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Research article

Effect of urban form on $PM_{2.5}$ concentrations in urban agglomerations of China: Insights from different urbanization levels and seasons

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ABSTRACT

Planned urban form has become an important strategy to improve air quality in urban agglomerations (UAs), especially pollution due to $PM_{2.5}$, but the influencing mechanisms are not yet clear. This study explores the relationship between four metrics of urban form (size, fragmentation, shape, and dispersion) as determined by analysis of remotely sensed images at 30-m resolution and $PM_{2.5}$ concentrations in 19 Chinese UAs. The influence of level of urban development and season is examined. Five control variables, including population density, temperature, precipitation, wind speed, and the normalized difference vegetation index (NDVI) are selected for use in multiple linear regression models. Size, fragmentation, and shape of urban form, but not dispersion, were found to have significant effects on $PM_{2.5}$ concentrations of different urbanization-level UAs. Urban size and fragmentation have stronger impacts on $PM_{2.5}$ concentrations in UAs with lower urbanization levels while urban shape has a greater impact in higher-level UAs. In terms of seasonal variation in all UAs, urban form is more pronouncedly associated with $PM_{2.5}$ concentrations during spring and autumn than summer and winter. Urban size and fragmentation are positively associated with $PM_{2.5}$ concentrations whereas urban shape and dispersion are on the contrary. The relationships between urban form and $PM_{2.5}$ uncovered here underscore the importance of urban planning as a tool to minimize $PM_{2.5}$ pollution. Specifically, local government should encourage polycentric urban form with lower fragmentation in urban agglomerations. UAs with lower urbanization levels should control the disordered expansion of construction land and higher-level UAs should promote the mix of green land and construction land. Moreover, measures to control air pollution from anthropogenic activities in spring, autumn and winter are likely to be more effective in decreasing $PM_{2.5}$ concentrations in UAs.

1. Introduction

Industrialization and urbanization over the past thirty years have led to continuous deterioration of regional air quality in China, especially that caused by $PM_{2.5}$ (Chen et al., 2020; Han et al., 2014; Li et al., 2016). This pollutant is characterized by a long residence time in the air and significant transmission distances and thus is a major cause of atmospheric haze, which reduces visibility, interferes with transportation (Pui et al., 2014), and poses a serious threat to the public health (Faridi et al., 2018; Liu et al., 2016). Between 2014 and 2016, more than 80% of the population in China was exposed to high $PM_{2.5}$ concentrations, i.e. $>10\ \mu g/m^3$ (Song et al., 2017). Moreover, although $PM_{2.5}$ concentrations underwent a generalized downward trend between 2015 and 2017, average annual $PM_{2.5}$ concentrations at more than 70% of China's monitoring sites exceeded the Chinese Ambient Air Quality Standards (CAAQS) Grade II standard (Shen et al., 2019). $PM_{2.5}$ pollution in China thus continues to be major environmental threat.

Alleviation of $PM_{2.5}$ pollution requires a deep understanding of the socioeconomic factors that govern its formation, especially those related to urbanization, as well as knowledge about the meteorological

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conditions that influence its dispersion (Fan et al., 2019; Guo et al., 2019; Liu et al., 2020). Scientific methods of construction land planning have received significant attention as tools to maintain air quality during urbanization (Liang et al., 2020). At a macroscopic scale, urban form directly affects the spatial dynamics of source-sink relationships involving roads, industrial land, and green space (Lee, 2020; She et al., 2017). At a microscopic scale, the diffusion and deposition of surface $PM_{2.5}$ in local areas are determined in part by the microclimate created by the three-dimensional structure of urban buildings, which conditions the urban heat island and the urban street canyon effects (Yang et al., 2020b). Detailed analysis with a variety of metrics has shown that cities with higher fragmentation and shape complexity experience more serious air pollution (Liu et al., 2018a) than cities that are compact and less complex. Smaller cities with scattered and polycentric urban forms have relatively good air quality in China (Li et al., 2021a), but the relationships between urban form and $PM_{2.5}$ concentrations are nevertheless variable and remain uncertain.

In addition, a large body of research has been done to explore the response of annual mean $PM_{2.5}$ concentrations to urban form based on cross-sectional data or long time series panel data (Lee, 2019; Zhou et al., 2018), but only a few studies focused on the seasonal discrepancies of urban form's influence on $PM_{2.5}$ concentrations. Due to the variation of weather, human activities, and other factors that are related to seasonal differences, $PM_{2.5}$ concentrations have obvious seasonal differences, which cannot be ignored, generally maximized in winter and minimized in summer (Li et al., 2019). Moreover, urban form is an important modulator of changes of meteorological conditions which has palpable seasonal change (e.g. affect temperature with urban heat island effect, wind speed with urban canyon effect), although it varies little over the short term. Seasonal considerations are consequently crucial in the study of relationship between $PM_{2.5}$ concentrations and urban form (Tian et al., 2019), but the role of urban form on seasonal change of $PM_{2.5}$ concentrations is still inconclusive. For example, some studies showed that urban form metrics were more significantly related to $PM_{2.5}$ concentrations in spring and winter than summer and autumn (Liu et al., 2022; Shi et al., 2019a); however, another study conducted in 83 Chinese cities claimed that $PM_{2.5}$ concentrations tended to be more sensitive to urban form metrics in spring and summer (Liu et al., 2018b). Hence, more exploration should be done to clarify the difference in urban form-$PM_{2.5}$ concentration relationship across seasons.

An urban agglomeration of China is a huge urbanized area composed of several cities which includes one or more mega-cities at the core and at least three other large cities around the core and planned urban agglomeration has been a key pathway for achieving regional economic growth in China (Fang, 2015). Agglomeration generates efficiencies by consolidating, concentrating, and intensifying human activities (Wang et al., 2021), but it also can elevate $PM_{2.5}$–associated haze pollution (Tian et al., 2020; Zhang et al., 2019). Clarifying urban form-$PM_{2.5}$ concentrations relationship is not only conductive to reducing the damage of haze pollution to human health, but also critical for achieving the sustainable development of UAs. The mechanisms by which urban form regulates $PM_{2.5}$ concentrations are nevertheless complex and dependent on location as well as the metrics and statistics used for analysis of urban size, shape, and distribution. These relationships have been examined in a few very high level urban agglomerations (UAs) such as Beijing-Tianjin-Hebei and the Yangtze River Delta (Liang et al., 2020; Xu et al., 2020), but much less is known about the larger number of diverse, variously sized UAs where $PM_{2.5}$ is a growing issue and where planning steps could be taken to minimize the problem (Wang et al., 2021). Here we examine a cohort of 19 such UAs that have been classified into three levels of comprehensive development (Fang, 2015) to answer three questions: (i) How is urban form related to $PM_{2.5}$ concentrations in UAs of China; (ii) what are the differences in the influences of urban form on $PM_{2.5}$ concentrations among UAs with distinct urbanization levels; and (iii) how does urban form affect $PM_{2.5}$ concentrations in different seasons in UAs of China?

2. Data and methods

2.1. Definition and location of UAs

Nineteen UAs representing three levels of comprehensive development as defined by China's National New Urbanization Plan (2014–2020) were selected for analysis. The levels are hierarchical; proceeding from the zonal-level to the regional- and national-levels, they reflect increasing strength as measured by progress in planning, achieving efficiency of urban functions, and attaining complementarity across the entire UA (Fang, 2015). As shown in Fig. 1a, each of the six zonal-, eight regional-, and five national-level UAs is relatively large in geographical area. In aggregate, they encompass 28.6% of the land area of China but represent a disproportionate 74.1% of the total population and 84.1% of the national gross domestic product (GDP) as of 2015. Differences among the three levels are given in Fig. 1b–d, which show population density (POPD), GDP density of secondary industry (GDPD-SI), and GDP density of tertiary industry (GDPD-TI). Although the average values of the regional-level indicators generally match or slightly exceed those for the entire cohort, the values of national-level indicators are always highest and those of zonal-level indicators are always lowest. Thus it is clear that the levels defined by the National New Urbanization Plan reflect quantifiable differences in degree of urbanization and socioeconomic development.

2.2. Data sources, metrics, and experimental design

2.2.1. $PM_{2.5}$ concentrations

Monthly $PM_{2.5}$ concentrations in the 19 UAs were obtained from the 2015 ChinaHigh$PM_{2.5}$ dataset (https://zenodo.org/). These data have high accuracy with R^2 values ranging from 0.92 to 0.94, root mean square error values ranging from 5.1 to 10.0 μg/m^3, and mean absolute error values ranging from 3.7 to 6.8 μg/m^3 (Wei et al., 2021). A space-time extremely randomized trees model was used to estimate $PM_{2.5}$ concentrations at 1-km spatial resolution based on ground measurements, Multi-Angle Implementation of Atmospheric Correction (MAIAC) aerosol optical depth (AOD) products, land-cover, surface conditions, population distributions, and meteorological data (Wei et al., 2020).

2.2.2. Urban form metrics

Accurate selection of indicators is a necessary prerequisite for evaluation of the impact of urban form on $PM_{2.5}$ concentrations (Lu et al., 2018a; Tu et al., 2019). Most existing studies have employed traditional landscape pattern indices, but a detailed rationale for index selection is usually absent, leading to possible redundancy and omission of important indices (Cushman et al., 2008). To depict urban form reasonably and comprehensively, we selected a set of commonly accepted metrics based on four dimensions of urban form characteristics. These include urban size (total class area, percent of landscape), urban fragmentation/continuity (number of patches, patch density, largest patch index), urban shape (landscape shape index, mean perimeter area ratio, area-weighted mean fractal dimension index, area-weighted mean shape index), and urban compactness/dispersion (mean Euclidean nearest neighbor distance, clumpiness, proportion of like adjacencies, patch cohesion index, landscape division index, splitting index, aggregation index). These indicators were assigned to four urban form metrics based on (i) their high frequency use in previous studies (Liang and Gong, 2020; Łowicki, 2019; She et al., 2017; Shi et al., 2019b; Wang et al., 2019), (ii) Pearson correlation analysis of their relationship to $PM_{2.5}$ concentrations, (iii) rankings according to their correlation coefficients, and (iv) application of the VIF (Variance Inflation Factor) test with $PM_{2.5}$ concentrations and the control variables described in Section 2.2.3. Metrics that failed to pass the VIF test were replaced with metrics of the same type and the process repeated until collinearity was eliminated.

The four quantifiable metrics of urban form are described in Table 1.

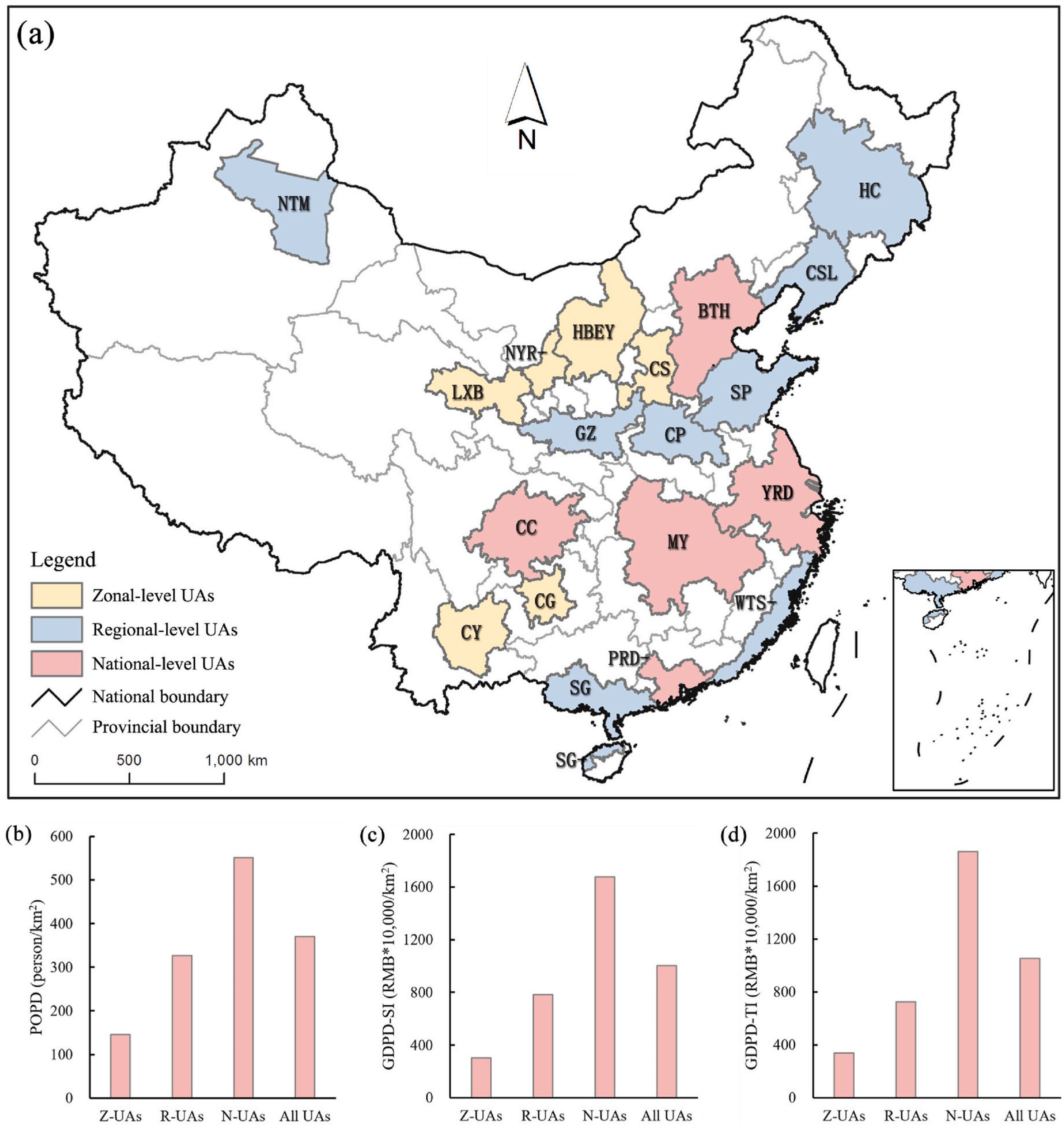

Fig. 1. Location and categorization of UAs. (a) Map of China showing the locations of the UAs. The five national-level UAs include the Yangtze River Delta (YRD), the Pearl River Delta (PRD), Beijing-Tianjin-Hebei (BTH), the Middle Yangtze (MY), and Chengdu-Chongqing (CC); the eight regional-level UAs include the West Taiwan Strait (WTS), Central and Southern Liaoning (CSL), the Shandong Peninsula (SP), the Central Plain (CP), Guanzhong (GZ), Southern Guangxi (SG), Harbin-Changchun (HC), and the Northern Tianshan Mountains (NTM); the six zonal-level UAs include Hohhot-Baotou-Erdos-Yulin (HBEY), Ningxia-Yellow River (NYR), Lanzhou-Xining-Baiyin (LXB), Central Shanxi (CS), Central Guizhou (CG), and Central Yunnan (CY). Differences in POPD, GDPD-SI, and GDPD-TI are shown in (b), (c), and (d), respectively. The abbreviations All-UAs, N–UAs, R–UAs, and Z-UAs respectively refer to all 19 UAs, and the national-, regional-, and zonal-level UAs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Class area (CA) is defined as the total urban patch area; high values of this metric correspond to large urban size. Number of patches (NP) evaluates the degree of urban fragmentation and continuity; lower values indicate greater urban continuity. The mean perimeter area ratio (PARA_MN) reflects the complexity of urban shape; smaller values correspond to higher regularity of shape. The mean Euclidean nearest neighbor distance (ENN-MN), which is the average distance between any two nearest neighboring patches measures dispersion and compactness of urban patches; the higher the value, the greater the dispersion. The urban form metrics were generated by Fragstats4.2 using construction land use data from 2015. These data have a 30-m spatial resolution and were generated by the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences through visual interpretation of Landsat TM or ETM images (http://www.aircas.cas.cn/). There are two levels of land cover types in this dataset, with classification accuracy above 94.3% for the first-level land category (Liu et al., 2017). In aggregate, the above operations allowed us to address complex issues such as the emergence of satellite urban areas, which is usually accompanied by increased urban fragmentation, while infill development or edge expansion often changes the roundness and aggregation of urban patches (Gong et al., 2018). They also addressed development of multi-center urban areas, which is accompanied by an increase in the distances among urban patches and a decrease in scattered urban patches (Han et al., 2020).

Table 1
Description of urban form metrics.

Urban Form Metric	Urban Form characteristics	Formula	Description
CA	Large size/Small size	$CA = \sum_{j=1}^{n} a_j(1/10000)$	a_j represents the area (m^2) of patch j
NP	Fragmentation/ Continuity	$NP = n$	n represents the number of patches
PARA_MN	Irregularity/ Regularity	$PARA\_MN = \frac{\sum_{j=1}^{n}(l_j/a_j)}{n}$	l_j represents the perimeter (m) of patch j; a_j represents the area (m^2) of patch j
ENN_MN	Dispersion/ Compactness	$ENN\_MN = \frac{\sum_{i=1}^{m_i}\sum_{j=1}^{n_j} d_{ij}}{N}$	d_{ij} represents the minimum adjacency distance between patch i and j

2.2.3. *Control variables*

Besides urban form, socioeconomic and natural factors are known to directly or indirectly affect $PM_{2.5}$ concentrations (Bai et al., 2019; Duan et al., 2021; Zhang et al., 2020), and thus appropriate metrics among these factors must be controlled to improve the assessment accuracy of models adopted to explore the relationship between $PM_{2.5}$ and urban form (Bereitschaft and Debbage, 2013). On the basis of previous studies and analysis for collinearity, we finally chose five metrics as control variables, including population density (POPD), precipitation, wind speed, temperature, and the normalized difference vegetation index (NDVI). Specifically, POPD was selected to represent the intensity of human activities which could directly influence the discharge of air pollutants (Yan et al., 2020). Annual POPD data with 1-km spatial resolution were from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn/). Meteorological factors, including precipitation, wind speed, and temperature, were evaluated because of their recognized effects on the dilution and emission of fine particulate matter by affecting atmospheric environment and human behaviors (Hajiloo et al., 2019). Monthly data were produced at 1-km spatial resolution by the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn/). The normalized difference vegetation index (NDVI) was chosen to reflect the influence of vegetation, a known

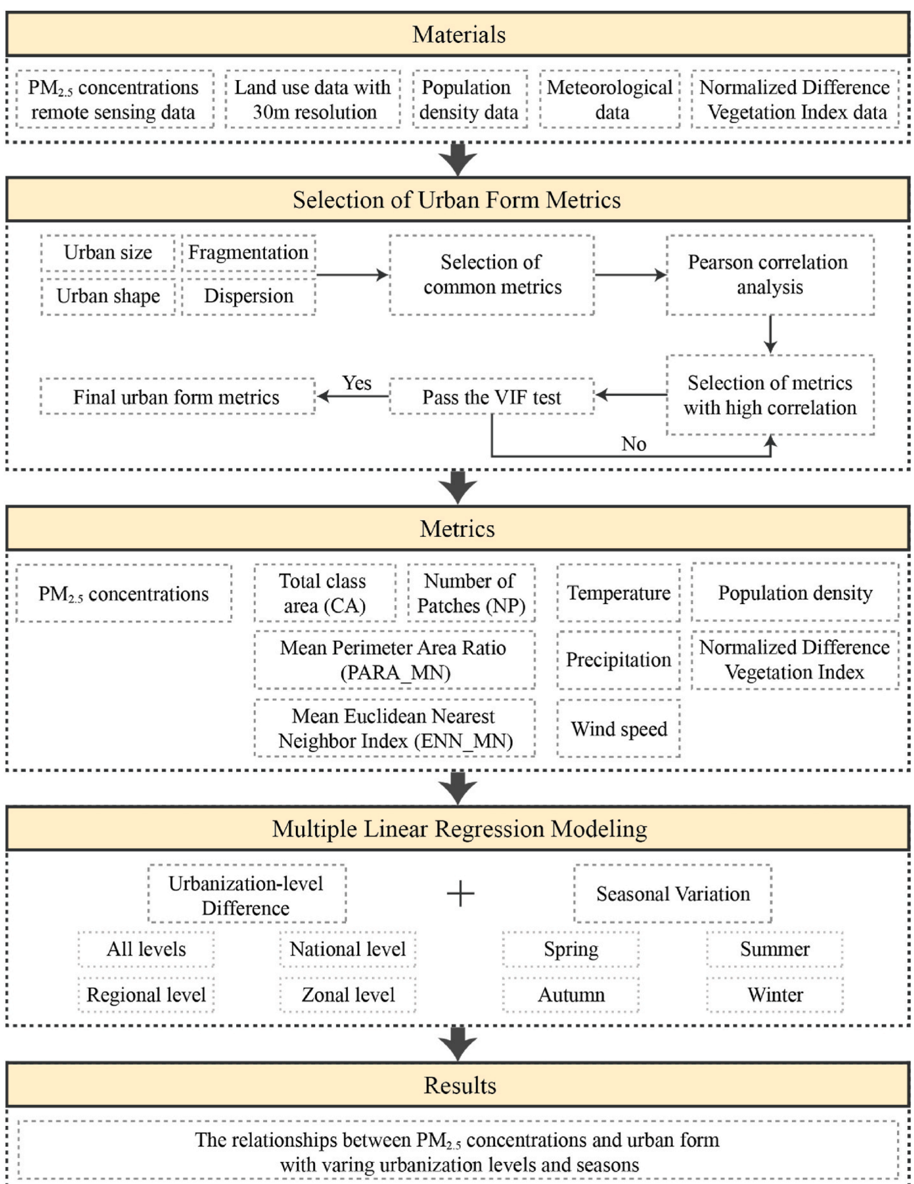

Fig. 2. Flowchart for data processing and modeling.

ameliorator of air quality (Wu et al., 2021). Monthly NDVI data provided by the Geospatial Data Cloud were obtained from the synthetic calculation of MYDLT1D product at 500-m spatial resolution (http://www.gscloud.cn/). Annual and seasonal meteorological and NDVI data were generated by calculating the arithmetic means of monthly measurements. Four seasons were defined as spring (March through May), summer (June through August), autumn (September through November), and winter (December through February).

2.2.4. Data processing and modeling

The flowchart for data processing and modeling is given in Fig. 2. Gridded data products, including monthly remote sensing data of $PM_{2.5}$ concentrations, meteorological factors, NDVI, and POPD at 1-km resolution, were combined with high-precision land use data and aggregated to construct a spatial dataset of the entire study area. We quantified each metric with grid-based 20◊20 km cell size for higher accuracy of $PM_{2.5}$ data in each statistical cell as there is $PM_{2.5}$ data incompleteness in some areas due to the disturbance of snow and cloud on data inversion. Then we selected four urban form metrics in four dimensions, and analyzed the characteristics of $PM_{2.5}$ concentrations and urban form. Multiple linear regressions were used to explore the relationship between annual $PM_{2.5}$ concentrations and urban form at the national-, regional- and zonal-levels of agglomeration. Anticipated seasonal effects were examined by linear correlation between $PM_{2.5}$ concentrations and urban form during all four seasons.

2.3. Multiple linear regression

Multiple linear regression modeling has been widely used to explore the linear statistical relationships between dependent variables and multiple independent variables (Lee, 2019; She et al., 2017; Yuan et al., 2018b) We exploited traditional multiple linear regression (MLR) models with ordinary least squares (OLS) estimation to establish the relationship between urban form and $PM_{2.5}$ concentrations in the UAs. Four linear regression models correspond to the zonal-, regional-, national-, and the average-level of urban development; four models incorporate the spring, summer, autumn, and winter seasons. Nine independent variables comprised of four urban form metrics (main variables), a socioeconomic factor, and four natural factors (control variables) were included in all models, which were conducted in SPSS software (version 26.0).

The MLR equation is as follows:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

Where, Y represents the dependent variable; β_0 represents the intercept; β_i represents the partial regression coefficients of the independent variable X_i; n represents the number of independent variables; ε represents the error term.

We also tested the collinearity among independent variables based on VIF values calculated by the following formula:

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

$$R^2 = \frac{SST - SSE}{SSE} \tag{3}$$

where, SST represents the total sum of squares; SSE represents the minimum sum of squared residuals of linear model.

The VIF values of all variables ranged from 1.067 to 9.014, confirming that there was no collinearity among variables according to the commonly recognized standard, i.e., when the VIF of the selected variables is less than 10, the model is stable and acceptable (Lin and Billa, 2021). Moreover, the validity and accuracy of the models were evaluated based on the coefficient of determination (R^2) and the significance of the F statistic (Nazif et al., 2018). Better fit of the models is indicated by the closeness of R^2 values to 1 and lower P-values of the F-statistic (Yang et al., 2020b).

3. Results

3.1. Relationships between $PM_{2.5}$ concentrations and levels of urban agglomeration

Annual mean $PM_{2.5}$ concentrations increased sharply but then plateau with increasing levels of urbanization (Fig. 3a). Thus the mean concentration for zonal-level UAs (35.6 μg/m^3) is only three-quarters of that for regional-level UAs (47.1 μg/m^3), but that of national-level UAs (48.2 μg/m^3) is virtually identical to that of lesser developed, regional-level agglomerations. Seasonal differences in $PM_{2.5}$ concentrations are pronounced, with maxima (64.5 μg/m^3) invariably appearing in winter and minima (27.1 μg/m^3) in summer (Fig. 3b).

3.2. Relationships between urban form and levels of urban agglomeration

Four indices were used for detailed characterization the urban form at three levels of agglomeration. The values of CA and NP increased with increasing levels of urbanization, but those of ENN_MN declined (Fig. 4), providing evidence that expansion of urban footprints was accompanied by growth in the number of urban patches but not by dispersion of the patches. The magnitude of these differences, which was substantial between zonal- and regional-level UAs, levelled off between regional- and national-level UAs. PARA_MN decreased slightly between zonal- and regional-level UAs but then increased between regional- and national-level UAs, indicating the differentiated change of irregularity with increasing levels of urbanization.

3.3. Relationships between $PM_{2.5}$ concentrations, urban form, and metrics of socioeconomic and natural conditions

The statistical relationships between $PM_{2.5}$ concentrations and metrics of urban form, socioeconomic, and natural conditions are given in Table 2, which confirms that all of the regression models satisfy the F test, with R^2 coefficients ranging from 0.571 to 0.672. This provides strong evidence for good fitness of the models and statistical accuracy in defining linear relationships between the metrics and concentrations. Concentrations of the pollutant were always positively correlated with NP, but the corresponding correlation with CA was negative at the zonal-level and positive at higher levels (Table 2). The coefficients of CA and NP were uniformly stronger at the two lower levels and weaker at the national-level.

The opposite pattern of correlations was apparent with PARA_MN, where the relationship was positive at the zonal-level but negative at higher levels of agglomeration. Coefficients involving PARA_MN were generally weak, and correlations with ENN_MN at all three levels of agglomeration were nonsignificant. These relationships confirm that patch area, total patch number, and to a lesser extent regularity are the most important metrics of form associated with $PM_{2.5}$ pollution. Negative relationships between $PM_{2.5}$ concentrations and precipitation and wind speed are generally evident, and the coefficients are strong, but there were no clearcut patterns between $PM_{2.5}$ concentrations and other socioeconomic and natural metrics.

3.4. Seasonal influences on $PM_{2.5}$ concentrations

As shown in Table 3, all of the regression models involving seasonality satisfy the F test, with R^2 coefficients ranging from 0.340 to 0.541. Patterns in the seasonal relationships between urban form and $PM_{2.5}$ concentrations are obvious. Relationships with CA and NP are uniformly positive with relatively high coefficients, but those with PARA_MN and ENN_MN are uniformly negative with relatively low coefficients, except

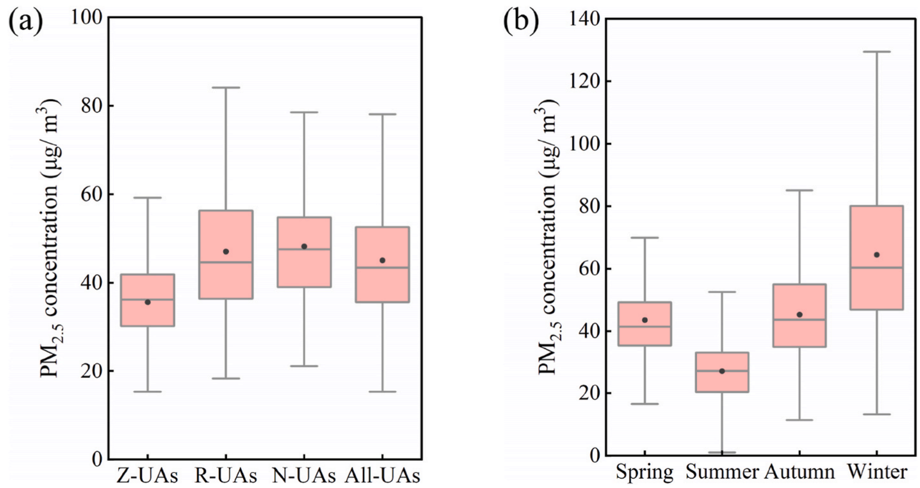

Fig. 3. $PM_{2.5}$ concentrations in 2015; (a) in different levels of urban agglomeration; (b) in different seasons.

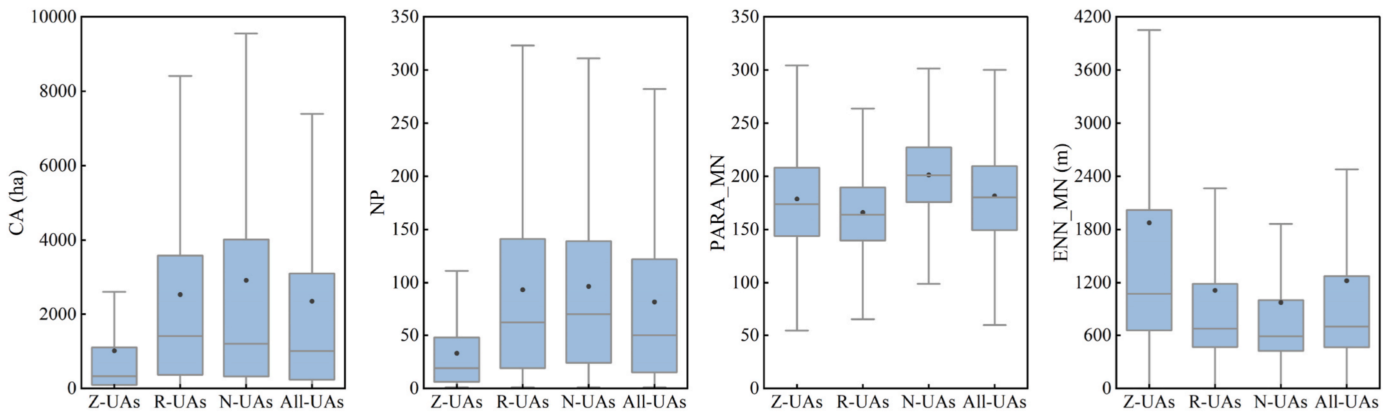

Fig. 4. Urban form metrics for different urbanization-level urban agglomerations in 2015.

Table 2
Statistical relationships between $PM_{2.5}$ concentrations and metrics of urban form, socioeconomic conditions, and natural conditions of urban agglomerations. Statistical significance is at the 1% level. NS = nonsignificant, and all p-values are less than 0.001. Summary statistics are given in italics.

Metric	Statistical relationship (R^2 coefficient)			
	Zonal-level UAs	Regional-level UAs	National-level UAs	All UAs
CA	- (0.242)	+ (0.220)	+ (0.099)	+ (0.203)
NP	+ (0.243)	+ (0.327)	+ (0.105)	+ (0.268)
PARA_MN	+ (0.121)	- (0.080)	- (0.137)	- (0.052)
ENN_MN	NS	NS	NS	- (0.028)
Population density	+ (0.275)	NS	- (0.077)	NS
Temperature	- (0.146)	NS	+ (0.407)	NS
Precipitation	NS	- (0.409)	- (0.512)	- (0.314)
Wind speed	- (0.502)	- (0.311)	- (0.410)	- (0.476)
NDVI	- (0.303)	+ (0.179)	- (0.118)	+ (0.152)
R^2	*0.672*	*0.628*	*0.578*	*0.571*
F	*340.843*	*575.619*	*399.255*	*1065.111*
Number of samples	*1509*	*3073*	*2633*	*7215*

in winter, when they become weakly positive and nonsignificant, respectively. Patch number and size are thus more important factors than regularity and dispersion in influencing $PM_{2.5}$ concentrations, which have little or no relationship to population density (Table 3). Whereas temperature is always positively related to concentrations of the pollutant, the relationships to wind speed, precipitation, and NDVI are uniformly negative across all seasons.

Table 3
Statistical relationships between $PM_{2.5}$ concentrations and metrics of urban form, socioeconomic conditions, and natural conditions of urban agglomerations. Statistical significance is at the 1% level. NS = nonsignificant, and all p-values are less than 0.001. Summary statistics are given in italics.

Metric	Statistical relationship (R^2 coefficient)			
	Spring	Summer	Autumn	Winter
CA	+ (0.249)	+ (0.128)	+ (0.123)	+ (0.117)
NP	+ (0.273)	+ (0.175)	+ (0.428)	+ (0.292)
PARA_MN	- (0.072)	- (0.063)	- (0.080)	+ (0.045)
ENN_MN	- (0.042)	- (0.027)	- (0.069)	NS
Population density	- (0.042)	NS	NS	NS
Temperature	+ (0.279)	+ (0.466)	+ (0.355)	- (0.100)
Precipitation	- (0.318)	- (0.672)	- (0.221)	- (0.126)
Wind speed	- (0.186)	- (0.291)	- (0.172)	- (0.424)
NDVI	- (0.046)	- (0.049)	- (0.196)	NS
R^2	*0.340*	*0.541*	*0.481*	*0.460*
F	*413.254*	*942.273*	*740.923*	*681.782*
Number of samples	*7215*	*7215*	*7215*	*7215*

4. Discussion

4.1. The influencing paths of urban form on $PM_{2.5}$ concentrations

The known direct and indirect paths by which the four dimensions of urban form examined here can influence $PM_{2.5}$ concentrations are diagrammed in Fig. 5. Higher emissions due to industry, transportation, and residential activities are associated with an increase of urban size and can directly aggravate $PM_{2.5}$ pollution and also generate ground dust (Shi et al., 2019b; Wang et al., 2022). Moreover, larger urban size can exacerbate the urban heat island effect, increasing urban temperatures and leading to more energy consumption; associated patterns of urban-rural wind circulation can also cause air pollutants to gather over the city, increasing $PM_{2.5}$ pollution (Liang and Keener, 2015; Ngarambe et al., 2021). Fragmentation and dispersion can affect $PM_{2.5}$ concentrations via impacts on energy consumption due to traffic and energy efficiency of industrial production. Specifically, fragmented urban structure can lead to long travel distances and reduced accessibility to public transportation but more utilization of private cars, which directly increase the energy consumption due to traffic (Fan et al., 2018; Muñiz and Sánchez, 2018). These issues are of less importance when urban form is compact, but dense buildings may cause the urban canyon effect, which leads to the retention and accumulation of air pollutants (Liang et al., 2020).

Polycentric urban form can effectively separate human activities in space. It accelerates the deposition and diffusion of air pollutants and is conducive to the improvement of public infrastructure, which can boost the use of public transportation and lessen traffic emissions (Cárdenas Rodríguez et al., 2016; He et al., 2022; Tao et al., 2020). Centralized urban form can also give full play to the advantages of economic agglomeration, which lead to lower transportation costs and enhanced use of technology. This improves production efficiency and reduces industrial emissions (Cao et al., 2016; Wang et al., 2020; Xu et al., 2022). In addition, irregular urban form can directly worsen $PM_{2.5}$ pollution, because it generates a complex pattern of highways and smaller roads, and this results in more traffic congestion and energy consumption (Zhou et al., 2018). Irregular shape can nevertheless indirectly alleviate $PM_{2.5}$ pollution by improving the flow of air pollutants between construction land and other land types, especially forest land (Lu et al., 2017). This is conducive to strengthening the purification effect of vegetation on air pollutants and optimizing the urban microclimate, so as to promote the rapid removal of fine particles from the air and thus mitigate $PM_{2.5}$ pollution (Cai et al., 2020; Łowicki, 2019).

4.2. The influencing characteristics of urban form and levels of urban development on $PM_{2.5}$ concentrations

The total size of the urbanized footprint (CA), the extent to which it is fragmented into patches (NP), and the regularity of patch shape (PARA_MN) are strongly related to $PM_{2.5}$ concentrations in Chinese UAs at all three levels of development, but statistical relationship to a fourth metric of urban form, compactness (ENN_MN), is only significant in all UAs. Specifically, the urban size (CA) has stronger impact on $PM_{2.5}$ concentrations in zonal-level UAs and surprisingly shows negative correlation contrary to that of more developed UAs. A similar result was obtained by Liang and Gong (2020), demonstrating that area metrics had stronger effect on the change of $PM_{2.5}$ concentrations at the early

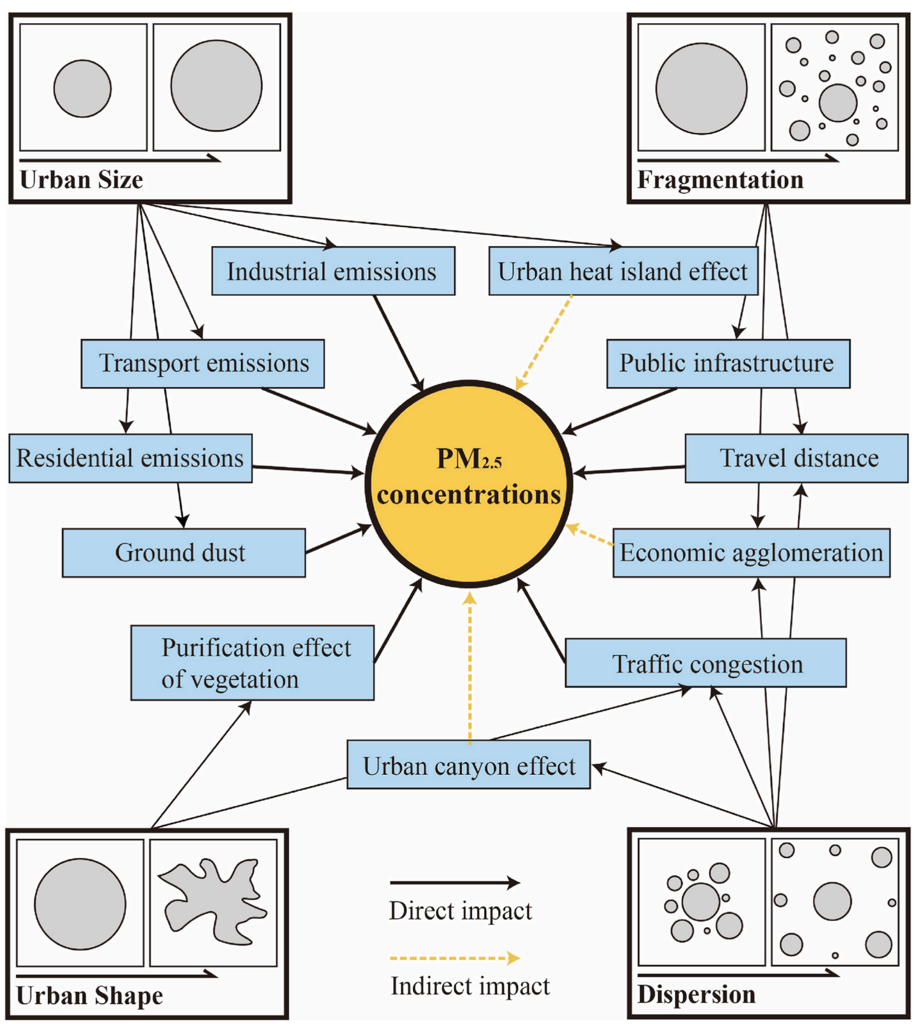

Fig. 5. Known influencing paths of urban form on $PM_{2.5}$ concentrations and their relationships to urban form.

urbanization stage and lower $PM_{2.5}$ concentrations appeared in larger built-up area. This can partly be explained by the phenomenon of ghost cities, which mainly appears in undeveloped regions of China as a result of the overdevelopment of real estate since the late 1970s (Jiang et al., 2017; Lu et al., 2018b; Williams et al., 2019). Due to fewer population and human activities, the areas with a relatively high proportion of built-up land, especially rural and suburban areas, have lower $PM_{2.5}$ concentrations (Xia et al., 2022), but this doesn't imply minor $PM_{2.5}$ pollution in the cores of cities (Liang and Gong, 2020). Therefore, controlling the rational and orderly expansion of cities is still of great importance in zonal-level UAs, in view of the salient effect of urban size on $PM_{2.5}$ concentrations.

The coefficient positively associated with fragmentation (NP) at the regional-level is relatively large compared to the corresponding coefficient at the more developed national-level. This is in line with the results of several existing studies. For example, Tao et al. (2020) found that $PM_{2.5}$ concentrations in small and medium-sized cities had stronger response to urban fragmentation than that of large cities in the Yangtze River Delta region. A greater positive correlation between $PM_{2.5}$ concentrations and urban fragmentation in medium cities was also observed in a case study of 250 Chinese cities (Shi et al., 2019b). Owing to the high level of fragmentation in regional-level UAs (Fig. 4), energy consumption would rise with increasing travel distance and the imperfect public infrastructure (Lee, 2020; Lu and Liu, 2016). Besides, the level of management, urban planning and production technology in regional-level UAs which are conducive to less air pollution is relatively lower than those in national-level UAs (Wang et al., 2020; Yang et al., 2020a). All of these can accelerate the deterioration of air quality, and thus urban expansion with many scattered patches should be replaced by relatively continuous ones in regional-level UAs of China.

In national-level UAs, urban shape described by PARA_MN has a greater influence on the decline of $PM_{2.5}$ concentrations. This suggests that higher irregularity of built-up land is beneficial to the improvement of air quality. Similarly, Yuan et al. (2018a) pointed out that large cities in China should develop a multi-center urban form with high landscape diversity and a spatially balanced pattern of green land. Taking cities in the Yangtze River Delta as examples, Lu et al. (2018)also claimed that irregular shape of landscape patch was instrumental in alleviating $PM_{2.5}$ pollution. Duan et al. (2021) further explored the influencing factors of $PM_{2.5}$ in high-density cities and found that land use mix was conductive to decreasing $PM_{2.5}$ concentrations and should be underlined in the construction of developed cities, especially the urban areas. The main reason is that the enhancement of urban irregularity can commendably increase the areas of construction land contacted with other lands and promote the deposition of air pollutants much more effectively (Łowicki, 2019; Lu et al., 2017). Hence, local planners should show more solicitude for the urban shape in national-level UAs and take measures able to boost urban irregularity.

4.3. The seasonal influence of urban form on $PM_{2.5}$ concentrations

Although the size and fragmentation of the urban area are both positively related to $PM_{2.5}$ levels in all four seasons, the strength of the relationship, as determined by the coefficient, varied considerably. The relationship between $PM_{2.5}$ levels and CA was strongest in spring, but that between levels of the pollutant and NP was strongest in the autumn. In contrast, the coefficients associated with PARA_MN and ENN_MN were generally weak and in one case nonsignificant. Moreover, PARA_MN was positively related to $PM_{2.5}$ levels in the winter but the relationship was negative in the other three seasons. The positive association between $PM_{2.5}$ and urban irregularity in winter is likely due to low vegetation coverage. Due to the attenuation of capacity of vegetation to eliminate pollutants, a positive effect on $PM_{2.5}$ concentrations caused by complex urban shape tends to be more apparent. For example, the complex road traffic systems are accompanied by more pollution emissions than simple transport systems, as it could bring about long commuting distances and high probability of traffic jams signifying more energy consumption (Shi et al., 2019a). Thus, it is crucial to plant more evergreen trees to enhance the ability of vegetation to diminish air pollutants during winter (He et al., 2020; Xu et al., 2020). For the negative effect of temperature in winter, the possible reason might be that under a generally lower temperature level than other seasons, the increase of temperature in winter could promote the diffusion of air pollutants and also reduce the use of heating equipment, thereby declining $PM_{2.5}$ concentrations in the air (Fan et al., 2018).

The seasonal regression models show that more attention should be paid to the relationship between urban form and $PM_{2.5}$ concentrations in spring and autumn rather than summer and winter, consistent with the findings in previous studies. For example, a study in 279 Chinese cities revealed that more urban form metrics had greater influence on $PM_{2.5}$ concentrations in spring (Shi et al., 2019a). Taking 83 Chinese cities as example, Liu et al. (2018b) concluded that the relationship between air pollution and urban form was more significant in spring. Since China has one of the most developed monsoon climates in the world, with moist sea breezes dominating in summer and dry land breezes dominating in winter (Li et al., 2021b; Zhang et al., 2010). These breezes improve atmospheric fluidity and thus promote the diffusion of air pollutants in summer and winter, but they also heighten water vapor supply and convergence level, which increase rainfall in summer and consequently favor of the settlement of air pollutants (Liu et al., 2018b; Sun et al., 2017). This is consistent with our observation that precipitation plays a more important role in alleviating $PM_{2.5}$ pollution than other variables during summer, but wind speed has a stronger effect in winter (Table 3), similar to the findings of Wang et al., 2021. Therefore, optimizing urban form of Chinese UAs would have better effect on the improvement of urban air quality in spring and autumn and polycentric urban form with lower fragmentation is more appropriate for local governments to adopt in urban planning.

4.4. Limitations and future directions

Although the current study provides significant insights into how urban form influences $PM_{2.5}$ concentrations, the collinearity problem reduced the number of socio-economic metrics to just one, population density. It thus would be useful to identify additional socio-economic factors of probable significance to haze pollution and incorporate them into future studies. Candidates include metrics related to industrial structure, foreign direct investment, and vehicle ownership (He et al., 2019; Yan et al., 2020). Panel data over several years and spatial regression models could also be employed to achieve higher reliability and accuracy of results (Li and Zhou, 2019). The construction land category is clearly significant in terms of $PM_{2.5}$ levels, and urban planning usually proceeds at the level of function (Yuan et al., 2019). Important insights could consequently be obtained by subdividing the construction land category according to function, i.e., residential, industrial, transportation, and other functions, prior to regression analysis. In the future, it will also be important to explore the response feature of $PM_{2.5}$ concentrations to urban form on various spatial scales (e.g. urban scale, provincial scale, UA scale and national scale) and the spatial spillover effect of urban form on $PM_{2.5}$ concentrations, clarifying whether certain urban form metrics should be regulated within UAs or coordinated by several UAs (Du et al., 2019; Li et al., 2021a; Yang et al., 2020c) In addition, we only compartmentalized different study areas based on the urbanization level of urban agglomerations urbanization to explore the effect of urbanization level on the relationship of $PM_{2.5}$ and urban form. Further research could divide study areas into several groups based on the urbanization level of each study unit. The spatial scale of research unit (20 km) used in our study was selected in view of the conditions of the study area and the availability of data but may not be appropriate for all kinds of study areas. Thus the effect of spatial scale on the relationship between $PM_{2.5}$ and urban form needs further exploration and each research should adopt proper spatial scales according to the specific condition (Li et al., 2021a).

5. Conclusions

This study explored the relationships between $PM_{2.5}$ concentrations and urban form with different urbanization levels and seasons in 19 Chinese UAs. There are several main findings: (1) except for dispersion with significant effect in all UAs, the influence strength of urban form on $PM_{2.5}$ concentrations varies with urbanization level, with stronger impact of urban size within lower-level UAs, fragmentation within regional-level UAs, and urban shape within national-level UAs; (2) urban form has more intense effects on $PM_{2.5}$ concentrations during spring and autumn rather than summer and winter; (3) generally, urban size and fragmentation tends to increase $PM_{2.5}$ concentrations while urban shape and dispersion have the opposite impact. Overall, urban planners should pay more attention to urban form metrics with stronger effects on air pollution in various urbanization-level UAs. Prevention and control of air pollutants in spring, autumn and winter can effectively ameliorate $PM_{2.5}$ pollution.

Credit author statement

Genhong Gao: Conceptualization; Methodology; Visualization; Writing - Original Draft, **Steven G. Pueppke:** Writing - Review & Editing, **Qin Tao:** Investigation, **Jing Wei:** Resources, **Weixin Ou:** Supervision, **Yu Tao: Supervision:** Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

Bai, L., Jiang, L., Yang, D., Liu, Y., 2019. Quantifying the spatial heterogeneity influences of natural and socioeconomic factors and their interactions on air pollution using the geographical detector method: a case study of the Yangtze River Economic Belt, China. J. Clean. Prod. 232, 692–704.
Bereitschaft, B., Debbage, K., 2013. Urban form, air pollution, and CO_2 emissions in large U.S. Metropolitan areas. Prof. Geogr. 65 (4), 612–635.
Cai, L., Zhuang, M., Ren, Y., 2020. Spatiotemporal characteristics of NO_2, $PM_{2.5}$ and O_3 in a coastal region of southeastern China and their removal by green spaces. Int. J. Environ. Health Res. 32 (1), 1–17.
Cao, G., Shi, Q., Liu, T., 2016. An integrated model of urban spatial structure: insights from the distribution of floor area ratio in a Chinese city. Appl. Geogr. 75, 116–126.
Cárdenas Rodríguez, M., Dupont-Courtade, L., Oueslati, W., 2016. Air pollution and urban structure linkages: evidence from European cities. Renew. Sustain. Energy Rev. 53, 1–9.
Chen, T., Li, M., Luo, L., Deng, S., Zhou, R., Chen, D., 2020. Simulating the effects of land urbanization on regional meteorology and air quality in Yangtze River Delta, China. Appl. Geogr. 120, 102228.
Cushman, S.A., McGarigal, K., Neel, M.C., 2008. Parsimony in landscape metrics: strength, universality, and consistency. Ecol. Indicat. 8 (5), 691–703.
Du, Y., Wan, Q., Liu, H., Liu, H., Kapsar, K., Peng, J., 2019. How does urbanization influence $PM_{2.5}$ concentrations? Perspective of spillover effect of multi-dimensional urbanization impact. J. Clean. Prod. 220, 974–983.
Duan, S., Liu, Q., Jiang, D., Jiang, Y., Lin, Y., Gong, Z., 2021. Exploring the Joint impacts of natural and built environments on $PM_{2.5}$ concentrations and their spatial heterogeneity in the context of high-density Chinese cities. Sustainability 13 (21), 11775.
Fan, C., Tian, L., Zhou, L., Hou, D., Song, Y., Qiao, X., Li, J., 2018. Examining the impacts of urban form on air pollutant emissions: Evidence from China. J. Environ. Manag. 212, 405–414.
Fan, S., Li, X., Dong, L., 2019. Field assessment of the effects of land-cover type and pattern on PM_{10} and $PM_{2.5}$ concentrations in a microscale environment. Environ. Sci. Pollut. Control Ser. 26 (3), 2314–2327.
Fang, C., 2015. Important progress and future direction of studies on China's urban agglomerations. J. Geogr. Sci. 25 (8), 1003–1024.
Faridi, S., Shamsipour, M., Krzyzanowski, M., Künzli, N., Amini, H., Azimi, F., Malkawi, M., Momeniha, F., Gholampour, A., Hassanvand, M.S., Naddafi, K., 2018. Long-term trends and health impact of $PM_{2.5}$ and O_3 in Tehran, Iran. Environ. Int. 114, 37–49, 2006–2015.
Gong, J., Hu, Z., Chen, W., Liu, Y., Wang, J., 2018. Urban expansion dynamics and modes in metropolitan Guangzhou, China. Land Use Pol. 72, 100–109.
Guo, L., Luo, J., Yuan, M., Huang, Y., Shen, H., Li, T., 2019. The influence of urban planning factors on $PM_{2.5}$ pollution exposure and implications: a case study in China based on remote sensing, LBS, and GIS data. Sci. Total Environ. 659, 1585–1596.
Hajiloo, F., Hamzeh, S., Gheysari, M., 2019. Impact assessment of meteorological and environmental parameters on $PM_{2.5}$ concentrations using remote sensing data and GWR analysis (case study of Tehran). Environ. Sci. Pollut. Control Ser. 26 (24), 24331–24345.
Han, L., Zhou, W., Li, W., Li, L., 2014. Impact of urbanization level on urban air quality: a case of fine particles ($PM_{2.5}$) in Chinese cities. Environ. Pollut. 194, 163–170.
Han, S., Sun, B., Zhang, T., 2020. Mono- and polycentric urban spatial structure and $PM_{2.5}$ concentrations: Regarding the dependence on population density. Habitat Int. 104, 102257.
He, C., Qiu, K., Alahmad, A., Pott, R., 2020. Particulate matter capturing capacity of roadside evergreen vegetation during the winter season. Urban For. Urban Green. 48, 126510.
He, L., Liu, Y., He, P., Zhou, H., 2019. Relationship between air pollution and urban forms: evidence from prefecture-level cities of the Yangtze River basin. Int. J. Environ. Res. Publ. Health 16 (18), 3459.
He, Q., Rao, Y., Dai, J., Dai, D., Ou, A.G., 2022. Effect of urban structure on $PM_{2.5}$ in China: a multiscale landscape analysis of 362 cities. J. Urban Plann. Dev. 148 (2), 05022010.
Jiang, Y., Mohabir, N., Ma, R., Zhu, P., 2017. Sorting through neoliberal variations of ghost cities in China. Land Use Pol. 69, 445–453.
Lee, C., 2019. Impacts of urban form on air quality in metropolitan areas in the United States. Comput. Environ. Urban Syst. 77, 101362.
Lee, C., 2020. Impacts of multi-scale urban form on $PM_{2.5}$ concentrations using continuous surface estimates with high-resolution in U.S. metropolitan areas. Landsc. Urban Plann. 204, 103935.
Li, F., Zhou, T., 2019. Effects of urban form on air quality in China: an analysis based on the spatial autoregressive model. Cities 89, 130–140.
Li, F., Zhou, T., Lan, F., 2021a. Relationships between urban form and air quality at different spatial scales: a case study from northern China. Ecol. Indicat. 121, 107029.
Li, G., Fang, C., Wang, S., Sun, S., 2016. The effect of economic growth, urbanization, and industrialization on fine particulate matter ($PM_{2.5}$) concentrations in China. Environ. Sci. Technol. 50 (21), 11452–11459.
Li, R., Wang, Z., Cui, L., Fu, H., Zhang, L., Kong, L., Chen, W., Chen, J., 2019. Air pollution characteristics in China during 2015–2016: spatiotemporal variations and key meteorological factors. Sci. Total Environ. 648, 902–915.
Li, Y., An, X., Zhang, P., Yang, J., Wang, C., Li, J., 2021b. Influence of East Asian winter monsoon on particulate matter pollution in typical regions of China. Atmos. Environ. 260, 118213.
Liang, L., Gong, P., 2020. Urban and air pollution: a multi-city study of long-term effects of urban landscape patterns on air quality trends. Sci. Rep. 10 (1), 18618.
Liang, M.S., Keener, T.C., 2015. Atmospheric feedback of urban boundary layer with implications for climate adaptation. Environ. Sci. Technol. 49 (17), 10598–10606.
Liang, Z., Wei, F., Wang, Y., Huang, J., Jiang, H., Sun, F., Li, S., 2020. The context-dependent effect of urban form on air pollution: a panel data analysis. Rem. Sens. 12 (11), 1793.
Lin, J.M., Billa, L., 2021. Spatial prediction of flood-prone areas using geographically weighted regression. Environmental Advances 6, 100118.
Liu, J., Han, Y., Tang, X., Zhu, J., Zhu, T., 2016. Estimating adult mortality attributable to $PM_{2.5}$ exposure in China with assimilated $PM_{2.5}$ concentrations based on a ground monitoring network. Sci. Total Environ. 568, 1253–1262.
Liu, Q., Wu, R., Zhang, W., Li, W., Wang, S., 2020. The varying driving forces of $PM_{2.5}$ concentrations in Chinese cities: insights from a geographically and temporally weighted regression model. Environ. Int. 145, 106168.
Liu, W., Liu, J., Kuang, W., Ning, J., 2017. Examining the influence of the implementation of Major Function-oriented Zones on built-up area expansion in China. J. Geogr. Sci. 27 (6), 643–660.
Liu, Y., He, L., Qin, W., Lin, A., Yang, Y., 2022. The effect of urban form on $PM_{2.5}$ concentration: evidence from China's 340 prefecture-level cities. Rem. Sens. 14 (1), 7.
Liu, Y., Wu, J., Yu, D., 2018a. Disentangling the complex effects of socioeconomic, climatic, and urban form factors on air pollution: a case study of China. Sustainability 10 (3), 776.
Liu, Y., Wu, J., Yu, D., Ma, Q., 2018b. The relationship between urban form and air pollution depends on seasonality and city size. Environ. Sci. Pollut. Control Ser. 25 (16), 15554–15567.

Łowicki, D., 2019. Landscape pattern as an indicator of urban air pollution of particulate matter in Poland. Ecol. Indicat. 97, 17–24.
Lu, C., Liu, Y., 2016. Effects of China's urban form on urban air quality. Urban Stud. 53 (12), 2607–2623.
Lu, D., Mao, W., Yang, D., Zhao, J., Xu, J., 2018a. Effects of land use and landscape pattern on $PM_{2.5}$ in Yangtze River Delta, China. Atmos. Pollut. Res. 9 (4), 705–713.
Lu, D., Xu, J., Yang, D., Zhao, J., 2017. Spatio-temporal variation and influence factors of $PM_{2.5}$ concentrations in China from 1998 to 2014. Atmos. Pollut. Res. 8 (6), 1151–1159.
Lu, H., Zhang, C., Liu, G., Ye, X., Miao, C., 2018b. Mapping China's ghost cities through the combination of nighttime satellite data and daytime satellite data. Rem. Sens. 10 (7), 1037.
Muñiz, I., Sánchez, V., 2018. Urban spatial form and structure and greenhouse-gas emissions from commuting in the metropolitan zone of Mexico valley. Ecol. Econ. 147, 353–364.
Nazif, A., Mohammed, N.I., Malakahmad, A., Abualqumboz, M.S., 2018. Regression and multivariate models for predicting particulate matter concentration level. Environ. Sci. Pollut. Control Ser. 25 (1), 283–289.
Ngarambe, J., Oh, J.W., Su, M.A., Santamouris, M., Yun, G.Y., 2021. Influences of wind speed, sky conditions, land use and land cover characteristics on the magnitude of the urban heat island in Seoul: an exploratory analysis. Sustain. Cities Soc. 71, 102953.
Pui, D.Y.H., Chen, S., Zuo, Z., 2014. $PM_{2.5}$ in China: measurements, sources, visibility and health effects, and mitigation. Particuology 13, 1–26.
She, Q., Peng, X., Xu, Q., Long, L., Wei, N., Liu, M., Jia, W., Zhou, T., Han, J., Xiang, W., 2017. Air quality and its response to satellite-derived urban form in the Yangtze River Delta, China. Ecol. Indicat. 75, 297–306.
Shen, Y., Zhang, L., Fang, X., Ji, H., Li, X., Zhao, Z., 2019. Spatiotemporal patterns of recent $PM_{2.5}$ concentrations over typical urban agglomerations in China. Sci. Total Environ. 655, 13–26.
Shi, K., Li, Y., Chen, Y., Li, L., Huang, C., 2019a. How does the urban form-$PM_{2.5}$ concentration relationship change seasonally in Chinese cities? A comparative analysis between national and urban agglomeration scales. J. Clean. Prod. 239, 118088.
Shi, K., Wang, H., Yang, Q., Wang, L., Sun, X., Li, Y., 2019b. Exploring the relationships between urban forms and fine particulate ($PM_{2.5}$) concentration in China: a multi-perspective study. J. Clean. Prod. 231, 990–1004.
Song, C., He, J., Wu, L., Jin, T., Chen, X., Li, R., Ren, P., Zhang, L., Mao, H., 2017. Health burden attributable to ambient $PM_{2.5}$ in China. Environ. Pollut. 223, 575–586.
Sun, L., Shen, B., Sui, B., Huang, B., 2017. The influences of East Asian monsoon on summer precipitation in Northeast China. Clim. Dynam. 48, 1647–1659.
Tao, Y., Zhang, Z., Ou, W., Guo, J., Pueppke, S.G., 2020. How does urban form influence $PM_{2.5}$ concentrations: insights from 350 different-sized cities in the rapidly urbanizing Yangtze River Delta region of China. Cities 98, 102581, 1998–2015.
Tian, Y., Yao, X., Chen, L., 2019. Analysis of spatial and seasonal distributions of air pollutants by incorporating urban morphological characteristics. Comput. Environ. Urban Syst. 75, 35–48.
Tian, Z., Fang, D., Chen, B., 2020. Three-scale input-output analysis for energy and water consumption in urban agglomeration. J. Clean. Prod. 268, 122148.
Tu, M., Liu, Z., He, C., Fang, Z., Lu, W., 2019. The relationships between urban landscape patterns and fine particulate pollution in China: a multiscale investigation using a geographically weighted regression model. J. Clean. Prod. 237, 117744.
Wang, Z., Shi, X., Pan, C., Wang, S., 2021. Spatial and temporal characteristics of environmental air quality and its relationship with seasonal climatic conditions in eastern China during 2015–2018. Int. J. Environ. Res. Publ. Health 18 (9), 4524.
Wang, J., Wang, S., Li, S., 2019. Examining the spatially varying effects of factors on $PM_{2.5}$ concentrations in Chinese cities using geographically weighted regression modeling. Environ. Pollut. 248, 792–803.
Wang, S., Gao, S., Li, S., Feng, K., 2020. Strategizing the relation between urbanization and air pollution: Empirical evidence from global countries. J. Clean. Prod. 243, 118615.
Wang, Z., Liang, L., Wang, X., 2021. Spatiotemporal evolution of $PM_{2.5}$ concentrations in urban agglomerations of China. J. Geogr. Sci. 31 (6), 878–898.
Wang, L., Niu, D., Fan, H., Long, X., 2022. Urban configuration and $PM_{2.5}$ concentrations: evidence from 330 Chinese cities. Environ. Int. 161, 107129.
Wang, Y., Yao, L., Xu, Y., Sun, S., Li, T., 2021. Potential heterogeneity in the relationship between urbanization and air pollution, from the perspective of urban agglomeration. J. Clean. Prod. 298, 126822.
Wang, N., Zhu, Y., Yang, T., 2020. The impact of transportation infrastructure and industrial agglomeration on energy efficiency: evidence from China's industrial sectors. J. Clean. Prod. 244, 118708.
Wei, J., Li, Z., Cribb, M., Huang, W., Xue, W., Sun, L., Guo, J., Peng, Y., Li, J., Lyapustin, A., Liu, L., Wu, H., Song, Y., 2020. Improved 1 km resolution $PM_{2.5}$ estimates across China using enhanced space-time extremely randomized trees. Atmos. Chem. Phys. 20 (6), 3273–3289.
Wei, J., Li, Z., Lyapustin, A., Sun, L., Peng, Y., Xue, W., Su, T., Cribb, M., 2021. Reconstructing 1-km-resolution high-quality $PM_{2.5}$ data records from 2000 to 2018 in China: spatiotemporal variations and policy implications. Rem. Sens. Environ. 252, 112136.
Williams, S., Xu, W., Tan, S.B., Foster, M.J., Chen, C., 2019. Ghost cities of China: Identifying urban vacancy through social media data. Cities 94, 275–285.
Wu, T., Zhou, L., Jiang, G., Meadows, M.E., Zhang, J., Pu, L., Wu, C., Xie, X., 2021. Modelling spatial heterogeneity in the effects of natural and socioeconomic factors, and their interactions, on atmospheric $PM_{2.5}$ concentrations in China from 2000–2015. Rem. Sens. 13 (11), 2152.
Xia, S., Liu, X., Liu, Q., Zhou, Y., Yang, Y., 2022. Heterogeneity and the determinants of $PM_{2.5}$ in the Yangtze River economic belt. Sci. Rep. 12 (1).
Xu, G., Ren, X., Xiong, K., Li, L., Bi, X., Wu, Q., 2020. Analysis of the driving factors of $PM_{2.5}$ concentration in the air: a case study of the Yangtze River Delta, China. Ecol. Indicat. 110, 105889.
Xu, M., Tan, R., He, X., 2022. How does economic agglomeration affect energy efficiency in China?: evidence from endogenous stochastic frontier approach. Energy Econ. 108, 105901.
Xu, X., Xia, J., Gao, Y., Zheng, W., 2020. Additional focus on particulate matter wash-off events from leaves is required: a review of studies of urban plants used to reduce airborne particulate matter pollution. Urban For. Urban Green. 48, 126559.
Yan, D., Ren, X., Kong, Y., Ye, B., Liao, Z., 2020. The heterogeneous effects of socioeconomic determinants on $PM_{2.5}$ concentrations using a two-step panel quantile regression. Appl. Energy 272, 115246.
Yang, D., Chen, Y., Miao, C., Liu, D., 2020a. Spatiotemporal variation of $PM_{2.5}$ concentrations and its relationship to urbanization in the Yangtze river delta region, China. Atmos. Pollut. Res. 11 (3), 491–498.
Yang, J., Shi, B., Zheng, Y., Shi, Y., Xia, G., 2020b. Urban form and air pollution disperse: key indexes and mitigation strategies. Sustain. Cities Soc. 57, 101955.
Yang, X., Lu, Y., Zhu, X., He, J., Jiang, Q., Wu, K., Wang, H., Zhang, X., Wang, S., 2020c. Formation and evolution mechanisms of severe haze pollution in the Sichuan basin, Southwest China. Aerosol Air Qual. Res. 20 (11).
Yuan, M., Huang, Y., Shen, H., Li, T., 2018a. Effects of urban form on haze pollution in China: spatial regression analysis based on $PM_{2.5}$ remote sensing data. Appl. Geogr. 98, 215–223.
Yuan, M., Song, Y., Huang, Y., Hong, S., Huang, L., 2018b. Exploring the association between urban form and air quality in China. J. Plann. Educ. Res. 38 (4), 413–426.
Yuan, M., Song, Y., Huang, Y., Shen, H., Li, T., 2019. Exploring the association between the built environment and remotely sensed $PM_{2.5}$ concentrations in urban areas. J. Clean. Prod. 220, 1014–1023.
Zhang, L., Liao, H., Li, J., 2010. Impacts of Asian summer monsoon on seasonal and interannual variations of aerosols over eastern China. J. Geophys. Res. 115 (D7).
Zhang, T., Zang, L., Wan, Y., Wang, W., Zhang, Y., 2019. Ground-level $PM_{2.5}$ estimation over urban agglomerations in China with high spatiotemporal resolution based on Himawari-8. Sci. Total Environ. 676, 535–544.
Zhang, X., Chen, L., Yuan, R., 2020. Effect of natural and anthropic factors on the spatiotemporal pattern of haze pollution control of China. J. Clean. Prod. 251, 119531.
Zhou, C., Li, S., Wang, S., 2018. Examining the impacts of urban form on air pollution in developing countries: a case study of China's megacities. Int. J. Environ. Res. Publ. Health 15 (8), 1565.