

Assessment of meteorology vs control measures in China fine particular matter trend from 2013-2019 by an environmental meteorology index

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Abstract

A framework was developed to quantitatively assess the contribution of meteorology variations to the trend of fine particular matter (PM_{2.5}) concentrations and to separate the impacts of meteorology from the control measures in the trend, based upon an Environmental Meteorology Index (EMI). The model-based index EMI realistically reflects the role of meteorology in the trend of PM_{2.5} and is explicitly attributed into three major factors: deposition, vertical accumulation and horizontal transports. Based on the 2013-2019 PM_{2.5} observation data and re-analysis meteorological data in China, the contributions of meteorology and control measures in nine regions of China were assessed separately by the EMI-based framework. Monitoring network observations show that the PM_{2.5} concentrations have been declined about 50% on national average and about 35% to 53% for various regions. It is found that the nation-wide emission control measures were the dominant factor in the declining trend of China PM_{2.5} concentrations, contributing to about 47% of the PM_{2.5} decrease from 2013 to 2019 on

1 the national average and 32% to the 52% for various regions. The meteorology has a
2 variable and sometimes critical contribution to the year by year variations of PM_{2.5}
3 concentrations, 5% on annual average and 10-20% for the fall-winter heavy pollution
4 seasons.

5 **1. Introduction**

6 Recent observation data from the Ministry of Ecology and Environment of China (MEE)
7 has shown a steady improvement of air quality across the country, especially in particular
8 matter (PM) concentrations (Hou et al., 2019). According to 2013-2019 China Air Quality
9 Improvement Report issued by MEE, compared to 2013, the average concentrations of
10 particulate matter with an aerodynamic diameter of less than 2.5 μm (PM_{2.5}) in 74 major
11 cities of China have decreased by more than 50% in 2019. From scientific and
12 management point of views, a quantitative apportionment of the reasons behind the
13 trend is critical to assess the reduction strategies implemented by the government and to
14 guide future air quality control policy. However, the assessment of the improvements of
15 air quality is a complicated process that involves the quantification of changes in the
16 emission sources, meteorological factors, and other characteristics of the PM_{2.5} pollution,
17 which are also interacting with each other. In order to separate the relative degree of
18 these factors, a comprehensive analysis, including observational data and model
19 simulation, is needed.

1 Researches have been done extensively on the impacts of weather systems on air
2 quality. Synoptic and local meteorological conditions have been recognized to influence
3 the PM concentrations at various scales (Beaver and Palazoglu, 2006;He et al., 2017a;He
4 et al., 2017b;Pearce et al., 2011a;Pearce et al., 2011b). For the atmospheric aerosol
5 pollution, the dynamic effect of the downdraft in the "leeward slope" and "weak wind
6 area" of the Qinghai Tibet Plateau in winter is not conducive to the diffusion of air
7 pollution emissions in the urban agglomerations of eastern China (Xu et al., 2015;Xu et al.,
8 2002). The evolution of circulation situation is an important factor driving the change of
9 haze pollution (He et al., 2018). The local circulations, such as mountain and valley wind
10 and urban island circulation, have significant impact on local pollutant concentration
11 (Chen et al., 2009;Yu et al., 2016). Previous studies also revealed that PM_{2.5} concentration
12 is significantly correlated with local meteorological elements, such as temperature,
13 humidity, wind speed, and boundary layer height (He et al., 2017b;Bei et al., 2020;Ma et
14 al., 2019;He et al., 2016).

15 In the Beijing-Tianjin-Hebei (BTH) Region, a correlation analysis and principal
16 component regression method (Zhou et al., 2014) was used to identify the major
17 meteorological factors that influenced the API (Air Pollution Index) time series in China
18 from 2001-2010, indicating that air pressure, air temperature, precipitation and relative
19 humidity were closely related to air quality with a series of regression formulas. Yet, the
20 analysis was assumed a relatively unchanged emission whose impacts were not taken into
21 account. On a local scale, an attempt (Zhang et al., 2017) has been made to correlate the
22 air pollutant levels with a combination of meteorological factors with the development of

1 the Stable Weather Index (SWI) at CMA. The SWI is a composite index which includes the
2 advection, vertical diffusion and humidity and other meteorological factors that are
3 related to the formation of air pollutions in a specific region or city. A higher value of SWI
4 means a weaker diffusion of air pollutants. This index had some success in assessing the
5 meteorological impacts on air pollution, especially calibrated for a specific region, i.e.
6 Beijing. However, when applied to different areas where the emission patterns and
7 meteorological features are different, this index failed to give a universal or comparable
8 indication of meteorological assessment of pollution levels across the nation.

9 Using the Kolmogorov-Zurbenko (KZ) wave filter method, Bai et al (2015) separated
10 the API time series in three Chinese cities into short-term, seasonal and long-term
11 components, and then used the stepwise regression to set up API baseline and short-term
12 components separately and established linear regression models for meteorological
13 variables of corresponding scales. Consequently, with the long-term representing the
14 change of emissions removed from the time series, the meteorological contributions
15 alone were assumed and analyzed, pointing out that unfavorable conditions often lead to
16 an increase by 1-13 whereas the favorable conditions to a decrease by 2-6 in the long-
17 term API series, respectively. Though the contributions of emissions and meteorological
18 variations were separated by the research, it was only done by mathematical
19 transformations and far from the reality. The mechanisms behind the variation of the time
20 series were not investigated.

1 A chemical transport model (CTM) is an ideal tool to carry the task of assessment by
2 taking the meteorology, emissions and processes into considerations altogether.

3 Andersson et al. (2007) used a CTM to study the meteorologically induced inter-annual
4 variability and trends in deposition of sulphur and nitrogen as well as concentrations of
5 surface ozone (O₃), nitrogen dioxide (NO₂) and PM and its constituents over Europe during
6 1958-2001. It is found that the average European interannual variation, due to
7 meteorological variability, ranges from 3% for O₃, 5% for NO₂, 9% for PM, 6-9% for dry
8 deposition, to about 20% for wet deposition of sulphur and nitrogen. A multi-model
9 assessment of air quality trends with constant anthropogenic emissions was also carried
10 out in Europe (Colette et al., 2011) and found that the magnitude of the emission-driven
11 trend exceeds the natural variability for primary compounds, concluding that that
12 emission management strategies have had a significant impact over the past 10 years,
13 hence supporting further emission reductions strategies. Model assessments of air quality
14 trends at various regions and time periods (Wei et al., 2017; Li et al., 2015) in China were
15 also done and yielded some useful results. For the BTH Region, Li et al. (2015) used the
16 Comprehensive Air Quality Model with extensions (CAMx) plus the Particulate Source
17 Apportionment Technology (PSAT) to simulate the contributions of emission changes in
18 various sectors and changes in meteorology conditions for the PM_{2.5} trend from 2006 to
19 2013. It was found that the change of source contribution of PM_{2.5} in Beijing and northern
20 Hebei was dominated by the change of local emissions. However, for Tianjin, and central
21 and southern Hebei province, the change of meteorology condition was as important as
22 the change of emissions, illustrating the regional difference of impacts by meteorology

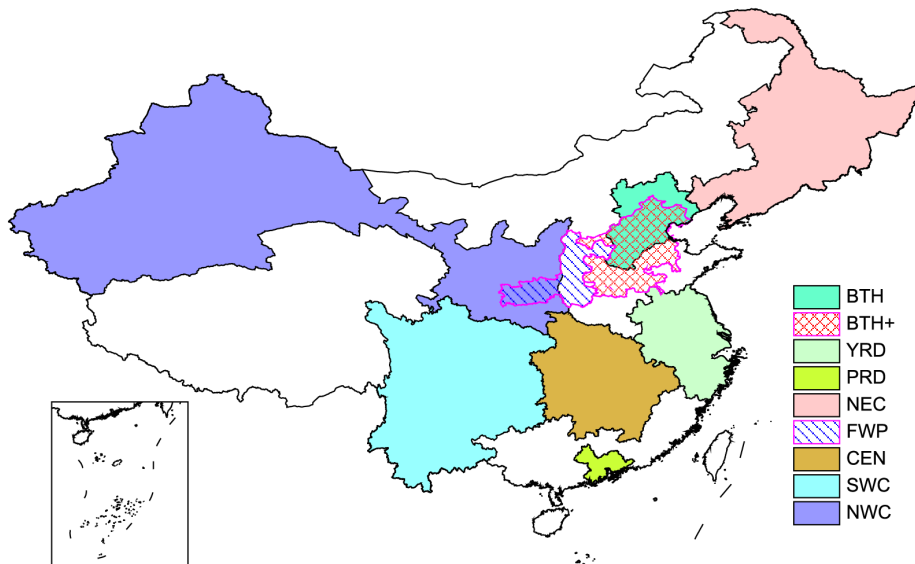
1 and emissions. However, the emission changes in the simulations were assumed and did
2 not reflect the real spatio-temporal variations.

3 There is no surprise that previous studies could not systematically catch the
4 meteorological impacts across the whole nation as the controlling meteorological factors
5 involving the characteristics of plenary boundary layers (PBL), wind speed and turbulence,
6 temperature and stability, radiation and clouds, underlying surface as well as pollutant
7 emissions, vary greatly from region to region. A single index or correlation cannot be
8 applied to the entire nation. Obviously, in order to systematically assess the impacts of
9 meteorology on air pollution, these factors have to be taken into consideration in a
10 framework and be assessed simultaneously. This paper presents a methodology to assess
11 the individual impacts of meteorology and emission changes, based on a model-derived
12 index EMI, i.e., Environmental Meteorology Index, and observational data, providing a
13 comprehensive analysis of the air quality trends in various regions of China, with
14 mechanistic and quantitative attributions of various factors.

15 **2. Methodology**

16 The assessment is carried out through the combination of observational data and EMI
17 index from model analysis. Since the emission and air quality characteristics vary greatly
18 from region to region in China, the analysis is divided into 9 focused regions (Figure 1).
19 Regional air quality data ($PM_{2.5}$) provides the basis for the trend analysis. Separating the

1 trend contribution from regional emission reduction and meteorological variation entails
2 a framework, which is discussed below.



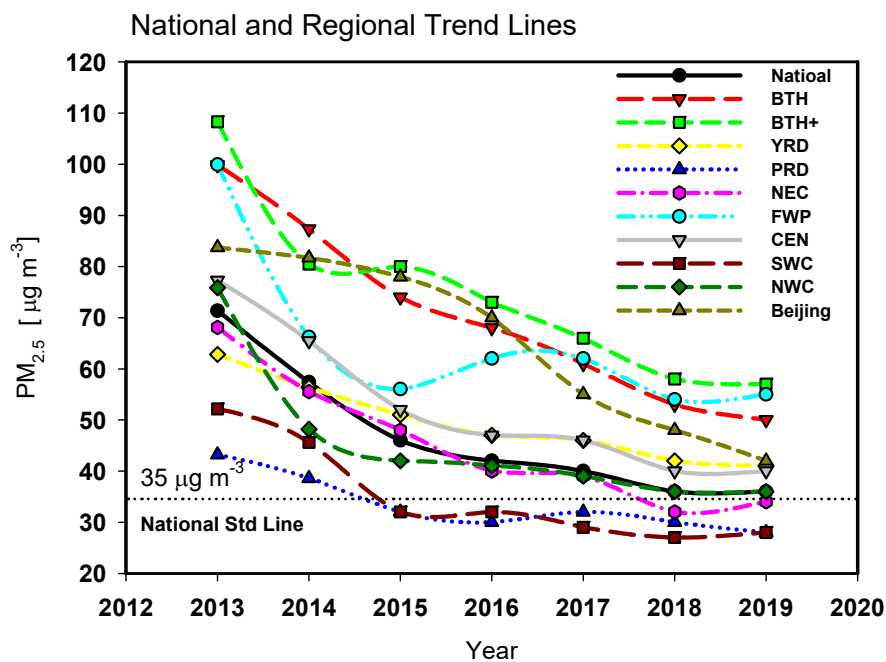
Note: **BTH**: Beijing, Tianjin and Hebei; **BTH+**: BJ, TJ + 26 cities; **YRD**: Shanghai, Jiangsu, Zhejiang and Anhui; **PRD**: 9 cities in Guangdong; **NEC**: Heilongjiang, Jilin and Liaoning; **FWP**: 11 cities in Shanxi, Shannxi and Henan; **CEN**: Hubei, Hunan and Jiangxi; **SWC**: Yunnan, Guizhou, Sichuan, Chongqing; **NWC**: Shannxi, Gansu, Ningxia and Xinjiang

3
4 Figure 1: Analysis region separation and definition.

5 **2.1. Particular Matter (PM) Observation Data**

6 The observational pollution data of PM_{2.5} concentrations used in this study were from
7 the monitoring network of the Ministry of Ecology and Environment (MEE) of China
8 ([http:// english.mee.gov.cn/](http://english.mee.gov.cn/)). From 2013 to 2019, the concentrations have shown a large
9 change in the country where most regions see a declined trend in the annual
10 concentrations. Data show that from 2013 to 2019, the national annual averaged PM_{2.5}

1 concentrations have dropped about 50% (Fig. 2), where the haze days have been
 2 shortened by 21.2 days from the China Meteorological Administration (CMA) monitoring
 3 data (Table 1), with some regional differences. Regionally, by 2019, the PM_{2.5} reduction
 4 rate from 2013 ranges from 35 to 53%. Detailed analysis will be given in the Results and
 5 Discussions section.



6
 7 Figure 2: National and regional trend lines of PM_{2.5} in China from 2013 to 2019.

8 It is noted that the PM_{2.5} mass concentrations by MEE are now reported under
 9 observation site's actual conditions of temperature and pressure from September 1, 2018
 10 before which the values were reported under the standard state (STP), i.e. 273 K and
 11 101.325 kPa. In order to maintain the consistence of the data series, the PM_{2.5}
 12 concentrations used in this study have all been converted according to the new standard
 13 (MEE, 2012)(GB3095-2012) under actual conditions. Research has shown that after the

1 change of reporting standard, the PM_{2.5} concentration in most cities decreased, and the
2 number of good days to meet the standard increased (Zhang and Rao, 2019).

3 **2.2. Meteorological Data**

4 Conventional meteorological data can provide qualitative assessment of the
5 contributions of meteorological factors to the changes of air quality. The data used in this
6 study are from 843 national base weather stations of the CMA from 2013 to 2019. The
7 wind speed (WS), day with small wind (DSW), relative humidity (RH) and haze days are
8 used to analyze the pollution meteorological conditions. When the daily average wind
9 speed is less than 2 m s⁻¹, a DSW day is defined. Since the haze formation is always related
10 to stable meteorological conditions and high aerosol mass loading, haze observation from
11 CMA is also used to analyze the haze trends and the impact of air quality on visibility. A
12 haze day is defined with daily averaged visibility less than 10 km and relative humidity less
13 than 85% (Wu et al., 2014), excluding days of low visibility due to precipitation, blowing
14 snow, blowing sand, floating dust, sandstorms and smoke.

15 The 2019 national annual averaged WS has increased by 4.5%, DSW dropped by
16 15.1%, and RH decreased by 3.9% compared with 2013, with regional differences (Table
17 1). Slightly changes occurred when compared with 2015 that WS has decreased by 0.7%,
18 DSW dropped by 11.3%, and RH decreased by 2.2%. Overall, it can be seen that the annual
19 haze days have a certain degree of correlations negatively with WS and positively with

- 1 DSW. Detailed analysis linking PM_{2.5} and meteorology will be given in the Results and
- 2 Discussions section.
- 3

1 Table 1: National and regional environmental meteorology in 2019 and comparisons with
 2 2015 and 2013

Region	Wind Speed			Days with Small Wind			Relative Humidity			Haze (days)		
	AVG (m s ⁻¹)	vs 2015 (%)	vs 2013 (%)	Days	vs 2015 (%)	vs 2013 (%)	%	vs 2015 (%)	vs 2013 (%)	Days	vs 2015	vs 2013
National	2.2	-0.7	+4.5	129.8	-11.3	-15.1	60.1	-2.2	-3.9	25.7	-19.0	-21.2
BTH	2.0	-8.6	-2.2	131.0	+14.7	+9.0	56.7	-2.6	-4.2	45.2	-20.4	-26.1
BTH+	2.0	-9.9	-1.0	114.4	+11.4	-5.6	58.3	-3.9	+0.6	54.5	-34.8	-30.3
YRD	2.1	+2.1	-4.7	114.1	-11.2	+5.2	76.3	-0.9	+5.5	34.0	-43.8	-54.9
FWP	1.9	+0.3	+10.9	122.8	-12.1	-25.2	59.9	-2.9	+3.3	51.6	-44.2	-43.8
PRD	2.0	+1.9	-10.4	118.5	+16.2	+14.4	79.7	-8.0	+10.3	3.1	-10.3	-34.3
NEC	2.7	+3.6	+12.9	55.8	-33.7	-38.4	61.6	-2.8	-5.8	13.6	-30.8	-12.4
CEN	1.8	+3.2	+0.4	172.1	-9.4	-2.8	77.9	-1.9	+6.9	30.3	-27.9	-23.2
SWC	1.7	+3.7	+12.2	180.7	-13.3	-16.3	74.7	-0.9	+5.7	11.1	-12.1	-12.4
NWC	1.9	-8.4	+4.3	146.8	-2.7	-9.5	58.5	1.5	+2.8	20.2	-14.7	-6.6

3 Note: "+" increased; "-" decreased

4 2.3. EMI – the Environmental Meteorological Index

5 Due to the complicated interactions of emissions, meteorology and atmospheric
 6 processes, a single set of meteorological factors or a combination of them cannot
 7 quantitatively attribute the individual factor to the changes of concentration observed.

8 In order to quantitatively assess the impacts of meteorological conditions to the
 9 changes of air pollution levels, an index EMI (Environmental Meteorological Index) is

1 defined as follows. For a defined atmospheric column (h) at a time t, an EMI is defined
 2 as an indication of atmospheric pollution level:

$$3 \quad EMI(t) = EMI(t_0) + \int_{t_0}^t \Delta EMI * dt$$

4 (1)

5 where the ΔEMI is the tendency that causes the changes of pollution level in a time
 6 interval dt defined as:

$$7 \quad \Delta EMI = iEmid + iTran + iAccu$$

8 (2)

9 where the $iEmid$ is the difference between emission and deposition, and $iTran$ and
 10 $iAccu$ are the net (in minus out) advection transports and the vertical accumulation by
 11 turbulent diffusion in the column, respectively. A positive sign of each factor indicates a
 12 net flow of pollutants into the column, and vice versa.

12 Mathematically, these factors are expressed as:

$$13 \quad iTran = \frac{1}{hC_0} \int_0^h \left(u \frac{\partial C}{\partial x} + v \frac{\partial C}{\partial y} + w \frac{\partial C}{\partial z} \right) dz$$

$$14 \quad iAccu = \frac{1}{hC_0} \int_0^h \left[\frac{\partial C}{\partial x} \left(Kx \frac{\partial C}{\partial x} \right) + \frac{\partial C}{\partial y} \left(Ky \frac{\partial C}{\partial y} \right) + \frac{\partial C}{\partial z} \left(Kz \frac{\partial C}{\partial z} \right) \right] dz$$

$$15 \quad iEmid = \frac{1}{hC_0} \int_0^h [Emis - (V_d + L_d)] dz$$

16 (3)

17 where the tendency is normalized by a factor C_0 . For an application of EMI to the $PM_{2.5}$,
 18 C_0 is set to equal $35 \mu g m^{-3}$, the national standard for $PM_{2.5}$ in China (MEE, 2012), and

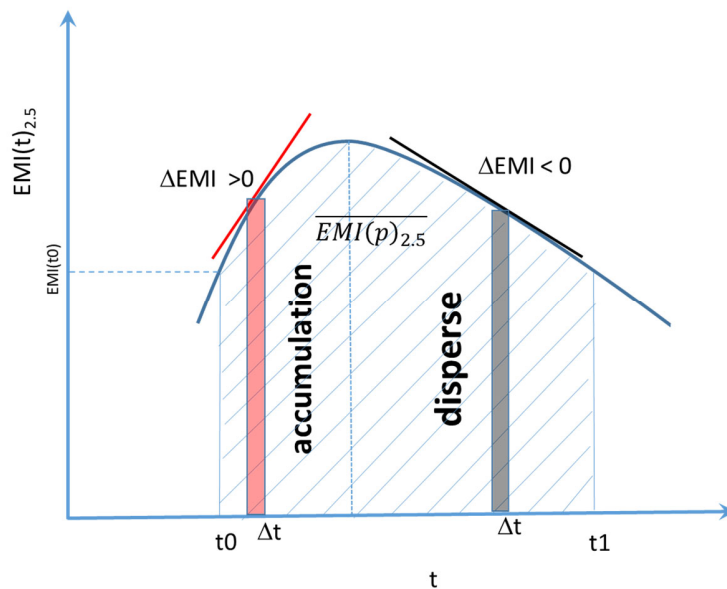
1 the $EMI(t)$ is written as $EMI(t)_{2.5}$. If the $EMI_{2.5}$ is less than 1, the concentration level will
2 reach or be better than the national standard.

3 It can be seen here that these key parameters account for the major
4 meteorological factors which control the air pollutant levels, including wind speed and
5 directions (u, v, w), turbulent diffusion coefficients (K_x, K_y, K_z) as well as dry and wet
6 depositions (V_d and L_d). Therefore, under the conditions of an unchanged emissions
7 ($Emis$), the EMI variation reflects the impacts of meteorological factors on the levels of
8 atmospheric pollutants. Furthermore, because of the inclusion of individual factors such
9 as $iTran$, $iAccu$ and $iEmid$, the variation of $EMI(t)_{2.5}$ can be attributed to the variation of
10 each factor, which gives more detailed information to the meteorological influence on
11 the ambient pollutant concentration variations. It should be pointed out that the
12 current EMI index has only been accounted explicitly for three major physical processes
13 of $iTran$, $iAccu$, and $iEmid$ that are closely related to the meteorological influences.
14 However, the secondary formation of aerosols is only implicitly considered in the EMI as
15 the three major physical processes are calculated from the concentrations of aerosols
16 (C) as indicated in Equation (3).

17 For a period of time p (t_0 to t_1) when the averaged pollutant level (e.g. $PM_{2.5}$) is
18 compared with $EMI(t)_{2.5}$, the time integral has to be done to obtain the averaged index
19 for the period, such as:

$$20 \overline{EMI(p)_{2.5}} = \frac{1}{t_1 - t_0} \int_{t_0}^{t_1} EMI(t)_{2.5} dt \quad (4)$$

1 The relationship among the ΔEMI , $EMI(t)_{2.5}$ and $\overline{EMI(p)}_{2.5}$ is illustrated in Figure
 2 3. It is clear that the $EMI(t)_{2.5}$ is a function of time and can be used to reflect the
 3 pollution level at any time t , while the $\overline{EMI(p)}_{2.5}$ is the area under the $EMI(t)_{2.5}$ from
 4 time t_0 to t_1 , which gives the averaged pollution levels for the period. The derivatives of
 5 $EMI(t)_{2.5}$ are the ΔEMI , which is a positive value when the pollution is being accumulated
 6 and a negative value when the pollution is being dispersed.



7

8 Figure 3: Relationship between the ΔEMI , $EMI(t)_{2.5}$ and $\overline{EMI(p)}_{2.5}$.

9 Therefore, for the period p with n discrete steps from t_0 to t_1 , the $\overline{EMI(p)}_{2.5}$
 10 represents the averaged meteorological influences on $PM_{2.5}$, while the sum of the
 11 positive ΔEMI is the accumulation potentials and the sum of the negative ΔEMI is the
 12 dispersing potentials as illustrated in Figure 3. The relationship between them is derived
 13 as follows:

$$\begin{aligned}
& \overline{EMI(p)}_{2.5} = \frac{1}{n} [EMI(0) + EMI(1) + EMI(2) + \dots + EMI(n - 1)] \\
& = \frac{1}{n} [nEMI(t_0) + (n - 1)\Delta EMI(1)\Delta t + (n - 2)\Delta EMI(2)\Delta t \\
& \quad + (n - 3)\Delta EMI(3)\Delta t + (n - 4)\Delta EMI(4)\Delta t + \dots + \Delta EMI(n - 1)\Delta t]
\end{aligned}
\tag{5}$$

where n is the time steps in the period and the averaged EMI has been linked to the starting point $EMI(0)$ and the changing rates of EMI, i.e. $\Delta EMI(n)$, at each time step. For monthly simulations, the initial values $EMI(t_0)$ for each month was set up by the averaged $PM_{2.5}$ concentrations for the first day from 2013 to 2019 divided by the constant C_0 ($35 \mu g m^{-3}$).

2.4. Assessment Framework of Emission Controls

The $EMI_{2.5}$ index provides a way to assess the meteorological impacts on the changes of $PM_{2.5}$ concentrations at two time periods, i.e. January 2013 (p_0) and January 2016 (p_1) under the assumption of unchanged emissions. However, due to the national efforts of improving air quality, the year-by-year emissions are changing rapidly and unevenly across the country. The changes in both emissions and meteorology are tangled together to yield the observed changes in ambient concentrations. For policy makers, the emission reduction quantification is critical to guide the further air quality improvements. The framework proposed here is to combine changes in the observed

1 concentration levels and meteorology factors $\overline{EMI(p)}_{2.5}$ to quantify the changes caused
2 by emission changes only at two time periods.

3 The observed concentrations at $p0$ and $p1$ are defined as $PM(m0, e0)$ and $PM(m1,$
4 $e1)$ where $(m0, e0)$ and $(m1, e1)$ indicate the meteorology and emission status at $p0$ and
5 $p1$, respectively. The contribution to the observed concentration changes between $p0$
6 and $p1$ by sole emission changes or control measures is defined as:

$$7 \quad \Delta EMIS = \frac{PM(m0,e1) - PM(m0,e0)}{PM(m0,e0)} \times 100\% \quad (6)$$

8 where $PM(m0, e1)$ is an assumed concentration of pollutant under the conditions of
9 unchanged meteorology at $p0$ but with new emission at $p1$, which cannot be observed.

10 Since the ratio of $\overline{EMI(p0)}_{2.5} / \overline{EMI(p1)}_{2.5}$ can be used to reflect the impact ratio of
11 sole meteorology variations on the concentrations between $p0$ and $p1$ with the same
12 emissions at $p1$. Therefore, $PM(m0, e1)$ is estimated from the averaged EMI ratio and
13 the observed concentrations at $p1$ as follows:

$$14 \quad PM(m0, e1) = \frac{\overline{EMI(p0)}_{2.5}}{\overline{EMI(p1)}_{2.5}} \times PM(m1, e1) \quad (7)$$

15

16 **2.5. Quantitative Estimate of EMI**

17 Finally, a process-based method is developed to calculate the EMI and its
18 components, i.e. *iEmid*, *iTran* and *iAccu*. The main modeling frame-work used is the
19 chemical weather modeling system MM5/CUACE, which is a fully coupled atmospheric

1 model used at CMA for national haze and air quality forecasts (Gong and Zhang,
2 2008;Zhou et al., 2012). CUACE is a unified atmospheric chemistry environment with
3 four major functional sub-systems: emissions, gas phase chemistry, aerosol microphysics
4 and data assimilation (Niu et al., 2008). Seven aerosol components, i.e. sea salts,
5 sand/dust, EC, OC, sulfates, nitrates and ammonium salts are sectioned in 12 size bins
6 with detailed microphysics of hygroscopic growth, nucleation, coagulation,
7 condensation, dry depositions and wet scavenging in the aerosol module (Gong et al.,
8 2003). The gas chemistry module is based on the second generation of Regional Acid
9 Deposition Model (RADM II) mechanism with 63 gaseous species through 21 photo-
10 chemical reactions and 121 gas phase reactions applicable under a wide variety of
11 environmental conditions especially for smog (Stockwell et al., 1990) and prepares the
12 sulfate and SOA production rates for the aerosol module and for the aerosol equilibrium
13 module ISORROPIA (Nenes et al., 1998) to calculate the nitrate and ammonium aerosols.
14 This is the default method to treat the secondary aerosol formations in CUACE. For the
15 EMI application of CUACE, another option was also adapted to compute the secondary
16 aerosol formations by a highly parameterized method (Zhao et al., 2017), that computes
17 the aerosol formation rates directly from the pre-cursor emission rates of SO₂, NO₂ and
18 VOC. This option was added to facilitate timely operational forecast requirements for
19 CMA. Both primary and pre-cursor emissions of PM are based on the 2016 MEIC
20 Inventory (<http://www.meicmodel.org/>) developed by Tsinghua University for China.

21 In order to quantitatively obtain each term defined in Equation 3, the CUACE
22 model was modified to extract the change rates for the processes involved. Driven by

1 the re-analysis meteorological data, the new system CUACE/EMI can be used to
2 calculate each term in ΔEMI at each time step (Δt).

3 In summary, this section presents a systematic platform to separate and assess the
4 impacts of the meteorology and emissions on the ambient concentration changes. The
5 $\overline{\text{EMI}(p)}_{2.5}$ and ΔEMIS form the basis for the assessment. In the Results and Discussions
6 section, the application of the platform is presented to assess the fine particular matter
7 ($\text{PM}_{2.5}$) changes in China.

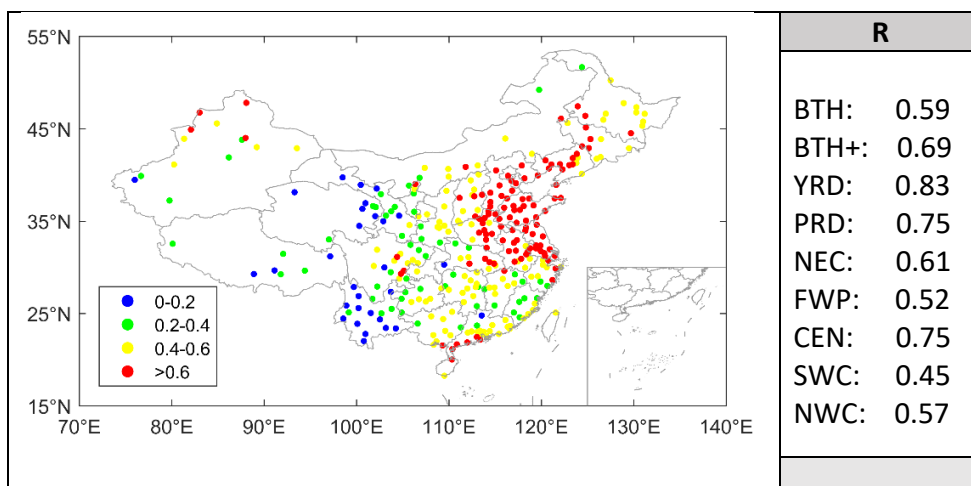
8 **3. Results and Discussions**

9 **3.1. Validation of EMI by Observations**

10 Under the conditions of no changes in annual emissions for $\text{PM}_{2.5}$ and its precursors,
11 the daily $\text{EMI}_{2.5}$ was computed by CUACE from 2013 to 2019 on a 15×15 km resolution
12 across China and accompanied by its contribution components: *iTran*, *iAccu* and *iEmid*.
13 However, in order to reflect the significant changes of industrial and domestic energy
14 consumptions within a year in China, a monthly emission (Wang et al.) variation was
15 applied to the emission inventory for computing the $\text{EMI}_{2.5}$, which is more realistically
16 reflecting the meteorology contributions to the $\text{PM}_{2.5}$ concentrations.

17 To evaluate the applicability of $\text{EMI}_{2.5}$, the index was compared with the
18 observed $\text{PM}_{2.5}$ concentrations. Figure 4 shows the spatial distribution of correlation
19 coefficients between $\text{PM}_{2.5}$ and $\text{EMI}_{2.5}$ for 2017 for all China. The correlation coefficients

1 between $EMI_{2.5}$ and $PM_{2.5}$ concentrations are greater than 0.4 for most of the Eastern
 2 China and greater than 0.6 for most of the assessment regions. Less satisfactory
 3 correlation was found in Western China, possibly due to complex terrain and less
 4 accurate emission data over there. Furthermore, due to the uncertainty in emissions
 5 and the difference in model performance for year-to-year meteorology simulations, the
 6 correlation coefficients may differ for different years. Overall, the good correlation
 7 between them merits the application of $EMI_{2.5}$ to quantify the meteorology impact on
 8 $PM_{2.5}$.

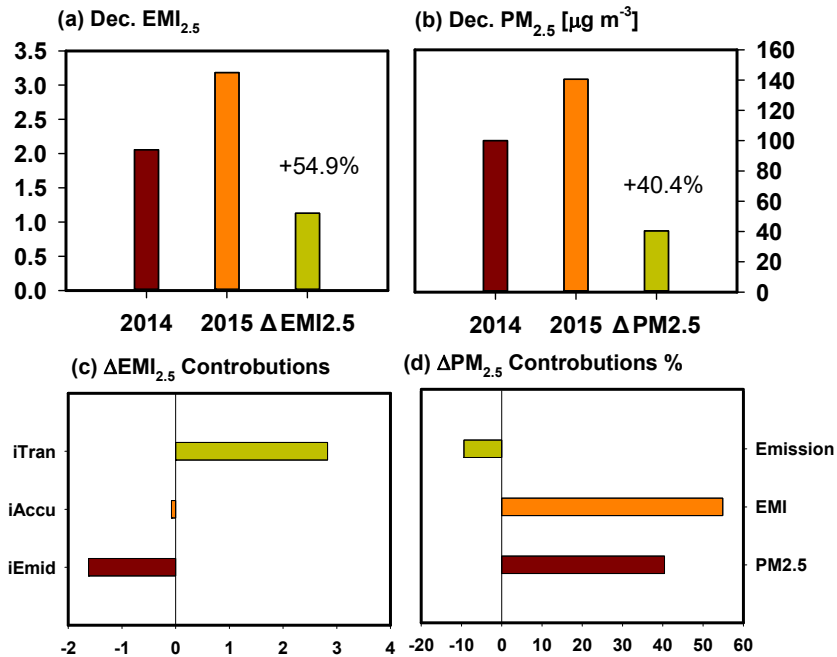


9
 10 Figure 4: Correlation coefficients (R) between the $EMI_{2.5}$ and the observed $PM_{2.5}$ daily
 11 concentrations across China for 2017 and for typical regions averaged between 2013 and 2019.

12
 13 To further illustrate the applicability of $EMI_{2.5}$, the difference of various
 14 conditions between December 2014 and December 2015 in BTH region was also
 15 analyzed when a significant change of air quality and meteorological conditions
 16 occurred. The winter of 2015 was accompanied by a strong El Nino (ENSO) event,

1 resulting in significant anomalies for meteorological conditions in China. Analysis shows
2 that the meteorological conditions in December 2015 (compared to December 2014)
3 had several important anomalies, including that the surface southeasterly winds were
4 significantly enhanced in the North China Plain (NCP) and the wind speeds were
5 decreased in the middle-north of eastern China, while slightly increased in the south of
6 eastern China. Study suggests that the 2015 El Nino event had significant effects on air
7 pollution in eastern China, especially in the NCP region, including the capital city of
8 Beijing, in which aerosol pollution was significantly enhanced in the already heavily
9 polluted capital city of China (Chang et al., 2016).

10 Figure 5 shows the monthly average $EMI_{2.5}$, $PM_{2.5}$ and the contribution of sub-
11 index to total $EMI_{2.5}$ in December 2014 and 2015 over BTH region. The monthly average
12 $EMI_{2.5}$ increases about 54.9% from 2.1 in December 2014 to 3.2 in December 2015,
13 indicating worsening meteorological conditions for $PM_{2.5}$ pollution. The increase of
14 $EMI_{2.5}$ is mainly contributed by adverse atmospheric transport conditions (Fig. 5c), which
15 results in the increase of $EMI_{2.5}$ reaching 3.2. With the increase of background
16 concentration, the deposition and vertical diffusion also increase, and offset the impact
17 of adverse transport conditions to some extent.

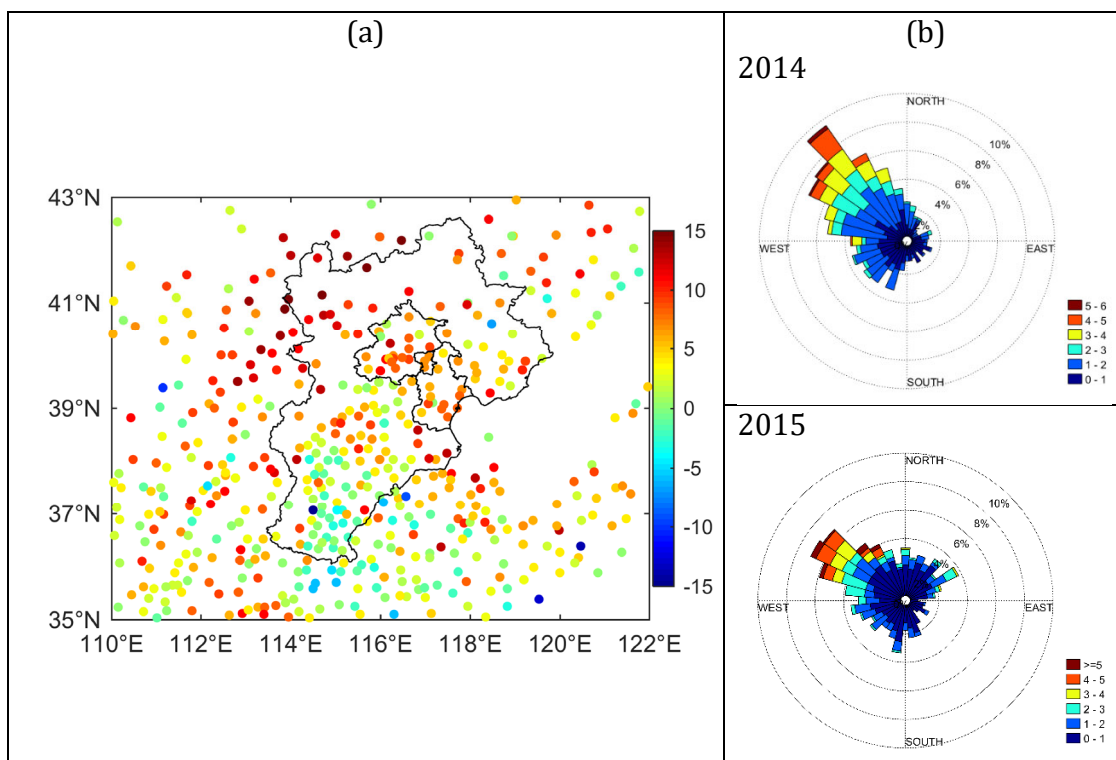


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 2 Figure 5: (a) the monthly averaged $EMI_{2.5}$ and (b) monthly $PM_{2.5}$ for Decembers of 2014 and
 3 2015 over BTH. (c) contributions of sub-index to the $EMI_{2.5}$ change and (d) contributions of
 4 emission and meteorology changes to $PM_{2.5}$ change for Decembers from 2014 to 2015,
 5 respectively.

6

7 The worsening meteorological conditions represented by $EMI_{2.5}$ were also
 8 supported by the observations for the two periods. The observed day with small wind
 9 (DSW, wind speed less than $2 m s^{-1}$) reveals that, except for part of southern Hebei
 10 province, the DSW increases 5-15 days for 2015 in most meteorological stations in BTH
 11 region (Fig. 6a), which indicates a large decrease of local diffusion capability. The
 12 comparison of wind rose map shows that the decrease of northwest wind and the
 13 increase of southwest and northeast wind occurred in December 2015 (Fig. 6b). The
 14 change of wind fields indicates more pollutants were transported to BTH region from
 15 Shandong, Jiangsu, Henan, and Northeast China. These variations indirectly validate the

1 conclusions of adverse atmospheric transport conditions with high iTran in December
2 2015.



4
5 Figure 6: (a) The change of DSW (days) from December 2014 to December 2015 (December
6 2015 – December 2014) and (b) Wind rose maps in December 2014 and December 2015 over
7 BTH region.

8
9 Based on the assessment method of emission contribution to the observed trend
10 (Eqs. 6 and 7), the emissions reduction in December 2015 as compared to 2014 was
11 estimated to contribute about 9.4% (Fig. 5d) to the PM_{2.5} concentration decrease,
12 compensating the large increase caused by meteorology, which is comparable with
13 previous studies of about 8.6% reduction in emissions (Liu et al., 2017; He et al., 2017a)
14 for the same two months. In other words, without the regional emission reduction efforts,

1 the observed PM_{2.5} concentration in December 2015 would have had a similar rate of 54.9%
2 increase as the worsening meteorology conditions would bring about as compared with
3 December 2014. This assessment of emission reduction is supported by the estimate of
4 emission inventories for the BTH region in the Decembers of 2014 and 2015 by Zheng et
5 al. (2019) who found out that the monthly emission strengths for PM_{2.5}, SO₂, NO_x, VOCs
6 and NH₃ in 2015 were reduced by 22.0%, 6.9%, 2.5%, 2.5% and 2.5%, respectively, as
7 compared with 2014. The sensitivity and the nonlinear response of PM_{2.5} concentrations
8 to the air pollutant emission reduction in the BTH region (Zhao et al., 2017) have been
9 estimated to be about 0.43 for both primary inorganic and organic PM_{2.5}, 0.05 for SO₂, -
10 0.07 for NO_x, 0.15 for VOCs, 0.1 for NH₃. Combining the emission reduction percentages
11 between Decembers 2014 and 2015 and the nonlinear response of emissions to the PM_{2.5}
12 concentrations results in an approximately 10.2% ambient PM_{2.5} concentration reduction
13 due to the emission changes. This is very close to the estimate of emission reduction
14 contribution to the December PM_{2.5} concentration difference of about 9.4% between
15 2014 and 2015 by the EMI framework.

16 **3.2. PM_{2.5} Trends and Meteorological Contributions**

17 The annual averaged PM_{2.5} concentrations in China have been decreased
18 significantly from 2013 to 2019. Figure 7 shows the observed spatial distribution of
19 national PM_{2.5} concentrations from 2013 to 2019, respectively. These spatial
20 distributions are consistent with those of primary and precursor emissions of PM_{2.5}

1 (Wang et al.), pointing out the fundamental cause of the air pollution in China. From the
2 spatial distributions, it is clear that the regions of BTH, FWP, CEN and NWC had the
3 highest PM_{2.5} concentrations among the 9 regions. Even though the national
4 concentrations have been reduced significantly from 2013 by reducing emissions, the
5 pollution center of particular matters has not been changed very much, locating at the
6 southern Hebei Province and indicating the macroeconomic structure has not been
7 gone through a great change yet. Another phenomenon can be seen from the
8 distribution is that in the North-west China, especially in some cities of the Xinjiang and
9 Ningxia Provinces, the PM_{2.5} concentrations were on an increasing trend, due to certain
10 migrating industries from developed regions in East China.

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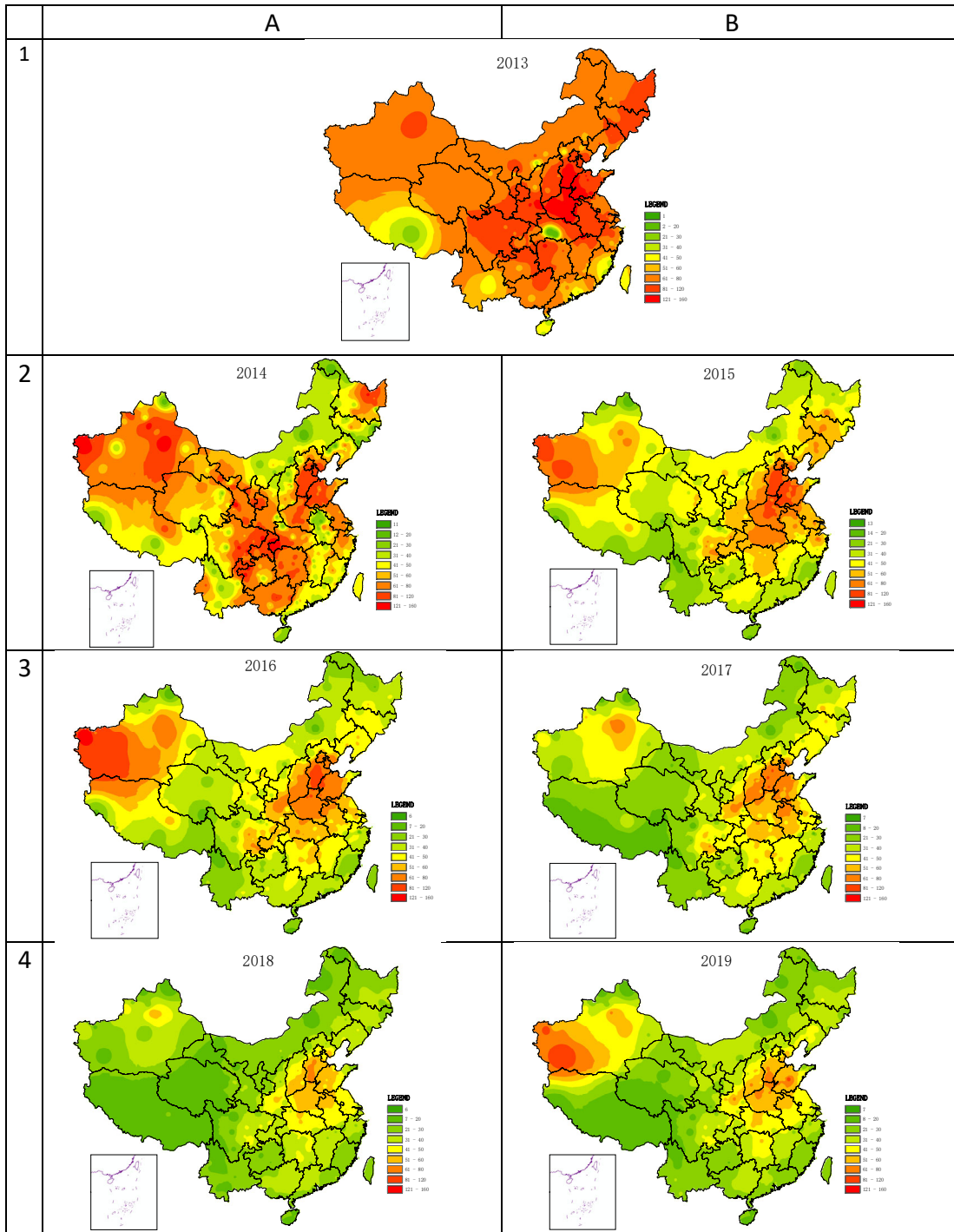
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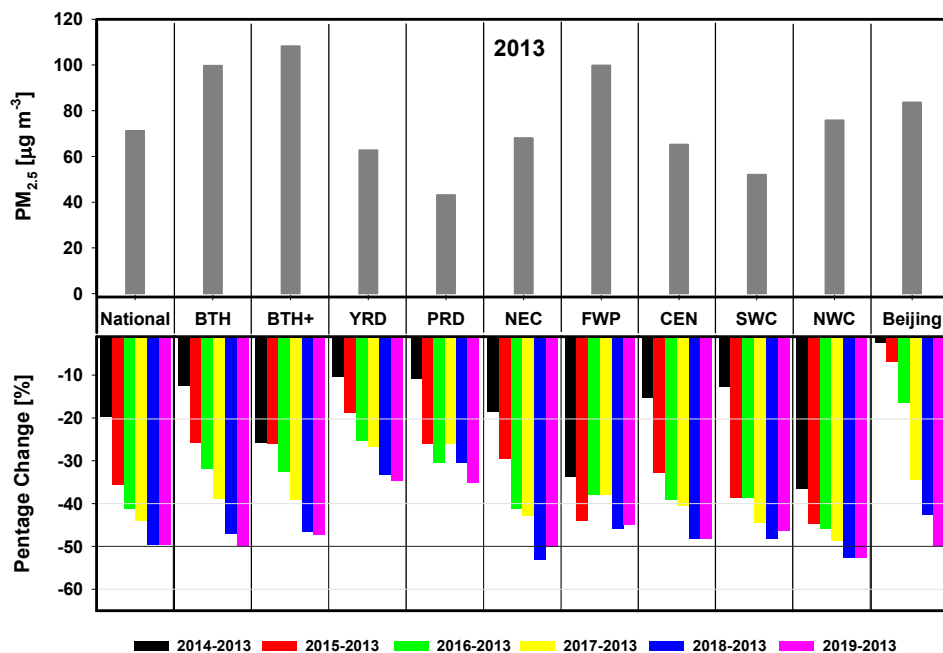


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2 Figure 7: Regional annual PM_{2.5} concentration distributions from 2013 to 2019.

3

1 Averaged for the nation, 9 focused regions and Beijing, the PM_{2.5} trend lines
 2 were shown in Figure 2. It is seen that all regions have had a large reduction of more
 3 than 35% in surface PM_{2.5} concentrations in 2019 as compared with those in 2013. The
 4 averaged national annual concentration at 36 μg m⁻³ has been very close to the national
 5 standard of 35 μg m⁻³ while the concentrations in PRD, SWC and NEC regions have been
 6 below the standard. Regions above the standard are BTH+, BTH, YRD, CEN and FWP.
 7 Regionally, the largest drop percentage of PM_{2.5} was seen in NEC and NWC regions (Fig.
 8 8), reaching over 50% compared with 2013. In the BTH, BTH+, FWP and CEN regions, the
 9 reduction was in the range of 45% to 50% while in YRD and PRD the reduction was
 10 around 35%.



11

12 Figure 8: Annual averaged PM_{2.5} concentrations in 2013 (top) and corresponding changing rates
 13 (bottom) from 2014 to 2019 as compared with 2013 for the nation, 9 regions and Beijing City.

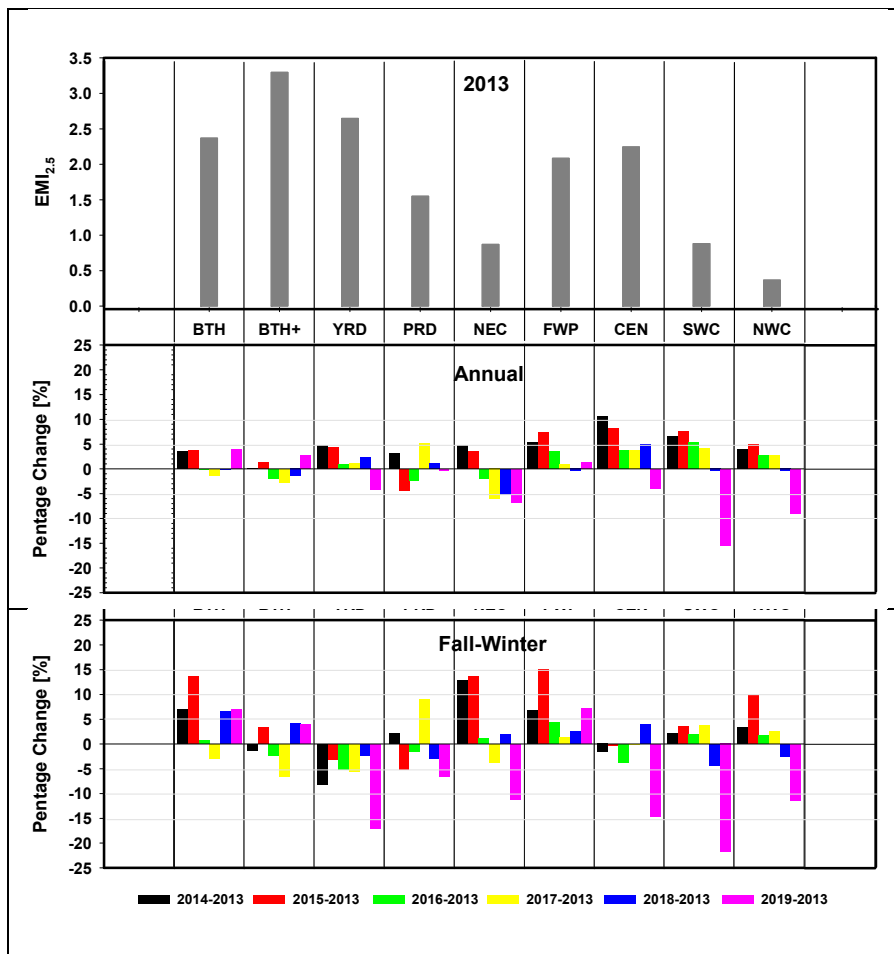
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2 As one of the key factors in controlling the ambient PM_{2.5} concentration
3 variations, the annual meteorological fluctuations, i.e. EMI_{2.5}, from 2014 to 2019 with
4 2013 as the base year, are shown in Figure 9 for nine regions. Generally, the annual
5 EMI_{2.5} shows a positive or negative variation, reflecting the meteorological features for
6 that specific region. Except for a couple of regions or years, most of the fluctuations are
7 within 5% as compared with 2013 and have a no definite trend. It can be inferred that
8 the meteorological conditions are possibly responsible for about 5% of the annual PM_{2.5}
9 averaged concentration fluctuations from 2013 to 2019 (Fig. 9 middle). This is consistent
10 with what has been assessed in Europe by Andersson et al. (2007).

11 The variations in meteorological contributions (EMI_{2.5}) to PM_{2.5} for the heavy
12 pollution seasons of fall and winter (October 1 to March 31) generally follow the same
13 fluctuating pattern as the annual average but are much larger than the average (Fig. 9
14 bottom), over 5% for most of the regions and years. For specific regions and years, e.g.
15 BTH, YRD, NEC, SWC and CEN, the variations are between 10-20% as compared with
16 2013. Since the PM_{2.5} concentrations are much higher in the pollution season, the larger
17 meteorology variations in fall-winter would exercise more controls to the heavy
18 pollution episodes than the annual averaged concentrations, signifying the importance
19 of meteorology in regulating the winter pollution situations.

20 It is found that though most of the regions have a fluctuating EMI_{2.5} in the
21 pollution season during the 2014-2019 period (Fig. 9 bottom), the YRD and FWP show a

1 consistent favorite and unfavorable meteorological conditions, respectively. BTH has
 2 witnessed the same unfavorable conditions as FWP except in 2017. In other words, in BTH
 3 and FWP, the decrease in ambient concentrations of PM_{2.5} from 2014 to 2019 has to
 4 overcome the difficulty of worsening meteorological conditions with larger control
 5 efforts.



6
 7 Figure 9: Annual averaged EMI_{2.5} in 2013 (top) and corresponding changing rates for annual
 8 average (middle) and for fall-winter seasons (bottom) from 2014 to 2019 as compared with 2013
 9 in 9 regions.

10

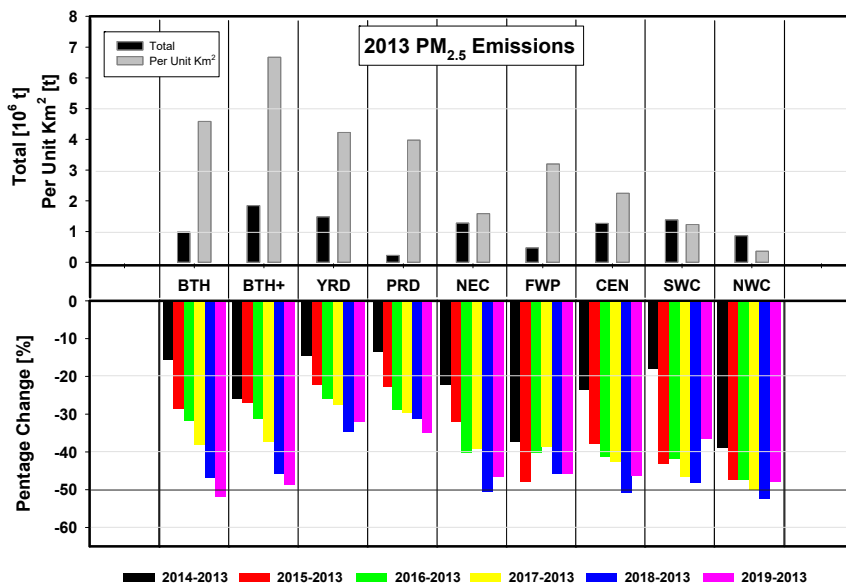
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3.3. Attribution of Control Measures to the PM_{2.5} Trend

As it is well known that the final ambient concentrations of any pollutants are resulted from the emission, meteorology and atmospheric physical and chemical processes. Separating emissions and meteorology contributions to the pollution level reduction entails a combined analysis of them. The analysis in Section 3.2 shows that from 2013 to 2019, the national averaged PM_{2.5} as well as those for 9 separate regions were all showing a gradual decline trend (Fig. 8). By 2019, 45% - 50% of reductions in surface PM_{2.5} concentrations were achieved while the meteorology contributions did not show a definite trend as from 2013, clearly pointing out the contribution of emission reductions in the trend. Using the analysis framework for separating emissions from meteorology based on the monitoring data of PM_{2.5} and EMI_{2.5} (Section 2.4), the emission change contributions are estimated.

Figure 10 shows the 2013 base emissions of PM_{2.5} (Zhao et al., 2017) and the annual changes in the emission contributions to the PM_{2.5} concentrations from 2014 to 2019 as estimated from the EMI_{2.5} and observed PM_{2.5}. For the emissions, it is found that the unit area emissions match better with ambient concentrations of PM_{2.5} in regions than the total emissions and the high emission regions are BTH, BTH+, YRD, PRD and FWP in 2013. Nationally by 2019, the emission reduction contributions to the ambient PM_{2.5} trend accounted for ranging from 32% to 52% of the total PM_{2.5} decrease percentage, while in BTH and BTH+ regions the reduction was more than 49% from 2013 base year emissions, leading the national emission reduction campaign. The emission reduction rates clearly illustrate the effectiveness of the national-wide emission control strategies implemented since 2013 and the emission

1 reduction is the dominate factor for ambient PM_{2.5} declining trend in China. Taking the analysis
 2 data of PM_{2.5} and EMI_{2.5} from this study for BTH+ region from 2013 to 2017, it is found that
 3 control strategy contributed more than 90% to the PM_{2.5} decline. Chen et al (2019) has
 4 estimated that the control of anthropogenic emissions contributed to 80% of the decrease in
 5 PM_{2.5} concentrations in Beijing from 2013 to 2017.



6
 7 Figure 10: Annual PM_{2.5} emissions (total and per unit Km²) for 2013 (top) and corresponding changing
 8 rates (bottom) from 2014 to 2019 as compared with 2013 in 9 regions.

9
 10 Regionally, the emission reduction trends from 2014 to 2019 display some unique
 11 characteristics. For the regions of BTH, BTH+ and PRD, the year-by-year reduction rate is
 12 consistent, indicating that regardless of fluctuations in meteorology, these regions have had an
 13 effective emission control strategy and maintained the emission reduced year by year since
 14 2014. However, in some regions such as FWP, NEC, SWC and NWC, the emission reduction rates
 15 were fluctuating from 2014 to 2019, implying the emissions in these regions were increased in

1 certain years. Especially in FWP from 2016 to 2017, the emissions were estimated to be
2 increased by about 10%, and then decreased in 2018 and 2019, despite of the factor that FWP
3 has experienced unfavorable meteorological conditions during this period.

4 The year of 2015 is a special year in the history of China air pollution control. Though the
5 systematical and network observations of $PM_{2.5}$ started in China from 2013, it took about two
6 years (until 2015) to evolve to the current status in terms of spatial coverage and observational
7 station numbers, establishing a consistent and statistically comparable national network. At the
8 same year, the Environmental Protection Law of People's Republic of China was taken into
9 effect in January, signaling the stage of lawfully control of air pollution. For the regulation
10 assessment point of view, the impact by emission changes from 2015 was relevant to the
11 interests of management to show how effective the law was.

12 Table 2 summarizes the $PM_{2.5}$ difference between 2019 and 2015 and the relative
13 contributions of meteorology and emission changes to the difference for all China, Beijing and
14 nine regions. Once again, as of the end of 2019, the $PM_{2.5}$ concentrations are all reduced from
15 2015, ranging from -1.8% in FWP to -46.2% in Beijing. During this period of time, regions of BTH,
16 BTH+, PRD and Beijing had encountered unfavorable meteorological conditions with positive
17 $EMI_{2.5}$ changes, which indicated that for these regions, emission reductions were not only to
18 maintain the decline trend but also to offset the unfavorable meteorological conditions in order
19 to achieve the observed reductions in ambient $PM_{2.5}$ concentrations. On the contrary, for the
20 regions of FWP and SWC, the emission control impacts were to deteriorate the concentrations,
21 implying an increase in emissions to restrain the $PM_{2.5}$ concentration decrease by favorable
22 meteorological conditions. For other regions, both meteorology and emission controls

1 contributed to PM_{2.5} decrease from 2015 to 2019, with the control measures contributing from
2 -7.9% in NWC to -68.4% in NEC (Table 2).

3 Therefore, due to the diversity of meteorological conditions and emission distributions in
4 China, their impacts on ambient PM_{2.5} concentrations display unique regional characteristics.
5 Overall, the emission controls are the dominant factor in contributing the decline trend in China
6 from 2013 to 2019. However, in certain regions or certain period of years, emissions were
7 found to be increased even with favorable meteorological conditions, which means the design of
8 national control strategies has to take both meteorology and emission impacts simultaneously
9 in order to achieve maximum results.

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1 Table 2: Observed PM_{2.5} difference between 2019 and 2015 as well as its attributions to
 2 meteorology and control measures for all China, Beijing and nine regions.

Regions	Observed PM _{2.5} Difference		Attributions			
			Meteorology (EMI)		Emission Controls	
	($\mu\text{g m}^{-3}$)	(%)	($\mu\text{g m}^{-3}$)	Relative %	($\mu\text{g m}^{-3}$)	Relative %
National	-10	-21.7	-4.1	-40.9	-5.9	-59.1
BTH	-24	-32.4	+0.1	+0.4	-24.1	-100.4
BTH+	-23	-28.8	+1.2	+5.4	-24.2	-105.4
YRD	-10	-19.6	-4.0	-39.7	-6.0	-60.3
PRD	-4	-12.5	+1.4	+36.0	-5.4	-136.0
NEC	-14	-29.2	-4.4	-31.6	-9.6	-68.4
FWP	-1	-1.8	-3.6	-362.2	+2.6	+262.2
CEN	-12	-23.1	-5.5	-45.5	-6.5	-54.5
SWC	-4	-12.5	-8.5	-211.5	+4.5	+111.5
NWC	-6	-14.3	-5.5	-92.1	-0.5	-7.9
Beijing	-36	-46.2	+3.4	+9.4	-39.4	-109.4

3 Note: "+" increased; "-" decreased

4 4. Conclusions

5 Based on a 3-D chemical transport model and its process analysis, an Environmental
 6 Meteorological Index (EMI_{2.5}) and an assessment framework have been developed and applied
 7 to the analysis of the PM_{2.5} trend in China from 2013 to 2019. Compared with observations, the
 8 EMI_{2.5} can realistically reflect the contribution of meteorological factors to the PM_{2.5} variations
 9 in the time series with impact mechanisms and can be used to as an index to judge whether the
 10 meteorological conditions are favorite or not to the PM_{2.5} pollutions in a region or time period.
 11 In conjunction to the observational trend data, the EMI_{2.5}-based framework has been used to

1 quantitatively assess the separate contribution of meteorology and emission changes to the
2 time series for 9 regions in China. Results show that for the period of 2013 to 2019, the PM_{2.5}
3 concentrations have been dropped continuously throughout China, by about 50% on national
4 average. In the regions of NWC, NEC, BTH, BEIJING, CEN, BTH+, SWC, the reduction was in the
5 range of 46% to 53% while in FWP, PRD and YRD, the reduction was from 45% to 35%. It is
6 found that the control measures of emission reduction are the dominant factors in the PM_{2.5}
7 declining trends in various regions. By 2019, the emission reduction contributes about 47% of
8 the PM_{2.5} decrease from 2013 to 2019 on the national average, while in BTH region the
9 emission reduction contributes more than 50% and in YRD, PRD and SWC regions, the
10 contributions were between 32% and 37%. For most of the regions, the emission reduction
11 trend was consistent throughout the period except for FWP, NEC, SWC and NWC where the
12 emission amounts were increased for certain years. The contribution by the meteorology to the
13 surface PM_{2.5} concentrations from 2013 to 2019 was not found to show a consistent trend,
14 fluctuating positively or negatively about 5% on annual average and 10-20% for the fall-winter
15 heavy pollution seasons.

16

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1 5. References

- 2 Andersson, C., Langner, J., and Bergstroumm, R.: Interannual variation and trends in air pollution over
3 Europe due to climate variability during 1958–2001 simulated with a regional CTM coupled to the ERA40
4 reanalysis, *Tellus B: Chemical and Physical Meteorology*, 59, 77-98, 10.1111/j.1600-0889.2006.00231.x,
5 2007.
- 6 BAI, H.-M., SHI, H.-D., GAO, Q.-X., LI, X.-C., DI, R.-Q., and WU, Y.-H.: Re-Ordination of Air Pollution Indices
7 of Some Typical Cities in Beijing-Tianjin-Hebei Region Based on Meteorological Adjustment, *Journal of
8 Ecology and Rural Environment*, 31, 44-49, 2015.
- 9 Beaver, S., and Palazoglu, A.: Cluster Analysis of Hourly Wind Measurements to Reveal Synoptic Regimes
10 Affecting Air Quality, *J. Applied Meteorology and Climatology*, 45, 1710–1726, 2006.
- 11 Bei, N. F., Li, X. P., Tie, X. X., Zhao, L. N., Wu, J. R., Li, X., Liu, L., Shen, Z. X., and Li, G. H.: Impact of
12 synoptic patterns and meteorological elements on the wintertime haze in the Beijing-Tianjin-Hebei
13 region, *China from 2013 to 2017*, *Sci. Total Environ.*, 704, 12, 10.1016/j.scitotenv.2019.135210, 2020.
- 14 Chang, L., Xu, J., Tie, X., and Wu, J.: Impact of the 2015 El Nino event on winter air quality in China,
15 *SCIENTIFIC REPORTS*, 6, 2016.
- 16 Chen, Y., Zhao, C. S., Zhang, Q., Deng, Z. Z., Huang, M. Y., and Ma, X. C.: Aircraft study of Mountain
17 Chimney Effect of Beijing, China, *J. Geophys. Res.-Atmos.*, 114, 10, 10.1029/2008jd010610, 2009.
- 18 Chen, Z., Chen, D., Kwan, M.-P., Chen, B., Gao, B., Zhuang, Y., Li, R., and Xu, B.: The control of
19 anthropogenic emissions contributed to 80% of the decrease in PM_{2.5} concentrations in Beijing from
20 2013 to 2017, *Atmos. Chem. Phys.*, 19, 13519–13533, 2019.
- 21 Colette, A., Granier, C., Hodnebrog, Ø., Jakobs, H., Maurizi, A., Nyiri, A., Bessagnet, B., D'Angiola, A.,
22 D'Isidoro, M., Gauss, M., Meleux, F., Memmesheimer, M., Mieville, A., Rouil, L., Russo, F., Solberg, S.,
23 Stordal, F., and Tampieri, F.: Air quality trends in Europe over the past decade: a first multi-model
24 assessment, *Atmospheric Chemistry and Physics*, 11, 11657-11678, 10.5194/acp-11-11657-2011, 2011.
- 25 Gong, S. L., Barrie, L. A., Blanchet, J.-P., Salzen, K. v., Lohmann, U., Lesins, G., Spacek, L., Zhang, L. M.,
26 Girard, E., Lin, H., Leaitch, R., Leighton, H., Chylek, P., and Huang, P.: Canadian Aerosol Module: A size-
27 segregated simulation of atmospheric aerosol processes for climate and air quality models 1. Module
28 development, *J. Geophys. Res.*, 108, 4007, 10.1029/2001JD002002, 2003.
- 29 Gong, S. L., and Zhang, X. Y.: CUACE/Dust – An Integrated System of Observation and Modeling Systems
30 for Operational Dust Forecasting in Asia, *Atmos. Chem. Phys.*, 8, 2333-2234, 2008.
- 31 He, J. J., Yu, Y., Xie, Y. C., Mao, H. J., Wu, L., Liu, N., and Zhao, S. P.: Numerical Model-Based Artificial
32 Neural Network Model and Its Application for Quantifying Impact Factors of Urban Air Quality, *Water Air
33 Soil Pollut.*, 227, 16, 10.1007/s11270-016-2930-z, 2016.
- 34 He, J. J., Gong, S. L., Liu, H. L., An, X. Q., Yu, Y., Zhao, S. P., Wu, L., Song, C. B., Zhou, C. H., Wang, J., Yin, C.
35 M., and Yu, L. J.: Influences of Meteorological Conditions on Interannual Variations of Particulate Matter
36 Pollution during Winter in the Beijing-Tianjin-Hebei Area, *J. Meteorol. Res.*, 31, 1062-1069,
37 10.1007/s13351-017-7039-9, 2017a.
- 38 He, J. J., Gong, S. L., Yu, Y., Yu, L. J., Wu, L., Mao, H. J., Song, C. B., Zhao, S. P., Liu, H. L., Li, X. Y., and Li, R.
39 P.: Air pollution characteristics and their relation to meteorological conditions during 2014-2015 in
40 major Chinese cities, *Environ. Pollut.*, 223, 484-496, 10.1016/j.envpol.2017.01.050, 2017b.
- 41 He, J. J., Gong, S. L., Zhou, C. H., Lu, S. H., Wu, L., Chen, Y., Yu, Y., Zhao, S. P., Yu, L. J., and Yin, C. M.:
42 Analyses of winter circulation types and their impacts on haze pollution in Beijing, *Atmos. Environ.*, 192,
43 94-103, 10.1016/j.atmosenv.2018.08.060, 2018.

1 Hou, X. W., Zhu, B., Kumar, K. R., and Lu, W.: Inter-annual variability in fine particulate matter pollution
2 over China during 2013-2018: Role of meteorology, *Atmos. Environ.*, 214, 10,
3 10.1016/j.atmosenv.2019.116842, 2019.

4 Li, X., Zhang, Q., Zhang, Y., Zheng, B., Wang, K., Chen, Y., Wallington, T. J., Han, W., Shen, W., Zhang, X.,
5 and He, K.: Source contributions of urban PM_{2.5} in the Beijing–Tianjin–Hebei region: Changes between
6 2006 and 2013 and relative impacts of emissions and meteorology, *Atmos. Environ.*, 123, 229-239, 2015.

7 Liu, T. T., Gong, S. L., He, J. J., Yu, M., Wang, Q. F., Li, H. R., Liu, W., Zhang, J., Li, L., Wang, X. G., Li, S. L.,
8 Lu, Y. L., Du, H. T., Wang, Y. Q., Zhou, C. H., Liu, H. L., and Zhao, Q. C.: Attributions of meteorological and
9 emission factors to the 2015 winter severe haze pollution episodes in China's Jing-Jin-Ji area,
10 *Atmospheric Chemistry and Physics*, 17, 2971-2980, 10.5194/acp-17-2971-2017, 2017.

11 Ma, T., Duan, F. K., He, K. B., Qin, Y., Tong, D., Geng, G. N., Liu, X. Y., Li, H., Yang, S., Ye, S. Q., Xu, B. Y.,
12 Zhang, Q., and Ma, Y. L.: Air pollution characteristics and their relationship with emissions and
13 meteorology in the Yangtze River Delta region during 2014-2016, *J. Environ. Sci.*, 83, 8-20,
14 10.1016/j.jes.2019.02.031, 2019.

15 MEE: Ambient air quality standards: GB 3095-2012, China Environmental Science Press, Beijing, China,
16 2012.

17 Nenes, A., Pandis, S. N., and Pilinis, C.: ISORROPIA: A new thermodynamic equilibrium model for
18 multiphase multicomponent inorganic aerosols, *Aquatic Geochemistry*, 4, 123–152, 1998.

19 Niu, T., Gong, S. L., Zhu, G. F., Liu, H. L., Hu, X. Q., Zhou, C. H., and Wang, Y. Q.: Data Assimilation of Dust
20 Aerosol Observations for CUACE/Dust Forecasting System, *Atmos. Chem. Phys.*, 8, 2717-2728, 2008.

21 Pearce, J. L., Beringer, J., Nicholls, N., Hyndman, R. J., and Tapper, N. J.: Quantifying the influence of local
22 meteorology on air quality using generalized additive models, *Atmos. Environ.*, 45, 1328-1336,
23 10.1016/j.atmosenv.2010.11.051, 2011a.

24 Pearce, J. L., Beringer, J., Nicholls, N., Hyndman, R. J., Uotila, P., and Tapper, N. J.: Investigating the
25 influence of synoptic-scale meteorology on air quality using self-organizing maps and generalized
26 additive modelling, *Atmos. Environ.*, 45, 128-136, 10.1016/j.atmosenv.2010.09.032, 2011b.

27 Stockwell, W. R., Middleton, P., Change, J. S., and Tang, X.: The second generation Regional Acid
28 Deposition Model Chemical Mechanism for Regional Air Quality Modeling, *J. Geophys. Res.*, 95,
29 16343~16376, 1990.

30 Wang, S., Xing, J., Chatani, S., Hao, J., Klimont, Z., Cofala, J., and Amann, M.: Verification of
31 anthropogenic emissions of China by satellite and ground observations, *Atmos. Environ.*, 45, p.6347-
32 6358.

33 Wei, Y., Li, J., Wang, Z.-F., Chen, H.-S., Wu, Q.-Z., Li, J.-J., Wang, Y.-L., and Wang, W.: Trends of surface
34 PM_{2.5} over Beijing-Tianjin-Hebei in 2013-2015 and their causes: emission controls vs. meteorological
35 conditions, *Atmospheric and Oceanic Science Letters*, 10, 276-283, 2017.

36 Wu, D., Chen, H. Z., Meng, W. U., Liao, B. T., Wang, Y. C., Liao, X. N., Zhang, X. L., Quan, J. N., Liu, W. D.,
37 and Yue, G. U.: Comparison of three statistical methods on calculating haze days-taking areas around the
38 capital for example, *China Environmental Science*, 34, 545-554, 2014.

39 Xu, X., Zhou, M., Chen, J., Bian, L., Zhang, G., Liu, H., Li, S., Zhang, H., Zhao, Y., Suolongduoji, and Jizhi,
40 W.: A comprehensive physical pattern of land-air dynamic and thermal structure on the Qinghai-Xizang
41 Plateau, *Sci. China Ser. D-Earth Sci.*, 45, 577–594, 2002.

42 Xu, X. D., Wang, Y. J., Zhao, T. L., Cheng, X. H., Meng, Y. Y., and Ding, G. A.: “Harbor” effect of large
43 topography on haze distribution in eastern China and its climate modulation on decadal variations in
44 haze China *Chin Sci Bull*, 60, 1132-1143, 2015.

45 Yu, Y., He, J. J., Zhao, S. P., Liu, N., Chen, J. B., Mao, H. J., and Wu, L.: Numerical simulation of the impact
46 of reforestation on winter meteorology and environment in a semi-arid urban valley, Northwestern
47 China, *Sci. Total Environ.*, 569, 404-415, 10.1016/j.scitotenv.2016.06.143, 2016.

1 Zhang, H., Zhang, B., Lu, M., and An, L.: Developmenot and Application of Stable Weather Index of
2 Beijing in Environmental Meteorology, *Meteorological Monthly*, 43, 998-1004, 2017.
3 Zhang, Q., and Rao, C.: A Comparative Study of PM2.5 in Typical Cities after the Standard Conditions
4 Turn to Actual Conditions, *Energy Conservation & Environmental Protection*, 2019.
5 Zhao, B., Wu, W., Wang, S., Xing, J., Chang, X., Liou, K.-N., Jiang, J. H., Gu, Y., Jang, C., Fu, J. S., Zhu, Y.,
6 Wang, J., Lin, Y., and Hao, J.: A modeling study of the nonlinear response of fine particles to air pollutant
7 emissions in the Beijing–Tianjin–Hebei region, *Atmos. Chem. Phys.*, 17, 12031–12050, 2017.
8 Zheng, H., Zhao, B., Wang, S., Wang, T., Ding, D., Chang, X., Liu, K., Xing, J., Dong, Z., Aunan, K., Liu, T.,
9 Wu, X., Zhang, S., and Wu, Y.: Transition in source contributions of PM2.5 exposure and associated
10 premature mortality in China during 2005-2015, *Environ Int.*, 132, 105111, 2019.
11 Zhou, C., Gong, S., Zhang, X., Liu, H., Xue, M., Cao, G., An, X., Che, H., Zhang, Y., and Niu, T.: Towards the
12 improvements of simulating the chemical and optical properties of Chinese aerosols using an online
13 coupled model – CUACE/Aero, *Tellus B*, 64, 10.3402/tellusb.v64i0.18965, 2012.
14 Zhou, Z., Zhang, S., Gao, Q., Li, W., Zhao, L., Feng, Y., Xu, M., and Shi, L.: The Impact of Meteorological
15 Factors on Air Quality in the Beijing-Tianjin-Hebei Region and Trend Analysis, *Resources Science*, 36,
16 0191-0199, 2014.

17