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

Ziyue Chen[1,2] , Xiaoming Xie[1], Jun Cai[3], Danlu Chen[1], Bingbo Gao[4], Bin He[1,2], Nianliang Cheng[5], Bing Xu[3]*

[1] College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Haidian, Beijing, 100875, China
[2] Joint Center for Global Change Studies, Beijing 100875, China
[3] Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China
[4] National Engineering Research Center for Information Technology in Agriculture, 11 Shuguang Huayuan Middle Road, Beijing 100097, China
[5] Beijing Municipal Environmental Monitoring Center, Beijing 100048, China

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 yet been examined comprehensively. This research employs the CCM (Cross Convergent 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 are of 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 meteorological influences on local $PM_{2.5}$ concentrations, this research suggests pertinent environmental projects for air quality improvement should be designed accordingly for specific regions.

Keywords: $PM_{2.5}$; Meteorological factors; Causality analysis; CCM

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* Corresponding author. Email address: bingxu@tsinghua.edu.cn. Telephone No. 0086(10) 62773906

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 concerned 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/) revealed that $PM_{2.5}$ induced pollution episodes occurred in 25 provinces and more than 100 middle-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 that 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；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; Zhang, F. et al., 2015; Zhen et al., 2016; Zhang 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; Chen, Y. et al. 2016; Chen, Z. 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. (2015) suggested that air pressure and temperature were positively correlated with $PM_{2.5}$ concentrations in Chengdu. For Nanjing (Chen, T. 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. Zhang et al. (2015b) quantified the correlations between meteorological factors and 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, Z. 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 factors 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 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 (Cross Convergent 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, Z., 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 are of 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 a 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 PM25.in. This website collects official data of PM$_{2.5}$ concentrations provided by China National Environmental Monitoring Center (CNEMC) and publishes hourly air quality information for all monitoring cities. Before Jan 1st, 2015, PM25.in publishes data of 190 monitoring cities. Since Jan 1st, 2015, the number of monitoring cities has increased to 367. By calling specific API (Application Programming Interface) provided by PM25.in, we collect hourly PM$_{2.5}$ data for target cities. The daily PM$_{2.5}$ concentrations 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 March 1st, 2014 to February 28th, 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 National Science and Technology Infrastructure. The meteorological data are collected through thousands of observation stations across China. Previous studies (Zhang et al., 2015b; 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 largest temperature difference for the day), precipitation (total precipitation from 8am-8pm, total precipitation from 8pm-8am 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), wind direction (max wind direction for the day). Some meteorological factors are briefly explained here. Evaporation indicates 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 10cm (30cm) during 24 hours (unit: mm). Generally, the measured values using the two types of equipment are of 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 minutes within a day's time. The extreme wind speed indicates the max instant (for 1s) 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 March 1st, 2014 to February 28th, 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. 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 a convergent cross mapping (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 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 $\{X\}= [X(1), \dots, X(\mathrm{L})]$ and $\{Y\} = [Y(1), \dots, Y(\mathrm{L})]$ are defined as the temporal variations of two variables X and Y. For r = S to L (S < L), two partial time series $[X(1), \dots, X(\mathrm{L_P})]$ and $[Y(1), \dots, Y(\mathrm{L_P})]$ 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 $\mathrm{x}(t) = <X(t), X(t-\tau), ..., X(t-(E-1)\tau)>$ 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 $t_1, ..., t_{E+1}$. These time index 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 (Equation 1).

$$\hat{Y}(t)|M_X = \sum_{i=1}^{E+1} w_i Y(t_i) \qquad \text{(E1)}$$

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 Equation 2.

$$w_i = u_i \Big/ \sum_{j=1}^{E+1} u_j \qquad \text{(E2)}$$

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

In our previous research, interactions between the air quality in neighboring cities (Chen, Z. et al., 2016), and bidirectional coupling between individual meteorological factors and

$PM_{2.5}$ concentrations (Chen, Z. et al., 2017) were quantified effectively using the CCM method. By comparing the performance of correlation analysis and CCM method, Chen, Z. 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; Chen, Y. et al., 2016; Chen, Z. et al., 2016), Nanjing (Shen et al., 2014), Shandong Province (Yang and Christakos, 2015) and the Beijing-Tianjin-Hebei region (Wang et al. 2015; Chen, Z. 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, Jinchang, 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 March 1st, 2014 and May 31st, 2014; summer was set as the period between June 1st, 2014 and August 31st, 2014; autumn was set as the period between September 1st, 2014 and November 30th, 2014; and winter was set as the period between December 1st, 2014 and February 28th, 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 few parameters need to be set for running this algorithm: E (number of dimensions for the attractor reconstruction), τ (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 τ 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 τ was set as 2 days and the value of E was set 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 the highest, as an example. Four major meteorological 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, Figure 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.

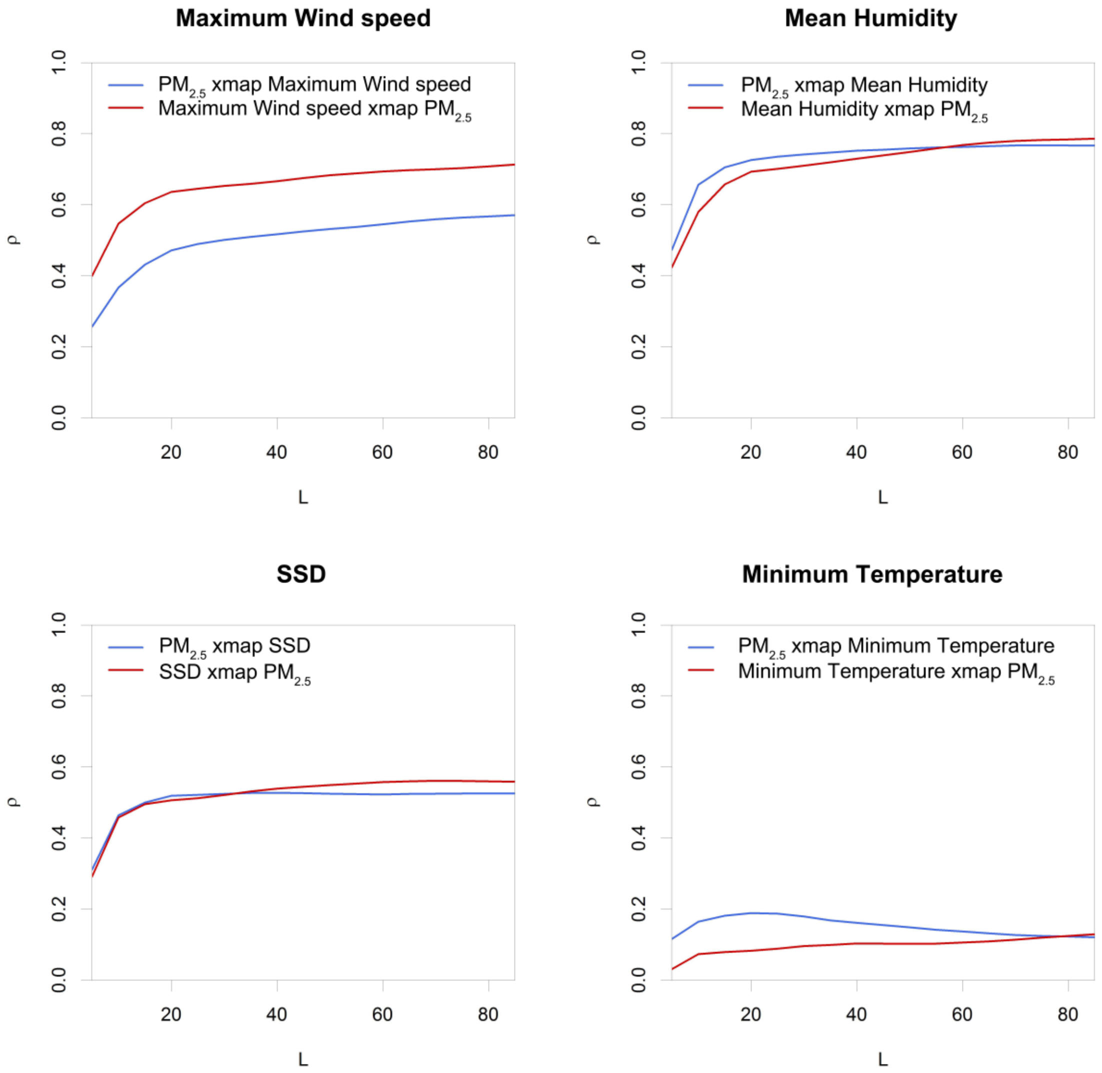


Fig 1. Illustrative CCM results to demonstrate the bidirectional coupling between meteorological factors and $PM_{2.5}$ concentrations in Beijing (2014, winter)

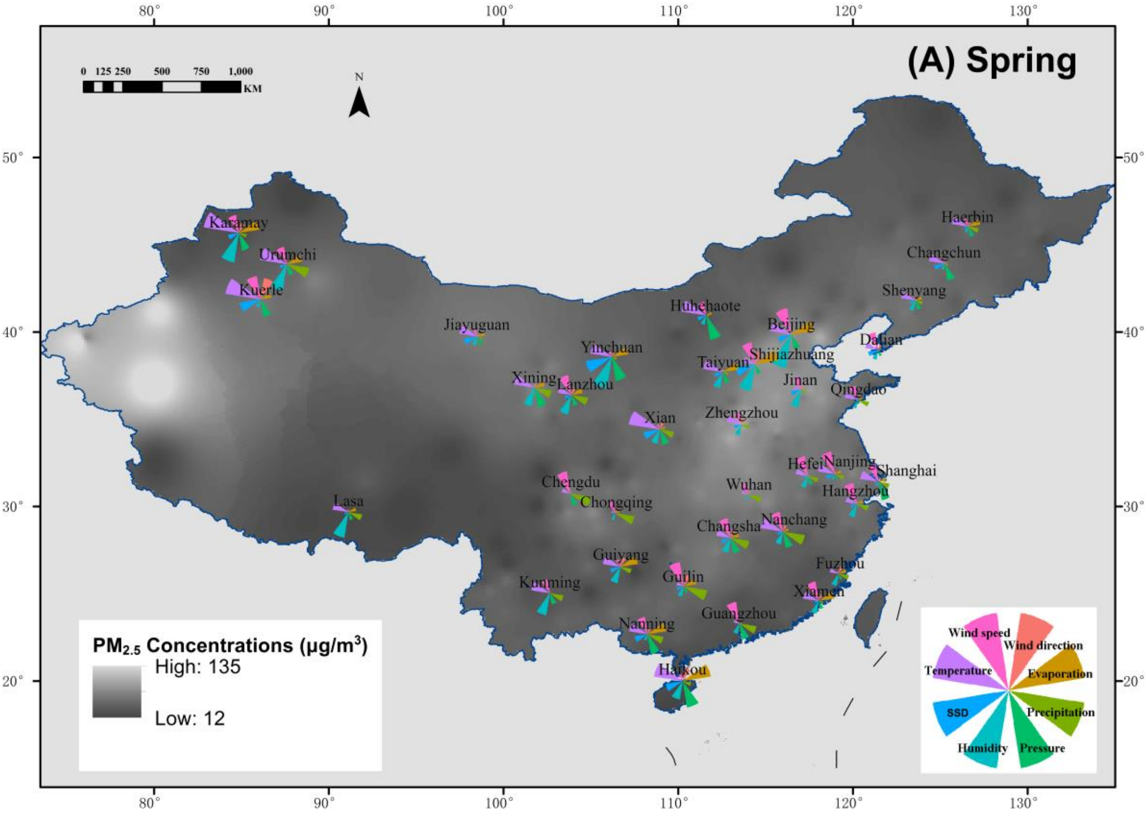
ρ: predictive skills. L: the length of time series. A xmap B stands for convergent cross mapping B from A, in other words, the causality of variable B on A. For instance, $PM_{2.5}$ xmap mean humidity stands for the causality of mean humidity on $PM_{2.5}$ concentrations. Mean humidity xmap $PM_{2.5}$ 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.

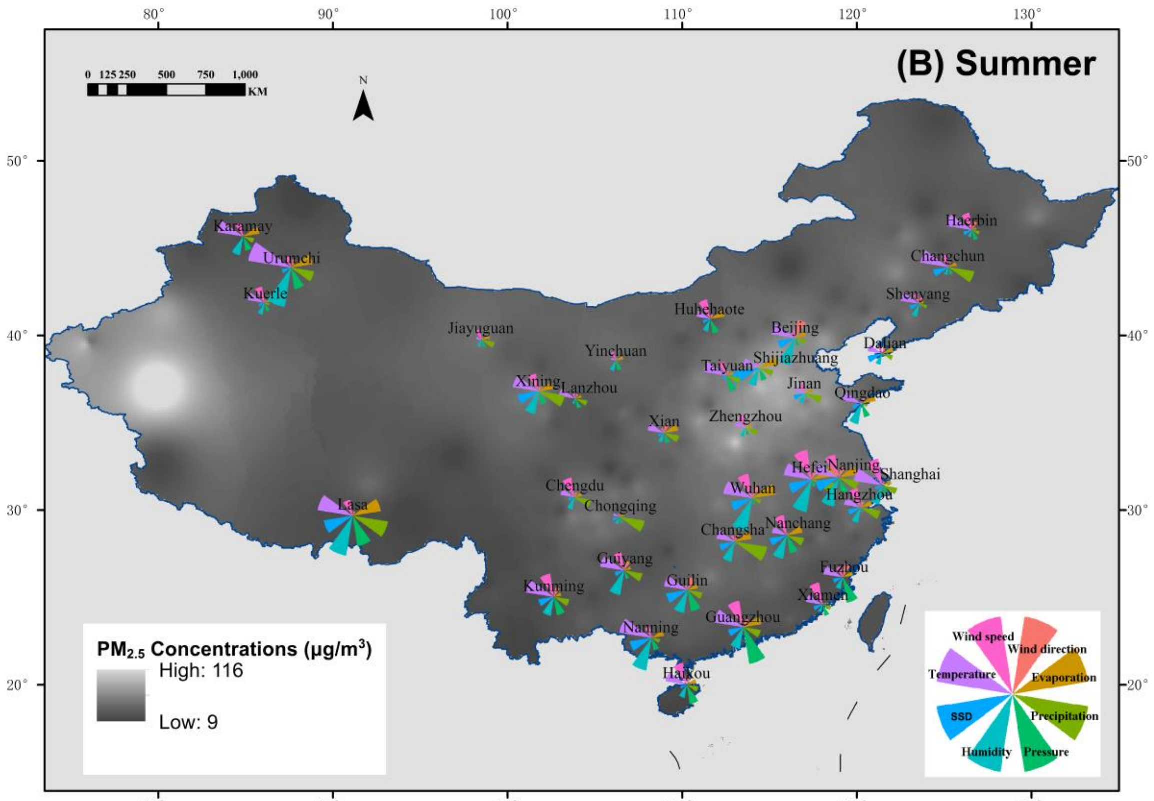
According to Fig 1, one can see that the quantitative influence of individual meteorological factors on $PM_{2.5}$ was well extracted using the CCM method whilst the feedback effect of $PM_{2.5}$ on specific meteorological factors was revealed as well. For Beijing, mean humidity and maximum wind speed 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 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 $PM_{2.5}$ concentrations, 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 as well 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 details herein.

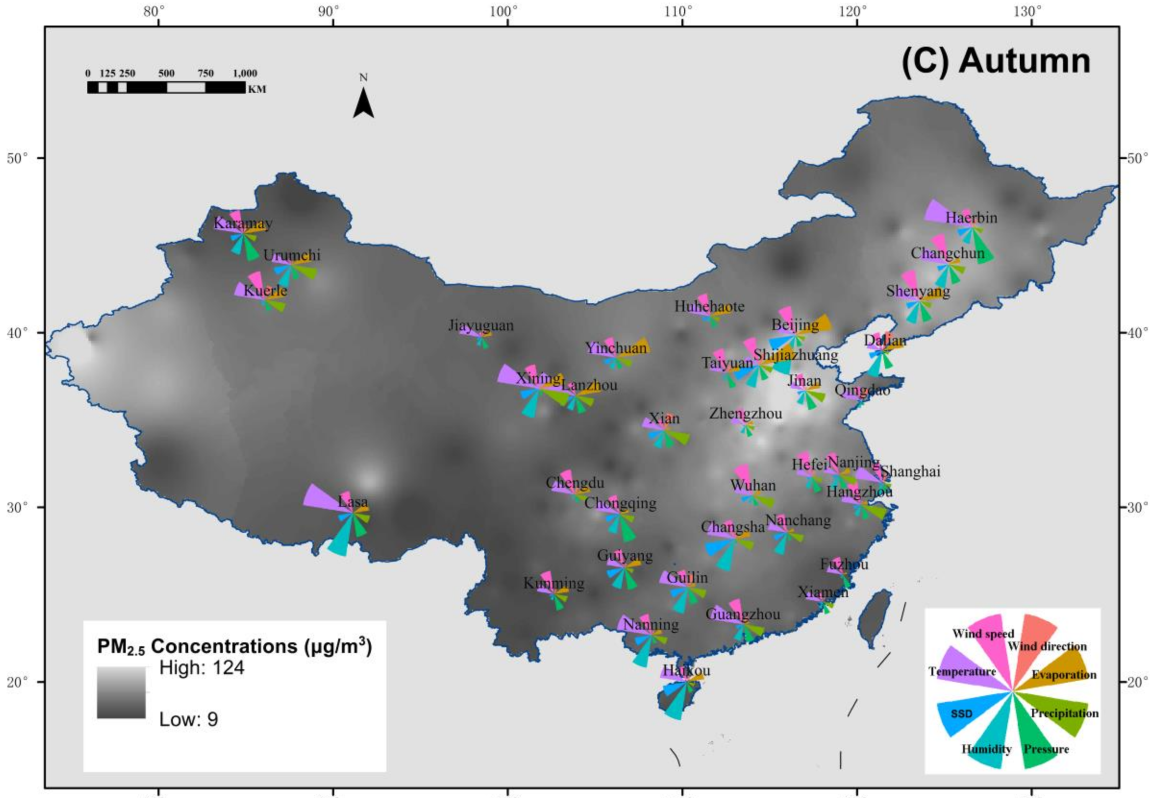
The ρ value is a direct indicator of quantitative causality. For this research, the maximum ρ value of all sub-factors in the same category was used as the causality of this specific meteorological factor on $PM_{2.5}$ concentrations. E.g. for a specific city, the maximum ρ value of max temperature, mean temperature, minimum temperature, and 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 three 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).




(B) Summer
0 125 250 500 750 1,000 KM
N
80° 90° 100° 110° 120° 130°
50° 40° 30° 20°
Karamay
Urumchi
Kuerle
Jiayuguan
Yinchuan
Xining
Lanzhou
Lasa
Huhehaote
Beijing
Dalian
Taiyuan
Shijiazhuang
Jinan
Qingdao
Xian
Zhengzhou
Chengdu
Chongqing
Hefei
Nanjing
Shanghai
Hangzhou
Wuhan
Changsha
Nanchang
Guiyang
Kunming
Guilin
Fuzhou
Xiamen
Guangzhou
Nanning
Haikou
Haerbin
Changchun
Shenyang
PM$_{2.5}$ Concentrations (μg/m^3)
High: 116
Low: 9
Wind speed
Wind direction
Temperature
Evaporation
SSD
Precipitation
Humidity
Pressure


(C) Autumn
0 125 250 500 750 1,000 KM
N
80° 90° 100° 110° 120° 130°
50° 40° 30° 20°
Karamay
Urumchi
Kuerle
Jiayuguan
Yinchuan
Xining
Lanzhou
Lasa
Huhehaote
Beijing
Dalian
Taiyuan
Shijiazhuang
Jinan
Qingdao
Xian
Zhengzhou
Chengdu
Chongqing
Hefei
Nanjing
Shanghai
Hangzhou
Wuhan
Changsha
Nanchang
Guiyang
Kunming
Guilin
Fuzhou
Xiamen
Guangzhou
Nanning
Haikou
Haerbin
Changchun
Shenyang
PM$_{2.5}$ Concentrations (μg/m^3)
High: 124
Low: 9
Wind speed
Wind direction
Temperature
Evaporation
SSD
Precipitation
Humidity
Pressure

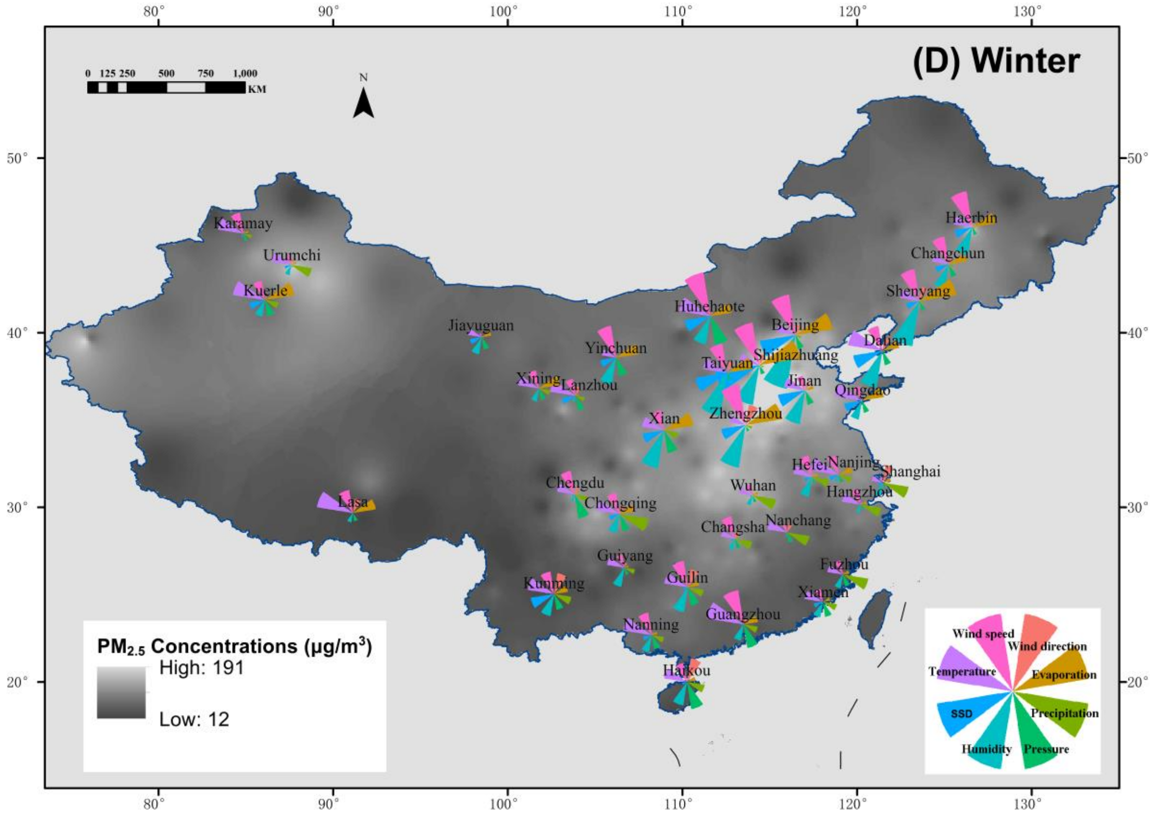


Fig 2. Wind rose map of influences of eight individual meteorological factors on $PM_{2.5}$ concentrations across mainland China (37 representative cities) during 2014-2016

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. E.g. 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). Furthermore, 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 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.

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）

2. In spite of notable differences in the shape and size of wind roses, meteorological influences on $PM_{2.5}$ concentrations cities are of 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 Shijiangzhuang, 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, were also of 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 influence meteorological factors exerts 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, $PM_{2.5}$ 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 for the form and persistence of high $PM_{2.5}$ concentrations within the North China region.

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	temperature	SSD	
		0.39	0.34	0.25	
	Winter	humidity	wind	evaporation	SSD
		0.76	0.57	0.52	0.50
Tianjin	**Summer**	precipitation	air pressure	temperature	
		0.34	0.25	0.22	
	Winter	humidity	wind	evaporation	SSD
		0.56	0.50	0.44	0.41
Shijiazhuang	**Summer**	SSD	humidity	evaporation	
		0.4	0.26	0.26	
	Winter	SSD	wind	evaporation	humidity
		0.62	0.60	0.58	0.56
Taiyuan	**Summer**	temperature	air pressure	precipitation	
		0.32	0.23	0.20	
	Winter	humidity	SSD	wind	
		0.61	0.44	0.41	

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:

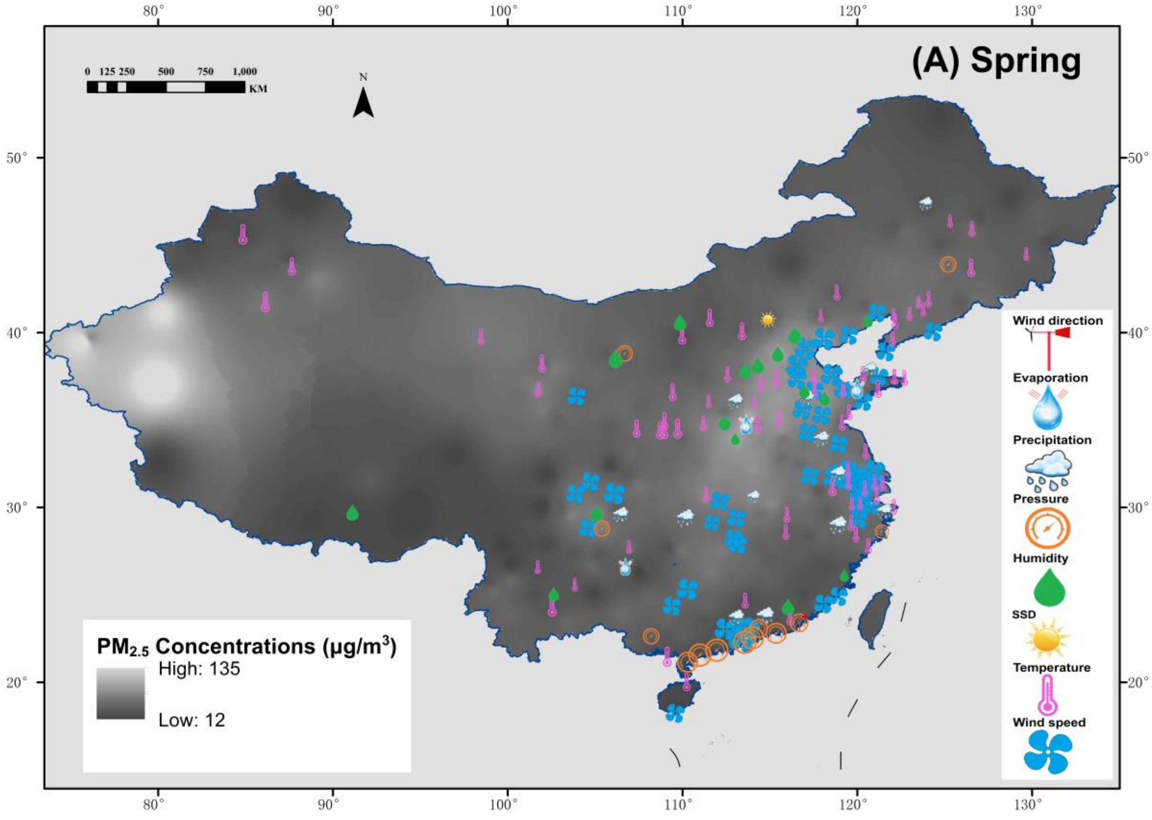
1. The dominant meteorological factor for $PM_{2.5}$ concentrations is closely related to geographical conditions. For instance, the factor of precipitation may exert a key influence on local $PM_{2.5}$ concentrations in some coastal cities and cities within the Yangtze River Basin whilst this meteorological factor exerts limited influence on $PM_{2.5}$

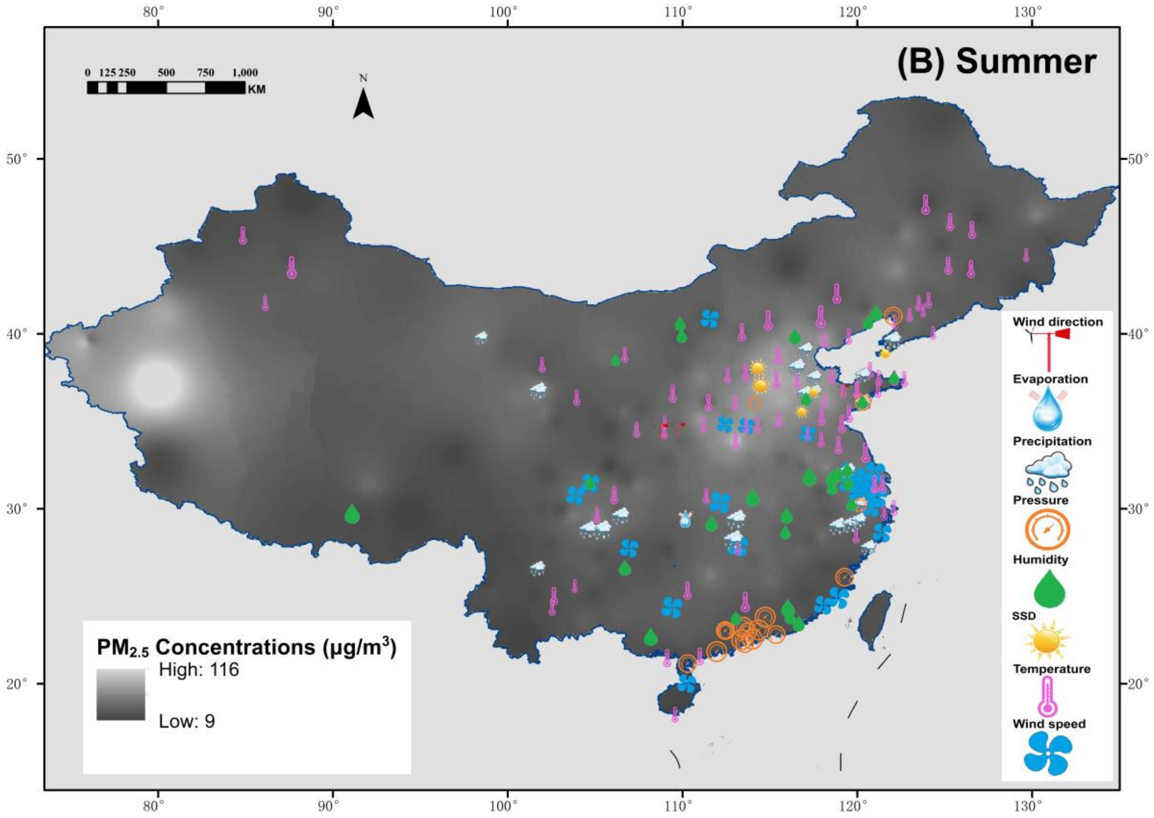
concentrations within some inland regions. Here we analyzed the ρ value of precipitation in cities within the Yangtze River Basin and cities within the Beijing-Tianjin-Hebei region respectively. For winter, precipitation was the dominant factor for $PM_{2.5}$ concentrations in Shanghai, Hangzhou and 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.

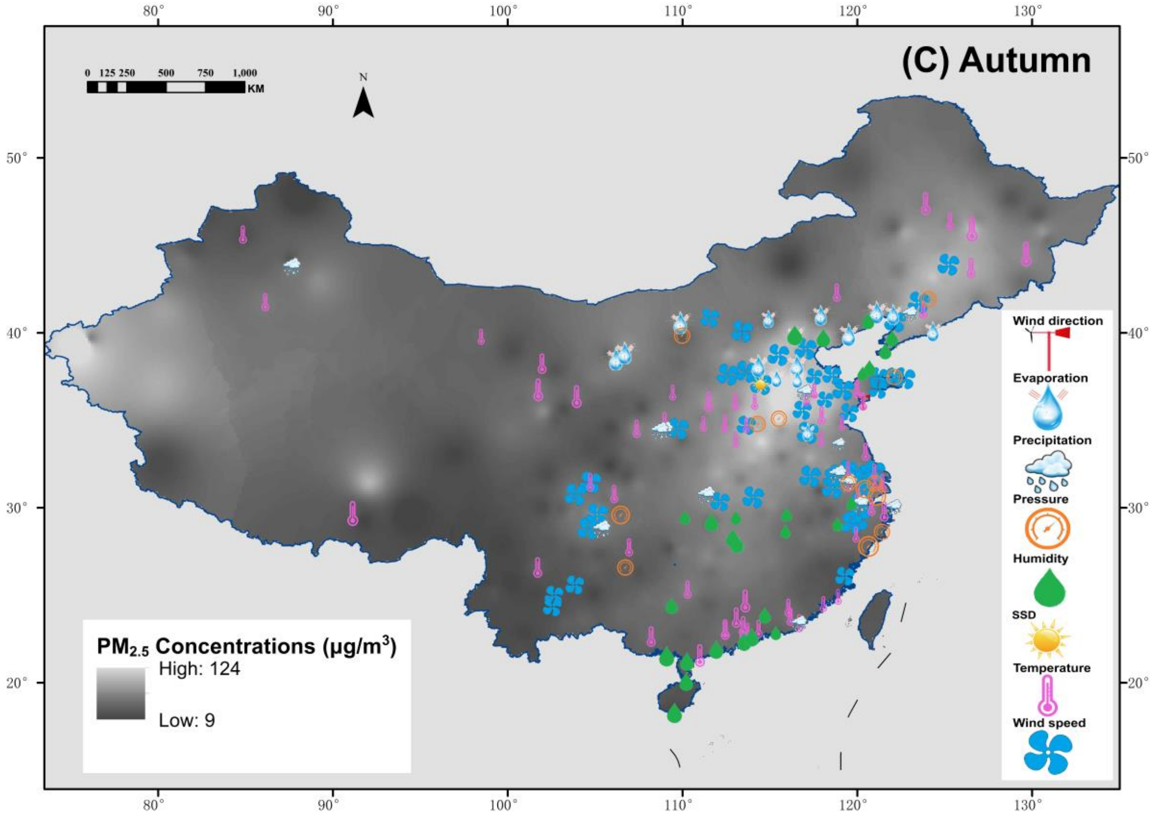
2. Some meteorological factors can be the dominant factor for cities within different regions whilst some (e.g. evaporation and SSD) are mainly the dominant meteorological factor for $PM_{2.5}$ concentrations in cities within some specific regions. In other words, some factors can be regarded as regional and national meteorological influencing factors for $PM_{2.5}$ concentrations, yet some meteorological factors are context-related influencing 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. Specially, 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 (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 North China region for instance. For winter, the dominant meteorological factors for Beijing, Tianjin, Taiyuan, Zhangjiakou, Handan and Jining was 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 was 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 presence of high air pressure in northwest 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.




(B) Summer
0 125 250 500 750 1,000 KM
N
PM$_{2.5}$ Concentrations (μg/m^3)
High: 116
Low: 9
Wind direction
Evaporation
Precipitation
Pressure
Humidity
SSD
Temperature
Wind speed
80° 90° 100° 110° 120° 130°
20° 30° 40° 50°


(C) Autumn
0 125 250 500 750 1,000 KM
N
PM$_{2.5}$ Concentrations (μg/m^3)
High: 124
Low: 9
Wind direction
Evaporation
Precipitation
Pressure
Humidity
SSD
Temperature
Wind speed
80° 90° 100° 110° 120° 130°
20° 30° 40° 50°

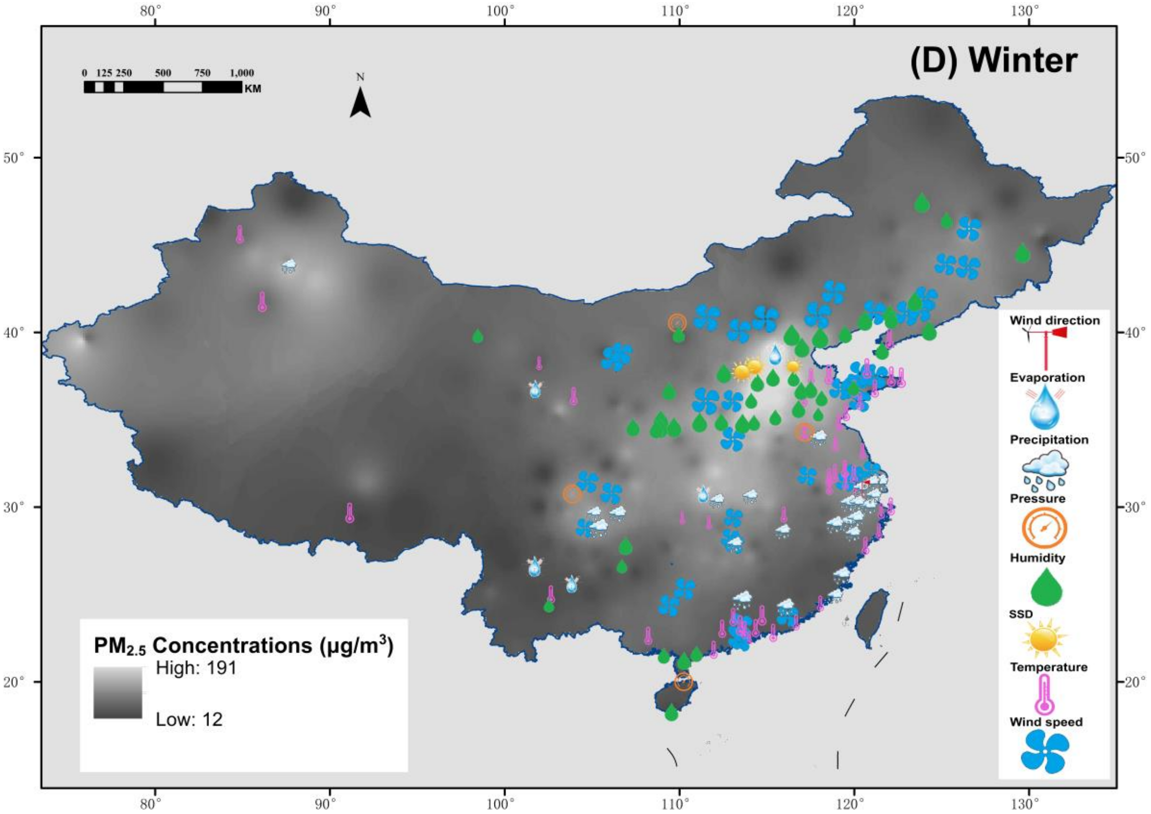


Fig 3. The dominant meteorological factor for local PM$_{2.5}$ concentrations in 188 monitoring cities across mainland China

The size of symbols indicates the ρ value of the meteorological factor on local PM$_{2.5}$ concentrations.

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.

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[1]**	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

[1] 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.

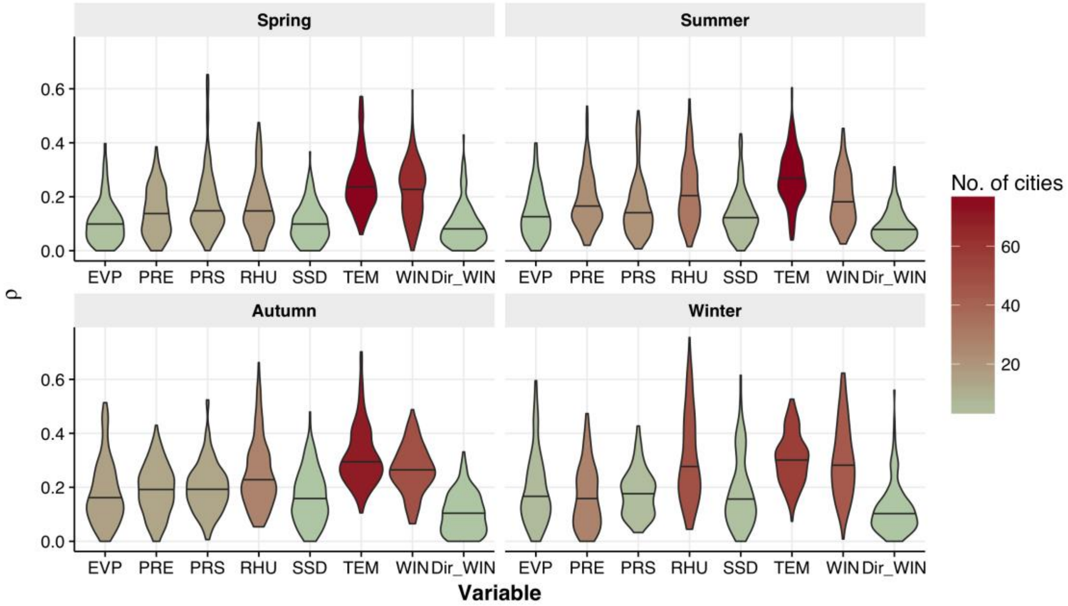


Fig 4. Violin plots of the influence of eight different meteorological factors on local $PM_{2.5}$ concentrations in 188 cities across China

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.

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⊆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 is 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 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.

5 Discussion

Correlations between individual meteorological factors and $PM_{2.5}$ concentrations have been analyzed in such mega cities as Nanjing (Chen, T. 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 (Chen, T. 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 $PM_{2.5}$ concentrations 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. North China region or 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. Correlations analysis, as introduced above, may lead to 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 and 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 of humidity due to hygroscopic increase 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, J., & Ogawa, S. (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 PM2.5 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 of $PM_{2.5}$ 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 $PM_{2.5}$, characteristics 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 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 are of 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; etc) 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 useful reference for improving existing statistical models. By incorporating the ρ value, instead of the correlation coefficient, of different factors into corresponding GAM (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) 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,Z. 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 of 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 on 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 of wind speed than that of other meteorological factors (Gao et al., 2016). Meanwhile, wind-speed induced climate change led to the change of $PM_{2.5}$ concentrations by as much as 12.0 μgm^{-3}, compared with the change of $PM_{2.5}$ concentrations by up to 4.0 μgm^{-3} in south-eastern, northwestern and south-western 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.

Acknowledgement

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