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Air pollution health and economic co-benefits of keeping warming below 2 °C in India

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The current trajectory of emissions will increase warming and deteriorate air quality in India, leading to severe health and economic impacts. We comparatively assess ambient $PM_{2.5}$-related health and economic consequences for mid-century under GAINS-simulated business-as-usual (BAU) pathway, which considers current emissions, policies, and mitigation measures will resume in future; and 2°C warming scenario (2°C-WS) that may restrict the warming upto 2°C by 2100. Ambient $PM_{2.5}$ exposure would change from 14.6–126.4 μg m^{-3} in baseline across India to 13–136.1 μg m^{-3} under BAU pathway, but to reduce between 7.4 and 84.4 μg m^{-3} under 2°C-WS. Projecting socio-demographic determinants, we estimate that the 2°C-WS driven control measures could prevent 0.77 ± 0.19 million annual premature deaths and 18.7 ± 4.3 million DALYs by mid-century, benefiting 18.9 ± 2.8 billion Euros. Emission controls in the domestic, energy, and waste sectors would be pivotal. Here, we show that India should accelerate climate actions to meet 2°C target and align clean-air and health policies for substantial health benefits.

The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) emphasized the urgent need for rapid reductions in both greenhouse gases (GHGs) and particulate matter by 2030 to meet the essential requirements of the Paris Agreement's net-zero target[1,2]. While the effects of CO_2 emissions on deteriorating climatic stability and leading to global warming may last over a long time horizon, the impacts of fine particulate matter ($PM_{2.5}$) on air quality and public health are more immediate and localized[3]. The chronic exposure to airborne $PM_{2.5}$ has claimed 0.95 million (95% confidence intervals, CIs: 0.62–1.26) premature deaths and 27.4 million (17.7–36.3) disability adjusted life years (DALYs) in 2021 in India[4]. Recent global estimates have reported that ~82% of mortality was attributable to anthropogenic emissions, where ambient air pollution from fossil fuel usage claimed 5.13 million (3.63–6.32) premature deaths[5,6]. Studies have used various exposure-response functions to estimate health benefits upon airborne $PM_{2.5}$ abatement[7,8]. However, the future evolution of source contributions to air quality and their attributable health impacts is not well understood at the subnational level. The complex interrelation between air pollution and its impacts on public health is influenced by various socio-demographic factors[9–12]. Despite growing attention to the determinants of air pollution and health[11,13], it remains unclear how these drivers would collectively shape the future trends in air pollution-related health impacts.

Rafaj et al.[14] have demonstrated that India could reap substantial health benefits by reducing $PM_{2.5}$ exposure through the implementation of ambitious climate change mitigation policies. To address the high burden of air pollution, India has implemented several environmental policies, including the National Clean Air Program launched in 2019, which aims to reduce $PM_{2.5}$-exposure levels by 40% by the end of 2026[15]. Despite a recent improvement in air quality, the annual $PM_{2.5}$ levels in all major cities and peri-urban regions remain above the World Health Organization's (WHO) air quality guideline of 5 μg m^{-3} [16]. Several attempts have been made to project the future health burden under various mitigation scenarios for India[17–20]. However, none have differentiated the impact of local emissions from regional sources at the state level under contrasting air pollution mitigation pathways.

Secondly, most studies have assessed the economic impacts attributed to projected air pollution-related health burden using the conventional willingness-to-pay (WTP) method, which assesses the out-of-pocket expenditure that individuals spend to reduce their unit-risk of air pollution-related burden[11,13,14]. The monetary weightage considered for each

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individual depends on the nation's Gross Domestic Product (GDP), where higher value is placed for each human life of developed countries as compared to the developing countries like India; therefore this approach carries moral dilemma and larger uncertainty while monetizing the health impacts. Additionally, this method does not provide the framework to segregate the economic impacts among premature deaths and morbidity[7]. However, the cost-of-illness (CoI) approach, adopted by the recent Global Burden of Disease (GBD)-India study, estimates the contribution from each human life in the net productivity of India during the future years if that person had not suffered from premature mortality and morbidity attributable to ambient $PM_{2.5}$ exposure[21]. This approach incorporates the projected GDP-growth for the foreseeable future and possesses the framework to segregate net economic impacts attributable to premature deaths and morbidity, thus providing greater clarity. Studies attempting to project the air pollution-related economic impacts in the future are limited temporally and geographically[20]. The quantification of potential economic co-benefits of stringent mitigation measures is missing at the subnational level in India, which will be a handful for the policymakers to justify and drive control measures. The latest GBD-India study has estimated economic losses attributed to air pollution-related health impacts across the states, considering all individuals between 15 and 84 years to contribute equally to the nation's GDP[21]. However, to our understanding, different-age groups have differential contributions to the overall productivity of India, and assuming an equal contribution from all sub-population may lead to larger uncertainty in the assessment. Secondly, current life expectancy in India is 72 years[22,23], hence statistically, the older age groups (over 72 years) should not have any contribution to the nation's GDP. These two aspects clearly establish that the latest India-GBD assessment overestimated the aggregated economic losses. Moreover, existing literature lacks an analysis of the potential discrepancies in net productivity across these age groups, considering the working-age population of 15–70 years.

In this work, we perform comparative assessments to estimate air pollution and its impacts on health and economic burden across the states of India under the Business-as-Usual (BAU) pathway and the 2°C Warming Scenario (2°C-WS) for 2050 [see *Methods* for details]. We integrate the Greenhouse gas and Air pollution Interactions and Synergies (GAINS)-model simulated sectoral contributions of primary and secondary $PM_{2.5}$ from local and regional sources into the GBD framework[4,24]. This allows us to allocate air pollution-related premature deaths and DALYs among sectors for the baseline (2015) and project for mid-century, considering changes in age-distributed population and baseline mortality and DALYs rates (BMRs) at the subnational level. We further decompose the aggregated health burden into contributions from four social determinants (population size, aging factor, BMRs, and $PM_{2.5}$ exposure) to assess the key drivers that would shape the changes in future health burdens attributable to air pollution. Subsequently, the health benefits are disaggregated into secondary $PM_{2.5}$ and primary sectors to identify the major sources to minimize future health fatalities. Finally, using the CoI method, we estimate the economic impacts attributable to these two contrasting pathways. We bring a novel aspect into our assessment by incorporating the per-capita wage (based on the National Mental Health Survey) as a proxy to segregate the sub-population contributions to GDP among different-age groups between 15 to 70 years (see *Methods*).

Results

Health benefit assessment of climate actions

Across the states, GAINS-simulated annual population-weighted ambient $PM_{2.5}$ exposure ranged between 14.6–126.4 $\mu g\,m^{-3}$ in the baseline and projected to vary between 13–136.1 $\mu g\,m^{-3}$ in mid-century following the BAU pathway. Exposure would increase in 13 out of 23 GAINS-simulated subregions of India (in the range of 0.2 $\mu g\,m^{-3}$ in Assam to 12.1 $\mu g\,m^{-3}$ in Punjab) [Table S1]. We estimate that ambient $PM_{2.5}$ exposure would reduce or remain static across most of the high and Middle SDI (socio-demographic index, see *Methods*) subregions as compared to the baseline, while the air pollution level would increase across most of the low SDI states. In low SDI states, reliance on polluting sources such as solid fuels for cooking and heating, coupled with inadequate waste management and unpaved infrastructure, poor socioeconomic conditions of the populace, higher illiteracy rates, and larger population growth contributes to elevated $PM_{2.5}$ levels. Traditional end-of-pipe controls in sectors like power, industry, and transport may inadequately address these localized sources. Conversely, in high and middle SDI states, stricter pollution control measures across sectors generally result in lower or stable $PM_{2.5}$ exposure[25,26]. This could potentially lead to reduction or minor change in ambient $PM_{2.5}$ level across the wealthier subregions of India as compared to the underdeveloped states. Furthermore, meteorological and geographical factors, such as weather patterns and terrain, significantly influence $PM_{2.5}$ concentrations, further contributing to observed interstate variations in exposure. Under the BAU pathway, air pollution attributable premature deaths would increase from 0.72 million (95% confidence intervals, CIs: 0.53–0.89) in 2015 to 2.12 million (1.62–2.63) by 2050, whereas DALYs are projected to increase from 24.2 million (15.4–30.5) to 51.6 million (39.9–63.4). The lower SDI states are expected to bear the largest share of the health burden, accounting for 46% of premature deaths and 48% of DALYs, followed by middle and high SDI states (Fig. S2). The Indo-Gangetic Plain (IGP) and other states with high population density would bear a substantial health burden, whereas the states in the southern peninsula and northeast subregions would have lower health impacts (Fig. 1).

Under the 2°C-WS, $PM_{2.5}$ exposure would range between 7.4 $\mu g\,m^{-3}$ in Kerala to 84.4 $\mu g\,m^{-3}$ in Delhi. The air pollution level would reduce in all subregions relative to the BAU-driven estimates, ranging from 20.5% across the northeastern subregion to 63% in Orissa (Table S1). As a result, premature deaths and DALYs would drop to 1.35 million (1.04–1.66) and 32.9 million (25.6–40.2), respectively. The low SDI states would possess larger health benefits (0.34 million deaths and 8.52 million DALYs), followed by middle and high SDI states (Figs. 1 and S2). The central and IGP states would have a larger reduction (35–48%) in health burden as compared to the subregions in southern peninsular and northeastern India.

The role of socio-demographic factors in driving future health burden

While decomposing the aggregated changes in premature deaths from 2015 to 2050 in terms of the four drivers, we find that population growth, its aging or the shift in age-distribution, and the change in BMRs would play predominant roles in shaping the health burden. We estimate that population drivers, including growth and aging, cumulatively increase the health burden by ~150–200% across the states (Fig. 2). In contrast, age-distributed BMRs are projected to decline sharply in most states except for type-2 diabetes (T2D) among the 70+ age group (Fig. S4). These reductions would alleviate premature deaths by 40–60% as compared to the base year 2015, partially offsetting the effects of population growth. However, the effect of exposure change under the BAU pathway would be negligible, but would lead to a substantial reduction under the 2°C-WS scenario if other determinants remain static. In Goa, the effect of population growth would be outweighed by the changes in the other three drivers (Fig. 2). Three of the four non-communicable diseases (NCDs) that we consider in our analysis (see *Methods*), namely ischemic heart disease (IHD), Chronic Obstructive Pulmonary Disease (COPD), and stroke, were the leading causes of health burden in 2015. While IHD and COPD would continue to be key contributors, T2D would emerge as a larger contributor to health casualties in mid-century. On the contrary, the relative contributions of lower respiratory infection and preterm birth among children would reduce (Fig. S5).

Local and regional contributions to air pollution attributable to health burden

We find that secondary $PM_{2.5}$ dominates over primary $PM_{2.5}$ in driving health burden in 16 out of 23 subregions during 2015 (Fig. S6) and will continue to do so in the BAU pathway in low and middle SDI states (Fig. 3). Emissions from domestic, energy (power plant and industry), and transportation sectors would be the primary contributors to health fatalities. The

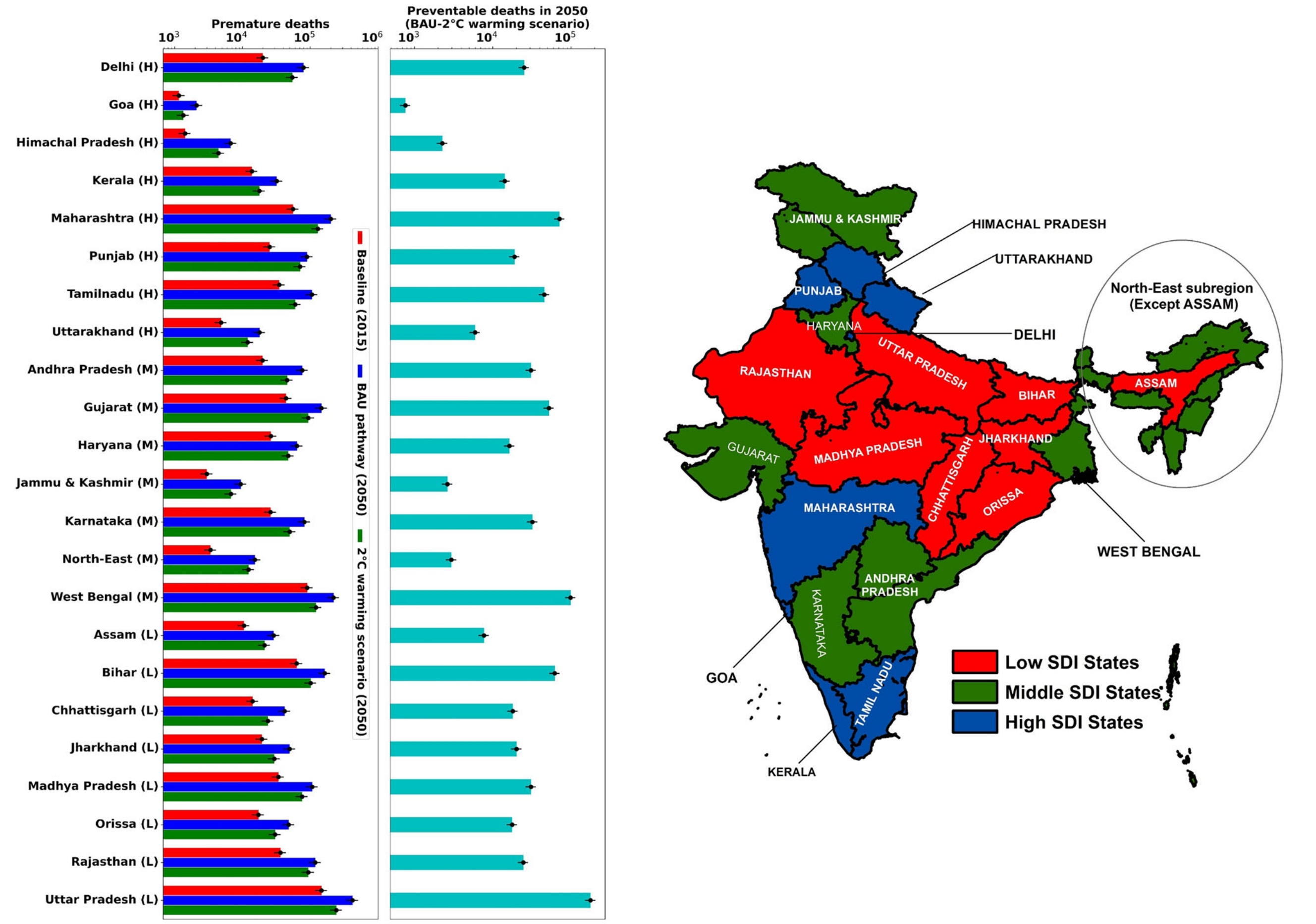

Fig. 1 | Estimated annual premature deaths attributable to air pollution in 2050 under the BAU and 2°C-WS pathways (left panel). The cyan bars in the right panel depict the preventable premature deaths in 2050 under the 2°C-WS relative to the BAU pathway. The spatial map of India shows the geographic locations of the 23 subregions across India. Black circles denote mean estimates, and the whiskers represent the 95% confidence intervals (CIs). The corresponding DALYs burden and their attributable health benefits are provided in Supplementary Fig. S1. The horizontal numeric axes are presented on a logarithmic scale, and states are classified into the categories of high (H), middle (M), and low (L) Socio-Demographic Index (SDI).

domestic sector would make a larger contribution to the IGP and southern peninsular states, whereas emissions from biomass burning would largely impact the northwestern subregions. Our estimates highlight larger contributions from energy sectors in industry-driven central states; however, the high SDI states, namely Delhi, Maharashtra, and Goa, would exhibit a larger health burden attributed to emissions from waste management (Fig. S7). Most states would experience substantial contributions from their neighboring subregions. In contrast, the contributions would reduce from distant states and outside India, albeit with larger uncertainties.

Under the 2°C-WS scenario, the composite shares of health burden from states' own sources and neighboring regions would decrease significantly by 2050 as compared to the BAU (Fig. 3), including reduced contributions from primary $PM_{2.5}$ sectors. Contributions from domestic, biomass burning, energy, and transport sectors would decrease across most of the subregions (Fig. S7C, D). On the contrary, premature deaths and DALYs attributable to open-waste burning would significantly increase in the high SDI states. Additionally, a significant share of secondary $PM_{2.5}$ would persist in the future. One takeaway from Fig. 3 is that the contribution from natural sources would increase under the 2°C-WS scenario as compared to the proportion under the BAU pathway. Given the huge uncertainties in the projection of natural sources across the subregions[27,28], same natural contribution is considered[25] under these two pathways as per the baseline proportion (Table S3). Since the contributions from most of the primary-emission sources would reduce, partially under the BAU pathway, but significantly under the 2°C-WS, the relative proportion of the naturally-originated $PM_{2.5}$ attributable health burden is expected to increase by mid-century. However, the absolute value of premature deaths is taken the same as per the baseline estimates across the subregions.

Sectoral contributions to health benefits due to climate actions

India could prevent 0.77 million (0.58–0.97) premature deaths and 18.7 million (14.3–23.2) DALYs annually by 2050 by meeting the 2°C-WS relative to the BAU pathway. In terms of preventable deaths, the low SDI states would have the largest share [0.36 million (0.25–0.46) premature deaths and 9.1 million (6.9–11.3) DALYs], followed by middle (30.2% and 28.9% of total benefits), and high SDI states (23.7% and 22.5%, respectively). The states that are projected to have higher population growth, namely Uttar Pradesh, West Bengal, Maharashtra, and Bihar, are expected to achieve larger health benefits due to climate actions. Abatement in primary $PM_{2.5}$ would contribute to avoidable deaths by two-thirds (64.5%), mostly from industrial, biomass burning, and domestic sectors across the IGP and central states. Conversely, high SDI states would possess larger benefits from reducing emissions from transport and waste-management sectors (Fig. 4). Most of the northeastern and southern peninsular states would have considerable health benefits from secondary $PM_{2.5}$ abatement (>60%).

For the regional contribution, we estimate that controlling emissions within a state and its neighboring subregions would be essential to achieve substantial health benefits in the future (>75%), particularly across the IGP, central India, and northwestern subregions. In contrast, prioritizing emissions from long-distance states would lead to considerable health benefits

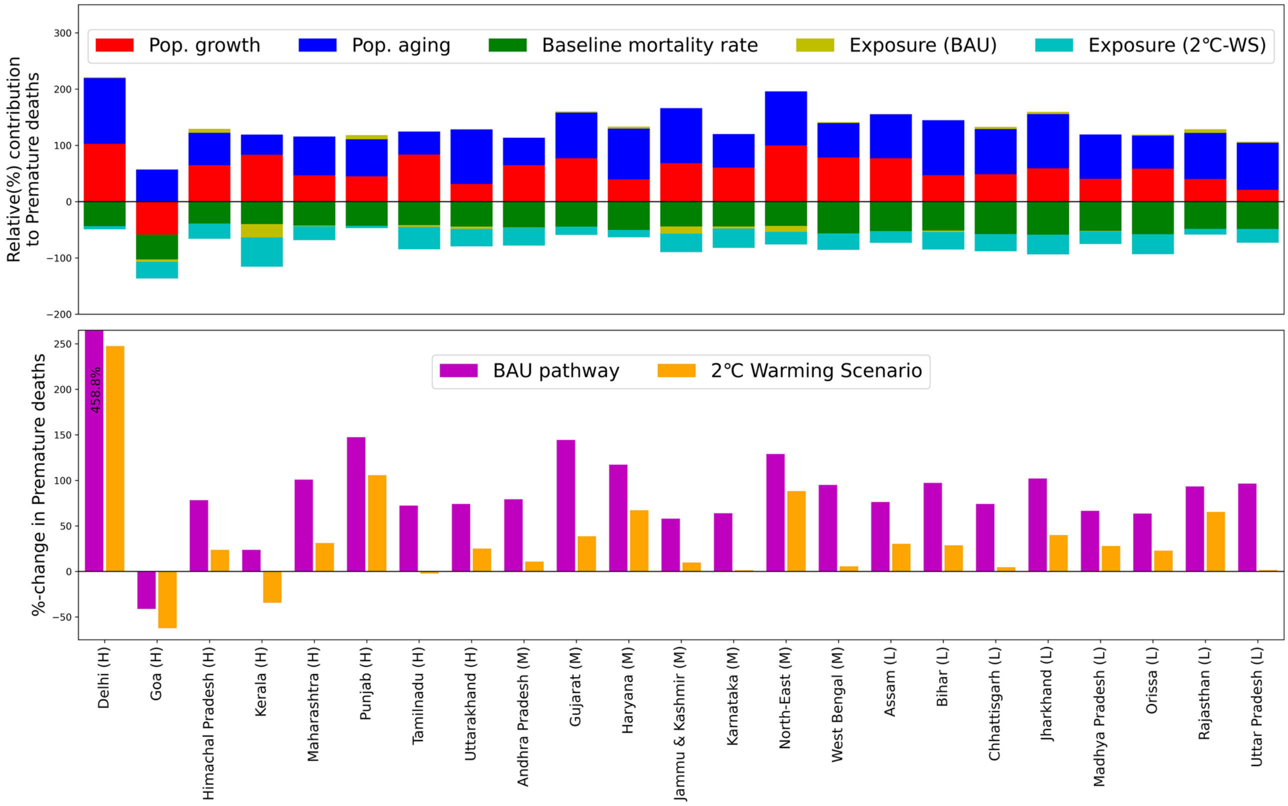

Fig. 2 | Relative contributions of individual determinants, namely population growth and aging, changes in baseline mortality rate, and changes in $PM_{2.5}$ exposure (BAU and 2°C-WS) on the change in premature deaths under the two air pollution emission pathways (top panel). The individual effect of each socio-demographic determinant is denoted by different colors. A positive change indicates that the individual determinant will increase in magnitude by mid-century and could elevate the attributable premature deaths, assuming other determinants remain unchanged at their baseline estimate, and vice-versa. The bottom panel shows the net changes in aggregated premature deaths under the BAU and 2°C-WS pathways relative to the estimates for the base year 2015. The assessment for ambient $PM_{2.5}$ attributable DALYs is documented in Fig. S3. The aggregated premature deaths (in thousands) and DALYs (in thousands) are documented in supplementary Table S2.

for subregions in eastern, northeastern, and southern peninsular India (~20–30%). It is important to note that the GAINS-model framework considers constant $PM_{2.5}$ exposures from natural sources and emissions outside India for 2050 as per their baseline estimates across the subregions; therefore, health benefits from these regional sources cannot be quantified in this study.

Economic consequence attributable to air pollution burden in mid-century

If India follows the BAU pathway, the aggregated annual economic loss attributable to air pollution health burden would be 75.5 billion (58.9–92.1) Euros by 2050, in which premature deaths and DALYs would account for 62.1 billion (53.4–70.8) and 13.4 billion (11.4–15.4), respectively. However, by adopting the 2°C-WS pathway with the strictest control measures, the net productivity loss can be reduced to 56.6 billion (47.5–65.6) [premature deaths and DALYs would contribute 46.5 and 10.1 billion, respectively], resulting in a gain of 18.9 billion (16.1–21.7) Euros annually. Sensitivity analyses using various combinations of labor's share to GDP (a reduction in the range of 5–20%) and the non-market/household contribution to overall productivity (in the range of 0.25 to 0.35) in the future (see *Methods*) reveal that net economic benefit of climate actions would vary between 14.3–18.9 billion Euros due to various combinations of α and λ (Table S6).

Under the BAU pathway, the high and middle SDI states would have the largest economic impact (26.2–26.7 billion Euros) as compared to the low SDI states (22.6 billion Euros). However, the middle SDI states would possess the largest economic benefit (6.6 billion Euros), followed by high (6.5 billion Euros) and low SDI subregions (5.8 billion Euros). The aggregated economic benefit would vary between 0.1–2.6 billion Euros across the states (Fig. 5), with the highest in the states of Uttar Pradesh (2.6 billion Euros) followed by Maharashtra (2.4 billion Euros), Tamil Nadu (2.1 billion Euros), and West Bengal (1.9 billion Euros). The estimated per-capita economic benefits in India would be 11.3 Euros, with a variation between 0.3 and 32 Euros. The benefit as a percentage share of projected GDP would be 0.12% (0.1–0.13%) in India, which would vary across the states from 0.03% to 0.78%. Goa would possess the highest relative share (0.78%), followed by Tamil Nadu and Uttar Pradesh (0.16% each) and Chhattisgarh (0.15%) [Table S4].

Discussion

While climate actions are expected to result in air quality co-benefit, quantitative assessments for India, the most populous and one of the most polluted countries, are lacking. Here, we address this critical knowledge gap and assess the potential air quality co-benefits in terms of attributable health burden and economic consequences across 23 Indian subregions for keeping warming below 2°C relative to the BAU scenario.

Following the BAU pathway, air pollution-related premature deaths and DALYs (per year) would increase by 194.4% and 108.1%, respectively, in mid-century relative to 2015. The translated economic burden will rise to 75.5 billion Euros per year if air pollution is not aggressively controlled and managed, impeding the growth of the human capital stock. However, immediate cut-down in end-of-pipe pollutant emissions through structural transformations, particularly targeting domestic, transport, waste, and energy sectors, could prevent 0.77 ± 0.19 million deaths and 18.7 ± 4.4 million DALYs annually in 2050. Our GAINS-simulated premature deaths [2.12 million (1.62–2.63)] for 2050 are consistent with the estimates from other contemporary studies (in the range of 1.8–2.5 million)[13,14,17–20,29]. Much

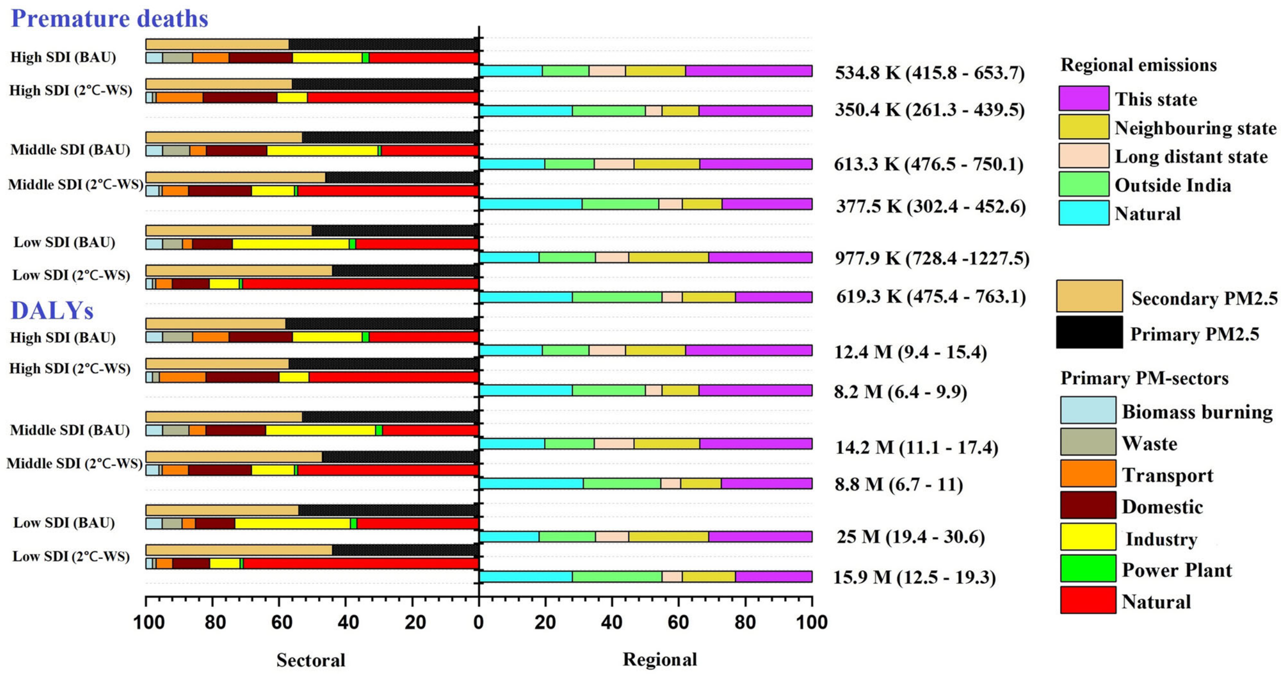

Fig. 3 | The distribution of health burden (premature deaths and DALYs) attributed to regional and sectoral emissions of airborne $PM_{2.5}$ exposure under the BAU and 2°C-WS in 2050 (per year). The numeric values at the right side of each stacked-bar plot denote the aggregated estimate of air pollution-related premature deaths (in thousands, K) and DALYs (in millions, M) burdens across high, middle, and low SDI states, presented for both the BAU and 2°C-WS, respectively. The numeric values in brackets denote the 95% confidence intervals (CIs). Subregion-specific breakdowns of the health burdens (for premature deaths and DALYs) are depicted in Fig. S7.

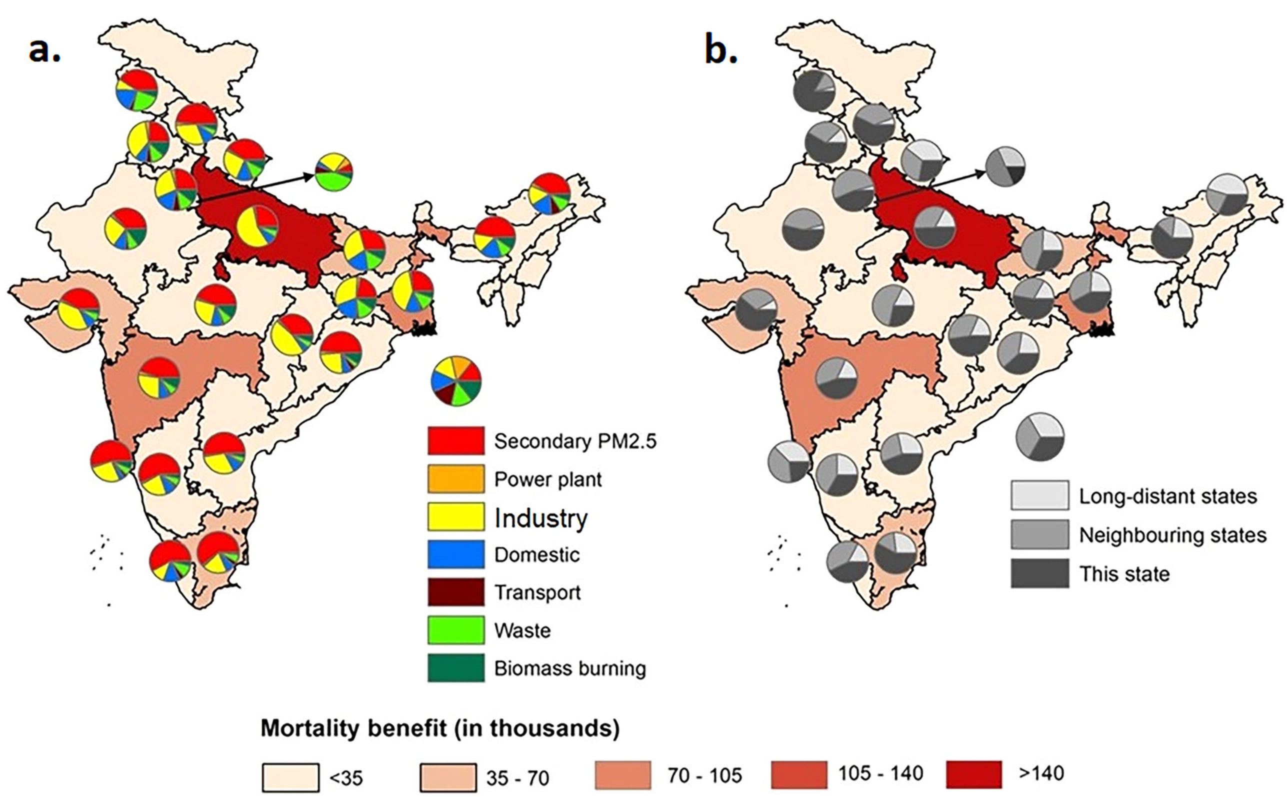

Fig. 4 | Relative contributions in avoidable premature deaths (BAU - 2°C-WS, in thousands) from sectoral emissions and regional sources across the 23 GAINS-simulated subregions by 2050. a We segregate the avoidable premature deaths into contributions from secondary particulates and six primary $PM_{2.5}$ sectors, and **b** depicts the avoidable premature deaths across the contributions from three regional sources. Note that, under the BAU and 2°C-WS, the GAINS-model simulated $PM_{2.5}$ exposures from the natural sources (both for regional and sectoral emissions) and outside India (regional emissions) are considered the same; hence, we do not estimate any contribution to health benefits from these sources. The sectoral apportionment to aggregated health benefits for Delhi is denoted by an arrow. Figure S8 illustrates the sectoral-specific contributions to the DALYs benefit (in millions).

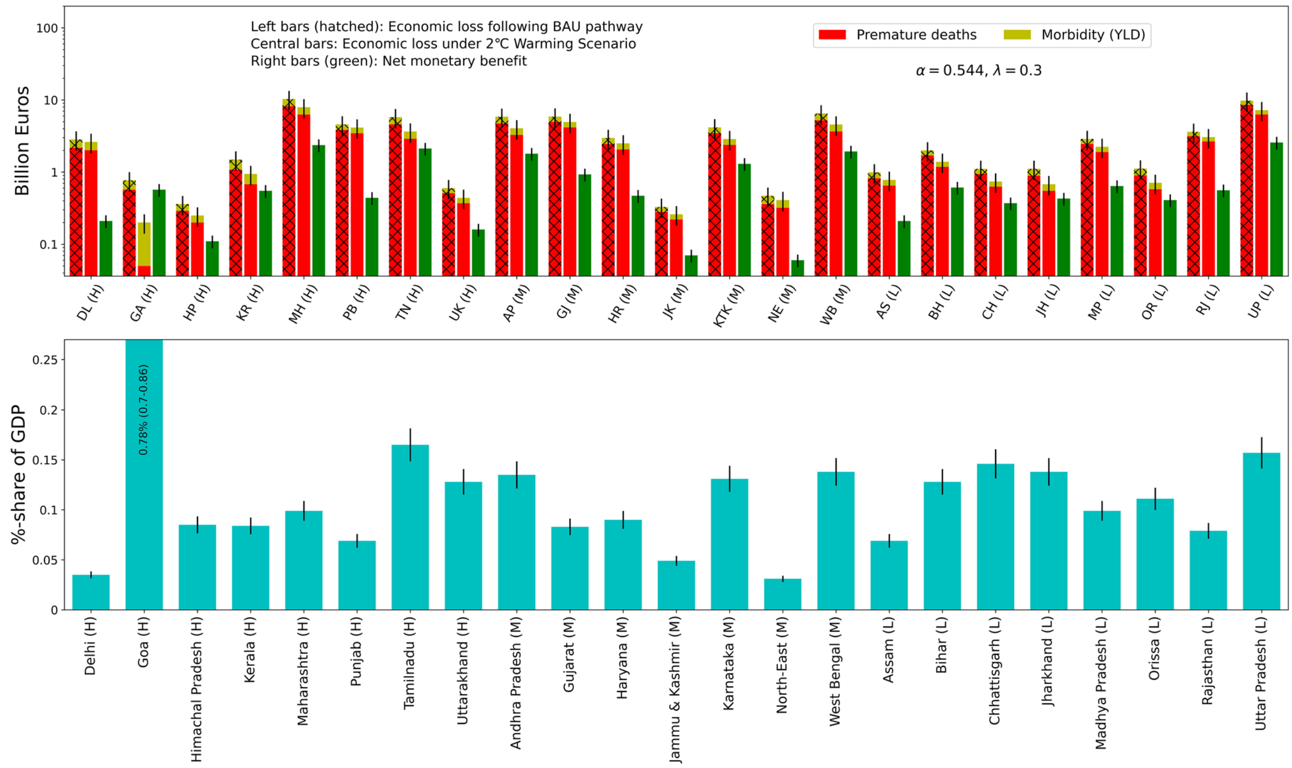

Fig. 5 | Economic assessments (per year) for mid-century across the subregions following the BAU and 2°C-WS pathways. For each state in the top panel, the left (hatched) and central bars denote the net economic losses following the BAU and 2°C-WS, respectively, where they are apportioned into air pollution-related premature deaths (red bars) and Years Lived with Disability (YLDs, see *Methods*) [yellow bars]. The green bars (right) denote the net economic co-benefits by mid-century attributable to the baseline estimates of α (0.544) and λ (0.3). The bottom panel illustrates the net monetary benefit (attributable to the difference between BAU and 2°C-WS) in terms of percentage (%) share of projected GDP by 2050. The black whiskers are the 95% confidence intervals (CIs) associated with the mean estimates. The state-specific economic assessments are tabulated in Tables S4 and S5. The sensitivity analysis of economic assessments from various combinations of α (a reduction of 5–20%) and λ (0.25–0.35) across the high, middle, and low SDI states is documented in Table S6. The *Y* axes are on a logarithmic scale.

of the variation across the states for these scenarios would be driven by differences in potential air pollution mitigation measures, demography, and epidemiologic drivers.

Alike other south Asian countries, the relative contribution from desert-dust, sea salts, and other naturally-originated chemical constituents vary significantly in India across the seasons; strongly governed by changes in meteorology[30]. Under the projected climate change scenarios, the changes in meteorological parameters would be more abrupt and drastic over these regions; eventually, they would carry huge uncertainty in the projection from these natural sources[27,28]. The larger dust contributions reflected in measurements are difficult to model with high precision due to substantial inter-annual variability. Due to this uncertainty, GAINS tends to underestimate the $PM_{2.5}$ measurements, particularly at higher concentrations (Fig. S13). To avoid this large uncertainty from these source contributions and their attributable proportions in ambient $PM_{2.5}$ loading over the Indian landmass, the same natural-sourced attributable ambient $PM_{2.5}$ level is considered for the subregions for 2050 under the two GAINS-simulated pathways as per the baseline proportion[25]. As the emissions from sources contributing to primary $PM_{2.5}$ are expected to decline - marginally under BAU but significantly under 2°C-WS - the relative contribution from natural sources seems to increase (Fig. 3).

Previous CTM-based contemporary studies (2015–19) focusing on India have estimated 4–10% natural contributions to ambient $PM_{2.5}$ and its attributable mortality burden[31–34], as compared to our estimated ~20% during the baseline. Such discrepancy may be partially due to differential simulation chemistry across various CTM-frameworks, differences in meteorological and emission inventories used as inputs, variation in exposure-response functions, and number of chronic diseases used for the health burden assessment. Additionally, the discrepancy could stem due to GAINS-model's adoption of a linearized approach in using transfer coefficient for natural sources to simplify the non-linearity in its dispersion over the subregions. This approach may lead to a slight overestimated contribution from this source. Moreover, most of the studies (except *Chowdhury* et al.[34].) have incorporated the emissions of particulate matter and precursor gasses from each sector to estimate their relative contribution to ambient $PM_{2.5}$ using the brute-force method. It is understandable that since the gas-to-particle phase transformation leads to the formation of secondary $PM_{2.5}$, which elevates the proportion of each sectoral contribution, thus lower contribution from natural sources has been estimated in other studies. Conversely, in the GAINS-model framework, the primary contributions from the sectors are solely attributable to the particulate matter emission as the precursor gasses are separately culminated for the secondary $PM_{2.5}$ assessment over India. This factor may further account for the discrepancy in estimated natural contributions between the GAINS-simulation and other CTM-based studies.

Previous simulation-based studies have estimated a considerably wider range of ambient $PM_{2.5}$ exposure over India (~30–80 μg m^{-3}), while the global studies have used a limited number of ground-based measurements in India for validation. Conversely, our GAINS-simulated $PM_{2.5}$ estimate is validated over pan-India (10-km × 10-km, see *Methods*) and shows strong agreement with the satellite-derived ambient $PM_{2.5}$ estimate (Fig. S14). More importantly, previous studies clearly lacked primary-secondary segregation and future projections of air quality and its attributable health and economic impacts under different climate change scenarios. Currently, no research outlines the extent to which subregions in India would benefit in terms of air quality, health, and economy if criteria pollutants are mitigated alongside GHGs to limit warming below 2°C by 2100. Such quantifications, along with insights into key emission sources and sectors, would be valuable for the policymakers to conduct proactive assessments. This is where our study stands out, offering a novel blueprint with detailed quantifications at the subregional level for both the baseline and for future scenarios.

We obtain that state-specific expenditures would be driven by the state's total population, while the expected economic co-benefits would be determined by the per-capita GDP (Table S4 and S5). The economic impact, as a percentage of states' GDP, would be higher among IGP and low SDI states. However, these states would experience lower economic benefits compared to the wealthier states (Fig. 5). The Government of India should encourage increased expenditures in underdeveloped states to achieve larger economic gains in the foreseeable future. Our results also suggest that a higher contribution from household care (high λ) could lead to greater economic benefits across states. To facilitate this, India should implement refinements in wage distributions among the working subgroups, increase employment, and raise the *per-capita wage*.

Previous studies adopted the WTP method to estimate economic welfare losses and have reported higher estimates of productivity losses (0.5–1 trillion Euros) compared to our assessment. The large difference between these estimates is from the adjustment in life expectancy and age-specific wealth of valuation measure[9,14,35]. Additionally, this discrepancy may be due to the fact that the amount people are willing to pay to reduce their unit-risk of death from air pollution is generally higher than the present value of lost output (in terms of GDP) over a long time horizon[36]. Studies suggested that when regulatory measures disproportionately affect populations of different-age groups, adopting a uniform valuation method might not accurately reflect the preferences of the affected population[37]. Moreover, the estimated economic impact following the WTP approach does not segregate the contribution from premature deaths and morbidity among the populace, as well as, it does not incorporate the differences in labor force dynamics and their distributions across various age groups[21]. Whereas, our adopted cost-of-illness approach places the framework, which renders the air pollution-related premature deaths and years lived with disabilities (YLDs) among working-age groups from other risk factors, and incorporates various societal components to project the economic impacts under contrasting climate change scenarios. To add a note, the WTP method is highly sensitive to the estimated value per statistical life, which varies significantly in studies reported in India[21]. Moreover, the latest India-GBD study assumes that every individual aged between 15–84 years contributes equally to the national GDP, which highly overestimates the economic assessments. We attempt to address this discrepancy by using the sample weighted per-capita wage from the National Mental Health Survey [https://ruralindiaonline.org/en/library/resource/national-mental-health-survey-of-india-2015-16-summary/] as a proxy to differentiate GDP contributions among various age groups between 15 and 70 years (Fig. S11). Air pollution control in India should be viewed not merely as expenditure but as an essential investment for the country's future economic growth. Strengthening current efforts to manage and prevent air pollution will help avoid substantial economic losses across Indian states.

Our results indicate that the composite share of secondary $PM_{2.5}$ will rise more rapidly under the BAU pathway and remain substantial even under the 2°C-WS scenario. While India's current clean air action plan primarily targets primary $PM_{2.5}$[38], greater emphasis must be placed on reducing precursor gas emissions to achieve larger health benefits. Realizing the full social, economic, and health co-benefits of cleaner fuels and advanced control technologies will require accelerated policy incentives to overcome barriers to adoption. In the GAINS-model framework, precursor emissions are aggregated into a total secondary $PM_{2.5}$ estimate rather than apportioning them across the sectors[25]. Global CTM-based studies, as well as a few regional assessments for India and South Asia, have allocated precursor emissions across specific sectors and combined them with primary $PM_{2.5}$ to estimate total sectoral contributions[31–34]. Therefore, sector-specific apportionment of secondary $PM_{2.5}$ is not available in the existing literature. A subset of these studies aggregated precursor emissions into total secondary $PM_{2.5}$ estimates over India[31,32], consistent with our modeling framework. However, such approaches are subject to critical limitations, including discrepancies in representing complex atmospheric processes, substantial uncertainties in emission inventories, constraints in spatial resolution, and very high computational demands[33]. By contrast, the GAINS model is a reduced complexity model that employs parameterization schemes to approximate the complex interactions between physio-chemical processes and sectoral emissions, while substantially reducing computational costs[25]. This framework enables long-term projections of precursor emissions, such as those presented for 2050 in this study. Nonetheless, we acknowledge that applying the brute-force method to apportion secondary $PM_{2.5}$ across individual sectors in such long-term projections could introduce considerable uncertainty and compromise the robustness of our study outputs. For this reason, secondary $PM_{2.5}$ is treated as an aggregated component in both the GAINS-model framework and the present analysis.

We estimate that population factors, its growth and aging, would cumulatively increase air pollution-related premature deaths by approximately 150–200% by mid-century, assuming other determinants remain fixed at their baseline levels (Fig. 2). Consistent with reports from recent studies[20,23], India's population is expected to expand steadily and age (Fig. S9), and given that age-distributed population is the most influential driver in health burden assessments, this demographic shift largely explains the substantial rise in projected $PM_{2.5}$-attributable premature deaths. Conversely, Goa emerges as a notable exception to this national trend. In this state, the effect of population aging among older age groups would be offset by an anticipated decline in overall population size, driven by demographic and socioeconomic transitions. According to the Census-India projections [https://ruralindiaonline.org/en/library/resource/national-mental-health-survey-of-india-2015-16-summary/], Goa is expected to face population contraction due to a gradual reduction in fertility rate, outward migration of younger adults, and sustained socioeconomic development. As a result, in Goa, the amplifying influence of population aging would be outweighed by reductions in population size, baseline mortality rates, and ambient $PM_{2.5}$ exposure, leading to a net decline in air pollution-attributable premature deaths under both the BAU and 2°C-WS scenarios.

India, like many LMICs, has been undergoing a socio-demographic transformation. Currently, the adults and middle-aged (25–69 years) subgroups possess the largest population share (>60%) in India. However, expected population aging and increasing life expectancy may shift the distribution of population size (25–49 to above 50 years), thereby increasing vulnerability to air pollution. Relative to the base year 2015, the low SDI states are expected to undergo larger population growth and aging or a shift in age-structure by mid-century (Fig. S9). For instance, in 2015, the population shares of the over-50-year age group across the low, middle, and high SDI states were 46.9%, 27.4%, and 25.7%, respectively; and are projected to change to 49.8%, 26.5%, and 23.7%, respectively, by mid-century (Fig. S9). Along with these, the BMRs (per 100,000 population) for IHD, T2D, and COPD are expected to increase substantially by mid-century (Fig. S4). The cumulative effect from these three determinants would pull up the ambient $PM_{2.5}$-related health burden in India, especially across the low and middle SDI states, despite only minor changes in ambient $PM_{2.5}$ exposure level under the BAU scenario compared to the baseline.

India possesses one of the highest BMRs globally for middle-aged and older populations[4]. To protect human health in the foreseeable future, our core findings imply that India must implement immediate mandates to strengthen healthcare infrastructure and integrate clean-air and climate actions with major health policies targeting to address other co-risk factors for non-communicable diseases by promoting healthy diet, physical activity, and lower stress[39–42]. These interconnected social barriers of climate, air pollution, and health need to be tackled urgently to accelerate the potential to achieve the envisioned SDG targets, as recommended in the latest NITI-Aayog report[43].

Our study has several limitations. *First*, we project the age-specific BMRs at the subregional level, assuming the same trend would be followed as per the projected national estimates (2020–2040, GBD-India Foresight) [https://vizhub.healthdata.org/gbd-foresight/]. The temporal change (increasing or decreasing) of BMRs shows linear trends over the last three decades for the six concerned diseases; however, the projected estimates may deviate depending upon the long-term effects of various socio-demographic factors and potential interventions adopted by the national and state governments. *Secondly*, we assume that the present-day non-linearity in the MR-BRT exposure-risk functions (ERFs) would hold true for the future as well. *Third*, we consider that $PM_{2.5}$ toxicity in the MR-BRT splines used to estimate *RR* would hold true in the future decades as well. *RR*s in the MR-BRT depend only on the $PM_{2.5}$ mass concentration, not on the composition, and integrated dose-response functions do not yet exist to address this. *Fourth*, the GAINS model incorporated only the national policies and action plans for forecasting the sectoral contributions to total $PM_{2.5}$ under different emission pathways. Though state-specific action plans are broadly aligned with national policies, there could be new technologies in the future for emission controls. *Fifth*, since the brute-force method inherently accounts for non-linear response among source and the receptor, in the GAINS-modeling framework, a linearized approach is assumed for the transfer coefficients in order to assess the dispersion of sectoral contributions; although, the aggregated $PM_{2.5}$ from the sources showed strong correlation with the ground-based measurements over subregional-level in India, if not much at the grid-level in some parts of the country; this justifies that linearized approach could be used for the source apportionment of ambient $PM_{2.5}$ across the sectors. *Sixth*, for 2050, estimating natural contributions involves significant uncertainty due to limited knowledge of how emissions from natural sources may evolve under climate change scenarios. Hence, the baseline contribution is considered across sub-regions for the mid-century[25]. As the emissions from sources contributing to primary $PM_{2.5}$ are expected to decline, marginally under BAU but significantly under 2°C-WS, the relative contribution from natural sources appears to increase. *Seventh*, our GAINS-model framework does not apportion secondary $PM_{2.5}$ across individual emission sectors, as applying a brute-force method for sectoral attribution over long time horizons (such as 2050 in this study) may introduce substantial uncertainties in model outputs, primarily due to a lack of comprehensive representations of atmospheric physio-chemical processes and limitations in emission inventories with high spatio-temporal resolution. To preserve the robustness of the results, secondary $PM_{2.5}$ is therefore treated as an aggregated component in this study. Note that subregional source apportionment of secondary $PM_{2.5}$ in India by integrating updated emission inventories and sector-specific emission factors into the GAINS model framework will be presented in a separate study. *Lastly*, we assume the states belonging to high, middle, and low SDI states in the base year 2015 will have socioeconomic upgradation at similar rates till 2050; thus, we categorize the states for mid-century as per their socioeconomic status in the baseline. We lack the projected data for mean education and fertility rates among women across the states; thus, we could not calculate the projected SDIs for the states till mid-century.

We recommend three important areas for additional research. *First*, more detailed and comprehensive impact assessments are required to understand the overall implications on health and prosperity. This means combining the assessment of air pollution with health and economic impacts performed in this study with additional assessments of other climate stressors, such as heat, changes in diet affected by nutritional pathways, and extreme events. While the global studies have tried to synthesize the literature findings in multi-dimensional impacts[44,45], many of them do not always use consistent assumptions and modeling frameworks, making the quantitative assessment challenging. More importantly, new modeling capabilities are needed to address these complexities. For instance, the energy and emission scenarios used in this study are constructed without the feedback loop that future climate deterioration may have on overall socioeconomic development. Thus, our projected GDP could be overestimated, and a fossil-fuel-intensive future (i.e., BAU) might result in higher BMRs and a manifold sub-population-level vulnerability. Therefore, our assessment of air pollution-related health impacts may underestimate the true health impacts. Although it goes beyond the scope of our study to estimate this feedback, future studies may incorporate these complex system dynamics to identify potential synergy and trade-offs between competing societal goals.

Secondly, the local heterogeneity in air pollution and health impacts may persist in the future and could even widen. Slower economic growth may delay the implementation of air pollution control measures, leading to higher pollution levels. It could also be due to slower improvements in healthcare facilities, which might exacerbate the health burden from pollution exposure[46]. Moreover, a transition towards decarbonization requires capacity building in the low SDI states to facilitate leapfrogging towards cleaner and more advanced yet energy-expensive choices. Incorporating insights from relevant social sciences and demography may strengthen the modeling framework of interactions between environmental policies, socioeconomic drivers, climate, and health. A wide range of determinants can influence the health burden in the future climate. For instance, improvements in educational attainment could accelerate economic growth, which could directly affect the drivers for air pollution and health, energy demand and distribution, policy efforts, and life expectancy[46,47]. Future research should leverage these evolving scientific findings and explore ways to quantitatively bridge the coupled human-natural systems.

Finally, more robust scientific evidence is needed to address the uncertainties encountered in this study. We use the MR-BRT ERFs to estimate the air pollution-related health burden, which needs modifications at a local scale and improvement of the functions specific to the Indian context. Age group-specific ERFs for other diseases (COPD and T2D) need to be elaborated while incorporating more scientific evidence, strengthening the research ecosystem, and deploying regional cohorts. Our core insight is that socio-demographic factors influence public health effects; hence, a more complex modeling framework is required to project the BMRs while incorporating these determinants, which are now known to have a strong influence on these estimates[11,48]. Modeling uncertainties in simulating the effects of local and regional sectors on $PM_{2.5}$ exposure needs to be evaluated, along with deep uncertainties on the socioeconomic and technical systems that may influence precursor emissions and population vulnerabilities.

Methods

GAINS model framework and exposure attribution

Our current analysis utilizes sector-specific $PM_{2.5}$-concentrations across the 23 subregions reported by Purohit et al.[25] using the GAINS (Greenhouse gas —Air pollution INteractions and Synergies) model for the base year 2015 and projects for mid-century under two contrasting emission pathways, namely BAU and 2°C Warming Scenario (2°C-WS). The model incorporates various emissions control options and has previously served as a tool for managing air quality in Europe[49] and China[50]. The year of 2015 has been considered as the "*baseline*" in the GAINS model framework, as it was the onset of the Sustainable Development Goals (SDGs) millennium[https://sdgs.un.org/goals], when India embarked on implementing stricter air pollution and climate control policies and interventions in view of achieving several "*SDG targets*" by 2030 and more importantly, meeting the aspirational "*Net-Zero target*" by 2070[51]. Since the year 2020 was significantly impacted by COVID-19 lockdowns, leading to unusual emission levels, we chose 2015 as the baseline year for our analysis to ensure a more representative starting point. In addition, the year 2015 marked the introduction of significant air pollution control policies and regulations in India[51]. Among many, the significant ones are the Pradhan Mantri Ujjwala Yojana (PMUY), launched in May 2016, which sought to provide deposit-free LPG connections to adult women from economically disadvantaged households, benefiting over 100 million households to date. In 2016, the Ministry of Environment, Forest and Climate Change (MoEFCC) revised the Solid Waste Management Rules to enhance waste collection, segregation, processing, and disposal practices. The National Green Tribunal (NGT) also banned agricultural residue burning in Delhi and neighboring states in December 2015. Using 2015 as a baseline, this study evaluates air quality trends, intervention effectiveness, and emission changes across BAU and 2°C decarbonization scenarios. Energy and transportation activity projections for India, generated using the customized Global Change Assessment Model (GCAM), are integrated into the GAINS model to simulate the current and future $PM_{2.5}$ levels under both BAU and alternative scenarios[25,52]. The BAU pathway considers both the existing and planned air pollution control policies and regulations to remain unchanged in the foreseeable future, as per the baseline. In contrast, the 2°C-WS pathway incorporates projections of energy use, energy systems' transitions, and economic activities required to keep global warming below the 2°C target[41]. The GAINS model explored cost-effective multi-pollutant emission control strategies that meet environmental objectives on air quality impacts (on human health and ecosystems) and GHGs[53]. This model, developed by the International Institute for Applied Systems Analysis (IIASA), incorporated information on future economic, energy, and agricultural growth, emission control potentials and costs, atmospheric dispersion, and environmental sensitivities toward air pollution[25,53,54]. It explored, for each of the source regions considered in the model, the cost-effectiveness of >2000 measures to control emissions to the atmosphere[49]. It computed the atmospheric dispersion of pollutants and analyzed the costs and environmental impacts of pollution control strategies[53]. In its optimization mode, GAINS identified the least-cost balance of emission control measures across pollutants, economic sectors and countries that meet user-specified air quality and climate targets[49,55].

Additionally, GAINS modeled current and future activity projections for industrial processes, agriculture, waste, and other sectors[54]. The Indian version of GAINS model has a disaggregated representation of 23 subregions[56], where the emission for a particular emission scenario is considered (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 took into account the spatial heterogeneities in emissions and their transport, and incorporated the physio-chemical processes involved in the modeling framework. GAINS model first estimated emissions of primary particulates and secondary precursor gases from various sectors, utilizing socioeconomic and demographic drivers as inputs. Subsequently, the annual population-weighted $PM_{2.5}$ exposure was estimated by employing transfer coefficients constrained by chemical transport model simulations at a much lower computational cost, which allowed consideration of multiple emission control strategies[25]. Due to their small size, $PM_{2.5}$ particles remain in the atmosphere for several days and are transported with the wind over several hundred to thousands of kilometers. To represent this long-range transport of pollution, GAINS considered the contributions from emissions within the particular subregion as well as the inflow from its neighboring subregions, from the rest of India, and neighboring countries. For this purpose, transfer coefficients were used to describe the impacts of emission changes from each source region and pollutant on ambient $PM_{2.5}$ concentrations throughout the model domain[57,58]. These coefficients have been derived from brute-force perturbation simulations with the European Monitoring and Evaluation Program (EMEP) chemistry transport model[59], in which, for the meteorological conditions of the baseline (2015), emissions of one pollutant (primary $PM_{2.5}$, SO_2, NO_x, NH_3, NMVOC) across each subregion were reduced by 15% at a time for sensitivity assessment, considering the non-linear chemistry. To properly account for the different dispersion behavior of near-ground sources, emissions from urban and rural low-level (residential + traffic) PPM were reduced separately[53].

The linearization of atmospheric calculations was a simplification that has been used in all regional implementations of GAINS so far, as it enabled efficient scenario comparison as well as source attribution due to faster computational times; it also ensures that the sum of sectoral contributions automatically equals the total $PM_{2.5}$ concentrations. The linear assumption in transfer coefficients for exposure dispersion has shown reasonably good performance in high emission scenarios for Asia. Amann et al.[53] have compared the EMEP CTM-model simulated estimates with the resulting concentrations when using the linear approach transfer coefficients. This illustrates the point that, compared to total ambient $PM_{2.5}$ concentrations, particularly when including natural dust, the biases of the linear approach seem acceptable (Fig. S10) also for a low emission scenario, as long as results are interpreted at the region level and not for individual grid cells. The lower level of uncertainty is due to the variation in the dust composition, especially in the Indian context, while the errors appear to be distributed fairly randomly in China[60]. The potential uncertainties by this step have been discussed in previous literature[49]; however, biases were small enough to justify the use of the linearization approach to model the local to regional transport of the pollutants. The brute-force method adopted in the GAINS framework inherently accounts for non-linear model response during the source apportionment method[61], thus may suffer limitations when the model response includes an indirect effect resulting from the influence of chemicals other than the primary precursor. However, the error is less for secondary aerosols, the source apportionment methods responded nearly linearly to the emission reductions (up to 20–100%). Because the source-receptor relationship for primary-PM is essentially linear and not affected by the indirect effects, Koo et al.[61] have reviewed multiple studies using the brute-force method and reported that the linearized assumption across those CTM-based studies has obtained very good agreement with the in-situ measurements of ambient $PM_{2.5}$, especially when estimating the secondary $PM_{2.5}$ source contributions. This justifies that the linearized approach could be accepted (with reasonable confidence) for the source apportionment of ambient $PM_{2.5}$, which simplifies the non-linear interactions among $PM_{2.5}$ and the meteorology. The model is run over the whole south-east Asian region with a spatial resolution of 0.1° × 0.1° (~10-km × 10-km) for most emission sources [except for high-stack emission, the model ran over a spatial resolution of 0.5° × 0.5° (~50-km × 50-km)], giving combined estimates of $PM_{2.5}$ concentrations at 0.1° resolution. These air pollution estimates are then overlaid with gridded population to assess the population-weighted $PM_{2.5}$ exposure across the 23 subregions of India. Supplementary Fig. S1 depicts the modeling framework of the GAINS-simulation. The model simulates ambient $PM_{2.5}$ concentrations under two air pollution emission pathways (Table 1).

We use the GAINS model to estimate population-weighted annual exposure to ambient $PM_{2.5}$ in the baseline and projected for the 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 are identified in the GAINS model as the emissions from a given source sector, pollutant, and region, multiplied with the appropriate transfer coefficient. Further, the sectoral contributions are segregated among the primary and secondary $PM_{2.5}$ (Table 1) for each state; and then, the primary-$PM_{2.5}$ is apportioned into seven major sectors including the natural sources (emissions from non-anthropogenic sources; primarily from wind-blown dust, sea salts, and other natural sources), power plant (coal-fired or other biofuels-sourced energy sectors), industry (emission from the brick kilns), domestic (emissions attributable to all types of household 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). States with arid and semi-arid regions, such as the Rajasthan desert, the Rann of Kutch, and areas influenced by the rain shadow of the Western Ghats (including Maharashtra, Karnataka, and Tamil Nadu), exhibit the highest contribution from natural dust. While estimates of natural dust emissions have inherent uncertainties, the overall concentrations align reasonably well with observed data. Previous studies have reported that natural-sourced ambient $PM_{2.5}$ possesses critical health risk among Indian populace[31–33], hence it is necessary to estimate health impacts attributable to natural sources. 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 a detailed description of the sectoral emissions and their considered sources, refer to Purohit et al.[25]. The sectoral contributions to primary particulates are estimated by turning off primary PM emissions from that sector through each successive simulation. For each sector, across the local to regional sources, the emission estimates are multiplied by their corresponding transfer coefficients to obtain the $PM_{2.5}$ concentrations, respectively.

We validate the GAINS-simulated $PM_{2.5}$ exposure at 10-km × 10-km scale against satellite-derived $PM_{2.5}$ exposure[16] across 23 subregions of India

Table 1 | Description of the two GAINS model pathways and emission scenarios

GAINS Pathways[25]	Description
Business-as-Usual (BAU)	Considers the socioeconomic, demographic, and the existing and planned air pollution control policies, measures, regulations that will resume in the future following the current practices.
2°C Warming Scenario (2°C-WS)	The 2°C-WS pathway incorporates projections for energy consumption, the transformation of energy systems, and economic activities within the framework of devising strategies to keep the warming level below 2°C temperature increase by the year 2100. Furthermore, it assumes the complete implementation of advanced emission control technologies.
Emission scenarios	**Sectors**
Local vs regional contributions	Emissions from the state itself, from the neighboring states, from other states within India, from outside India or transboundary pollution, and natural sources.
Sectoral contributions	Segregated into primary emissions (natural sources, power plants, industry, domestic, transport, waste, and biomass burning) and secondary $PM_{2.5}$.

for the base year 2015. Since the satellite-$PM_{2.5}$ is available at 1-km × 1-km scale, it is re-gridded to match the 10-km × 10-km GAINS scale. We estimate a statistically significant correlation ($r = 0.75$, $p < 0.001$) and a root mean square error (RMSE) of 22.8 μg m^{-3} (Fig. S14), suggesting that the GAINS-simulated exposure outputs can be used for subsequent analysis.

Estimation of health burden apportioned to local and regional $PM_{2.5}$ contributions from various sectors

We use the Global Burden of Disease (GBD) framework[4,24] to estimate the impact of $PM_{2.5}$ exposure on health, measured in terms of premature deaths and DALYs. We use six diseases for our health burden assessments namely ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and type-2 diabetes (T2D) for adults (>25 years); lower respiratory infection (LRI), and preterm birth (PTB) for children (<5 years). Our estimations consider sectoral contributions of $PM_{2.5}$ for baseline and for 2050 under the BAU and 2°C-WS scenarios. The analysis is conducted across four different age groups: children (<5 years), adults (25–49 and 50–69 years), and the elderly (70+ years), focusing on various states of India. For each state, age group, and disease type, the premature deaths and DALYs associated with chronic exposure to ambient $PM_{2.5}$ were estimated as,

$$\textbf{Health} - \textbf{burden} = \textbf{POP} \times \textbf{BMR} \times \textbf{PAF} \tag{1}$$

Where *BMR* is the baseline mortality or DALYs rates (per 100,000 population) for the age-distributed population-at-risk, *PAF* is the population attributable fraction, and *POP* is the exposed population. PAF is calculated as ($1 - \frac{1}{RR}$), where *RR* is the relative risk attributable to mean population-weighted $PM_{2.5}$ exposure. The data sources and methods for each parameter are described below.

POP. We obtain an age-distributed population [child (< 5 years), adults (25–49 and 50–69 years, respectively), and aged (70+ years)] for the baseline from the census projected report of India [https://ruralindiaonline.org/en/library/resource/national-mental-health-survey-of-india-2015-16-summary/]. We interpolate the state-specific population estimates for 2015 from the census projected report at every 5-year interval between 2011 and 2036. To project the age-distributed population for the states by mid-century, we fit the auto-regressive integrated moving average (ARIMA) function among the population estimates (2011–2036) and extrapolate the non-linear function (higher order) till mid-century.

BMR. To obtain the disease-specific BMRs (per 100,000 population), we first extract the BMRs for 2015 by states, both genders combined, and different-age groups [child (<5 years), adults (15–49 and 50–69 years), and aged (70+ years) population]. For the disease-specific BMRs at the state level for 2050, we first fit a higher-order ARIMA model on the BMRs estimates obtained from GBD-India Foresight from 2020 to 2040 [https://vizhub.healthdata.org/gbd-foresight/], and then apply this function to project the disease-specific BMRs for mid-century while taking the initial values as of 2019 (Fig. S4). To cross-check the validity of this mapping method, we perform this operation (higher order ARIMA model-fit) on the GBD-India estimates from 1990 to 2019 compiled in the GBD-India study[21] against the rates reported by the GBD study and found that they are highly comparable for premature deaths and DALYs (Fig. S15), which validates our statistical model selection.

PAF. The *RR*s of premature deaths from IHD, stroke, COPD, T2D, LRI, and PTB at different $PM_{2.5}$ exposure levels are obtained using the meta-regression Bayesian, regularized, trimmed (MR-BRT) functions. Reported with 95% confidence intervals (CIs), the *RRs* are age-specific for IHD and stroke (25 to 95+ years with 5-year intervals) and are for all age groups combined for other diseases. We consider the theoretical minimum risk exposure level between 2.4 and 5.9 μg m^{-3}, as reported in recent GBD-India studies[4,21,24,26]. To estimate the health burden attributable to emissions from local and regional sources, we consider the difference in estimated health burden from total $PM_{2.5}$ of a state (considering all sources from all regions) and the estimated burden from $PM_{2.5}$ without emissions from that specific sector or region. This method may result in a slightly lower estimate as compared to the attributable burden from total $PM_{2.5}$ because of the flatter exposure-risk functions (ERFs) at higher exposure[24]. However, this technique conserves the facts that *PAFs* are non-additive and the non-linearity of ERFs if we attribute the health burden among the sectors using their proportional shares to total $PM_{2.5}$ exposure across the subregions. More importantly, this method is consistent with the GAINS-modeling framework of attributing the $PM_{2.5}$ contributions from the sectors. To add a note, we consider the same health burden estimates (premature deaths and DALYs) attributable to the natural sources, under BAU and 2°C-WS, as per its baseline estimate across the subregions.

We report findings of burden apportionment analysis from 23 major geographical units in India and exclude the smaller union territories (UTs) in this study, as air pollution exposure is not simulated for these regions. We classify the states into three socio-demographic indices [low SDI (≤0.53), middle SDI (0.54–0.6), and high SDI (>0.6)] as presented in the GBD-India study[26] using a combination of log-distributed per-capita income, mean education (15 years or above), and fertility rate in women (<25 years). We report premature death estimates with 95% confidence intervals (CIs) in the main manuscript and the DALYs in the SI.

Isolating the effects of socio-demographic drivers

Following the GBD framework, four socio-demographic determinants play dominant roles in air pollution attributable health burden (premature deaths and DALYs) within any geographic region[4,24]. *First*, the attributable relative risk (*RR*) corresponding to different levels of ambient $PM_{2.5}$ exposure; *secondly*, the baseline mortality or DALYs rates (per 100,000 population), and two population factors, namely the size of various age groups and the shift in age-structure or the aging factor, as these are critical for ambient $PM_{2.5}$-related health risks for different diseases[9]. Previous studies have formulated the metrics to segregate the relative contribution from each socio-demographic determinant on the changes in air pollution-related health burden[9,62], which we adopt in this study to identify key determinant/s that may have larger impacts on the changes in health burden across the subregions for the concerned diseases. For each subregion, we calculate the percent contribution of the four socio-demographic factors to projected changes in health burden - effect of population growth and aging (change in age-structure), effect of exposure change (following BAU and 2°C-WS), and the effect of changes in baseline mortality/DALYs rates which could be due to changes in health infrastructure, treatment, and care[9,62].

To calculate the effect of each determinant contributing to changes in aggregated health burden in 2050 relative to 2015, we first estimate the total health burden attributable to air pollution in 2015 and in mid-century from the health impact assessment described in the previous section,

$$\textbf{Health burden}_{2015} = \sum_a \boldsymbol{Pop}_{2015a} \times \boldsymbol{BMR}_{2015a} \times \boldsymbol{PAF}_{2015a} \quad (2)$$

$$\textbf{Health burden}_{2050} = \sum_a \boldsymbol{Pop}_{2050a} \times \boldsymbol{BMR}_{2050a} \times \boldsymbol{PAF}_{2050a} \quad (3)$$

Where *Pop* is the age-distributed population, *BMR* is the baseline mortality/DALYs rate, *PAF* is the population attributable fraction corresponds to the individual population-weighted mean exposure of the states, and *a* is the four different-age groups considered in our study.

We then estimated,

$$\textbf{PG} = \sum_a \boldsymbol{Pop}_{2050a} \times \frac{\sum_a \boldsymbol{PAF}_{2015a} \times \boldsymbol{Pop}_{2015a}}{\sum_a \boldsymbol{Pop}_{2015a}} \times \boldsymbol{PAF}_{2015a-all\ ages} \quad (4)$$

$$\textbf{PA} = \sum_a \boldsymbol{Pop}_{2050a} \times \boldsymbol{BMR}_{2015a} \times \boldsymbol{PAF}_{2015a} \quad (5)$$

$$\text{HB}_{\text{BMR}} = \sum_a \boldsymbol{Pop}_{2050a} \times \boldsymbol{PAF}_{2050a} \times \frac{\mathbf{1} - \boldsymbol{PAF}_{2050a}}{\mathbf{1} - \boldsymbol{PAF}_{2015a}} \times \boldsymbol{PAF}_{2015a} \quad (6)$$

Using the Eqs. (2) to (6), we estimate the percent contribution of each determinant as follows,

- Effect (%) of population growth: (PG—total aggregated health burden in 2015) / total aggregated health burden in 2015
- Effect (%) of population aging: (PA - PG) / total aggregated health burden in 2015
- Effect (%) of change in baseline mortality/DALYs rate: (HB_{BMR}—PA) / total aggregated health burden in 2015
- Effect (%) of exposure change: (total aggregated health burden in 2050–HB_{BMR}) / total aggregated health burden in 2015

And lastly, total attributable change (%) = (total aggregated health burden in 2050—total aggregated health burden in 2015) / total aggregated health burden in 2015

Estimation of economic consequences due to $PM_{2.5}$-attributable health burden

We compute the Gross State Domestic Product per worker (Y_i/L_i) by dividing the per-capita GDP (Y_i/N_i) in state *i* by the ratio of active workers or laborers to the total population (L_i/N_i). Labors' share of GDP (α) is assumed to be the same for all the subregions, based on the World Bank estimate of 0.544 for the baseline period (2015)[63]. In the main manuscript, we show the economic assessments computed with α value of 0.544 for mid-century; however, α may vary in the future, and we report the results of sensitivity analyses with different estimates of α (in the range of 5–20%) in Table S6. Recent economic assessments have projected that the labor share of GDP may reduce in the foreseeable future due to the upgradation of socio-economic status in low and middle-income countries, including India[64,65].

Other parameters that vary by state are the ratio of workers to the total population and age-specific survival rates (π_{ij}). For the base year 2015, we assume that the Census 2011-derived Total Worker to Total Population ratio persisted till 2015 across the states and used the state-specific estimates of Active Workers to Total Population ratio for 2050 from a recently published work focusing on India[49]. We use the per-capita wage for the individual age groups between 15 and 70 years as a proxy to segregate their contributions to net productivity [https://cdn.who.int/media/docs/default-source/searo/india/health-topic-pdf/summary.pdf]. Our higher-order polynomial function (degree = 8) shows that the contribution to GDP-share is maximum for the age groups of 40–60 years and reduces among the lower and higher age groups [$r = 0.78$ ($p < 0.001$), relative RMSE = 33.7%; see Fig. S12]. To estimate the annual survival rates from age *j* for each suffered individual, the life expectancy is taken as 72 for 2015[22,23] and assume to be 75 years by mid-century[https://ourworldindata.org/]. Then, the survival probability (π_{ij}) from age *j* is computed using the life table provided by the GBD 2019[21].

The present discounted value of lost output depends on the rate of growth in output per worker (*g*) and the discount rate (*r*). We use the KLEMS database to estimate these rates[66]. For the baseline, the real rate of per-capita income growth of the workers over the period 1990–2000 to 2014–15 is 6.47%. Adjusting this for the rate of growth of the working force over this time domain yields an annual rate of growth in output per worker of 4.83%[44]. The rate of interest (*r*) is chosen to be 6%, the rate of return on a 10-year government bond in India. We assume the ratio of $[(1+g)/(1+r)]$ to be 0.989 for all combinations of *g* and *r* in our analysis, both in the base year 2015 and in the mid-century.

The present discounted value of loss in GDP attributable to $PM_{2.5}$-related premature deaths for the baseline period and for mid-century is calculated as follows. The loss in GDP in state *i*, if a worker dies, is equal to labor's share of GDP (α) multiplied by GDP (Y_i), divided by the number of persons who are working (L_i). Because not all persons of age *j* are working, the expected value of GDP per worker for a person of age *j* (W_{ij}) is equal to ($\alpha Y_i/L_i$) times the ratio of the number of workers of age *j*, L_{ij} to the population of age *j*, N_{ij},

$$\boldsymbol{W}_{ij} = (\boldsymbol{\alpha Y}_i/\boldsymbol{L}_i) \times (\boldsymbol{L}_{ij}/\boldsymbol{N}_{ij}) \quad (7)$$

To calculate the loss in market and non-market outputs for the study periods, Eq. (7) is modified to allow for household production (λ). For the base year 2015, we consider the household production to be 30% of the overall GDP, whereas, for mid-century, we perform our analysis with the share of non-market output (λ) of 0.3 as well, but conduct a series of sensitivity analyses with various combinations of λ (0.25 to 0.35) [Table S6]. Therefore, W'_{ij} is calculated as,

$$\boldsymbol{W'}_{ij} = (\boldsymbol{\alpha Y}_i/\boldsymbol{L}_i) \times (\boldsymbol{L}_{ij}/\boldsymbol{N}_{ij}) + \boldsymbol{\lambda}_j(\boldsymbol{\alpha Y}_i/\boldsymbol{L}_i) \times [\mathbf{1} - (\boldsymbol{L}_{ij}/\boldsymbol{N}_{ij})] \quad (8)$$

Here λ_j represents the fraction of output attributable to non-market production for a person of age *j*. We considered that children (<15 years) and the older population (70 and above) would not contribute to both the market and non-market outputs. Hence, the terms L_{ij}/N_{ij} and λ_j are taken as zero in Eq. (8) for these population age groups for every state.

If a person of age *j* dies in the current year, their contribution to GDP will be lost for all future years of their working life. To compute the GDP for the baseline, we use the Reserve Bank of India's Handbook of Statistics report for 2015–16 for the states and assume a moderated growth of 6.7% (per year) in the future years, consistent with the projection of NITI-Aayog's between 2012 and 2047[43], which is also incorporated in the recent GAINS model framework for India[25]. We also assume that the labor's share of GDP and the fraction of the population of working age (L_{ij}/N_{ij}) would remain constant for all *i* and *j*. This implies that lost GDP at age *t* of a person currently of age *j* will equal $(\alpha Y_i/L_i) \times (L_{it}/N_{it}) \times (1+g)^{t-j}$. This must be weighted by the survival probability of an individual to age *t*, where π_{ijt} is the probability that a person of age *j* in state *i* would survive to age *t* (LE). The value of GDP lost in the future is discounted at the annual rate *r*.

Incorporating the previous assumptions, the present discounted value of lost market and non-market output for a person of age j in state i who dies in the baseline period and in mid-century, PV_{ij}, is

$$\mathrm{PV}_{ij} = \sum_{t=j}^{LE} \pi_{ij,t} \times \left\{ \left(\alpha \frac{Y_i}{L_i} \right) \times \left(\frac{L_{it}}{N_{it}} \right) + \lambda_j \left(\alpha \frac{Y_i}{L_i} \right) \times \left[1 - \left(\frac{L_{it}}{N_{it}} \right) \right] \right\} \times \left(\frac{1+g_t}{1+r_t} \right)^{t-j} \tag{9}$$

Equation (9) is calculated based on the value of $j = 15$–70 years, following the assumption of α, λ, g, and r discussed above. The total output lost due to air pollution is the parameter PV_{ij}, the number of deaths due to air pollution in the baseline period and in mid-century of persons of age j in state i, summed over all j. The 95% confidence intervals (CIs) for total economic losses due to air pollution are calculated using the confidence intervals of estimated air pollution-related premature deaths in our analysis.

The lost output due to morbidity associated with air pollution in 2015 is computed by multiplying the number of years an individual lost their healthy life (YLDs) associated with air pollution in the base year 2015 and in the mid-century. We extract the state-specific YLDs for 2015 from India-GBD estimates[4,24], and assume the estimates for different-age groups would change till mid-century (either increase or decrease) as per the rates of India, projected in the GBD-India Foresight[https://vizhub.healthdata.org/gbd-foresight/]. The output loss associated with morbidity for persons of age j in state i, M_{ij} is given by,

$$M_{ij} = W'_{ij} \times YLD_{ij} \tag{10}$$

Morbidity losses, summed across all age groups, are reported across the subregions. We report the 95% confidence intervals (CIs) of the estimated monetary losses in accordance with the confidence intervals reported in our analysis. So, to summarize, the net lost output in human capital due to air pollution-related premature deaths and YLDs is $PV_{ij}+M_{ij}$ for persons of age j in the state i.

We compare our model-estimated state-specific economic losses for 2015 (Table S7) with the India-GBD estimate[21] for 2017 across the 23 subregions considered in our analysis and find a statistically significant correlation ($r = 0.92$, $p < 0.001$) within the uncertainty ranges (see Fig. S16). The aggregated economic losses are lower following our method as compared to the India-GBD estimates, possibly due to lower age-distributed population sizes in 2015 (relative to 2017 by India-GBD) and segregated contributions to productivity from different-age groups (15–70 years) adopted in our analysis.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Source data are provided with this paper, as a Source data file and is deposited in the figshare under accession code [https://doi.org/10.6084/m9.figshare.27135846]. The demographic and epidemiologic information used in this study can be accessed using the same figshare accession code. Python codes for the data analysis in the main text and SI are available at [https://doi.org/10.6084/m9.figshare.27135846].

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Author contributions

D.S. and S.D. conceptualized the problem. D.S. performed the core analysis with the help of F.I. and A.K. under the guidance of S.D. and wrote the initial draft. P.P., G.K., and Z.K. provided the GAINS model output data. S.C. and A.P. provided feedback on the results and interpretation. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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