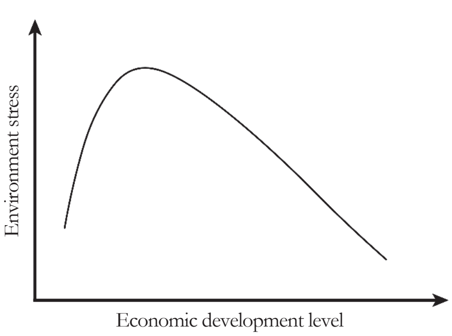


Fig.5 Environment Kuznets Curve

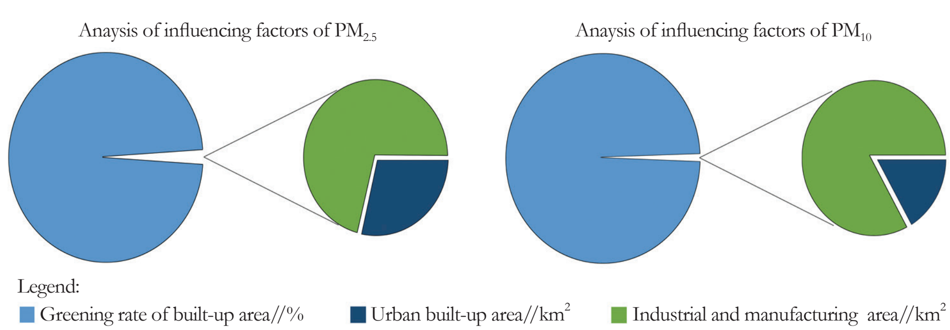


Fig.6 Pie chart illustrating the relative contributions of influencing factors on the concentration of $PM_{2.5}$ and PM_{10}

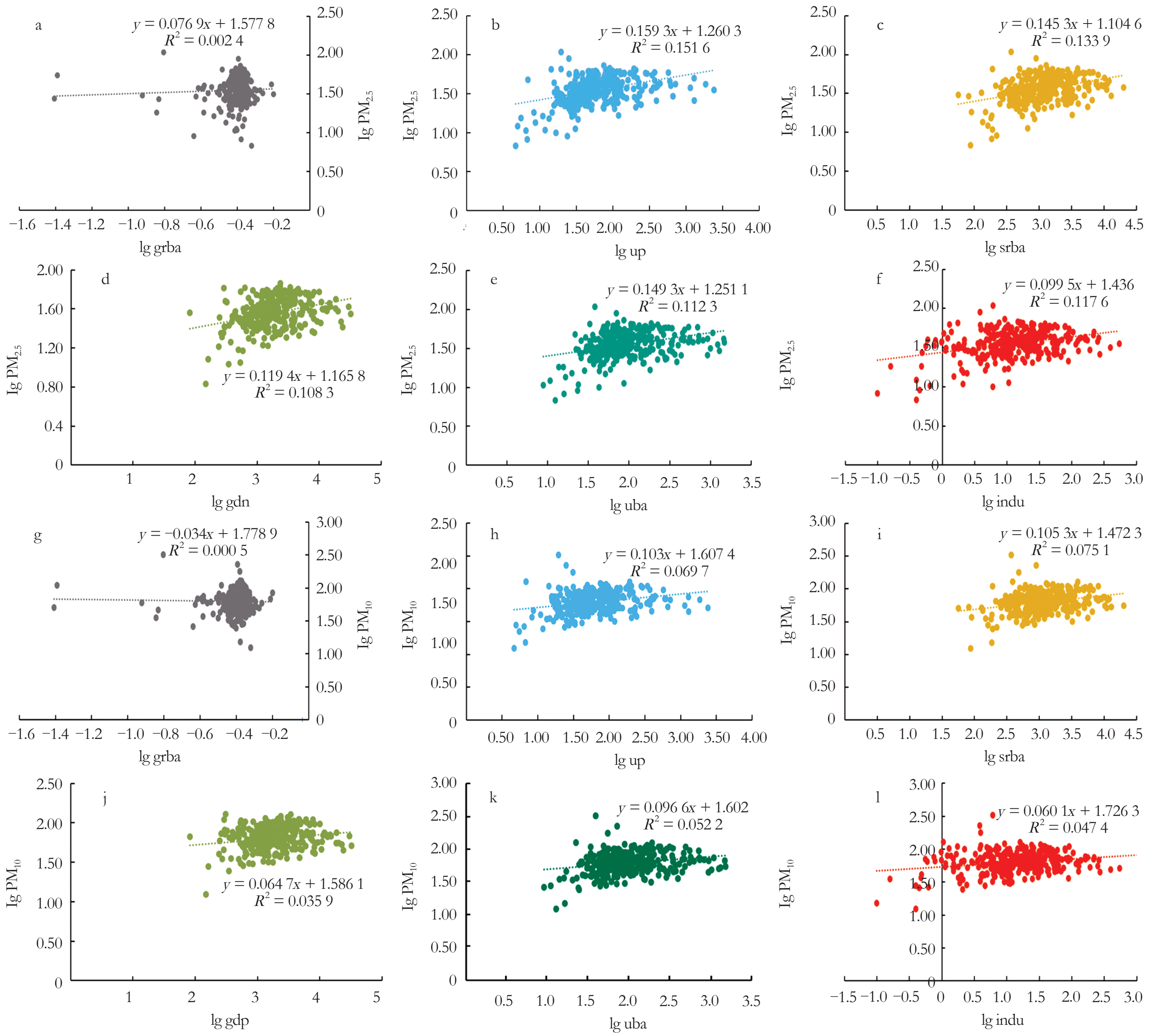


Fig.7 Allometric relationship between the 6 influencing factors of urban size and the inhalable particulate concentration ($PM_{2.5}$ and PM_{10}) in China in 2018 under double logarithmic coordinates

it is evident that the Green rate of built-up areas plays a paramount role in influencing air quality indicators such as $PM_{2.5}$ and PM_{10} concentrations during urban development. The industrial and manufacturing area, representing the scale of secondary industries and built-up areas, emerges as the second most significant factor. These implications hold great importance for cities actively promoting urbanization; thus, prioritizing attention to the inhibitory effect of green coverage rate in built-up areas on inhalable particulate matter like $PM_{2.5}$ and PM_{10} is crucial.

This study successfully validates the Kuznets curve through a two-step approach, examines six factors influencing urban size along with distribution patterns of $PM_{2.5}$ and PM_{10} concentrations, and conducts relevant data fitting analysis. The results demonstrate a long-term inverted "U"-shaped relationship between airborne pollutants represented by inhalable particulate matter ($PM_{2.5}$ and PM_{10}) and urbanization development; specifically, environmental pollution worsens with increasing levels of urbanization but gradually decreases with further economic development.

In recent years, the level of air pollution in the pollution complex cities in the central China, especially in some small and medium-sized cities, is still increasing sharply with the increase in urban size. There is a need to focus on these regional cities, restructure industries, improve energy efficiency, increase investment in environmental protection, and formulate reasonable population plans to prevent and control urban air pollution.

5.2 Conclusions

This study presents a comprehensive overview of the origin and academic advancement of the Allometry Growth Law (AGL), encompassing

Table 2 Evaluation of factors influencing urban size on inhalable particulate matter ($PM_{2.5}$ and PM_{10})

The influencing factors of Urban size	Degree of influence on $PM_{2.5}$ concentration	Degree of influence on PM_{10} concentration
Green rate of built-up area	H	H
Urban population	L	L
Surface area of road in built area	L	L
GDP	L	L
Urban built-up area	M	M
Industrial and manufacturing area	M	M

its validation, explanation, and exploration. The primary focus lies in investigating the influencing factors of $PM_{2.5}$ and PM_{10} concentrations concerning urban size. By employing an allometry growth model, the study explores the scalable relationship between various influencing variables related to urban size and mass concentrations of $PM_{2.5}$ and PM_{10}. The findings indicate that these variables demonstrate a sublinear relationship when plotted on logarithmic coordinates.

(1) In 2018, the annual average concentrations of $PM_{2.5}$ and PM_{10} exhibits distinct spatial clustering. The southeastern region is divided as a low-concentration area by the Hu Huanyong Line, while the northwestern and central regions shows high concentration.

(2) The impact of urban scale on inhalable particulate matter ($PM_{2.5}$ and PM_{10}) concentrations varies across different regions, following an inverted "U" shape relationship. During the initial stage of urbanization, expanding urban scale tends to worsen the pollution level of inhalable particulate matter. However, once the urban scale reaches a certain threshold in later stages, pollution indicators for inhalable particulate matter tend to stabilize and are no longer influenced by urban size.

When formulating policies for air pollution prevention and control, it is crucial to consider the weightage of factors related to urban scale as identified in this study. In western regions during the process of urbanization, priority should be given to improving green coverage within built-up areas while avoiding blind expansion of built-up areas and secondary industry zones. In eastern regions with resource advantages, optimizing resource allocation through technological advancements and talent attraction can facilitate transformation in traditional industries. This approach not only contributes to achieving long-term goals such as "dual carbon" targets but also enhances urban resilience.

References

[1] McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: present and future risks. *The Lancet*, *367*(9513), 859-869.

[2] U.S. EPA. (2001). *40 CFR Part 50*: *National primary and secondary ambient air quality standards*. Washington D.C.: Office of Federal Register.

[3] Xue, T., Liu, J. & Zhang, Q. et al. (2019). Rapid improvement of PM2.5 pollution and associated health benefits in China during 2013–2017. *Science China Earth Sciences*, (62), 1847-1856.

[4] Yayun, R., Guanglai, Z. (2020). Can city innovation dispel haze? *China Population*, *Resources and Environment*, *30*(2), 111-120.

[5] Huxley, J. S. (1924). Constant differential growth ratios and their significance. *Nature*, (114), 895-896.

[6] Kleiber, M. (1947). Body size and metabolic rate. *Physiological Review*, *27*(4), 511-541.

[7] Hilbers, J., Schipper, A. & Hendriks A, et al. (2016). An allometric approach to quantify the extinction vulnerability of birds and mammals. *Ecology*, *97*(3), 615-626.

[8] Naroll, R. S., Bertalanffy, L. (1956). The principle of allometry in biology and social sciences. *Geographical Review*, (56), 213-225.

[9] Ortman, S. G., Cabaniss, A. H. & Sturm, J. O. et al. (2014). The pre-history of urban scaling. *PLoS ONE*, *9*(2), e87902.

[10] Lee, Y. (1989). An allometric analysis of the US urban system: 1960-80. *Environment and Planning A*, *21*(4), 463-476.

[11] Schlapfer, M., Bettencourt, L. M. & Grauwin, S. et al (2014). The scaling of human interaction with city size. *Journal of the Royal Society Interface*, *11*(98), 20130789.

[12] Shi, Y. L., Wang, L., Xia, Z. (2014). The latest progress in the study of allometric growth and resource-limited biomass models. *Science Technology and Engineering*, *14*(19), 159-166.

[13] Li, X., Chen, G. Q., Xun, X. Q. (2009). Analysis of allometric growth of Chinese cities. *Acta Geographica Sinica*, *64*(4), 399-407.

[14] Lan, T., Li, Z. L., Zhang, H. (2019). Urban allometric scaling beneath structural fractality of road networks. *Annals of the American Association of Geographers*, *109*(3), 943-957.

[15] Chun, S. Z. (2013). *Urban size hierarchy and service industry development different in the Beijing–Tianjin–Hebei urban agglomeration* (Master's thesis). Retrieved from China National Knowledge Infrastructure.

[16] Chao, J. X. (2009). Discussion on the scale of Chinese cities based on environmental quality. *Geographical Research*, *28*(3), 792-802.

[17] National Bureau of Statistics of China (2018). *2018 Urban Construction Statistical Yearbook*. Retrieved from https://www.zgtjnj.org/index.aspx. (Accessed on June 2020).

[18] Lorin, B, Amanda, M. L, Adam, M. D. (2023). The transition from field emission to collisional spacecharge limited current with nonzero initial velocity. *Scientific Reports*, *13*(1), 14505.

[19] Batty, M. (2008). The size, scale, and shape of cities. *Science*, *319*(5864), 769-771.

[20] Xu, Z. M, Chen, G. D, Qiu, G. Y. (2005). ImPACTS equation for sustainability assessment. *Journal of Geographical Sciences*, *60*(2), 198-208.

[21] Zhu, C. W., Wang, B., Qian, W. H. (2008). Why do dust storms decrease in northern China concurrently with the recent global warming? *Geophysical Research Letters*, *35*(18), L18702.

[22] Wang, L. M., He, K. L. (2008). Analysis of spatial variations in environmental impact based on the STIRPAT model: A case study of energy consumption. *Acta Scientiae Circumstantiae*, *28*(5), 1032-1037.

[23] Luís, M. A. B., José, L. & Dirk, H. et al. (2007). Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(17),7301-7306.

[24] Grossman, G. M., Krueger, A. B. (1992). Environmental impacts of the North American Free Trade Agreement. *Social Science Electronic Publishing*, *8*(2), 223-250.

[25] Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at difference stages of economic development. *Ilo Working Papers*, (4), 1-42.

[26] Mi, T. (2013). *Characteristics of $PM_{2.5}$ and its precursors pollutants during haze pollution in Beijing-Tianjin-Hebei region* (Master's thesis). Retrieved from China National Knowledge Infrastructure.

[27] Wei, W. X. (2010). Spatial-temporal characteristics of haze in Hebei Province. *Meteorological Monthly*, *36*(3), 77-82.

[28] Yang, L. X. (2008). *Characteristics, source apportionment, and influence on a visual range of $PM_{2.5}$ in Jinan* (Master's thesis). Retrieved from China National Knowledge Infrastructure.