Source contributions and potential reductions to health effects of particulate matter in India

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Abstract

Health effects of exposure to fine particulate matter ($PM_{2.5}$) in India were estimated in this study based on a source-oriented version of the Community Multi-scale Air Quality (CMAQ) model. Contributions of different sources to premature mortality and years of life lost (YLL) were quantified in 2015. Premature mortality due to cerebrovascular disease (CEV) was the highest in India (0.44 million), followed by ischaemic heart disease (IHD, 0.40 million), chronic obstructive pulmonary disease (COPD, 0.18 million) and lung cancer (LC, 0.01 million), with a total of 1.04 million deaths. The states with highest premature mortality were Uttar Pradesh (0.23 million), Bihar (0.12 million) and West Bengal (0.10 million). The highest total YLL was two years in Delhi, and the Indo-Gangetic plains and east India had higher YLL (~ 1 years) than other regions. The residential sector was the largest contributor to $PM_{2.5}$ concentrations (~ 40 μg/m^3), total premature mortality (0.58 million), and YLL (~ 0.2 years). Other important sources included industry (~ 20 μg/m^3), agriculture (~ 10 μg/m^3), and energy (~ 5 μg/m^3) with their national averaged contributions of 0.21, 0.12, and 0.07 million to premature mortality, and 0.12, 0.1, and 0.05 years to YLL. Reducing $PM_{2.5}$ concentrations would lead to a significant reduction of premature mortality and YLL. For example, premature mortality in Uttar Pradesh (including Delhi) due to $PM_{2.5}$ exposures would be reduced by 79% and YLL would be reduced by 83% when reducing $PM_{2.5}$ concentrations to 10 μg/m^3.

Keywords: Premature mortality, YLL, India, $PM_{2.5}$ exposure, CMAQ

1. Introduction

Due to insufficient control of emissions from a rapid increase in population, industries, urbanization and energy consumption, health effects associated with air pollution in developing countries in Asia are severe (Cohen et al., 2005). India, the second most populous country in the world, has been experiencing extremely high concentrations of fine particulate matter ($PM_{2.5}$) in recent decades. In 2015, $PM_{2.5}$ concentrations in south, east, north and west Indian cities were 6.4, 14.8, 13.2 and 9.2 times of the World Health Organization (WHO) annual guideline value of 10 $\mu g/m^3$ (Garaga et al., 2018). In the Global Burden of Disease Study 2016 (GBD, 2017), India accounted for 1.034 million of 4.093 million global premature mortalities from ambient $PM_{2.5}$ exposure, and ambient $PM_{2.5}$ exposure was the second largest risk for health in India. It is estimated that India accounted for 0.65 million out of the 3.3 million deaths resulted from air pollution caused by $PM_{2.5}$ globally in 2010 (Lelieveld et al., 2015). .

Efforts have been made to estimate the premature deaths associated with $PM_{2.5}$ in India. For example, Sahu and Kota (2017) estimated that 41 out of 100 thousand lives in Delhi could be saved by meeting the World Health Organization (WHO) suggested annual $PM_{2.5}$ guideline based on time series analysis. Such studies require extensive data, which is not available in all Indian cities. Several studies have estimated the health effects using regional and global models, and satellite data. Lelieveld et al. (2015) estimated the global premature mortality of chronic obstructive pulmonary disease (COPD), cerebrovascular disease (CEV), ischaemic heart disease (IHD) and lung cancer (LC) using predicted $PM_{2.5}$ concentrations from a global atmospheric model and exposure-response equations from Burnett et al. (2014). The impacts of different sources on ambient $PM_{2.5}$ concentrations and the associated disease burden in global scale were also studied in Silva et al. (2016) and Lelieveld (2017). Giannadaki et al. (2016) and Conibear et al. (2018) studied the health impacts from applying different air quality standards and explored the non-linear response of health impacts to $PM_{2.5}$ in India. The GBD MAPS Working Group (2018) and Venkataraman et al. (2018) focused on source contributions and potential reductions of $PM_{2.5}$ in India in the present day and the future using the brute force method by removing certain sources. In addition to premature mortality, years of life lost (YLL), which accounts for the ages of those who die and age distribution of population, is also informative and meaningful for estimation of the burden of air pollution on health and environmental policy decision. Ghude et al. (2016)

predicted 0.57 million premature deaths and 3.4 ±1.1 years of YLL associated with $PM_{2.5}$ in India for 2011.

To effectively design pollution control strategies, the contributions of different emission sources to $PM_{2.5}$ concentrations are crucial. Source-oriented chemical transport models (CTM) based on tagged tracer technique have been developed and used for source apportionment of gases (Kota et al., 2014) and PM (Ying et al., 2015;Kota et al., 2015;Zhang and Ying, 2010) in the past. Guo et al. (2017), which was the first study to use the source-oriented Community Multi-scale Air Quality (CMAQ) model in India, showed residential sector contributed the most (~ 80 $\mu g/m^3$) to total $PM_{2.5}$, followed by industry sector (~ 70 $\mu g/m^3$) in 2015. Recently, Hu et al. (2017) estimated the premature mortality caused by different sources of $PM_{2.5}$ in China and showed that industrial and residential sources contributed to 0.40 (30.5%) and 0.28 (21.7%) million premature deaths, respectively. Although previous studies have addressed different aspects of health impact of $PM_{2.5}$ in India, a comprehensive understanding on source contributions and potential reductions to both premature mortality and YLL using a tagged tracer method with updates to better predict $PM_{2.5}$ in India is missing.

The objective of this study is to estimate contributions of each emission sectors to $PM_{2.5}$ related mortality and YLL in India using a tagged tracer method after improving the model performance on $PM_{2.5}$ in companion papers. The potential health benefits of reducing $PM_{2.5}$ concentrations in different Indian states are also explored. Such study would be of tremendous value for the government to channel their resources in reducing pollution in India.

2. Method

2.1 Model application for $PM_{2.5}$ prediction and source apportionment

The models used in this study were based on CMAQ 5.0.1 with a modified SAPRC11 photochemical mechanism and aerosol module version 6 (AERO6). Heterogeneous formation of SO_4, NO_3, and SOA formation from surface uptakes was incorporated to improve model performance (Ying et al., 2015;Hu et al., 2016). Source contributions of primary PM (PPM) and its chemical components were estimated using tagged non-reactive tracers. The tracers from each source sector go through all atmospheric processes similar to other species. Detailed information on this source apportionment method could be found in Guo et al. (2017) and the references therein. The source contributions to secondary inorganic aerosol (SIA) were determined by tracking SO_2, NOx, and NH_3 through atmospheric processing using tagged reactive tracers. Both the photochemical mechanism and aerosol module were expanded so that SO_4, NO_3, and NH_4 and their precursors from different sources are tracked separately throughout the model calculations (Zhang et al., 2012;Qiao et al., 2015;Zhang et al., 2014).

The default vertical distributions of concentrations that represented clean continental conditions provided by the CMAQ model were used for the 36-km domain covering the whole India (Figure S1). Figure S2 shows the states and main cities referred in this study. The Weather Research & Forecasting model (WRF) v3.7.1 was utilized to generate meteorology inputs for CMAQ, and Emissions Database for Global Atmospheric Research (EDGAR) version 4.3 (http://edgar.jrc.ec.europa.eu/overview.php?v=431) were used for six anthropogenic emissions: energy, industry, residential, on-road, off-road and agriculture. The biogenic emissions were generated by Model for Emissions of Gases and Aerosols from Nature (MEGAN) v2.1 (Guenther et al., 2012) and wildfire emissions, which is assigned as open-burning sector, were from the Fire Inventory from NCAR (FINN), which was based on satellite observations (Wiedinmyer et al., 2011). Dust and sea salt emissions were generated in line during simulations. Model performance was validated against available observations from ground based national ambient air quality monitoring stations in major cities. Model performance of O_3 and $PM_{2.5}$ meets the criteria suggested by the US Environmental Protection Agency (EPA). The performance of model was especially good on days with high O_3 and $PM_{2.5}$ levels. Details of the model application and the performance in 2015 can be found in Kota et al. (2018). Also, the source apportionment results are comparable with Sharma et al., (2016) using positive matrix factorization (PMF) as Guo et al. (2017) introduced.

2.2 Estimation of premature mortality

The relative risk (RR) due to COPD, CEV, IHD and LC related mortality associated with long-term exposure of $PM_{2.5}$ concentrations is calculated using integrated exposure-response function estimated by Burnett et al. (2014) as described in Eq. (1) and Eq. (2).

$$RR = 1, \quad for\ c < c_{cf} \tag{1}$$

$$RR = 1 + \alpha\left\{1 - \exp\left[-\gamma\left(c - c_{cf}\right)^{\delta}\right]\right\}, \quad for\ c \geq c_{cf} \tag{2}$$

where C_{cf} is the threshold concentration below which there is no additional risk. A total of 1000 sets of α, γ, δ and C_{cf} values generated using Monte Carlo simulations for each disease were obtained from the Global Health Data Exchange website (http://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_CRCurve_parameters.csv). C is the predicted $PM_{2.5}$ concentration. RR values are calculated for each set of α, γ, δ and C_{cf} for all people above the age of 25 and for each grid cell in the domain. Then, the premature mortality is calculated as Eq. (3).

$$\Delta Mort = y_o[(RR-1)/RR]Pop \ldots\ldots (3)$$

where y_o refers to baseline mortality rate for a particular disease in India as listed in Table S1, obtained from based on the WHO Mortality Database and Pop is the population in a certain grid cell as listed in Table S2. The mean, lower (2.5%) and upper (97.5%) limits of premature mortality associated with each disease in a grid are estimated using the 1000 RR values. Total premature mortality is calculated by adding premature mortality for each disease in a grid. Total average premature mortality in a state is obtained by adding all average premature mortalities of all grids in the state multiplied by the fraction of the grid inside the state. A similar approach is used for calculating the upper and lower limits of premature mortality.

2.3 Estimation of years of life lost

Years of life lost (YLL) is another important index to reflect the health impact of $PM_{2.5}$ concentrations (Yim and Barrett, 2012;Guo et al., 2013;Pope III et al., 2009;Romeder and McWhinnie, 1977). It is a measure of the average years a person would have lived if he or she had not died prematurely due to some specific reason. YLL is usually calculated as a summation of the number of deaths at each age group multiplied by the number of years remaining as shown in Eq. (4).

$$YLL = \sum_{i=1}^{n-1} a_i\, d_i = \sum_{i=1}^{n-1}(n - y(i) - 0.5)\, \Delta Mort_i \ldots\ldots (4)$$

Where $\Delta Mort_i$ is the number of deaths in age group i (i = 1, 7) as shown in Table S2. a_i is the remaining years of life left when death occurs in age group i. n is the life expectancy of India (male= 66.2 and female= 69.1 in 2013) and y(i) is the mean age of age group i. In this study, the overall YLL was divided by population in a certain grid cell to get life expectancy loss per person (Pope III et al., 2009).

3. Results

3.1 Predicted premature mortality and YLL

Figure 1 shows the predicted annual $PM_{2.5}$ concentrations in India for 2015, with the highest concentration of ~120 μg/m^3 in Delhi and some states in east India. The spatial distribution of $PM_{2.5}$ concentration shows that the Indo-Gangetic plains have a higher concentration than other regions. East and parts of central India also have high $PM_{2.5}$ concentrations, while west and south India are less polluted. The population-weighted concentration (PWC) throughout the country is 32.8 μg/m^3 (Table 1). This value is lower compared to 57.2 μg/m^3 in Conibear et al. (2018) and 74.3 μg/m^3 in GBD MAPS Working Group (2018) due to differences in model and configurations (Table 2). East India is the most polluted with 47.8 μg/m^3, closely followed by north India 43.1 μg/m^3. PWC values are 31.2 μg/m^3 in south, 25.4 μg/m^3 in the northeast, 23.9 μg/m^3 in the west and 23.5 μg/m^3 in central India. Delhi is the state with the highest PWC of 66.3 μg/m^3. The states apart from Delhi, where PWC is higher than the national average, are Sikkim 54.7 μg/m^3, West Bengal 54.1 μg/m^3, Bihar 53.1 μg/m^3, Haryana 47.3 μg/m^3, Uttar Pradesh 47.3 μg/m^3, Jharkhand 39.2 μg/m^3 and Punjab 35.5 μg/m^3.

The total premature mortality for adults (≥ 25 years old) and those due to COPD, LC, IHD, and CEV are also shown in Figure 1. The total premature mortality peaks at populous megacities at coastal area, Indo-Gangetic plains, and west India. For example, in Indo-Gangetic plains, where the population density is more than 1 million per gird (i.e., 36 km×36 km), premature mortality can be as high as 3000 deaths per 100,000 persons. Premature mortalities of COPD, LC, IHD, and CEV show a similar spatial distribution with the total. CEV is the largest contributor and has peak values at Indo-Gangetic plains. COPD and IHD are also important with a peak of ~ 1400 deaths per 100,000 persons at Indo-Gangetic plains. LC contributes the least to total premature mortality.

Table 1 also shows that the total premature mortality for adults in India for 2015 is approximately 1.04 million with CI95 of 0.53-1.54 million. High premature mortality is in the populous states such as Uttar Pradesh (0.23 million), Bihar (0.12 million) and West Bengal (0.10 million) as shown in Figure S3. In addition, states such as Maharashtra (0.09 million) and Andhra Pradesh (0.06 million) also have high premature mortality. Generally, the states in Indo-Gangetic plains and east India have a higher premature mortality than other states. South states have lower premature mortality. Premature mortality due to CEV is highest in India (0.44 million), followed by IHD

(0.43 million), COPD (0.18 million) and LC (0.01 million) (Table 1). States with high PWC have slightly higher CEV premature mortality compared to IHD. IHD and CEV constitute about 81 % of the total premature mortality over the country in 2015.

Table 2 shows the comparison of the results with other studies. This study predicted higher total premature mortality (1.04 million) compared to Lelieveld et al. (2015) (0.65 million), Ghude et al. (2016) (0.57 million) and Giannadaki et al. (2016) (0.58 million), and comparable results compared to and GBD MAPS Working Group (2018) (1.09 million) and Conibear et al. (2018) (0.99 million). Considering the uncertainty range (0.53 - 1.54 million), this study is consistent with these studies. The difference may be caused by different models (updated CMAQ in this study vs. EMAC, GEOS-Chem and WRF-Chem), different resolutions, and different simulation episodes. The ratios of COPD and CEV are close for all studies except GBD MAPS Working Group (2018) and Conibear et al. (2018) predicted higher ratios for COPD but lower ratios for CEV. Giannadaki et al. (2016) predicts higher LC ratio (5.1%) than other studies (0.5-2.1%), while IHD ratios are similar for all studies.

Figure 2 shows the total YLL and to the contributions of COPD, LC, IHD, and CEV. The YLL for entire India is the highest for CEV (0.8 years) and closely followed by IHD (0.7 years). LC has the least YLL (0.03 years), while COPD has the YLL of 0.45 years. YLL for states in north, east, south and west India are 1.2, 1.0, 0.2 and 0.4 years, respectively. The highest total YLL is ~ 2 years in Delhi, indicating $PM_{2.5}$ concentrations strongly threaten the health of people living in the capital of India. Indo-Gangetic plains and east India have higher YLL (~ 1 years) compared to other regions. Another study conducted in India for 2011 showed that $PM_{2.5}$ concentration associated lost life expectancy is 3.4 ± 1.1 years (Ghude et al., 2016). The difference is due to the different episodes and methods in calculating YLL. In Ghude et al (2016), YLL was calculated based on the linear relationship assumption that an increase of 1 $\mu g/m^3$ in $PM_{2.5}$ exposure decreases mean life expectancy by about 0.061 ± 0.02 years (Pope III et al., 2009).The linearity assumption between YLL and $PM_{2.5}$ concentration may introduce additional uncertainties to their result.

3.2 Source apportionment of premature mortality and YLL

Figure 3 shows the annual contributions of different sources to total $PM_{2.5}$ concentration. Residential sector contributes highest to total $PM_{2.5}$ with ~ 40 $\mu g/m^3$ maximum, followed by industry sector (~20 $\mu g/m^3$). Energy sectors and agriculture sector contribute to ~5 $\mu g/m^3$ and ~8 μg/m^3 maximum. In north India, residential sector (~ 40 μg/m^3) have the maximum contributions to total $PM_{2.5}$. Open burning has significant high contributions (~ 1 μg/m^3) in northeast India. Energy $PM_{2.5}$ concentrations have significant high concentration point at north (~ 30 μg/m^3) and east (~ 15 μg/m^3) India compared to other parts of the country as several coal-based power plants are located there (Guttikunda and Jawahar, 2014). On the contrary, industry, residential and agriculture sector distribute evenly at Indo-Gangetic plain. Residential source peaks in north Pakistan and dust source peaks in desert areas in other countries. In most states, residential is the largest contributor because residential heating during October to December are the main sources of $PM_{2.5}$ (Vadrevu et al., 2011). As shown in Figure S4, biogenic related species such as isoprene (ISOP) and monoterpenes (TERP) are the major components of SOA.

The total premature mortality due the eight source sectors and SOA is shown in Figure 4 and portions of the contribution of each source type of each state in India is listed in Table S3. Residential (55.45%), Industry (19.66%), Agriculture (11.90%), and Energy (6.80%) are the major sources contributing to premature mortality due to $PM_{2.5}$ concentrations. Contributions of residential, industry, agriculture and energy sectors are maximum in Bihar (62.01%), Delhi (40%), Assam (24.37%) and Chhattisgarh (22.63%), respectively. Overall premature mortality in more than 90% of the states is dominated by residential source. The uses of primitive methods of cooking instead of cooking gas and electric heaters could be a top factor. Burning of solid fuels for cooking and other purposes could be another important factor. Highest contributions to premature mortality from residential sources are in states at Indo-Gangetic plains and east India. Premature mortality of residential sector in south Indian states is lower compared with other parts of India, while premature mortality of industry sector is more important in western states. Delhi is affected the most among all states by industrial source, and premature mortality due to the energy sector is higher in mineral-rich states such as Chhattisgarh. Agriculture $PM_{2.5}$ contributes highest to premature mortality in Assam. Premature mortality in other northeast states such as Meghalaya, Mizoram, Tripura, Manipur, Nagaland, and Sikkim are also contributed significantly by agriculture $PM_{2.5}$. Table 2 shows the comparison of this study with previous studies. In comparison with Lelieveld et al. (2015), this study predicts higher contributions from industry and agriculture sectors but lower from traffic and dust sectors due to the differences in emissions. The GBD MAPS Working Group (2018) shows similar results in energy and traffic sectors but predicts lower in residential sector. Conibear et al. (2018) is consistent with this study in residential sector but predicts higher contribution in energy and traffic sectors.

Figure 5 showed YLL attributed to different source types and SOA. Similar to the pattern of premature mortality in Figure 4, residential is the top factor, which reduces ~ 0.6 years in severe polluted and populous area like Delhi, followed by industry, energy, and SOA. A significant peak of industry YLL is at west India and high YLL occurs at Indo-Gangetic plains. Unlike the spatial distribution of industry contributions to YLL, YLL for energy sector shows some point sources of energy emission in central India. For SOA, YLL is ~ 0.1 years for majority parts of India with a high YLL (~ 0.35 year) in southeast India. YLL for agriculture sector distributes evenly at Indo-Gangetic plains and peaks at west India (~ 0.12 year).

3.3 Potential reduction of premature mortality with reduced $PM_{2.5}$ concentrations

The reduction of $PM_{2.5}$ was calculated by multiplying the original $PM_{2.5}$ concentration with reduction fraction. The mortality was then calculated using the reduced $PM_{2.5}$ concentration. Figure 6 shows the normalized premature mortality with a fractional reduction in $PM_{2.5}$ concentrations (relative to 2015 concentrations) for the whole of India and top $PM_{2.5}$ polluted states, Bihar, Maharashtra, Uttar Pradesh (including Delhi), West Bengal. It shows that the decrease of premature mortality is slower in the beginning when $PM_{2.5}$ concentrations are higher, and the marginal benefit of $PM_{2.5}$ reduction to premature mortality increases as PM concentrations decrease. A 30% of reduction in $PM_{2.5}$ in whole India only lead to a 25% reduction in mortality from the 2015 level without considering population increases, but 90% reduction in mortality could be achieved with an 80% decreasing in $PM_{2.5}$. $PM_{2.5}$ concentrations need to be reduced by 65%, 50%, 60% and 65%, respectively, for Bihar, Maharashtra, Uttar Pradesh (including Delhi) and West Bengal to achieve a 50% reduction in $PM_{2.5}$-related premature mortality.

Figure 7 evaluates the premature mortality and YLL benefit when $PM_{2.5}$ concentrations in the whole of India and top $PM_{2.5}$ polluted states, Bihar, Maharashtra, Uttar Pradesh (including Delhi) and West Bengal are reduced to four different standards, i.e., Indian National Ambient Air Quality Standard (INAAQS) of 40 $\mu g/m^3$, WHO interim target 3 (WHO IT3) of 15 $\mu g/m^3$, the United States (U.S.) Ambient Air Quality Standards (NAAQS) annual standard of 12 $\mu g/m^3$, and the WHO guideline level of 10 $\mu g/m^3$. The reductions of the premature mortality when $PM_{2.5}$ concentrations in the highly polluted regions (annual average concentration $\geq 40 \mu g/m^3$) are shown in Table S4.

For example, the premature mortality in Uttar Pradesh (including Delhi) due to $PM_{2.5}$ exposure will be reduced by 79% from 0.25 million to approximately 0.06 million and the YLL will be reduced by 83% from 1.27 year to 0.22 year when $PM_{2.5}$ concentrations drop to 10 $\mu g/m^3$. The reductions of premature mortality are also more significant in most populous states such as Uttar Pradesh (79%) and West Bengal (80%). However, the decrease is not significant when $PM_{2.5}$ concentrations drop to current INAAQS standards of 40 $\mu g/m^3$ as it only reduces premature mortality by 13.10% and YLL by 9.85% for the whole India. When $PM_{2.5}$ concentrations drop to 15 $\mu g/m^3$, premature morality for India will reduce to 0.37 million and YLL will decrease to 0.56 year. In 12 $\mu g/m^3$ case, premature mortality and YLL will be reduced to 0.17 million and 0.39 year respectively. This indicates that the current INAAQS standards are not sufficient to reduce health impacts of air pollution in India.

4. Conclusion

A source-oriented CMAQ modeling system with meteorological inputs from the WRF model was used to quantify source contributions to concentrations and health effects of $PM_{2.5}$ in India for 2015. The predicted annual $PM_{2.5}$ concentrations in India for 2015 could reach 120 $\mu g/m^3$ in Delhi and some states in east India has a total mortality greater than 3000 deaths per 100,000 persons. The total premature mortality in India for adult $\geq$ 25 years old in 2015 was approximately 1.04 million. Uttar Pradesh (0.23 million), Bihar (0.12 million) and West Bengal (0.10 million) had higher premature mortality compared to other states. YLL peaks at Delhi with ~ 2 years and Indo-Gangetic plains and east India have high YLL (~ 1 years) compared to other regions in India. The residential sector is the top contributor (55.45%) to total premature mortality and contributes to ~ 0.2 years to YLL with source contribution of ~ 40 $\mu g/m^3$ maximum to total $PM_{2.5}$. Reducing the $PM_{2.5}$ concentrations to the WHO guideline value of 10 $\mu g/m^3$ would result in a 79% reduction of premature mortality and 83% reduction of YLL in Uttar Pradesh (including Delhi) due to $PM_{2.5}$ exposures. The total mortality and YLL of whole India would also be significantly reduced by decreasing current $PM_{2.5}$ level to 10 $\mu g/m^3$.

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Table 1. Population (×10^6), population-weighted concentration (PWC, μg/m^3) and premature mortality (×10^4 deaths) due to COPD, LC, IHD, and CEV in each state or union territory in India.

State	Population	PWC	COPD	LC	IHD	CEV	Total
Andhra Pradesh	85.3	22.45	0.96 (0.37, 1.63)	0.07 (0.01, 0.11)	2.48 (1.73, 3.54)	2.18 (0.83, 3.42)	5.69 (2.94, 8.70)
Arunachal Pradesh	2.2	10.08	0.01 (0.00, 0.02)	0.00 (0.00, 0.00)	0.03 (0.02, 0.05)	0.01 (0.01, 0.03)	0.05 (0.03, 0.09)
Assam	28.5	23.86	0.34(0.13, 0.57)	0.02 (0.01, 0.04)	0.86 (0.61, 1.23)	0.80 (0.30, 1.25)	2.03 (1.04, 3.09)
Bihar	103.2	53.06	2.25 (1.08, 3.33)	0.17 (0.05, 0.24)	4.10 (3.14, 7.05)	5.63 (1.79, 6.90)	12.15 (6.07, 17.52)
Chandigarh	0.2	30.51	0.00 (0.00, 0.01)	0.00 (0.00, 0.00)	0.01 (0.00, 0.01)	0.01 (0.00, 0.01)	0.02 (0.01, 0.03)
Chhattisgarh	25.8	25.75	0.33 (0.13, 0.55)	0.02 (0.01, 0.04)	0.81 (0.58, 1.17)	0.80 (0.29, 1.26)	1.97 (1.01, 3.01)
Dadra & Nagar Haveli	0.5	20.91	0.00 (0.00, 0.01)	0.00 (0.00, 0.00)	0.01 (0.01, 0.02)	0.01 (0.00, 0.02)	0.03 (0.02, 0.04)
Daman & Diu	0.1	19.6	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.01)	0.00 (0.00, 0.01)	0.01 (0.00, 0.01)
Goa	1.9	18.11	0.02 (0.01, 0.03)	0.00 (0.00, 0.00)	0.05 (0.04, 0.07)	0.04 (0.02, 0.06)	0.11 (0.06, 0.16)
Gujrat	62.4	18.53	0.57 (0.21, 1.01)	0.04 (0.01, 0.07)	1.61 (1.07, 2.27)	1.19 (0.48, 1.95)	3.42 (1.77, 5.30)
Haryana	37.4	47.32	0.75 (0.35, 1.13)	0.06 (0.02, 0.08)	1.43 (1.08, 2.39)	1.88 (0.61, 2.38)	4.12 (2.06, 5.98)
Himachal Pradesh	8.8	15.08	0.06 (0.02, 0.11)	0.00 (0.00, 0.01)	0.18 (0.12, 0.26)	0.12 (0.05, 0.20)	0.37 (0.19, 0.58)
Jammu & Kashmir	12.4	9.80	0.04 (0.01, 0.09)	0.00 (0.00, 0.01)	0.16 (0.08, 0.26)	0.06 (0.02, 0.14)	0.27 (0.11, 0.50)
Jharkhand	36.4	39.25	0.65 (0.29, 1.00)	0.05 (0.01, 0.07)	1.33 (0.99, 2.14)	1.66 (0.54, 2.20)	3.68 (1.82, 5.41)
Karnataka	63.0	16.23	0.51 (0.18, 0.94)	0.04 (0.01, 0.06)	1.56 (1.04, 2.12)	0.97 (0.45, 1.55)	3.08 (1.67, 4.67)
Kerala	35.3	19.44	0.34 (0.12, 0.59)	0.02 (0.00, 0.04)	0.93 (0.63, 1.33)	0.73 (0.29, 1.18)	2.03 (1.05, 3.14)
Madhya Pradesh	77.9	22.62	0.89 (0.34, 1.51)	0.06 (0.01, 0.11)	2.32 (1.65, 3.22)	2.06 (0.82, 3.26)	5.35 (2.81, 8.10)
Maharashtra	117.1	28.61	1.58 (0.65, 2.57)	0.11 (0.03, 0.18)	3.72 (2.68, 5.44)	3.73 (1.38, 5.52)	9.14 (4.74, 13.70)
Manipur	2.7	21.13	0.03 (0.01, 0.05)	0.00 (0.00, 0.00)	0.08 (0.05, 0.11)	0.06 (0.03, 0.10)	0.17 (0.09, 0.26)
Meghalaya	4.3	22.07	0.05 (0.02, 0.08)	0.00 (0.00, 0.01)	0.13 (0.09, 0.17)	0.11 (0.04, 0.17)	0.29 (0.15, 0.43)
Mizoram	1.5	19.72	0.02 (0.01, 0.03)	0.00 (0.00, 0.00)	0.04 (0.03, 0.06)	0.03 (0.01, 0.05)	0.09 (0.05, 0.14)
Nagaland	3.2	19.51	0.03 (0.01, 0.06)	0.00 (0.00, 0.00)	0.09 (0.06, 0.12)	0.07 (0.03, 0.11)	0.19 (0.10, 0.29)
Delhi	8.1	66.28	0.21 (0.10, 0.29)	0.02 (0.01, 0.02)	0.34 (0.27, 0.61)	0.49 (0.16, 0.57)	1.06 (0.54, 1.50)
Odisha	43.4	29.59	0.63 (0.26, 1.01)	0.05 (0.01, 0.07)	1.44 (1.05, 2.17)	1.57 (0.54, 2.32)	3.69 (1.86, 5.57)
Puducherry	1.2	15.40	0.01 (0.00, 0.02)	0.00 (0.00, 0.00)	0.03 (0.02, 0.04)	0.02 (0.01, 0.03)	0.05 (0.03, 0.08)
Punjab	28.9	35.46	0.48 (0.21, 0.75)	0.04 (0.01, 0.05)	1.02 (0.75, 1.61)	1.22 (0.40, 1.66)	2.75 (1.37, 4.07)
Rajasthan	71.4	20.86	0.74 (0.28, 1.28)	0.05 (0.01, 0.09)	2.00 (1.39, 2.80)	1.64 (0.67, 2.54)	4.44 (2.35, 6.71)
Sikkim	4.5	54.72	0.09 (0.05, 0.13)	0.01 (0.00, 0.01)	0.16 (0.12, 0.29)	0.22 (0.07, 0.26)	0.48 (0.24, 0.69)
Tamil Nadu	70.2	13.82	0.45 (0.15, 0.87)	0.03 (0.00, 0.06)	1.47 (0.88, 2.13)	0.77 (0.33, 1.38)	2.72 (1.36, 4.44)
Tripura	3.7	26.04	0.05 (0.02, 0.08)	0.00 (0.00, 0.01)	0.12 (0.08, 0.17)	0.12 (0.04, 0.19)	0.29 (0.15, 0.44)
Uttar Pradesh	211.2	47.19	4.26 (1.98, 6.41)	0.32 (0.09, 0.45)	8.10 (6.14, 13.63)	10.80 (3.45, 13.59)	23.48 (11.66, 34.09)
Uttarakhand	11.9	15.04	0.08 (0.03, 0.14)	0.01 (0.00, 0.01)	0.23 (0.14, 0.33)	0.16 (0.06, 0.26)	0.47 (0.24, 0.74)
West Bengal	88.9	54.13	1.93 (0.94, 2.86)	0.14 (0.04, 0.20)	3.51 (2.68, 6.00)	4.75 (1.53, 5.81)	10.34 (5.20, 14.87)
India	1254.0	32.78	18.36 (7.94, 29.14)	1.34 (0.35, 2.05)	40.36 (29.22, 62.78)	43.94 (15.27, 60.36)	103.99 (52.78, 154.34)

Table 2. Comparison of methods and excess mortality by diseases and sources from this study with other studies in India.

	This study	Lelieveld (2017) and Lelieveld et al. (2015)	GBD MAPS Working Group (2018)	Conibear et al. (2018)	Ghude et al. (2016)	Giannadaki et al. (2016)
Models application	Source-oriented CMAQ	EMAC	GEOS-Chem	WRF-Chem	WRF-Chem	EMAC
Source apportionment	Tagged tracer	Zero-out	Zero-out	Zero-out		
Emission inventory	EDGAR	EDGAR	Own inventories	EDGAR	EDGAR	EDGAR
Resolution	36km	~110km	56×74 km	30km	36km	~110km
PWC (μg/m^3)	32.8		74.3	57.2		
Mortality estimation	IER	IER	IER	IER	IER	IER
Excess mortality (million)	1.04 (0.53,1.54)	0.65	1.09	0.99	0.57	0.58
COPD (%)	17.7	17.3	~30	31.2	20.5	11.9
LC (%)	1.3	2.1	~2	2.6	0.5	5.1
IHD (%)	38.8	45.7	~40	34.8	43.9	34.3
CEV (%)	42.4	34.9	~18	11.6	35.1	41.6
Source contributions (%)						
Energy	6.8	14	7.6	21		
Industry	19.7	7	7.5	16		
Residential	55.5	50	24.6	52		
Agriculture	11.9	6		0		
Traffic	1.9	5	2.1	10		
Dust	4	11	28.7	0		

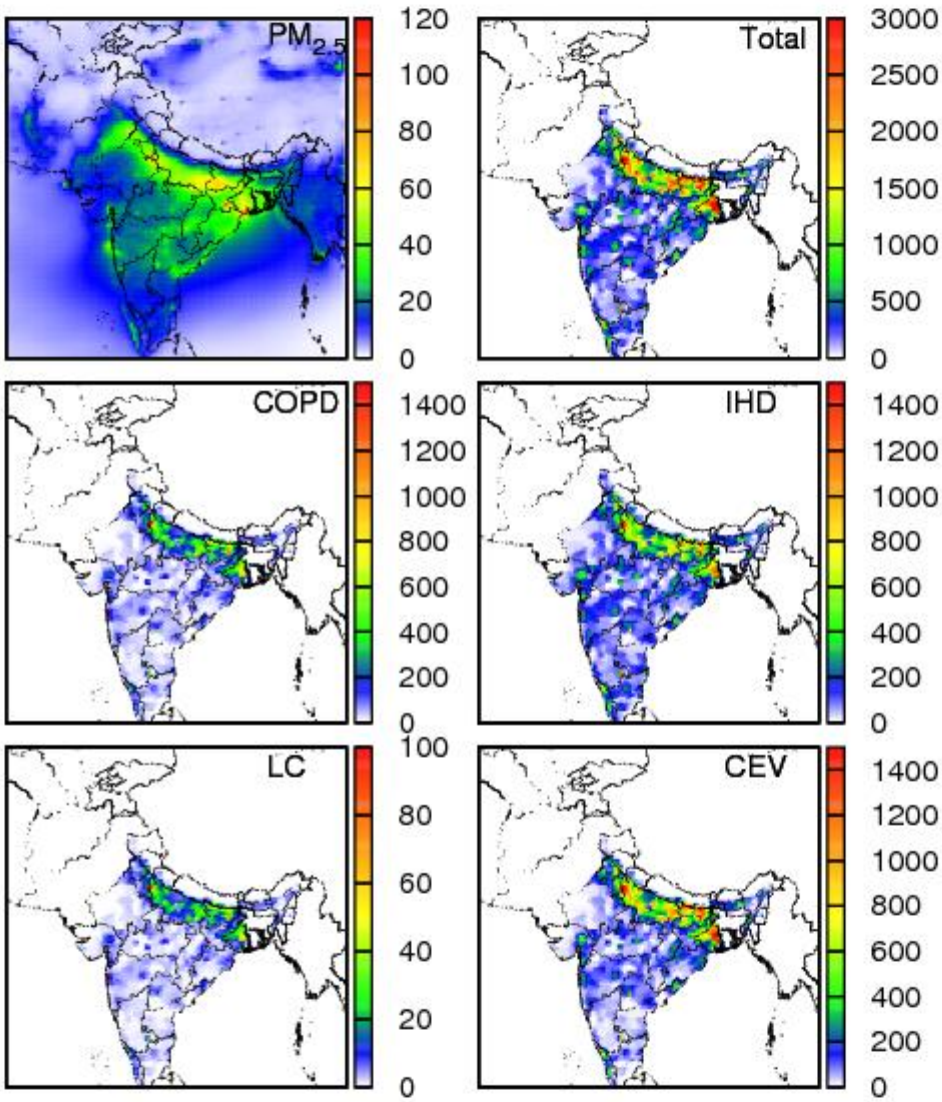


Figure 1. Predicted annual $PM_{2.5}$ concentrations (μg/m^3), total premature mortality (death per grid of 36 × 36 km^2) and premature mortality due to COPD, LC, IHD and CEV in India for 2015.

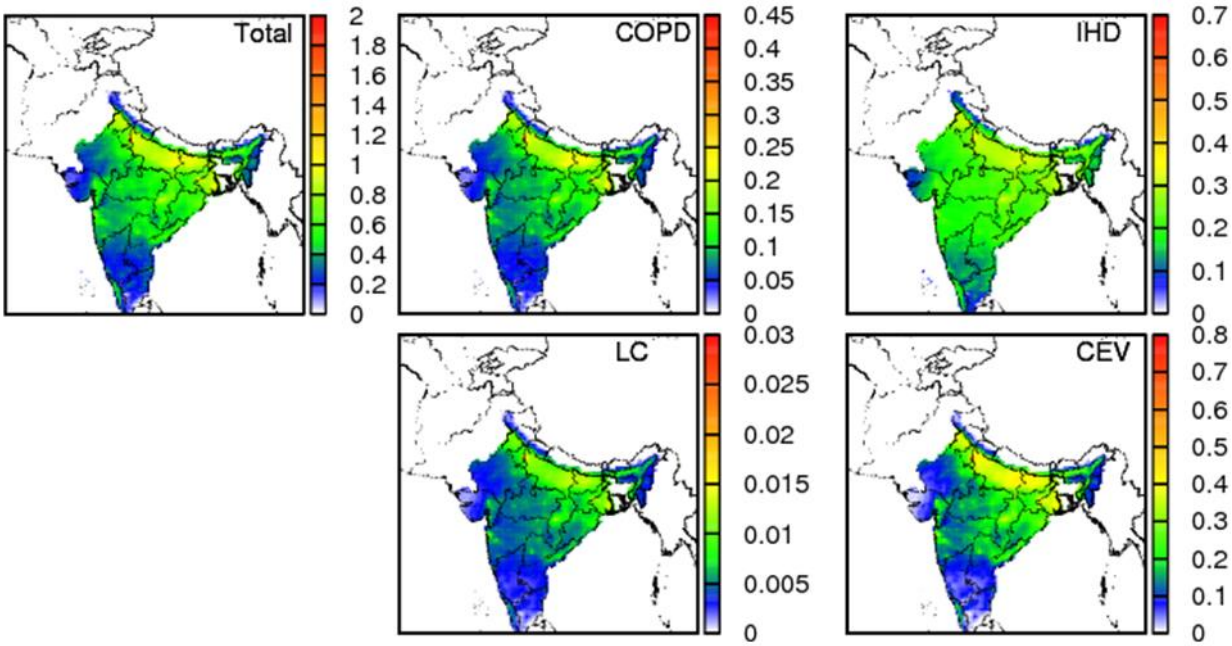


Figure 2. Year of life lost (YLL) based on population (years) due to COPD, LC, IHD, and CEV.

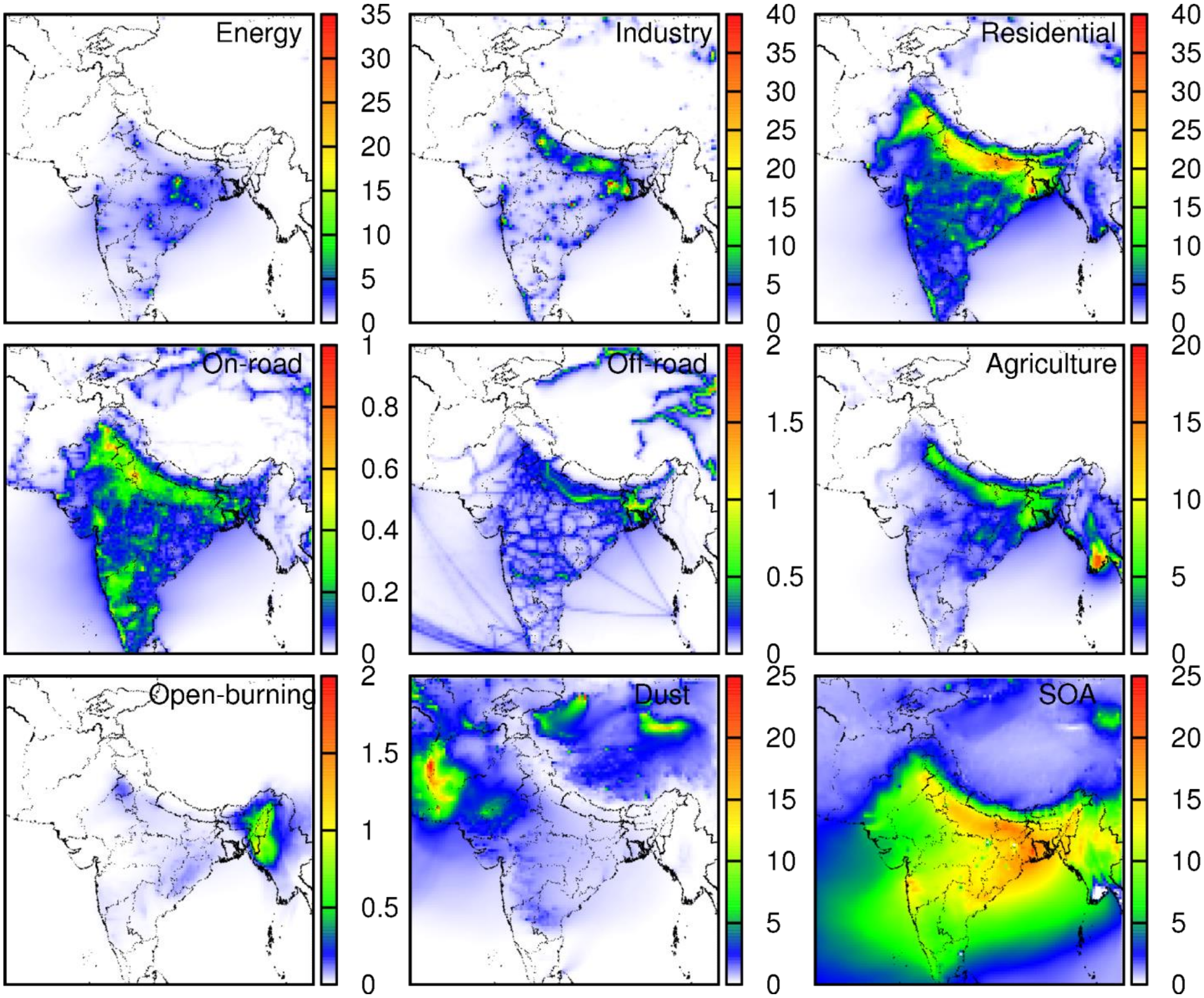


Figure 3. Source contributions to total $PM_{2.5}$ concentration (Units are in μg/m^3).

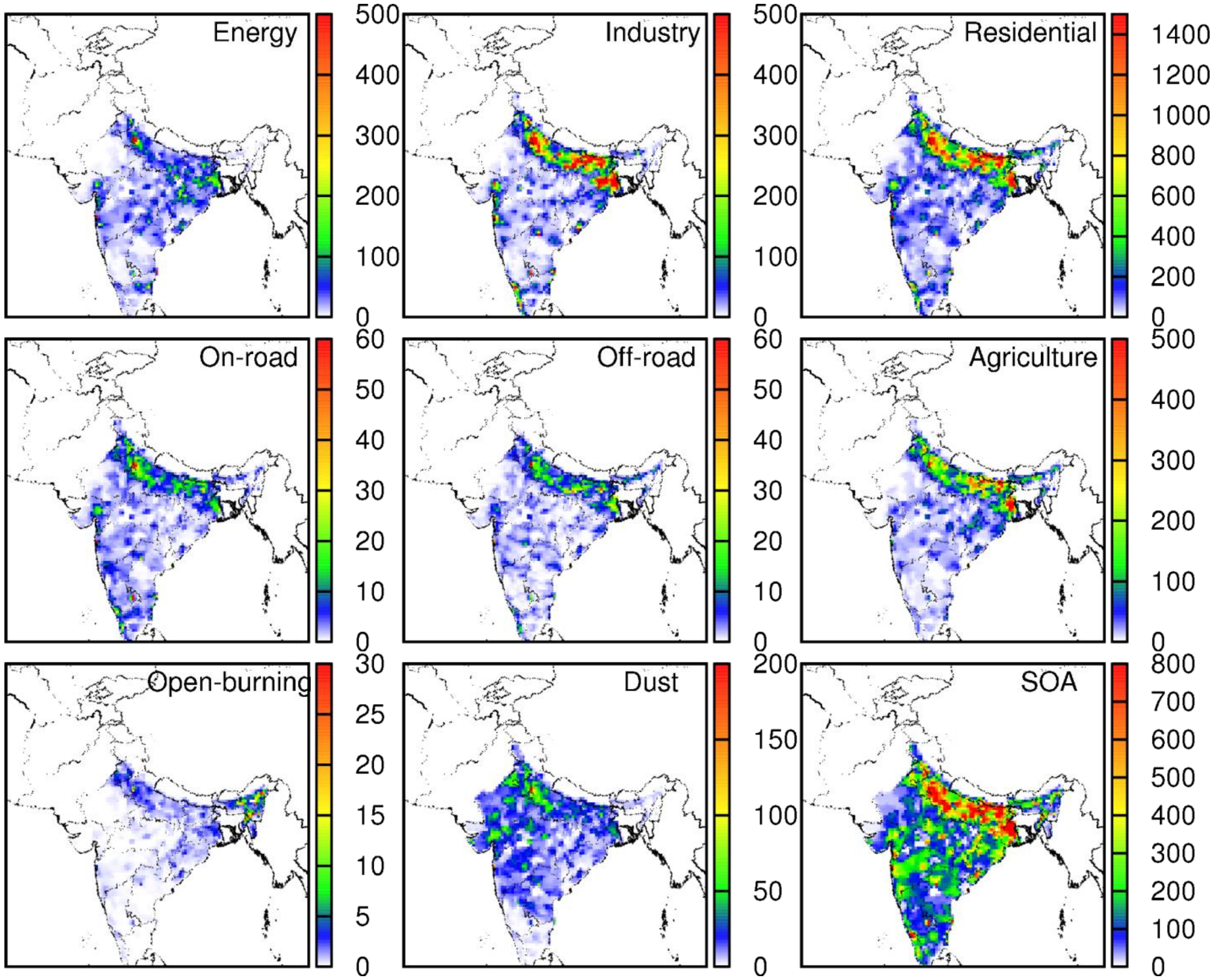


Figure 4. Source contributions to total premature mortality (deaths per grid 36 × 36 km) due to COPD, LC, IHD, and CEV.

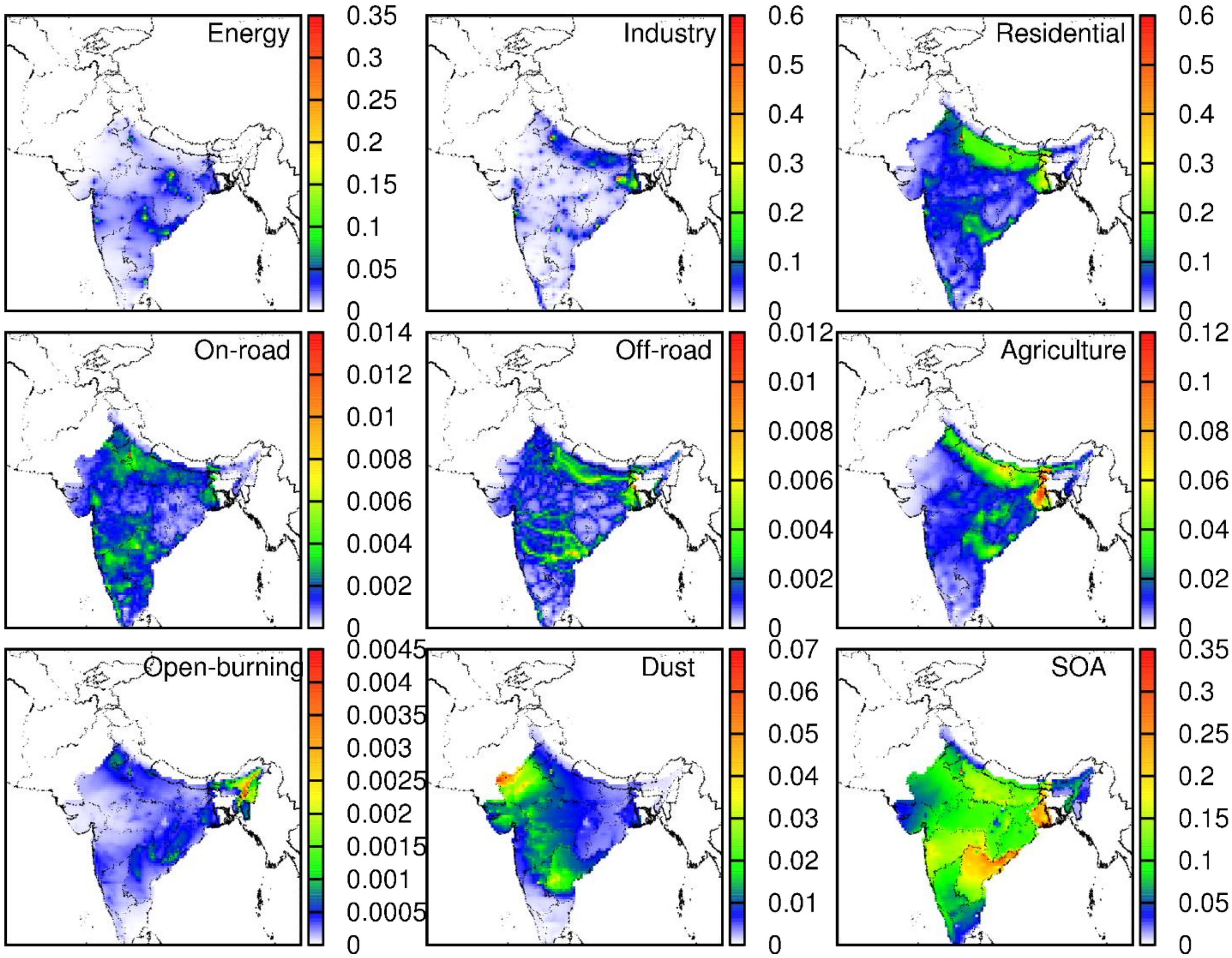


Figure 5. Contributions of different sources to years of life lost (YLL) based on population (years).

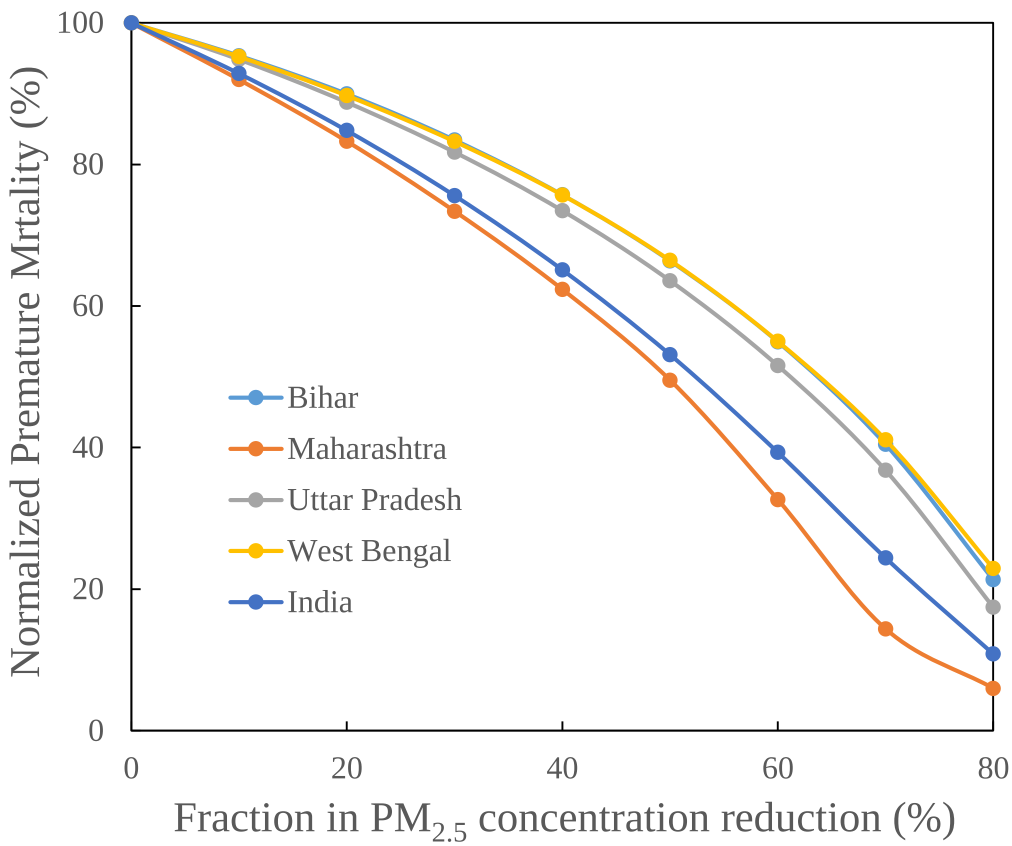
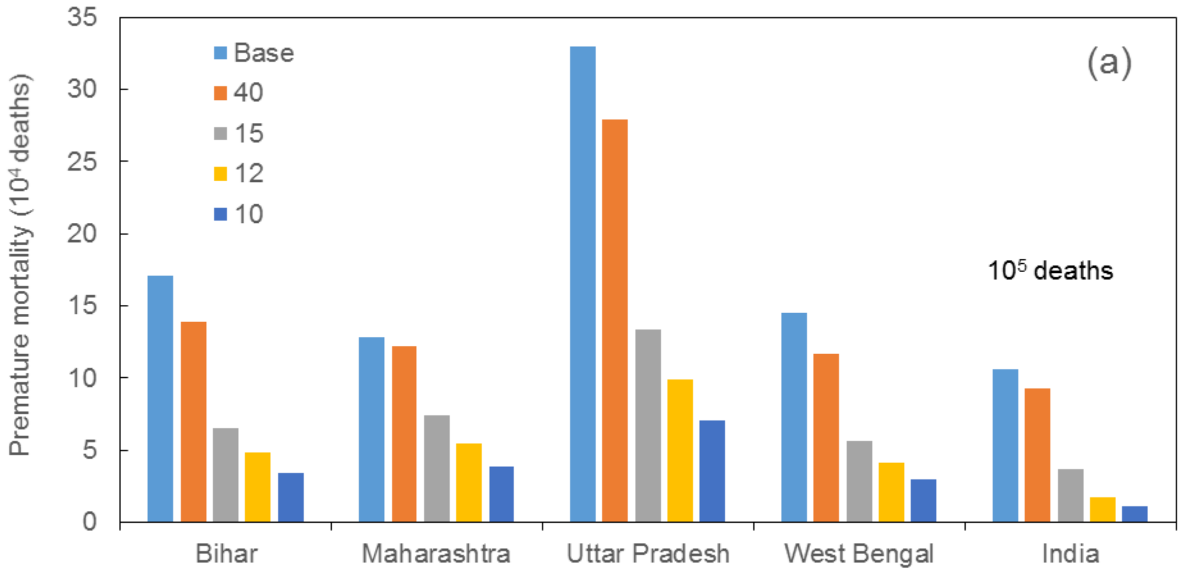


Figure 6. Premature mortality (normalized to 2015 deaths) as a function of the fractional reduction in $PM_{2.5}$ concentrations (relative to 2015 concentrations) for the whole of India and top $PM_{2.5}$ polluted states, Bihar, Maharashtra, Uttar Pradesh (including Delhi), West Bengal.



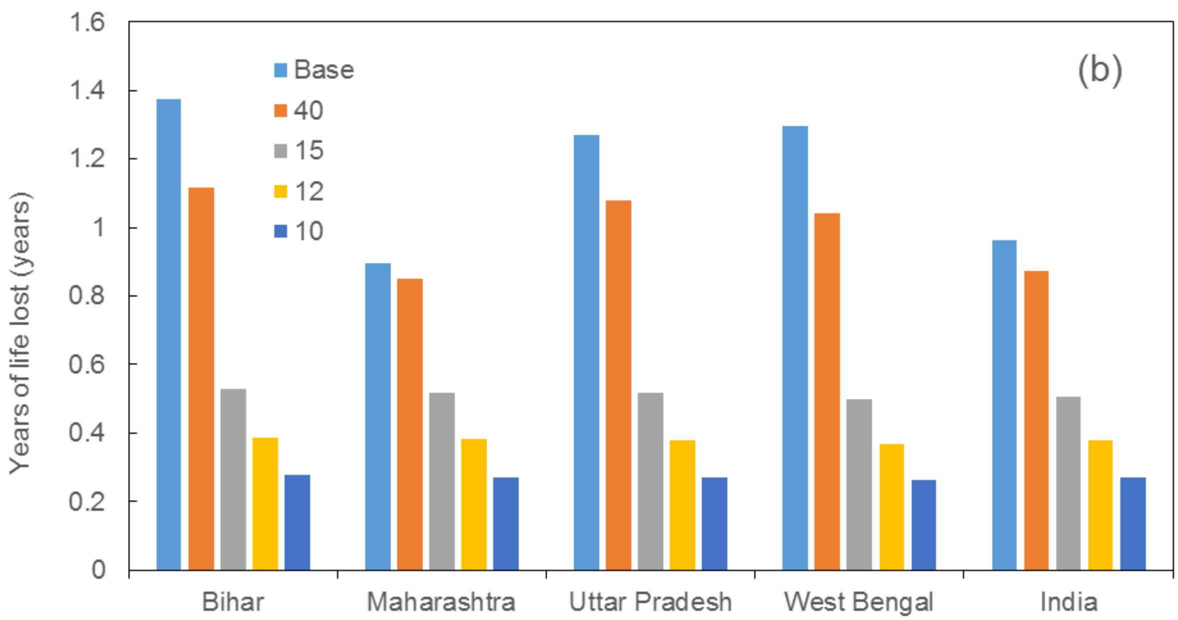


Figure 7. Number of premature deaths (a) and YLL (b) in the whole of India and top $PM_{2.5}$ polluted states, Bihar, Maharashtra, Uttar Pradesh (including Delhi) and West Bengal corresponding to the cases when $PM_{2.5}$ reduced to 40μg/m^3, 15 μg/m^3, 12μg/m^3 and 10/μg m^3 (WHO guideline level). "Base" refers to $PM_{2.5}$ in 2015.