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Integrating air pollution-health feedback into climate projections: towards endogenous environmental-social links in the integrated models

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ABSTRACT

Integrated assessment models (IAMs), often coupling Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs), simulate how socioeconomic drivers, technology, policy, and environmental processes interact over time. However, these models typically treat socioeconomic drivers as exogenous input, overlooking how environmental outcomes, like air pollution, can in turn affect health and demographics. This limits our understanding of health co-benefits and weakens the basis for climate-health policy integration. Here, we tackle this gap by linking ambient $PM_{2.5}$ concentrations from four SSP-RCP scenarios to the cause-specific risk functions and use the resulting risk impacts to adjust the age- and sex-specific demographic projections from the SSPs. This allows for more coherent estimation of how air quality trajectories influence health outcomes across 186 countries and territories through 2050. Our results reveal notable deviations from conventional SSP-based projections. In low-emission scenario (SSP1-1.9), $PM_{2.5}$-related deaths over 2020–2050 are overestimated by 8 % (10 million) due to improved air quality. In contrast, deaths are underestimated by 6 % (15 million) in high-emission scenario (SSP3-7.0), where pollution worsens. These differences translate into life expectancy at birth changes of +0.23 and −0.16 years, respectively. The feedback effects are pronounced in Southeast Asian countries with elevated pollution exposure and population vulnerability, exacerbating the Global North-South mortality gaps under SSP3-7.0 while narrowing them in SSP1-1.9/2.6. Our findings underscore the need and potential of incorporating air pollution-health feedback into the integrated modeling frameworks, which would enhance the realism of long-term demographic projections, especially in pollution-prone regions, and support better-aligned climate and public health strategies.

1. Introduction

Integrated assessment models (IAMs) combine socioeconomic dynamics, technological development, policy choices, and environmental processes to explore long-term climate and sustainability outcomes (Moss et al., 2010; van Vuuren et al., 2012). IAMs link how energy, land use, the economy and emissions evolve, assess how the climate responds and evaluate "what-if" futures and policy options. The Shared Socioeconomic Pathways (SSPs) describe alternative futures of societal development (e.g., SSP1 "sustainability," SSP2 "middle-of-the-road," SSP3 "regional rivalry"), while the Representative Concentration Pathways (RCPs) represent trajectories of radiative forcing (the additional energy trapped by greenhouse gases, in $W{\cdot}m^{-2}$, typically referenced for 2100) based on different emission profiles (O'Neill et al., 2016). The coupled SSP-RCP scenarios enable IAMs to simulate emissions, land use, and climate responses under distinct socioeconomic assumptions, and is widely used to inform assessments by the Intergovernmental Panel on Climate Change (IPCC) (Calvin et al., 2023; O'Neill et al., 2020a; van Beek et al., 2020). While initially focused on climate mitigation and adaptation, climate change analyses using SSP-RCP scenarios are now

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increasingly used to investigate broader sustainability issues, such as food security and air pollution (Fujimori et al., 2019; Yang et al., 2023; Yue et al., 2024).

In the integrated modeling framework, socioeconomic variables like population are typically treated as exogenous inputs (Fig. S1), overlooking the important feedback between environmental change, human health, and changes in population size and age structure (O'Neill et al., 2020b; Verburg et al., 2016; Wiebe et al., 2023). One key example is air pollution: climate mitigation policies that reduce fossil fuel use can lower emissions of air pollutants, such as ambient particulate matter ($PM_{2.5}$), decreasing exposure risk and associated deaths—an effect rarely reflected in current models (McCollum et al., 2013). Given that air pollution remains one of the leading environmental hazards to human health, such feedback could alter existing projections of demographic outcomes (IHME, 2024; Rafaj et al., 2018; WHO, 2021; Xu et al., 2023; Yim et al., 2024). Addressing the feedback is crucial to improving how integrated modeling frameworks capture environmental health risks and to move towards more comprehensive wellbeing-related assessments under climate change (Chaplin-Kramer et al., 2024; Madaniyazi et al., 2015; Ravindra et al., 2019).

Several country-level studies that explore air pollution-health feedback have revealed significant impacts on both $PM_{2.5}$-related premature deaths and life expectancy at birth (LE_0) under different mitigation scenarios. By directly adjusting the mortality rates based on $PM_{2.5}$ concentration levels across different legislation scenarios, Sanderson et al. (2013) demonstrated a potential LE_0 gain of 2.8 years and 2.5 million averted deaths in India by 2030, compared to projections without feedback. Similarly, accounting for the feedback effects of policy-driven $PM_{2.5}$ change on mortality rates, Dimitrova et al. (2021) projected up to 8 million averted deaths and a 0.7-year LE_0 gain by 2050 in India. In England and Wales, Milner et al. (2023) projected potential gains of 13.7 million life-years by 2100 under a multisectoral mitigation scenario, compared to a 2020-constant baseline scenario.

Yet, two key limitations remain. First, the underlying mortality rates applied in these studies are either fixed or obtained from other studies, which reflect historical trends but fail to capture future trends under alternative socioeconomic pathways. Second, there is a lack of comprehensive, global-scale assessments that integrate the air pollution-health feedback. While recent global studies have begun incorporating scenario-based mortality rates using models like International Futures (Hughes et al., 2011), these rates still lack direct linkage to specific air pollution levels such as $PM_{2.5}$ concentrations (Huang et al., 2023; Yang et al., 2023; Yue et al., 2024). A consistent approach that integrates global emission trajectories, air pollution, and dynamic health responses would facilitate the global long-term demographic projections, enhance our understanding of the health co-benefits of sustainability strategies, and better inform climate-health policy integration.

The objective of this study is to improve understanding of the air pollution-health feedback in integrated modeling frameworks, thereby advancing a more nuanced assessment of health impacts under climate change and socioeconomic pathways. We integrate scenario-based $PM_{2.5}$ projections, exposure–response functions, and SSP demographic pathways into a coherent modeling framework. By dynamically adjusting mortality rates in response to varying pollution levels, we project health impacts beyond the limitations of conventional approaches that fix the mortality rate change solely to socioeconomic trends. Our approach provides the first explicit global estimate of the air pollution-health feedback across 186 countries and territories under long-term scenarios. Specifically, we focus on three assessments: (1) the overall magnitude of health impacts under divergent $PM_{2.5}$ trajectories across varying environmental and socioeconomic pathways, (2) regional and demographic variation in the strength of the air pollution-health feedback, and (3) the identification of population-disease combinations most vulnerable to its effects. This study delivers insights into the public health implications of climate and development trajectories based on an integrated modeling framework, with particular relevance for regions and populations most vulnerable to pollution exposure.

2. Materials and methods

2.1. Study scope and analytical framework

This study analyses the global health impacts of air pollution exposure under four SSP-RCP scenarios, with a specific focus on integrating air pollution-health feedback in demographic projections. We quantify $PM_{2.5}$-related premature deaths for six $PM_{2.5}$-related diseases, by sex and 5-year age cohorts, and assess corresponding impacts on LE_0 across 186 countries and territories from 2020 to 2050. Our analysis combines three inputs (Fig. 1): (1) Ambient $PM_{2.5}$ concentrations from scenario-specific SSP-RCP trajectories, representing the levels of air pollution to which populations are exposed. (2) SSP demographic projections providing population counts and baseline all-cause mortality rates. (3) Forecasts of the share of specific diseases to total deaths and risk curves for each $PM_{2.5}$-related disease from the Global Burden of Disease Study 2021 (GBD 2021), showing how all-cause deaths are distributed across $PM_{2.5}$-related diseases and how risks vary with exposure levels.

We proceed in three steps. First, we disaggregate all-cause mortality rates from SSP demographic projections into cause-specific mortality rates using the GBD 2021 forecasts. Second, we combine ambient $PM_{2.5}$ concentration levels with corresponding risk functions to derive scenario-specific relative risk levels and calculate the excess relative risk relative to SSP2-4.5 as the effects of air pollution-health feedback. Third, we adjust the cause-specific mortality rates and quantify the effects of air pollution-health feedback on health outcomes.

2.2. SSP-RCP scenarios

This study employs the SSP-RCP scenarios, which form the scenario foundation for the Scenario Model Intercomparison Project (ScenarioMIP) within the Coupled Model Intercomparison Project Phase 6 (CMIP6), used in IPCC assessments (Calvin et al., 2023; O'Neill et al., 2016; Tebaldi et al., 2021). The SSP-RCP scenarios integrate socioeconomic and environmental changes, enabling a comprehensive assessment of climate impacts, adaptation, and mitigation strategies across divergent development pathways. The SSPs describe plausible global socioeconomic developments through qualitative narratives and quantitative projections of key factors such as population growth, economic development, urbanization and education attainment (Cuaresma, 2017; Jiang & O'Neill, 2017; K.C and Lutz, 2017). These development variables are commonly required by impact and emissions models (e.g. IAMs) and are internally linked, for example, education informs both population and GDP projections (O'Neill et al., 2020a). Importantly, the SSPs do not include mitigation or adaptation policies or climate impacts (Fig. S1). Each SSP represents a unique pathway of development, such as sustainable development (SSP1) or a fragmented and inequitable world (SSP3). Complementarily, the RCPs define climate futures through radiative forcing levels (W/m^2) projected up to 2100. The RCPs represent various greenhouse gas emissions trajectories and mitigation policies (Riahi et al., 2017; Van Vuuren et al., 2011). They are designed to provide inputs for climate models and represent a range of mitigation scenarios, from very low emissions (RCP1.9) to high emissions (RCP7.0). For example, RCP2.6 aligns with ambitious mitigation efforts to limit global warming to below 2.0 °C, while RCP7.0 represents high-emissions pathways that could result in 4 °C warming by 2100 (Calvin et al., 2023). While multiple societal pathways can lead to similar forcing levels, combined SSPs and RCPs are a common and consistent practice where an SSP provides the socioeconomic context and the paired RCP specifies the climate forcing used to drive Earth system models (O'Neill et al., 2020b).

Here we rely on the SSP-RCP scenarios commonly adopted in ScenarioMIP. We consider four combinations of SSPs and RCPs to allow a multidimensional exploration of future pathways, as illustrated in

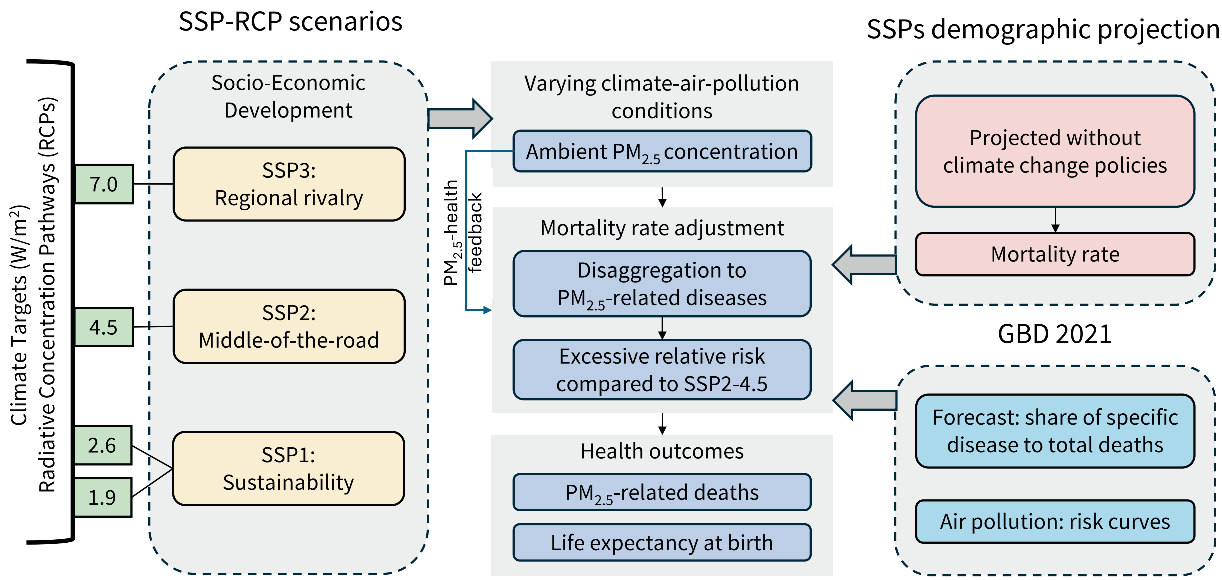

Fig. 1. Analytical framework linking SSP-RCP scenarios, demographic projections, and air pollution risk data to estimate $PM_{2.5}$-related health outcomes. The framework combines scenario-based ambient $PM_{2.5}$ concentrations, age- and sex-specific populations and mortality rates from SSP demographic projections, and cause-specific relative risk functions from GBD 2021. It enables dynamic adjustments of mortality rates to account for the health effects of air pollution under divergent development and climate trajectories.

Fig. S2. We select three SSP-RCP scenarios from Tier 1 in the ScenarioMIP for CMIP6, including SSP1-2.6 (sustainable development with strong mitigation), SSP2-4.5 (middle-of-the-road development with moderate mitigation) and SSP3-7.0 (regional rivalry with minimal mitigation efforts). SSP5-8.5 is excluded due to concerns about its plausibility and its demographic patterns resembling those of SSP1 (Hausfather & Peters, 2020; Ritchie & Dowlatabadi, 2017). Additionally, SSP1-1.9, which represents sustainable development with stringent mitigation, is selected to represent the optimistic scenario corresponding to the Paris Agreement's goal of limiting global mean temperature rise to 1.5 °C (Bevacqua et al., 2025; Rogelj et al., 2018).

2.3. Modeling air pollution-health feedback within the SSP-RCP scenarios

2.3.1. Demographic projections from the SSPs

The SSP demographic projections provide narrative-consistent population and human capital data across different socioeconomic development trajectories. These projections serve as exogenous inputs for climate models that forecast future emissions, including air pollutants (O'Neill et al., 2016; Rafaj et al., 2018). The SSP demographic projections were first published in 2013 and recently updated in 2024 to incorporate the 2020 population baseline and major events such as the COVID-19 pandemic (K.C. et al., 2013, K.C et al., 2024; K.C and Lutz, 2017). The SSP demographic projections consider future changes in four key elements: fertility, mortality, migration and educational attainment, corresponding to differentiated SSP storylines. SSP1 assumes a low-population-growth trajectory, characterized by high levels of education and health improvements, while SSP3 envisions rapid population growth in developing regions alongside persistent inequality and limited progress in education. We obtain the population data and generate the mortality rates from the 2024 updated demographic projections from the SSPs. The calculation of the mortality rates is detailed in Supplementary note 1.

2.3.2. Integrating air pollution-health feedback

The SSP demographic projections do not explicitly account for changes in air quality impacts under different trajectories, as they generally exclude climate change effects (Fig. S1). We address this gap by introducing air pollution-health feedback. Our methodology firstly employs an all-cause mortality rates disaggregation approach utilizing cause-specific forecast data from the GBD 2021 (Dimitrova et al., 2021; Vollset et al., 2024). The GBD 2021 forecast study projects cause-specific health metrics for 2022–2050 across alternative scenarios based on key health determinants including income, education, fertility, and exposure to risk factors. In this study, we use the cause-specific share of total deaths data from the 'Reference' scenario, which represents the environmental conditions that align with the SSP2-4.5 trajectory (Brauer et al., 2024). Leveraging this forecast data, we disaggregate all-cause mortality rates into two components: (1) diseases unaffected by ambient air pollution, and (2) six diseases associated with $PM_{2.5}$ exposure including ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer, lower respiratory infection (LRI), and type 2 diabetes. Here we use the GBD 'Tracheal, bronchus, and lung cancer' category to represent lung cancer. The trend for the share of six $PM_{2.5}$-related diseases to total deaths is represented in Fig. S3. To test the reliability of this disease-disaggregation method, we compare our estimates with the empirical data of GBD 2021 and find them consistent (Table S1).

We incorporate air pollution-health feedback to account for excess health impacts from air pollution exposure in the scenario of interest compared to the reference scenario. We choose SSP2-4.5 as the reference scenario based on the settings of the SSP demographic projection and the 'Reference' scenario in the GBD 2021 forecast. Specifically, the "middle-of-the-road" scenario SSP2 represents moderate development, reflecting continuing historical trends. It is used as a reference scenario for SSP demographic modeling. The key parameters of other SSPs are derived through quantitative adjustment to the 'medium' assumptions in SSP2. For example, the 'high' mortality trends (in SSP3) are derived by reducing the gain in LE_0 by one year for both sexes from the 'medium' scenario baseline for every ten years, and vice versa for 'low' mortality trends (in SSP1). Hence, the mortality rates of SSP2 represent the 'reference' scenario of the future demographic changes, which reflects the baseline for all associated risk factors, including air pollution (K.C. et al., 2024). Meanwhile, the 'Reference' scenario data of the cause-specific share of total deaths we use is consistent with the SSP2-4.5 environmental conditions (Vollset et al., 2024). This approach allows us to assess how differing air pollution trajectories modify conventional SSP-based projections while preserving their fundamental demographic structure by (1) incorporating scenario-specific air pollution impacts on cause-specific mortality rates, (2) maintaining consistency with the underlying demographic assumptions of the SSP framework and (3) isolating and quantifying the specific health effects attributable to varying $PM_{2.5}$ exposure across scenarios.

The air pollution-health feedback is incorporated as a risk-mediated multiplier to adjust each cause-specific mortality rate. This multiplier is defined as the ratio of the relative risk under the scenario of interest to the relative risk under the reference scenario SSP2-4.5. This construction preserves the SSP2-4.5 baseline (multiplier equals 1) and passes through the non-linear exposure–response function of relative risks. This adjustment approach follows life table methods in health impact assessments that rescale hazards to reflect changes in mortality impacts (Miller & Hurley, 2003). Dimitrova et al (2021) applied a similar approach in demographic projection for India, adjusting mortality rates using varying hazard ratios from $PM_{2.5}$ exposure levels under different mitigation scenarios compared to 2010 conditions. The approach is also consistent with the GBD comparative risk assessment, in which exposure-specific risks are applied to cause-specific mortality to derive attributable burdens (Brauer et al., 2024). We apply population-weighted $PM_{2.5}$ concentrations at the country level to estimate health impacts. $PM_{2.5}$ concentration projection data are obtained from Yang et al. (2023) and processed into a 5-year interval from 2020 to 2050 (Supplementary note 2).

For each pathway p, country/territory c, age group a and sex s and disease d in a certain year t, the adjusted mortality rates are calculated as:

$$Rate^{Adjusted}_{p,c,a,s,d}(t) = Rate^{all-cause,Unadjusted}_{p,c,a,s}(t) \times Share_{SSP2-4.5,c,a,s,d}(t) \times \frac{RR_{p,c,a,d}(t)}{RR_{SSP2-4.5,c,a,d}(t)} \tag{1}$$

Here, the $Rate^{Adjusted}_{p,c,a,s,d}(t)$ represents the adjusted mortality rates with air pollution-health feedback. $Rate^{all-cause,Unadjusted}_{p,c,a,s}(t)$ is the baseline all-cause mortality rates from SSP demographic projections. $Share_{SSP2-4.5,c,a,s,d}(t)$ denotes the share of deaths attributable to disease d relative to the total deaths, in which the environmental conditions align with the 'reference' scenario SSP2-4.5. $RR_{p,c,a,d}(t)$ is the relative risk associated with the corresponding $PM_{2.5}$ concentration level for pathway p, while $RR_{SSP2-4.5,c,a,d}(t)$ is the relative risk for SSP2-4.5. Hence, the air pollution-health feedback are quantified by the multiplier $\frac{RR_{p,c,a,d}(t)}{RR_{SSP2-4.5,c,a,d}(t)}$, and the change in health impacts due to this difference in mortality rates with and without this multiplier represents the effects of incorporating air pollution-health feedback. The relative risk values are derived using state-of-the-art $PM_{2.5}$ risk functions from the GBD 2021 study (Brauer et al. 2024). Detailed description of cause-specific relative risk is illustrated in Supplementary note 3 and the relative risk curves are shown in Fig. S4.

Then, combining all six diseases with the unaffected part together, we get an adjusted all-cause mortality rates with air pollution-health feedback, as expressed in the following equation:

$$Rate^{all-cause,Adjusted}_{p,c,a,s}(t) = Rate^{all-cause,Unadjusted}_{p,c,a,s}(t) \times \left(1 - \sum_{d=1}^{6} Share_{SSP2-4.5,c,a,s,d}(t)\right) + \sum_{d=1}^{6} Rate^{Adjusted}_{p,c,a,s,d}(t) \tag{2}$$

The $Rate^{all-cause,Adjusted}_{p,c,a,s}(t)$ is the adjusted all-cause mortality rates incorporating the air pollution-health feedback.

2.4. Evaluating impacts from air pollution-health feedback

The effects of the air pollution-health feedback on health outcomes are measured by comparing the difference between the adjusted results with the air pollution-health feedback and the conventional SSP-based results. Specifically, the adjusted results are obtained using the mortality rates obtained in equations (1) and (2) with the air pollution-health feedback multiplier. The conventional SSP-based results are calculated using the unadjusted mortality rates without the air pollution-health feedback multiplier. For uncertainty, we report the central estimates and include 95 % confidence interval (CI) obtained by propagating parameter uncertainty from the GBD 2021 exposure–response functions (2.5th–97.5th percentiles of the resulting draws) through the relative risk multiplier and health outcome calculations. More details can be found in Supplementary note 3.

2.4.1. Life expectancy at birth (LE_0)

The LE_0 results are estimated through life tables generated in the SSPs demographic projections. The life tables connect age- and sex-specific mortality rates with the survival ratio of the population cohorts. They are generated by combining the SSPs-projected survival rate data and life tables forecasts from the World Population Prospective by the United Nations (UN WPP). Further details can be found in K.C et al. (2024) and UN WPP (2022). The generated life tables are pathway-, country-, time- and sex-specific, corresponding to the mortality rates at the same resolution. We use the adjusted all-cause mortality rates incorporating the air pollution-health feedback obtained in equation (2) to replace the previous unadjusted mortality rate. Then we recalculate the life table using these adjusted all-cause mortality rates and get a new LE_0. The gain or loss in LE_0 due to air pollution-health feedback is estimated as the difference between the new LE_0 and conventional SSP-based LE_0. Note here we report period LE_0, which reflects the life expectancy under the age-specific mortality rates in a given year or period.

2.4.2. $PM_{2.5}$-related premature deaths

The premature deaths associated with $PM_{2.5}$ exposure are calculated as:

$$Mort_{p,c,a,s,d}(t) = Rate^{Adjusted}_{p,c,a,s,d}(t) \times POP_{p,c,a,s}(t) \times AF_{p,c,a,d}(t) \tag{3}$$

Where $Mort_{p,c,a,s,d}$ represents the premature deaths attributable to $PM_{2.5}$ exposure for a specific pathway p, country/territory c, age group a and sex s and disease d in a certain year t. $POP_{p,c,a,s}$ is the population size of each exposed demographic group: we adhere to the categorization from GBD 2021 by applying the population above 25 years old for IHD, stroke, COPD, lung cancer, and type 2 diabetes while applying the population of all ages for LRI. $AF_{p,c,a,d}$ refers to the corresponding attributable fraction (calculation detailed in Supplementary note 3). Cumulative premature deaths per scenario are obtained by summing results across time, demographic subgroups and the six diseases. We also calculate the premature deaths using the conventional SSP-based mortality rates without the air pollution-health feedback. The change in premature deaths due to air pollution-health feedback is estimated as the difference between these two results.

3. Results

3.1. Air pollution-health feedback alters global health trajectories and amplifies scenario-based disparities

Accounting for the air pollution-health feedback leads to important differences in absolute health outcomes across the SSP-RCP scenarios, compared to conventional SSP-based projections (Fig. 2a, b). In the low-emission scenarios (SSP1-1.9 and SSP1-2.6), improved air quality leads to average gains of 0.23 years (95 % CI based on the relative risk functions: 0.12–0.40 years) and 0.18 years (CI: 0.09–0.31 years) in global LE_0 from 2020 to 2050, respectively. These improvements translate into 10.0 and 8.7 million fewer cumulative premature deaths, suggesting that ignoring these pollution-related benefits would overestimate the global premature deaths by approximately 6–8 %. In contrast, under the high-emission scenario SSP3-7.0, sustained air

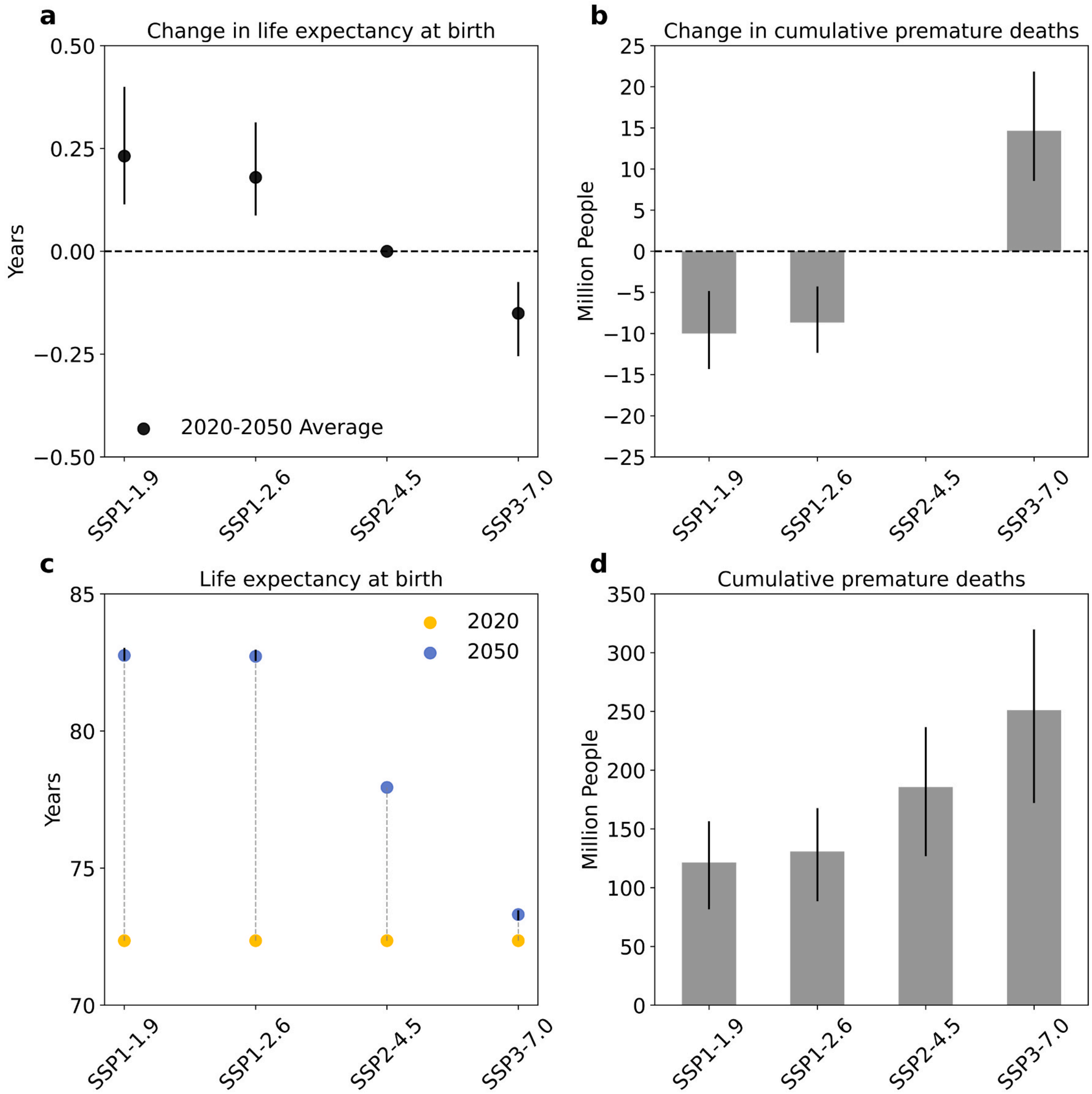

Fig. 2. The effects of air pollution-health feedback on global health outcomes under various SSP-RCP scenarios. (a) Change in global LE_0 due to air pollution-health feedback, representing the 2020–2050 average. (b) Change in $PM_{2.5}$-related cumulative premature deaths in 2020–2050 due to air pollution-health feedback. (c) Global LE_0 in 2020 (baseline) and 2050 (adjusted with air pollution-health feedback). (d) $PM_{2.5}$-related cumulative premature deaths in 2020–2050 (adjusted with air pollution-health feedback). Notes: 1) Values in (a–b) represent the difference between adjusted results with the air pollution-health feedback minus the conventional results. 2) Values in (c–d) represent the absolute health outcome results calculated with the air pollution-health feedback. 3) SSP1 represents sustainability pathways with low challenges to mitigation and adaptation; SSP2 represents middle-of-the-road development with moderate challenges to both mitigation and adaptation; SSP3 represents regional rivalry with high challenges to both mitigation and adaptation. The RCP numbers following SSP indicate target radiative forcing levels (W/m^2) by 2100. More information can be found in Section 2.2 SSP-RCP scenarios. 4) Main bars/points and the error bars show the central estimates, and 95% CI estimates of the relative risk functions of the GBD 2021 respectively.

pollution exacerbates health outcomes, causing an additional 14.6 million premature deaths and an average loss of 0.15 years (CI: 0.08–0.25 years) in global LE_0 over the same period.

Incorporating the air pollution-health feedback thus widens health disparities across the SSP-RCP scenarios (Fig. 2a–d). The gap in global LE_0 between SSP1-1.9 and SSP3-7.0 increases by an average of 0.38 years (CI: 0.19–0.65 years) when the air pollution-health feedback is included. Similarly, the air pollution-health feedback adds 24.6 million deaths to the cumulative premature deaths gap between SSP1-1.9 and SSP3-7.0, contributing 19 % of the total disparity from 2020 to 2050 between the two scenarios. By 2050, global LE_0 adjusted for the air pollution-health feedback spans a wide range from 73.3 years under SSP3-7.0 to 82.8 years under SSP1-1.9, up from 72.4 years in 2020. $PM_{2.5}$-related cumulative premature deaths between 2020 and 2050 vary from 121 million (SSP1-1.9) to 251 million (SSP3-7.0). In the reference case SSP2-4.5, global LE_0 rises moderately to 78 years by 2050, with cumulative premature deaths of 186 million, representing a health trajectory following business-as-usual trend.

Despite scenario-specific improvements, exposure to ambient $PM_{2.5}$ remains a major health threat globally. $PM_{2.5}$-related premature deaths are projected to account for 5.7 % of global total deaths in 2050 even under SSP1-1.9, which rises to 10.2 % in SSP3-7.0, compared to 7.7 % in 2020. Annual $PM_{2.5}$-related premature deaths decline only in SSP1-1.9 and SSP1-2.6, while doubling in SSP3-7.0 to reach 10.7 million per year by 2050, compared to 4.8 million in 2020 (Fig. S5). Furthermore, the life expectancy at age 65 (LE_{65}, an indicator of the expected remaining years of life for those aged 65) shows gains of 0.20 years (CI: 0.10–0.34 years) in SSP1-1.9 and a loss of 0.13 years (CI: 0.07–0.22

years) in SSP3-7.0 due to air pollution-health feedback, while the increase in LE_{65} between 2020 and 2050 is only half of that in LE_0 (Fig. S6a, b).

3.2. Air pollution-health feedback alters Global North-South mortality gaps depending on the scenario

The regional disparities in $PM_{2.5}$-related health outcomes are altered by the air pollution-health feedback across the SSP-RCP scenarios. Under SSP1-1.9 and SSP1-2.6, health gains are concentrated in low- and middle-income countries (Global South) with air quality improvement, narrowing the gap relative to the high-income countries (Global North) (Fig. 3a,b,d,e). In contrast, under SSP3-7.0, continued high emissions and limited mitigation efforts exacerbate this gap: premature deaths rise most sharply in already heavily affected low- and middle-income countries, while high-income countries experience relatively minor changes (Fig. 3c, f).

India and China, which together account for 61 % of the global $PM_{2.5}$-related cumulative premature deaths in 2020, illustrate this contrast. In SSP1-1.9, reduced $PM_{2.5}$ levels lead to 6.5 million and 1.3 million fewer deaths in India and China, respectively, compared to conventional SSP-based projections of 42 and 34 million in 2020–2050. Conversely, under SSP3-7.0, the effects of air pollution-health feedback add over 5 million deaths in both countries, pushing cumulative totals to 75–81 million. Other highly polluted countries in Southeast Asia (including Bangladesh, Nepal, Indonesia, and Pakistan) also exhibit large shifts in premature deaths due to air pollution-health feedback. Regions including Central and Eastern Europe & Central Asia (CEEUCA), high-income countries (HICs), and Latin America & the Caribbean (LAC) contribute less than 9 % of total $PM_{2.5}$-related premature deaths and experience relatively minor changes across all scenarios—less than 0.2 million additional or avoided deaths compared to conventional results.

Air pollution-health feedback also plays a role in shaping regional inequality in LE_0 (Fig. 3d, e, f & Fig. S8). Most health benefits occur in South Asia countries under SSP1-1.9, where LE_0 gains of up to 0.8 years in 2050 due to air pollution-health feedback compared to the conventional SSP-based projections. For India and Bangladesh, the average LE_0 gains during 2020–2050 are 0.8 years. However, under SSP3-7.0, Southeast Asia countries experience the most severe declines, with average losses in LE_0 reaching 0.5 years in 2050. The most impacted countries, including Vietnam, North Korea, and China, experience declines of around 0.4 years.

Compared to the considerable health improvements in South and Southeast Asia, the air pollution-health feedback in Sub-Saharan Africa (SSA) and North Africa & the Middle East (NAME) result in relatively modest gains in LE_0 under SSP1 scenarios. These smaller benefits from air quality improvements cause SSA and NAME's combined share of the global $PM_{2.5}$-related premature deaths to increase from 14 % in 2020 to 24 % under SSP1-1.9. Nonetheless, several countries such as Burundi, Rwanda (in SSA) and Uzbekistan (in CEEUCA) see moderate LE_0 increases exceeding 0.26 years. In a contrasting trend, a few SSA countries, including Guinea-Bissau and Gambia, exhibit slight health gains even under SSP3-7.0. These arise from air pollution-health feedback tied to lower $PM_{2.5}$ levels in SSP3-7.0 relative to SSP2-4.5, likely driven by slower economic and industrial development.

3.3. Heterogeneous health impacts across demographics, regions and scenarios

$PM_{2.5}$-related health risks vary widely across demographic groups,

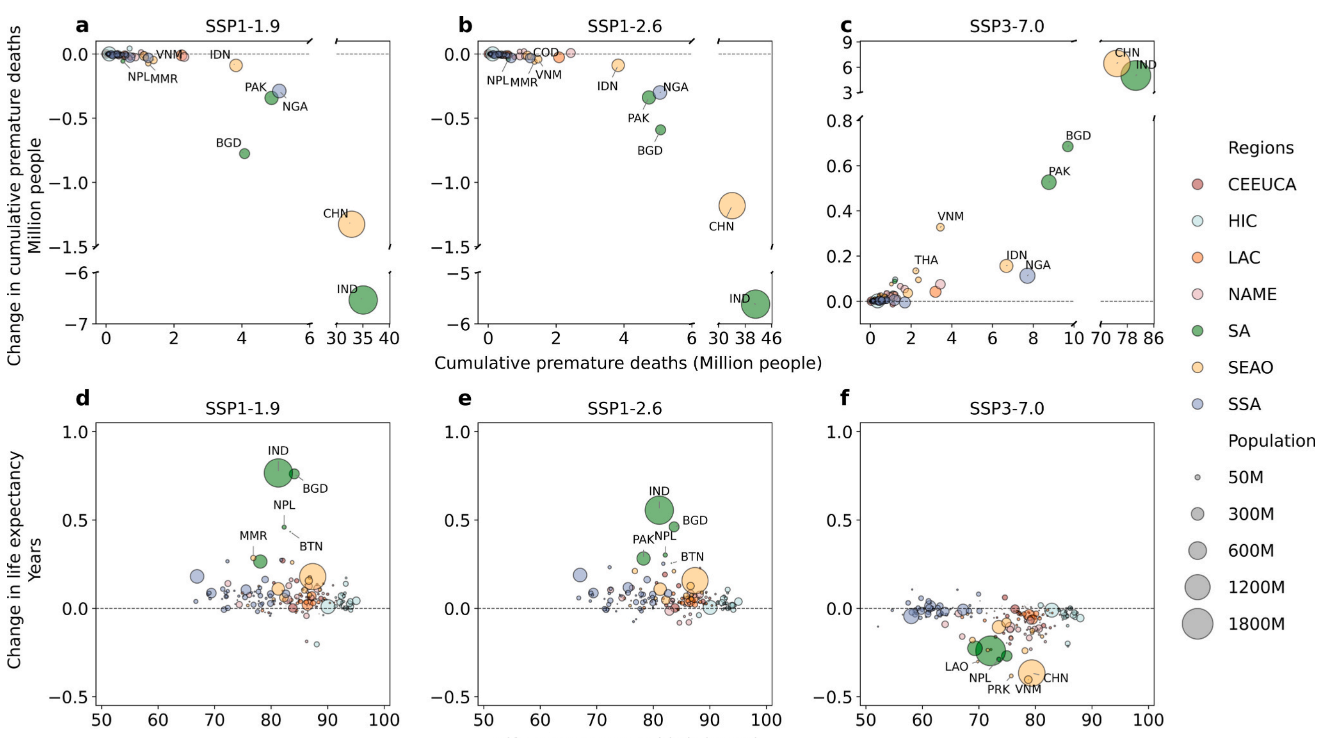

Fig. 3. The change due to air pollution-health feedback against absolute results adjusted by air pollution-health feedback of health outcomes per country/territory under various SSP-RCP scenarios. (a, b, c) Change in cumulative premature deaths due to air pollution-health feedback against cumulative premature deaths in 2020–2050. (d, e, f) Average change in LE_0 due to air pollution-health feedback in 2020–2050 against LE_0 in 2050. The dot color suggests the super region and the dot size represents the population size (M: million) in 2050. The countries/territories with the most values according to the y-axis are noted using 3-letter ISO code. Abbreviations included in the figure: South Asia (SA): India (IND), Bangladesh (BGD), Pakistan (PAK), Nepal (NPL), Bhutan (BTN); Southeast Asia, East Asia, and Oceania (SEAO): China (CHN), Vietnam (VNM), Indonesia (IDN), Thailand (THA), Myanmar (MMR), North Korea (PRK), Laos (LAO); Sub-Saharan Africa (SSA): Nigeria (NGA), Democratic Republic of the Congo (COD); North Africa and the Middle East (NAME); Central Europe, Eastern Europe, and Central Asia (CEEUCA); High income (HIC) and Latin America and the Caribbean (LAC). The full information of the super regions can be found in Fig. S7.

geographies and pollution trajectories (Fig. 4). Among all age groups, older adults (aged 65 and above) consistently face the highest $PM_{2.5}$-related health risks due to their elevated baseline mortality rates, which also leads to the largest changes in mortality rates from the air pollution-health feedback (Fig. 4a, d). By 2050, the share of older adults among $PM_{2.5}$-related premature deaths is projected to rise from 71 % in 2020 to 80 % under SSP3-7.0 and 85 % under SSP1-1.9/2.6, driven by the population aging trend and pollution pattern (Fig. S9a–d). The young (below 25) and the working-age adults (25–64) face significantly less health risk are expected to account for at most 2 % and 18 % of premature deaths under SSP3-7.0, respectively.

Significant regional disparities also emerge in $PM_{2.5}$-related health outcomes. South and Southeast Asia exhibit the highest $PM_{2.5}$ mortality rates and the strongest effects of air pollution-health feedback across all six diseases and scenarios (Fig. 4b, c). In stark contrast, HICs show relatively low mortality rates even among their most vulnerable subpopulations. For instance, under SSP3-7.0, older adults in HICs experience at most 22 deaths per 100,000 people from IHD, whereas in the same scenario, working-age adults in South Asia face 36 deaths per 100,000 people, surpassing even the most at-risk age group in HICs (Fig. 4d). Notably on country level, older residents in Turkmenistan (in CEEUCA) and Chad and Niger (in SSA) face the highest aggregated $PM_{2.5}$ mortality rates for six diseases, reaching around 1000 deaths per 100,000 people under SSP1-1.9/2.6. (Fig. 4e, f).

The leading $PM_{2.5}$-related diseases also differ by region and scenario. For the older adults in South Asia who are most at-risk, COPD becomes the dominant health burden among older adults under the higher polluted SSP2-4.5 and SSP3-7.0 scenarios, overtaking IHD, which remains dominant in cleaner scenarios (SSP1-1.9/2.6). Stroke consistently poses the greatest threat for adults (25+) in SEAO across all scenarios and emerges as the leading cause in SSA under SSP2-4.5 and SSP3-7.0. IHD, however, remains the primary contributor in most other region-scenario combinations. Overall, the total of six $PM_{2.5}$-related diseases is expected to account for 40 % of all-cause deaths from 2020 to 2050 (Fig. S3b), with IHD (32–35 %), COPD (18–23 %), and stroke (23 %) being the most significant contributors at the global scale. Notably, under SSP3-7.0, COPD-induced deaths are projected to increase and equal IHD in their portion (28 % each) to $PM_{2.5}$-related premature deaths globally by 2050.

Gender disparities also persist across scenarios. While regional patterns are similar, men consistently face higher $PM_{2.5}$-related health risks than women. This is primarily due to higher baseline mortality rates among males, which heighten their sensitivity to air pollution exposure and amplify the effects of air pollution-health feedback (Fig. S10).

4. Discussion and conclusion

Our findings show that mortality impacts from future $PM_{2.5}$ exposure would remain substantial under different climate and socioeconomic scenarios. By 2050, we project that $PM_{2.5}$-related premature deaths will range from 121 million in SSP1-1.9 to 251 million under SSP3-7.0. These impacts are unevenly distributed: they are more pronounced in lower-middle-income countries and among older adults, who are already exposed to higher baseline health risks and elevated $PM_{2.5}$ levels. In the health impact projections, we introduce the air pollution-health feedback in the integrated modeling framework. This approach allows mortality rates to be adjusted dynamically in response to varying $PM_{2.5}$ exposure levels, compared to conventional approaches that fix mortality rates to socioeconomic pathways. Beyond the direct assessments of absolute health impacts, we find that including air pollution-health feedback from climate projections leads to notable differences in future mortality and life expectancy outcomes, depending on the emissions and development pathway. Under SSP1-1.9, the effects of air pollution-health feedback reduce cumulative premature deaths by 7–8 % and increase LE_0 by 0.23 years; in contrast, under SSP3-7.0, they increase premature deaths by 6 % and reduce LE_0 by 0.15 years. The largest absolute changes in premature deaths occur in South and Southeast Asia, particularly in India and China, due to their large populations and elevated exposure levels. At the disease level, IHD, COPD and stroke account for the largest shares of both the mortality burden and feedback sensitivity. The results highlight both the substantial future burden of $PM_{2.5}$-related mortality and the necessity of accounting for environmental-social feedback in long-term projections using integrated modeling framework. We also emphasize the need for continued global action to reduce air pollution, especially for older populations in lower-middle-income countries and those with pre-existing cardiovascular and respiratory conditions.

This work, to our knowledge, represents the first global, demographically explicit quantification of how air pollution-health feedback could potentially bias conventional health impact assessments under climate and socioeconomic scenarios. Our findings provide empirical evidence for integrating environmental-health feedback into long-term scenario planning and underscore a key methodological implication for the IAMs: the exclusion of dynamic feedback between environmental conditions and human health can potentially deviate long-term projections and thus weaken the interpretation. IAMs are central to projecting sustainability outcomes under climate change, yet many models treat demographic and health parameters as exogenous, missing critical feedback through which environmental changes like air pollution affect human systems. By incorporating feedback effects from $PM_{2.5}$ exposure into SSP-based mortality trajectories, our study demonstrates how scenario realism can be improved. As well-being-oriented projections gain prominence in sustainability research, integrating such feedback will be essential for enhancing the credibility and policy relevance of projections based on IAMs (Chaplin-Kramer et al., 2024; Emmerling et al., 2021; Liu et al., 2024; Lutz et al., 2021).

This study focuses on a single feedback mechanism linking air pollution, mortality rate, and socioeconomic scenario, but this represents only part of a broader system of interactions. Future research should extend this approach to capture additional feedback mechanisms, such as heat-related mortality and morbidity, extreme weather events, and food scarcity (Ebi et al., 2021; Hasegawa et al., 2016; Huang et al., 2011; Yuan et al., 2024). Moreover, given the localized nature of environmental health impacts, more granular demographic modeling, e.g., at subnational or urban–rural levels, is needed to capture within-country disparities and better inform targeted policy responses (Chowdhury et al., 2018; K.C. et al., 2018).

Several limitations should be acknowledged when interpreting the results. First, we assume a static population size and structure that does not respond to changes in deaths due to the air pollution-health feedback. This simplification may lead to underestimation of deaths in low-emission scenarios (e.g., SSP1-1.9) and overestimation in high-emission scenarios (e.g., SSP3-7.0), as extra lives survive to the next stage, the exposed population will increase, which amplifies the deaths. However, because most saved lives occur among the older age groups, the demographic impact on fertility or the younger population remains minimal. The period life expectancy estimates derived from life tables are based on age-specific mortality rates and are therefore not influenced by changes in the absolute size or structure of the population. Second, this study focuses solely on ambient $PM_{2.5}$ exposure, excluding other important pollutants such as ozone and household air pollution due to data limitations. This may particularly underestimate risks in low-income regions where indoor pollution is prevalent (Ferguson et al., 2020; Meng et al., 2019; Rao et al., 2021). Third, the approach of adjusting mortality risk with a relative risk multiplier assumes proportional risks and immediate translation of exposure changes into mortality (no explicit lag structure). It does not account for behavioral, health-system, or other responses, nor for interactions beyond the six $PM_{2.5}$-related causes as it provides limited treatment of competing risks. Accordingly, the relative risk multiplier should be interpreted as a conservative, first-order approximation consistent with GBD comparative risk assessment and life-table applications, providing a transparent

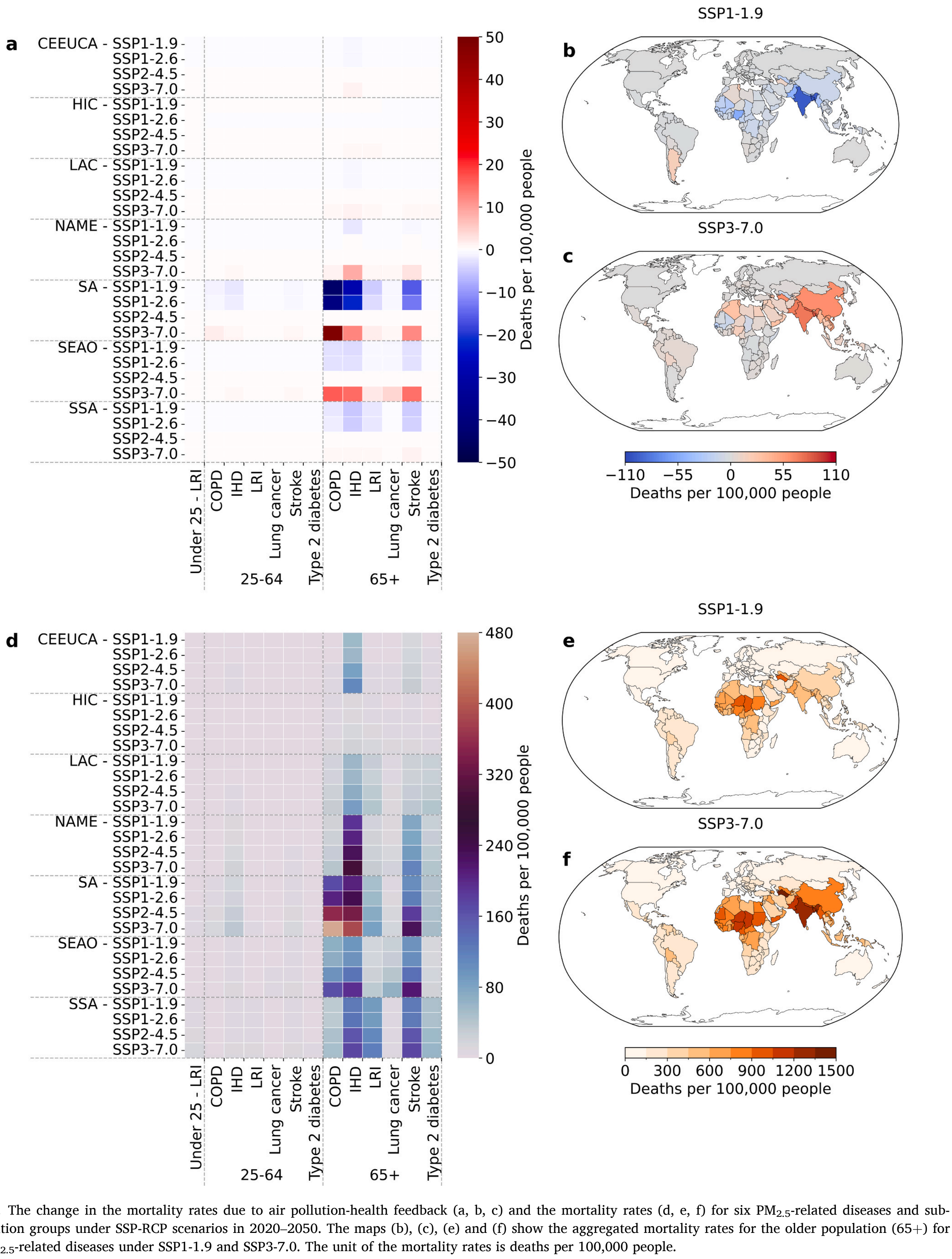

Fig. 4. The change in the mortality rates due to air pollution-health feedback (a, b, c) and the mortality rates (d, e, f) for six $PM_{2.5}$-related diseases and sub-population groups under SSP-RCP scenarios in 2020–2050. The maps (b), (c), (e) and (f) show the aggregated mortality rates for the older population (65+) for six $PM_{2.5}$-related diseases under SSP1-1.9 and SSP3-7.0. The unit of the mortality rates is deaths per 100,000 people.

way to propagate risk-mediated changes rather than a full causal. We therefore present the results as scenario-based projections rather than forecasts. Finally, our estimates are subject to multiple sources of uncertainty, including: (1) the relative risk functions from the GBD 2021 study, (2) the baseline demographic projections from the SSPs (K.C. et al., 2024), (3) the assumption that the SSP2-4.5 $PM_{2.5}$ exposure level is implicit in the demographic modeling for all scenarios, (4) modeled $PM_{2.5}$ concentrations from Earth system model outputs (Yang et al., 2023), and (5) the disease burden forecasts from the GBD 2021 foresight study (Vollset et al., 2024). Despite these limitations, the direction and magnitude of the feedback effects have been carefully verified.

To conclude, this study quantifies the global air pollution-health feedback within a scenario-based integrated modeling framework, advancing the integration of human health into climate projections. Our results show that failing to account for the feedback can lead to systematic misestimation of future health outcomes, particularly in regions with high pollution exposure and aging populations. The findings highlight the importance of incorporating further feedback into integrated modeling frameworks to improve the realism and policy relevance of long-term sustainability projections. Beyond the air pollution scope, our approach may be extended to other climate-health feedback mechanisms, such as those related to heat stress, extreme weather events, and food insecurity. Finally, we call for the development of higher-resolution, subnational projections to capture urban–rural and intra-regional disparities, which are essential for designing more targeted and equitable mitigation strategies.

Data and code availability

The data and code used to generate the results and figures in this study are made available. (1) The $PM_{2.5}$ concentration data is requested from Yang et al. (2023). (2) The SSP population data is obtained from https://dataexplorer.wittgensteincentre.org/wcde-v3/. (3) The air pollution risk curves are obtained from https://ghdx.healthdata.org/record/ihme-data/gbd-2021-air-pollution-exposure-estimates-1990–2021. (4) The forecast data for specific diseases is retrieved from https://vizhub.healthdata.org/gbd-foresight/. All the data associated with this paper are made available upon request from the corresponding authors. All codes are available at https://github.com/kkedliu/air-pollution-health-feedbacks.

CRediT authorship contribution statement

Kedi Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ranran Wang:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Samir K.C.:** . **Anne Goujon:** Writing – review & editing, Supervision, Formal analysis. **Gregor Kiesewetter:** Writing – review & editing, Supervision, Methodology. **Rutger Hoekstra:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109817.

Data availability

Data will be made available on request.

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