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

the national average and 32% to the 52% for various regions. The meteorology has a

variable and sometimes critical contribution to the year by year variations of $PM_{2.5}$

concentrations, 5% on annual average and 10-20% for the fall-winter heavy pollution

seasons.

1. Introduction

Recent observation data from the Ministry of Ecology and Environment of China (MEE)

has shown a steady improvement of air quality across the country, especially in particular

matter (PM) concentrations (Hou et al., 2019). According to 2013-2019 China Air Quality

Improvement Report issued by MEE, compared to 2013, the average concentrations of

particulate matter with an aerodynamic diameter of less than 2.5 μm ($PM_{2.5}$) in 74 major

cities of China have decreased by more than 50% in 2019. From scientific and

management point of views, a quantitative apportionment of the reasons behind the

trend is critical to assess the reduction strategies implemented by the government and to

guide future air quality control policy. However, the assessment of the improvements of

air quality is a complicated process that involves the quantification of changes in the

emission sources, meteorological factors, and other characteristics of the $PM_{2.5}$ pollution,

which are also interacting with each other. In order to separate the relative degree of

these factors, a comprehensive analysis, including observational data and model

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

the Stable Weather Index (SWI) at CMA. The SWI is a composite index which includes the

advection, vertical diffusion and humidity and other meteorological factors that are

related to the formation of air pollutions in a specific region or city. A higher value of SWI

means a weaker diffusion of air pollutants. This index had some success in assessing the

meteorological impacts on air pollution, especially calibrated for a specific region, i.e.

Beijing. However, when applied to different areas where the emission patterns and

meteorological features are different, this index failed to give a universal or comparable

indication of meteorological assessment of pollution levels across the nation.

Using the Kolmogorov-Zurbenko (KZ) wave filter method, Bai et al (2015) separated

the API time series in three Chinese cities into short-term, seasonal and long-term

components, and then used the stepwise regression to set up API baseline and short-term

components separately and established linear regression models for meteorological

variables of corresponding scales. Consequently, with the long-term representing the

change of emissions removed from the time series, the meteorological contributions

alone were assumed and analyzed, pointing out that unfavorable conditions often lead to

an increase by 1-13 whereas the favorable conditions to a decrease by 2-6 in the long-

term API series, respectively. Though the contributions of emissions and meteorological

variations were separated by the research, it was only done by mathematical

transformations and far from the reality. The mechanisms behind the variation of the time

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 (O_3), nitrogen dioxide (NO_2) 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 O_3, 5% for NO_2, 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
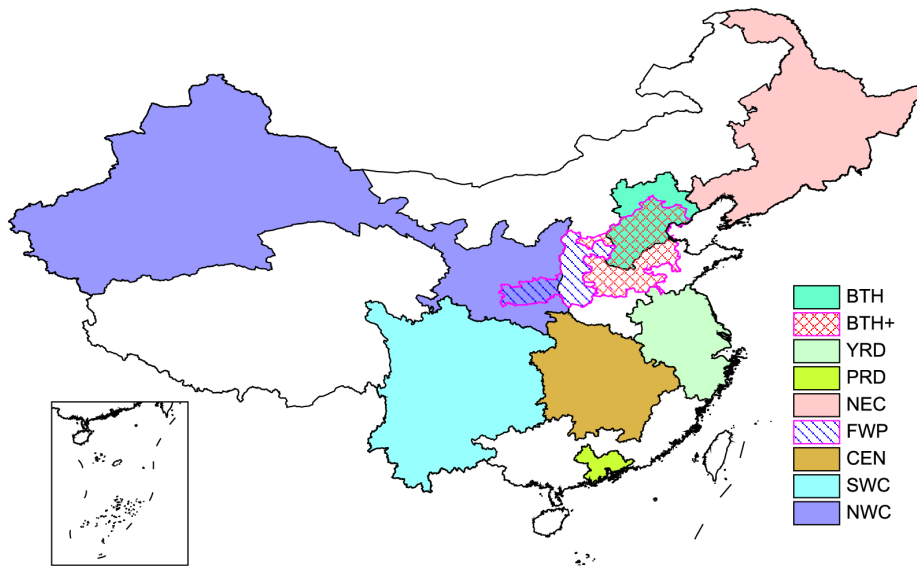
1 and emissions. However, the emission changes in the simulations were assumed and did

2 not reflect the real spatia-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 dada (PM$_{2.5}$) provides the basis for the trend analysis. Separating the

1   trend contribution from regional emission reduction and meteorological variation entails

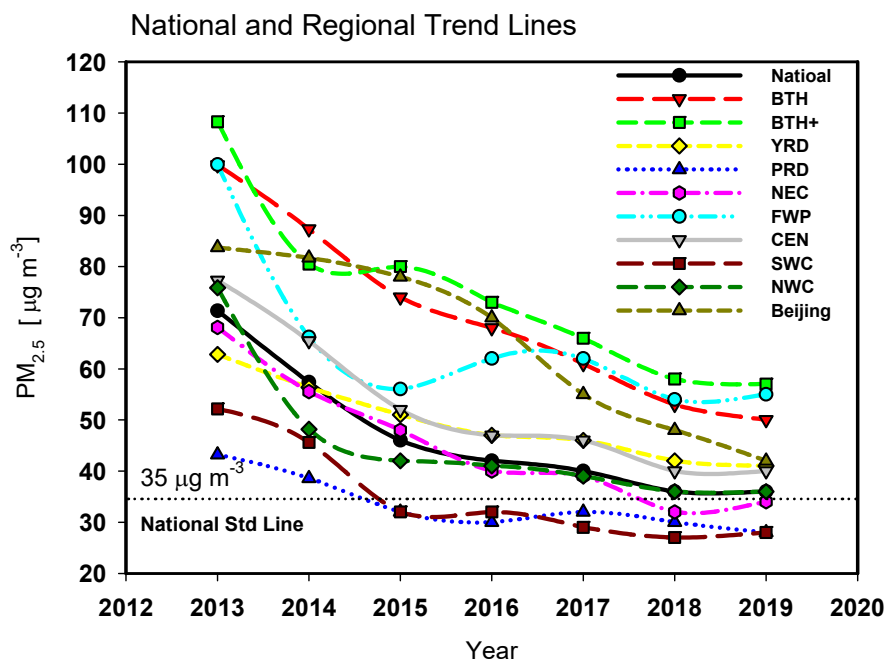2   a framework, which is discussed below.

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/). 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

change of reporting standard, the $PM_{2.5}$ concentration in most cities decreased, and the

number of good days to meet the standard increased (Zhang and Rao, 2019).

2.2. Meteorological Data

Conventional meteorological data can provide qualitative assessment of the

contributions of meteorological factors to the changes of air quality. The data used in this

study are from 843 national base weather stations of the CMA from 2013 to 2019. The

wind speed (WS), day with small wind (DSW), relative humidity (RH) and haze days are

used to analyze the pollution meteorological conditions. When the daily average wind

speed is less than 2 m s^{-1}, a DSW day is defined. Since the haze formation is always related

to stable meteorological conditions and high aerosol mass loading, haze observation from

CMA is also used to analyze the haze trends and the impact of air quality on visibility. A

haze day is defined with daily averaged visibility less than 10 km and relative humidity less

than 85% (Wu et al., 2014), excluding days of low visibility due to precipitation, blowing

snow, blowing sand, floating dust, sandstorms and smoke.

The 2019 national annual averaged WS has increased by 4.5%, DSW dropped by

15.1%, and RH decreased by 3.9% compared with 2013, with regional differences (Table

1). Slightly changes occurred when compared with 2015 that WS has decreased by 0.7%,

DSW dropped by 11.3%, and RH decreased by 2.2%. Overall, it can be seen that the annual

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 $$\text{EMI}(t) \;=\; \text{EMI}(t0) \;+\; \int_{t0}^{t} \Delta\,\text{EMI} * \text{dt}$$

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 ΔEMI = iEmid + i*Tran* + i*Accu*   (2)

8 where the iEmid is the difference between emission and deposition, and i*Tran* and

9 i*Accu* are the net (in minus out) advection transports and the vertical accumulation by

10 turbulent diffusion in the column, respectively. A positive sign of each factor indicates a

11 net flow of pollutants into the column, and vise versa.

12 Mathematically, these factors are expressed as:

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

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

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

16 (3)

17 where the tendency is normalized by a factor C_0. For an application of EMI to the $PM_{2.5}$,

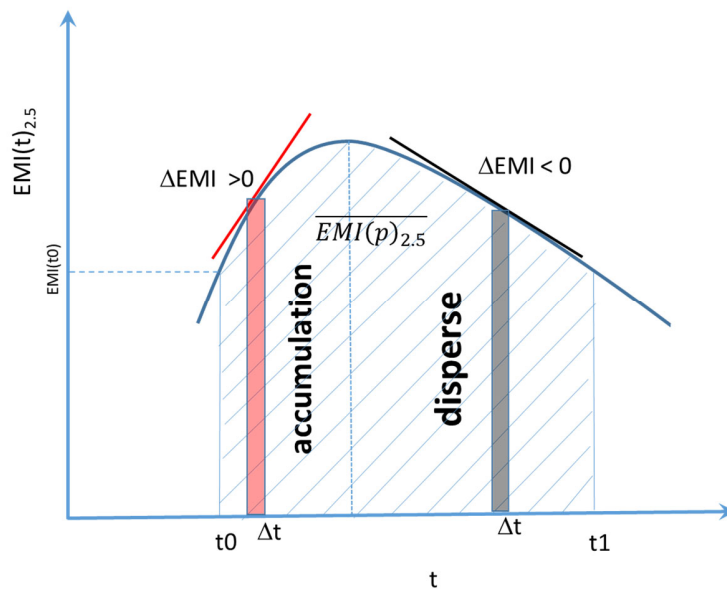18 C_0 is set to equal 35 μg m^{-3}, the national standard for $PM_{2.5}$ in China (MEE, 2012), and

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 (t0 to t1) 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   $$\overline{EMI(p)_{2.5}} = \frac{1}{t1-t0} \int_{t0}^{t1} EMI(t)_{2.5} dt \qquad\qquad (4)$$

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 t0 to t1, 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 t0 to t1, 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:

$$\overline{EMI(p)_{2.5}} = \frac{1}{n+1}[EMI(0) + EMI(1) + EMI(2) + \cdots + EMI(n)]$$

$$= \frac{1}{n+1}[(n+1)EMI(t0) + n\Delta EMI(1)\Delta t + (n-1)\Delta EMI(2)\Delta t$$

$$+ (n-2)\Delta EMI(3)\Delta t + (n-3)\Delta EMI(4)\Delta t + \cdots + \Delta EMI(n)\Delta t]$$

$$(5)$$

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. ΔEMI(n), at each time step. For

monthly simulations, the initial values EMI(t0) 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 μg 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 (p0) and January 2016

(p1) 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 $\Delta EMIS = \frac{PM(m0,e1)-PM(m0,e0)}{PM(m0,e0)} \times 100\%$ (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 $PM(m0,e1) = \overline{EMI(p0)}_{2.5} \Big/ \overline{EMI(p1)}_{2.5} \times PM(m1,e1)$ (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 (RADMII) 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 SO_2, NO_2 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 $\overline{EMI(p)}_{2.5}$ 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 (PM$_{2.5}$) changes in China.
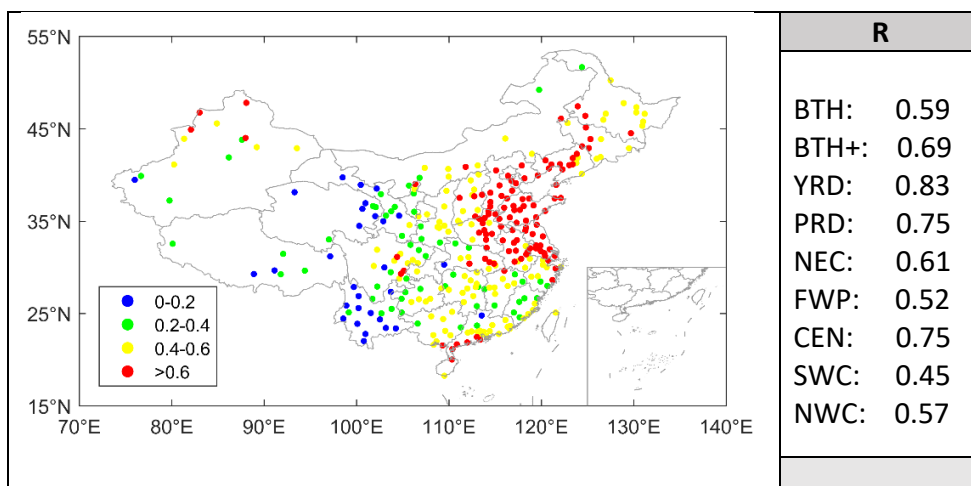
8 **3. Results and Discussions**

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

10   Under the conditions of no changes in annual emissions for PM$_{2.5}$ and its precursors,

11 the daily EMI$_{2.5}$ was computed by CUACE from 2013 to 2019 on a 15$\times$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., 2011) variation

15 was applied to the emission inventory for computing the EMI$_{2.5}$, which is more

16 realistically reflecting the meteorology contributions to the PM$_{2.5}$ concentrations.

17   To evaluate the applicability of EMI$_{2.5}$, the index was compared with the

18 observed PM$_{2.5}$ concentrations. Figure 4 shows the spatial distribution of correlation

19 coefficients between PM$_{2.5}$ and 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    $PM_{2.5}$.

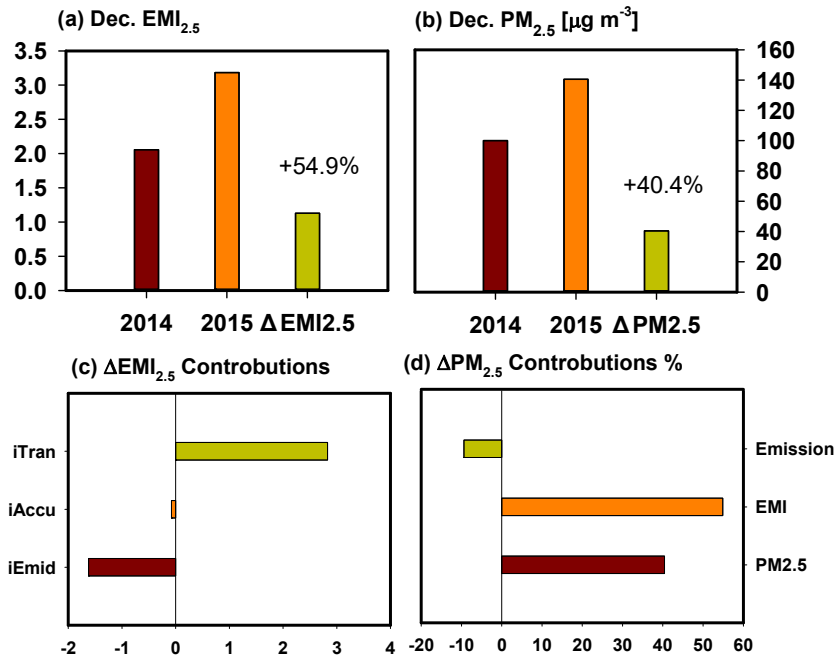| R |
|---|
| BTH: 0.59 |
| BTH+: 0.69 |
| YRD: 0.83 |
| PRD: 0.75 |
| NEC: 0.61 |
| FWP: 0.52 |
| CEN: 0.75 |
| SWC: 0.45 |
| NWC: 0.57 |

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

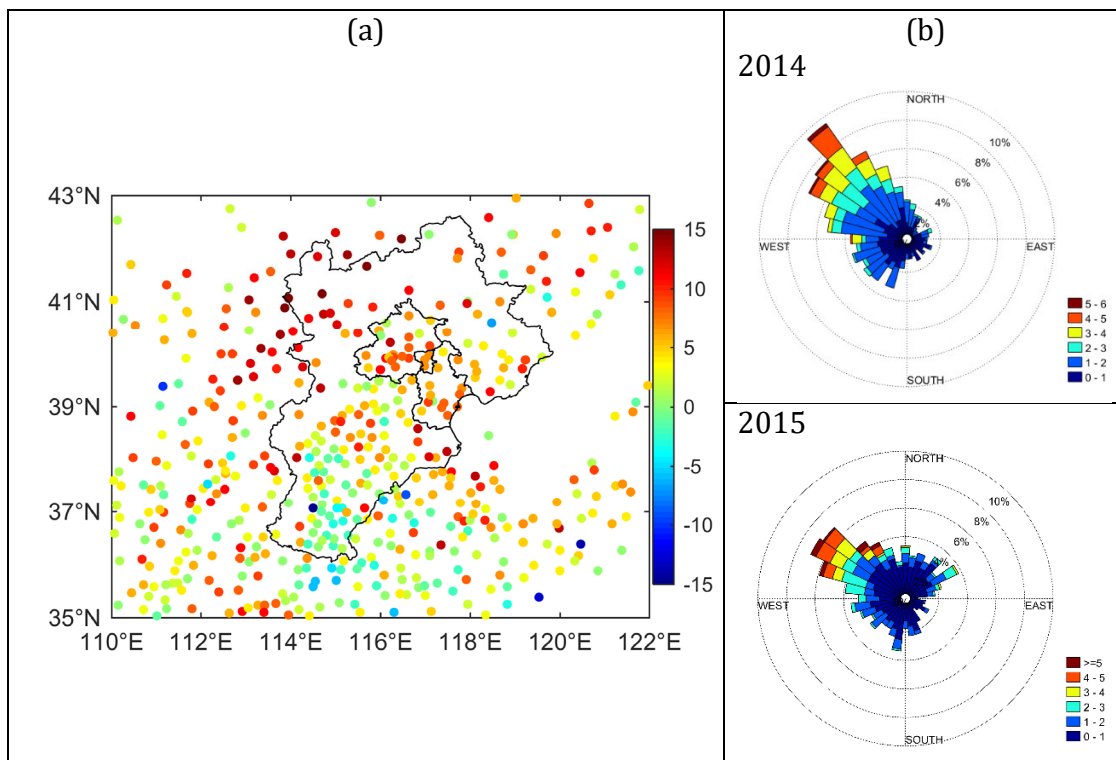9   polluted capital city of China (Chang et al., 2016).

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.

(a) Dec. EMI$_{2.5}$

(b) Dec. PM$_{2.5}$ [µg m^{-3}]

+54.9%

+40.4%

2014   2015 ΔEMI2.5

2014   2015 ΔPM2.5

(c) ΔEMI$_{2.5}$ Controbutions

(d) ΔPM$_{2.5}$ Controbutions %

iTran

iAccu

iEmid

Emission

EMI

PM2.5

1

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.

3

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

7

8   Based on the assessment method of emission contribution to the observed trend

9   (Eqs. 6 and 7), the emissions reduction in December 2015 as compared to 2014 was

10   estimated to contribute about 9.4% (Fig. 5d) to the $PM_{2.5}$ concentration decrease,

11   compensating the large increase caused by meteorology, which is comparable with

12   previous studies of about 8.6% reduction in emissions (Liu et al., 2017;He et al., 2017a)

13   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$_{2.5}$, SO$_2$, NOx, VOCs

6   and NH$_3$ 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 SO$_2$, -

10   0.07 for NOx, 0.15 for VOCs, 0.1 for NH$_3$. 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 Provence 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

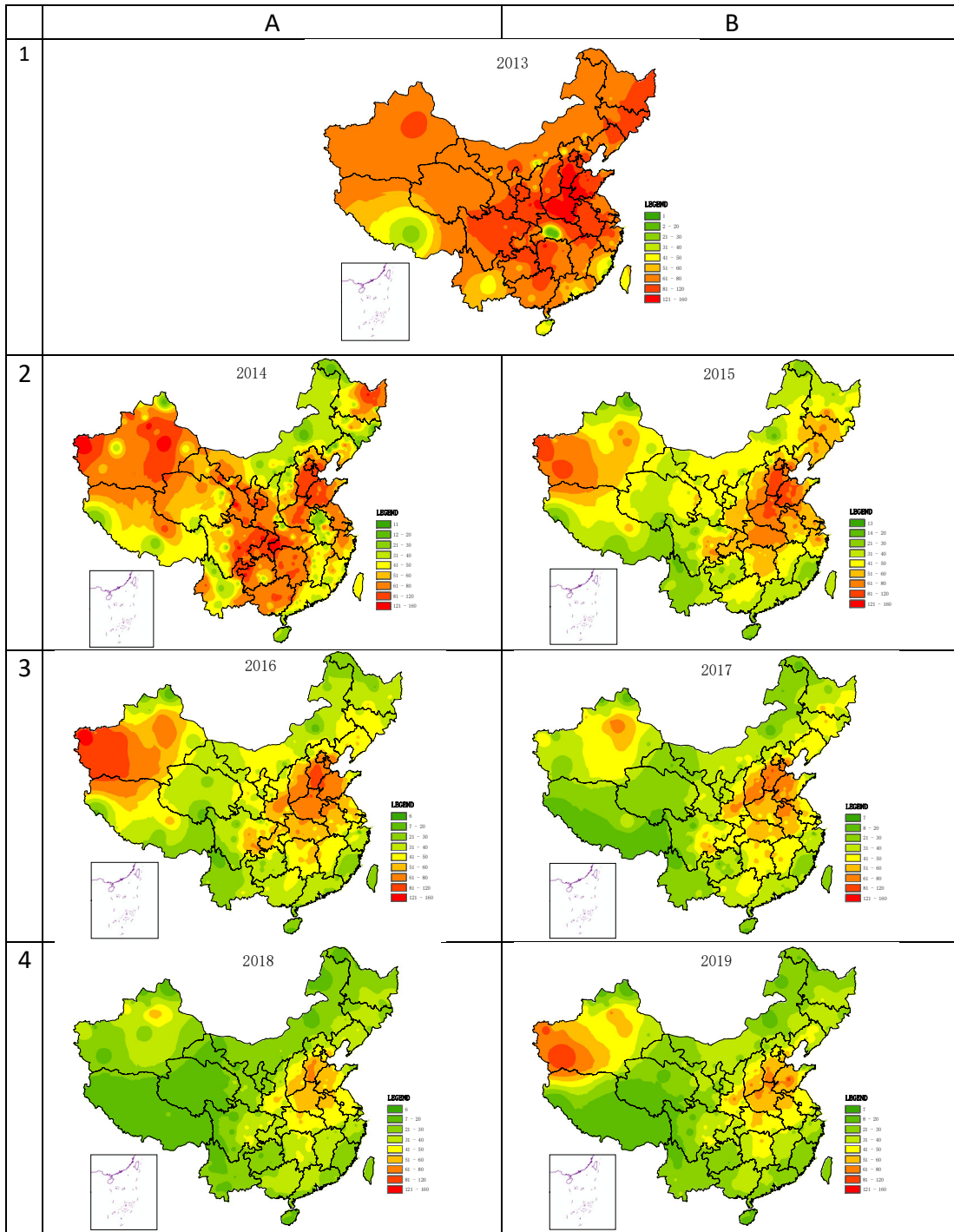10 migrating industries from developed regions in East China.
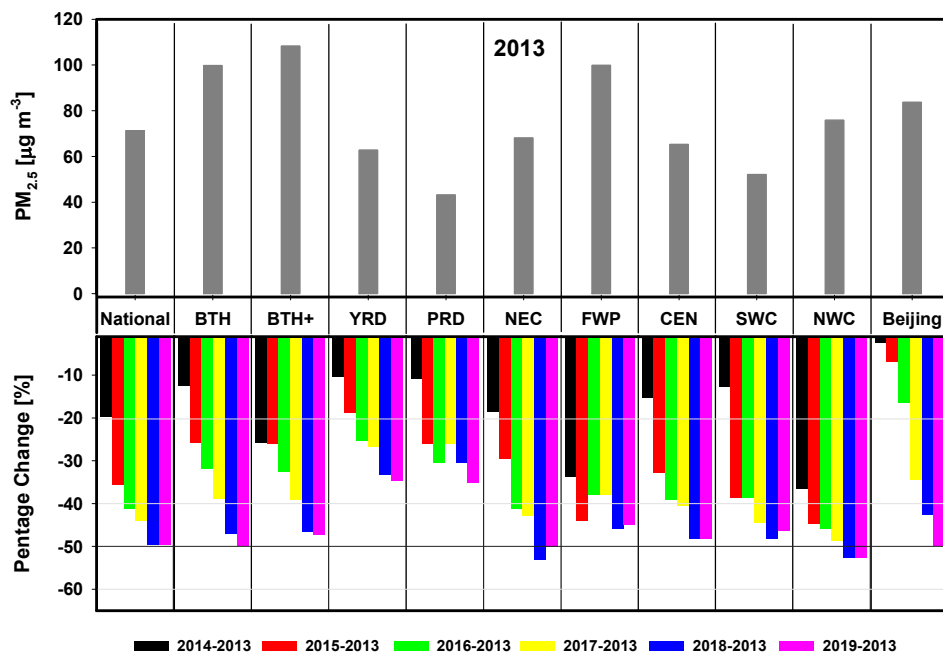
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	A	B
1	2013	
2	2014	2015
3	2016	2017
4	2018	2019

Figure 7: Regional annual PM$_{2.5}$ concentration distributions from 2013 to 2019.

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
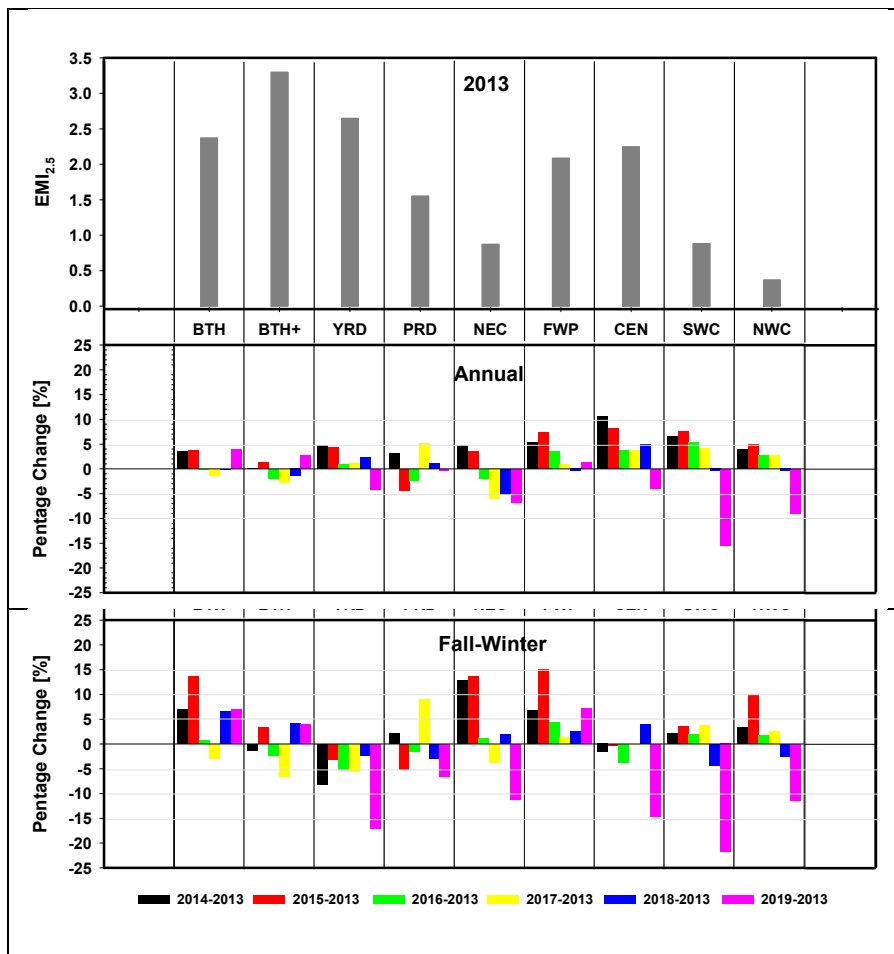13   (bottom) from 2014 to 2019 as compared with 2013 for the nation, 9 regions and Beijing City.

1

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 unfavorite meteorological conditions, respectively. BTH has

2 witnessed the same unfavorite 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
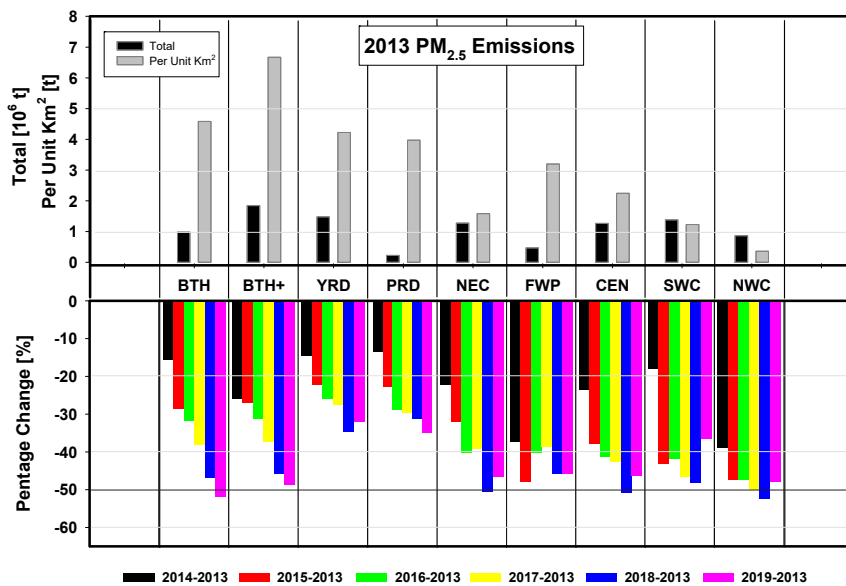9 in 9 regions.

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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 Km^2) 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

certain years. Especially in FWP from 2016 to 2017, the emissions were estimated to be

increased by about 10%, and then decreased in 2018 and 2019, despite of the factor that FWP

has experienced unfavorite meteorological conditions during this period.

The year of 2015 is a special year in the history of China air pollution control. Though the

systematical and network observations of $PM_{2.5}$ started in China from 2013, it took about two

years (until 2015) to evolve to the current status in terms of spatial coverage and observational

station numbers, establishing a consistent and statistically comparable national network. At the

same year, the Environmental Protection Law of People's Republic of China was taken into

effect in January, signalizing the stage of lawfully control of air pollution. For the regulation

assessment point of view, the impact by emission changes from 2015 was relevant to the

interests of management to show how effective the law was.

Table 2 summarizes the $PM_{2.5}$ difference between 2019 and 2015 and the relative

contributions of meteorology and emission changes to the difference for all China, Beijing and

nine regions. Once again, as of the end of 2019, the $PM_{2.5}$ concentrations are all reduced from

2015, ranging from -1.8% in FWP to -46.2% in Beijing. During this period of time, regions of BTH,

BTH+, PRD and Beijing had encountered unfavorite meteorological conditions with positive

$EMI_{2.5}$ changes, which indicated that for these regions, emission reductions were not only to

maintain the decline trend but also to offset the un- favorite meteorological conditions in order

to achieve the observed reductions in ambient $PM_{2.5}$ concentrations. On the contrary, for the

regions of FWP and SWC, the emission control impacts were to deteriorate the concentrations,

implying an increase in emissions to restrain the $PM_{2.5}$ concentration decrease by favorite

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

Regions	Observed PM$_{2.5}$ Difference		Attributions			
			Meteorology (EMI)		Emission Controls	
	(µg m^{-3})	(%)	(µg m^{-3})	Relative %	(µg 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

Note: "+" increased; "-" decreased

4. Conclusions

Based on a 3-D chemical transport model and its process analysis, an Environmental

Meteorological Index (EMI$_{2.5}$) and an assessment framework have been developed and applied

to the analysis of the PM$_{2.5}$ trend in China from 2013 to 2019. Compared with observations, the

EMI$_{2.5}$ can realistically reflect the contribution of meteorological factors to the PM$_{2.5}$ variations

in the time series with impact mechanisms and can be used to as an index to judge whether the

meteorological conditions are favorite or not to the PM$_{2.5}$ pollutions in a region or time period.

In conjunction to the observational trend data, the EMI$_{2.5}$-based framework has been used to

quantitatively assess the separate contribution of meteorology and emission changes to the

time series for 9 regions in China. Results show that for the period of 2013 to 2019, the $PM_{2.5}$

concentrations have been dropped continuously throughout China, by about 50% on national

average. In the regions of NWC, NEC, BTH, BEIJING, CEN, BTH+, SWC, the reduction was in the

range of 46% to 53% while in FWP, PRD and YRD, the reduction was from 45% to 35%. It is

found that the control measures of emission reduction are the dominant factors in the $PM_{2.5}$

declining trends in various regions. By 2019, the emission reduction contributes about 47% of

the $PM_{2.5}$ decrease from 2013 to 2019 on the national average, while in BTH region the

emission reduction contributes more than 50% and in YRD, PRD and SWC regions, the

contributions were between 32% and 37%. For most of the regions, the emission reduction

trend was consistent throughout the period except for FWP, NEC, SWC and NWC where the

emission amounts were increased for certain years. The contribution by the meteorology to the

surface $PM_{2.5}$ concentrations from 2013 to 2019 was not found to show a consistent trend,

fluctuating positively or negatively about 5% on annual average and 10-20% for the fall-winter

heavy pollution seasons.

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