

Global Air Pollution Exposure and Benefits of Emissions Reductions for Global Health

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Key Points:

- Estimates of recent global air pollution-associated mortality are sensitive to the choice of observation dataset.
- Uncertainties in projected global avoided mortality under reduced emissions are smaller than uncertainties in recent estimates.
- If global emissions are aggressively reduced, avoided cumulative deaths could exceed a quarter-billion by 2100.

Abstract

Exposure to fine particulate matter (PM_{2.5}) air pollution is associated with large-scale health consequences, but the uncertainties in estimates of PM_{2.5}-related global premature mortality remain understudied. Using four observation-based PM_{2.5} datasets and six Coupled Model Intercomparison Project Phase 6 (CMIP6) climate models, we compare uncertainties in current PM_{2.5}-related mortality estimates to the impacts of emissions reductions on global health. Although estimates of current mortality are sensitive to the PM_{2.5} dataset (6.54 to 8.27 million/year using the Global Exposure Mortality Model), the projected near-term and long-term benefits of emissions reductions for reduced mortality are much more certain. Specifically, uncertainties in projected avoided deaths are consistently less than half the magnitude of uncertainties in recent mortality estimates. Under a low-emissions scenario, avoided cumulative deaths would exceed a quarter-billion by 2100.

Plain Language Summary

Most people on Earth are exposed to unsafe levels of fine particulate matter air pollution (PM_{2.5}). This outdoor PM_{2.5} exposure is associated with a variety of health consequences, including premature mortality. Despite the importance of PM_{2.5} exposure, global estimates of premature mortality associated with air pollution exposure are often based on one observation-based dataset of air pollution. Here we examine the uncertainties in estimates of global air pollution-associated mortality due to choice of observation dataset and compare these uncertainties to the projected future impacts of emissions reductions on global health. We

find that estimates of global mortality in recent years are sensitive to the observation $\text{PM}_{2.5}$ dataset (6.54 to 8.27 million/year, depending on dataset). We also use the latest climate model simulations to estimate how air pollution exposure and associated mortality would change in the future under a high emissions scenario and a low emissions scenario. We find that climate models agree that reducing emissions would lead to rapid, large-scale reductions in air pollution exposure and associated premature mortality. Specifically, if emissions reductions are aggressively implemented, avoided cumulative deaths would exceed a quarter-billion by the end of the century.

1 Introduction

Exposure to ambient fine particulate matter ($\text{PM}_{2.5}$) is a major global health issue (Murray et al., 2020). Specifically, exposure to elevated levels of $\text{PM}_{2.5}$ is associated with an increased risk of childhood respiratory infections, chronic obstructive pulmonary disease (COPD), ischaemic heart disease, lung cancer, and stroke, among other outcomes (Murray et al., 2020; Thurston et al., 2017). Due to the negative impact of poor air quality on global health, in September of 2021 the World Health Organization (WHO) updated its Global Air Quality Guidelines (AQG) from annual mean $\text{PM}_{2.5}$ concentrations of $10 \mu\text{g}/\text{m}^3$ to concentrations of $5 \mu\text{g}/\text{m}^3$. Previous work has suggested that 95% of the world’s population is exposed to outdoor ambient $\text{PM}_{2.5}$ concentrations of at least $10 \mu\text{g}/\text{m}^3$ (Shaddick et al., 2018). $\text{PM}_{2.5}$ -associated premature deaths could be as high as ~9-10 million/year (Burnett et al., 2018; Lelieveld et al., 2019; Vohra et al., 2021), and air pollution-associated global welfare losses are estimated to be US\$4.6 trillion per year (Landrigan et al., 2018).

Despite the negative impacts of ambient $\text{PM}_{2.5}$ exposure on human health and well-being, a comparison of global $\text{PM}_{2.5}$ exposure and its consequences (e.g., (Farrow, 2020)) using the latest global observation-based estimates (e.g., (Alvarado et al., 2019)) has not been conducted. Furthermore, although air quality outcomes across Shared Socioeconomic Pathways (SSPs) have been examined using a simplified global air quality model (Rao et al., 2017), future global air pollution exposure and associated consequences (Allen et al., 2021; Shindell et al., 2021; Vandyck et al., 2018) under higher and low emissions scenarios in a suite of the latest climate models have not been addressed.

Here, we use four observation-based datasets to compare current estimates of global, annual-mean ambient $\text{PM}_{2.5}$ exposure. We also estimate $\text{PM}_{2.5}$ -associated premature mortality using the Global Exposure Mortality Model (GEMM), which draws on studies covering a wide range of $\text{PM}_{2.5}$ exposure across multiple countries, including high ($>35 \mu\text{g}/\text{m}^3$) concentrations (Burnett et al., 2018). We then compare observation-based estimates of global mortality to estimates from six Coupled Model Intercomparison Project, Phase 6 (CMIP6) models (Eyring et al., 2016; Turnock et al., 2020) adjusted to better represent all aerosol components at a higher spatial resolution (Shindell et al., 2022; Shindell et al., 2021). Specifically, we contrast global $\text{PM}_{2.5}$ exposure under a low-emissions ‘sustainability’ scenario (SSP1-2.6) with exposure under a higher

emissions ‘regional rivalry’ scenario (SSP3-7.0) in which emissions are generally not curtailed (O’Neill et al., 2016). We show that there is a large range in observation-based estimates of global exposure and mortality, and adjusted CMIP6 models simulate global $PM_{2.5}$ exposure that generally falls within this observational estimated range. The projected uncertainties in the health benefits of emissions reductions using the GEMM remain substantially smaller than the uncertainties in observation- and model-based estimates of near present-day premature mortality.

2 Data and Methods

2.1 $PM_{2.5}$ air pollution in observation-based gridded data products

We compare $PM_{2.5}$ exposure and associated health impacts in four observation-based $PM_{2.5}$ datasets that use models to relate satellite column Aerosol Optical Depth (AOD) with surface $PM_{2.5}$ and include model calibration against station data. Specifically, we compare globally gridded, annual mean ambient $PM_{2.5}$ from: (1) Shaddick et al. (2018) (hereafter ‘Shaddick’), Modern-Era Retrospective analysis for Research and Applications, Version 2 (hereafter ‘MERRA-2’; (Gelaro et al., 2017)), the 2019 Global Burden of Disease ((Network, 2021); hereafter ‘GBD2019’), and van Donkelaar et al. (2021) (hereafter ‘van Donkelaar’). We use mean annual ambient $PM_{2.5}$ over years 2015-2019 for all of these datasets, except the Shaddick dataset, for which we use the mean 2014-2016 values. For each data product, we interpolate to a common spatial grid structure ($\sim 0.3^\circ \times 0.3^\circ$), overlay the spatial $PM_{2.5}$ estimates on $\sim 0.3^\circ \times 0.3^\circ$ Gridded Population of the World, version 4 (GPWv4) population data (Center for International Earth Science Information Network - CIESIN - Columbia University, 2016) for the year 2015, and average population-weighted $PM_{2.5}$ over the globe to estimate current global-mean air pollution exposure (Figure 1).

2.2 $PM_{2.5}$ air pollution in CMIP6 models

We use atmospheric concentrations of $PM_{2.5}$ from CMIP6 models published by Turnock et al. (2020). The six CMIP6 models analyzed here are shown in Table S1. $PM_{2.5}$ is defined as:

$$PM_{2.5} = BC + OA + SO_4 + (0.25 * \text{Sea Salt}) + (0.1 * \text{Dust})$$

where BC is black carbon, OA is organic aerosols, and SO_4 is sulfate, and nitrate is excluded because few models provided nitrate data. In Turnock et al. (2020), a uniform fraction of sea salt and mineral dust are less than or equal to the 2.5-micron cutoff because size-resolved information of these species is not provided in the CMIP6 models analyzed here.

We adjusted the CMIP6 $PM_{2.5}$ data described above using output from the GISS model, which simulates both nitrate and size-resolved dust (and uses a smaller fixed portion of sea-salt, 0.1, as $PM_{2.5}$). Specifically, we calculated the ratio of the GISS $PM_{2.5}$, including the model’s nitrate and size-resolved local dust fraction ≤ 2.5 microns, to its $PM_{2.5}$, using the definition given above, then multiplied the standard $PM_{2.5}$ for each model by that ratio. Furthermore, we

used a previously developed method to simulate $\text{PM}_{2.5}$ in the GISS model at higher resolution that uses higher-resolution emissions data and the first-order horizontal moments of the native grid box resolution tracers. Use of this method has been shown to improve the realism of the model’s $\text{PM}_{2.5}$, especially in urban areas (Shindell et al., 2018). We therefore reran segments of the 2015-2100 period for SSP3-7.0 and SSP1-2.6 using the same GISS-E2-1-G model used for CMIP6 but this time including the high-resolution $\text{PM}_{2.5}$ method, calculated the ratio of simulated $\text{PM}_{2.5}$ in each $0.5^\circ \times 0.5^\circ$ grid box to that in the native $2^\circ \times 2.5^\circ$ box, and then multiplied all models’ $\text{PM}_{2.5}$ by that ratio during the transformation to a common $0.5^\circ \times 0.5^\circ$ grid. These adjustments are dependent upon the realism of the GISS model used to create the gridded scalings applied to all other models, but Shindell et al. (2018) have found the high-resolution GISS $\text{PM}_{2.5}$, including the model’s nitrate and internally-defined fine-mode dust loading, generally agrees well with observations.

Figure S1 shows global maps of CMIP6 multi-model median, annual mean $\text{PM}_{2.5}$ in the SSP1-2.6 and SSP3-7.0 simulations and in observations. Figure S2 shows the difference among observations and CMIP6 multi-model median $\text{PM}_{2.5}$ in the SSP1-2.6 and SSP3-7.0 simulations.

2.3 Sensitivity of $\text{PM}_{2.5}$ air pollution exposure estimates in observation-based data

We tested the sensitivity of estimates of global-mean, population-weighted $\text{PM}_{2.5}$ exposure to the choice of spatial resolution of population data ($\sim 5\text{km}$, $\sim 30\text{km}$, $\sim 55\text{km}$ spatial resolution), year of population data (i.e., 2015 vs 2020 GPWv4 data) and use of mean $\text{PM}_{2.5}$ exposure over the 2015-2019 time period as opposed to an individual year of data in this time period. First, we reassessed global exposure using population and air pollution data on a $\sim 5\text{km}$, $\sim 30\text{km}$, and a $\sim 55\text{km}$ spatial grid. We found this change in spatial resolution (from $\sim 5\text{km}$ to $\sim 55\text{km}$) of data increases global mean, population-weighted exposure by between 1 and 5%, depending on dataset (Table S2). Second, if we use GPWv4 population data for the year 2020 in place of the year 2015, global mean exposure changes by $\sim 0.3\text{-}0.6 \mu\text{g}/\text{m}^3$ (2020 GPWv4 mean exposure: $40.2 \mu\text{g}/\text{m}^3$, range: $28.1 - 53.63 \mu\text{g}/\text{m}^3$), or less than 1% relative to the results obtained using the GPWv4 2015 data. Third, we tested the sensitivity of the results to interannual variability in $\text{PM}_{2.5}$. Our main results use multi-year (2015-2019) averages of $\text{PM}_{2.5}$ (with the exception of the Shaddick data, which includes data from 2014-2016), but we find that global exposure varies by less than 3%/year (relative to the 5-year average) over this time period in the van Donkelaar, MERRA-2, and GBD 2019 datasets. Therefore, the disagreement among observation-based $\text{PM}_{2.5}$ exposure estimates presented in the Results section is much larger ($\sim 30\%$ in spread relative to the global mean exposure across all datasets) than choice of spatial resolution of data, interannual variability in global, annual mean $\text{PM}_{2.5}$ exposure, or choice of year of population data 2015-2019.

2.4 Calculating premature deaths associated with ambient air pollution exposure

Following previously published methods from Shindell et al. (2021), we evaluate premature mortality associated with ambient $\text{PM}_{2.5}$ exposure using the exposure-response functions produced by the Global Exposure Mortality Model (GEMM), which was created from a meta-analysis including 41 cohort studies from around the world (Burnett et al., 2018). All-cause risk of premature death increases by about 1% per $\mu\text{g}/\text{m}^3$ additional exposure for low exposures ($< \sim 20 \mu\text{g}/\text{m}^3$), but for higher exposures ($> \sim 60 \mu\text{g}/\text{m}^3$) the increase drops to about half this value. Deaths are evaluated for adults older than 25 using separate risk functions for each 5-year age bin, with a low exposure threshold for impacts set at $2.4 \mu\text{g}/\text{m}^3$. Premature mortalities associated with $\text{PM}_{2.5}$ exposure are estimated using the equation:

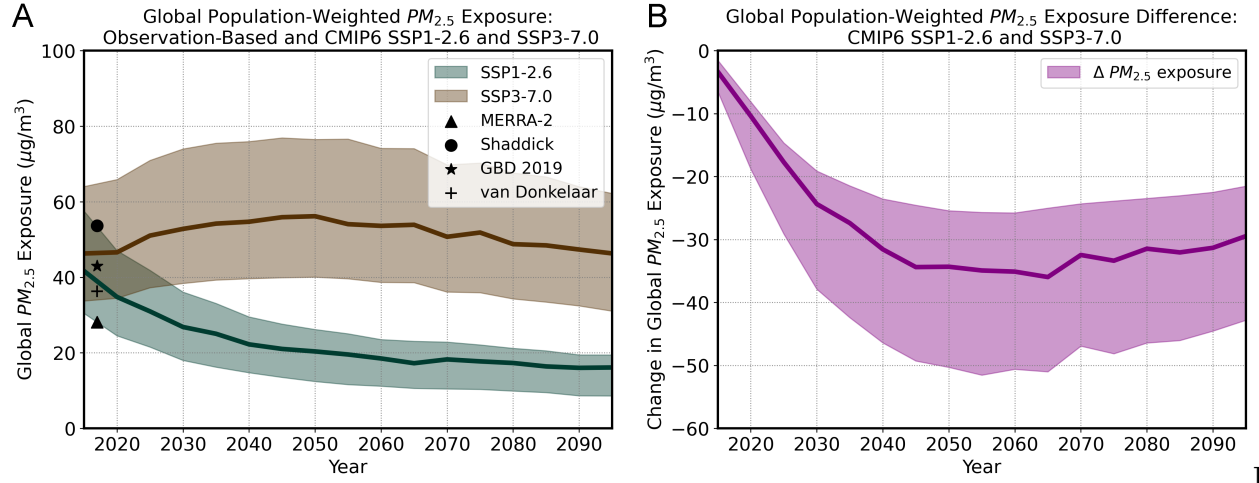
$$\text{Deaths} = \frac{\text{AF} \times \text{HR} \times \text{Population}}{\text{AF} \times \text{HR} \times \text{Population}}$$

where the attributable fraction (AF) is defined using the hazard ratio (HR) as $(\text{HR}-1)/\text{HR}$, y_0 is the all-cause baseline mortality rate, and Population is the local population over 25 years of age. The hazard ratio $\text{HR} = \exp(\beta \times \text{T}(z))$ incorporates the regression coefficient β from the meta-analysis from Burnett et al. (2018) and a set of non-linear functions of $\text{PM}_{2.5}$ exposure $\text{T}(z)$. The uncertainties in this exposure-response function are approximately $\pm 16\%$ (Burnett et al., 2018) and are omitted from our analysis to make it clear when the CMIP6 scenarios’ health impacts are statistically different based on the multi-model analysis. Mortalities are evaluated at the grid cell level ($0.5^\circ \times 0.5^\circ$) then summed within a country’s borders or across all grid points for global totals. Grid-level baseline mortality rates are from the 2015 Global Burden of Disease (Stanaway et al., 2018).

3 Results

3.1 Global air pollution exposure in observations and CMIP6 models

We first examine global-mean, population-weighted $\text{PM}_{2.5}$ exposure using four observation-based $\text{PM}_{2.5}$ datasets (Figure 1). The global-mean observation-based estimates of global $\text{PM}_{2.5}$ exposure is $39.9 \mu\text{g}/\text{m}^3$ (range: $27.8 - 53 \mu\text{g}/\text{m}^3$). Notably, all of the observation-based estimates are well above the WHO global AQG of $5-10 \mu\text{g}/\text{m}^3$, and also generally exceed the WHO Interim-Target 1 guideline of $35 \mu\text{g}/\text{m}^3$, indicating that regardless of dataset, the average person is exposed to high levels of mean annual ambient $\text{PM}_{2.5}$. These estimates of global-mean, population-weighted $\text{PM}_{2.5}$ exposure change by $< 3-5\%$ if different spatial resolution population data, year of population data, or year of air pollution data are chosen 2014-2019 (Section 2.3).



1. Global-mean $PM_{2.5}$ exposure in observations and climate models. (A) Global, population-weighted annual mean ambient surface $PM_{2.5}$ exposure in Coupled Model Intercomparison Project, Phase 6 (CMIP6) simulations (colored lines and shading) and in observation-based $PM_{2.5}$ estimates (black symbols). (B) Avoided $PM_{2.5}$ exposure in a high (SSP3-7.0) vs low (SSP1-2.6) emissions scenarios. Population is fixed at 2015 levels for all calculations to highlight differences in global average $PM_{2.5}$ exposure in the two emissions scenarios and among observation-based datasets.

We find that the range of $PM_{2.5}$ exposure simulated by CMIP6 models, after adjustment (Section 2.2), generally falls within the range of observation-based estimates (SSP1-2.6 multi-model median global exposure: 41.7, range: 30.5 - 57.5 $\mu\text{g}/\text{m}^3$), with the exception of two SSP3-7.0 CMIP6 simulations, which show higher $PM_{2.5}$ exposure than the observation-based estimates (SSP3-7.0 multi-model median: 46.3, range: 33.7 - 64.0 $\mu\text{g}/\text{m}^3$). Despite the differences among observations and two of these CMIP6 models, the CMIP6 multi-model median SSP3-7.0 global $PM_{2.5}$ exposure aligns well with the observation-based Shaddick global exposure, and the CMIP6 multi-model median SSP1-2.6 global $PM_{2.5}$ exposure aligns well with the van Donkelaar observation-based global exposure. Spatially, the adjusted CMIP6 models tend to simulate near-surface $PM_{2.5}$ concentrations that are higher than observations over eastern China and slightly lower than observation-based estimates over most other regions (Figures S1, S2), suggesting that the CMIP6 multi-model median estimates used here are likely conservative in most locations.

3.2 Global population exposure to WHO Air Quality Guidelines

Following on the recently updated WHO AQGs for annual mean, ambient $PM_{2.5}$ exposure, we also compare CMIP6 and observation-based estimates of global population exposure to annual mean $PM_{2.5}$ exceeding the updated WHO AQG of 5 $\mu\text{g}/\text{m}^3$, the older WHO AQG of 10 $\mu\text{g}/\text{m}^3$, and the WHO Interim-Target 1 guideline of 35 $\mu\text{g}/\text{m}^3$ (Figure 2). All of the observation-based gridded $PM_{2.5}$

data agree that at least 91% of the global population is exposed to $\text{PM}_{2.5}$ exceeding annual mean concentrations of $5 \mu\text{g}/\text{m}^3$ (mean: 95%, range: 91% - 99%), at least 84% of global population is exposed to $\text{PM}_{2.5}$ exceeding $10 \mu\text{g}/\text{m}^3$ (mean: 86%, range: 84% - 88%), and at least 32% of global population is exposed to $\text{PM}_{2.5}$ exceeding $35 \mu\text{g}/\text{m}^3$ (mean: 44%, range: 32% - 54%). These results do not noticeably change if GWPv4 2020 population data are used in place of GPWv4 2015 data, and results change by $<5\%$ if higher spatial resolution population data ($\sim 0.05^\circ$) are chosen (Section 2.3).

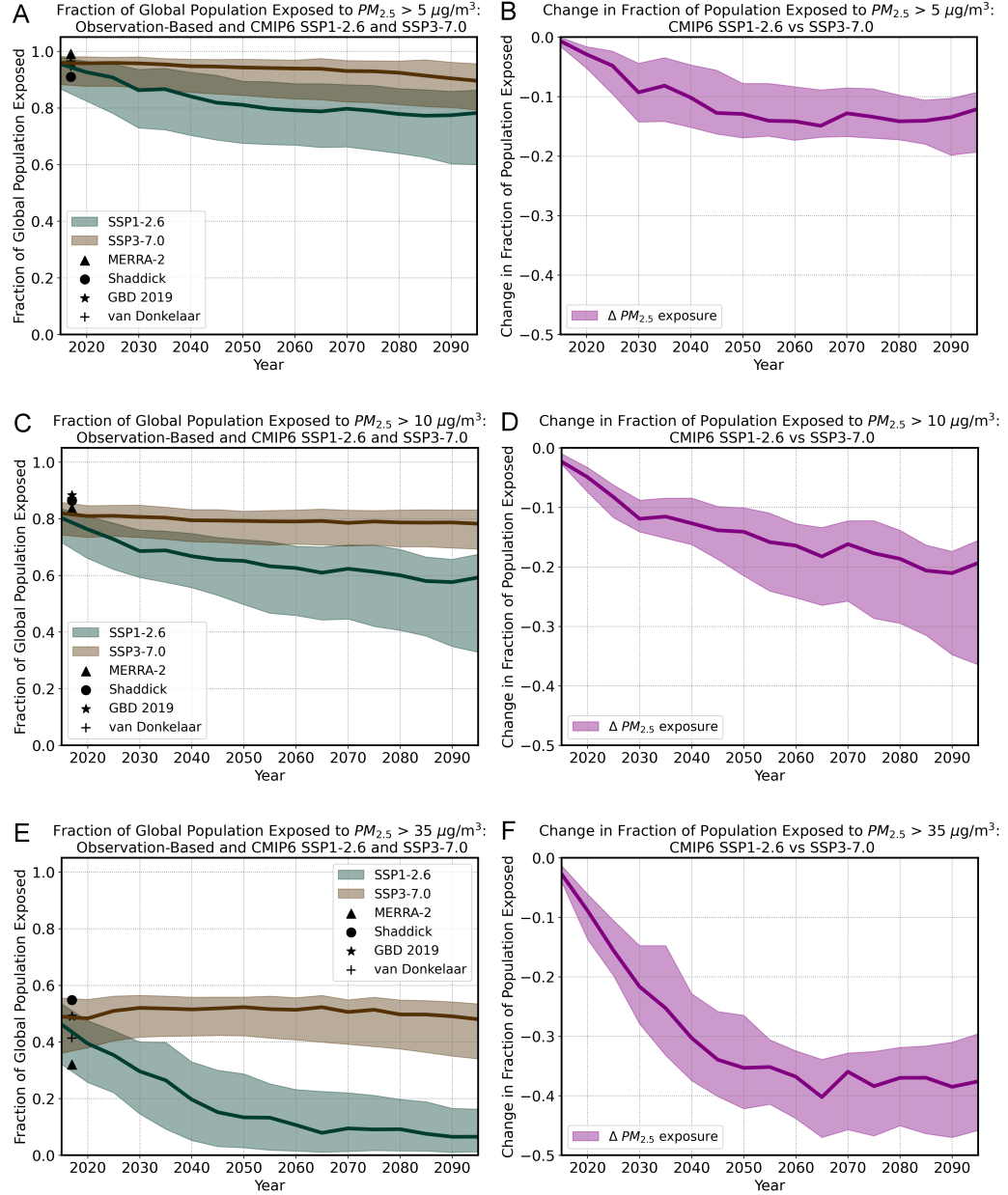


Figure 2. Fraction of global population exposed to $PM_{2.5}$ concentration thresholds. Fraction of global population exposed to $PM_{2.5}$ concentrations above $5 \mu\text{g}/\text{m}^3$, (A) $10 \mu\text{g}/\text{m}^3$ (C), and $35 \mu\text{g}/\text{m}^3$ (E) in Coupled Model Intercomparison Project, Phase 6 (CMIP6) simulations (colored lines and shading) as well as in observation-based estimates (black symbols). Avoided exposure in high vs low CMIP6 emissions scenarios (B, D, F). Population is fixed at 2015 levels

for all calculations to highlight differences in global $\text{PM}_{2.5}$ exposure in the two emissions scenarios and among observation-based datasets.

This wide range in observation-based estimates suggests caution should be used when reporting values from only one dataset to estimate global exposure to ambient $\text{PM}_{2.5}$ exceeding certain concentration thresholds, or for determining if climate models are accurately simulating $\text{PM}_{2.5}$ exposure, particularly in regions with relatively few in-situ monitoring stations (e.g., (Alvarado et al., 2019)). The adjusted CMIP6 simulated global $\text{PM}_{2.5}$ population exposure to these three concentration thresholds generally falls in the range of observation-based estimates, with the exception of the $10 \mu\text{g}/\text{m}^3$ concentration threshold; all of the CMIP6 simulations slightly underestimate global population exposure to this threshold (Figure 2).

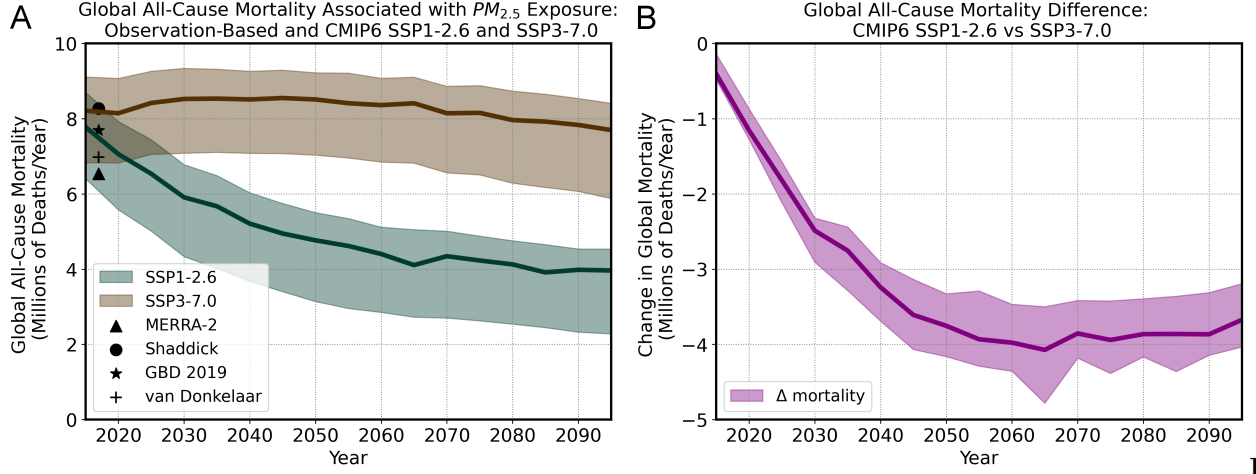
Although there is a large spread in estimates of current global $\text{PM}_{2.5}$ exposure in observations and climate models, CMIP6 models agree that emissions reductions produce significant changes in future $\text{PM}_{2.5}$ exposure. Under the SSP3-7.0 pathway, global $\text{PM}_{2.5}$ exposure remains high for the remainder of the century. By contrast, under SSP1-2.6, global air pollution exposure rapidly declines, with the largest reductions for air pollution exposure for $\text{PM}_{2.5}$ concentrations exceeding $35 \mu\text{g}/\text{m}^3$, and more modest declines for the lower exposure thresholds (Figure 3). By mid century (2050-2055), assuming no population growth, the differences in the SSP1-2.6 vs SSP3-7.0 $\text{PM}_{2.5}$ exposure indicate that emissions reductions would lead to a 13% (range: 8 - 17%) reduction in global population exposure to annual $\text{PM}_{2.5}$ concentrations exceeding $5 \mu\text{g}/\text{m}^3$, a 14% (range: 10 - 22%) reduction for $\text{PM}_{2.5}$ concentrations exceeding $10 \mu\text{g}/\text{m}^3$, and a 35% (range: 27 - 42%) reduction for $\text{PM}_{2.5}$ concentrations exceeding $35 \mu\text{g}/\text{m}^3$. The rate of increased avoided air pollution exposure slows after mid-century (Figure 2) due to lower late-century emissions in SSP3-7.0.

3.3 Global premature mortality associated with $\text{PM}_{2.5}$ exposure

As we have shown, almost all (91-99%) of the globe’s population is exposed to $\text{PM}_{2.5}$ exceeding the new WHO AQG annual mean concentrations of $5 \mu\text{g}/\text{m}^3$ (Figure 2). Following on previous work focused on regional impacts (Shindell et al., 2022; Shindell et al., 2021), we examine global premature mortality associated with ambient $\text{PM}_{2.5}$ exposure (Section 2.4). Although air pollution and its impacts are not limited to ambient $\text{PM}_{2.5}$, the mortality burden associated with ambient $\text{PM}_{2.5}$ tends to be much larger than mortality associated with ozone and other air pollution species (Romanello et al., 2021), so here we focus on ambient $\text{PM}_{2.5}$ exposure and its impacts. Specifically, we use observation-based $\text{PM}_{2.5}$ data, CMIP6 $\text{PM}_{2.5}$ data, the GEMM model, and recent population (2015 GPWv4 population data) to estimate recent mortality associated with $\text{PM}_{2.5}$ exposure and the impacts of emissions reductions on global mortality under the assumption of no future changes in population.

Using observation-based $\text{PM}_{2.5}$ data, we estimate that air pollution over the 2015-2019 time period was associated with average annual premature deaths

of about 7.37 million/year (range: 6.54 - 8.27 million/year across observation datasets; Figure 3a). When we estimate global, annual premature deaths using adjusted CMIP6 $PM_{2.5}$ data from the same time period, we find that the CMIP6-based estimates fall within the range of observation-based estimates, with a mean annual premature mortality of 8.2 million/year (range: 6.8 - 9.1 million/year) in SSP3-7.0 and 7.8 million/year (range: 6.4 - 8.7 million/year) in SSP1-2.6 (Figure 3).



3. Global all-cause mortality associated with annual mean, ambient surface $PM_{2.5}$ exposure. (A) Global all-cause mortality associated with surface $PM_{2.5}$ exposure in Coupled Model Intercomparison Project, Phase 6 (CMIP6) simulations (colored lines and shading) and in observation-based estimates (black symbols). (B) Avoided mortality associated with avoided $PM_{2.5}$ exposure in CMIP6 high (SSP3-7.0) vs low (SSP1-2.6) emissions scenario (right). Population is fixed at 2015 levels for all calculations to highlight differences in the impacts of $PM_{2.5}$ exposure in the two emissions scenarios and among observation-based datasets.

If global emissions reductions are rapidly implemented, the difference between these simulations indicates millions of lives could be saved annually. Specifically, if emissions are reduced from those in SSP3-7.0 to those in SSP1-2.6, 1.1 million (range: 0.9 - 1.3 million) premature deaths/year could be avoided within 5-10 years of the start of emissions reductions (Figure 3). Within 10-20 years, 2.6 million (range: 2.3 - 2.9 million) deaths/year could be avoided, and by 2060, 3.9 million (range: 3.5 - 4.4 million) deaths/year could be avoided (Figure 3). Notably, the CMIP6 multi-model spread in projected avoided deaths/year (range: 0.3 to 1.0 million/year) associated with emissions reductions remains substantially smaller than the spread in observation-based estimates (~ 1.75 million/year) or CMIP6-based estimates (~ 2.3 million/year) of recent annual mortality.

Cumulatively over the 2015-2099 time period, 275 million (range: 243-301 million) premature deaths could be avoided if global emissions follow a lower emis-

sions pathway (SSP1-2.6) as compared to a higher emissions pathway (SSP3-7.0). Spatially, these cumulative avoided premature deaths under the lower emissions pathway (SSP1-2.6) are concentrated in eastern Europe, southern Asia, and eastern Asia (Figure 4; grid-point level results for each CMIP6 model are shown in Figure S3). Eleven countries show at least 40,000 cumulative avoided deaths per million people by the end of the century, and over 100 countries show at least 10,000 cumulative deaths per million people (Table S3). Specifically, China, South Korea, North Korea, and India experience the largest benefits from reduced emissions and associated air pollution exposure, with cumulative avoided losses (2015-2099) of over 73,000 per million in China, 63,000 per million in both North and South Korea, and 49,000 per million in India.

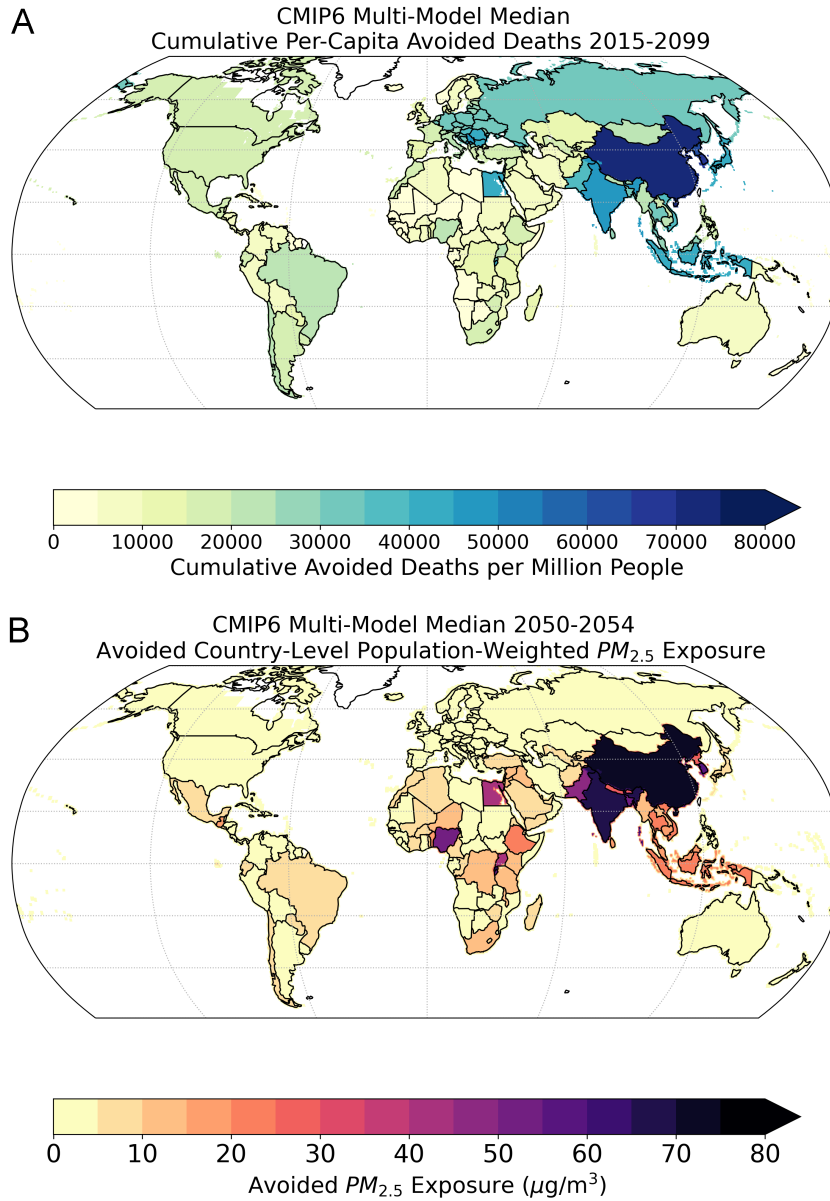


Figure 4. Avoided premature mortality and avoided $PM_{2.5}$ exposure under a low emissions pathway. (A) Country-level cumulative avoided premature mortality associated with surface $PM_{2.5}$ exposure and (B) avoided population-weighted surface $PM_{2.5}$ exposure in Coupled Model Intercomparison Project, Phase 6 (CMIP6) simulations. Avoided premature mortality (A) is calculated from the difference in cumulative (2015-2099) deaths per million people in CMIP6 low (SSP1-2.6) and high (SSP3-7.0) emissions scenarios. Avoided sur-

face $\text{PM}_{2.5}$ exposure (B) is calculated from the difference in mean surface $\text{PM}_{2.5}$ exposure 2050-2054 in CMIP6 low (SSP1-2.6) and high (SSP3-7.0) emissions scenarios. Population is fixed at 2015 levels for all calculations.

4 Discussion and Conclusions

Here we have shown that estimates of global exposure to air pollution can vary substantially based on observation-based $\text{PM}_{2.5}$ dataset. Specifically, estimates of global-mean, population-weighted $\text{PM}_{2.5}$ in recent years can range from 27.8 to 53 $\mu\text{g}/\text{m}^3$, and estimates of the fraction of the global population exposed to the updated 2021 WHO AQG of 5 $\mu\text{g}/\text{m}^3$ can range from 91-99% of the population. Similarly, there is a large spread in observation-based estimates of global premature mortality associated with annual $\text{PM}_{2.5}$ exposure; using the same gridded population data and exposure response function (GEMM; (Burnett et al., 2018)), observation-based premature mortality ranges from 6.54 to 8.27 million/year.

As Figure 1 shows, the spread in observation-based $\text{PM}_{2.5}$ exposure estimates is comparable to the spread in $\text{PM}_{2.5}$ global exposure simulated by adjusted CMIP6 models over a similar time period (SSP1-2.6 range: 30.5 - 57.5 $\mu\text{g}/\text{m}^3$; SSP3-7.0 range: 34 - 64 $\mu\text{g}/\text{m}^3$). Despite the large spread in current global exposure estimates, we show that CMIP6 models agree that emissions reductions (under the SSP3-7.0 vs SSP1-2.6 pathways) show rapid, widespread benefits for global air quality, and that these benefits grow through the middle of the century (Figure 2). These results are qualitatively similar to those of (Rao et al., 2017), who examined regional air quality changes under various SSPs using a simplified global air quality model. Rao et al. (2017) found that by mid-century, in weaker pollution control scenarios (SSP3, SSP4), a higher fraction of the population will be exposed to high concentrations of air pollution than is currently exposed. These authors found that air quality is the worst in Asia, with China and India driving most of the high population exposure to poor air quality and receiving most of the benefits of emissions reductions. Additionally, in arid regions such as the Middle East and northern Africa, mineral dust is responsible for a large portion of the higher concentrations of air pollution, so Rao et al. (2017) suggested that pollution controls will show weaker benefits in these areas. However, our analysis of adjusted CMIP6 $\text{PM}_{2.5}$ data indicates that emissions reductions (in SSP1-2.6 vs SSP3-7.0) will also lead to large air quality improvements in countries including, but not limited to, Nigeria, Egypt, Uganda, Pakistan, Bangladesh, and South Korea, so that major benefits of emissions reductions for air quality are not limited to India and China (Figure 4).

Reduced global air pollution exposure under low as compared to high emissions scenarios would also have rapid, large-scale impacts on $\text{PM}_{2.5}$ -associated premature mortality. Specifically, 1.1 million (range: 0.9 - 1.3 million) premature deaths/year could be avoided within 5-10 years of the start of emissions reductions, and 3.9 million (range: 3.5 - 4.4 million) premature deaths/year could be avoided by the middle of the century. Throughout the century, the uncertainty

in benefits of emissions reductions remain substantially smaller than the uncertainty in estimates of recent (2015-2019) annual premature mortality (Figure 3).

We have presented uncertainties in recent and projected $\text{PM}_{2.5}$ exposure and associated mortality, but we have not shown epidemiological uncertainties related to health outcomes associated with air pollution exposure. The GEMM uncertainty, which is approximately $\pm 16\%$ (Burnett et al., 2018), is systematic across mortality estimates from CMIP6 models and observations, so we do not show it in our analysis. We used the GEMM because this model includes studies covering a wide range of $\text{PM}_{2.5}$ exposure across multiple countries, including high ($>35 \mu\text{g}/\text{m}^3$) concentrations (Burnett et al., 2018). However, the Integrated Exposure-Response (IER) model (Burnett et al., 2014), which was employed in recent WHO, Global Burden of Disease (GBD), and Lancet studies (Bourne & Collaborators, 2016; Cohen et al., 2017; Fuller et al., 2022; Romanello et al., 2021), yields global estimates of ~ 4.14 (range: 3.45 - 4.8) million annual deaths. By contrast, Burnett et al. (2018), using the GEMM, report ~ 8.9 (range: 7.5 - 10.3) million deaths in 2015. The GEMM-IER difference is partly because the GEMM includes “all-cause” mortality, whereas previous models included a more limited range of health outcomes. However, even if the GEMM is restricted to a more limited range of outcomes, it still produces larger global mortality estimates than the IER (Burnett et al., 2018). Furthermore, Vohra et al. (2021), using a response function from Vodonos et al. (2018), report an even larger estimate of global $\text{PM}_{2.5}$ -related deaths (~ 10.2 million/year, although with a substantially larger uncertainty range). Therefore, the uncertainty associated with choice of response model (range: ~ 4 - 6 million deaths/year among response models) is significantly larger than the 95% confidence interval range of from either GEMM or IER (95% range: ~ 1.35 - 1.95 million deaths/year, depending on model), the uncertainty from the choice of observation-based $\text{PM}_{2.5}$ dataset (range: ~ 1.75 million deaths/year across observation-based $\text{PM}_{2.5}$ datasets), and the uncertainty associated with CMIP6 model physics (range: ~ 2.3 million deaths/year for 2015-2019 across CMIP6 models in one SSP).

In addition to uncertainties related to epidemiological and physical models, several assumptions and potential limitations of this study should be mentioned. First, here we have assumed no changes in future population or vulnerability in our calculations of future air pollution exposure and associated premature mortality. Although there will be future population and other demographic changes (United, 2019), this analytical choice has allowed us to focus on the impacts of emissions and associated air pollution exposure without complicating these projected values by overlaying varying population projections from SSP1 and SSP3. Second, here we have compared a low emissions scenario (SSP1-2.6) with the SSP3-7.0 pathway. However, although historical emissions closely track higher emissions pathways (Pedersen et al., 2020), recent United Nations (UN) emissions reports indicate that global emissions are projected to fall below those used in the SSP3-7.0 pathway (UNEP, 2020).

Despite the aforementioned uncertainties in the analysis, these results have important implications. First, estimates of global mortality associated with air pollution exposure are highly sensitive to choice of exposure response model, suggesting a need for more studies relating health outcomes to air pollution exposure (Schraufnagel et al., 2019) in locations with a range of pollution levels. Second, the large range in estimated observation-based current air pollution exposure and associated mortality highlight the need for more high-quality on-the-ground air quality monitoring stations to better constrain satellite-derived observations, particularly in locations with relatively few stations with poor air quality (Alvarado et al., 2019). Third, our results show that even though there is a large spread in observation and climate model-based estimates of current mortality, emissions reductions to slow global warming will lead to significant, widespread improvements in air quality. These air pollution reductions will be particularly impactful in many low- and middle-income countries with poor air quality. Specifically, many countries in eastern Europe, Africa, southern Asia, and eastern Asia see large benefits from reduced emissions and associated air pollution exposure, with over 100 countries showing at least 10,000 cumulative avoided deaths per million people by the end of the century (Figure 4; Figure S4; Table S3). Many of these countries are currently facing a decision point: continued use and investment in fossil fuel-intensive infrastructure, or a lower emissions pathway. Our work builds on previous research (Rao et al., 2017; Saari et al., 2019; Sampedro et al., 2020; Shindell et al., 2022; West et al., 2013) that has highlighted the relatively rapid, large-scale air quality benefits of low-emissions infrastructure investment and development.

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Open Research

Data are available at the following links: the GISS model: <https://www.giss.nasa.gov/tools/modelE/>; CMIP6 simulations from GISS and other groups: <https://esgf-node.llnl.gov/projects/esgf-llnl/>; gridded population data: <https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11/data-download>; MERRA-2 PM_{2.5} data: https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/; GBD 2019 PM_{2.5} data: <https://ghdx.healthdata.org/record/global-burden-disease-study->

2019-gbd-2019-air-pollution-exposure-estimates-1990-2019; van Donkelaar PM_{2.5} data: <https://sites.wustl.edu/acag/datasets/surface-pm2-5/>; Shaddick PM_{2.5} data: https://pubs.acs.org/doi/suppl/10.1021/acs.est.8b02864/suppl_file/es8b02864_si_003.zip.

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