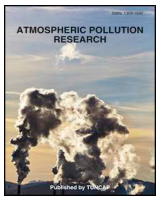
Atmospheric Pollution Research 11 (2020) 190–202

HOSTED BY

Contents lists available at ScienceDirect

Atmospheric Pollution Research

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



Spatiotemporal variations of $PM_{2.5}$ concentration at the neighborhood level in five Chinese megacities



Fei Dai[a], Ming Chen[a,*], Bo Yang[b]

[a] School of Architecture & Urban Planning, Huazhong University of Science and Technology, Wuhan, 430074, PR China
[b] School of Landscape Architecture and Planning, The University of Arizona, Tucson, AZ, 85719-0075, USA

ARTICLE INFO

Keywords:
$PM_{2.5}$
Spatiotemporal variation
Neighborhood level
China

ABSTRACT

A thorough understanding of the spatiotemporal variations of $PM_{2.5}$ concentrations is crucial for mitigating $PM_{2.5}$ pollution with effective measures; however, few studies have investigated this issue based on the neighborhood scale. This study investigated the spatiotemporal variations of $PM_{2.5}$ concentrations in 40 sites from five megacities by using hourly $PM_{2.5}$ concentrations derived from air quality monitoring stations. Two relative indicators—the range and rate of change in $PM_{2.5}$ concentration—were calculated to exclude the background levels of $PM_{2.5}$ in different cities. Therefore, the differences between both the regions and between the sites within the same city were taken into consideration. Results showed that the within-city differences in $PM_{2.5}$ concentration gradually increased from 2015 to 2017, and the differences were greater at a lower pollution level. Neighborhood-level $PM_{2.5}$ concentration fluctuated mainly between 80% and 120% of each city's overall $PM_{2.5}$ level. Combined with urban structure, the distribution of $PM_{2.5}$ concentration during the four seasons presented three spatial patterns: the $PM_{2.5}$ concentration was higher in the transition area, the $PM_{2.5}$ concentration was higher in the core area than other areas, and the $PM_{2.5}$ concentration had a relatively even distribution. Furthermore, the regional differences in the variations of $PM_{2.5}$ concentrations depended on the $PM_{2.5}$ concentrations differences among the cities; and the higher the $PM_{2.5}$ pollution level, the greater was the observed regional difference. In addition, the range and rate of change in $PM_{2.5}$ concentration had no significant differences among most sites at different pollution levels.

1. Introduction

Fine particulate matter ($PM_{2.5}$) is a serious problem in China (Fontes et al., 2017). Statistics from the Ministry of Ecology and Environment of China (MEE) show that among the 338 cities at prefecture level and above, about 74.2% of the 365 days had heavy and severe pollution in 2017 and predominated with $PM_{2.5}$. The $PM_{2.5}$ pollution resulted in adverse effects on health, climate changes, low visibility, and socio-economic issues (Kan et al., 2012; Li and Zhang, 2014; Li et al., 2017). As a result, a series of policies were promulgated by the Chinese government.

Many studies have been conducted to explore the spatiotemporal characteristics of $PM_{2.5}$ in the world, especially in China. Among these studies, those with the yearly, seasonally, monthly, and daily distributions of $PM_{2.5}$ concentration and their variations among different regions or cities showed extensively concerning problems (Cheng et al., 2016; Jin et al., 2017; Ye et al., 2018). In studying the spatial patterns of $PM_{2.5}$ concentration, spatial autocorrelation analysis was one of the commonly used methods at the city level to explore the spatial effects or spatial hotspots of $PM_{2.5}$ concentration among different cities, finding that $PM_{2.5}$ levels showed certain cluster characteristics (e.g., high-high clusters, low-low clusters, etc.) in different Chinese regions (Zhou et al., 2018; Chen et al., 2019c; Yang et al., 2020). Other published methods have included geographically weighted regression models (Wang and Fang, 2016), standard deviation ellipse analysis (Peng et al., 2016), meta-analysis (Fontes et al., 2017), and so on. Regarding temporal patterns, in general, monthly variations in $PM_{2.5}$ levels presented with a U-shaped change pattern in Chinese cities (Zhou et al., 2018). $PM_{2.5}$ levels also varied significantly across the seasons, with the highest $PM_{2.5}$ levels in winter and the lowest in summer (Jiang et al., 2020; Zhou et al., 2018). Furthermore, the coefficient of variation (CV) has been widely used to show the extent of spatial or temporal variation of $PM_{2.5}$ concentration among different study objects in recent years (Jin et al., 2017; Song et al., 2017; Xu et al., 2017).

Peer review under responsibility of Turkish National Committee for Air Pollution Research and Control.
* Corresponding author. School of Architecture & Urban Planning, Huazhong University of Science and Technology, Wuhan, 430074, PR China.
E-mail addresses: 58801365@qq.com (F. Dai), hustchenming@163.com (M. Chen), boyang17@email.arizona.edu (B. Yang).

https://doi.org/10.1016/j.apr.2020.03.010
Received 3 January 2020; Received in revised form 23 March 2020; Accepted 27 March 2020
Available online 03 April 2020
1309-1042/ © 2020 Turkish National Committee for Air Pollution Research and Control. Production and hosting by Elsevier B.V. All rights reserved.

Currently there are some gaps in the knowledge regarding the spatiotemporal variations of $PM_{2.5}$. First, the relevant studies mainly focus on a large scale, such as a city (Li et al., 2019), province (Song et al., 2017), region (Xu et al., 2020; Yang et al., 2020), or even the nation scale (Fang et al., 2020). Few studies have investigated the spatiotemporal patterns of $PM_{2.5}$ level based on the neighborhood scale, and most of these focused on only one city (Xu and Zhang, 2020). In reality, there are significant differences in $PM_{2.5}$ concentration within a city (Merbitz et al., 2012). Neighborhood-level $PM_{2.5}$ pollution should be one of the main concerns because of its close relationship to people's daily life and the important role of neighborhood as regarded as a basic component of urban fabric, function, and management. Second, an averaged value of daily, monthly, seasonal, and annual $PM_{2.5}$ concentrations were widely used in previous studies. Few studies have examined the significant changes in $PM_{2.5}$ concentration, such as the variations of $PM_{2.5}$ concentration during the entire cycle of a haze event. In fact, the hourly variations of $PM_{2.5}$ concentration present significant differences during a day (Zhao et al., 2016). Especially during the period of a haze event, the change in $PM_{2.5}$ concentration shows a certain pattern—the $PM_{2.5}$ concentration continuously increases from a stable low level to a peak and then decreases to a stable status (Chen et al., 2019b). Accordingly, it is essential to further explore the spatiotemporal patterns of $PM_{2.5}$ variations to an extent that reveals $PM_{2.5}$ evolution. This is also essential to develop effective policies and urban plan strategies to alleviate $PM_{2.5}$ pollution. In addition, based on the difference of the neighborhood-level $PM_{2.5}$ concentration in a city, the spatial pattern of $PM_{2.5}$ level in that city can be further examined to provide targeted control measures.

This study analyzed spatiotemporal variations of $PM_{2.5}$ concentration for 40 sites from five representative megacities. The study objectives of this study are as follows:

(1) to examine the temporal variations of seasonal, monthly, and diurnal $PM_{2.5}$ concentrations;
(2) to investigate the spatial differences in neighborhood-level $PM_{2.5}$ concentrations within a city and across the regions; and
(3) to examine the spatial patterns of $PM_{2.5}$ concentration in each city.

2. Materials and methodology

2.1. Study area and sample sites

Five megacities (Hefei, Shanghai, Wuhan, Nanjing, and Hangzhou) located in the Mid-Lower Yangtze Area in China live a large population and experience serious $PM_{2.5}$ levels (Zhang et al., 2017) (Fig. 1). As the capital cities, the rapid development of the five cities is high density with a population of more than 7 million for each city. Located in the same climate zone, these cities have similar climate conditions and $PM_{2.5}$ pollution levels. They also share several similar urban characteristics. Moreover, more air quality monitoring stations are centrally distributed in these cities than in most other cities in China. Based on the high-precision longitude and latitude coordinates (presented at four decimal places) of these stations, their locations can be accurately determined with an error of less than 1.1%.

There are a total of 50 stations available in the five cities. To apply the research results to a common urban neighborhood, 40 stations located in built-up areas that have the features of common urban neighborhoods were used in this study. The remaining 10 stations were removed because nine of them were basically formed by natural land, such as urban parks, forests, farmland, and lakes, and one of them was installed with monitoring station after July 2016.

2.2. $PM_{2.5}$ data and quality assurance

Based on the monitoring stations, we collected hourly ambient $PM_{2.5}$ concentrations data provided by the China National Environmental Monitoring Center. These measurement data for the 40 sites were generated according to the same standards with the use of the same equipment and methods. The periods of available data ranged from 2014 to 2018. However, there were some data lacking for 2014 and 2018; therefore, data from 2015 to 2017 were selected for analysis. Before the analysis, a screening of the raw data was conducted to ensure and control the quality of $PM_{2.5}$ data. First, the outliers, including missing data and maximal or minimal data for abrupt growth or reduction, were removed. The hourly data were then used to generate daily mean for a day when there were at least 20 h of valid data. Second, the daily mean data were used to calculate the monthly mean when there were more than 27 days (25 days for February) of the valid data available for that sampling month. These data were then used to generate the seasonal mean. Third, the valid data for sample years with more than 324 days of data were used to calculate the annual mean. In this study, the patterns for missing data of the sample sites in the five cities were similar in general, and all the sample sites met these criteria. We finally selected 337–351, 341–353, and 330–346 valid days in 2015, 2016, and 2017 for the five cities, respectively, with narrow differences in the amount of $PM_{2.5}$ data.

The average $PM_{2.5}$ concentration across the air monitoring stations in each city was calculated as the $PM_{2.5}$ concentration at the city level (Wang et al., 2018; Zhang et al., 2018). Several baselines, including 24-h mean concentrations that was less than 35 and 75 $\mu g/m^3$ for levels 1 and 2, respectively, were proposed based on the National Ambient Air Quality Standard (NAAQS, 2012) to better understand the $PM_{2.5}$ pollution level at different periods. “Non-attainment” refers to the daily $PM_{2.5}$ concentration that is greater than 75 $\mu g/m^3$.

2.3. Assessment for spatiotemporal variations of $PM_{2.5}$

2.3.1. Variations in $PM_{2.5}$ of different sites within cities

First, CV was used to quantitatively investigate the relative difference in $PM_{2.5}$ concentrations among the sites within a city. In the previous studies, it was widely used to describe the dispersion degree of $PM_{2.5}$ concentration among different cities or provinces (Jin et al., 2017; Song et al., 2017; Xu et al., 2017). A higher value refers to the degree of greater fluctuation of $PM_{2.5}$ concentrations in a city (He et al., 2017). For each city, the value of CV was calculated with Equation (1):

$$CV = \frac{1}{\bar{x}}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (1)$$

where x_i is the $PM_{2.5}$ concentration of the ith site; $\bar{x}$ refers to the mean $PM_{2.5}$ concentration of all the sites in a city; and n represents the number of the site.

Second, to further examine the magnitude of the above-mentioned difference, we calculated the fluctuation range of neighborhood-level $PM_{2.5}$ concentrations based on each city's overall $PM_{2.5}$ level during the same period. With this indicator, the higher pollution sites can be more targeted in their $PM_{2.5}$ reduction.

Third, we explored a common characteristic of the $PM_{2.5}$ concentration distribution within a city based on urban spatial structure. We used analysis of variance (ANOVA), a method to test whether the research variables had a significant difference based on certain factors, to analyze the seasonally spatial differences in $PM_{2.5}$ concentrations of the sample sites in different urban space levels. ANOVA has been used in the field of $PM_{2.5}$ pollution to examine the differences in $PM_{2.5}$ concentration among neighborhoods with different green space coverage levels (Chen et al., 2019a). For each city, the sample sites were classified into three spatial layers, namely, urban core, urban transition, and urban fringe area, according to the urban structure (mainly based on the urban ring road) of each city to define their spatial distribution (Fig. 1). For each site, daily mean data were used for analyses. $PM_{2.5}$ concentrations of different spatial layers were multiply compared by using the least significant difference method. The spatial layers of the

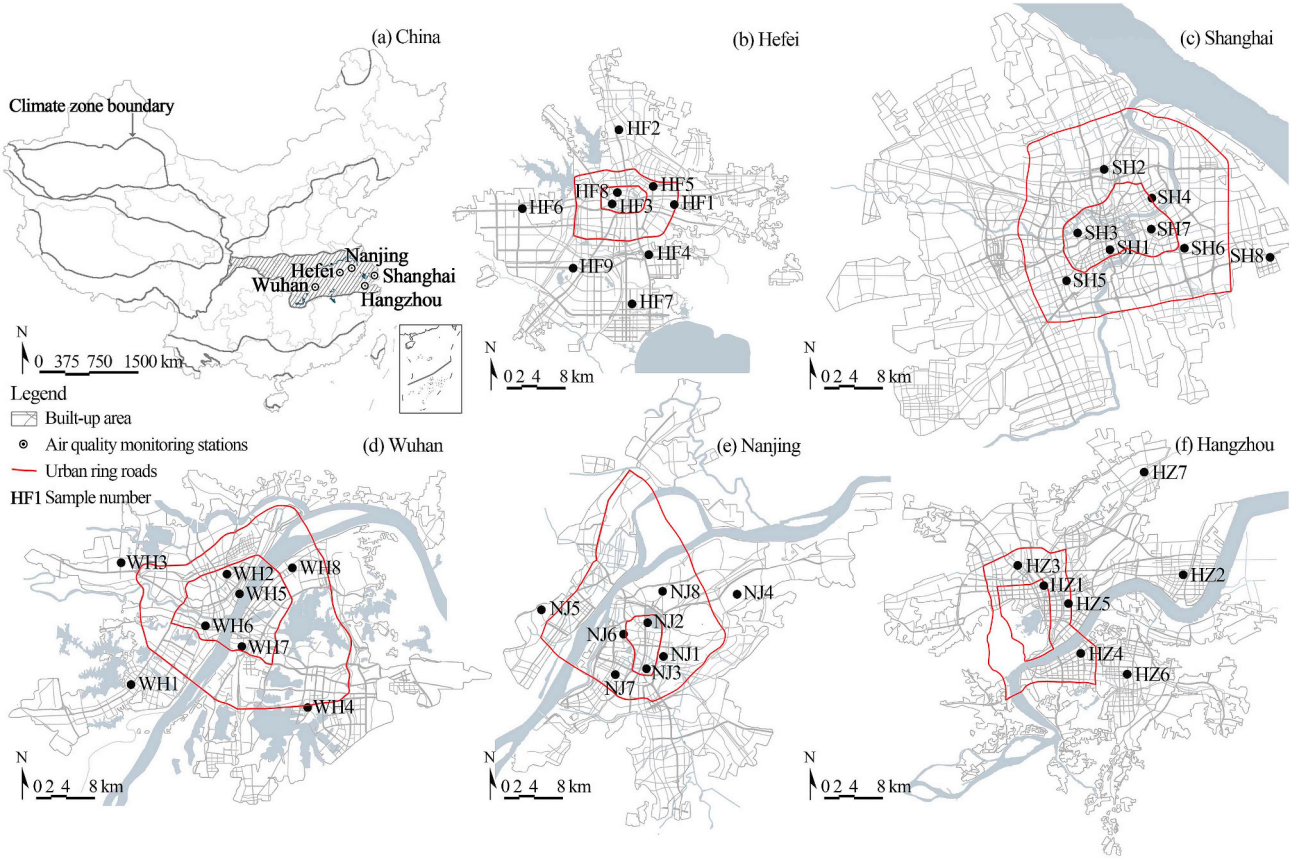


Fig. 1. Locations of the five cities and the monitoring stations.

sites with significant differences of $PM_{2.5}$ concentration were then obtained according to the threshold of significance level of < 0.05. Furthermore, the differences of $PM_{2.5}$ concentration between two spatial layers were quantified with the use of Equation (2):

$$\Delta C_i = (C_h - C_l)/C_h \times 100\,\%\ (i = 1,\ 2,\ 3) \tag{2}$$

where ΔC_i represents the difference of $PM_{2.5}$ concentration (ΔC_1, ΔC_2, and ΔC_3 refer to the difference of $PM_{2.5}$ concentration between urban core and transition, urban core and fringe, and urban transition and fringe, respectively); and C_h and C_l are the $PM_{2.5}$ concentrations in the area that recorded the higher and lower values, respectively.

2.3.2. *Variations in $PM_{2.5}$ of different sites among cities*

First, a widely used metric in the field of the regional difference measurement known as the Theil index (T) was calculated to quantitatively estimate the regional differences in $PM_{2.5}$ concentration at 40 sample sites; this index was previously used to measure the regional differences in primary PM emissions in the Yangtze River Delta of China (Xia et al., 2019). A higher T value indicates a greater difference in $PM_{2.5}$ concentration among the cities. For each season or month, T is expressed with the use of Equation (3):

$$T = \sum_{j=1}^{J} \frac{N_j}{N}\left(\sum_{i \in N_j} \frac{1}{N_j} \ln \frac{\bar{x}_j}{x_i}\right) + \sum_{j=1}^{J} \frac{N_j}{N} \ln \frac{\bar{X}}{x_j} \tag{3}$$

where T is the Theil index; N represents the total number of sample sites; J denotes the five cities; N_j refers to the number of site in city j; $\bar{x}_j$ is the mean level of $PM_{2.5}$ concentration in city j; x_i is the $PM_{2.5}$ concentration of the ith site; and $\bar{X}$ is the mean value of $PM_{2.5}$ concentration of the five cities.

Second, in comparison of the spatial variations in $PM_{2.5}$ concentration of different sites in the five cities, we used an additional two relative indicators—the range and the rate of the change in $PM_{2.5}$ concentrations—to consider the potential background difference in $PM_{2.5}$ concentrations in different cities. These indicators were also used by Chen et al. (2019b) to investigate the influence of green space spatial pattern on $PM_{2.5}$ variations. We kept the uncontrollable factors at a similar level to avoid obvious variations. For each site, we focused on the entire cycle of each haze disappearance event during the study period, when $PM_{2.5}$ concentration continuously decreased from a stable high level to a minimum (Fig. 2). These data were then selected and used to calculate the relative indicators of $PM_{2.5}$ concentrations. To better and more comprehensively understand the $PM_{2.5}$ variations, three $PM_{2.5}$ pollution levels similar to Chen et al. (2019b) were adopted. In addition, $PM_{2.5}$ data for the three pollution levels were selected only when the day was windless, or breezy, and without rain or snow. Based on the pollution situation throughout 2015–2017 of five cities and the above criterion, $PM_{2.5}$ data for different pollution levels with significant decreases trends were best selected by the proportion of 10%. To make comparable these data in different cities, the days of the selected data had the similar distributions in the twelve months of each year. Finally, matching data from 36 days were selected (Table 1).

$$C_{\downarrow} = (C_0 - C)/C_0 \tag{4}$$

$$\Delta t_{\downarrow} = t - t_0 \tag{5}$$

$$C_{\vee} = C_{\downarrow}/\Delta t_{\downarrow} \tag{6}$$

where $C_{\downarrow}$ and $C_{\vee}$ are the range (%) and rate (%/h) of change in $PM_{2.5}$ concentration, respectively; C_0 and C refer to the initial and final concentrations before and after $PM_{2.5}$ concentration decreases, respectively ($\mu g/m^3$); $\Delta t_{\downarrow}$ denotes decrease duration (h); and t_0 and t represent the initial and final time before and after $PM_{2.5}$ concentration change, respectively (h).

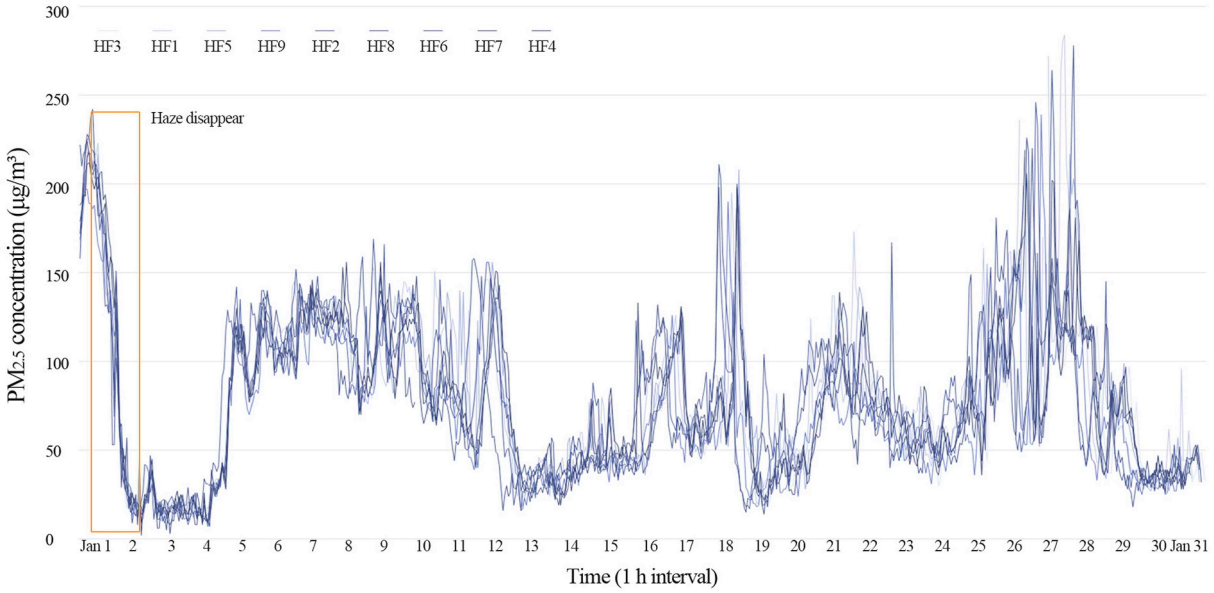


Fig. 2. Example of $PM_{2.5}$ concentration change trends in Hefei.

Table 1
The amount of data used for calculating relative indicators of $PM_{2.5}$ variations.

Pollution level	Amount of data/d		
	2015	2016	2017
Slight pollution	8	8	8
Moderate pollution	2	3	2
Heavy pollution	2	2	1

3. Results

3.1. Overview of $PM_{2.5}$ concentration

Table 2 summarizes the annual averages of $PM_{2.5}$ concentration averages, days of non-attainment, and days of heavy pollution in the 40 sites during 2015–2017. In general, the annual mean $PM_{2.5}$ concentration in the five cities showed a downward trend, as well as the days of non-attainment and heavy pollution of $PM_{2.5}$. $PM_{2.5}$ concentrations for the five cities decreased by 10.5, 13.9, 18.9, 16.1, and 12.7 μg/m^3 (16.1%, 26.4%, 26.9%, 27.7%, and 21.3%, respectively) from 2015 to 2017, respectively. However, $PM_{2.5}$ pollution should be of concern because the days of non-attainment of the five cities still accounted for 24%, 8%, 19%, 9%, and 12% in 2017, respectively, and there were some heavy pollution days, especially in Hefei and Wuhan. The range and rate of change in $PM_{2.5}$ concentration present differences among the 40 sites. At a slight (moderate, heavy) pollution level, the rate of change in $PM_{2.5}$ concentration at 40 sites ranged from 8.0%/h (6.4%/h, 6.6%/h) to 13.6% (13.9%/h, 14%/h) with a mean of 11.0%/h (9.3%/h, 9.8%/h), and the range of change in $PM_{2.5}$ concentration ranged from 48.0% (49.0%, 46.0%) to 59.6% (65.3%, 69.5%) with a mean of 53.3% (55.3%, 59.1%), respectively.

3.2. Temporal variations of $PM_{2.5}$ concentration within and among the study sample sites

Seasonal $PM_{2.5}$ concentrations in five cities presented similar trends during 2015–2017 (Fig. 3), with the highest value in winter, followed by spring and autumn, and the lowest value in summer. $PM_{2.5}$ concentrations in the four seasons decreased from 2015 to 2017. The minimal, maximal, and the quartile range of $PM_{2.5}$ concentration showed that the period with the higher $PM_{2.5}$ concentration also recorded larger fluctuation range of concentrations. Because of the differences in the city population, scale, and meteorological conditions in five cities, their seasonal variations of $PM_{2.5}$ concentration showed certain differences. In general, Wuhan and Hefei recorded relatively higher $PM_{2.5}$ concentrations, especially in winter. In summer, the

Table 2
Overview of $PM_{2.5}$ in five cities during 2015–2017.

	Year/pollution level	Hefei	Shanghai	Wuhan	Nanjing	Hangzhou
Mean concentration/μg·m^{-3}	2015	65.1	52.6	70.3	58.2	59.5
	2016	57.8	44.7	57.2	49.2	51.9
	2017	54.6	38.7	51.4	42.1	46.8
Days of non-attainment/d	2015	101	79	119	77	69
	2016	82	47	89	64	60
	2017	87	30	69	34	42
Days of heavy pollution/d	2015	13	7	19	11	5
	2016	7	2	7	2	3
	2017	6	3	6	2	2
$C_{\downarrow}$/%	Slight pollution	51.6	53.7	52.2	56.7	52.4
	Moderate pollution	51.8	53.8	57.4	55.1	59.5
	Heavy pollution	58.6	57.7	51.4	61.9	66.9
$C_{\downarrow}$/%·h^{-1}	Slight pollution	11.5	10.3	9.2	12.0	12.1
	Moderate pollution	7.5	7.9	10.2	10.0	11.3
	Heavy pollution	8.7	11.1	9.5	10.0	9.7

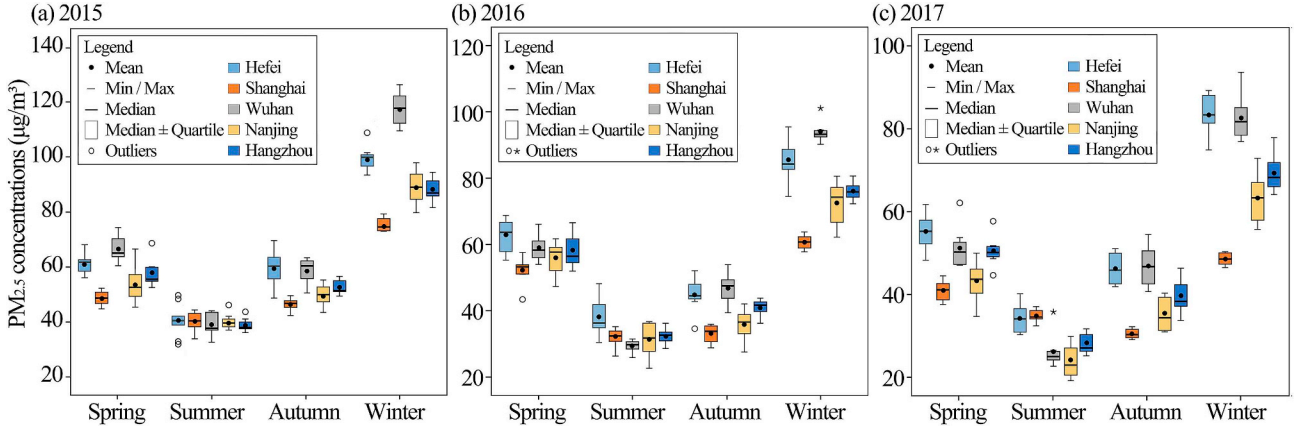


Fig. 3. Variations in seasonal $PM_{2.5}$ levels in five cities.

differences in $PM_{2.5}$ seasonal variations among five cities were small. This may be because the lowest ambient concentration occurred during summer.

Similarly, monthly $PM_{2.5}$ concentrations in five cities had differences, but they all presented with a U-shaped pattern during 2015–2017, with a downward trend from January to June and lowest values in July or August, followed by a growth trend (Fig. 4). Comparisons of $PM_{2.5}$ concentration during the 3 years showed that $PM_{2.5}$ concentration also presented a downward trend in the corresponding months. $PM_{2.5}$ concentrations in the 3 months in winter were significantly higher than those in other months. $PM_{2.5}$ concentrations in the neighborhood level of five cities that compose the study area remained between 35 and 75 μg/m^3 from March to November in 2015 and rose to above 75 μg/m^3 in the final 3 months. In 2016 and 2017, $PM_{2.5}$ concentrations declined to below 35 μg/m^3 for 4 and 3 months (from July to October) for most cities and were lower than 75 μg/m^3 for most of remaining months, indicating the gradual and clear mitigation of $PM_{2.5}$ pollution.

The hourly $PM_{2.5}$ concentration also exhibited differences in five cities. There was little hourly $PM_{2.5}$ variation in Shanghai, and the diurnal variation trend was similar for the other four cities (Fig. 5). In general, the greater differences in hourly mean $PM_{2.5}$ concentrations during a day appeared at the periods with higher pollution levels, whereas the minimal differences occurred in summer. Hourly mean $PM_{2.5}$ concentration presented a bimodal distribution in winter, spring, and autumn. There was a slight change before dawn. Two peak $PM_{2.5}$ levels appeared in the morning and evening rush hours, respectively, and were greater during daytime. The peak mean $PM_{2.5}$ concentrations showed a time difference in different seasons, which were concentrated in local standard time (LST) 10: 00–11: 00 and 21: 00–22: 00 LST in winter and 8: 00–9: 00 LST and 22: 00–23: 00 LST in other seasons. The minimum values were all observed at 16: 00–17: 00 LST throughout the year.

3.3. Spatial variations of $PM_{2.5}$ concentration within a city and across five cities

3.3.1. Spatial variations within a city

The annual and seasonal mean $PM_{2.5}$ concentrations presented consistent spatial and temporal trends during 2015–2017, with noticeable variations among the five cities (Figs. 6 and 7). As a coastal city, the sites in Shanghai recorded the lowest $PM_{2.5}$ concentrations, which are mainly influenced by the relatively frequent and strong wind flows (Fontes et al., 2017). The annual mean $PM_{2.5}$ concentrations at the sites in Hefei and Wuhan were the highest, with 3-year mean values of 59.6 and 59.2 μg/m^3, respectively, followed by the sites in Hangzhou and Nanjing. These differences may be associated with their geographical location and meteorological conditions; located in the inner area of China, the relatively low air temperature and high relative humidity of Wuhan and Hefei resulted in the heavy $PM_{2.5}$ pollution (Ye et al., 2018).

In the internal area of cities, the distribution of $PM_{2.5}$ concentrations showed variations with different patterns in the five cities (Fig. 6). For example, lower $PM_{2.5}$ concentrations tended to be distributed in the center of the built-up area in Wuhan, whereas higher values were recorded scattered around the edge. However, $PM_{2.5}$ concentration within Shanghai showed a reverse trend. In general, $PM_{2.5}$ concentrations are higher in central urban areas because of the high-density built

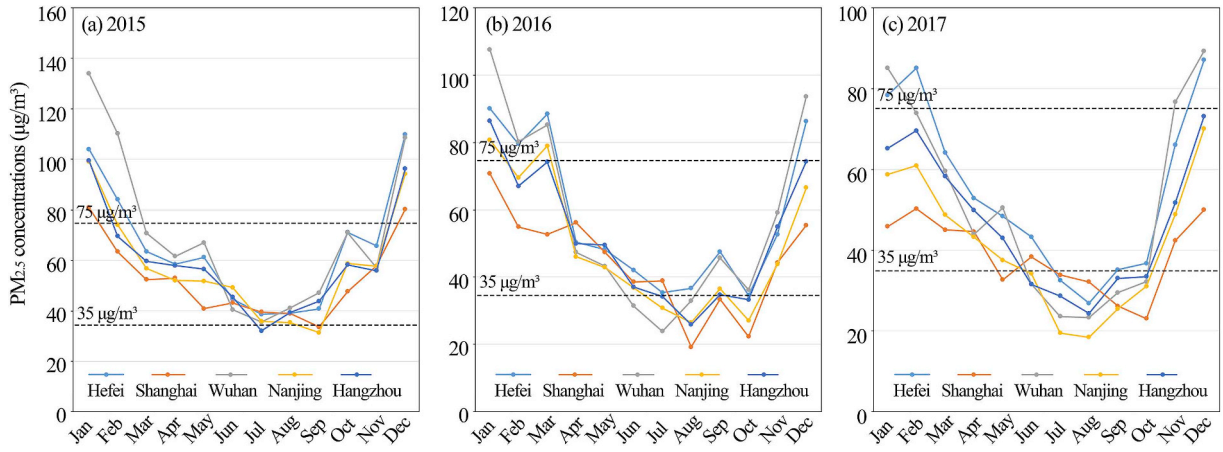


Fig. 4. Variations in monthly mean $PM_{2.5}$ levels in five cities.

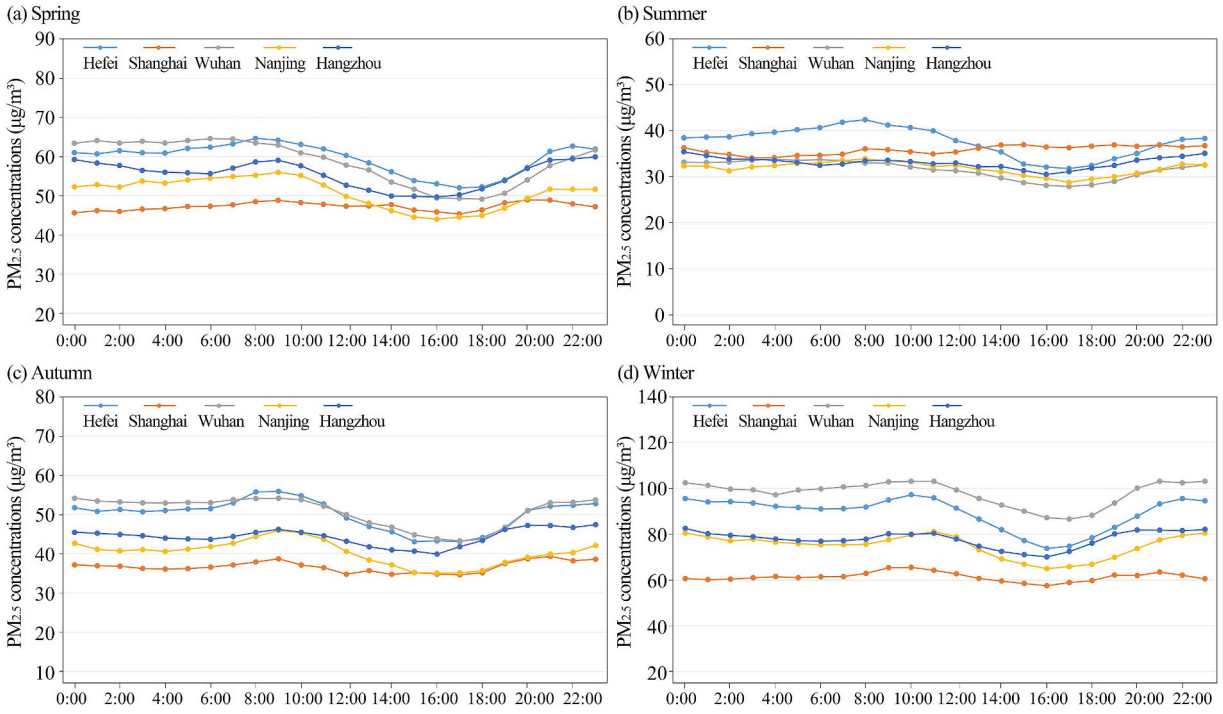


Fig. 5. Variations in diurnal $PM_{2.5}$ concentrations of five cities in four seasons.

environment and human activities and gradually decrease toward the urban fringe; however, the placement of large-scale ecological sources will reduce $PM_{2.5}$ levels to some extent (Chen and Feng, 2019). Shanghai presents a typical urban form with extremely dense central spaces. In Wuhan, the intersection of the Yangtze River and the Hanjiang River and the location of some lakes in the center dilute $PM_{2.5}$ concentrations in this area. In addition, the arrangement of land use leads to the different $PM_{2.5}$ patterns. $PM_{2.5}$ concentrations in the east and north sides of Hefei, which mainly consist of industrial and old residential areas, were higher in other areas. The change rates of $PM_{2.5}$ concentration from 2015 to 2017 in inner cities also presented significant differences. The sites in Hefei had lower change rates (16% for the mean value) than those of the sites in other cities. Urban construction activities and lack of effective implementation strategies during the study period may be the factors that resulted in the less improvement in $PM_{2.5}$ pollution in Hefei. Sample site NJ8 in Nanjing had the highest change rate (35.7%), whereas the lowest value (8.8%) occurred at site HF4 in Hefei. In sum, all sample sites in the five cities exceeded the standard of mean annual $PM_{2.5}$ concentrations (35 μg/m^3).

CV of mean annual $PM_{2.5}$ concentration presented an upward trend from 2015 to 2017. $PM_{2.5}$ concentrations among the sample sites in Shanghai had the minimum differences (CV = 0.032, 0.054, and 0.037 during 2015–2017), and the maximum difference appeared in Nanjing (CV = 0.065, 0.089, and 0.092 during 2015–2017). The seasonal and monthly means for 3 years of CV values represented with a reverse trend (^-shaped pattern) to the $PM_{2.5}$ concentration for Hefei, Shanghai, Wuhan, and Nanjing (Fig. 8). The highest CV appeared in summer throughout the year, when the $PM_{2.5}$ pollution was the slightest, followed by autumn and spring. The lowest CV occurred in winter, when there was heavy $PM_{2.5}$ pollution. The CV values for the four seasons and 12 months were little different for Hangzhou and showed a different trend from that of the other four cities. This might have been caused by some special urban activities in Hangzhou during that period.

Neighborhood-level $PM_{2.5}$ fluctuated substantially compared with the city-level $PM_{2.5}$ concentration (Fig. 9). The fluctuation range mainly varied from 80% to 120% and was stable for each site in different seasons. Among five cities, Nanjing had the relatively greater fluctuation range, which rose to 134% in summer 2017. Shanghai had the minimum fluctuation range. This is consistent with the CV of the five cities. The long-term differences in neighborhood-level $PM_{2.5}$ concentration implies the potential for $PM_{2.5}$ decline in the high pollution site through the optimization of built environment.

$PM_{2.5}$ data for 2017 were used to further test the spatial variations within a city by using ANOVA because of the upward trend of the CV from 2015 to 2017. In addition to Shanghai, there were significant differences in $PM_{2.5}$ concentration among the urban core, transition, and fringe area sites (Fig. 10). Three spatial patterns of $PM_{2.5}$ concentration distribution in the four seasons were as follows: (1) Hefei, Wuhan, and Nanjing had $PM_{2.5}$ concentrations in urban transition area that were significant higher than those in the urban core and fringe areas, with ΔC_1 and ΔC_3 ranging from 9.5% to 9.9% and 9.7%–10.0% in Hefei, from 15.7% to 32.2% and 8.7%–28.9% in Wuhan, and from 8.7% to 22.4% and 17.4%–26.7% in Nanjing, respectively. The differences in $PM_{2.5}$ concentrations between urban transition and fringe area sites were usually greater than those between urban transition and core area sites in Hefei and Nanjing. Relative greater ecological resources in Wuhan may lead to a reverse phenomenon. (2) In Hangzhou, $PM_{2.5}$ concentrations in the urban core area were significantly higher than those in the urban transition and fringe areas, with ΔC_1 and ΔC_2 ranging from 13.1% to 16.8% and 11.5%–16.9%, respectively. (3) In Shanghai, as the CV shows, $PM_{2.5}$ concentrations among the sites had the least differences; the significance difference was only between the urban core and fringe area sites in spring with ΔC_2 of 10.1%. In addition, there was a tendency for $PM_{2.5}$ concentrations in different urban area sites to record the greatest and the minimum difference in summer and winter, respectively, which was consistent with the trend of CV.

3.3.2. *Spatial variations among five cities*

The seasonal and monthly mean T values for 3 years in five cities presented U-shaped patterns (Fig. 11). The similar trends with $PM_{2.5}$ concentrations and the contrary trends with the CV indicated that the regional difference of $PM_{2.5}$ concentration among the sites was greater at a higher pollution level. This difference was mainly caused by the great differences among five cities. On the one hand, meteorological conditions had significant impacts on $PM_{2.5}$. Although these cities are

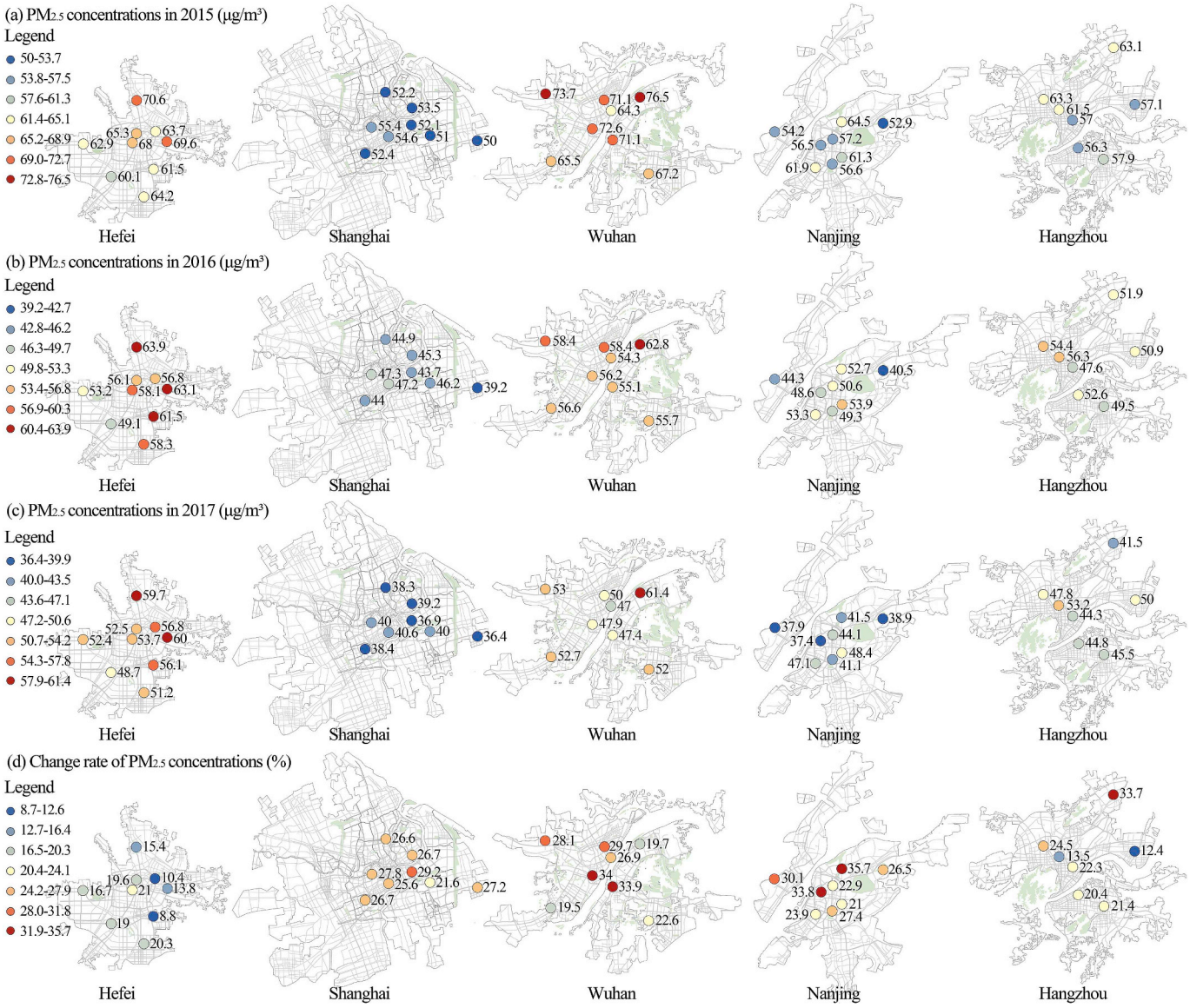


Fig. 6. Spatial distribution of annual mean (a~c) and change rates (d) of $PM_{2.5}$ concentrations during 2015–2017.

located in the same climate zone, there are somewhat at variance with the air temperature and humidity. Wuhan had a relatively lower temperature and higher humidity, as opposed to Shanghai (Chen et al., 2019b). Accordingly, sites in Wuhan recorded the relatively higher seasonal and monthly mean $PM_{2.5}$ concentrations, and sites in Shanghai recorded the relatively lower value, with the maximal differences of 48 and 54 μg/m^3 for the seasonal and monthly mean $PM_{2.5}$ concentrations, respectively. In addition, affected by the different wind speed and directions, $PM_{2.5}$ levels varied among cities in Yangtze River Delta, including Nanjing, Hangzhou, and Shanghai in this current study (Xu et al., 2020). On the other hand, pollution source distribution in the five cities differed. The main source of $PM_{2.5}$ pollution was vehicle exhaust in Wuhan (Xiong et al., 2017), industry and residential combustion in Shanghai (Timmermans et al., 2017), industry and fuel burning in Hefei (Xue et al., 2019), construction sites and unpaved roads in Nanjing (Cui et al., 2019), and long-range transport in Hangzhou (Ni et al., 2018). These are all potential factors that affect regional $PM_{2.5}$ differences.

Differences in the relative indicators, including the range ($C_{\downarrow}$) and rate (C_{v}) of change in $PM_{2.5}$ concentration, were examined with ANOVA (Fig. 12). In general, there were no significant differences in $C_{\downarrow}$ and C_{v} among most sites at different pollution levels. At a slight pollution level, $C_{\downarrow}$ were significantly different among five sites in Nanjing and 12 sites in other cities. For example, the significant differences in $C_{\downarrow}$ ranged from 8.1% to 11.6% between Nanjing site NJ2 and nine other sites in the other four cities and from 8.2% to 10.2% between Nanjing site NJ4 and six other sites. The differences were substantially less than 5% among most other sites. At moderate pollution, the significant difference in $C_{\downarrow}$ appeared only between sites NJ1 and HZ7, with mean a value of 19.1%. At heavy pollution, for $C_{\downarrow}$ values between sites WH6 and HZ2, site HZ6 had significant differences, ranging from 23.3% to 23.5%. Compared with $C_{\downarrow}$, C_{v} had a similar tendency; however, a few additional sites with significant differences in C_{v} were found at different pollution levels. A significant difference in C_{v} ranged from 2.9%/h to 5.6%/h at slight pollution, from 4.8%/h to 7.5%/h at moderate pollution, and from 6.9%/h to 7.4%/h at heavy pollution. Overall, the sites had greater significant differences in $C_{\downarrow}$ and C_{v} at a higher pollution level.

4. Discussion

The current study contributes to knowledge of the spatiotemporal variations in $PM_{2.5}$ concentrations at the neighborhood scale. First,

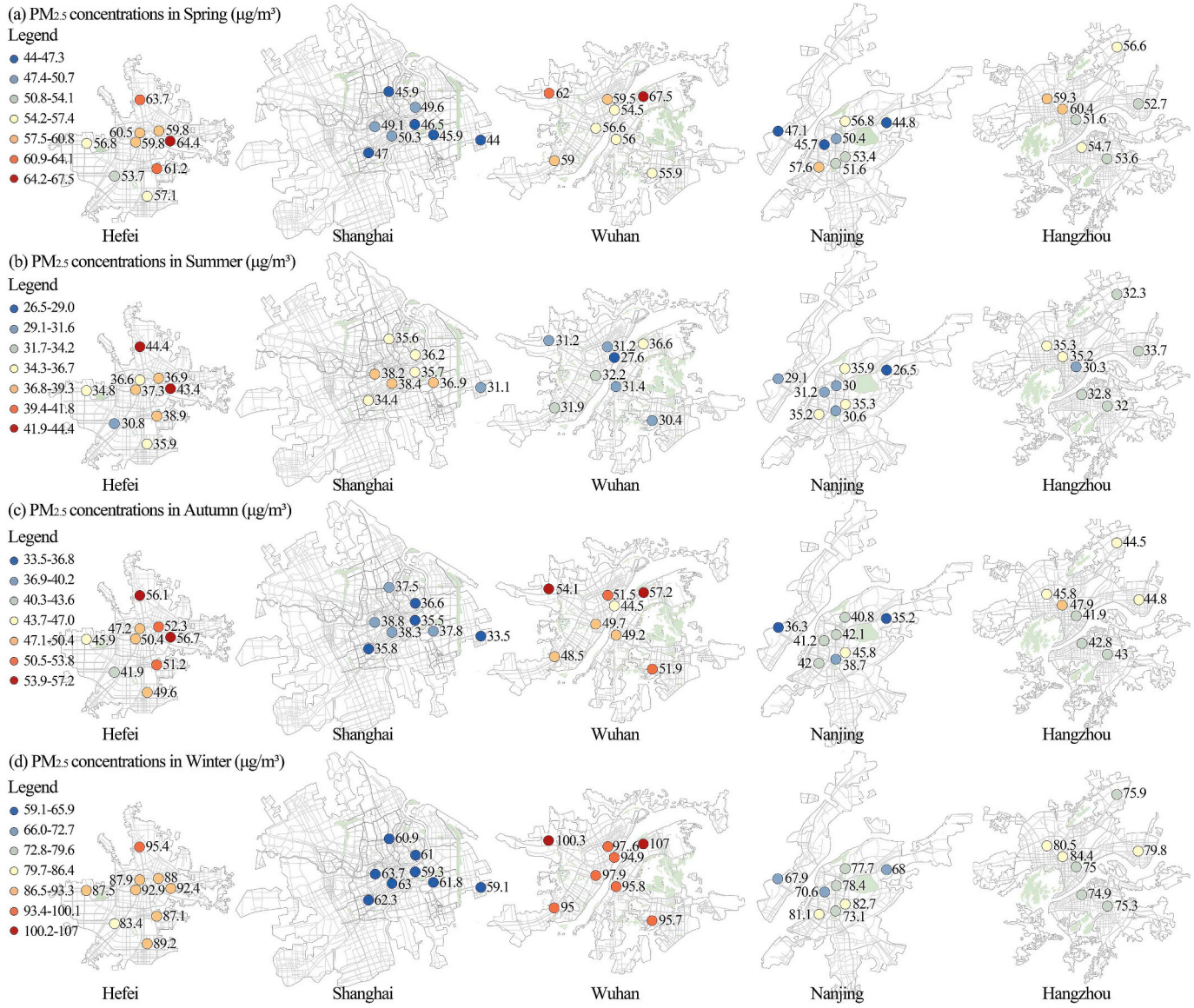


Fig. 7. Spatial distribution of seasonal mean for the three years of $PM_{2.5}$ levels during 2015–2017.

based on the relatively even distribution of air quality monitoring stations inside the five cities, the differences in urban internal $PM_{2.5}$ concentrations are quantified by the CV, and these variations vary among cities. Second, the differences are implemented for the specific spatial positions based on the urban structure, and three spatial patterns of the differences in urban internal $PM_{2.5}$ concentrations are proposed, thereby providing supports for the spatial strategies for air quality improvement. Third, this study considerably extends the understanding of neighborhood-scale $PM_{2.5}$ variations, in that $PM_{2.5}$ levels in a region with the same climate conditions present great differences and show seasonal differences. In addition, the specific fluctuation range of neighborhood-level $PM_{2.5}$ level based on the city's overall pollution level was presented.

4.1. Temporal variations in $PM_{2.5}$ concentration

As demonstrated by many studies that seasonal and monthly variations in $PM_{2.5}$ concentrations at the city scale presented U-shaped patterns (Xu et al., 2017; Zhou et al., 2018; Li et al., 2019), the sites within a city displayed similar patterns. This phenomenon indicates that although there are differences among the sites in a city, $PM_{2.5}$ concentrations at these sites show similar trends. That is, the temporal difference in $PM_{2.5}$ concentrations during an entire haze event, such as the range of change in $PM_{2.5}$ concentration, may reflect levels after excluding background concentrations, which can be compared across cities (Chen et al., 2019b). $PM_{2.5}$ concentrations measured by urban air quality monitoring stations can reflect and represent different $PM_{2.5}$ pollution levels of a city, according to the Methods for Ambient Air Quality Monitoring (SEPA, 2007), which requires a similar condition around the monitoring stations, especially far from a pollution source such as chimneys.

The bimodal pattern of diurnal $PM_{2.5}$ concentration was similar to the results of previous studies in which diurnal variations of $PM_{2.5}$ presented a similar W-shaped trend in China (Song et al., 2017; Ye et al., 2018), which was influenced by both anthropogenic emissions and meteorological conditions. The morning peak in $PM_{2.5}$ level may be associated with the fumigation effect in the boundary layer, which brings aerosols from the nocturnal residual layer shortly after the sunrise (Stull, 1988). In addition, vehicular traffic flows increased during the study period, which increases automobile exhaust emissions and contributes to $PM_{2.5}$ concentrations (Li et al., 2014). The lowest mean $PM_{2.5}$ concentration occurred during the afternoon (16: 00–17:

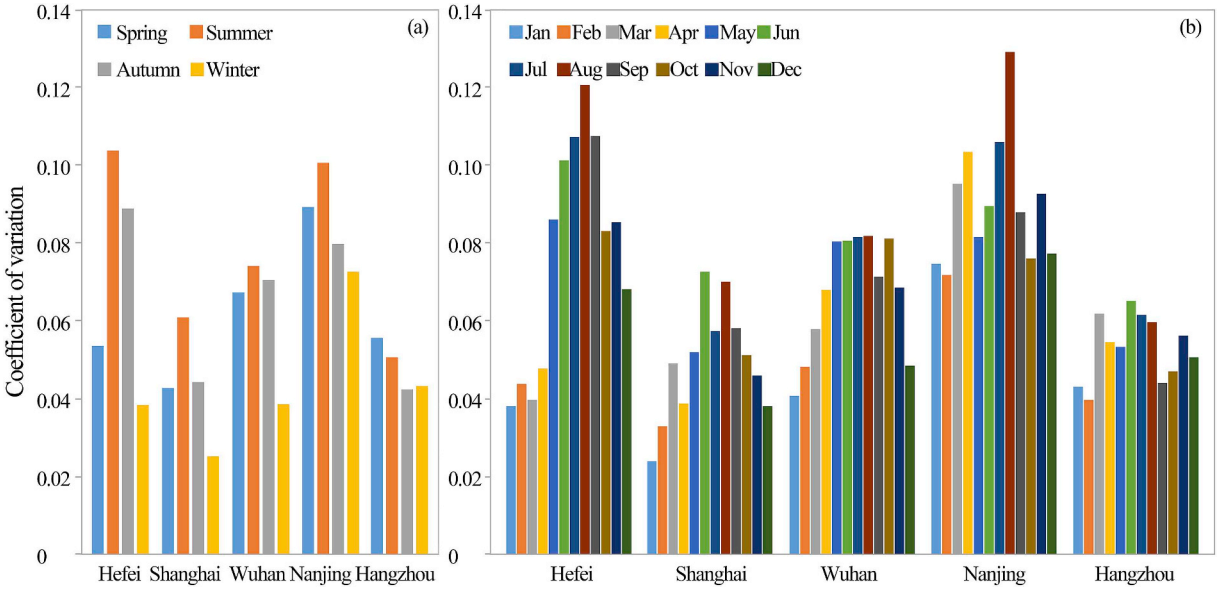


Fig. 8. Seasonal (a) and monthly (b) mean for 3 years of CV of five cities.

00 LST). This can be explained by the larger boundary layer and stronger atmospheric ventilation (Zhang and Cao, 2015). During the late afternoon, increased solar heating accelerates the dispersion of aerosols and results in the attenuation of $PM_{2.5}$ concentration because of the increased turbulent effects and a deeper boundary layer. Thereafter, $PM_{2.5}$ concentration gradually increased and reached a peak in the evening. This may be because the formation of surface inversion after sunset traps more air pollutants related to $PM_{2.5}$ (Tiwari et al., 2013). In addition, there was a slight change in hourly $PM_{2.5}$ concentration before dawn. This may due to a reduction in human activities during this time.

4.2. Spatial variations of $PM_{2.5}$ concentration in different sites within a city and across cities

There were differences in $PM_{2.5}$ levels among the sites within a city

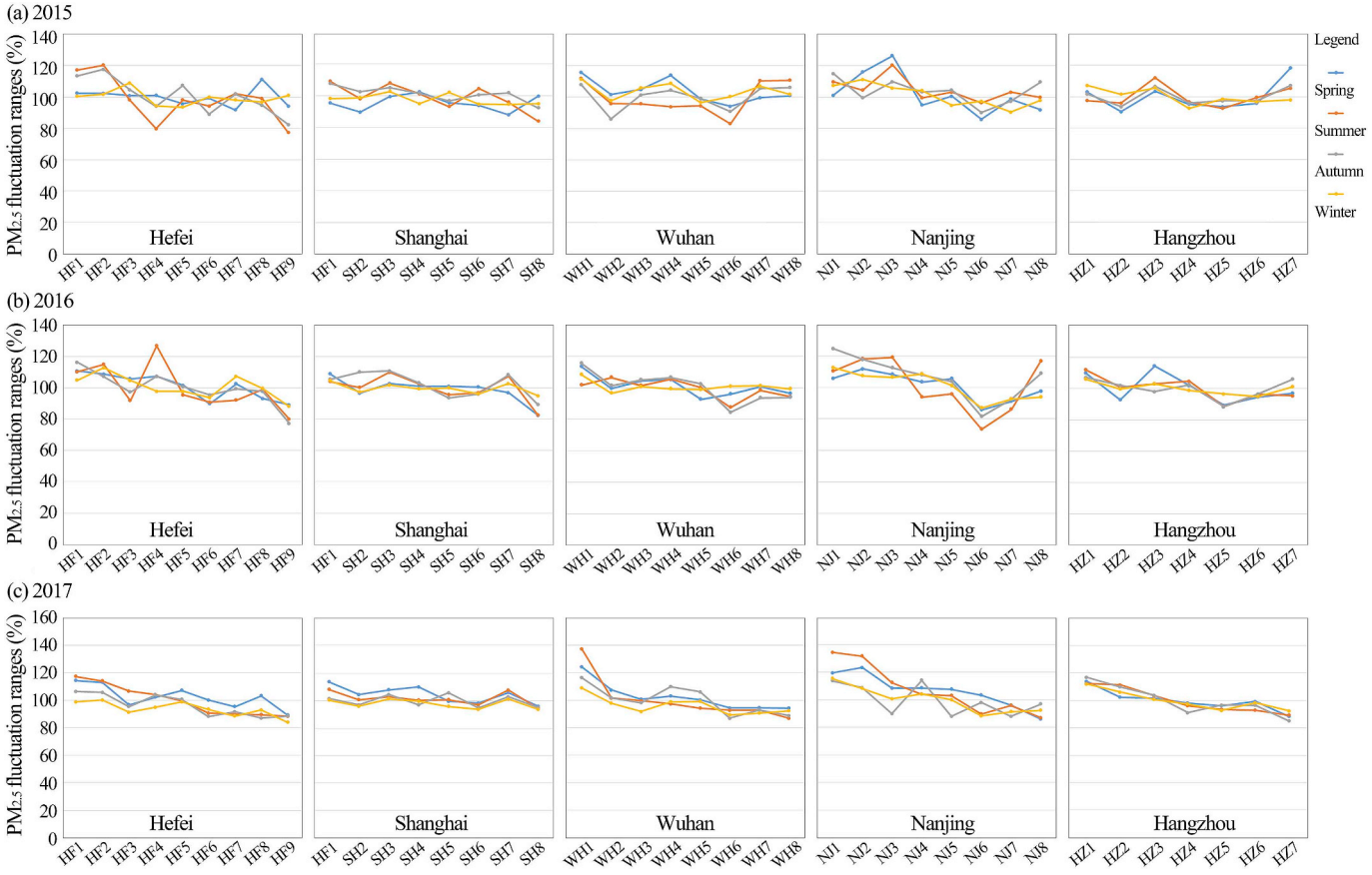


Fig. 9. Fluctuation ranges of neighborhood-level $PM_{2.5}$ concentration within the city.

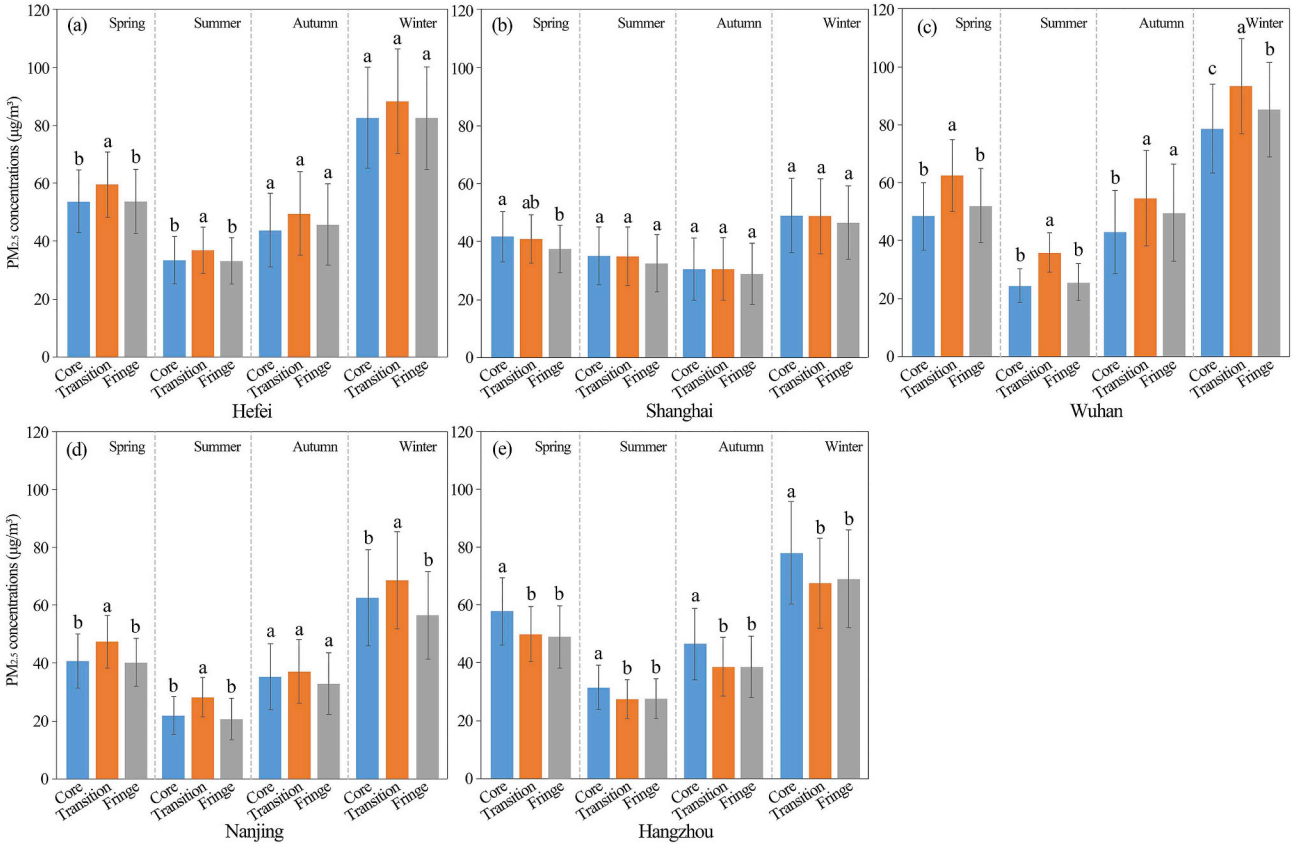


Fig. 10. Seasonal mean $PM_{2.5}$ concentrations at urban core, transition, and fringe sites in Hefei (a), Shanghai (b), Wuhan (c), Nanjing (d), and Hangzhou (e) in 2017. For each season in a city, the same letter represents a nonsignificant difference in $PM_{2.5}$ concentration in those areas.

and the variations varied among the five cities in this study. Various factors result in variation in $PM_{2.5}$ levels varying from site to site, including the overall planning and layout of the city (Yuan et al., 2017), landform (Romero et al., 1999; Zheng et al., 2017), traffic and the proximate built environment characteristics (Boarnet et al., 2011; Edussuriya et al., 2011), and other human-related activities such as construction sites (Lenschow et al., 2001). From a macro perspective, the layout of urban land use has a crucial role in the air quality. $PM_{2.5}$ level in the area with a dense industrial zone is higher than that in other land areas because of the emission of smoke or particles, which forms primary and secondary particle pollution (Feng et al., 2017). In this study, the site WH8 is the nearest site to the largest industrial zone in Wuhan, leading to the significantly higher $PM_{2.5}$ level than that in other sites. The rapid expansion of the built-up area and the loss of ecological land also produce environmental problems, especially urban heat island effects, that result in the uneven distribution and easier accumulation of air pollutants and the formation of secondary pollution, therefore enhancing $PM_{2.5}$ pollution (Aslam et al., 2017; Liu et al., 2016). From a micro perspective, the variations in $PM_{2.5}$ levels in different areas of a city are also caused by the local traffic-related sources (Wolf-Benning et al., 2009), which vary among sites in the city. Other anthropogenic activities, especially construction sites, generate a lot of dust and greatly contribute to $PM_{2.5}$ pollution (Lu et al., 2018), such as site NJ7. In addition, the different micro-meteorological conditions in the sites formed by a complicated built environment can significantly influence $PM_{2.5}$ levels (Chu et al., 2009; Cheng et al., 2015; Zhang et al., 2015).

Both the variations in $PM_{2.5}$ concentrations within a city and across the five study cities showed seasonal differences. The spatial variation

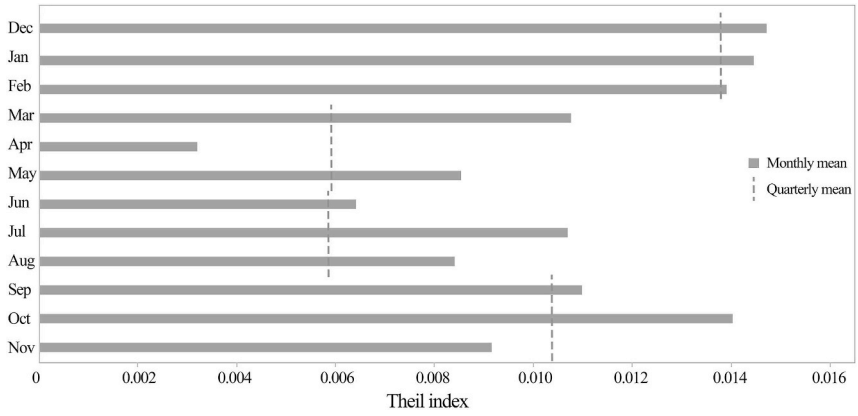


Fig. 11. Seasonal and monthly mean for 3 years of T of five cities.

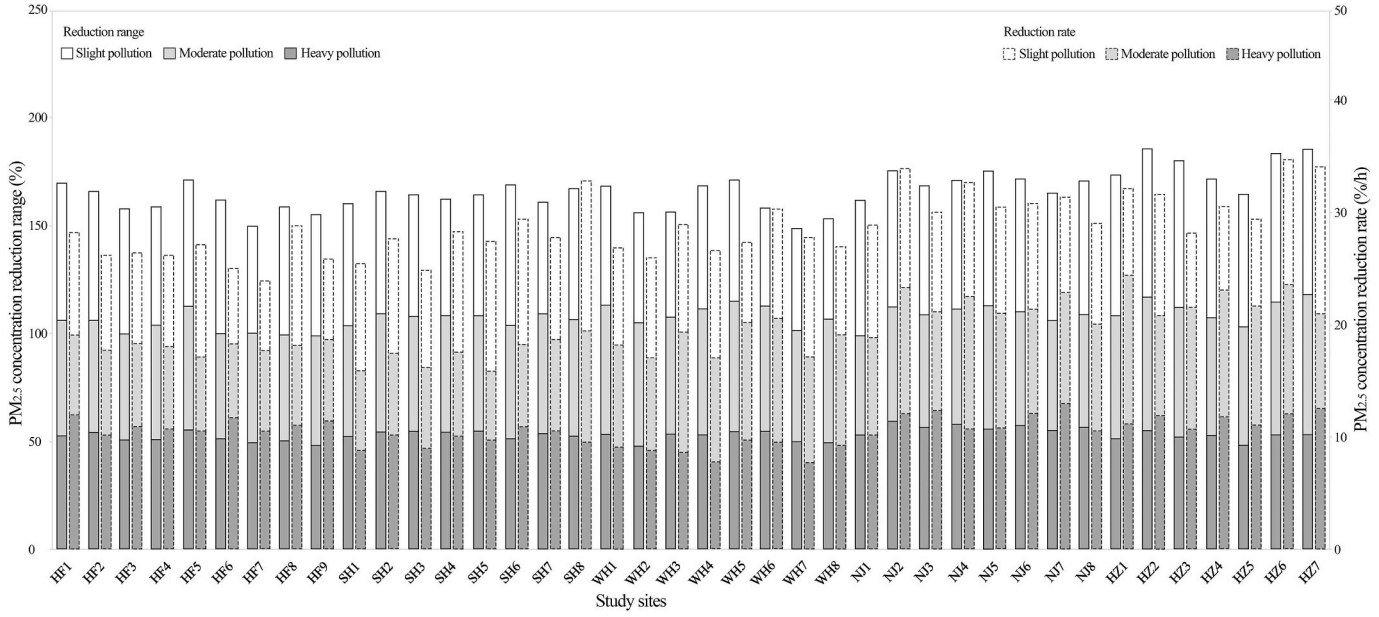


Fig. 12. The range and rate of change in $PM_{2.5}$ concentration among the 40 sites.

in $PM_{2.5}$ concentrations within a city was higher in summer than that in other seasons, which is in accordance with the result that the relative variation of $PM_{2.5}$ levels among the 23 cities in China was the highest in summer (Xu et al., 2017). The higher spatial variation in summer may result from the increased frequency of atmospheric convection in the vertical direction, which leads to acceleration of the transport of $PM_{2.5}$ because of the high temperature. The high temperatures also strengthen the photosynthesis and adsorption of $PM_{2.5}$ by vegetation (Nowak et al., 2006; Dawson et al., 2007; Liu et al., 2014). In addition, the most efficient effects of vegetation on $PM_{2.5}$ reduction caused by both the high temperature and leaf-on period and the significant differences in green space coverage in different neighborhoods within a city in summer result in the greatest differences in $PM_{2.5}$ levels (Chen et al., 2019a). However, the regional variation in $PM_{2.5}$ concentration showed a reverse trend, with the highest variation in winter. This is mainly because the differences in $PM_{2.5}$ concentration in different sites across cities are more dominant than the differences within a city; the greatest differences were recorded in winter. These phenomena indicate that although the diffusion of $PM_{2.5}$ is not restricted by urban boundaries, differences still exist among cities that are influenced by socio-economic, meteorological, and other factors (Liu et al., 2018; Tecer et al., 2008).

Among the five cities, although the distribution of $PM_{2.5}$ concentrations had seasonal differences, in general, three spatial patterns presented. Three inland cities—Hefei, Wuhan, and Nanjing—had similar distribution characteristics of $PM_{2.5}$ concentrations, with $PM_{2.5}$ concentrations in the urban transition area higher than those in the urban core and fringe areas. In these three cities, there are high-quality and large-scale ecological resources in or around the core areas, such as the annular parks around the urban core area in Hefei, the intersection of two rivers in Wuhan, and the great mountain and lake in Nanjing, that may result in an improvement in $PM_{2.5}$ levels. Hangzhou presented a conventional spatial pattern. The eastern estuary may have a greater influence on the sites in transition and fringe areas. However, $PM_{2.5}$ concentrations were relatively uniform in different areas in Shanghai as a result of the location of riverside and seafront, the simplest flat terrain without any mountains, and the corresponding meteorological conditions. Here is one point that requires further emphasis. Limited by the number of stations, there may be only one site in a spatial layer. However, this has no significant impact on the analysis. Stations in each city are planned and relatively evenly arranged in the built-up area by MEE according to the built-up area, population, and other factors. In addition, the monitoring range of these stations can reach 4 km. The setting principle of these stations thereby effectively reflects the $PM_{2.5}$ pollution level of that area.

5. Conclusion

This study presented the spatiotemporal variations of $PM_{2.5}$ concentration at the neighborhood scale in five megacities in China from 2015 to 2017. Although $PM_{2.5}$ pollution has been improved in recent years, the days of non-attainment of the five cities accounted for 24%, 8%, 19%, 9%, and 12% in 2017, respectively, and there were some heavy pollution days in winter. In addition to the U-shaped pattern of seasonal and monthly changes in $PM_{2.5}$ concentration and bimodal distribution of diurnal changes, $PM_{2.5}$ concentration in neighborhood-level had great differences within each city. CV indicated that the differences in neighborhood-level $PM_{2.5}$ concentration gradually increased from 2015 to 2017 and were greater in summer when there is a lower pollution level. It is noteworthy that neighborhood-level $PM_{2.5}$ concentration fluctuated mainly between 80% and 120% of each city's overall $PM_{2.5}$ level. Combined with urban structure, the distribution of $PM_{2.5}$ concentrations in the four seasons presented three spatial patterns. Hangzhou exhibited a conventional $PM_{2.5}$ concentration distribution with $PM_{2.5}$ higher at the urban core and lower at the urban fringe area. The difference in $PM_{2.5}$ concentration between the urban core area and the fringe area ranged from 11.5% to 16.9%. However, $PM_{2.5}$ concentration was higher at the urban transition area and lower at the urban core area in Wuhan, Hefei, and Nanjing. The maximum difference in $PM_{2.5}$ concentration between the urban core area and the transition area was high as 32.2% in Wuhan. Furthermore, two relative indicators—the range and rate of change in $PM_{2.5}$ concentration—reflecting the dynamic change of $PM_{2.5}$ concentration were used to determine region variations in $PM_{2.5}$ concentrations, showing no significant differences among most sites at different pollution levels.

Because of the number of monitoring stations in a city, data from more sampling sites are needed to obtain more elaborate patterns of the spatiotemporal variations in $PM_{2.5}$ concentrations. Future studies should also investigate the drivers that significantly influence neighborhood-scale $PM_{2.5}$ concentrations, which can help to provide effective spatial strategies to cope with $PM_{2.5}$ pollution.

Credit author statement

Fei Dai: Conceptualization, Supervision, Validation. **Ming Chen:** Data curation and analyses, Investigation, Methodology, Software, Writing- Original draft preparation, Visualization. **Bo Yang:** Writing-Reviewing and Editing, Validation.

Declaration of competing interest

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

Acknowledgements

This study was supported by the General program of National Natural Science Foundation of China (No. 51778254).

References

Aslam, M.Y., Krishna, K.R., Beig, G., Tinmaker, M.I.R., Chate, D.M., 2017. Diurnal evolution of urban heat island and its impact on air quality by using ground observations (SAFAR) over New Delhi. Open J. Air Pollut. 6, 52–64.

Boarnet, M.G., Houston, D., Edwards, R., Princevac, M., Ferguson, G., Pan, H., Bartolome, C., 2011. Fine particulate concentrations on sidewalks in five Southern California cities. Atmos. Environ. 45, 4025–4033.

Chen, M., Dai, F., Yang, B., Zhu, S., 2019a. Effects of neighborhood green space on $PM_{2.5}$ mitigation: evidence from five megacities in China. Build. Environ. 156, 33–45.

Chen, M., Dai, F., Yang, B., Zhu, S., 2019b. Effects of urban green space morphological pattern on variation of $PM_{2.5}$ concentration in neighborhoods of five Chinese megacities. Build. Environ. 158, 1–15.

Chen, X., Feng, J., 2019. Health effects of built environment based on a comparison of walkability and air pollution: a case study of Nanjing City. Prog. Geogr. 38 (2), 296–304.

Chen, Z., Chen, D., Xie, X., Cai, J., Zhuang, Y., Cheng, N., He, B., Gao, B., 2019c. Spatial self-aggregation effects and national division of city-level $PM_{2.5}$ concentrations in China based on spatio-temporal clustering. J. Clean. Prod. 207, 875–881.

Cheng, Y., Lee, S.C., Gao, Y., Cui, L., Deng, W., Cao, J., Shen, Z., Sun, J., 2015. Real-time measurements of $PM_{2.5}$, $PM_{10\text{-}2.5}$, and BC in an urban street canyon. Particuology 20, 134–140.

Cheng, Z., Luo, L., Wang, S., Wang, Y., Sharma, S., Shimadera, H., Wang, X., Bressi, M., de Miranda, R.M., Jiang, J., Zhou, W., Fajardo, O., Yan, N., Hao, J., 2016. Status and characteristics of ambient $PM_{2.5}$ pollution in global megacities. Environ. Int. 89–90, 212–221.

Chu, N., Kadane, J.B., Davidson, C.I., 2009. Identifying likely $PM_{2.5}$ sources on days of elevated concentration: a simple statistical approach. Environ. Sci. Technol. 43 (7), 2407–2411.

Cui, M., Lu, H., Etyemezian, V., Su, Q., 2019. Quantifying the emission potentials of fugitive dust sources in Nanjing, East China. Atmos. Environ. 2017, 129–135.

Dawson, J.P., Adams, P.J., Pandis, S.N., 2007. Sensitivity of $PM_{2.5}$ to climate in the eastern US: a modeling case study. Atmos. Chem. Phys. 7 (16), 4295–4309.

Edussuriya, R., Chan, A., Ye, A., 2011. Urban morphology and air quality in dense residential environments in Hong Kong. Part I: district-level analysis. Atmos. Environ. 45 (27), 4789–4803.

Fang, K., Wang, T., He, J., Wang, T., Xie, X., Tang, Y., Shen, Y., Xu, A., 2020. The distribution and drivers of $PM_{2.5}$ in a rapidly urbanizing region: the Belt and Road Initiative in focus. Sci. Total Environ. 716, 137010.

Feng, H., Zou, B., Tang, Y., 2017. Scale-and region-dependence in landscape-$PM_{2.5}$ correlation: implications for urban planning. Rem. Sens. 9 (9), 918.

Fontes, T., Li, P., Barros, N., Zhao, P., 2017. Trends of $PM_{2.5}$ concentrations in China: a long term approach. J. Environ. Manag. 196, 719–732.

He, J., Gong, S., Yu, Y., Yu, L., Wu, L., Mao, H., Song, C., Zhao, S., Liu, H., Li, R., Li, X., 2017. Air pollution characteristics and their relation to meteorological conditions during 2014-2015 in major Chinese cities. Environ. Pollut. 223, 484–496.

Jiang, L., He, S., Zhou, H., 2020. Spatio-temporal characteristics and convergence trends of $PM_{2.5}$ pollution: a case study of cities of air pollution transmission channel in Beijing-Tianjin-Hebei region. China. J. Cleaner Prod. 256, 120631.

Jin, Q., Fang, X., Wen, B., Shan, A., 2017. Spatio-temporal variations of $PM_{2.5}$ emission in China from 2005 to 2014. Chemosphere 183, 429–436.

Kan, H., Chen, R., Tong, S., 2012. Ambient air pollution, climate change, and population health in China. Environ. Int. 42, 10–19.

Lenschow, P., Abraham, H.J., Kutzner, K., Lutz, M., Preu, J.D., Reichenbacher, W., 2001. Some ideas about the sources of PM10. Atmos. Environ. 35 (S1), S23–S33.

Li, M., Zhang, L., 2014. Haze in China: current and future challenges. Environ. Pollut. 189, 85–86.

Li, R., Wang, Z., Cui, L., Fu, H., Zhang, L., Kong, L., Chen, W., Chen, J., 2019. Air pollution characteristics in China during 2015-2016: spatiotemporal variations and key meteorological factors. Sci. Total Environ. 648, 902–915.

Li, Y., Li, Z., Jiang, Y., Liu, H., 2014. International experience study: explored the strategy of mitigation of traffic pollution. Environ. Prot. Z1 75–77.

Li, Y., Huang, H., Griffith, S.M., Wu, C., Lau, A.K.H., Yu, J., 2017. Quantifying the relationship between visibility degradation and $PM_{2.5}$ constituents at a suburban site in Hong Kong: differentiating contributions from hydrophilic and hydrophobic organic compounds. Sci. Total Environ. 575, 1571–1581.

Liu, X., Yu, X., Zhang, Z., Liu, M., Ruan, S., 2014. Pollution characteristics of atmospheric particulates in forest belts and their relationship with meteorological conditions. China J. Ecol. 33, 1715–1721.

Liu, Y., Wu, J., Yu, D., 2018. Disentangling the complex effects of socioeconomic, climatic, and urban form factors on air pollution: a case study of China. Sustainability 10 (3), 776.

Liu, Z., Wang, Y., Hu, B., Ji, D., Zhang, J., Wu, F., Wan, X., Wang, Y., 2016. Source appointment of fine particle number and volume concentration during severe haze pollution in Beijing in January 2013. Environ. Sci. Pollut. Res. 23 (7), 6845–6860.

Lu, D., Mao, W., Yang, D., Zhao, J., Xu, J., 2018. Effects of land use and landscape pattern on $PM_{2.5}$ in Yangtze River Delta, China. Atmos. Pollut. Res. 9 (4), 705–713.

Merbitz, H., Fritz, S., Schneider, C., 2012. Mobile measurements and regression modeling of the spatial particulate matter variability in an urban area. Sci. Total Environ. 438, 389–403.

National ambient air quality standard (NAAQS). Available at: http://www.mep.gov.cn/, Accessed date: 24 April 2019.

Ni, Z., Luo, K., Zhang, J., Feng, R., Zheng, H., Zhu, H., Wang, J., Fan, J., Gao, X., Cen, K., 2018. Assessment of winter air pollution episodes using long-range transport modeling in Hangzhou, China, during World Internet Conference, 2015. Environ. Pollut. 236, 550–561.

Nowak, D.J., Crane, D.E., Stevens, J.C., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban for. Urban Green 4 (34), 115–123 . .

Peng, J., Chen, S., Lü, H., Liu, Y., Wu, J., 2016. Spatiotemporal patterns of remotely sensed $PM_{2.5}$ concentration in China from 1999 to 2011. Remote Sens. Environ. 174, 109–121.

Romero, H., Ihl, M., Rivera, A., Zalazar, P., Azocar, P., 1999. Rapid urban growth, land-use changes and air pollution in Santiago, Chile. Atmos. Environ. 33, 4039–4047.

State Environmental Protection Administration (SEPA), 2007. Available at: http://www.mee.gov.cn/gkml/zj/gg/200910/t20091021_171691.htm, Accessed date: 24 April 2019.

Song, C., Wu, L., Xie, Y., He, J., Chen, X., Wang, T., Lin, Y., Jin, T., Wang, A., Liu, Y., Dai, Q., Liu, B., Wang, Y., Mao, H., 2017. Air pollution in China: status and spatiotemporal variations. Environ. Pollut. 227, 334–347.

Stull, R., 1988. An Introduction to Boundary Layer Meteorology. Springer, New York.

Tecer, L.H., Süren, P., Alagha, O., Karaca, F., Tuncel, G., 2008. Effect of meteorological parameters on fine and coarse particulate matter mass concentration in a coal-mining area in Zonguldak, Turkey. J. Air Waste Manag. Assoc. 58, 543–552.

Timmermans, R., Kranenburg, R., Manders, A., Hendriks, C., Segers, A., Dammers, E., Zhang, Q., Wang, L., Liu, Z., Zeng, L., Denier van der Gon, H., Schaap, M., 2017. Source apportionment of PM2.5 across China using LOTOS-EUROS. Atmos. Environ. 164, 370–386.

Tiwari, S., Srivastava, A.K., Bisht, D.B., Parmita, P., Srivastava, M.K., Attri, S.D., 2013. Diurnal and seasonal variations of black carbon and $PM_{2.5}$ over New Delhi, India: influence of meteorology. Atmos. Res. 125–126, 50–62.

Wang, X., Zhang, L., Yao, Z., Ai, S., Qian, Z., Wang, H., BeLue, R., Liu, T., Xiao, J., Li, X., Zeng, W., Ma, W., Lin, H., 2018. Ambient coarse particulate pollution and mortality in three Chinese cities: association and attributable mortality burden. Sci. Total Environ. 628–629, 1037–1042.

Wang, Z., Fang, C., 2016. Spatiotemporal characteristics and determinants of $PM_{2.5}$ in the Bohai rim urban agglomeration. Chemosphere 148, 148–162.

Wolf-Benning, U., Draheim, T., Endlicher, W., 2009. Spatial and temporal differences of particulate matter in Berlin. Int. J. Environ. Waste Manag. 4 (1–2), 3–16.

Xia, H., Wang, H., Ji, G., 2019. Regional inequality and influencing factors of primary PM emissions in the Yangtze River Delta, China. Sustainability. 11 (8), 2269.

Xiong, Y., Zhou, J., Schauer, J.J., Yu, W., Hu, Y., 2017. Seasonal and spatial differences in source contributions to $PM_{2.5}$ in Wuhan, China. Sci. Total Environ. 577, 155–165.

Xu, G., Ren, X., Xiong, K., Li, L., Bi, X., Wu, Q., 2020. Analysis of the driving factors of PM2.5 concentration in the air: a case study of the Yangtze River Delta, China. Ecol. Indicat. 110, 105889.

Xu, L., Batterman, S., Chen, F., Li, J., Zhong, X., Feng, Y., Rao, Q., Chen, F., 2017. Spatiotemporal characteristics of $PM_{2.5}$ and PM_{10} at urban and corresponding background sites in 23 cities in China. Sci. Total Environ. 599, 2074–2084.

Xu, X., Zhang, T., 2020. Spatial-temporal variability of $PM_{2.5}$ air quality in Beijing, China during 2013–2018. J. Environ. Manag. 262, 110263.

Xue, H., Liu, G., Zhang, H., Hu, R., Wang, X., 2019. Similarities and differences in PM_{10} and $PM_{2.5}$ concentrations, chemical compositions and sources in Hefei City, China. Chemosphere 220, 760–765.

Yang, D., Chen, Y., Miao, C., Liu, D., 2020. Spatiotemporal variation of $PM_{2.5}$ concentrations and its relationship to urbanization in the Yangtze river delta region, China. Atmos. Pollut. Res. 11, 491–498.

Ye, W., Ma, Z., Ha, X., 2018. Spatiotemporal patterns of $PM_{2.5}$ concentrations for 338 Chinese cities. Sci. Total Environ. 631–632, 524–533.

Yuan, M., Song, Y., Hong, S., Huang, Y., 2017. Evaluating the effects of compact growth on air quality in alreadyhigh-density cities with an integrated land use-transport-emission model: a case study of Xiamen, China. Habitat Int. 69, 37–47.

Zhang, M., Ma, Y., Wang, L., Gong, W., Hu, B., Shi, Y., 2017. Spatiotemporal characteristics of aerosol loading over the Yangtze River basin during 2001-2015. Int. J. Climatol. 38, 2138–2152.

Zhang, N., Ma, F., Qin, C., Li, Y., 2018. Spatiotemporal trends in $PM_{2.5}$ levels from 2013 to 2017 and regional demarcations for joint prevention and control of atmospheric pollution in China. Chemosphere 210, 1176–1184.

Zhang, H., Xu, T., Zong, Y., Tang, H., Liu, X., Wang, Y., 2015. Influence of meteorological conditions on pollutant dispersion in street canyon. Procedia Eng. 121, 899–905.
Zhang, Y., Cao, F., 2015. Fine particulate matter ($PM_{2.5}$) in China at a city level. Sci. Rep. 5, 14884.
Zhao, S., Yu, Y., Yin, D., He, J., Liu, N., Qu, J., Xiao, J., 2016. Annual and diurnal variations of gaseous and particulate pollutants in 31 provincial capital cities based on in situ air quality monitoring data from China National Environmental Monitoring Center. Environ. Int. 86, 92–106.
Zheng, S., Zhou, X., Singh, R.P., Wu, Y., Ye, Y., Wu, C., 2017. The Spatiotemporal distribution of air pollutants and their relationship with land-use patterns in Hangzhou City, China. Atmosphere 8 (6), 110.
Zhou, C., Chen, J., Wang, S., 2018. 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. Sci. Total Environ. 619, 436–445.