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Article

Pathways for India to Reduce Ambient Air Pollution Health Burden and Achieve the Sustainable Development Goal (SDG-3.4)

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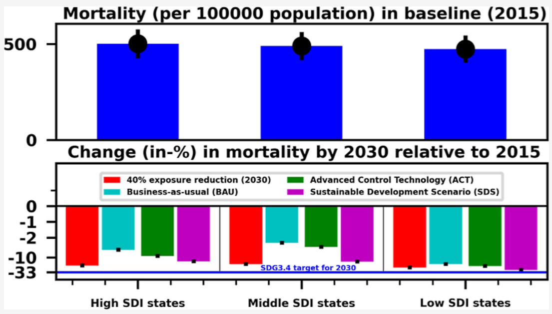
ABSTRACT: Sustainable Development Goal 3.4 (SDG-3.4) aims to reduce non-communicable disease (NCD) mortality by one-third by 2030, compared to 2015 levels. First, we examined whether the National Clean Air Program (NCAP) is sufficient to allow India to achieve this target. Subsequently, we integrated GAINS-simulated sector-specific $PM_{2.5}$ concentrations across three pathways—business-as-usual (BAU), advanced control technology (ACT), and sustainable development scenario (SDS)—with the Global Burden of Disease framework to assess potential health benefits for 2030 at a subnational scale and evaluate the feasibility of accomplishing SDG-3.4. In 2015, ambient $PM_{2.5}$ attributable premature deaths were 0.72 million (95& UIs: 0.53−0.89), and an aggregated 0.12 million (0.08−0.16) deaths could be prevented if the NCAP target is met by 2026. However, states could reduce 3.6−10.8% of targeted NCD mortality by 2030 with a lagged 40% reduction in $PM_{2.5}$ levels relative to the baseline. $PM_{2.5}$-attributable deaths would change to 0.79 million (0.57−1.1), 0.76 million (0.6−1.1), and 0.63 million (0.48−0.81) in 2030 under the BAU, ACT, and SDS pathways, respectively. Implementing stringent emission controls through policy and technological interventions, primarily focusing on household and energy sectors, would reduce NCD mortality by 5−13% across subregions. Simultaneously controlling other risk factors would accelerate India's journey toward achieving SDG-3.4.



KEYWORDS: *non-communicable disease, sustainable development goal, GAINS model, mortality, India*

1. INTRODUCTION

Long-term exposure to ambient fine particulate matter ($PM_{2.5}$) has emerged as the largest environmental risk factor (RF) for public health in India, which claimed 0.95 million (95% uncertainty intervals, UIs: 0.62−1.26) premature deaths and 27.4 million (17.7−36.3) disability-adjusted life years (DALYs) lost in 2021.[1] Recent source apportionment studies have identified that emissions due to residential solid fuel burning, industrial activity, and vehicular exhaust are leading contributors to high $PM_{2.5}$ levels in India.[2] Though household air pollution exposure has diminished over the years, it continues to pose a considerable hazard to the Indian populace.[3] Studies have postulated three major mechanistic pathways underlying the effects of air pollution on various health outcomes, viz., oxidative stress and inflammation, autonomic nervous imbalance, and direct particle translocation.[4,5] Their pathways are highly interconnected with effects and may converge to increase the risks of various cardiovascular and respiratory diseases.[6] The co-emitted precursor gases from the primary sectors undergo a series of chemical reactions in the atmosphere to form secondary particulate matter (PM),[7,8] which poses a substantial health burden in India,[2,7] but the subregional assessment is missing.

To mitigate the rising air pollution burden, India launched the National Clean Air Program (NCAP) in 2019 with a target to reduce $PM_{2.5}$ levels by 40% across 131 cities by the year 2026 relative to their 2017 levels.[9] By 2020, only a quarter of the proposed clean air action plans had been put into action.[10] Though mitigation measures accelerated in the last two years after the COVID-19 risk subsided, annual $PM_{2.5}$ levels in all non-attainment cities remained above the World Health Organization (WHO) air quality guideline of 5 $\mu g\ m^{-3}$. The United Nations' Sustainable Development Goal-3.4 (SDG-3.4) has set a target to reduce the mortality burden of non-communicable diseases (NCDs) by one-third by 2030, relative to 2015. Ram et al.[11] have estimated that India could avoid one-fourth of the total disease burden if multiple RFs are controlled together. In 2021, ambient $PM_{2.5}$ ranked as the third largest RF for public health in India that claimed 11.96% of total non-communicable disease (NCD) mortality.[1,12] Being

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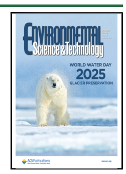

one of the major threats for public health, how much of India's aspired SDG-3.4 target is achievable by controlling ambient $PM_{2.5}$ alone is yet to be quantified at the subnational level.

There have been several attempts to project the health burden attributable to air pollution in the foreseeable future under various air pollution mitigation scenarios, primarily focusing on national assessments,[13−16] but none of them has estimated the contributions from various regional and sectoral emissions, especially at the subregional level. Chatterjee et al.[2] estimated the mortality burden attributable to ambient $PM_{2.5}$ emitted from various sources for 2019 but did not isolate the regional contribution from local sources. Moreover, comparative state-level statistics to understand the progress of the SDG-3.4 goal in view of clean-air targets were not available in the existing studies.

Here, we addressed these key policy gaps and projected changes in health burden attributable to ambient $PM_{2.5}$ from 2015 to 2030 and assessed how much health benefits could be achieved if the states successfully meet the NCAP target and continue clean air actions until 2030. We examined three contrasting pathways to identify the most desirable one for alleviating air pollution health burden maximally in India, which would contribute to the SDG-3.4 target in the foreseeable future.

2. METHODOLOGY

2.1. GAINS-Model Framework and Exposure Attribution. Our current analysis utilized sector-specific $PM_{2.5}$ concentrations across the 23 subregions reported by Purohit et al. (2019)[17] using the GAINS (Greenhouse gases—Air pollution INteractions and Synergies) model for the base year 2015 and projected for 2030 under three contrasting emission pathways, namely, business-as-usual (BAU), advanced control technology (ACT), and sustainable development scenario (SDS). The GAINS model explores cost-effective multi-pollutant emission control strategies that meet environmental objectives on air quality impacts (on human health and ecosystems) and greenhouse gases.[18] GAINS, developed by the International Institute for Applied Systems Analysis (IIASA), brings together data on economic development, the structure, control potential and costs of emission sources, the formation and dispersion of pollutants in the atmosphere, and an assessment of environmental impacts of pollution.[17−19] GAINS explores, for each of the source regions considered in the model, the cost-effectiveness of more than 2000 measures to control emissions to the atmosphere.[20] It computes the atmospheric dispersion of pollutants and analyses the costs and environmental impacts of pollution control strategies; depending upon countries projected economic growth, its vision in expenditure across different sectors and adoption of control measures and mitigation mandates over a long time horizon.[18] In its optimization mode, GAINS identifies the least-cost balance of emission control measures across pollutants, economic sectors, and countries that meet user-specified air quality and climate targets.[20,21]

Energy and transportation activity projections for India, generated using the customized Global Change Assessment Model (GCAM-IIMA), were integrated into the GAINS model to simulate the current and future $PM_{2.5}$ levels under both BAU and alternative scenarios.[17,22] Additionally, GAINS modeled current and future activity projections for industrial processes, agriculture, waste, and other sectors.[19] The Indian version of GAINS model has a disaggregated representation of 23 subregions,[23] where the emission estimates for a particular emission scenario considers (1) the detailed sectoral structure of the sources, (2) their technical features (fuel quality, plant types, etc.), and (3) the emission control measures applied. It also takes into account the spatial heterogeneities in emissions and their transport, along with incorporating the physiochemical processes involved in the modeling framework. GAINS first estimates emissions of primary PM and secondary precursor gases and then computes annual $PM_{2.5}$ concentration based on the transfer coefficients constrained by chemical transport model simulations at a much lower computational cost, which allows consideration of multiple emission control strategies.[17,24] The model was run over the whole southeast Asian region with a spatial resolution of roughly 50 × 50 km^2, from which the model outputs ($PM_{2.5}$ concentrations, in μg m^{-3}) were masked using the states' shapefiles.[25] These air pollution estimates were then integrated with the population database to assess the population-weighted $PM_{2.5}$ exposure across the 23 subregions over India. Supplementary Figure S1 depicts the modeling framework of the GAINS simulation. The model simulates ambient $PM_{2.5}$ concentrations under three air pollution emission pathways, (Table 1).

Table 1. Description of Three GAINS-Model Pathways and Emission Scenarios

GAINS pathways	description
Business-As-Usual (BAU)	Considers the socioeconomic, demographic, and the existing and planned air pollution control policies, measures, and regulations, which will resume in the future following the current practices.
Advanced Control Technology (ACT)	Focuses more on mitigating the regional emission sources and assumes more stringent standards in India and partial implementation of cost-effective technologies in the commercial sectors. This scenario envisions the adoption of cleaner technologies occurring primarily during capacity expansions or regular equipment replacement, without prematurely phasing out existing capital stock. Additionally, it assumes that India will implement more stringent standards with a 10 year lag compared to other industrialized nations. This scenario confines the application of ACT solely to emission control equipment and does not take into account broader structural changes in the economy that could result from a wider and more accelerated adoption of other advanced technologies, such as improvements in energy efficiency and advanced production processes.
Sustainable Development Scenario (SDS)	The SDS pathway explores the potential air quality gains from policy interventions, which are aspired at a wider development context. This scenario projects the anticipated energy use across various sectors, energy system transformation, and economic activities within the framework of devising strategies, at the national and subnational levels, to keep the warming level below 2 °C temperature increase by the year 2100.[22] In addition, it assumes full application and implementation of advanced emission control technologies as in the advanced technology scenario (ACT pathway). Furthermore, it assumes the complete implementation of advanced emission control technologies, mirroring the approach taken in the ACT scenario.
emission scenarios	**sectors**
local vs regional contributions	emissions from the state itself, from the neighboring states, from other states in India, from outside India, and the natural sources.
sectoral contributions	segregated into primary emissions (natural sources, power plant, high stack, household, transport, waste, and biomass burning) and secondary $PM_{2.5}$

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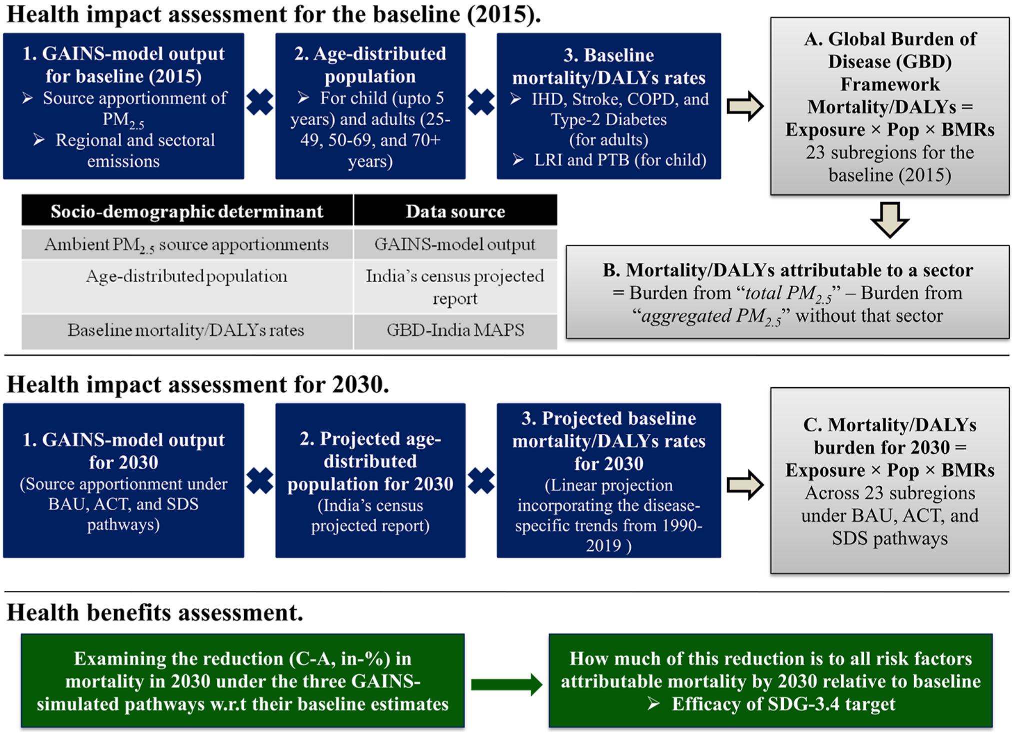

Figure 1. Modeling framework of the health burden assessment.

We used the GAINS model to estimate population-weighted annual exposure to ambient $PM_{2.5}$ in the baseline and projected future scenarios. For each state, contributions of emissions from within the state, from neighboring states (with which each state shares its borders), from other states within India (long-distant states; not sharing borders), outside India (transboundary pollution), and natural sources were segregated by switching off the respective emissions in successive simulations in the GAINS model.[17] Further, the sectoral contributions were segregated among the primary and secondary $PM_{2.5}$ (Table 1) for each state, and then, the primary PM was apportioned into seven major sectors including the natural sources (non-anthropogenic sources), power plant (coal-fired or other biofuels-sourced energy sectors), high stack (brick kiln emissions), household (emissions attributable to all types of domestic activities), transport (all types of roadways vehicular sources and shipping emissions), waste (emissions from the waste-treatment sectors), and biomass burning (emissions due to agricultural residue burning). The secondary $PM_{2.5}$ is the aggregated PM composition sourced from precursor gases (SO_x, NO_x, NH_3, and NMVOC) across all primary emission sources. For detailed description of the sectoral emissions and their considered sources, refer to Purohit et al., 2019.[17] The sectoral contributions to primary PM were estimated by turning off primary PM emissions from that sector through each successive simulation. The modeling framework also allowed segregation of the local (within the states and the neighboring subregions) and regional (long-range transport) contributions of each emitting sector by switching off the emissions from a particular sector in each state and comparing the annual $PM_{2.5}$ with the simulations considering emissions from all sources. Furthermore, switching off precursor gas emissions provided the relative contributions of secondary $PM_{2.5}$ to total $PM_{2.5}$. This was done for the baseline and for the three future scenarios. Overall, a total of 16 simulations were run for the baseline (2015). Broadly, the initial simulation for "total $PM_{2.5}$" (including all sectors from all regions), switching-off the precursor gases, switching-off all the primary sectors, and consecutively switching-off each seven primary sectors (totaling 10). Similarly for the regional emissions, the initial simulation for "total $PM_{2.5}$" and switching-off each five regional sources (totaling 6). For 2030, same sets of simulation were run thrice for the three GAINS pathways.[17]

We validated the GAINS-derived population-weighted $PM_{2.5}$ exposure with satellite-derived $PM_{2.5}$ exposure[25] for the baseline year of 2015 (at 10 × 10 km^2 spatial resolution, consistent with GAINS-model output), as India's in-situ $PM_{2.5}$ monitoring network was not adequate for national-scale exposure estimates in 2015.[26] We found a statistically significant correlation (r = 0.75, p < 0.001) and a root-mean-square error (RMSE) of 22.8 $\mu g\ m^{-3}$ (Figure S2), suggesting that the GAINS-simulated exposure outputs can be used for subsequent analysis.

2.2. Estimation of Health Burden Apportioned to Local and Regional Sources. We used the Global Burden of Disease (GBD) framework to estimate the health burden (premature deaths and disability-adjusted life years, DALYs) of six diseases attributable to ambient $PM_{2.5}$ exposure and its sectoral components. The relative risks (RRs) of premature deaths and DALYs for ischemic heart disease (IHD) and stroke (both are age-dependent), chronic obstructive pulmonary disease (COPD), type-2 diabetes (T2D), lower respiratory infection (LRI), and preterm birth (PTB) at different $PM_{2.5}$ exposure levels were estimated using the meta-regression Bayesian, regularized, trimmed (MR-BRT) exposure-risk functions.[27] In order to maintain consistency while incorporating MR-BRT into our analysis framework, we excluded the assessment for lung cancer as its exposure-risk function was not available in the MR-BRT.

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In India, last census commenced in 2011.[28] However, the People's Archive of Rural India (PARI) provides the age-distributed population projections across the subregions at every five-year interval between 2011 and 2036.[29] We interpolated the state-level estimates for the baseline period and for 2030 from this database. We segregated the subpopulations into four age-group categories [child (<5 years), adults (25−49 and 50−69 years), aged (70+ years), and all ages]. Lastly, we extracted the disease-specific baseline mortality and DALYs rates (BMRs, per 100,000 population) for 2015 by states, both genders combined (male and female), and for the four age-groups and extrapolated linearly until 2030 based on the past trends from 1990 to 2019 compiled in the GBD-India study.[30] The projected BMRs are shown in Table S1. We then estimated air pollution attributable health burden for each disease, for different age-groups, and across the subregions following the GBD methodology and added up for the total health burden[27,31]

$$\text{Mortality/DALYs burden} = \text{PAF} \times \text{Pop} \times \text{BMRs} \tag{1}$$

Here, *PAF* is the population attributable fraction, the proportion of age-distributed population which is at larger risk of health impacts attributable to ambient $PM_{2.5}$; *Pop* is the age-distributed population across the states, and *BMRs* is the baseline mortality/DALYs rates for the six diseases considered in this study. The theoretical minimum risk exposure level (TMREL) was taken between 2.4 and 5.9 μg m^{-3}, as reported in recent GBD studies.[27,30,31] To apportion the health burden attributable to emissions across the regional and sectoral emission sources, we considered the difference in estimated health burden attributable to "total $PM_{2.5}$" of a state (considering all sources from all regions) and the estimated burden attributable to the "aggregated $PM_{2.5}$" without the emission from that sector or the region. This approach is consistent with the GAINS-model framework for apportioning the $PM_{2.5}$ concentrations across the regional and sectoral emission sources.[17] The aggregated health burden from the sectors may not be equal to the estimated health burden attributable to "total $PM_{2.5}$" across the states, possibly due to the nonlinearity in the MR-BRT exposure-risk functions.[27] However, this approach is more robust with the GAINS-modeling framework and possesses clarity as compared to attributing the health burden among the sectors using their proportional shares of PM level to the total $PM_{2.5}$ exposure across the subregions. The detailed modeling framework for health burden assessment is furnished in Figure 1.

We reported findings of our burden apportionment analysis from 23 major subregions in India and excluded the smaller union territories in this study, as BMRs could not be obtained separately. The GAINS-simulation outputs were not processed separately for the smaller geographical units; for instance, the northeastern states (excluding Assam) were combined as a single region.[17] To maintain consistency with the GAINS-model framework, we performed the health burden assessment over this region as a single entity. We averaged the BMRs over this region but aggregated the age-distributed population across the states. We classified the states into three socio-demographic indices (SDIs)—low SDI (≤0.53), middle SDI (0.54−0.6), and high SDI (>0.6)—as presented in the GBD-India[31] using a combination of log-distributed per-capita income, mean education (15 years or above), and fertility rate in women (<25 years). We reported premature death estimates with 95% uncertainty intervals (UIs) in the main paper and the DALYs in the Supporting Information (SI).

2.3. Health Benefit Assessment and Setting the BMR Reduction Target for 2030. For the health benefit assessment across the subregions, we repeated state-level mortality burden estimates following the GBD framework (as explained in the previous subsection) assuming a 40% reduction in $PM_{2.5}$ exposure by 2026 and using projected age-distributed population and BMRs. We obtained the changes (in %) in estimated mortality burden for 2026 with respect to the baseline estimates (2015). Given the current air quality trend,[25] we considered the possibility of a delay in clean-air progress with the states eventually meeting the NCAP target in 2030. For this case, we estimated the potential delay in health benefit (relative to the 2026 target) and how much it may reduce the NCD mortality, in view of achieving the aspirational SDG-3.4 target in 2030.

For this assessment, we considered IHD, COPD, stroke, and T2-diabetes (PTB and LRI are not considered in NCD target) and population aged >25 years. For the assessment of potential pathways which may lead to accomplishing the SDG-3.4 target by 2030, we first estimated the mortality burden attributable to ambient air pollution following the three GAINS-simulated emission control pathways (BAU, ACT, and SDS) and compared them with the baseline estimate to examine how much of total aggregated mortality burden can be pulled down if ambient air pollution is restricted. Since SDG-3.4 aims of reducing mortality burden only, we assessed the temporal changes (2015 to 2030) for this indicator itself, not for the DALYs.

For those states that are not expected to achieve this target (even though they achieve the SDS-driven exposure), we calculated how much (in %) BMRs of the considered four NCDs need to be reduced (from the projected 2030 estimates) so that SDG-3.4 can be achieved. For this, we first assumed that these subregions would meet their SDS-envisioned exposure by 2030 and their disease-specific all *RF*-attributable mortality burdens would be one-third in 2030 relative to that of in 2015. Then, we estimated the reduced baseline mortality rates at which following equation holds based on the projected age-distributed population,

$$\text{BMR}_{kj} = \frac{\text{Mortality burden in } 2030_{kj}\left(\frac{1}{3}\text{ of } 2015\right)}{\text{Pop}_{ij} \times \left(1 - \frac{1}{\text{RR}_{\text{SDS exposure-}k}}\right)} \tag{2}$$

Here, Pop_{ij} is the age-distributed population for age group i in subregion j, $\text{RR}_{\text{SDSexposure-}k}$ is the RR attributable to SDS-driven exposure for disease k, and BMR_{kj} is the expected baseline mortality rate for disease k at which SDG-3.4 would be met in that respective subregion if SDS-envisioned exposure is accomplished. We then quantified the reduction (in %) in BMRs across the diseases and subregions from their projected 2030 level. In an additional analysis, we estimated how much AAP attributable mortality burden could be achieved if the states reduce their exposure subsequently as per their respective next clean-air target (CAT) in 2030, such as the National Ambient Air Quality Standard (NAAQS) of 40 μg m^{-3} or the three WHO Interim-Targets (35, 25, and 15 μg m^{-3}, respectively), after meeting the NCAP mandate by 2026 (Table S2). For example, the GAINS-simulated annual mean $PM_{2.5}$ exposure was 126.4 μg m^{-3} in the base year 2015 in Delhi, which would be 75.8 μg m^{-3} in 2026 (a reduction by

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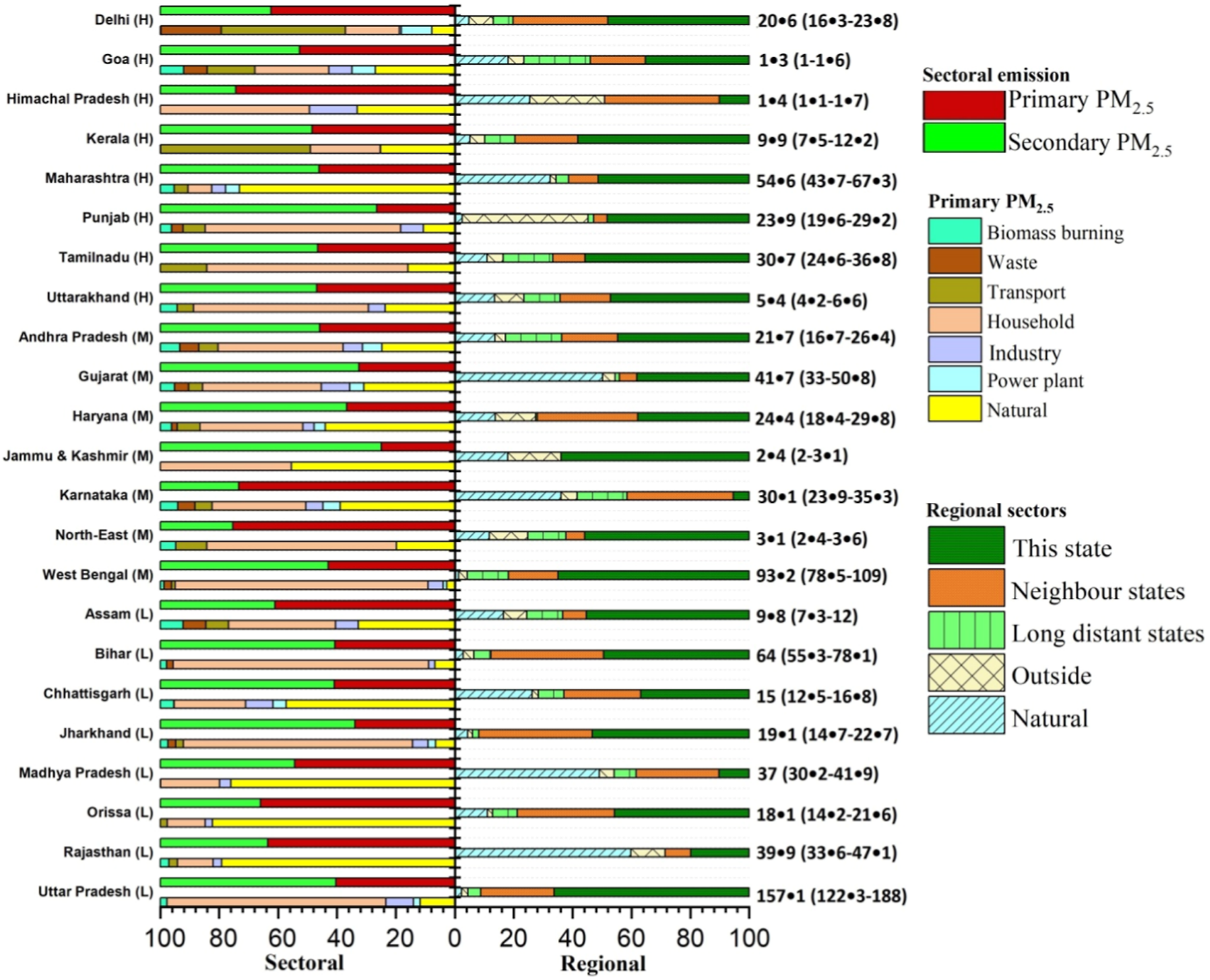

Figure 2. Apportionment of mortality burden attributable to GAINS-simulated regional and sectoral emissions in the baseline. For the sectoral contributions (left panel) in each state, bars at the top represent the relative proportions (%) of mortality burden apportioned into primary and secondary PM, and the bottom bars represent the proportions of primary source contributions from each sector. The stacked bars at the right panel represent the burden apportionments from local to regional contributions. (H), (M), and (L) indicate states belonging to high, middle, or low SDI groups, respectively. The numeric values are the premature death estimates (in thousands), with the numbers in brackets being the 95% UIs. The detailed estimates of mortality burden (with 95% UIs) are documented in Table S3A,B. The regional and sectoral contributions to DALYs are reported in Figure S5.

40%) if Delhi meets the NCAP target (Figure S3). Since this is higher than the Indian NAAQS target of 40 $\mu g\ m^{-3}$, for Delhi, 40 $\mu g\ m^{-3}$ is set as the next possible clean-air target for 2030. If, for another state, annual $PM_{2.5}$ exposure reduces below the NAAQS in 2026 but remains above 35 $\mu g\ m^{-3}$, its next clean-air target for 2030 will be WHO IT-1, and so on (Table S2). The results of this detailed analysis are documented in supplementary Figure S4.

3. RESULTS AND DISCUSSION

3.1. Subnational Level Health Burden Apportionment for the Baseline. GAINS-derived annual mean $PM_{2.5}$ exposure ranged between 14.6 and 126.4 $\mu g\ m^{-3}$ in 2015 (Table S2), and associated premature deaths and DALYs were estimated as 0.72 million (0.53–0.89) and 24.2 million (15.4–30.5), respectively. The low SDI states possessed the highest share (48–55%) of the health burden, almost twice that of the middle and high SDI groups (Figure 2). The highly populous states, namely Uttar Pradesh, West Bengal, Bihar, and Maharashtra, suffered from the highest health causalities. Segregating the sectoral contributions to premature deaths, secondary $PM_{2.5}$ had a larger contribution than primary PM in 16 out of 23 subregions. Among the primary sources, household solid-fuel burning (0.18 million, 0.12–0.23) was responsible for the largest premature deaths in the low and middle SDI states. However, larger influences were estimated from power plants and industries (15–20%) as well. In high SDI states, large contributions were observed from the emissions attributed to the transport and waste-management sectors (25–30%).

At the subregional level, we estimated variation in contributions to the health burden from the point sources. For instance, emissions from medium- to large-scale industries had larger influence on health burden in the IGP and central Indian states, subregions in southern peninsula suffered from power plant-attributed health impacts, and the contribution

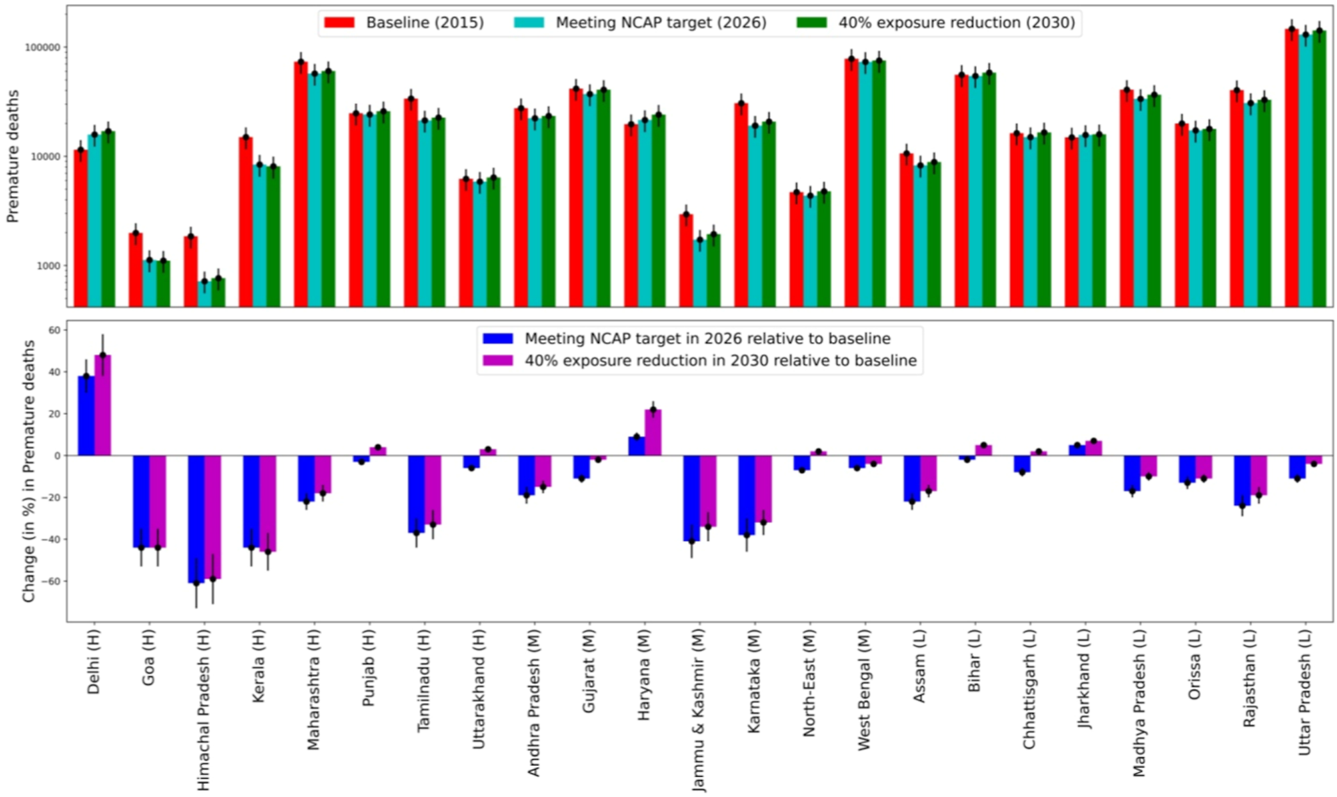

Figure 3. Changes in mortality burden across the states from baseline to the near future (2026 and 2030) under the current NCAP mandate. In the top panel, for 2015 burden estimates (red bars), we used the GAINS-simulated $PM_{2.5}$ exposure and assumed the states would meet the NCAP mandate by 2026 (cyan bars) or they would successfully mitigate the $PM_{2.5}$ exposure by 40% by 2030 (green bars). The circles indicate the mean estimates of premature deaths, and the whiskers are the associated 95% UIs. The *Y*-axis is in logarithmic scale. The bottom panel depicts the changes (in %) in premature death burden in 2026 (blue bars) and 2030 (maroon bars) with respect to the states' baseline estimate. The detailed DALYs estimates are depicted in Figure S8.

from biomass burning was higher in Punjab, Haryana, and Uttar Pradesh (Figure 2). Emissions from the state and its neighboring subregions were leading contributors to premature deaths; however, the proportions from the other three sources varied regionally. Transboundary pollution and natural sources claimed larger health burden contributions among borderline states (i.e., Rajasthan, Gujarat, Punjab, and NE states). In Madhya Pradesh and Karnataka, we estimated a larger mortality share attributable to natural sources (40–45%), as compared to the widespread believed power plant contribution. Our results are consistent with the GAINS-simulated source contributions across these states (14 and 5.5 $\mu g\ m^{-3}$ from natural sources as compared to 0.5 and 0.3 $\mu g\ m^{-3}$ attributable to power plant, respectively). We also segregated the air pollution-related health burden among the disease shares and found that IHD (0.28 million, 0.2–0.36) was the leading cause of premature deaths, followed by COPD (0.17 million, 0.11–0.21) and stroke (0.15 million, 0.11–0.2), while the contributions from T2-diabetes and child diseases (LRI and PTB) were lesser (Figure S6). For DALYs, the burden shares apportioned into various sectoral contributions were estimated to be very similar for premature deaths across the states, where IHD, COPD, and stroke claimed the largest shares for DALYs (Figure S7).

3.2. Health Benefit Assessments of Meeting the NCAP Target. Figure 3 depicts that if the states successfully meet the NCAP target (for consistency with GAINS-simulated baseline estimates, we assumed a 40% reduction in exposure by 2026 relative to 2015), the aggregated premature deaths are expected to decline subsequently to 0.61 million (0.47–0.75). The high SDI states would have the largest health benefits (25.8% in 2026 relative to the baseline), followed by middle (15.9%) and low SDI states (13.3%). Six states (Goa, Himachal Pradesh, Kerala, Tamil Nadu, Jammu and Kashmir, and Karnataka) across high and middle SDI categories would possess considerable health benefits (40–60%) if NCAP-mandate is met; however, the remaining states may possess avoidable deaths by 10–20%. In contrast, air pollution-related deaths would increase in Delhi, Haryana, and Jharkhand (5–38%). In a case where the states could reduce their exposure by 40% by 2030, the attributable health benefits would reduce by 3–8% relative to the NCAP-mandated health benefits by 2026 (Figure 3, bottom panel). Five states across northern Himalaya and southern peninsular regions would achieve considerable health benefits (>35%); moreover, a total of 9–10 states of middle and low SDI categories would possess health benefits by 5–20% relative to the baseline. In contrast, the states in the IGP and NE regions would not achieve meaningful health benefits, especially Delhi and Haryana. In these subregions, the ambient $PM_{2.5}$-related deaths are expected to further increment (8–48%).

The GAINS-simulated $PM_{2.5}$-attributable aggregated DALYs were 24.2 million (15.4–30.5) in the baseline period, which is projected to decline to 17.9 million (15.8–20) by 2026 if the states successfully achieve the NCAP target (Figure S8). Similar to premature deaths, the low SDI states possessed the

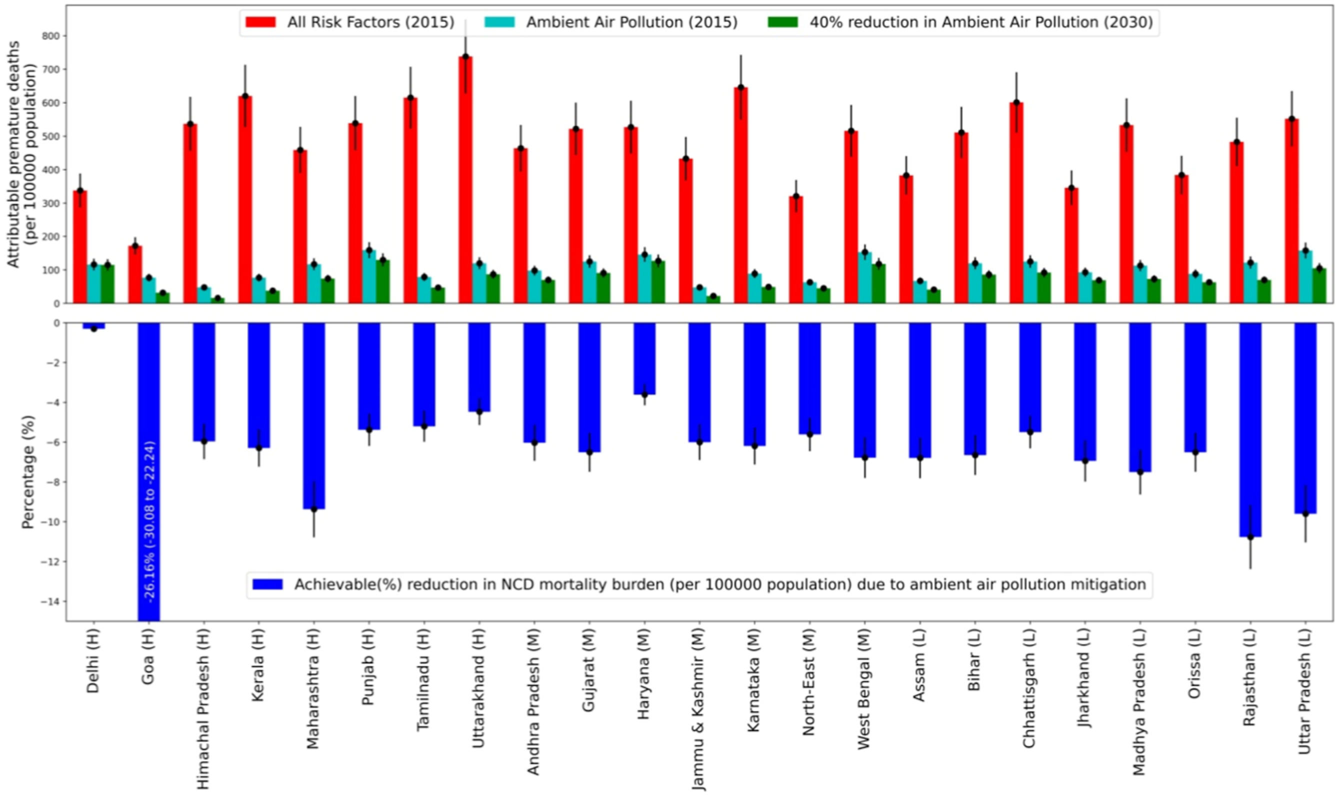

Figure 4. The mortality burden scenario in the baseline and achievable (in %) SDG-3.4 target by 2030 across the states attributable to ambient $PM_{2.5}$ mitigation. In the top panel, the red bars denote the mortality burden (per 100,000 populations) attributable to all RFs, and the cyan bars indicate the mortality attributable to ambient air pollution. The green bars depict the changes in mortality burden by 2030 if the states succeed in reducing their AAP exposure by 40%. The blue bars in the bottom panel depict the achievable (in %) reduction in aggregated NCD mortality by mitigating the AAP by 40% by 2030 relative to that of 2015. The circles indicate the mean estimates of mortality burden, and the whiskers are the associated 95% UIs. The detailed morality burdens across the states are documented in Table S5.

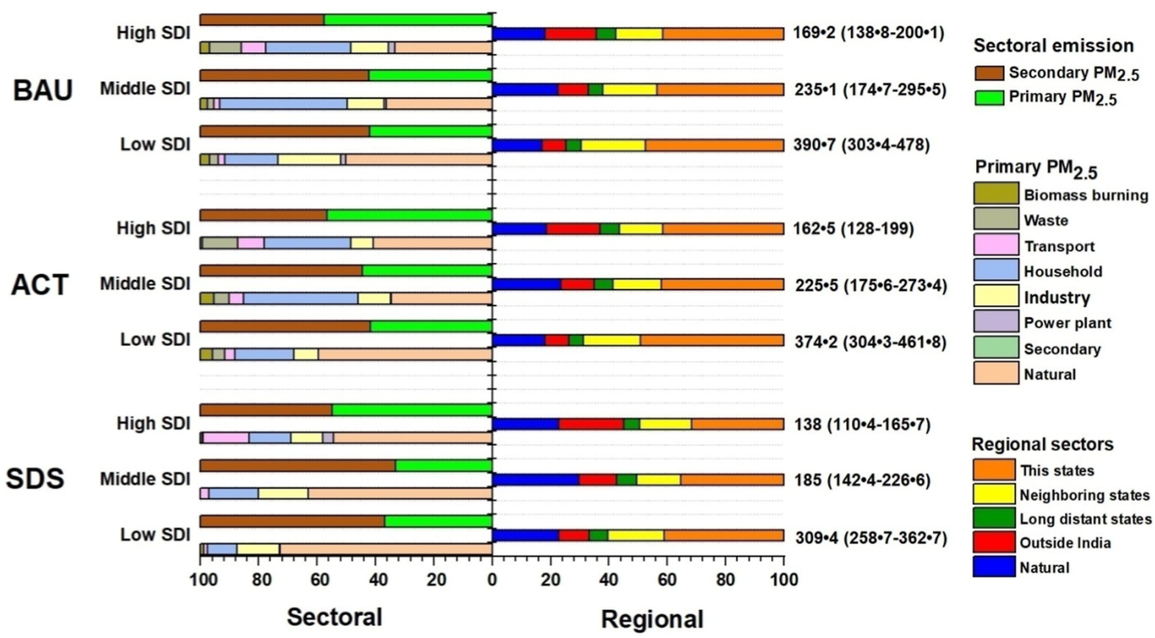

Figure 5. Premature deaths apportioned into regional (right panel) and sectoral (left panel) emissions across the three SDI states (aggregated) under the GAINS-simulated contrasting air pollution emission pathways for 2030. For the sectoral apportionment in every state, the top bars denote primary vs secondary $PM_{2.5}$ proportion, and the bottom bars highlight the apportionment of primary $PM_{2.5}$ by sectors. The numeric values are the premature death estimates (in thousands) with the numbers in brackets representing the 95% UIs. The estimated mean mortality is shown in Table S6, and the estimated mortality burden across the sectoral and regional sources is reported in Table S3C,D. The detailed state level statistics for burden contributions from these sectoral emissions are summarized in Figure S9.

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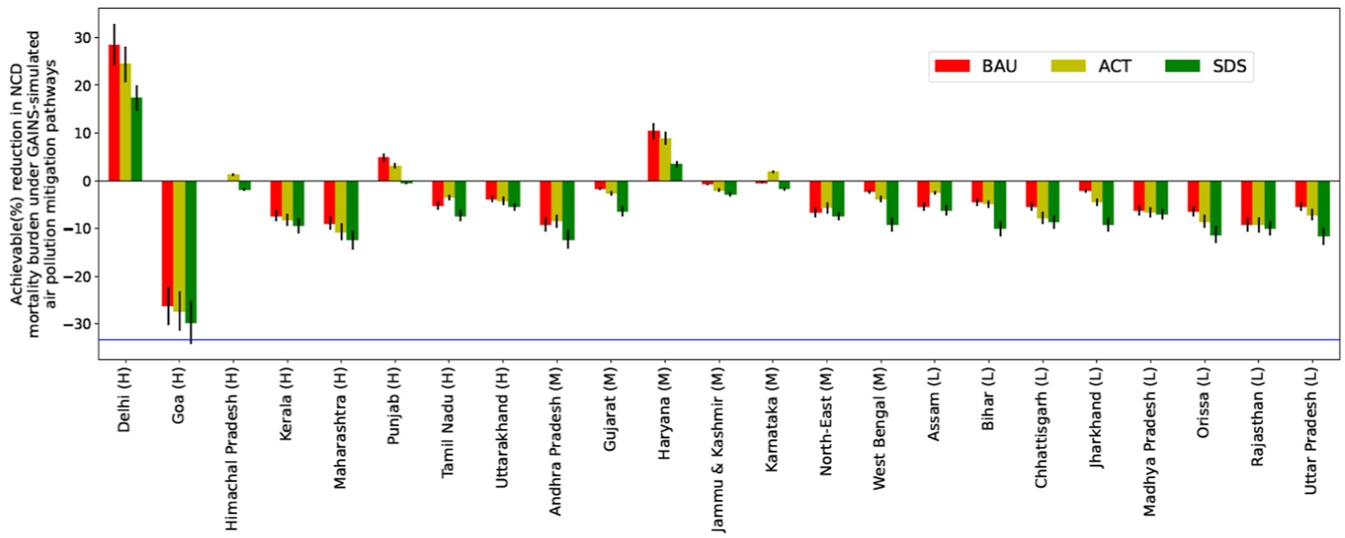

Figure 6. Changes in all-RF-attributable mortality burden (per 100,000 populations) by temporal changes in ambient air pollution exposure following the three GAINS-simulated emission pathways—BAU (red), ACT (yellow), and SDS (green)—with respect to the baseline period of 2015. The black whiskers are the associated 95% UIs with the mean estimated change from each scenario. A positive change indicates health burden would increase by 2030, compared to the baseline year of 2015, and vice versa. The blue horizontal line is the SDG-3.4 target (33.3% reduction in all-RF-attributable mortality burden by 2030 relative to that of 2015) for the states. States meeting or crossing this line are projected to achieve the goal through following the respective pathway/s. The detailed morality burdens across the states are documented in Table S6.

largest share of the DALYs burden [12.66 million (11.27−14.05)], followed by middle and high SDI states; however, the low and high SDI states (29.28% and 23.63%, respectively) would gain larger DALYs benefits relative to middle SDI subregions during the NCAP-era. In a scenario where the states could abate their exposure by 40% by 2030, the aggregated DALYs burden would be 13.57 million (13.26−16.88), while most of the states could achieve substantial health benefits of 20−90% with respect to the baseline.

3.3. Progress toward Achieving the SDG3.4 Target Due to Ambient Air Pollution Abatement. The red bars (Figure 4, top panel) depict the mortality burden (per 100,000) attributable to all RFs, which varied between 172 (146−198) in Goa and 738 (605−871) in Uttarakhand (Table S6). The high and middle SDI states had the largest mortality burden (>600 deaths) as compared to for the low SDI states. The cyan bars denote the AAP attributable mortality burden in the baseline, and its contribution to all RF-attributable mortality was higher in the low and high SDI states (average 23.1−23.3%), followed by less among middle SDI subregions (average 21%). Among the states, the highest contribution to aggregated NCD mortality from AAP was found in Goa (44.8%), followed by Delhi, West Bengal, and Punjab (29.5−34.3%). In comparison, AAP attributed to around 15−25% of all-*RF*-attributed mortality across most of the other middle and low SDI states, with the lowest estimates obtained in Tamil Nadu, Kerala, Jammu and Kashmir, and Himachal Pradesh (<13%). If the states succeed in meeting the NCAP mandate by 2030, the AAP attributable mortality would reduce between 18 (14−22) in northeast states and 53 (45−61) in Uttar Pradesh. The low SDI states (average mortality, 36 deaths) would possess the largest reduction in mortality, followed by high (32 deaths) and middle SDI (29 deaths) subregions. The bottom panel (Figure 4) indicates that a maximum of 26.16% (22.24%−30.08%) health benefits (reduction in all-RF-attributable mortality) could be achieved in Goa by reducing its AAP exposure by 40% alone; however, except in Delhi (0.3%), other states may possess avoidable mortality by a considerable amount of 3.6−10.8% by 2030. The avoidable mortality burden would be larger in low and high SDI states (average 7.89% and 7.53%, respectively) than in middle SDI states (5.82%).

3.4. Potential Mitigation Pathways for India to Alleviate Ambient $PM_{2.5}$ Attributable Health Burden. To investigate which pathway may accelerate the states' progress toward achieving the aspirational SDG-3.4 target, we comparatively assessed the mortality burden apportioned to local and regional sources under the BAU, ACT, and SDS pathways for 2030 (Figure 5). Following these pathways, the $PM_{2.5}$ exposures are projected to vary within 13.2 to 114.4 μg m^{-3}, 12.9 to 109.6 μg m^{-3}, and 9.5 to 82 μg m^{-3}, respectively (Table S3). Under the BAU pathway, the share of secondary $PM_{2.5}$ and most of the primary sector-attributable health burden would be similar by 2030; only the contributions from household and transport sectors would reduce (Figure S9). Under all three scenarios, secondary $PM_{2.5}$ will have a larger share of the health burden over primary PM in middle and low SDI states; however, primary $PM_{2.5}$ would dominate in high SDI states. The contributions to total mortality burden from IHD, COPD (0.29−0.36 million), and stroke (0.12−0.18 million) would be largest; moreover, premature deaths due to diabetes (0.06−0.08 million) would increase significantly with respect to the baseline while declining substantially for PTB and LRI (Figure S10).

Following the BAU pathway, the aggregated premature deaths would be 0.79 million (0.57−1.1), an 8−10% increase as compared to the baseline, and estimated DALYs would be 24.8 million (16.9−32.3) [Figure S10A]. The increase in AAP-related mortality would induce an increment in all-*RF* mortality in three states, namely, Delhi, Haryana, and Punjab (4.8−28.4%). However, most of the remaining states may prevent NCD mortality by 0.2−9.1% following this pathway, with the largest reduction in Goa (26.2%) [Figure 5]. Similar to the baseline, the low SDI states would possess largest share

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in premature deaths [390,724 (303,419−479,029)], followed by middle and high SDI subregions. Regionally, premature deaths attributable to the emissions from the states and their neighboring subregions would have leading shares among the underdeveloped states. On the contrary, pollution from long-distant states and outside India will pose severe threats to public health in the high SDI states (Figure 5). Our model simulations depict that the sectoral contributions from industries, power plants, and transportation would have increased share on premature deaths, especially in the IGP and central states; whereas the contribution to premature deaths from household emission is expected to decline (Figure S9). Moreover, we would expect a reduction in health burden from biomass burning in Punjab, Haryana, and Uttar Pradesh but the burden contribution from waste management to increase sharply in high SDI states.

Under the ACT pathway, the attributable premature deaths and DALYs are expected to decline to 0.76 million (0.6−1.1) and 23.4 million (15.3−30.3) by 2030, respectively, a 5−10% reduction relative to the BAU-derived estimates. Following this pathway, most of the states would alleviate their all-*RF* mortality by 2−10.8%, while maximum reduction is expected in Goa (27.3%). In contrast, mortality would increase in five states, namely Delhi, Haryana, Punjab, Kerala, and Himachal Pradesh (1.3−24.4%). The contributions to health causalities attributable to the emissions from the states' and their neighboring subregions would decline significantly. On the other hand, the proportions to health burden from household and energy (industry and power plant) sectors would reduce in the northern and central states, but the contributions from waste and transport sectors would increase in high SDI states. A comparatively larger reduction in premature deaths is expected from biomass burning among the northwestern states of India (Figure S9). The contribution to health burden attributable to transportation and waste management would be higher in Maharashtra, Karnataka, and Goa (30−40%), but the contributions from energy sectors and household emissions would be larger in Madhya Pradesh, Chhattisgarh, Jharkhand, Kerala, and Tamil Nadu (>50%).

The stringent air pollution mitigation pathway or the SDS would result in a significantly lower aggregated premature death burden [0.63 million (0.48−0.81)] in India. The all-RF-attributable mortality could be averted by >10% in 17 out of 23 states. Relative to the baseline, the middle and low SDI states would possess larger avoidable NCD mortality (20.8−21.3%), as compared with high SDI states (Figure 6). The emissions from the states and their neighboring to long-distant subregions would reduce substantially, in which, the IGP and other highly populous states would possess larger avoidable mortality (15−20%). Although most of the states would have potential gains in survival through restricting the emissions from primary sectors, a considerable death share from secondary $PM_{2.5}$ would persist, which will be alarming for 6 high and middle SDI states (Figure S9).

We comprehensively picturize the air pollution-related health burden by incorporating the demographic and epidemiologic changes and various sectoral contributions following three contrasting air pollution mitigation pathways to have an ahead-of-time assessment of the states' progress toward achieving the SDG-3.4 target. Our estimated premature deaths [0.72 million (0.53−0.89)] attributable to the GAINS-derived $PM_{2.5}$ exposure for the baseline is consistent with the estimates from other contemporary studies [in the range 0.67−0.85 million (0.55−1)].[2,7,16,30−34]

Differences may arise due to our inclusion of waste and commercial sectors and also driven by differential simulation chemistry. In the baseline, largest contributions on health burden were estimated from household emissions, along with contributions from industry, power plant, and transport sectors in the IGP, eastern, and central parts of India, consistent with the contemporary estimates (for 2019) over India using the high-performance GEOS-Chem model.[2] The usage of solid fuels for domestic practices is highly prevalent across Indian households,[35] which is simulated as the largest primary sector contributing to total ambient $PM_{2.5}$.[17] The states over the IGP region and central India suffer from household-sourced $PM_{2.5}$, where unfavorable meteorology and topographic barriers lead the polluted air to mostly oscillate west to east and remain confined within the valley.[25,36] The health burden attributed to primary-secondary PM showed contrasting patterns among different SDI states. The middle and low SDI states suffered predominantly from secondary $PM_{2.5}$, where the coemitted gaseous precursors, inorganic ions, and carbonaceous compounds undergo chemical alterations to form secondary PM.[2,37,38] Several environmental policies were implemented to restrict the primary PM emissions in India,[30,39] but no action plan exists currently which would control the secondary PM. India should implement stricter mandates of having sector-specific emission standards for precursor gases, source-specific strictest policies to prioritize the energy (power plants and industries), waste, and transport sectors and targeted innovative subsidies and interventions for cleaner fuels in the needy households.

India is expected to undergo growing population aging (Figure S11), which may exacerbate the BMRs among the older age groups (>50 years).[16,33] However, a substantial reduction in exposure could reduce premature deaths and DALYs in many states. For instance, India could prevent 0.12 million (0.08−0.16) deaths and 6.3 million (5.5−7.1) DALYs if NCAP is successfully implemented across the subregions. Although the NCAP is envisioned for 131 cities across India,[9,10] we generalized the target at the subregional level, for the sake of this study and consistency with the GAINS-model outputs. We note that meeting the currently envisioned NCAP target would be more beneficial for southern peninsular states due to marginal growths in population and BMRs, but having a sharper drop in RRs for most of the diseases (steeper slope in exposure-response functions at lower $PM_{2.5}$ exposure, see Figure S12). However, the IGP and central states would not obtain health benefits that much, which is evident from the estimated increase in health burden across three IGP states, namely Delhi, Punjab, and Haryana (Figure 3). These three states are expected to undergo larger growth in population sizes for older age groups (Figure S11); however, the reduction in $PM_{2.5}$ exposure may not compensate for the increments in the population factors. Conversely, the expected increase in mortality in these subregions would be attributed to a steeper increase in BMRs for IHD, COPD, and T2-diabetes (Figure S13). However, if the states succeed to abate their $PM_{2.5}$ exposure by 40% in 2030, Goa would substantially accelerate its progress toward achieving the aspirational SDG-3.4 target (26.16% reduction in all-RF mortality). Moreover, the remaining states may reduce their total RF-attributable mortality burden by a considerable amount of 3.6−10.8%. We examined that the largely populous states, namely Uttar

Pradesh, Rajasthan, Maharashtra, and Madhya Pradesh along with Goa, would possess more avoidable mortality (>40 deaths per 100,000), as compared to other subregions. The projected growth of age group between 25 and 69 years is expected to remain static in these states, while the BMRs are expected to decline sharply for most of the diseases.

The three future scenarios (BAU, ACT, and SDS) analyzed in this study span a large range of possible combinations for ambitious emission control measures. Under the BAU pathway (Table S1), the premature deaths would rise aggregately to 0.79 million (0.57−1.1) in 2030, of which the secondary $PM_{2.5}$ would possess the leading share in most of the states. Conversely, household emission would be the largest contributor to the health burden among the primary sectors. Although the mortality attributed to the emissions from the states and their neighboring subregions would cease as compared to the baseline, the contributions due to pollution from long-distant states and outside India would be a major concern for most of the states (Figure 4), which are beyond their jurisdiction. We estimated that the attributable health burden from most of the primary sectors would increase in magnitude, possibly due to socioeconomic transition, progressive urbanization, and increased population density in the near future.[40,41] However, more realistically, implementing the control measures following the ACT pathway, India may achieve a slight reduction in the estimated health burden [0.76 million (0.6−1.1)] as compared to the BAU estimates. Such interventions may lead to reductions in premature deaths and DALYs burden attributed to the emissions of primary sectors, especially from biomass burning. The abatement in health burden attributable to biomass burning would be due to adaptation of agri-residue management techniques in biomass pellets-coal-co-firing and the usage of happy seeders in Punjab, Haryana, and Uttar Pradesh.[34]

The SDS pathway examined to be most aspirational in which strictest and full technological interventions across all sectors would result in a 30−35% reduction in $PM_{2.5}$ exposure by 2030 and thus would maximize health benefits [5.5−12.5% reduction in all-RF mortality, largest in Goa (29.7%); Figures 6 and S14]. Such a larger abatement in mortality burden would be predominantly by restricting the primary PM; however, this benefit can be elevated by controlling the precursor gases which translate into secondary $PM_{2.5}$. The underdeveloped states would be least benefited as the projected growth in population and BMRs would outweigh the substantial $PM_{2.5}$ abatement. Sub-populations in the low SDI states possess lower per-capita income and educational level, unhygienic livelihood, and lesser access to healthcare facilities.[42,43] Under these circumstances, the health burden attributable to other dietary, metabolic, and poor lifestyle-related RFs would increase, along with increase in vulnerability from other environmental extreme events.[44−47]

We further estimated that the states need to reduce their BMRs by 20−80% for IHD, COPD, stroke, and T2-diabetes from their projected values of 2030 (Figure S15) after they successfully meet their SDS-envisioned exposure. We observed that the required reduction amount (in %) is inversely related to the projected increment in BMRs, especially for IHD and T2-diabetes. Government of India (GoI) should implement larger subsidies for public access to healthcare facilities in under-developed states and strengthen the medical infrastructure to control various other RFs which have coimpacts on the growing BMRs. India has aspired to meet clean-air targets in the forthcoming decades. Supplementary Figure S4 depicts that Goa (−34.2%) could achieve its SDG-3.4 target by meeting the CAT alone, in a sense, if the next feasible Interim-Target is met by 2030. Moreover, substantial health benefits of 5−16% could be achieved by the remaining states across the low and high SDI categories.

To summarize, this nationwide analysis provides a comprehensive assessment of disease burden attributable to ambient $PM_{2.5}$ under three emission pathways for 2030, segregated to sectoral emissions from within the state, neighboring states, and beyond. The study identifies the states where the SDG-3.4 target of reducing disease burden attributable to ambient $PM_{2.5}$ by one-third by 2030 (relative to 2015) can be achieved following the SDS-aspired emission control mandates. For the other states, BMR benchmarks required to meet the SDG-3.4 goal and associated pathways are demonstrated. In India, air pollution mitigation efforts are constrained within the NCAP mandate. This study advocates for the efficacy of the potential mitigation pathways beyond NCAP and provides critical scientific evidence for prioritizing sectoral interventions, both of which are critical for decision making. The study demonstrates that meeting the NCAP target is not enough, and the efforts should continue with a greater impetus beyond NCAP at a regional scale to meet the goals of SDG-3.4 for most of the Indian states. The study also demonstrates that the exposure targets to meet SDG-3.4 for most states are difficult to achieve even in the most stringent pathway, unless the BMRs of IHD, stroke, and type-2 diabetes also reduce substantially. This requires policies addressing other RFs for diseases to be integrated and implemented simultaneously.

After the great pollution episode of 2016 in India, numerous control strategies and graded action plans were implemented in Delhi and the surrounding IGP states. GoI also started various initiatives to push for a multisectoral approach to combat air pollution.[36] These efforts are extremely necessary to facilitate betterment in air quality through an airshed approach inclusive of interstate coordination, which is critical to reducing exposure faster compared to a disaggregated urban-centric approach in the NCAP implementation, which has been echoed in a recent World Bank South Asia flagship study.[48] Considering the fact that controlling the population growth would be extremely challenging in India in the foreseeable future, hence combating the air pollution level and reducing the BMRs could be more efficient alternatives for the decision-makers to achieve the aspirational SDG-3.4 target. Conjugate efforts across multiple ministries and stakeholders are required, along with good governance and strategic investments, especially when India has embarked on dealing with these environmental hazards seamlessly.

3.5. Assumptions and Uncertainty. Our study has several assumptions. First, we projected the age-specific BMRs at the subregional level assuming a linear trend in the future as per the past 30 years (1990−2019) trend. The temporal change (either increasing or decreasing) of the BMRs showed linear trends over the last three decades; however, the projected estimates may vary depending upon the effects from various socio-demographic factors and undertaken interventions. Second, we assumed that the present-day nonlinearity in the MR-BRT exposure-risk functions would hold true for the future as well. Third, we considered that $PM_{2.5}$ toxicity in the MR-BRT splines used to estimate RR would hold true in future decades as well. RR in the MR-BRT

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depends only on the $PM_{2.5}$ mass concentration and not on the composition. The MR-BRT splines may be updated in the future with the inclusion of new cohort studies. Fourth, our estimates considered averaged BMRs for IHD and stroke for age groups 25−49, 50−69, and 70+ years, as per the availability of projected population data. Fifth, we assumed that the impacts of other RFs to NCDs would remain static in the foreseeable future; however, with the effective implementation of various environmental, societal, and climatic policies and action plans along with the abatement of ambient $PM_{2.5}$, the aggregated impacts from such RFs to the public health would reduce, which could not be simulated in this analysis. And last, improvements in the healthcare system through effective implementation of public health policies and action plans will reduce the BMRs for the diseases altogether. Such progress could not be simulated in this analysis while estimating the disease-specific BMR reduction targets for the foreseeable future. Deviation from these assumptions would alter the estimated premature mortality and DALYs burden, but we feel that the major conclusions would remain unaltered.

Our estimated air pollution-related health burden may be under- or overestimated due to the consideration of two facts into account. First, if the emissions are not controlled substantially, larger emissions of pollutants and greenhouse gases under the current BAU mandate may destabilize the climate in the foreseeable future. These may lead to enhancement in surface warming, under which the frequency and intensity of other climatic stressors would increase across the subregions.[49] These would exacerbate the baseline mortality or DALYs rates and subpopulations vulnerability and thus elevating the health fatalities attributable to these climatic stressors along with our estimated air pollution-related health burden. In contrast, the air pollution and climate change mitigation pathways (ACT and SDS), especially the SDS pathway, which is envisioned to keep the warming level below 2°C by the end of the century,[17] would minimize the risks from such environmental stressors, and gradual improvement in sub-populations socioeconomic status may reduce the BMRs for the diseases and surely would reduce the aggregated health burden and offset the growing population and its aging effects. More importantly, we considered that only the impact of AAP would change following the three pathways relative to the baseline, while the impacts of other RFs would remain unchanged. As the combined impact of AAP and other RFs is examined to be synergistic,[4] a reduction in ambient air pollution along with the implementation of various environmental, social, and climate policies and action plans may alleviate the impacts from such RFs as well. Thus, the estimated reduction in aggregated NCD mortality burden in this study sets the lower bound as the numbers could be elevated if various other RFs are controlled simultaneously, which requires a more dynamic and complex modeling approach to project the spatiotemporal variations of such interactions.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.4c08697.

Acronyms of the key abbreviations used in this study; list of GAINS-simulated 23 subregions of India; GAINS-model framework; correlation statistics between GAINS-derived and satellite-derived population-weighted annual ambient $PM_{2.5}$ exposure at state levels in the baseline year of 2015; ambient $PM_{2.5}$ exposure variations across SDI states in 2015 and in 2026 assuming 40% reduction with respect to the baseline period following the NCAP target; changes in mortality burden (per 100,000 populations) under the three air pollution mitigation pathways; state-wise DALYs apportionment attributable to GAINS model-simulated regional and sectoral emissions in 2015; disease apportionments to the total air pollution-related premature deaths in each 23 states for the baseline year of 2015; DALYs burden from the six diseases attributable to GAINS-simulated ambient $PM_{2.5}$ exposure for three SDI states in India for the baseline; changes in DALYs burden across the states from baseline to the near future (2026 and 2030) under the current NCAP mandate; health burden (premature deaths) apportionment among the regional and sectoral $PM_{2.5}$ emission in different SDI states under the three GAINS-simulated pathways; DALYs burden from the six diseases attributable to ambient $PM_{2.5}$ exposure for three SDI states in India for the three GAINS-simulated pathways; percentage change in age-distributed population from 2015 to 2030 for different age groups; MR-BRT exposure-risk functions for six diseases correspondent to the mean $PM_{2.5}$ exposure levels; percentage change in baseline mortality rates for six diseases; comparative assessment of health burden (premature deaths and DALYs) from the GAINS model-derived pathways; estimated required reduction in baseline mortality rates for IHD, stroke, COPD, and T2-diabetes; table of projected baseline mortality rates (per 100,000 population) for all the diseases in 2030; table of the post-NCAP clean-air targets and the projected ambient $PM_{2.5}$ exposure for the GAINS-simulated pathways across the subregions of India in 2030; table of estimated premature deaths across the states for the baseline (2015); table of estimated premature deaths across the states for the baseline (2015); table of estimated premature deaths across the states for the three GAINS-simulated pathways for 2030; table of estimated premature deaths across the states for the three GAINS-simulated pathways for 2030; table of estimated mortality burden (per 100,000 population) attributable to ambient air pollution exposure; table of estimated mortality burden (per 100,000 population) attributable to all RFs and ambient air pollution; and table of estimated premature deaths attributed to ambient $PM_{2.5}$ exposure following the GAINS-simulated pathways in 2030 (PDF)

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Notes

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