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Effects of urban form on haze pollution in China: Spatial regression analysis based on $PM_{2.5}$ remote sensing data

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ABSTRACT

In recent years, haze pollution has posed a great threat to public health in any Chinese cities. It is necessary to explore different prevention methods for haze, and shaping a reasonable urban form may be a good way to improve air quality. This study selected 269 cities as sample cities, used $PM_{2.5}$ remote sensing data, and employed spatial regression models to explore the effects of urban form on haze pollution. The results show that urban form can affect the concentration of $PM_{2.5}$ through vehicle use, green land regulation, pollutant diffusion, and the heat island effect. The results suggest that the effects of population density, degree of centering, and compactness on air quality depend on population size. Therefore, different development strategies should be used for cities of different sizes. Regional transmission is an important source of haze pollution, and regional joint management strategies for combating haze pollution should be strengthened.

1. Introduction

In recent years, large-scale and long-term haze pollution has occurred in many cities in China, largely due to $PM_{2.5}$ pollution. $PM_{2.5}$ can damage the respiratory and cardiovascular systems of the human body, as it can enter the lungs and blood via the respiratory tract (Cao et al., 2011; Dominici et al., 2006; Tu & Tu, 2018). Air pollution causes the premature death of 1.2 million people every year in China (Lim, Vos, Flaxman, Danaei, Shibuya, & Adair-Rohani, 2010), and reducing the concentration of $PM_{2.5}$ is crucial to improving the health of residents.

Past studies have shown that rapid urbanization and industrialization have greatly contributed to air pollution in China, and some socioeconomic development factors, including urbanization, urban expansion, per capita gross domestic product (GDP), industry, and transport, affect air quality (Fang, Liu, Li, Sun, & Miao, 2015; Hao & Liu, 2015; Liu et al., 2017; Tao et al., 2015). These studies have shown that urban activities are the main sources of haze pollution in China, but research studies on whether and how urban form would affect $PM_{2.5}$ pollution are limited. Studies in European and American cities have shown that urban form could affect the source and diffusion of air pollutants through urban traffic and climatic conditions, leading to the deterioration of air quality (Bereitschaft & Debbage, 2013; Schweitzer & Zhou, 2010; Stone, 2008). For example, low-density urban sprawl can lead to longer commutes, excessive motor vehicle dependence, and increased emissions, causing higher concentrations of air pollutants (Song et al., 2014). For Chinese cities, tailpipe emissions from vehicles, especially private cars, have become significant sources of haze pollution (Fang et al., 2015; Hao & Liu, 2015; Zhang, Sun, Wang, Li, Zhang, 2013). However, Chinese cities are quite different from European and American cites in terms of urban form, and research on this topic is limited for Chinese cities. Hence, it is necessary to fully investigate the actual situation in Chinese cities. This calls for empirical research based on pollution data and urban spatial data.

This study selects 269 Chinese cities as sample cities and utilizes $PM_{2.5}$ remote sensing data, GIS data, social and economic statistical data alongside spatial regression models to explore the influence of urban form on haze pollution, which may enhance policy decisions to better deal with the air pollution in Chinese cities.

2. Literature review

As motor vehicles gradually became the main source of urban air pollution (Fenger, 1999; Rojasrueda, De, Teixidó, & Nieuwenhuijsen, 2012), a large number of studies in Europe and America began to explore the relationship between urban form and air quality. However, there are still different views on which urban forms may help in improving air quality.

Some studies suggest that dense and compact urban forms can help

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to improve air quality. This viewpoint is based on studies of residents' travel patterns, in which compact urban forms are shown to increase bus sharing rates, reduce dependence on private cars, and reduce vehicle travelling distances (Ewing & Cervero, 2010; Bento, Cropper, Mobarak, & Vinha, 2005; Cervero & Murakami, 2010). With the development of urban simulation models, land use–traffic–emission models have been applied to some cities in Europe and America, and the results show that emissions of air pollutants are lower in compact development scenarios (Borrego et al., 2006; Morton, Rodríguez, Song, & Cho, 2007; Civerolo et al., 2007; Hankey & Marshall, 2010). Pollution monitoring networks provide more data support and promote empirical studies. For example, Ewing, Pendall, and Chen (2003) and Stone (2008) found that population density is negatively correlated with O_3 concentrations in American metropolitan areas. Sovacool and Brown (2010) compared CO_2 emissions from 12 capital cities, and the result showed that compact cities tend to have lower levels of energy consumption and pollution emissions. Bereitschaft and Debbage (2013) discussed the situation in the 86 metropolitan areas of the United States and concluded that low-density urban sprawl may lead to higher concentrations of air pollution. In addition, some studies have shown that the spatial fragmentation of urban land is positively correlated with air pollution (Bechle, Millet, & Marshall, 2011; McCarty & Kaza, 2015).

Conversely, other scholars have argued that a high-density compact urban form does not significantly improve air quality and may even lead to more serious air pollution. Using a panel data analysis of 17 cities in South Korea, Cho and Choi (2014) found that compact urban forms have no significant effect on improving air quality and their high density may even lead to an increase in SO_2 and CO concentrations. Clark, Millet, and Marshall (2011) selected 111 cities in the United States as samples and found that $PM_{2.5}$ pollution levels increase as population density increases. Rodríguez, Dupont-Courtade, and Oueslati (2016) found that high-density cities are vulnerable to high concentrations of SO_2 by studying 249 European cities. In addition, some studies have argued that high-density urban forms will increase the number of people exposed to air pollution, leading to even greater health threats (De Ridder et al., 2008; Hixson et al., 2010; Kahyaoğlu-Koračin, Bassett, Mouat, & Gertler, 2009).

In addition, urban form could affect air quality in a variety of ways. For example, although urban green spaces can purify air and absorb particulate matter (Groenewegen & Vries, 2012), how urban forms can make the most effective use of this purification effect is still unknown. The geometric shape of city streets is also important, and it is generally understood that excessive building density is not conducive to the diffusion of pollutants (Buccolieri, Sandberg, & Di Sabatino, 2010; Gaigné, Riou, & Thisse, 2012; Taseiko, Mikhailuta, Pitt, Lezhenin, & Zakharov, 2009). At the same time, urban form is related to the urban heat island effect, and the increase in urban air temperature not only increases electricity consumption and CO_2 production (through air conditioning) but may also promote the formation of $PM_{2.5}$ and O_3 pollutants (Sarrat, Lemonsu, Masson, & Guedalia, 2006; Schwarz & Manceur, 2014a; Taha, 2008).

In recent years, some scholars have begun to focus on the relationship between urban form and air quality in China, but there are not yet any consistent and clear conclusions. Some scholars believed that the low density and dispersed urban form is one of the causes of long-distance commutes and traffic congestion (Wang, Chai, & Li, 2011; Yang, Shen, Shen, & He, 2012; Zhao, Lü, & de Roo, 2010) and that compact, high-density urban forms with mixed land use and better bus service can reduce vehicle travel distances and tailpipe exhaust emissions (Qin & Han, 2013). Other studies argue that the compact urban form is not applicable to Chinese cities with already high densities and mixed land use (Juhee, 2014). With the establishment of air pollution monitoring networks in China, some scholars tried to use observation data to conduct empirical studies, but they could not arrive at a clear conclusion. For example, Liu, Arp, Song, and Song (2016) analyzed the panel data for 30 cities in China and found that the increase in urban land compactness may increase the concentration of PM_{10}. By studying the pollution data for 287 Chinese cities, Lu and Liu (2016) found that land-use compactness is generally negatively correlated with concentrations of NO_2 and SO_2, but the effect varies from region to region. By analyzing the pollution data for 84 cities in China, Yuan, Song, Huang, Hong, and Huang (2017) found that population density is negatively correlated with the concentrations of $PM_{2.5}$, PM_{10}, and O_3.

In summary, the existing research has not yet reached a unanimous conclusion, and conclusions from European and American cities cannot be applied directly to cities in China due to differences in both urban forms and pollution sources. The $PM_{2.5}$ pollution monitoring network does not cover all cities in China, and it is difficult to carry out a robust regression analysis using only a small number of urban samples. Satellite remote sensing data have the advantage of full coverage and high-precision earth observations, and $PM_{2.5}$ concentration data can be acquired from remote sensing aerosol data (Li, Shen, Zeng, Yuan, & Zhang, 2017; Martin, 2008). In addition, $PM_{2.5}$ regional transmission is also an important source of urban haze, and there exists a spatial autocorrelation of $PM_{2.5}$ concentration for nearby cities. However, most existing research ignores this effect, making the model results somewhat biased.

3. Data and methodology

Taking 269 Chinese cities above the prefecture level as samples, this study adopts spatial regression models to eliminate the influence of $PM_{2.5}$ regional transmission and explore the effects of urban form on $PM_{2.5}$ concentrations in China. According to conventions established by previous research, this study assumes that urban form will influence $PM_{2.5}$ concentration through vehicle use, green land regulation, pollutant diffusion, and the heat island effect and then quantifies urban form metrics in these four aspects. The work on data collection, model building, and metric selection is described in detail below.

3.1. Study area and data

As Fig. 1 shows, the sample includes 4 municipalities, 26 provincial capitals, and 239 prefecture-level cities. The data used in this study include nighttime light data, $PM_{2.5}$ remote sensing data, population spatial distribution data, land-use data, meteorological data, and social and economic statistical data. DMSP/OLS satellite remote sensing nighttime light data from 2012 were used to extract the built-up area of each city (Jiang, 2015), which laid the foundation for the calculation of urban form metrics. The haze pollution level of each city was measured using $PM_{2.5}$ remote sensing data (Li et al., 2017). These data were based on the 2014 MODIS satellite remote sensing aerosol data and the national air pollution ground monitoring data. A deep learning method was used to retrieve spatial patterns of $PM_{2.5}$ concentrations, with a spatial resolution of 3 km × 3 km and a concentration accuracy of 82%, which meets the requirements of this study. By overlaying $PM_{2.5}$ concentrations on maps of built-up areas, the mean $PM_{2.5}$ concentrations were calculated for each city (Fig. 2-a). The population distribution data used is from the 2014 ORNL LandScan global population distribution at approximately 1-km resolution and represents an ambient population (averaged over 24 h) for each city (Fig. 2-b). Land-cover data are from the 2010 GlobeLand30 dataset (http://www.globallandcover.com/GLC30Download/index.aspx) with a spatial resolution of 30 m and an accuracy of over 80% (Fig. 2-c). Tan & Li, 2015 Open Street Map (OSM) road data (Fig. 2-d), 2014 MODIS land surface temperature data (Fig. 2-e), and 2015 China city statistical yearbook (with data for 2014) were also used in this study.

3.2. Spatial regression model

This study uses a spatial autocorrelation analysis to evaluate whether the $PM_{2.5}$ concentration is related to geographical position, which

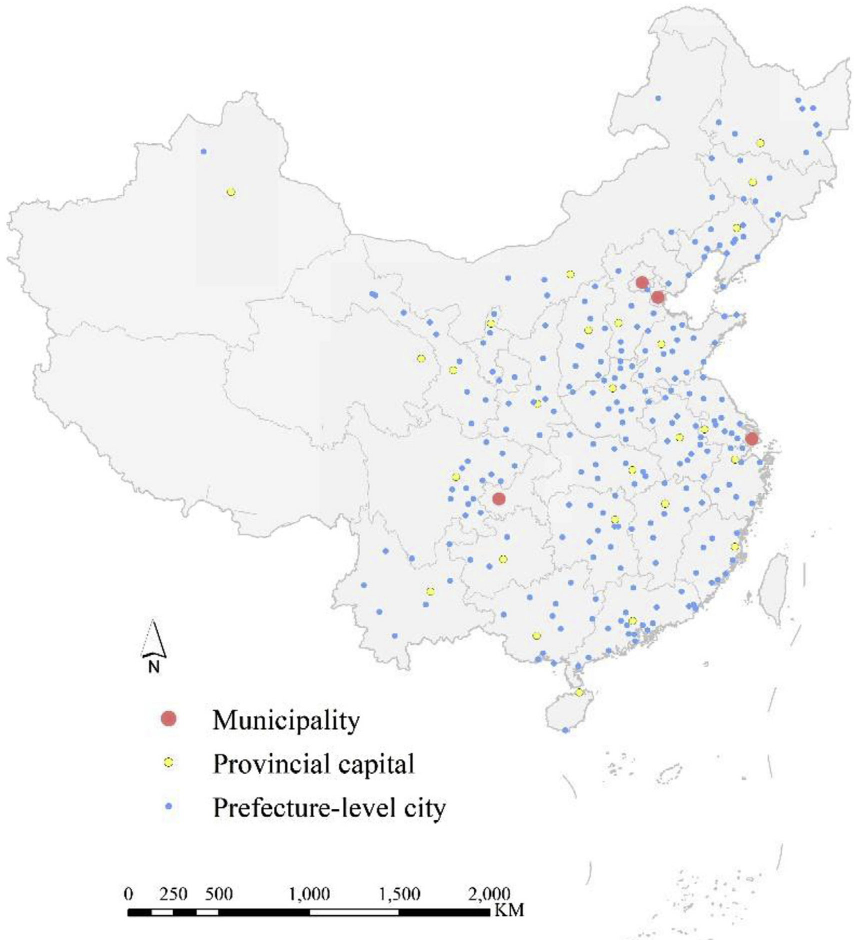

Fig. 1. Locations of the 269 cities selected in this study.

lays the foundation for the use of spatial regression models. A global spatial autocorrelation coefficient, Moran's I, is used to identify the influence of the regional transmission of pollution across the country, and a local spatial autocorrelation coefficient, LISA, is used to identify the effects of pollution from neighboring cities at different locations. The spatial weight matrix is defined with an inverse distance weighting method for the spatial autocorrelation analysis in the study.

Instead of traditional OLS regressions, this study uses spatial regression models to analyze the effect of urban form on haze pollution to consider the effect of regional transmission of pollution. Three main types of spatial regression models, namely the Spatial Lag Model (SLM, equation (1)), Spatial Error Model (SEM, equation (2)), and Spatial Durbin Model (SDM, equation (3)) (Anselin, 1988), are used in this study. These spatial econometric models have been used to control for the spatial effects of air pollution in various studies (Fang et al., 2015; Hao & Liu, 2015; Liu et al., 2017), which validates the effectiveness of the models:

$$y = \rho W_y + \sum a_i X_i + \varepsilon, \tag{1}$$

$$y = \sum a_i X_i + u, \ \ u = \lambda W_u + \varepsilon, \tag{2}$$

$$y = \rho W_y + \sum a_i X_i + u, u = \lambda W_u + \varepsilon, \tag{3}$$

where y is the dependent variable of $PM_{2.5}$ concentration; ρ is a spatial regression coefficient that shows the spatial dependence of the sample observations; λ is a spatial autoregressive coefficient that reflects the spatial dependence of the residuals; W_y and W_u are the spatial lag operators calculated with y, the residual u, and spatial weight matrix W; X_i represents the urban form metric or control variable, and a_i is the corresponding coefficient; and ε is the error term. The SLM contains the spatial dependence effects of the dependent variable y; the SEM contains the spatial dependence effects of the residual u; and the SDM contains both effects. The SLM and SEM were run using GeoDa with the maximum likelihood (ML) method, and the SDM was run using GeoDaSpace software with the Generalized Method of Moments (GMM).

3.3. Metrics

(1) Urban form metric

Urban form metrics are measured in four dimensions, namely vehicle use, green land regulation, pollutant diffusion, and heat island effect, and ArcGIS and Fragstats were used to calculate these metrics.

Population density, degree of centering, accessibility, and compactness are usually correlated with vehicle usage (Zhao et al., 2010), and this study focuses on these metrics. For each city, population density is calculated with LandScan population data and the calculated built-up area. Degree of centering is the ratio of the standard deviation and the mean value of the LandScan population in the built-up area, which reflects the spatial clustering degree of the population (Ewing, Pendall, & Chen, 2002). The larger the value, the higher the level of population aggregation in urban centers. Conversely, smaller values indicate homogeneous population distributions, where there are no obvious urban centers. A landscape metric, SHAPE, is used to reflect the compactness of artificial land (Bereitschaft & Debbage, 2013; She et al., 2017), and this study considers a negative value of SHAPE to evaluate the compactness. The larger the value, the more compact the urban

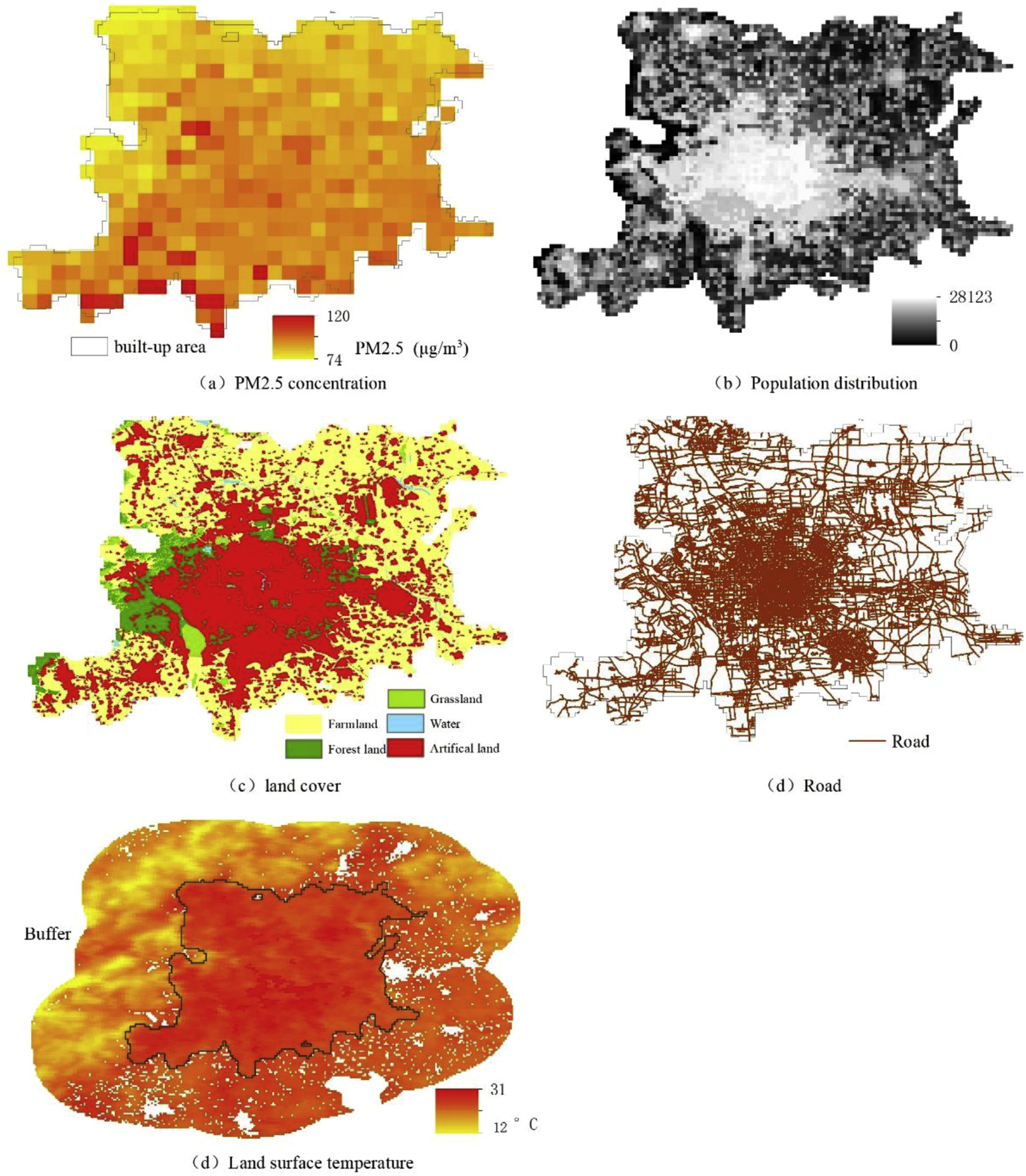

Fig. 2. Example data for Beijing.

form (Wang, Madden, & Liu, 2017). Road density is used to measure the accessibility of urban traffic, which is calculated using OSM road data.

The increase in urban green space may help to reduce pollutant concentrations, but it remains to be confirmed which spatial pattern of green land can improve air quality most effectively (Chen, Zhu, Fan, Li, & Lafortezza, 2016; Janhäll, 2015). A Shannon landscape diversity index (SHDI) is used to characterize the spatial pattern of green land. The larger the value, the higher the spatial mixing degree of different land types, and the more balanced the spatial distribution of green land. The green land data is based on GlobeLand30 land-cover data, and data with a resolution of 30 m could properly reflect the spatial pattern of urban green space (as Fig. 2-c shows).

Urban form may affect air quality by influencing pollutant diffusion, and a landscape index, "Aggregation Index," is used to measure the spatial continuity of artificial land. Higher values of continuity indicate higher building densities, which may have a stronger effect on pollution diffusion.

The urban heat island effect may be one of the driving forces of haze pollution, and it is also closely related to urban form (Connors, Galletti, & Chow, 2013; Huang, Yuan, & Lu, 2017). Therefore, the urban heat island intensity is taken as an independent variable in the spatial regression model. Satellite remote sensing has been widely used in studies on urban heat island effects (Schwarz & Manceur, 2014b; Zhou, Zhao, Liu, Zhang, & Chao, 2014), and the Terra MODIS remote sensing product MOD11A1 is used to calculate the average annual land surface temperature in this study (observation period: January to December 2014, observation time: 10:30 a.m., resolution: 1 km). The urban heat island intensity (UHI) of each city is determined by calculating the difference in the average land surface temperature between an urban built-up area and the surrounding rural area (Fig. 2-e). The surrounding rural area is the buffer from the built-up area (the radius = $\sqrt{\frac{S}{2\pi}}$, S is the area of the corresponding built-up area), and artificial land is excluded from the buffer (Tan & Li, 2015).

(2) Control variables

Both anthropogenic and natural factors have impacts on air quality (Bereitschaft & Debbage, 2013; Clark et al., 2011; Fang et al., 2015; Hao & Liu, 2015; Liu et al., 2017), and the following factors are taken as control variables in the study. The per capita GDP reflects the level of urban economic development (Hao & Liu, 2015), and the ratio of secondary industry to tertiary industry (GDP2_3) reflects the industrial structure (Fang et al., 2015; Liu et al., 2017). The total amount of central heating (Heat) represents the pollution from urban heating in winter, and industrial emissions (Emi) are calculated by summing the amount of SO_2 and smoke from industry (Yuan et al., 2017). The above data are gathered from the 2015 China city statistical yearbook (which contains data for 2014). Only the statistical data for "districts under city" (*shixiaqu*) are used in this paper, which may exclude data from the county (*xiaxian*) or county-level city (*xiaxianjishi*) under its jurisdiction. The total population of each city (PopSum) is calculated using LandScan data and the calculated built-up area. The mean value of the wind speed and air temperature are used to reflect meteorological conditions (Liu et al., 2017; Yuan et al., 2017), and these values are calculated from the interpolation values of climatological data from the China Meteorological Data Service Center.

4. Results and discussion

4.1. Spatial patterns of $PM_{2.5}$ concentrations

Statistics of $PM_{2.5}$ concentrations and metrics are shown in Table 1. Xingtai, Shijiazhuang, Baoding, Handan, and Hengshui, all located in Hebei Province, were the five cities with the most severe haze pollution, while the five cities with the best air quality were Sanya, Haikou, Jiayuguan, Yuxi, and Kunming. The global spatial autocorrelation coefficient, Moran's I, of the $PM_{2.5}$ concentration is 0.77 ($p < 0.001$), which indicates a spatial agglomeration of haze pollution. As Fig. 3 shows, there are three highly correlated areas of haze pollution, namely the high $PM_{2.5}$ concentration Jingjinji urban agglomeration area, the low $PM_{2.5}$ concentration southeastern coastal area, and the low $PM_{2.5}$ concentration Yunnan province. Hence, haze pollution may be closely related to regional pollution transmission, which provides the basis for the application of spatial regression models.

4.2. Results of the regressions

Due to the spatial autocorrelation from the analysis above, an OLS model was used firstly as a pre-judgement test. As Table 2 shows, compactness, continuity, SHDI, per capita GDP, industrial emissions, heating amount, and wind speed have significant effects on $PM_{2.5}$ concentrations. The variance inflation factor (VIF) for each variable is smaller than three, so multicollinearity may have no impact on the results. However, the highly significant Moran's I of the OLS residuals suggests that the OLS regression model cannot solve the spatial autocorrelation problem when dealing with $PM_{2.5}$ concentrations, and it may lead to bias in the significance, size, and sign of the regression coefficients as well as misleading conclusions. The Lagrange multiplier (LM) and robust LM tests for the SLM and SEM are significant, and these two spatial regression models are both used in the following estimations.

To determine which spatial regression model is most appropriate, SLM, SEM and SDM are used with different explanatory variables in Models 1–7 (Table 3, Table 4). Model 1 includes all urban form metrics, excluding other control variables. Model 2 only considers the control variables in order to examine the correlation between different socioeconomic factors and $PM_{2.5}$ concentrations. Models 3 and 4 add control variables to Model 1 to improve the fitness of the model. Instead of R^2, log-likelihood (LL) is used to reflect the goodness of fit for the spatial regression models, where a higher value of LL indicates better fitting of the models. The OLS model has the lowest LL value (Table 2), suggesting that the spatial regression model is better than the OLS model in terms of the goodness of fit. The spatial regression coefficient ρ in SLM and the spatial autoregressive coefficient λ in the SEM are significantly positive, and it is not necessary to depend on the SDM due to the insignificance of λ in the SDM (Models 1, 3, 4). The SLM and SEM are used in Models 5–7 with the quadratic or interaction term of some variables. For most models, the SLM has a higher log-likelihood value than does the SEM, and the SLM is considered the more appropriate model in the following analysis. Meanwhile, the spatial lag of the $PM_{2.5}$ concentrations ρW_y in the SLM may help to explain the $PM_{2.5}$ regional transmission between neighboring cities.

4.3. Effects of urban form

Population density has a significant positive effect on $PM_{2.5}$ concentrations in Model 1, but it becomes insignificant when the total population is controlled, as in Model 3. The insignificant interaction term between population density and total population in Model 5 also suggests that the effect of population density on $PM_{2.5}$ concentrations may depend on population size. Compared to most western countries, the population density of Chinese cities is high (Huang, Lu, & Sellers,

Table 1
Statistic of metrics.

ID	Metric	Min	Max	Mean	Std. D	Unit
$PM_{2.5}$	$PM_{2.5}$ concentration	22	125	63	17	μg/m^3
PopDen	Population Density	835	11071	3540	1438	person/km^2
Center	Degree of centering	1.04	3.62	1.91	0.47	
RoadDen	Road density	0.2	5.7	1.5	0.8	km/km^2
Compact	Compactness	−20.31	−1.72	−5.23	2.74	
Contin	Continuity	90.22	99.52	96.13	1.45	
SHDI	Landscape diversity	0.62	1.71	1.11	0.25	
PopSum	Total population	51438	21838398	1318307	2305891	person
GDP	Per capita GDP	10265	467749	71787	54172	yuan/person
Emi	Industrial emission	1210	786853	100454	90656	ton
Heat	Central heating	0	35466	1093	3195	10,000 GJ
GDP2_3	Industrial structure	0.23	4.24	1.25	0.62	
Wind	Wind speed	9	44	21	5	0.1 m/s
Temp	Air temperature	−5	254	151	48	0.1 °C
UHI	Urban heat island	−1.9	4.4	1.7	1.1	°C

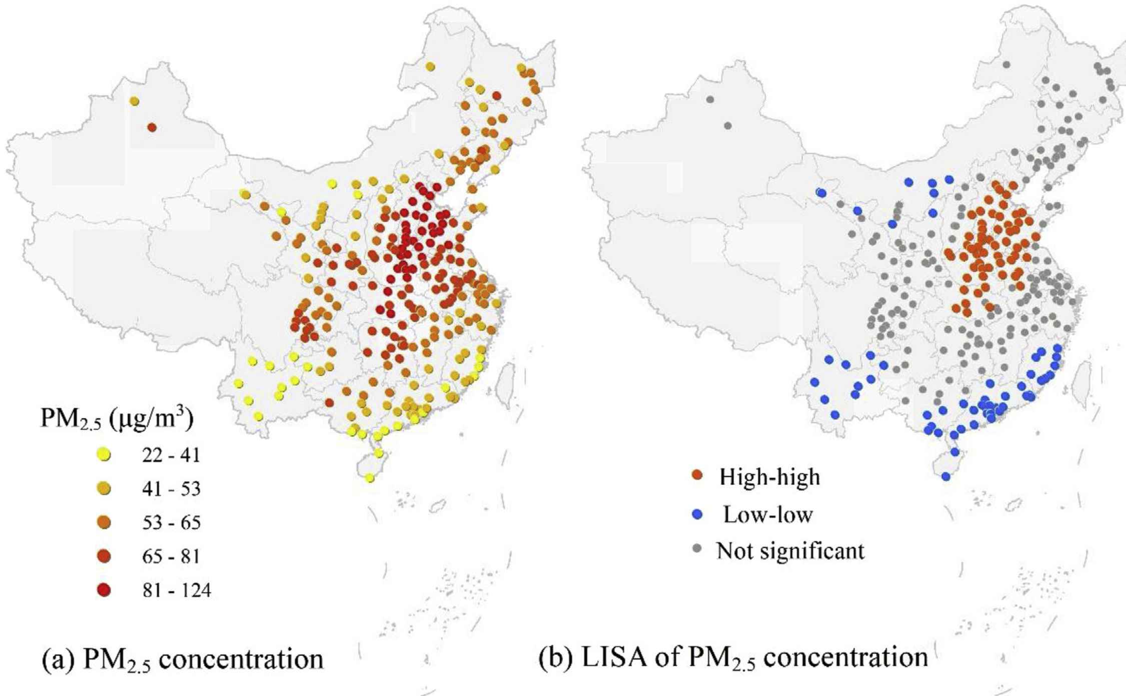

Fig. 3. $PM_{2.5}$ concentrations and local spatial autocorrelation analyses.

Table 2
Results of the OLS estimation.

Variable	Coefficient	Probability	VIF	Spatial dependence	Value	Probability
PopDen	4.16E-04	0.556	1.4	Adjusted R^2	0.35	
Center	−1.667	0.443	1.41	Log likelihood	−1085.17	
RoadDen	−1.093	0.368	1.38	Moran's I (error)	0.412	0
Compact	**−1.435**	**−0.001**	1.9	LM (lag)	708.3696	0
Contin	**1.868**	**0.007**	1.36	Robust LM (lag)	83.5597	0
SHDI	**−28.978**	**0**	1.35	LM (error)	Infinity	0
PopSum	−6.23E-07	0.283	2.41	Robust LM (error)	Infinity	0
GDP	**−3.68E-05**	**0.094**	1.91			
Emi	**2.48E-05**	**0.016**	1.17			
Heat	**5.43E-04**	**0.097**	1.47			
GDP2_3	1.429	0.35	1.22			
Wind	**−0.516**	**0.007**	1.39			
Temp	0.005	0.842	1.61			
UHI	**2.782**	**0**	1.16			

Note: values in bold are significant at 0.1 level.

2007). For large cities, excessive population density may lead to excessive agglomeration of roads and other infrastructures, which may, in turn, bring greater environmental pressure. Excessive population density is likely to cause traffic congestion in urban centers, and vehicle engines will produce more pollutants under idle conditions. Hence, reducing population density appropriately will help to mitigate traffic congestion and improve air quality in large cities. For small- and medium-sized cities, low population density may increase commuting distances, the number of private cars, and the energy consumption of the power grid and heating, leading to more vehicle and industrial emissions. Total population is not significant in Models 2–4, so the $PM_{2.5}$ concentrations are not necessarily related to urban size. Although the increase in the urban population will put some pressure on the environment, poorly planned urban forms may be the main cause of air pollution. These results also suggest that haze pollution is not only occurring in large cities, but that some small- and medium-sized cities also show high levels of $PM_{2.5}$ concentrations. More attention should be paid to air pollution in small- and medium-sized cities in the future.

Degree of centering is negatively correlated with the $PM_{2.5}$ concentration, which indicates that urban centrality may contribute to improved air quality. The metric is closely related to the spatial distribution of the urban population and thus has an impact on traffic flow, commuting distance, and exhaust emissions. Compactness is negatively associated with $PM_{2.5}$ concentrations, because a compact urban form helps to shorten travel distances and reduce residents' dependence on motor vehicles (Bereitschaft & Debbage, 2013). In addition, compact urban forms are conducive to a centralized layout for industrial enterprises, which not only can improve the energy efficiency in industrial production but is also beneficial to the layout, construction, and operation of environmental protection facilities (Lu & Liu, 2016). The interaction term between compactness and total population was added to Model 6, and its coefficient was significantly positive. Hence, the coefficient of compactness could be expressed as $-0.766 + 4.11E\text{-}08 \times$ PopSum (a negative value). This suggests that the absolute value of the coefficient of compactness may decrease as total population increases. The smaller the city size, the greater the effect of compactness on improving air quality; as the size of the city increases, the effect of compactness gradually weakens. For small- and medium-sized cities, a

Table 3
Results of spatial regressions.

variable	Model 1			Model 2			Model 3			Model 4		
	SLM	SEM	SDM	SLM	SEM	SDM	SLM	SEM	SDM	SLM	SEM	SDM
ρ	**0.883**		**0.975**	**0.915**		**0.83**	**0.872**		**0.96**	**0.873**		**0.96**
	(0)		**(0)**	**(0)**		**(0)**	**(0)**		**(0)**	**(0)**		**(0)**
λ		**0.93**	0.088		**0.944**	**0.292**		**0.945**	0.122		**0.945**	0.11
		(0)	(0.447)		**(0)**	**(0.057)**		**(0)**	(0.336)		**(0)**	(0.388)
PopDen	**7.44E-04**	3.53E-04	4.20E-04				2.62E-04	4.06E-05	8.52E-05			
	(-0.09)	(0.428)	(0.282)				(-0.537)	(0.922)	(0.823)			
Center	**−2.62**	**−2.45**	**−2.633**				**−2.44**	**−3.149**	**−2.407**	**−2.7**	**−3.09**	**−2.466**
	(-0.055)	**(0.083)**	**(0.03)**				**(-0.06)**	**(0.021)**	**(0.041)**	**(-0.029)**	**(0.02)**	**(0.028)**
RoadDen	0.509	**1.235**	**1.176**				**1.43**	**1.958**	**1.881**	**1.41**	**1.852**	**1.794**
	(-0.486)	**(0.096)**	**(0.079)**				**(-0.05)**	**(0.009)**	**(0.005)**	**(-0.048)**	**(0.011)**	**(0.006)**
Compact	**−0.496**	**−0.464**	**0.36**				**−0.544**	**−0.44**	**−0.424**	**−0.508**	−0.363	−0.35
	(-0.03)	**(-0.041)**	**(0.083)**				**(-0.036)**	**(-0.077)**	**(-0.073)**	**(-0.035)**	(-0.113)	(-0.109)
Contin	0.387	0.344	0.166				**0.69**	0.481	0.424	**0.718**	0.456	0.408
	(-0.356)	(0.433)	(0.663)				**(-0.097)**	(0.247)	(0.263)	**(-0.076)**	(0.262)	(0.269)
SHDI	**−7.85**	**−6.51**	−4.03				**−7.37**	−4.386	−3.768	**−6.9**	−4.335	−3.622
	(-0.002)	**(0.037)**	(0.131)				**(-0.003)**	(0.133)	(0.136)	**(-0.004)**	(0.13)	(0.139)
PopSum				3.32E-07	3.08E-07	2.00E-07	−2.41E-07	−3.11E-07	−3.00E-07			
				(-0.313)	(0.35)	(0.504)	(-0.489)	(0.379)	(0.33)			
GDP				**−3.31E-05**	**−3.05E-05**	**−3.12E-05**	**−2.66E-05**	**−2.43E-05**	**−2.35E-05**	**−3.04E-05**	**−2.89E-05**	**−2.8E-05**
				(-0.009)	**(0.017)**	**(0.01)**	**(-0.044)**	**(0.066)**	**(0.048)**	**(-0.013)**	**(0.017)**	**(0.013)**
Emi				**1.45E-05**	**1.13E-05**	**1.44E-05**	**1.08E-05**	**1.06E-05**	**1.00E-05**	**1.04E-05**	9.778E-06	**9.30E-06**
				(-0.022)	**(0.081)**	**(0.018)**	**(-0.082)**	**(0.089)**	**(0.074)**	**(-0.092)**	(0.113)	**(0.093)**
Heat				**3.57E-04**	3.04E-04	2.94E-04	**3.55E-04**	3.24E-04	2.49E-04	**3.09E-04**	2.66E-04	1.91E-04
				(-0.08)	(0.142)	(0.12)	**(-0.069)**	(0.108)	(0.159)	**(-0.095)**	(0.163)	(0.252)
GDP2_3				**1.68**	**1.77**	0.587	**2.28**	**2.625**	**1.45**	**2.39**	**2.78**	**1.61**
				(-0.075)	**(0.054)**	(0.498)	**(-0.013)**	**(0.004)**	**(0.078)**	**(-0.008)**	**(0.002)**	**(0.047)**
Wind				**−0.279**	−0.18	**−0.228**	**−0.274**	−0.168	**−0.207**	**−0.278**	−0.168	**−0.203**
				(-0.017)	(0.202)	**(0.059)**	**(-0.017)**	(0.226)	**(0.054)**	**(-0.014)**	(0.226)	**(0.055)**
Temp				7.43E-03	**0.124**	3.81E-03	1.99E-02	**0.127**	1.70E-02	1.89E-02	**0.123**	0.015
				(-0.585)	**(0.014)**	(0.816)	(-0.147)	**(0.01)**	(0.21)	(-0.163)	**(0.011)**	(0.263)
UHI				**2.1**	**2.518**	**2.117**	**2.1**	**2.542**	**1.89**	**2.09**	**2.52**	**1.85**
				(0)	**(0)**	**(0)**	**(0)**	**(0)**	**(0)**	**(0)**	**(0)**	**(0)**
LL	−989.37	−992.53	–	−983.179	−980.94	–	−967.791	−969.02	–	−968.178	−969.4	–

Note: Values in bold are significant at 0.1 level.
Only GMM estimation is used in SDM in GeoDaSpace, and there is no log-likelihood value.

compact urban form should be promoted, and single center structures should be set up to facilitate public transport systems, thus reducing pollution from private cars. For large cities, multi-center structures should be set up to shift the population from the urban center to various subcenters, reducing the negative effects of crowding on air quality.

In contrast to results for western countries, increased continuity in artificial land may increase $PM_{2.5}$ concentrations in China. In European and American cities, low urban continuity refers to fragmented, "leapfrog"-style development, and it may significantly increase vehicle travelling distance (Bereitschaft & Debbage, 2013; Rodríguez et al., 2016). However, Chinese cities are much denser than western cities, and a higher continuity of artificial land with higher building density may impede the diffusion process of air pollutants (Hang, Sandberg, Li, & Claesson, 2009; Taseiko et al., 2009). Landscape diversity is significantly negative in most models, and a spatially balanced pattern of green land may help to clean the air and absorb particulate matter.

Road density is significantly positively correlated with $PM_{2.5}$ concentrations in most models, and its squared term is not significantly negative in Model 7. Increases in road density will improve the accessibility of streets, which may induce more cars to travel. Because there is not an inverted U-shape relationship between air pollution and road density, increasing road density may result in more traffic and air pollution. This suggests that the new "small street block, high-density road network" initiative may not currently be suitable for most Chinese cities.

The urban heat island effect significantly boosts the formation of haze pollution, showing a significantly positive coefficient. The heat island effect will lead to higher air temperatures, lower air densities, and lower wind speeds, which will not only make it more difficult for air pollutants to disperse but will also push pollutants from surrounding rural areas toward urban centers. The urban heat island intensity is closely related to some urban form metrics. For example, building density and continuity of artificial land is positively correlated with the urban heat island intensity, and green land will reduce the urban heat island intensity (Huang et al., 2017; Zhou, Zhang, Li, Huang, & Zhu, 2016; Zhang, Qi, Ye, Cai, Ma, Chen, 2013). In addition, particulate matter will retain heat and increase the urban heat island intensity, which would form a positive feedback loop between haze pollution and urban heat island effects (Chang et al., 2016).

4.4. Effects of control variables

The per capita GDP is significantly negative in most models, which indicates that air quality may gradually improve with economic growth in China. In cities with high levels of economic development, the government has a higher awareness of pollution control and more financial input on environmental protection, and there are also fewer high-pollution vehicles and more clean energy vehicles. Industrial emissions and the ratio of secondary industry to tertiary industry are significantly positive in most models, showing that industrial production is still a significant source of air pollution, particularly with respect to the highly polluting and energy-consuming industries. Central heating tends to be significantly positive in the models, showing that air pollution caused by coal burning is still not negligible, and clean heating methods should be promoted in northern China. Wind speed is significantly negative in the SLM, and air temperature shows a significant positive relationship with $PM_{2.5}$ concentrations in the SEM.

Table 4
Results of spatial regressions (with squared term and interaction term).

variable	Model 5		Model 6		Model 7	
	SLM	SEM	SLM	SEM	SLM	SEM
ρ	**0.871**		**0.868**		**0.874**	
	(0)		**(0)**		**(0)**	
λ		**0.946**		**0.946**		**0.944**
		(0)		**(0)**		**(0)**
Center	**−2.802**	**−3.33**	**−2.75**	**−3.323**	**−2.712**	**−3.112**
	(0.023)	**(0.011)**	**(-0.025)**	**(0.01)**	**(0.027)**	**(0.017)**
RoadDen	**1.515**	**2.01**	**1.5**	**1.953**	**3.157**	**3.14**
	(0.036)	**(0.006)**	**(-0.036)**	**(0.007)**	**(0.074)**	**(0.067)**
Compact	**−0.598**	**−0.481**	**−0.766**	**−0.627**	**−0.535**	**−0.384**
	(-0.021)	**(-0.054)**	**(-0.005)**	**(-0.17)**	**(-0.027)**	**(-0.095)**
Contin	**0.774**	0.522	**0.825**	0.569	**0.749**	0.473
	(0.058)	(0.202)	**(-0.042)**	(0.163)	**(0.064)**	(0.244)
SHDI	**−6.87**	−4.255	**−7.22**	−4.58	**−6.582**	−4.185
	(0.004)	(0.137)	**(-0.002)**	(0.108)	**(0.006)**	(0.145)
GDP	**−2.65E-05**	**−2.30E-05**	**−2.59E-05**	**−2.32E-05**	**−3.23E-05**	**−3.03E-05**
	(0.041)	**(0.078)**	**(-0.038)**	**(0.061)**	**(0.009)**	**(0.013)**
Emi	**1.08E-05**	**1.05E-05**	**1.06E-05**	**1.04E-05**	9.58E-06	9.22E-06
	(0.081)	**(0.089)**	**(-0.083)**	**(0.091)**	(0.122)	(0.137)
Heat	**3.51E-04**	**3.27E-04**	**3.59E-04**	**3.26E-04**	**3.10E-04**	2.67E-04
	(0.066)	**(0.097)**	**(-0.054)**	**(0.089)**	**(0.094)**	(0.161)
GDP2_3	**2.226**	**2.577**	**2.22**	**2.639**	**2.441**	**2.81**
	(0.015)	**(0.005)**	**(-0.014)**	**(0.003)**	**(0.007)**	**(0.002)**
Wind	**−0.292**	−0.17	**−0.29**	−0.164	**−0.284**	−0.163
	(0.01)	(0.218)	**(-0.01)**	(0.233)	**(0.012)**	(0.239)
Temp	0.021	**0.129**	2.15E-02	**0.13**	0.019	**0.122**
	(0.131)	**(0.008)**	(-0.111)	**(0.01)**	(0.161)	**(0.013)**
UHI	**2.116**	**2.529**	**2.08**	**2.47**	**2.067**	**2.49**
	(0)	**(0)**	**(0)**	**(0)**	**(0)**	**(0)**
PopDen*PopSum	−6.46E-11	−8.56E-11				
	(0.366)	(0.236)				
Compact*PopSum			**4.11E-08**	**4.27E-08**		
			(-0.058)	**(-0.047)**		
RoadDen*RoadDen					−0.412	−0.301
					(0.281)	(0.406)
LL	−967.77	−968.7	−966.4	−967.44	−967.6	−969.06

Note: Values in bold are significant at 0.1 level.

5. Conclusions and implications

Haze pollution has become a serious challenge for China, and a better understanding of the effect of urban form on haze pollution can help guide urban planning and development policy. Using remote sensing monitoring data of $PM_{2.5}$ concentrations, this study explored the association between urban form and $PM_{2.5}$ concentrations for 269 prefectural-level cities in China using spatial regression models, and the main conclusions are as follows: (1) There is a significant spatial autocorrelation of $PM_{2.5}$ concentrations, and regional pollution transmission should be considered when exploring the driving forces of haze pollution; (2) Urban form can affect $PM_{2.5}$ concentrations through vehicle use, green land regulation, pollutant diffusion, and the heat island effect; (3) The effects of population density, degree of centering, and compactness will vary with city size, and different planning policies should therefore be formulated for cities of varying size.

The results of this study have the following policy implications for reducing haze pollution in Chinese cities. The association between urban form and $PM_{2.5}$ concentrations is not universal, and it is necessary to develop different development policies based on city size. For small- and medium-sized cities, the population density should be appropriately increased, and it is better to develop a compact, single-center urban structure. For large cities, a multi-center structure should be developed to decrease excessive population density in the urban center. This approach will contribute to reducing commuting distance and traffic congestion as well as alleviating negative environmental externalities. In addition to increasing the green land area, the spatial balancing of green land should be also be improved, which may help to reduce $PM_{2.5}$ concentrations and urban heat island effects. Regional pollution transmission is one of the important sources of haze pollution in Chinese cities, and it is necessary to promote the concepts of "joint prevention and control" and cooperation for cities in heavily polluted areas in order to tackle this issue.

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