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# Driving factors behind the continuous increase of long-term PM2.5-attributable health burden in India using the high-resolution global datasets from 2001 to 2020

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Title Page

# Driving factors behind the continuous increase of long-term $PM_{2.5}$-attributable health burden in India using the high-resolution global datasets from 2001 to 2020

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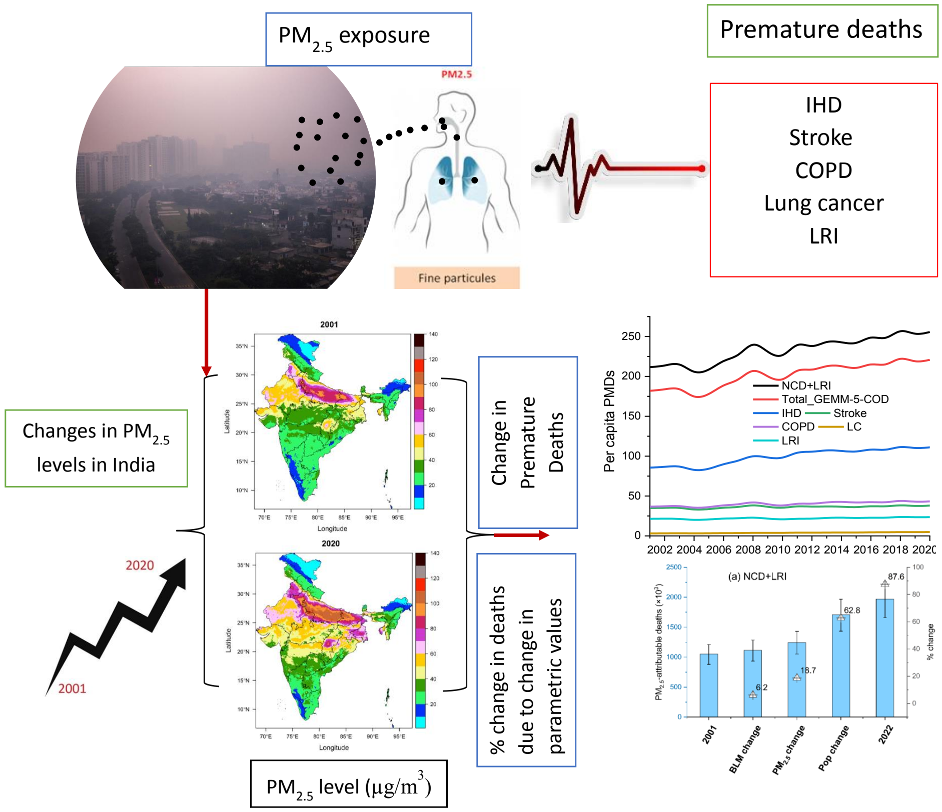
**Abstract:**

Air pollution is the fourth leading global risk factor, whereas in India air pollution is reported as the highest risk factor with millions of premature deaths every year. Despite implementation of several air pollution control plans, $PM_{2.5}$ levels over India have not noticeably reduced. $PM_{2.5}$-associated health burdens in India have increased significantly in past decades. A fine resolution (0·01° × 0·01°) analysis of $PM_{2.5}$-attribulable premature deaths (rather than the coarse-level analysis) may elucidate the reason for this increase and inform and effective start-of-the-art state-level and national emission control strategies. This study quantified the spatiotemporal dynamics of $PM_{2.5}$-attributable premature deaths from 2001 to 2020 and applied a decomposition analysis to dissect the contribution of various associated parameters, such as $PM_{2.5}$ concentration, population distribution and disease-specific baseline death rate. Results show significant spatiotemporal variations of $PM_{2.5}$ and associated health burden in India. During the study period, population weighted $PM_{2.5}$ value increased from 46.0 to 59.5μg/m$^3$ and associated non-communicable death increased around 87.6%, from 1,050 [95% (CI): 880-1,210] thousand to 1,970 (95% CI: 1,658-2,259) thousand. The states of Uttar Pradesh, Bihar, West Bengal, Maharashtra, Rajasthan, and Madhya Pradesh had the highest $PM_{2.5}$-attributable deaths. In these states, non-accidental deaths increased from 232.1, 112.7, 81.4, 79.1, 66.3 and 58.5 thousand in 2001 to 424.1, 226.7, 156.2, 154.5, 123.3 119.7 thousand in 2020. In per capita population (/10$^5$ population), the highest $PM_{2.5}$-attributable deaths were observed in Delhi, Uttar Pradesh, Bihar, Haryana and Punjab. Throughout the study period, demographic changes outweighed the health burden and were responsible for ~62.8% increase of $PM_{2.5}$-

related non-accidental deaths across India, whereas the change in $PM_{2.5}$ concentration influenced only 18.7%. The change in baseline mortality rate impacts differently for the estimation of disease-specific mortality changes. Our findings suggest more dynamic and comprehensive policies at state-specific level, especially for North India is very indispensable for the overall decrease of $PM_{2.5}$-related deaths in India.

**Keywords:** India, Long-term $PM_{2.5}$-exposure, Fine-resolution data, Premature deaths,

**Graphical Abstract**



**Highlights:**

- $PM_{2.5}$-attribulatle deaths with finer resolution (0·01° × 0·01°) from 2001 to 2020 in India is analyzed.
- The GEMM and IER health risk model used to quantify methodological result difference.
- Population-weighted $PM_{2.5}$ increased from 46.0 to 59.5μg/m$^3$ and associated death increased by 87.6%.
- Highest $PM_{2.5}$-attributable deaths were in Uttar Pradesh, Bihar, West Bengal, Maharashtra and Rajasthan
- Demographic changes alone responsible for ~62.8% increase of $PM_{2.5}$-related non-accidental deaths in India.

# Driving factors behind the continuous increase of long-term $PM_{2.5}$-attributable health burden in India using the high-resolution global datasets from 2001 to 2020

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**Keywords:** India, Long-term $PM_{2.5}$-exposure, Fine-resolution data, Premature deaths, Contributing Factor.

## 1. Introduction:

Particulate matter ($PM_{2.5}$) (particulate matter with an aerodynamic diameter of equal to less than 2.5µm) pollution in fast-developing country like India has become an essential research topic (Pandey et al., 2021). As, a rapid increase in $PM_{2.5}$ across India over the recent decade, has resulted from poorly managed rapid urban and agricultural expansion, and industrial revolution. Crop residue burning, power plants, industries, solid waste burning, landfills, vehicles, brick kilns, and diesel generator all add to India's $PM_{2.5}$ burden (Nagpure et al., 2015; Srivastava, 2021; Gulia et al., 2022). Severe air pollution events have become more frequent in urban areas in winter the (Kumari et al., 2021; Ravishankara et al., 2020). Ambient $PM_{2.5}$ is one of the main constituents of air pollution and has become a critical environmental and social issue. A growing body of epidemiological evidence reports that long-term exposure to $PM_{2.5}$ contributes to increased risk of mortality by asthma, lung cancer, respiratory infection, respiratory disorder, diabetes, chronic respiratory disease, chronic obstructive pulmonary disease, hypertension, heart rate variability, heart attack, cardiopulmonary disease, ischemic heart disease, and stroke (Özkaynak et al., 2013; Pope et al., 2020; Sun and Zhu, 2019; Wesselink et al., 2021). Ambient $PM_{2.5}$ is now the leading health burden in India and responsible for 980 thousand premature deaths in 2019 (Global Burden of Disease (GBD) study 2019) (Murray et al., 2020).

In most cities in India, annual mean $PM_{2.5}$ concentrations are 5–25 times higher (CPCD, 2020) than the WHO Air Quality Guidelines of 5 µg/m³ (WHO, 2021). During the last decade, $PM_{2.5}$ over India shows a significant increase of >1 µg/m³/year (Dey et al., 2020). Similarly, Srivastava (2021) reported an increase in average $PM_{2.5}$ in India of 15%/year from 1998 to 2019, reporting Delhi as the state with the worst average $PM_{2.5}$ and Uttar Pradesh having the most cities with high $PM_{2.5}$. Despite this increase in $PM_{2.5}$ pollution, only a few studies have investigated the health impacts caused by $PM_{2.5}$ exposure over a long-term timeframe. Many studies mainly rely on limited surface monitoring data (Nair et al., 2021; Saini and Sharma, 2020), which may be insufficient to reproduce the long-term spatial and temporal variations of $PM_{2.5}$. In India, ground-based measurements of $PM_{2.5}$ are scarce and do not cover all the urban areas. Currently, India's monitor density is 1 monitor/6.8 million people, which is well below than other highly populated countries (Brauer et al., 2019). A long-term database with high spatial resolution is vital for effective health risk assessment in urban and rural areas and for better air quality management (Dey et al., 2020). Satellite-retrieved observations provide valuable additional information with better spatial coverage, but there are substantial uncertainties in quantifying the surface $PM_{2.5}$ relevant to health (Liu et al., 2017). Chemical transport models are better for temporal and spatial coverage than observations, but long-term characterisation of $PM_{2.5}$ sources for large areas is difficult (Wang et al., 2016). For that reason, a database is needed that integrates information from satellite-retrieved aerosol optical depth, chemical transport modelling, and ground monitor data, and that is highly consistent for fine resolution surface-level $PM_{2·5}$ concentrations. Hammer et al., (2020) and van Donkelaar et al., (2021) developed such a model for global estimation of monthly and annual $PM_{2.5}$ concentration with 0.01°×0.01° resolution for 1998–2020. We used this newly developed database, as a previous study had observed that the coarse-level (0.1°×0.1°) database would bias results whilst the finer resolution data could potentially improve the accuracy of health impact estimations (Liu et al., 2019).

Quantitative $PM_{2.5}$-attributable mortality has previously been assessed based on different exposure-response functions, mostly Integrated exposure-response (IER) model (Burnett et al., 2014), which was also used for the GBD study. The IER model has a number or uncertainties when used for the Asian countries (Lelieveld et al., 2020). A global exposure mortality model (GEMM) was developed by Burnett et al., (2018) to reduce these uncertainties. Recent studies indicate that the inclusion of global cohort studies with a large range of ambient $PM_{2.5}$ concentrations in the GEMM model provides improved function for highly pollution areas in Asia (Lelieveld et al., 2020).

In this study, we aimed to improve to estimate trends in $PM_{2·5}$-associated mortality for 36 geographical units in India (28 states; three union-territory of Delhi, Jammu and Kashmir, and Ladakh, and other five small union-territories) by: (1) using finer scale $PM_{2·5}$ concentration estimates [0·01° × 0·01° (approximately 1km$^2$) compared with 0·1° × 0·1° (approximately 100 km$^2$) for GBD study], (2) using the Global Exposure Mortality Model (GEMM) compatible with Integrated Exposure-Response (IER) model used in GBD 2019 study for health risk assessment and (3) estimating the leading factors influencing the $PM_{2.5}$-attributable deaths in India. The resulting $PM_{2·5}$-attributable health impact estimates can inform air quality management approaches at state and national scales.

## 2. Methodology

### 2.1. Ambient $PM_{2.5}$ concentration and population data

The GBD study provide database for ambient $PM_{2\cdot5}$ concentrations at a 0·1° × 0·1° resolution, although in the present study we used fine resolution $PM_{2.5}$ concentration estimates at 0.01°×0.01° resolution covering the period from 2001 to 2020, obtained from the Atmospheric Composition Analysis Group at Washington University in St. Louis (https://sites.wustl.edu/acag/datasets/surface-pm2-5/). Annual and monthly mean Global/Regional Estimates (V5.GL.02) data was selected. The $PM_{2\cdot5}$ concentrations dataset is integrated information from satellite-retrieved aerosol optical depth, chemical transport modelling, and ground monitor data. Further details on the method for estimating global ambient $PM_{2.5}$ is reported in the van Donkelaar et al.,( 2021) study. The downloaded datasets were in NetCDF format data. We converted them to "Geotiff" format then cropped and masked the raster with India's shapefile.

The gridded Indian population counts data with a resolution of 1×1 km from 2001 to 2020 were obtained from the WorldPop datasets (https://www.worldpop.org/). WorldPop spatial datasets are principally produced by integrating contemporary census data, settlements mapping, bottom-up population mapping, and intra-urban population mapping, then adjusted with the United Nations (UN) population growth model (12,106,108 grid). The gridded India population was then resampled using nearest neighbour approach to match the resolution of $PM_{2.5}$ data (8,889,515 grid) (Lim et al., 2020; Tan et al., 2022). Finally, the re-gridded $PM_{2.5}$ data and population data were used to estimate the population-weighted exposure level of $PM_{2.5}$ concentration and premature deaths.

## 2.2. Health impact function

We used a health risk model to estimate mortality attributable to $PM_{2\cdot5}$, following the method used in previous studies by Castillo et al., (2021), Yin, (2021), Anenberg et al., (2019), Zhang et al., (2022) and Nansai et al., (2021). The health impact function incorporates annual average $PM_{2\cdot5}$ concentrations, population counts, baseline mortality rates, and epidemiologically derived exposure-response functions relating $PM_{2\cdot5}$ concentrations and health outcomes. The population attributable fraction ( $PAF_{i,d}$ ) is the percentage of disease in a given population that is attributable to $PM_{2\cdot5}$ based on exposure-response functions, incorporating the relative risk ( $RR_{i,d}$) derived from the integrating cohort studies. $PAF_i$ calculated for each grid area ( $i$ ) for disease-specific health endpoint ( $d$ ) is calculated using equation 1.

$$PAF_{i,d} = (RR_{i,d} - 1) / RR_{i,d} \tag{1}$$

The $PM_{2\cdot5}$-attributable mortality burden was then calculated using the following equation:

$$PMD_{i,d} = PAF_{i,d} \times Pop_i \times BM_d \quad (2)$$

in which $PMD_{i,d}$ represents the $PM_{2.5}$-related premature death for health endpoint $d$ in a grid $i$, $Pop_i$ is the number of population with age ≥25 years in a grid $i$ and $BM_d$ is the baseline mortality for the health endpoint $d$.

The GEMM is parameterized for disease-specific incremental relative risk ($RR_{i,d}$) assessment (Burnett et al., 2018). The GEMM consider $PM_{2.5}$ related total non-accidental mortality [non-communicable disease (NCD)+lower respiratory infections (LRI)] estimation called GEMM-NCD+LRI and five cause-specific mortality, ischemic heart disease (IHD), stroke (STR), chronic obstructive pulmonary disease (COPD), lung cancer (LC) and lower respiratory infections (LRI) estimation called GEMM-5COD based on the Chinese male cohort. For comparisons with past studies, the integrated exposure-response (IER) model study was also used (Burnett et al., 2014) for five cause-specific death estimations (i.e., IHD, STR, COPD, LC and LRI) (IER-5COD). More details about IER and GEMM models are reported in Supplementary Material. We present uncertainty in attributable mortality estimates from the health impact function by estimating results at a 95% confidence interval (95% CI). We obtained India-specific, age-specific, and cause-specific baseline disease rates from the GBD study data exchange platform for 2001 to 2019 (2019 values are used thereafter). The ratios of ≥25 years old over the entire population between 2001 and 2020 were derived from the national age structure data (https://www.populationpyramid.net/india/). According to equation (2), $PM_{2.5}$-attributable premature mortality is determined by three quantifiable variables and the changes in these variables contribute to the changes in $PM_{2.5}$-related mortality. We quantify the impacts of the changes in each of these three factors on the changes in premature mortality during the 2001 and 2020 period.

### 2.3. Driving factors analysis

We separated the effects of baseline mortality (BM) rate, $PM_{2.5}$ concentration and population (Pop) on increase/decrease of $PM_{2.5}$-attributable premature deaths using the decomposition approach adopted by GBD study (Cohen et al., 2017). Since the sequence of changing factors may affect the estimated contribution, we performed the decomposing process under all six possible sequences of the three factors. It is worth noting that the impact factors may interact and influence each other. For example, air pollutant emissions are strongly associated with population, and thus population would have a notable impact on the levels of $PM_{2.5}$; exposure to $PM_{2.5}$ itself would affect the baseline incidence rate. The decomposition method estimates the contribution of factors by sequentially introducing each factor into the Equation 1. The difference between each consecutive step provides an estimate of the relative contribution of each factor. As the sequence of adding factors also influences the results, we estimated the results under all 6 possible sequences of the three factors The final estimation of contributions from different factors is the average value of the results for each factor (Yue et al., 2020; He et al., 2020). Detailed equations and processes are shown in Supplementary Fig. S1.

## 3. Results and Discussions

### 3.1. Pattern in $PM_{2.5}$ concentration

The annual spatial distribution of $PM_{2.5}$ in 2001, 2010, 2011 and 2020 over India is shown in Figure 1 (and Fig. S2-S3). Four points are notable in these Figures: (1) ambient $PM_{2.5}$ exceeds the annual NAAQS of 40 μg/m$^3$ in 12 states in 2001 and 16 states in 2020. The highest annual average $PM_{2.5}$ concentrations were observed during this period in Delhi, Uttar Pradesh, Bihar, Haryana, and Punjab. In these states, from 2001 to 2010, $PM_{2.5}$ concentration increased from 95.5±4.8, 77.0±18.8, 70.9±17.9, 69.1±16.1 and 61.5±12.9 μg/m$^3$ to 127.4±5.8, 92.4±18.4, 78.4±15.5, 93.1±16.2 and 79.8±14.5 μg/m$^3$ respectively. In the same states average $PM_{2.5}$ concentrations reduced to 111.7±5.1, 91.6±17.7, 86.2±13.9, 85.5±13, 73.1±10.9 μg/m$^3$ in 2020 from 130.4±4.8, 98.1±18.8, 88.9±16.1, 95.4±17.9, 77.8±12.9 μg/m$^3$ in 2011 (Table S1). In some states annual average $PM_{2.5}$ concentration in 2020 was lower than in 2019, possibly due to COVID-19 lockdown restrictions (Venter et al., 2021). The lowest annual average $PM_{2.5}$ concentrations (<20 μg/m$^3$) were observed in Ladakh, Arunachal Pradesh and Kerala, where the population is scattered and state is in high covered by mountains, and low number of polluting industries (Thomas et al., 2020; Dey et al., 2020). (2) All the states with the highest-level $PM_{2.5}$ are in the Indo-Gangetic Plain (IGP) and the western region of India. The IGP is a low-lying fertile alluvial plain bounded by the Himalayas in the north and central Indian highlands in the south. It is a densely populated region with more than 480 million people, about 40% of India' population (Shagun, 2019). Continuous increase of emissions of primary and secondary $PM_{2.5}$ coupled with unfavourable topography and meteorology leads to a large build-up of $PM_{2.5}$ in this region. (3) A more severe situation is observed during winter (December to January), as due to low wind speeds, $PM_{2.5}$ is trapped in the valley and does not disperse (Dey and Di Girolamo, 2010) and causing high $PM_{2.5}$ (~300 μg/m$^3$ in some places) (Fig. S1). A substantially decrease in $PM_{2.5}$ was observed during the monsoon season, as particles are washed out of the air by monsoon rain. The $PM_{2.5}$ concentration reduced to below

40μg/m$^3$, except for in large cities, with the largest reduction observed over the eastern IGP and the west coast region (Fig. S2) (Dey et al., 2020). (4) There is an area in the IGP region with 2-times higher than the annual average $PM_{2.5}$ NAAQS which increases significantly from 2001 to 2020.

**Fig. 1.** Spatial distributions of annual average $PM_{2.5}$ averages in 2001, 2010, 2011 and 2020.

### 3.2. $PM_{2.5}$-attributable premature deaths in India

Population-weighted $PM_{2.5}$ concentrations increased from 46.0 to 56.0μg/m$^3$ during 2001 to 2010, then remained relatively stable during 2011 to 2020 with concentrations of 60.2 and 59.5μg/m$^3$ respectively. Figure 2 shows the increase in $PM_{2.5}$ concentration in India and the two factors (i.e., demographic and baseline death rate change) that influenced the quantitative estimation of $PM_{2.5}$-related deaths. India's population increased significantly in the past 20 years, from 1075 million in 2001 to 1380 million in 2020. Of these, 496 million and 770 million respectively were ≥25 years old. In 2001, around 285, 420, 485 and 494 million residents aged ≥25 years were exposed to $PM_{2.5}$ concentrations above proposed WHO 2021 air quality interim targets (IT) 1 to 4 (35, 25, 15 and 10 μg/m$^3$) (WHO, 2021). This exposed population increased by 167, 163, 129 and 124% for the four ITs in 2010. In 2020, around 598, 726, 765 and 768 million residents were exposed to $PM_{2.5}$ concentrations above the four ITs an increase of only 20 to 23% compared to 2011. Of the total population, around 57.4, 84.6, 97.8 and 99.5% of residents were exposed above IT1, IT2, IT3 and IT4 WHO guideline values in 2001, changing to 77.6, 94.2, 99.3 and 99.7% in 2020.

The baseline disease incidence rates differed from each other. The sum of NCD and LRI had the highest incidence rate (791~826 mortalities per 100,000 people) in India. At the disease-specific level, IHD had the highest baseline death rate (174~201 per 100,000), while LC had the lowest baseline value (9~12 mortalities per 100,000 people). During the study time frame, the baseline incidence rate decreased for STR (101~93 per 100,000) and was stable for COPD (118~120 per 100,000) and LRI (38.7~38.8 per 100,000) related deaths.

**Fig. 2.** Time series of percentage of population over 25 years, total population ≥ 25 years, and disease-specific baseline mortality rate in India from 2001 to 2020.

### 3.2.1. Country-level premature deaths

Our health risk assessment focused on estimating premature deaths attributable to ambient $PM_{2.5}$ exposure from 2001 to 2020 in India. Two sets of age-specific Global Exposure Mortality Model (GEMM) were used to estimate non-accidental deaths (NCD+LRI related deaths) with the GEMM-NCD+LRI model, five types of disease-specific deaths were estimated with the GEMM-5COD model, and for comparison, the same five types of disease-specific deaths were also estimated using the IER-5COD model. For each model, the same set of global databases for $PM_{2.5}$ exposure and population, percentage of population ≥25 and age-specific baseline death values were used. The methodology-specific estimated premature mortalities for selected years are shown in Table 1 and Figure 3. More detailed results are reported in Table S2 (Supplementary Material).

In 2001, $PM_{2.5}$-attributable total non-accidental deaths (GEMM-NCD+LRI model) were 1,050 [95% Confidence Interval (CI): 880-1,210] thousand [GEMM-5COD: 903 (95%CI: 660-1,093) thousand and IER-5COD: 537 (279-790) thousand], increasing to 1,404 (1,181-1,613) thousand [GEMM-5COD: 1,217 (909-1,451) thousand and IER-5COD: 723 (386-1,051) thousand] in 2010. Non-accidental deaths further increased during 2011-2020 from 1,517 (1,277-1,740) thousand [GEMM-5COD: 1,313 (985-1,559) thousand and IER-5COD: 780 (420-1,129) thousand] to 1,970 (1,658-2,259) thousand [GEMM-5COD: 1,701 (1,277-2,021) thousand and IER-5COD: 1,007 (543-1,459) thousand].

Previously unaccounted for non-communicable diseases (other-NCD) (GEMM-NCD+LRI *minus* GEMM-5COD) connected to premature deaths from $PM_{2.5}$ numbered 148 thousand in 2001 and increased to 269 thousand in 2020. In total nonaccidental deaths, 'other-NCD', IHD, STR, COPD, LC and LRI contributed 13.6, 42.5, 15.6, 17.2, 1.7 and 9.5% respectively during the period studied (Table 1). In the IER-5COD model, IHD, STR, COPD, LC and LRI contributed 39.8, 29.1, 17.1, 1.9 and 12.1% respectively. The ratio of averted deaths from GEMM-5COD to GEMM-NCD+LRI and IER-5COD to GEMM-NCD+LRI was 0.51 and 0.86. A slightly lower ratio of 0.46 and 0.84 was observed in 2015 by (Burnett et al., 2018), this difference is likely to be due to our use of different $PM_{2.5}$ datasets. Total non-accidental deaths increased to 33.7% from 2001 to 2010 and 29.8% from 2011 to 2020, and an overall increase of 87.6% from 2001 to 2020. The GBD and WHO studies (NHP, 2019; WHO, 2020) report 3773 thousand and 6099 thousand all-cause NCD+LRI deaths in 2001 and 2020 in India. Our study found that the contribution of $PM_{2.5}$-related deaths to all-cause NCD+LRI slowly increased from 27.2% to 32.3%. The $PM_{2.5}$-attributable premature mortality increased continuously from 2001-2020. With a faster increase during the first decade for more contributing health endpoints (IHD: 43.1%, STR: 26.1%, COPD: 29.9%, LC: 52.0%, LRI: 21.3%) than during the second decade (IHD: 29.5%, STR: 24.7%, COPD: 30.8%, LC: 43.1%, LRI: 33.6%). We found age-standardised per capita death rate (per $10^5$-population age ≥ 25 years) increased ~21% during the 2001-2020 [GEMM-NCD+LRI: 212 to 256 and IER-5COD: 108 to 131]. Southerland et al., (2022) reported a 33% increase in per capita $PM_{2.5}$-attributable mortality for urban areas in India from 2000 to 2019 (Figure 4). In general, the overall increasing trend in both mortality values and percentage of total NCD+LRI in India indicates a weakness of $PM_{2.5}$ related emission policies that impaired health conditions in India.

Table 1. Annual $PM_{2.5}$ attributed premature death (with 95% CI) in India using GEMM model and IER model.

**Fig. 3.** (a) Annual $PM_{2.5}$ attributed premature deaths in India from 2001 to 2020. The black error lines represent the 95% confidence intervals. (b) and (c) represent percentage contribution of cause-specific death in 2001 and 2020.

**Fig 4.** Per-capita non-accidental and cause-specific premature deaths in Indian from 2001-2020 based on (a) GEMM and (b) IER model.

### 3.2.2. State-level premature deaths

Figure 5 is an abstract view of state-level adverse health impacts caused by $PM_{2.5}$ pollution in 2001 and 2020. A wide variation in $PM_{2.5}$-attributable premature deaths was observed between different the states. The highest numbers of non-accidental deaths (GEMM-NCD+LRI model) were observed in Uttar Pradesh, Bihar, West Bengal, Maharashtra, Rajasthan, and Madhya Pradesh. From 2001 to 2010, non-accidental deaths increased from 232.1 (196.3-264.9), 112.7 (95.2-128.9), 81.4 (68.1-94.1), 79.1 (65.7-91.9), 66.3 (55.6-76.2), 58.5 (48.8-67.6) thousand to 310.1 (263.3-352.5), 150.7 (127.6-171.9), 106.2 (89.1-122.2), 108.6 (90.5-125.7), 90.5 (76.3-

103.7), 81.1 (67.9-93.4) thousand, respectively. From 2011 to 2020, non-accidental deaths increased from 331.4 (281.9-376.3), 167.3 (142.0-190.4), 119.8 (100.8-137.4), 116.4 (97.1-134.6), 93.9 (79.1-107.6), 89.5 (75.1-102.9) thousand to 424.1 (360.1-482.2), 226.7 (192.3-258.0), 156.2(131.7-178.9), 154.5 (129.1-178.5), 123.3 (103.8-141.3), 119.7 (100.5-137.6) thousand in Uttar Pradesh, Bihar, West Bengal, Maharashtra, Rajasthan, and Madhya Pradesh respectively. However, per capita population, there were more premature deaths in Delhi, Uttar Pradesh, Bihar, Haryana and Punjab, with approximately 325 (276-369), 288 (244-329), 280 (236-320), 272 (229-311) and 250 (210-287) in 2001 and 360 (307-408), 327 (277-372), 322 (274-367), 321 (272-365), 290 (245-332) in 2020, respectively. The lowest numbers of per capita deaths were in Ladakh, Arunachal Pradesh, Kerala, Nagaland and Tamil Nadu. More details on state-level and model-specific values are reported in Table S2.

Rapid urbanization over the past decades has caused growing concerns about the environmental, social and health impacts on Asia's urban population (Ravishankara et al., 2020; Wu et al., 2020). India has witnessed rapid inter-state migration, a key issue of the urbanization process often considered detrimental to the urban environmental and residential energy transition. Due to the considerable gap between state-to-state energy consumption and economic investment level, large-scale migration places extra impacts on air pollutant emissions and create uncertainties for quantitative health risk assessment (Shen et al., 2017; Shi et al., 2020). Up till the 2011 Census, Maharashtra and Delhi, two states with high per capita income, had received 9.1 million and 7.2 million migrants born in other states (Census of India, 2011a). In 2001, the corresponding numbers were 7.9 million and 5.5 million, indicating a sharp rise in migration over the decade (Census of India., 2001). The Indian government predicted that in 2021, the migrating population would increase to 12.2 and 8.5 million in Maharashtra and Delhi (Census of India, 2011b). Of the total migrating population, only 40% of people stay more than one year. If we assume the migrating population settled equally as per the distribution of state population, then the $PM_{2.5}$-exposure attributable to non-communicable premature deaths among the migration population was 7.1 (6.1-8.1) thousand and 5.0 (4.2-5.8) thousand in 2001 and 12.2 (10.4-13.9) thousand and 10.5 (8.3-11.5) thousand in 2020 in Delhi and Maharashtra.

**Fig. 5.** State-level annual $PM_{2.5}$ attributed premature deaths (GEMM model) for the years (a) 2001 and (b) 2020.

### 3.3. Factors affecting premature deaths

Variations in $PM_{2.5}$-related premature deaths over India are due to the non-linear interactive changes of associated parameters. The health risk model was based on the input data for the corresponding year, including gridded annual average $PM_{2.5}$ values, population aged ≥25 years, and disease-specific baseline death rate. Relative risk caused by $PM_{2.5}$ is log-linearly associated in Eq. (2). This data allowed us to comprehensively assess each factor's effect on the estimated premature mortality in order to explain trends. Figure 6 illustrates the changes for each factor to NCD+LRI-related $PM_{2.5}$-attributable mortality and individual diseases specific mortality over India from 2001 to 2020. In general, the change in baseline mortality rate (BM) and $PM_{2.5}$ exposure, accounted for 65 (55-75) thousand (6.2%) and 196 (171-218) thousand (18.7%) increase in $PM_{2.5}$-related deaths in 2020 compared to 2001. By contrast, demographic changes outweighed the health burden alone resulting in a 660 (555-758) thousand increase (62.8%) in NCD+LRI related $PM_{2.5}$ exposure mortality for those years. In the absence of changes in baseline values, changes in both $PM_{2.5}$ exposure and population accounted for an 81.5% increase [856 (725-976) thousand] in total $PM_{2.5}$-related non-accidental deaths between 2001 and 2020. Among the five diseases (GEMM-5COD model), change in baseline mortality alone increased premature deaths related to IHD by 21.4% [91 (85-96) thousand], LC by 43% [6.8 (4.4-8.6) thousand], decreased by -11.6% [21 (11-27) thousand] for STR, and had minor fluctuations in COPD (2.1%) and LRI (0.3%).

From 2001 to 2020, the only change of spatiotemporal increase of $PM_{2.5}$ in India was responsible for 65 (63-67), 35 (22-42), 35 (21-43), 3.6 (2.6-4.2) and 12 (9-13) thousand increases in premature deaths for IHD, STR, COPD, LC and LRI, which was only about 15.4, 20.2, 19.2, 23.0 and 11.3% of total addition. Changes in baseline disease rates had more impact on $PM_{2.5}$-attributable mortality than the change of $PM_{2.5}$ concentrations for IHD and LC. Individually, the effects of demographic changes on the disease-specific mortality were influencing above 60% increase of premature deaths during 2001-2020, and accountable for 276 (258-293), 104 (57-139), 113 (60-155), 11.3 (7.4-14.4) and 63 (38-78) thousand increase in premature deaths for IHD, STR, COPD, LC and LRI, respectively. Our results demonstrate that the driving factors on the $PM_{2.5}$-attributable premature deaths varied spatially according to disease.

**Fig. 6.** Change in $PM_{2.5}$ attributable premature deaths in India between 2001 and 2020, due to baseline mortality (BM) change, changes in exposure to $PM_{2.5}$, and change of population ≥ 25 years old for $PM_{2.5}$-related non-communicable disease, IHD, STR, COPD, LC and LRI.

The estimated $PM_{2.5}$-attributable premature deaths differ significantly between studies, mainly due to (1) use of different methods to estimate ground-level $PM_{2.5}$ concentration, like spatial interpolation of ground-level measurement, satellite remote sensing data or a combination of satellite and machine learning model, chemical transport model and land-use regression model. Each model predicts incompatible results and has its advantages and disadvantages (Liang et al., 2020; Zhang et al., 2021). (2) Studies focused on spatial resolution (0.1°×0.1° or 0.01°×0.01°) have dissimilar attributable values. The high spatial resolution data can sharply capture the pollution level in areas with diverse emissions, topography, green space, and demography. As such, high-resolution data are particularly beneficial for evaluating the health impacts, as the exposed concertation is not far from the overall personal-exposure value. (3) The application of non-identical health risk assessment model (linear, near-linear, log-linear, non-linear exposure-response models) estimate significant different result (Nasari et al., 2016). (4) The use of different baseline mortality rates and demographic age distribution will produce distinct results.

Notably, (Liao et al., 2022) developed a random forest model to predict ambient $PM_{2.5}$ concentrations at a 0.1°×0.1° spatial resolution over India, which predicted a population-weighted annual average $PM_{2.5}$ value of 67.7μg/m$^3$ in 2010, higher than the values reported by Hammer et al., (2020) (64.6μg/m$^3$) and van Donkelaar et al., (2016) (50.2μg/m$^3$). For 2017 Liao et al., (2022) predicted a value of 72.3μg/m$^3$, which stand between the predicted value by Shaddick et al., (2018) (89.9μg/m$^3$) and van Donkelaar et al., (2021) (58.7μg/m$^3$). Balakrishnan et al., (2019) and Stanaway et al., (2018) (GBD study 2017) used the same ambient $PM_{2.5}$ dataset and the IER-5COD model to estimate $PM_{2.5}$-attributable premature deaths, however the results are notably different from each other, 673 (552-793) thousand and 889 (704-1,084) thousand. Balakrishnan et al., 2019) study underestimates the overall impact of $PM_{2.5}$ because it did not include diseases for which the evidence is emerging but not fully established in India. In our study, we estimated higher premature deaths [925 (497-1,343) thousands] using the same IER model. Our higher estimate values are probably related to the use of a different $PM_{2.5}$

database with higher resolution (0.01°×0.01°) and demographic structure. When using the same $PM_{2.5}$-database for 2019, from van Donkelaar et al., (2021) and same IER-5COD model, Pandey et al., (2021) and our study estimate very similar $PM_{2.5}$-attributable premature deaths, 980 (770-1,192) thousand and 978 (527-1,418) thousand.

Burnett et al., (2018) estimated 2,219, 1,867 and 1,022 thousand premature deaths in India with the GEMM-NCD+LRI, GEMM-5COD and IER-5COD health-risk models by employing the Shaddick et al., (2018) $PM_{2.5}$-database for 2015, which was higher than our study, as the population-weighted $PM_{2.5}$ was higher in Shaddick et al., (2018) study (74.0µg/m$^3$) than van Donkelaar et al., (2021) study (56.7µg/m$^3$). Use of a single relative risk in the non-linear exposure-response model estimated much higher premature deaths than any other health risk model (Maji et al., 2018), like Vohra et al., (2021) reported 2,458 thousand deaths attributable to $PM_{2.5}$ air pollution In India from fossil fuel combustion only, for 2012. Consequently, the non-linear power-law exposure-response model generates the lowest $PM_{2.5}$-attributable premature deaths as reported by Chowdhury and Dey, (2016).

In the state-level studies, for 2019 using the IER-5COD model, Pandey et al., (2021) reported the highest premature deaths attributable to ambient $PM_{2.5}$ in Uttar Pradesh [217 (166-273) thousand], Maharashtra [95 (74-117) thousand] and West Bengal [70 (52-89) thousand], whereas our study estimated 209 (117-291), 79 (41-118) and 75 (40-109) thousand premature deaths, respectively, for the same method category. Southerland et al., (2022) reported an increase of 17 to 30 thousand of premature deaths (76% increase) (IER-5COD model) in the National Capital Region (NCR)-Delhi from 2000 to 2019, and our study estimated a similar increase of premature deaths (78%) in Delhi [IER-5COD model; 2001: 10.5 (5.8-14.5) thousand and 2020: 18.8 (10.9-25.7)] during 2001 to 2020.

In an update from previous studies, our study took advantage of newly available finer spatial scale, high-resolution $PM_{2.5}$ data for total and cause-specific $PM_{2.5}$-attributable deaths available for the 2001 to 2020 period. Our study also employed year-to-year population distribution data. The added spatiotemporal richness allowed us to quantitatively decompose the effects of changes in influencing factors, helping to pinpoint relevant driving forces in India's $PM_{2.5}$-attributable health burden. New information has been brought to light, which enriches the understanding of "other-NCD" deaths and ageing-population effects that was previously neglected in India-specific study.

Compared with previous studies, our results demonstrate that the choice of the $PM_{2.5}$-related health risk model gives distinctly different $PM_{2.5}$-attributable premature deaths values. We are not able to say which model most accurately predicts $PM_{2.5}$-related mortality values for India, as both models have not included any epidemiological study from India, due to not availability. The GEMM model may provide more accurate predictions, as it includes a cohort study from China, where $PM_{2.5}$-exposure level is similar to India. The GEMM model predicted higher premature death values than the IER model, but the relative contribution factors (i.e., by change of $PM_{2.5}$, population and baseline rate) did not apparently change, indicating that that the central idea made by this study still win.

Another benefit of our study was the high-resolution estimates of gridded $PM_{2.5}$ values, which advanced the spatial scale of $PM_{2.5}$-related deaths compared with previous low-resolution data (0.1°×0.1°) studies including the GBD study. Due to the lack of historical ground-level $PM_{2.5}$ observations in India before 2015, the calibration between ground-level $PM_{2.5}$ measured value and satellite aerosol optical depth cannot be quantified directly and may bias historical predictions of $PM_{2.5.}$ Data used for large rural areas where ground-level measurements were not available and often lack of validation.

The consistent growth of population ≥25 years led to an increase in $PM_{2.5}$-attributable premature mortality for India in the past 20 years. In addition, the effect of population change may be partly attributable to the interstate migration of the population to the more polluted urban regions, like Maharashtra and Delhi. It is unavoidable and difficult to control population growth and natural ageing compared with other controlling factors. Thus, along with strict state/location/city specific air pollution control policies, proper health advises and strengthened medical facilities are required to lower the cause-specific baseline death rate. To reduce premature death induced by $PM_{2.5}$ exposure, a joint $PM_{2.5}$ pollution mitigation and health improvement policies should be developed.

The cause-specific incidence rate has minimal influence on increase in $PM_{2.5}$-attributed deaths in India. In the last two decades, the improvement of economic and medical conditions in India has increased life expectancy by over 7 years (WB, 2022). This improvement in health conditions has reduced the baseline death rate, somewhat hiding what would otherwise have been an even sharper increase in $PM_{2.5}$-related NCD+LRI deaths. The change in disease-specific baseline death rate had a complicated effect on changes in $PM_{2.5}$-attributable mortality. Promoting a healthier lifestyle that reduces the disease-specific mortality rates can help reduce pollution-related deaths in India.

The present study has several limitations, including our inability to fully account for uncertainties. Uncertainty was inherent in the estimates for each input in the health impact function, including the relative risk estimates, population estimates, $PM_{2\cdot5}$ concentration estimates, and baseline mortality rates. Baseline mortality rates were uncertain, one of the reasons being because we applied country-level baseline disease rates, although urban baseline disease rates and demographics could differ from country-level or state-level averages. Poor areas may have much higher baseline mortality rate than rich areas, that have not considered due to unavailability of data. In our resampling process, we lost 0.01% population data. The resampling method cannot guarantee the total population identical to that without the resampling, that may introduce some uncertainty, although aggregation based on area weights can reduce this uncertainty (Figure S6).

## 4. Conclusions

Our study investigated the $PM_{2.5}$-trend and associated premature mortality in India from 2001 to 2020 and the driving factors of $PM_{2.5}$-related deaths during this period. A significant spatiotemporal variation of the $PM_{2.5}$-trend and attributable health impact were observed during the study period. All the states with the highest-level $PM_{2.5}$ were in the Indo-Gangetic Plain and the western region of India where population density is highest. The total non-accidental deaths due to $PM_{2.5}$ increased by ~87.6% during the study period, although cause-specific deaths increased around 69-137%. Uttar Pradesh, Bihar, West Bengal, Maharashtra, Rajasthan, and Madhya Pradesh were the six states with the highest number of premature deaths. Together these states contributed 61% of the total $PM_{2.5}$-related accounted deaths. Delhi, Uttar Pradesh, Bihar, Haryana, and Punjab had the highest per capita mortality, as these states were exposed to high $PM_{2.5}$ concentration. Overall $PM_{2.5}$-attributable deaths increased in India over the study period, and our findings suggested the principal driving factor for the increase was demographical changes from 2001 to 2020, contributing ~62.8% to the total increase. The change in baseline cause-specific death rate did not bring significant changes in total premature deaths, but changes in ischemic heart disease and lung cancer increased the health burden. A comprehensive, state-of-the-art intervention strategy should be implemented to reduce spatiotemporal heterogeneity in $PM_{2.5}$ and corresponding attributed deaths. Joint action is needed from central and state government pollution control boards to implement source-specific policies for future reductions in $PM_{2.5}$. No epidemiological study has been conducted in India that identifies the effects of long-term $PM_{2.5}$ exposure for different age groups and non-accidental or cause-specific mortality. To refine the exposure-response model, a cohort study should be conducted to improve understanding and policies to reduce India-specific quantitative $PM_{2.5}$-related premature deaths.

**CRediT authorship contribution statement:**

**KJM**: Conceptualization, curation, resources, methodology and formal analysis. **KJM and AN**: Writing original draft preparation. **KJM, AN and LB**: Writing-review and manuscript revisions and supervision.

**Declaration of competing interest:**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 1. Annual $PM_{2.5}$-attributed premature death (with 95% CI) in India using GEMM model and IER model.

| Year | Population-weighted $PM_{2.5}$ ($\mu g/m^3$) (mean ± SD) | GEMM-NCD+LRI model ($\times 10^3$/year) | GEMM-5-COD model ($\times 10^3$/year) | | | | | | IER model ($\times 10^3$/year) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | NCD+LRI | Total | Disease-specific mortality | | | | | Total | Disease-specific mortality | | | | |
| | | | | IHD | STR | COPD | LC | LRI | | IHD | STR | COPD | LC | LRI |
| 2001 | 46.0 (39.0±18.7) | 1050 (880-1210) | 903 (660-1093) | 425 (396-452) | 174 (94-235) | 182 (96-251) | 16 (10-20) | 106 (63-134) | 537 (279-790) | 205 (141-308) | 168 (59-227) | 90 (42-137) | 9 (3-13) | 64 (33-105) |
| 2005 | 49.5 (40.6±19.5) | 1143 (959-1316) | 975 (715-1176) | 462 (431-490) | 185 (101-249) | 198 (104-272) | 18 (12-23) | 113 (68-142) | 583 (304-854) | 223 (154-337) | 180 (63-239) | 99 (47-149) | 10 (3-15) | 71 (37-114) |
| 2010 | 56.0 (44.9±22.9) | 1404 (1181-1613) | 1217 (909-1451) | 608 (569-644) | 219 (121-292) | 236 (126-323) | 24 (16-30) | 129 (78-160) | 723 (386-1051) | 293 (203-445) | 210 (75-275) | 121 (59-178) | 14 (5-20) | 85 (45-133) |
| 2011 | 60.2 (47.5±24.1) | 1517 (1277-1740) | 1313 (985-1559) | 661 (619-699) | 235 (130-312) | 255 (136-347) | 26 (17-33) | 136 (83-168) | 780 (420-1129) | 317 (220-484) | 223 (80-290) | 132 (66-192) | 15 (5-21) | 92 (50-141) |
| 2015 | 56.7 (46.1±22.5) | 1683 (1415-1932) | 1465 (1097-1744) | 736 (689-779) | 251 (139-335) | 291 (155-397) | 30 (20-38) | 157 (95-195) | 865 (464-1257) | 354 (245-539) | 240 (85-313) | 149 (73-219) | 17 (6-24) | 105 (56-162) |
| 2020 | 59.5 (47.2±23.1) | 1970 (1658-2259) | 1701 (1277-2021) | 856 (802-906) | 293 (162-389) | 334 (178-454) | 37 (25-47) | 182 (110-225) | 1007 (543-1459) | 411 (285-628) | 279 (99-360) | 172 (85-251) | 22 (7-30) | 124 (66-189) |

**List of Figures:**

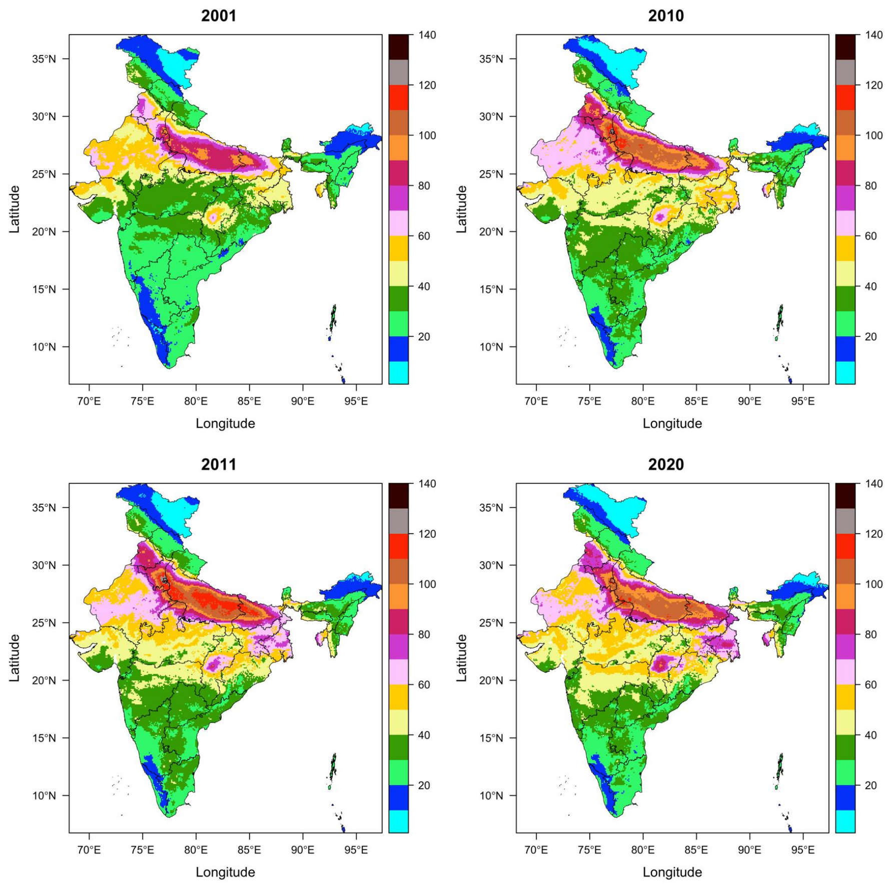


**Fig. 1.** Spatial distributions of annual average $PM_{2.5}$ concentration ($\mu g/m^3$) in 2001, 2010, 2011 and 2020.

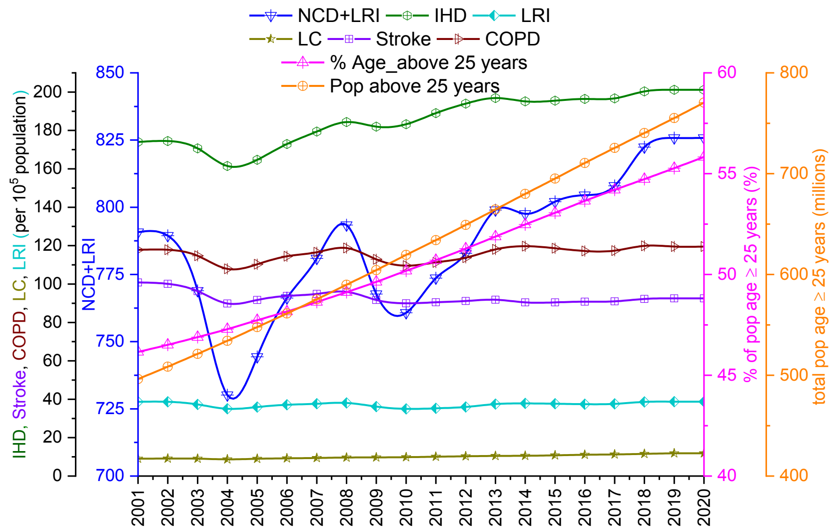


**Fig. 2.** Time series of percentage of population over 25 years, total population ≥ 25 years, and disease-specific baseline mortality rate in India from 2001 to 2020.

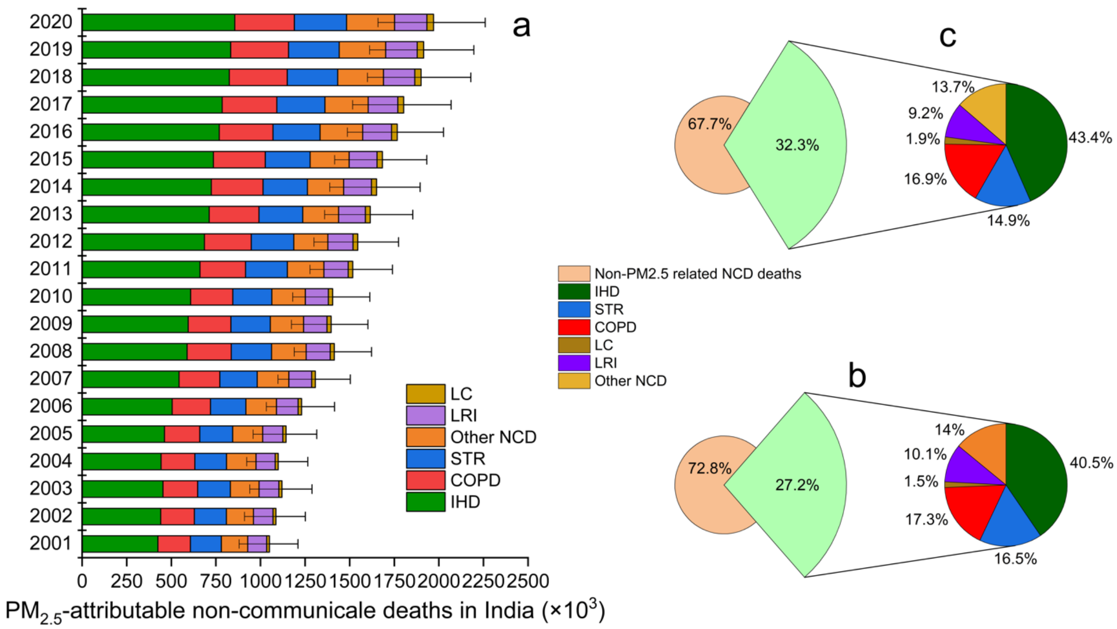


**Fig. 3.** (a) Annual $PM_{2.5}$-attributed premature deaths in India from 2001 to 2020 in India. The black error lines represent the 95% confidence intervals. (b) and (c) represent percentage contribution of cause-specific death contribution in 2001 and 2020.

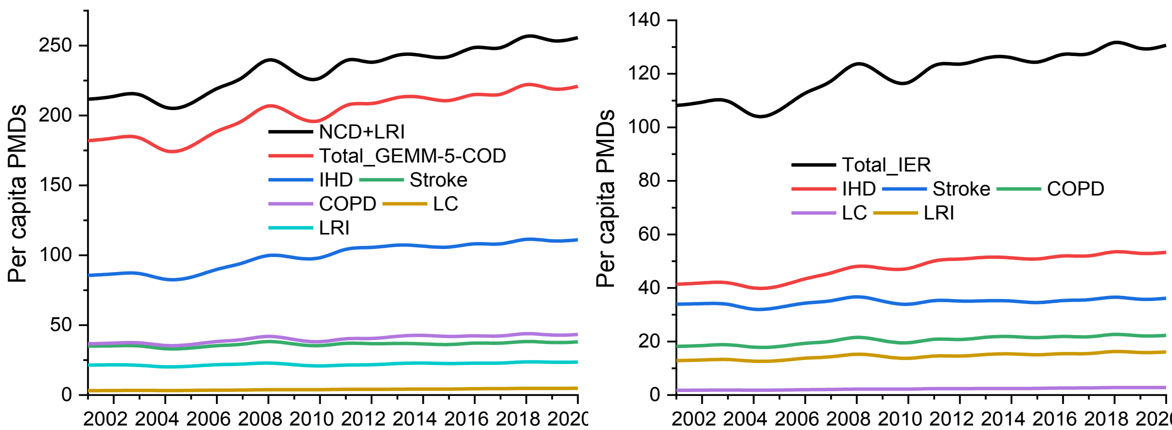


**Fig 4.** Per-capita non-accidental and cause-specific premature deaths in Indian from 2001-2020 based on (a) GEMM and (b) IER model.

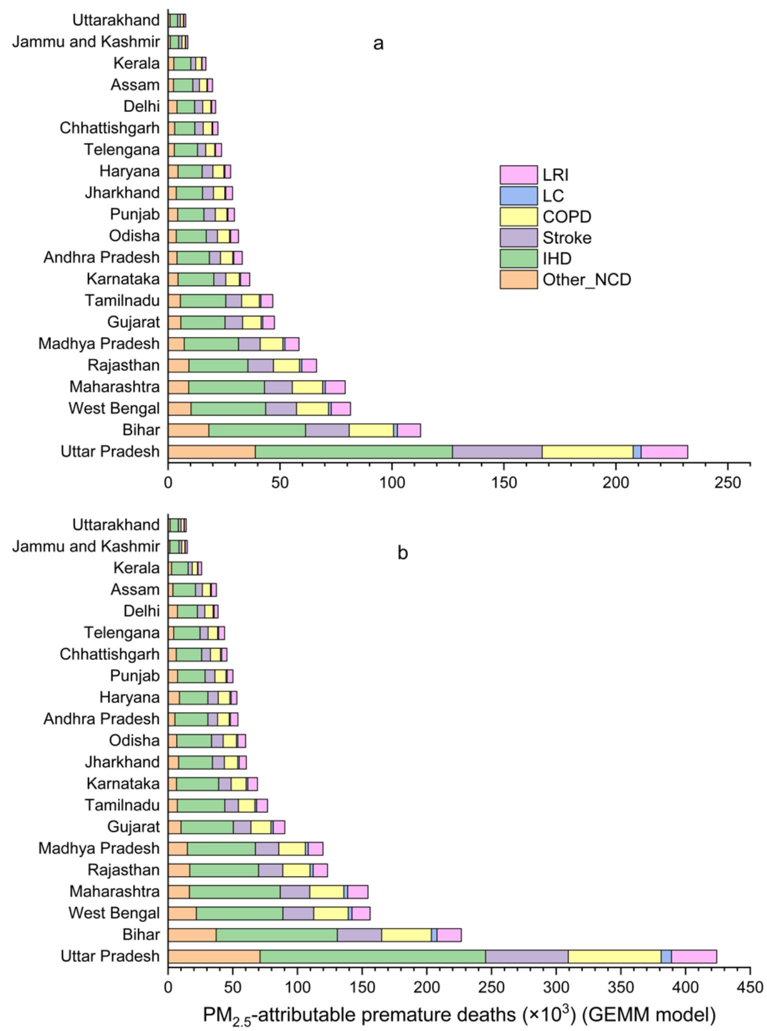


**Fig. 5.** State-level annual $PM_{2.5}$-attributed premature deaths (GEMM model) for the year (a) 2001 and (b) 2020.

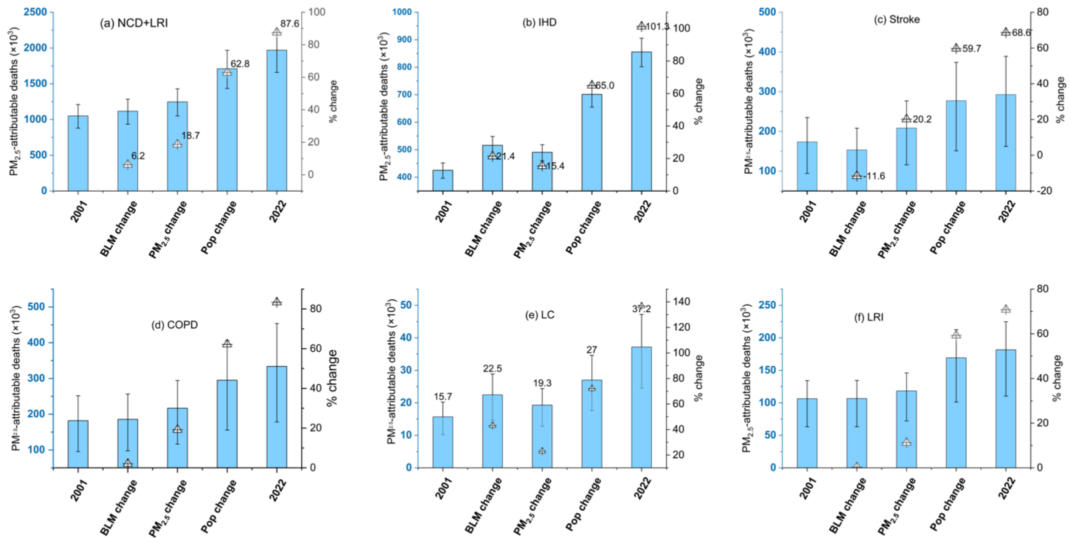


**Fig. 6.** Change in PM$_{2.5}$-attributable premature deaths in India between 2001 and 2020, due to baseline mortality (BLM) change, changes in exposure to PM$_{2.5}$, and change of population ≥ 25 years old, for PM$_{2.5}$-related non-communicable disease, IHD, STR, COPD, LC and LRI.