A Section 508–conformant HTML version of this article
is available at https://doi.org/10.1289/EHP4157.

Estimated Contributions of Emissions Controls, Meteorological Factors, Population Growth, and Changes in Baseline Mortality to Reductions in Ambient $PM_{2.5}$ and $PM_{2.5}$-Related Mortality in China, 2013–2017

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Background: In 2013, China released the Air Pollution Prevention and Control Action Plan (Action Plan), which set the roadmap for national air pollution control actions for the period of 2013 to 2017. A decrease in the fine particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$) concentration may lead to a substantial benefit for human health.

Objective: We aimed to quantify the relative contributions four factors: emission reductions, changed meteorology, population growth, and a change in baseline mortality rates to the reduced $PM_{2.5}$-related mortality ($PM_{2.5}$-mortality) during the 2013–2017 period and evaluate the importance of emission controls for human health protection in China.

Methods: The integrated exposure–response function was adopted to estimate the chronic health effects of $PM_{2.5}$. The annual $PM_{2.5}$ concentrations were estimated from chemical transport model simulations combined with surface observations for 2013 and 2017. Relative contributions to $PM_{2.5}$-mortality from emission reductions and the three factors were individually quantified through scenario analysis.

Results: The estimated total $PM_{2.5}$-mortality in China was 1.389 million [95% confidence interval (CI): 1.005 million, 1.631 million] in 2013 but was substantially reduced to 1.102 million (95% CI: 0.755 million, 1.337 million) in 2017. Emission controls contributed 88.7% to this reduction in $PM_{2.5}$-mortality, while changed meteorology, the change in baseline mortality rates, and population growth during 2013–2017 contributed 9.6, 3.8, and −2.2%, respectively.

Conclusions: The implementation of the Action Plan has significantly reduced the $PM_{2.5}$ concentration in regions of China where population density is high, dominating the decline in $PM_{2.5}$-mortality during 2013–2017. However, the health burden of $PM_{2.5}$ pollution in China is still extremely high compared with that in other developed countries. An aggressive air pollution control strategy should be implemented in densely populated areas to further reduce the health burden. https://doi.org/10.1289/EHP4157

Introduction

Severe and frequent fine particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$) pollution has aroused unprecedented public concern in China. Epidemiologists have confirmed the association between $PM_{2.5}$ concentration and health impacts, which include short-term (acute) and long-term (chronic) effects (Chen et al. 2017, 2013; Dockery et al. 1993; Pope et al. 2002; Pope and Dockery 2006; Yin et al. 2017). An increasing number of epidemiological studies have estimated the adverse health effects from exposure to airborne $PM_{2.5}$ in China (Cheng et al. 2013; Li et al. 2018; Xie et al. 2016; Zheng et al. 2015, 2017). Many literatures have evaluated the health burden related to air pollution in China. Wang et al. (2015) estimated that the short-term deaths attributable to $PM_{2.5}$ were 13,162 cases in 2010 in the Yangtze River Delta (YRD). Liu et al. (2016) estimated that the adult mortalities attributed to $PM_{2.5}$ long-term exposure were 1.37 million in 2013 in China. Some have further evaluated the burden of disease from different emission sources. The GBD MAPS Working Group (2016) estimated the burden of disease attributable to air pollution from major sources and found that coal combustion in 2013 was the largest source, contributing to 40% of the $PM_{2.5}$-related deaths in China. Hu et al. (2017) quantified the contributions to mortality from major sources of pollutant emissions in 2013, and showed that industrial and residential sectors were the two leading sources, which contributed to 30.5 and 21.7% of the deaths, respectively. Others have evaluated the potential health benefits after achieving air quality standard targets. Song et al. (2017) showed that the potential health benefits will be 24.0, 44.8, 70.8, and 85.2% of the total current mortalities (1.5 million) for achieving World Health Organization (WHO) interim target 1, interim target 2, interim target 3, and air quality guidelines (WHO 2006), respectively. However, few studies have attempted to quantitatively distinguish the factors (such as changes in meteorology and emissions) driving changes in $PM_{2.5}$-related mortality (hereafter referred to as $PM_{2.5}$-mortality), which is a prerequisite for the design of effective air pollution control policies.

In 2013, China released the Air Pollution Prevention and Control Action Plan (hereafter referred to as Action Plan), which set the roadmap for national air pollution control actions for the 2013–2017 time period (State Council of the People's Republic of China 2013). The Action Plan focused on three key regions: Beijing–Tianjin–Hebei (BTH), YRD, and the Pearl River Delta (PRD), and proposed targets of $PM_{2.5}$ concentration reductions for BTH (25%), YRD (20%), and PRD (15%). From 2013 to 2017, the measured values of the annual average $PM_{2.5}$ concentrations in the three key regions reduced from $106\ \mu g/m^3$ to $64\ \mu g/m^3$ in BTH, from $67\ \mu g/m^3$ to $44\ \mu g/m^3$ in YRD, and from $47\ \mu g/m^3$ to $34\ \mu g/m^3$ in PRD (China Ministry of Ecological Environment 2013, 2017). Such a remarkable improvement in air quality during the 2013–2017 period provides a good opportunity to evaluate the effectiveness of emission controls in reducing $PM_{2.5}$-mortality.

In this study, we evaluated the changes in $PM_{2.5}$-mortality in China between 2013 and 2017. The relative contributions of four factors to the mortality, including emission reductions, changes in meteorology, population growth, and the change in baseline

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Supplemental Material is available online (https://doi.org/10.1289/EHP4157).
The authors declare they have no actual or potential competing financial interests.
Received 10 July 2018; Revised 30 May 2019; Accepted 30 May 2019; Published 24 June 2019.

mortality rates, are quantified for mainland China. BTH, YRD, Guangdong Province, and Sichuan Province and Chongqing city (Sichuan-Chongqing), which are metropolitan areas and the heaviest haze regions that have large populations, were selected for analysis (locations shown in Figure 1). The importance of emission controls for human health protection is evaluated and highlighted.

Methods

Anthropogenic Emissions in 2013 and 2017

We used the most recent high resolution anthropogenic multiple-pollutant [sulfur dioxide (SO_2), nitrogen oxides (NO_x), $PM_{2.5}$, volatile organic compounds (VOCs), ammonia (NH_3)] emission inventory for mainland China (Cai et al. 2017) for the year of 2013 and updated it for the year of 2017. Emission sources of SO_2, NO_x, and $PM_{2.5}$ were divided into 10 sectors: power plants, industrial combustion, industrial process, cement plants, iron and steel plants, domestic fossil fuel burning, domestic biomass burning, on-road transportation, off-road transportation, and open burning. Emission sources of VOCs were divided into nine sectors: domestic solvent use, industry solvent use, industrial combustion, domestic combustion, open burning, industry process, on-road transportation, off-road transportation, and other domestic use. Emission sources of NH_3 were divided into four sectors: livestock farming, fertilizer application, industrial process, and domestic sources. The emissions from industrial sectors such as power plant, industrial boiler, and iron and steel production (large point sources) were estimated by applying the unit-based method (Zheng et al. 2019). The formula is provided in Supplemental Material, "Emission calculation method." The emission inventory for other sources (area sources), including residential sector, transportation, solvent use, and biomass open burning, was developed based on the "emission factor method" described in our previous work (Wang et al. 2014; Zhao et al. 2013a, 2013b). The method was used to estimate the provincial emissions from activity data, uncontrolled emission factors, removal efficiencies, and application rates of control technologies.

The activity data and technology distribution for each sector were derived based on Chinese statistics, Chinese technology reports, and the energy demand approach. Table S1 shows the corresponding references for activity data and penetrations of control technologies. The activity data is referred to as the energy consumption, product yields, etc., for different sectors. The data for the product yields were obtained from the China Statistical Yearbook (2018). The data for energy consumption were obtained from the China Energy Statistical Yearbook (2017a). The bottom-up provincial activity data were mainly derived from the China Statistical Yearbook (National Bureau of Statistics of China (2017a, 2018). The data for the China Statistical Yearbook were updated to the year 2017, but the data for energy consumption were unavailable in 2017. Therefore, the provincial activity levels of sectors related to coal combustion were predicted based on the provincial statistical yearbooks (for example, data of Beijing was obtained from Beijing Municipal Bureau of Statistics 2018), the National Bureau of Statistics of China (2017a), and the CNEMC (2017). Provincial installation rates of removal technologies were mainly derived from the National Environmental Statistics Database (CNEMC 2017) and the Management System

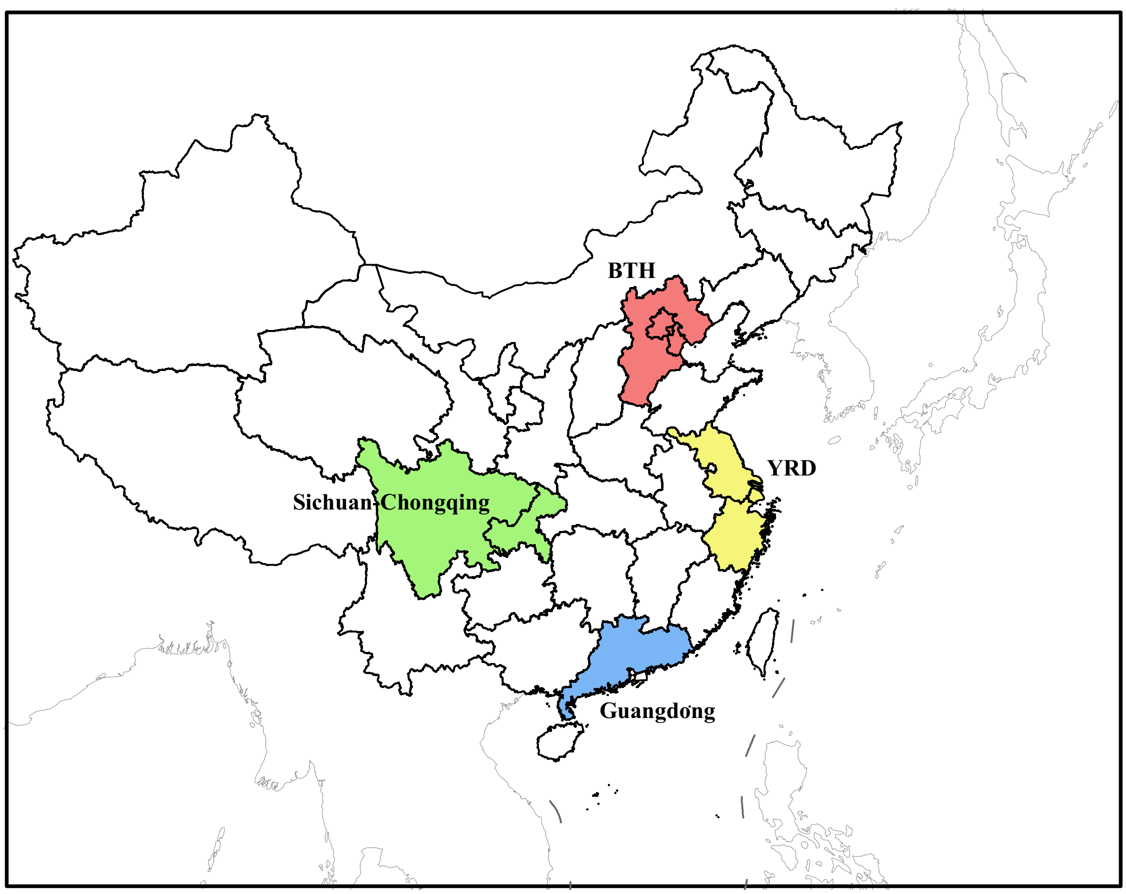

Figure 1. Community Multiscale Air Quality (CMAQ) simulation domain (outermost black border) and the location of Beijing–Tianjin–Hebei (BTH) (in red), Yangtze River Delta (YRD) (in yellow), Guangdong (in blue), and Sichuan Province and Chongqing city (Sichuan-Chongqing) (in green) regions.

of Pollutant Emission Permit (2018). The activity levels and penetration rates were mainly updated for industrial sectors in this study. The emissions from solvent use, transportation, and agricultural sectors were predicted based on the assumptions in the research of Cai et al. (2017). Table S2 lists the provincial activity level for main emission sources in 2013 and 2017. The coal consumption of coal-fired power plants was slightly decreased by 2.8%. The coal consumption of industrial coal-fired boilers was slightly increased by 1.5%. The cement products were decreased by 3.3%. The iron and steel products were increased by 6.9%. The coal consumption for residential coal combustion was slightly decreased by 1.0%. The biomass fuel consumption for residential biomass combustion was decreased by 47.0%. On-road vehicle population was largely increased by 70.1%.

Emissions of large point sources, such as power plants, iron and steel plants, and cement plants, were allocated to the grid cell by the exact location of emission sources. Emissions of other area sources were allocated to grid cells by using spatial surrogate ratios, including gross domestic product (GDP) (primary/secondary/tertiary industry), population, road maps, and land use, as shown in Table S3. First, the provincial emissions were allocated to county emissions by using the GDP ratio of each county to that of the province. Then they were allocated to grid cells by using population or road maps. Land use data were only available in Beijing, Tianjin, Hebei, Shanxi, part of Inner Mongolia, Shandong, and Henan, including industrial land, rural residential land, and cropland. In these regions, the provincial emissions were allocated to city emissions by using the GDP ratio of each city to that of the province. Then they were allocated to grid cells by using the ratio of land use area, as shown in Table S4.

$PM_{2.5}$ Concentrations in 2013 and 2017

The Community Multiscale Air Quality (CMAQ) model [version 5.2; U.S. Environmental Protection Agency (U.S. EPA)] (Appel et al. 2018) was applied to simulate the annual $PM_{2.5}$ concentrations in China. The simulation was conducted on a national domain, including China and portions of surrounding countries (the outermost black border in Figure 1), discretized with a grid of 27×27 km horizontal resolution and 14 vertical layers up to 100 hPa (~ 15 km) above the ground based on sigma pressure coordinates. The heights of the first four layers were ~ 38, 75, 148, and 300 m, respectively. The provincial anthropogenic emission data were gridded to 27×27 km. The emissions of the surrounding foreign countries were obtained from 2015 mosaic Asian anthropogenic emission with 0.5×0.5 degree resolution (Li et al. 2017). Biogenic emissions (emission from natural sources) were generated by the Model for Emissions of Gases and Aerosols from Nature (MEGAN), software version 2.04 (Guenther et al. 2006). The emission data were combined and used as the input for the simulation of $PM_{2.5}$ concentration. A 5-d simulation spin-up was performed to minimize the effects of initial conditions. Carbon Bond 6 (CB6) (Sarwar et al. 2008) and the AERO6 aerosol module (Appel et al. 2013) were used for gas-phase and particulate matter chemical mechanisms, respectively. The meteorology fields for CMAQ were derived from simulations with the Weather Research and Forecasting Model (WRF) (version 3.8; National Center for Atmospheric Research) (Skamarock et al. 2008). The WRF configuration included: Morrison double-moment microphysics scheme (Morrison et al. 2009), the Rapid Radiative Transfer Model, a radiation scheme (Iacono et al. 2008), Kain-Fritsch cumulus cloud parameterization (Kain 2004); Pleim-Xiu land surface physics scheme (Xiu and Pleim 2001), and the Asymmetric Convective Model, a planetary boundary layer (PBL) physics scheme (Pleim 2007). Initial and boundary conditions for the WRF are provided by the National Centers for Environmental Prediction Final (NCEP FNL) Operational Global Analysis data (NCEP FNL 2000). The meteorological parameters simulated by the WRF were compared with the observational data downloaded from the National Climatic Data Center (Smith et al. 2011). The variables include the temperature at 2 m, wind speed (WSP) at 10 m, and humidity at 2 m. The statistical indices used include the mean observation, mean simulation, mean bias, gross error, root mean square error, and index of agreement. Detailed explanations of the indices can be found in Emery and Tai (2001).

To improve the accuracy of the $PM_{2.5}$ concentration estimation, a data fusion method, i.e., the gradient-adjusted Voronoi neighbor averaging (eVNA), was applied to fuse annual average model simulated and monitored $PM_{2.5}$ concentrations (Ding et al. 2016). This interpolation method is shown by the following equation.

$$\mathrm{GridCell}_E = \sum_{i=1}^{n} Weight_i \times Monitor_i \times \frac{Model_E}{Model_i}$$

where n is the number of neighboring monitoring sites of grid cell E, $Weight_i$ is the inverse distance (between center of grid cell E and location of site i) weight for site i, $Monitor_i$ is the observed data at site i, $Model_E$ is the model data at cell E, $Model_i$ is the model data at the grid cell that contains monitoring site i, and $GridCell_E$ is the fused value at grid cell E. The hourly $PM_{2.5}$ monitoring data was obtained from the China National Environmental Monitoring Centre (http://106.37.208.233:20035/). Figure S1 shows the location of the monitoring sites. Sites are chosen only when more than 75% of the total hourly $PM_{2.5}$ monitoring data during a year are available. There were 411 monitoring sites available in 2013 and 1,490 monitoring sites available in 2017. Since 351 common sites were available both in 2013 and 2017, their monitor data were used for data fusion, while information at the remaining locations was used for model validation.

Estimates of $PM_{2.5}$-Mortality in China for the Years 2013 and 2017

In this study, the relative risk model method (Fann et al. 2013; Kan and Chen 2004) was used to estimate the health impacts of $PM_{2.5}$ as follows:

$$\Delta Y = Y_0(1 - 1/\mathrm{RR})\mathrm{Pop}$$

where ΔY is an attributable case of health end point related to $PM_{2.5}$ exposure, Y_0 is the baseline incidence rate, Pop is the total exposed population, RR is the relative risk for the specific health end point, and (1-1/RR) represents the fraction of incidence rates attributable to $PM_{2.5}$.

Chronic health effects of ambient annual $PM_{2.5}$ concentration were mostly estimated based on integrated exposure–response functions (IERs), which were first developed by Burnett et al. (2014) and used for the Global Burden of Disease (GBD) study. Cohen et al. (2017) updated IERs from those used in the GBD in 2013 by adding additional risk estimates from more recent epidemiological studies and refining the statistical estimation techniques. The updated IERs were used for the GBD 2015 study. They have provided RRs and associated uncertainties. RR was estimated based on the IERs shown as follows:

$$\mathrm{RR}(z) = 1 + \alpha \times \left(1 - e^{\beta(z - z_{cf})^{\gamma}}\right)$$

where z is the $PM_{2.5}$ concentration; z_{cf} is the theoretical minimum risk exposure level; and α, β, and γ are the unknown parameters.

In the IERs model, five health end points are considered, including ischemic heart disease (IHD, age range: 25–99), cerebrovascular disease (ischemic stroke and hemorrhagic stroke, age range: 25–99), lung cancer (age range: 0–99), chronic obstructive pulmonary disease (COPD, age range: 0–99), and lower respiratory infections (LRI, age range: 0–99). The functions for IHD and cerebrovascular disease are age specific and were fitted into 5-year age groupings. The annual Chinese national mortality rates of specific ages and genders in 2013 and 2016 (2017-specific data was not available during the conduct of this study) were obtained from the GBD results tool (http://ghdx.healthdata.org/gbd-results-tool). Mortality rates were slightly decreased from 2013 to 2016 due to the improvement in medical and health conditions (Figure S2).

The age-specific population was aggregated to match the gridded $PM_{2.5}$ concentration by combining the 1×1 km LandScan population dataset (Bright et al. 2013) with the population structures in 2013 and 2016 (2017-specific information was not available during the conduct of this study) from the China Statistical Yearbook (National Bureau of Statistics of China 2017b). The population in most of the provinces in China increased from 2013 to 2016, except in northeast China, where it declined (Figure S3).

Health impact assessments were conducted by using the U.S. EPA's Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE), version 1.4 (Fann et al. 2018; Sacks et al. 2018). The U.S. EPA parameterized the IERs by fitting a 5-knot degree-1 spline so that it could be incorporated in BenMAP-CE (Munoz and Sinha 2015). Age-specific functions of IHD and cerebrovascular disease were represented by broader age groupings of 25 to 44, 45 to 64, and 65 to 99. Gridded information on fused $PM_{2.5}$ concentration, age/gender-specific population, and the annual national age/gender-specific mortality rates was used as input to the BenMAP-CE model.

Monetizing the health improvement related to air quality was used to evaluate air pollution control strategies. The monetary value of a statistical life (VSL) is commonly applied in quantifying economic benefits related to air quality improvement. This study refers to the results reported by Huang et al. (2017), who conducted a choice experiment survey to estimate the willingness to pay (a method used to estimate the VSL) to reduce health risks related to air quality in Beijing, China. The VSL from Huang's study was estimated to be 5.24 million [95% confidence interval (CI): 3.51 million, 6.98 million] Chinese yuan (CNY), and it was used in this study to quantify economic benefits associated with health improvement related to air quality.

Quantification of Relative Contributions to $PM_{2.5}$-Mortality from Individual Factors

To quantify the influences of the key driving factors, especially changes in emission and meteorological conditions, we conducted simulations with CMAQ for four scenarios: *a*) the 2013 baseline case using both the emissions and meteorological data in 2013 (denoted as 2013BASE), *b*) a hypothetical scenario that used the anthropogenic and biogenic emissions representative of 2013 but the meteorological data from 2017 (denoted HYPO1), *c*) another hypothetical scenario that used anthropogenic emissions of 2013 but the biogenic emissions and meteorological data of 2017 (denoted HYPO2), and *d*) the 2017 baseline case using both the emissions and meteorological data in 2017 (noted as 2017BASE). The configuration of scenarios is shown in Table 1. The difference between 2013BASE and 2017BASE represents the total change of the $PM_{2.5}$ concentration (ΔTOT) due to the emissions changes and the differences in the meteorological conditions in 2013 and 2017. The impact of the meteorological conditions (ΔTmet-drive) is quantified by the difference between 2013BASE and HYPO2; this is the sum of the impact of biogenic emissions changes associated with meteorological variation (ΔBio-drive), which is estimated from (HYPO2 - HYPO1), and the impact of the change only in meteorological conditions (ΔMet-drive), which is estimated from (HYPO1 - 2013BASE). The impact of the anthropogenic emission reduction (ΔEmis-drive) is quantified by the difference between HYPO2 and 2017BASE. $PM_{2.5}$ concentrations of 2013BASE and 2017BASE were adjusted by the data fusion method. The change in $PM_{2.5}$ concentration attributable to meteorology change and emission reduction was calculated based on the change ratios (using simulation results) and the data-fused baseline concentrations in 2013 and 2017. The relationship is shown in the equation below:

Table 1. Configuration of simulation scenarios.

Scenario	Anthropogenic emission	Biogenic emission	Meteorology
2013BASE[a]	2013	2013	2013
HYPO1[b]	2013	2013	2017
HYPO2[c]	2013	2017	2017
2017BASE[d]	2017	2017	2017

[a]The 2013 baseline case using both the emissions and meteorological data in 2013.
[b]Hypothetical scenario that used the anthropogenic and biogenic emissions representative of 2013 but the meteorological data from 2017.
[c]Hypothetical scenario that used anthropogenic emissions of 2013 but the biogenic emissions and meteorological data of 2017.
[d]The 2017 baseline case using both the emissions and meteorological data in 2017.

$$\Delta PM_i' = \frac{\Delta PM_i}{\Delta TOT} \times \Delta TOT'$$

where i refers to the factors of meteorology change or emission reduction, ΔPM_i is the change of $PM_{2.5}$ concentration due to ΔTmet-drive or ΔEmis-drive, ΔTOT is the difference of $PM_{2.5}$ concentration between 2013BASE and 2017BASE, $\Delta TOT'$ is the difference of data-fused $PM_{2.5}$ concentrations in 2013 and 2017, and $\Delta PM_i'$ is the adjusted change of $PM_{2.5}$ concentration due to two factors.

Similar to our previous study (Wang et al. 2017; Xing et al. 2011), a scenario analysis was conducted to evaluate the individual contribution to the change in $PM_{2.5}$-related health effects by the emission changes (i.e., the implementation of the Action Plan), meteorology change, population growth, and baseline mortality decrease owing to improved medical and health conditions. The method of quantifying the contribution to the change in health impacts from each factor is shown in Table 2. The burden of disease in 2013 was calculated using the concentration, population, and mortality rate in 2013. The burden of disease in 2017 was calculated using the 2017 concentration data and the population and mortality rate in 2016. The difference in the health impacts between 2 y included the impact of improved air quality, changed population, and changed mortality rates. Given that the health impacts of different factors (concentration, population, mortality rates) are nonlinear, the sum of their independent effects are not equal to their combined effect (i.e., synergistic effects). Thus, the independent impacts of the individual factors are normalized by dividing each impact by the sum of the independent impacts multiplied by the total impact.

Results

Anthropogenic Emission Changes from 2013 to 2017 in China

In 2013, the anthropogenic emissions of SO_2, NO_x, $PM_{2.5}$, VOC, and NH_3 in mainland China were 21.8, 27.3, 10.0, 22.6, and 9.8 Million tons (Mt), respectively (Cai et al. 2017). In 2017, the emissions of SO_2, NO_x, $PM_{2.5}$, and VOC were reduced by 33, 25, 30, and 4%, respectively, relative to 2013, while NH_3 increased by 7%. During this period, the major pollution control

Table 2. Scenarios and input data used to estimate the relative contributions of individual factors to fine particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$)–related mortality.

Scenarios	Input data		
	$PM_{2.5}$	Population	Mortality rate
Burden of diseases (2013)	$PM_{2.5}$ in 2013	2013	2013
Burden of diseases (2017)	$PM_{2.5}$ in 2017	2016	2016
Relative impact of individual factors, 2013–2017			
$PM_{2.5}$	Change in $PM_{2.5}$ due to meteorology	2013	2013
$PM_{2.5}$	Change in $PM_{2.5}$ due to emissions	2013	2013
Population	Total change in $PM_{2.5}$	2013–2016	2013
Baseline mortality rate	Total change in $PM_{2.5}$	2013	2013–2016

targeted three pollutants (SO_2, NO_x, and $PM_{2.5}$). The national anthropogenic emissions of SO_2, NO_x, and $PM_{2.5}$ in 2013 and 2017 are compared in Figure 2. Approximately 52% and 32% of the total SO_2 reduction is from power plant and industrial combustion, respectively. Approximately 84% and 8% of the total NO_x reduction resulted from controls on power plants and cement manufacturing, respectively. Our estimates suggest that the reduction in primary $PM_{2.5}$ emissions was mainly due to reduced emissions from domestic combustion and steel and cement production, which accounted for 32, 19, and 18% of the total estimated reduction in primary $PM_{2.5}$ emissions, respectively. Figure 3 and Table S5 present the emission reduction in the four key regions. Emissions of SO_2, NO_x, and $PM_{2.5}$ were reduced by 44, 28, and 41% in BTH; 45, 32, and 30% in YRD; 37, 20, and 18% in Guangdong; and 46, 15, and 35% in Sichuan-Chongqing.

Differences in Meteorological Conditions between 2013 and 2017 in China

The WRF model performance, as compared with the observations in 2013 and 2017, is shown in the supplementary material (Tables S6–S7). Generally, the model reproduced the meteorological conditions in 2013 and 2017 well. Figure S4 shows the differences between 2013 and 2017 in temperature at 2 meters above ground, WSP at 10 meters above ground, the water vapor mixing ratio, and the PBL from simulation results. Compared with 2013, the annual average 2 m temperature in 2017 increased in BTH, YRD, and Guangdong by 1.01, 0.26, and 0.41 K, respectively, and slightly decreased in Sichuan-Chongqing by 0.16 K. The annual average 10 m WSP increased 0.08, 0.03, 0.09, and 0.22 m/s in BTH, YRD, Guangdong, and Sichuan-Chongqing, respectively. The water vapor mixing ratio increased in YRD, Guangdong, and Sichuan-Chongqing by 0.172, 0.423, and 0.177 g/kg, respectively, and slightly decreased in BTH by 0.003 g/kg. PBL height increased in BTH, YRD, and Guangdong by 58, 20, and 25 m, respectively, and decreased in Sichuan-Chongqing by 19 m. The relatively higher PBL height and slightly higher WSP in 2017 also likely resulted in more dispersion of pollutants, thereby also contributing to reduced $PM_{2.5}$ concentration in northern China.

Changes of $PM_{2.5}$ Concentrations in 2013 and 2017 in China

The simulation results are shown in Figure S5. The model data were able to capture the spatial variation of observations, but the

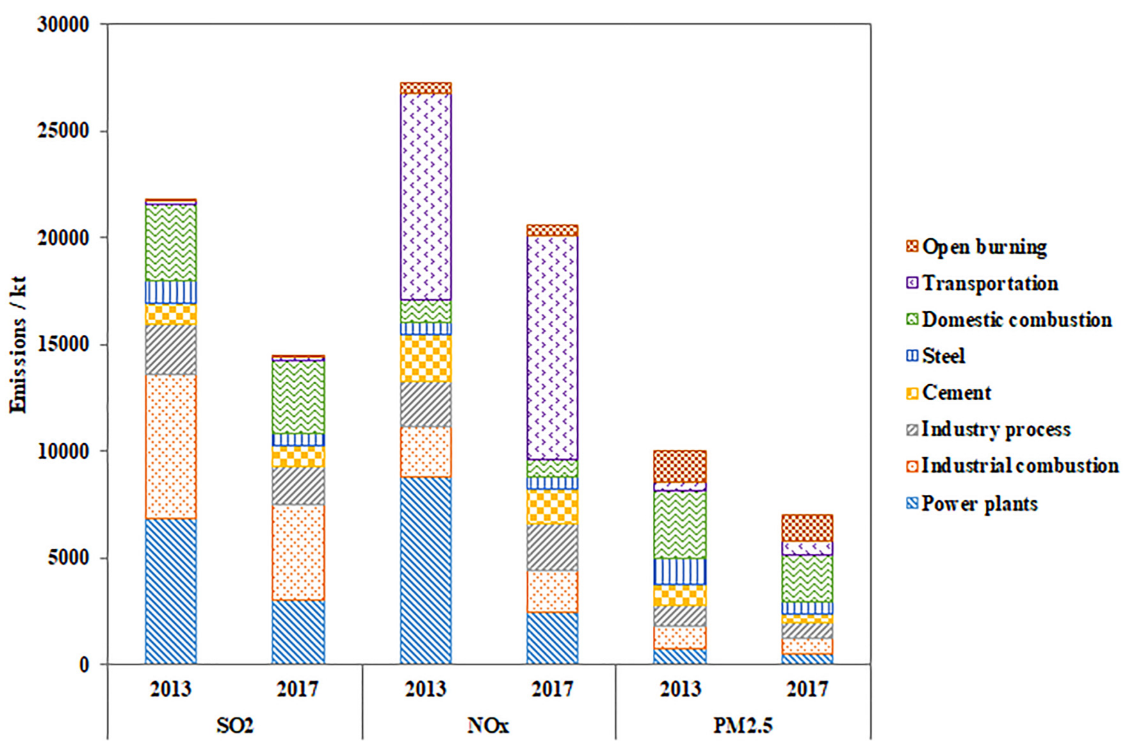

Figure 2. Anthropogenic emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and fine particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$) in China in 2013 and 2017.

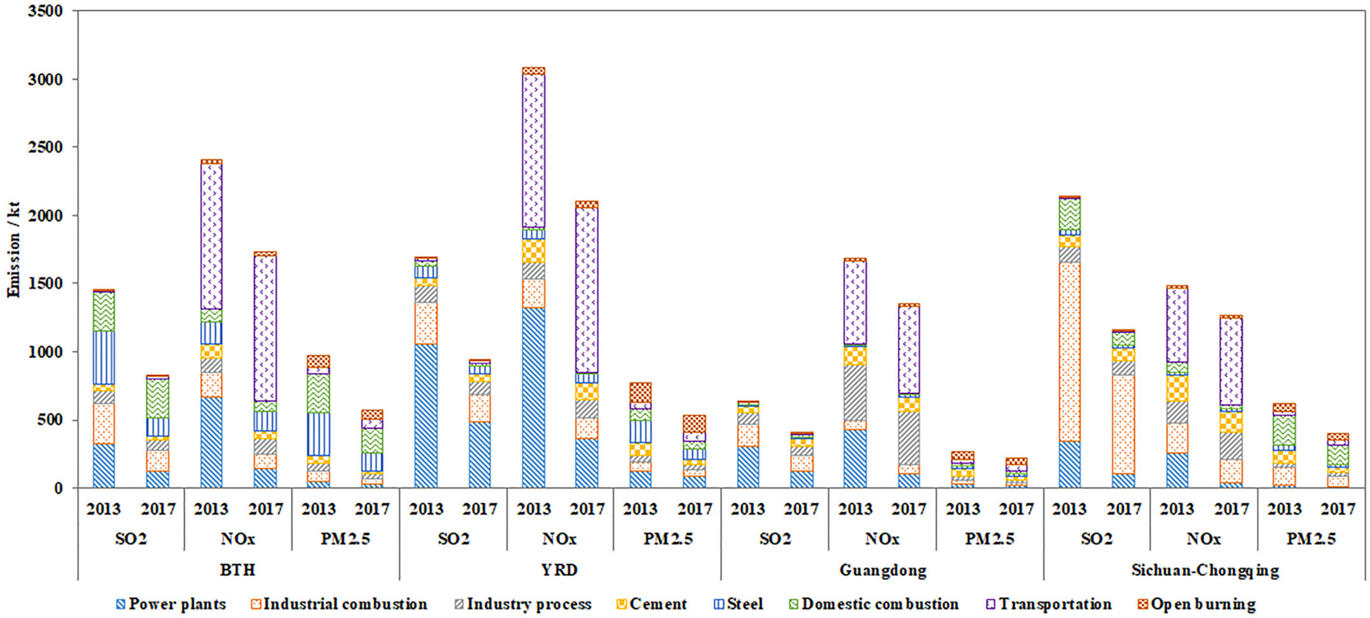

Figure 3. Anthropogenic emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and fine particulate matter with aerodynamic diameter ≤2.5 μm ($PM_{2.5}$) in the Beijing–Tianjin–Hebei, Yangtze River Delta, Guangdong, and Sichuan Province and Chongqing city (Sichuan-Chongqing) regions in 2013 and 2017.

model underestimated the $PM_{2.5}$ concentration by 18.9% in 2013 and by 16.4% in 2017. Figure S6 shows the validation of simulated and fused $PM_{2.5}$. Both in 2013 and 2017, simulation results were underestimated, especially in north and southwest China. The bias of the fused baseline $PM_{2.5}$ was significantly reduced after applying eVNA. The average mean normalized bias of the monitoring sites used for the interpolation was decreased to zero. Figure 4 presents the changes in the fused $PM_{2.5}$ concentrations from 2013 to 2017. Northern, eastern, and central China had the largest reductions (Figure 4C). The national average of $PM_{2.5}$ concentration declined by $\sim 9\,\mu g/m^3$. Figure 4D shows the box plot of the $PM_{2.5}$ concentration in grid cells for the four key regions in 2013 and 2017. Significant decreases are shown in the high concentration range. The annual $PM_{2.5}$ concentration over the BTH region was ~ 77 (up to 182) $\mu g/m^3$ and 48 (up to 97) $\mu g/m^3$ in 2013 and 2017, respectively. The average annual $PM_{2.5}$ of BTH declined $30\,\mu g/m^3$, or 39% of the 2013 concentration. The annual $PM_{2.5}$ concentration over the YRD region was ~ 59 (up to 87) $\mu g/m^3$ and 39 (up to 72) $\mu g/m^3$ in 2013 and 2017, respectively. The average annual $PM_{2.5}$ of YRD declined $20\,\mu g/m^3$, or 35% of the 2013 concentration. The annual $PM_{2.5}$ concentration over Guangdong was ~ 35 (up to 59) $\mu g/m^3$ and 24 (up to 46) $\mu g/m^3$ in 2013 and 2017, respectively. The average annual $PM_{2.5}$ of Guangdong declined $11\,\mu g/m^3$, or 30% of the 2013 concentration. The annual $PM_{2.5}$ concentration over Sichuan-Chongqing was ~ 25 (up to 104) $\mu g/m^3$ and 17 (up to 60) $\mu g/m^3$ in 2013 and 2017, respectively. The average annual $PM_{2.5}$ of Sichuan-Chongqing declined $9\,\mu g/m^3$, or 35% of the 2013 concentration. In 2017, ~63, 62, 6, and 15% of the spatial areas of BTH, YRD, Guangdong, and Sichuan-Chongqing, respectively, have grid cell $PM_{2.5}$ concentrations above the national air quality standards ($35\,\mu g/m^3$). Approximately 100, 100, 100, and 53% of the spatial areas of BTH, YRD, Guangdong, and Sichuan-Chongqing, respectively, have grid cell $PM_{2.5}$ concentrations above the WHO guideline of $10\,\mu g/m^3$.

The contribution of meteorology variation to $PM_{2.5}$ ambient concentrations is represented in Figure S7A by the percentage change in 2013Base relative to the HYPO2 scenario in which the emissions are from 2013, and the meteorological conditions are the same as those in 2017 (i.e., ΔTmet-drive/2013BASE). In 2017, the meteorological conditions were favorable for pollution reduction in northeast and north China due to relatively high PBL heights and slightly high WSP (see Figure S4), while the conditions were unfavorable for pollution reduction in east and northwest China due to relatively low PBL heights. Affected by the changes in meteorology, the regional average $PM_{2.5}$ concentrations in BTH, Guangdong, and Sichuan-Chongqing were reduced by 11.4, 1.3, and 0.1%, respectively, from 2013 to 2017; the regional average $PM_{2.5}$ concentration in YRD increased by 0.7%. The $PM_{2.5}$ reduction due to ΔTmet-drive contributed 29.2, 4.4, and 0.3% to that of ΔTOT in BTH, Guangdong, and Sichuan-Chongqing, respectively, while it increased 2.0% in the YRD. The change in $PM_{2.5}$ concentration attributable to ΔTmet-drive is the sum of the effects due to ΔBio-drive and ΔMet-drive. The change in the biogenic emissions has a very limited impact on $PM_{2.5}$ concentration, with the range from -1.3 to $0.5\,\mu g/m^3$. The main contribution is attributable to changes in the meteorological parameters between the years. Figure S7B,C shows the percentage of change attributable to ΔBio-drive and ΔMet-drive (i.e., ΔBio-drive/2013BASE2013, ΔMet-drive/2013BASE 2013).

Similarly, the contribution of the reduction in anthropogenic emissions to $PM_{2.5}$ ambient concentrations is represented in Figure S7D by the percentage change in 2017 emissions (2017BASE) relative to the HYPO2 scenario; the emissions are from 2013, and the meteorological conditions are the same as those in 2017 (i.e., ΔEmis-drive/2017BASE 2017). It shows a reduction across the entire country due to air pollution control, particularly in the four regions. Due to emission reduction, $PM_{2.5}$ concentrations in most of China were reduced by >10% from those in 2013. In addition, the regional average $PM_{2.5}$ concentrations in BTH, YRD, Guangdong, and Sichuan-Chongqing were reduced by 27, 35, 29, and 35%, respectively, from 2013 to 2017. Our estimates suggest that the $PM_{2.5}$ reduction due to ΔEmis-drive contributed 70.8, 95.6, and 99.7% to that of ΔTOT in BTH, Guangdong, and Sichuan-Chongqing, respectively; the changes of emissions reduced $PM_{2.5}$ and offset the slightly increased $PM_{2.5}$ attributable to changed meteorology in the YRD. Overall, emission reductions dominated the decline of ambient $PM_{2.5}$ concentration, but the contributions of meteorology varied greatly in the different regions.

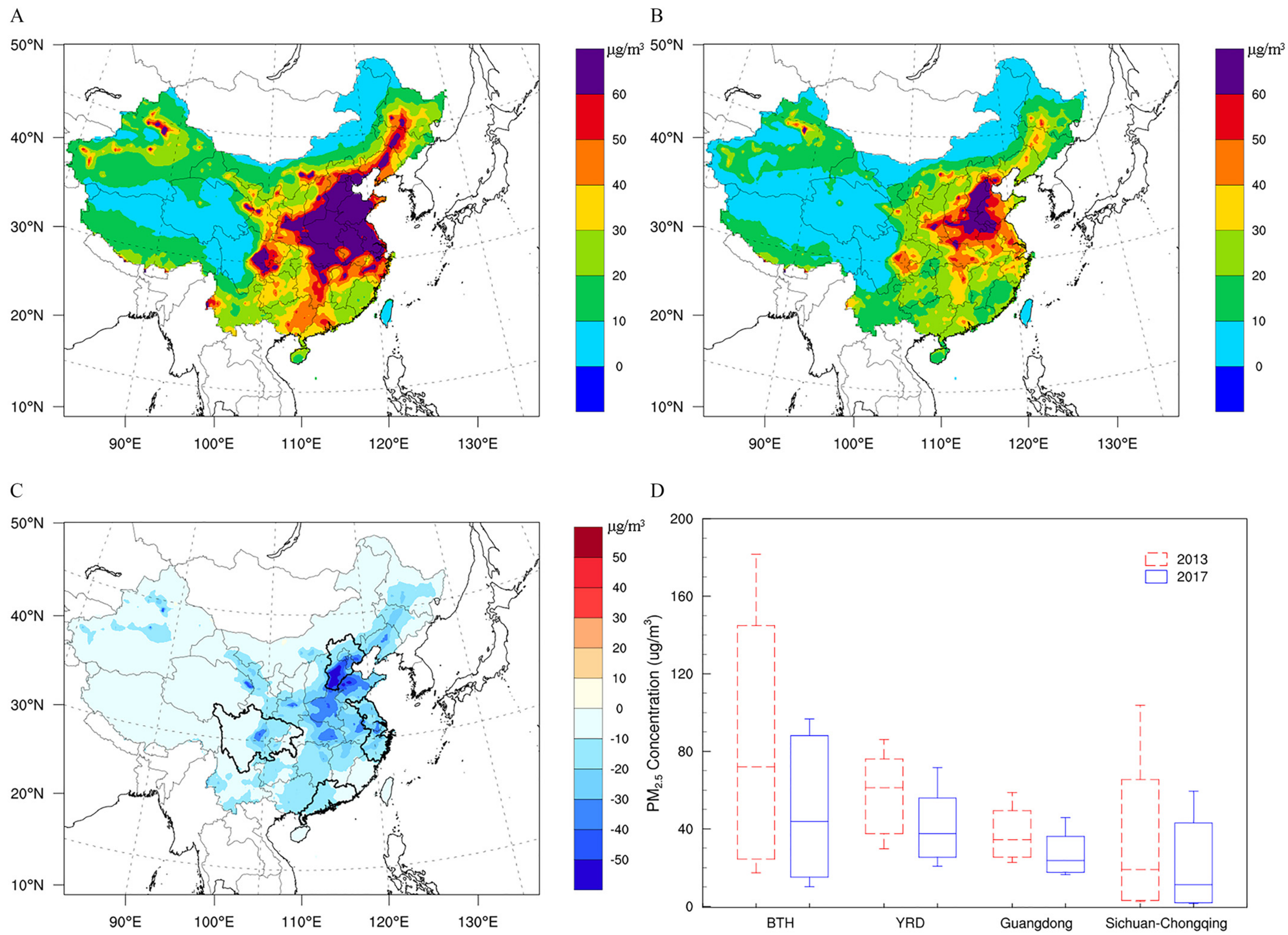

Figure 4. (A) Annual average fine particulate matter with aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$) concentration in 2013 (μg/m^3). (B) Annual average $PM_{2.5}$ concentration in 2017 (μg/m^3). (C) Change in annual average $PM_{2.5}$ concentration between 2013 and 2017 (μg/m^3). (D) $PM_{2.5}$ concentration distribution of the Beijing–Tianjin–Hebei, Yangtze River Delta, Guangdong, and Sichuan Province and Chongqing city (Sichuan-Chongqing) regions in 2013 and 2017. Note: Boxes show the range of 25th and 75th percentiles values. Whiskers are maximum and minimum values. The segment inside the rectangle is the median value.

Estimated $PM_{2.5}$-Mortality in 2013 and 2017 in China

Total $PM_{2.5}$-related deaths are estimated to be 1.389 million (95% CI: 1.005 million, 1.631 million) and 1.102 million (95% CI: 755,000; 1.337 million) per year in 2013 and 2017, respectively. Figure 5 presents the deaths attributed to $PM_{2.5}$ exposure across China in 2013 and 2017. Northern, eastern, and central China exhibit the largest health burden due to the dense population and the large amount of emissions. Disease-specific deaths in China and four key regions are presented in Figure S8. IHD, stroke, COPD, lung cancer, and LRI contribute 33, 28, 24, 11, and 4%, respectively, to the total $PM_{2.5}$-attributable deaths by these specific causes in 2017. The population-normalized rate of $PM_{2.5}$-attributable deaths in China in 2017 was estimated to be 80 deaths per 100,000 people, which is 2.9 times higher when compared with other developed countries (e.g., United States,

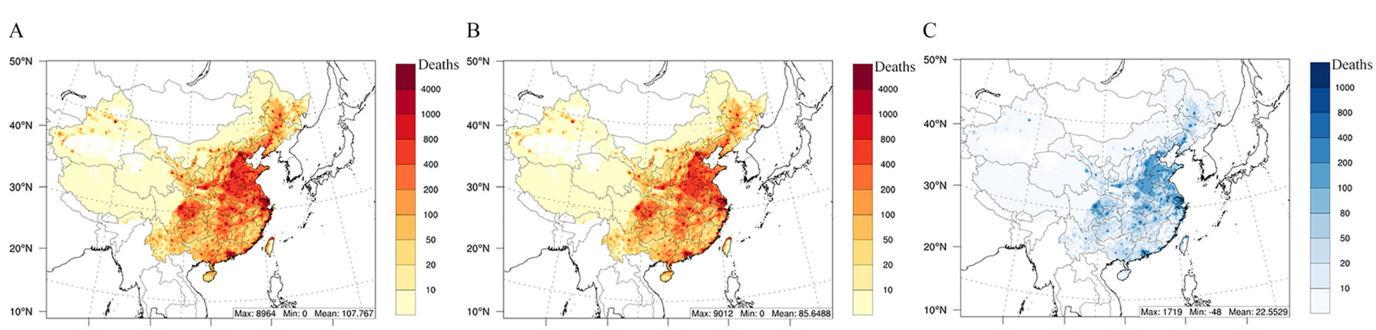

Figure 5. Estimated numbers of deaths attributed to fine particulate matter with aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$) in (A) 2013, and (B) 2017. (C) Avoided deaths between 2013 and 2017.

Table 3. Estimated numbers of total deaths and deaths/km^2 attributed to fine particulate matter with aerodynamic diameter ≤2.5 μm ($PM_{2.5}$) in the 31 provinces (95% confidence intervals).

Province[a]	2013 Deaths (in thousands)[b]	2013 Deaths/km^2 [c]	2017 Deaths (in thousands)[b]	2017 Deaths/km^2 [c]
Shandong	124.4 (93.0, 143.0)	0.81 (0.60, 0.93)	98.1 (69.9, 116.0)	0.64 (0.45, 0.75)
Henan	116.7 (88.3, 133.2)	0.70 (0.53, 0.80)	92.9 (67.5, 108.8)	0.56 (0.40, 0.65)
Jiangsu	98.6 (72.1, 114.9)	0.96 (0.70, 1.12)	77.8 (54.2, 93.4)	0.76 (0.53, 0.91)
Hebei	98.4 (75.6, 111.2)	0.52 (0.40, 0.59)	77.1 (56.3, 89.8)	0.41 (0.30, 0.48)
Sichuan	87.8 (62.7, 103.8)	0.18 (0.13, 0.22)	68.8 (46.5, 84.2)	0.14 (0.10, 0.17)
Guangdong	80.2 (56.0, 96.7)	0.45 (0.31, 0.54)	66.1 (43.4, 82.4)	0.37 (0.24, 0.46)
Anhui	70.0 (51.7, 81.4)	0.50 (0.37, 0.58)	56.7 (39.8, 67.6)	0.41 (0.29, 0.48)
Hubei	68.0 (50.1, 79.0)	0.37 (0.27, 0.42)	52.5 (36.8, 63.0)	0.28 (0.20, 0.34)
Hunan	67.2 (47.8, 79.6)	0.32 (0.23, 0.38)	53.8 (36.1, 65.9)	0.25 (0.17, 0.31)
Zhejiang	57.6 (41.3, 67.7)	0.56 (0.41, 0.66)	45.0 (30.6, 55.0)	0.44 (0.30, 0.54)
Liaoning	50.0 (35.9, 59.0)	0.34 (0.25, 0.40)	37.0 (24.7, 45.7)	0.25 (0.17, 0.31)
Shaanxi	41.1 (30.3, 47.8)	0.20 (0.15, 0.23)	33.3 (23.5, 39.8)	0.16 (0.11, 0.19)
Guangxi	39.5 (27.4, 47.5)	0.17 (0.12, 0.20)	30.7 (19.8, 38.5)	0.13 (0.08, 0.16)
Jiangxi	38.1 (26.7, 45.6)	0.23 (0.16, 0.27)	29.1 (19.0, 36.4)	0.17 (0.11, 0.22)
Shanxi	36.7 (26.9, 42.7)	0.23 (0.17, 0.27)	30.2 (21.2, 36.2)	0.19 (0.14, 0.23)
Heilongjiang	33.7 (23.3, 40.7)	0.07 (0.05, 0.09)	25.5 (16.4, 32.0)	0.06 (0.04, 0.07)
Yunnan	31.0 (20.5, 38.4)	0.08 (0.05, 0.10)	23.2 (13.9, 30.3)	0.06 (0.04, 0.08)
Chongqing	29.9 (20.8, 35.9)	0.36 (0.25, 0.44)	24.8 (16.3, 30.6)	0.30 (0.20, 0.37)
Jilin	26.9 (18.9, 32.0)	0.14 (0.10, 0.17)	20.7 (13.8, 25.4)	0.11 (0.07, 0.14)
Guizhou	26.3 (17.8, 32.2)	0.15 (0.10, 0.18)	20.6 (12.9, 26.2)	0.12 (0.07, 0.15)
Beijing	26.0 (19.5, 29.8)	1.55 (1.16, 1.78)	25.8 (18.5, 30.4)	1.53 (1.10, 1.81)
Fujian	25.8 (17.0, 32.0)	0.21 (0.14, 0.26)	22.0 (13.7, 28.0)	0.18 (0.11, 0.23)
Shanghai	25.4 (18.4, 29.7)	4.03 (2.92, 4.72)	19.7 (13.5, 23.8)	3.12 (2.14, 3.79)
Gansu	21.3 (14.8, 25.6)	0.05 (0.03, 0.06)	16.2 (10.5, 20.4)	0.04 (0.02, 0.04)
Tianjin	19.1 (14.5, 21.8)	1.69 (1.29, 1.93)	15.9 (11.6, 18.6)	1.40 (1.02, 1.64)
Inner Mongolia	17.9 (12.0, 21.9)	0.02 (0.01, 0.02)	13.6 (8.6, 17.1)	0.01 (0.01, 0.01)
Xinjiang	15.8 (11.0, 19.0)	0.01 (0.01, 0.01)	12.5 (8.1, 15.7)	0.01 (0.00, 0.01)
Hainan	5.4 (3.4, 6.8)	0.16 (0.10, 0.20)	4.3 (2.6, 5.7)	0.13 (0.08, 0.17)
Ningxia	4.8 (3.3, 5.8)	0.07 (0.05, 0.09)	4.2 (2.8, 5.2)	0.06 (0.04, 0.08)
Qinghai	4.0 (2.8, 4.8)	0.01 (0.00, 0.01)	2.5 (1.6, 3.2)	0.00 (0.00, 0.00)
Xizang	1.6 (1.1, 1.9)	0.00 (0.00, 0.00)	1.3 (0.8, 1.6)	0.00 (0.00, 0.00)

[a]The order of the provinces is arranged according to the size of the deaths attributable to $PM_{2.5}$ in 2013.
[b]Total deaths attributable to $PM_{2.5}$.
[c]Total deaths attributable to $PM_{2.5}$ divided by the area of the province.

about 28 deaths per 100,000 people in 2015). Clearly, the burden of disease remained high in China in 2017, and more aggressive air pollution control strategies should be implemented in the near future.

The deaths attributed to $PM_{2.5}$ in 31 provinces are summarized in Table 3. In 2013, the provinces of Shandong, Henan, Jiangsu, Hebei, Sichuan, and Guangdong exhibited the largest health burden, and the related deaths in these regions are 124,000 (95% CI: 93,000; 143,000), 117,000 (95% CI: 88,000; 133,000), 99,000 (95%: CI: 72,000; 115,000), 98,000 (95% CI: 76,000; 111,000), 88,000 (95% CI: 63,000; 104,000), and 80,000 (95% CI: 56,000; 97,000) cases per year, respectively. In 2017, the same six provinces had the highest numbers of deaths attributable to $PM_{2.5}$, but they were lower by 18–22%. This is largely affected by the population. The six most populous provinces are Guangdong, Shandong, Henan, Sichuan, Jiangsu, and Hebei, accounting for 8.0, 7.2, 6.9, 6.0, 5.9, and 5.4% of the total national population, respectively. Guangdong has the lowest $PM_{2.5}$ concentration among these provinces, so it ranks sixth. The results will be different if the population density is considered. After dividing the number of deaths by the area of the province, the results show that Shanghai, Tianjin, and Beijing experienced the highest health burden per unit area in 2013, which was 4.03, 1.69, and 1.55 cases per km^2. The ranking in 2017 changed to Shanghai, Beijing, and Tianjin. The three cities are municipalities of China with strong economic strength. Shanghai is one of the economic powerhouses of China, and it has the highest population density, with a population of 24 million in $\sim 6{,}300\,km^2$. Strengthening pollution control in megacities with dense populations is more effective and will bring large health benefits.

From 2013 to 2017, our results suggest that $\sim$287,000 deaths per year were avoided across China. Approximately 25,000; 39,000; 14,000; and 24,000 deaths per year were avoided in BTH, YRD, Guangdong, and Sichuan-Chongqing, respectively. We assumed a linear reduction of $PM_{2.5}$-attributable deaths during this period, since annual $PM_{2.5}$ concentrations exhibited approximate linear declining trends during 2013 to 2017 (Figure S9). Avoided cases were estimated to be about 72,000; 144,000; 215,000; and 287,000 in 2014, 2015, 2016, and 2017, respectively. The total avoided deaths in China were estimated to be 718,000 cases during 2013–2017. Therefore, the health benefits of the Action Plan are $\sim$3,762 billion (95% CI: 2,520 billion; 5,012 billion) CNY during 2013 to 2017. The benefits of BTH, YRD, Guangdong, and Sichuan-Chongqing are $\sim$328 (95% CI: 219, 436), 511 (95% CI: 342, 681), 183 (95% CI: 123, 244), and 314 (95% CI: 211, 419) billion CNY during 2013 to 2017.

The health benefits from the Action Plan were estimated separately from other factors (i.e., meteorological, mortality rates, and population) through scenario analysis. Figure 6 presents the change of deaths due to the Action Plan as well as the other factors. The reduction of deaths shown in blue indicates that the change in the factor is beneficial for health. High $PM_{2.5}$ has an association with a dense population. The emission reduction of the Action Plan is the largest in areas with high $PM_{2.5}$ pollution. Therefore, the concentration reduction in the grid cells with larger population and a higher baseline concentration is the most significant (Figure S7E,F). Thus, the reduction in anthropogenic emissions by the Action Plan is clearly the largest contribution to the health benefits from 2013 to 2017. A large number of avoided deaths due to emission reductions from the Action Plan were found in northern, eastern, and central

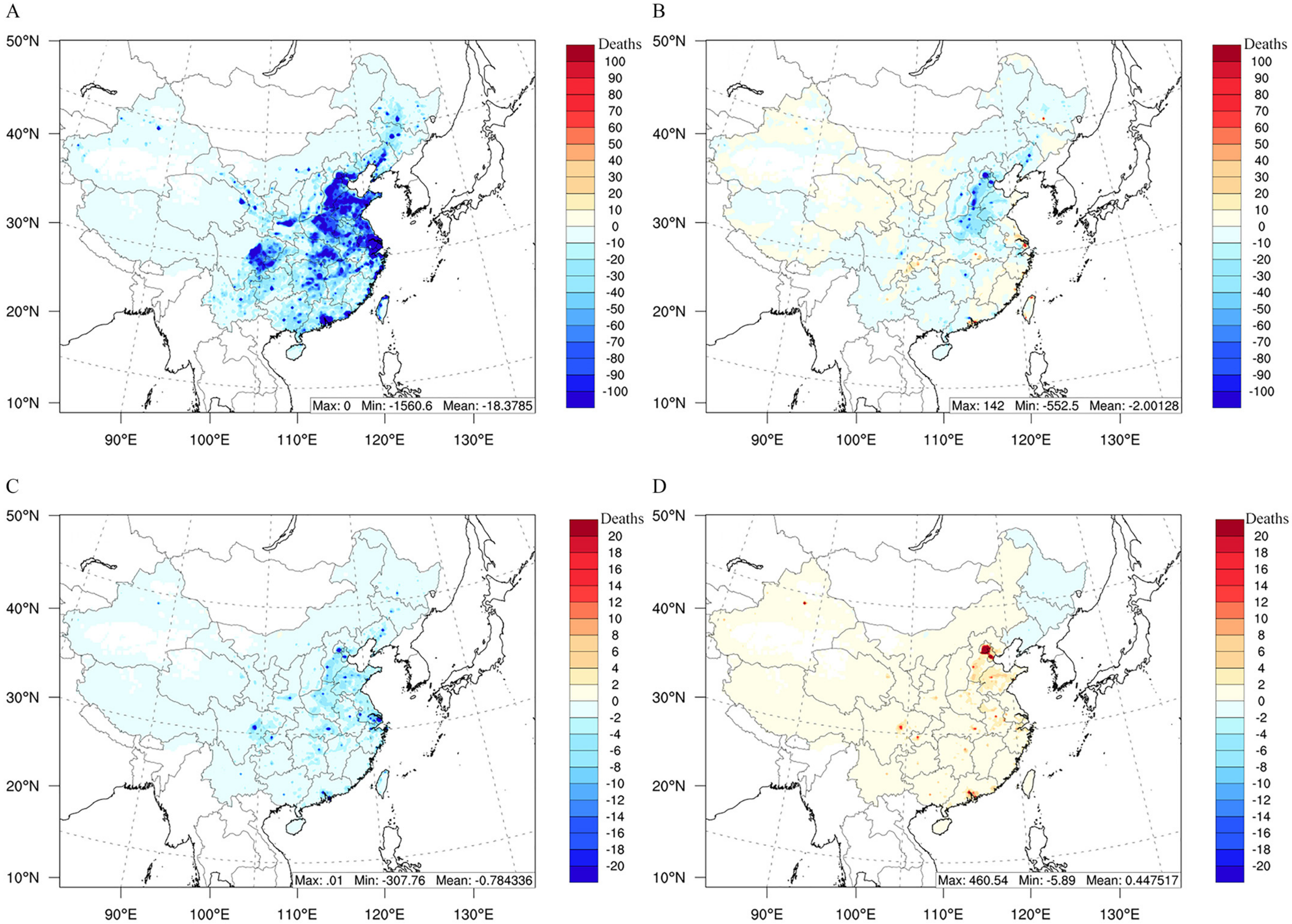

Figure 6. Estimated numbers of deaths due to the change in (A) anthropogenic emissions (by the Air Pollution Prevention and Control Action Plan), (B) meteorological conditions, (C) mortality rates, and (D) population. Negative values indicate that the change in the factor is beneficial for health.

China, as well as in some urban areas. Similar to the spatial distribution of $PM_{2.5}$ concentration response to meteorological variations, the meteorological conditions in 2017 were beneficial in reducing $PM_{2.5}$ concentrations and associated health impacts in northeast China and the Northern China Plain. The reduction in mortality rates slightly contributed to the reduction of health burden, while the increased population in most of China slightly increased the health burden, except for in northeast China. The avoided deaths attributable to different factors were aggregated by provinces (Figure S10). Overall, the emission reductions due to the Action Plan were more important than any other factors for reducing the adverse health outcomes during 2013 to 2017.

The avoided deaths are compared in four regions, as shown in Figure 7. In this study, $\sim$19,000; 39,000; 14,000; and 24,000 deaths were avoided due to emission reductions in BTH, YRD, Guangdong, and Sichuan-Chongqing, accounting for 75.5, 99.1, 97.3, and 99.3% of the total health benefits in these regions, respectively (Table 4). The meteorological variation has a considerable contribution to the health effect in BTH but presents little impact in other regions. The reduced baseline mortality rates slightly contribute to the health benefit, with $\sim$3–4% across all regions. Population growth lead to a large health burden, especially in BTH, and accounted for -7.2%. Overall, changes in anthropogenic emissions, meteorology, mortality rates, and population contributed 88.7, 9.6, 3.8, and -2.2%, respectively, to the total health benefit in China between 2013 and 2017.

Discussion and Conclusions

This study conducted assessments of the environmental and health benefits by the implementation of the Action Plan during 2013 to 2017. $PM_{2.5}$-mortality was estimated based on the spatially resolved fused concentration and population data using the IER model. To better understand the effectiveness of the Action Plan, the relative contributions to the health impacts from four factors, emission reductions, changed meteorology, population growth, and the change in baseline mortality rates, were quantified for mainland China and four key regions. Our results suggest that the estimated total $PM_{2.5}$-mortality in China was 1.389 million (95% CI: 1.005 million, 1.631 million) in 2013 and substantially reduced to 1.102 million (95% CI: 755,000; 1.337 million) in 2017. Emission controls contributed 88.7% of the total reduction in $PM_{2.5}$-mortality during this period, while changed meteorology, the change in baseline mortality rates, and population growth contributed 9.6, 3.8, and -2.2% of the total reduction in $PM_{2.5}$-mortality, respectively. In the BTH region, the relative contributions of emission controls and changed meteorology to the reduction of $PM_{2.5}$-mortality are estimated to be $\sim$75.5 and 28.2%, respectively.

Although the interannual variation of meteorological conditions will affect regional air quality, emission controls are the dominating factor for the air quality improvement and related health benefits. Currently, the $PM_{2.5}$ pollution levels and related

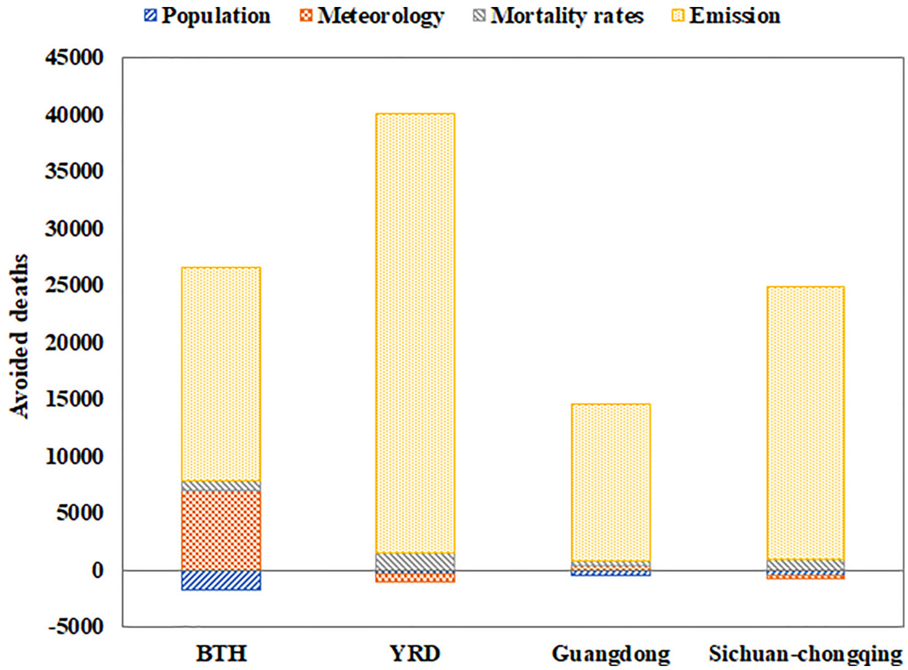

Figure 7. Estimated numbers of avoided deaths attributable to factors in the Beijing–Tianjin–Hebei, Yangtze River Delta, Guangdong, and Sichuan Province and Chongqing city (Sichuan-Chongqing) regions.

health burden are still at a relatively high level in China when compared with other developed countries. Therefore, the emission controls implemented in densely populated areas, such as large urban agglomerations, will maximize the health benefits because of the strong positive correlations between the spatial distributions of air pollution and population (Wang et al. 2017). With the continual decrease in anthropogenic emissions and changes in the regional climate, interannual variation of meteorology will need to be taken into account in future control policy designs.

The large health burden is mainly located in northern, eastern, and central regions in China. Total $PM_{2.5}$-mortality of BTH, YRD, Guangdong, and Sichuan-Chongqing, which accounts for 12.2% of the area of China and 35.9% of the population of China, contributed 38.2% of the national $PM_{2.5}$ exposure–related health burden in 2017. Greater air pollution control efforts are suggested for those regions to gain larger health benefits. However, other regions, such as Shandong and Henan, also experience a high health burden, so controls in those provinces need to be strengthened as well.

This study is subject to some uncertainties commonly presented in the analysis of health impacts that mainly come from the air quality data, relative risks, population, and mortality rates. The mean value and 95% CI of health effects were used to reflect the error range from IER models. Population and mortality rates were obtained from reliable data sources to reduce uncertainties. We used population and mortality rates from 2016 when conducing the analysis in 2017, and they may slightly underestimate the effect of the changed population and mortality rates on health. But the changes between 2016 and 2017 are very small (population in 2016: 1,383 million; population in 2017: 1,390 million), so the impact is negligible. In addition, the spatial variability of the mortality rates also affects the results. Chowdhury and Dey (2016) estimated that the annual deaths to be ~15% lower when assuming a uniform baseline mortality across India compared with the estimate adjusted for state-specific baseline mortality. Since we adopted the uniform mortality rates across China due to the lack of province-specific mortality, our estimates may have some uncertainties toward actual health effects. Overall, our results are comparable with those of recent studies. In this study, exposure to $PM_{2.5}$ caused 1.102 million deaths in China in 2017. The analysis of the GBD study in 2015 shows 1.108 million deaths attributable to $PM_{2.5}$ pollution (Cohen et al. 2017). Approximately 1.367 million deaths were attributed to $PM_{2.5}$ exposure in 2013 (Liu et al. 2016). The health burden attributable to $PM_{2.5}$ in 2015 was ~1.515 million deaths (Song et al. 2017).

In summary, about 287,000 deaths per year in China were avoided between 2013 and 2017 due to the implementation of the Action Plan. The health benefits of the Action Plan are ~3,762 billion CNY during 2013 to 2017. To control air pollution, the Chinese government has invested considerable financial resources. According to the pre-evaluation of Dong and Yuan (2016), the total investment in the Action Plan is 1,840 billion CNY. Compared with the cost of pollution control, our estimates suggest that the health benefits are ~two times higher, showing that the investment in air pollution control actually gets paid back through the significant cost savings resulting from the resultant reductions in the health burden. In addition, air quality improvement has mental health benefits as well (Xue et al. 2019). The results of benefit attributable to the Action Plan in this study may be underestimated. Despite the uncertainty in health benefit monetization, the value highlights the importance of air pollution controls. The improvement in air quality during the Action

Table 4. Estimated relative contributions of changes in anthropogenic emissions, meteorological conditions, mortality rates, and population to avoided deaths in the four regions and nationwide, 2013–2017.

Region	Anthropogenic emission	Meteorology	Mortality rates	Population
BTH	75.5%	28.2%	3.5%	−7.2%
YRD	99.1%	−1.8%	3.7%	−1.0%
Guangdong	97.3%	2.8%	3.2%	−3.3%
Sichuan-Chongqing	99.3%	−1.0%	3.8%	−2.1%
China	88.7%	9.6%	3.8%	−2.2%

Note: BTH, Beijing–Tianjin–Hebei; Sichuan-Chongqing, Sichuan Province and Chongqing City; YRD, Yangtze River Delta.

Plan reduced the burden of disease by 20.7%. However, the $PM_{2.5}$-mortality in 2017 was still high. It is expected that much larger health benefits will be achieved if a more aggressive control strategy is implemented in the future.

Acknowledgments

This work was supported in part by National Science Foundation of China (21625701), National Key Research and Development (R&D) program of China (2016YFC0207601), and National Research Program for Key Issues in Air Pollution Control (DQGG0301 and DQGG0304). This work was completed on the Explorer 100 cluster system of Tsinghua National Laboratory for Information Science and Technology. We appreciate that Dr. R. Mathur helped improve the language of the paper.

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