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Spatiotemporal pattern of air quality index and its associated factors in 31 Chinese provincial capital cities

L.J. Xu[1] · J. X. Zhou[1] · Y. Guo[2] · T.M. Wu[1] · T.T. Chen[1] · Q.J. Zhong[1] · D. Yuan[1] · P.Y. Chen[1] · C.Q. Ou[1]

Abstract Understanding the spatiotemporal characteristics of ambient air quality and identifying the associated factors are helpful to develop integrated interventions to prevent and control air pollution. Based on daily data of air quality index (AQI) in 31 Chinese provincial capital cities in 2014, this study aimed to investigate the spatiotemporal variations of ambient air pollution and the influencing factors. The spatial and temporal patterns of AQI were presented using GIS map and heat map, respectively. We constructed a hierarchical linear model to quantify the effects of meteorological and socioeconomic factors on AQI. In 2014, the air quality nonattainment (AQI >100) rate was 34.6% on average (1.9 to 74.4%). Air pollution levels were highest in winters and lowest in summers. We found substantial spatial variations of AQI, with the highest values in the middle-east area of the North China Plain. The city-level AQI was positively associated with vehicle population, industrial dust emission, and GDP per capital, which cumulatively explained 67.5% of spatial variations of AQI. The city-level AQI also increased with city's annual atmospheric pressure but decreased with annual mean temperature. Daily AQI within a city decreased with daily temperature, sunshine duration, wind speed, precipitation, and relative humidity. The national analyses indicate that the ambient air quality in China exhibits significant geographical and seasonal variations which were mainly driven by socioeconomic and meteorological factors. The findings would help to understand the underlying reasons for spatial health disparities and would provide important information to guide targeted policy response to ambient air pollution.

Introduction

Ambient air pollution is a major environmental hazard, deleteriously affecting population health, such as increasing cardiorespiratory morbidity and hospital admissions and adverse birth outcomes (Dominici et al. 2005; Park et al. 2013; Wang et al. 2013; Vanos et al. 2015). Substantial spatial and temporal variations in air quality are observed in many regions, in terms of pollution sources, levels, and components of particulate matter (Denby et al. 2010; Lee et al. 2011; Mallik and Lal 2014; Wang et al. 2014; Kumar et al. 2015; Rooney et al. 2012; Rogula-Kozłowska et al. 2014).

The investigation of socioeconomic gradients in air pollution exposure would provide important information to develop and implement targeted programs and policy to prevent and control air pollution. It is also helpful to understand inequalities in air pollution exposure which may play an important role in health disparities (Eitan et al. 2010). Rowangould (2013) found greater traffic volume and density among larger shares of non-white residents and lower median household incomes, suggesting a higher exposure to traffic-related air pollution among people with lower socioeconomic status. Two national studies in the USA have also demonstrated a

✉ P.Y. Chen
chenpy99@126.com

✉ C.Q. Ou
ocq@smu.edu.cn

[1] State Key Laboratory of Organ Failure Research, Department of Biostatistics, Guangdong Provincial Key Laboratory of Tropical Disease Research, School of Public Health and Tropical Medicine, Southern Medical University, Guangzhou 510515, China

[2] Division of Epidemiology and Biostatistics, School of Population Health, The University of Queensland, Brisbane, Queensland 4006, Australia

spatial cluster of benzene and NO_2 pollution exposure by census tract-level sociodemographic factors (Clark et al. 2014; Zou et al. 2014), while Padilla et al. (2014) found contrasting results in the strength and direction of the association between deprivation and NO_2 estimates in four French metropolitan areas, suggesting that the influence of socioeconomic conditions on ambient air pollution may vary geographically. Considering the difference in the distribution and components of air pollution and socioeconomic conditions between China and other countries, it is necessary to reveal environmental and socioeconomic gradients in ambient air pollution exposure in China.

In China, since 2000, air pollution index (API) calculated based on the concentration of three criterion pollutants (i.e., SO_2, NO_2, and particulate matter with aerodynamic diameter <10 μm (PM_{10})) was used for air quality monitoring in major cities (Jiang et al. 2014). In 2012, the Ministry of Environmental Protection (MEP) of the People's Republic of China updated National Ambient Air Quality Standards (NAAQS). $PM_{2.5}$, O_3, and CO are added into the new NAAQS. The daily concentrations of all six criterion pollutants are used to calculate air quality index (AQI). AQI can more comprehensively and rigorously reflect air quality than API (You 2014). With the accumulation of available air pollution data, the spatiotemporal pattern of air pollution in China has become a research focus. Lin et al. (2014) estimated $PM_{2.5}$ concentrations based on satellite-observed aerosol optical depth and examined the spatiotemporal variations of $PM_{2.5}$ in China. Previous studies based on ground monitoring have focused on a particular place and mainly considered the meteorological effects (Chu et al. 2008; Li et al. 2013, 2014). Recently, the association between economic development and air quality has been concerned in a few studies at a large spatial scale. For example, Luo et al. (2014) examined solely the effects of gross regional product percapital on API and the concentrations of single pollutants (i.e., SO_2, NO_2, and PM_{10}) in 31 cities. Jiang et al. (2014) investigated the relationship between annual API in 80 cities in 2011 and urbanization index and meteorological conditions.

To our best knowledge, no study has investigated the spatiotemporal variations of AQI in China because of the unavailability of data previously. Since the level of air pollution is affected by multiple factors, univariate analysis of potential influencing factors may bias the effect estimates. There is a need to simultaneously examine various meteorological, environmental, social, and economic contributors to temporal variations and regional inequalities in air pollution. Based on daily data of AQI in 31 Chinese provincial capital cities in 2014, this paper aims to investigate the temporal and spatial characteristics of AQI. Furthermore, we constructed hierarchical linear models to examine potential factors associated with the spatiotemporal variations. We performed a three-step analysis. Three sets of variables, including demographic and socioeconomic factors at the city level, annual average meteorological variables, and daily meteorological variables, were added into the model in a stepwise manner.

Materials and methods

Site information

Considering the availability of data, this study focused on four municipalities (Beijing, Shanghai, Chongqing, and Tianjin) and all 27 provincial capital cities with varying socioeconomic conditions and diverse climates in Mainland China, including Haikou, Nanning, Guangzhou, Kunming, Fuzhou, Guiyang, Changsha, Nanchang, Lhasa, Nanjing, Hangzhou, Chengdu, Wuhan, Hefei, Xi'an, Zhengzhou, Lanzhou, Xining, Jinan, Taiyuan, Shijiazhuang, Yinchuan, Hohhot, Shenyang, Changchun, Urumqi, and Harbin (Fig. 1).

Data source

Daily air quality data (AQI and primary pollutants) of 31 cities in 2014 were ascertained from the website of the MEP of the People's Republic of China. The Department of Environmental Protection in each city reports on the daily concentration data of six criterion pollutants (i.e., CO, NO_2, PM_{10}, $PM_{2.5}$, O_3, and SO_2) collected at each monitoring station to the MEP of the People's Republic of China. Daily concentrations for a city are evaluated by averaging the daily concentrations across all monitoring stations within the city. As an integrated index, AQI is defined as the maximum of the indexes for six criterion pollutants (Hu et al. 2015). There are two or three missing values of AQI in each city in the whole year, with a proportion of missing values less than 0.1%. The data availability for each city meets the regulation that at least 324 daily data are available in calculating annual average, specified in the document of GB 3095-2012 by the MEP of the People's Republic of China. We did not replace any missing values. Daily air quality is classified into six grades based on the AQI value, including grades I (<50), II (51–100), III (101–150), IV (151–200), V (201–300), and VI (>300) (You 2014). The pollutant with the maximum index was defined as the primary pollutant, while no primary pollutant is defined in the case of grade I air quality.

Daily meteorological data in 2014 for each city, including daily mean temperature, relative humidity, atmospheric pressure, wind speed, precipitation, and sunshine duration, were acquired from the China meteorological data sharing service system (http://cdc.nmic.cn/home.do). Demographical and socioeconomic data were retrieved from the China Statistical Yearbook 2014, compiled by the National Bureau of Statistics of China, including population density, gross domestic product (GDP) per capital, urban greening rate, and industrial dust emissions for each city. The data of proportions of the

Fig. 1 Annual air quality index (*AQI*) and the proportion of days with grade-specific daily AQI in 31 provincial capital cities in Mainland China in 2014

primary, secondary, and tertiary industries were obtained from the statistical communique of the 2014 National Economic and Social Development. The municipal bureaus of statistics in 31 cities provided the information of vehicle population.

Statistical methods

The spatial and temporal pattern of AQI was presented using a GIS map (Fig. 1) and heat map (Fig. 2), respectively. In order to explore factors associated with spatiotemporal variations of AQI, we considered three aspects of potential factors including socioeconomic characteristics and annual average of meteorological measures in 2014 at the city level and daily meteorological measures within each city.

AQI was measured repeatedly on 365 days in each city, leading to intracorrelation among the observations within a city. In this case, using the ordinary least squares regression models that assume independence of observations would bias the estimates of parameters and standard errors. The hierarchical model (i.e., multilevel model) with random effects

accounts for the dependence within a city and allows for the analyses of between-city and within-city factors simultaneously (Raudenbush and Liu 2000). Therefore, we developed hierarchical linear models (HLMs) to regress AQI on potential predictors of interest. Firstly, we constructed a fully unconditional model which partitioned the total variations in AQI into within- and between-city components using a random-effects analysis of variance. Then, if the variance of the random effects was statistically significant, indicating spatial variations of AQI between cities, we built a conditional HLM including two level predictors. To avoid the multicollinearity problem which may lead to wrong estimates of parameters and standard errors, we excluded the factors with a multilevel variance inflation factor (MVIF) higher than 5 (Shieh and Fouladi 2003), including annual average precipitation, annual average relative humidity, and daily pressure. In order to estimate the contributions of different types of factors, we establish three models step by step. The first model only included demographic and socioeconomic factors at the city level. The second model included all level 2 factors
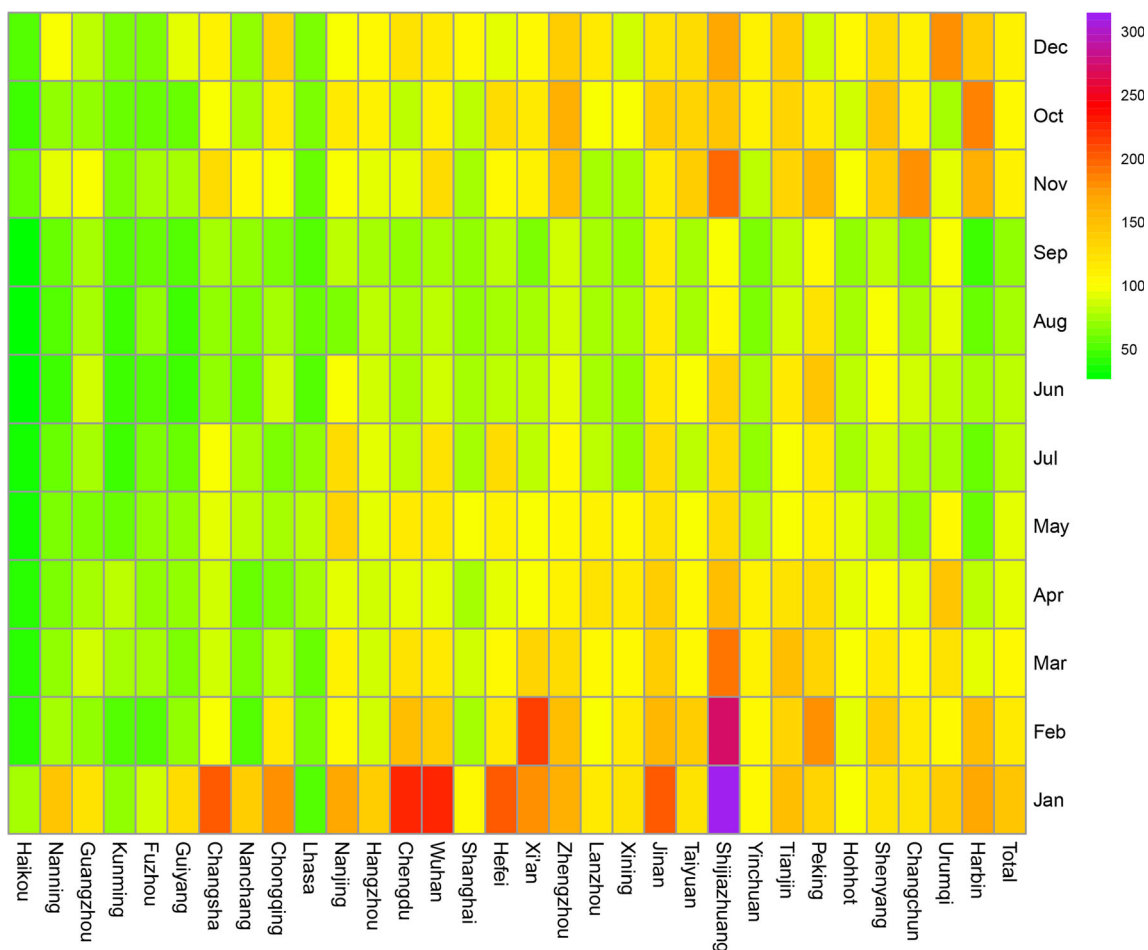
Fig. 2 Heat map of monthly air quality index (AQI) in 31 Chinese provincial cities in 2014. The *x-axis* list 31 cities from the south to the north

(between-city variables) with the addition of annual average meteorological variables. Finally, the third model further included level 1 factors (i.e., within-city daily meteorological variables) to examine the effects of all possible factors on the spatial and temporal distribution of AQI. Model 3 also included several indicator variables of holiday and day of the week. We calculated the reduction percentage of residual by comparing to the previous model. Based on the full model 3, a stepwise model was constructed to further select significant factors ($p < 0.05$) using the likelihood ratio test.

All data analyses were performed using R language version 3.2.2 and SAS version 9.1.

Results

AQI presented substantial spatial variations and clusters in China (Fig. 1). The average AQI in 2014 ranged from 43 in Haikou to 168 in Shijiazhuang. Generally, AQI was lowest in the southwest and south cities and highest in the middle-east area of the North China Plain. Besides, the pie pictures show the proportion of days with a specific grade of daily air quality

in each city in 2014. There were, on average, 126 days (range 7 to 270) on which the AQI exceeded the Chinese NAAQS of 100, with an air quality nonattainment rate (grade III or above) of 34.6% (range 1.9 to 74.4%). Particularly, air quality did not attain the Chinese NAAQS in more than half of the study days in Jinan (74.4%), Shijiazhuang (71.3%), and Beijing (53.6%), while there were approximately 98% of days in 2014 with good air quality (grade I or II) in Lhasa, Kunming, and Haikou (Fig. 1).

The heat map of monthly AQI reveals a consistent seasonality in all 31 cities. All cities suffered from the most severe air pollution during wintertime and had relatively cleaner air in summer (Fig. 2). Generally, southern cities had a better air quality than northern cities in the whole year.

Figure 3 reveals that the primary pollutants on most days of 2014 were particulate pollutants (i.e., PM_{10} and $PM_{2.5}$). Particularly, $PM_{2.5}$ was the primary pollutant in half days of October–March. O_3, a photochemical pollutant, was the most problematic pollutant in more than 20% of summer days (June–August). SO_2 and NO_2 were the primary pollutants infrequently in the whole year, and CO was never the primary pollutant in all cities. In addition, the last box plot reflects that
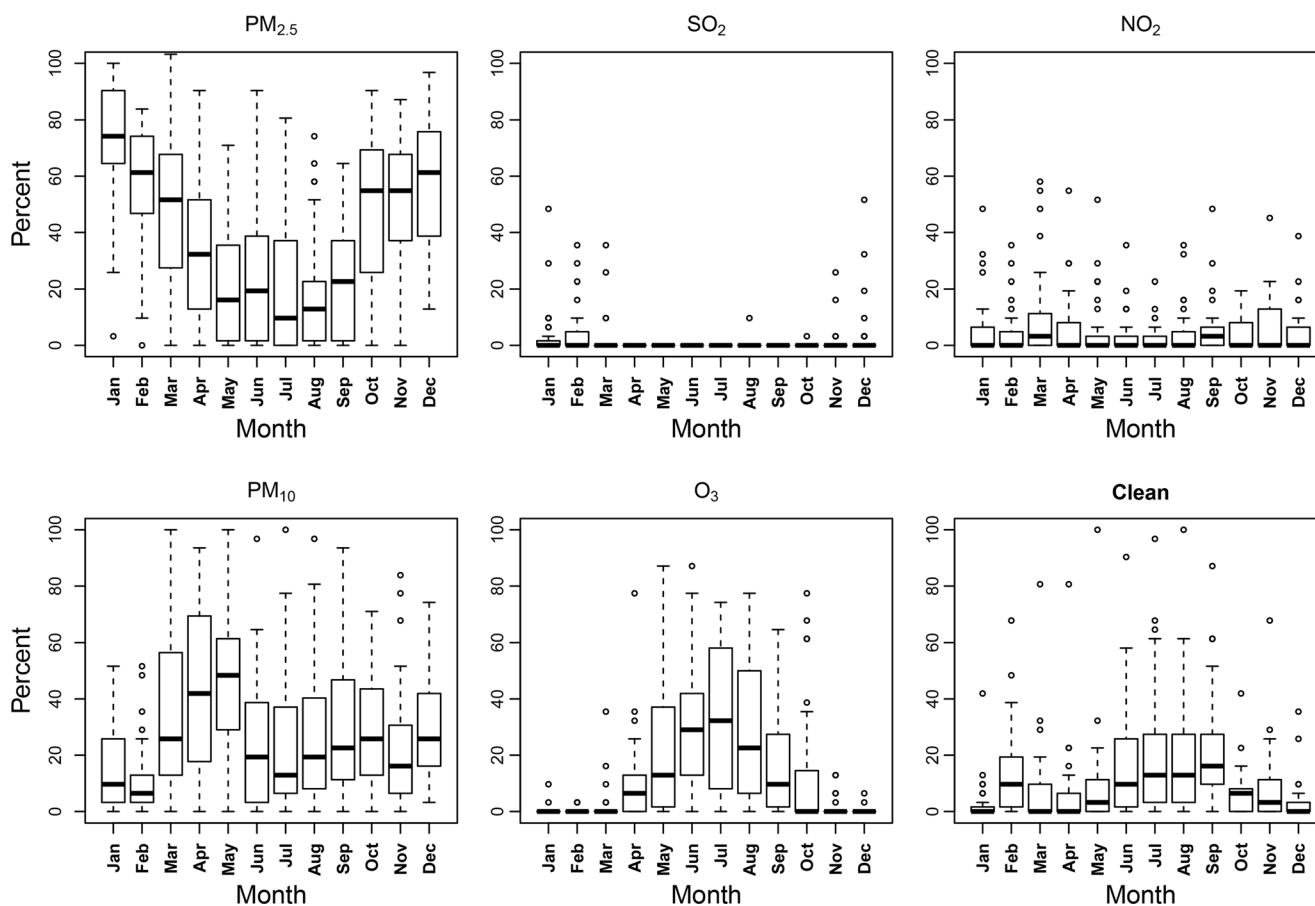
Fig. 3 Box plots of percentage of days with each particular pollutant as the primary pollutant in 31 Chinese provincial cities in 2014. Clean means no primary pollutant identified when AQI was lower than 50

there were more clean days (daily AQI lower than 50) in summer and early autumn.

Table 1 shows the results of variance component analysis of daily AQI, in which the variance of the random effects was statistically significant ($z = 3.84$, $p < 0.0001$), indicating that the mean AQI varied significantly across the cities. The majority (82.0%) of the total variations in daily AQI was attributable to within-city variations, and the remaining 18.0% were due to between-city variations. After adding city-level socio-economic variables into the model, the between-city variations reduced from 590.91 to 192.25. That is, these variables explained more than half (67.5%) of the spatial differences in the mean AQI between cities. Additionally, annual meteorological differences among the cities explained approximately 20.2% of the spatial variations of AQI. Daily meteorological variables accounted for about 9.2% of the within-city variations.

Table 2 shows the effects of specific factors on AQI. Among the city-level variables of interest, greening rate ($p = 0.426$), population ($p = 0.808$), and the proportions of primary and secondary industries ($p = 0.884, 0.519$) were not significant spatial determinants of AQI and, therefore, were excluded in the stepwise model. According to the results of the

stepwise model, per one million increase in vehicle population was associated with an increase of 6.29 in city mean AQI ($b = 6.29$, $p = 0.001$). GDP per capita and emissions of industrial dust also had significantly positive effects on the AQI level, with an increase of 2.10 and 2.62 in AQI associated with per 10,000 yuan (i.e., 1544 USD) increase in GDP per capita ($b = 2.10$, $p = 0.020$) and per 10,000 ton increase in emissions of industrial dust ($b = 2.62$, $p < 0.001$), respectively. Cities with higher atmospheric pressure and lower annual mean temperature had a higher level of air pollution. The day-to-day fluctuations within a city were negatively modulated by meteorological conditions, including daily sunshine hours, mean temperature, wind speed, relative humidity, and precipitation.

Discussion

For a long time, the Chinese government has delivered air quality information to the public using air pollution index rather than the concentrations of specific air pollutants. One of our previous studies (Li et al. 2015) revealed that air pollution index can be used to communicate the health risks of air

Table 1 Decomposition of total variations by unconditional ANOVA model and the proportional reduction in residual variance for conditional models

Component	Unconditional model variance (%)	Conditional hierarchical linear model (HLM)		
		Model 1[a] Variance (%)[b]	Model 2[a] Variance (%)[b]	Model 3[a] Variance (%)[b]
Between-city residual	590.91 (18.0)	192.25 (67.5)	79.59 (86.5)	72.48 (87.7)
Within-city residual	2691.17 (82.0)	2691.17 (0)	2691.17 (0)	2444.22 (9.2)
Total residual	3282.08 (100)	2883.42 (12.1)	2770.76 (15.6)	2516.7 (23.3)

[a] Model 1 included city-level socioeconomic variables, model 2 included city-level socioeconomic variables and meteorological variables, and model 3 included city-level variables and within-city variables

[b] The proportional reduction in residual variances, calculated by the formula (σ^2 (unconditional) $- \sigma^2$ (conditional)) / σ^2 (conditional)

pollution. Hence, compared with the specific pollutant concentration, air pollution indices have become more widely accepted in terms of public availability and public communication. Our analysis of AQI in 31 provincial capital cities revealed that ambient air pollution is still a serious problem in most major cities, although various policies and actions have been implemented to manage and control air pollution in China in recent years. Particulate matter is the key pollutant. On average, the number of days with air quality not attaining the grade II NAAQS accounted for more than one third of total days. The nonattainment rate was even up to 70% in

some cities like Jinan and Shijiazhuang. The new air quality standard reset in 2012 becomes more stringent than before, while programs and policy are imperative to promote adherence to the standard. Air quality is influenced by both local pollutant emissions and long-range transport pollutants from outside (Tao et al. 2016). This study showed spatial clusters of air pollution, suggesting that the joint control of air pollution is necessary especially in heavily polluted regions.

Previous studies of air pollution distributions focused on temporal variations in air pollution in a particular place (Li et al. 2014; Mallik and Lal 2014). A few studies used

Table 2 The factors associated with air quality index (AQI) in 31 Chinese capital cities in 2014

Factors	Full model		Stepwise model	
	Coefficient	p value	Coefficient	p value
Level 2 (between-city) factors				
Socioeconomic factors				
Vehicle population	6.35	0.013	6.29	0.001
Per capital GDP	2.02	0.057	2.10	0.020
Industrial dust	0.28	0.000	2.62	0.000
Greening rate	0.54	0.426	–	–
Population	1.31E−3	0.806	–	–
Primary industry	−0.11	0.884	–	–
Secondary industry	0.16	0.519	–	–
Climate factors				
Annual atmospheric pressure	0.10	0.006	0.09	0.005
Annual temperature	−0.84	0.116	−1.22	0.017
Annual wind speed	−6.18	0.204	–	–
Annual sunshine hours	0.09	0.093	–	–
Level 1 (within-city) factors				
Meteorological factors				
Daily sunshine hours	−6.47	0.000	−6.60	0.000
Daily temperature	−0.10	0.000	−1.15	0.000
Daily wind speed	−1.15	0.000	−0.10	0.000
Daily relative humidity	−0.18	0.000	−0.18	0.000
Daily precipitation	−0.07	0.000	−0.07	0.000

aggregated data (e.g., annual mean air pollution level) to investigate driving factors of spatial pollution inequities (Hajat et al. 2013; Rowangould 2013; Zou et al. 2014). In the present study, we constructed a hierarchical model of daily data to simultaneously identify contributors to temporal and spatial variations. We added important evidence to the literature of environmental injustice by identifying city-level socioeconomic determinants of spatial inequalities in air quality exposure, which could help understand the cause of spatial health disparities by socioeconomic conditions. Furthermore, pollution exposure inequalities may be the underlying reason of the phenomena that subpopulations with low socioeconomic status were observed to be more susceptible to air pollution effects in some previous studies (Kan et al. 2008; Ou et al. 2008; Bell et al. 2013).

This study highlighted spatial clusters of air pollution exposure inequity by GDP per capita. In the last decade, GDP per capita grows from 14,300 yuan in 2005 to 46,600 yuan in 2014 in China with an average annual increasing rate of 12.5%. Meanwhile, urban ambient air pollution, particularly particulate pollution, generally has an upward trend, although SO_2 emissions reduced by 10% during the Chinese 11th Five-Year Plan period (2005–2010) (Wang and Hao 2012). Furthermore, the continuing growth of economy is associated with further increases in energy consumption, electricity generation, and vehicle population. Coal is still the dominant source of energy in China. The development of clean coal technologies and clean energy resources is crucial to reduce pollutant emissions. Unexpectedly, we did not find a significant association between AQI and the proportions of the primary, secondary, and tertiary industries. Similarly, Jiang et al. (2014) found a linear correlation between API and the proportions of primary and secondary industries, while the effects were nonsignificant after adjusting for climate and other factors in a multiple linear regression.

Our study found that the difference in city vehicle population plays an important role in the large spatial perspective of air quality inequities. According to the data from the National Bureau of Statistics of China, civil vehicles in China are sharply increasing from 3.16 million in 2005 to 14.60 million in 2014 at an average annual increasing rate of 16.54%. Meanwhile, Cai and Xie (2007) estimated that the vehicle emissions of main pollutants increased at an annual average rate of 15% from 1990 to 2005. Vehicle emissions have become one of the major sources of air pollution across the entire country, especially in the metropolitan cities such as Beijing, Shanghai, and Guangzhou. Light-duty gasoline-powered vehicles and heavy-duty diesel-powered vehicles are the largest contributors (Song et al. 2012). In recent years, some cities in China have taken a series of traffic limitation policy to solve the traffic problem, including car license limitation policy, odd-even car ban, and traffic restriction on out-of-town vehicles in rush hours. These measures would control traffic-

related air pollution to some extent. On the other hand, there is a continuous increase in vehicle population and diesel fuel consumption. Therefore, more measures are required for emission control of in-use vehicles and new vehicles, such as fuel quality improvement and introduction of clean fuel vehicle technology.

In addition, we demonstrated a positive association between industrial dust emissions and AQI, indicating that local industrial sources play a significant role in contributing to observed spatial variations. Industrial dust emissions reduced by nearly 65% from 1998 to 2009 mainly through the installation of end-of-pipe treatment equipment (Fujii et al. 2013), while industrial dust is still one of major sources of ambient particulate pollution. Furthermore, industrial dust emission is an important indicator of industrial pollution emission. It is very likely that the cities with large dust emissions also have large emissions of industrial gaseous pollutants. Air quality is worst in Chinese northern cities than southern cities, mainly because there are coal-fired central heating system and more coal power plants in northern cities, causing more industrial pollution emissions. It is an undoubted fact that cutting emissions of industrial pollution through the development of clean energy resources and promotion of clean and efficient coal use can directly improve air quality (Wang and Hao 2012).

Consistent with previous studies (McKendry 2000; Tu et al. 2007; Li et al. 2014), we confirmed that temporal variations of air pollution were associated with daily changes in the weather. We found that daily AQI was negatively associated with daily mean temperature, in accordance with the spatiotemporal pattern that the cold and dry continental air mass in winter, particularly in northern cities, marked the episode of elevated air pollution level. In addition, we found significant spatial inequities of air quality by annual meteorological factors. The cities with lower atmospheric pressure and higher temperature had better air quality, and in the same city, daily air quality was better on days with more sunshine, higher temperature, wind speed, relative humidity, and precipitation, because such weather conditions strongly favorable for pollutant dispersion, dilution, and deposition (Dominick et al. 2012; Han et al. 2015). Precipitation and humidity have a washing effect on air pollutants. Particles tend to gather mass and fall to the ground rather than suspend in air on days with high relative humidity (Giri et al. 2008; Chen et al. 2016). These findings have important implications for air pollution control by supporting the application of climate-friendly air pollution control measures such as artificial rainfall. It is suggested that careful consideration of the impact of meteorological variability is necessary for forecasting air quality and interpreting trends and regional difference in air quality. Meanwhile, meteorological factors should be controlled for as important confounders when assessing socioeconomic

effects in spatiotemporal studies of air pollution. The sole investigations of socioeconomic determinants without considering climate effects would lead to a bias.

There are some limitations in this study. Firstly, we analyzed AQI as a measure of ambient air quality because of data availability. AQI is defined as the maximum of the indices of six criterion pollutants and cannot reflect the whole picture of air pollution. Further multicity analyses of specific air pollutants if data can be accessed would help better understand spatiotemporal patterns of air pollution. Secondly, similar to other ecological studies, we examined the factors associated with city-level AQI. Therefore, we could not incorporate individual exposure level or individual characteristics such as socioeconomic status. The causal hypothesis cannot be tested. We considered the total dust emissions from all industries as an indicator of industrial pollution. The effects of industrial pollution emissions on ambient air quality is yet to be further studied with more detailed data to guide the setting of emission standard of specific pollutant and industries. Finally, the analyses were restricted to Chinese provincial capital cities with relatively similar characteristics, such as fewer first industries and lower greening rate compared to other noncapital cities. The generalization of the findings must be made with caution. Further studies with more cities with greater differences in both air pollution level and various potential associated factors may promote a broader understanding of the socioeconomic determinants of air pollution exposure inequalities.

Conclusions

Urban air pollution is a serious environmental problem in China. Air quality was worst in winter and best in summer. The day-to-day fluctuations of air quality were mainly driven by meteorological factors, including daily temperature, sunshine duration, wind speed, relative humidity, and precipitation. The southern cities generally had better air quality than the northern cities. The majority of spatial inequities were explained by city's differences in GDP per capita, industrial dust emissions, and vehicle population. The findings would help to understand the underlying reasons for spatial health disparities by SES and would provide information to guide city-specific policy response to ambient air pollution. It is suggested that there is a clear and present need to mitigate industrial emissions and limit the increase in vehicle population in Chinese major cities.

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