Science of the Total Environment 619–620 (2018) 436–445

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Examining the effects of socioeconomic development on fine particulate matter ($PM_{2.5}$) in China's cities using spatial regression and the geographical detector technique

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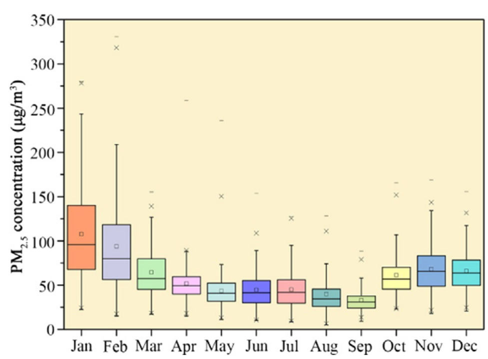
HIGHLIGHTS

- The direction and strength of the link between $PM_{2.5}$ level and their drivers are analyzed.
- Spatial regression and geographical detector techniques are used.
- A spatial agglomeration effect was identified in city-level $PM_{2.5}$ level.
- Population density, industrial structure, industrial dust, and road density increase $PM_{2.5}$ level.
- Trade openness and electricity consumption have no significant effect on $PM_{2.5}$ level.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 29 September 2017
Received in revised form 9 November 2017
Accepted 10 November 2017
Available online xxxx

Editor: Xuexi Tie

Keywords:
$PM_{2.5}$ concentrations
Spatial regression
Geographical detector technique
China

ABSTRACT

The frequent occurrence of extreme smog episodes in recent years has begun to present a serious threat to human health. In addition to pollutant emissions and meteorological conditions, fine particulate matter ($PM_{2.5}$) is also influenced by socioeconomic development. Thus, identifying the potential effects of socioeconomic development on $PM_{2.5}$ variations can provide insights into particulate pollution control. This study applied spatial regression and the geographical detector technique for assessing the directions and strength of association between socioeconomic factors and $PM_{2.5}$ concentrations, using data collected from 945 monitoring stations in 190 Chinese cities in 2014. The results indicated that the annual average $PM_{2.5}$ concentrations is 61 ± 20 μg/m^3, and cites with more than 75 μg/m^3 were mainly located in North China, especially in Tianjin and Hebei province. We also identified a marked seasonal variation in concentrations levels, with the highest level in winter due to coal consumption, lower temperatures, and less rainfall than in summer. Monthly variations followed a "U-shaped" pattern, with a down trend from January and an inflection point in September and then an increasing trend from October. The results of spatial regression indicated that population density, industrial structure, industrial soot (dust) emissions, and road density have a significantly positive effect on $PM_{2.5}$ concentrations, with a significantly negative influence exerted only by economic growth. In addition, trade openness and electricity consumption were found to have no significant impact on $PM_{2.5}$ concentrations. Using the geographical detector technique, the strength of association between the five significant drivers and $PM_{2.5}$ concentrations was further analyzed. We found notable differences among the variables, with industrial soot (dust) emissions playing a greater role in the $PM_{2.5}$ concentrations than the other variables. These results will be helpful in

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https://doi.org/10.1016/j.scitotenv.2017.11.124

understanding the dynamics and the underlying mechanisms at work in $PM_{2.5}$ concentrations in China at the city level, and thereby assisting the Chinese government in employing effective strategies to tackle pollution.

1. Introduction

Air pollution, especially in the form of fine particulate matter ($PM_{2.5}$), has become a serious issue not only for developed countries but also for the developing world (Cheng et al., 2016; Peng et al., 2016). China, the world's largest developing country, has suffered frequent extreme smog episodes in recent years. In addition, international headlines from 2013 onwards report that haze weather has become a common phenomenon in China (Guan et al., 2014; Rohde and Muller, 2015; Zhang et al., 2015; S.J. Wang et al., 2017a; Yang et al., 2017; Zhou et al., 2017). The urbanization rate in China increased from 17.9% in 1978 to 54.8% in 2015 and continues to grow (Wang et al., 2014, 2015, 2016a, b; Li et al., 2017; Liu et al., 2017). The country's continued urbanization means that more people will live in urban areas, resulting in greater pollutant emissions (NBSC, 2015). The core problems linked to the intense concentrations of $PM_{2.5}$ include increasing death rates due to cancer, reduced atmospheric visibility, and changes to ecosystems and to the global climate (Brauer et al., 2012; Kan et al., 2012; Madrigano et al., 2013). Due to its negative impacts on human health, a growing body of literature has explored the potential drivers of $PM_{2.5}$ concentrations, finding that meteorological conditions play an important role in $PM_{2.5}$ variations. However, in addition to such conditions, $PM_{2.5}$ concentrations are also influenced by human activities. Therefore, understanding the characteristics and potential socioeconomic drivers of $PM_{2.5}$ concentrations will be of benefit in the task of improving air quality.

The determinants of $PM_{2.5}$ concentrations are garnering much attention from scholars globally. A growing number of studies have dedicated enormous efforts to analyzing the causes of $PM_{2.5}$. These studies have found that natural conditions such as temperature, humidity, slope, ozone concentrations, and wind velocity have varying effects on $PM_{2.5}$ concentrations. For example, Pateraki et al. (2012) undertook research on the generation of fine particles, finding that humidity fluctuations and temperature values ranging from 1.9 °C to 21.7 °C maintain a strong correlation with urban $PM_{2.5}$ concentrations. He and Lin (2017) employed the generalized additive model (GAM) to examine the influencing factors of $PM_{2.5}$ concentrations variation in the Chinese city of Nanjing. $PM_{2.5}$ concentrations variation was found to be strongly associated with temperature, pressure, and water vapor pressure. Although a linear relationship was identified between wind and $PM_{2.5}$ concentrations variation, increased wind speeds were not found to cause changes in $PM_{2.5}$ concentrations levels. Some scholars have conversely argued that wind speeds above 2 m/s can decrease $PM_{2.5}$ exposures (Onat and Stakeeva, 2013). In addition to natural conditions, recent socioeconomic impact assessments have established an association between the concentrations of $PM_{2.5}$ and socioeconomic determinants including urban population, urban secondary industry fraction, per capita GDP, and energy consumption (Paatero et al., 2003; Wang and Fang, 2016; Lou et al., 2016). For instance, through their analysis of the concentrations of $PM_{2.5}$ from 2001 to 2010 in China, Lin et al. (2014) found that population, local economic growth, and urban area are the main driving factors influencing $PM_{2.5}$ concentrations. Han et al. (2014) used satellite data to examine the impact of urbanization on urban $PM_{2.5}$ concentrations. Their results suggested that urban population and the urban secondary industry fraction have a strong correlation with urban $PM_{2.5}$ concentrations. Hao and Liu (2016) used spatial regression to explore the relationship between $PM_{2.5}$ concentrations and urban development in China, showing that vehicles and industry strongly influenced $PM_{2.5}$ concentrations levels. Hua et al. (2015) suggested that industrial activities and vehicles were the main contributors to $PM_{2.5}$ in the Yangtze River Delta (YRD). Most previous large-scale estimations of $PM_{2.5}$ levels have depended on satellite data and satellite aerosol optical depth (AOD) combing with meteorological parameters (J. Wang et al., 2010; Kloog et al., 2012). For example, using remote sensing technique, scholars found that the annual $PM_{2.5}$ concentrations of most cities were much higher than 10 μg/m^3, the air quality guideline offered by the World Health Organization (WHO) (Han et al., 2014; Van et al., 2015). In addition, Cheng et al. (2016) found that Delhi, Cairo, Xi'an, Tianjin and Chengdu were the five most polluted megacities, with annual average $PM_{2.5}$ concentrations higher than 89 μg/m^3. The same study found that east-central China and the Indo-Gangetic Plain constitute highly-polluted nesting zones. However, the lack of sustained accuracy in such satellite data, which uses remotely-sensed AOD as a proxy for $PM_{2.5}$ concentrations, frequently misses values because of cloudy or hazy conditions, making it difficult to estimate the temporal characteristics and spatial distributions of near-ground $PM_{2.5}$. For this reason, it has been difficult to identify the characteristics of $PM_{2.5}$ concentrations in different time scales for a given region (Liu et al., 2005; Gupta et al., 2006; Paciorek and Liu, 2009; Hoff and Christopher, 2009). Compared to satellite data, monitoring data collected from China's National Environmental Monitoring Centre (CNEC) shows 24 h $PM_{2.5}$ concentrations for 190 cities utilizing 945 monitoring stations. Such data, which has been collected since 2014 in China, has the potential to reflect the spatial and temporal (annual average, seasonal, and monthly) characteristics of $PM_{2.5}$ level at both the national scale and for a target region.

Nowadays, a variety of models are available that can be used to identify the socioeconomic determinants of $PM_{2.5}$, including econometric analysis (S.J. Wang et al., 2017b), input-output models (Guan et al., 2014; Fang et al., 2013), the classical ordinary least square model, spatial regression (Hao and Liu, 2016), Geographically Weighted Regression (GWR) (Hu et al., 2013), and land-use regression (Mao et al., 2012). The merit of spatial model is that it can depict the $PM_{2.5}$ concentrations of different cities of spillover effects. So here employ the spatial to explore the direction of the $PM_{2.5}$ concentrations determinants. Besides, mechanism studies have not yet been conducted using the geographical detector technique for air pollutants. This technique is widely applied in evaluating the influence of factors which do not need a linear hypothesis to reveal the driving factors behind spatial stratified heterogeneity (J.F. Wang et al., 2010; Y. Wang et al., 2017). Given this, this present study used geographical detector technique in order to avoid factors that should be removed due to collinearity in the models, and to explore the spatial correlations between $PM_{2.5}$ concentrations (using monitoring data) and socioeconomic variables.

Mechanism research on $PM_{2.5}$ concentrations using monitoring data and the geographical detector technique is rare. Here, we employed data collected from continuous, year-long monitoring in 190 cities to describe the spatial and temporal (annual average, seasonal, and monthly) distribution of $PM_{2.5}$ concentrations. We also undertook a spatial regression and used the geographical detector technique to reveal the directions and strength of the impact of socioeconomic factors on $PM_{2.5}$ concentrations. The results of this analysis are beneficial for policy makers in formulating appropriate measures to enhance air quality.

2. Material and methodology

2.1. Conceptual framework

The main goal of this study was to highlight the influencing mechanisms of $PM_{2.5}$ levels from a socioeconomic perspective. As such, we began by selecting a series of drivers capable of explaining $PM_{2.5}$ levels. We then described the spatial-temporal (annual average, seasonal, and monthly) characteristics of $PM_{2.5}$ concentrations at the national cities level, subsequently employing spatial regression to determine the significances and directions of the drivers. The geographical detector technique was then utilized in order to explore the magnitude of the significant drivers in detail. Finally, the mode of action through which the drivers impact on $PM_{2.5}$ levels was investigated.

2.2. Data and data sources

The identification of the sources of $PM_{2.5}$ is a task that has aroused considerably attention among scholars internationally (Liang et al., 2016). Previous studies have argued that particulate sources generally originate from industrial activities, traffic density, electric power plants, fossil fuels, biomass burning, agriculture activities, and soil dust, as well as marine aerosols (Squizzato et al., 2012; Barker, 2013; Tiwari et al., 2013; Wu et al., 2016). In addition, existing studies have also suggested that human activities lead to energy consumption and emissions, thereby influencing concentrations levels. Based on the results of these previous studies, we selected influencing variables referring to economic growth, population density, industrial structure, industrial soot (dust) emissions, road density, trade openness, and energy consumption. Per capita GDP here represented the economic development level, the secondary industry share represented the industrial structure, foreign direct investment as a proportion of GDP represented trade openness, and energy consumption was measured using electricity consumption.

Table 1 shows statistical information for each of the variables, as well as the excepted directions of the variables for $PM_{2.5}$ levels, in accordance with the findings of previous studies.

2.2.1. Economic growth (GDP)

The impact of per capita GDP (GDP) on $PM_{2.5}$ concentrations has been widely discussed in a range of previous studies (Shao et al., 2016; S.J. Wang et al., 2017b). A number of scholars have found that $PM_{2.5}$ concentrations in cities—for instance, in the case of cities in the Bohai Rim Urban Agglomeration (BRUA)—are negatively correlated with per capita GDP; scholars have thus argued that this correlation reflects the enhanced environmental awareness that comes with economic prosperity (Wang and Fang, 2016). Following this previous work, the hypothesized direction of the relation between GDP and $PM_{2.5}$ was negative.

2.2.2. Population density (PD)

Previous studies have found that $PM_{2.5}$ pollution is greater in more populated cities as a result of living and production activities and their link to polluting gas emissions; higher population levels are thus understood to result in greater energy consumption and increased emissions (Lou et al., 2016). Following the findings of Tong and Wang (2014) and Hua et al. (2015), and in order to avoid obscuring differences in the population size of different administrative districts, we used population density as a proxy for population scale. The expected direction of the relation was positive.

2.2.3. Industry structure (IS)

We took the share of secondary industry as a proxy for industrial structure. Because industrial sectors depend on energy consumption for profits, industrial activity can generally be expected to increase $PM_{2.5}$ concentrations (Wang and Fang, 2016). Previous studies have also indicated that secondary industries play an important role in $PM_{2.5}$ levels (S.J. Wang et al., 2017b). As such, the expected direction of the relation between IS and $PM_{2.5}$ levels was positive.

2.2.4. Industrial soot (dust) emission (ISE)

Usually, the large-scale industry will produce a lot of dust by production, transportation and consumption, resulting in dust emissions will cause serious increases in $PM_{2.5}$ concentrations. One example of such a process is cement production, the raw materials for which can enhance $PM_{2.5}$ concentrations during both the production and transportation of cement (Remoundaki et al., 2013). Following Wang and Fang (2016) and Shao et al. (2016), we used industrial soot (dust) emissions as a proxy for industrial dust, expecting it to act as a positive indicator.

2.2.5. Road density (RD)

Transportation is one of the most important sources of $PM_{2.5}$ formation. Because CO, NO, and SO_2 from motor vehicle exhaust contribute to $PM_{2.5}$, and referring to previous research by Hua et al. (2015) and Shao et al. (2016), we used road density as a proxy for traffic intensity. Taking account of road density was also beneficial in obtaining possible provincial variations over time. The expected direction of this relationship is positive.

2.2.6. Trade openness (FDI)

Here, we used foreign direct investment (FDI) as a proportion of GDP as a proxy for trade openness. On the one hand, increased FDI may improve the technical level of a given city, region, or country, thereby reducing energy consumption per unit GDP and lowering $PM_{2.5}$ concentrations. Previous studies have, in support of this theory, found that efficiency gains associated with FDI fully offset emissions growth triggered by economic growth and other drivers (Guan et al., 2014). List and Co (2000), however, found that FDI maintains the inverse relation with respect to the environment of the receiving state, meaning that the investing country may simply transfer high-pollution industries to the receiving state, thus raising $PM_{2.5}$ concentrations. Given these divergent positions, the effect of this factor may therefore be either positive or negative. In the present study, we assume that it maintains a negative correlation with respect to $PM_{2.5}$ concentrations levels.

2.2.7. Energy consumption (EC)

We measured energy consumption using electricity consumption. Quite simply, the greater the level of electricity consumption, the greater the power supply. Previous studies have suggested that coal-fired power plants produce large amounts of $PM_{2.5}$ in producing power (Ma et al., 2014; GBD MAPS Working Group, 2016). However, the emissions of $PM_{2.5}$ will be controlled by reforming the gas treatment facilities in coal-fired power plants (Sun et al., 2015). As such, theoretically, electricity consumption might be either positive or negative, and is treated as such here.

Table 1
Statistical summary of the variables.

Variables definition	Symbol	Expected direction	Min	Max	Mean	Std. dev
Per capita GDP (10000Yuan)	GDP	−	2.05	20.02	6.780	3.60
Population density (peoples/km^2)	PD	+	17.86	2648.11	528.81	354.12
Urban secondary industry share (%)	IS	+	9.09	78.93	50.34	9.09
Industrial soot (dust) emission (ton)	ISE	+	458	536,092	46,723.70	56,571.33
Road density (km/km^2)	RD	+	3.42	41.14	14.97	5.34
FDI as a share of GDP (%)	FDI	−	0.05	25.83	2.613	3.132
Electricity consumption (10,000 kWh)	EC	+	4626	13,465,607	1,353,036.12	1,778,135.94

Notes: Data on the seven socioeconomic factors referring to 190 cities of China in the Table were derived from the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and the City Statistical Yearbook.

The $PM_{2.5}$ concentrations data used in this study was derived from the urban air quality monitoring sites of the CNEC. This sample covers 190 cities throughout the southeast coastal, central, and northeastern regions of China, recording 24-hour average $PM_{2.5}$ concentrations levels in 2014. In accordance with the definitions set out in GB3095-2012, herein "monthly average" means the arithmetic average of the mean concentrations levels of each day in a calendar month; "seasonal average" means the arithmetic average of the mean concentrations levels of each day in a calendar quarter; "annual (yearly) average" means the arithmetic average of the mean concentrations levels of each day in a calendar year; "spring" refers to the period March to May; "summer" covers June to August; "autumn" refers to the period September to November; and "winter" covers December, January, and February.

Data on the seven socioeconomic drivers mentioned above (GDP, PD, IS, ISE, RD, FDI, and EC) were derived from the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and the City Statistical Yearbook. All data was collected for the year 2014.

2.3. Methods

2.3.1. Regression analysis

The classical ordinary least square (OLS) model has been widely used to explore the underlying mechanisms of $PM_{2.5}$ concentrations. However, the OLS model does not take into account spatial effects. The First Law of Geography suggests that all objects on a geographic surface are related to one another, and that geographic units are more strongly related to closer units than to more distant units (Tobler, 1970). Such spatial effects, if ignored, can lead to biased results in relation to potential factors. As a result, here we used a non-spatial regression model (OLS) and a spatial regression model in order to estimate the effects of socioeconomic drivers on $PM_{2.5}$ concentrations.

OLS is a linear regression model, which can be used to estimate the linear relationship between dependent and independent variables. In the model setting, all variables are independent and the spatial properties of variable data are ignored. The ordinary least squares method is usually employed in order to estimate coefficients, which can be written as follows:

$$y_s = x_{si} + {}_s \tag{1}$$

where $s = 1, \ldots, 190$, representing the cities in this study; y_s is the dependent variable ($PM_{2.5}$ concentrations); x_{si} ($i = 1, \ldots, 7$) is the explanatory variables, including GDP, PD, IS, ISE, RD, FDI, and EC; β is the coefficient of the regression model; and ε_s denotes the random error.

In the spatial model, there are various kinds of spatial models to depict different sources of spillover effects such as spatial error model (SEM), spatial lag model (SLM), and spatial Durbin model (SDM). Due to spatial autocorrelation may exist among variables because of the spatial spillover effects between adjacent regions. This indicates that spatial autocorrelation with no independent error term may lead to biased or even misleading conclusions. So a spatial error model (SEM) was used to report the impact of spatial units on other near units. And the problem of error term can be solved using a spatial error model. The spatial error model is generally based on autoregressive model which can be written as follows:

$$y_s = \beta x_{si} + \varepsilon_s \tag{2}$$

$${}_s = \sum_{j=1}^{n} w_{ss} + {}_s \ , \left[{}_s \sim i.i.d\left(0, {}^2\right)\right] \tag{3}$$

where ρ is the spatial autocorrelation coefficient of the error term, and ε_s is the error term of the spatial autocorrelation; w_s is a diagonal weighting matrix; μ_s is the white noise (Table 2 provides the results of the regression). And get the regression results from the software of Geoda.

Table 2
Estimation results of regressions.

	Coefficient	Standard error	t/z-Value	$Pr(>\|t\|)$
Non-spatial model				
Intercept	30.9413***	8.79286	3.51891	0.00055
GDP	−1.28969***	0.435073	−2.96431	0.00344
PD	0.00841898**	0.00420341	2.00289	0.04669
IS	0.367536**	0.156077	2.35483	0.01961
ISE	0.000112743***	2.57823e−005	4.3729	0.00002
RD	0.643343**	0.255568	2.5173	0.01270
FDI	−0.131655	0.428757	−0.307061	0.75915
EC	2.10675e−007	1.02649e−006	0.205239	0.83762
R-squared: 0.425846; adjusted R-squared: 0.195740; F-statistic: 7.50169; P-value: 0.00000				
Spatial model				
Intercept	29.5198***	7.34947	4.01659	0.00006
GDP	−0.667509**	0.399128	−1.67242	0.04444
PD	0.0102116***	0.00364666	2.80027	0.00511
IS	0.311775**	0.127681	2.44184	0.01461
ISE	7.05664e−005***	2.11726e−005	3.33291	0.00086
RD	0.480104**	0.217422	2.20817	0.02723
FDI	−0.374594	0.376278	−0.995525	0.31948
EC	5.37641e−007	8.76951e−007	0.613079	0.53982
R-squared: 0.634294; log likelihood: −781.779621; (AIC): 1579.56; lambda: 0.00000; Breusch-Pagan test: 0.17217; P-value: 0.00000				

*** The 1% level of significance.
** The 5% level of significance.
* The 10% level of significance.

2.3.2. Geographical detector technique

Geographical detector technique, proposed by J.F. Wang et al. (2010), does not need a linear hypothesis to reveal the driving factors behind spatial stratified heterogeneity. This means that if a factor contributes to $PM_{2.5}$, $PM_{2.5}$ concentrations take on a spatial distribution similar to that of the given factor. The principle is that if the sum of the variances of subareas which are classified by the factor is less than the variance of the whole area, spatially stratified heterogeneity exists, and the q-statistic can be used to detect influencing factors (Wang and Xu, 2017). The power of influencing factors $I = \{I_j\}$ to the $PM_{2.5}$ concentrations can be written as:

$$q = 1 - \frac{1}{n^2_{PM}} \sum_{j=1}^{m} n_{I,j} {}^2_{PM_{I,j}} \tag{4}$$

where q is the power of the influencing factor I_j; I_j ($j = 1, 2, 3\ldots$) are the influence factors of $PM_{2.5}$ concentrations, denoted as $I = \{I_j\}$. Usually, the value of q is within the range [0,1]. If the value of the q tends towards 1, the stronger the influence of factor I_j is in explaining the distribution of the $PM_{2.5}$ concentrations. We therefore first classified the whole $PM_{2.5}$ area into three parts (so, here the m is 3): a high-level part, a middle-level part, and a low-level part, based on the influential factors $I = \{I_j\}$. Table 3 provides the threshold of the sub-regions, where n is the number of the whole study area, $n_{I,j}$ is the number of samples in the sub-region j of the influencing factor I_j, m is the number of sub-region, σ^2_{PM} is the variance of the whole area of determinants, ${\sigma_{PM_{I,j}}}^2$ is the variance of the sub-region of determinants and (I,j) denotes a sub-regions. The model was based on the hypothesis ${\sigma_{PM_{I,j}}}^2 \neq 0$, with $q \in [0,1]$.

Table 3
The geographic influencing factors for PM2.5 concentrations (μg/m^3).

Threshold	I_1 (10^4Yuan)	I_2 (persons/km^2)	I_3 (%)	I_4 (10^4 tons)	I_5 (km/km^2)
Low level	≦5	≦500	≦45	≦5	≦10
Middle level	5–10	500–1000	45–55	5–10	10–20
High level	≧10	≧1000	≧55	≧10	≧20

I_1: per capita GDP; I_2: population density; I_3: urban secondary industry share; I_4: industrial soot (dust) emission; I_5: road density.

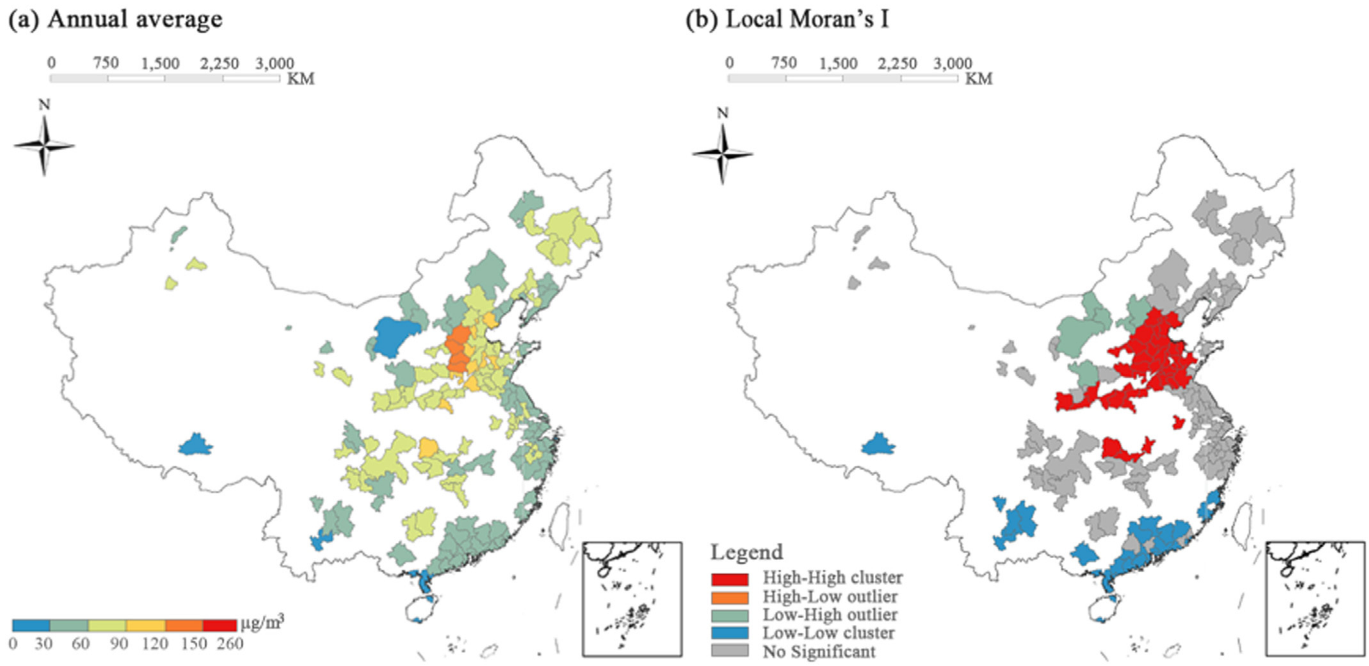

Fig. 1. Spatial distribution of (a) annual average $PM_{2.5}$ concentrations (μg/m^3), and (b) Local Moran's *I*.

3. Results

3.1. The spatial-temporal pattern of $PM_{2.5}$ concentrations

Fig. 1a shows that the annual mean $PM_{2.5}$ concentrations of the 190 Chinese cities that made up the study area in 2014 is 61 ± 20 μg/m^3. We found that 88 cities maintained levels beyond this mean level, and only 14 cities conformed with the National Ambient Air Quality Standard (NAAQS, 2012), which proscribes an annual mean $PM_{2.5}$ concentrations of 15 μg/m^3 and 35 μg/m^3 for level 1 and level 2, and an annual mean of under 35 μg/m^3 for level 2. Results show that 36 cities maintained $PM_{2.5}$ levels beyond the 75 μg/m^3 mark, which is 2.6 times the level that denotes "good health" in cities (i.e., 35 μg/m^3). The cities with annual mean $PM_{2.5}$ levels above 75 μg/m^3 were mainly situated within the Beijing-Tianjin-Hebei urban agglomeration. Shijiazhuang and Xingtai of Hebei province were found to have an annual mean $PM_{2.5}$ level even greater than 130 μg/m^3. The "good health" category took in cities such as Sanya, Lasa, and Zhoushan, which are principally located in south-east coastal areas and the provinces of Yunnan, Xizang, and Inner Mongolia.

In addition, we utilized the Moran's *I* index in order to examine the spatial autocorrelation of the dataset. The Global Moran's *I* value was 0.2762, which suggested a positive autocorrelation of annual mean $PM_{2.5}$ concentrations. In addition, we also calculated Local Moran's *I*, the results of which showed a detailed local pattern of spatial clustering in relation to changes in $PM_{2.5}$ concentrations (Fig. 1b). High-high clusters were mainly distributed in the northern provinces of China, including Beijing, Tianjin, Hebei, Shaanxi, Shanxi, Henan, Hubei, Anhui, and Shandong. In contrast, low-low clusters were mainly located in the southeast provinces of China, including Xizang, Sichuan, Yunnan, Guangxi, Hainan, Guangdong, and Fujian. The 17 (of the 190 total) cities located in the province of Guangdong accounted for 59% of the total number of low-low cluster cities.

Obvious seasonal features are present in the data (Fig. 2), with the highest mean $PM_{2.5}$ level in 2014 occurring in the winter, and the lowest level appearing in the summer. Results show that 23 cities had mean $PM_{2.5}$ levels in excess of 130 μg/m^3 during the winter, while 60 cities had mean $PM_{2.5}$ levels under 35 μg/m^3 in the summer. The four seasons can thus be ranked in terms of average $PM_{2.5}$ values in the following order: winter (89 μg/m^3), autumn (54 μg/m^3), spring (53 μg/m^3), and summer (43 μg/m^3). However, for cities located in desert-like region in Northwest and West-Central China, the most polluted season was spring and not winter due to sand dust storms (Zhao et al., 2016). For example, Korla city in Xinjiang province recorded 168 μg/m^3 in spring and only 77 μg/m^3 in winter. In contrast, there were only 3 cities—Sanya, Lasa, and Zhoushan—with mean $PM_{2.5}$ level under 35 μg/m^3 for all four of the seasons. There were 6 cities—Xingtai, Shijiazhuang, Baoding, Handan, Hengshui, and Tangshan, which all belong to Hebei province—with mean $PM_{2.5}$ levels in excess of 75 μg/m^3 from spring to winter.

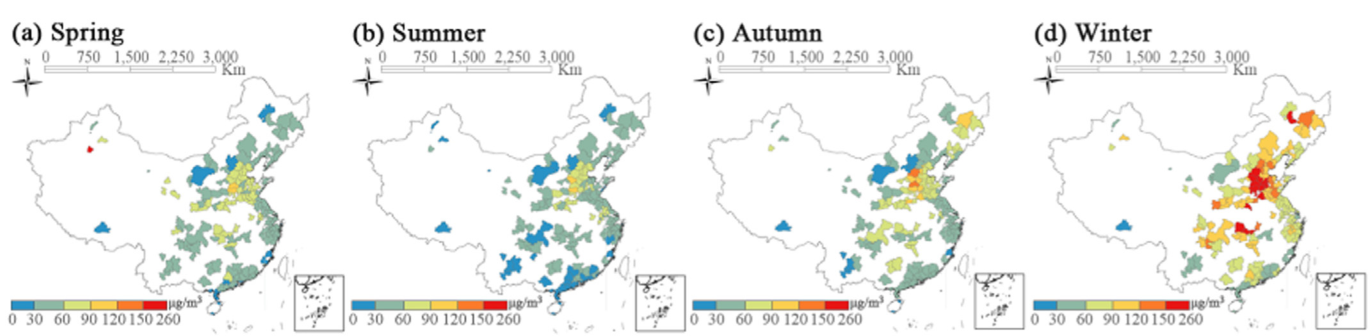

Fig. 2. Spatial distribution of $PM_{2.5}$ concentrations (μg/m^3) in (a) spring, (b) summer, (c) autumn, and (d) winter in China's major cities in 2014.

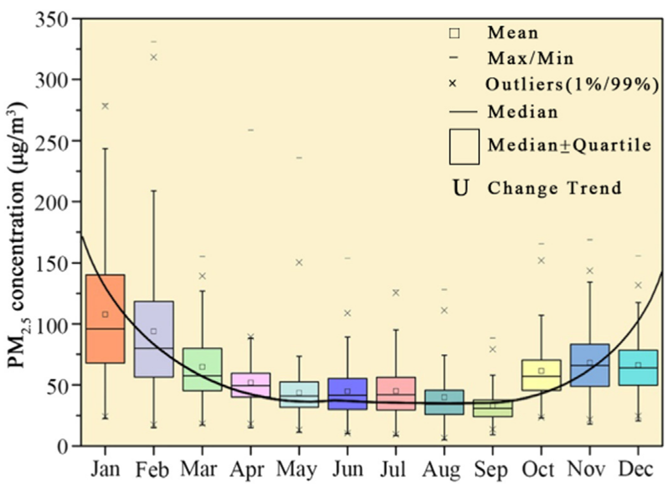

Fig. 3. Statistical variations in monthly $PM_{2.5}$ concentrations (μg/m^3).

Monthly variations in average $PM_{2.5}$ concentrations presented a U-shaped pattern, with a down trend from January to May and a stable period from June to September, followed by an increasing trend from October to December (Fig. 3). Average $PM_{2.5}$ concentrations for the 190 Chinese cities that make up the study area remained, in 2014, between 35 μg/m^3 and 75 μg/m^3 for 9 months of the year, in September sinking below 35 μg/m^3 and in January and February rising to above 75 μg/m^3. In addition, 29 cities maintained average $PM_{2.5}$ concentrations exceeding 75 μg/m^3 for more than 6 months of the year; these cities were predominantly located in Hebei and Shandong provinces. The 25 cities that maintained average $PM_{2.5}$ concentrations under 35 μg/m^3 for more than 6 months of the year were mainly located in the southeastern coastal areas and the provinces of Yunnan, Xizang, and Inner Mongolia (Fig. 4).

3.2. Factors influencing $PM_{2.5}$ concentrations

In order to understand the effect of socioeconomic indicators on $PM_{2.5}$ concentrations, this paper employed both non-spatial and spatial model. Besides, both spatial error model (SEM) ($P = 0.00000$) and spatial lag model (SLM) (0.00000) pass the Lagrange multiplier. However, the robust Lagrange multiplier of SEM ($P = 0.00000$) is better than the value of robust Lagrange multiplier with SLM ($P = 0.00015$), so here choose SEM as the spatial model. The results of the regression analysis are showed in Table 2.

The results of the non-spatial model indicated that PD, IS, RD, ISE, and GDP significantly influenced $PM_{2.5}$ concentrations at the national scale in China. In addition, with the exception of GDP, which showed a negative direction, the relationship between remainder of the significant factors and $PM_{2.5}$ concentrations were all positive. FDI and EC were found to have no significant effect on $PM_{2.5}$ concentrations. A spatial model was also used to ensure that potential spatial effects were not ignored, and the results of the spatial model ($R^2 = 0.634$) were more significant than those of the non-spatial model ($R^2 = 0.426$). The results of the spatial regression model showed that PD, IS, RD, ISE, GDP correlated significantly with $PM_{2.5}$ concentrations, and that FDI and EC were not

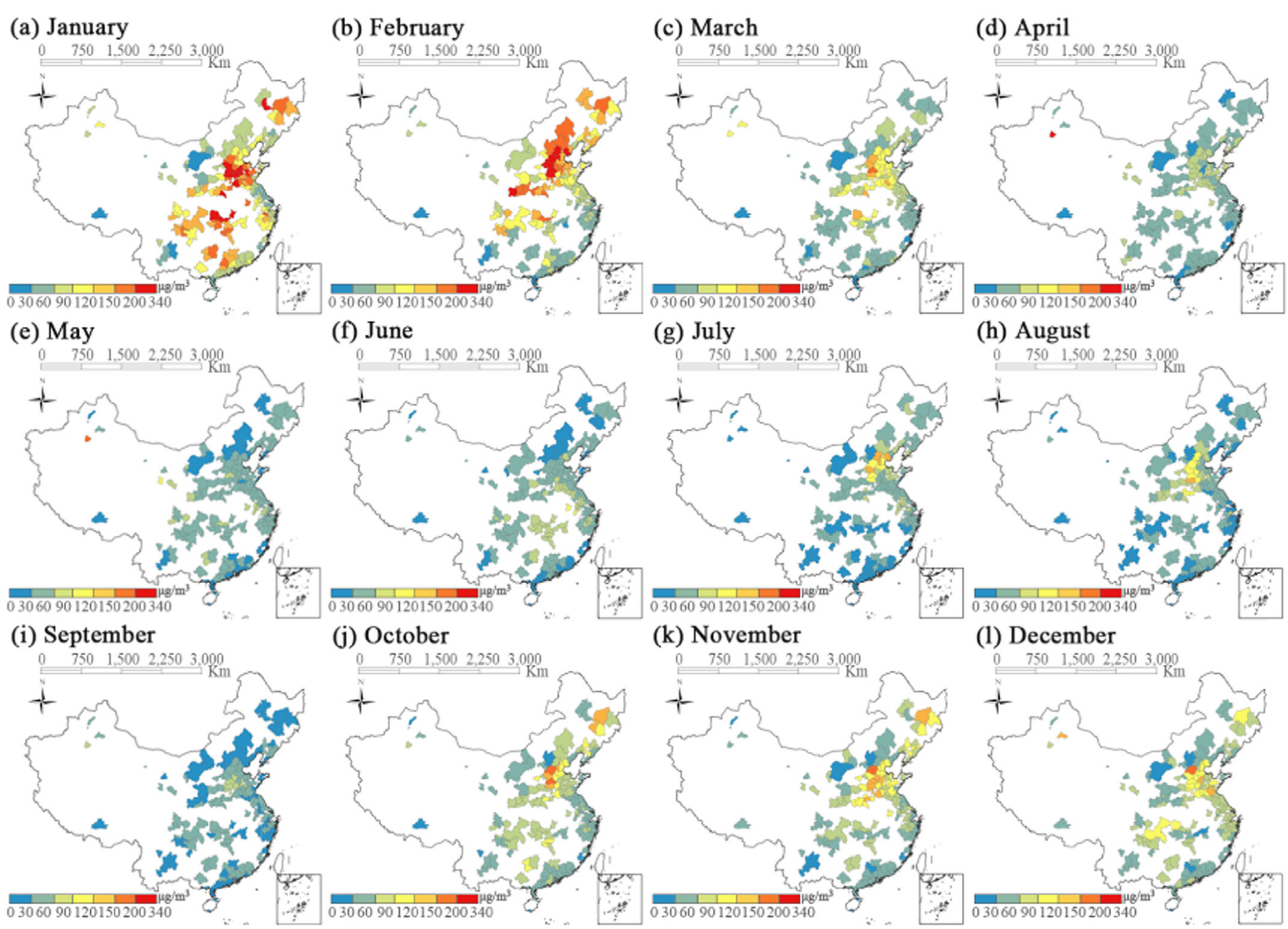

Fig. 4. The spatial distribution of monthly $PM_{2.5}$ concentrations (μg/m^3) in China's major cities in 2014.

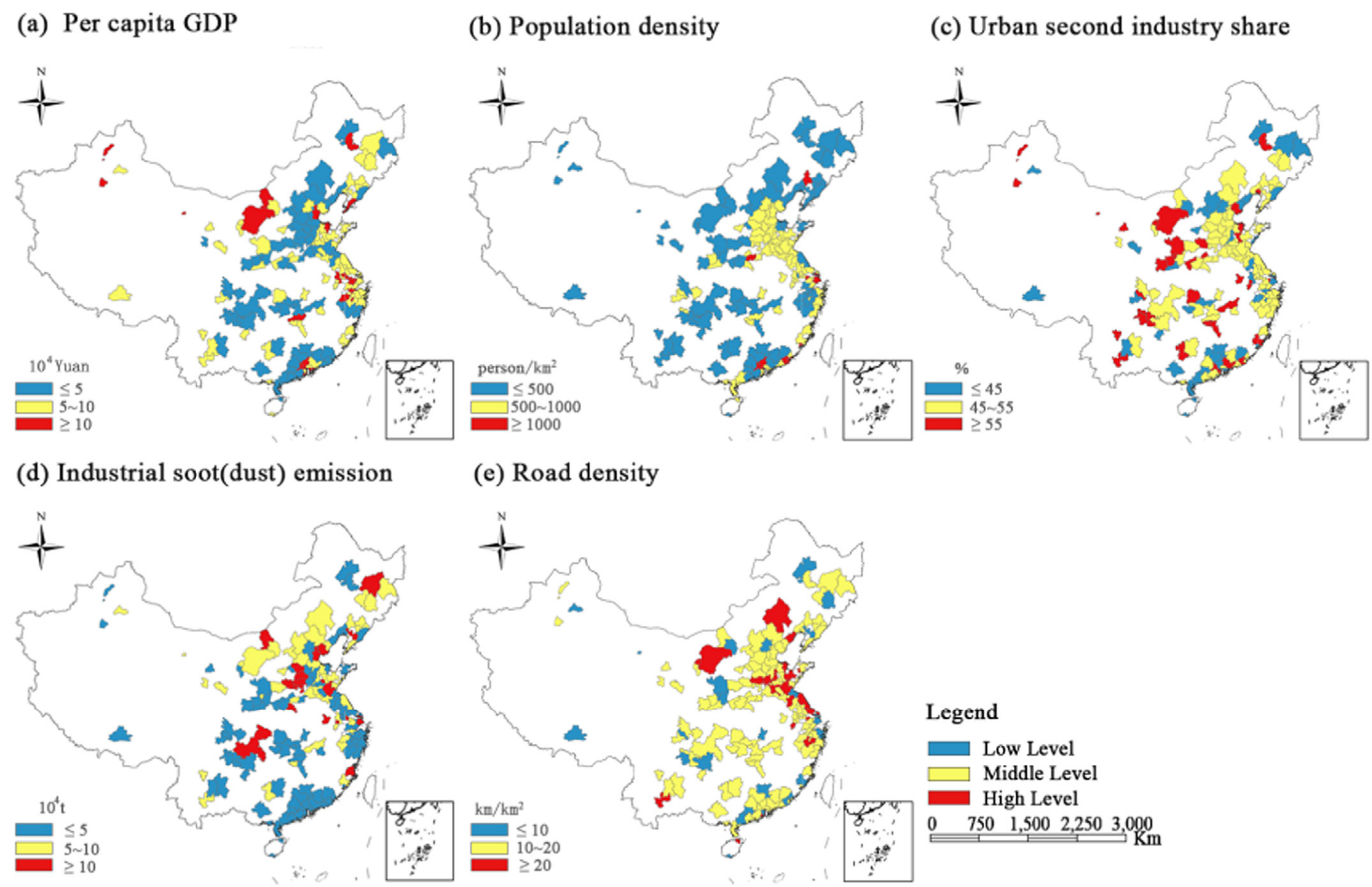

Fig. 5. Maps of six factors in relation to $PM_{2.5}$ concentrations (μg/m^3) in the major cities of China in 2014.

significant. After identifying the significances and directions of influence of the potential indicators on $PM_{2.5}$ levels, the next step was to explore the magnitude of the significant indicators.

We employed the geographical detector technique in order to evaluate the effect of determinants on $PM_{2.5}$ levels. First, cities were divided into three sub-regions according to each factor's original value. The thresholds of the sub-regions for these detectors are shown in Table 3. In order to examine the relationship between per capita GDP and $PM_{2.5}$ concentrations, the 190 cities that made up the study area were placed in categories of "less than 50 thousand Yuan," "between 50 and 100 thousand Yuan," and "larger than 100 thousand Yuan." We also classified the 190 cities into those with "0–500 persons/km^2," those with "500–1000 persons/km^2," and those that were "larger than 1000 persons/km^2," in order to better understand the relationship between urban population size and $PM_{2.5}$ concentrations. In order to understand the relationship between the share of secondary industry and $PM_{2.5}$ levels, the cities were again divided into three groups, this time based on their respective shares of secondary industry—i.e., "less than 45%," "45–55%," and "more than 55%." In addition, cities were also classified into three groups in terms of industrial soot (dust) emissions—namely, "less than 50 thousand tons," "between 50 and 100 thousand tons," and "larger than 100 thousand tons." Finally, we divided cities into three categories based on their road density—"less than 10 km/km^2," "between 10 and 50 km/km^2," and "larger than 50 km/km^2"—in order to reveal the nature and extent of the correlation between transportation and $PM_{2.5}$ level. Their distributions are displayed in Fig. 5.

Using the geographical detector technique, we then calculated the power of determinant (q) values, in order to determine the strength of the significant indicators influencing $PM_{2.5}$ levels (Fig. 6). As showed in Fig. 6, the q value of the factors was between 0.0213 and 0.1112, showing a marked difference that can be ranked as follow: ISE (0.1112) > IS (0.0499) > PD (0.0465) > RD (0.0221) > GDP (0.0213). The results indicate that industrial soot (dust) emissions, which had the highest q value, can predominantly explain the spatial heterogeneity of $PM_{2.5}$ concentrations, followed by the share of secondary industry and the population density. Road density and per capita GDP proved to have a weak explanatory influence.

The results of the spatial regression model and the geographical detector technique paint a clear picture of the mechanisms underlying the uneven distributions of $PM_{2.5}$ concentrations at a national scale in China. First, the industrial soot (dust) emission was found to have a marked, strong influence on $PM_{2.5}$ concentrations in China, implying that industrial soot (dust) emissions are the most important driver in increasing $PM_{2.5}$ concentrations. Wang and Fang (2016) have previously suggested that $PM_{2.5}$ concentrations maintain a positive relationship with the building industry. Building and related industries such as cement, iron,

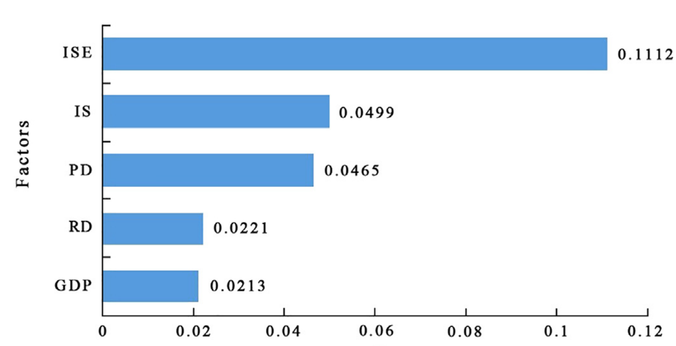

Fig. 6. The power of determinant (q) for the 5 factors guiding the $PM_{2.5}$ concentrations effect.

and steel both directly generate smoke and dust and were also high-energy-consuming sectors.

Second, the spatial regression results suggest that the share of secondary industry correlated significantly with $PM_{2.5}$ levels, a relationship reflected in a higher q value for this variable (0.0499). Similar findings have been generated by previous studies, which have found the proportion of secondary industry to positively influence average $PM_{2.5}$ levels (Hao and Liu, 2016), and exert a stronger influence than transportation or agricultural factors in the accumulation phase of $PM_{2.5}$ during pollution episodes (Lou et al., 2016). The results from an analysis of input-output framework indicated that as the "world's manufacturing hub", China's construction, metal, and machinery production sectors were the industrial sectors driving the greatest changes in $PM_{2.5}$ emissions (Guan et al., 2014; Guan and Reiner, 2009).

Third, the level of population density contributed a rather prominent, positive influence in relation to $PM_{2.5}$ concentrations levels in China, generating a q value of 0.0465. Previous studies have argued that anthropogenic emissions are the main contributors to haze pollution. A 1% increase in population density could, scholars have argued, cause a 0.214% rise in the daily increase rate of $PM_{2.5}$ (Zhao et al., 2009; Han et al., 2014; Lou et al., 2016). The results of this study indicate that population density played a significant role in $PM_{2.5}$ concentrations in the long term and at the national scale in China in 2014.

Fourth, road density was found to exert a positive influence on $PM_{2.5}$ concentrations in China, with results showing a q value of 0.0221. Road density plays an important role in transportation, and is an important reflection of an area's economic level. Lou et al. (2016) found that the impact of vehicle use cannot be ignored in relation to the accumulation phase of $PM_{2.5}$ during pollution episodes in China. Li et al. (2014) also explored the relationship between transportation and $PM_{2.5}$ concentrations, suggesting that automobile exhaust emission contributed to 22%, 25%, and 16% of $PM_{2.5}$ emissions in Beijing, Shanghai, and Tianjin, respectively. The larger the road density, the greater vehicle traffic is likely to be; as a result, increasing road density risks increasing automobile exhaust emissions, an issue that must be raised in relation to increasing $PM_{2.5}$ concentrations in China.

Finally, per capita GDP was found to contribute a small negative influence in relation to $PM_{2.5}$ levels in China, with a q value of only 0.0213. It is therefore difficult to describe GDP as a driver of $PM_{2.5}$ concentrations at the national level. Previous studies have argued that in 43 out of 53 cities in the BRUA, $PM_{2.5}$ concentrations maintained a negative relationship with per capita GDP (Wang and Fang, 2016). Supporting the findings listed above, the results of this paper also demonstrated the existence of a negative correlation between per capita GDP and $PM_{2.5}$ level across sub-regions. This may be because the higher per capita GDP is, the greater environmental awareness, a factor which in turn might reduce $PM_{2.5}$ concentrations.

4. Discussion

A better understanding of potential socioeconomic drivers of $PM_{2.5}$ concentrations is beneficial to policy makers in the task of formulating pollution control strategies and improving air quality. Using spatial regression model and the geographical detector technique, the results of this study highlight the important role that socioeconomic factors play in determining $PM_{2.5}$ concentrations levels. The results revealed the different strength of a range of socioeconomic factors that influence the distribution of $PM_{2.5}$ concentrations, providing a more detailed analysis through the use of monitoring data at a national scale.

Previous studies suggested that there was a U-shaped relationship between per capita GDP (GDP) and $PM_{2.5}$ concentrations, while the other found an inverted U-shaped one (Shao et al., 2016; S.J. Wang et al., 2017b). However, our results indicate a negative influence of per capita GDP (GDP) on $PM_{2.5}$ concentrations. Similar study is also taken by Wang and Fang (2016). Therefore, China should continue to maintain sustained and stable economic growth to improve the public environmental awareness to reduce pollution behaviors. Even previous studies have argued that large cities pose advantages in terms of pollution disposal, and that a higher population density can therefore be helpful in improving the urban environmental (Stone, 2008), our findings contribute to the research which argued a significant positive relation between population density and $PM_{2.5}$ concentrations (Zhao et al., 2009; Han et al., 2014); as a result, government in China should continue to promote sustained population urbanization (Wang and Liu, 2017). Previous researches argued that secondary industry and associated energy consumption can be linked to the production and emission of a range of pollutants (Han et al., 2014; Zhao et al., 2014; Ma and Zhang, 2014; Cheng et al., 2016; S.J. Wang et al., 2017b), at present, the share of secondary industry shows a similar result which has a positive relation with $PM_{2.5}$ concentrations. Thus, China should enhance technology progress, reduce the share of high-energy-consuming industries and greatly develop the third industry. The industrial soot (dust) emission is here shown to positively affect $PM_{2.5}$ concentrations which contributes to the research which show a positively relationship between building industry and $PM_{2.5}$ concentrations (Wang and Fang, 2016). Similar to previous research suggested that the development of the traffic network brought about significant additive effects in relation to regional smog pollution (Shao et al., 2016), in this study, result of regression on road density also showed a positive impact on $PM_{2.5}$ concentrations. In order to reduce emissions, the government should introduce policy of restrictions widely, while increasing the production of new energy vehicles and encouraging residents shift from private motor vehicles to public transport (Redman et al., 2013). There are positive (Guan et al., 2014) and negative (List and Co, 2000) statements about the impact of FDI on $PM_{2.5}$ concentrations. However, our results show that FDI does not have influence on $PM_{2.5}$ concentrations. In China, electricity is generated from fossil and non-fossil fuels. Electricity generated from non-fossil energy which including Hydro, Nuclear, and Wind firstly reached over 25% in 2014 based on the data from China Electricity Council (CEC, 2015). In addition, Sun et al. (2015) discussed that by using the wet electrostatic precipitator (ESP) technology power plant can control the emissions of $PM_{2.5}$ efficiency. Hao et al. (2007) identified the effect of power plant emissions on air quality in Beijing, the results indicated that emitted by power plants is 11% of the total PM_{10} emissions in Beijing but the average contributions to ambient concentrations were 0.9%. Moreover, the average concentration increments of PM_{10} reduce by 86% from 2000 to 2008, by the controlled measures such as fuel substitution, flue gas desulphurization (FGD), dust control improvement and flue gas denitration. Hence, power plants emissions have no great influence on air quality especially for the effect on PM. Similar study is also taken by Chen et al. (2003). Thus, there was no significant relationship between electricity consumption and $PM_{2.5}$ concentrations in the present study.

It is important to discuss, however, the results from the geographical detector technique may be affected by some factors. For example, the thresholds of socioeconomic factors are subjective to some degree which will influence the impact on $PM_{2.5}$ concentrations. Despite these limitations, our findings are helpful in the task of formulating policies in order to improve air quality.

Overall, environmental protection is led by governments and promoted by academia and corporations (Liang et al., 2016). As such, without scientific city planning, profound academic research, organizational support, and air pollution will be difficult to solve. Does an academic worker, future study of this issue is therefore vitally important, scholars should pay attention to the influence of the interaction between determinations which will benefit to understand the determinations of $PM_{2.5}$ concentrations in a more comprehensive perspective.

5. Conclusions

The results of the study indicate annual average $PM_{2.5}$ concentrations of $61 \pm 20\,\mu g/m^3$ in cities in China. Cites with $PM_{2.5}$ concentrations of more than 75 μg/m^3 were mainly located in northern and northeastern China. In addition, $PM_{2.5}$ concentrations showed notable seasonal variability, with the highest $PM_{2.5}$ level occurring during the winter and the lowest during the summer. Monthly variations were found to conform to a U-shaped curve, and the annual distribution of average $PM_{2.5}$ concentrations levels in China showed positive spatial dependence characteristics. High-high clusters were mainly found to be located in the Beijing-Tianjin-Hebei-Shandong region, and low-low clusters were situated in Fujian-Guangdong-Hainan-Guangxi-Xizang.

The factors underlying the uneven distribution of $PM_{2.5}$ concentrations in the 190 cities addressed in this study were investigated. Our results suggest that population densities, the share of secondary industry, industrial soot (dust) emissions, and road density all significantly positively influenced $PM_{2.5}$ concentrations, while per capita GDP exerted a significant negative influence. In contrast, FDI and electricity consumption did not demonstrate a significant relation to $PM_{2.5}$ concentrations at the national scale. Besides, the findings also indicated that industrial soot (dust) emissions play the most important role in stimulating $PM_{2.5}$ concentrations levels. Therefore, industrial soot (dust) emissions were thus the dominant influencing factor underlying China's $PM_{2.5}$ concentrations, followed by the share of secondary industry, and population density. While road density and per capita GDP showed smaller influence of $PM_{2.5}$ concentrations than those of other factors.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (41601151; 41371138), National Social Science Foundation of China (17BRK010) and the Natural Science Foundation of Guangdong Province (2016A030310149).

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