Dear Dr Sally E. Pusede:

Thanks so much for giving us a chance to revise and submit our manuscript for the potential publication in ACP. According to the reviewer’s comment, we realized that more in-depth analysis, especially those studies related to this research and well explained some phenomena proposed in this research should be added. In the revised manuscript, we have added a large body of references and much more discussion and explanation to the revised manuscript according to the comments. All the descriptive discussion in the previous manuscript, has been replaced with more in-depth discussion, as well as the comparison with previous studies. By explaining these previous studies, readers can see that the findings from this research is consistent with and a major extension of previous studies. Meanwhile, for some specific issues raised by the reviewer (e.g. the reason for variations of meteorological influences across China, and the sensitivity of PM$_{2.5}$ variations to the change of different meteorological factors, e.g. wind speed and precipitation), we have added some references to explain and prove our suggestions with previous case studies and experiments. By making these revisions, we believe this manuscript has been significantly improved. Thanks again for the valuable comments from you and the reviewer. We are more than willing to further revise this manuscript if additional comments are given.

With regards
Ziyue

General Comments

The authors have made a good effort to respond to the reviewer comments. My main remaining concern is that I still think that the paper as written is mostly descriptive and I think it would benefit from more in-depth discussion of the significance of the work. I've pointed out a few specific areas where I think discussion could be added/improved in the comments below.
Dear Reviewer, thanks so much for your valuable suggestions. By revising this manuscript according to your general comments, we believe we have replaced all those descriptive discussion with in-depth discussion, supported by previous studies and the manuscript has been greatly improved. Thanks again for your time and help. We are more than willing to further revise this manuscript if additional comments are given.

Specific Comments

pp 2, ln 38-42 – I wonder if it would be more effective to frame the opening here in terms of the air pollution itself, rather than haze, which I think of as being one of the side effects of air pollution.

R: Thanks so much for this comment. In the revised manuscript, we have replaced the word "haze" with "high PM\textsubscript{2.5} concentrations" or "PM\textsubscript{2.5} pollution".

pp 2, ln 47 – Similarly, I think the opening would be stronger if you provided more specifics about the health impacts of PM

R: This is a very good suggestion. In the revised manuscript, we have added some details concerning specific influence of PM\textsubscript{2.5} concentration on human health as follows:

Garrett and Casimiro, (2011) revealed that the relative risk for cardiovascular disease-related mortality for older groups (>65 years) was 2.39\% (95\%C.I. 1.29\%, 3.50\%) for each 10 µg/m\textsuperscript{3} PM\textsubscript{2.5} increase. Guaita et al. (2011) Qiao et al. (2014) found an interquartile range increment in PM\textsubscript{2.5} concentration (36.47 µg/m\textsuperscript{3}) led to a 0.57\% [95\% confidence interval (CI): 0.13\%, 1.01\%] increase in emergency room visits. Through experiments in nine French cities, Pasca et al. (2014) observed a notable effect of PM\textsubscript{2.5} (+0.7\%, [-0.1; 1.6]) on all year non-accidental mortality for all age groups. In five European cities, estimation results suggested that a 12.4 µg/m\textsuperscript{3} increase in the PM\textsubscript{2.5} concentration can lead to 3.0\% [-2.7\%; 9.1\%] increase in cardiovascular mortality (Lanzinger et al.,
Li et al. (2015) found that temperature played an important role in PM$_{2.5}$ induced mortality in Beijing. Under the condition of the lowest temperature range (-9.7~2.6 °C), a 10 μg/m$^3$ increase in PM2.5 concentration led to an increase of 1.27 % (95 % CI 0.38~2.17 %) in the relative risk (RR) of cardiovascular mortality, which was the highest for all temperature ranges.

R: We are sorry that we did not make this part clear. This should PM, ozone and NO2 and we have revised this sentence in the revised manuscript.

It would be nice to have some discussion in the paper (not necessarily in this section) of why different factors are more important in different regions.

R: Thanks so much for this valuable comment. Yes, we should add more discussion, especially the comparison with existing literatures to better explain this issue. We have added a large body of relevant references and some possible explanations to discuss the reasons why different factors are more important in different regions.

The explanation added to the revised manuscript: Firstly, the meteorological conditions varied significantly in different regions across China. Secondly, interactions between meteorological factors and PM$_{2.5}$ concentrations can be highly complicated, subject to meteorological conditions and local PM$_{2.5}$ concentrations. A large body of references and relevant explanation included in the revised manuscript is listed as follows, marked red:

The finding from this research was consistent with and a major extension of that from previous studies by quantifying the influence of individual meteorological factors in a large number of cities across China, instead of several scattered cities, using a more robust causality analysis method, other than the correlation analysis. Similar to previous studies, this study also revealed notable differences in meteorological influences on PM$_{2.5}$ concentrations at the national scale, the major reason for which was 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 effects on PM$_{2.5}$ concentrations and notably reduce PM$_{2.5}$ concentrations. Meanwhile, slight precipitation may not effectively remove the high-concentration PM$_{2.5}$. Instead, the slight precipitation may induce enhanced relative humidity and thus lead to the increase 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).
Similarly, I think it would be valuable here to have some discussion of why winds are important in the Beijing-Tianjin-Hebei, but less important in summer. I'd imagine it has to do with having stronger, and more large-scale, circulation in winter?

R: Thanks so much for this suggestions. Yes, you are right. Large-scale circulation in winter is the major reason for strong winds in winter. We added to two references to the revised manuscript to prove this.

The results show that the presence of high air pressure in northwest Beijing (NW-High) generally produced strong northwest winds with clean upwind air. As a result, the NW-High played an important role in cleaning Beijing’s PM$_{2.5}$ (Tie et al., 2015). In spring and winter, with strong northwesterly synoptic winds, the sea-breeze circulation is confined in the coastal area, and the MPC is suppressed. (Miao et. al, 2015)


Why do you think precip might be more important in places with lower pollution levels? Is the air cleaner because the regions are wetter, or for another reason?

R: This is a very good point. You proposed a comment above that why meteorological influences on PM$_{2.5}$ concentrations varies across China. And precipitation is a good example that exerts different influences on PM$_{2.5}$ concentrations. We have added some relevant references to the revised manuscript to address the question.
Luo et al. (2017) pointed out that there may be thresholds for the negative influences of precipitations on PM$_{2.5}$ concentrations. Heavy precipitation can have a strong washing-off effect on PM$_{2.5}$ concentrations and notably reduce PM$_{2.5}$ concentrations. Meanwhile, slight precipitation may not effectively remove the high-concentration PM$_{2.5}$. Instead, the slight precipitation may induce enhanced relative humidity and thus lead to the increase of PM$_{2.5}$ concentrations. So either large amount of precipitation or low PM$_{2.5}$ concentrations can lead to a large influence of precipitation on PM$_{2.5}$ concentrations. This was also proved by some experiments. Through experiments, it was revealed that 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, a city with lower PM$_{2.5}$ concentrations. (Guo et al., 2016). In this research, we found that precipitation mainly exerted a major role in influencing PM$_{2.5}$ concentrations in coastal areas and Yangtze River Basins, which is consistent with these findings. The precipitation in coastal areas and Yangtze River Basins is much larger than that in North parts of China, where the PM$_{2.5}$ concentrations are higher and thus the washing-off effects of precipitations are significantly limited. Studies in Nanjing (Chen, T. et al., 2016), a mega city in the Yangtze River, and Hong Kong (Fung et al., 2016), a mega coastal city, also proved that precipitation is the most important meteorological factors for PM$_{2.5}$ concentrations.

In the revised manuscript, the following text has been added:

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 washing-off effects 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.
pp 22, footnote 6- For completeness, I think you should probably report the correlation coefficients or cite a paper that does.

R: Thanks so much for this comment. In the revised manuscript, a reference, Chen et al. (2017), which introduced some calculated correlation coefficients, as well as the p value, has been cited.

pp 24, ln 548 – 552 – I’m still not convinced of this point. I think there is a difference between showing which meteorological factor is most dominant vs. showing sensitivity to changes in meteorological factors (for example, the anthropogenic greenhouse effect is dominated by CO2, but the atmosphere is much more sensitivity to changes in CH4). You said in your response that you looked at year-to-year variability, but I didn’t see any discussion of it in the paper. Did it add any insights?

R: Thanks so much for this point. With this comment, as well as some other comments, we realized that we did not make this part clear. And the CCM method itself may not well reveal the sensitivity of PM2.5 variations to the change of meteorological factors. So in the revised manuscript, firstly, we added some relevant studies, which employed local scale analysis to prove a similar finding from this research (e.g. the major influencing factor for Beijing in winter is wind speed whilst the factor is precipitation in Yangtze River Basin and coast areas, such as Nanjing, Guangzhou). In addition, some other issues, such as why strong wind is prevailing in Beijing is in winter and why precipitation has a large washing-off effects in coastal areas, has been added as well in above responses. Most importantly, we added several papers that well proved the hypothesis presented here. In terms of wind speed, in North China, PM2.5 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 PM2.5 concentrations by as much as 12.0 μgm-3, compared with the change of PM2.5 concentrations by up to 4.0 μgm-3 in south-eastern, northwestern and south-western China (Tai et al., 2010). Therefore, wind speed is BOTH the dominant influencing factor and the factor that PM2.5 variations are most sensitive to in North China, and thus meteorological means for encouraging strong winds are more likely to reduce PM2.5 concentrations considerably in North China. Similarly, Luo et al. (2017) revealed that there was a threshold for precipitation to have
washing-off effects for PM$_{2.5}$ concentrations and Guo et al. (2016) revealed that the same amount of precipitation had a stronger washing-off effect 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.

In the revised manuscript, the following text has been added to the discussion and conclusion part:

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, 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). Considering the strong winds in winter, the dominant influence of wind speed on PM$_{2.5}$ concentrations and the sensitivity of PM$_{2.5}$ feedbacks to the change of wind speed, 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.
pp 24-25, conclusions section – I think this section could be deepened by making clear how this study fits in with the existing literature. How do these results compare to the literature, and what new knowledge has been added? As someone who is admittedly not well versed in the literature on air quality-meteorology interactions in China, this was not clear to me.

R: Thanks so much for this valuable comment. As explained above, in the discussion part, we have added a large part of literature review, concerning existing research on the correlations between individual meteorological factors and PM$_{2.5}$ concentrations. As you can see, previous studies mainly focused on the meteorological influences on PM$_{2.5}$ concentrations in several specific cities, and thus a comprehensive comparison has yet been conducted. Furthermore, previous studies mainly employed the correlation analysis, which may be biased in quantifying meteorological influences on PM$_{2.5}$ concentrations. The findings from this research was generally consistent with that from previous studies. Firstly, by comparing the results from different studies, one can see that meteorological influences varied significantly in different cities across China, which was further proved by this research conducted at the national scale. Secondly, the extracted dominant meteorological factors for some cities in most polluted winter (e.g. wind for Beijing, precipitation for Nanjing and Hong Kong) were similar to findings from this research. This research is a major extension of previous studies by extending the study sites from scattered cities to 188 cities all over China. In this case, regional similarity in meteorological influences on PM$_{2.5}$ concentrations, which cannot be extracted based on local scale case studies, was revealed. Meanwhile, the CCM method provides more reliable quantitative analysis of meteorological influences on PM$_{2.5}$ concentrations, compared with the correlation coefficient. Thirdly, this research analyzed a complete set of eight meteorological factors, whilst previous studies generally focused on a smaller number of meteorological factors. Fourthly, the study period of previous studies conducted in specific cities varied significantly, ranging from weeks to years. Instead, this research used a unified three-year observation data to compare meteorological influences on PM$_{2.5}$ concentrations in different cities, and thus the comparison result is more robust. Finally, some statistics of the general influence of individual meteorological factors
(e.g. wind, precipitation) was rarely compared and thus the three major factors, temperature, humidity and wind for PM$_{2.5}$ concentrations all over China, revealed in this research, were a major contribution to the existing literatures.

So compared with previous studies, this research further proved the diversity of meteorological influences on PM$_{2.5}$ concentrations in China, and revealed some regional patterns which were rarely studied, and provided decision makers with a comprehensive understanding of meteorological influences across China, which is of practical significance for management of local and regional air quality.

Thanks again for this valuable comment. By responding to this comment, we reviewed many relevant papers, and better linked this research to other studies. This manuscript, especially the discussion and conclusion part, has been improved significantly.

In the revised manuscript, the following text has been added to the discussion and conclusion part:

**Discussion:**

Despite the lack of a comprehensive comparison of meteorological influences on PM$_{2.5}$ concentrations in different regions, some studies concerning meteorology-PM$_{2.5}$ relationship in specific areas have been conducted and 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 mainly employed correlation analysis to quantify the influence of several meteorological factors on PM$_{2.5}$ concentrations and suggested that meteorological influences on PM$_{2.5}$ concentrations varied significantly across regions. The dominant meteorological factors for PM$_{2.5}$ concentrations (presented as the largest correlation coefficients in previous studies and the $\rho$ value in this research) demonstrated notable regional
For Nanjing (Chen, T. et al., 2016), a mega city in the Yangtze River, and Hong Kong (Fung et al.), 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. These studies generally analyzed and compared the influences of different meteorological factors on PM$_{2.5}$ concentrations and extracted the dominant meteorological influencing factors for specific areas. However, most studies were conducted at the local scale and few studies have focused on the comparison and statistics of meteorological influences on PM$_{2.5}$ concentrations in different areas. Meanwhile, although the correlation coefficient can be used to understand and compare the general magnitude of the influence of individual meteorological factors, the correlation analysis, as explained above, may lead to large bias in quantifying the meteorological influences on PM$_{2.5}$ concentrations.

**Conclusion part:**
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 2014.3 to 2017.2. Similar to previous studies conducted at the local scale, this research further proved 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 PM2.5 concentrations, which cannot be understood through small-scale case studies.

Technical corrections

pp 1, ln 20-22 – The wording of this sentence is unclear.
R: This sentence has been revised from "For the heavily polluted North China region, the higher PM2.5 concentrations, the larger influences meteorological factors exert on PM2.5 concentrations." To "For the heavily polluted North China region, when PM2.5 concentrations are high, meteorological influences on PM2.5 concentrations are strong."

pp 2, ln 63 – should read "ozone concentrations were linearly correlated..."
R: Corrected.

pp 3, ln 66 – should read "... during the summer monsoon."
R: Corrected.

pp 3, ln 86 – should read "... humidity and solar radiation..."
R: Corrected.

pp 5, ln 141 – should read "8am-8pm"
R: Corrected.

pp 9 – Figure 1 appears blurry in the pdf file.
R: This Figure 1 has been reproduced.

pp 13, ln 312-313 – should read "... are influenced by similar dominant meteorological factors..."
R: Corrected.

pp 14, ln 318 – should read "the higher the local PM2.5 concentrations,"
R: Corrected.

pp 14, ln 322 – should read "spring and summer are comparatively low,"
R: Corrected.

pp 20, ln 410-413 – this sentence is a bit unclear.
R: Thanks so much for this. We changed the sentence from, "As a result, when analyzing meteorological influences on local PM2.5 concentrations for a specific city, the influence of meteorological factors that have little influence on PM2.5
concentrations at a large scale should be carefully examined at the local scale. “

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.”

R: in the revised manuscript, we changed the sentence from “dynamic statistical models comprehensively consider the meteorological influences on PM$_{2.5}$ concentrations” to “dynamic statistical models additionally consider the meteorological influences on PM$_{2.5}$ concentrations”.
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 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, the higher when PM$_{2.5}$ concentrations are high, the larger influences meteorological factors exert 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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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. Recently, the frequency of haze events, 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 since 2013. Statistical records from the national air quality publishing platform (http://113.108.142.147:20035/emcpublish/) revealed that PM$_{2.5}$ induced pollution haze events 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.

Serious haze High PM$_{2.5}$ concentrations not only influence people’s daily life (e.g. the cause of severe traffic jam during haze episodes), but also severely threatens the health of residents that suffer from polluted air quality. Recent studies (Garrett and Casimiro, 2011; Qiao et al., 2014; Pasca et al., 2014; Lanzinger et al., 2015; Li et al., 2015a, etc.) have proven that airborne pollutants, PM$_{2.5}$ in particular, are closely related to all-cause and cause-specific mortality. Garrett and Casimiro, (2011) revealed that the relative risk for cardiovascular disease-related mortality for older groups (>65 years) was 2.39% (95% C.I. 1.29%, 3.50%) for each 10 μg/m$^3$ PM$_{2.5}$ increase. Guaita et al. (2011) Qiao et al. (2014) found an interquartile range increment in PM$_{2.5}$ concentration (36.47 μg/m$^3$) led to a 0.57% [95% confidence interval (CI): 0.13%, 1.01%] increase in emergency room visits. Through experiments in nine French cities, Pasca et al. (2014) observed a notable effect of PM$_{2.5}$ (+0.7%, [-0.1; 1.6]) on all year non-accidental mortality for all age groups. In five European cities, estimation results suggested that a 12.4 μg/m$^3$ increase in the PM$_{2.5}$ concentration can lead to 3.0% [-2.7%; 9.1%] increase in cardiovascular mortality (Lanzinger et al., 2015). Li et al. (2015a) found that temperature played an important role in PM$_{2.5}$ induced mortality in Beijing. Under the condition of the lowest temperature range (-9.7~2.6 °C), a 10 μg/m$^3$ increase in PM2.5 concentration led to an increase of 1.27% (95% CI 0.38~2.17 %) in the relative risk (RR) of cardiovascular mortality, which was the highest for all temperature ranges. Due to its strong negative influences on public health, in consequence, scholars have been working towards a better understanding of sources (Guo et al., 2012; Zhang et al., 2013;
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$_{2.5}$ 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 controversial, 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 were 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 speed, dominated the fluctuation of PM$_{10}$ over the Klang Valley during the summer monsoon. In Melbourne, Pearce et al. (2011) found that local temperature led to strongest responses of different pollutants (PM, ozone and NO$_2$), whilst other meteorological factors (e.g. winds, water vapor pressure, radiation, precipitation) affected one or more specific pollutants. In the city of Elche, Spain, Galindo et al. (2011) revealed that fractions of three different PM sizes (PM$_1$, PM$_{2.5}$ and PM$_{10}$) were negatively correlated with wind speed in winter, whilst coarse fractions were strongly correlated with temperature and solar radiation. At a site of the Egyptian Mediterranean coast, El-Metwally and Alfaro (2013) found 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 pollutants 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.

Although correlations between airborne pollutants and meteorological factors have been well 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 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 1$^{st}$, 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 1$^{st}$, 2014 to February 28$^{th}$, 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) 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 PM$_{2.5}$ concentrations, these factors are further categorized into some sub-factors: evaporation (small evaporation and large evaporation, short for smallEVP and largeEVP$^2$), temperature (daily max temperature, smallEVP and LargeEVP indicate the evaporation amount measured using small-diameter and large-diameter equipments respectively. Generally, the measured values using the two types of equipment are of slight
mean temperature, min temperature, and largest temperature difference for the day, short for maxTEM, meanTEM, minTEM and difTEM), precipitation (total precipitation from 8am-21pm-8pm, total precipitation from 21pm-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\(^3\) for the day, short for SSD), wind speed (mean wind speed, max wind speed, extreme wind speed\(^4\), short for meanWIN, maxWIN and extWIN), wind direction (max wind direction\(^5\) 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.

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

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\(^3\) Sunshine duration represents the hours of sunshine measured during a day for a specific location on earth.

\(^4\) 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.

\(^5\) The max wind direction indicates the dominant wind direction for the period with the max wind speed.
moderate coupling in ecological time series. By analyzing the temporal variations of two

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 $\rho$ 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 $\{X\} = \{X(1), \ldots, X(L)\}$ and $\{Y\} = \{Y(1), \ldots, Y(L)\}$ are defined as the temporal
variations of two variables $X$ and $Y$. For $r = S$ to $L$ ($S < L$), two partial time series
$[X(1), \ldots, X(L_P)]$ and $[Y(1), \ldots, Y(L_P)]$ are extracted from the original time series ($r$ is the
current position whilst $S$ is the start position in the time series). Following this, the
shadow manifold $M_X$ is generated from $\{X\}$, which is a set of lagged-coordinate vectors
\begin{equation}
 x(t) = <X(t), X(t-\tau), \ldots, X(t-(E-1)\tau)> \text{ for } t = 1+(E-1)\tau \text{ to } t = r.
\end{equation}
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 $t_1, \ldots, t_{E+1}$. 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).
\begin{equation}
 \hat{Y}(t)|M_X = \sum_{i=1}^{E+1} w_i Y(t_i)
\end{equation}
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.
\begin{equation}
 w_i = \frac{1}{\sum_{j=1}^{E+1} u_j}
\end{equation}
Where $u_i = e^{-d_i^2/[d_i^2 + d_{ij}^2]}$ whilst $d_i(x(t), x(t_j))$ 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 may 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 $\rho$ 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 $\rho$ 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 $\rho$ 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 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 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), $\tau$ (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 \( \tau \) 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 \( \tau \) 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).

![Illustrative CCM results to demonstrate the bidirectional coupling between meteorological factors and PM$_{2.5}$ concentrations in Beijing (2014, winter)](image-url)
\( \rho \): predictive skills. \( L \): the length of time series. \( A \text{xmap} B \) stands for convergent cross mapping \( B \) from \( A \), in other words, the causality of variable \( B \) on \( A \). For instance, \( \text{PM}_{2.5} \text{xmap} \text{meanRHU} \) stands for the causality of \( \text{meanRHU} \) on \( \text{PM}_{2.5} \) concentrations. \( \text{meanRHU} \text{xmap} \text{PM}_{2.5} \) stands for the feedback effect of \( \text{PM}_{2.5} \) on \( \text{meanRHU} \) concentrations. \( \rho \) indicates the predictive skills of using \( \text{meanRHU} \) to retrieve \( \text{PM}_{2.5} \) concentrations.

According to Fig 1, one can see that the quantitative influence of individual meteorological factors on \( \text{PM}_{2.5} \) was well extracted using the CCM method whilst the feedback effect of \( \text{PM}_{2.5} \) on specific meteorological factors was revealed as well. For Beijing, \( \text{meanRHU} \) and \( \text{maxWIN} \) exerted a strong influence on local \( \text{PM}_{2.5} \) concentrations in Winter (\( \rho > 0.4 \)) whilst \( \text{SSD} \) and \( \text{minTEM} \) also had a weaker influence on local \( \text{PM}_{2.5} \) concentrations. (\( \rho \) close to 0.2). On the other hand, serious haze weather (high \( \text{PM}_{2.5} \) concentrations) had an even stronger feedback influence on \( \text{meanRHU} \), \( \text{maxWIN} \) and \( \text{SSD} \) (\( \rho \) close to 0.6) whilst \( \text{PM}_{2.5} \) had little influence on \( \text{minTEM} \) (\( \rho \) close to 0). The bidirectional coupling between \( \text{PM}_{2.5} \) 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 low SSD) in winter results in high \( \text{PM}_{2.5} \) concentrations, which in turn causes lower wind speed (higher humidity and lower SSD). In consequence, \( \text{PM}_{2.5} \) concentrations are increased further by the changing wind (humidity and SSD) situation. This mechanism causes a quickly rising \( \text{PM}_{2.5} \) 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. Similarly, bidirectional interactions between \( \text{PM}_{2.5} \) 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 \( \text{PM}_{2.5} \) concentrations across China, the feedback effect of \( \text{PM}_{2.5} \) concentrations on specific meteorological factors is not explained in details herein.

The \( \rho \) value is a direct indicator of quantitative causality. For this research, the maximum \( \rho \) value of all sub-factors in the same category was used as the causality of this specific meteorological factor on \( \text{PM}_{2.5} \) concentrations. E.g. for a specific city, the maximum \( \rho \) value of \( \text{maxTEM} \), \( \text{meanTEM} \), \( \text{minTEM} \) and \( \text{difTEM} \) is used as the influence of temperature on local \( \text{PM}_{2.5} \) 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 $\rho$ value during 2014-2016 for each city.

Generally, it is difficult to properly demonstrate the influence of eight meteorological factors on PM$_{2.5}$ concentrations for all 188 cities on a comprehensive map. Therefore, two cartography 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 $\rho$ 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).
Fig 2. Wind rose map of influences of eight individual meteorological factors on PM$_{2.5}$ concentrations across 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:

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 PM$_{2.5}$ concentrations cities are of some regional patterns. For instance, PM$_{2.5}$ concentrations in cities within the North China region (or the Northeast China region) are influenced by similar dominant meteorological factors, especially in winter, when PM$_{2.5}$ concentrations in these cities was high. Meanwhile, meteorological influences on PM$_{2.5}$ concentrations in cities within the Yangtze River basin were also highly similar in all seasons. 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).

c. 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 haze 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 value of these meteorological factors is notably larger in winter. 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 haze events within the North China region.

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 188 monitoring cities. Hence, we employed another cartography 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 $\rho$ 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 can be the dominant factor for cities within different regions but 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. For instance, 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.

c. Similar to patterns revealed in Fig 2, the $\rho$ 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. 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. According to this pattern, when a regional haze 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 haze events 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.
Fig 3. The dominant meteorological factor for local PM$_{2.5}$ concentrations in 188 monitoring cities across China. The size of symbols indicates the $\rho^2$ 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 1 and Fig 4.

Table 1. The comparison of the influence of individual meteorological factors on PM$_{2.5}$ concentrations in 188 cities across China (2014-2016)

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

1No. of cities: the number of cities with this factor as the dominant meteorological factor (its $\rho$ 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 $\rho$ value is the largest amongst eight factors) on local PM$_{2.5}$ concentrations. The shape of the violin bars indicated the frequency distribution of $\rho$ value for 188 cities.

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

a. From a national perspective, temperature, humidity, and wind exert stronger influences on local PM$_{2.5}$ concentrations than other factors. The annual mean $\rho$ 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 proved to be the most influential meteorological factor for general PM$_{2.5}$ concentrations in China. In addition to the largest mean $\rho$ value, temperature was the dominant meteorological factors for most cities in all seasons. Furthermore, the Coefficient of Variation (SD /mean $\times$100%) for temperature was much smaller than other factors, indicating the consistent influence of temperature on local PM$_{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 local PM$_{2.5}$ concentrations. As shown in Table 1, the max $\rho$ value for each
A 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, the influence of meteorological factors that have little influence on PM$_{2.5}$ concentrations at a large scale should also be comprehensively considered.[1] At the local scale, some factors (e.g. precipitation in summer and winter) may be the dominant meteorological factors for a large number of cities, though the mean $\rho$ 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 the general PM$_{2.5}$ concentrations are not high. Taking the precipitation as an example, Luo et al. (2017) pointed out that there may be thresholds for the negative influences of precipitations on PM2.5 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

Despite the lack of a comprehensive comparison of meteorological influences on PM$_{2.5}$ concentrations in different regions over China, some studies concerning meteorology-PM$_{2.5}$ relationship in specific areas have been conducted and 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 mainly employed correlation analysis to quantify the influence of several meteorological factors on PM$_{2.5}$ concentrations in the local scale.
concentrations and revealed suggested that meteorological influences on PM$_{2.5}$ concentrations varied significantly across regions. The dominant meteorological factors for PM$_{2.5}$ concentrations (presented as the largest correlation coefficients in previous studies and the $\rho$ value in this research) demonstrated notable regional differences in different cities. For Nanjing (Chen, T. et al., 2016), a mega city in the Yangtze River, and Hong Kong (Fung et al.), 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. These studies generally analyzed and compared the influences of different meteorological factors on PM$_{2.5}$ concentrations and extracted the dominant meteorological influencing factors for specific areas. However, most studies were conducted at the local scale and few studies have focused on the comparison and statistics of meteorological influences on PM$_{2.5}$ concentrations in different areas. Meanwhile, although the correlation coefficient can be used to understand and compare the general magnitude of the influence of individual meteorological factors, the correlation analysis, as explained above, may lead to large bias in quantifying the meteorological influences on PM$_{2.5}$ concentrations.

Different from previous studies conducted at the local scale, this research conducted at the national scale better understood spatial and temporal patterns of meteorological influences on PM$_{2.5}$ concentrations that will not be revealed in small-scale studies. The finding from this research was consistent with and a major extension of that from previous studies by quantifying the influence of individual meteorological factors in a large number of cities across China, instead of several scattered cities, using a more robust causality analysis method, other than the correlation analysis. Similar to previous studies, this study also revealed notable differences in meteorological influences on PM$_{2.5}$ concentrations at the national scale, the major reason for which was 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, 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 effects on PM$_{2.5}$ concentrations and notably reduce PM$_{2.5}$ concentrations. Meanwhile, slight precipitation may not effectively remove the high-concentration PM$_{2.5}$. Instead, the slight precipitation may induce enhanced relative humidity and thus lead to the increase 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 influences of individual meteorological factors on PM$_{2.5}$ concentrations should be further investigated for specific regions across China respectively based on long-term observation data.
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 1$^{st}$, 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. 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 influence on PM$_{2.5}$ concentrations. In addition, the wind factor decreases humidity, as well as increases SSD and evaporation. Since the factor humidity (SSD and evaporation) has a strong positive (negative) influence 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

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6 Although the CCM method did not give a positive(negative) direction of interactions between two variables, the direction of interactions can be easily understood according to the correlation coefficient (Chen et al., 2017).
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 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. Due to highly complicated atmospheric environment and the difficulty in acquiring true data of exhaust emission, commonly used models (e.g. CAMx, CMAQ and WRFChem) may lead to large biases and uncertainty when applied to China. On the other hand, without prior 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). Compared with the static models, dynamic statistical models comprehensively consider the meteorological influences on PM$_{2.5}$ concentrations and some meteorological factors that are of stable, representative and strong correlations with PM$_{2.5}$ 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 in their models for PM$_{2.5}$ estimation. However, most PM$_{2.5}$ estimation and forecasting models mainly...
employed correlation analysis to reveal the influence of individual meteorological factors on PM$_{2.5}$ concentrations. Due to complicated interactions in atmospheric environment, the correlation coefficient between meteorological factors and PM$_{2.5}$ concentrations is usually much larger than the $\rho$ 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 $\rho$ 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.

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 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](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. Some scholars ([http://china.cnr.cn/yxw/201411/t20141123_516839830.shtml](http://china.cnr.cn/yxw/201411/t20141123_516839830.shtml) [http://health.people.com.cn/n1/2016/0413/c398004-28271979.html](http://health.people.com.cn/n1/2016/0413/c398004-28271979.html)) pointed out that the wind-corridor project could only exerted limited influence on the reduction of PM$_{2.5}$ concentrations and major efforts should be made on emission-reduction. 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. Given the diversity of
dominant meteorological factors on local PM$_{2.5}$ concentrations in different regions
and seasons, which has been proved by previous studies and this research, 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, 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). Considering the strong winds in winter, the dominant
influence of wind speed on PM$_{2.5}$ concentrations and the sensitivity of PM$_{2.5}$
feedbacks to the change of wind speed, 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 the robust causality analysis method CCM–CCM method, 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 2014.3 to 2017.2. Similar to previous studies conducted at the local scale, the results of this research further proved 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.
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References


5-6. Cheng, Z., Li, L., Liu, J. 2017. Identifying the spatial effects and driving factors of urban pm 2.5 pollution in China. Ecological Indicators. 82, 61-75.


23-29. Kong, L.B., Xin, J.Y., Zhang, W.Y., Wang, Y.S. 2016. The empirical correlations between PM$_{2.5}$, PM$_{10}$ and AOD in the Beijing metropolitan region and the PM$_{2.5}$, PM$_{10}$ distributions retrieved by MODIS. Environmental Pollution. 216, 350-360.


46.


38. Tai, A. P., Mickley, L. J., Jacob, D. J. 2010. Correlations between fine particulate
matter (PM₂.₅) and meteorological variables in the United States: Implications for the sensitivity of PM 2.5 to climate change. Atmospheric Environment, 44(32), 3976-3984.


concentrations (PM$_{2.5}$, PM$_{10}$, PM$_{2.5}$–10). Meteorology and Atmospheric Physics, 1-10.


