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Reducing Inequities in the Future Air Pollution Health Burden Over Europe

Connor J. Clayton[1], **Steven T. Turnock**[1,2], **Daniel R. Marsh**[3], **Ailish M. Graham**[1], **Carly L. Reddington**[1], **Karn Vohra**[4,5], **and James B. McQuaid**[1]

[1]Institute of Climate and Atmospheric Science, University of Leeds, Leeds, UK, [2]Met Office, Exeter, UK, [3]School of Physics and Astronomy, University of Leeds, Leeds, UK, [4]Department of Geography, University College London, London, UK, [5]Now at School of Geography, Earth & Environmental Sciences, University of Birmingham, Birmingham, UK

Key Points:

- A high climate mitigation scenario could result in a reduction in $PM_{2.5}$-attributable mortality of over 50%
- Failing to mitigate climate change could result in yearly O_3-attributable mortality in Europe doubling by 2050
- Strong climate mitigation would reduce the inequity in $PM_{2.5}$ mortality rate between the most and least deprived regions of Europe

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

C. J. Clayton and J. B. McQuaid,
eecjc@leeds.ac.uk;
j.b.mcquaid@leeds.ac.uk

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Author Contributions:

Conceptualization: Connor J. Clayton, Steven T. Turnock, Daniel R. Marsh, James B. McQuaid
Formal analysis: Connor J. Clayton
Funding acquisition: James B. McQuaid
Investigation: Connor J. Clayton
Methodology: Connor J. Clayton, Steven T. Turnock, Ailish M. Graham, James B. McQuaid
Resources: Daniel R. Marsh, Carly L. Reddington, Karn Vohra
Software: Ailish M. Graham, Carly L. Reddington, Karn Vohra
Supervision: Steven T. Turnock, Daniel R. Marsh, James B. McQuaid
Visualization: Connor J. Clayton
Writing – original draft: Connor J. Clayton

Abstract The strategies that policymakers take to mitigate climate change will have considerable implications for human exposure to air quality, with air quality co-benefits anticipated from climate change mitigation. Few studies try to model these co-benefits at a regional scale and even fewer consider health inequalities in their analyses. We analyze the health impacts across Western and Central Europe from exposure to fine particulate matter ($PM_{2.5}$) and surface level ozone (O_3) in 2014 and in 2050 using three scenarios with different levels of climate change mitigation, using a high-resolution atmospheric chemistry model to simulate future air quality. We use recent health functions to estimate mortality related to the aforementioned pollutants. We also analyze the relationship between air quality mortality rate per 100,000 people and Human Development Index to establish if reductions in air quality mortality are achieved equitably. We find that air quality-related mortality ($PM_{2.5} + O_3$ mortality) will only reduce in the future following a high-mitigation scenario (54%). It could increase by 7.5% following a medium-mitigation scenario and by 8.3% following a weak mitigation scenario. The differences are driven by larger reductions in $PM_{2.5}$-related mortality and a small reduction in O_3-related mortality following the high-mitigation scenario, whereas for the other scenarios, smaller improvements in $PM_{2.5}$-related mortality are masked by worsening O_3-related mortality. We find that less developed regions of European countries have higher mortality rates from $PM_{2.5}$ and O_3 exposure in the present day, but that this inequity is reduced following greater climate change mitigation.

Plain Language Summary We use a very detailed air quality model to estimate how mortality related to poor air quality could change in Europe by 2050 when different levels of climate mitigation are implemented. We find that strong climate mitigation results in large reductions in air quality mortality, but scenarios with less mitigation do not. We also find that strong climate mitigation reduces the inequitable mortality from poor air quality in more deprived parts of Europe.

1. Introduction

Poor air quality is the largest environmental risk factor for early deaths in the world (Health Effects Institute, 2020) and has a health burden of an estimated 6.7 million deaths per year globally, considering both ambient and household exposure (World Health Organisation, 2022). This is through a range of pathways including cardiovascular disease, respiratory disease, cancers, diabetes and a range of other conditions (Schraufnagel et al., 2019). Estimations of future mortality in Europe from air pollution often reach hundreds of thousands, but vary depending on the methodology used (Burnett & Cohen, 2020; Juginović et al., 2021; Vohra et al., 2021). The World Health Organisation (WHO) have published guideline values for different air pollutants that impact human health (World Health Organisation, 2021): $PM_{2.5}$ (any airbourne particulate with diameter under 2.5 microns), PM_{10} (any airbourne particulate with diameter less than 10 microns), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and carbon monoxide (CO).

As greenhouse gases and primary air pollutants share many sources, it is expected that climate mitigation could provide air quality co-benefits (von Schneidemesser et al., 2020). Policymakers could be encouraged to adopt climate mitigation measures as they could improve multiple environmental issues at the same time. This topic is not new to the literature and studies investigating air quality and the subsequent health impacts are long established. For example, Anenberg et al. (2009) investigated global health impacts from O_3 following climate policy and to what extent O_3 changes in each continent were affected by policies in other regions. Future health impacts from $PM_{2.5}$ and O_3 pollution following climate scenarios were investigated by Silva et al. (2016) and

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subsequently the proportion of these health burdens attributable to climate change alone were investigated by Silva et al. (2017). A systematic review of older literature in the field was performed by von Schneidemesser et al. (2020), finding 47 such papers focusing on the health impacts of air quality through climate mitigation. They note that one of the limitations of existing literature is the lack of standardization in approach, including the use of many very different scenarios that hamper comparability between research.

Many studies use the Representative Concentration Pathways (RCPs; van Vuuren et al., 2011) as climate mitigation scenarios to drive co-benefits modeling studies. These provide decadal pathways of emissions up to different climate forcings in 2100, however, the representation of socioeconomic factors in these pathways is limited. The Shared Socioeconomic Pathways (SSPs; O'Neill et al., 2017) have built upon the RCPs, introducing a matrix in which storylines describing societal actions toward sustainable development and socioeconomic changes. This additional refinement could be key for understanding future air quality, due to the increased consideration given to pollution control in parallel to climate as part of the scenarios. For both RCPs and SSPs, studies tend to find that scenarios with greater levels of climate mitigation result in air quality co-benefits globally and in Europe (Clayton et al., 2024; Fenech et al., 2021; Turnock et al., 2020).

A weakness of using RCPs and SSPs for future air quality co-benefit analysis is that the inputs are not optimized for regional air quality models, which have higher horizontal resolution (often 50 km by 50 km at the coarsest) and more detailed chemistry schemes. Some studies make use of RCP or ScenarioMIP output or simulations using global earth system/climate models despite this limitation (Silva et al., 2016; Turnock et al., 2020; Yang et al., 2022) and some use reduced-form models that output general trends (Ingole et al., 2022; Markandya et al., 2018).

Other studies use regional air quality models driven by SSP emissions to estimate co-benefits. These usually ignore the influence of climate change itself on air quality, for example, Clayton et al. (2024) find that following SSP1-2.6, average $PM_{2.5}$ exposure in European countries could reduce by 52.4% by 2050 compared to 2014 in the present day and that maximum 6-monthly-mean daily maximum 8 hr O_3 (6mDM8h O_3) at surface level could reduce by 25%. They also find however, that following SSP3-7.0, European countries would see a reduction in population-weighted $PM_{2.5}$ of only 18.1% and an average increase in 6mDM8h O_3 of 8%.

Few studies have examined the health impacts of air quality following SSPs. The SSPs provide extra data useful for understanding how mortality may respond to air quality, such as population age profiles, whereas the RCPs include only total population (Kc & Lutz, 2017). Turnock et al. (2023) estimate the health burden of future air quality following SSP3-7.0, but use air quality generated from CMIP6 models, which have a coarse horizontal resolution; often at the 100 km scale or greater, and thus may miss regional trends and lack some relevant chemistry, for example, nitrate aerosol chemistry. A study by Yang et al. (2022) aims to quantify the health impacts of a greater range of SSPs, but also uses a coarse-resolution Earth System model. Another study by Chen et al. (2023) uses an AI neural network model to generate $PM_{2.5}$ gridded at 10 km by 10 km horizontal resolution for the SSPs and uses this to estimate future mortality. Notably, the SSPs and RCPs are not the only scenarios in use for work of this kind, for example, some works use scenarios more specific to expected trajectories or policies implemented in individual countries. For example, work by Macintyre et al. (2023) use scenarios designed for the UK with a model optimized for understanding impacts of air quality policy in the UK to assess health impacts of $PM_{2.5}$ and NO_2 following UK-specific mitigation scenarios. Marais et al. (2023) similarly use UK-specific policies but with a less specific model and novel health-impact function optimized for capturing impacts on $PM_{2.5}$ air quality on health in low-$PM_{2.5}$ environments.

Another consideration for policymakers that deal with air quality is equity of exposure between more and less socioeconomically disadvantaged populations. Around Europe, deprived regions often have worse air quality than higher-income areas (Laurent, 2022). In the UK for example, it was found that NO_x emissions per km^2 in the most deprived decile of neighborhoods were more than double those of the least deprived decile (Gray et al., 2023). Across Europe, the European Environment Agency (2019) found that the poorest quintile (defined using GDP per capita) small administrative regions of countries had approximately 1/3 higher population-weighted $PM_{2.5}$ concentrations than the richest quintile. The gap in exposure between these quintiles has not significantly narrowed, resulting in a persistent inequity in exposure even though air pollution has reduced across Europe. This is supported by work from Richardson et al. (2013) which finds higher PM_{10} concentrations in subregions of European countries with lower household income. They note this is mostly driven by an East-West division in Europe and Neither Eastern nor Western Europe show this trend when considered separately. They also note that some of the wealthiest areas of Europe also have comparatively high PM_{10}.

There is evidence that climate change may widen global unequal exposure to O_3 as well as worsen O_3-related health impacts (Ban et al., 2022). This is due to increasing O_3 formation in warmer, often less developed regions of the globe. Thus suggesting that improved climate mitigation may prevent a worsening of air pollution exposure inequity. Some regional studies disagree with the idea that climate change mitigation could improve equity of overall air quality exposure. For example, Picciano et al. (2023) find that US decarbonization policies, would be unlikely to reduce air quality exposure disparities between different racial communities in North America. Conversely, some studies find that air pollution mitigation measures in urban areas do reduce exposure disparities (Demetillo et al., 2021; Kerr et al., 2021).

The varying conclusions of research into climate mitigation and how this affects inequity of air pollution exposure suggest that more research is needed in this area (Mailloux et al., 2021). Few studies model future air quality and use this to assess change in equity. One example is Williams et al. (2018), which focuses on the potential benefits of the UK meeting the targets of the Climate Change Act and develops scenarios for different methods of complying with this act. They find that more deprived populations are exposed to worse air quality in the present day and that these gaps remain following the future scenarios, albeit with a small reduction in inequity.

Reddington et al. (2023) consider the health impacts of SSPs, and to our knowledge have published the only paper that consider the equity of the impacts. They find that while all income groups benefit from increased decarbonization, countries with lower income had the fewest health benefits. They considered this on a global scale using CMIP6 output to scale a $PM_{2.5}$ reanalysis product to determine future air quality. To consider equity, they used projections of Gross Domestic Product (GDP) consistent with the SSPs. It is very important to establish if these trends differ when examined at finer scales for policymakers to consider the impacts from climate mitigation on health and equity from air quality at sub-national scales that are more relevant for policy implementation.

We aim to address these challenges by estimating the mortality related to air quality following climate mitigation scenarios, and analyzing the equity of the changes over Europe. For this, we use model output from work by Clayton et al. (2024). This paper estimated surface air quality in Europe using anthropogenic emissions and chemical boundary conditions consistent with SSP1-2.6 (high mitigation), SSP2-4.5 (medium mitigation) and SSP3-7.0 (low mitigation) in 2050 compared to 2014. They use a regional air quality model, thus giving us an improved platform for assessing regional health impacts following these scenarios compared to previous literature. This finer spatial resolution also allows us to assess change in equity of air pollution exposure following shared socioeconomic pathways.

2. Methods

2.1. Model Simulations and Model Data Correction

The initial work by Clayton et al. (2024) that we build upon produced a year-long model simulation using emissions representative of 2014 and three year-long simulations with anthropogenic emissions representing SSP1-2.6, SSP2-4.5, and SSP3-7.0 in 2050. The model used for these simulations was WRF-Chemv4.2 at 30 km horizontal resolution with gridded emissions from the Coupled Model Intercomparison Project 6 (CMIP6) that were designed to be consistent with the present-day and future scenarios we use (Feng et al., 2020; Hoesly et al., 2018). We use 2014 as the present-day control year for the model simulations because this is the final year considered in the CMIP6 "historical" period and for which the emissions are not primarily future projections (Hoesly et al., 2018). We use chemical boundary conditions from the same present and future scenarios generated using CESM2-WACCM (Danabasoglu, 2019). Using Chemical boundary conditions from the SSPs this way is valuable, as intercontinental transport of air pollutants is a considerable contributor toward air pollutant concentrations in Europe (Liang et al., 2018) and the SSPs consider varying emissions trajectories across the world.

Meteorological data from ECMWF ERA5 (Hersbach et al., 2020) for 2014 was used as driving data in all simulations. A full list of model specifications and validation can be found in Clayton et al. (2024). Much of the difference between scenarios across the domain is represented by differing trajectories in emissions of CO, NH_3 and CH_4. In short, all scenarios saw reductions in most of the air pollutant species, however, SSP1-2.6 has far larger reductions and also assumes reductions of NH_3 (approx 18%) and CH_4 (approx 58%) emissions from the agricultural sector, whereas the other scenarios do not. Emissions of CO differ as it barely reduces following

SSP3-7.0 whereas it sees strong mitigation (over 40%) following the other scenarios. These emissions differences can be seen quantitatively in Clayton et al. (2024).

The model output from the present-day simulation by Clayton et al. (2024) was not used directly as input into the mortality functions. This is because a $PM_{2.5}$ overestimation was noted by Clayton et al. (2024) which would be consequential for estimating $PM_{2.5}$-related mortality. Instead, the percentage difference in annual mean primarily anthropogenic $PM_{2.5}$ (here defined as the sum of nitrate (NO_3 - here representing ammonium nitrate), ammonium (NH_4- all other ammonium-based particulate matter), sulfate (SO_4), organic carbon (OC) and black carbon (BC)) between the present-day model simulation and each future scenario model simulation was calculated to create scenario-specific scaling factors. As a better representation of present-day $PM_{2.5}$ concentrations for use with mortality functions, we use the observational-correction approach adopted by Reddington et al. (2023) and Turnock et al. (2023) but with finer resolution model data. To do this, we take 2014 surface $PM_{2.5}$ concentrations from a reanalysis product (van Donkelaar et al., 2021) (hereon referred to as the VD reanalysis). This uses satellite and ground observations to generate high-resolution (approximately 10 km) gridded data. We used this data regridded to the resolution of the model simulations directly as the present-day data input into mortality functions. To generate $PM_{2.5}$ data for SSP1-2.6, SSP2-4.5, and SSP3-7.0 in 2050 suitable for use with mortality functions, we scale the VD reanalysis 2014 surface $PM_{2.5}$ by the respective scaling factors for each scenario.

As an example, if the percentage change between the present-day annual mean anthropogenic $PM_{2.5}$ and the anthropogenic $PM_{2.5}$ following SSP1-2.6 in one grid cell is a reduction of 40% in the model output, then the VD reanalysis in that grid cell is reduced by 40% to generate the SSP1-2.6 annual mean $PM_{2.5}$ used for the mortality calculations. Only the percentage difference in the anthropogenic components listed above is considered because Clayton et al. (2024) introduced an estimation of dust (not one of the listed components) that they found to be responsible for an overestimation of $PM_{2.5}$ in their results. This meant this overestimation was not factored into the scaling factors. We chose to scale by the percentage change in anthropogenic $PM_{2.5}$ instead of the absolute change because using the absolute change resulted in artificially low $PM_{2.5}$ concentrations in some regions. There is a trade-off in using the VD reanalysis in that there may be some smoothing of peak $PM_{2.5}$ concentrations due to not all of the observations and satellite products input into the reanalysis being at as fine a resolution as the product itself (van Donkelaar et al., 2021).

O_3 was not bias-corrected in this manner due to the model output showing a reasonable representation of observed values (mean absolute bias of -3.40 μg/m^3 for monthly mean O_3 compared to 21 observation sites across Europe), as shown in Clayton et al. (2024) and due to a lack of O_3 products capable of providing hourly output (needed for the O_3 mortality function) at high resolution. However, this bias did vary over time and space with larger underestimations in Central Europe and smaller underestimations in O_3 in Southern Europe. Summer O_3 showed an overall small overestimation at most observation sites (Clayton et al., 2024). Our results may subsequently provide a pessimistic estimation of O_3 mortality as it the summer months that tend to be factored into O_3 mortality functions.

The use of 2014 meteorology may have an influence on the results. Notably, at the time, 2014 had the warmest yearly average temperatures in Europe (Uhe et al., 2016). Notably, since 2014, average annual temperatures in Europe have surpassed this at least 5 times European Centre for Medium-Range Weather Forecasts (2024). Elevated temperatures can speed up formation of O_3 and has a variable impact on $PM_{2.5}$, causing decreases due to ammonium nitrate evaporation, but increases due to increases in biogenic emissions (Megaritis et al., 2013). 2014 was also notable in Europe for a mild winter and high levels of precipitation in Winter (van Oldenborgh et al., 2015). Cold temperatures and high pressure in Winter often result in air pollutants being trapped near the surface, elevating pollutant levels. High precipitation also speeds up deposition of air pollutants. Thus, 2014 being used as a meteorology year could result in higher summer concentrations of air pollutants and lower winter concentrations, particularly of $PM_{2.5}$ compared to other years.

2.2. Air Pollution Health Impact Functions

To estimate the premature mortality in adults aged 25 years and above attributable to long-term exposure to $PM_{2.5}$, we use our annual mean $PM_{2.5}$ concentration from each scenario. Following the approach of Reddington et al. (2023), we use an exposure-response function from Weichenthal et al. (2022) which uses the extended Shape Constrained Health Impact Function (eSCHIF) (Brauer et al., 2022) that covers low $PM_{2.5}$ concentrations and the Fusion model (Burnett et al., 2022) for higher $PM_{2.5}$ concentrations, up to 83 μg m^3.The transition point between the functions is at 9.8 μg m^3, this from Marais et al. (2023) and provides an alternative to the default transition point of 5 μg m^3 as used by Weichenthal et al. (2022). We chose the alternate transition point to avoid inflated mortality at $PM_{2.5}$ concentrations at higher concentrations. As a comparison to the Fusion-eSCHIF results, we also provide $PM_{2.5}$-attributable premature mortality calculations from the Global Exposure Mortality Model (GEMM) including a supplemental Chinese cohort (Burnett et al., 2018) with $PM_{2.5}$ mortality hazard ratios determined from the association with non-communicable disease + lower respiratory infection mortality. Uncertainty in the Fusion-eSCHIF was estimated at the 95% confidence level by sampling 1,000 different effect estimates to derive a distribution in the attributable fraction from $PM_{2.5}$ exposure. Uncertainty in the GEMM results is accounted for using the uncertainty intervals from the GEMM function provided by Burnett et al. (2018). GEMM assumes a counterfactual $PM_{2.5}$ concentration of 2.4 μg m^3 below which no additional health risks are assumed. The counterfactual we used for the Fusion-eSCHIF function was a random distribution between 2.5 and 5 μg m^3 as described by Weichenthal et al. (2022).

The eSCHIF-Fusion function provides the attributable fraction used with the following formula to estimate $PM_{2.5}$ mortality:

The eSCHIF function used for defining relative risk for $PM_{2.5}$ concentrations between 2.4 and 9.8 μg m^3 is the same as Marais et al. (2023) and defined as follows:

$$eSCHIF(z) = \exp\left\{\frac{\phi 1n\left(\frac{z-z_c f}{\alpha}+1\right)}{\left(1+\exp\left(-\frac{z-z_c f-\tau}{U}\right)\right)} + \omega 1n\left(\frac{(z-z_c f)}{\delta}+1\right)\right\}$$

For the above, z represents annual mean $PM_{2.5}$, $z_c f$ is the counterfactual $PM_{2.5}$ concentration. The parameters ω, τ, δ, ϕ, α and U are best-fit parameters from the cohort used by Weichenthal et al. (2022) and Brauer et al. (2022).

The function for defining the relative risk at $PM_{2.5}$ concentrations above 9.8 is as follows:

$$Fusion(z) = \exp\left\{\gamma\left(\min(z,\mu) + \int_{\mu}^{z}\left(\left(1+\frac{1-\rho}{\rho}\left(\frac{x-\mu}{\theta-\mu}\right)\frac{\theta-\mu}{\theta(1-\rho)}\right)^{-1}dx + \rho\theta 1n(\max(z,\theta)/\theta)\right)\right\}$$

The parameters μ, ρ, γ and θ are also best-fit parameters from Weichenthal et al. (2022) and Brauer et al. (2022). The spreadsheets for all best-fit parameters for both eSCHIF and Fusion are available with Weichenthal et al. (2022).

The relative risks generated from the above functions are used to generate the $PM_{2.5}$-attributable fraction for each grid cell using the following equations where z is the modeled annual mean $PM_{2.5}$ for that cell:

$$AF = 1 - \frac{1}{eSCHIF(z)}$$

where 2.5 μg m^3 $< z <$9.8 μg m^3

$$AF = 1 - \frac{1}{Fusion(z)}$$

where $z \geq 9.8$ μg m^3

To estimate premature adult mortality attributable to long-term exposure to ground-level O_3 pollution, we use a function consistent with the Global Burden of Disease 2019 (C. J. L. Murray et al., 2020) which uses a hazard ratio function for Chronic Obstructive Pulmonary Disorder (COPD) mortality. We input maximum 6-monthly-mean daily maximum 8-hr O_3 (6mDM8h O_3) as the O_3 exposure value for this hazard ratio. The relative risk used to generate the attributable function for this function ranges from 1.03 to 1.05 per 10ppb in 6mDM8h O_3. A mixing ratio of 35.7 ppb was used that corresponds to the 5th percentile value of Turner et al. (2016) as the counterfactual, below this value no associated mortality is assumed. As Fusion-eSCHIF takes mortality from all

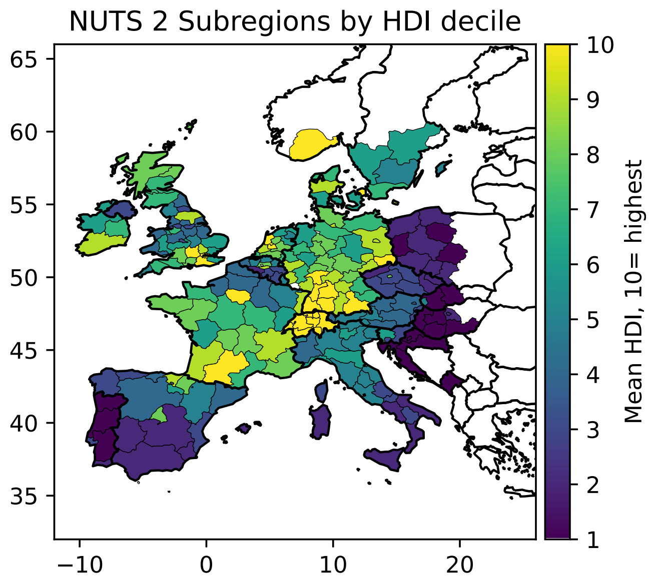

Figure 1. Choropleth map of European NUTS 2 regions in the domain split into 10 categories based on the average subnational human development index of grid cells within the region.

non-accidental disease, (which includes COPD), there is a possibility of some double counting of O_3 mortality, however, due to the relative risk for O_3 being much lower than $PM_{2.5}$ mortality, this is unlikely to vastly affect the overall mortality estimates.

The attributable fractions are used to estimate mortality for each grid cell by multiplying this value by the population and the baseline mortality. To provide population projections matching the SSP scenarios used in the model simulations for these health functions, we use the SSP-consistent population projections from Jones and O'Neill (2016). These are gridded products, which we used at a $0.125° \times 0.125°$. Population age profiles and baseline mortality rates for adults aged 25–80 years in 5-year age intervals and for 80 years plus were taken from data published by the Frederick S. Pardee Center for International Futures (2021) version 7.78. Baseline mortality rates were for non-communicable disease, respiratory infections from communicable disease and non-communicable respiratory disease (for Chronic Obstructive Pulmonary Disorder (COPD)) and are aggregated at country level. For the present-day health impact calculations, 2020 population, population age and baseline mortality were used. We also performed mortality estimations using the future air quality output and 2020 population, population age and baseline mortality to show the impact of projections of changing patterns in these factors on our results.

There are a lack of robust health functions for estimating air quality mortality from long-term exposure to other air pollutants (Cohen et al., 2017; Pozzer et al., 2023). Thus, $PM_{2.5}$ and 6mDM8h O_3 are the only pollutants we use for estimating future mortality associated with long-term ambient air pollution.

2.3. Indicators of Deprivation

To establish the links between air quality changes and socioeconomic development, we use gridded subnational human development index (HDI) data published by Kummu et al. (2018). HDI combines a range of deprivation indices: Gross income per capita, life expectancy, mean years of schooling completed and expected years of schooling upon entering education. This means it considers deprivation more broadly than as an economic issue. This source is provided as a gridded product. We classified both the HDI and mortality calculation data on the European Commission's NUTs level 2 regions as these were defined for the application of regional policies and they matched the spatial scale we wished to analyze. The NUTs-2 subregions ranked in deciles (to match with other studies) of subnational HDI is shown in Figure 1. This demonstrates that in general, Western European regions (excluding Portugal) tend to have higher HDI than Central/Eastern European regions. HDI is highest in areas such as London, Paris, Southern Norway, Switzerland and Southern Germany. It is lowest in Poland, Slovakia, Hungary and Croatia. For many countries (e.g., the UK, Spain, France. The Netherlands, The Czech Republic) HDI is higher in regions in and around the capital/largest cities than the rest of these countries, demonstrating a rural-urban split.

We chose subnational HDI as opposed to similar products, such as gridded gross domestic product projections for the SSPs from Wang and Sun (2021) or the Global Gridded Deprivation Index (Center for International Earth Science Information Network, 2022) as we found that HDI data provided a more realistic indication of socio-economic deprivation and a less binary rural/urban split. We averaged gridded subnational HDI for each NUTs 2 subregion. These subregions were also used for averaging mortality rates for comparison with the HDI. We use present-day HDI for all equity assessments, assuming that the relationship of subregions to each other in terms of deprivation does not change. This may not be true, however, to our knowledge, no gridded projections of HDI consistent with the SSPs have been published.

3. Results and Discussion

The present and future $PM_{2.5}$ concentrations for each scenario are shown in Figure 2. It shows that in 2014, surface $PM_{2.5}$ was usually higher in Central and Eastern Europe than Western Europe, with particularly elevated concentrations in the Po Valley (Italy), Bosnia & Herzegovina, and Southern Poland. Following the future

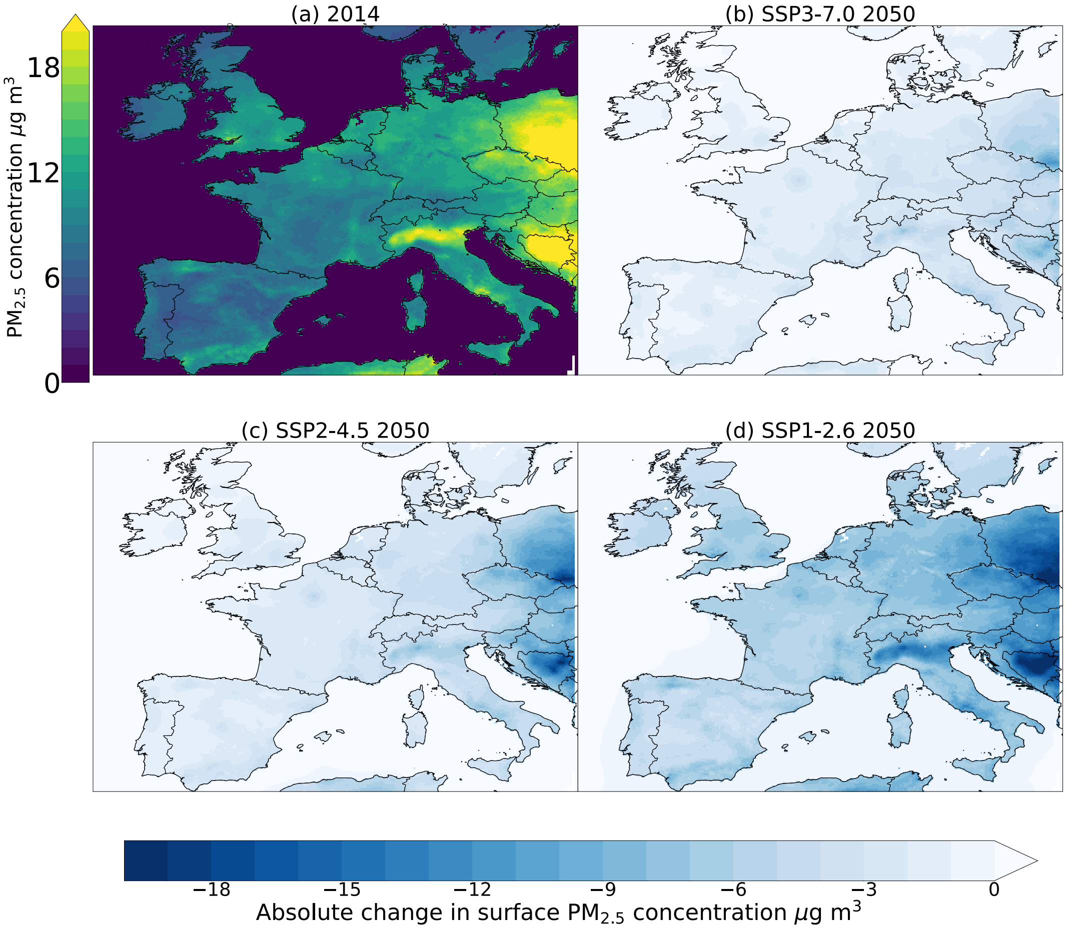

Figure 2. (a) Annual mean $PM_{2.5}$ from the Van Donkelaar reanalysis in 2014, (b) percentage change in $PM_{2.5}$ from the present in the scaled VD reanalysis for SSP3-7.0 in 2050, (c) SSP2-4.5 in 2050 SSP1-2.6 in 2050.

scenarios, surface $PM_{2.5}$ reduces with the largest reductions in Central Europe (particularly South-West Germany) and some urban centers, such as Paris. These reductions are highest following SSP1-2.6, for example, over 90% reductions in SW Germany and in Paris. SSP1-2.6 also shows a larger generalized reduction over most of the domain than SSP2-4.5 and SSP3-7.0, where only the aforementioned regions see reductions of over 20%. Based on the findings of Clayton et al. (2024), this is likely due to the extra mitigation of NH_3 emissions following SSP1-2.6.

3.1. Population Exposure in Comparison to Guideline Values

Figure 3 shows the proportion of the European population exposed to different levels of air pollutants in the present and future scenarios. SSP1-2.6 showed the largest reductions in population exposure to air pollutants compared to SSP2-4.5 and SSP3-7.0. It was the only scenario for which most of the population of Europe (approximately 75%) met the WHO guideline value of 5 μg m^3 annual exposure to $PM_{2.5}$ (Figure 3a) and 10 μg m^3 for NO_2 (Figure 3c) (approximately 52%). Notably, in all other scenarios under 10% of the population are exposed to less than 5 μg m^3 $PM_{2.5}$, demonstrating how impactful following SSP1-2.6 is for $PM_{2.5}$ exposure compared to scenarios with less climate and air pollution mitigation. No scenario resulted in any of the population of Europe being exposed to peak season O_3 under the WHO guideline value of 60 μg m^3. Over 40% of the population of Europe would however be exposed to under 80 μg m^3 peak season O_3 following SSP1-2.6. Less than 10% of the population following the other scenarios would be exposed to peak season O_3 concentrations below this (Figure 3b).

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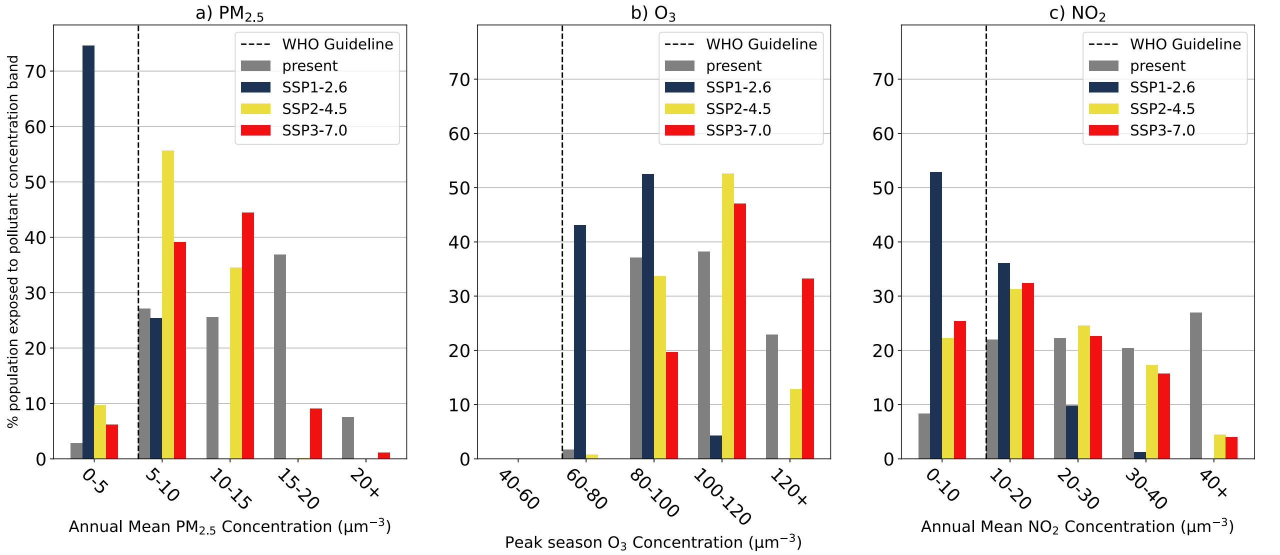

Figure 3. The proportion of the population of Europe exposed to different bands of exposure to (a) annual mean $PM_{2.5}$, (b) peak season O_3, (c) annual mean NO_2 (e.g the bars closest to the *y*-axis of (a) represent the percentage of the population whose annual exposure is between 0 and 5 $\mu g/m^3$). The vertical lines on each figure represent WHO guideline values.

3.2. Health Impacts From Poor Air Quality

We found that the health impacts across the continent from $PM_{2.5}$ reduce following SSP1-2.6 by over 200,000 deaths per year, but worsen following SSP2-4.5 (11,000 per year) and SSP3-7.0 (12,000 per year) when using Fusion-eSCHIF. This suggests that to see meaningful air quality co-benefits of climate mitigation in Europe, climate mitigation and pollution control need to accelerate to more closely match the pathway set out by SSP1-2.6, as opposed to SSP2-4.5, however it also demonstrates the clear societal health benefits of doing so.

Table 1 compares the results found using both Fusion-eSCHIF and GEMM. We find similar $PM_{2.5}$ mortality (mid 400,000s) using either function. As Fusion-eSCHIF is age-agnostic, the breakdown by age group is produced only using GEMM. We find that Fusion-eSCHIF projects higher mortality at lower $PM_{2.5}$ concentrations, which may be because it includes a function designed to better reflect mortality at these levels, which results in marginally higher total mortality following all future scenarios than GEMM. The age profiles in GEMM show that in the future scenarios, overall mortality increases in the older age groups due to population aging following this method and older people being more vulnerable to air pollution health impacts. We also show the impacts when population is kept constant - in this scenario, instead of air quality mortality increasing following SSP2-4.5 and SSP3-7.0, it reduces by 99,000 and 65,000 deaths per year. This demonstrates that the increased population is responsible for the overall increase in mortality following these scenarios. It does however demonstrate that SSP1-2.6 results in much smaller mortality than either SSP2-4.5 or SSP3-0.70 in the absence of population change (approx 180,000 fewer deaths per year than SSP2-4.5), showing that considerable reductions in mortality can be attributed to the emissions reductions.

Figure 4 shows the spatial distribution of $PM_{2.5}$ mortality rate in the present day and the percentage change in each of the future scenarios. In the present day, $PM_{2.5}$-attributable mortality is highest in urban and industrial regions around the domain, notably the Rhine-Ruhr (Germany), the Po Valley (Italy), Midlands & London (UK) and the Hook of Holland (Netherlands). Following SSP3-7.0, there are reductions of up to 20% across many countries of the domain (France, Germany, the UK and Italy). Increases in mortality of up to 40% are seen across much of Spain and up to 60% across most of Ireland, although it should be noted that these countries have low present-day $PM_{2.5}$-attributable mortality. Similar reductions are seen following SSP2-4.5 and SSP1-2.6, but to greater degrees than SSP3-7.0, especially following SSP1-2.6, where mortality reduces by over 80% across parts of Central Europe. With this and the results in Table 1, we see that only SSP1-2.6 is sufficient for achieving an improvement in total $PM_{2.5}$-related mortality across Europe as a whole. This is despite the $PM_{2.5}$ reductions following these scenarios shown in Figure 2 as these reductions do not outweigh the increases in overall mortality caused by population change.

10.1029/2024EF005404

Table 1
Summed $PM_{2.5}$ Mortality in Each Scenario and Mean Mortality Rate per 100,000 Population Using Both Fusion-eSCHIF and GEMM

Metric	2014 VD reanalysis	SSP1-2.6	SSP2-4.5	SSP3-7.0
Mortality (1000s)	444 (405–486)	199 (127–271)	455 (415–494)	456 (419–495)
Mortality (1000s) (GEMM)	470 (386–552)	160(132–190)	447 (361–520)	451 (376–540)
Mortality 2020 pop	444 (405–486)	138 (88–189)	325 (297–353)	379 (349–411)
Mortality rate	83 (75–91)	31 (17–45)	84 (76–92)	99 (90–107)
Mortality rate (GEMM)	89 (73–107)	25 (21–30)	82 (67–96)	97 (79–114)
Mortality rate 2020 pop	89 (78–99)	23 (13–33)	63 (57–69)	74 (67–80)
Age 25–29	0.68 (0.56–0.79)	0.12 (0.1–0.15)	0.32 (0.26–0.38)	0.34 (0.28–0.4)
Age 30–34	1.2 (1–1.4)	0.21 (0.17–0.24)	0.53 (0.44–0.6)	0.56 (0.46–0.66)
Age 35–39	2.1 (1.7–2.5)	0.37 (0.3–0.44)	0.97 (0.8–1.1)	1 (0.83–1.2)
Age 40–44	3.9 (3.2–4.5)	0.64 (0.53–0.76)	1.72 (1.4–2)	1.78 (1.5–2.1)
Age 45–49	7.3 (6–8.5)	1.13 (0.93–1.34)	3.1 (2.5–3.6)	3.16 (2.6–3.7)
Age 50–54	13.2 (10.9–15.4)	2.14 (1.76–2.53)	5.78 (4.75–6.8)	5.95 (4.9–7)
Age 55–59	20.6 (17–24.2)	3.74 (3.1–4.4)	10 (8.2–11.7)	10.3 (8.5–12.1)
Age 60–64	28.5 (23.5–33.4)	5.8 (4.78–6.9)	15.2 (12.8–18.3)	16.1 (13.2–18.9)
Age 65–69	36.9 (30.4–43.3)	8.2 (6.7–9.7)	21.9 (18–25.8)	22.7 (18.7–26.7)
Age 70–74	45.6 (37.5–53.6)	12.2 (9.9–14.4)	32.9 (27–38.7)	33.8 (27.8–39.8)
Age 75–79	56.2 (46.1–66)	17.3 (14.1–20.5)	47.7 (39.1–56.2)	48.5 (39.8–57)
Age 80+	253.7 (208.1–298.4)	108.9 (87.9–127.8)	307 (251.1–362.2)	306.7 (251.1–361.3)
Mortality ($PM_{2.5}$)[a]	Approx 400,000			
Mortality ($PM_{2.5}$ + O_3)[b]	Approx 320,000			

Note. Confidence intervals in brackets. These are compared to total present-day $PM_{2.5}$ or $PM_{2.5}$ + O_3 mortality in Europe from other literature. Where the mortality is for a particular age group, GEMM has been used. [a]Juginović et al. (2021). [b]European Environment Agency (2023).

Mortality associated with 6mDM8h O_3 increased compared to the present day following SSP3-7.0 and SSP2-4.5 but decreased following SSP1-2.6 (Table 2). We see that overall O_3 mortality increases are almost universal across the domain following both SSP2-4.5 and SSP3-7.0, but are limited to some European urban areas (Paris, the Hook of Holland, The Rhine-Ruhr etc) following SSP1-2.6, which instead sees decreases across much of the domain 5. Peak season O_3 concentrations increase universally across the domain following SSP3-7.0, but only in some urban areas following SSP2-4.5 (Clayton et al., 2024). The reason SSP2-4.5 sees near universal increases in O_3 mortality, but not 6mDM8h O_3 is likely the result of population increases, as fixing population shows a considerable influence on this.

Clayton et al. (2024) attribute the 6mDM8h O_3 trends following SSP2-4.5 and SSP3-7.0 to the combined impact of increasing CH_4 emissions and reductions of NO_x emissions in populated areas. Following SSP1-2.6, 6mDM8h O_3 decreases universally across the domain because the influence of CO and CH_4 emissions decreases on O_3 outweigh increases in O_3 driven by NO_x emissions reductions. It is also plausible that changes in O_3-related mortality are muted compared to $PM_{2.5}$ as in Europe, O_3 related mortality is more sensitive to emissions changes outside the continent than locally, whereas local changes in emissions dominate contribution to $PM_{2.5}$ mortality (Liang et al., 2018).

Our present-day mortality results of 444,000 total $PM_{2.5}$-related deaths is comparable with other studies. Some studies using different exposure-response functions estimated lower total mortality for example, Juginović et al. (2021) estimate approximately 400,000 total deaths and the European Environment Agency (2023) estimate 420,000 total deaths. Our results estimate lower present-day mortality than some other studies, for example, Burnett et al. (2018), predict approximately 650,000 lives saved with a 100% reduction in air pollution over Europe. We also find lower total mortality attributable to air pollution than Tarín-Carrasco et al. (2019) do for

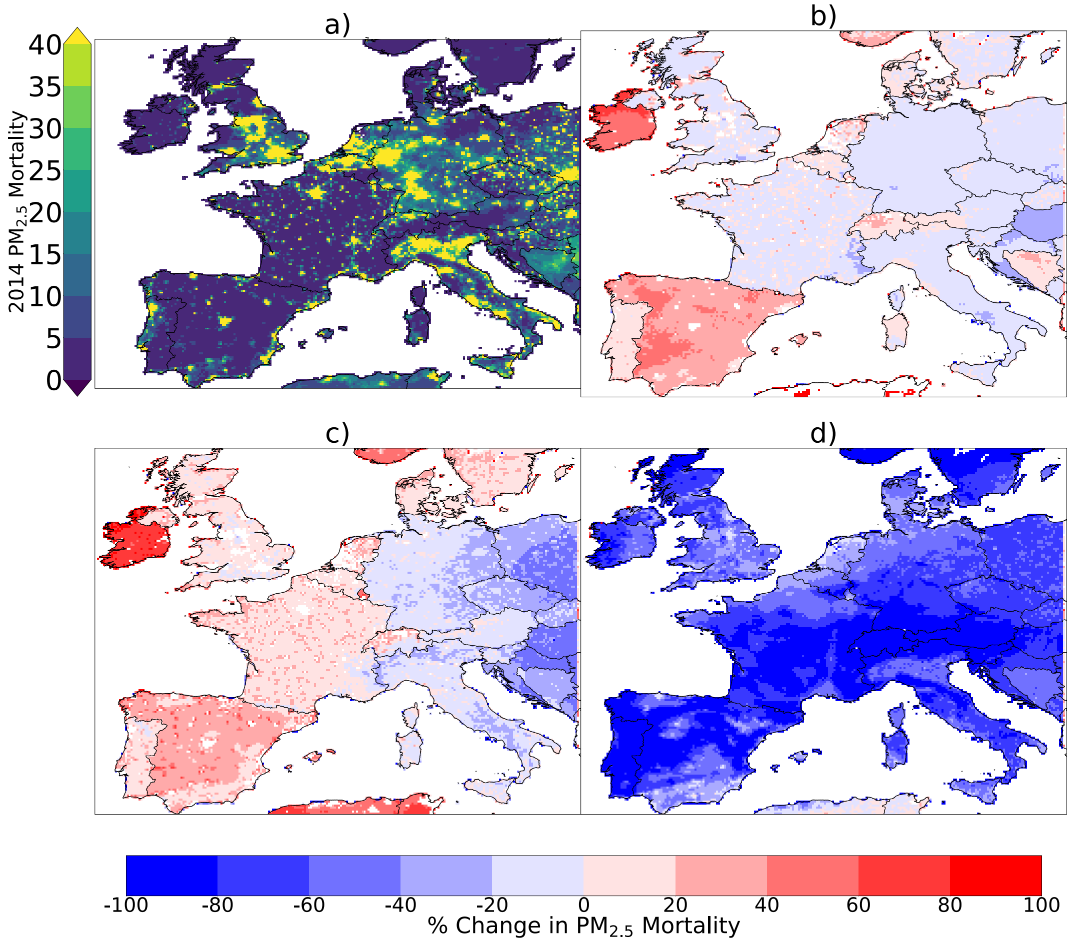

Figure 4. (a) Annual $PM_{2.5}$ mortality in 2014, (b) $PM_{2.5}$ mortality % change from the present day in 2050 following SSP3-7.0 (c) as (b) following SSP2-4.5 (d) as (b) following SSP1-2.6.

$PM_{2.5}$ alone across Europe (904,000 deaths in 2010). Our results are also comparable with the total air quality deaths across Europe found using GEMM by Lelieveld et al. (2019) of approximately 700,000. While our domain will be smaller than many of these studies, this demonstrates that our present-day mortality calculations are consistent with others in the literature.

Our projections of future $PM_{2.5}$ air quality mortality are considerably lower than the estimations for Europe from Chen et al. (2023), although our domain focuses on Western and Central Europe, so a smaller result would be expected. Chen et al. (2023) for example, project excess mortality in Europe of approximately 650,000–750,000 in each scenario (the same scenarios we project, with the addition of SSP5-8.5) from $PM_{2.5}$ based on an average year in the 2050s, compared to our projections of 199,000 for SSP1-2.6, 455,000 for SSP2-4.5 and 456,000 for SSP3-7.0 in the year 2050. This is likely because Chen et al. (2023) project increased excess deaths for all scenarios in Europe, this could be driven by a range of methodological differences, such as population aging, as they also project $PM_{2.5}$ reductions in Europe and reductions in mortality among the 25–74 age group, but increases in the 75+ age group. Yang et al. (2022) provide limited regional assessment of change in air pollution mortality, but project only small changes to $PM_{2.5}$ related mortality following all future scenarios, with some worsening outcomes in Southern Europe. This differs from our assessment that SSP1-2.6 will see considerably reduced air quality-related mortality. Turnock et al. (2023) estimate that in Western Europe, a scenario with SSP3-7.0 climate but present-day emissions would see approximately 20 fewer deaths per 100,000 per year (considering both $PM_{2.5}$ and O_3) in the 2050s, a similar, but lower magnitude trend to our results, in which our present-day scenario has 43 fewer deaths per 100,000 than our SSP3-7.0. Notably, we do not factor in the impact of climate change, which is likely to worsen O_3 health burden (Fann et al., 2012) and could worsen the $PM_{2.5}$

Table 2
O_3 *Air Quality Mortality in Each Scenario and Mortality Rate per 100,000 Population*

Metric	2014 simulation	SSP1-2.6	SSP2-4.5	SSP3-7.0
Total Mortality (thousands)	23.3 (19.6–27)	17 (14.3–19.9)	47.4 (39.9–55)	49.9 (42.1–57.8)
Total Mortality (thousands) (2020 pop)	23.3 (19.6–27)	8.1 (6.8–9.5)	23.7 (19.9–27.4)	29.3 (24.6–33.8)
Age 25–29	0.013 (0.011–0.016)	0.006 (0.005–0.007)	0.019 (0.015–0.02)	0.02 (0.017–0.023)
Age 30–34	0.019 (0.016–0.022)	0.006 (0.005–0.007)	0.016 (0.013–0.018)	0.018 (0.015–0.021)
Age 35–39	0.031 (0.026–0.035)	0.009 (0.008–0.011)	0.025 (0.021–0.029)	0.029 (0.024–0.033)
Age 40–44	0.056 (0.047–0.065)	0.016 (0.013–0.019)	0.044 (0.037–0.051)	0.049 (0.041–0.057)
Age 45–49	0.12 (0.099–0.14)	0.029 (0.024–0.034)	0.081 (0.068–0.094)	0.089 (0.075–0.1)
Age 50–54	0.25 (0.21–0.29)	0.067 (0.056–0.078)	0.19 (0.16–0.22)	0.2 (0.17–0.24)
Age 55–59	0.5 (0.42–0.58)	0.15 (0.13–0.18)	0.43 (0.36–0.5)	0.46 (0.39–0.54)
Age 60–64	0.91 (0.77–1.1)	0.3 (0.25–0.35)	0.86 (0.72–0.99)	0.93 (0.78–1.1)
Age 65–69	1.48 (1.24–1.71)	0.54 (0.45–0.63)	1.53 (1.29–1.78)	1.65 (1.4–1.92)
Age 70–74	2.13 (1.8–2.47)	1.06 (0.89–1.24)	3.06 (2.58–3.56)	3.28 (2.77–3.8)
Age 75–79	3.25 (2.74–3.78)	1.79 (1.5–2.1)	5.12 (4.31–5.93)	5.44 (4.59–6.3)
Age 80+	14.5 (12.2–16.8)	13.1 (10.9–15.2)	36.1 (30.3–41.8)	37.8 (31.9–43.7)
Mean mortality rate	5.1 (4.3–5.9)	2.5 (2.1–2.9)	8.9 (7.5–1.03)	11.1 (9.3–12.8)
Mean mortality rate (2020 pop)	5.1 (4.3–5.9)	1.3 (1.1–1.5)	4.6 (3.9–5.4)	5.8 (4.9–6.7)

health burden (Turnock et al., 2023). Overall, our findings suggest considerable larger reductions in air quality-related mortality than other literature in the field. This is likely a product of the better resolution of our model, as we capture large decreases in mortality in urban centers. Work using coarser models may miss the peaks in air pollutant concentrations in urban areas and subsequently may also miss how much mortality reductions are achieved by air quality improvements in these regions (Fenech et al., 2018). The improved ability of Fusion-eSCHIF to represent mortality at lower $PM_{2.5}$ concentrations may also contribute.

The results in Table 1 demonstrate the importance of population change in future mortality. While the mortality calculations using population projections for SSP2-4.5 and SSP3-7.0 are similar to each other and the present day, if the population is kept constant at present-day levels, we see that SSP2-4.5 does result in 54,000 fewer air quality-related deaths per year than SSP3-7.0. This is not unexpected - previous research suggests that changes in population and baseline mortality outweigh changes in air pollutant concentrations when determining changes in air quality relating to mitigation policies (Vohra et al., 2022).

We see that $PM_{2.5}$ mortality is by far the dominant factor in air quality mortality in the domain, but that O_3 mortality becomes a more important proportional factor in future air quality mortality compared to the present day, going from being responsible for approximately 5% of total air quality-related mortality in the present day, to approximately 10% for each of the future scenarios. This is despite small overall reductions in $PM_{2.5}$, demonstrating that unless ambitious policies to cause large improvements in air quality are put in place, poor air quality will become an increasingly dominant factor toward ill health in Europe.

One limitation of our methodology is not factoring in the impact of climate change itself on air quality mortality. Climate change is expected to cause a penalty to O_3 reduction and is projected to have complex effects on $PM_{2.5}$ that can cause increases or decreases depending on how climate change modifies local meteorology (Doherty et al., 2017). Comparison with previous research suggests that the impacts of emissions change will eclipse the impacts of climate change itself. For example, Silva et al. (2017) estimate that by 2100 following RCP8.5, a scenario that projects much greater climate change than the scenarios we use, the combined excess $PM_{2.5}$ and O_3 deaths in Europe attributable to climate change number less than 13,000 per year (<3,000 O_3, <10,000 $PM_{2.5}$), which are far lower than the number of deaths we expect could be prevented by emissions reductions. Another study by L. T. Murray et al. (2024) also suggests that impacts of climate change on air quality will be muted but that $PM_{2.5}$ deaths could actually decrease, suggesting that globally, O_3 deaths in the 2090s following SSP3-7.0 could increase by approximately 34,600 and $PM_{2.5}$ deaths could reduce by around 60,000. A study by Zanis et al. (2022) suggests that climate change could also have non-linear impacts on O_3 chemistry, and actually cause a small reduction in surface O_3 concentrations over most global regions, excluding the heavily polluted areas, despite the common expectation that higher temperatures result in greater O_3 concentrations. This demonstrates that the impacts of climate change on both $PM_{2.5}$ and O_3 are expected to be small, and subject to considerable uncertainty.

Notably, climate change meteorology could also impact on mortality from extreme heat. Extreme heat events have been shown to have notable impacts on mortality in Europe, for example, a set of heatwaves in 2022 in Europe was estimated to result in 60,000 deaths from heat stress across Europe (Ballester et al., 2023). Increases in temperature from climate in Europe are widely expected to increase temperature-related mortality due to heat-related mortality increases outweighing decreases in cold-related mortality (García-León et al., 2024). The impacts of heat-related mortality in Europe, even following pessimistic scenarios until 2100 are however smaller than the reductions in air-quality related mortality possible from stringent emissions reductions. For example, Masselot et al. (2025) estimate that following SSP3-7.0, by 2100 excess annual heat-related deaths in European cities could reach approximately 80,000 per year and García-León et al. (2024) estimate 51,000 annual heat-related deaths in 2100 following current climate policies. While these are significant numbers of deaths, they serve to demonstrate just how important air pollutant emissions reductions are for securing population health in comparison to other health threats. This emphasizes the importance of ensuring that air quality improves to mitigate other population health pressures that will emerge in Europe over the coming century.

3.3. Equity in Reductions in Air Quality-Related Mortality

Figure 5 shows the average subnational HDI of NUTS-2 subregions of European countries plotted against their adult mortality rate per 100,000 people attributable to $PM_{2.5}$. The present-day is shown in Figure 6a. Figures 6b–6d use the $PM_{2.5}$ attributable mortality rate from SSP3-7.0, SSP2-4.5 and SSP1-2.6 respectively. All panels use present-day subnational HDI. We see that in the present day, on average subregions with lower HDI have higher mortality rate attributable to $PM_{2.5}$, for example, the subregions in the lowest decile of HDI have an air quality-related mortality rate of 120 per 100/000 people per year, whereas the subregions in the highest decile have a mortality rate of approximately 70 per 100,000 people. This trend is statistically significant based on a Fisher-z transformation test, and the relationship between $PM_{2.5}$-attributable mortality and subnational HDI continues to be statistically significant in each future scenario. While this trend persists following the future scenarios, we find that in all future scenarios, the reductions in $PM_{2.5}$ mortality rate in lower HDI areas is larger than in higher HDI areas, meaning that inequity in poor health outcomes from $PM_{2.5}$ exposure is mitigated following the emissions reductions in each scenario. The key difference however is between SSP2-4.5 and SSP1-2.6. We see here that the overall reductions in $PM_{2.5}$ mortality rate are larger following SSP1-2.6, however, SSP2-4.5 is more "equitable" in terms of outcomes as it does not show as clearly a trend of higher HDI areas having reduced mortality rates than lower HDI areas, whereas SSP1-2.6 does. Our results in the present day are similar to those of Reddington et al. (2023), that lower income groups experience worse health outcomes from $PM_{2.5}$. We do not find the same overall result that more deprived groups get the lowest benefits from decarbonization; we instead find that more deprived groups get increased benefits from decarbonization overall, but that this varies by scenario. In scenarios with smaller emissions reductions, for example, SSP3-7.0 the benefits are greater in less deprived regions. The additional emissions reductions that differentiate SSP1-2.6 from SSP2-4.5 result in greater improvements in higher HDI regions. This suggests that the findings of Reddington et al. (2023) on the inequity of decarbonization on a global scale may not be replicated in Europe.

Table 3 shows the line gradients and Pearson coefficients of the relationships between $PM_{2.5}$ mortality rate and HDI where subregions of European countries have been separated by a range of characteristics (e.g., rural/Urban classification as defined by De Beer et al. (2014), whether the subregions is coastal or inland etc.). The corresponding scatter plots are available in Supporting Information S1; see Figures S1 and S8 in Supporting Information S1. This may help explain the differences between SSP2-4.5 and SSP1-2.6. For example, when urban subregions are isolated, a similar pattern to the overall trend is seen (Figure S2 in Supporting Information S1). In contrast, in rural regions, there is far greater clear inequity in $PM_{2.5}$ mortality rate in all scenarios (Figure S1 in Supporting Information S1). This is because $PM_{2.5}$ mortality rate in higher HDI urban subregions does not reduce as strongly as in lower HDI urban regions following SSP2-4.5. We can also see from Table 3 that population change is not the driving factor in the more equitable $PM_{2.5}$ exposure across the continent following SSP2-4.5

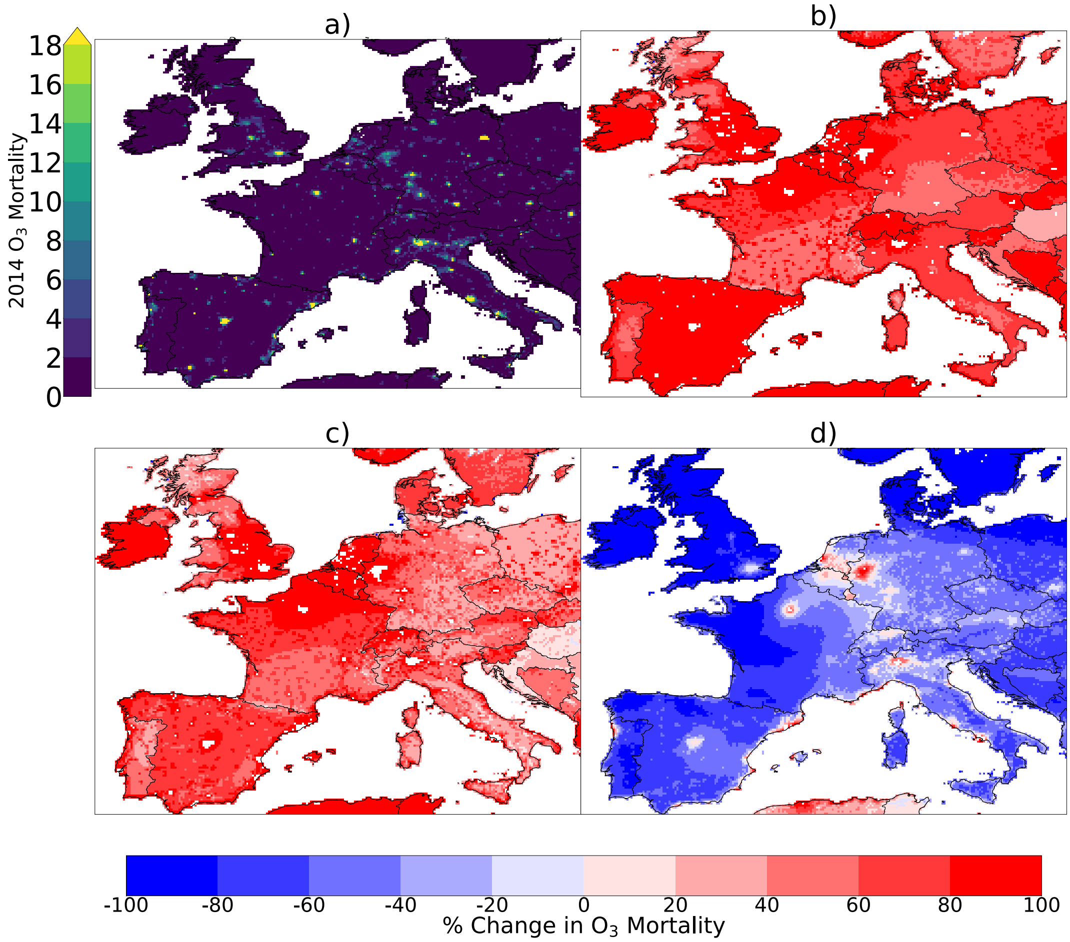

Figure 5. (a) Annual O_3 mortality in 2014, (b) Annual O_3 mortality % change from the present day in 2050 following SSP3-7.0 (c) as (b) following SSP2-4.5 (d) as (b) following SSP1-2.6.

than SSP1-2.6. When the population is kept consistent, we see a similar trend in equity to when it is not (Figure S8 in Supporting Information S1).

The trends driving the underlying $PM_{2.5}$ concentration changes described by Clayton et al. (2024) can explain why there is a rural/urban split in the trend we observe; following SSP2-4.5, across Eastern parts of the domain, which tend to have lower HDI, reductions in urban residential emissions, have greater influence on surface $PM_{2.5}$ than in Northern/Western Europe, which generally have higher HDI. In these regions, urban emissions are more likely to be associated with transport and Nitrogen Oxides (NO_x) form a larger proportion of emissions. SSP2-4.5 sees $PM_{2.5}$ reductions hampered by increased formation of secondary $PM_{2.5}$ due to reductions of one precursor, NO_x in the absence of reductions of NH_3. SSP1-2.6, on the other hand, has more regions that see NH_3 emissions reductions than SSP2-4.5. This may result in the impact of increased secondary $PM_{2.5}$ formation on overall $PM_{2.5}$ concentrations and mortality in high-HDI urban regions being lessened. This suggests that reducing agricultural emissions will improve the equity of $PM_{2.5}$-attributable mortality across Europe.

The only types of areas that do not see the same trend of greater inequity of exposure following SSP1-2.6 than SSP2-4.5 are Coastal subregions (Figure S4 in Supporting Information S1) and those in Northern Europe (Figure S5 in Supporting Information S1). These two classifications have considerable overlap and exclude many of the major cities in Central Europe where urban residential emissions dominate. Both show a clear trend of improving equity in the scenarios with more ambitious emissions reductions. Coastal regions are more likely to have natural $PM_{2.5}$ from sea salt as a significant portion of overall $PM_{2.5}$ (Manders et al., 2010), and thus do not show as strong reductions in $PM_{2.5}$ (Figure 2). The lower contribution of anthropogenic $PM_{2.5}$ to the total concentration may mean that the impacts of emissions change on equity of $PM_{2.5}$ exposure is lessened as there is a higher background

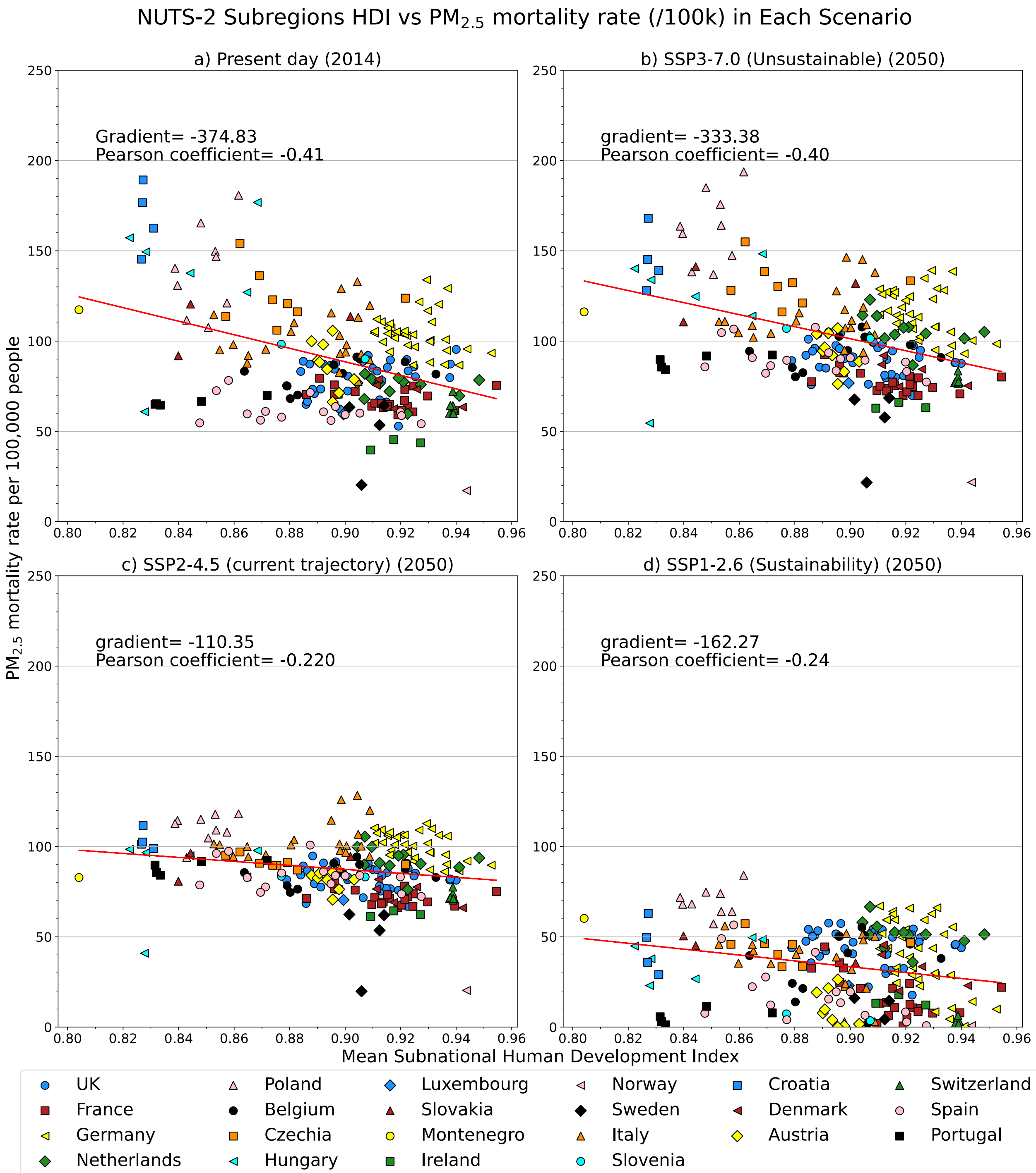

Figure 6. Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs. mean human development index (HDI)) in NUTS 2 subregions in panel (a) the present day (b) SSP1-2.6 2050, (c) SSP2-4.5 2050, and (d) SSP3-7.0. Each point on the plot is color-coded by the Country the subregion is in. The *r*-value of the correlation and the gradient of the linear regression line (the change in $PM_{2.5}$ mortality rate per 0.1 increase in HDI) are also provided.

level of $PM_{2.5}$. Additionally, the exclusion of the parts of the domain with high residential emissions of primary $PM_{2.5}$ means that the trends in these subregions will be determined by the formation of secondary $PM_{2.5}$. This supports our hypothesis that the overall trend in equity of $PM_{2.5}$ exposure following SSP2-4.5 is caused by larger emissions reductions in areas where $PM_{2.5}$ is dominated by emissions from the residential sector (usually inland areas in Central Europe) compared to areas in which NO_x and NH_3 emissions contribute more to $PM_{2.5}$.

Table 3
Pearson Coefficient and Gradient of the Linear Regression Line Between $PM_{2.5}$-Related Mortality Rate per 100,000 People and HDI of NUTs-2 Subregions of European Countries Selected by Different Parameters (Or All Subregions in the Case of Consistent Population, Where the Population Change is Assumed To Be 0 Between Scenarios When Calculating Mortality)

	Pearson coefficient (R) and Gradient (G)			
	Present day	SSP3-7.0	SSP2-4.5	SSP1-2.6
Rural only	**R:-0.6 G:-577.7**	**R:-0.6 G:-528.4**	**R:-0.4 G:-217.3**	**R:-0.3 G:-202**
Urban only	**R:-0.19 G:-211.1**	**R:-0.13 G:-127.2**	**R:-0.02 G: -17**	**R:-0.1 G: -108.1**
Inland only	**R:-0.5 G:-475.7**	**R:-0.5 G:-392.8**	**R:-0.2 G:-76**	**R:-0.3 G:-216.9**
Coastal only	**R:-0.3 G:-264.9**	R:-0.4 G:-282.7	R:-0.3 G:-196.9	**R:-0.1 G:-60.9**
Northern Europe	**R:-0.22 G:-197.6**	R:-0.23 G:-241	R:-0.18 G:-145.5	**R:-0.13 G:-106.9**
Central Europe	**R:-0.59 G:-546.1**	**R:-0.64 G:-593.9**	**R:-0.35 G:-158.9**	**R:-0.57 G:-421.2**
Southern Europe	**R:-0.37 G:-385.7**	R:-0.28 G:-186.9	**R:-0.03 G:-14.84**	**R:-0.35 G:-199.2**
Consistent population	**R:-0.41 G:-374.8**	**R:-0.36 G:-234.4**	**R:-0.15 G:-64.5**	**R:-0.22 G:-111.8**

Note. Where a statistically significant relationship is present, defined using Fisher's *z*-transformation to generate a 95% confidence interval from the *p*-value, the data is highlighted in bold.

We do not see a trend of increasing inequity in the population-weighted $PM_{2.5}$ concentrations, finding that annual mean $PM_{2.5}$ is approximately 1/3 higher in the least deprived quintile of regions compared to the most deprived, almost the opposite result to the European Environment Agency (2023). Notably, however, The European Environment Agency (2023) cover a wider domain (including more countries in Eastern Europe), use GDP per capita for deprivation as opposed to HDI and use smaller subregions (NUTS 3). The size of the subregions may explain the differing trends - NUTS 3 subregions can capture differences within larger urban areas, there may be a greater number of urban regions with lower GDP, rather than what we see with most urban areas being less deprived than the surroundings. The NUTS 3 subregions were too small for us to use with our model output. The differing trend between overall $PM_{2.5}$ concentration and $PM_{2.5}$ attributable mortality rate is likely because we project high $PM_{2.5}$ in urban centers, such as Paris and London. These areas have high population, often higher than other sub-regions, but a lower proportion will die from air quality-related conditions, potentially due to a different age profile.

We do not see a strong trend linking O_3 mortality rate and HDI, as shown by Figure 7, which is the same format as Figure 7, but instead plots O_3-attributable mortality rate against subnational HDI. In the present day, we see a marginally (but non-significant) higher mortality rate from O_3 in lower HDI subregions (109/100,000 in the most deprived decile compared to 101/100,000 in the least deprived). This relationship is statistically significant at the 95% confidence level based on a Fisher-z transformation test. There is not a statistically significant relationship between overall O_3-attributable mortality rate and HDI for any of the future scenarios. There is a clear split between Northern and Southern Europe, with Southern European countries such as Italy, Spain, Portugal and Croatia having higher O_3 mortality rate than in countries such as the UK, Ireland and The Netherlands. This is consistent with the findings of Clayton et al. (2024) who show higher peak season O_3 in Southern European countries than Northern European countries. Following SSP2-4.5 and SSP3-7.0 we see increases in O_3 mortality rate and these increases are larger in subregions of Southern European countries. Notably, population change is expected to have a larger impact on the O_3 results than for $PM_{2.5}$, evidenced by the limited change in equity of O_3 when population is kept consistent (Table 4) compared to when it is not (Figure 7).

We find that the trend of lower HDI subregions having slightly higher O_3 mortality rate increases following SSP3-7.0. This is likely due to the increases seen in Southern Europe, where the subregions have on average lower HDI. The opposite is seen however following SSP2-4.5 where proportionally higher increases in O_3-attributable mortality rate are seen in higher HDI regions, although lower HDI regions do still see worse O_3 mortality rate overall. Notably, when Northern, Central and Southern Europe are isolated (Figures S13–S15 in Supporting Information S1) this trend changes, for example, Southern Europe sees Higher HDI regions have an even larger burden from O_3 mortality than the overall trend, but it stays mostly constant for Central Europe. Conversely, there is no observable trend between O_3 mortality rate and HDI for Northern European regions (Table 4).

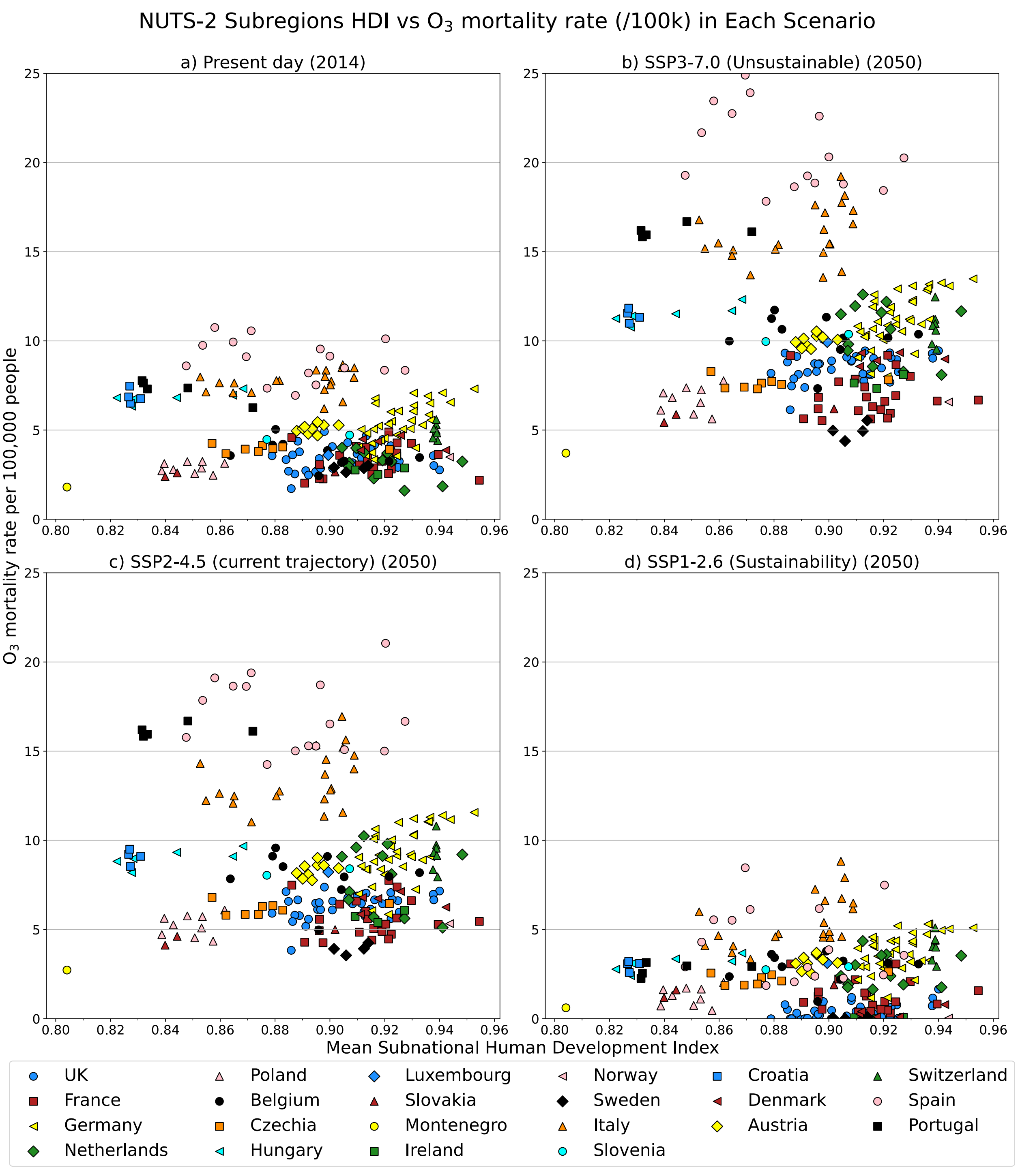

Figure 7. Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs. mean human development index (HDI)) in NUTS 2 subregions in panel (a) the present day (b) SSP3-7.0 2050, (c) SSP2-4.5 2050, and (d) SSP3-7.0. Each point on the plot is color-coded by the Country the sub-region is in. The r-value of the correlation and the gradient of the linear regression line (the change in O_3 mortality rate per 0.1 increase in HDI) are also provided.

The predominate differences between SSP2-4.5 and SSP3-7.0 in terms of emissions that may explain these trends as there are significantly larger increases in CH_4 emissions assumed following SSP3-7.0 compared to the present day than following SSP2-4.5 (which may result in greater increases in rural areas where agricultural emissions are high). CO emissions also increase following SSP3-7.0, but reduce following SSP2-4.5. The increase in CO emissions could suggest that a larger increase in O_3 mortality rate could be seen where there is a large combustion

Table 4
Pearson Coefficient and Gradient of the Linear Regression Line Between O_3-Related Mortality Rate per 100,000 People and HDI of NUTs-2 Subregions of European Countries Selected by Different Parameters (Or All Subregions in the Case of Consistent Population, Where the Population Change is Assumed To Be 0 Between Scenarios When Calculating Mortality)

	Pearson coefficient (R) and Gradient (G)			
	Present day	SSP3-7.0	SSP2-4.5	SSP1-2.6
Rural only	**R:-0.32 G:-22.2**	**R:-0.34 G:-35.22**	**R:-0.24 G:-30.4**	**R:-0.37 G:-17.9**
Urban only	R:-0.12 G:-11.26	R:-0.11 G:-19.3	R:-0.07 G:-11	R:0.03 G:3
Inland only	R:-0.21 G:-13.9	P:-0.12 G:-16.2	R:-0.1 G:-12	**R:0 G:0.17**
Coastal only	**R:-0.45 G:-38**	R:-0.4 G:-72.2	R:-0.42 G:-64.5	**R:-0.36 G:-27.8**
Northern Europe	R:0.07 G:2.88	R:0.16 G:15.1	R:0.13 G:10.4	R:0.1 G:5.4
Central Europe	**R:0.49 G:20.4**	R:0.59 G:42.9	R:0.62 G:40.9	**R:0.58 G:24**
Southern Europe	**R:0.03 G:1.7**	R:0.17 G:24.2	R:0.2 G:24.6	R:0.24 G:14.21
Consistent population	R:-0.21 G:-13.9	R:0.03 G:2.47	R:0.05 G:2.34	R:0.01 G:0.45

Note. Where a statistically significant relationship is present, defined using Fisher's *z*-transformation to generate a 95% confidence interval from the *p*-value, the data is highlighted in bold.

power sector, which is supported by an increase in energy sector emissions across most of the domain. The O_3 mortality rate increases in SSP3-7.0 are by far highest in urban regions of Spain. These subregions do not see as proportionally high an increase following SSP2-4.5. Spain notably sees large increases in agricultural and energy sector emissions following SSP3-7.0. Despite this, it is the also proportionally larger increases in O_3 mortality rate following SSP3-7.0 than following SSP2-4.5 in rural regions of low-HDI Central European countries (Croatia, Hungary, Poland) that causes the widening inequity following SSP3-7.0.

Following SSP1-2.6, where there is the least influence of HDI on O_3-related mortality, the higher HDI subregions do see slightly higher O_3 mortality rate than lower HDI regions. These trends may be explained by spatial patterns and the diverging trend in O_3 following the scenarios. We see worsening O_3 for much of the domain following SSP2-4.5 and across the entire domain following SSP3-7.0. This is stronger however in Southern Europe (Spain, Italy) which largely has HDI in the medium range, and in some higher-income countries on the continent (Germany, Switzerland the Netherlands) than more deprived countries including Poland and Slovakia. While the increases in O_3 mortality rate following both SSP2-4.5 and SSP3-7.0 are proportionally similar in both rural and urban regions, the improvements following SSP1-2.6 are stronger in rural regions (Figure S9 in Supporting Information S1). This may be why the reductions in O_3 mortality favor less deprived regions, thus making mortality rate more equitable between the different socioeconomic groups. It must be considered that the trends in equity of O_3 exposure differ when the population is kept consistent; although there is a higher O_3-related mortality rate in lower-HDI subregions of Europe following SSP3-7.0 and SSP2-4.5, this effect is much more muted with a consistent population (Table 4; Figure S16 in Supporting Information S1) suggesting that the distribution of population change is a considerable factor toward this trend.

4. Conclusions

We find that on average, only SSP1-2.6 is projected to reduce annual mortality and mortality rate from $PM_{2.5}$ in 2050 compared to the present day (by 55%), whereas SSP2-4.5 and SSP3-7.0 have small increases from $PM_{2.5}$ mortality (1.2% and 19.3% respectively). This is likely due to the impact of population increases following the latter two scenarios outweighing the influence of reduced $PM_{2.5}$ concentrations. The use of the Fusion-eSCHIF function for calculating mortality may also contribute to this effect, as using GEMM, SSP2-4.5 instead shows small decreases in mortality and mortality rate.

SSP1-2.6 brings over 70% of the population of Western and Central Europe below the WHO's $PM_{2.5}$ guideline value, while all other scenarios have less than 10% under this value, but no scenario is sufficient for meeting the WHO's O_3 guideline value. This demonstrates the clear value of targeting a high mitigation scenario for achieving air quality co-benefits of climate mitigation in Europe.

We find that the present-day air quality mortality rate from both $PM_{2.5}$ and O_3 is worse in more deprived sub-regions of Europe. This gap is expected to reduce for both $PM_{2.5}$ and O_3 compared to the present day for both SSP2-4.5 and SSP1-2.6. In contrast, there is limited change from the present day for $PM_{2.5}$ mortality rate and increased inequity for O_3 mortality rate following SSP3-7.0. Following SSP2-4.5, inequity in $PM_{2.5}$ exposure completely changes pattern, with very little difference in mortality rate evident comparing higher and lower HDI regions, whereas O_3 continues with the same pattern of higher mortality rate in lower HDI regions as the present day. Overall, we see that ambitious emissions reductions decrease the inequity of mortality rate from air quality. Although for $PM_{2.5}$, inequity appears to lessen more following SSP2-4.5 compared to SSP1-2.6, this is due to ineffective air quality mitigation in high-HDI regions. Both high and low HDI regions benefit more in terms of reduced mortality rate from the more ambitious emissions reductions following SSP1-2.6.

Our results suggest directions policymakers could take to ensure public health is protected and equity issues are managed as we aim to mitigate climate change. We believe that the results provide strong evidence for a focus on mitigating agricultural emissions to maximize co-benefits of climate mitigation. This is because we see that the smaller improvements in $PM_{2.5}$ mortality rate following SSP1-2.6 are seen in deprived, rural regions. We also see that following SSP3-7.0, it is rural regions that experience more mortality from O_3, in part driven by increasing CH_4 emissions. Policymakers in Europe can improve air quality across Europe through conventional climate change mitigation methods targeting sectors such as power, industry and transport, but these improvements can only be equitable if predominant sources of air pollutants in rural areas, particularly agriculture see strong mitigation efforts alongside these and that focus is given to more deprived regions that already have worse health outcomes associated with poor air quality.

We do not factor in the implications of climate change on health, only the emissions changes as the computational expense of the model used did not allow for simulations long enough to capture climate variability. It will be important to consider the separate impacts of both emissions and climate change for driving policy decisions, especially as our work, found that increases in O_3-related mortality could cause worsening overall air quality-related mortality despite $PM_{2.5}$ reductions. Because climate change itself is expected to worsen O_3 pollution, this could mean that future populations could be even more badly affected by poor air quality without strong mitigation action. Quantifying this could be of great value to understanding the health risks to the population of Europe from failing to adequately mitigate climate change.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Model output and mortality output on which this article are based are available at Clayton (2024a, 2024b). The CMIP6 emissions inputs for the model as described by Hoesly et al. (2018) and Feng et al. (2020) are freely available online. This is also true of the CMIP6 output as decribed by Danabasoglu (2019), the ECMWF ERA5 meteorology data (Hersbach et al., 2020) the VD Reanalysis (Van Donkelaar et al., 2021), the gridded HDI data set (Kummu et al., 2018), the population projections and baseline mortality rates consistent with the SSPs (Jones & O'Neill, 2016), Frederick S. Pardee Center for International Futures (2021).

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