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ABSTRACT

Emissions from power plants in China and India contain a myriad of fine particulate matter ($PM_{2.5}$, PM ≤ 2.5 μm in diameter) precursors, posing significant health risks among large, densely settled populations. Studies isolating the contributions of various source classes and geographic regions are limited in China and India, but such information could be helpful for policy makers attempting to identify efficient mitigation strategies. We quantified the impact of power generation emissions on annual mean $PM_{2.5}$ concentrations using the state-of-the-art atmospheric chemistry model WRF-Chem (Weather Research Forecasting model coupled with Chemistry) in China and India. Evaluations using nationwide surface measurements show the model performs reasonably well. We calculated province-specific annual changes in mortality and life expectancy due to power generation emissions generated $PM_{2.5}$ using the Integrated Exposure Response (IER) model, recently updated IER parameters from Global Burden of Disease (GBD) 2015, population data, and the World Health Organization (WHO) life tables for China and India. We estimate that 15 million (95% Confidence Interval (CI): 10 to 21 million) years of life lost can be avoided in China each year and 11 million (95% CI: 7 to 15 million) in India by eliminating power generation emissions. Priorities in upgrading existing power generating technologies should be given to Shandong, Henan, and Sichuan provinces in China, and Uttar Pradesh state in India due to their dominant contributions to the current health risks.

1. Introduction

Exposure to fine particulate matter ($PM_{2.5}$) has been linked to mortality from a variety of causes in both adults (ischemic heart disease, stroke, chronic obstructive pulmonary disease, lung cancer) and children (acute lower respiratory infections) (Dockery et al., 1993; Hoek et al., 2013). In Asia, particularly China and India, $PM_{2.5}$ pollution has been an increasingly important research topic, and has attracted worldwide attention. A large fraction of the world's population lives in these two countries where they are exposed to extremely unhealthy air. Lim et al. (2012) estimated that ambient $PM_{2.5}$ pollution is the 4th largest contributor to deaths in China and the 5th in India.

Anthropogenic activities, including industry, power generation, transportation, and residential energy usage (heating and cooking), contribute to the total ambient concentrations of $PM_{2.5}$ directly and indirectly through gas-to-particle conversions. In China and India, secondary inorganic aerosols account for a large portion of the ambient $PM_{2.5}$ mass concentration (Huang et al., 2014; Singh et al., 2017),

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which is mainly formed from sulfur dioxide (SO_2) and nitrogen oxides (NO_x). A significant use of coal in China and India generates large amounts of SO_2 and NO_x (Lu et al., 2011). In both China and India, power and industrial sectors are the largest sector consumers of coal (Lu et al., 2011). According to statistics in Li et al. (2017), the power generation sector contributes 28.5% and 32.5% to SO_2 and NO_x emissions in China, and 59.1% and 25.0% in India.

For decades, the influence of power generation emissions on health damages in the United States has been of interest (Buonocore et al., 2014; Fann et al., 2013; Levy and Spengler, 2002; Levy et al., 2002, 2009). With growing attention to serious air pollution in China and India, the resulting health risks have become the focus of many studies. The 2010 Global Burden of Disease report (Lim et al., 2012) analyzed the worldwide impacts of $PM_{2.5}$ and estimated that 1.2 million lives (corresponding to 25 million DALYs (Disability-Adjusted Life Year)) were lost in China and 0.6 million lives (corresponding to 17.7 million DALYs) in India each year due to ambient $PM_{2.5}$ exposure, but results were not disaggregated to identify the impacts of various emission sources. Lelieveld et al. (2015) provided a similar assessment of the worldwide mortality impacts of $PM_{2.5}$; they estimated that 1.3 million deaths each year in China and 0.6 million in India were attributable to ambient $PM_{2.5}$ exposure, suggesting additionally that 18% and 14% of deaths attributable to $PM_{2.5}$ exposure, respectively, were linked to power generation. More recently, GBD MAPS Working Group (2016) analyzed the mortality impacts of $PM_{2.5}$ in China and estimated that 0.9 million lives were lost in 2013 due to ambient $PM_{2.5}$ exposures. GBD MAPS Working Group (2016) also provided a breakdown of the contributions of multiple major source classes to this impact and the geographic distribution of the contributions.

These studies present quite different pictures of the importance of utility coal combustion. In any study of the impacts of $PM_{2.5}$ on mortality, the analyst faces several important choices:

- What emissions inventory to use;
- What approach to employ for atmospheric modeling, at what spatial resolution;
- Which exposure-response coefficients to use;
- Whether to focus on marginal or average impacts; and
- Whether to report results as ‘attributable deaths,’ ‘years of life lost,’ and/or ‘DALYs.’

The choices underlying several previous studies are summarized in Table 1. Some of these studies relied on relatively simple global chemical transport models, in which important mesoscale information (i.e. boundary layer processes, cloud physics, etc.) might be missing and/or oversimplified. In addition, some are driven by older emissions inventories, which now have been replaced. Finally, many of the studies use older estimates (2010 or 2013) of the IER parameters, and fail to show convincing evidence of that their atmospheric fate and transport models agree with ground based $PM_{2.5}$ measurements.

This study fills these gaps by using a regional scale chemistry-meteorology model WRF-Chem (Weather Research Forecasting-Chemistry, Gao et al., 2015, 2016a, 2016b, 2016c, 2017; Marrapu et al., 2014); nationwide surface $PM_{2.5}$ measurements in both China and India; a state-of-the-art emission inventory; and the newly updated IER parameters from GBD 2015 (Cohen et al., 2017). We present our results in terms of both the number of deaths attributable to $PM_{2.5}$ exposure and the number of years of life lost (YLL) due to $PM_{2.5}$ exposure.

2. Materials and methods

2.1. Atmospheric modeling

In this study, the WRF-Chem model version 3.6.1 was implemented to cover both China and India. WRF-Chem is a fully online coupled regional scale meteorology-chemistry model that enables aerosol-radiation-cloud interactions (Grell et al., 2005), and includes multiple options for physical and chemical parameterizations. The main chosen options for physical parameterizations of the Planetary Boundary Layer (PBL), cloud microphysics, and land surface are listed in Table S1, which include the Yonsei University PBL scheme (Hong et al., 2006), the Noah land surface scheme, the Goddard shortwave radiation scheme (Chou et al., 1998), the RRTM (Rapid Radiative Transfer Model) long wave radiation scheme (Mlawer et al., 1997), and the Lin cloud microphysics scheme (Lin et al., 1983). We use the Carbon Bond Mechanism version Z (CBMZ, Zaveri and Peters, 1999) for gas-phase chemistry, and the Model for Simulating Aerosol Interactions and Chemistry (MOSAIC, Zaveri et al., 2008), which calculates size resolved sulfate, nitrate, ammonium, black carbon, organic carbon, and secondary organic aerosol (SOA). Dust and sea-salt are also considered in the model configuration. Simulations are conducted for the entire year of 2013, and the model was initialized at the beginning of each month, with the last 5 days of the previous month employed as model spin-up. The model is configured with a horizontal resolution of 60 km and with 27 vertical levels up to 50 hPa. Meteorological initial and boundary conditions are obtained from the National Centers for Environmental Prediction final analysis (NCEP FNL) 6-hourly $1^\circ \times 1^\circ$ data, and analyses of wind, temperature and water vapor are nudged to correct model meteorology fields using the four-dimensional data assimilation (FDDA) method. Chemical initial and boundary conditions are taken from the Model for Ozone and Related chemical Tracers, version 4 (MOZART-4) global simulations (Emmons et al., 2010).

2.2. Emissions

Anthropogenic emissions are adopted from the MIX emission inventory (Li et al., 2017), which combines five emission inventories for Asia and is considered as the most advanced inventory for Asia to date. Among them, the Multi-resolution Emission Inventory for China (MEIC) developed by Tsinghua University is used over China, and the ANL

Table 1
Summary of choices of estimation inputs in previous studies.

Study	Emissions inventory	Atmospheric model & resolution	Exposure-response coefficients	Marginal or average impacts	Results reported
Lim et al., 2012[a]	n/a	n/a	2010	Marginal	Attributable deaths & DALYs
Lelieveld et al., 2015	EDGAR	EMAC, $1.1^\circ \times 1.1^\circ$ degree	2010	Marginal	Attributable deaths
GBD MAPS Working Group (2016)	MIX	GEOS-Chem, 0.5×0.667 degree	2013	Marginal	Attributable deaths
GBD 2015[b]	n/a	n/a	2015	Marginal	Attributable deaths & DALYs

[a] Global estimates of $PM_{2.5}$ at $0.1^\circ \times 0.1^\circ$ scale: combination of TM5 global chemical transport model simulated $PM_{2.5}$ (at $1^\circ \times 1^\circ$ resolution), satellite aerosol optical depth (AOD) derived $PM_{2.5}$ (the relationship between AOD and $PM_{2.5}$ is calculated using GEOS-Chem at $2^\circ \times 2.5^\circ$ resolution), and surface PM measurements (Brauer et al., 2012).

[b] Global estimates of $PM_{2.5}$ at $0.1^\circ \times 0.1^\circ$ scale: combined estimates from satellite AOD, chemical transport models (GEOS-Chem) and ground-level measurements (Cohen et al., 2017; van Donkelaar et al., 2015).

emission inventory developed at the Argonne National Laboratory is used over India (ANL-India). Power plant emissions in MEIC are taken from the China coal-fired Power Plant Emission Database (CPED), which includes estimates of emissions for each generation unit considering fuel consumption rates, fuel quality, combustion technology and emission control technology (Li et al., 2017). In ANL-India, power plant emissions are calculated also for each generation unit based on the reports of the Central Electricity Authority (CEA), which includes detailed information on geographical location, capacity, fuel type, electricity generation, time the plant was commissioned/decommissioned, etc. (Li et al., 2017). The ANL-India emission inventory covers only some MIX species (SO_2, BC, and OC for all sectors, and NO_x for power plants), and emissions of other species are taken from the REAS2 (Regional Emission Inventory in Asia version 2, Kurokawa et al., 2013) inventory (Li et al., 2017). The MIX inventory includes 10 species, namely SO_2, NO_x, CO, non-methane volatile organic compounds (NMVOCs), ammonia (NH_3), $PM_{2.5}$, PM_{10}, black carbon (BC), organic carbon (OC), and carbon dioxide (CO_2). In this study, the MEIC data for 2010 are replaced in MIX with the revised results from MEIC 2013, but emissions for India are not changed.

Biogenic emissions are calculated online using the MEGAN model (Model of Emissions of Gases and Aerosols from Nature, Guenther et al., 2012), and the driving variables of this model include land cover, weather, and atmospheric chemical composition. GFEDv4 (Global Fire Emissions Database, Version 4) emissions are used for open biomass burning, based on satellite information on fire activity and vegetation productivity (Randerson et al., 2015). Other emissions including online dust emissions and online sea-salt emissions are also considered.

2.3. Study design

We explore the impact of each emission sector on annual mean $PM_{2.5}$ concentrations for the year 2013 through a series of simulations. Descriptions of these simulations are listed in Table S2. The BASE case includes all anthropogenic emission sectors, biogenic emissions, and biomass burning emissions. In the noIND case, the anthropogenic emissions from the industrial sector are excluded, and all the other settings are the same as in the BASE case. The remaining cases are similar. The noPOW case excludes power plant emissions, the noAGR case excludes agriculture emissions, the noTRA case excludes transportation emissions, the noRES case excludes residential emissions, and the noBB case excludes biomass burning emissions. The differences between BASE and noIND, BASE and noPOW, BASE and noAGR, BASE and noTRA, BASE and noRES, and BASE and noBB, are considered estimates of the impact of eliminating industrial emissions, power plant emissions, transportation emissions, residential emissions, and biomass burning emissions respectively. The contributions of source sectors outside the domain are not further separately quantified in this study.

2.4. Observational networks

This study benefits from a wealth of nationwide surface $PM_{2.5}$ measurements in China and India which allow us to evaluate the performance of the WRF-Chem simulated $PM_{2.5}$ concentrations. Since January 2013, the China National Environmental Monitoring Center (CNEMC) has released monitored $PM_{2.5}$ concentrations to the public. The CNEMC monitoring sites (shown as red dots in Fig. S1) are located mostly in east China. Hourly average $PM_{2.5}$ concentrations for 2013 were downloaded from the www.cnemc.cn website. This dataset has been used widely to statistically evaluate air quality models across China (Hu et al., 2017). Modeling of Atmospheric Pollution and Networking (MAPAN) was set up by the Indian Institute of Tropical Meteorology (IITM) under the project SAFAR (System of Air Quality and weather Forecasting And Research) (Beig et al., 2015, WMO report) across all of India to measure various pollutants, including ozone (O_3), NO_x, $PM_{2.5}$, PM_{10}, CO, hydrocarbon, BC and OC, as well as weather parameters. The measured $PM_{2.5}$ at the MAPAN sites are used in this study to evaluate model performance for India.

2.5. Mortality analysis

The lack of cohort mortality evidence in developing countries, such as China and India, hinders research on health impacts attributable to $PM_{2.5}$ exposure. Burnett et al. (2014) developed integrated exposure response (IER) functions to include data from western cohort studies of exposures to $PM_{2.5}$ in ambient air and the smoke from active and second-hand tobacco smoking as well as from the burning of solid fuels for household cooking and heating. We rely on the 2015 GBD IER because it is the most widely accepted and employed synthesis of the epidemiological evidence on the mortality impacts of $PM_{2.5}$. In this study, annual mean ambient $PM_{2.5}$ concentrations derived from the WRF-Chem model are taken into the IER functions to examine mortality attributable to $PM_{2.5}$ exposure.

In GBD the mortality burden attributable to $PM_{2.5}$ is calculated for four diseases among adults, namely ischemic heart disease (IHD), stroke (STK, including both ischemic and hemorrhagic stroke), lung cancer (LC), and chronic obstructive pulmonary disease (COPD), and for one disease among young children, acute lower respiratory infections (LRI). The RR for each disease is calculated as,

$$RR_{i,j,k}(C_l) = \begin{cases} 1 + \alpha_{i,j,k}(1 - e^{-\beta_{i,j,k}(Cl - C_0)^{\gamma_{i,j,k}}}), & Cl \geq C_0 \\ 1, & Cl < C_0 \end{cases} \tag{1}$$

where C_l is the annual $PM_{2.5}$ concentrations calculated from the WRF-Chem model in the l[th] geographic region, and C_0 is the counterfactual concentration; $\alpha_{i,\,j,\,k}$, $\beta_{i,\,j,\,k}$ and $\gamma_{i,\,j,\,k}$ are the parameters used to describe the shape of IER curves in the i[th] age and j[th] sex group for the k[th] disease.

Our calculations rely on the GBD 2015 IER parameter estimates reported by Cohen et al. (2017) for $\alpha_{i,\,j,\,k}$, $\beta_{i,\,j,\,k}$, $\gamma_{i,\,j,\,k}$ and C_0,. These new parameters reflect all cohort studies conducted on subjects living in the US and Western Europe published as of mid-2016. More detailed explanations for the revised methods are documented in the appendix for Cohen et al. (2017).

The relative risk (RR) factors are used then to calculate population attributable fractions (PAF, Eq. (2)), for each disease for each age and sex subgroup.

$$PAF_{i,j,k} = \frac{RR_{i,j,k}(C_l) - 1}{RR_{i,j,k}(C_l)} \tag{2}$$

$$\Delta M_{i,j,k,l} = PAF_{i,j,k,l} \times y_{0i,j,k,l} \times Pop_{i,j,l} \tag{3}$$

Eq. (3) is used to calculate mortality, M, attributable to $PM_{2.5}$ exposure for each disease. $y_{0i,\,j,\,k,\,l}$ represents the current age-sex-specific mortality rate for the k[th] disease, and $Pop_{i,\,j,\,l}$ reflects the size of the exposed population in that age-sex-specific group in that grid cell.

The United Nations (UN)-adjusted population distribution for years 2010 and 2015 from the Center for International Earth Science Information Network (CIESIN) are used to calculate the population exposure. To represent the population in 2013, we average data for years 2010 and 2015. The estimates for year 2013 are re-gridded to $0.5^\circ \times 0.5^\circ$ horizontal resolution, which approximates the WRF-Chem model resolution. National baseline age-sex-disease-specific dependent mortality rates for IHD, STK, LC, COPD, and LRI for years 2010 and 2015 are obtained from the GHDx (Global Heath Data Exchange) database. We interpolate to year 2013 based on the trends observed from 2005 to 2015. For China, provincial level baseline rates are estimated using the relationships between provincial and national rates shown in Xie et al. (2016).

While it is common to report the number of ‘premature deaths attributable to air pollution’ calculated in this manner, it has long been known that estimates of ‘premature deaths’ based on the attributable

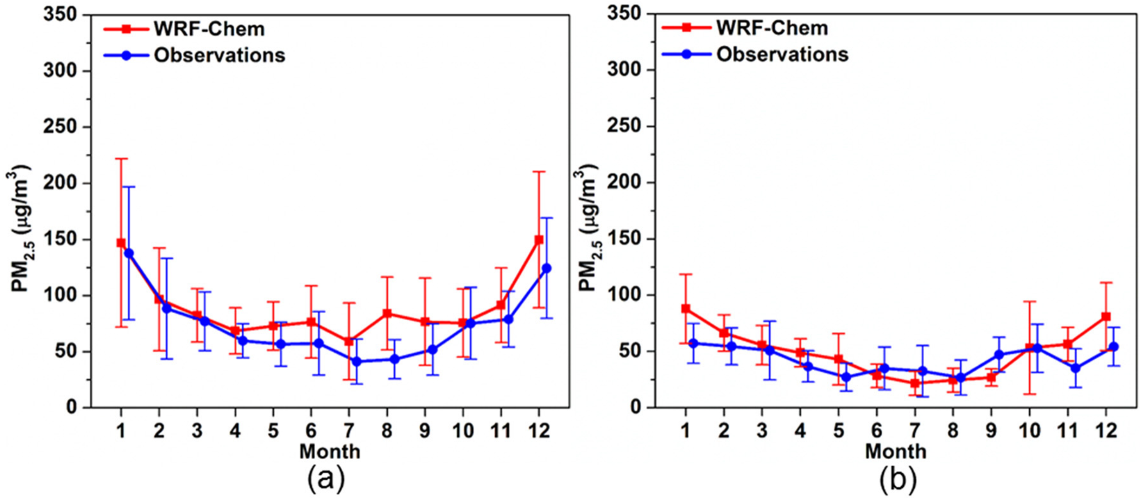

Fig. 1. Simulated and observed monthly mean $PM_{2.5}$ concentrations averaged across China (a) and India (b).

fraction may be biased in either direction and misleading (Robins and Greenland, 1989; Greenland and Robins, 1991). Fortunately, estimates of the impacts of PM on life expectancy are not affected by these issues and are therefore preferred.

The impact of PM exposure on the life expectancy of the population is calculated by multiplying the number of deaths ($N_{i,\ j}$) in each age and sex group by the remaining life expectancy ($L_{i,\ j}$) for that age and sex group and summing across all age and sex groups:

$$YLL = \sum_{i,j} N_{i,j} \times L_{i,j}$$

In this study, life tables for China and India for 2013, downloaded from the World Health Organization website, are used. In 2013, the life expectancy at birth for Chinese males and females were 74.1 and 77.2 years, respectively, and for Indian males and females 66.2 and 69.1 years, respectively (Table S3).

It is important to note that the approach we use is different from that used in the GBD studies. The GBD uses the life tables from Japan (which has the highest life expectancy in the world – 80.3 years for men and 86.7 for women) in the calculation of disability adjusted years lost (DALYs) rather than using country-specific life tables. They do so in an effort to reflect the potential benefits of improvements in air quality in a world where other public health risks had already been mitigated. As a result of this difference in approach, our estimates of life expectancy impacts will be lower by 5 to10% than those given by studies which use DALYs and rely on Japanese life tables.

2.6. Source sector attribution

The gridded annual surface $PM_{2.5}$ concentrations from the BASE case and the noPOW case are used to calculate the fraction of $PM_{2.5}$ health impacts attributable to power generation emissions using the following equation:

$$F_{pow} = \frac{PM_{BASE} - PM_{noPOW}}{PM_{BASE}}$$

where PM_{BASE} and PM_{noPOW} denote annual mean surface $PM_{2.5}$ concentrations from the WRF-Chem BASE and noPOW cases, respectively.

This approach is similar to that used in the China MAPS (Major Air Pollution Sources project) study for apportioning mortality impacts to various source classes. It differs however from the approach used by Lelieveld et al. (2015) – in which the contribution of a source class was computed using:

$$F_{source\ class} = \frac{M(PM_{BASE}) - M(PM_{without\ source\ class})}{M(PM_{BASE})},$$

where M denotes mortality.

It is important to recognize that the approaches taken by China MAPS and by Lelieveld et al. (2015) differ in the question they seek to answer. The approach of Lelieveld et al. (2015) follows the tradition of forward-looking 'consequential' analysis. It seeks to determine how large of a reduction in mortality would be expected if emissions from a single source class were eliminated. In contrast the China MAPS approach is rooted in backward-looking 'attributional analysis' and seeks to determine what fraction of total $PM_{2.5}$ related mortality is attributable to (caused by) emissions of a single source.

In cases where the exposure-response function is linear, these two approaches will give the same answer. However, given the strong nonlinearities of the IER concentration-response function, they will not in the current case. At current levels of PM exposure in China, the consequential approach used by Lelieveld et al. (2015) will give estimates of source class impacts that are significantly smaller – perhaps by a factor of 2 or 3 – than those from the attributional approach.

3. Results

3.1. Evaluation of surface $PM_{2.5}$

In this study, we compare the WRF-Chem outputs from the BASE case against surface $PM_{2.5}$ observations in the CNEMC network in China and the MAPAN network in India. Fig. 1 shows how our model performs in capturing temporal variations of $PM_{2.5}$ concentrations in China and India. In general, the simulated monthly and seasonal trends of $PM_{2.5}$ surface concentrations in China are consistent with surface measurements, with extremely high monthly $PM_{2.5}$ during winter months and relatively low concentrations during summer months (Fig. 1(a)). The calculated R^2 value for China is as high as 0.87. In China, $PM_{2.5}$ concentrations during summer are overestimated by our model, which is likely due to errors in model wet deposition. Summer is the season with a large amount of precipitation, but the 60 km horizontal resolution in this study is insufficient to capture the variability in summer precipitation. The calculated R^2 value for India is 0.54, and the simulated magnitudes of surface $PM_{2.5}$ concentrations are close to the measurements across India. Detailed comparisons for each observation site in China and India are presented in Fig. S2 and S3 in the supporting information.

For estimates of $PM_{2.5}$ exposure, spatial features are more important. We also evaluate the spatial distribution of simulated yearly

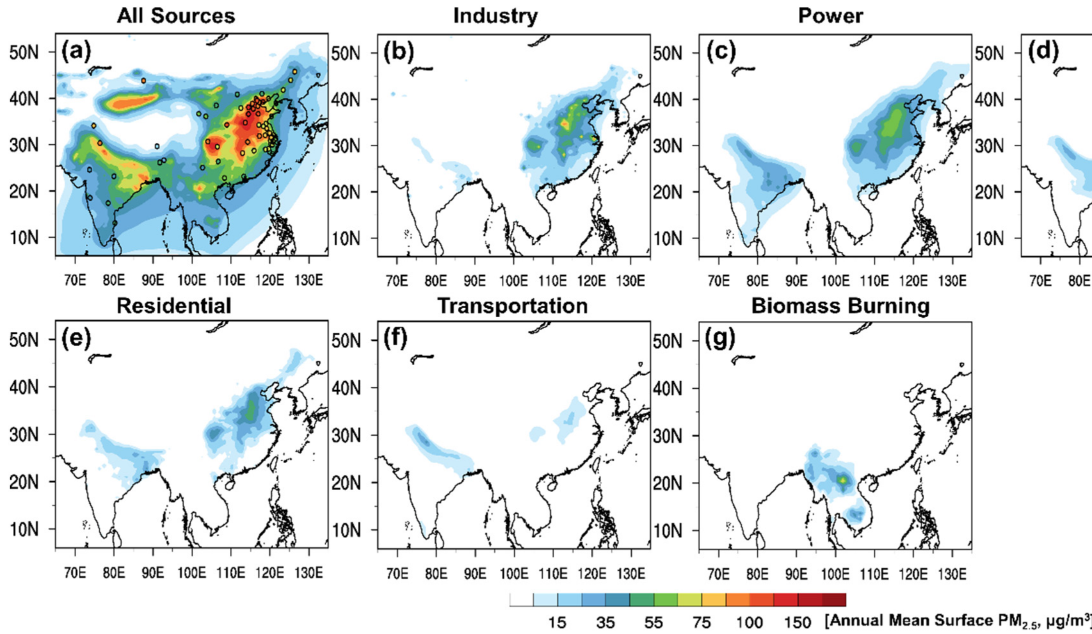

Fig. 2. Spatial distributions of annual mean surface $PM_{2.5}$ concentrations (a: observations are shown in dots) and sector contributions from industry, power plants, agriculture, residential, transportation and biomass burning (b–f).

Table 2
Estimated mortality attributable to $PM_{2.5}$ concentrations due to all sources and power plant emissions over China in 2013 (95% uncertainty confidential intervals are based on IER parameters) (thousand).

	Stoke	IHD	COPD	LC	LRI	Total
China						
All sources	365.7 (203.7–542.0)	388.1 (227.6–606.0)	345.4 (225.1–477.1)	150.3 (106.0–190.5)	81.7 (62.5–99.0)	1331.1 (824.8–1914.6)
Power plant	144.4 (81.0–213.6)	152.8 (90.2–238.9)	130.9 (86.0–180.5)	59.8 (42.4–75.5)	32.1 (24.6–38.7)	520.0 (324.3–747.3)
India						
All sources	123.2 (64.4–185.6)	191.4 (106.3–295.5)	300.9 (184.5–419.3)	18.0 (12.0–23.8)	170.4 (126.3–211.0)	803.8 (493.3–1135.2)
Power plant	41.0 (21.6–61.6)	63.4 (35.4–98.1)	100.4 (62.0–139.7)	6.1 (4.0–8.0)	57.0 (42.5–70.3)	267.9 (165.6–377.6)

mean $PM_{2.5}$ surface concentrations by comparing the model results against observations at 58 cities in China and 9 sites in India. As shown in Fig. 2(a), in China, high $PM_{2.5}$ concentrations are located mainly in eastern China and southwestern China (Sichuan Basin) due to high local emissions of air pollutants. Relatively high $PM_{2.5}$ concentrations in Xinjiang, in the northwest, result partly from windblown dust. In India, $PM_{2.5}$ pollution hotspots are located mostly in the Indo-Gangetic Plain (IGP), not only because of high emissions of air pollutants. Reduced ventilation due to obstruction from the Tibetan Plateau may also play a role. The calculated mean bias, index of agreement, and normalized mean bias are −15.7 (−5.7), 0.8 (0.77), and 21.1% (−12.5%) for China (India), respectively.

The model generally reproduces well the spatial patterns of observed $PM_{2.5}$ concentrations in 2013, with high magnitudes of $PM_{2.5}$ over South Hebei, Shandong and Henan provinces in China. Relatively low $PM_{2.5}$ magnitudes in south China are also well reproduced well by the model. For India, high measured concentrations of $PM_{2.5}$ over the IGP is simulated well by the model, and relatively low concentrations observed in southern regions are also consistent with the model results.

The above evaluations show that the WRF-Chem model has reasonable success in simulating both the temporal and spatial features of $PM_{2.5}$ concentrations in China and India, and results are consequently reliable for use in analysis of health exposures.

3.2. Impacts of source sectors on $PM_{2.5}$ concentrations

$PM_{2.5}$ in the atmosphere is emitted either directly or formed through gas-to-particle conversions from various emission source sectors. Understanding the contributions of source sectors on air quality and climate forcing is of great importance for policy makers, charged with design of emission control strategies. In this study, we examine the relative importance of individual source sectors on $PM_{2.5}$ concentrations in China and India excluding them one-by-one from model emission inputs in simulations (listed in Table S2). Fig. 2(b–g) shows the individual impact of industrial, power plant, agriculture, residential, transportation, and biomass burning emissions on annual mean $PM_{2.5}$ concentrations in China and India. In China, the industrial sector is the largest contributor, followed by power generation. In India, emissions from power generation significantly increase $PM_{2.5}$ concentrations, and have a larger effect compared with residential and other source sectors. Transportation emissions play a minor role in both countries and $PM_{2.5}$ increases induced by biomass burning are significant only in Southeast Asian countries. Over Laos and northern Thailand, $PM_{2.5}$ increases resulting from biomass burning can reach as high as 50 $\mu g/m^3$.

In China and India, secondary inorganic aerosols (mostly sulfate and nitrate formed via oxidation of SO_2 and NO_x emissions) account for a large fraction of the $PM_{2.5}$ mass concentration (Huang et al., 2014; Singh et al., 2017). In China, emissions from power generation contribute 28.5% of SO_2 and 32.5% of NO_x emissions. In India, the contribution of power generation of SO_2 emissions is almost 60% (Fig. S4). These significant emissions of SO_2 and NO_x by power generation in China and India lead to substantial increments in $PM_{2.5}$ mass concentrations, as shown in Figs. 2(c) and S5.

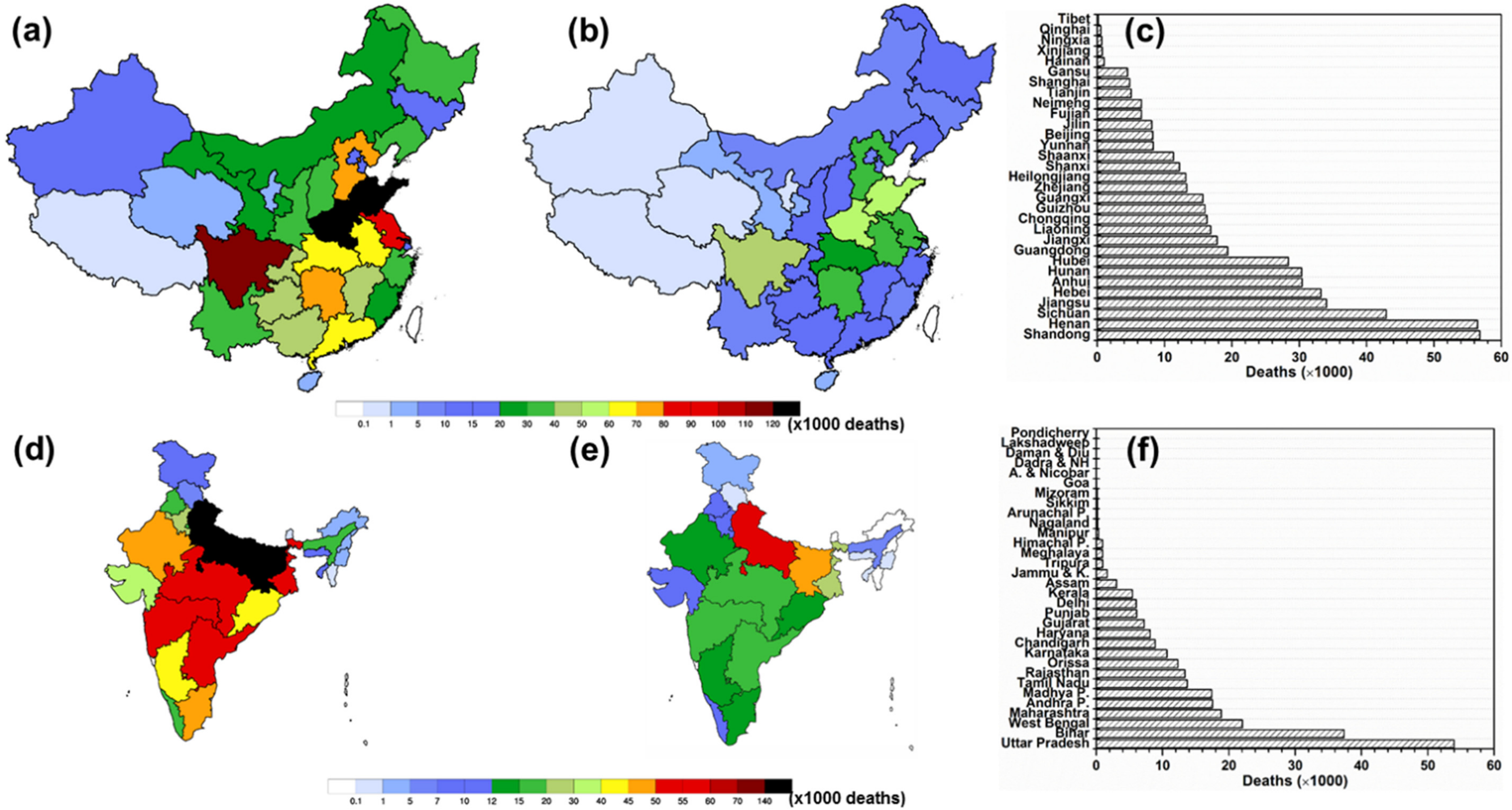

Fig. 3. Maps of provincial-level estimates of mortality attributable to $PM_{2.5}$ exposure due to all emissions (a), and power plant emissions (b), and provincial rankings of power plants induced mortality (c) in China; (d–f) are for India.

Table 3
Estimated YLL attributable to $PM_{2.5}$ concentrations due to all sources and power plant emissions over China in 2013 (95% uncertainty intervals are based on IER parameters) (million).

	Stoke	IHD	COPD	LC	LRI	Total
China						
All sources	5.6 (3.1–8.1)	6.0 (3.6–9.2)	16.3 (10.6–22.5)	7.1 (5.0–9.0)	3.9 (3.9–4.7)	38.9 (25.2–53.5)
POW	2.2 (1.2–3.2)	2.4 (1.4–3.6)	6.2 (4.1–8.5)	2.8 (2.0–3.6)	1.5 (1.2–1.8)	15.1 (9.9–20.7)
India						
All sources	1.7 (0.9–2.5)	2.8 (1.6–4.3)	17.1 (10.5–23.9)	1.0 (0.7–1.4)	9.7 (7.2–12.0)	32.3 (20.9–44.1)
POW	0.6 (0.3–0.8)	0.9 (0.5–1.4)	5.7 (3.5–7.9)	0.3 (0.2–0.5)	3.2 (2.4–4.0)	10.7 (6.9–14.6)

3.3. Mortality and YLL attributable to $PM_{2.5}$ exposure

Estimates of mortality attributable to $PM_{2.5}$ exposure due to all emissions and power generation emissions in China and India are listed in Table 2. The 95% uncertainty confidence intervals (CIs) are calculated based only on the uncertainties of IER curve parameters. Other sources of uncertainty, such as the uncertainty in air quality modeling (emissions, model setup, etc.), population datasets and the fundamental uncertainties inherent in applying a concentration-response function developed largely on the basis of epidemiology conducted in the US and Western Europe at much lower concentrations than those now prevalent in China and India to populations with a different genetic makeup, access to health care, diet and so forth to predict risks in China and India (Dockery and Evans, 2017), are not included. Total ambient $PM_{2.5}$ concentrations resulting from all sources would have led to 1331.1 (95% Confidence Interval: 824.8–1914.6) thousand deaths attributable to $PM_{2.5}$ exposure in China in 2013. Large fractions of the effect come from stoke, IHD and COPD diseases.

Power plants are responsible for approximately 39% of ambient $PM_{2.5}$ across China, and therefore are responsible for this share of the mortality attributable to $PM_{2.5}$ exposure – some 500 thousand annual deaths (CI: 320 to 750 thousand deaths). However, because of the nonlinearity in the IER, replacing all traditional coal-fired power generation in China with clean energy sources would be expected to reduce the mortality attributable to $PM_{2.5}$ by a fraction less than this value (Lelieveld et al., 2015). Of course, if such a strategy were coupled with other aggressive air pollution controls, the mortality benefits of replacing power plants with clean energy could be significantly larger.

In India, ambient $PM_{2.5}$ concentrations resulting from all sources are projected to be responsible for 803.8 (493.3–1135.2) thousand premature deaths. Specifically, COPD contributes about 37.4%, IHD is responsible for 23.8%, LRI contributes about 21.2%, stroke (both ischemic and hemorrhagic) contributes about 15.3%, with a negligible contribution from LC. Emissions from power generation account for about 60% of total SO_2 emissions in India, but their influence on ambient $PM_{2.5}$ concentrations (accounting for only 32% of $PM_{2.5}$ mass) is lower than in China (where power plant emissions account for 39% of $PM_{2.5}$ mass).

Provincial health impacts attributable to $PM_{2.5}$ exposure depend on both population and ambient $PM_{2.5}$ concentrations. In China, the Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), the Pearl River Delta (PRD), and the Sichuan Basin (SCB) are densely populated (Fig. S6). In India, the IGP and east India are densely populated. As shown in Fig. 2(a), the BTH (and Shandong, Henan provinces), YRD and the SCB regions in China, and the IGP region in India exhibit the highest $PM_{2.5}$ exposure. Fig. 3(a, d) shows the distributions of mortality attributable to $PM_{2.5}$ exposure by province, in China and India. Shandong, Henan and Sichuan provinces in China, and Uttar Pradesh state in India exhibit the largest mortality impacts of $PM_{2.5}$. When attention is focused on the impacts of emissions from power generation, Shandong and Henan provinces show the largest impacts in China (Fig. 3(b, c)). In India, the largest impacts of power plants are evident in the state of Uttar Pradesh (Fig. 3(e, f)).

Estimates of YLL attributable to $PM_{2.5}$ exposure due to all emissions and power generation emissions in China and India are summarized in Table 3. In China, the estimated YLL attributable to $PM_{2.5}$ concentrations due to all sources are about 38.9 million years. In India, the total YLL number attributable to $PM_{2.5}$ exposure is only slightly lower (32.3 million) than in China, in contrast to the large dissimilarity in mortality.

The calculations of YLL involve age specific life expectancy. In this study, we take the average based on the distributions of ages in the populations. Since the birth rate in India is higher than in China, and its population is younger, the remaining life expectancy (L) value for India for all-age disease is higher than for China. This leads to high numbers of YLL attributable to $PM_{2.5}$ exposure. In India, power generation emissions contribute about 33.1% of the YLL attributable to $PM_{2.5}$ exposure. Fig. 4 shows the spatial distributions of provincial-level estimates of YLL attributable to $PM_{2.5}$ exposure due to all emissions and power generation emissions in China and India. Similar to the spatial distributions of mortality attributable to $PM_{2.5}$ exposure, Shandong, Henan and Sichuan provinces in China and Uttar Pradesh state in India exhibit the largest YLL.

4. Discussion

4.1. Comparing health impacts with other studies

Several previous studies have estimated the mortality attributable to $PM_{2.5}$ exposure in China and India (GBD MAPS Working Group, 2016; Ghude et al., 2016; Lelieveld et al., 2015; Liu et al., 2016), and our estimates, 1.3 million deaths in China and 0.8 million deaths in India in 2013, are consistent with the findings of these previous studies (Table 4).

When viewed in the context of the likely uncertainty in any of these estimates, the differences among the many estimates are relatively minor – especially considering that the studies used a variety of emissions estimates, atmospheric fate and transport models, and (to some extent) different syntheses of the epidemiological literature linking $PM_{2.5}$ exposure to mortality.

It may be of interest that although the estimates of the total mortality impact of $PM_{2.5}$ exposure are similar across all studies, there are differences in the relative importance of various causes of death. The more recent studies, which rely on the 2015 IER, tend to find greater impacts on COPD disease and smaller impacts on stroke. This is a reflection of differences between the IER 2015 parameter estimates from the 2010 and 2013 versions of the IER. It is also worth noting that the role of ambient $PM_{2.5}$ in the development of COPD is generally considered to be uncertain (Schikowski et al., 2013).

Even using the same GBD framework (GBD 2015), estimates can differ. Cohen et al. (2017) estimated 1108.1 thousand deaths attributable to $PM_{2.5}$ (LRI: 66.3, LC: 146.0, IHD: 291.8, COPD: 281.7, and Stroke: 322.3) in China and 1090.4 thousand deaths attributable to $PM_{2.5}$ (LRI: 200.7, LC: 22.5, IHD: 365.6, COPD: 349.0, Stroke: 152.5) in India in 2015. In our study, the fractions of each disease in all-cause death are similar to Cohen et al. (2017), but the all-cause deaths are higher in China (1331.1 thousand), and lower in India (803.8 thousand).

The differences of annual mean $PM_{2.5}$ concentrations in 2015 and

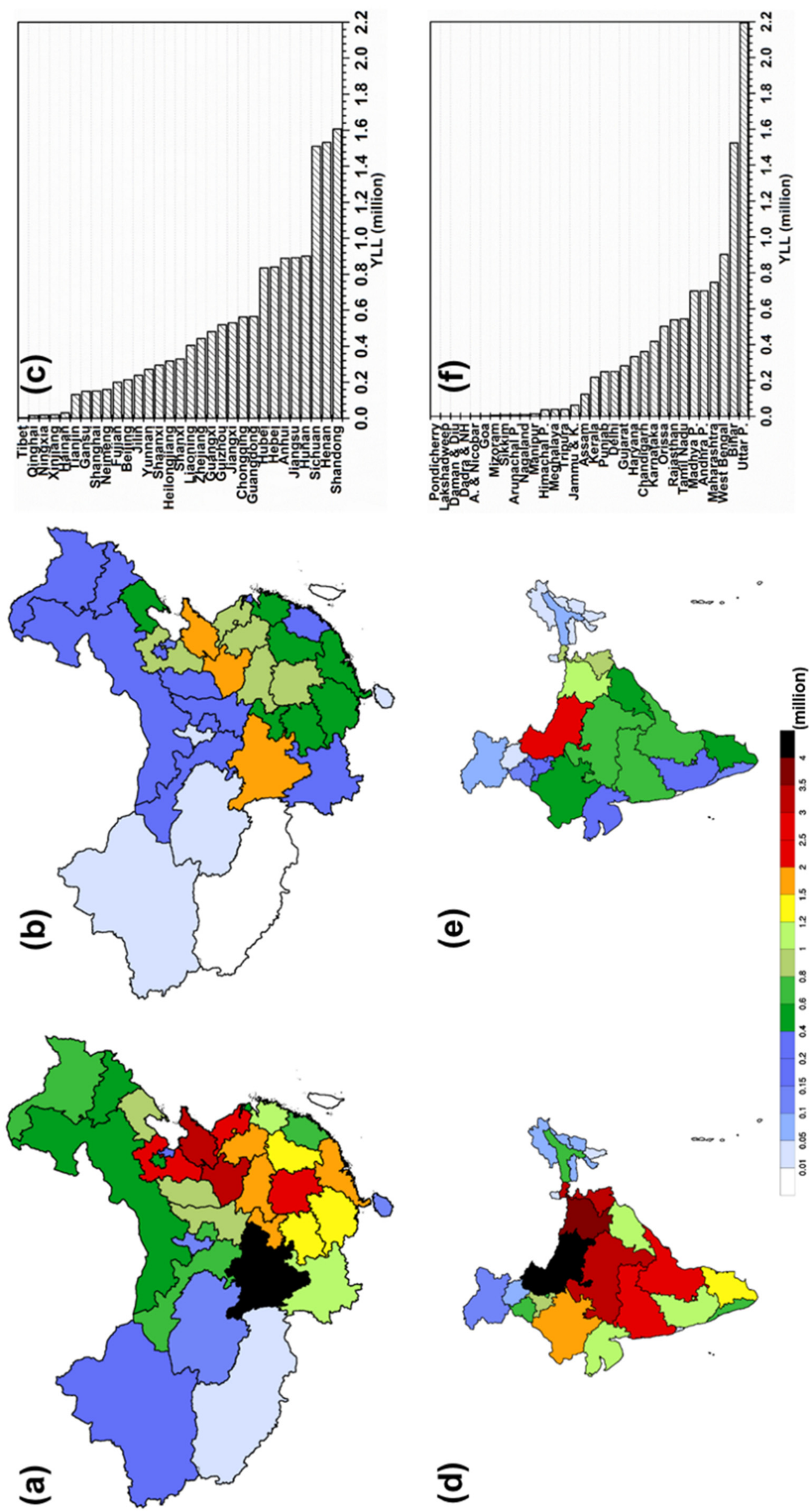

Fig. 4. Maps of provincial-level estimates of YLL attributable to $PM_{2.5}$ exposure due to all emissions (a), and power plant emissions (b), and provincial rankings of power plants induced YLL (c) in China; (d–f) are for India.

Table 4
Summary of Health Impacts from This Study and Other Studies.

Author	Year analyzed	Sources	China		India	
			Deaths (million)	YLL (million)	Deaths (million)	YLL (million)
Lelieveld et al. (2015)	2010	All	1.4		0.6	
Ghude et al. (2016)	2011	All	–		0.6	
Liu et al. (2016)	2013	All	0.9		–	
This study	2013	All	1.3	38.9	0.8	32.3
HEI China MAPS, 2017	2015	All	1.1			

2013 are likely to represent the major cause for these disparities. From 2013 to 2015, $PM_{2.5}$ concentrations in China decreased significantly (Clean Air Alliance of China, 2016) because of the strict air pollution control measures taken since 2013. The emission inventory used for India is based on the year 2010 in this study, so it might have led to underestimations of all-cause deaths, and lower results for India than Cohen et al. (2017).

Large uncertainties are embodied in the calculations of source sector contributions because of the uncertainties in emission inventories, and different responses to emission perturbations in different atmospheric chemistry models. Lelieveld et al. (2015) concluded that residential energy was dominant in outdoor air pollution in 2010 in both China (32%) and India (50%), while industry accounted for only 8% in China and 7% in India. Both the GBD MAPS study and this study found that industrial sources are the largest sectoral contributor to air pollution in China. The differences result very likely from the dissimilarities in the emission inventories employed, and partially from the differences of atmospheric chemistry models. Lelieveld et al. (2015) used the Emission Database for Global Atmospheric Research (EDGAR), and this study used a state-of-the-art emission inventory for Asia (MIX, Li et al., 2017). Table S4 shows the comparison between these two datasets and shows that NO_x non-methane volatile organic compounds (NMVOC) and NH_3 emissions differ greatly, which might have led to the dominant role of the agriculture sector in the results of Lelieveld et al. (2015). EDGAR ignores primary $PM_{2.5}$ emissions in the simulation, which could show an even larger contribution to $PM_{2.5}$ than BC and OC, leading to reduced contributions from sectors with high primary $PM_{2.5}$ emissions. Besides, the coarser global model resolution (~100 km × 100 km) used in Lelieveld et al. (2015) might have missed mesoscale information important for assessments on a regional scale.

4.2. Limitations

Although a complex regional meteorology-chemistry model, a state-of-the-art emission inventory in Asia, and more accurate IER parameters were used in this study compared to previous studies, there are still a number of limitations, involving each step in the calculation procedures. We used relatively high model resolution to represent regional pollution features (60 km) compared to ~100 km in Lelieveld et al. (2015), but 60 km is still not good for precipitation simulations, and detailed urban and sub-grid information might have been missed. In this study, we need to run six one-year simulations (Table S2), and used 60 km due to computational limitations. Besides, we did not include health impacts resulting from ozone exposure, mainly because the mortality due to ozone exposure is small compared to that from $PM_{2.5}$ (Ghude et al., 2016).

Second, although thorough and detailed energy use information was used in the development of the emission inventories, there is still a great deal of uncertainty related to emission estimates from power plants and other sectors. The uncertainties for different species differ greatly, and uncertainties for particles are much larger than those for gases. For example, the uncertainties of BC and OC emissions in MIX are ± 208% and ± 258% in China, but uncertainties of SO_2 and NO_x are only ± 12% and ± 31% (Li et al., 2017). The uncertainties in emissions will be propagated into the meteorology-chemistry modeling. In terms of the source attribution to power plants, the uncertainties are relatively low because of low uncertainties in gases and the importance of gases in power plant emissions. In addition, SO_2 and NO_x emissions from power plants were constrained using satellite retrievals (Streets et al., 2013). Compared to the sector contributions in Lelieveld et al. (2015), we found that different inventories can lead to large differences. Thus we used the most advanced emission estimates (MIX, Li et al., 2017) in this study.

Third, uncertainties also arise from chemistry-meteorology modeling, related to chemical reactions, atmospheric dispersion, and deposition. Although we use nationwide surface $PM_{2.5}$ measurements to evaluate model performance, comparisons of other air pollutants, including SO_2, NO_x, VOCs, and ozone, were not presented due to inaccessibility of relevant measurements. Yet the WRF-Chem performance was comprehensively evaluated in China and India in many previous studies (Gao et al., 2015, 2016a, 2016b, 2016c, 2017; Marrapu et al., 2014), and the results were encouraging, increasing confidence to our findings. Atmospheric chemistry modeling is the only approach to examine sector-specific contributions to exposure. Errors can be reduced further with advances in modeling approaches.

Fourth, the GBD 2015 IER parameters used in this study represent only the current best understanding, which will be enhanced with regular GBD updates in the future. For example, the IERs were developed based on observed cohort studies in the US, Canada, and west Europe (Cohen et al., 2017), implying large uncertainties when applied to China and India. In addition, the province-specific health benefits do not quantify the effect of inter-province transport due to computational complexity, which may be redressed in the future using source apportionment techniques embodied in atmospheric chemistry models.

5. Conclusion

We estimate province-specific mortality and YLL attributable to ambient $PM_{2.5}$ exposure, and examine the changes in ambient $PM_{2.5}$ and the health benefits expected to flow from eliminating power plant emissions, by combining atmospheric modeling and health impact analyses. Several previous studies have evaluated the global mortality attributable to $PM_{2.5}$ exposure, but few have as yet explored the contributions of source classes.

The mortality burdens attributable to $PM_{2.5}$ are estimated to be 1.3 million in China and 0.8 million in India, which are consistent with previous studies. We further quantified the impact of power generation emissions and found that power generation emissions contribute to 0.5 million death in China and 0.3 million in India. We estimated also that 15 million (95% Confidence Interval (CI): 10 to 21 million) years of life lost can be avoided in China each year and 11 million (95% CI: 7 to 15 million) in India by eliminating power generation emissions. The spatial distribution of these results reveals that priorities in upgrading existing power generating technologies should be given to Shandong, Henan, and Sichuan provinces in China, and Uttar Pradesh state in India due to their dominant contributions to the current health risks.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2018.09.015.

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