Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-376
Manuscript under review for journal Atmos. Chem. Phys.
Discussion started: 24 July 2017

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

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Abstract

With frequent haze events 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 causality influence of individual meteorological factors on local $PM_{2.5}$ concentrations in 189 monitoring cities across China. Results indicate that meteorological influences on $PM_{2.5}$ concentrations are of notable seasonal and regional variations. Generally, the higher $PM_{2.5}$ concentrations, the larger influences meteorological factors exert on $PM_{2.5}$ concentrations. 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, temperature, humidity, wind and air pressure exert stronger influences on $PM_{2.5}$ concentrations than other meteorological factors. 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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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. Amongst these environmental elements, ambient air quality has become one of the most concerned social and ecological issues. Recently, the frequency of haze events and the number of cities influenced by haze have increased notably in China since 2013. Statistical records from the national air quality publishing platform (http://113.108.142.147:20035/emcpublish/) revealed that haze events occurred in 25 provinces and more than 100 middle-large cities whilst there were on average 30 days with haze for each monitoring city in 2014.

Serious haze not only influences people's daily life, but also severely threatens the health of residents that suffer from polluted air quality. Recent studies (Garrett and Casimiro, 2011; Guaita et al., 2011; Qiao et al., 2014; Pasca et al., 2014; Lanzinger et al., 2015; Li et al., 2015) have proven that airborne pollutants, $PM_{2.5}$ in particular, are closely related to all-cause and specific-cause mortality. In consequence, 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., 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 $PM_{2.5}$ and other airborne pollutants. Meanwhile, large-scale research on the variation and distribution of $PM_{2.5}$ 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 controversy, meteorological influences on airborne pollutants have been examined in depth by more and more scholars. Recently, massive studies have been conducted to extract quantitative correlations between meteorological factors and air pollutants. Blanchard et al. (2010) indicated that ozone concentrations was linearly correlated with temperature and humidity, and non-linearly correlated with other meteorological factors. Juneng et al. (2011) suggested that such meteorological factors as temperature, humidity and wind

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speed, dominated the fluctuation of PM_{10} over the Klang Valley during summer monsoon. In Melbourne, Pearce et al. (2011) found that local temperature led to strongest responses of different pollutants, whilst other meteorological factors (e.g. winds, water vapor pressure, radiation, precipitation) affected one or more specific pollutants. Galindo et al. (2011) revealed that fractions of three different sizes were negatively correlated with wind speed in winter, whilst coarse fractions were strongly correlated with temperature and solar radiation. El-Metwally and Alfaro (2013) suggested that the wind speed not only influenced the dilution of airborne pollutants, but also affected the composition of airborne pollutants. For a Western Indian location, Udaipur, Yadav et al. (2014) proved that precipitation exerted a stronger influence on PM_{10} than on $PM_{2.5}$. High temperature diluted the emission of surface pollutants whilst strong winds diminished the trend of air pollution in May. Grundstrom et al. (2015) suggested that low wind speeds and positive vertical temperature gradients were favorable meteorological conditions for elevated NOx and particle number concentrations (PNC). 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 airborne pollutant 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 radiation were major meteorological factors that significantly influenced local $PM_{2.5}$ concentrations in winter.

Although correlations between airborne pollutants and meteorological factors have been massively studied, analyzing the sensitivity of airborne pollutants to individual meteorological parameters remains challenging (Pearce et al., 2011). This is because different meteorological factors are inherently interacting and can thus influence airborne pollutants through direct and indirect mechanisms. 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. Our previous research (Chen, Z., 2017) proved that the CCM (Cross Convergent Mapping) method performed better in quantifying the causality 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, interactions between meteorological factors and airborne pollutants are of great variations for different regions, yet most relevant studies have been conducted at the local or regional scale. 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.

In accordance with these challenges, this research aims to quantify and compare influences of individual meteorological factors on $PM_{2.5}$ concentrations in different cities across China. Based on the causality analysis, dominant meteorological factors for $PM_{2.5}$ concentrations can be extracted for each city and spatio-temporal patterns of meteorological influences on $PM_{2.5}$ concentrations across China can be revealed. In addition to its theoretical significance, this research may provide useful reference for evaluating pertinent environmental projects and enhancing air quality through meteorological measures.

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 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, $PM_{2.5}$ data from March 1st, 2014 to February 28th, 2015 were employed for following analysis.

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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) proved that such meteorological factors as relative humidity, temperature, wind speed, wind direction, solar radiation, evaporation, precipitation, and air pressure may 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 these meteorological factors in affecting local PM2.5 concentrations, these factors are further categorized into some sub-factors: *evaporation* (small evaporation and large evaporation, short for smallEVP and largeEVP), *temperature* (max temperature for the day, mean temperature for the day, min temperature for the day, largest temperature difference for the day, short for maxTEM, meanTEM, minTEM and difTEM), *precipitation* (total precipitation from 8am-20pm, total precipitation from 20pm-8am and total precipitation for the day, short for PRE8-20, PRE20-8 and totalPRE), *air pressure* (daily max pressure, mean pressure and min pressure, short for maxPRS, meanPRS and minPRS), *humidity* (daily mean and min relative humidity, short for meanRHU and minRHU), *radiation* (sunshine duration for the day, short for SSD), *wind speed* (mean wind speed, max wind speed, extreme wind speed, short for meanWIN, maxWIN and extWIN), *wind direction* (max wind direction for the day, short for dir_maxWin). 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.

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, where continuous valid meteorological data were not available) during the study period were selected for this research. The 189 cities included most major cities (Beijing, Shanghai, Guangzhou, etc.) in China. For regions (e.g. Beijing-Tianjin-Hebei region) with heavy

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air pollution, the density of monitored cities was much higher than the density in regions with good air quality.

3 Methods

Due to complicated interactions in the atmospheric environment, it is highly difficult to quantify the causality influence 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 bi-directional coupling can be featured with a convergent map. If the causality 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 influence exists. The predictive skill (defined as ρ value), which ranges from 0 to 1, suggests the quantitative causality influence of one variable on the other.

The principle of The CCM algorithms is briefly explained as follows (Luo et al. 2014). Two time series {X}= [X(1), …X(L)] and {Y} = [Y(1), …Y(L)] are defined as the temporal variations of two time-series variables X and Y. For r = S to L (S< L), two partial time series [X(1), …, X(LP)] and [Y(1), …, Y(LP)] are extracted. Following this, the shadow manifold MX is generated from {X}, which is a set of lagged-coordinate vectors x(t) = $<X(t), X(t-\tau),..., X(t-(E-1)\tau)>$ for t = 1+(E-1) to t = r. To generate a cross-mapped estimate of Y(t) ($\hat{Y}(t)|MX$), the contemporaneous lagged-coordinate vector on MX, 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(ti) 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 MX. Y(ti) 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(ti)] 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) proved that the CCM method not only detected mirage correlations, but also extracted weak coupling, which may not be detected by correlation analysis. Additionally, Chen, Z et al. (2017) indicated that the ρ value was a more reliable indicator of quantitative meteorological influences on $PM_{2.5}$ concentrations than the correlation coefficient. 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 proved by a large body of studies (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). Hence, the research period was divided into four seasons. According to traditional season division for China, spring was set as the period between March 1^{st}, 2014 and May 31^{st}, 2014; summer was set as the period between June 1^{st}, 2014 and August 31^{st}, 2014; autumn was set as the period between September 1^{st}, 2014 and November 30^{th}, 2014; and winter was set as the period between December 1^{st}, 2014 and February 28^{th}, 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. In this research, to acquire optimal presentation 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).

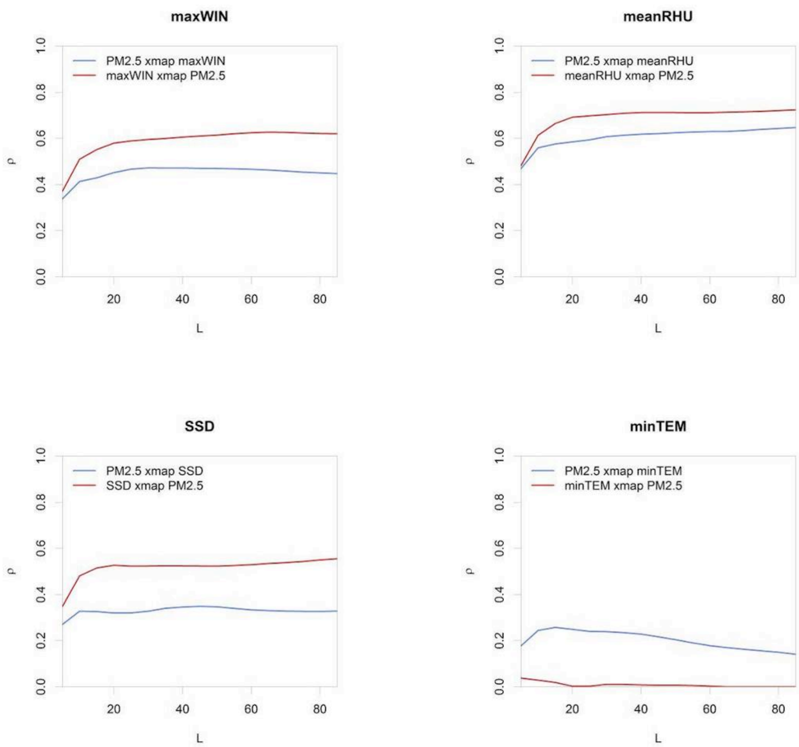

Fig 1. Illustrative CCM results to demonstrate the bidirectional coupling between meteorological factors and $PM_{2.5}$ concentrations in Beijing in winter

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 influence of variable B on A. For instance, $PM_{2.5}$ xmap meanRHU stands for the causality influence of meanRHU on $PM_{2.5}$ concentrations. meanRHU xmap

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$PM_{2.5}$ stands for the feedback effect of $PM_{2.5}$ on meanRHU concentrations. ρ indicates the predictive skills of using meanRHU 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, meanRHU and maxWIN exerted a strong influence on local $PM_{2.5}$ concentrations in Winter (ρ > 0.4) whilst SSD and minTEM also had a weaker influence on local $PM_{2.5}$ concentrations. (ρ close to 0.2). On the other hand, serious haze weather (high $PM_{2.5}$ concentrations) had an even stronger feedback influence on meanRHU, maxWIN and SSD (ρ close to 0.6) whilst $PM_{2.5}$ had little influence on minTEM (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 serious haze events. For Beijing, low wind speed (high humidity and SSD[2]) in winter results in high PM2.5 concentrations, which in turn causes lower wind speed (higher humidity and lower SSD). In consequence, $PM_{2.5}$ concentrations is 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, the haze is unlikely to disperse and persistent haze weather usually lasts for a long period in this region. By analogy, 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.

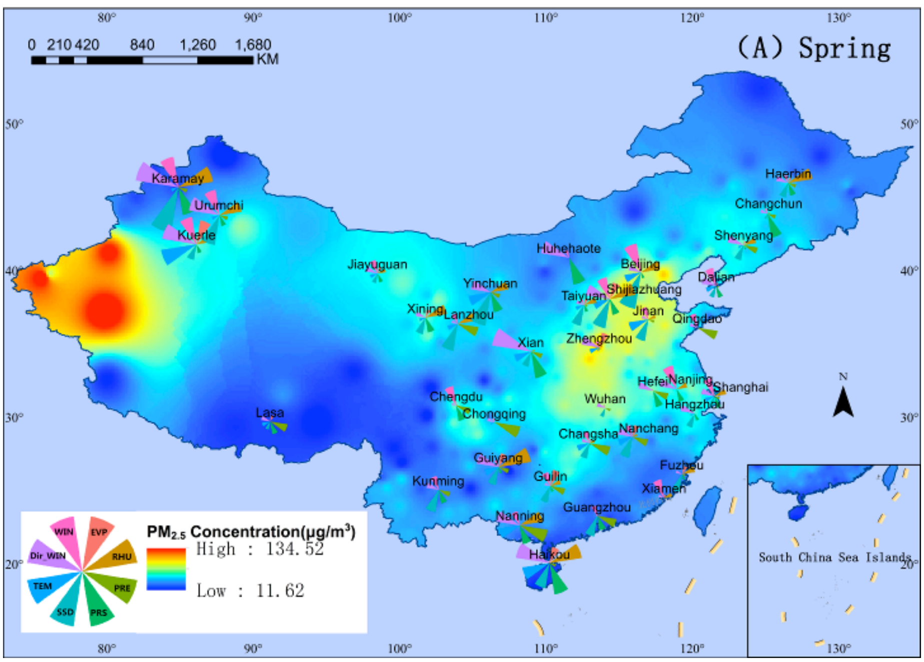
The ρ value is a direct indicator of quantitative causality influences. For this research, the maximum ρ value of all sub-factors in the same category was used as the causality influence of this specific meteorological factor on $PM_{2.5}$ concentrations. E.g. for a specific city, the maximum ρ value of maxTEM, meanTEM, minTEM and difTEM is used as the influence of temperature on local $PM_{2.5}$ concentrations. Generally, it is difficult to properly demonstrate the influence of eight meteorological factors on $PM_{2.5}$ concentrations for all 189 cities on a comprehensive map. Therefore, two cartography

[2] The interaction between some individual meteorological factors (e.g. SSD) and $PM_{2.5}$ concentrations may be difficult to understand, and a brief explanation is given in the discussion part.

strategies were employed to explain the meteorological influences on $PM_{2.5}$ concentrations across China.

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 influence of all individual meteorological factors on $PM_{2.5}$ concentrations, can be produced for each city. It is not feasible to present all 189 wind roses simultaneously, due to severe overlapping effects. Thus, considering the social-ecological factors, 37 regional representative cities (including all 31 provincial capital cities in mainland China) were selected to produce a wind rose map of meteorological influences on $PM_{2.5}$ concentrations across China (Fig 2).



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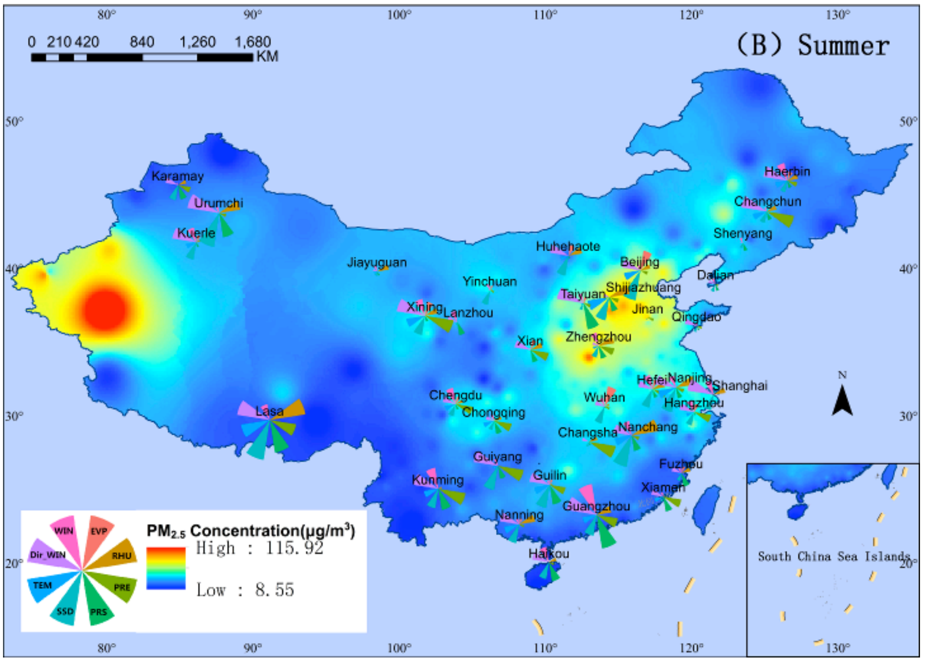

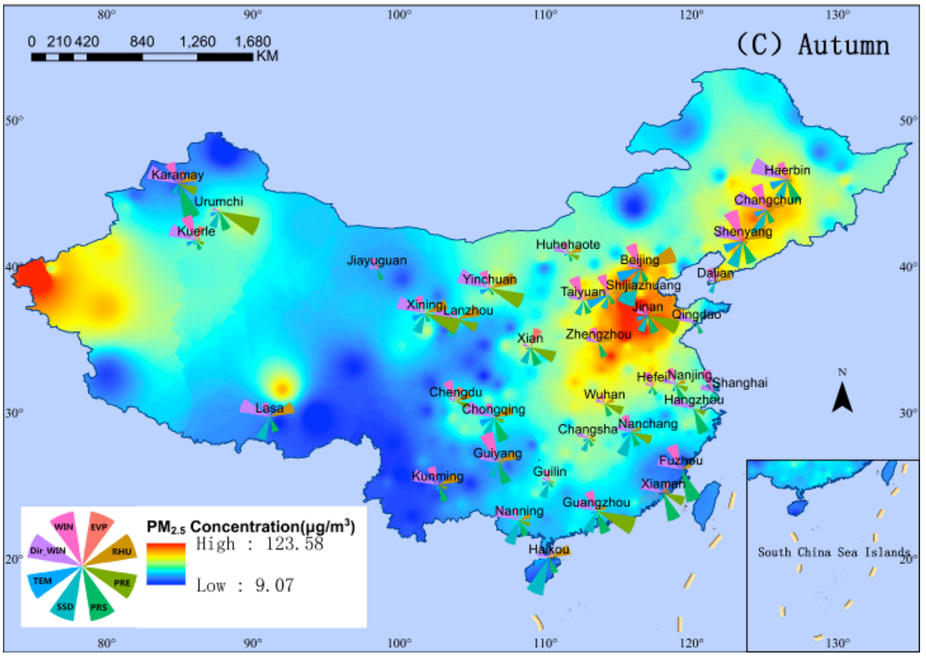

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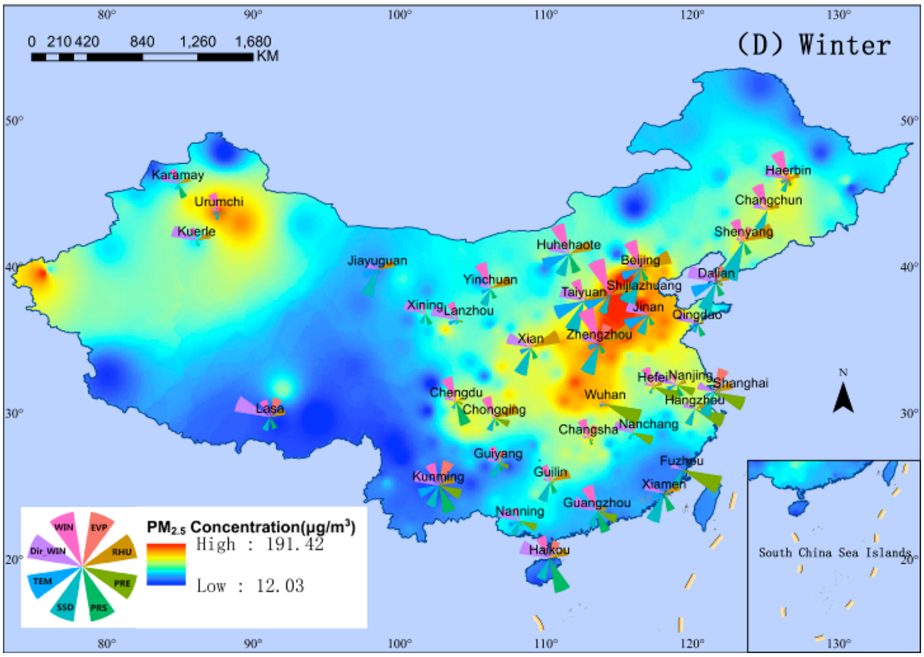

Fig 2. Wind rose map of influences of eight individual meteorological factors on $PM_{2.5}$ concentrations across China (37 representative cities)

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:

a. 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*, which exerts little influence on $PM_{2.5}$ concentrations in summer. 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.

b. In spite of notable differences in the shape and size of wind roses, meteorological influences on PM2.5 concentrations cities are of some regional patterns, subject to local PM2.5 concentrations. For instance, $PM_{2.5}$ concentrations in cities within the

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Beijing-Tianjin-Hebei region (or North China region) is influenced by similar dominant meteorological factors, especially in winter, when $PM_{2.5}$ concentrations in these cities was high. By analogy, meteorological influences on $PM_{2.5}$ concentrations in the Kuerle and Karamay (within Xinjiang province) are similar. However, meteorological influences on $PM_{2.5}$ concentrations in their neighboring city, Urumchi, are quite different. This may attribute to the fact that $PM_{2.5}$ concentrations in Urumchi is much higher than that in Kuerle and Karamay. As we can see, meteorological influences on PM2.5 concentrations in China are mainly controlled by both geographical conditions (e.g. terrain and landscape patterns) and local $PM_{2.5}$ concentrations per se.

c. Except for some specific cities (e.g. Lasa), the higher local $PM_{2.5}$ concentrations, the larger influence meteorological factors exerts on $PM_{2.5}$ concentrations. $PM_{2.5}$ concentrations is usually the highest in winter, causing serious smog events across China, the North China region in particular, whilst $PM_{2.5}$ concentrations in spring and summer is comparatively low. Accordingly, there are more influencing meteorological factors on $PM_{2.5}$ concentrations for most cities and the ρ value of these meteorological factors is notably larger in winter. As explained above, 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 haze events within the North China region, which experiences the most frequent and severe air pollution in China.

Although some general patterns of meteorological influences on $PM_{2.5}$ concentrations across China may be concluded according to Fig 2, spatial and temporal variations of meteorological influences on $PM_{2.5}$ concentrations should be further examined in depth based on the statistics of all 189 monitoring cities. Hence, we employed another strategy to demonstrate spatial and temporal variations of meteorological influences on local $PM_{2.5}$ concentrations across China.

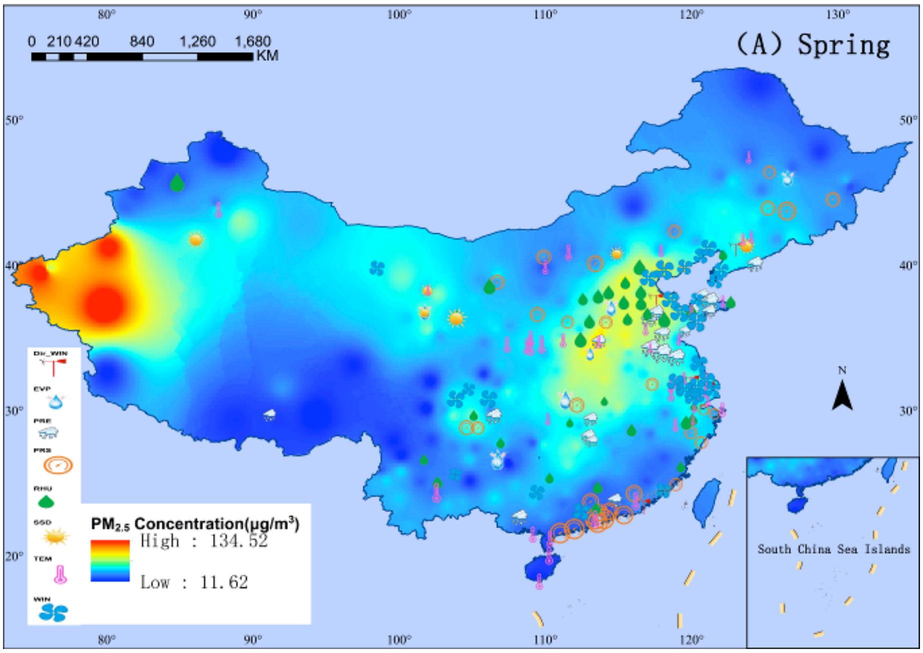
4.2 Spatial and temporal variations of the dominant meteorological influence on local $PM_{2.5}$ concentrations across China

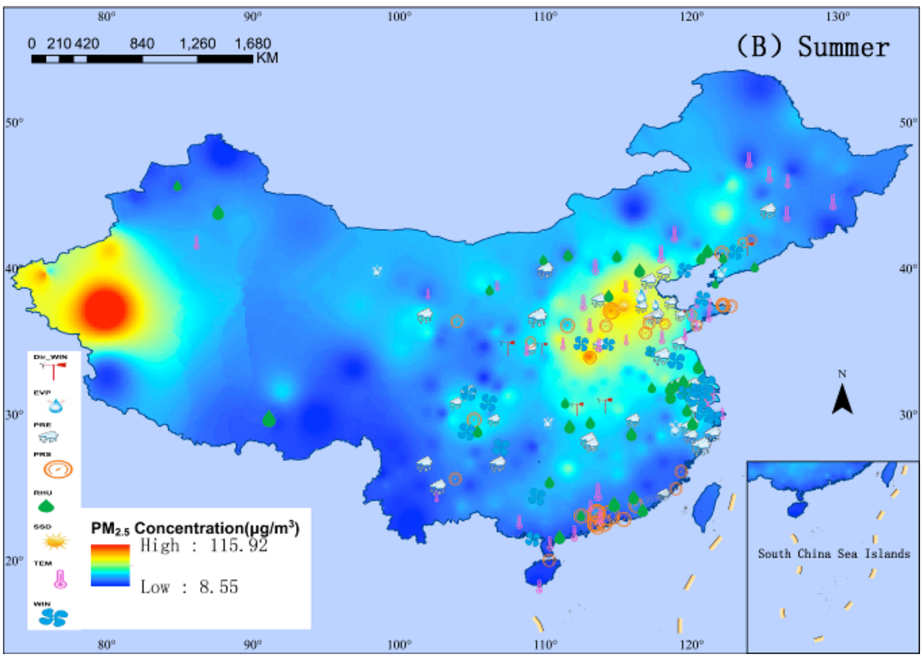
Through statistical analysis, we selected the factor with the largest ρ value as the dominant meteorological factor for local $PM_{2.5}$ concentrations. The spatial and temporal variations of the dominant meteorological influence on local $PM_{2.5}$ concentrations across China are demonstrated as Fig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

a. 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 (e.g. the Beijing-Tianjin-Hebei region).

b. Some meteorological factors (e.g. *temperature*, *wind* and *humidity*) 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 factors for $PM_{2.5}$ concentrations, yet some meteorological factors are context-related influencing factors for local $PM_{2.5}$ concentrations.

c. Similar to patterns revealed in Fig 2, the ρ value for the dominant meteorological factors is the largest in winter than that in summer. Furthermore, it is noted that the dominant meteorological factors demonstrates more regional similarity when $PM_{2.5}$ concentrations is high. For instance, 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 *wind*, *temperature*, *wind direction* and *air pressure*) for $PM_{2.5}$ concentrations is irregularly distributed within this region in summer. Based on this pattern, when a regional haze event 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 haze events in the Beijing-Tianjin-Hebei region can be considerably mitigated by strong winds. On the other hand, regional air pollution in summer can hardly be solved simultaneously through one specific meteorological factor.


(A) Spring
0 210 420 840 1,260 1,680
KM
PM2.5 Concentration(μg/m³)
High : 134.52
Low : 11.62
South China Sea Islands
80°
90°
100°
110°
120°
130°
50°
40°
30°
20°
N


(B) Summer
0 210 420 840 1,260 1,680
KM
PM2.5 Concentration(μg/m³)
High : 115.92
Low : 8.55
South China Sea Islands
80°
90°
100°
110°
120°
130°
50°
40°
30°
20°
N

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Manuscript under review for journal Atmos. Chem. Phys.
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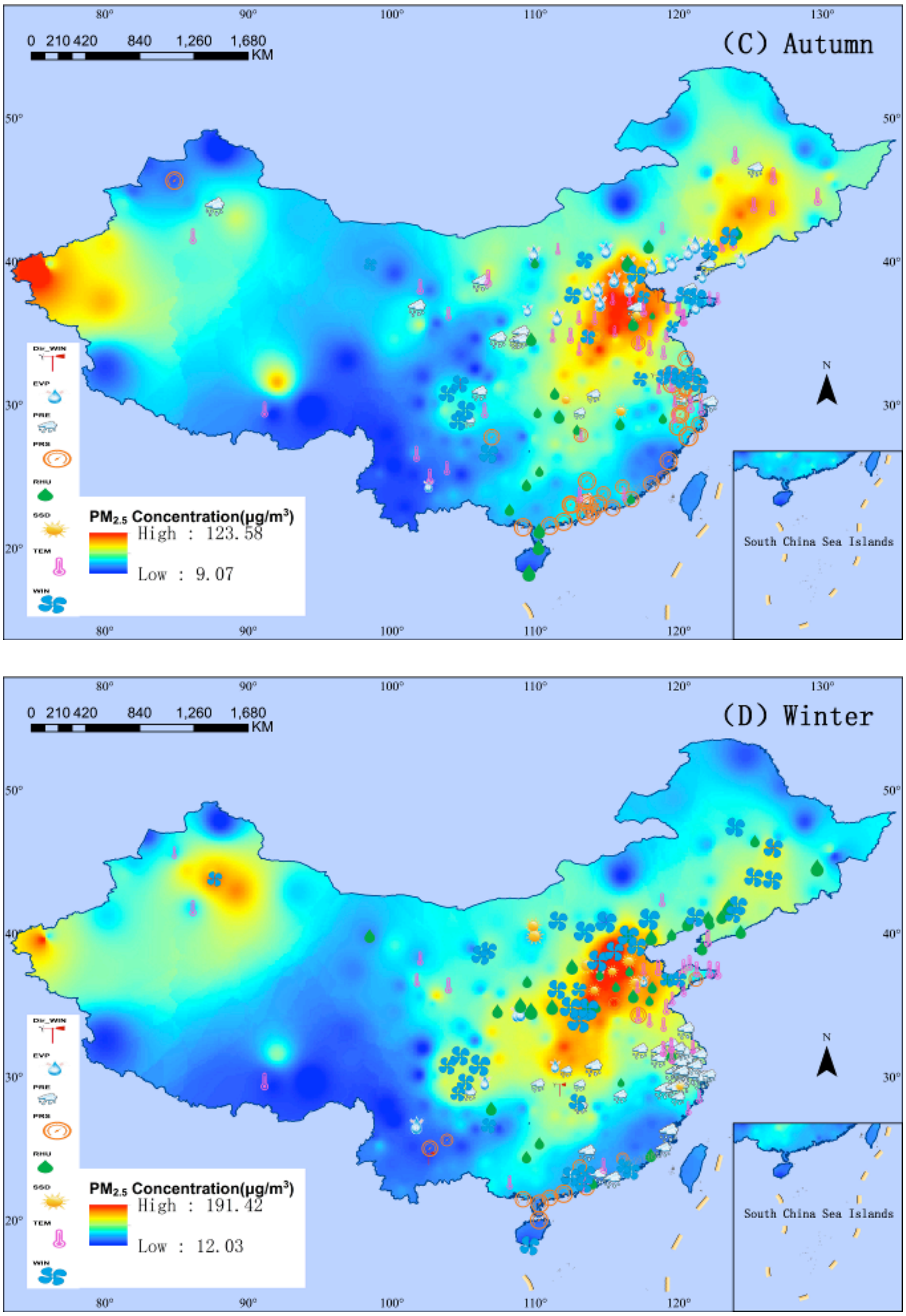

Fig 3. The dominant meteorological factor for local $PM_{2.5}$ concentrations in 189 monitoring cities across China

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

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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 1 and Fig 4.

Table 1. The comparison of the influence of individual meteorological factors on $PM_{2.5}$ concentrations in 189 cities across China

Season	Factors	*TEM*	*SSD*	*PRE*	*EVP*	*PRS*	*RHU*	*WIN*	*Dir_WIN*
Spring	No. of cities[1]	45	8	22	8	31	34	35	6
	Mean ρ value	0.281	0.138	0.152	0.131	0.209	0.204	0.215	0.104
	SD of ρ value	0.024	0.019	0.024	0.021	0.028	0.028	0.019	0.015
	Max ρ value	0.747	0.617	0.723	0.610	0.714	0.796	0.555	0.502
Summer	No. of cities	38	1	37	7	35	41	23	7
	Mean ρ value	0.244	0.107	0.179	0.119	0.175	0.221	0.168	0.067
	SD of ρ value	0.019	0.014	0.023	0.014	0.021	0.024	0.015	0.007
	Max ρ value	0.611	0.507	0.716	0.625	0.676	0.694	0.536	0.364
Autumn	No. of cities	58	3	18	21	43	20	23	3
	Mean ρ value	0.330	0.132	0.159	0.176	0.271	0.225	0.230	0.082
	SD of ρ value	0.020	0.014	0.025	0.027	0.029	0.028	0.018	0.009
	Max ρ value	0.641	0.472	0.714	0.637	0.697	0.773	0.556	0.452
Winter	No. of cities	43	8	40	8	14	34	40	2
	Mean ρ value	0.310	0.172	0.200	0.185	0.198	0.300	0.255	0.115
	SD of ρ value	0.017	0.019	0.045	0.025	0.019	0.028	0.033	0.015
	Max ρ value	0.626	0.611	0.770	0.591	0.634	0.721	0.746	0.525

[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.

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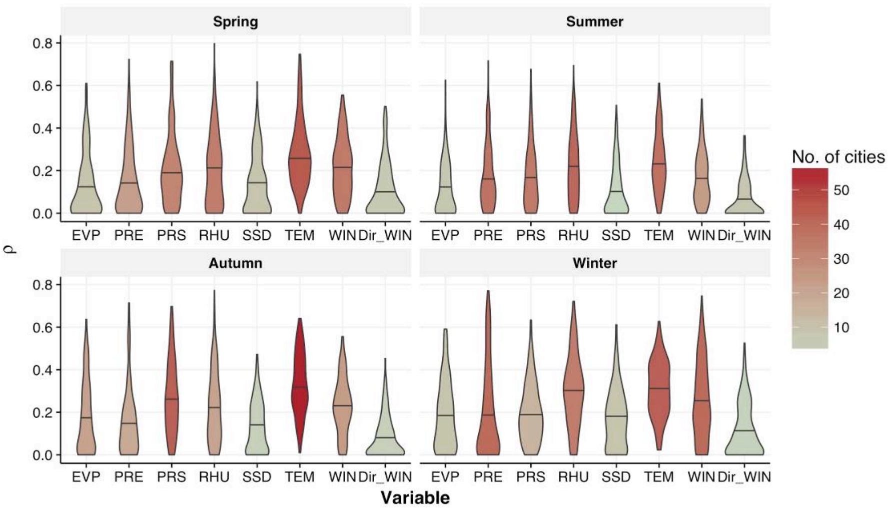

Fig 4. The comparison of the influence of eight different meteorological factors on local $PM_{2.5}$ concentrations in 189 cities across China (violin plot)

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 distribution frequency of ρ value for 189 cities.

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

a. From a national perspective, *temperature*, *humidity*, *wind* and *air pressure* exert stronger influences on local $PM_{2.5}$ concentrations than other factors. The annual mean ρ value for *temperature*, *humidity*, *wind* and *air pressure* was 0.291, 0.238, 0.217 and 0.213, compared with *wind direction* (0.092), *SSD* (0.137), *evaporation* (0.153) and *precipitation* (0.173). Amongst the eight factors, *temperature* was proved 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.

b. 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

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local $PM_{2.5}$ concentrations. As shown in Table 1, the max ρ value for the eight meteorological factors in each season was large than 0.5 (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, the influence of some meteorological factors, which have little influence on $PM_{2.5}$ concentrations at a large scale, should be carefully examined at the local scale.

c. 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. In this case, as explained above, comprehensive meteorological influences on $PM_{2.5}$ concentrations are limited considerably.

5 Discussion

5.1 Underlying mechanisms for bidirectional coupling between $PM_{2.5}$ concentration and individual meteorological factors

Although the CCM method quantified the causality between $PM_{2.5}$ concentration and individual meteorological factors, it did not explain how these variables were interacted. To better understand meteorological influences on $PM_{2.5}$ concentration and its feedback effects, we attempt to give some brief explanation on the mechanisms of some typical bidirectional coupling. As we know, that one meteorological factor may influence $PM_{2.5}$ concentrations through different mechanisms and here we only explain some fundamental interactions between $PM_{2.5}$ concentrations and individual meteorological factors.

Interactions between wind and $PM_{2.5}$: On one hand, winds, especially strong winds blow airborne pollutants away and reduce $PM_{2,5}$ concentration effectively. On the other hand, high $PM_{2.5}$ concentration, especially a quickly rising $PM_{2.5}$ concentration brings the atmospheric environment to a comparatively stable status, which prevents the form of winds and reduces the wind speed in smog-covered areas.

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Interactions between humidity and $PM_{2.5}$: Higher humidity causes more vapor attached to the Particulate Matter and significantly increases the size and mass concentration of PM, namely the hygroscopic increase and accumulation of $PM_{2.5}$ (Fu et al., 2016). On the other hand, the larger mass and higher concentration makes it difficult for $PM_{2.5}$ to disperse and leads to a stable polluted atmospheric environment, which is not favorable for the vapor evaporation and further increase the environmental humidity.

Interactions between SSD and $PM_{2.5}$: Previous studies (Guo et al., 2012; Zhang et al., 2013; Cao et al., 2014; etc) have proved that organic carbon (OC) is an important component for $PM_{2.5}$, and atmospheric photolysis could occur on OC to reduce $PM_{2.5}$ concentration. Therefore, longer SSD has a negative influence on $PM_{2.5}$ concentration. On the other hand, SSD is a general indicator of cloudiness （https://en.wikipedia.org/wiki/Sunshine_duration）. The more cloud, the less SSD received on the ground observation station. By analogy, serious smog (thick black fog) caused by high $PM_{2.5}$ concentration notably blocked radiation emitted to the ground and thus the $PM_{2.5}$ concentration has a negative feedback effect on the SSD.

Interactions between Precipitation and $PM_{2.5}$: On one hand, previous studies (Tai et al., 2010) show that an increase in precipitation causes a decrease in all $PM_{2.5}$ components through scavenging. On the other hand, the influence of $PM_{2.5}$ on precipitation are more complex: $PM_{2.5}$ can serve as cloud nuclei influencing precipitation (suppressing the light rain and strengthen the heavy rain) by acting on the size and number of cloud droplets (Rosenfeld et al., 2014). Meanwhile, $PM_{2.5}$ can also modulate precipitation by changing the atmospheric vertical static stability via the aerosol radiative effect (Jacobson, 2001).

Interactions between Temperature and $PM_{2.5}$: Temperature is one important meteorological factors affecting the transformation of pollutants and the temperature inversion is one major cause for haze episodes in winter. The temperature inversion leads to an unfavorable condition for the dispersion of $PM_{2.5}$ and an increase of $PM_{2.5}$ concentrations. On the other hand, high $PM_{2.5}$ concentrations may lead to a stable atmospheric environment, and further improve the temperature inversion phenomenon.

Interactions between Air pressure and $PM_{2.5}$: When the atmospheric environment is controlled by low air pressure, it demonstrates an unstable status and the near-ground air is pushed upward, which is favorable for the transportation of airborne pollutants and the reduction of $PM_{2.5}$ concentrations. On the other hand, high $PM_{2.5}$ concentrations may lead to the temperature inversion phenomenon, usually accompanied with a stable atmospheric controlled by high air pressure.

Interactions between Evaporation and $PM_{2.5}$: Liu et al (2015) suggested that the loss of $PM_{2.5}$ concentrations increased with an increase of evaporation. Meanwhile, high $PM_{2.5}$ concentrations lead to a stable atmospheric environment, in which the evaporation rate is low.

Interactions between Wind direction and $PM_{2.5}$: The influence of wind direction on $PM_{2.5}$ concentrations and its feedback effects is majorly dependent on the geographical conditions and local landscape patterns. For instance, due to the specific geographical conditions surrounded by hills on three sides, northwest wind in Beijing leads to an improvement of air quality whilst southeast wind leads to the accumulation of airborne pollutants. However, the influence of wind direction on $PM_{2.5}$ concentrations varies significantly in other cities. So the interactions between wind direction and $PM_{2.5}$ is context-related.

5.2 Understanding the formation mechanisms of haze episodes and improving air quality from a meteorological perspective

With rapidly growing haze events, meteorological influences on $PM_{2.5}$ concentrations have become a hot social-economic topic not only studied by scholars, but also considered by government officials and decision makers. On December 1st, 2016, Beijing published the latest regulations for the prevention and control of meteorological hazards (http://www.bjrd.gov.cn/zt/cwhzt1431/hywj/201612/t20161201_168233.html) and included haze events as one type of meteorological hazards, sparking widespread controversy. Although the meteorological influences on $PM_{2.5}$ concentrations are well acknowledged, quantifying meteorological contribution, compared with exhaust emission, to airborne pollution remains challenging. Hence, criticisms have been raised that since traffic and industry induced exhaust emission is the main cause for airborne pollution, the emphasis on the meteorological causes for haze hazards is to avoid governmental responsibilities. Some of our previous research may provide reference for a better understanding of this issue from different perspectives. Chen, Z et al. (2016) pointed out that more than 180 days in Beijing experienced notable and sudden air quality change (the Air quality Index, AQI, difference between one day and its previous day is larger than 50) in 2014. Considering that the industrial, automobile and household exhaust emission, which are main sources for $PM_{2.5}$ and other airborne pollutants, is unlikely to change dramatically in one day, meteorological factors seem to exert an important influence on local $PM_{2.5}$ concentrations. Chen, Z et al. (2017) proved that such meteorological factors as *SSD*, *wind* and *humidity* exerted strong influences on winter $PM_{2.5}$ concentrations in the Beijing-Tianjin-Hebei Region. Furthermore, Chen, Z et al. (2017) quantified the interactions between different meteorological factors and suggested that one meteorological factor may influence $PM_{2.5}$ concentrations through both direct and indirect means. Take winter $PM_{2.5}$ concentrations in Beijing for instance. The *wind* factor has a strong negative causality influence on $PM_{2.5}$ concentrations. In addition, the *wind* factor has a negative causality on *humidity*, as well as positive causality on *SSD* and *evaporation*. Since the factor *humidity* (*SSD* and *evaporation*) has a strong positive (negative) influence[3] on local $PM_{2.5}$ concentrations, increasing *wind* speeds can reduce $PM_{2.5}$ concentrations indirectly through reduced (increased) *humidity* (*SSD* and *evaporation*). In this research, we further revealed that meteorological influences on $PM_{2.5}$ concentrations varied significantly across China. In the most polluted winter, the dominant meteorological factors for $PM_{2.5}$ concentrations in the North China region are mainly the *wind* and *humidity* factor whilst the dominant meteorological factor on $PM_{2.5}$ concentrations in coastal cities are mainly *precipitation* and *temperature*. Furthermore, this research proved that the meteorological influences on $PM_{2.5}$ concentrations were the strongest in winter, when the $PM_{2.5}$ concentrations was the highest. With strong bidirectional coupling between individual meteorological factors and $PM_{2.5}$ concentrations in winter, $PM_{2.5}$ concentrations can be further enhanced through complicated atmospheric mechanisms, leading to more haze events. Based on these studies, we are not attempting to challenge the fundamental contribution of human-induced exhaust emission to $PM_{2.5}$ concentrations. Instead, our

[3] Although the CCM method did not give a positive(negative) direction between interactions between two variables, the direction of interactions can be easily understood according to the correlation coefficient.

research suggested that with a stable amount of exhaust emission, meteorology was a key factor for the persistence and deterioration of haze events, especially in winter. On one hand, the pollutant emission should be strictly restricted, as human-induced emission is the major cause of haze pollution. Meanwhile, since meteorological factors play an important role in the accumulation and dispersion of $PM_{2.5}$, meteorological influences should be comprehensively considered for a better understanding and management of haze episodes.

In spite of a diversity of prediction models, air quality forecast, especially $PM_{2.5}$ forecasting in China, remains challenging. Commonly used air quality forecast models include CAMx (ENVIRON Company, US), CMAQ (Environmental Protection Agency, US), WRFCHEM (National Center for Atmospheric Research, US) and NAQ PMS (Institute of Atmospheric Physics, Chinese Academy of Sciences, China). Due to highly complicated atmospheric environment and the difficulty in acquiring true data of exhaust emission, these models may lead to large biases and uncertainty when applied to China. On the other hand, without priori knowledge of mechanisms of haze formation and information of exhaust emission, statistical models can achieve satisfactory forecasting results based on massive historical data (Cheng et al., 2015). However, Cheng et al. (2015) pointed out that most statistical models were static model and did not consider the meteorological influences on airborne pollutants. Even if some models consider meteorological influences on $PM_{2.5}$ concentrations, they only employ correlation analysis, which has been proved to problematic in complicated atmospheric environment. In this case, this research provides useful reference for improving existing statistical models. The ρ value is a better indicator than the correlation coefficient to demonstrate the quantitative influence of individual meteorological factors on local $PM_{2.5}$ concentrations. By incorporating the ρ value, instead of the correlation coefficient, of different factors into corresponding GAM (Generalized Additive Models) and adjusting parameters accordingly, we can significantly improve the reliability of future forecasting of $PM_{2.5}$ concentrations.

With the understanding of strong meteorological influences on $PM_{2.5}$ concentrations across China, especially in some heavily polluted regions, decision makers are placing special emphasis on improving local and regional air quality through meteorological means. Targeting this, quantified causality influence 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, yet its potential effects arouse wide controversies. 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. In consequence, the wind-corridor project may directly allow in more strong wind, which thus leads to a larger value of *SSD* and *EVP* and a smaller value of *RHU*. The change of *SSD*, *RHU* and *EVP* 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 to the wind-corridor project, 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 the process of 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, meteorological influences on $PM_{2.5}$ concentrations vary notably across China. Considering 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 in winter, meteorological means for encouraging strong winds are more likely to reduce $PM_{2.5}$ concentrations considerably whilst meteorological means for inducing precipitation are more likely to improve air quality in coastal cities and cities within the Yangtze River basin.

6 Conclusions

Based on the CCM method, we quantified the causality influence of eight meteorological factors on local $PM_{2.5}$ concentrations for 189 monitoring cities across China. The results suggest that meteorological influences on $PM_{2.5}$ are of notable seasonal and spatial variations. For most cities, the higher $PM_{2.5}$ concentrations, the

Atmos. Chem. Phys. Discuss., https://doi.org/10.5194/acp-2017-376
Manuscript under review for journal Atmos. Chem. Phys.
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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, temperature, humidity, wind and air pressure exert stronger influences on local $PM_{2.5}$ concentrations than other factors. The causality 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

This research is supported by National Natural Science Foundation of China (Grant Nos. 210100066), the National Key Research and Development Program of China (NO.2016YFA0600104) and Beijing Training Support Project for excellent scholars 2015000020124G059

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