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 reviewers' comments, we managed to collect additional two years' $PM_{2.5}$ and meteorological data and conduct a multiple year analysis using the CCM method. By comparing the one year's result in the previous manuscript with the multiple-year analysis result in the revised version, we found that there is no large differences at both regional and national scale, especially for the heavily polluted North China region. At the national scale, the dominant meteorological factors remain temperature, wind and humidity. The similar analysis results acquired using one year and multiple-year analysis indicated that meteorological influences on $PM_{2.5}$ concentrations across China are generally stable at the inter-annual scale. In addition to the requirement for multiple-year analysis, we also added many details to the revised manuscript and the response file to explain the mechanisms of CCM. In this case, the advantage of CCM compared with the correlation analysis can be clearly demonstrated.

Reviewers suggested that the $PM_{2.5}$-meteorology relationship is well-known to the chemistry society and thus we deleted this part of discussion. Instead, according to their suggestions, we added more in-depth discussion concerning the potential reasons for the large variations of meteorological influences on $PM_{2.5}$ concentrations across China and potential applications of employing the p value to better estimate and predict $PM_{2.5}$ concentrations.

We also addressed all the cartography and technical issues raised by reviewers.

Thanks again for considering our manuscript. We are willing to conduct any further revisions according to other requirements from you and the reviewers.

The very best

Ziyue Chen

acp-2017-376-RC1 Anonymous Referee #3

R: Dear Referee, thanks so much for your comments, which helped us improve this manuscript a lot. We have fully revised this manuscript according to your general and detailed comments.

Yes, as you pointed out, the principle of CCM and its advantages compared with the correlation analysis are not well-known to all scholars and thus a better explanation of the CCM method would be needed. Due to limited space, we did not add all details to the modified manuscript and some responses and explanations are given here according to your specific comments. Meanwhile, some other issues were also addressed. As your suggested that multiple year data are required, we have extended the research period from one year to three years using latest published data. Other issues are responded as follows. Thanks again for all your valuable comments and we are willing to conduct further revisions if you have further requirements.

General Comments This is an interesting paper that applies an exciting and fairly new statistical method (convergent cross mapping) to quantify the relationship between local air quality and local meteorology (wind, temperature, precipitation, etc.). The authors argue that unlike a simple correlation analysis, this method is able to demonstrate causal relationships between variables. My understanding is that this method is quite new, and it is central to this study, so I think this paper would benefit from a clearer discussion of why it is better than correlation at determining causal relationships. Would the authors' findings have differed significantly if they used correlation instead of CCM?

R: The CCM method was proposed by Sugihara et al. (2012).

1 Sugihara, G., May, R., Ye, H., Hsieh, C., Deyle, E., Fogarty, M., Munch, S. 2012. Detecting Causality in Complex Ecosystems. Science, 338, 496-500.

Sugibara et al. (2012) pointed out that correlation analysis could extract mirage correlations, especially in complicated ecosystems. For instance, two variables A and B that have no causality may demonstrate significant correlations due to the existence of an agent variable C, which interacts with both A and B. Through a series of experiments, Sugihara et al. (2012) proved that this type of mirage correlations could be detected using the CCM method by calculating a p value of 0. The CCM method not only performed better than the correlation analysis in causality analysis by excluding the influence of other variables, but also demonstrated the advantage of detecting weak causality compared with other causality analysis method (e.g. Granger Causality), which may fail to detect weak to moderate coupling between variables.

In our previous studies, we employed both the correlation and the CCM method to examine the influence of individual meteorological factors on $PM_{2.5}$ concentrations in the Beijing-Tianjin-Hebei region and compared the performance of correlation and CCM method.

2 Chen, Z., Cai, J., Gao, B.B., Xu, B., Dai, S., He, B., Xie, X.M. Detecting the causality influence of individual meteorological factors on local PM2.5 concentration in the Jing-Jin-Ji region. Scientific Reports 2017. 7:407352

The comparison suggests that the causality influence of individual meteorological factors on PM2.5 concentration is better revealed using the CCM method than the correlation analysis. By comparing the correlation coefficient and ρ value in Table 2, one can see that some correlations between meteorological factors and PM2.5 concentration may result from mirage correlations (e.g. the correlation between meanRHU and PM2.5 concentration in Hengshui in summer). Secondly, CCM analysis reveals weak or moderate coupling (e.g. the interactions between SSD and PM2.5 concentration in Cangzhou in summer) whilst correlation analysis cannot. Additionally, due to interactions between different meteorological factors, the value of correlation coefficients cannot interpret the quantitative influence of individual meteorological factors on PM2.5

concentration. Instead, the ρ value from CCM method is designed to understand the coupling between two variables by excluding influences from other factors. Through comparison, the value of the correlation coefficient for some meteorological factors is notably different from the ρ value for these meteorological factors. A large correlation coefficient for one meteorological factor may correspond to a much smaller ρ value from the CCM analysis, indicating that the value of the correlation coefficient usually overestimates the influence of individual meteorological factors on $PM_{2.5}$ concentration.

The previous research (Chen et al., 2017) proved that the CCM method outperform the correlation analysis in many aspects. And this research extended the study area from the Beijing-Tianjin-Hebei region to a national scale, so the CCM method, instead of the correlation analysis, remains the ideal tool for quantifying meteorological influences on $PM_{2.5}$ concentration over China.

There are some aspects of CCM that were not clear to me. Does CCM account for relationships between meteorological factors? E.g. if wind is affecting both precipitation and PM, how is the affect of wind on precip on PM counted?

R: Yes, you made a very good point here. The exclusion of influences from other variables and solely focus on the interactions between two target variables are the most important advantages of the CCM. Sugihara et al. (2012) proposed the CCM method and examined its performance in removing the influence of agent variables through a diversity of experiments. The result proved that mirage correlations caused by the influence of other variables could be detected and removed by the CCM method. For instance, Sugihara (2012) suggested that the CCM method could quantify the bi-directional interactions between two individual variables without being affected other variables, which were also proved by a diversity of studies. So for your question, for each calculation, the CCM method simply examine the bi-directional coupling between two selected variables in complicated ecosystem whilst the influence of other factors was excluded. For your

instance, we could calculated the coupling between PM and wind speed, and the coupling between precipitation and wind speed using the CCM method respectively, and the results for both calculations would not influence each other.

Another question I have is what produces a large value. For example, are the values higher in winter simply because there is more PM available to be effected?

R: Generally, the CCM method simply calculates the quantitative influences of individual meteorological factors on PM concentrations, whilst the mechanisms were not revealed. The mechanisms how even one individual meteorological factor influences local PM concentrations can be highly complicated. The chemical compositions, size and mass concentrations of particulate matters actually vary significantly across locations and seasons. There is no comprehensive research on how one individual meteorological factor influence $PM_{2.5}$ concentrations through different mechanisms. The large ρ value in winter may result from both the much higher $PM_{2.5}$ concentrations, which may be easily influenced by meteorological factors, and unique meteorological conditions. For instance, $PM_{2.5}$ induced haze weather occurred frequently in winter in the Beijing, indicating a much higher $PM_{2.5}$ concentration. Meanwhile, some meteorological factors in Beijing in winter were quite different from those in other seasons. For instance, the northwest wind prevails in winter and it has become a common scene and a popular saying that "the best solution for haze in Beijing is to wait for the wind". Thus the ρ value for wind speed in many cities within the Beijing-Tianjin-Hebei region was much larger in winter than in other seasons for both $PM_{2.5}$ concentrations due to both high PM concentrations and strong wind speeds. Another instance is that the chemical composition of PM, which is related to photochemical reaction and solar radiations, also varied significantly in different seasons. Hence, the reason for the variation of ρ value across seasons is highly complicated, and the high $PM_{2.5}$ concentration is one of major reasons. Thanks so much for pointing this out. I believe systematic research on the influencing mechanism of

individual meteorological factors should be examined in-depth by scholars from a diversity of backgrounds.

Or as another example, is precipitation more effective at removing PM along the coasts because it rains more? If there were a way to normalize by the amount of total rainfall, would precip still be more important along the coasts than in the drier interior?

R: Yes, it is highly possible that precipitation is more effective at removing PM along the coasts because it rains at a higher frequency and intensity. As we know that the $PM_{2.5}$ concentrations drop significantly after a heavy rain whilst light rain may not reduce $PM_{2.5}$ concentrations significantly. Meanwhile, $PM_{2.5}$ concentrations may also affect the influence of precipitation. Light rains may have limited washing-off effects on high-concentration $PM_{2.5}$ concentrations and may increase the relative humidity in the environment, which is favorable for the rising of $PM_{2.5}$ concentrations. In the drier interior, the $PM_{2.5}$ concentrations are usually much higher and the intensity and frequency of precipitation are much lower than those along coasts. These two factors may both be the reason that precipitation is more effective at removing PM along the coasts. Due to these influencing factors, precipitation may still be a less important meteorological driving force for $PM_{2.5}$ concentrations in the drier interior, even if there were a way to normalize by the amount of total rainfall. In the revised manuscript, we added a new part to briefly introduce the underlying reasons for the variation of

My second major concern is that this study uses a single year of data to make general comments about PM-meteorology relationships. This gives us little sense of how much year-to-year variability may exist in these relationships and generally weakens the conclusions. If CCM is too computationally expensive to use on multiple years, perhaps a different method could be used to supplement it.

R: This is a very good point. When we were preparing this manuscript, there were only one-year's data available. And now, we endeavored to acquire another two years' data for multiple year analysis. Although the CCM is computationally expensive, we still believe it is more persuasive to use multiple years' data for drawing conclusions. So thanks so much for this suggestions. We have re-calculated the CCM results using three years' data, and the updated results have been added to the revised manuscript. By comparing the mean annual p value for eight variables for 2014 with the mean annual p value for eight variables during 2014-2016, we can see that the meteorological influences on $PM_{2.5}$ concentrations at the national scale did not change significantly in the past three years.

Finally, I would like to see a deeper discussion of the scientific significance of this work. As it is written currently, this paper is almost purely descriptive. The new method is interesting, but the paper could do a better job of articulating what we are learning from it. Perhaps some discussion about why different meteorological factors are more/less important in different regions/seasons, for example, would help give the paper more depth. I would also suggest spending more time discussing the implications for modeling, especially in the introduction and conclusions, as that was what I took away as the most important implication in this paper.

R: Thanks so much for this valuable suggestion. Yes, it is important to provide more in-depth discussion for the acquired results based on the CCM. And as you suggested, some discussion, e.g. the mechanisms between meteorology factors and $PM_{2.5}$ concentrations were well-known, and it is not necessary to introduce it in details. So in the revised manuscript, we have fully removed this part and left more space for the parts you suggested. We added some introduction on the potential applications the CCM method, instead of the correlation analysis, in research concerning meteorology-included $PM_{2.5}$ concentration estimation prediction. Meanwhile, the potential reason for large variations

of meteorological influences on $PM_{2.5}$ concentrations across China has been added to the revised version. Thanks again for this valuable comment.

Specific Comments

pp 3, ln 93-95 - Can you elaborate further on how your previous study showed that CCM is better than correlation for the benefit of readers who have not read that paper. It is important for your results here to make as clear as possible why CCM is a better method/provides new insights.

R: This is a very good point. We have mentioned the advantages of the CCM method, compared with the correlation analysis in the method parts. However, as you pointed out, we should give more information on how the CCM method performed better than the correlation analysis. So we added some extra details concerning the CCM method in the method part (since Line 197).

As mentioned above, our previous study (Chen et al., 2017) employed the correlation analysis and the CCM method to examine the influence of individual meteorological factors on $PM_{2.5}$ concentrations in the Beijing-Tianjin-Hebei region. In the paper, we demonstrated detailed results of both correlation and causality influence in two large tables. By comparing these results, we found that (1) some correlations between meteorological factors and PM2.5 concentration may result from mirage correlations. For instance, there was a correlation between meanRHU and PM2.5 concentration in Hengshui in summer whilst the causality influence of meanRHU on $PM_{2.5}$ concentrations is 0, indicating a mirage correlation.

(2) CCM analysis reveals weak or moderate coupling whilst correlation analysis cannot. For instance, the correlation between SSD and PM2.5 concentration in Cangzhou in summer was not significant whilst there is a weak causality influence of SSD on $PM_{2.5}$ concentrations detected.

(3) Due to interactions between different meteorological factors, the value of correlation coefficients cannot interpret the quantitative influence of individual meteorological factors on PM2.5 concentration. Instead, the ρ value from CCM method is designed to understand the coupling between two variables by excluding influences from other factors. Through comparison, the value of the correlation coefficient for some meteorological factors is notably different from the ρ value for these meteorological factors. A large correlation coefficient for one meteorological factor may correspond to a much smaller ρ value from the CCM analysis. We found that the correlation coefficient between individual meteorological factors and PM2.5 concentrations was usually much larger than the ρ value. This indicated that the causality of individual meteorological factors on PM2.5 concentrations was generally overestimated using the correlation analysis, due to the influences from other meteorological factors.

So the ρ value is a more reliable indicator for understanding and comparing quantitative influences of different individual meteorological factors than correlation coefficient.

Due to limited spaces, in the previous manuscript, we did not give all information on the comparison between correlation analysis and the CCM method. But according to your suggestion, more details have been added to the revised manuscript

pp 8 ln 221 – Are the results sensitive to the choice of parameters?

R: The CCM detects the bi-directional coupling between two variables highly automatically and only several parameters are required to run this model. However, the CCM result mainly depends on the time series data of the two variables and the several parameters mainly influence the presentation effects of the Convergent maps. We have tested different setting of these parameters, and the extracted ρ value was simply the same, only the presentation of convergent maps were more smooth with different settings. So the results were not sensitive to the choice of parameters, which is also the major advantage of the CCM method. Since CCM method is not sensitive to the choice of

parameters and the reliability of the causality analysis result has been proved by hundreds of studies from different ecosystems, this method has been widely employed.

pp 9 ln 237 – how is the value of determined? Are you calculating the limit or taking the value at a specific time series length?

R: This is a good question. When we determine whether a curve is convergent or not, we set a Δ to represent the variation of ρ value along with increasing time series length. If the Δ was less than a given threshold (e.g. 0.01) for a consecutive several date until the end of the time series, we consider that the ρ was convergent to the p value of last date.

What about cases such as PM2.5 xmap minTEM, which (at least by eye) does not appear to be converging? Wouldn't that suggest that minTEM was not influencing PM2.5 at all?

R: The CCM method considers strict causality influence of one variable on the other one and if the curve is convergent to 0 or demonstrates no generally convergent trend, then no causality influence exists based on long-term time series analysis of two variables. And for your instance, PM2.5 xmap minTEM demonstrate a generally convergent trend to a value approximating to 0.2. You may argue that this curve is not strictly convergent. However, the CCM method does not actually conducts a limit calculation and the CCM curve simply demonstrates a general trend of convergence. According to a diversity of instances provided by Sugihara et al. (2012), the curve shape of PM2.5 xmap minTEM can be regarded as a convergent curve, indicating a detected causality. Those instances from Sugihara et al. (2012) that demonstrated a non-convergent trend are near-linear shape or totally irregular shapes, which are quite different from the PM2.5 xmap minTEM. In summary, according to the PM2.5 xmap minTEM, minTEM exerted a weak influences on $PM_{2.5}$ concentrations.

pp 9 ln 244 – It's not clear here how PM is changing wind speed

R: High $PM_{2.5}$ concentrations may lead to haze episodes, which usually result in generally stable atmospheric environment. In this case, the formation of winds, especially strong

winds within this atmospheric environment are influenced significantly. And this is the reason why there are few winds within the urban areas during severe haze episodes. Meanwhile, winds across regions with haze episodes are also influenced notably.

Yang et al. (2015) observed four haze episodes during Oct to Nov, 2014 and during these four haze episodes in the North China plain, the very high PM2.5 concentrations all led to stagnant condition and weak high-pressure systems, which further led to slowed wind speed and disturbed wind direction. This phenomenon was also observed by Liu et al. (2014) in haze episodes in Beijing in 2013. Very high PM2.5 concentrations induced haze episodes further led to stagnant and stable high-pressure systems, which made megacities served as obstacles to significantly slowed down the wind speed (Yang et al., 2015). Therefore, the effects of aerosols, especially high-concentration PM2.5 concentrations, prevented the wind occurrence mainly through indirect mechanisms.

Yang, Y. R., Liu, X. G., Qu, Y., An, J. L., Jiang, R., & Zhang, Y. H., et al. (2015). Characteristics and formation mechanism of continuous hazes in china: a case study during the autumn of 2014 in the north china plain. Atmospheric Chemistry & Physics, 15(14), 10987-11029.

Liu, X. G., Li, J., Qu, Y., Han, T., Hou, L., & Gu, J., et al. (2013). Formation and evolution mechanism of regional haze: a case study in the megacity beijing, china. Atmospheric Chemistry & Physics, 13(9), 4501-4514.

pp 10 ln 270 - I would guess that (out of the 189 cities) those clustered regionally would show similar maps. Is that true? I.e. are the 37 cities shown representative of the cities not shown?

R: The main reason we selected some representative cities, instead of all cities for presenting wind rose maps is that there is limited space in the map. As one can see, it is already very crowded to demonstrate 37 wind roses and we should pay special attention to the selection of representative cities. Since the provincial capital in each province is the most important city(and usually the largest city) within the province and thus the meteorological influences on $PM_{2.5}$ concentrations for the provincial capital city usually receive the most emphasis. In this case, we selected the provincial capital for 31 provinces to present meteorological influences on $PM_{2.5}$ concentration in each province, which considers both the spatial locations and the importance of the representative cities. For most provinces, especially provinces with low $PM_{2.5}$ concentrations, the number of monitoring cities and the variations of $PM_{2.5}$ concentrations are small. For regions with heavy air pollution (e,g, , the number of monitoring cities and the variations of $PM_{2.5}$ concentrations are large, so we selected 6 additional cities for these regions. In that case, we believe that the selective cities can be representative of no-shown cities within the same province.

pp 13 ln 292-296 – This only seems to be true in some seasons.

R: Thanks so much for this point. We also noticed that this part should be described more rigorously. So in the revised manuscript, we have fully revised this part.

pp 13 ln 299-300 - Can you quantify this more rigorously? By eye, it seems like there are enough outliers to call this in to question

R: Thanks for pointing this out. We realized that this conclusion may not apply to all regions in China. Instead, this pattern " the higher $PM_{2.5}$ concentrations, the stronger meteorological influences on $PM_{2.5}$ concentrations" was most obvious for the North China region, which is the most polluted region in China. In the revised manuscript, we have rephrased this statement to "For the North China region". Thanks again for this suggestions.

pp 14 ln 337-339 – This seems true for winter vs. summer, but what about spring vs autumn?

R: Again, thanks for pointing this out. Generally, $PM_{2.5}$ concentrations for one specific city are highest in winter and the lowest in summer. So in the paper, when we mention the season when $PM_{2.5}$ concentration is high (low), we mainly mean winter (summer). Meanwhile, the characteristics of $PM_{2.5}$ concentrations in spring and autumn are not obvious, so we mainly compare the characteristics of $PM_{2.5}$ concentrations in winter and summer, which provides the most important reference for the management of $PM_{2.5}$ induced haze episodes in winter. So thanks again for this comments and we realized that we should make the statement clearer to avoid some confusion. In the revised manuscript, this sentence has been rephrased.

pp 18 Fig 4 caption – Is there a particular argument for only including the dominant factor in each city?

R: Thanks for this comment. As explained in the text, there are more than 189 cities for this research and it requires some space in the map to place the wind rose map for each city without overlapping with each other. And as you can see, the wind rose map for 37 representative cities has already been filled with 37 wind roses with different sizes and it is impossible to present 189 wind roses on a single map without severe overlapping effects. So we employed an alternative approach to only present the dominant meteorological factor for all cities and an entire wind rose for 37 representative cities in separate maps.

Section 5.1 of the discussion feels out of place. This is more of a discussion of what we already know about aerosol-meteorology interactions than a discussion of the implications of the work done in this study. I would recommend either rewriting it so that it builds more on the results from this paper, or cut it and integrate the important information into earlier sections.

R: Thanks so much for your comments. As also suggested by another referee, this part has been well known to scholars with relevant background. So in the revised manuscript,

this part has been totally cut. Meanwhile, we have added a separate paragraph to explain the underlying reasons for large variations of meteorological influences

pp 24 ln 562-566 – as per my earlier comment, I am not sure that you have shown this. If Beijing were to receive the same amount of precipitation that a coastal city does, is it possible that precipitation would become more important in Beijing? Does looking at how a specific factor changed PM in a year tell us about how effective changes in that factor would be?

R: Thanks for pointing this out. I thought it is a bit difficult to test the hypothesis using the CCM method. This is because the precipitation amount for most days in Beijing is 0 and thus it is difficult to normalize the 0 value to a value similar to that in coastal cities. As an alternative solution, as responded above, we added another two years data to conduct a multiple-year analysis and checked whether the influence of precipitation on $PM_{2.5}$ concentrations in Beijing vary with longer time series.

Technical Corrections pp 1, ln 17 (and later occurrences) - “causality influence” is redundant. “Influence” already implies causality.

R: All Corrected.

pp 2, ln 35-36 - “Amongst these environmental elements, . . . concerned social and ecological issues.” The wording of this sentence is unclear.

R: This sentence has been rephrased.

pp 2, ln 42 - “Serious haze not only influences peoples daily life,” this wording is vague. How does haze influence peoples daily lives?

R: Serious haze episodes, usually presented as very thick and heavy black fogs, cause serious negative influences on people’s daily life, especially the traffic. During a severe

haze episode in Beijing in January, the extreme high fog episodes led to very low visibility and heavy traffic jam. This is one instance how haze influence people's daily life.

pp 2, ln 57 - "controversy" should be changed to "controversial"

R: Corrected.

pp 3, ln 68 - ". . . fractions of three different sizes. . ." this is unclear. Authors should indicate that they are talking about aerosols, and specify the sizes.

R: Thanks for pointing this out. We have corrected this in the revised manuscript.

pp 3, ln 7 - what region is this study referring to?

R: The missing "research region" content has been added to the revised manuscript.

pp 3, ln 86 - word choice: I would suggest "well studied" instead of "massively studied"

R: Corrected.

pp 4, ln 119 – what does API stand for?

R: API (Application Programming Interface).

pp 5, ln 136-137 – I'm not clear on what small and large evaporation are.

R: Small evaporation indicates the evaporation amount calculated using a small-diameter measurement equipment and large evaporation indicates the evaporation amount calculated using a large-diameter measurement equipment. Generally, the amount calculated using the two types of equipment is usually the same, although slightly difference may exist between measured evaporation values. And the p value for the factor evaporation is decided by the larger value of the two indicators.

pp 5, ln 144 – sunshine duration for the day is a less widely used term and should be defined here

R: Thanks so much for pointing this out. Sunshine duration or sunshine hours is a climatological indicator, measuring duration of sunshine in given period (usually, a day or a year) for a given location on Earth. This definition has been added to the modified manuscript.

pp 5 ln 146 – what qualifies as extreme wind speed?

R: 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.

Thanks for pointing this out and the definition has been added to the modified manuscript.

pp 5 ln 146 – how is max wind direction defined?

R: The max wind direction indicates the dominant wind direction for the period with the max wind speed.

pp 6 ln 174 – "Two time series" is unnecessary. Suggest changing the sentence to "{X}=[X(1),. . .X(L)] and {Y}=[Y(1),. . .Y(L)] are defined as the temporal variations of variables X and Y."

R: Corrected according to your suggestions.

pp 6 ln 175 – It's unclear what r and S are.

R: Thanks for pointing this out.

r is the current position in the time series and the S presents the start position in the time series.

pp 8 ln 217 – why can E be 2 or 3?

R: This parameter decides at what dimension the CCM was calculated. When E equals 3, the calculation accuracy is higher. Through experiments, we found that the results were generally

the same using the value of 2 or 3. For this research, we set the value of E 3 for a theoretically optimal CCM result.

pp 14 ln 331-332 – the phrasing here is unclear.

R: This sentence has been rephrased.

pp 18 ln 374-376 – is there a way to test if these values are significant?

R: The CCM method is different from the correlation analysis and another classic causality analysis method , Granger causality, which provides readers with the significance for the coupling between two variables. The CCM did not give us a value to present the significance for the revealed causality. However, while the Granger causality mainly revealed the qualitative causality between two variables, the p value from the CCM method revealed the quantitative causality between them. And the CCM method suggests that if the significance between two variables was not significant, then the calculated p value would be 0. So the p value was a direct metric for the quantitative influence and an indirect metric for the significance.

pp 20 ln 419 – this wording is unclear

R: This part has been removed in the revised manuscript.

pp 20 ln 426 – Wikipedia is not an appropriate source. Better to cite a scientific paper that defines SSD.

R: In the revised manuscript, the $PM_{2.5}$-meteorology interaction part has been removed according to your and other referees' comments. However, here we would like specifically add the explanation here that SSD could reduce $PM_{2.5}$ concentrations not only through

atmospheric photolysis, but also by enhancing surface temperature and promoting upward movement of aerosols.

pp 20 ln 440 – Temperature inversion is certainly important, but none of the metrics in this study measure it directly.

R: Thanks for pointing this out. Although this part has been removed in the revised manuscript, we would like to add some other mechanisms. Actually, in addition to temperature inversion, another important mechanism is that Temperature is closely related to pollutant concentrations by affecting atmospheric turbulence and chemical reactions. The temperature is positively correlated with pollutant concentrations in the majority of cities (He et al., 2017).

He, J., Gong, S., Ye, Y., Yu, L., Lin, W., Mao, H., et al. (2017). Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major chinese cities. Environmental Pollution, 223, 484-496.

pp 21 ln 447 – what about horizontal transport (advection)?

R: Yes, horizontal transport of airborne pollutants should be major reason for the variation of $PM_{2.5}$ concentrations. i.e. Anticyclones (i.e., high pressure systems) induced low wind speed was not favorable for the dispersion of pollutants. On the other hand, low pressure systems may lead to large wind speeds, favorable for the dispersion of $PM_{2.5}$.

pp 21 ln 446 – change “social economic” to “socio-economic” pp 22 ln 492 – change “negative causality on” to “decreases” and “positive causality on” to “increases”

R: Corrected.

pp 23 ln 527-528 – do you have citations for this?

R: We have added more relevant references to the revised manuscript according to your comments.

pp 24 ln 544 – can you give more details/citations about the controversy?

R: Some reports concerning different effects of this project has been added to the revised manuscript.

acp-2017-376-RC2 Anonymous Referee #1

Interactive comment on “Understanding meteorological influences on PM2.5 concentrations across China: a temporal and spatial perspective” by Ziyue Chen et al. Anonymous Referee #1 Received and published: 21 August 2017 Chen et al. present an interesting analysis of the spatial and temporal variation of the relationships of meteorology and PM2.5 over most of China. The cross convergent mapping analysis provides a unique method of understanding the causality of the relationships, which might otherwise be missed with typical correlation analysis. They highlight that the meteorological influence on PM2.5 varies widely by location and season, and that attempts to engineer favorable air quality meteorology should take these differences into account. The paper is well-written and relatively thorough, however it requires some additional explanations and detail. Thus I recommend publication following minor revision.

Dear referee:

Thanks so much for your encouragement and valuable comments. We have fully revised this manuscript according to your general and detailed comments, as well as comments from other reviewers. We would like to make further revision in due stages if you have further requirements.

Page 2, lines 56-57: “Although quantitative contributions of different sources (e.g. coal burning and automobile exhaust) to airborne pollutants remain controversy” – It’s not clear what you mean here with the “controversial” – politically or scientifically? If scientifically – the direct emissions and/or subsequent chemistry?

R: Yes, the controversy mainly comes from the mixed understanding of relative contribution. For instance, some scholars claimed that automobile exhaust took up only 4% of relative contributions to $PM_{2.5}$ concentrations. However, many following papers

argued that the actual contribution from automobile exhaust took up more than 20%. The difference was that the former mainly considered the direct emissions whilst the latter ones comprehensively considered the direct emission and following secondary pollutants. So yes, your point was exactly the situation.

Page 4, section 2.1.1: How do you quality control the data and/or deal with missing data?

R: For this research, all released data were previously maintained by specific institutions and there are several stations for each city to report hourly $PM_{2.5}$ concentrations conditions. For some stations, missing data lead to 0 value. If there are stations with Non-0 value, then the mean $PM_{2.5}$ concentration for a specific city was calculated using these stations. So for most days in each city, a valid mean $PM_{2.5}$ concentration value could be calculated. For days when the measured $PM_{2.5}$ concentration from all stations was 0, then mean $PM_{2.5}$ concentration was 0. The record for this day was deleted. Only a very small proportion of cities experienced days with no daily average data. And since few missing records would not influence the order of time series of $PM_{2.5}$ and meteorological data, the CCM result would not be influenced by the missing data. Meanwhile, for cities (e.g. Liaocheng and Zhuji) with a large amount of missing meteorological data, we deleted this city for this research.

CCM method: How does the time lag parameter affect the results? The resolution of the map is mentioned but how does it affect the physical interpretation of the results? – Especially for those variables that may act on a shorter time scale.

R: We compared the CCM analysis result calculated using different parameters: 2 ,5, 10, 20 and the result was generally the same. Just the resolution of the map was higher with a small time lag. And you made a good point here that the physical interpretation of the results may lead to biased p value. Actually, the presented CCM map was simply for a

basic demonstration about how CCM works. For exact p value, the provided CCM algorithm actually calculated an accurate p value with the increase of time series, and the CCM map was produced based on a series of accurate p values. So for this research, it is not feasible and reliable to physically interpret the p value for 190*18*4 CCM maps and the p value used for producing the wind-rose and other maps were extracted directly from the program.

Page 13, lines 295-296: This causality seems to be backwards: i.e., why would differences in PM levels cause differences in meteorological influences? What mechanism would cause this?

R: This is a very good question. Actually, this phenomenon was revealed and proposed in Chen et al. (2017). Chen et al. (2017) found that in the Beijing-Tianjin-Hebei region, the causality influence of individual meteorological factors on $PM_{2.5}$ concentrations was the strongest in winter, when the $PM_{2.5}$ concentrations were the highest, for all cities, Meanwhile, the causality influence of individual meteorological factors on $PM_{2.5}$ concentrations was the weakest in winter, when the $PM_{2.5}$ concentrations were the lowest. The potential mechanism could be that similar meteorological conditions may lead to large variations of $PM_{2.5}$ concentrations when $PM_{2.5}$ concentrations were high. For instance, in winter, when the $PM_{2.5}$ concentrations were high and may lead to haze episodes, a strong northwester wind may immediately reduce the $PM_{2.5}$ concentrations to a very low level. Meanwhile, high wind-speed in summer may lead to small variations of $PM_{2.5}$ concentrations, as the original $PM_{2.5}$ concentrations are low. Similarly, other meteorological factors are more likely to change $PM_{2.5}$ concentrations significantly when the $PM_{2.5}$ concentrations are high. In the revised manuscript, we have rephrased this part to avoid unnecessary confusions.

Page 14, lines 330-333: This sentence is very vague – can you be more specific?

R: Thanks so much for pointing this out. Yes, this part should be explained with more details. Actually, what we mean here is that some meteorological factors can be dominant factors across China. For instance, according to Fig 3, you can see such factors as temperature and wind were dominant meteorological factors in many regions, including Northeast, Northwest, coastal areas and inland areas; Meanwhile, some meteorological factors such as wind direction, were the dominant meteorological factors for limited regions (Mainly middle inland cities). This part has been added to the revised manuscript.

Figure 2 and 3: I would suggest the background of concentrations be in a gray scale so the colored icons/wind roses stand out more. Also, how different would the maps be if the correlation coefficient were used instead? A statement or two would reinforce the argument for the use of CCM rather than correlation coefficient.

R: Thanks so much for the cartography suggestions. We have updated the Fig 2 and 3 according to your suggestions and made some further revisions to improve the quality of maps.

Another referee also mentioned that the difference between the p value and the correlation coefficient. And we are sorry that we did not make this clear in previous manuscript. Here we simply explained the advantages of CCM method and some findings concerning the comparison between correlation analysis and the CCM method from our previous studies.

The CCM method was proposed by Sugihara et al. (2012).

1 Sugihara, G., May, R., Ye, H., Hsieh, C., Deyle, E., Fogarty, M., Munch, S. 2012. Detecting Causality in Complex Ecosystems. Science, 338, 496-500.

Sugibara et al. (2012) pointed out that correlation analysis could extract mirage correlations, especially in complicated ecosystems. For instance, two variables A and B that have no causality may demonstrate significant correlations due to the existence of an agent variable C, which interacts with both A and B. Through a series of experiments, Sugihara et al. (2012) proved that this type of mirage correlations could be detected using the CCM method by calculating a p value of 0. The CCM method not only performed better than the correlation analysis in causality analysis by excluding the influence of other variables, but also demonstrated the advantage of detecting weak causality compared with other causality analysis method (e.g. Granger Causality), which may fail to detect weak to moderate coupling between variables.

In our previous studies, we employed both the correlation and the CCM method to examine the influence of individual meteorological factors on $PM_{2.5}$ concentrations in the Beijing-Tianjin-Hebei region and compared the performance of correlation and CCM method.

2 Chen, Z., Cai, J., Gao, B.B., Xu, B., Dai, S., He, B., Xie, X.M. Detecting the causality influence of individual meteorological factors on local PM2.5 concentration in the Jing-Jin-Ji region. Scientific Reports 2017. 7:407352

The comparison suggests that the causality influence of individual meteorological factors on PM2.5 concentration is better revealed using the CCM method than the correlation analysis. By comparing the correlation coefficient and ρ value in Table 2, one can see that some correlations between meteorological factors and PM2.5 concentration may result from mirage correlations (e.g. the correlation between meanRHU and PM2.5 concentration in Hengshui in summer). Secondly, CCM analysis reveals weak or moderate coupling (e.g. the interactions between SSD and PM2.5 concentration in Cangzhou in summer) whilst correlation analysis cannot. Additionally, due to interactions

between different meteorological factors, the value of correlation coefficients cannot interpret the quantitative influence of individual meteorological factors on PM2.5 concentration. Instead, the ρ value from CCM method is designed to understand the coupling between two variables by excluding influences from other factors. Through comparison, the value of the correlation coefficient for some meteorological factors is notably different from the ρ value for these meteorological factors. A large correlation coefficient for one meteorological factor may correspond to a much smaller ρ value from the CCM analysis.

The previous research (Chen et al., 2017) proved that the CCM method outperform the correlation analysis in many aspects.

Page 20, lines 414-420: While higher relative humidity does lead to hygroscopic growth of aerosols, this is probably not evident in the observed concentrations since most measurements are taken at a constant relative humidity (e.g, 35% in US and Europe). Measurements in China may not do this, and if so, should be explicitly stated since this can have a major effect to aerosol mass depending on the composition of the aerosol.

R: Thanks so much for this explanation. This information is very useful for future comparison of meteorological influences, especially the humidity factor, on $PM_{2.5}$ concentrations in China and other regions. The reason we added the general introduction of mechanisms how meteorological factors may interact with $PM_{2.5}$ concentration is that one referee during the first stage of ACPD review process suggested we do so. However, during this round of ACPD review, you and other referee all suggested that the part of introduction is well known to scholars with meteorological background and we have deleted this part in the revised manuscript.

Page 23, lines 515-535: This paragraph seems out of place with the rest of the section. Page 23, line 525: I am not able to read Cheng et al. (2015), but I'm wondering what the model is using for predictors? If they are "static" models, isn't that just the mean state? I'm having a hard time understanding. If the argument is to use CCM instead of correlations, an example (see above) would help to reinforce this.

R: Static statistical models did not consider the influence of meteorology on $PM_{2.5}$ concentrations whilst dynamic models select some reliable and key meteorological influencing factors for better predicting $PM_{2.5}$ concentrations. The advantage of p value compared with the correlation analysis has been explained above and added to the revised manuscript. As suggested by another referee, the improvement of models based on the CCM method could be important practical applications of the meteorological influences on $PM_{2.5}$. So more in-depth discussion concerning this part has been added to the revised manuscript.

Page 24, lines 562-566: How does the frequency of precipitation affect this statement? For example, if precipitation is rare in Beijing during winter, especially compared to the Yangtze River Basin.

R: This is a very good point and has also been pointed out by another referee. Yes, it is highly possible that precipitation is more effective at removing PM along the coasts because it rains at a higher frequency and intensity. As we know that the $PM_{2.5}$ concentrations drop significantly after a heavy rain whilst light rain may not reduce $PM_{2.5}$ concentrations significantly. Meanwhile, $PM_{2.5}$ concentrations may also affect the influence of precipitation. Light rains may have limited washing-off effects on high-concentration $PM_{2.5}$ concentrations and may increase the relative humidity in the

environment, which is favorable for the rising of $PM_{2.5}$ concentrations. In the drier interior, the $PM_{2.5}$ concentrations are usually much higher and the intensity and frequency of precipitation are much lower than those along coasts. These two factors may both be the reason that precipitation is more effective at removing PM along the coasts. Due to these influencing factors, precipitation may still be a less important meteorological driving force for $PM_{2.5}$ concentrations in the drier interior, even if there were a way to normalize by the amount of total rainfall. We have added more discuss on this in the revised manuscript.

Results/Discussion: Much of this review of meteorology-PM2.5 relationships in the discussion would probably be better suited in the introduction and in the results as it pertains to different locations within China. Many of the statements in the results are rather vague (e.g., page 14, line 330-333) and could be elaborated to include specific meteorological factors and specific locations.

R: Thanks so much for your comments. As explained above. the review of meteorology-PM2.5 relationships has been removed in the revised manuscript. And some vague statements in the previous manuscript have been re-phrased with more details.

Minor comments

Page 2, line 61: were correlated

R：**Corrected**

Page 3, line 68: “fractions of three different sizes” of particulate matter

R：Corrected

Page 4, lines 119-120: What does this sentence mean?

R：Sorry that we did not make this clear. The API (Application Programming Interface) tool we programmed can automatically downloaded hourly air pollution data since the execution of this tool.

Page 12, line 288: Awkward wording

R: Rephrased

Page 20, line 426: Wikipedia is not an appropriate citation.

R: Other definition has been added in the revised manuscript in other parts.

Page 20, line 427 and elsewhere: Check your usage of “by analogy” – you may be looking for a different phrase.

R: Thanks so much for this suggestion. We have changed this to “similarly”.

Page 20, line 433 and elsewhere: Check subject verb agreement, specifically for “PM2.5” and “concentration(s)”

R: Thanks so much for this. We have corrected all these incorrectly used format.

acp-2017-376-RC3 Anonymous Referee #2

Dear Referee:

Thanks so much for your valuable suggestions. We have fully revised the manuscript according to your suggestions in the revised manuscript. And we are willing to conduct further revision if you have additional requests.

This paper attempts to investigate the meteorological influence on PM2.5 concentra- tions in China at the national scale using a convergent cross-mapping (CCM) method. This method is somewhat new to the atmospheric chemistry community, but the physi- cal mechanism as discussed in this paper is very descriptive and already well-known. Overall I don't feel these results are significant enough to warrant publication in ACP. Here are my major concerns.

R: Thanks so much for pointing this out. Actually, the major aim of this research is to quantify the causality influence of individual meteorological factors on $PM_{2.5}$ concentrations in 190 monitoring cities across China. The spatial and seasonal variations of meteorological influences on $PM_{2.5}$ concentrations at a national scale have rarely been examined before. Meanwhile, previous studies for meteorological influences on $PM_{2.5}$ concentrations at local and regional scale mainly employed the Correlation analysis, which can lead to mirage correlations and unreliable correlation coefficient, due to complicated interactions between different meteorological factors. Thus the use of CCM method has the advantage to remove potential influences from other variables when analyzing the bi-directional coupling between two variables. The comparison and patterns of calculated p value (quantitative causality influence) of individual meteorological factors on $PM_{2.5}$ concentrations across China is the key findings for this research.

Yes, as you pointed out, the e physical mechanism We did not add the physical mechanism of $PM_{2.5}$-meteorology relationship in the first version of manuscript. One reviewer in the

first stage of ACPD review suggested this , and thus we added a brief discussion. However, in this round review, you and other referees all pointed out that this part was off the structure and was already well known to scholars with relevant background. So in the revised manuscript, according to your suggestions, we have deleted this part. And for other major issues you pointed out, e.g. the lack of multiple year analysis ,we have fully revised this manuscript accordingly and explained as follows. Thanks again for your valuable comments and we would like to make further revision in due stages if you have further requirements.

First, the authors just use the PM2.5 observations in one year, from Mar 2014 to Feb 2015, which is far from sufficient to draw any convincing conclusions. In Figure 2, they evaluate the influence of 8 different variables on PM2.5 in each season. This means they make these conclusions using only 90 data values, which is far from enough. When the authors prepare this manuscript, observations in 2015 and 2016 should already be available. Why not include a longer time series of observations into this study?

R: This is a very good point. Long-term observation data are more likely to present reliable causality influence of 8 different variables on $PM_{2.5}$ in each season, as one-year data may be influenced by abnormal meteorological conditions. So according to your suggestions, we managed to collect the $PM_{2.5}$ and meteorological data from Mar 2014 to Feb 2017. In the revised manuscript, we have added additional two years' data for multiple-year analysis and thus a comprehensive CCM analysis based on three year's analysis has been conducted. Thanks again for pointing this out, as the inclusion of multiple-year analysis made the results more robust.

Second, the discussion of the scientific significance of this work looks very superficial and unprofessional. Throughout Section 5.1, the authors made a lot of descriptive statements with little reference. For example in Line 410-413, the authors claim that rising PM2.5 concentrations prevents the occurrence of winds. Is this true? Can the authors list some references? In my understanding, the effect of aerosols on wind occurrence is much smaller than that from synoptic circulation patterns.

R： Thanks so much for this valuable suggestions. As explained above, we also know that $PM_{2.5}$－meteorology interactions, as you and another two referees pointed out， the mechanisms were well-known and may be off the focus of this manuscript. For this reason, we did not add this introduction of this part to the original manuscript. During the first stage of ACPD discussion, a referee kindly suggested that a brief introduction of PM2.5-meteorology relationship can be added, and thus we provided a general introduction of mechanisms in the previous manuscript. In the revised manuscript, according to the suggestions of you and other referees, we have deleted this part to make the aim and key findings highlighted. In addition, according to the comments of you and other referees, we have added some more in-depth discussion, concerning the potential applications of this research and underlying reasons for the large variations of meteorological influences on $PM_{2.5}$ concentrations across China, has been added to the revised manuscript.

Although the $PM_{2.5}$－meteorology interaction part has been removed, we would like to give some explanations on the example you suggested. Yes, we understood that synoptic circulation patterns were the major causes for wind occurrence and we are not claiming that the effects of aerosols were large enough compared with the synoptic circulations. We just pointed out that the potential mechanisms of the negative feedbacks of high $PM_{2.5}$ concentrations

Yang et al. (2015) observed four haze episodes during Oct to Nov, 2014 and during these four haze episodes in the North China plain, the very high $PM_{2.5}$ concentrations all led to

stagnant condition and weak high-pressure systems, which further led to slowed wind speed and disturbed wind direction. This phenomenon was also observed by Liu et al. (2014) in haze episodes in Beijing in 2013. Very high $PM_{2.5}$ concentrations induced haze episodes further led to stagnant and stable high-pressure systems, which made megacities serve as obstacles to significantly slow down the wind speed (Yang et al., 2015). Therefore, the effects of aerosols, especially high-concentration $PM_{2.5}$ concentrations, prevented the wind occurrence mainly through indirect mechanisms.

Yang, Y. R., Liu, X. G., Qu, Y., An, J. L., Jiang, R., & Zhang, Y. H., et al. (2015). Characteristics and formation mechanism of continuous hazes in china: a case study during the autumn of 2014 in the north china plain. Atmospheric Chemistry & Physics, 15(14), 10987-11029.

Liu, X. G., Li, J., Qu, Y., Han, T., Hou, L., & Gu, J., et al. (2013). Formation and evolution mechanism of regional haze: a case study in the megacity beijing, china. Atmospheric Chemistry & Physics, 13(9), 4501-45

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~~188 monitoring cities across China. Results indicate that meteorological influences on $PM_{2.5}$ concentrations are of notable seasonal and regional variations. ~~Generally~~For the heavily polluted North China region, 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, the influence of temperature, humidity~~,~~ and wind ~~and air pressure exert stronger influences~~ 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~~.~~ ~~Amongst these environmental elements, ambient~~, and 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.

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Serious haze not only influences people's daily life~~,~~, (e.g. the cause of severe traffic jam during haze epsiodes), 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 cause-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. 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 ~~controversy~~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 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 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. 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) ~~suggested~~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 ~~pollutant~~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 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~~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

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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 (Application Programming Interface) provided by PM25.in, we collect hourly $PM_{2.5}$ data for target cities. The daily $PM_{2.5}$ concentrations for each city is calculated using the averaged value of hourly $PM_{2.5}$ concentrations measured at all available local observation stations. For a consecutive division of different seasons~~,~~ and multiple-year analysis, We collected $PM_{2.5}$ data from March 1st, 2014 to February 28th, ~~2015 were employed~~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~~ for the day~~, mean temperature~~ for the day~~, min temperature~~ for the day,~~, and 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[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.

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2 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 differences.

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.

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 ~~189~~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 ~~the density~~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 ~~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~~bidirectional 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 $\cancel{\rho}$ 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 $\{X\}= [X(1), \dots, X(L)]$ and $\{Y\} = [Y(1), \dots, Y(L)]$ 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 $[X(1), \dots, X(L_P)]$ and $[Y(1), \dots, Y(L_P)]$ are extracted~~.~~ from the original time series (r is the current position whilst S is the start position in the time series). Following this, the shadow manifold M_X is generated from $\{X\}$, which is a set of lagged-coordinate vectors x(t) = $<X(t), X(t-\cancel{\tau}\cancel{),\dots,}\tau), \dots, X(t-(E-1)\cancel{\tau}\tau)>$ for t = 1+(E-1) τ to t = r. To generate a cross-mapped estimate of $Y(t)$ $\cancel{(\hat{Y}}(\hat{Y}(t)|M_X)$, the contemporaneous lagged-coordinate

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vector on M_X, x(t) is located, and then its E+1 nearest neighbors are extracted, where E+1 is the minimum number of points required for a bounding simplex in an E-dimensional space (Sugihara and May, 1990). Next, the time index of the E+1 nearest neighbors of x(t) is denoted as t_1, ..., t_{E+1}. These time index are used to identify neighbor points in Y and then estimate Y(t) according to a locally weighted mean of E+1 $Y(t_i)$ values (Equation 1).

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

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

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

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

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

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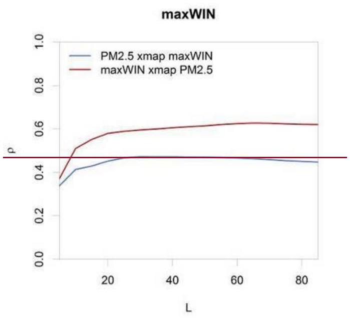
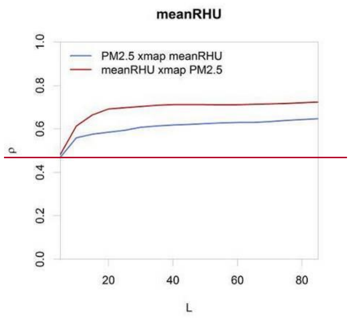
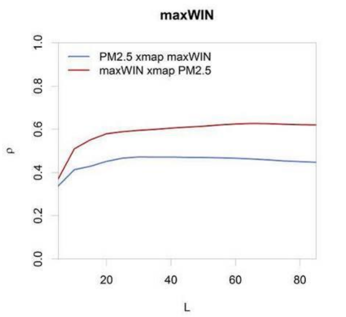
Chen et al. (2017) further revealed that the correlation coefficient between individual meteorological factors and $PM_{2.5}$ concentrations was usually much larger than the ρ value. This indicated that the causality of individual meteorological factors on $PM_{2.5}$ concentrations was generally overestimated using the correlation analysis, due to the influences from other meteorological factors. In this case, the CCM method is an appropriate tool for quantifying bidirectional interactions between $PM_{2.5}$ concentrations and individual meteorological factors in complicated atmospheric environment.

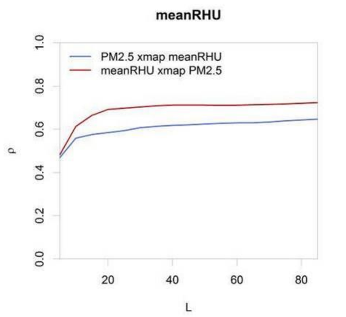
4 Results

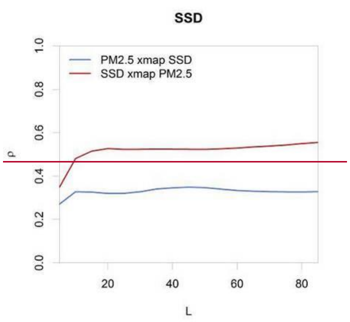
Seasonal variations of $PM_{2.5}$ concentrations have been proved by a large body of studies (Cao et al., 2012; Shen et al., 2014; Yang and Christakos, 2015; Wang et al., 2015; Chen et al., 2015; Chen, Y. et al. 2016; Chen, Z. et al., 2016). Hence, the research period was divided into four seasons. According 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~~), τ (~~), 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~~ τ leads to a fine-resolution convergent map, yet requires much more processing time. Through experiments, we found that the final results were not sensitive to the selection of parameters and different parameters mainly exerted influences on the presentation effects of CCM. In this research, to acquire optimal ~~presentation~~interpretation effects of convergent cross maps, the value of ~~τ~~ 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).

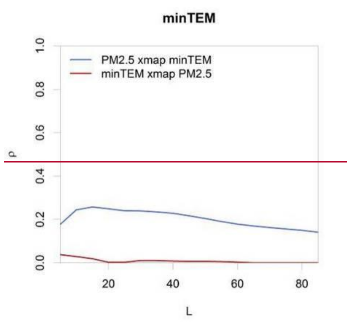

maxWIN
PM2.5 xmap maxWIN
maxWIN xmap PM2.5
ρ
L


meanRHU
PM2.5 xmap meanRHU
meanRHU xmap PM2.5
ρ
L


maxWIN
PM2.5 xmap maxWIN
maxWIN xmap PM2.5
ρ
L


meanRHU
PM2.5 xmap meanRHU
meanRHU xmap PM2.5
ρ
L


SSD
PM2.5 xmap SSD
SSD xmap PM2.5
ρ
L


minTEM
PM2.5 xmap minTEM
minTEM xmap PM2.5
ρ
L

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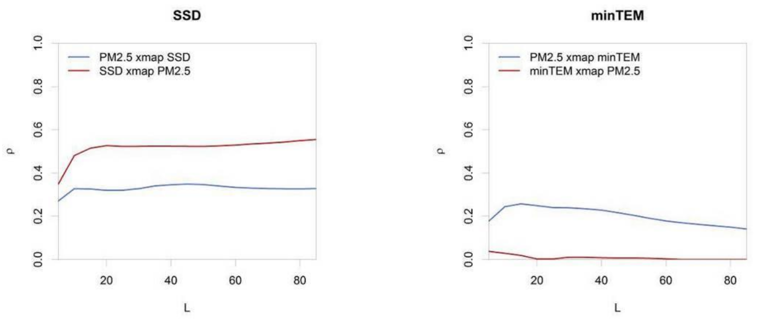


Fig 1. Illustrative CCM results to demonstrate the bidirectional coupling between meteorological factors and $PM_{2.5}$ concentrations in Beijing ~~in~~(2014, winter)

~~ρ :~~ ρ **: predictive skills.** ~~L :~~ 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 $PM_{2.5}$ stands for the feedback effect of $PM_{2.5}$ on meanRHU concentrations~~. ρ~~ . 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~~ ($\rho > 0.4$) whilst SSD and minTEM also had a weaker influence on local $PM_{2.5}$ concentrations. ~~(ρ~~ (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~~ (ρ close to 0.6) whilst $PM_{2.5}$ had little influence on minTEM ~~(ρ~~ (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 low SSD[6]) 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~~are increased further by the changing wind (humidity and SSD) situation. This mechanism causes a quickly rising $PM_{2.5}$ concentrations, which brings the atmospheric environment to a comparatively stable status.

[6] ~~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.~~

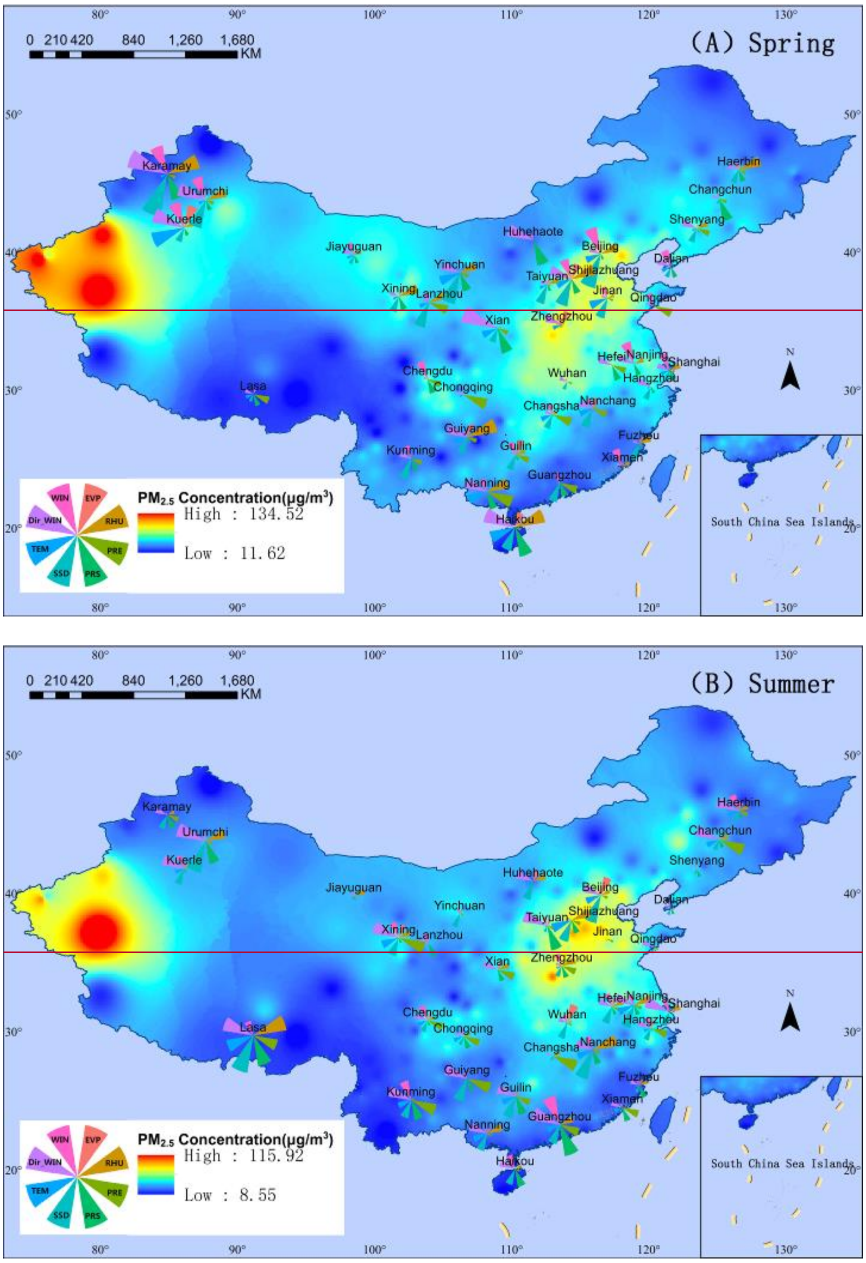
In this case, the haze is unlikely to disperse and persistent haze weather usually lasts for a long period in this region. ~~By analogy~~Similarly, bidirectional interactions between $PM_{2.5}$ concentrations and other meteorological factors can as well be quantified using the CCM method. Since the main aim of this research is to understand the influence of individual meteorological factors on $PM_{2.5}$ concentrations across China, the feedback effect of $PM_{2.5}$ concentrations on specific meteorological factors is not explained in details herein.

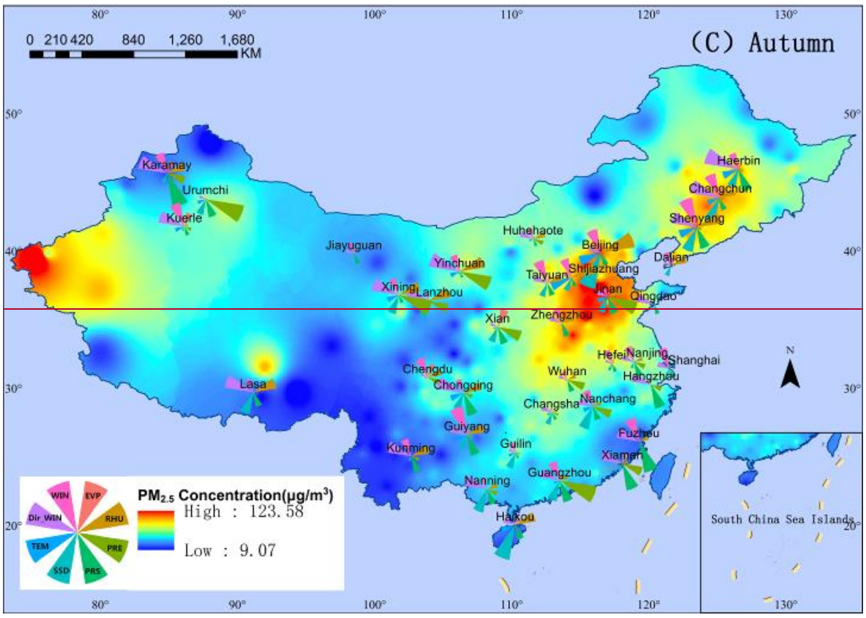
The $\cancel{\rho}$ ρ value is a direct indicator of quantitative causality ~~influences~~. For this research, the maximum $\cancel{\rho}$ ρ value of all sub-factors in the same category was used as the causality ~~influence~~ of this specific meteorological factor on $PM_{2.5}$ concentrations. E.g.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

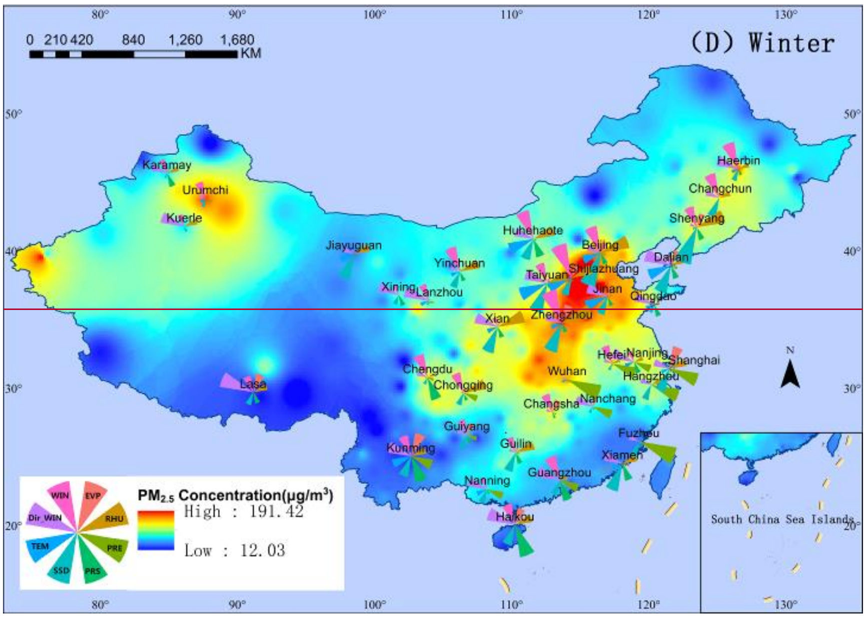
Generally, it is difficult to properly demonstrate the influence of eight meteorological factors on $PM_{2.5}$ concentrations for all ~~189~~188 cities on a comprehensive map. Therefore, two cartography strategies were employed to explain the meteorological influences on $PM_{2.5}$ concentrations across China.

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

When the $\cancel{\rho}$ ρ value for each meteorological factor was calculated, a wind rose, which presents the quantitative ~~influence~~influences of all individual meteorological factors on $PM_{2.5}$ concentrations, can be produced for each city. It is not feasible to present all ~~189~~188 wind roses simultaneously, due to severe overlapping effects. Thus, considering the social-~~ecological~~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).




(C) Autumn
0 210 420 840 1,260 1,680
KM
PM2.5 Concentration(μg/m3)
High : 123.58
Low : 9.07
WIN
EVP
Dir_WIN
RHU
TEM
PRE
SSD
PRS
South China Sea Islands
Haerbin
Changchun
Shenyang
Karamay
Urumchi
Kuerle
Jiayuguan
Huhehaote
Beijing
Dalian
Yinchuan
Taiyuan
Shijiazhuang
Xining
Lanzhou
Jinan
Qingdao
Xian
Zhengzhou
Hefei
Nanjing
Shanghai
Chengdu
Wuhan
Hangzhou
Lasa
Chongqing
Changsha
Nanchang
Guiyang
Fuzhou
Kunming
Guilin
Xiamen
Nanning
Guangzhou
Haikou


(D) Winter
0 210 420 840 1,260 1,680
KM
PM2.5 Concentration(μg/m3)
High : 191.42
Low : 12.03
WIN
EVP
Dir_WIN
RHU
TEM
PRE
SSD
PRS
South China Sea Islands
Haerbin
Changchun
Shenyang
Karamay
Urumchi
Kuerle
Jiayuguan
Huhehaote
Beijing
Dalian
Yinchuan
Taiyuan
Shijiazhuang
Xining
Lanzhou
Jinan
Qingdao
Xian
Zhengzhou
Hefei
Nanjing
Shanghai
Chengdu
Wuhan
Hangzhou
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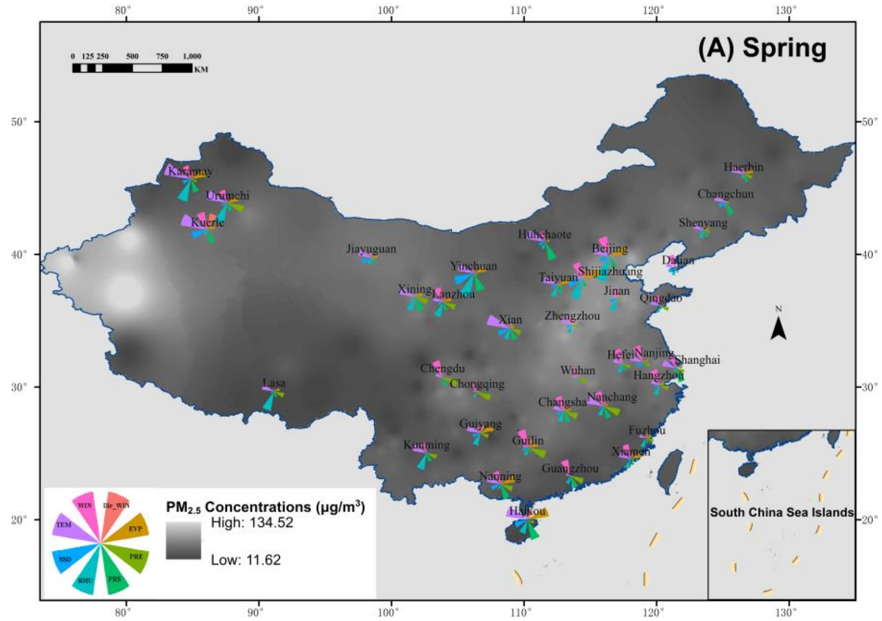
Guilin
Xiamen
Nanning
Guangzhou
Haikou


(A) Spring
0 125 250 500 750 1,000 KM
PM$_{2.5}$ Concentrations (μg/m^3)
High: 134.52
Low: 11.62
WIN
Dir_WIN
TEM
EVP
SSD
PRE
RHU
PRS
South China Sea Islands
Kacunay
Urumchi
Kuerle
Jiayuguan
Huhehaote
Haerbin
Changchun
Shenyang
Beijing
Dalian
Yinchuan
Taiyuan
Shijiazhuang
Xining
Lanzhou
Jinan
Qingdao
Xian
Zhengzhou
Lasa
Chengdu
Chongqing
Hefei
Nanjing
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Kunming
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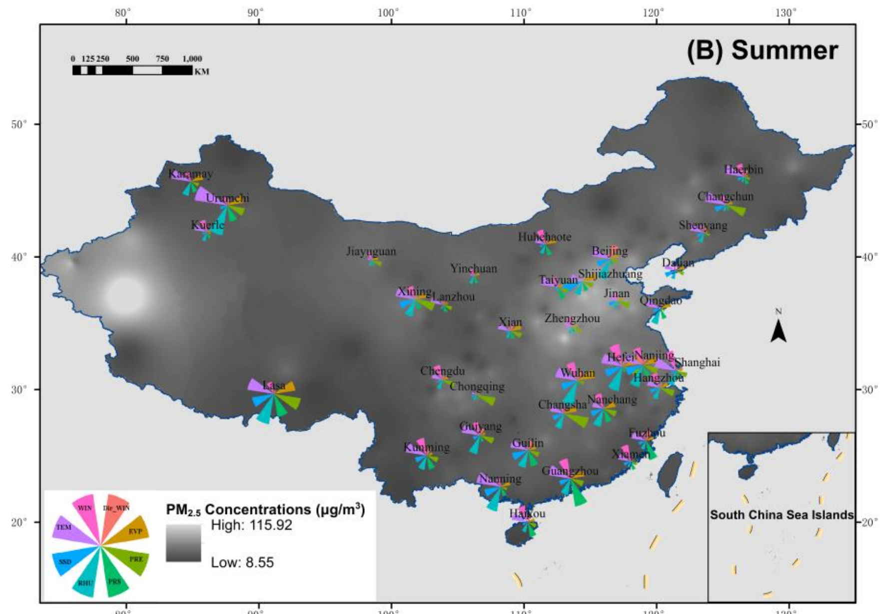
Fuzhou
Xiamen
Nanning
Guangzhou
Haikou


(B) Summer
0 125 250 500 750 1,000 KM
PM$_{2.5}$ Concentrations (μg/m^3)
High: 115.92
Low: 8.55
WIN
Dir_WIN
TEM
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SSD
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RHU
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South China Sea Islands
Kacunay
Urumchi
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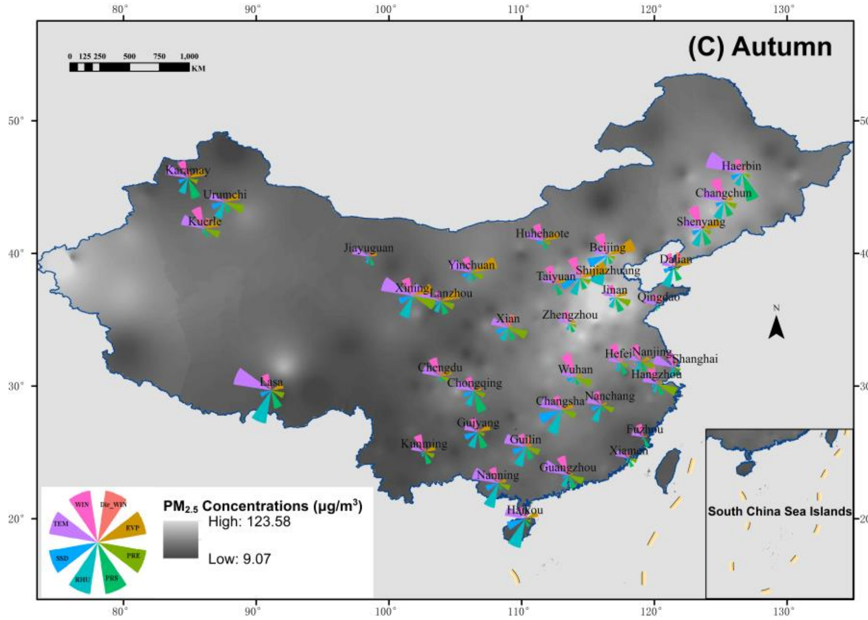

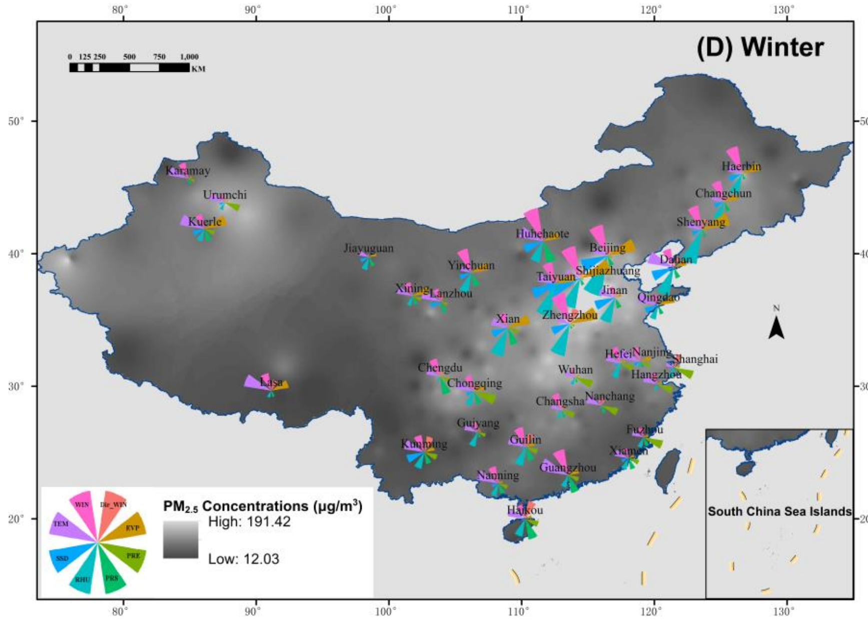

Fig 2. Wind rose map of influences of eight individual meteorological factors on $PM_{2.5}$ concentrations across China (37 representative cities) during 2014-2016

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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~~, subject to local $PM_{2.5}$ concentrations.~~. For instance, $PM_{2.5}$ concentrations in cities within the ~~Beijing-Tianjin-Hebei~~North China region (or ~~North~~the Northeast China region) is influenced by similar dominant meteorological factors, especially in winter, when $PM_{2.5}$ concentrations in these cities was high. ~~By analogy~~Meanwhile, meteorological influences on $PM_{2.5}$ concentrations in ~~the Kuerle and Karamay (~~cities within ~~Xinjiang province) are generally~~the Yangtze River basin were also highly similar~~, especially~~ in ~~winter. 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~~all seasons. As we can see, meteorological influences on $PM_{2.5}$ 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),~~c. For the heavily polluted North China region, the higher local $PM_{2.5}$ concentrations, the larger influence meteorological factors exerts on $PM_{2.5}$ concentrations. $PM_{2.5}$ concentrations ~~is~~are usually the highest in winter, causing serious ~~smog events~~haze episodes across China, the North China region in particular~~, whilst~~. Meanwhile, $PM_{2.5}$ concentrations in spring and summer is comparatively low. Accordingly, there are more influencing meteorological factors on $PM_{2.5}$ concentrations for ~~most~~ cities within this region and the ~~ρ~~ 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

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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~~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.

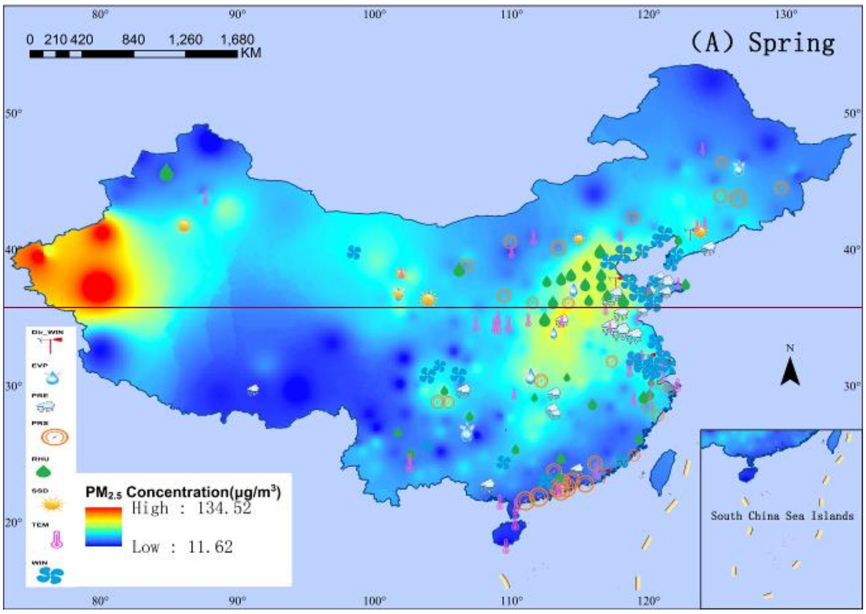
4.2 Spatial and temporal variations of the dominant meteorological influence on local $PM_{2.5}$ concentrations across China

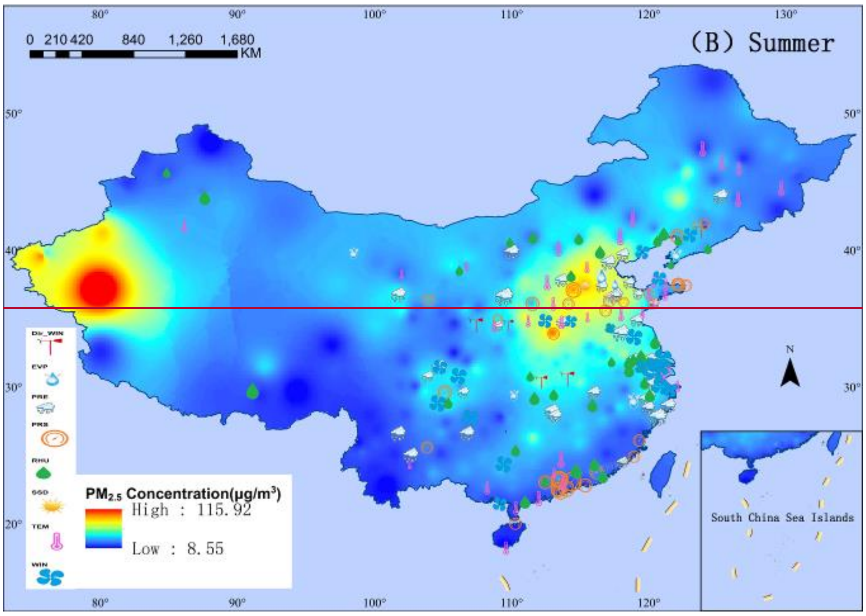
Through statistical analysis, we selected the factor with the largest ~~ρ~~ ρ value as the dominant meteorological factor for local $PM_{2.5}$ concentrations. The spatial and temporal variations of the dominant meteorological influence on local $PM_{2.5}$ concentrations across China are demonstrated 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~~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 ~~ρ~~ ρ value for the dominant meteorological factors is ~~the largest~~much larger in winter than that in summer. Furthermore, it is noted that the dominant meteorological factors ~~demonstrates~~demonstrate more regional similarity ~~when $PM_{2.5}$ concentrations is high~~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. ~~Based on~~According to this pattern, when a regional haze ~~event~~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 winds. On the other hand, regional air pollution in summer can hardly be solved simultaneously through one specific meteorological factor.




(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
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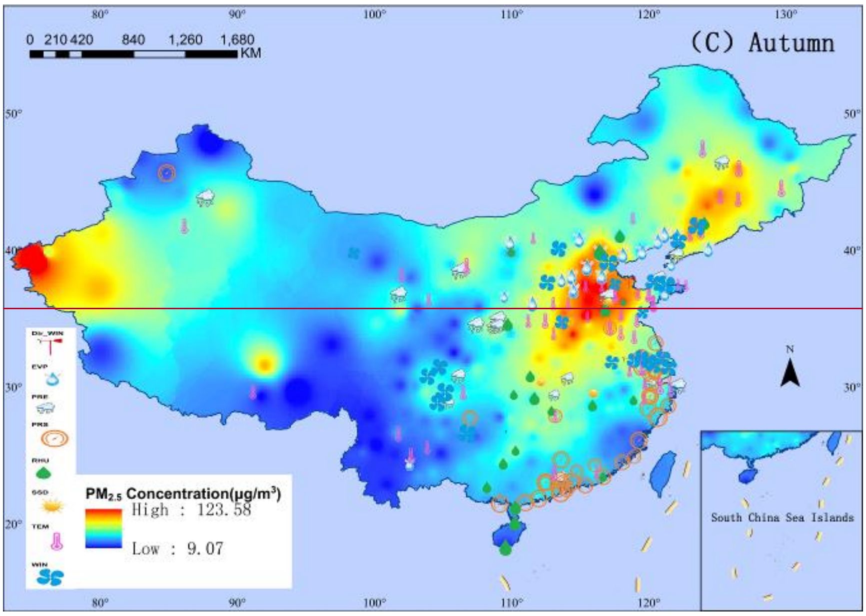
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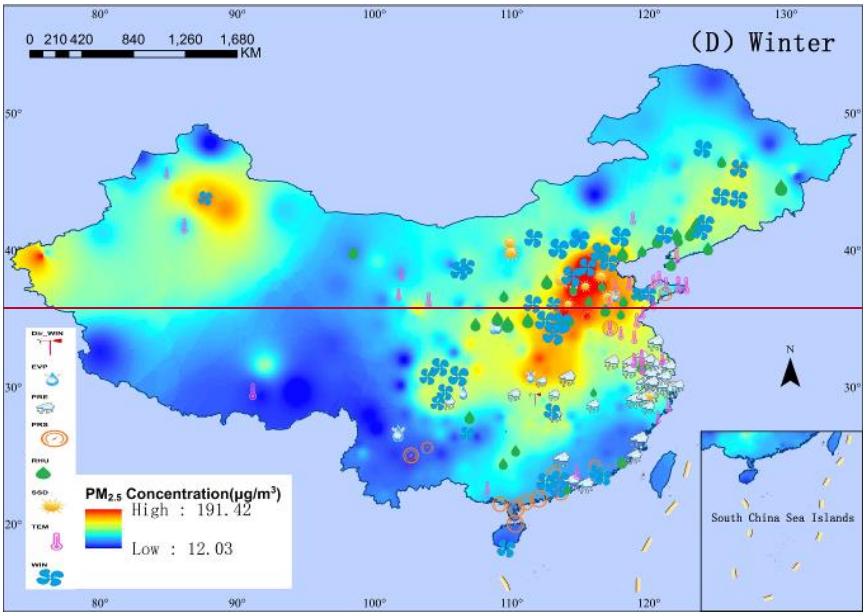
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50° 40° 30° 20°
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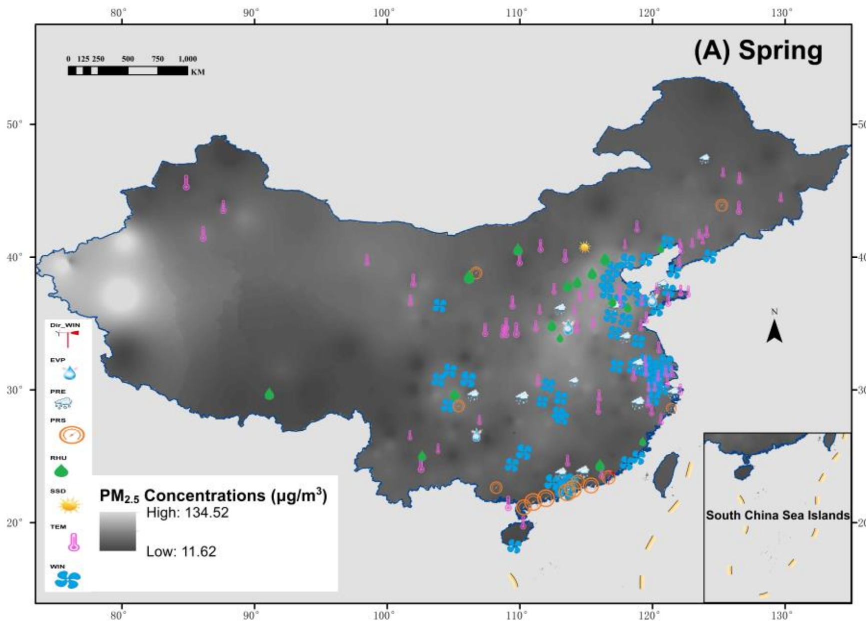
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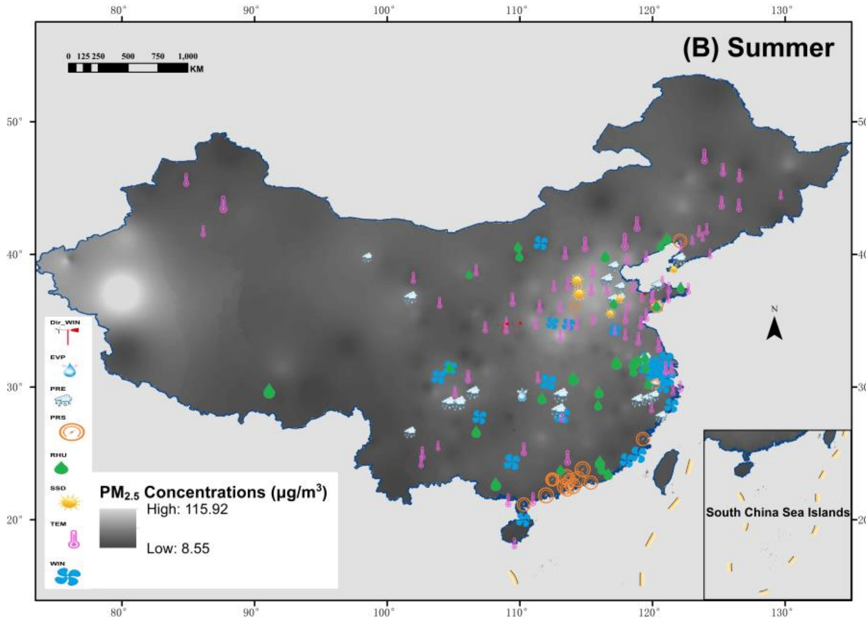
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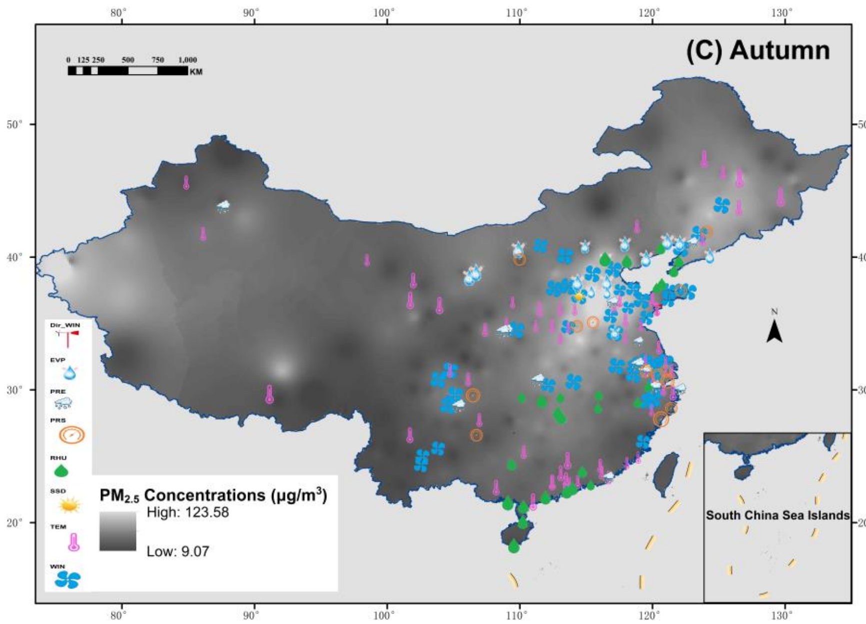
TEM
WIN
PM2.5 Concentrations (μg/m3)
High: 115.92
Low: 8.55
South China Sea Islands
80° 90° 100° 110° 120° 130°
20° 30° 40° 50°


(C) Autumn
0 125 250 500 750 1,000 KM
Dir_WIN
EVP
PRE
PRS
RHU
SSD
TEM
WIN
PM2.5 Concentrations (μg/m3)
High: 123.58
Low: 9.07
South China Sea Islands
80° 90° 100° 110° 120° 130°
20° 30° 40° 50°

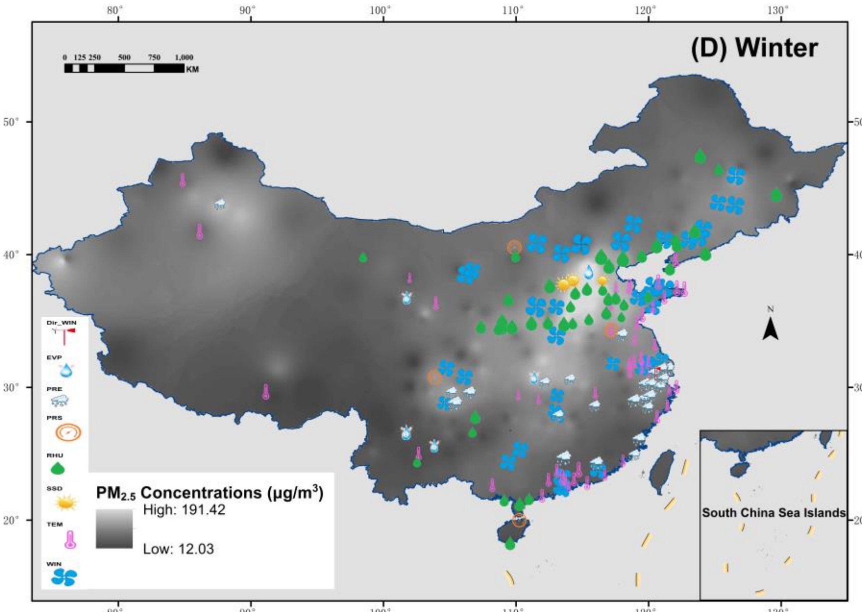


Fig 3. The dominant meteorological factor for local $PM_{2.5}$ concentrations in ~~189~~188 monitoring cities across China

The size of symbols indicates the ~~ρ~~ 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~~188 cities across China (2014-2016)

Season	~~Factors~~Factor	*TEM*	*SSD*	*PRE*	*EVP*	*PRS*	*RHU*	*WIN*	*Dir_WIN*
Spring	No. of cities[1]	~~45~~76	~~8~~1	~~22~~13	~~8~~3	~~31~~13	~~34~~17	~~35~~64	~~6~~1
	Mean ~~ρ~~ ρ value	0.~~281~~254	0.~~138~~102	0.~~152~~143	0.~~131~~108	0.~~209~~177	0.~~204~~161	0.~~215~~222	0.~~104~~094
	SD of ~~ρ~~ ρ value	0.~~024~~106	0.~~019~~071	0.~~024~~088	0.~~021~~081	0.~~028~~123	0.~~028~~105	0.~~019~~102	0.~~015~~077
	Max ~~ρ~~ ρ value	0.~~747~~572	0.~~617~~366	0.~~723~~385	0.~~610~~397	0.~~714~~653	0.~~796~~475	0.~~555~~595	0.~~502~~429
Summer	No. of cities	~~38~~78	~~1~~5	~~37~~22	~~7~~1	~~35~~20	~~41~~32	~~23~~27	~~7~~3
	Mean ~~ρ~~ ρ value	0.~~244~~272	0.~~107~~136	0.~~179~~183	0.~~119~~137	0.~~175~~163	0.~~221~~219	0.~~168~~191	0.~~067~~087
	SD of ~~ρ~~ ρ value	0.~~019~~098	0.~~014~~086	0.~~023~~099	0.~~014~~088	0.~~021~~109	0.~~024~~118	0.~~015~~095	0.~~007~~062
	Max ~~ρ~~ ρ value	0.~~611~~604	0.~~507~~433	0.~~716~~536	0.~~625~~399	0.~~676~~518	0.~~694~~562	0.~~536~~453	0.~~364~~311
Autumn	No. of cities	~~58~~70	~~3~~1	~~18~~13	~~21~~15	~~43~~13	~~20~~27	~~23~~48	~~3~~1
	Mean ~~ρ~~ ρ value	0.~~330~~316	0.~~132~~164	0.~~159~~191	0.~~176~~181	0.~~271~~199	0.~~225~~247	0.~~230~~265	0.~~082~~104
	SD of ~~ρ~~	0.~~020~~1	0.~~014~~0	0.~~025~~0	0.~~027~~1	0.~~029~~0	0.~~028~~1	0.~~018~~0	0.~~009~~0

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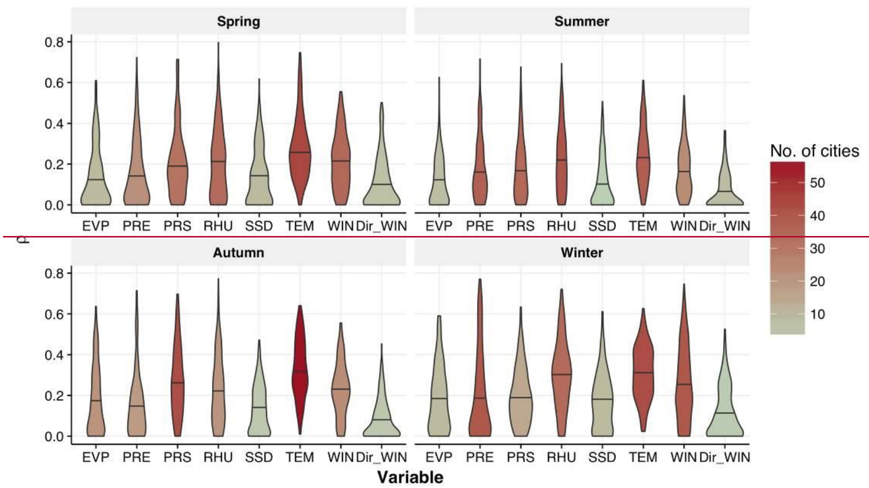
	ρ value	09	98	93	17	91	25	89	74
	Max ~~ρ~~	0.~~641~~7	0.~~472~~4	0.~~714~~4	0.~~637~~5	0.~~697~~5	0.~~773~~6	0.~~556~~4	0.~~452~~3
	ρ value	02	79	30	14	24	62	88	31
Winter	**No. of cities**	~~43~~56	~~8~~3	~~40~~27	~~8~~5	~~14~~4	~~34~~48	~~40~~44	~~2~~1
	Mean ~~ρ~~	0.~~310~~3	0.~~172~~1	0.~~200~~1	0.~~185~~1	0.~~198~~1	0.~~300~~3	0.~~255~~2	0.~~115~~1
	ρ **value**	06	83	66	90	80	04	99	19
	SD of ~~ρ~~	0.~~017~~0	0.~~019~~1	0.~~045~~1	0.~~025~~1	0.~~019~~0	0.~~028~~1	0.~~033~~1	0.~~015~~0
	ρ **value**	94	29	15	30	86	61	36	92
	Max ~~ρ~~	0.~~626~~5	0.~~611~~6	0.~~770~~4	0.~~591~~5	0.~~634~~4	0.~~721~~7	0.~~746~~6	0.~~525~~5
	ρ **value**	27	15	73	95	27	55	23	60

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



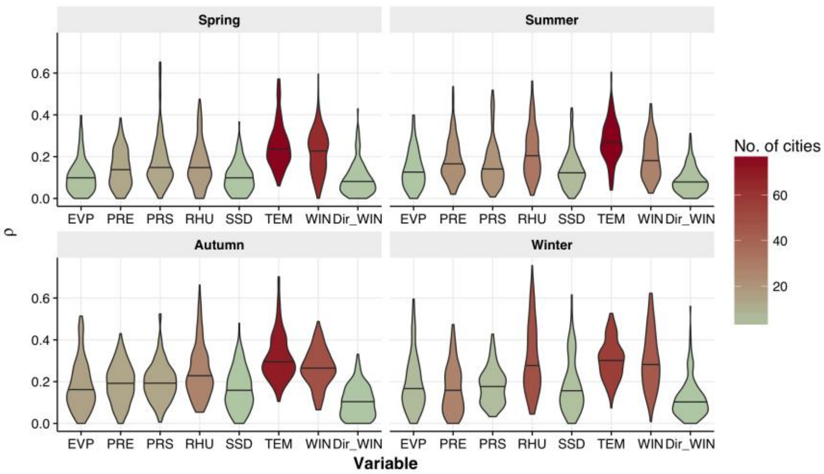


Fig 4. ~~The comparison~~Violin plots of the influence of eight different meteorological factors on local $PM_{2.5}$ concentrations in ~~189~~188 cities across China ~~(violin plot)~~

No. of cities: ~~The~~the number of cities with this factor as the dominant meteorological factor (its ~~ρ~~ ρ value is the largest amongst eight factors) on local $PM_{2.5}$ concentrations. The shape of the violin bars indicated the frequency distribution ~~frequency~~ of ~~ρ~~ ρ value for ~~189~~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*, ~~*wind*~~ and ~~*air pressure*~~*wind* exert stronger influences on local $PM_{2.5}$ concentrations than other factors. The annual mean ~~ρ~~ ρ value for *temperature*, ~~*humidity*,~~ *wind* and ~~*air pressure*~~*humidity* was 0.~~291~~287, 0.~~238, 0.217~~244 and 0.~~213~~233, compared with *wind direction* (0.~~092~~101), *SSD* (0.~~137~~146), *evaporation* (0.~~153) and~~155), *precipitation* (0.~~173~~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 ~~ρ~~ 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~~ ρ value for ~~the eight~~each meteorological ~~factors in each season~~factor was large than 0.~~5~~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 ~~some~~ meteorological factors~~, which~~ that 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~~ 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.~~

~~**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~~Due to different meteorological conditions and complicated mechanisms of $PM_{2.5}$-meteorology interactions, the influence of individual meteorological factors on $PM_{2.5}$ concentrations varied significantly at the national scale. 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, the interaction mechanisms between individual meteorological factors and $PM_{2.5}$ concentrations may be influenced significantly by the magnitude of local meteorological factors and $PM_{2.5}$ concentrations. For instance, 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, which leads to the hygroscopic increase and accumulation of $PM_{2.5}$ (Fu et al., 2016). In addition to precipitation, He et al. (2017) suggested that such meteorological factors as temperature and humidity were either positively or negatively correlated with $PM_{2.5}$ concentrations in different regions of China. 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.

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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~~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

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$PM_{2.5}$ 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~~decreases *humidity*, as well as ~~positive causality on~~increases *SSD* and *evaporation*. Since the factor *humidity* (*SSD* and *evaporation*) has a strong positive (negative) influence[7] 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 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

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

highly complicated atmospheric environment and the difficulty in acquiring true data of exhaust emission, ~~these~~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 ~~priori~~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). ~~However, Cheng et al. (2015) pointed out that most~~ Compared with the static models, dynamic statistical models ~~were static model and did not~~comprehensively consider the meteorological influences on ~~airborne pollutants. Even if some models consider~~ $PM_{2.5}$ 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 ~~$PM_{2.5}$ concentrations, they only employ~~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~~, which has been proved~~ to ~~problematic in~~ 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 ρ value and overestimates the influence of individual meteorological factors on $PM_{2.5}$ concentrations. In this case, this research provides useful reference for improving existing statistical models. ~~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~~ ρ value, instead of the correlation coefficient, of different factors into corresponding GAM (Generalized Additive Models) and adjusting parameters accordingly, we ~~can~~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~~ 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. Some scholars (http://china.cnr.cn/yxw/201411/t20141123_516839830.shtml 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. 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.

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6 Conclusions

Based on the CCM method, we quantified the ~~causality~~ influence of eight meteorological factors on local $PM_{2.5}$ concentrations for ~~189~~188 monitoring cities across China. The results suggest that meteorological influences on $PM_{2.5}$ are of notable seasonal and spatial variations. ~~For most cities~~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* ~~and air pressure exert stronger influences on~~ 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 ~~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.

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