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Expected health benefits from mitigation of emissions from major anthropogenic $PM_{2.5}$ sources in India: Statistics at state level☆

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ABSTRACT

Exposure to fine particulate matter ($PM_{2.5}$) is one of the leading risk factors for the mortality and morbidity burden in India. Health benefit expected from mitigation of emissions from individual sectors is the key policy information to address this issue. Here we quantify the relative shares of four major year-round anthropogenic sources to ambient $PM_{2.5}$ in India using a chemical transport model and estimate premature deaths that could have been avoided due to complete mitigation of emissions from these sources at state level. Population-weighted all-India averaged ($\pm 1\sigma$) annual ambient $PM_{2.5}$ exposures due to residential, transport, industrial and energy sectors in 2010 are estimated to be 26.2 ± 12.5, 3.8 ± 4.3, 5.5 ± 2.7 and $2.2 \pm 2.3\ \mu g\ m^{-3}$, respectively. Complete mitigation of emissions from the transport, industrial and energy sectors combined would avoid 92,380 (95% uncertainty interval (UI), 40,918–140,741) premature deaths annually, primarily at the urban hotspots. For the residential sector, this would result in avoiding 378,295 (95% UI, 175,002–575,293) premature deaths due to a reduction in ambient $PM_{2.5}$ exposure in addition to the benefit of avoiding all premature deaths from household exposure. Bihar and Goa are expected to have the largest (289) and smallest (48) premature mortality burden per 100,000 population due to anthropogenic $PM_{2.5}$ exposure. From policy perspective, controlling residential sources should be prioritized in view of the effectiveness of implementing mitigation measures and the expected larger health benefit at a regional scale. However, additional mitigation measures are advised at the urban hotspots to curb emissions from the other sectors to get maximum possible health benefit.

1. Introduction

Long-term as well as short-term exposure to $PM_{2.5}$ (particulate matter smaller than 2.5 μm aerodynamic diameter) results in various health impacts including premature death (Pope et al., 2002; Schwartz et al., 2002; West et al., 2016). In India, close to a billion people is exposed to annual ambient $PM_{2.5}$ concentration above the World Health Organization (WHO) air quality guideline (Dey et al., 2012). Recent Global Burden of Disease (GBD) studies (Murray et al., 2015; Cohen et al., 2017) and Disease Burden of India study (Dandona et al., 2017) initiatives have clearly highlighted the increasing risk of air pollution on morbidity and mortality burden in India. High background concentration throughout the year (*i.e.* annual exposure), especially in the Indo-Gangetic Basin (IGB) and urban pockets elsewhere (Dey and Di Girolamo, 2011), and episodes during the post-monsoon to winter seasons elevating short-term $PM_{2.5}$ exposure above 500–600 $\mu g\ m^{-3}$ for several days to weeks in the recent years (Sharma and Dixit, 2016) called for a comprehensive air quality management plan in India.

Emergency mitigation measures such as vehicle rationing where odd and even numbered vehicles were allowed to ply on the corresponding days failed due to implementation strategy (too many exemptions were given) and unfavorable meteorological condition (Chowdhury et al., 2017). Formulation of a successful air quality management plan to address the air quality problem in India requires the information of the relative contributions of various anthropogenic sources to ambient $PM_{2.5}$ at a regional scale. Source apportionment studies in India (e.g. Banerjee et al., 2015; Behera and Sharma, 2015; Gummeneni et al., 2011; NEERI, 2008; Pavuluri et al., 2011; Sharma et al., 2016) are mostly limited to

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few cities. Moreover, the short-term measures tailor-made for the cities are often being perceived as hindrance to the economic growth and social life, rendering the implementation strategy inefficient. Therefore, a regional scale source-apportionment study is required to assess the efficacy of the mitigation strategies from the perspective of expected health benefit of the exposed population.

Chafe et al. (2014) was one of the first studies to estimate contribution of emission from household activities towards ambient $PM_{2.5}$ exposure. Lelieveld et al. (2015) carried out a global analysis and showed large (>50%) contribution of household sources to ambient $PM_{2.5}$ in India. Several studies thereafter (eg. Butt et al., 2016; Conibear et al., 2018; Silva et al., 2016; GBD-MAPS, 2018) followed suit with similar conclusion but their estimates of the relative share of household sources to ambient $PM_{2.5}$ vary in the range 22–52%. Some of these studies also estimated the health benefits due to complete mitigation of emissions from various sectors. While these recent studies fulfilled the requirement of a regional scale source-apportionment study in India, they provided estimates at national level. Disease burden India study (Dandona et al., 2017) has demonstrated a large heterogeneity in health profiles across the Indian states. Therefore, there is a compelling need to estimate the expected health benefit from mitigation of major anthropogenic sources at state level for policy perspective.

In this study, we use version 3.6 of Weather Research Forecasting (WRF) model coupled with chemistry (hereafter WRF-Chem) to examine the contributions of four major unceasing anthropogenic sources - 'residential', 'transportation', 'industrial' and 'energy' sectors to ambient $PM_{2.5}$ exposure in India. We further determine the expected health benefits from the reduction of ambient $PM_{2.5}$ exposure due to complete mitigation of emission from each of these sectors and identify the states that are expected to get the most benefit. We provide statistics at state level, which are likely to be very useful in guiding policymaking towards achievement of a green and sustainable environment in India.

2. Methods

2.1. WRF-chem model set up, simulation and validation

WRF-Chem is an online coupled chemical transport model which simultaneously simulates meteorology and chemistry (Fast et al., 2006; Grell et al., 2005). This model is set-up over India for the domain - latitude 5.8–36.5 N and longitude 67.8 to 100.6 E at a horizontal resolution of 10 km. The model setup has 345 W-E and 345 S-N points, and 30 vertical levels with the pressure at top set at 50 hPa. Lin cloud microphysics scheme (Lin et al., 1983), RRTM long wave radiation scheme (Mlawer et al., 1997), Dudhia shortwave radiation scheme (Dudhia, 1989), YSU Planetary boundary layer scheme (Hong et al., 2006), Grell Freitas scheme for cumulus parameterization (Grell and Freitas, 2014) have been used in these simulations. RADM2 method for gas phase chemistry has been used along with GOCART aerosol treatment (Chin et al., 2002). NCEP final analysis (NCEP-FNL) data at $1^\circ \times 1^\circ$ resolution operationally generated for every 6 hour at NCAR has been used as meteorological input to generate the initial and boundary conditions. The topography and land use data for the domain have been taken from United States Geological Survey and MODIS (MODerate resolution Imaging Spectroradiometer).

Chemical initial and boundary conditions have been generated with version 2 of EDGAR (Emission database for global atmospheric research)-HTAP emission inventory developed at IIASA (International Institute for Applied Systems Analysis) at $0.1^\circ \times 0.1^\circ$ of spatial resolution for each month. Emission inventory is a key parameter for precise air quality modeling. Emission inventories for the developed countries are more robust because of better characterization of emission sources and a dense air quality monitoring network compared to the developing countries like India. EDGAR-HTAP inventory has been developed for 5 major sectors *viz.* residential, transportation, industry, energy and agriculture; where agriculture sector includes only NH_3 emissions (Janssens-Maenhout et al., 2012). Residential sector includes emission from household activities such as heating, cooling, lighting and cooking and emission from solid waste treatment through landfill and incineration, and waste water treatment. Transportation sector includes ground transport by road, railway, inland waterway, pipeline and other ground transport of mobile machinery. We note that re-suspended dust from pavement or tire and break wear is not included in the inventory. Industrial sector includes emissions from industrial non-power but large-scale combustion emissions and emissions from industrial processes and products. Energy sector considers power generation units by coal-fed thermal plants (Janssens-Maenhout et al., 2015). With the objective to choose an emission inventory that follows national level policy for each part of the world, MIX emission inventory has been used in EDGAR-HTAP for Asia. MIX inventory is a mosaic Asian anthropogenic emission inventory developed under Model Inter-comparison study for Asia Phase III (MICS Asia III). SO_2, BC and OC emission data in MIX were generated by ANL (Argonne National Laboratory) and other species CH_4, CO, NOx, NMVOC, NH_3, PM_{10} and $PM_{2.5}$ were taken from REAS2.1 for India (Janssens-Maenhout et al., 2015; Li et al., 2017). ANL has developed emission inventory using technology based methodology and similar consistent method has been used in development of REAS. These emission inventories were prepared from data collected at state level in India (Kurokawa et al., 2013; Ohara et al., 2007). Emission factors were taken from Indian studies. For example, SO_2 emission factor for biofuel combustion was taken from Habib et al. (2004) while emission factor for fossil fuel emission was taken from Reddy and Venkataraman (2002) and Chakraborty et al. (2008). NOx and CO emission from power plant was taken from Kurokawa et al. (2013). In final EDGAR-HTAP emission, EDGARv4.3 data has been used for gap filling for some regions and sectors (Li et al., 2017).

We have performed simulations for the year 2010 over India using EDGAR-HTAP emission inventory for the anthropogenic sources and GOCART module for the dust sources. Anthropogenic $PM_{2.5}$ has been estimated by subtracting natural $PM_{2.5}$ from the total simulated $PM_{2.5}$ concentration. Subtraction method (as demonstrated in Chambliss et al., 2014; Conibear et al., 2018; Silva et al., 2016) has been adopted to quantify the relative contributions of the four (residential, transport, industry and energy) major anthropogenic sources that emit $PM_{2.5}$ continuously throughout the year. All together, five sets of simulations have been carried out. The first one considers the total emission from these four sectors along with natural dust and the subsequent four simulations consider emission excluding one of these sectors. The difference in annual anthropogenic $PM_{2.5}$ from the first and subsequent simulations can be attributed to the contribution of that particular source that has not been considered in that simulation. These simulations are performed for the entire year 2010 over this domain and with mentioned meteorological and emission data.

WRF-Chem simulated $PM_{2.5}$ has been found to show statistically significant correlation ($R = 0.81$) with coincident in-situ data in India (Bran and Srivastava, 2017). We also compare our simulation with in-situ $PM_{2.5}$ from Delhi and found a moderate correlation with under prediction ($R = 0.56$). We observe that the negative side of bias (predicted − observed) shows a consistent linear relation with in-situ data that is significant at 95% CI (Fig. 1a). Part of this under prediction may be attributed to the fact that the model does not simulate natural $PM_{2.5}$ well enough, while the in-situ $PM_{2.5}$

data contains both natural and anthropogenic fractions. Moreover, $PM_{2.5}$ measurement was not as widespread in 2010 as it is now (www.cpcb.nic.in), and so we do not have in-situ dataset from any other site for the year of simulation to validate our model and measurements are not available for rural areas.

To address this challenge, we resort to satellite-based $PM_{2.5}$ product generated by van Donkelaar et al. (2016). The satellite-derived $PM_{2.5}$ is obtained from observed aerosol optical depth (AOD) data of multiple satellite products (MISR, MODIS Dark Target, MODIS and SeaWiFS deep blue and MODIS MAIAC) and GEOS-Chem derived conversion factor (the ratio of $PM_{2.5}$ and AOD). The uncertainty in AOD is calibrated with ground-based sun photometer (AERONET) observations for 1998–2010 and the satellite-derived $PM_{2.5}$ is adjusted towards in-situ observations using geographically-adjusted regression model with ~9% uncertainty in the south Asian region. More details about the satellite-derived $PM_{2.5}$ product are available in the literature (van Donkelaar et al., 2014, 2010; van Donkelaar et al., 2016; Li et al., 2018). The comparison between model simulated and satellite derived anthropogenic $PM_{2.5}$ (Fig. 1b) shows a strong correlation (Pearson's correlation coefficient = 0.89, significant at 99% CI for N = 56,873 grid points) with the bias showing a distinct spatial pattern (Fig. 1c).

The mean bias (difference of satellite derived and model simulated anthropogenic $PM_{2.5}$) is 1.4 $\mu g\ m^{-3}$ with a standard deviation of 9.0 $\mu g\ m^{-3}$. In the eastern and peninsular India, the model over-estimates the concentration by 4–15 $\mu g\ m^{-3}$, while it underestimates by similar margin in the western and central IGB. The bias is within $\pm 5\ \mu g\ m^{-3}$ in the rest of the country. The bias may be attributed to the missing anthropogenic sources that are seasonal in nature (e.g. crop and solid-waste burning) and the uncertainty in the model physics. Given the task at hand to examine the source attribution of annual exposure for the entire country at high spatial resolution, the model performance is considered to be quite reasonable.

2.2. *Estimate of premature mortality burden*

For this study we consider chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), stroke and lung cancer (LC) which is known to have causal relation with exposure to $PM_{2.5}$ (Dandona et al., 2017). Premature mortality burden (ΔM) from these diseases are estimated using traditional epidemiological relation (Anenberg et al., 2010; Chowdhury and Dey, 2016) for a district *i* and disease *j*;

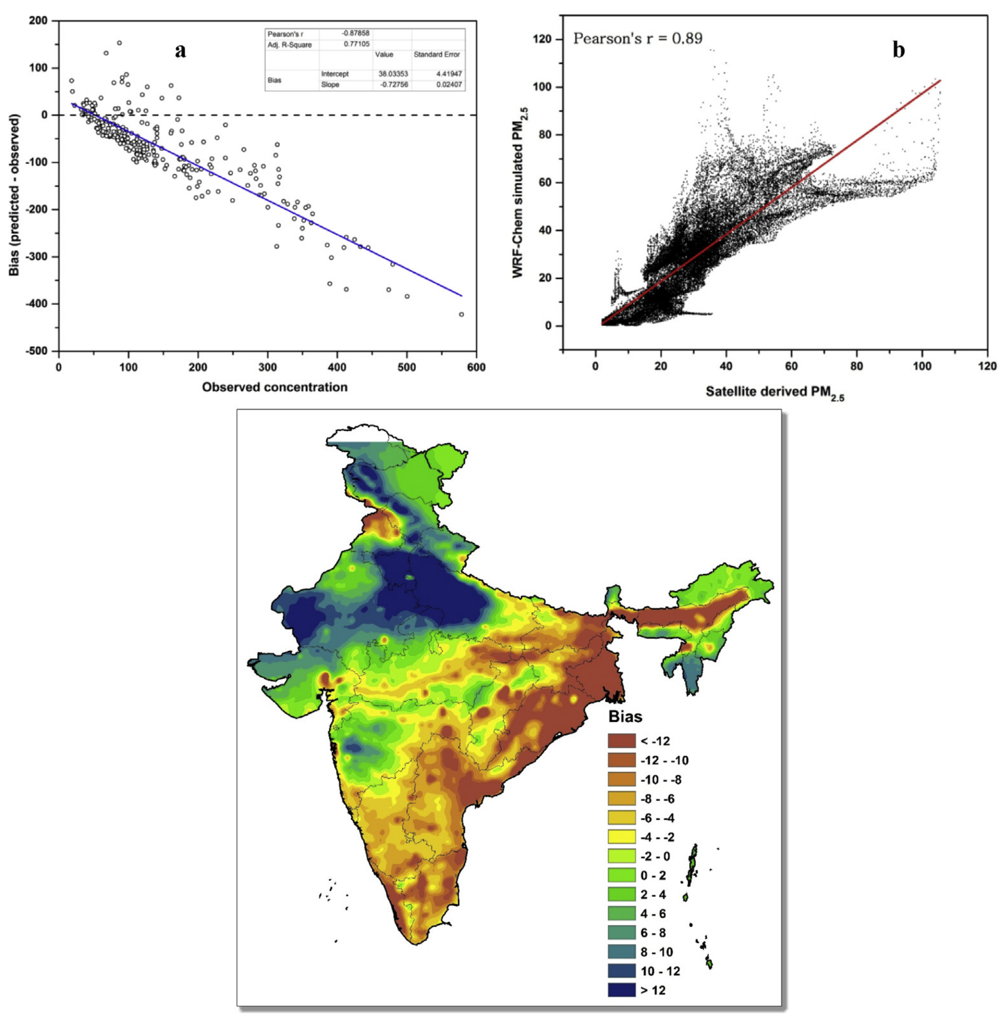

Fig. 1. (a) Scatter plot between simulated total $PM_{2.5}$ and in-situ $PM_{2.5}$ showing linear bias, (b) scatter plot between simulated and satellite-derived anthropogenic $PM_{2.5}$ and (c) the spatial bias (in $\mu g\ m^{-3}$) in simulated anthropogenic $PM_{2.5}$ (represented as satellite derived minus WRF-Chem simulated $PM_{2.5}$). Green to bluish tinge demonstrates under prediction and yellow to brown tinge demonstrates over prediction by the model in annual $PM_{2.5}$ concentration.

$$\sum_{i,j-1}^{N} \Delta M_{i,j} = \sum_{i,j-1}^{N} Y_{i,j} \times \frac{\sum_{i=1}^{N} RR_{ij} - 1}{\sum_{i=1}^{N} RR_{i,j}} \times \sum_{i=1}^{N} P_i \tag{1}$$

P_i is the adult population above the age of 25 for each district i obtained at every 5 year interval from the Census of India (2011). $RR_{i,j}$ is relative risk for a disease j at district i and is estimated using integrated exposure-response (IER) function used in the latest Global Burden of Disease GBD study (Cohen et al., 2017) and annual $PM_{2.5}$ exposure of district i. IER is developed in the GBD study by Burnett et al. (2014) and this is available for all four respiratory diseases and discussed age group. $\Delta Y_{i,j}$ represents baseline mortality for the disease j at district i, $\Delta Y_{i,j}$ of COPD, IHD and Stroke is adjusted to vary for each state as a function of Gross Domestic Product (GDP), it is discussed in details in our earlier work (Chowdhury and Dey, 2016). Baseline mortality for LC is considered uniform across India at 6.5 per 100,000 population (WHO, 2011). We estimate premature deaths (a) due to annual $PM_{2.5}$ exposure from total emissions of all four anthropogenic sources and (b) separately for annual $PM_{2.5}$ exposure without emission from one of the four sectors. The difference between (a) and (b) is attributed to the premature deaths that could be averted by completely mitigating emission from that particular sector and this will be maximum health benefit attributed to a particular source. Statistics are presented at the state level with uncertainty estimates (5%–95% UI, shown in parentheses after the reported central values). The uncertainty is evaluated based on uncertainty in the IER function in estimating RR (Burnett et al., 2014) and the uncertainty in estimating baseline mortality as a function of GDP (Chowdhury and Dey, 2016). The other source of uncertainty in our results stems from the uncertainty in the emission inventory and various parameterization schemes used in the model. We note that measures have been taken to reduce uncertainty in EDGAR-HTAP emission inventory as much as possible by incorporating regional datasets using state-of-the-art methodology (Janssens-Maenhout et al., 2012; Li et al., 2017). In future, inter-comparison of multiple inventories across ensemble modeling framework would help in reducing the uncertainty further.

3. Results

First, we present the spatial heterogeneity in anthropogenic $PM_{2.5}$ in India and the relative shares of the four major incessant emission sources. Then we show the maximum possible health benefit expected if emission from each of these sources could be curbed completely. We interpret our results in view of the studies published in recent times and provide a comparative discussion.

3.1. *Spatial distribution of anthropogenic $PM_{2.5}$ and its source attribution*

Model-simulated spatial distribution of annual ambient anthropogenic $PM_{2.5}$ over India is shown in Fig. 2. Anthropogenic $PM_{2.5}$ exposure is > 50 μg m^{-3} in the entire IGB with values exceeding 80 μg m^{-3} (double the Indian annual ambient air quality standard) in the eastern IGB, Delhi national capital region (NCR) and several industrial hotspots across the country. Emissions from various anthropogenic sources in the densely populated IGB are trapped by favorable meteorology and low-lying topography bounded by mountains in the north and south (Dey et al., 2012) inhibiting its dispersion. The exposure decreases spatially from north to south. Anthropogenic $PM_{2.5}$ exposure is below 25 μg m^{-3} in the mountainous regions in the north, northeast, parts of Western and Eastern Ghats along the west and east coast and the arid regions in the west.

Analysis of contributions of these four major sources (Fig. 3) reveals that residential sector contributes >70% to annual anthropogenic $PM_{2.5}$ concentration in India except in Delhi NCR and the industrial hotspots, where the contribution is <50%. In the Himalayan foothills and parts of eastern and northeastern India, the relative contribution of residential sector even exceeds 80%. Contribution of industrial sector mostly ranges in 8–24% over most parts of India. The relative share exceeds 24% in Gujarat and Mumbai industrial corridor and several industrial clusters in various states. Relative share of transportation sector exceeding 16% is noticeable in Delhi NCR, Kerala, west Gujarat, Himachal Pradesh and Jammu & Kashmir. In the rest of the country, this sector contributes mostly in the range 8–16% with even lesser contribution in the eastern and northeastern India. Energy sector contributes <8% in most of the country, but a higher (>16%) contribution is concentrated in the regions having coal-based thermal power plants.

Frequency distribution of the relative shares of these sectors in terms of spatial coverage further demonstrates that residential sources contribute in the range 45–65% in ~15% grids, 65–75% in ~45% grids and >75% in another ~20% grids across India. Only in the remaining 20% grids in India, relative share of residential sector to anthropogenic ambient $PM_{2.5}$ exposure is smaller than the combined shares of the other three sectors. Industrial sector contributes <15% in ~20% grids, in the range 15–25% in 65% grids and >25% in only ~10% grids. Similarly, energy sector contributes <15% in ~70% grids, in the range 15–25% in another ~15% grids and >25% in only 2–3% grids. For the transportation sector, relative shares of <15%, 15–25%, 25–35% and >35% are observed in ~60%, ~30%, ~5% and <1% grids, respectively. To summarize, the transportation, energy and industrial sectors seem to be the dominant sources at local urban scale, while the relative share of residential sources exceeds the combined share of the other three sources (and hence is important) at regional scale.

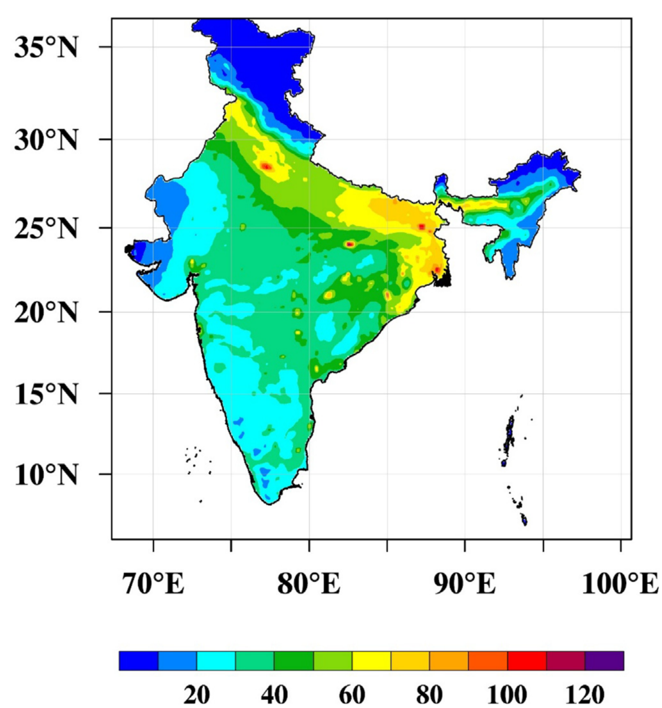

Fig. 2. Spatial distribution of WRF-Chem simulated annual ambient anthropogenic $PM_{2.5}$ exposure (μg m^{-3}) over India for the year 2010.

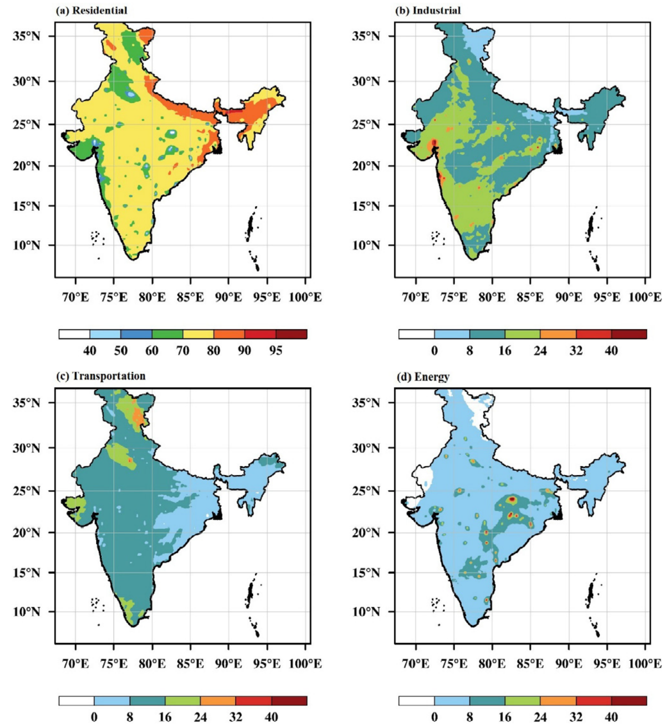

Fig. 3. Percentage shares of (a) residential, (b) industrial, (c) transportation and (d) energy sectors to annual ambient anthropogenic $PM_{2.5}$ exposure in India.

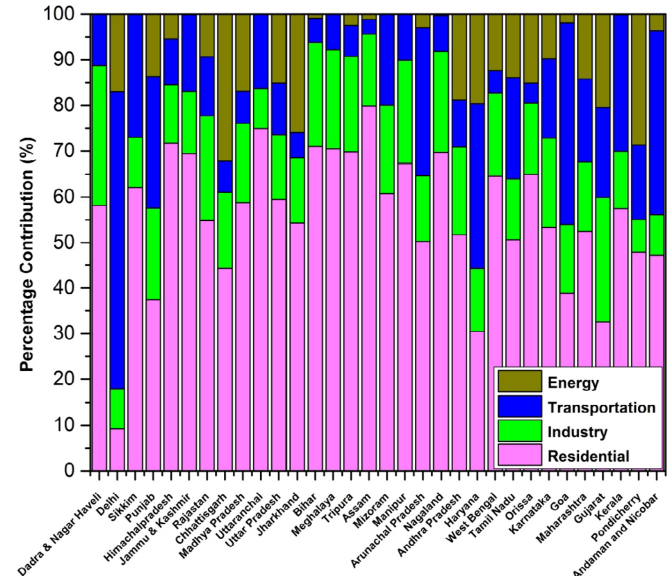

Fig. 4. Percentage shares of energy, transportation, industry, and residential sectors in total anthropogenic $PM_{2.5}$ emission for each Indian state. Emission data is from EDGAR-HTAP emission inventory.

The relative shares (in percentage) of these four major sources to annual anthropogenic $PM_{2.5}$ emission in each state are shown in Fig. 4. Share of residential sector is more than 50% in most of the states. Assam has the highest percentage contribution (80%) from residential sector followed by Uttaranchal (74%). Himachal Pradesh, Bihar Meghalaya, Tripura, Nagaland, Jammu & Kashmir have around 70% contribution from residential sector. Delhi has the least percentage contribution (9%) from residential sector, whereas transportation sector is the major contributor (65%). Union territory (UT) Dadra & Nagar Haveli (30.5%) and Gujarat (27.2%) have the highest percentage contribution from industrial sector among the states. Major mining state Chhattisgarh has 32% contribution from energy sector, which is highest among the states followed by Pondicherry (28.7%) and Jharkhand (26%). The states with the highest share from residential sector in total $PM_{2.5}$ emission like Assam, Bihar, some other North-eastern states Meghalaya, Tripura has high simulated $PM_{2.5}$ concentration from residential sector.

The share of solid fuel use for domestic activities influences the variability of share of household sources in annual anthropogenic $PM_{2.5}$ exposure across the states and UTs. The scatter plot (Fig. 5) reveals that nearly 62.5% variability in the data can be explained by the percentage of population using domestic solid fuel use alone. The remaining variability can be attributed to meteorology that modulates $PM_{2.5}$ transport in and out of a region. This clearly suggests that despite of the meteorological influence, share of the residential sources toward ambient anthropogenic $PM_{2.5}$ can be minimized by simply making clean fuel available to larger population in India. Such policy would have much larger societal impact since residential sources are observed to be dominant in almost all the states. Distribution pattern of residential emission is different from other sources, as the other sectors are localized to small region compare to widely distribution of residential emission. Thus, spatial distribution analysis shows hotspot peaks in some cities and industrial regions, whereas residential emission has widely distributed smaller peaks.

We estimate population-weighted annual anthropogenic $PM_{2.5}$ exposure with respect to anthropogenic $PM_{2.5}$ emission per unit area (*i.e.* source intensity) for each state and normalize the ratio for a comparative assessment. A higher value (Fig. 6) implies that anthropogenic $PM_{2.5}$ exposure in that state is large with respect to local source intensity, which can be interpreted as the pollution is dominated by emissions from outside the state boundary. On the contrary, lower value (*i.e.* low source intensity) implies that the annual anthropogenic $PM_{2.5}$ exposure per unit emission from within the state boundary is relatively small in general. However for Delhi, extremely large source intensity compared to other states results in the smallest normalized ratio. Another plausible explanation for this small number is that pollution gets transported out of Delhi towards the downwind regions in some seasons. Kerala also falls in this category where the pollution is mostly flushed out

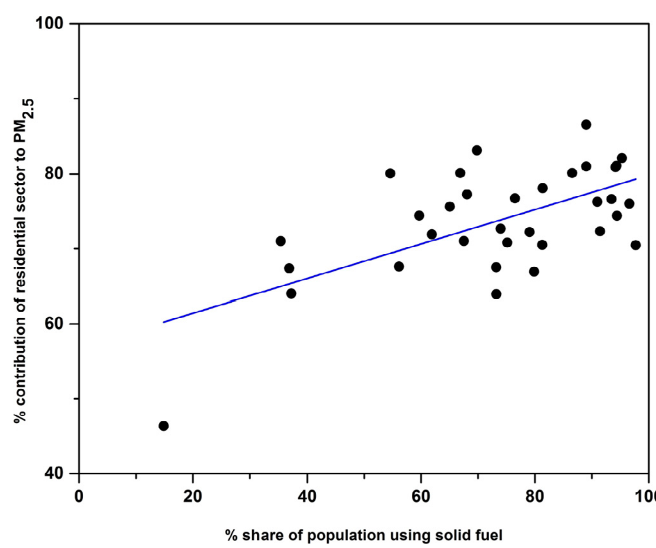

Fig. 5. Scatter plot between share of residential sources to ambient anthropogenic $PM_{2.5}$ exposure and the percentage of population using solid fuel for residential use in each state/UT (represented by each dot).

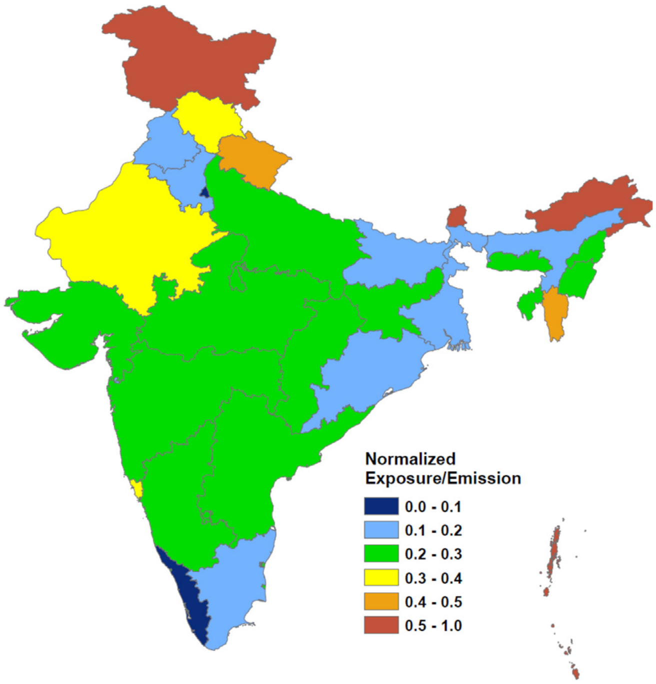

Fig. 6. Normalized ratio of population-weighted anthropogenic $PM_{2.5}$ exposure and $PM_{2.5}$ emission per square kilometer for each state.

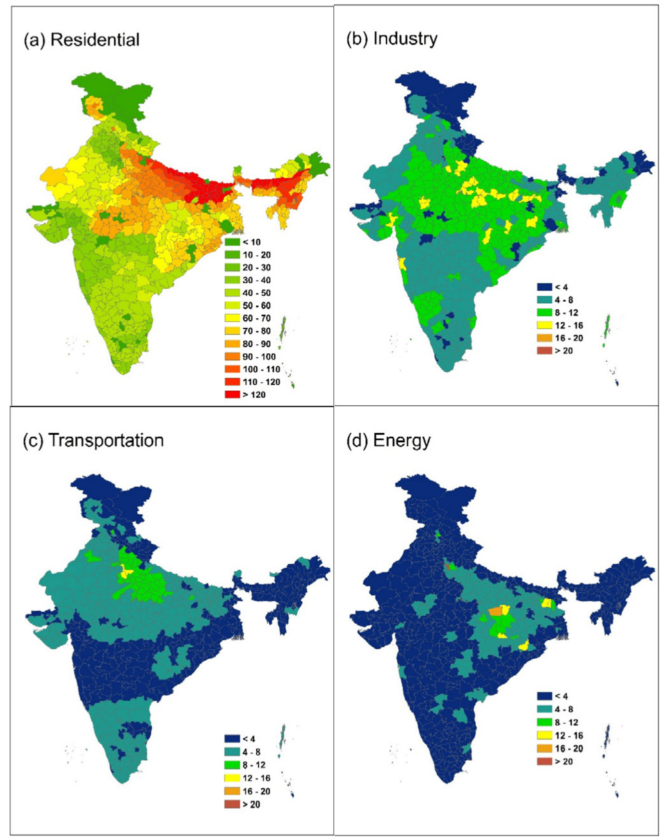

Fig. 7. Expected health benefit in terms of premature deaths (per 100,000 population) that could be avoided by complete mitigation of emission from (a) residential, (b) industrial, (c) transportation and (d) energy sectors.

to the ocean (Dey and Di Girolamo, 2011). Himalayan states like Jammu & Kashmir, Arunachal Pradesh, Sikkim and Uttaranchal show the highest ratio, implying that the annual anthropogenic $PM_{2.5}$ exposure in these states are quite high compared to emission intensity within the state. The inland states show moderate ratio. The analysis reveals that controlling sources within the states showing low to moderate ratio would be highly beneficial for these states as well as the states downwind.

3.2. *Expected health benefit due to complete mitigation of emission from individual sources*

We estimate premature mortality burden following the Global Burden of Disease approach (Cohen et al., 2017) for the annual anthropogenic $PM_{2.5}$ exposure attributed to each of these sources using population data from the Indian Census 2011. The difference in burden due to anthropogenic $PM_{2.5}$ exposure and exposure without a particular source is interpreted as the maximum possible health benefits expected in terms of premature deaths that could have been avoided by completely mitigating emission from that particular source across India. We present these health benefits normalized per 100,000 population (Fig. 7) for each state and UT in India in Table 1. By abating emissions from residential, industrial, transportation and energy sectors completely, 378,295 (175,002–575,293), 45,999 (20,682–70,021), 28,180 (12,459–42,934), and 18,201 (7777–27,786) premature deaths respectively could be avoided in India annually. State-wise estimates of premature mortality burden attributed to total anthropogenic $PM_{2.5}$ exposure normalized to 100,000 population is shown in Table 1 (right column). The states of Bihar and Uttar Pradesh depict very high premature morality rate (289 (77–557) and 216 (59–411), respectively) compared to the central and south Indian states.

In the regions dominated by rural population (primarily in Uttaranchal, Uttar Pradesh, Bihar, Jharkhand, West Bengal, Madhya Pradesh, Chhattisgarh, Orissa and the northeastern states), complete mitigation of emission from residential sources would save 60 to 140 (per 100,000 population) premature deaths just from reduction in ambient anthropogenic $PM_{2.5}$ exposure. We note that mitigation of emission from residential sources would further lead to large health benefit due to reduction in household exposure that is even larger than ambient $PM_{2.5}$ exposure in India (Balakrishnan et al., 2013). Even in the other parts of the country, the expected per capita health benefit from complete mitigation of residential sources is comparable to the benefit expected from mitigation of the other three sources. The health benefit by mitigating emission from the industrial sector completely is also large (8–16 premature deaths per 100,000 population) in the IGB, Mumbai and Gujarat industrial corridors. The largest benefit of mitigating emission from the transportation sector is expected in the Delhi NCR and western to central Uttar Pradesh. On the other hand, mitigating emission from the energy sector completely would avoid 8–25 premature deaths per 100,000 population each year in Delhi NCR and the central and eastern IGB. In the rest of the country, the health benefit of controlling these sectors is minimal and only effective in urban hotspots. The health benefit in the states of Delhi, Gujarat, Haryana and Punjab does not resemble with $PM_{2.5}$ emission distribution. For example, transportation sector is one of the biggest contributors to ambient $PM_{2.5}$ in Delhi but the expected health benefit of complete mitigation of emission from this sector is smaller than that from the residential sector. The probable reason behind this is regional transport of residential $PM_{2.5}$ from other states to Delhi.

Table 1
Premature deaths (95% UI are shown within parentheses) per 100,000 population in each state/union territory that could have been avoided by completely mitigating emission from the corresponding sector across the country. The last column represents premature mortality burden per 100,000 population attributed to total anthropogenic $PM_{2.5}$ exposure in each state.

	State/Union Territory	Health benefits from complete mitigation of emission sources				Premature Mortality (per 100,000 population)
		Residential	Transportation	Industrial	Energy	
1	Andhra Pradesh & Telangana	47 (24–73)	4 (2–6)	8 (4–12)	3 (2–5)	103 (28–196)
2	Arunachal Pradesh	64 (13–123)	3 (1–4)	4 (2–7)	1 (1–2)	67 (8–140)
3	Assam	119 (55–178)	3 (1–4)	6 (2–9)	1 (0–2)	172 (46–327)
4	Bihar	148 (61–225)	6 (2–10)	9 (3–13)	5 (1–8)	289 (77–557)
5	Chandigarh	30 (16–45)	3 (1–4)	4 (2–6)	1 (0–2)	72 (22–127)
6	Chhattisgarh	59 (28–88)	4 (2–6)	10 (5–14)	7 (3–11)	143 (38–271)
7	Dadra & Nagar Haveli	47 (23–70)	4 (2–6)	9 (5–14)	2 (1–3)	108 (26–209)
8	Daman & Diu	43 (21–64)	4 (2–6)	11 (6–17)	3 (1–4)	110 (27–212)
9	Delhi	15 (6–24)	8 (3–13)	4 (1–6)	4 (1–6)	81 (27–140)
10	Goa	21 (11–32)	3 (2–4)	5 (3–7)	1 (0–2)	48 (12–87)
11	Gujarat	34 (18–52)	4 (2–6)	8 (5–13)	2 (1–4)	81 (21–154)
12	Haryana	30 (16–45)	6 (3–10)	5 (3–8)	2 (1–3)	92 (29–164)
13	Himachal Pradesh	50 (20–82)	4 (2–6)	5 (3–8)	1 (0–2)	75 (16–148)
14	Jammu & Kashmir	76 (20–139)	5 (2–7)	6 (3–10)	1 (0–2)	98 (17–199)
15	Jharkhand	82 (37–121)	4 (2–7)	10 (4–14)	6 (2–9)	178 (49–328)
16	Karnataka	46 (23–69)	4 (2–6)	8 (4–12)	3 (1–4)	92 (22–175)
17	Kerala	40 (21–61)	6 (3–10)	6 (3–9)	2 (3–9)	85 (21–162)
18	Lakshadweep	60 (29–87)	5 (3–8)	11 (5–16)	3 (1–4)	79 (12–164)
19	Madhya Pradesh	80 (37–122)	6 (3–9)	11 (5–16)	4 (2–6)	161 (41–315)
20	Maharashtra	34 (18–52)	3 (2–4)	8 (4–12)	3 (1–4)	85 (21–162)
21	Manipur	101 (43–159)	2 (1–4)	7 (4–11)	1 (4–11)	138 (28–289)
22	Meghalaya	81 (40–119)	2 (1–3)	6 (3–9)	1 (0–2)	114 (28–221)
23	Mizoram	75 (28–123)	3 (2–5)	7 (3–10)	1 (0–2)	85 (13–176)
24	Nagaland	77 (36–116)	2 (1–4)	6 (3–9)	1 (0–2)	99 (22–193)
25	Orissa	77 (37–117)	3 (1–4)	8 (4–13)	4 (2–6)	158 (44–297)
26	Pondicherry	32 (17–49)	4 (2–6)	5 (3–8)	2 (1–4)	71 (19–131)
27	Punjab	40 (20–61)	6 (2–9)	7 (3–11)	1 (0–2)	113 (35–204)
28	Rajasthan	59 (29–89)	6 (3–10)	9 (4–13)	2 (1–3)	124 (31–239)
29	Sikkim	53 (26–131)	2 (1–3)	2 (2–5)	0 (0–1)	56 (16–164)
30	Tamil Nadu	38 (20–58)	5 (2–7)	6 (3–9)	3 (1–4)	82 (21–154)
31	Tripura	78 (38–117)	3 (2–5)	7 (4–11)	1 (0–2)	125 (32–239)
32	Uttar Pradesh	100 (44–150)	8 (3–13)	11 (4–17)	5 (2–7)	216 (59–411)
33	Uttaranchal	51 (22–83)	3 (2–5)	4 (2–6)	1 (0–2)	79 (18–150)
34	West Bengal	75 (35–114)	3 (1–5)	7 (2–10)	3 (1–5)	155 (46–283)

4. Discussion and conclusions

Air pollution has become a serious health concern in India. Framing an efficient clean air policy relies on the scientific knowledge of source attribution of ambient anthropogenic $PM_{2.5}$ exposure at a regional scale and the expected health benefit from controlling various anthropogenic sources. Since $PM_{2.5}$ distribution depends on meteorology, implementation of mitigation measures at local scale may not be successful (Chowdhury et al., 2017). Here we quantify the relative shares of residential, industrial, transportation and energy sectors (four major anthropogenic sources that emit $PM_{2.5}$ continuously throughout the year) to annual anthropogenic ambient $PM_{2.5}$ exposure in India using a chemical transport model. Emissions from the seasonal sources such as crop-waste and solid-waste burning, re-suspended dust and brick kilns are not considered in this study. Incorporation of these season-specific emissions would further reduce the relative shares presented here. Therefore, the relative shares of each sector may appear to be higher in comparison to some of the recent studies and should not be interpreted in absolute terms. We note that the objective here is to quantify the maximum expected health benefit at state level due to complete mitigation of emission from these sources.

Our analysis is consistent with the general consensus that residential sources are the largest contributor to the ambient anthropogenic $PM_{2.5}$ exposure in most parts of India (Conibear et al., 2018; GBD-MAPS, 2018; Lelieveld et al., 2015). However, we feel that a comparative discussion (Table 2) would help interpreting the results in view of the various estimates across the literature. The difference in estimated source attributed relative shares across these studies can be attributed to differences in model configuration, model physics and emission inventory. However, considering the health benefit estimates along with 95% uncertainty range, our results are comparable to most of the studies (GBD-MAPS, 2018; Conibear et al., 2018; Lelieveld et al., 2015). Our estimates of health benefit are larger than that in Silva et al. (2016) perhaps because they used an older emission inventory. Our transportation sector attributed burden is comparable to GBD-MAPS (2018), but smaller than the estimate by Conibear et al. (2018). We speculate that this difference could be due to use of a different aerosol and trace gas chemistry scheme in the simulation. Only simulations of source-attributed ambient $PM_{2.5}$ exposure by a single CTM using different emission inventories and by multiple CTMs using same inventory in future would resolve the issue of sensitivity of the estimated health burden to these critical factors.

The health benefit analysis presented here assumes complete mitigation of emissions from these sectors (residential, energy, transport and industry), which we acknowledge is realistically difficult to achieve. Though complete mitigation of residential emissions seems theoretically viable but on-field issues including compliance towards clean fuel usage and stacking of fuels (Smith and Pillarisetti, 2017) makes this a challenging problem to tackle. We understand that mitigating a fraction of emission from other sources like industry, transportation and energy sectors requires

Table 2
A comparative summary of source attributed health burden estimates for the four major continuous anthropogenic sources in India.

Methodology and Input data (Work Reference)				Health burden from different emitting sectors				
Model	Resolution Year	Emission Inventory	Reference	Residential	Transport	Industry	Energy	Total
WRF-Chem	10 × 10 km 2010	EDGAR-HTAP emission	This study	378,295 (175,002 −575,293)	28,180 (12459 −42934)	45,999 (20682 −70021)	18,201 (7777 −27786)	793,985
WRF-Chem	30 × 30 km 2014	EDGAR-HTAP emission	Conibear et al., 2018	256,000 (162000 −340000)	66,000 (45000 −90000)	43,000 (29000 −58000)	90,000 (60000 −122000)	990,000
GEOS-Chem	11 × 11 km 2015	IITB emission[a]	GBD-MAPS, 2018	267,700 (230000 −315000)	23,100	N/A[b]	N/A	1,090,400
EMAC general circulation model	110 × 110 km	EDGAR	Lelieveld et al., 2015	325,604	41,541	42,336	89,130	64,4993
TM5-FASST	110 × 110 km	GAINS and MESSAGE emission	Chafe et al., 2015	200,000 (For South Asia)	N/A	N/A	N/A	N/A
MOZART-4	55 × 73 km	RCP8.5 Global emission & GEIA-ACCENT emission	Silva et al., 2016	173,000	19,900	36,400	39,200	392,000

[a] Details about IITB (IIT Bombay) emission inventory can be obtained from Pandey et al. (2014); Pandey and Venkataraman (2014) and Sadavarte and Venkataraman (2014).
[b] Not available.

enormous effort towards constructing and enforcing policy guidelines throughout the country. Therefore, these estimates should be interpreted as the maximum expected health benefit construing to the fact that any measure to mitigate the emission from these sectors would associate with certain health benefits with these maximum health benefits as the upper bound.

We note that clean air policy should also focus on reducing emission from the transportation, industrial and energy sectors, especially at the urban centers. In response to the public health emergency called by the Indian Medical Association in Delhi NCR, BS-VI compliant fuel has been introduced already leapfrogging BS-V from the existing BS-IV fuel without requiring any change in vehicle technology. This is expected to reduce emission from transport sector by a large margin (80% reduction in SO_2 emission and a large cut in PAH emissions). Recently, the honourable Supreme Court of India has imposed a ban on the usage of dirty fuels like petroleum coke and furnace oil in industries situated in the NCR which in-turn demands better taxation policies for cleaner fuels to be used at large scale in industries. Though the coal-fed power plants offer cheaper cost per unit than the gas-based power plants, the Government of India is focused on improving and extending the capacities of the cleaner gas-based power plants in the NCR. As evident, most of the policies undertaken by the government are focused on curbing air pollution in and around Delhi, though it is obvious that the entire IGB is heavily polluted and requires immediate action plan similar to Delhi NCR. A recent study (Bergin et al., 2017) pointed out that the solar energy resource in India is affected severely by the pollution. Therefore, unless the pollution reduces, the solar energy resource is going to be depleted, especially when ambient $PM_{2.5}$ concentration is projected to increase in the next several decades under the RCP4.5 and RCP8.5 scenarios (Chowdhury et al., 2018). Through this paper, we call for major policy implementation to cut down emissions from these major sectors at regional scale to achieve sustainable development.

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