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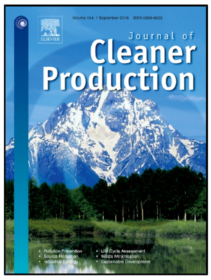

The driving factors of air quality index in China

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PII:	S0959-6526(18)31758-X
DOI:	10.1016/j.jclepro.2018.06.108
Reference:	JCLP 13254
To appear in:	*Journal of Cleaner Production*
Received Date:	10 September 2017
Accepted Date:	11 June 2018

Please cite this article as: Dongsheng Zhan, Mei-Po Kwan, Wenzhong Zhang, Xiaofen Yu, Bin Meng, Qianqian Liu, The driving factors of air quality index in China, *Journal of Cleaner Production* (2018), doi: 10.1016/j.jclepro.2018.06.108

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Amount of words: 8705

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Abstract: In recent years, serious air pollution episodes in China have received increasing academic attention due to their adverse impacts. Drawing on Air Quality Index data in 2015 across 338 Chinese cities, this study investigated the spatiotemporal patterns of the air pollution in China and identified the effect intensity and interaction among the driving factors using the geographical detector model. The results indicate that air pollution levels in 2015 in China are still high on the whole, with $PM_{2.5}$, PM_{10}, and O_3 as the major primary pollutants. Temporally, air pollution in China presents a U-shape pattern over the year, while the primary pollutants vary across seasons. Spatially, air pollution in China is characterized by spatial clustering and witnesses higher levels in Northern China and Xinjiang Province and lower levels in Southern China, but the location of some air pollution hot spots change by seasons. Spatial patterns of the primary pollutants are divided into five types of region according to their occurrence frequency. On average, natural factors are found to exert more effects on air pollution in China than socioeconomic factors. Additionally, interactions among the driving factors have either nonlinear-enhanced or bi-enhanced effects on air pollution. Findings from the study have several important policy implications for mitigating air pollution in China.
Key words: Air Quality Index; spatiotemporal patterns; driving factors; geographical detector model; interaction; China

1. Introduction

Since China's reform and opening up, rapid economic growth and urbanization are accompanied by a huge amount of resource and energy consumption, resulting in a substantial increase in air pollutant emissions (Han et al., 2015; Hao and Liu, 2016; Luo et al., 2014). In particular, a wide range and long duration of hazy weather occurred in January 2013, sweeping across the central and eastern regions in China and causing sharply growing public attention to urban air quality (Wang et al., 2014). Meanwhile, the increased episodes of serious air pollution have also been a major concern for the Chinese Central Government, which enacted a new National Ambient Air Quality Standards in 2012, implemented the Air Pollution Prevention and Control Action Plan in 2013 to cut down $PM_{2.5}$ concentration, and completed the nationwide monitoring of urban air quality for cities at the prefecture level and above in 2015. In addition, it is remarkable that Premier Keqiang Li made a commitment in the government work report of 2016 that the percentage of days with excellent and good air quality in a year should reach 80% for all Chinese cities at the prefecture level and above （including prefecture-level cities and municipalities） during the 13th Five-Year Plan period, of which is a roadmap for national development from 2016 to 2020.

Air pollution has been documented with substantial adverse effects in a large body of literature, including health outcomes such as respiratory and cardiovascular disease (Forbes et al., 2009), visibility impairment (Delucchi et al., 2002), outdoor activities (Chen et al., 2017), economic loss (Etchie et al., 2017), and climate change (Maione et al., 2016). For instance, the recent World Health Organization report indicated that ambient air pollution was estimated to cause about 3 million premature deaths worldwide in 2012, of which 88% of the premature deaths occurred in low- and middle-income countries and the greatest number occurred in the Western Pacific and South-East Asia regions (World Health Organization, 2016). An empirical study in China by Xia et al. (2016) found that considering the number of days affecting Chinese employees whose work time was reduced in 2007, the total economic loss in China caused by air pollution was up to 346.26 billion Yuan (about 1.1% of the national GDP), which is equivalent to the annual GDP of Vietnam in 2010. Therefore, it is essential to accurately identify the spatiotemporal characteristics of urban air quality in China and its main driving factors, which is of great significance for controlling and mitigating poor air pollution in China.

The spatiotemporal patterns of air pollution at different spatial scales have been reported in earlier literature. At small spatial scales, spatial variations in intra-city air pollution levels were frequently examined by land use regression models combined with ancillary variables (Lee et al., 2017). However, these studies have limited ability to depict air pollution patterns at large spatial scales. Other alternative studies focusing on large spatial scales used remotely sensed satellite data Aerosol Optical Depth and provided new insights to regional or national air pollution levels with a coarse spatial resolution. The estimated value for air pollution transformed from Aerosol Optical Depth, however, generally vary with place and time since they are influenced by some unstable factors (i.e., meteorological and topographic factors) (Chudnovsky et al., 2014; Gupta et al., 2006), which may generate biased results when compared with ground-monitored values. In the case of China, although there have been a growing number of studies focusing on the spatiotemporal patterns of air pollution over Chinese cities, most existing studies have been conducted at small scales like single large cities (Guo, H. et al., 2017; Liu et al., 2015) or several typical urban agglomerations (Hu et al., 2014), possibly because of incomplete data from ground-level monitoring stations. Research on the spatiotemporal patterns and characteristics of air pollution in China at the national scale are still very limited to date, especially the spatial dependency and heterogeneity of air pollution patterns over space.

Given that the identification and quantification of the contributing factors of air pollution levels can inform the development of more effective policies of air pollution mitigation and health impact control, extensive research has been conducted on the driving factors that cause spatial variations in air pollution levels. However, much of the existing literature has examined the effects of either socioeconomic factors or natural factors on air pollution separately, with only a few exceptions that combine both socioeconomic and natural factors (Liu et al., 2017; Luo, J.Q. et al., 2017). Numerous empirical studies have established the positive relationship between air pollution levels and a series of socioeconomic factors, including population, population density, GDP, urbanization level, the percentage of secondary industry, the number of vehicles, and energy consumption (Fang et al., 2015; Hao and Liu, 2016; Ma et al., 2016). However, whether per capita GDP has a positive or negative effect on air pollution levels in China is inconclusive to date (Lin and Wang, 2016; Ma et al., 2016). Further, a variety of empirical studies have found that air pollution levels are negatively associated with most natural factors, such as the proportion of several land use types (i.e., water, forest, grassland), Normalized Difference Vegetation Index (NDVI), elevation, and slope. On the other hand, air pollution levels are positively associated with many meteorological parameters, such as temperature, precipitation, relative humidity, and air pressure (Luo, J. et al., 2017; Zhang et al., 2016) but have mixed relationships with wind speed (Yang et al., 2017; Zhang et al., 2016). In light of these complex and sometimes inconsistent findings in earlier studies, much more research regarding the effects of both socioeconomic and natural factors on air pollution is still needed.

From a methodological point of view, there is little evidence on effect intensity and interaction among driving factors due to the use of traditional methods such as Ordinary Least Squares (Lin et al., 2013; Zhang et al., 2016). The geographical detector model is a spatial variation analysis method first developed to examine the effects of environmental factors on disease risk. Its basic idea is to test the spatial consistency between the driving factors and the dependent variable (Wang et al., 2010). The geographical detector model has two distinct advantages when compared to traditional regression models (Wang and Hu, 2012; Wang et al., 2016). One is that by calculating the effects of the explanatory variables separately, the geographical detector model does not need to consider the multicollinearity among them, while many natural and socioeconomic factors affecting urban air quality may be highly correlated (Luo, J. et al., 2017; Pu et al., 2017). The other is that the geographical detector model can be applied to identify the effect intensity (or relative importance) of each influencing factor (or explanatory variable), along with the interaction between the explanatory variables, which is rarely studied before.

With respect to the measurement of air pollution, most previous air pollution studies focused on only a single pollutant such as $PM_{2.5}$ and SO_2, but people are seldom exposed to a single pollutant (Choi et al., 2016; Dominici et al., 2010). The Air Quality Index (AQI) is a popular comprehensive indicator of overall air pollution level based on multiple air pollutants (Bao et al., 2015). Therefore, the main objectives of this study are to (1) examine the air pollution levels in China using the Air Quality Index data provided by the ground monitoring stations that cover all Chinese cities at the prefecture level and above, (2) analyze the spatial and temporal characteristics of the AQI in 2015 across Chinese cities at the national level, (3) identify the effect intensity and interactions between the driving factors, both natural and socioeconomic, on the spatial disparity of the AQI in China using the geographical detector model.

2. Methods and material

2.1. Methods

2.1.1. Globe spatial autocorrelation analysis

Spatial dependence is widespread for many geographical phenomena. This is also true for urban air quality in China as observed in previous studies. Globe spatial autocorrelation analysis has been widely used to measure spatial dependence over the entire study area. Moran's *I* is a popular measure of globe spatial autocorrelation of a specific attribute value, reflecting the degree to which spatial agglomeration of the specific attribute value occurs between a specific area and the adjacent areas (Anselin, 1995; Anselin et al., 1996). Its formula is as follows:

$$\mathrm{I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (2)$$

where *n* is the number of Chinese cities in the study area. x_i and x_j stand for the AQI of city i and city j, respectively. Then $\bar{x}$ is mean AQI across the cities. Moreover, w_{ij} is the spatial matrix between cities. If the two cities share a border, w_{ij} is equal to 1, otherwise w_{ij} is 0. The value of Moran's *I* ranges from -1 to 1, and the higher its absolute value, the stronger the spatial agglomeration is. A significant and positive Moran's *I* indicates a clustering of similar AQI values, and a significant and negative value suggests the clustering of dissimilar AQI values, while a Moran's *I* of 0 indicates no spatial autocorrelation (i.e., the AQI value of a particular area is not related to the AQI values of the adjacent areas).

2.1.2. Hot spot analysis

Globe spatial autocorrelation analysis can only reflect the general trend of urban air quality over the entire study area. To identify spatial heterogeneity of urban air quality at the local level, local spatial autocorrelation analysis is needed, which is commonly measured by local Moran's *I* (Anselin, 1995) and Getis-Ord *Gi** (Getis and Ord, 1992; Ord and Getis, 1995). In this study, Getis-Ord *Gi** was adopted to identify significant spatial clustering of high and low AQI values, which are also referred to as hot spots and cold spots respectively. Its formula is:

$$\mathrm{G}_{\mathrm{i}}^{*}(\mathrm{d}) = \sum_{i=1}^{n} W_{\mathrm{ij}}(d) X_j / \sum_{j=1}^{n} X_{\mathrm{j}} \quad (3)$$

where $\mathrm{G}_{\mathrm{i}}^{*}(\mathrm{d})$ refers to the local G statistic for an attribute *i* within a distance *d*. $W_{\mathrm{ij}}(d)$ is a spatial matrix between city *i* and *j*. X_{j} is the AQI of city j.

In order to facilitate comparison and interpretation, $\mathrm{G}_{\mathrm{i}}^{*}(\mathrm{d})$ is generally transformed into a standardized result as $\mathrm{Z}\left(G_{\mathrm{i}}^{*}\right)$:

$$\mathrm{Z}\left(G_{\mathrm{i}}^{*}\right) = \frac{G_{i}^{*} - E(G_{i}^{*})}{\sqrt{VAR(G_{\mathrm{i}}^{*})}} \quad (4)$$

where $\mathrm{Z}\left(G_{\mathrm{i}}^{*}\right)$ is standardized Gi* statistic. $E(G_{i}^{*})$ is the expectation value, while $VAR\left(G_{\mathrm{i}}^{*}\right)$ indicates the variance of the Gi*. Negative $\mathrm{Z}\left(G_{\mathrm{i}}^{*}\right)$ values below -1.65 ($P<0.1$) indicate low levels of the AQI and cold spots, while positive values above 1.65 ($P>0.1$) indicate high levels of the AQI and hot spots.

2.1.3. The geographical detector model

The geographical detector model is a spatial variance analysis method that can identify the explanatory variables that significant influenced the dependent variable. Its software code can be freely downloaded at the website (http://www.sssampling.org/Excel-Geodetector/). In this study, the geographical detector model was used to identify the key driving factors influencing the AQI in China by examining the association between the driving factors and the AQI according to the consistency of their spatial distributions. The geographical detector model consists of four basic models, involving the risk detector, the factor detector, the ecological detector, and the interaction detector (Wang et al., 2010). More specifically, the risk detector identifies potential risk areas of the dependent variable Y; the factor detector represented by q statistic measures the power of determinants X to the dependent variable Y; the ecological detector identifies the effect differences between two explanatory variables X1 and X2; and the interaction detector reveals whether the explanatory variables X1 and X2 (or other X) have an interactive effect on the dependent variable Y. In this study, the factor detector and the interaction detector were both employed to examine the effect intensity of driving factors and their interaction on urban air quality in China. The formula of the factor detector is as follows (Wang and Hu, 2012):

$$q = 1 - \frac{1}{\mathrm{n}\sigma^2} \sum_{h=1}^{L} n_h {\sigma_h}^2 \quad (5)$$

where q statistic is the power of determinant on the AQI. n and σ^2 stand for the sample size and variance of the AQI across all Chinese cities, respectively. n_h, ${\sigma_h}^2$ refer to the sample size and variance of the AQI in the specific layer. The value of q lies in the range of [0,1], and the greater the value, the stronger the power of determinant. When q equals 0 the driving factors have no relationship with the AQI, while a value of 1 indicates that the driving factors can completely explained the spatial difference of the AQI.

In addition, the interaction detector model is expressed as follows (Wang and Hu, 2012):

Nonlinear-weaken: $q(X1 \cap X2) < Min(q(X1), q(X2))$;

Uni-weaken: $Min(q(X1), q(X 2))<q(X1 \cap X2)<Max(q(X1)), q(X2))$;

Bi-enhance: $q(X1 \cap X2) > Max(q(X1), q(X2))$;

Independent: $q(X1 \cap X2) = q(X1)+ q(X2)$;

Nonlinear-enhance: $q(X1 \cap X2) > q(X1)+ q(X2)$

where $q(X1 \cap X2)$ indicates the q statistic for the interactive effect of driving factor X1 and X2. q(X1) and q(X2) stand for the separate effect of X1 and X2, respectively. Specifically, the nonlinear-weaken effect indicates a smaller interactive effect of the driving factors X1 and X2 than each separate effect, while the uni-weaken effect suggests a mild interactive effect lying between the separate effect of X1 and X2. Moreover, the bi-enhance effect means a relatively bigger interactive effect of the driving factors X1 and X2 than each separate effect, the independent effect implies the interactive effect amounting to the sum of the separate effect of X1 and X2, whereas the nonlinear-enhance effect shows the strongest interactive effect of the driving factors X1 and X2 over the sum of their separate effect.

2.2. Data

2.2.1. Data for the Air Quality Index

The Chinese government has devoted great efforts to monitoring ambient air quality in recent years. For example, in 2012, the Ministry of Environmental Protection in China made the third amendment to the National Ambient Air Quality Standards and promulgated a new Ambient Air Quality Standards (GB3095-2012), adding $PM_{2.5}$ concentration and O_3 concentration within 8 hours as two new indicators. The new monitoring system of ambient air quality in China has been gradually improved since then. Nevertheless, only 74 cities were monitored since the start year of 2012, and these cities are mainly municipalities and provincial cities located in the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta. In 2013, ambient air quality monitoring stations expanded to 113 cities, which are the major cities of national environmental protection. In 2014, monitoring stations further expanded to 161 cities nationwide, and they cover all the Chinese cities at the prefecture and above level for the first time in 2015. Such expansion of monitoring stations provides important support for exploring the spatiotemporal patterns of urban air quality in China at the national scale.

The air quality index data used in this study were downloaded in 2015 from the data center of the Ministry of Environmental Protection in China (http://datacenter.mep.gov.cn/index). The raw data cover 367 cities, including 335 cities at the prefecture level and above, and 32 county-level cities. In the end, only 3 county-level cities, namely Korla, Shihezi, and Wujiaqu, under the jurisdiction of Xinjiang province were retained and the other 29 county-level cities were excluded because of administrative regions situated in corresponding prefecture-level cities. Therefore, 338 cities are ultimately analyzed in this study.

The air quality index (AQI) quantifies overall air quality based on all ambient air pollutants in the monitored area. The formula of AQI is expressed as:

$$AQI = \max\{IAQI_1, IAQI_2, IAQI_3, \ldots, IAQI_n\} \quad (1)$$

where AQI stands for air quality index; IAQI is individual air quality index, including ambient air pollutants such as sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), PM_{10} (particulate matter with an aerodynamic diameter of 10 μm or less), $PM_{2.5}$ (particulate matter with an aerodynamic diameter of 2.5 μm or less). n is the number of ambient air pollutants.

Table 1 lists the basic characteristics of the relevant indicators to air quality index. As the table indicates, the lower the AQI, the higher the urban air quality and the lower the level of air pollution, and vice versa. According to the Technical Regulation on Ambient Air Quality Index (HJ633-2012) issued in China, the pollutant with the highest IAQI value is defined as the primary pollutant (e.g., SO_2, NO_2, CO, O_3, PM_{10} and $PM_{2.5}$) when the AQI is greater than 50. If two or more pollutants have the highest and same IAQI value, all of them will be considered as the primary pollutants.

Table 1

Characteristics of related indicators to Air Quality Index

Air Quality Index (AQI)	Levels of AQI	Categories of AQI
0-50	level 1	Excellent
51-100	level 2	Good
101-150	level 3	Slight pollution
151-200	level 4	Moderate pollution
201-300	level 5	Heavy pollution
>300	level 6	Serious pollution

2.2.2. Data of the explanatory variables

Both socioeconomic and natural factors were taken into account to identify the driving factors of urban air quality in China in this study. In view of data availability across all the Chinese cities at the prefecture level and above, the data of socioeconomic factors were mostly drawn from the China Statistical Yearbook for Regional Economy in 2014, including population, population density, GDP, GDP per capita, the number of vehicles and the percentage of secondary industry. Due to the incomplete record of urbanization level in many Chinese statistical yearbooks, urbanization levels were calculated using the urban population divided by the permanent (non-migrant) population, which were obtained from China County-Level Census Data in 2010. In addition, socioeconomic data for the three county-level cities were retrieved from local annual statistical reports.

With respect to the data of natural factors, Digital Elevation Model (DEM) and NDVI were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn/), with a spatial resolution of 90 m and 500 m respectively, whereas land relief was calculated based on the DEM data using the neighborhood statistics tool in ArcGIS 10.2. Meteorological data were obtained from the Chinese Meteorological Data Sharing Service System (http://data.cma.cn/), including monthly temperature, precipitation, relative humidity, wind speed, sunshine hours, and air pressure of 960 national meteorological stations from 2001 to 2014. To get citywide meteorological data, the Kriging interpolation method was employed to generate continuous meteorological surface over the entire study area at the first step, and then zonal statistics was used to obtain an annual average meteorological value for each studied city. Both of them were derived using ArcGIS 10.2.

3. Results

3.1. Descriptive statistics of urban air quality

The statistical results of urban air quality in 2015 across the Chinese cities examined in this study are listed in Table 2. As the table indicates, annual mean AQI in 2015 is 82.4±24.1 across the 338 Chinese cities, ranging from 36.6 in Diqing located in Xizhang Province to 209.6 in Hotan located in Xinjiang Province. In terms of the percentage of the days with excellent and good air quality (days without air pollution), its mean is 76.9%±16.9% in 2015 across the Chinese cities, suggesting that the number of days with the AQI>100 (air pollution days) across the Chinese cities reaches a high percentage of to 23.1% for 2015. Despite a mean of 76.9% which is close to the 80% expected by the Chinese Government, there are in total 46.1% of the cities having a percentage of the days with excellent and good air quality below 80%. The results of the above two indicators suggest that air pollution in 2015 across the Chinese cities was still serious. Moreover, statistical results of the primary pollutants that affects AQI show that $PM_{2.5}$, PM_{10} and O_3 are the main primary pollutants of the AQI in China, accounting for 41.7%, 29.3% and 23.7% respectively, whereas NO_2, SO_2 and CO only present a small proportion, ranging from 1.2% to 2.7%, which is supported by the finding of Song et al. (2017).

Table 2

Characteristics of urban air quality in 2015 in China

Indicators	Mean	Std	Min	Median	Max	Number of cities
Annual mean AQI	82.4	24.1	36.6	82.4	209.6	338
Percentage of excellent and good days	76.9%	16.9%	19.3%	78.9%	100%	338

3.2. Temporal characteristics of urban air quality

3.2.1. Changes in urban air quality by months

The changes of urban air quality in China by months in 2015 are illustrated in Fig.1. As shown in the figure, the mean AQI and its standard deviation both showed a U-shaped trend over the year, conforming to the findings of previous studies (Wang et al., 2017; Zhang et al., 2016). More specifically, the mean AQI shows a decreasing trend since January when it had the maximum AQI of 110.8, maintained a stable trend with an AQI of around 70 from May to July, reached its minimum of 64.9 in September, and gradually increased from October. To compare the seasonal change of the AQI in China, mean AQI in each season was further calculated. The result reveals a distinct seasonal variation of AQI with the mean ranked in a decreasing order as winter (104.0) > spring

(81.9) > autumn (74.4) > summer (69.4), indicating that urban air quality in 2015 across the Chinese cities is much worse in winter, but relatively better in summer. This result of more serious air pollution in winter is in line with many previous studies, which can be explained by two reasons (Wang et al., 2017; Zhang and Cao, 2015a). One reason is that weather conditions in winter are unfavorable to air diffusion for most of the Chinese cities, including the frequent occurrence of stagnant weather associated with high pressures, temperature inversion, and less precipitation. The other is generally attributed to increased air pollutant emissions due to winter heating, especially in Northern China. Furthermore, the possible reason for the relatively higher AQI in spring is dust storms that frequently occurred in Western China.

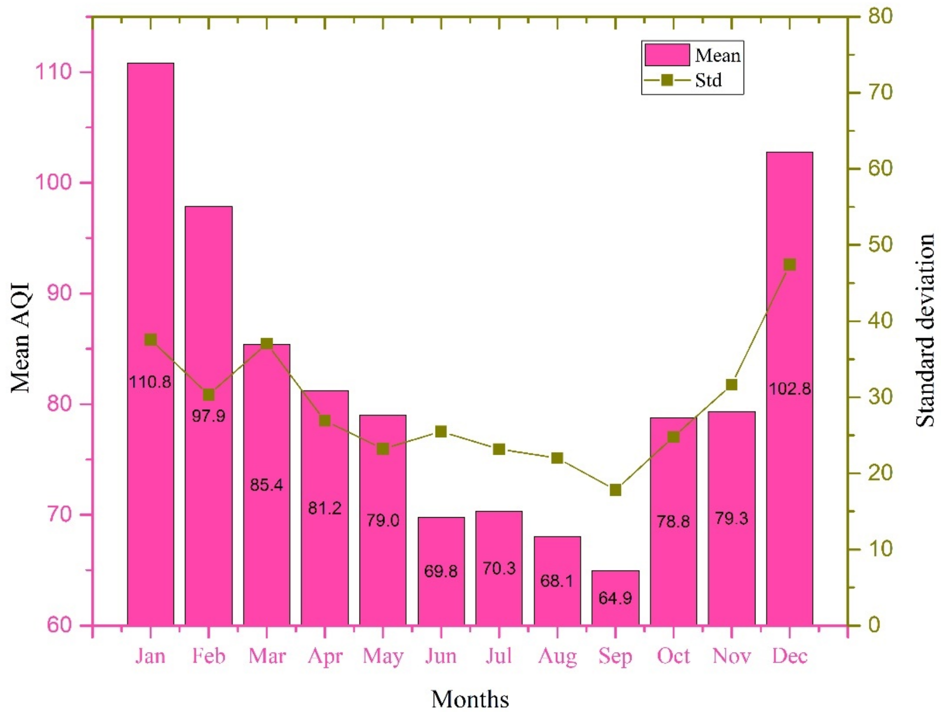

Fig.1 Characteristics of urban air quality in China by months in 2015

3.2.2. Changes of the primary pollutants by months

Figure 2 presents the characteristics of the primary pollutants that contributed to the AQI by months in 2015. With respect to the winter months (December to February), $PM_{2.5}$ and PM_{10} have become the dominant primary pollutants in the Chinese cities, which on average account for 67.4% and 23.1% of the AQI respectively. However, in the summer months (June to August), the main primary pollutant is O_3 which contributed 53.3% to the AQI, followed by PM_{10} which account for 25.0% of the AQI. The possible reason for increased O_3 in summer is that the longer duration of solar radiation and high temperature contribute to strong photosynthesis, which helps the conversion of nitrogen oxides and volatile organic pollutants into O_3 through a chemical reaction (Song et al., 2017). With respect to spring and autumn, the characteristics of the primary pollutants that contributed to the AQI is at transitional stages between winter and summer. The primary pollutants in the spring months (March to May) are characterized by increased O_3 and decreased $PM_{2.5}$ and PM_{10}, while the months in Autumn (September to November) showed an opposite trend with decreased O_3 and increased $PM_{2.5}$ and PM_{10}.

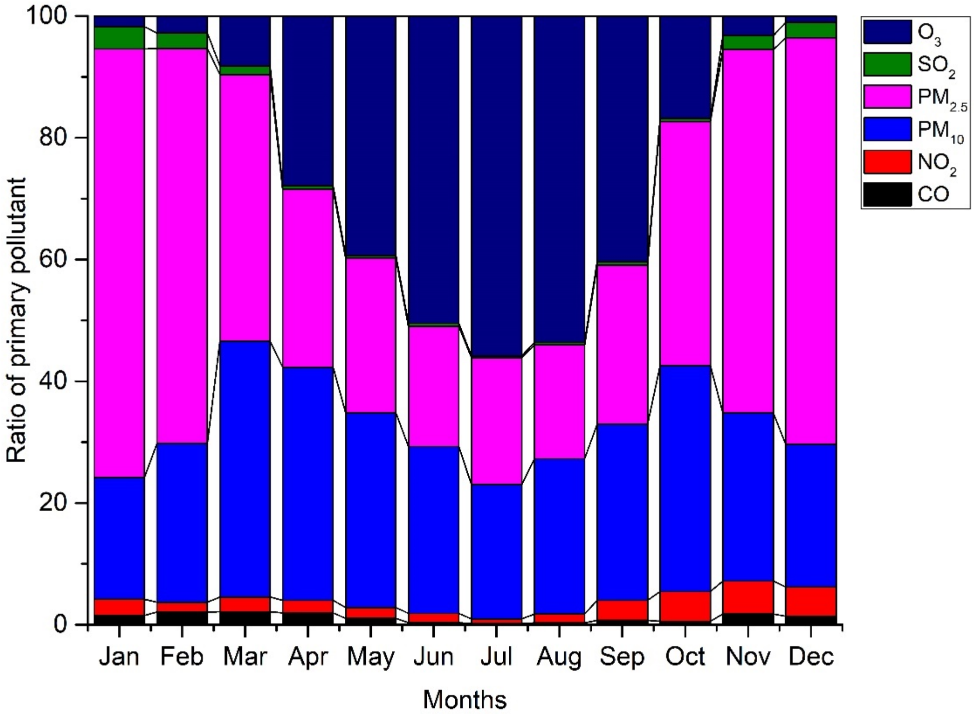

Fig.2 Characteristics of the primary pollutants to AQI in China by months in 2015

3.3. Spatial characteristics of urban air quality

3.3.1. Spatial patterns of urban air quality

Spatial patterns of the annual mean AQI in 2015 and its hot spots are shown in Fig.3. The results show a distinct spatial difference for the annual mean AQI between Northern China and Southern China, which are divided by the Yangtze River. This is consistent with many previous findings (Wang et al., 2017; Zhang et al., 2016), which indicate that the higher proportion of coal-dependent industries (i.e., cement, iron and steel, petrochemical and thermal power plant industries), and unfavorable meteorological conditions (i.e., less air convection and dilution) may lead to higher levels of air pollution in Northern China relative to Southern China. Hot spot analysis results reveal that AQI hot spots are mostly situated in the Bohai Rim region, Xinjiang Province, and the central region like Henan and Hubei Provinces. On the contrary, AQI cold spots distribute mainly within Tibet, Sichuan, Yunnan, Guizhou, Guangxi, Guangdong, Fujian and Jiangxi Provinces in Southern China, and encompasses only a few cities in Heilongjiang and Inner Mongolia Provinces.

Table 3 presents global spatial autocorrelation analysis results for mean AQI in China for the whole year and different seasons. Moran's I index of annual mean AQI is 0.688 and P value is significant at the 0.01 level, suggesting a significant and positive spatial clustering of urban air quality in China (Bao et al., 2015; Zhang et al., 2016). In other words, annual mean AQI in Chinese cities tends to be similar with their adjacent cities. With respect to seasonal characteristics, Moran's I indexes in the four seasons are also significant and follow an order as winter (0.706) > autumn (0.657) > spring (0.608) > summer (0.584). This result indicates the existence of spatial clustering of AQI in the four seasons across the Chinese cities, but the degree of spatial clustering is the strongest in winter and weakest in summer.

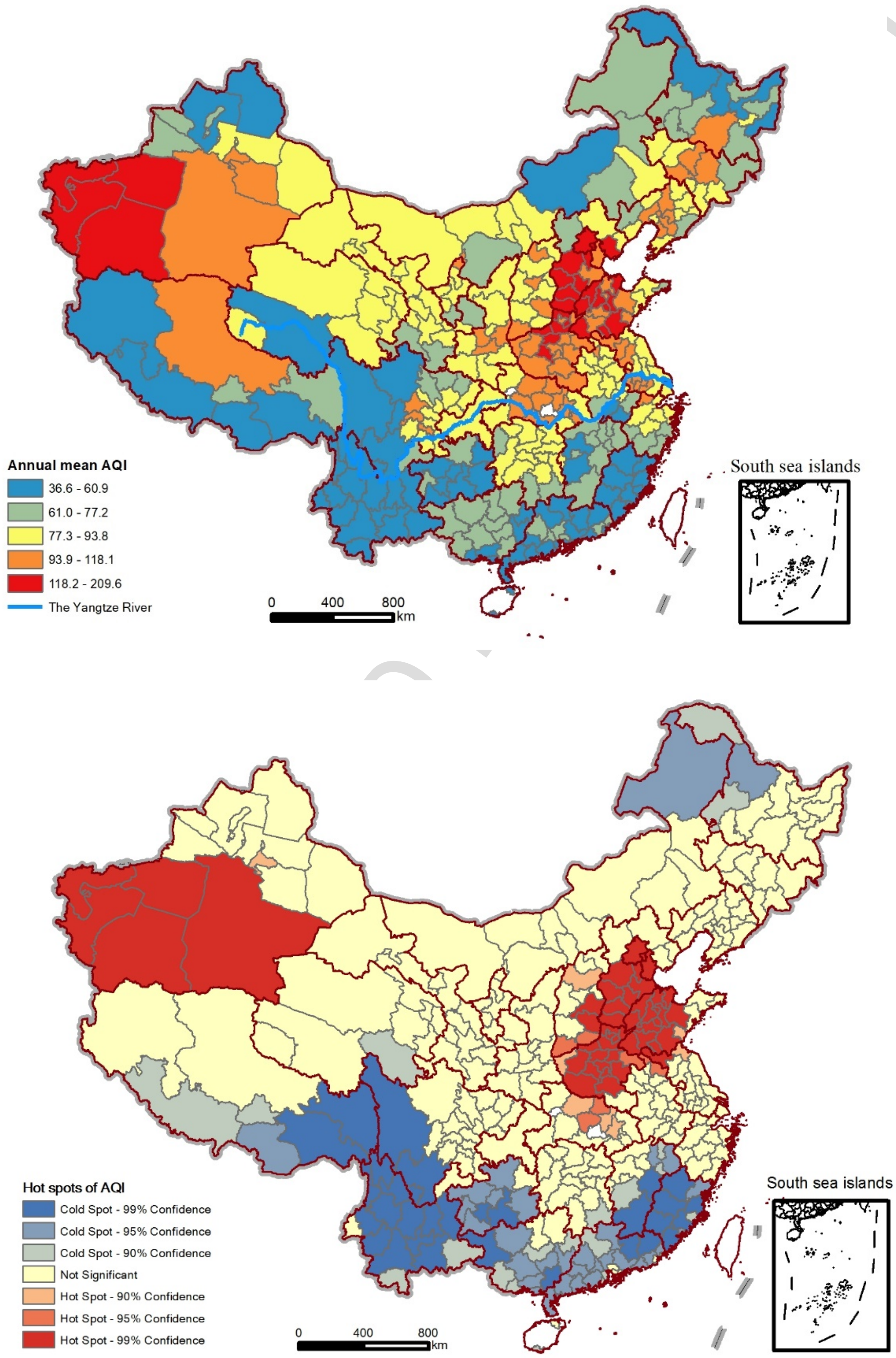

Fig.3 Spatial patterns and hot spots of annual mean AQI in China

Table 3

Spatial autocorrelation results of mean AQI in China

Mean AQI	Moran's I	Z score	P value	Number of cities
Annual	0.688	21.04	0.000	338
Spring	0.608	19.09	0.000	338
Summer	0.584	18.14	0.000	338
Autumn	0.657	20.05	0.000	338
Winter	0.706	21.48	0.000	338

3.3.2. Spatial patterns of AQI hot spots by seasons

The hot spots and cold spots of AQI in China by different seasons are shown in Fig.4. The results indicate that the identified hot spots and cold spots in the four seasons show the general feature that some stable cold spots are mainly concentrated in the south, involving Yunnan, Guizhou and Tibet Provinces, while stable hot spots are mainly found in the Bohai Rim region and Henan Province. However, the hot and cold spots of the AQI in China vary partly across the seasons. For instance, a large portion of the hot spots in spring is distributed in the northwest region, including Xinjiang, Gansu, Inner Mongolia, Qinghai and Tibet Provinces, which is possibly influenced by the high frequency of dust storms in spring (Zhang and Cao, 2015a). Although the extent of hot spots is a little smaller in summer relative to spring, a few new hots pots appear in Inner Mongolia Province. In autumn, hot spots decrease gradually from the northwestern region, but some cities situated in Liaoning and Jilin Provinces have become the new hot spots, a finding which may be caused by biomass burning during harvest time in Northeastern China (Zhang and Cao, 2015b). As for winter, hot spots distribute sporadically in the western region and appear mostly in the Bohai Rim region, Henan, and Hubei Provinces.

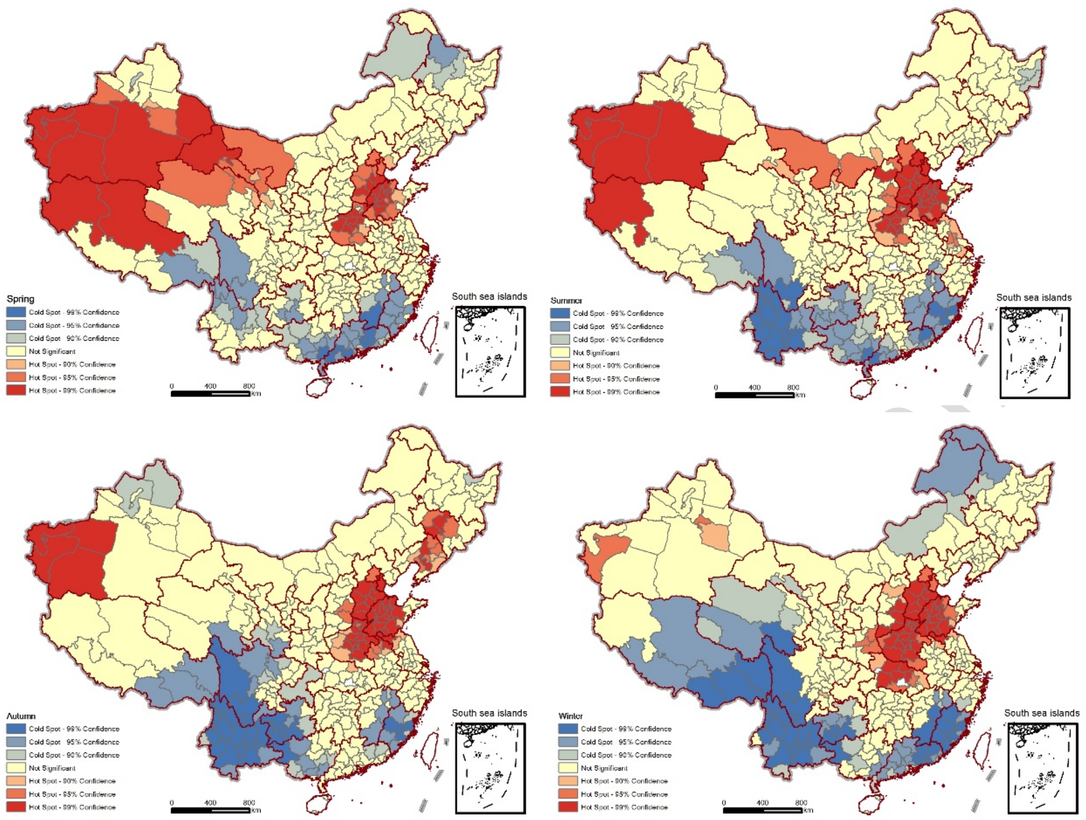

Fig.4 Hot spots and cold spots of AQI in China by seasons

3.3.3. Spatial patterns of primary pollutants

To illustrate the spatial patterns of the primary pollutants that contributed to the AQI, areas in China were classified into five types using a system clustering method based on the occurrence frequency of a primary pollutant. The mean frequency of the primary pollutants for SO_2, NO_2, CO, O_3, PM_{10} and $PM_{2.5}$ recorded across Chinese cities in 2015 is 4.0, 7.8, 3.5, 67.7, 83.7 and119.0 times, respectively. The first type (133 cities) is named as "O_3 + CO pollution" which have a higher mean frequency of O_3 and CO pollution reaching 82.1 and 3.7 times respectively. This type distributes mostly in the coastal and border cities, and a lower AQI value of 67.2 is observed. The second type (53 cities) is "composite pollution," with higher mean frequency for many air pollutants like PM_{10}, SO_2, CO, and O_3. The cities of this type have mean AQI of 86.7 and are located mainly in the northwestern region in China as well as distributed in Sichuan, Shanxi and Jiangxi Provinces for a few cities. The third type (147 cities) is "$PM_{2.5}$ pollution," where the mean frequency of $PM_{2.5}$ pollution is up to 179.0 times. The relevant cities witness a mean AQI of 93.2 and are mainly concentrated in the provinces of the northern and central regions, and other provinces including Chongqing, Shanxi, Sichuan, and Guangxi. The fourth type (4 cities) is known as "PM_{10} pollution" due to the mean frequency of PM_{10} pollution of up to 283.3 times. This type of cities witness the highest mean AQI of 131.6 and are mostly situated in the northwestern region, including Hotan, Kezilesu, Hami and Jiuquan. The fifth type (one city) is "CO + SO_2 pollution," and only one city in Shanxi Province named Lvliang is of this type. The primary pollutants here are CO and SO_2 of up to 132 and 30 times respectively, and its annual AQI is 82.4, the same as the annual mean AQI in China.

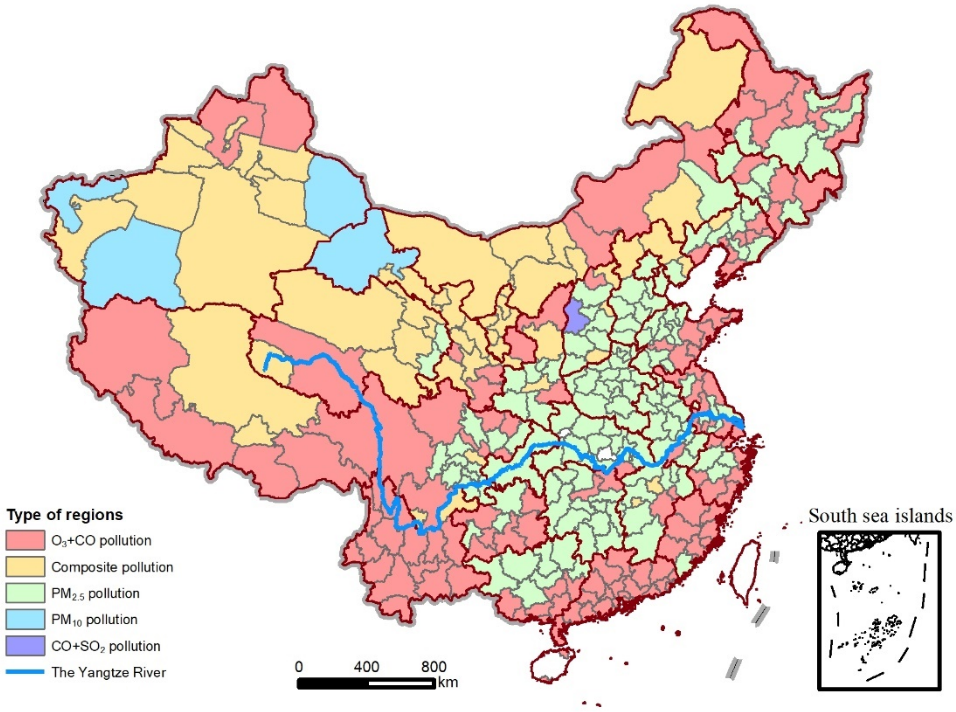

Fig.5 Type of regions for the primary pollutants in China

3.4. Driving factors of urban air quality

In this study, the geographical detector model was used to identify effect intensity and interactive effects of the driving factors on urban air quality in China. In the model, the variable of annual mean AQI in 2015 was selected as the dependent variable, while the independent variables include both socioeconomic and natural factors. To meet the requirement of the geographical detector model, all continuous variables among the independent variables were firstly discretized into five categories using the quantile method in ArcGIS 10.2. However, considering the geographical detector model can only measure the effect magnitude of the driving factors of AQI in China, Spearman Correlation Analysis was also employed to identify effect direction between them. Table 4 shows the magnitude of the q statistic. It suggests that natural factors on average contribute more to the AQI in China when compared to socioeconomic factors.

In terms of socioeconomic factors, all the explanatory variables are found to have significant and positive effects on the AQI in China with the exception of urbanization level, implying the intensity of human socioeconomic activities appear to be important factors that influence the AQI in China. However, comparing effect intensity among the socioeconomic factors, population density, the number of vehicles, GDP and population are the strongest predictors of the AQI in China in descending order, explaining from 8.0% to 13.6% of the variance of the AQI. Moreover, the percentage of secondary industry has a moderate effect on the AQI with the q statistic of up to 7.0%, while per capita GDP plays a minor role that explains only 2.9% of the variation of the AQI in China. These findings echo many previous studies which showed the positive association between the intensity of socioeconomic activities and the levels of air pollution in China (Lin et al., 2013; Luo, J. et al., 2017; Ma et al., 2016). Notably, the higher effect intensity of GDP and the lower one of per capita GDP seem to suggest the existence of the inverted U-shaped Environmental Kuznets Curve (EKC) in China, which has also been observed in previous studies (Hao and Liu, 2016; Ma et al., 2016; Wang et al., 2017). However, the finding of no significant relationship between urbanization level and the AQI in China in this study supports the results of some previous studies (Lin and Wang, 2016) but contrasts with other earlier findings (Li et al., 2016; Ma et al., 2016), suggesting that urbanization level may be not an important predictor of the AQI in China in a short period and at the national level. More research is needed to further investigate the role of urbanization level in influencing air quality.

In terms of natural factors, all natural factors except the NDVI are significantly associated with the AQI in China, with q statistic ranging from 4.9% to 32.9%. The power of determinant for the natural factors in descending order is: annual mean temperature > annual mean precipitation > relative humidity > land relief > wind speed > sunshine hours > DEM > air pressure, indicating that annual mean temperature, annual mean precipitation, relative humidity and land relief are the most important factors that explain the variance of the AQI in China. Moreover, significant positive relationships are observed between the AQI and most of the natural factors, including DEM, land relief, annual mean temperature, annual mean precipitation, relative humidity, whereas other natural factors such as wind speed, sunshine hours, and air pressure, tend to exert negative effects on the AQI. This finding is partly in agreement with previous studies (Luo, J. et al., 2017; Zhang et al., 2016), which suggest that increased DEM, land relief, temperature, precipitation, and relative humidity is likely to decrease the levels of air pollution through a series of influencing mechanisms, including enhancing air convection by high temperature, facilitating precipitation, increasing relative humidity, and blocking the entry of air pollutants by varied topography.

Correspondingly, there are positive relationships between the AQI in China and several other natural factors such as wind speed, sunshine hours, air pressure, which are partly consistent with other studies (Luo, J. et al., 2017). Among these, the positive effect of wind speed on the AQI seems to contradict the findings of some previous studies (Zhang et al., 2016) but seems reasonable as a result of the fact that both downwind areas and dust storm-prone areas are likely to suffer serious air pollution from increased wind speed (Feng et al., 2017; Yang et al., 2017). Sunshine hours in China show a distinct spatial disparity between Northwestern China and Southeastern China affected by the total could cover and relative humidity (Wang et al., 2018), and this is the possible reason why Northwestern China with more sunshine hours and low relative humidity suffer from more air pollution. Furthermore, many previous studies have linked NDVI with air pollution levels across Chinese cities at small spatial scales and found the levels of air pollution tend to be lower with increased NDVI (Wu et al., 2017; Zheng et al., 2017). However, this finding is not observed in our study, which may be resulted from the fact that the NDVI value in China decreases from the east to the west at the national level (Guo, X.Y. et al., 2017), whereas air pollution in China is characterized by lower levels in the south and higher levels in the north as mentioned before.

In addition to identifying the separate effects of driving factors on urban air quality in China, interaction relationships between them were further examined in this study. Fig.6 presents the q statistic of the interactive effects among the driving factors. In the figure, the q statistic on the diagonal line refers to the separate effects of each driving factor as shown in Table 4, the lower triangular matrix exhibits the q statistic of the interactive effects between the driving factors, while the missing values in the upper triangular matrix are filled by the same deep blue color. The interaction results reveal that interactions between most explanatory variables show nonlinear enhanced effects on the AQI in China, implying that interactive effects exceed the sum of separate effects, e.g., population and per capita GDP (14.0%), the number of vehicles and NDVI (16.3%), DEM and wind speed (14.8%). In addition, a part of the bi-enhance interactive effects are also observed between the driving factors, e.g., GDP and the number of vehicles (15.0%), the percentage of second industry and annual mean temperature (39.9%), annual mean precipitation and relative humidity (30.4%), a situation which indicate more interactive effects relative to the separate effects from any single driving factors. However, although no significant relationships are found between urbanization level or NDVI with urban air quality in China, their interactions with other driving factors still have effects on urban air quality in China. Overall, our findings show that the selected driving factors all have enhanced effects on the AQI in China through interaction effects.

Table 4

The power of determinants to AQI in China

Driving factors	Variables	Codes	q statistic	P value	Effect direction
Socioeconomic factors	Population	POP	8.0%**	0.000	+
	Population density	POPD	13.6%**	0.000	+
	Gross domestic product	GDP	9.3%**	0.000	+
	Per capita GDP	PGDP	2.9%**	0.049	+
	Percentage of second industry	PSI	7.0%**	0.000	+
	Number of vehicles	NOV	9.4%**	0.000	+
	Urbanization level	UL	1.7%	0.228	Not significant
Natural factors	Digital elevation model	DEM	5.5%**	0.000	-
	Land relief	LR	17.6%**	0.000	-
	NDVI	NDVI	1.0%	0.487	Not significant
	Annual mean temperature	AMT	32.9%**	0.000	-
	Annual mean precipitation	AMP	19.9%**	0.000	-
	Relative humidity	RH	19.8%**	0.000	-
	Wind speed	WS	7.3%**	0.000	+
	Sunshine hours	SH	6.5%**	0.000	+
	Air pressure	AP	4.9%**	0.004	+

Note: ** indicates significance at the 0.05 level. "+" and "-" indicate positive and negative correlation between explanatory variables and AQI respectively by Spearman correlation analysis.

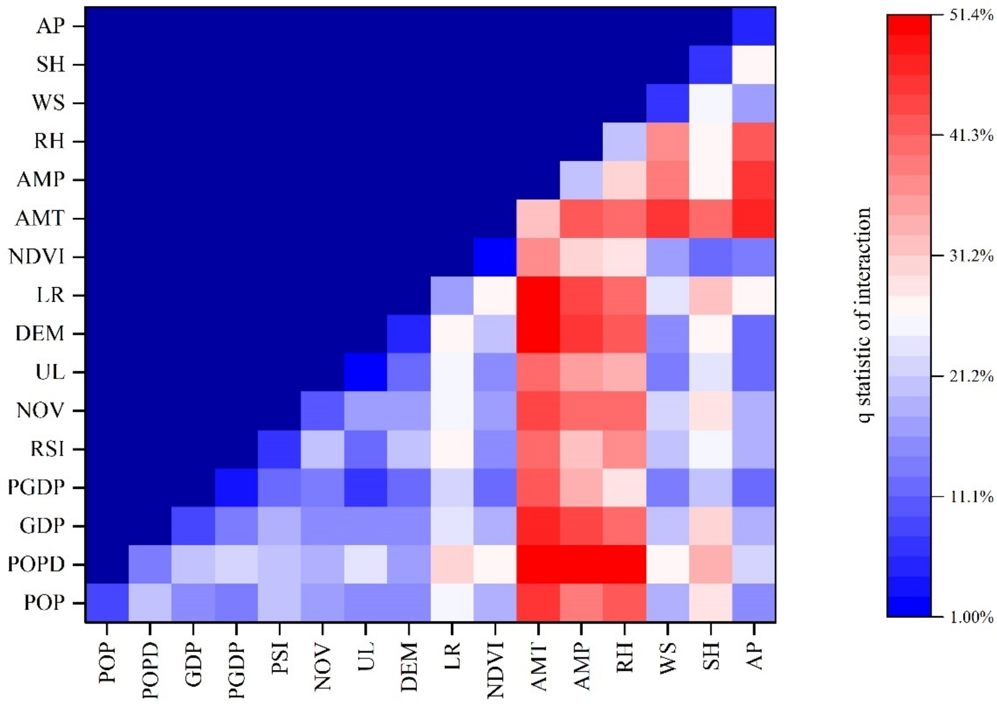

Fig.6 Interaction of driving factors on AQI in China

4. Policy implications

Some important policy implications drawn from these findings are as follows. First, the Chinese Central Government should effectively cope with air pollution across Chinese cities according to their specific location and time. For instance, more efforts should be devoted to control and mitigate air pollution in winter considering the time and in areas including Northern China and Xinjiang Province. Also, serious air pollution witnessed in Northwestern China in spring due to sandstorm and Liaoning and Jilin Provinces in autumn caused by straw burning deserve more attention.

Second, in view of the existence of significant spatial clustering in all the seasons and the whole year, mitigating air pollution in China should rely on regional cooperation. Initiatives such as enhancing overall planning to regional industrial structure and promoting ecological compensation will be beneficial to reducing the levels of air pollution in China.

Third, Chinese Government should be concerned about the main primary pollutants influencing the AQI in China, such as $PM_{2.5}$, PM_{10}, and O_3. More emphasis for controlling air pollution in China should be put to decreasing $PM_{2.5}$ in winter which is distributed mainly in northern and central regions, and O_3 pollution in summer which is located mainly in coastal and border cities.

Lastly, taking into account the driving factors of the AQI in China, Chinese Government should attach importance to natural factors when distributing industries. Northern China and Xinjiang Province should speed up the adjustment in their secondary industries due to locally unfavorable natural conditions, especially the over-reliance on heavy industries. Since positive relationships between socioeconomic factors and the AQI in China were observed in this study, it seems inevitable for air pollution in China to aggravate due to rapid economic development and industrialization. Yet, controlling the influence of human activities on the environment may help decrease the AQI in China through promoting the improvement of the industrial structure as well as adhering to environmental sustainability by using clean energy and reducing the level of car use.

5. Conclusions

Using AQI data in 2015 among 338 Chinese cities, this study has examined the spatiotemporal patterns of the AQI in China along with its primary pollutants at the national level and identified the major driving factors on the AQI in China. This study contributes to the existing literature on air pollution studies from several aspects, including using AQI data from ground monitoring stations that cover all the Chinese cities at the prefecture level and above, considering both natural and socioeconomic factors as the driving factors, employing a new method named the geographical detector model to explore the effect magnitude and interaction effects of the driving factors. Our findings, which are summarized below, provide new insights for making policies to control and mitigate air pollution in China.

The results showed that the annual mean AQI and the percentage of days with excellent and good air quality in 2015 across the Chinese cities were 82.4±24.1 and 76.9%±16.9% respectively, implying that the levels of air pollution in China was still serious on the whole. The primary pollutants were mainly $PM_{2.5}$, PM_{10} and O_3, accounting for 41.7%, 29.3% and 23.7% of the AQI respectively. With respect to temporal patterns, the AQI in China presented a U-shape pattern over the year and a seasonal trend with higher AQI values in winter and low values in summer. The primary pollutants, however, changed by season: $PM_{2.5}$ in winter, O_3 in summer, and PM_{10} for all seasons. Moreover, spatial patterns of the AQI in China revealed higher values in Northern China, Xinjiang Province and lower values in Southern China, as well as the existence of spatial clustering. AQI hot spots were mostly concentrated in the Bohai Rim region, Henan and Xinjiang Provinces, while AQI cold spots distributed mainly in the south provinces. According to occurrence frequency, spatial patterns of the primary pollutants were divided into five types of region, including O_3 + CO pollution, composite pollution, $PM_{2.5}$ pollution, PM_{10} pollution, CO + SO_2 pollution.

The results of the geographical detector model coupled with Spearman correlation analysis revealed that all the socioeconomic factors had significant and positive association with the AQI in China except urbanization level, with effect intensity in a descending order: population density > the number of vehicles > GDP > population > the percentage of second industry > per capita GDP. With respect to natural factors, DEM, land relief, annual mean temperature, annual mean precipitation, and relative humidity had negative effects on the AQI in China, while wind speed, sunshine hours, and air pressure, exert adverse effects. However, natural factors on average had more effects on the AQI in China than socioeconomic factors, with their q statistics in descending order: annual mean temperature > annual mean precipitation > relative humidity > land relief > wind speed > sunshine hours > DEM > air pressure. Moreover, interactions between the driving factors had either non-linear or bi-linear enhanced interactive effects on AQI in China.

However, this study has some limitations that should be noted. First, the spatiotemporal patterns and hot spots of the AQI in this study were derived from data of only one year (2015) and thus may not be stable since the AQI tend to vary considerably by year due to many influencing factors. With the accumulation of AQI data in China, multiyear data should be used in future studies. Moreover, considering the nature of the cross-sectional data used, this study could not reveal the underlying causal relationships accurately. Panel data and longitudinal models should be adopted to establish causality between the driving factors and the AQI in China in future research. In addition, the driving factors of the AQI in China among different seasons may be different. There is a need for future work to explore the linkage between the driving factors and the AQI in China through different periods of time.

Acknowledgements
This research was supported by the National Natural Science Foundation of China (#41230632) and the UCAS Joint PhD Training Program.

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- This paper examines spatiotemporal patterns of air quality index(AQI) among Chinese cities at prefecture level and above.
- AQI observes higher levels in Northern China and Xinjiang Province, and lower levels in Southern China, with the existence of spatial clustering.
- The primary pollutants (i.e., SO_2, NO_2, CO, O_3, PM_{10}, and $PM_{2.5}$) affecting AQI vary significantly by both time and space.
- Effect intensity and interaction of both socioeconomic factors and natural factors on AQI in China are analyzed using the geographical detector method.
- Natural factors averagely exert more impacts on AQI in China than socioeconomic factors.