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Article

Continued Rise in Health Burden from Ambient $PM_{2.5}$ in India under SSP Scenarios Until 2100 despite Decreasing Concentrations

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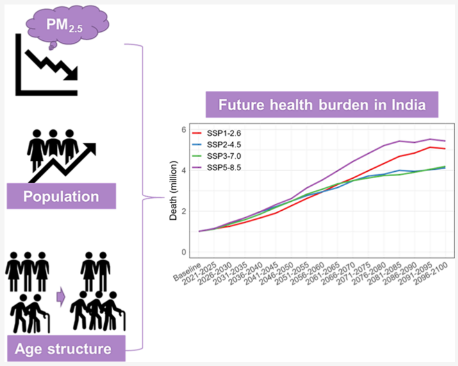
ABSTRACT: Forecasting alterations in ambient air pollution and the consequent health implications is crucial for safeguarding public health, advancing environmental sustainability, informing economic decision making, and promoting appropriate policy and regulatory action. However, predicting such changes poses a substantial challenge, requiring accurate data, sophisticated modeling methodologies, and a meticulous evaluation of multiple drivers. In this study, we calculate premature deaths due to ambient fine particulate matter ($PM_{2.5}$) exposure in India from the 2020s (2016−2020) to the 2100s (2095−2100) under four different socioeconomic and climate scenarios (SSPs) based on four CMIP6 models. $PM_{2.5}$ concentrations decreased in all SSP scenarios except for SSP3−7.0, with the lowest concentration observed in SSP1−2.6. The results indicate an upward trend in the five-year average number of deaths across all scenarios, ranging from 1.01 million in the 2020s to 4.12−5.44 million in the 2100s. Further analysis revealed that the benefits of reducing $PM_{2.5}$ concentrations under all scenarios are largely mitigated by population aging and growth. These findings underscore the importance of proactive measures and an integrated approach in India to improve atmospheric quality and reduce vulnerability to aging under changing climate conditions.



KEYWORDS: *ambient PM2.5, health burden, SSP scenarios*

■ INTRODUCTION

Long-term exposure to ambient fine particulate matter ($PM_{2.5}$) has been strongly confirmed to affect human mortality,[1−4] causing approximately seven million deaths globally in 2019.[5] It is worth noting that 5 of the top 10 cities with the most serious $PM_{2.5}$ pollution in the world are from India.[6] In addition, India is the second most populous country in the world, with a total population of 1.36 billion in 2019, accounting for 13.0% of the world population.[7] With a high population and excessive $PM_{2.5}$ emissions, India is suffering a growing number of $PM_{2.5}$-related deaths and allied healthcare challenges. Published studies have reported the $PM_{2.5}$-related premature mortalities in India of 0.57 million (95% confidence interval (CI95%): 0.32−0.73) in 2011[8] and 0.80 million (CI95%: 0.60−1.00) in 2019.[9] Projecting the future health burden associated with $PM_{2.5}$ and analyzing the main drivers provide important information for scientists and governments to develop effective mitigation measures in India.

However, predicting $PM_{2.5}$ exposure is a complex challenge, as it encompasses multiple interrelated factors. For instance, alterations in climatic and meteorological conditions can impact both $PM_{2.5}$ emissions and their atmospheric dispersion,[10,11] while advancements in technology and regulatory measures can influence emissions and exposure levels.[12,13] To address these complexities, the Coupled Model Intercomparison Project 6 (CMIP6) introduced a new set of shared socioeconomic pathways (SSPs) for climate scenarios, replacing the representative concentration pathways (RCPs) previously used in CMIP5.[14] The SSPs represent different socioeconomic developments and atmospheric greenhouse gas concentration pathways. Compared to the previous RCPs, the SSPs provide a more detailed representation of the drivers of future change, including specific assumptions about population growth, economic development, and energy consumption, which allows for a more nuanced assessment of the interactions between these drivers and their impacts on $PM_{2.5}$ concentrations and public health.[15] However, most of the published articles on projecting the $PM_{2.5}$-related death burden in India are still based on the RCP scenario.[16]

The population size and age structure also affect $PM_{2.5}$-related mortality. India is an ideal country to study the effects of population aging, as its youth share has yet to decline sharply, with 54% of the population under 25 in 2015.[17]

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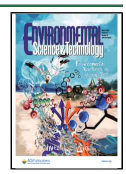

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Compared with the elderly, due to stronger physiological protective mechanisms, young people are less sensitive to air pollution and are less susceptible to chronic diseases.[18,19] At the same time, it is still unclear how $PM_{2.5}$-related mortality will change in the future as the population size and proportion of the elderly population continue to increase. Previous studies that estimated the disease burden associated with $PM_{2.5}$ exposure in India failed to account for the age structure and differential baseline mortality rates across age groups, leading to a higher degree of uncertainty in their projections of future $PM_{2.5}$-related disease burden.[16,20]

In this study, $PM_{2.5}$-related premature death changes in India from the 2020s (2016−2020) to the 2100s (2095−2100) under different SSPs are estimated. Additionally, the impact of three drivers, including $PM_{2.5}$ concentration, population size, and population age structure, on the $PM_{2.5}$-related premature deaths is evaluated. The results of this study offer valuable insights for developing countries in formulating long-term clean air policies under the changing climate.

■ MATERIALS AND METHODS

Scenario Settings. In this study, a set of socioeconomic climate scenarios (SSPs) describing plausible prospects for a range of demographic, economic, technological, social, and environmental factors was used to project the health burden of ambient $PM_{2.5}$ in India. The development of SSPs involves five main steps,[21] as shown in Figure 1: (1) narrative design to provide a basic underlying logic for each SSP; (2) expansion of the narrative based on model "input tables" to qualitatively describe the main SSP features and scenario assumptions; (3) detailed exposition of population, economic growth, and energy system parameters using quantitative models; and (4) quantitative estimates provided by an integrated assessment model (IAM), which offers emissions and concentration data of greenhouse gases (CO_2, N_2O, halogenated gases), and air pollutants (CH_4, SO_2, NO_x, VOC, CO, NH_y, BC, OC).[22] IAMs used the provided emission factor data and quantitative guidelines to individually develop SSP scenarios. The details on IAM emission inventories and driving factors can be found in Rao et al.[23] All data are openly accessible via an interactive

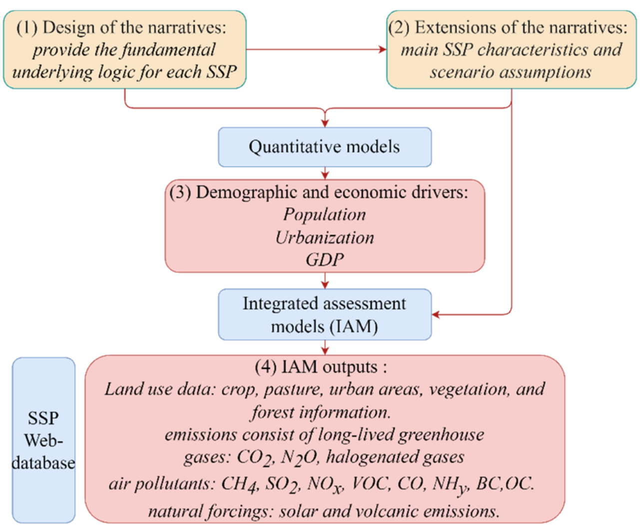

Figure 1. Schematic diagram for developing SSPs.

SSP network database (https://secure.iiasa.ac.at/web-apps/ene/SspDb).

We selected four scenarios with higher priority, namely SSP1−2.6, 2−4.5, 3−7.0, and 5−8.5. Among them, the SSP1−2.6 scenario focuses on sustainability and envisages relatively minor future mitigation and adaptation challenges. High priority is given to promoting the human well-being, environmental technology, and renewable energy. Under this scenario, CO_2 emissions are projected to reach greenhouse levels of 2.6 Wm^{2-} by 2100. The SSP2−4.5 scenario represents a " middle-of-the-road" scenario, where current social, economic, and technological trends continue, and CO_2 emissions will generate a forcing level of 4.5 Wm^{2-} in 2100. The SSP3:7.0 scenario depicts a future marked by intense regional competition and formidable challenges for both mitigation and adaptation. This scenario anticipates sustained rapid population growth in developing nations, sluggish economic progress, and a continued dependence on fossil fuels. Consequently, CO_2 emissions are projected to escalate, resulting in a forcing level of 7.0 Wm^{2-} by 2100.[21] The SSP5−8.5 represents the inequality pathway, emphasizing economic growth and technological progress, substantial investments in education and health, and adoption of resource- and energy-intensive lifestyles. Consequently, CO_2 emissions driven by energy-intensive fossil fuels are projected to result in a forcing level of 8.5 Wm^{2-} by 2100.

Air Pollution. Satellite-derived $PM_{2.5}$ from 2016 to 2020 at a resolution of 0.1° × 0.1° in India comes from Atmospheric Composition Analysis Group (https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.04). The annual $PM_{2.5}$ was estimate by combining aerosol optical depth (AOD) retrievals from the NASA MODIS, MISR, SeaWIFS, and VIIRS instruments with the GEOS-Chem chemical transport model and subsequently calibrating to global ground-based observations using a geographically weighted regression (GWR); the details can be found in van Donkelaar et al.[24]

Future $PM_{2.5}$ concentrations from 2016 to 2100 in India are projected every 5 years under the SSPs from the four CMIP6 models (GFDL-ESM4,[25] MIROC-ES2L,[26]MRI-ESM2−0,[27] and NorESM2-LM[28]). These projections are sourced from the CMIP6 dataset available at https://esgf-index1.ceda.ac.uk/search/cmip6-ceda/. The simulation method for this dataset is described by Turnock et al.[29] The ScenarioMIP provides land use, greenhouse gas, air pollutant emission, and concentration data from IAM to participating climate models (CMIP6 model) as input to their simulations.[30] The CMIP6 gridded emission dataset covers the period 1750 to 2100 and includes aviation emissions, all other anthropogenic emission sectors, and total open burning emissions.[31] Each CMIP6 model specifies future anthropogenic and biomass burning emissions from the same dataset, but the representation of other natural emissions such as dust and biogenic volatile organic compounds (BVOCs) differs depending on the configuration of each model.[29] Due to variations in how aerosols and their components are handled by the models, the results among the models are not consistent. For example, only GFDL-ESM4 offers data on the nitrate (NO_3) mass mixing ratios in the ESGF database. Therefore, to ensure consistent definitions across all models, we performed offline calculations of the $PM_{2.5}$ concentration. The surface $PM_{2.5}$ concentration is defined as the sum of the individual dry aerosol mass mixing ratios of black carbon (BC), total organic aerosol (OA) derived from both primary and secondary sources, sulfate

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(SO_4), sea salt (SS), and dust, as shown in eq 1. These mixing ratios are extracted from the lowest model level within the comprehensive 3D model fields. It is assumed that all BC, OA, and SO_4 aerosol masses are predominantly present in the fine size fraction (<2.5 μm). For SS and dust, factors of 0.25 and 0.1, respectively, have been utilized to estimate their approximate contributions to the fine aerosol size fraction.[29] Table S1 lists the names of the four CMIP6 models and their respective grid resolutions. Data for each model were interpolated onto a 1° × 1° grid using bilinear interpolation to eliminate inconsistencies between the grid resolutions of the four models

$$\mathrm{PM}_{2.5} = \mathrm{BC} + \mathrm{OA} + \mathrm{SO}_4 + \mathrm{NH}_4 + (0.25 \times \mathrm{SS}) + (0.1 \times \mathrm{dust}) \tag{1}$$

We averaged the simulation results from all four models for each scenario. The performance of CMIP6 models is assessed through the correlation coefficient (R) and statistical metrics of normalized mean bias (NMB) and normalized mean error (NME) by comparing simulated results with satellite observations. The formulas for each statistical parameter are as follows

$$R^2 = 1 - \frac{\sum_{j=1}^{n} (P_j - O_j)^2}{\sum_{j=1}^{n} (P_j - \bar{O}_j)^2} \tag{2}$$

$$\mathrm{NMB} = \frac{\sum (P_j - O_j)}{\sum O_j} - 1 \leq \mathrm{NMB} \leq +\infty \tag{3}$$

$$\mathrm{NME} = \frac{\sum |P_j - O_j|}{\sum O_j} O \leq \mathrm{NMB} \leq +\infty \tag{4}$$

where P and O are the CMIP6 model-derived $PM_{2.5}$ and satellited-derived $PM_{2.5}$, respectively.

However, almost all CMIP6 model simulations indicate lower AOD and $PM_{2.5}$ composition values in India compared to observations.[32] To account for this underestimation, we estimated the relative change in $PM_{2.5}$ from the baseline period (2016 to 2020) to the future (2016 to 2100) relative to the CMIP6 model estimates. We applied the relative change to the baseline period satellite-derived data from the baseline period to estimate future $PM_{2.5}$ exposure at a 1° × 1° grid. This method has been applied to Xu et al.;[33] this process can be represented by eq 5

$$\mathrm{PM}_{2.5}{}^{\mathrm{Calibrated}}_{\mathrm{Future}} = \mathrm{PM}_{2.5}{}^{\mathrm{Sat}}_{\mathrm{Baseline}} + \mathrm{PM}_{2.5}{}^{\mathrm{Sat}}_{\mathrm{Baseline}} \times \left[\frac{\mathrm{PM}_{2.5}{}^{\mathrm{model}}_{\mathrm{Future}} - \mathrm{PM}_{2.5}{}^{\mathrm{model}}_{\mathrm{Baseline}}}{\mathrm{PM}_{2.5}{}^{\mathrm{model}}_{\mathrm{Baseline}}} \right] \tag{5}$$

where $\mathrm{PM}_{2.5}{}^{\mathrm{Calibrated}}_{\mathrm{Future}}$ represents the future (2016–2100) $PM_{2.5}$ concentration after calibration; $\mathrm{PM}_{2.5}{}^{sat}_{\mathrm{Baseline}}$ represents the satellite-derived $PM_{2.5}$ concentration of the baseline period (2016–2100); $\mathrm{PM}_{2.5}{}^{\mathrm{model}}_{\mathrm{Baseline}}$ represents the CMIP6 model-derived $PM_{2.5}$ concentration of the baseline period (2016–2020); and $\mathrm{PM}_{2.5}{}^{\mathrm{model}}_{\mathrm{Future}}$ represents the CMIP6 model-derived $PM_{2.5}$ concentration in the future (2016–2100).

Population Data. In our study, we focused solely on assessing the burden of disease in individuals aged 25 and above. Population data by age groups every 5 years under SSPs from 2021 to 2100 in India were sourced from SSP Public Database Version 2.0 (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=30). The population changes are projected based on alternative assumptions on future, fertility, mortality, migration, and educational transitions that correspond to each of the four SSPs.[34] The population of the final year within each 5-year interval was used to calculate the 5-year average premature mortality burden. For instance, the population data for the year 2020 were used to calculate the baseline premature mortality burden due to environmental $PM_{2.5}$ exposure from 2016 to 2020. Population data by 5-year age groups in 2020 were obtained from the United Nations, Department of Economic and Social Affairs, Population Division (https://population.un.org/wpp/Download/Standard/Population/). To harmonize with the CMIP6 model output, we utilized population grid cells at 1 km resolution derived from the 2020 population census data obtained from WorldPop (https://www.worldpop.org/geodata/summary?id=31766). We assumed that the future population distribution would remain consistent with the distribution observed in the year 2020.

Health Risk Assessment of $PM_{2.5}$ Exposure. The total premature mortality for adults ≥25 years old from 2016 to 2100 in India due to chronic obstructive pulmonary disease (COPD, J40-J47), ischemic heart disease (IHD) (I20–I25), stroke (I60–I69), and lung cancer (LC, C34) was obtained from the 10th revised International Classification of Disease Statistics (ICD-10),[35] as calculated by eq 6

$$\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j} = \sum_{i=1}^{N} \mathrm{pop}_{i,m,n,s} \times y_{j,m} \times \left[\frac{\mathrm{RR}_{i,j,m,n,s} - 1}{\mathrm{RR}_{i,j,m,n,s}} \right] \tag{6}$$

where $\Delta\mathrm{Mort}_{m,n,s,j}$ is the premature mortality caused by $PM_{2.5}$ with disease categories j of specific age group m in years n under scenario s, $\mathrm{pop}_{i,m,n,s}$ is the population of specific age group m for grid i in years n under scenario s, and $y_{j,m}$ is the baseline mortality with disease categories j of specific age groups m obtained from the Global Burden of Disease study (https://vizhub.healthdata.org/gbd-results/), listed in table S3. $\mathrm{RR}_{i,j,m,n,s}$ is the relative risk for disease categories j of specific age group m at grid i in years n under scenario s caused by $PM_{2.5}$, and (RR-1)/RR is the attributable fraction (AF).

We applied a newly developed GEMM model by Burnett et al.[36] to estimate the RR attributable to $PM_{2.5}$ exposure, which incorporated recent epidemiological results from more countries, thus more suitable to provide accurate estimates than the previous models.[36]

$$\mathrm{RR}_{i,j,m,n,s}(\Delta Z_{i,n,s}) = \exp\left\{ \frac{\theta_{j,m} \times \ln((\Delta Z_{i,n,s}/\alpha_{j,m}) + 1)}{1 + \exp\{-((\Delta Z_{i,n,s} - \mu_{j,m})/\vartheta_{j,m})\}} \right\},$$
$$\Delta Z_{i,n,s} = \max(0, C_{i,n,s} - C_0) \cdots \cdots \tag{7}$$

where $C_{i,n,s}$ is the annual average $PM_{2.5}$ concentration at a grid i in years n under scenario s, C_0 is the theoretical minimum-risk concentrations of 2.4 $\mu g/m^3$ used in Burnett et al,[36] $\theta_{j,m}$, $\alpha_{j,m}$, $\mu_{j,m}$, and $\vartheta_{j,m}$ are parameters that determine the shape of the concentration–response relationships.[36]

Decomposition of Driving Factors. Premature mortality depends on the combined impacts of pollutant concentrations

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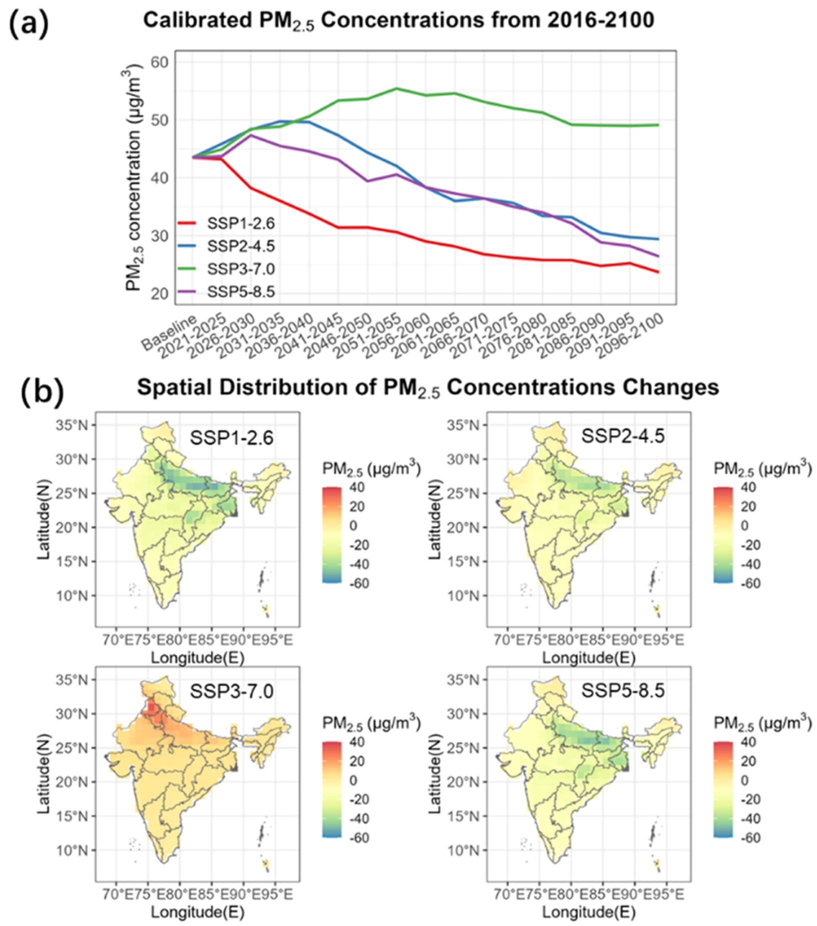

Figure 2. (a) Average $PM_{2.5}$ concentration of multiple models from the 2020s to the 2100s under SSP1−2.6, 2−4.5, 3−7.0, and 5−8.5 scenarios. (b) Spatial distribution of future changes in average $PM_{2.5}$ concentration in the 2100s relative to the 2020s.

driven by climate and emission changes, population size, and the population age structure. To assess the independent contribution of each determinant factor to premature mortality, we systematically control one factor at a time to align with the baseline (2020s) in the future, thereby nullifying its influence on mortality.

The pollutant concentration contribution rate (PCC (%)), the population age structure contribution rate (ASC (%)), and the population size contribution rate (PSC (%)) are calculated as described in eq 8−10

$$\mathrm{PCC}(\%) = \frac{A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} - \frac{B\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - B\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{B\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} \quad (8)$$

$$\mathrm{ASC}(\%) = \frac{A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{A\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} - \frac{\mathrm{C}\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - \mathrm{C}\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{BC\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} \quad (9)$$

$$\mathrm{PSC}(\%) = \frac{C\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - C\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{C\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} - \frac{D\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,n,s,j}\right) - D\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)}{D\left(\sum_{m,j=1}^{N} \Delta\mathrm{Mort}_{m,2020s,s,j}\right)} \quad (10)$$

where A represents deaths calculated using eq 6, B represents deaths calculated when the pollutant concentration remains unchanged in the future, C represents deaths calculated when the future age structure (proportion of population in each age group) remains unchanged, and D represents deaths calculated when the future population size remains unchanged. It is worth

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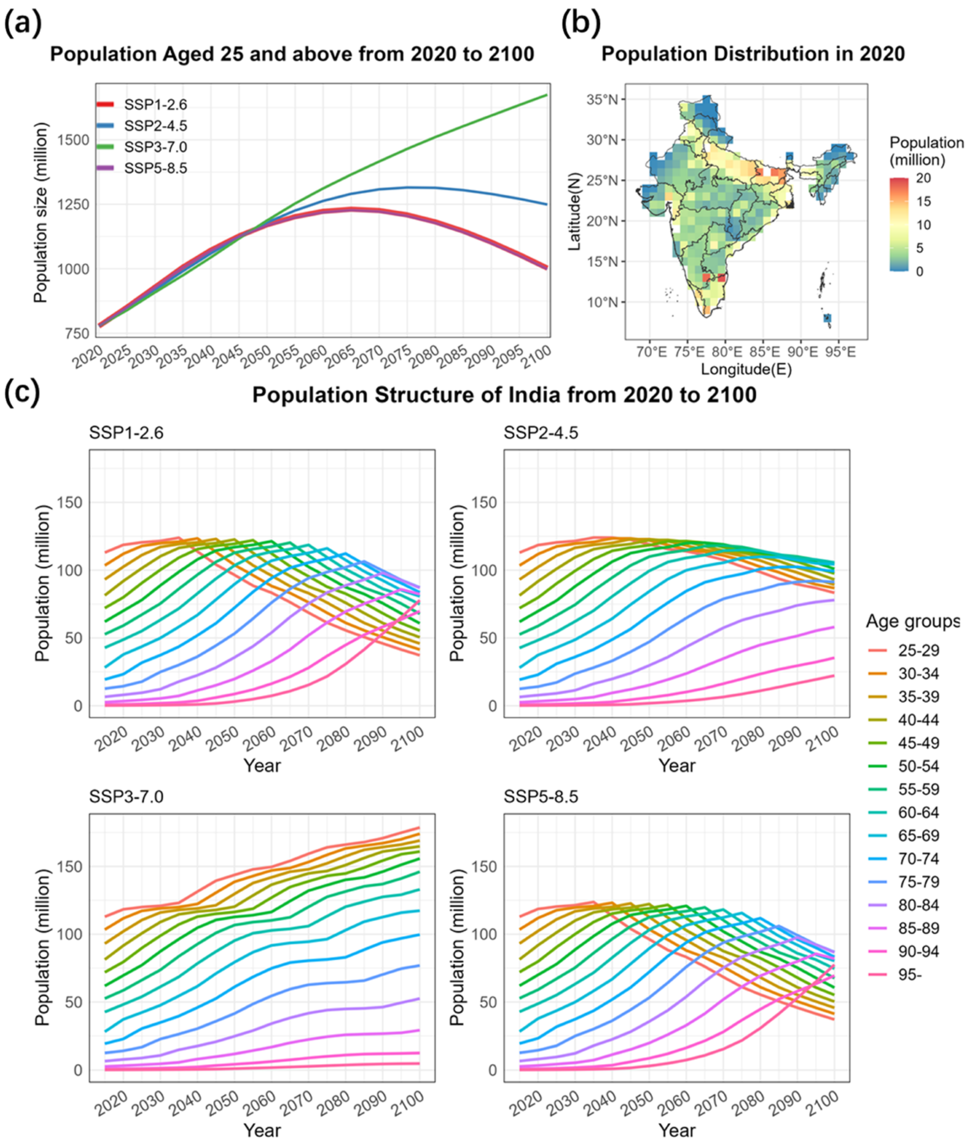

Figure 3. (a) Projected in exposed population size of all ages under SSPs (SSP1−2.6, 2−4.5, 3−7.0, and 5−8.5) in India from 2020 to 2100. (b) Population distribution of India in 2015. (c) Proportion of the population by the age group under four SSP scenarios in India from 2020 to 2100.

noting that when the population size does not change, the age structure remains constant, as well.

RESULTS

Future $PM_{2.5}$ Concentrations Driven by Climate and Emission Changes. We compared the satellite-derived $PM_{2.5}$ data with the CMIP6 model-derived $PM_{2.5}$ data under SSP scenarios from 2016 to 2020 and found that the $PM_{2.5}$ concentrations estimated by the CMIP6 models were generally consistent with those derived from satellite observations, with most points falling near the 1:1 line and R-squared values ranging from 0.76 to 0.78 (Figure S1), although high $PM_{2.5}$ concentrations were underestimated and the difference shows considerable spatial heterogeneity (Figure S2). Additionally, the results from the four CMIP6 models ($-0.06 \leq$ NMB $\leq$ 0.06, 0.17 $\leq$ NME $\leq$ 0.18) meet the criteria proposed by Boylan and Russell[37] (NMB $\leq \pm$ 0.15 and NME $\leq \pm$ 0.25) (Table S2). These findings are similar to those reported in a previous study.[32] We conducted a sensitivity assessment of the results from GFDL-ESM4, and we found that data from a single model alone cannot effectively evaluate the outcomes (0.19$\leq$ NMB $\leq$ 0.41, 0.23 $\leq$ NME $\leq$ 0.41, Table S2).

We calibrated the CMIP6 model-driven $PM_{2.5}$ data using satellite-driven $PM_{2.5}$ data. The $PM_{2.5}$ concentration, calibrated by satellite-derived $PM_{2.5}$, exhibits an inverted "U" shape between 2020s and 2100s, reaching its peak in 2035s or 2055s, except in the case of SSP1−2.6 in India (Figure 2a). Under the SSP1−2.6 scenario, the concentration decreases sharply in the initial stage and gradually decreases until the end of 2100. In contrast, under the SSP3−7.0 scenario, the concentration increases from the baseline to 2055 and then slightly decreases by 2100. The concentration ranges of $PM_{2.5}$ in each scenario are shown in the shaded parts of Figure S3. Figure 2b illustrates the spatial heterogeneity of $PM_{2.5}$ concentration changes in the 2100s relative to baseline $PM_{2.5}$ exposure. In the future, the greatest reduction in $PM_{2.5}$ concentration is anticipated in the Indo-Gangetic Basin for SSP1:2.6, 2:4.5, and 5:8.5. Conversely, for SSP3−7.0, the concentration of $PM_{2.5}$ is projected to increase in the Indo-Gangetic Basin by a greater magnitude.

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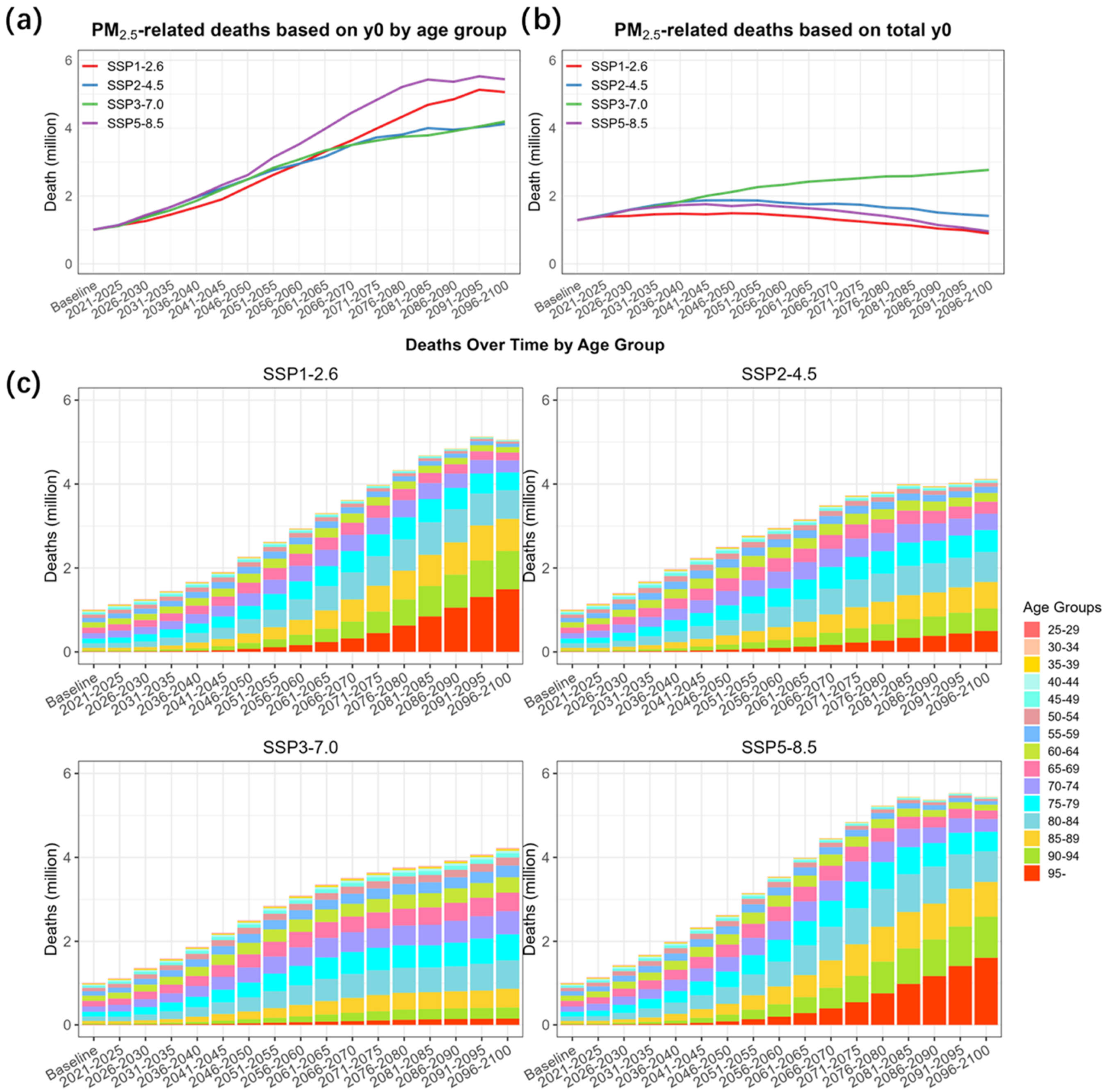

Figure 4. (a) $PM_{2.5}$-related deaths calculated by y0 of specific age groups. (b) $PM_{2.5}$-related death calculated total y0 of population aged 25 and above. (c) Number of deaths in each age group from the 2020s to the 2100s under the SSP1−2.6, 2−4.5, 3−7.0, and 5−8.5 scenarios.

Future Population Changes under Different SSP Scenarios. The size of India's population over the age of 25 in SSP1−2.6, SSP2−4.5, and 5−8.5 shows a trend of rising first and then falling, with an increase of 28.92% (from 777.5 to 1002.35 million), 60.65% (from 777.5 to 1249.13), and 28.84% (from 777.5 to 998.60 million) from 2020 to 2100, respectively (Figure 3a). Under the SSP3−7.0 scenario, the population size of individuals aged 25 and above increased substantially until 2100. From the population distribution map of India in 2020 (Figure 3b), we find that the region with the largest population size (>20 million) was in the Ganges Basin of India, which is highly industrialized or urbanized. In addition, population aging accelerates from 2020 to 2100, with the smallest increase in SSP 3−7.0 and the largest in the SSP5−8.5 scenario (Figure 3c).

Modification for $PM_{2.5}$-Related Death Burden. Figures 4a and S4 illustrate the premature deaths nationwide, calculated by age group, across four scenarios from the 2020s to the 2100s. In the 2020s, $PM_{2.5}$-related deaths in India were estimated to be 1.01 million (95% CI: 0.64−1.25) for SSPs. Subsequently, premature mortality sharply increased, peaking in the 2100s. The highest count was observed in SSP5−8.5 (5.44 million, 95% CI: 2.85−7.41), followed by SSP1−2.6 (5.06 million, 95% CI: 2.18−7.31), SSP3−7.0 (4.19 million, 95% CI: 2.44−5.44), and SSP2−4.5 (4.12 million, 95% CI: 1.83−5.70). From a spatial perspective, the areas with larger increases in deaths were concentrated in the entire Indo

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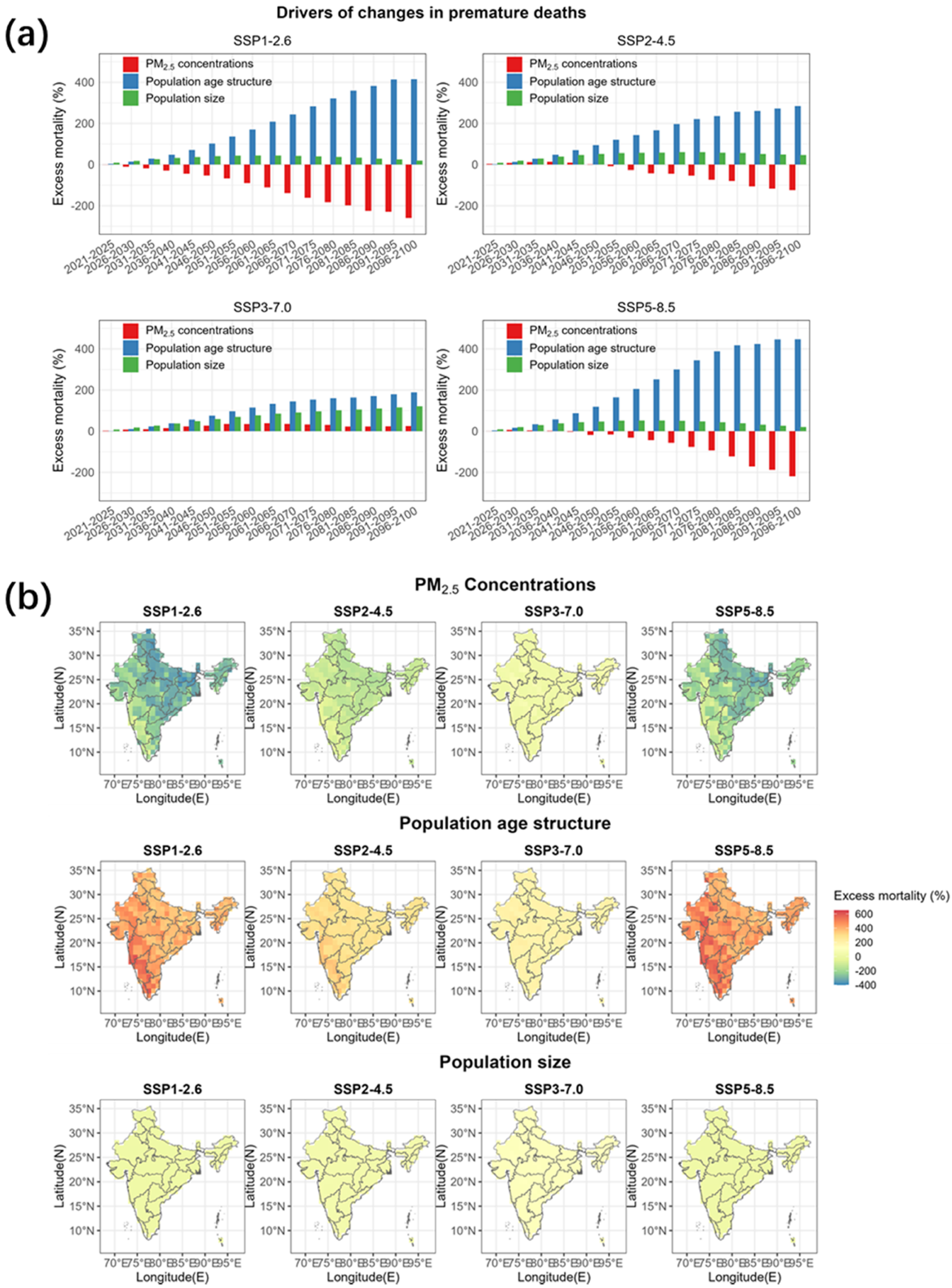

Figure 5. (a) Contribution of three drivers ($PM_{2.5}$ concentration, population size, and population age structure) to changes in $PM_{2.5}$-related excess mortality in India from the 2020s to the 2100s under different SSPs. (b) Spatial variation of the contributions of $PM_{2.5}$ concentration, population size, and the population age structure to $PM_{2.5}$-related mortality in India in the 2100s relative to the 2020s.

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Basin region in northern India during the SSP1−2.6 and 5−8.5 periods (Figure S5). Furthermore, from the 2020s to the 2100s, the number of deaths of people over 75 years of age increases significantly in all scenarios, especially in the SSP1−2.6 and SSP5−8.5 scenarios, where the number of deaths of people over 75 years of age rose by 12.51% (from 0.31 to 4.28 million) and 13.55% (from 0.31 to 4.61 million) (Figure 4c). Here, we also calculated the number of deaths using the total y0 of population aged 25 and above, and we found that this calculation method significantly underestimated the mortality burden (Figure 4b).

Drivers of Changes in Premature Deaths. Figure 5a shows the contribution of three drivers ($PM_{2.5}$ concentration, population size, and population age structure) on changes in $PM_{2.5}$-related excess mortality in India from the 2025s to the 2100s under different SSPs. The results indicate that the population age structure contributes to $PM_{2.5}$-related excess mortality to a far greater extent than the benefits of the population size and the changes in $PM_{2.5}$ exposure resulting from global climate and emission change. Specifically, in 2100, the contribution of the population age structure to excess mortality is estimated to be in the range of 189% (95%CI: 171−199) to 446% (95%CI: 366−488), while the contribution of $PM_{2.5}$ concentration and population size is estimated to be in the range of −259% (95%CI: (−407) -(−188)) to 24% (95%CI: (−1.88)-41) and 19% (95%CI: 18−22) to 121% (95%CI: 114- 125), respectively. Moreover, the contribution of the population age structure to excess mortality climbs rapidly from 2020s to 2100s, with SSP5−8.5 having the highest excess mortality scenario and SSP3−7.0 having the lowest excess mortality scenario. Under SSP1−2.6, SSP2−4.5, and SSP5−8.5, $PM_{2.5}$ exposure-related excess mortality decreases due to the effective control of $PM_{2.5}$ concentration driven by climate and emission change from the 2020s to the 2100s. In terms of population size, except for SSP3−7.0, the contribution to $PM_{2.5}$-related excess deaths increases first and then decreases until 2100, which is close to the baseline. In the SSP3−3.7 scenario, the contribution of rising $PM_{2.5}$ concentrations to mortality increases by 2 to 24% compared to the baseline, and the population size effects lead to a dramatic increase in mortality over time, reaching 121% by 2100.

We also calculated spatial variation of the contributions of $PM_{2.5}$ concentration, population size, and the population age structure to $PM_{2.5}$-related mortality in India in the 2100s relative to the 2020s (Figure 5b). The areas with greater impact on the population age structure are concentrated in southwestern India (>400) under SSP1−2.6 and 2−4.5 scenarios. However, for $PM_{2.5}$ concentration changes, the health benefits of reduced $PM_{2.5}$ concentration were concentrated in northeastern India under SSP1−2.6, 2−4.5, and 5−8.5 scenarios.

■ DISCUSSION

In this study, we projected premature mortality due to ambient $PM_{2.5}$ exposure in India from the 2020s to the 2100s under different SSPs. Our research provided insights into the health impact of three key driving factors, including the population age structure, pollutant concentrations, and population size. Our study used $PM_{2.5}$ concentrations from a number of CMIP6 modeling outputs and considered multiple factors under various scenarios, including climate change and socioeconomics. A series of comprehensive SSPs are used to construct air pollution exposure under future climate dynamics and provide reliable estimates in health impact analysis. Our assessment of the burden of deaths under multiple scenarios will be useful to guide future pathways in achieving a green and sustainable environment.

Consistent with our findings, previous studies estimated the number of premature deaths resulting from chronic exposure to ambient $PM_{2.5}$ in India to be 1.1 million (0.94−1.3 million) in 2015[20] and 0.67million (0.55−0.79 million) in 2017.[38] However, prior studies suggest that the burden of $PM_{2.5}$-related premature mortality will decrease in the future.[16,39] Our study predicts that the burden of premature death will continue to increase beyond 2020, reaching 4−5 times the baseline level by 2100. This is due to published studies failing to take into account the specific age composition of the Indian population and the susceptibility of different age groups to pollutants. One study[16] found a downward trend in future deaths, largely because the authors believed that baseline mortality from diseases associated with rising GDP would decline in the future. However, estimates of the relationship between GDP and baseline mortality from disease are subject to considerable uncertainty. SSP3−7.0 is the scenario with the lowest disease burden caused by $PM_{2.5}$ because of a lower proportion of the elderly. We estimated the effect of the age structure when calculating $PM_{2.5}$ deaths with different age groups having different susceptibilities to air pollutants and corresponding inconsistent baseline mortality and exposure−response coefficients. Numerous studies have neglected the heterogeneity in mortality rates across distinct age groups, with older in divisions exhibiting significantly elevated baseline mortality rates in comparison to their younger counterparts. Notably, the current demographic composition of India reveals that the working-age population (below 60 years) constitutes more than 50% of the total population. Consequently, employing the overall population's baseline mortality rates to estimate premature mortality may engender an overestimation of premature death counts.[16] Li et al.[40] observed a plateau in the global $PM_{2.5}$-attributable mortality trend, alongside a continued rise in mortality rates specifically in India, consistent with our findings. According to their study, the number of deaths in India reached 1.6 million by 2019, exceeding our estimate of 1.01 million (95% CI: 0.64−1.25) deaths for the 2020s, primarily due to their consideration of six specific diseases, including childhood and adult (under 5 years and 25 years and older) acute lower respiratory infections (LRI).

Based on the spatial distribution map of $PM_{2.5}$-related deaths, we observed that the most substantial increase in deaths occurred in the entire Indo Basin region in northern India. This region is characterized by high aerosol loads, with approximately 900 million people residing in areas that experience poor air quality due to severe haze, and smog during the postmonsoon/winter period as well as dust storm activity during the summer period. Thus, it is evident that additional policies and measures will be necessary in the future to alleviate the disease burden in this region.[41]

The analysis of the drivers of $PM_{2.5}$-related deaths found that the effects of population aging will far offset the benefits of reduced $PM_{2.5}$ concentrations in the future. India's population aging is a gradual process that is not characterized by rapid change, as shown in Figure 3c. At present, the young and middle-aged (under 60 years of age) population in India exceeds 50% of the total population. Cheap and young labor has enabled India to maintain a high economic growth rate in recent years, but in the long run, India faces catastrophic aging

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consequences in the future, as older people have slower metabolisms and are more vulnerable to environmental influences, which will place a heavy burden on the national healthcare system. To address this issue, India should take advantage of the current demographic structure to speed up reforms, rationally allocate public medical resources, and improve the healthcare of the elderly, which may help reduce the health cost of ambient air pollution.

Rapid population size growth in India is also an important factor in the increase in deaths, consistent with previously published articles. High population growth is mainly distributed in the southern foothills of the Himalayas in the north and the Indus-Ganges River Basin, especially in the Ganges delta in the east. In the future, stricter policies are needed to reduce pollutant concentrations, especially in areas with high population densities, to prevent more $PM_{2.5}$-related deaths.

Future declines in $PM_{2.5}$ concentrations, driven by climate and emission changes as a single factor, will reduce deaths. However, considering the impact of demographic factors, stricter emission reduction measures are required to alleviate the pressure of population growth and aging. On the one hand, residential, transport, and industry emissions are the major contributors to $PM_{2.5}$ in the Ganges Basin, India, and reducing short-lived climate pollutants emitted by biomass burning to mitigate climate change can help further reduce premature mortality.[42] On the other hand, the greatest health benefits can be achieved by prioritizing efforts in areas with higher concentrations of pollutants but with severely aging populations and densely population.

A few limitations exist in this study. First, we assume that the baseline mortality rates for different age groups in future scenarios remain unchanged from 2020. Future baseline mortality is related to multiple factors, such as improved health services and the occurrence of some extreme events, which will bring some uncertainty, and this is the insurmountable limitation of this study. Second, the shape of the exposure−response relationship between $PM_{2.5}$ and related diseases (depending on the parameters $\theta_{j,m}$, $\alpha_{j,m}$, $\mu_{j,m}$, and $\vartheta_{j,m}$) is mainly based on studies in the United States and European countries due to the lack of long-term large cohort health exposure studies in India. In our study, the GEMM model parameters were used, which found differences in parameter estimates with and without the Chinese male cohort assessed.[36] The model failed to include the Indian cohort, which would underestimate or overestimate the findings. Third, our study assumes that the spatial distribution and density of the population in the future will be consistent with the current stage, and factors such as population migration and urbanization are not considered, which will also bring some uncertainty. Finally, our study did not consider factors such as gender differences, individual differences, indoor air exposure, and behavioral patterns. Some studies began to focus on the health risk research of individual exposures, helping further reduce the uncertainty of calculating the disease burden in the future.

In conclusion, we found an increased future burden of death in India due to chronic exposure to $PM_{2.5}$ under all SSP scenarios from the 2020s to the 2100s. The decreased deaths due to air pollution reduction will be largely offset by rapid population aging from the 2020s to the 2100. Therefore, more aggressive air pollution reduction measures and medical measures for the elderly are needed to prevent premature deaths and related economic impacts more effectively.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.4c02264.

CMIP6 model information for predicting $PM_{2.5}$ concentration, model performance indicators of $PM_{2.5}$ for different models, y0 for the specific age group, scatter plots of satellited-derived $PM_{2.5}$ and CMIP6 model-derived $PM_{2.5}$ under SSPs in 2020s, distribution of the gap between satellite $PM_{2.5}$ and CMIP6 model $PM_{2.5}$ under SSP in the 2020s, $PM_{2.5}$ concentration changes from 2016 to 2100 under SSPs, death attribution to $PM_{2.5}$ from the 2020s to the 2100s under SSPs, spatial distribution of $PM_{2.5}$-related mortality changes from the 2020s to the 2100s under SSPs, and death rate in each age group from the 2020s to the 2100s under SSPs (PDF)

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Author Contributions

Y.W., L.H., and J.H. initiated the study. Y.W., J.H., K.G., and X.Y. collected the data. Y.W. performed the statistical analysis. Y.W. drafted the paper. All authors read and revised the paper and approved the final paper. Y.W. and J.H. created the cover art.

Notes

The authors declare no competing financial interest.

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