



Understanding meteorological influences on PM_{2.5} concentrations across China: a temporal and spatial perspective

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Received: 24 April 2017 – Discussion started: 24 July 2017

Revised: 14 March 2018 – Accepted: 1 April 2018 – Published: 19 April 2018

Abstract. With frequent air pollution episodes in China, growing research emphasis has been put on quantifying meteorological influences on PM_{2.5} concentrations. However, these studies mainly focus on isolated cities, whilst meteorological influences on PM_{2.5} concentrations at the national scale have not yet been examined comprehensively. This research employs the CCM (convergent cross-mapping) method to understand the influence of individual meteorological factors on local PM_{2.5} concentrations in 188 monitoring cities across China. Results indicate that meteorological influences on PM_{2.5} concentrations have notable seasonal and regional variations. For the heavily polluted North China region, when PM_{2.5} concentrations are high, meteorological influences on PM_{2.5} concentrations are strong. The dominant meteorological influence for PM_{2.5} concentrations varies across locations and demonstrates regional similarities. For the most polluted winter, the dominant meteorological driver for local PM_{2.5} concentrations is mainly the wind within the North China region, whilst precipitation is the dominant meteorological influence for most coastal regions. At the national scale, the influence of temperature, humidity and wind on PM_{2.5} concentrations is much larger than that of other meteorological factors. Amongst eight factors, temperature exerts the strongest and most stable influence on national PM_{2.5} concentrations in all seasons. Due to notable temporal and spatial differences in meteorologi-

cal influences on local PM_{2.5} concentrations, this research suggests pertinent environmental projects for air quality improvement should be designed accordingly for specific regions.

1 Introduction

With rapid social and economic growth in China, both the government and residents are placing more and more emphasis on the sustainability of the ambient environment, and air quality has become one of the most concerning social and ecological issues. Since 2013, the frequency of air pollution episodes with high PM_{2.5} concentrations and the number of cities influenced by PM_{2.5} pollution have increased notably in China. Statistical records from the national air quality publishing platform (<http://113.108.142.147:20035/emcpublish/>, last access: 18 October 2017) revealed that PM_{2.5}-induced pollution episodes occurred in 25 provinces and more than 100 medium–large cities, whilst there were on average 30 days with hazardous PM_{2.5} concentrations for each monitoring city in 2014.

High PM_{2.5} concentrations not only influence people's daily life (e.g., high PM_{2.5} concentrations caused severe traffic jam), but also severely threaten the health of residents, who suffer from polluted air quality. Recent studies have

suggested that airborne pollutants, PM_{2.5} in particular, are closely related to cardiovascular disease-related mortality (Garrett and Casimiro, 2011; Li et al., 2015a; Lanzinger et al., 2015), emergency room visits (Qiao et al., 2014) and all-year non-accidental mortality (Pasca et al., 2014). Due to its strong negative influences on public health, scholars have been working towards a better understanding of sources (Guo et al., 2012; Zhang et al., 2013, 2016; Gu et al., 2014; Liu et al., 2014; Cao et al., 2014), characteristics (Wei et al., 2012; Zhang et al., 2013; Hu et al., 2015; F. Zhang et al., 2015; Zhen et al., 2016) and seasonal variations (Cao et al., 2012; Shen et al., 2014; Yang and Christakos, 2015; Wang et al., 2015; Chen et al., 2015; Y. Chen et al., 2016; Z. Chen et al., 2016) of PM_{2.5}. Meanwhile, large-scale research on the variation and distribution of PM_{2.5} concentrations has been conducted using a variety of remote sensing sources and spatial data analysis methods (Ma et al., 2014; Kong et al., 2016).

One key issue for air quality research is to find the source and influencing factors for airborne pollutants. Although quantitative contributions of different sources (e.g., coal burning and automobile exhaust) to airborne pollutants remain controversial, meteorological influences on airborne pollutants have been examined in depth by more and more scholars. Recent studies conducted in different countries indicated that PM_{2.5} concentrations were closely related to temperature (Pearce et al., 2011; Yadav et al., 2014; Grundstrom et al., 2015), wind speed (Galindo et al., 2011; El-Metwally and Alfaro, 2013; Yadav et al., 2014) and precipitation (Yadav et al., 2014). Meanwhile, meteorological influences on PM_{2.5} concentrations across China have also become a hot research topic. Yao (2017) revealed a generally negative correlation between evaporation and PM_{2.5} concentrations in a series of cities within the North China Plain. Huang et al. (2015) and Yin et al. (2016) found a negative influence of sunshine duration and a positive influence of relative humidity on PM_{2.5} concentrations in Beijing. Li et al. (2015b) suggested that air pressure and temperature were positively correlated with PM_{2.5} concentrations in Chengdu. For Nanjing (T. Chen et al., 2016) and Hong Kong (Fung et al., 2014), precipitation exerted a strong influence on PM_{2.5} concentrations in winter, when the influence of wind speed on PM_{2.5} concentrations was weak. Meanwhile, wind speed exerted a major influence on PM_{2.5} concentrations in Beijing in winter. Through experiments, Guo et al. (2016) found that the influence of precipitation on PM_{2.5} concentrations in Xi'an was weaker than that in Guangzhou. H. Zhang et al. (2015) quantified the correlations between meteorological factors and the main airborne pollutants in three megacities, Beijing, Shanghai and Guangzhou, and pointed out that the influences of meteorological factors on the formation and concentrations of PM_{2.5} varied significantly across seasons and geographical locations. Chen et al. (2017) quantified the meteorological influences on local PM_{2.5} concentrations in the Beijing–Tianjin–Hebei region and revealed that wind, humidity and solar radiation were major meteorological fac-

tors that significantly influenced local PM_{2.5} concentrations in winter. These studies revealed the correlations between PM_{2.5} concentrations and a diversity of meteorological factors in some specific cities. However, findings from these studies conducted at a local scale cannot reveal regional and national patterns of meteorological influences on PM_{2.5} concentrations in China. In addition, these studies mainly employed short-term observation data (e.g., one season or one year) and thus revealed that characteristics of meteorological influences on PM_{2.5} concentrations may be biased by inter-annual variations.

Due to the diversity of meteorological factors and complicated interactions between them, Pearce et al. (2011) suggested that multiple models and methods should be comprehensively employed to quantify the influence of meteorological factors on local airborne pollutants. For complicated interactions between different factors, Sugihara et al. (2012) suggested that correlation analysis between two variables in a complicated ecosystem might lead to mirage correlations and the extracted correlation coefficient between two variables could be influenced significantly by other variables in the ecosystem. Therefore, Sugihara et al. (2012) proposed a CCM (convergent cross-mapping) method to qualify the bi-direction coupling between two variables without the influence from other variables. The CCM method can effectively remove mirage correlations and extract reliable causality between two variables. Our previous research (Chen et al., 2017) found that the CCM method performed better in quantifying the influence of individual meteorological factors on PM_{2.5} concentrations than traditional correlation analysis through comprehensive comparison. However, this study mainly focused on the meteorological influences on PM_{2.5} concentrations in a specific region. As pointed out by some scholars (He et al., 2017), interactions between meteorological factors and airborne pollutants have great variations across different regions. China is a large country, including many regions with completely different air pollution levels, geographical conditions and meteorological types. To better understand the variations of meteorological influences on PM_{2.5} concentrations, a comparative study at the national scale is required.

According to these challenges, this research aims to analyze and compare the influence of individual meteorological factors on PM_{2.5} concentrations across China. Based on the CCM causality analysis, we quantified the influence of eight meteorological factors on PM_{2.5} concentrations in 188 monitoring cities across China using the observation data from March 2014 to February 2017. To comprehensively understand the spatio-temporal patterns of meteorological influences on PM_{2.5} concentrations across China, we (a) investigated comprehensive meteorological influences on PM_{2.5} concentrations in 37 regional representative cities, (b) extracted the seasonal dominant meteorological factor for each monitoring city, and (c) conducted comparative statistics of

the influence of different meteorological factors on PM_{2.5} concentrations at the national scale.

2 Materials

2.1 Data sources

2.1.1 PM_{2.5} data

PM_{2.5} data are acquired from the website www.PM25.in (last access: 18 October 2017). This website collects official data of PM_{2.5} concentrations provided by the China National Environmental Monitoring Center (CNEMC) and publishes hourly air quality information for all monitoring cities. Before 1 January 2015, PM25.in published data of 190 monitoring cities. Since 1 January 2015, the number of monitoring cities has increased to 367. By calling a specific API (Application Programming Interface) provided by PM25.in, we collect hourly PM_{2.5} data for target cities. The daily PM_{2.5} concentration for each city is calculated using the averaged value of hourly PM_{2.5} concentrations measured at all available local observation stations. For a consecutive division of different seasons and multiple-year analysis, we collected PM_{2.5} data from 1 March 2014 to 28 February 2017 for the following analysis.

2.1.2 Meteorological data

The meteorological data for these monitoring cities are obtained from the “China Meteorological Data Sharing Service System”, part of the National Science and Technology Infrastructure. The meteorological data are collected through thousands of observation stations across China. Previous studies (H. Zhang et al., 2015; Pearce et al., 2011; Yadav et al., 2014) revealed that such meteorological factors as relative humidity, temperature, wind speed, wind direction, solar radiation, evaporation, precipitation, and air pressure might be related to PM_{2.5} concentrations. Therefore, to comprehensively understand meteorological driving forces for PM_{2.5} concentrations in China, all these potential meteorological factors were selected as candidate factors. To better quantify the role of individual meteorological factors in affecting local PM_{2.5} concentrations, these factors are further categorized into some sub-factors: evaporation (small evaporation and large evaporation), temperature (daily max temperature, mean temperature, minimum temperature, and the largest temperature difference for the day), precipitation (total precipitation from 08:00 to 20:00, total precipitation from 20:00 to 08:00 and total precipitation for the day), air pressure (daily max pressure, mean pressure and minimum pressure), humidity (daily mean and minimum relative humidity), radiation (sunshine duration for the day, short for SSD), wind speed (mean wind speed, max wind speed and extreme wind speed), and wind direction (max wind direction for the day). Some meteorological factors are briefly explained here. Evaporation indi-

cates the amount of evaporation-induced water loss during a certain period and is usually calculated using the depth of evaporated water in a container. For this research, small (large) evaporation indicates the amount of evaporated water measured using a container with a diameter of 10 cm (30 cm) during 24 h (unit: mm). Generally, the measured values using the two types of equipment have slight differences. SSD represents the hours of sunshine measured during a day for a specific location on earth. The max wind speed indicates the max mean wind speed during any 10 min within a day's time. The extreme wind speed indicates the max instant (for 1 s) wind speed within a day's time. The max wind direction indicates the dominant wind direction for the period with the max wind speed. As there are one or more observation stations for each city, the daily value for each meteorological factor for each city was calculated using the mean value of all available observation stations within the target city. To conduct time-series comparison, we also collected meteorological data from 1 March 2014 to 28 February 2017.

2.2 Study sites

For a comprehensive understanding of meteorological influences on local PM_{2.5} concentrations across China, all monitoring cities (except for Liaocheng and Zhuji, where continuous valid meteorological data were not available) during the study period were selected for this research. The 188 cities included most major cities (Beijing, Shanghai, Guangzhou, etc.) in China. For regions (e.g., the Beijing–Tianjin–Hebei region) with heavy air pollution, the density of monitored cities was much higher than that in regions with good air quality.

3 Methods

Due to complicated interactions in the atmospheric environment, it is highly difficult to quantify the causality of individual meteorological factors on PM_{2.5} concentrations through correlation analysis. Instead, a robust causality analysis method is required.

To extract the coupling between individual variables in complex systems, Sugihara et al. (2012) proposed the CCM method. Different from Granger causality (GC) analysis (Granger, 1980), the CCM method is sensitive to weak to moderate coupling in ecological time series. By analyzing the temporal variations of two time-series variables, their bidirectional coupling can be featured with a convergent map. If the influence of one variable on the other variable is presented as a convergent curve with increasing time-series length, then the causality is detected; if the curve demonstrates no convergent trend, then no causality exists. The predictive skill (defined as the ρ value), which ranges from 0 to 1, suggests the quantitative causality of one variable on the other.

The principle of CCM algorithms is briefly explained as follows (Luo et al., 2014). Two time series $\{X\} = [X(1), \dots, X(L)]$ and $\{Y\} = [Y(1), \dots, Y(L)]$ are defined as the temporal variations of two variables X and Y . For $r = S$ to L ($S < L$), two partial time series $[X(1), \dots, X(L_P)]$ and $[Y(1), \dots, Y(L_P)]$ are extracted from the original time series (r is the current position, whilst S is the start position in the time series). Following this, the shadow manifold M_X is generated from $\{X\}$, which is a set of lagged-coordinate vectors $x(t) = \langle X(t), X(t - \tau), \dots, X(t - (E - 1)\tau) \rangle$ for $t = 1 + (E - 1)\tau$ to $t = r$. To generate a cross-mapped estimate of $Y(t)|\hat{Y}(t)|M_X$, the contemporaneous lagged-coordinate vector on M_X , $x(t)$ is located, and then its $E + 1$ nearest neighbors are extracted, where $E + 1$ is the minimum number of points required for a bounding simplex in an E -dimensional space (Sugihara and May, 1990). Next, the time index of the $E + 1$ nearest neighbors of $x(t)$ is denoted as t_1, \dots, t_{E+1} . These time indexes are used to identify neighbor points in Y and then estimate $Y(t)$ according to a locally weighted mean of $E + 1$ $Y(t_i)$ values (Eq. 1).

$$\hat{Y}(t)|M_X = \sum_{i=1}^{E+1} w_i Y(t_i), \quad (1)$$

where w_i is a weight calculated according to the distance between $X(t)$ and its i th nearest neighbor on M_X . $Y(t_i)$ are contemporaneous values of Y . The weight w_i is determined according to Eq. (2).

$$w_i = u_i / \sum_{j=1}^{E+1} u_j, \quad (2)$$

where $u_i = e^{-d[\underline{x}(t), \underline{x}(t_i)]/d[\underline{x}(t), \underline{x}(t_1)]}$, whilst $d[\underline{x}(t), \underline{x}(t_i)]$ represents the Euclidean distance between two vectors.

In our previous research, interactions between the air quality in neighboring cities (Z. Chen et al., 2016), and bidirectional coupling between individual meteorological factors and PM_{2.5} concentrations (Chen et al., 2017) were quantified effectively using the CCM method. By comparing the performance of correlation analysis and CCM method, Z. Chen et al. (2017) suggested that correlation analysis might lead to a diversity of biases due to complicated interactions between individual meteorological factors. Firstly, some mirage correlations (two variables with a moderate correlation coefficient) extracted using the correlation analysis were revealed effectively using the CCM method (the ρ value between two variables was 0). Secondly, some weak coupling, which was hardly detected using the correlation analysis (the correlation between the two variables were not significant), was extracted using the CCM method (a small ρ value). Meanwhile, as Sugihara et al. (2012) suggested, the correlation between two variables could be influenced significantly by other agent variables and thus the value of correlation coefficient between two variables could not reflect the actual causality between them. Chen et al. (2017) further revealed that the correlation coefficient between individual meteorological factors and PM_{2.5} concentrations was usually much

larger than the ρ value. This indicated that the causality of individual meteorological factors on PM_{2.5} concentrations was generally overestimated using the correlation analysis, due to the influences from other meteorological factors. In this case, the CCM method is an appropriate tool for quantifying bidirectional interactions between PM_{2.5} concentrations and individual meteorological factors in complicated atmospheric environment.

4 Results

Seasonal variations of PM_{2.5} concentrations have been revealed in Beijing (Chen et al., 2015; Y. Chen et al., 2016; Z. Chen et al., 2016), Nanjing (Shen et al., 2014), Shandong Province (Yang and Christakos, 2015) and the Beijing–Tianjin–Hebei region (Wang et al., 2015; Z. Chen et al., 2017). In addition to these local and regional studies, Cao et al. (2012) further compared seasonal variations of PM_{2.5} concentrations in seven southern cities (Chongqing, Guangzhou, Hong Kong, Hangzhou, Shanghai, Wuhan, and Xiamen) and seven northern cities (Beijing, Changchun, Jin-chang, Qingdao, Tianjin, Xi'an, and Yulin) across China. Hence, the research period was divided into four seasons. According to traditional season division for China, spring was set as the period between 1 March and 31 May 2014; summer was set as the period between 1 June and 31 August 2014; autumn was set as the period between 1 September and 30 November 2014; and winter was set as the period between 1 December 2014 and 28 February 2015. For each city, the bidirectional coupling between individual meteorological factors and PM_{2.5} concentrations in different seasons was analyzed, respectively, using the CCM method. The CCM method is highly automatic and only a few parameters need to be set for running this algorithm: E (number of dimensions for the attractor reconstruction), ρ (time lag) and b (number of nearest neighbors to use for prediction). The value of E can be 2 or 3. A larger value of E produces more accurate convergent maps. The variable b is decided by E ($b = E + 1$). A small value of ρ leads to a fine-resolution convergent map, yet requires much more processing time. Through experiments, we found that the final results were not sensitive to the selection of parameters and different parameters mainly exerted influences on the presentation effects of CCM. In this research, to acquire optimal interpretation effects of convergent cross maps, the value of ρ was set as 2 days and the value of E was set to 3. For each meteorological factor, its causality coupling with PM_{2.5} concentrations can be represented using a convergent map. Since it is not feasible to present all these convergent maps here, we simply display some exemplary maps to demonstrate how CCM works (Fig. 1). As a heavily polluted city, we presented the interactions between PM_{2.5} concentrations and meteorological factors in Beijing in winter, when the local PM_{2.5} concentration was highest, as an example. Four major meteorologi-

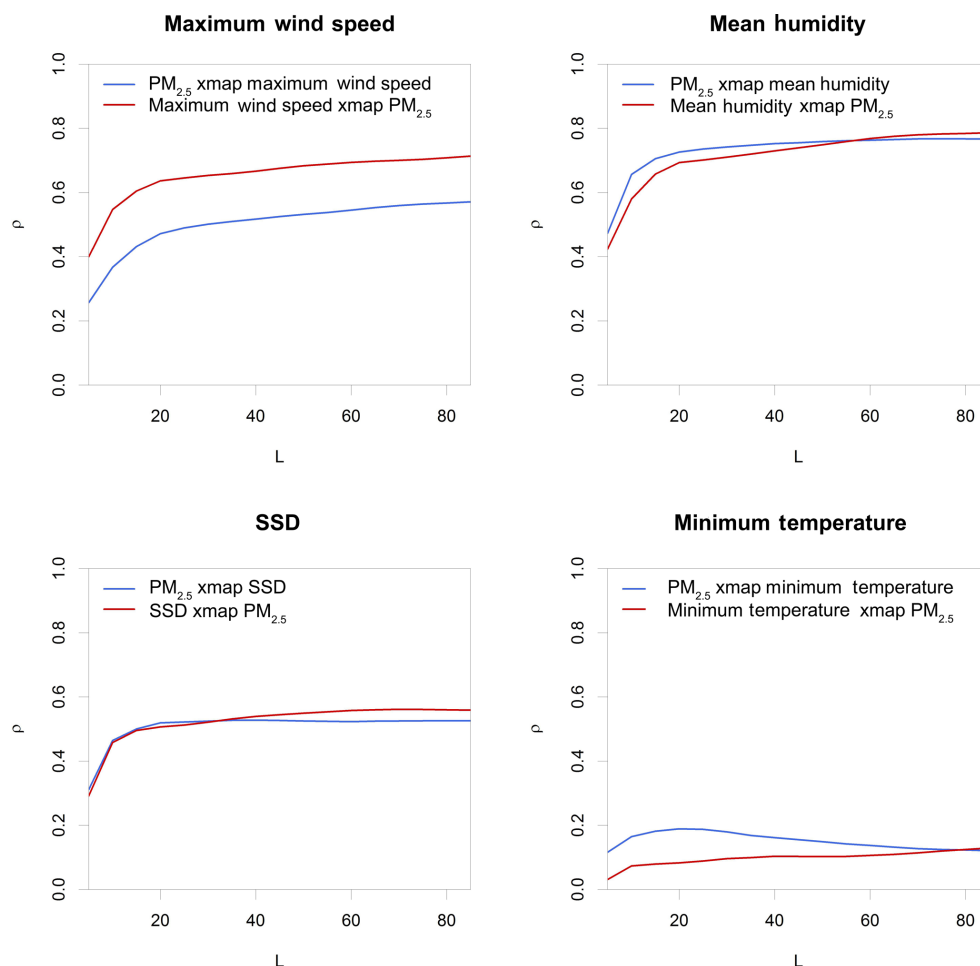


Figure 1. Illustrative CCM results to demonstrate the bidirectional coupling between meteorological factors and PM_{2.5} concentrations in Beijing (2014, winter). ρ : predictive skills. L : the length of time series. A xmap B stands for convergent cross mapping B from A, in other words, the causality of variable B on A. For instance, PM_{2.5} xmap mean humidity stands for the causality of mean humidity on PM_{2.5} concentrations. Mean humidity xmap PM_{2.5} stands for the feedback effect of PM_{2.5} concentrations on mean humidity. ρ indicates the predictive skills of using mean humidity to retrieve PM_{2.5} concentrations.

cal factors, wind, humidity, radiation and temperature, which exerted much stronger influences on PM_{2.5} concentrations than other factors, were employed. Due to the strong bidirectional coupling between PM_{2.5} concentrations and these meteorological factors, Fig. 1 not only demonstrates how CCM output could be interpreted, but also provides readers with a general comparison of the magnitude of simultaneous influences of different meteorological factors on the local PM_{2.5} concentration and its feedback effects.

According to Fig. 1, one can see that the quantitative influence of individual meteorological factors on PM_{2.5} was well extracted using the CCM method, whilst the feedback effect of PM_{2.5} on specific meteorological factors was revealed as well. For Beijing, mean humidity and maximum wind speed exerted a strong influence on local PM_{2.5} concentrations in winter ($\rho > 0.4$), whilst SSD and minimum temperature also had a weaker influence on local PM_{2.5} concentrations (ρ

close to 0.2). On the other hand, high PM_{2.5} concentrations had an even stronger feedback influence on mean humidity, maximum wind speed and SSD (ρ close to 0.6), whilst PM_{2.5} had little influence on minimum temperature (ρ close to 0). The bidirectional coupling between PM_{2.5} concentrations and individual meteorological factors provides a useful reference for a better understanding of the form and development of PM_{2.5}-induced air pollution episodes. For Beijing, low wind speed (high humidity and low SSD) in winter results in high PM_{2.5} concentrations, which in turn causes lower wind speed (higher humidity and lower SSD). In consequence, PM_{2.5} concentrations are increased further by the changing wind (humidity and SSD) situation. This mechanism causes a quickly rising PM_{2.5} concentration, which brings the atmospheric environment to a comparatively stable status. In this case, persistent high-concentration PM_{2.5} is unlikely to disperse and usually lasts for a long period in this

region. Similarly, bidirectional interactions between PM_{2.5} concentrations and other meteorological factors can also be quantified using the CCM method. Since the main aim of this research is to understand the influence of individual meteorological factors on PM_{2.5} concentrations across China, the feedback effect of PM_{2.5} concentrations on specific meteorological factors is not explained in detail herein.

The ρ value is a direct indicator of quantitative causality. For this research, the maximum ρ value of all sub-factors in the same category was used as the causality of this specific meteorological factor on PM_{2.5} concentrations. For example, for a specific city, the maximum ρ value of max temperature, mean temperature, minimum temperature, and the largest temperature difference for the day is used as the influence of temperature on local PM_{2.5} concentrations. For this research, we collected meteorological and PM_{2.5} data for 3 consecutive years. To avoid the analysis of inconsecutive time series, which may influence the CCM result, we did not calculate the general influence of individual meteorological factors on PM_{2.5} concentrations during 2014–2016 by analyzing three isolated periods (e.g., April–June 2014, April–June 2015, and April–June 2016) as a complete data set. Instead, for each city, we quantified the influence of individual meteorological factors on PM_{2.5} concentrations for each season in 2014, 2015 and 2016, respectively, and calculated the mean ρ value during 2014–2016 for each city.

4.1 Comprehensive meteorological influences on PM_{2.5} concentrations in some regional representative cities

When the ρ value for each meteorological factor was calculated, a wind rose, which presents the quantitative influences of all individual meteorological factors on PM_{2.5} concentrations, can be produced for each city. It is not feasible to present all 188 wind roses simultaneously, due to severe overlapping effects. Thus, considering the social-economic factors, 37 regional representative cities (including all 31 provincial capital cities in mainland China), which are the largest and most important cities for specific regions, were selected to produce a wind rose map of meteorological influences on PM_{2.5} concentrations across China (Fig. 2).

According to Fig. 2, some spatial and temporal patterns of meteorological influences on PM_{2.5} concentrations at the national scale can be found as follows.

1. Like seasonal variations of PM_{2.5} concentrations, the influences of individual meteorological factors on local PM_{2.5} concentrations vary significantly. For a specific city, the dominant meteorological driver for PM_{2.5} concentrations in one season may become insignificant in another season. For example, in winter, one major meteorological influencing factor for Beijing is wind (the mean ρ value during 2014–2016 was 0.57), which exerts little influence on PM_{2.5} concentrations in summer (the mean ρ value during 2014–2016 was 0.10). Fur-

thermore, it is noted that seasonal variations of meteorological influences on PM_{2.5} concentrations apply to all these representative cities, as the shape and size of the wind rose for each city change significantly across different seasons. Take several mega-cities in different regions for instance. During 2014–2016, the three major meteorological influencing factors for PM_{2.5} concentrations in Beijing (North China Plain), Shanghai (Yangtze River Basin), Wuhan (Central China region) and Guangzhou (South China region) were listed as Table 1. According to Table 1, notable seasonal variations of meteorological influences on PM_{2.5} concentrations were found in these mega-cities across China.

2. In spite of notable differences in the shape and size of wind roses, meteorological influences on PM_{2.5} concentrations have some regional patterns. PM_{2.5} concentrations in cities within the North China region are influenced by similar dominant meteorological factors, especially in winter, when PM_{2.5} concentrations in these cities are high. Take four major cities, Beijing, Tianjin, Taiyuan and Shijiazhuang, in the North China Plain for example. For winter, SSD, evaporation, humidity and wind were the major meteorological factors for PM_{2.5} concentrations in the four cities and the ρ value of these four factors was 0.50, 0.52, 0.76 and 0.57 for Beijing, 0.41, 0.44, 0.56 and 0.50 for Tianjin, 0.44, 0.36, 0.61 and 0.41 for Taiyuan, and 0.62, 0.58, 0.56 and 0.60 for Shijiazhuang, respectively, presenting a similar regional pattern. Meanwhile, meteorological influences on PM_{2.5} concentrations in cities within the Yangtze River Basin, especially the dominant factors, also had some regional similarities. Take four major cities in the Yangtze River Basin, Shanghai, Nanjing, Hangzhou and Nanchang, for example. For summer, precipitation, humidity, temperature and wind were the major meteorological factors for PM_{2.5} concentrations in these four cities and the ρ value of these factors was 0.21, 0.27, 0.40 and 0.38 for Shanghai, 0.29, 0.41, 0.34 and 0.33 for Nanjing, 0.28, 0.27, 0.23 and 0.27 for Hangzhou, and 0.24, 0.33, 0.21 and 0.29 for Nanchang. Despite some differences in the ρ values, similar dominant meteorological factors and the similar magnitude of meteorological influences demonstrated regional similarities of meteorological influences on PM_{2.5} concentrations in the Yangtze River Basin. As we can see, meteorological influences on PM_{2.5} concentrations in China are mainly controlled by geographical conditions (e.g., terrain and landscape patterns).
3. For the heavily polluted North China region, the higher the local PM_{2.5} concentrations, the larger the influence meteorological factors exert on PM_{2.5} concentrations. PM_{2.5} concentrations are usually the highest in winter, causing serious air pollution episodes across China, the North China region in particular. Meanwhile, PM_{2.5}

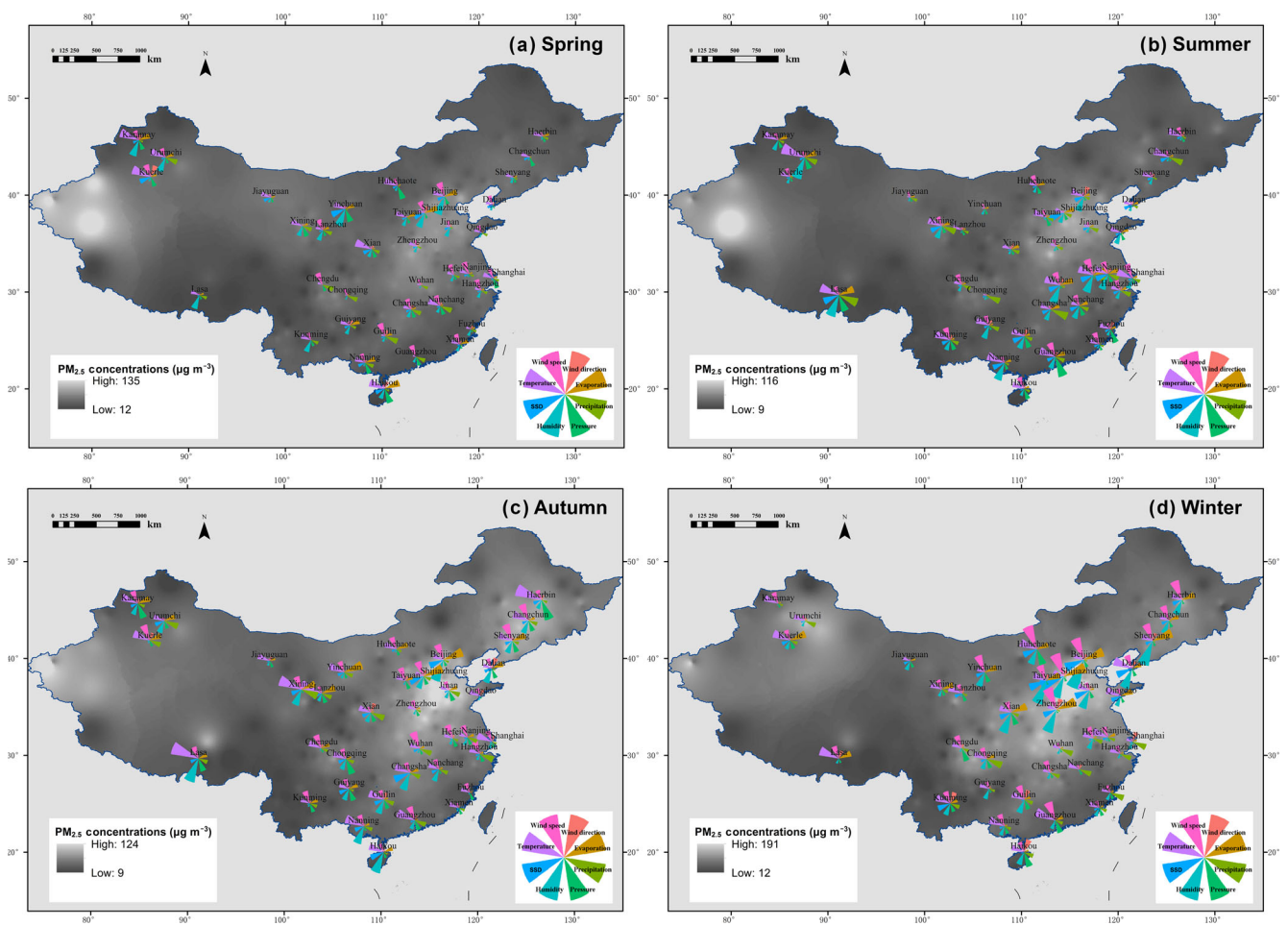


Figure 2. Wind rose map of influences of eight individual meteorological factors on PM_{2.5} concentrations across mainland China (37 representative cities) during 2014–2016.

Table 1. Major meteorological influencing factors for PM_{2.5} concentrations in four mega-cities within different regions.

City	Season	Three major meteorological factors		
Beijing	Spring	Humidity (0.48)	Wind (0.37)	Evaporation(0.31)
	Summer	Humidity (0.39)	Temperature (0.34)	SSD (0.25)
	Autumn	Humidity (0.56)	Evaporation (0.51)	Wind (0.41)
	Winter	Humidity (0.76)	Wind (0.57)	Evaporation (0.52)
Shanghai	Spring	Temperature (0.264)	Air pressure (0.260)	Wind (0.25)
	Summer	Temperature (0.40)	Wind (0.38)	Humidity (0.27)
	Autumn	Temperature (0.39)	Wind (0.28)	Humidity (0.17)
	Winter	Precipitation (0.36)	Wind direction (0.25)	Humidity (0.19)
Wuhan	Spring	Precipitation(0.18)	Wind (0.16)	Temperature (0.09)
	Summer	Humidity (0.47)	Temperature (0.41)	Wind (0.34)
	Autumn	Wind (0.44)	Precipitation (0.31)	Temperature (0.26)
	Winter	Precipitation (0.33)	Temperature (0.19)	Wind (0.15)
Guangzhou	Spring	Wind (0.31)	Precipitation (0.24)	Air pressure (0.23)
	Summer	Air pressure (0.51)	Temperature (0.41)	Wind (0.37)
	Autumn	Temperature (0.47)	Wind (0.36)	Precipitation (0.29)
	Winter	Temperature (0.52)	Wind (0.48)	Air pressure (0.33)

concentrations in spring and summer are comparatively low. Accordingly, there are more influencing meteorological factors on PM_{2.5} concentrations for cities within this region and the ρ value of these meteorological factors is notably larger in winter. Take the summer and winter major influencing meteorological factors for PM_{2.5} concentrations in four major cities in the North China region for instance (as shown in Table 2). As explained, bidirectional interactions between meteorological factors and PM_{2.5} concentrations may lead to complicated mechanisms that further enhance local PM_{2.5} concentrations significantly. Therefore, strong meteorological influences on PM_{2.5} concentrations in winter are a major cause of the form and persistence of high PM_{2.5} concentrations within the North China region.

4.2 Spatial and temporal variations of the dominant meteorological influence on local PM_{2.5} concentrations across China

Through statistical analysis, we selected the factor with the largest ρ value as the dominant meteorological factor for local PM_{2.5} concentrations. The spatial and temporal variations of the dominant meteorological influence on local PM_{2.5} concentrations across China are demonstrated as Fig. 3. According to Fig. 3, some spatio-temporal characteristics of meteorological influences on PM_{2.5} concentrations can be further concluded.

1. The dominant meteorological factor for PM_{2.5} concentrations is closely related to geographical conditions. For instance, the factor of precipitation may exert a key influence on local PM_{2.5} concentrations in some coastal cities and cities within the Yangtze River Basin, whilst this meteorological factor exerts limited influence on PM_{2.5} concentrations within some inland regions. Here we analyzed the ρ value of precipitation in cities within the Yangtze River Basin and cities within the Beijing–Tianjin–Hebei region, respectively. For winter, precipitation was the dominant factor for PM_{2.5} concentrations in Shanghai, Hangzhou and Nanchang within the Yangtze River Basin and the ρ value of precipitation was 0.36, 0.29 and 0.31, respectively. Meanwhile, the ρ value of precipitation in Beijing, Tianjin and Shijiazhuang within the Beijing–Tianjin–Hebei region was 0.08, 0.01 and 0.06, respectively.
2. Some meteorological factors can be the dominant factor for cities within different regions, whilst some (e.g., evaporation and SSD) are mainly the dominant meteorological factor for PM_{2.5} concentrations in cities within some specific regions. In other words, some factors can be regarded as regional and national meteorological influencing factors for PM_{2.5} concentrations, yet some meteorological factors are context-related, influ-

encing factors for local PM_{2.5} concentrations. Specifically, such factors as temperature, wind and humidity serve as the dominant meteorological factors in many regions, including Northeast, Northwest, coastal areas and inland areas; meanwhile, such factors as SSD and wind direction serve as the dominant meteorological factors mainly in some inland regions. The prevalence of different meteorological factors across China can also be reflected according to the number of cities where this specific factor is the dominant factor for local PM_{2.5} concentrations. For winter, the number of cities with temperature, wind or humidity as the dominant factor was 56, 48 and 44, respectively. Meanwhile, the number of cities with SSD or wind direction as the dominant factor was 3 and 1, respectively.

3. Similar to patterns revealed in Fig. 2, the ρ value for the dominant meteorological factors is much larger in winter than that in summer. Furthermore, it is noted that the dominant meteorological factors demonstrate more regional similarity in winter. Specifically, the dominant meteorological factors for PM_{2.5} concentrations in the heavily polluted North China region are more concentrated and homogeneously distributed in winter (mainly the wind and humidity factor), whilst a diversity of dominant meteorological factors (that includes humidity, temperature, SSD and air pressure) for PM_{2.5} concentrations is irregularly distributed within this region in summer. Take some major cities in the North China region for instance. For winter, the dominant meteorological factors for Beijing, Tianjin, Taiyuan, Zhangjiakou, Handan and Jining were humidity (0.76), humidity (0.56), humidity (0.61), wind (0.62), humidity (0.43) and humidity (0.52), respectively. Meanwhile, for summer, the dominant meteorological factors for Beijing, Tianjin, Taiyuan, Zhangjiakou, Baoding, Handan and Jining were humidity (0.39), precipitation (0.28), temperature (0.23), temperature (0.47), air pressure (0.21) and SSD (0.18). According to this pattern, when a regional PM_{2.5}-induced air pollution episode occurs in winter, the regional air quality is more likely to be simultaneously improved by the same meteorological factor. This is consistent with the common scene in winter that regional air pollution episodes in the Beijing–Tianjin–Hebei region can be considerably mitigated by strong northwesterly synoptic winds, which are produced by the presence of high air pressure in northwestern Beijing (NW-High; Tie et al., 2015; Miao et al., 2015). On the other hand, regional air pollution in summer can hardly be solved simultaneously through one specific meteorological factor.

Table 2. Summer and winter major influencing meteorological factors for PM_{2.5} concentrations in four major cities in the North China region.

City	Season	Major influencing meteorological factors			
Beijing	Summer	Humidity 0.39	Temperature 0.34	SSD 0.25	
	Winter	Humidity 0.76	Wind 0.57	Evaporation 0.52	SSD 0.50
Tianjin	Summer	Precipitation 0.34	Air pressure 0.25	Temperature 0.22	
	Winter	Humidity 0.56	Wind 0.50	Evaporation 0.44	SSD 0.41
Shijiazhuang	Summer	SSD 0.4	Humidity 0.26	Evaporation 0.26	
	Winter	SSD 0.62	Wind 0.60	Evaporation 0.58	Humidity 0.56
Taiyuan	Summer	Temperature 0.32	Air pressure 0.23	Precipitation 0.20	
	Winter	Humidity 0.61	SSD 0.44	Wind 0.41	

4.3 Comparative statistics of the influence of individual meteorological factors on local PM_{2.5} concentrations across China

In addition to meteorological influences on PM_{2.5} concentrations for individual cities, we examined and compared the comprehensive influence of individual meteorological factors on PM_{2.5} concentrations at a national scale. The results are presented as Table 3 and Fig. 4.

We compared the influence of individual meteorological factors on PM_{2.5} concentrations from different perspectives.

1. From a national perspective, temperature, humidity, and wind exert stronger influences on local PM_{2.5} concentrations than other factors. The annual mean ρ value for temperature, wind and humidity was 0.287, 0.244 and 0.233, compared with wind direction (0.101), SSD (0.146), evaporation (0.155), precipitation (0.171) and air pressure (0.180). Amongst the eight factors, temperature was found to be the most influential meteorological factor for general PM_{2.5} concentrations in China. In addition to the largest mean ρ value, temperature was the dominant meteorological factors for most cities in all seasons. Furthermore, the Coefficient of Variation ($SD/mean \leq 100\%$) for temperature was much smaller than other factors, indicating the consistent influence of temperature on local PM_{2.5} concentrations across China.
2. Although some meteorological factors exert a limited influence on PM_{2.5} concentrations at a national scale, these factors may be a key meteorological factor for local PM_{2.5} concentrations. As shown in Table 1, the

max ρ value for each meteorological factor was large than 0.35 for all seasons (except for the wind direction factor in summer and autumn), indicating a very strong influence on local PM_{2.5} concentrations in some specific regions. As a result, when analyzing meteorological influences on local PM_{2.5} concentrations for a specific city, meteorological factors that have little influence on PM_{2.5} concentrations at a large scale should also be comprehensively considered.

3. Some factors (e.g., precipitation in summer and winter) may be the dominant meteorological factors for a large number of cities, though the mean ρ value remained small. This may be attributed to the fact that these meteorological factors mainly exert influence on local PM_{2.5} concentrations in those cities (seasons) where (when) the general PM_{2.5} concentrations are not high. Taking the precipitation as an example, Luo et al. (2017) pointed out that there may be thresholds for the negative influences of precipitations on PM_{2.5} concentrations and Guo et al. (2016) found that the same amount of precipitation led to a weaker washing-off effect in areas with higher PM_{2.5} concentrations. Hence, precipitation mainly exerts a dominant influence on local PM_{2.5} concentrations in winter for the Yangtze River Basin or coastal cities, where the amount of precipitation is large and the PM_{2.5} concentration is low, whilst precipitation exerts a limited role in northern China, where the amount of precipitation is small and the PM_{2.5} concentration is high. Therefore, as explained above, comprehensive meteorological influences on PM_{2.5} concentrations are limited considerably.

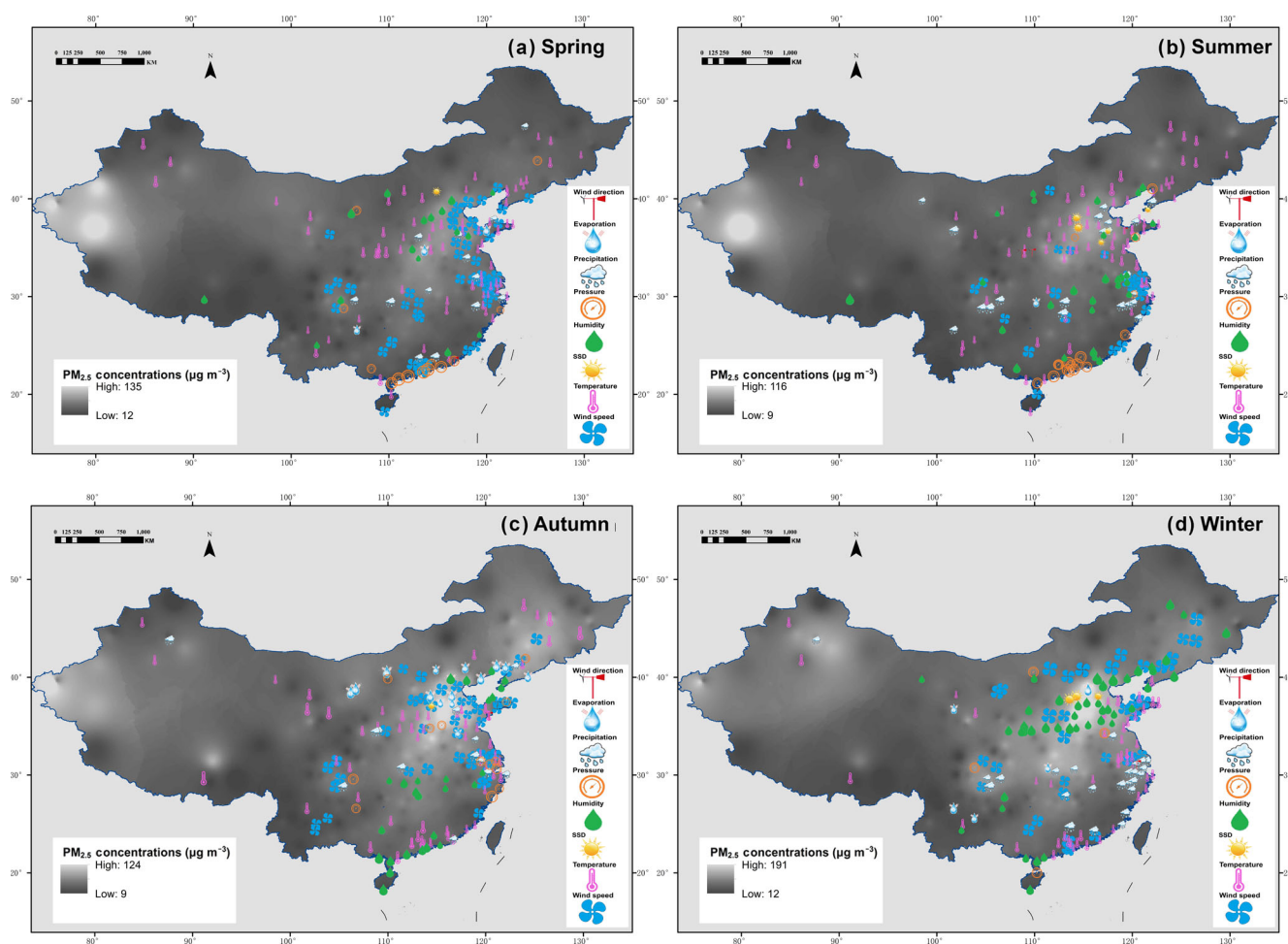


Figure 3. The dominant meteorological factor for local PM_{2.5} concentrations in 188 monitoring cities across mainland China. The size of symbols indicates the ρ value of the meteorological factor on local PM_{2.5} concentrations.

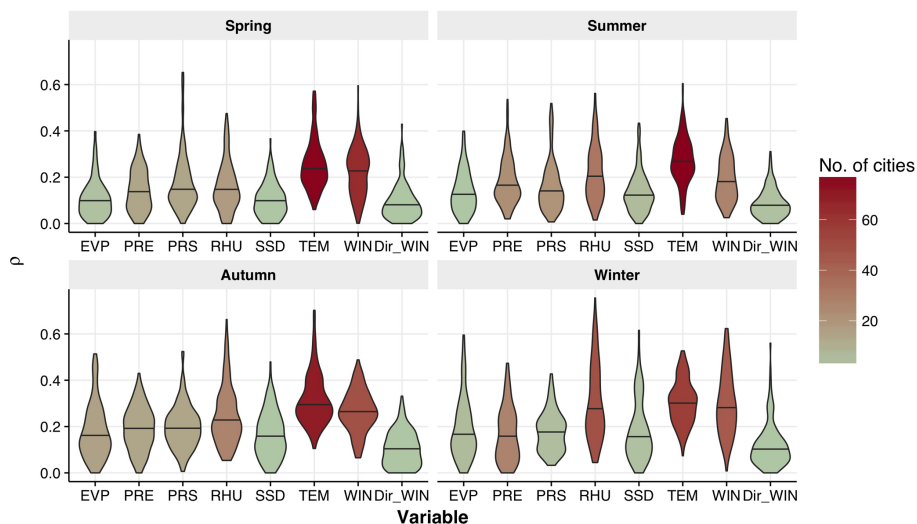


Figure 4. Violin plots of the influence of eight different meteorological factors on local PM_{2.5} concentrations in 188 cities across China. No. of cities: the number of cities with this factor as the dominant meteorological factor (its ρ value is the largest amongst eight factors) on local PM_{2.5} concentrations. The shape of the violin bars indicated the frequency distribution of ρ value for 188 cities.

Table 3. The comparison of the influence of individual meteorological factors on PM_{2.5} concentrations in 188 cities across China (2014–2016).

Season	Factor	TEM	SSD	PRE	EVP	PRS	RHU	WIN	Dir_WIN
Spring	No. of cities*	76	1	13	3	13	17	64	1
	Mean ρ value	0.254	0.102	0.143	0.108	0.177	0.161	0.222	0.094
	SD of ρ value	0.106	0.071	0.088	0.081	0.123	0.105	0.102	0.077
	Max ρ value	0.572	0.366	0.385	0.397	0.653	0.475	0.595	0.429
Summer	No. of cities	78	5	22	1	20	32	27	3
	Mean ρ value	0.272	0.136	0.183	0.137	0.163	0.219	0.191	0.087
	SD of ρ value	0.098	0.086	0.099	0.088	0.109	0.118	0.095	0.062
	Max ρ value	0.604	0.433	0.536	0.399	0.518	0.562	0.453	0.311
Autumn	No. of cities	70	1	13	15	13	27	48	1
	Mean ρ value	0.316	0.164	0.191	0.181	0.199	0.247	0.265	0.104
	SD of ρ value	0.109	0.098	0.093	0.117	0.091	0.125	0.089	0.074
	Max ρ value	0.702	0.479	0.430	0.514	0.524	0.662	0.488	0.331
Winter	No. of cities	56	3	27	5	4	48	44	1
	Mean ρ value	0.306	0.183	0.166	0.190	0.180	0.304	0.299	0.119
	SD of ρ value	0.094	0.129	0.115	0.130	0.086	0.161	0.136	0.092
	Max ρ value	0.527	0.615	0.473	0.595	0.427	0.755	0.623	0.560

* No. of cities: the number of cities with this factor as the dominant meteorological factor (its ρ value is the largest amongst eight factors) on local PM_{2.5} concentrations.

5 Discussion

Correlations between individual meteorological factors and PM_{2.5} concentrations have been analyzed in such mega-cities as Nanjing (T. Chen et al., 2016; Shen and Li, 2016), Beijing (Huang et al., 2015; Yin et al., 2016), Wuhan (Zhang et al., 2017), Hangzhou (Jian et al., 2012), Chengdu (Zeng and Zhang et al., 2017) and Hong Kong (Fung et al., 2014). These studies suggested that meteorological influences on PM_{2.5} concentrations varied significantly across regions. The dominant meteorological factors for P_{2.5} concentrations demonstrated notable regional differences. For Nanjing (T. Chen et al., 2016), a mega-city in the Yangtze River, and Hong Kong (Fung et al., 2014), a mega coastal city, precipitation exerted the strongest influence, whilst wind speed exerted a weak influence on PM_{2.5} concentrations in winter. On the other hand, for winter, wind speed was the dominant meteorological factor for PM_{2.5} concentrations in Beijing (Huang et al., 2015), a mega-city in North China, and precipitation played a weak role in affecting local PM_{2.5} concentrations. Compared with studies at a local or regional scale, this research conducted at the national scale provided a better understanding of spatial and temporal patterns of meteorological influences on PM_{2.5} concentrations across China, for the following reasons. (a) A national perspective. Previous studies conducted at a local scale mainly focused on a specific city (e.g., Beijing), and can hardly reveal spatio-temporal patterns of meteorological influences on PM_{2.5} concentrations at a large scale (e.g., the North China Plain). This research, on the other hand, quantified the influence of meteorological factors on PM_{2.5} concen-

trations for 188 cities across China, and thus revealed some regional patterns of meteorological influences on PM_{2.5} concentrations in some typical regions (e.g., the North China region or the Yangtze River Basin). (b) A unified research period and set of meteorological factors. Previous studies employed short-term observation data (e.g., one season or one year) in specific cities. Due to the discrepancy in research periods and sets of meteorological factors, the findings from different local-scale studies cannot be compared and comprehensively understood. This research employed daily PM_{2.5} and meteorological data of three consecutive years and a unified set of eight meteorological factors for all 188 monitoring cities, and thus meteorological influences on PM_{2.5} concentrations across China can be effectively compared without significant influences from inter-annual variations. (c) A robust causality analysis method. Correlation analysis, as introduced above, may lead to a large bias in quantifying the meteorological influences on PM_{2.5} concentrations. Similarly, the correlation coefficient cannot be used as a reliable indicator to compare quantitative influences of individual meteorological factors on PM_{2.5} concentrations across different cities. This research employed a robust CCM method, which removes the influence of other factors, and effectively quantified the coupling between PM_{2.5} concentrations and a set of meteorological factors. The ρ value of each meteorological factor on PM_{2.5} concentration can be compared between different cities. Based on national statistics across China, this research concluded that the influence of temperature, humidity and wind, especially temperature, on PM_{2.5} concentrations was much larger than that of other meteorological

factors, which could not be revealed by previous local- and regional-scale studies.

The findings from this research were consistent with a major extension of those from previous studies by quantifying the influence of individual meteorological factors in a large number of cities across China using a more robust causality analysis method. Similar to previous studies, this study also revealed notable differences in meteorological influences on PM_{2.5} concentrations at the national scale, which was mainly attributed to different meteorological conditions and complicated mechanisms of PM_{2.5}–meteorology interactions. Firstly, notable differences existed in meteorological conditions across China. For instance, in winter, the frequency and intensity of precipitation are much higher and stronger in coastal areas than those in the North China region, where the frequency of strong winds is high in winter. Therefore, precipitation exerts a large influence on PM_{2.5} concentrations in coastal regions, whilst wind is the key influencing factor for PM_{2.5} concentrations in the North China region in winter. Secondly, in addition to the large variations in the values of correlation coefficients, the interaction mechanisms between individual meteorological factors and PM_{2.5} concentrations may also vary significantly across regions. For such meteorological influences as wind speed, its negative effect on PM_{2.5} concentrations was consistent in China (He et al., 2017). On the other hand, He et al. (2017) suggested that temperature and humidity were either positively or negatively correlated with PM_{2.5} concentrations in different regions of China. In terms of humidity, when the humidity is low, PM_{2.5} concentration increases with the increase in humidity due to hygroscopic increase in and accumulation of PM_{2.5} (Fu et al., 2016). When the humidity continues to grow, the particles grow too heavy to stay in the air, leading to dry (particles drop to the ground; Wang and Ogawa, 2015) and wet deposition (precipitation; Li et al., 2015b), and the reduction of PM_{2.5} concentrations. Similarly, there may be thresholds for the negative influences of precipitations on PM_{2.5} concentrations (Luo et al., 2017). Heavy precipitation can have a strong washing-off effect on PM_{2.5} concentrations and notably reduce PM_{2.5} concentrations. Meanwhile, slight precipitation may not effectively remove the high-concentration PM_{2.5}. Instead, the slight precipitation may induce enhanced relative humidity and thus lead to the increase in PM_{2.5} concentrations. Meanwhile, the washing-off effect from the same amount of precipitation on PM_{2.5} concentrations in Xi'an, a city with higher PM_{2.5} concentrations, was lower than that in Guangzhou (Guo et al., 2016), indicating local PM_{2.5} concentrations also exerted a key role in the negative effects of precipitation. Meanwhile, temperature can either be negatively correlated with PM_{2.5} concentrations by accelerating the flow circulation and promoting the dispersion of PM_{2.5} (Li et al., 2015b), or positively correlated with PM_{2.5} concentrations through inversion events (Jian et al., 2012). Given the complexity of interactions between meteorological factors and PM_{2.5}, character-

istics and variations of meteorological influences on PM_{2.5} concentrations should be further investigated for specific regions across China, respectively, based on long-term observation data.

Due to a highly complicated atmospheric environment and the difficulty in acquiring true data of exhaust emission, commonly used models for air quality prediction (e.g., CAMx, CMAQ and WRFChem) may lead to large biases and uncertainty when applied to China. On the other hand, statistical models can achieve satisfactory forecasting results based on massive historical data (Cheng et al., 2015). Compared with the static models, dynamic statistical models additionally consider the meteorological influences on PM_{2.5} concentrations, and some meteorological factors that have stable, representative and strong correlations with PM_{2.5} concentrations are selected for forecasting PM_{2.5} concentrations. Meanwhile, many recent studies (Cheng et al., 2017; Guo et al., 2017; Lu et al., 2017; Ni et al. 2017) have recognized the meteorological influences on the evolution of PM_{2.5} concentrations and included some key meteorological factors for PM_{2.5} estimation. However, most PM_{2.5} estimation and forecasting models mainly employed correlation analysis, and the correlation coefficient between meteorological factors and PM_{2.5} concentrations is usually much larger than the ρ value and overestimates the influence of individual meteorological factors on PM_{2.5} concentrations. In this case, this research provides a useful reference for improving existing statistical models. By incorporating the ρ value, instead of the correlation coefficient, of different factors into corresponding GAMs (generalized additive models) and adjusting parameters accordingly, we may significantly improve the reliability of future estimation and forecasting of PM_{2.5} concentrations.

Quantified causality of individual meteorological factors on PM_{2.5} concentrations provides useful decision support for evaluating relevant environmental projects. Specifically, a forthcoming Beijing wind-corridor project (http://www.bj.xinhuanet.com/bjyw/yqphb/2016-05/16/c_1118870801.htm, last access: 18 November 2017) has become a hot social and scientific issue. Herein, our research suggests that wind is a dominant meteorological factor for winter PM_{2.5} concentrations in Beijing and can significantly influence PM_{2.5} concentrations through direct and indirect mechanisms (Chen et al., 2017). In consequence, the wind-corridor project may directly allow in more strong wind, which thus leads to a larger value of SSD and evaporation and a smaller value of humidity. The change in SSD, humidity and evaporation values can further induce the reduction of PM_{2.5} concentrations. From this perspective, the Beijing wind-corridor project has good potential to improve local and regional air quality. In addition, some scholars and decision-makers have proposed other meteorological means for reducing PM_{2.5} concentrations. For instance, Yu (2014) suggested that water spraying from high buildings and water towers in urban areas was an efficient way to reduce PM_{2.5} concentrations rapidly by simulating precipitation.

However, some limitations, such as the humidity control and potential icing risk, remained. In the near future, with growing attention to the improvement of air quality, more environmental projects should be properly designed and implemented. According to this research given the diversity of dominant meteorological factors on local PM_{2.5} concentrations in different regions and seasons, it is more efficient to design meteorological means accordingly. For the heavily polluted North China region, especially the Beijing–Tianjin–Hebei region, the northwesterly synoptic wind (Tie et al., 2015; Miao et al., 2015) is much stronger in winter than winds in summer and exerts a dominant influence on PM_{2.5} concentrations (Chen et al., 2017). Furthermore, in North China, the PM_{2.5} concentration is much more sensitive to the change in wind speed than that of other meteorological factors (Gao et al., 2016). Meanwhile, wind-speed-induced climate change led to a change in PM_{2.5} concentrations by as much as $12.0\text{ }\mu\text{g m}^{-3}$, compared with the change in PM_{2.5} concentrations by up to $4.0\text{ }\mu\text{g m}^{-3}$ in southeastern, northwestern and southwestern China (Tai et al., 2010). Therefore, meteorological means for encouraging strong winds are more likely to reduce PM_{2.5} concentrations considerably in North China. Similarly, Luo et al. (2017) suggested that only precipitation with a certain magnitude can lead to the washing-off effect of PM_{2.5} concentrations, whilst Guo et al. (2016) revealed that the variation of PM_{2.5} concentrations was more sensitive to the same amount of precipitation in areas with lower PM_{2.5} concentrations. Therefore, meteorological means for inducing precipitation are more likely to improve air quality in coastal cities and cities within the Yangtze River Basin, where there is a large amount of precipitation and relatively low PM_{2.5} concentrations.

6 Conclusions

Previous studies examined the correlation between individual meteorological influences and PM_{2.5} concentrations in some specific cities and the comparison between these studies indicated that meteorological influences on PM_{2.5} concentrations varied significantly across cities and seasons. However, these scattered studies conducted at the local scale cannot reveal regional patterns of meteorological influences on PM_{2.5} concentrations. Furthermore, previous studies generally selected different research periods and meteorological factors, making the comparison of findings from different studies less robust. Thirdly, these studies employed the correlation analysis, which may be biased significantly due to the complicated interactions between individual meteorological factors. This research is a major extension of previous studies. Based on a robust causality analysis method CCM, we quantified and compared the influence of eight meteorological factors on local PM_{2.5} concentrations for 188 monitoring cities across China using PM_{2.5} and meteorological observation data from

March 2014 to February 2017. Similar to previous studies conducted at the local scale, this research further indicated that meteorological influences on PM_{2.5} concentrations were of notable seasonal and spatial variations at the national scale. Furthermore, this research revealed some regional patterns and comprehensive statistics of the influence of individual meteorological factors on PM_{2.5} concentrations, which cannot be understood through small-scale case studies. For the heavily polluted North China region, the higher PM_{2.5} concentrations, the stronger influence meteorological factors exert on local PM_{2.5} concentrations. The dominant meteorological factor for PM_{2.5} concentrations is closely related to geographical conditions. For heavily polluted winter, precipitation exerts a key influence on local PM_{2.5} concentrations in most coastal areas and the Yangtze River basin, whilst the dominant meteorological driver for PM_{2.5} concentrations is wind in the North China regions. At the national scale, the influence of temperature, humidity and wind on local PM_{2.5} concentrations is much larger than that of other factors, and temperature exerts the strongest and most stable influences on national PM_{2.5} concentrations in all seasons. The influence of individual meteorological factors on PM_{2.5} concentrations extracted in this research provides more reliable reference for better modelling and forecasting local and regional PM_{2.5} concentrations. Given the significant variations of meteorological influences on PM_{2.5} concentrations across China, environmental projects aiming for improving local air quality should be designed and implemented accordingly.

Data availability. The PM_{2.5} data used for this research are available at the website (<http://pm25.in/>; China National Environmental Monitoring Center, 2017.), whilst meteorological data are available at the website (<http://www.cma.gov.cn/2011qxw/2011qsjgx/>; China Meteorological Data Sharing Service System, 2017.). Real-time hourly PM_{2.5} data can be collected, whilst historical PM_{2.5} data can be obtained upon request.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This research is supported by the National Natural Science Foundation of China (grant nos. 210100066), the National Key Research and Development Program of China (no. 2016YFA0600104), the Open Project of the State Key Laboratory of Earth Surface Processes and Resource Ecology (2017-KF-22), the Fundamental Research Funds for the Central Universities, the Ministry of Environmental Protection (201409005) and the Beijing Training Support Project for excellent scholars (2015000020124G059).

Edited by: Sally E. Pusede

Reviewed by: three anonymous referees

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