

UNIVERSITY OF LEEDS

The Air Quality Co-benefits of a Low Carbon Economy in Europe

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Abstract

Air quality in Europe has improved since the Industrial Revolution, however, Europe still experiences greater than average mortality due to air pollutant exposure. Many of the sources of air pollutants are the same as those of greenhouse gases and thus, in theory, societal developments designed to mitigate climate change could also improve air quality. This is however, more complex than it seems on the face of it, as the dominant sources of air pollutants can modify the efficacy of climate mitigation for achieving air quality co-benefits. Secondary pollution can also pose an issue, particularly regarding ozone, which is projected to increase as the climate changes. Nevertheless, if air quality co-benefits of climate change mitigation can be achieved in Europe, this could be very impactful for public health, counteract any mitigation costs and help position European policymakers as climate leaders, potentially encouraging more ambitious mitigation in countries that emit more greenhouse gases.

There are many studies that consider co-benefits, however, this is challenging to model. Modelling air quality tends to require very detailed and computationally expensive models that run at a fine enough resolution to capture elevated urban concentrations and have a detailed representation of chemistry. Modelling climate change however, is best undertaken using global climate models, which trade resolution and chemistry for the ability to capture physical changes in the climate system over very long periods. Up to now, most of the research uses the latter. Additionally, recently, new scenarios for driving these models were developed. These Shared Socioeconomic Pathways provide a greater representation of the societal changes, many of which would be extremely meaningful for air quality, than the prior Representative Concentration Pathways upon which much of the existing research is based. This thesis uses the more recent SSPs and a regional atmospheric chemistry model to model air quality co-benefits of a low-carbon economy in Europe compared to a "business as usual" pathway and a "low mitigation pathway". This better represents the impacts at a scale relevant to European policymakers,

and allows for more detailed analysis of the drivers of future air quality local to Europe. It does however, have a limitation in that the physical effects of climate change on air quality are not considered. This thesis presents three chapters:

In the first, I used a detailed regional atmospheric-chemistry model (WRF-Chem v4.2) to model European air quality in 2050 compared to 2014 following three climate change mitigation scenarios.Different climate futures are respresented by using air pollutant emissions and chemical boundary conditions (from CESM2-WACCM output) for three shared socioeconomic pathways (SSP1-2.6, SSP2-4.5 and SSP3-7.0: high-, medium- and low-mitigation pathways respectively).

In this, I show that in 2050, following SSP1-2.6, mean population-weighted $PM_{2.5}$ concentrations across European countries are reduced by 52% compared to 2014. Under SSP2-4.5, this average reduction is 34%. The smallest average reduction is 18%, achieved following SSP3-7.0. Maximum 6-monthly-mean daily-maximum 8h (6mDM8h) ozone (O_3) is reduced across Europe by 15% following SSP1-2.6 and by 3% following SSP2-4.5, but it increases by 13% following SSP3-7.0. This demonstrates clear co-benefits of climate mitigation. The additional resolution allows us to analyse regional differences and identify key sectors. We find that the mitigation of agricultural emissions will be key for attaining meaningful co-benefits of mitigation policies, as evidenced by the importance of changes in NO_3^- aerosol mass to future $PM_{2.5}$ air quality and changes in CH_4 emissions to future O_3 air quality.

In the second, I analyse 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 the same model output from the first chapter. I use recent health functions to estimate mortality related to the aforementioned pollutants. I also present a first-of-its kind analysis of 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.

I 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. I 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.

In the final chapter, I aim to mitigate the limitation of the regional model by using heatwaves as an analogue for climate change and estimating how they modify UK air pollution. In this study, I use WRF-Chem 4.2 to estimate summer concentrations of $PM_{2.5}$ and O_3 air quality with CMIP6 emissions representative of the year 2014 and 2050 following a scenario with little climate change mitigation (SSP3-7.0) and 2014 meteorology. I compare this to model simulations where meteorology from a year with a notable heatwave (2022) has instead been used. This allows me to test whether conditions that will become much more frequent in a low-mitigation future cause air pollution episodes in the UK.

I demonstrate that a summer with frequent heatwaves has limited impact on $PM_{2.5}$ concentrations in the UK (ranging from a decrease of -0.22 $\mu g/m^3$ in the North West to maximum of 1.53 $\mu g/m^3$ increase in London). Although these changes are small, the increased number of days in most UK regions that see elevated $PM_{2.5}$ concentrations exceed the decreases they would see if only emissions changes from a weak mitigation scenario were considered resulting in a net increase of up to 7 days of elevated population exposure in Wales and South-West England.

This effect is amplified for O_3 concentrations, which are considerably elevated in the heatwave conditions (maximum of 14.15 increase $\mu g/m^3$ in the East Midlands). I find that the increases in O_3 in these periods can considerably exacerbate the worsening O_3 air quality seen in the UK from following a weak climate mitigation scenario, to a degree larger than the impacts of the emissions change itself. Regions of the UK can see up to 22 more days with elevated O_3 concentrations (in Wales) where both emissions and heatwave conditions are considered compared to a maximum increase from emissions alone of 12 days (London). This emphasises the potential co-benefits of stringent mitigation of anthropogenic emissions associated with climate change and air quality; stringent mitigation scenarios will not only have reduced long-term air pollutant concentrations, but less frequently see heatwave conditions that cause considerably elevated short-term O_3 concentrations.

Intellectual Property

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This thesis is submitted using the University of Leeds alternative thesis format. The requirements of this are three primary research chapters, one published, one submitted with permissions to resubmit and one formatted close to being ready for submission. These are to be presented with an introduction section of not more than 15000 words and a discussion and conclusions section of not more than 10000. Two of the primary research chapters I present have been peer reviewed and published and the third has been written and formatted with the intention of submission. I am the first author of all primary research chapters presented in this thesis.

The published papers included are:

Clayton, C. J., Marsh, D. R., Turnock, S. T., Graham, A. M., Pringle, K. J., Reddington, C. L., Kumar, R., and McQuaid, J. B.: The co-benefits of a low-carbon future for PM2.5 and O3 air pollution in Europe, Atmos. Chem. Phys., 24, 10717–10740, https://doi.org/10.5194/acp-24-10717-2024, 2024.

This paper makes up the 2nd chapter in the thesis and is described as "paper 1". The text is the same as the version accepted by the publisher, with some formatting changes in the tables and figures to maintain consistency in the thesis. Tables and figures have been re-numbered so as to have a consistent system throughout the thesis.

I conceptualised the paper with support from JM, DM, ST and KP. I performed all model simulations, produced all figures and wrote the manuscript. AG provided support with model

setup and producing chemical boundary conditions (the input files for which were provided by DM. CR also helped with model setup. RK contributed guidance on the development of anthropogenic emissions files. All co-authors assisted with production of the final manuscript.

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The text is the same as the version accepted by the publisher, with some formatting changes in the tables and figures to maintain consistency in the thesis. Tables and figures have been re-numbered so as to have a consistent system throughout the thesis. The author contribution is expanded in the chapter so as to communicate the contribution of each author more clearly.

In this, I conceptualised the paper with support from JM, DM and ST. I developed the methodology for assessing equity and performed all data analysis. The code for health impacts estimations was provided by CR and guidance on/ input on writing about the function was provided by KV. AG assisted with bias correction. All co-authors assisted with production of the final manuscript.

The 3rd paper has not yet been submitted and is presented in chapter 4 of this thesis.

I performed all model simulations, produced all figures and wrote the manuscript for this chapter. I conceptualised the methodology with input from ST.

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Signed 

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Chapter 1

Introduction

1.1 Air Pollution Health Impacts

Poor air quality is the largest environmental risk factor for early deaths globally, with an estimated health burden of 8.1 million deaths per year, considering both ambient and household exposure (Health Effects Institute, 2024). Even in Europe, where air quality is generally better than high-risk regions such as South Asia, the expected yearly mortality is approximately 300,000 (Juginovic et al. 2021) to nearly 800,000 (Lelieveld et al. 2019a). Although there are many harmful air pollutants, much of the research into health impacts focuses on $PM_{2.5}$ (all suspended solid or liquid particles with a diameter under 2.5 microns) and surface-level ozone (O_3).

Poor air quality is associated with several health conditions; long-term, ambient $PM_{2.5}$ exposure is considered to have a causal link with ischaemic heart disease (IHD), strokes, lung cancer (LC) and worse outcomes from lower respiratory infections (LRI). Surface-level O_3 is similarly associated with cardiovascular (CVD) and respiratory disease (Jerrett et al 2009). Where health impacts associated with air pollution are estimated, some early functions consider only causal links and provide health impact functions for individual conditions (Burnett et al. 2014). The health impacts of air quality are known to expand far beyond these conditions; Schraufnagel et al. (2019) review the literature on noncommunicable disease burden. Figure 1.1 and Table 1.1 summarise the relevant impacts, including outcomes for which there is currently insufficient evidence to determine causality. More recent health impacts functions quantify $PM_{2.5}$ mortality with all non-communicable disease and LRI to capture these wider morbidities (Burnett et al.

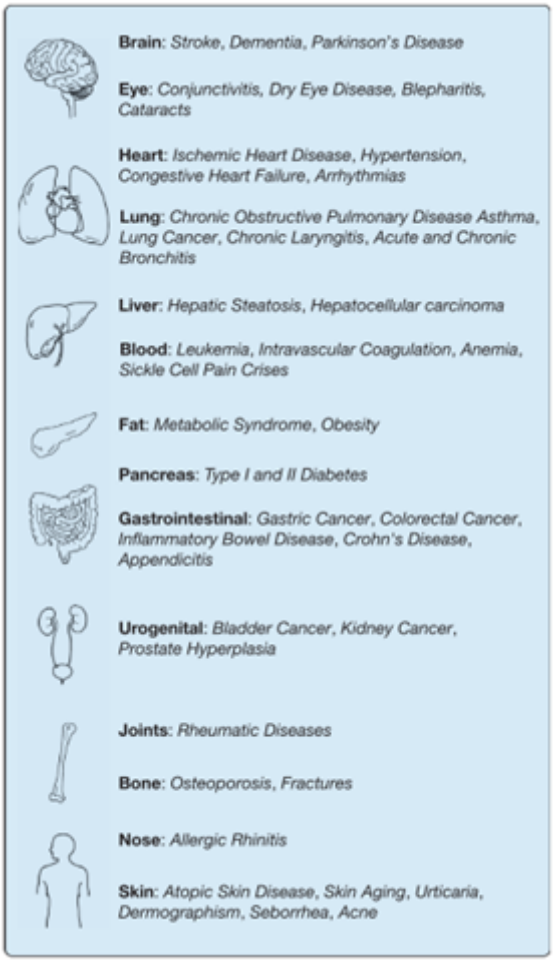


Figure 1.1: Systemic health impacts of air pollution exposure (Schraufnagel et al. 2019)

2018).

The high air quality health burden is despite considerable reductions in anthropogenic air pollutant emissions over the late 20th century and early 21st century. $PM_{2.5}$ air quality in most of Europe has improved over the past half-century; between 1960 and 2009, population-weighted $PM_{2.5}$ concentrations in the European Union decreased by 55.3% (Butt et al. 2017), similarly, Crippa et al. (2016) demonstrate that had air pollutant emissions remained stagnant in Europe since 1970, $PM_{2.5}$ concentrations could be 69% higher, NO_x 71% higher and sulphur dioxide (SO_2) 129% higher. This holds true in some higher-risk regions; even in a short time frame of 2015-2017 emissions control policies have reduced $PM_{2.5}$-attributable mortality by approximately 150,000 deaths per year in China (Silver et al. 2020). India, however, has seen worsening air quality since the end of the 20th Century (Guttikunda & Nishadh, 2022) although this trend may be turning with recent emissions controls (Gopikrishnan & Kuttippurath, 2025).

Affected System	**Pathological Process**
Allergy	Allergic sensitisation
Blood & Blood Vessels	Endothelial dysfunction, atherosclerosis, thrombosis, impaired haemoglobin formation, carboxyhaemoglobinemia
Bone	Bone demineralisation
Brain	Cognitive dysfunction, impaired psychomotor & intelligence development, stress, mood disorders, emotional symptoms
Cancer	Shortened telomere length, detrimental DNA damage and repair gene expression, epigenetic effects, immune & oxidative stress response, inflammation
Diabetes & Metabolism	Increased glycosylated haemoglobin, insulin resistance, leptin and endothelin-1 levels, lower glucogen-like peptide-1, ghrelin & glucogen levels
Eye	Increased acute tearing and chronic drying
Heart	Change in heart rate and vascular tone, reduced heart rate variability, conduction defects
Kidney	Decreased glomerular filtration rate, increased mortality in patients undergoing dialysis
Respiratory Tract	Cough, phlegm, breathing difficulties, bronchial hyperresponsiveness, exacerbated respiratory conditions, impeded lung development, development of COPD from asthma, decreased performance during exercise, decreased lung function
Reproductive	Premature birth, low birth weight, poor sperm quality, impaired foetal growth, intrauterine inflammation, increased miscarriage/spontaneous abortion risk, exposure during pregnancy associated with childhood neoplasms & asthma
Skin	Aging
Sleep	Increased sleep apnea
Overall	Shortened life expectancy, especially in vulnerable people

Table 1.1: Summary of pathological processes associated with air quality exposure, adapted from Schraufnagel et al. (2019)

This demonstrates that primary air pollution responds quickly to emissions controls, potentially resulting in lower population exposure. Air pollution responsiveness to emissions changes was demonstrated during the COVID-19 pandemic by the reduction in $PM_{2.5}$ on national and global scales (Jephcote et al. 2021; Venter et al 2021; Putaud et al 2023). Many sources of air pollutants are key target sectors for mitigating climate change; e.g Vohra et al. (2021) suggest that fossil fuel use alone could be responsible for 10.2 million $PM_{2.5}$-attributable deaths per year (more than the Health Effects Institute. (2024) predict for overall air quality -demonstrating the uncertainty that can present itself using different mortality functions). Similarly, Lelieveld et al. (2019b) suggest that eliminating fossil fuel use could reduce global air pollution-related mortality by 65%. Consequently, it is well established that climate mitigation could provide air quality co-benefits (Von Schneidemesser et al. 2020, Turnock et al. 2020, Deng et al. 2017; Markandya et al. 2017). A complicating factor here is secondary air quality; ozone (O_3), for example, is formed via non-linear reactions between oxygen, nitrogen oxides (NO_x) and volatile organic compounds (VOCs). NO_x (a product of combustion) is also commonly reduced when fossil fuel use is targeted (although it is formed through all combustion, not just of fossil fuels), however in some regions reductions in NO_x can cause increases in O_3. This may explain increases in historical observed O_3 concentrations in the UK and Europe (Finch & Palmer, 2020; Archibald et al. 2020). Similarly, while the covid-19 pandemic reduced $PM_{2.5}$ and NO_2 concentrations, in some regions increases in O_3 concentrations were observed (Lee et al. 2020).

1.2 Key Air Pollutants

Air pollutants is a broad umbrella term that covers several airbourne substances that have potential direct or indirect health impacts. These can be emitted from both natural and anthropogenic sources, or form as secondary pollutants by a range of chemical pathways. Key pollutants include:

$PM_{2.5}$: $PM_{2.5}$ can be both primary and secondary and comes from a range of natural and anthropogenic sources; thus, its composition can vary considerably depending on the local area and how it responds to air quality policy can depend on the specific speciation of $PM_{2.5}$ that any given policy is likely to affect. The following aerosols are often key components of $PM_{2.5}$:

-Organic carbon (OC) and Elemental/Black carbon (BC) are catch-all terms for carbonaceous

aerosols. The differentiation between them is based on the optical properties; where OC scatters light, BC absorbs it, giving them different impacts on radiative balance. BC is almost always primary, whereas a proportion of OC can be a secondary pollutant (Wu & Yu. 2016). Primary sources of OC and BC include fossil fuel energy production, biomass burning, residential/commercial heating and cooking. In Europe, OC, BC and Secondary organic aerosol (SOA) are a considerable component of $PM_{2.5}$ and expected to contribute 20-63% of $PM_{2.5}$ depending on location (Crippa et al. 2014).

Secondary OC (SOC) is referred to in some studies and is differentiated in some model setups as SOA (e.g Agarwal et al. 2024). This is not entirely true to reality - SOC is simply the secondary carbon mass within SOA. SOA is formed from oxididation of volatile organic compounds (VOCs), either from anthropogenic sources or from natural sources (Crippa et al. 2014).

-Nitrate (NO_3^-): An inorganic compound of $PM_{2.5}$ which is normally a secondary pollutant formed by multiple pathways. One is the formation of Nitric Acid (HNO_3) through reactions between Nitrogen Oxides (NO_x) and the hydroxyl radical (OH) which, in the presence of ammonia (NH_3), subsequently forms NO_3^- aerosol. HNO_3 is also formed by N_2O_5 hydrolysis. While there is still limited consensus on the dominant chemical pathways for NO_3^- aerosol formation, some key reactions (R1-R5) for the formation of the precursor HNO_3 are summarised by Jeon et al. (2024):

R1

$NO + O_3 \rightarrow NO_2 + O_2$

R2

$NO_2 + OH + M \rightarrow HNO_3 + M$

R3

$NO_2 + O_3 \rightarrow NO_3 + O_2$

R4

$NO_3 + NO_2 \rightarrow N_2O_5$

R5

$N_2O_5(gas) + H_2O(aqueous) \rightarrow 2HNO_3(aqueous)$

The latter reaction represents the heterogenous hydrolysis of N_2O_5 on aqueous aerosol surface. This HNO_3 then reacts with NH_3 to produce ammonium nitrate (NH_4NO_3):

R6

$HNO_3 + NH_3 \rightarrow NH_4NO_3$

NO_3^- aerosol in the chemistry scheme used primarily represents NH_4NO_3 and its constituent NO_3^- ion, but also includes NO_3^- from other sources e.g calcium nitrate.

As NO_x and NH_3 emissions are both key to production of NO_3^- $PM_{2.5}$, there are a range of associated sectors. NO_x is a product of combustion and is therefore emitted by energy production wherever combustion is involved, vehicular transport and industrial combustion. It can also be produced by natural combustion e.g wildfires and lightning strikes (Mebust & Cohen, 2013; Stockwell et al. 1999; Gharaylou et al. 2024).

NH_3 is primarily a product of agriculture and sewage treatment formed through the decomposition of organic matter (Wyer et al. 2022). Agriculture also produces NH_3 through fertiliser emissions. The presence of NH_3 contributing to the formation of NO_3^- demonstrates the importance to agriculture to this $PM_{2.5}$ species; it has been suggested that ammonia emissions result in up to 50% of European $PM_{2.5}$ concentrations (Wyer et al. 2022).

-Ammonium (NH_4^+) $PM_{2.5}$ is also associated with agriculture, generally in this case referring to ammonium ions present from NH_4NO_3.

-Sulphate (SO_4^{2-}) is a secondary inorganic $PM_{2.5}$ fraction closely associated with sulphur dioxide (SO_2). By and large, SO_2 in the aqueous phase (dissolved in clouds) is oxidised by H_2O_2 or O_3. The dominant pathway is H_2O_2 oxidation, but at higher pH, the O_3 pathway becomes more competitive (Gao et al .2024). These interactions are shown in R7- R11:

Sulphate aerosol can also be formed by gas phase oxidation with the OH radical, however this is of lesser importance globally than formation via aqueous reactions in clouds (Gao et al. 2024). These gas-phase reactions are shown in R12-R14:

SO_2 Atmospheric Oxidation Pathways

(1) Dissolution and Ionization in Cloud/Fog Water:

$$SO_2(g) \leftrightharpoons SO_2(aq) \quad \text{(R7)}$$

$$SO_2(aq) + H_2O \leftrightharpoons H^+ + HSO_3^- \quad \text{(R8)}$$

$$HSO_3^- \leftrightharpoons H^+ + SO_3^{2-} \quad \text{(R9)}$$

(2) Aqueous-Phase Oxidation:

$$\text{By } H_2O_2\text{: } HSO_3^- + H_2O_2 \longrightarrow SO_4^{2-} + H^+ + H_2O \qquad \text{(R10)}$$

$$\text{By } O_3\text{: } SO_3^{2-} + O_3 \longrightarrow SO_4^{2-} + O_2 \qquad \text{(R11)}$$

(3) Gas-Phase Oxidation:

$$SO_2 + OH \longrightarrow HOSO_2^\bullet \qquad \text{(R12)}$$

$$HOSO_2^\bullet + O_2 \longrightarrow HO_2^\bullet + SO_3 \qquad \text{(R13)}$$

$$SO_3 + H_2O \longrightarrow H_2SO_4(g) \qquad \text{(R14)}$$

$H_2SO_4(g)$ subsequently nucleates or condenses onto particles, forming sulphate aerosol.

Its limited interactivity with other pollutants means the relationship of SO_4^{2-} concentrations to SO_2 emissions is somewhat linear (Clappier et al. 2021). It may also be the result of SO_2 emissions being so low that ammonium sulphate formation (another major source) is limited by SO_2 and not NH_3.

Some $PM_{2.5}$ sources are natural e.g sea salt aerosols and mineral dust. (Manders et al. 2010). In Europe, sea salt $PM_{2.5}$ concentrations vary considerably, and are larger nearer the coasts, between 0.3 and 13 $\mu g/m^3$ across the continent with a maximum 5 $\mu g/m^3$ contribution expected 300km from the coastline (Manders et al. 2010). Mineral dust is often airbourne dust from deserts, and thus in Europe is most commonly associated with dust transport from the Sahara (Rodrigues & Lopez-Darias, 2024).

Ozone (O_3): O_3 is a key pollutant in the troposphere due to its abundance and clear link to poor health outcomes (Turner et al. 2016; Murray et al. 2024). It is a secondary pollutant formed by reactions of oxygen with chemical precursors, primarily NO_x and VOCs in the presence of sunlight e.g methane (CH_4) and carbon monoxide (CO), which are primarily anthropogenic, and isoprene, which is biogenic. A Simplified equation for the formation of tropospheric O_3 adapted from Archibald et al. (2020) is shown below:

$$O_3 + hv \longrightarrow O_2 + O(^1D) \quad \text{(R15) Ozone photolysis} \quad (1.1)$$

$$O(^1D) + H_2O \longrightarrow 2\,OH\cdot \quad \text{(R16) OH radical formation} \quad (1.2)$$

$$CO + OH\cdot + O_2 \longrightarrow CO_2 + HO_2\cdot \quad \text{(R17) CO oxidation} \quad (1.3)$$

$$HO_2\cdot + NO \longrightarrow NO_2 + OH\cdot \quad \text{(R18) OH regeneration} \quad (1.4)$$

$$NO_2 + hv \longrightarrow NO + O(^3P) \quad \text{(R19) NO2 photolysis} \quad (1.5)$$

$$O(^3P) + O_2 + M \longrightarrow O_3 + M \quad \text{(R20) } O_3 \text{ formation} \quad (1.6)$$

In these equations, CO can represent any VOC. M refers to third molecules that are involved in the reaction, but are not chemically altered. P refers to the state of the atom, here indicating that the O atom must be in its lowest energy-excited state for the reaction to apply. D means that this is an excited oxygen atom. In short, O_3 is formed via NO_2 photolysis, however that O_3 can subsequently react with NO to reform NO_2, making this a closed system. The presence of VOCs allows for oxidation of these to produce the peroxy radical (HO_2). This radical reacts with NO, producing NO_2 in a way that does not use up available NO - thus meaning there is less of the "sink" (NO) and more of the "fuel" (NO_2).

Methane (CH_4) is another important O_3 precursor. Oxidation of CH_4 by the hydroxyl radical results in production of the methylperoxy radical and formaldehyde (a VOC) that can similarly interrupt the NO_2 to O_3 cycle. Methylperoxy radicals can react with available NO and produce NO_2 in a similar manner to the peroxy radical's role in O_3 formation. Not only that, but this reaction produces methoxy radicals, that subsequently form formaldehyde and peroxy radicals, the latter of which can directly react with NO. The formaldehyde itself can then be photolysed to produce yet more peroxy radicals. The long lifetime of CH_4 means that it gets well dispersed through the atmosphere. This means that it is associated with an increased "background" level of O_3 more so than extremely enhanced concentrations near the emissions source (McDuffie et al. 2023).

Methane (CH_4) Atmospheric Oxidation Pathway

(1) Initiation by OH attack:

$$CH_4 + OH \longrightarrow CH_3^\bullet + H_2O \qquad (R21)$$

(2) Formation of Methylperoxy Radical:

$$CH_3^\bullet + O_2(+M) \longrightarrow CH_3O_2^\bullet \qquad (R22)$$

(3) Reaction with NO:

$$CH_3O_2^\bullet + NO \longrightarrow CH_3O^\bullet + NO_2 \qquad (R23)$$

(4) Formation of Formaldehyde and HO_2:

$$CH_3O^\bullet + O_2 \longrightarrow HCHO + HO_2^\bullet \qquad (R24)$$

(5) Radical Recycling:

$$HO_2^\bullet + NO \longrightarrow OH + NO_2 \qquad (R25)$$

The chemistry driving O_3 concentrations is non-linear and the balance of O_3 precursors is vital in determining how it responds to emissions reductions; in some areas, primarily those in which NO_x concentrations are low in comparison to VOC concentrations, O_3 concentrations can be "NO_x limited" and best controlled by further reductions in NO_x. Whereas, in most of Europe, O_3 concentrations are VOC limited due to VOC concentrations being low in comparison to NO_x. For example, in low NO_x environments, CH_4 oxidation can result in the formation of methyl hydroperoxide, which can suppress O_3 concentrations (Fiore et al. 2008). Functionally, for many of the O_3-forming reactions, VOCs are a "fuel" whereas NO_x is a "catalyst". The NO_x in the atmosphere can act as an O_3 sink where NO_x is abundant due to reactions between O_3 and NO (Sadanaga et al. 2008).

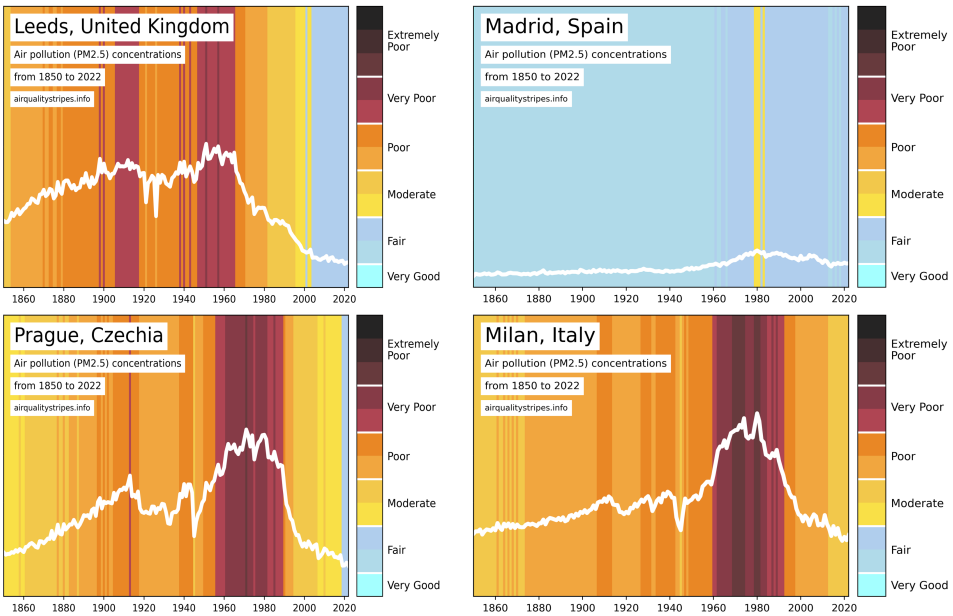


Figure 1.2: Figure 1: Air quality stripes for Leeds, Madrid, Milan and Prague showing their $PM_{2.5}$ trajectories since the pre-industrial period

1.3 European Air Quality Mitigation

European countries have implemented many air pollution mitigation activities and targets. Air quality in Europe has improved significantly since the industrial period (Butt et al. 2017; Turnock et al. 2016; Crippa et al. 2016). The improvements are not uniform across the continent; Figure 1.2 shows output from the "air quality stripes" project described by Pringle et al. (2025) that visualises changes in $PM_{2.5}$ air quality plotted from bias-corrected historical UKESM simulations. This shows for each city, a reasonably similar pattern of lower $PM_{2.5}$ in the late 1800s leading into elevated periods in the mid-late 1900s before rapid reductions reaching pre-industrial levels (or in the case of Leeds, reductions even below these levels). Madrid is an outlier due to lower baseline $PM_{2.5}$ over the course of the simulations, but still sees elevated air quality in the late 1970s and early 1980s before recent reductions.

On a continental scale, in December 2024 the Ambient Air Quality Directives (European Union, 2024) were revised, increasing the stringency of the legal standards for a range of air pollutants, including cutting the annual ambient $PM_{2.5}$ standard by more than half from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. There are however arguments from the academic community, including an editorial from the Lancet Public Health (2023), accusing the European Commission of not showing adequate ambition and urging adoption of controls equivalent to the guideline values set by the World Health Organisation. Similarly, they were criticised for only providing targets for

O_3 concentrations as opposed to legally-defined standards (Boogaard et al. 2023). Although it is clear that air quality improvements could go further, there is evidence that immediate local benefits are being observed due to mitigation actions in Europe.

Low emissions zones or congestion charging zones are an example of a policy frequently adopted in European cities; a review of studies investigating impacts of these by Chamberlain et al. (2023) found that these (which mostly focused on Germany, London and Milan) were largely associated with reductions in cardiovascular mortality, but no clear association with respiratory mortality were found. In London, adoption of the Ultra low emissions zone (ULEZ), the most stringent low emissions zone scheme of any city in the world, was found to have reduced NO_2 concentrations by 12.4% and PM_{10} by 27% compared to a 2005-2009 pre-LEZ period, leading to economic savings of over £960 million (Beshir & Fichera, 2025). In Bradford a clean air zone introduced following research by Mueller et al. (2018) for the "Born in Bradford; Bradford Breathes" project demonstrated that up to 10% of mortalities in the city could be attributed to poor air quality alongside poor physical activity, noise and green space access. Recent research by Mebrahtu et al. (2025) evaluating this found that after only one year of implementation the resulting reduction in primary care visits could be saving the local health service over £30,000 per month.

Wood burning emissions are also the targets of many contemporary policies for improving European air quality. Recent promotion of biomass as a renewable energy source has occurred alongside increasing adoption of domestic wood burning in many countries (United Nations Economic Commission for Europe, 2024; DEFRA, 2025a) - this could be having a major impact on $PM_{2.5}$ concentrations e.g. Srivastava et al. (2025) report that biomass burning could be responsible for up to 25% of $PM_{2.5}$ mass in Birmingham, approximately 7 times higher than the contribution in 2008-2010. Intervention options for this are fairly exploratory, for example DEFRA's Burn Better, Breathe Better campaign in the UK (DEFRA, 2025b). Currently little research evaluates the efficacy of these projects. Lopez-Aparicio & Grythe (2020) do however evaluate a stove exchange scheme in Oslo. They note that while modelling the impacts suggests PM reductions, there is limited evidence that the scheme has changed wood consumption or emissions. Studies that project the impacts of such policies tend to suggest they could be impactful for air quality, for example Ó Broin et al. (2022) suggest that programmes to retrofit heat pumps in dwellings in Ireland could effectively eliminate many of the $PM_{2.5}$ hotspots

outside of Dublin and Cork.

A potential gap in current air quality policy in Europe is mitigating the role of agriculture in European air quality. Agriculture is the dominant source of $PM_{2.5}$-attributable mortality for much of Europe (Lelieveld et al. 2015). There are some provisions for reducing agricultural emissions; e.g The National Emissions Ceilings Directive 2016/2284/EU obligates member states to reduce NH_3 emissions by 19% relative to 2005 by 2030. Notably, 16 out of 28 member states in 2016 exceeded the ceilings set for 2020 (6% relative to 2005) and it has been estimated that European countries that exceeded this could have reduced $PM_{2.5}$-attributable mortality by up to 13% (in Finland) had they complied (Giannakis et al. 2019). The reform of the "Common Agricultural Policy" in the EU, a potential opportunity for promoting environmental sustainability in agriculture and including air quality and climate change mitigation actions, has also been criticised for lack of ambition and conditionality (Heyl et al. 2020; Röder et al. 2024).

1.4 Air Quality Co-benefits of Climate Change Mitigation

Co-benefits such as $PM_{2.5}$ reductions are widely suggested as a motivator for more stringent climate mitigation (Bain et al. 2016; Bollen & Brink, 2014; Scorovnick et al. 2019, West et al. 2013; Workman et al. 2019). Health is considered to be particularly compelling for engaging with policy (Sauerborn et al. 2009). There is, however, evidence that suggests that research has yet to fully change public support of climate policy (Bernauer & McGrath, 2016) and there is limited evidence of co-benefits of climate mitigation being fed into policy decisions (Karlsson et al. 2020). This suggests there is still a way to go in emphasising air quality co-benefits of climate mitigation and framing the outcomes in ways that policymakers can use to drive more stringent mitigation.

Air quality co-benefits of climate mitigation and the subsequent health and economic co-benefits that may occur in connection with these could be a particularly effective, especially if displayed on a local to regional level. A challenge faced by policymakers regarding climate change noted by Mayrhofer & Gupta (2016) is that the benefits and co-benefits of climate change mitigation may be expected to occur over long periods of time, can be uncertain and on the global spatial scale, whereas the costs are often immediate, certain and felt locally. Air pollution may not

follow this trend - as shown by the work analysing ULEZ and clean air zones, there is clear evidence that local policy leads to local air quality improvements.

While air quality co-benefits of climate mitigation are expected, the realities of how they materialise are far from simple. Research in the field is widespread as researchers tackle the complexities in these linkages. The following subsections outline key underlying concepts to studying air quality co-benefits of climate mitigation and what challenges they provide for researchers and policymakers.

1.4.1 Complex air pollutant responses to emissions and climate

The interactions between air quality and climate change mitigation policies are complicated and non-linear (Von Schneidemesser et al. 2015). Surface level O_3, for example, may worsen following NOx reductions, as discussed previously (Miyazaki et al. 2021). Complexity is also added by climatic impacts of surface level O_3 (Archibald et al. 2020) and secondary organic aerosol (Scott et al. 2018; Raes et al. 2010). Climate change will also affect the prevailing meteorological conditions, and impact the dispersion of air pollutants, thereby affecting human exposure (Graham et al. 2020). Additionally, not all climate mitigation strategies will reduce primary air pollutant emissions as it depends on the strategy used. Modelling is therefore needed to understand how climate change mitigation and air quality might interact, considering differing strategies for climate mitigation. Von Schneidemesser et al (2015) identify the following key categories of air quality/climate interactions:

- Atmospheric composition change
- Aerosol-radiation effects
- Aerosol-cloud interactions
- Atmosphere-cryosphere interactions
- Atmosphere-biosphere interactions

Figure 1.3 from von Schneidemesser et al. (2015) shows processes within these categories of interactions. The following subsections discuss in more detail how emissions and climate changes may affect air quality.

The response of air quality to emissions changes isn't always linear. An example of this is the changing response of O_3 to precursor mitigation in NO_x-limited vs VOC-limited regimes, as

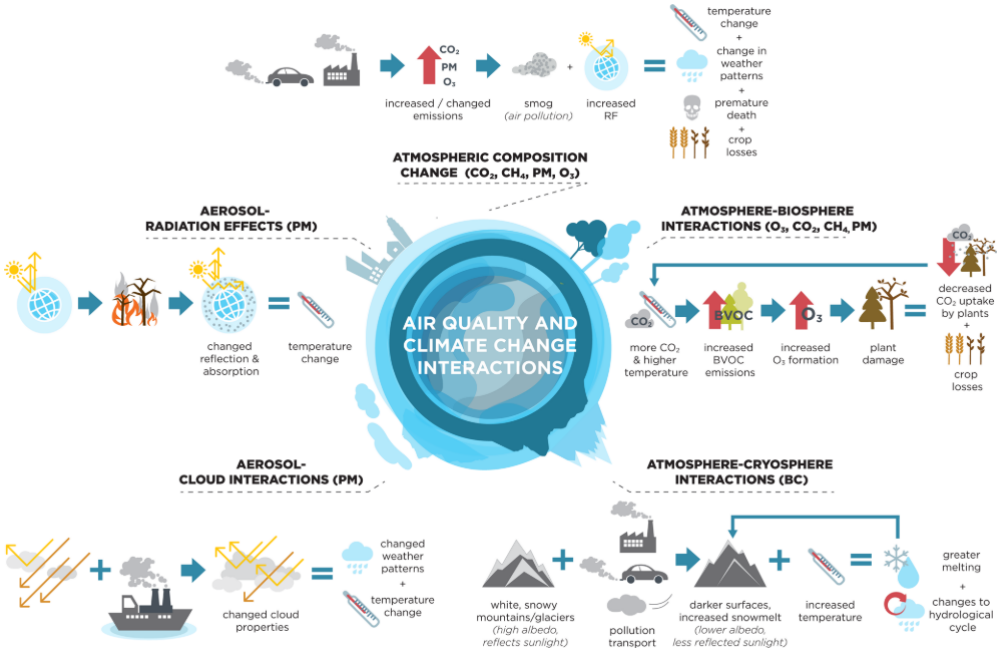


Figure 1.3: Diagram showing several of the interactions between air pollutants and the climate, from von Schneidemesser et al. (2015)

described in the "Key air pollutants" section above. In Europe, the North-West is generally considered to be VOC-limited and the South and East of Europe generally NO_x-limited, although this may vary based on urbanisation and seasonality (Beekman & Vautard, 2010). Generally, in urban areas (which are more likely to be VOC-limited) reductions in NO_x emissions can cause increases in surface level O_3, including within Europe (Lee et al. 2020; Finch & Palmer, 2020). This means that in VOC-limited areas, without policies that also reduce VOCs, including CH_4 in addition to NO_x, pollution mitigation policies may be counterproductive. Policies targeting VOCs can however be very impactful; the O_3 response to CH_4 reductions is so strong that it has been shown that following a low-mitigation scenario, but eliminating anthropogenic CH_4 emissions would result in lower global population-weighted O_3 exposure by 2050 than following a high-mitigation scenario by approximately 3ppb (Staniaszek et al. 2022).

$PM_{2.5}$ reductions also depend on the balance of emissions reductions; NO_x emissions reductions limit the secondary formation of NO_3^- and NH_4^+ particulates (Pusede et al. 2016) however, where only NO_x is reduced, in some regions (usually NO_x-abundant regions) the increased oxidising capacity of the atmosphere can result in increased formation of SOA. This impact can be mitigated by joined reductions of both NO_x and NH_3 (Clappier et al. 2021). Similarly, some research suggests that small NO_x reductions in a high-NO_x environment can actually exacerbate $PM_{2.5}$ (Thunis et al. 2021). Similarly, the balance of sulphurous and ammonia emissions can be

important for the formation of NO_3^- aerosol- SO_4^{2-} and NO_3^- precursors compete for available NH_3; where SO_4^{2-} precursors are low, the added availability of NH_3 can result in more NO_3^- aerosol production (Bauer et al. 2007).

Anthropogenic secondary organic aerosol (ASOA) is a complex pollutant which, despite significant predicted impact on global health, has considerable uncertainty in the processes that form it and how it responds to mitigation of various precursors (Nault et al. 2021; Srivastava et al. 2022). Both biogenic secondary organic aerosol (BSOA) and ASOA respond to mitigation of NO_x emissions but this effect is non-linear and poorly understood. Different model schemes have been shown to cause SOA to both increase and decrease following NO_x mitigation depending on model chemistry (Wang et al. 2024).

1.4.2 Changes to weather

Changes in weather are very impactful for air pollutant transportation, deposition and creation, adding to uncertainty in how surface air pollution will change along different scenarios. As examples, Tainio et al (2013) suggested that increased precipitation in future scenarios with increased radiative forcing results in lower PM_{10} exposure. Feasibly, changes in weather patterns caused by climate change could either exacerbate or mitigate air pollution exposure in scenarios with increased radiative forcing.

Work into future meteorological changes following climate projections in the UK by Hanlon et al. (2021) suggests that climate change could result in meteorological changes such as; more frequent heatwaves, more frequent high-rainfall events, weather types associated with winter lasting for shorter periods and longer periods of summer weather.

Hotter weather, particularly heat waves, could exacerbate air polution in summer (Scortichini et al. 2018, Analitis et al. 2018) triggering short-term air pollution episodes. Similarly, climate change is likely to increase the frequency and duration of wildfires (Spracklen et al. 2009; Jones et al. 2020). Wildfires result in extremely elevated $PM_{2.5}$ concentrations in affected areas and therefore climate impact on wildfires may modify $PM_{2.5}$ exposure enough to influence health impacts (Neumann et al. 2021). Despite overall reductions in $PM_{2.5}$, the proportion of $PM_{2.5}$ exposure attributable to wildfires in Europe more than doubled between 1990 and 2019 (Chowdhury et al. 2024). Although in this study this is mostly driven by reductions of anthropogenic emissions, the authors find that absolute exposure to $PM_{2.5}$ from wildfires has

steadily increased across the continent in the same time period.

There is some evidence of a global slowing of wind speeds (Roderick et al. 2007; McVicar et al. 2012) and CMIP5/CMIP6 modelling studies project this to continue (Wohland et al. 2021; Shen et al. 2022). Lower wind speeds may result in lesser dispersion of air pollutants and result in a greater chance of pollution events. Conversely, for many regions, including Europe, transboundary pollution is a significant source of many pollutants. There is a possibility that climate impacts on transboundary pollution could reduce pollution where this constitutes a large proportion of overall air pollution and increase pollution in regions where these emissions dominate, but this impact is expected to be small (Huang et al. 2008; Cai et al. 2017; Doherty et al. 2017a). Vertical transport may be relevant for O_3, e.g Allen et al. (2020) demonstrate that one potential pathway for climate impacts on O_3 is through the changing climate system favouring transport of stratospheric O_3 to the troposphere.

Climate change is expected to increase temperature and humidity in Europe (Robinson et al. 2021; European Environment Agency, 2025). Rising temperatures have impacts on O_3 precursor emissions and their reactions. These include increased biogenic emissions of volatile organic compounds including isoprene and monoterpenes (Lee et al. 2006). Related are the effects of increasing temperatures on peroxyacetyl nitrate (PAN). This is formed from isporene and is an NO_x reservoir; however at higher temperatures it decomposes more rapidly into peroxyacetyl radicals and NO_2, which increases the availability of NO_x and therefore the rate of O_3 production (Archibald et al. 2020). Figure 1.4 (also from Archibald et al. 2020) shows how temperatures modify these precursors. Increased temperatures can also change the partitioning of NO_x into NO_2 and NO, with NO_2 favoured at higher temperatures (Doherty et al. 2017b). Higher temperatures can also lead to increased CH_4 emissions from the land surface, particularly wetlands (Shindell et al. 2004; Zhen Zhang et al. 2017). Several climate feedbacks on the CH_4 cycle are irreversible, even with stringent climate mitigation (Folberth et al. 2025).

Increased humidity can mean increased atmospheric water vapour, which encourages absorption of O_3 through increased production of OH radicals and therefore reduce concentration (Doherty et al. 2013; Li et al. 2021). $PM_{2.5}$ may increase with humidity due to NO_3^- being increasingly partitioned to $PM_{2.5}$ (Megaritis et al. 2014). Humidity may increase due to increased precipitation in some regions (Kunkel et al. 2013; Robinson et al. 2021; Hanlon et al. 2021). Precipitation can increase pollutant wet deposition and reduce air pollution (Fang et al. 2011;

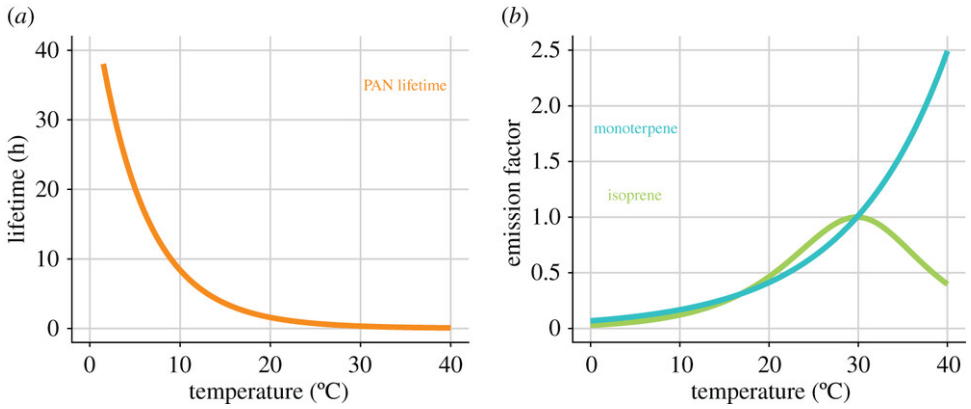


Figure 1.4: a) response of PAN to temperature increases. b) response of isoprene emissions to temperature increases, from Archibald et al. (2020)

Tainio et al. 2013). Much of the climate impact on precipitation is expected to be on variability and frequency of extreme events and several regions are also predicted to have more frequent droughts, including much of Europe (Gudmundsson & Seneviratne, 2016; Spinoni et al. 2017; Grillakis, 2019). These contribute to air pollution episodes through natural dust emissions and through vegetation feedbacks on O_3. Thus such air pollution events may be expected to become more frequent with climate change (Wang et al. 2017; Achakulwisut et al. 2018; Lin et al. 2020; Wu et al. 2025).

Temperature and humidity impacts on $PM_{2.5}$ are variable. Increased temperatures can accelerate NH_44NO_3 aerosol degradation. This is a key source of particulate matter in Europe. Conversely, secondary SO_4^{2-} aerosol and organic aerosol production can increase during warmer temperatures, meaning $PM_{2.5}$ from these sources could increase (Tai et al. 2012). BVOC response to temperature is also relevant to $PM_{2.5}$; isoprene and monterprene-deprived SOA is a considerable source of $PM_{2.5}$ (Bartik et al. 2024). Tai et al. (2012) note regional variation in BVOC contribution to $PM_{2.5}$ across the US; in some parts, temperature impacts increase $PM_{2.5}$ concentrations but in others a decrease, meaning that wildfire change is likely to be the dominant "overall" driver of the $PM_{2.5}$ penalty.

Low-level cloud cover has also reduced over time (Loeb et al. 2024) and is projected to reduce with climate change over most continents (Mendoza et al. 2021; Liu et al. 2023). This is associated with air quality as higher cloud cover and the resulting enhanced atmospheric mixing, precipitation and humidity can increase deposition of $PM_{2.5}$ and reduce SOA production (VanRenken et al. 2017; Belle et al. 2017). Reduced cloud cover allows more radiation to reach

the surface, promoting O_3 formation (Deroubaix et al. 2021).

1.4.3 How air quality affects the climate

The aerosol cooling effect is an example of the impact of air quality on climate; many aerosols have a net negative radiative forcing effect (Scovronick et al. 2019; Von Schneidemesser et al. 2015). Therefore, reductions in air pollution could affect the efficacy of climate change mitigation. Gettelman et al. (2021) suggested that the reduction in global air pollution resulting from lockdowns during the Covid-19 pandemic resulted in a minor increase in global surface temperature because of this. Reduced aerosol cooling could be very impactful for physical climate change; von Salzen et al. (2022) project that the sulphur emissions reductions projected following a high-mitigation scenario could by 2050 cause Arctic warming to increase by 0.8 °C, however targeted reductions of carbonaceous particulates could provide similar climate benefits to CO_2 reductions.

Particulates also affect cloud albedo; aerosols form cloud-condensing nuclei from which cloud droplets form. Where more cloud condensing nuclei are available, cloud droplets become smaller - these are lighter in colour and this increases surface albedo and reflects sunlight. As such particulate air quality is widely expected to mask the true impact of climate change (Andreae etc al. 2005; Manshausen et al. 2022; Kok et al. 2023). Some results suggest that this impact is now reversing and that aerosol radiative forcing is now positive (Quaas et al. 2022). Particulates also have "darkening" effects on ice sheets, e.g speeding up their melting and reducing albedo (Goelles et al. 2015) or by feeding algal blooms (Cook et al. 2020; McCutcheon et al. 2021).

Air pollution can worsen climate change. Some air pollutants (O_3, black carbon and CH_4) are often referred to as "near-term climate forcers " (NTCFs). Emissions or production of these can drive regional climate extremes (Turnock et al. 2022). Another potential feedback identified by Cheesman et al. (2024) is between O_3 and the ability of forests to act as a CO_2 sink; in short, temperature increases and promotes excess emissions of isoprene and monterpenes, which act as O_3 precursors. The O_3 damages the forests and therefore their ability to uptake CO_2, thus increasing the temperature and potential for biogenic VOC emissions. Similarly, Arnold

et al. (2018) demonstrate that O_3 damage to plants in the tropics can have a significant impact on weather patterns, reducing low-level cloud cover and increased surface warming, which can promote global reductions in snow cover, both of which can reduce overall albedo and thus promote further climate change.

1.4.4 The Climate penalty/benefit

The range of interactions between climate change and air quality, with many of them appearing to worsen air quality, means it is widely expected that there will be a climate penalty to any mitigation actions (e.g that the mitigation is not as effective as it would be without climate change), especially in the case of O_3. Generally the impacts of emissions change are expected to eclipse the impacts of climate change when determining long-term future air quality trends (Doherty et al. 2017b; Chemel et al. 2014; Wu et al. 2019). Studies considering the impact of climate change alone on $PM_{2.5}$ tend to agree that the climate impact on concentrations will be under 2 $\mu g/m^3$ (Tai et al. 2012; Nolte et al. 2018; Fann et al. 2021 Murray et al. 2024; Bhattarai et al. 2024).O_3 climate penalties are more uncertain. Notably, Zanis et al. (2022) suggests that in Europe there is a climate benefit to O_3 from climate change, but that this is primarily in remote regions, and a benefit of up to 2ppb per 1 degree celsius increase in temperature is possible in polluted regions. An earlier study by Colette et al. (2015) comparing climate penalty studies found that while there is a lot of uncertainty, a long-term O_3 penalty in Europe would be unlikely to exceed 5ppb.

These numbers suggest it is not critical to capture climate-driven impacts on air quality when modelling co-benefits of climate mitigation. In fact, it is generally argued that until after 2050, the signal of climate change on O_3 and $PM_{2.5}$ are low enough that the signal does not show beyond standard model variability (Zanis et al. 2022; Pienkosz et al.2019). This does come with caveats, firstly is that even small changes in air quality can be meaningful for human mortality, e.g Silva et al.(2017) estimate that climate change alone could account for approximately 100,000 combined additional deaths per year globally by 2100, counteracting 16% of the benefits achieved by $PM_{2.5}$ reductions. Westerveldt et al. (2019) find that 62,000 deaths per year could occur in China by 2050 due to an O_3 climate penalty. Climate penalties also show spatial differences and seasonality; Zanis et al. (2022) note that there is a much stronger penalty in polluted regions (e.g Eastern China and the Indo-Gangetic Plain) or regions with a

strong BVOC response (some parts of Africa and South America) compared to a climate benefit in Europe and North America. This implies that the climate penalty and mitigation efforts are interlinked e.g more effective mitigation can also reduce the penalty. Seasonality is also important; Zanis et al. (2022) find a strong O_3 penalty in the Arctic during Winter, whereas Schnell et al. (2016) and Nolte et al. (2018) find O_3 penalties are higher in summer. Additionally, climate change could cause more heatwaves, which may cause short-term pollution events (Gao et al. 2013).

1.5 Climate Change Scenarios

A long-standing challenge in modelling the future in any field is uncertainty added by the assumptions made about how the future will develop. To meaningfully compare between modelling studies, some consistency and standardisation is necessary in the underlying assumptions. For modelling the future climate and atmosphere this means that comparable scenarios are required that can cover a range of futures, including climatic conditions, emissions required to reach those climatic conditions and assumptions about the behaviours that result in those emissions.

Climate scenarios have a long history, a good summary of which is provided by Cointe, (2024). Three scenarios as an example were used in the seminal paper by Hansen et al. (1988) that demonstrated that greenhouse gas forcing would increase temperature beyond natural climate variability. Not long after, standardised emissions scenarios for the IPPC's 1992 report (Leggett et al. 1992) were developed. Work was also undertaken by Morita & Lee (1998) to map emissions scenarios generated across research institutions and store data in a centralised repository. The next step was the Special Report on Emission Scenarios (SRES) scenarios (Nakicenovic et al. 2000) which introduced different future "storylines" and expanded anthropogenic inputs for models to cover other greenhouse and reactive gases. It was with the SRES scenarios that air quality co-benefits studies began to appear, e.g Heal et al. (2013); Tainio et al. (2013). Climate scenarios are usually developed using "integrated assessment models" (IAMs). These are primarily economic models that simulate the drivers behind and processes involved in energy consumption and land use system change, how this ties in with the global and regional economy and what it means for development of a range of economic sectors, but they can vary greatly in scope and focus (Weyant et al. 2017, Wilson et al. 2021). IAM scenarios can then be used as

a basis from which inputs for environmental models can be developed. IAMs do receive considerable criticism in the climate modelling field for limited transparency in how they operate and the assumptions used by them, limited ability to consider emerging sectors and representation of human behaviour (Gambhir et al. 2019).

As GCMs became more sophisticated, the ability to factor in a greater range of inputs available and scenarios evolved further. CMIP5 (described by Taylor et al. 2012) came with the introduction of the representative concentration pathways (RCPs) (van Vuuren et al. 2011). These were used by the IPCC to introduce the range of climate possibilities in the IPCC's 5th Assessment report. The RCPs are RCP2.6, RCP4.5, RCP6.0 and RCP8.5

The number given to each of these corresponds to the overall radiative forcing in the year 2100 that the greenhouse gas pathways lead to.

The RCPs were used as the basis for the Coupled Model Intercomparison Project 5 (CMIP5). This project was designed to model historical climate conditions since the preindustrial period up to the year 2100 with climate models used in different institutions providing a range of estimates for each future climate, providing scientists with the ability to use multi-model means and providing variability estimates for climate model output. To use the RCPs in this way model inputs consistent with the RCPs needed to be developed. Anthropogenic and biomass burning emissions consistent with the RCPs were developed using integrated assessment models. Similarly, inputs to represent changes in land use are also available. The RCPs also consider pollution control to a degree although they prioritise pollutants relevant to climate, with emissions for air pollutants such as NO_x, SO_2, CH_4, CO, organic carbon and black carbon all available.

The provision of these inputs for the RCPs and the ability to model them gives them applications beyond the climate modelling space. With the introduction of the RCPs, studies investigating the impacts of climate change in air quality or the air quality co-benefits of climate change mitigation have become commonplace. Examples include Wild et al. (2012), West et al. (2013), Young et al. (2013), Sun et al. (2015), Silva et al. (2016), Silva et al. (2017), Turnock et al. (2018), Patarnen et al. (2018) who focus on global air quality changes, Colette et al. (2013) who focus on Europe and Pfister et al. (2013), Gao et al. (2013), Hedegaard et al. (2013), Val

Martin et al. (2015), Goto et al. (2016), Li et al. (2016), Sa et al. (2016), Wilson et al. (2016), Lee et al. (2017), Pannullo et al. (2017), Yuqiang Zhang et al. (2017), Yang Zhang et al. (2017), Yahya et al. (2017), Kumar et al. (2018), Nolte et al.(2018), Chowdhury et al. (2018), Hong et al. (2019), Tarin-Carrasco et al. (2019), Wu et al. (2019), Zhu et al. (2019), Park et al. (2020), Upadhyay et al. (2020), Fenech et al. (2021), Liu et al. (2021), Amnuaylojaroen et al. (2022) all of whom focus on specific countries or sub-continental regions.

A weakness of using the RCPs, particularly for air quality modelling, is the very prescriptive and linear description of how emissions change globally. This doesn't reflect the different strategies that may be taken to achieve the same levels of climate mitigation and limited reflection of real world socioeconomic realities, such as the possibility of very different strategies in different parts of the world. Additionally, the RCPs are potentially pessimistic and lacked a pathway where stringent mitigation was achieved.

To combat some of the limitations of the RCPs the Shared Socioeconomic Pathways were introduced (O'Neill etc al. 2014; O'Neill etc al. 2017; Riahi et al. 2017). At their core, the shared socio-economic pathways are a range of narratives describing assumptions about 5 different scenarios of socioeconomic change relevant to climate change (for example population change, development of fossil fuel and agriculture industries, international cooperation etc). The individual scenarios can be summarised as:

SSP1 "Taking the Green Road" (Van Vuuren et al. 2017); a scenario assuming a major global shift towards sustainability and pollution control, e.g reduced fossil fuel use, a shift towards plant-based diets, improved global healthcare, increased global trade and a reduction in socioeconomic inequality between global regions.

SSP2 "The Middle Road" (Fricko et al. 2017) is the narrative with the least deviation from historical trends in climate mitigation. It largely assumes some climate mitigation and pollution control beyond the present day but not at the rate needed to meet climate goals.

SSP3 "A Rocky Road" (Fujimori et al. 2017) assumes a world where politics of individual countries become more individualistic at the expense of cooperation towards climate mitigation and pollution control. Mitigation progress slows down considerably.

SSP4 (Calvin et al. 2017) describes a very unequal world in which some progress in mitigation is achieved in richer countries but that poorer countries lag way behind.

SSP5 (Kreigler et al. 2017) is a scenario that assumes fossil fuel use accelerates and countries embrace climate change in exchange for economic growth. Thus the scenario assumes advances in healthcare etc.

These are arranged in a matrix with an enhanced version of the RCPs (introductions of pathways to represent 1.9 W $m^{-}2$, 3.4 W $m^{-}2$ and 7.0 W $m^{-}2$ forcing) meaning that each RCP can in theory be paired with each SSP. Each combination of RCP and SSP (e.g SSP3-7.0; SSP2-6.0, SSP5-8.5 etc) is input into integrated assessment models to establish which pairings between narrative and pathway are actually feasible and these integrated scenarios are the ones commonly referred to as the SSPs. While a range of combinations are "feasible" a number of these integrated scenarios are designated as priority scenarios for further research, either due to additional feasibility or interest to research as best/worst case scenarios. These are SSP1-1.9 SSP1-2.6, SSP2-4.5, SSP3-3.4, SSP3-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5. These scenarios have been studied in more detail and are used as the basis of the ScenarioMIP project (O'Neill et al. 2017) which uses the climate models from CMIP6 (the successor to CMIP5) to produce climate model output for each of these priority scenarios. This constitutes a big step forward from previous scenarios as even prior to the RCPs it was recognised that different socioeconomic conditions could lead to the same outcome, or that one individual socioeconomic scenario could lead to a range of "futures" (Moss et al. 2010). The scenario matrix is shown in figure 1.5 from O'Neill et al. (2017). In this, each square on the figure represents an integrated scenario, where there is no square, the concentration pathway is considered to be incompatible with the SSP. Priority scenarios are highlighted in blue.

While most existing studies use the RCPs as the basis of air quality research, use of the SSPs is increasingly common, although most of this research was not yet published at the start of this project in October 2020; examples include Markandya et al. (2017), Turnock et al. (2018) (who compare O_3 response to both RCP and SSP changes), Allen et al. (2020), Kim et al. (2020), Murray et al. (2024), Turnock et al. (2020), Shim et al. (2021), Cheng et al. (2021), Ingole et al. (2022), Shindell et al. (2022), Tang et al. (2022), Liu et al. (2022), Staniaszek et al. (2022), Wang et al. (2022), von Salzen et al. (2022), Reddington et al. (2023), Chen et al. (2023), Im et al. (2023), Parsons et al. (2023), Turnock et al. (2023), Yang et al. (2023) and Bhattarai et al. (2024). These are mostly global-scale in focus - the studies with regional or local focuses here are Cheng et al. (2019), Shim et al. (2021), Ingole et al. (2022), Shindell

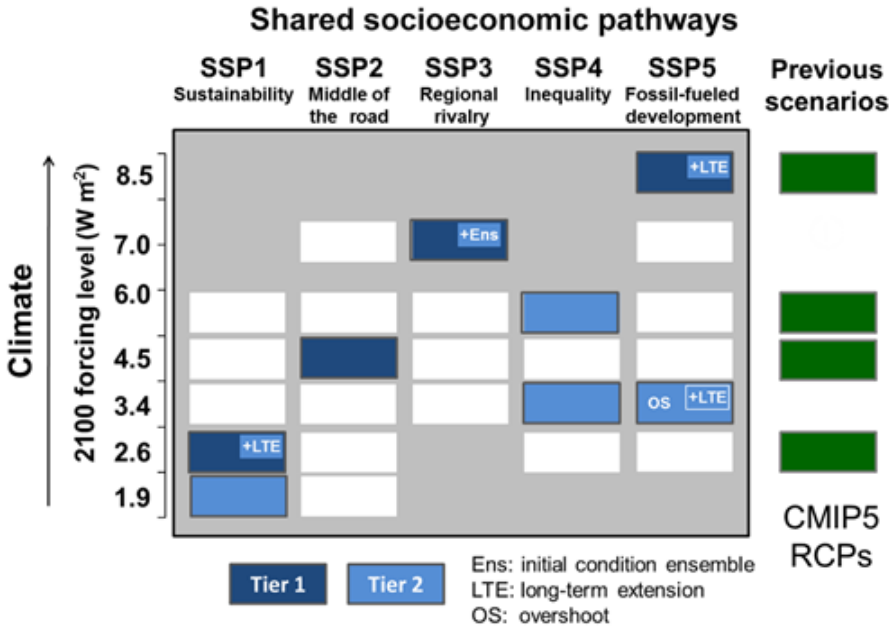


Figure 1.5: Scenario matrix showing all SSP/RCP integrated scenarios. From O'Neill et al. (2017)

et al. (2022), Tang et al. (2022), Wang et al. (2022) and Kim et al. (2020). Aside from Ingole et al. (2020) all regional studies identified focus on Asia. Several of the SSP studies focus on specific chemical responses, e.g the CH_4 impact on future air quality and climate (Staniaszek et al. 2022) or that of non-CH_4 forcers (Allen et al. 2020; Turnock et al. 2023). Brown et al. (2022) is a similar study in that it investigates the impact of climate change represented by SSPs on surface O_3 in Africa and South America, however, this paper investigates O_3 due to its ecosystem impacts rather than health. Im et al. (2021) uses output from a singular CMIP6 model to model Arctic aerosol pollution following SSPs, but with a climate impacts focus. The same simulations are later used with a global air quality focus by Im et al. (2023); Aerosol forcing following the SSPs is the focus of work by von Salzen et al. (2022).

For brevity, henceforth, when the SSPs are referred to, I mean the integrated scenarios. Where I refer to the narrative, I will use "SSP narrative". The SSP narratives consider pollution control to a much greater degree than the RCPs (Rao et al. 2017) however the emissions species available for use in models are the same as for the RCPs. The SSPs of primary relevance to this thesis are SSP1-2.6, SSP2-4.5 and SSP3-7.0. Figure 1.6 shows the trajectories in the OECD of some demographic/social trends up to 2050 from the SSP database (Riahi et al. 2017), including population, GDP, fossil fuel use and livestock production as examples. The

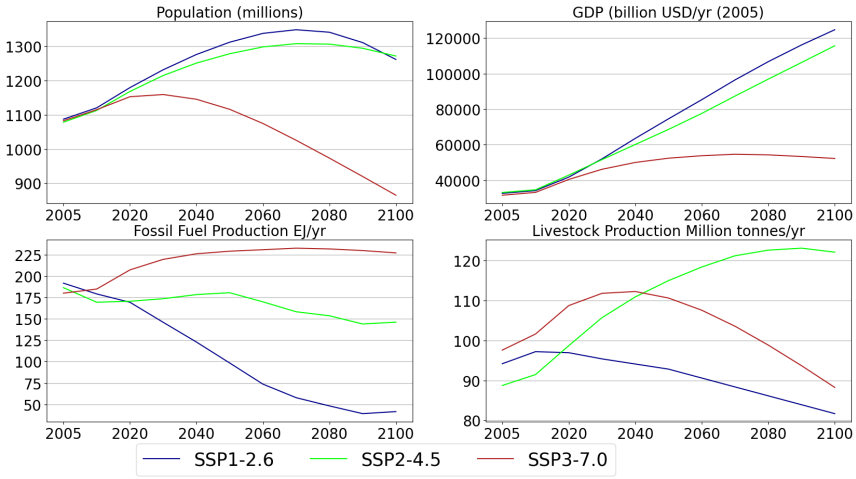


Figure 1.6: Figure 1: Time series of four social indicators in the OECD following key SSP scenarios

OECD designation is used as the database does not provide a grouping for "Europe". These underlying trends are then used to generate likely emissions of key climate and air quality-relevant pollutants. Trajectories of total emissions of these for these three scenarios, also from the SSP database are shown in figure 1.7. This demonstrates that for all species, SSP1-2.6 results in the greatest decrease in emissions. NH_3 and CH_4 emissions are the only species to see emissions increases, both seeing strong increases by mid-century following SSP3-7.0. NH_3 emissions following SSP2-4.5 track SSP3-7.0 emissions quite closely until about 2040 where they begin to drop. CH_4 emissions following SSP2-4.5 show the opposite pattern, with decreases up until midcentury, at which point they begin to increase again. These figures show how the socioeconomic assumptions underpin the emissions; e.g livestock production following SSP3-7.0 increases alongside NH_3 and CH_4 emissions. Not all the factors leading to these emissions are shown however. The decrease in NH_3 emissions in the latter half of the 21st century in SSP2-4.5 despite increased livestock farming as an example, may be the result of assumptions about more stringent pollution control.

RCP 8.5 and SSP5-8.5 are sometimes criticised by sources that see the acceleration of GHG emissions as unrealistic and misused as a "business as usual"/"baseline" scenario (Pielke & Ritchie, 2021, Hausfather & Peters, 2020). This is supported by the original literature describing RCP8.5 as a "worst case scenario" pathway (Van Vuuren et al. 2011). Some of the literature focuses on these worst case scenarios, e.g RCP8.5 is the only scenario considered by Sun et al. (2015), Tarin-Carrasco et al. (2019), Park et al. (2020) and Sa et al. (2016) and either RCP8.5 or SSP5-8.5 are used as the "baseline" by Colette et al. (2013), Kumar et al. (2018),

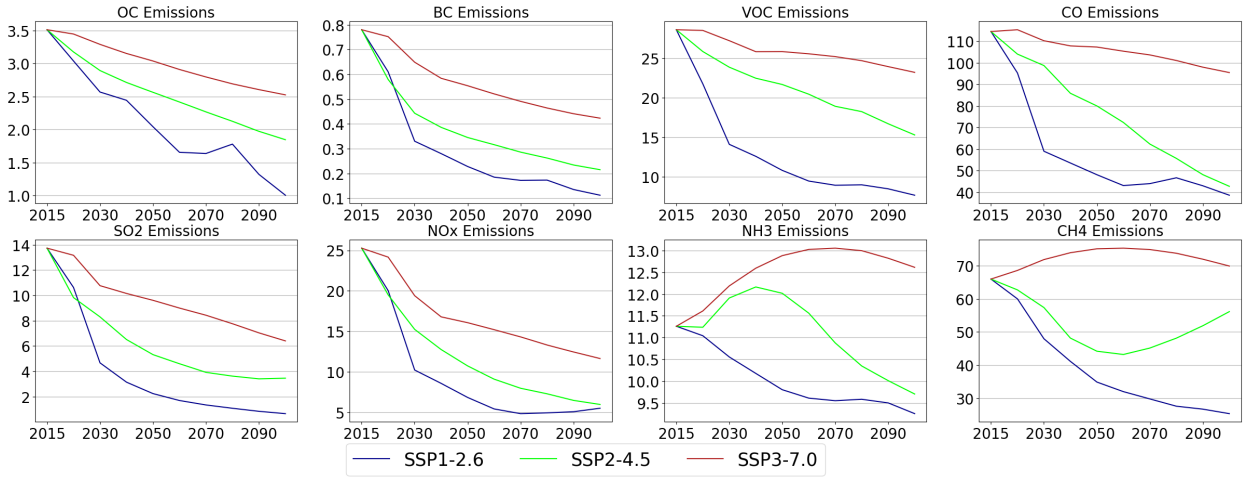


Figure 1.7: Figure 2: Time series of total emissions to atmosphere from the OECD of key pollutant species shown by scenario. All expressed in Mt/Year

Shim et al. (2021), Ingole et al. (2022) and Fenech et al. (2021) among others. Schwalm et al (2020) disagree, claiming that RCP 8.5 closely mirrors historic cumulative CO_2 emissions and is a good match for the effects of current policies continuing to mid-century. Solecki et al. (2021) notes that when communicating the importance of effective climate policies to decision-makers in city authorities, that the decision-makers often want to know what the worst-case scenario in their area is. This suggests that there is value in continuing to study RCP 8.5 & SSP5-8.5. Ho et al. (2019) note that there is disagreement about what should be considered a "baseline" scenario, noting that SSP2-4.5 is sometimes used for this purpose too. Examples in the air quality co-benefits space include West et al. (2013), Hedegaard et al. (2013), Goto et al. (2016) and Reddington et al. (2023). It is also common to see RCP4.5 or SSP2-4.5 used as the "sustainable" scenario in comparison with an 8.5 baseline, e.g Upadhyay et al. (2020), Yahya et al. (2017).

Some recent research uses SSP3-7.0 as the "unsustainable" or "baseline" scenario, including Turnock et al. (2023), Staniaszek et al. (2022) and Allen et al. (2020). In this thesis, I also use this to represent a low mitigation future. SSP3-7.0 differs from SSP5-8.5 in that it assumes mitigation efforts will decelerate as opposed to reversing.

1.6 Air Quality and Climate Models

The difficulty of modelling air quality and climate simultaneously makes modelling air quality/ climate mitigation co-benefits challenging. The RCPs and SSPs are designed for use with

coupled general circulation models, often paired with basic chemistry. These are referred to as chemistry-climate models. A wide range of these models are used in the Intercomparison projects CMIP5 and CMIP6. Much of our current understanding of climate change comes from the output of these projects. The CMIP5 and CMIP6 models, while they constitute the best available techniques for long-term climate modelling, are not designed to simulate tropospheric air quality. These models have been optimised to simulate long periods (e.g from the pre-industrial period up to 2100) at a global scale and represent a range of climate phenomena that may take place over multiple years.

The output from these is publicly available and several studies into air quality co-benefits use this output as their basis (e.g Silva etc al. 2016; Turnock et Al. 2020, Reddington et al. 2023). Others don't use CMIP output directly, but use models that form part of it or similar models (Partanen et al. 2018, Fenech et al 2021; Bhattarai et al. 2024). GCMs are however not optimised for modelling air quality at local levels; these model tend to have a coarser horizontal resolution (100km +) than regional air quality models (usually under 50km). Fine resolution is important for air quality research to simulate chemical processes that impact on air pollutants at local and urban scales (Adedeji et al. 2020; Fenech et al. 2018). The chemistry schemes are often less detailed too, to allow for the model to run for timeframes that can represent long-term climate phenomena. This research provides excellent indications of future air quality at a global scale and can provide analysis of the drivers. Air quality policy, however, is rarely implemented globally and air quality changes drastically at a local level. These studies cannot represent the changes as effectively and may be of lesser interest to local and regional policymakers. Some studies using CMIP6 output (Turnock et al. 2023; Reddington et al. 2023) are making progress in improving the representation and resolution of present-day air quality by combining CMIP6 output with observational and reanalysis data, however, the approaches taken by these studies still use a coarser grid for future simulations. Similarly, some studies use "reduced form" models, most frequently TM5-FASST (Van Dingenen et al. 2018), that prioritise speed over detail (e.g Markandya et al. 2017; Ingole et al. 2022). These models also have less detailed chemistry schemes than regional air quality models. The simple parameterisation approaches taken by Wild et al. (2013) and Turnock et al. (2018) are also designed with similar priorities. These research methods are of use for rapidly synthesising an overview of how following certain scenarios or policies can affect air quality, with the ability to run several sensitivity tests. The lack of response to chemistry and the resolution, like with

GCM model output, hamper the ability of these models to resolve the complex processes that determine air pollutant concentrations and distribution.

Some works aim to circumvent some of these issues, for example, some studies have run the regional air quality model WRF-Chem for decadal simulations using a setup that allows for greenhouse gas forcings to be fed into the meteorology scheme (usually representing RCPs6.0 and 8.5). This model version is usually referrred to as NRCM-Chem. This approach was used by Kumar et al. (2018), Wu et Al. (2019), Upadhyay et al. (2020), Amnuaylojaroen et al. (2022) and Jena et al. (2023). This approach allows these studies to simultaneously model air quality and climate with a model optimised for air quality, but these studies make compromises to do so. Jena et al. (2023) for example, uses the twice-superseded SRES scenarios, thus may not factor in recent expectations for climate mitigation and socioeconomic development. Kumar et al. (2018), Wu et al. (2019) and Amnuaylojaroen et al. (2022) use the RCPs, but all note that due to model difficulties, the pessimistic RCP6.0 was used as the "higher mitigation" scenario. Therefore, while these studies can give an indication of the impacts of failure to mitigate climate change, they do not showcase the benefits of climate mitigation. Kumar et al. (2018) also note that this methodology still involves incredible computational expense. To manage this, they change the model chemistry timestep to 6 hours instead of 1 hour. This means the method may be less able to represent processes involved in secondary pollutants, particularly O_3 formation. This method may be unsuitable for estimating O_3 health impacts (as functions for this tend to require 8hr-rolling O_3 data as an input). This methodology allows for some representation of meteorological uncertainty, and improves the ability of studies to quantify climate vs emissions change. Upadhyay et al. (2020) do not simulate air quality over long periods of time, instead using bias-corrected CESM meteorological output consistent with the RCPs as the meteorological conditions for year-long scenarios. This may have the weakness of not representing meteorological variability effectively. Other research on regional air quality following future scenarios consider only the impacts of emissions changes. Fenech et al. (2021) is an example, considering only the impacts of anthropogenic, biomass burning and biogenic emissions change.

Typically, another challenge faced by researchers wishing to use regional air quality models with RCPs and SSPs is the procurement of input data for emissions and for chemical and meteorological boundary conditions that represent changes outside the model domain. The emissions

inputs for CMIP5 and CMIP6 are designed to be input into GCMs and thus extra processing is needed to use this with regional models. As an example, emissions and boundary conditions compatible with CMIP6 were developed for the GEOS-Chem chemical transport model (Murray et al. 2021). Studies using NCRM-Chem tend to use chemical boundary conditions based on the RCPs developed by Lamarque et al. (2012) and CMIP5 output from the CESM model to drive meteorology. This is due to errors in the CESM CMIP5 output for RCP2.6, which prevents the use of high mitigation scenarios (Kumar et al. 2018). CMIP5- consistent meteorological boundary conditions were developed by Westerveldt et al. (2016). To my knowledge, no such boundary conditions have been developed that are consistent with CMIP6.

To summarise, both the complex chemical behaviour of air pollutants near the surface and the long-term climate-driven changes to weather are important to understand future air quality responses to emissions scenarios. Chemical transport models, such as WRF-Chem are generally better at representing the former and can do so at smaller, more "policy relevant" scales. GCMs on the other hand are better at representing the climate system, so are more likely to capture the changes to weather, especially as the computational expense of using chemical transport models makes long-term simulations very challenging. Existing research into SSP impacts on air quality tends to use GCM outputs, or reduced-form models due to pre-existing inputs being available. Models that bridge this gap are in development, e.g MUSICA, described by Schwantes et al. (2022) but their use is currently exploratory.

1.7 Making Co-benefits Research "Policy Relevant"

The concept of air quality co-benefits of climate mitigation is not new. Studies often differentiate themselves in methodology or focus. Some simply focusing on specific regions of the world to be of interest to regional policymakers, a number of which either do not use RCPs/SSPs and instead use country/region specific scenarios designed to represent policy options. Examples include Macintyre et al. (2023), who drive their model with emissions derived from projections of UK emissions policies or Pisoni et al. (2023), who estimate the health co-benefits of the EU "Fit for 55" package. Some studies use a combination of specific policy scenarios and RCPs/SSPs (Zhu et al. 2019, Liu et al. 2021). Studies using more generic climate scenarios often enhance the methodology beyond simply estimating future air quality, generally showcasing unique methodologies, analysing drivers of the results or aiming to quantify the impacts of the

air quality changes.

Estimating health impacts is a means of improving policy relevance and encouraging scientific engagement from decision makers and is often an aspect of future air quality modelling studies. Quantifying health impacts of air pollution and the benefits of mitigation of air pollution comes with its own set of challenges. The primary challenge is in the choice of function used to estimate health impacts. Health impact functions usually derive mortality associated with individual air pollutant concentrations from retrospective cohort studies. Generally, functions focus on $PM_{2.5}$, such as the integrated exposure response (IER) functions (Burnett et al. 2014) which provide individual functions for different mortality types associated with poor air quality and replaced earlier log-linear functions, the Global Exposure Mortality Model (GEMM) (Burnett et al. 2018) which associates exposure with all non-communicable disease and LRI mortality. O_3 mortality is estimated with log-linear functions including Jerett et al. (2009), Turner et al. (2016) or Murray et al. (2020). These tend to only associate O_3 mortality with CVD. The functions suggested by The Committee of Medical Effects of Air Pollutants (COMEAP, 2018 - who focus on UK air quality) also provide the option of using NO_2 concentrations as the indicator for combined $PM_{2.5}$ and NO_2 air quality. These are rarely used outside of UK government-associated studies. COMEAP (2018) note the challenge of disentangling the health impacts of NO_2 and $PM_{2.5}$. More widely, standard practice is to use $PM_{2.5}$-focused functions due to a lack of a clear and robust function linking NO_2 to its individual health outcomes (Burnett & Cohen, 2020).

Studies estimating health impacts based on RCPs include Silva et al. (2016) and Silva et al. (2017) who both use the IER functions and population projections/baseline mortality rates designed to be consistent with the RCPs (with the latter paper focusing only on climate change impacts). Partanen et al. (2013) use the same health impacts function but keep population and baseline death rates constant at present-day levels. Projections are also not used in estimations of O_3 mortality attributable to climate change by Wilson et al. (2017) (focusing on the US) and Hong et al. (2019) (focusing on China). Goto et al. (2016) use an early linear function but use Japan-specific projections of future populations (with no difference in future population between climate change scenarios). Linear functions are also used by Sun et al. (2015), Yuqiang Zhang et al. (2017). Sun et al. (2015) identify the weaknesses inherent in keeping baseline mortality and population static and in using projections, and provide mortality estimates using both

methods. The GEMM is used by Upadhyay et al. (2020), who also provide mortality estimates with both projections and static population. Panullo et al. (2017) and Fenech et al. (2021) differ from other research by using functions associated with COMEAP. Fenech et al. (2021) also combine RCP emissions with population projections created by Jones & O'Neill (2017) to be consistent with the SSPs for their mortality calculations.

Studies considering health impacts of air quality following SSPs are fewer in number. TM5-FASST (described by Van Dingenen et al. 2018), a rapid assessment model with built-in health impact estimations, is used by some recent studies using SSPs e.g Markandya et al. (2017), Ingole et al. (2022) and von Salzen et al. (2022). Although the former uses the SSPs solely as the socioeconomic component underlying their assumptions, and not directly quantifying the emissions used. Some studies rapidly screen the air quality and health impacts of alternative mitigation scenarios (Van Dyck et al. 2020). Shindell et al. (2022), Im et al. (2023), Turnock et al. (2023) and Reddington et al. (2023) all also use GEMM with projections of baseline mortality and population consistent with the SSPs. Turnock et al. (2023) use an O_3 health impacts function, but their work is primarily based on the mitigation of NTCFs. Im et al. (2023) project global mortality using the GEMM and the function from Jerett et al. (2009) for O_3. Wang et al. (2022) use the same functions but focus specifically on China. Shindell et al. (2022) only consider $PM_{2.5}$ and focus purely on the African domain, whereas Tang et al. (2022) use GEMM for China. Parsons et al. (2023) use the GEMM but fix population and baseline mortality at present day levels to reduce the uncertainty external to the models. Chen et al. (2023) similarly use the GEMM with population projections but they do not project baseline mortality. Yang et al. (2023) differ from other research by using the GBD functions and performing sensitivity tests to disentangle the impacts of $PM_{2.5}$ exposure, baseline death rate, population growth and change in age structure. Shim et al. (2021) do not estimate health impacts directly when using SSP CMIP6 output to consider regional $PM_{2.5}$ changes over different sub-regions of Asia, however, they do assess if it changes the air quality index band.

The efficacy of using health co-benefits alone to encourage more stringent policy is questionable, e.g Workman et al. (2019) find that health co-benefits of climate mitigation are explicitly included in EU policy development however there is limited evidence of them being used to justify new policies. There are many reasons for this, e.g Dinh et al. (2024) find that the majority of health co-benefits of climate mitigation studies are published in environmental

science focused journals and thus may miss the public health audience.

Some studies aim to improve the policy relevance of health impact estimates by estimating healthcare financial savings. This was pioneered by West et al. (2013) and is also used by Yuqiang Zhang et al. (2017). Tarin-Carrasco et al. (2019) use a similar approach following RCP8.5 in Southern Europe. Some of the TM5-FASST driven studies (in this case Markandya et al. 2017 and Vandyck et al. 2020) also consider economic impacts. This method could assuage fears of low benefit versus cost among some policymakers, who may underestimate the economic risks of failure to transition to a low carbon economy according to Battison et al. (2021), as studies estimating economic benefits tend to find that the financial benefits of mitigation significantly outweigh the mitigation costs (Karlsson et al. 2020). Economic co-benefits of climate mitigation are not considered to be solely the result of lower healthcare costs; studies focusing on economic benefits also highlight the creation of green jobs, avoiding increases in food prices and the potential public funds that could be raised through carbon taxes (Siegmeier et al. 2017), although to my knowledge these ancillary economic benefits have not been quantified along with air quality change. Notably, some economic studies criticise the common methods of assessing economic benefits of climate policy (including beyond those considering just air pollution), e.g Kotchen et al. (2023) find that the IAM models used to consider economic benefit often project lower costs of mitigation compared to purely economic models. Rosen & Guenther (2015) argue that IAMs provide an unreliable view of mitigation costs and state that mitigation actions should proceed regardless of the results of long-term economic analysis using these methods.

Another potential avenue is considering health equity, although this is an emerging topic in terms of future air quality. In Europe, studies tend to find that deprived regions are more badly affected by poor air quality than less deprived regions (Richardson et al. 2013; the European Environment Agency, 2019; Laurent, 2022; Gray et al. 2023). Health equity is increasingly considered an important criteria for driving health policy (Brownson et al. 2021). Climate change mitigation could improve health equity depending on methods, and failure to mitigate could increase inequity (Munro et al. 2020). Thus, integrating health equity in climate policy is necessary for optimising the costs and benefits of mitigation (Bolte et al. 2023, Wild et al. 2025). Currently, there is limited research examining how equity of air quality exposure could change in the future following RCPs or SSPs. Pannullo et al. (2017) address socioeconomic inequality

but primarily as a factor included in the log-linear function they employ to estimate health impacts. Reddington et al. (2023) also consider the equity impacts of $PM_{2.5}$ changes following SSPs using gridded GDP per capita and splitting the world's population into 4 categories based on this, grid cell by grid cell, finding that middle income areas benefited the most from following SSP1-2.6 and SSP2-4.5 and that a disparity in $PM_{2.5}$ exposure between the highest and lowest income groups of 30% would be expected even with strong mitigation. The comparative wealth of Europe means the majority of the continent falls within the least deprived quarter, meaning this methodology will not capture intra-continental variability.

Some studies are designed for a primarily scientific audience as opposed to a policy audience, focusing on new methodologies or deep analysis of the chemical changes responsible for the air quality impacts. Examples include Wild et al. (2013) who focus on comparing the RCPs to the SRES scenarios and using a parameterised approach, estimating O_3 responses to RCP changes based on less specific model simulations and Turnock et al. (2018) who use a similar, updated methodology. Some studies use output from model intercomparison projects to establish the level of agreement and performance of different models e.g Young et al. (2013), Colette et al. (2013), Park et al. (2020). Some studies could be argued to be focusing both on impacts and differentiation of the underlying methodology, e.g Chen et al. (2023), as discussed, estimate health impacts but much of the focus of the study is on the machine learning approach taken for estimating global $PM_{2.5}$ concentrations and Parsons et al.(2023) estimate health impacts, but with the aim of comparing estimates between CMIP6 models. Similarly, some future air quality studies (with or without health impacts) on a regional level highlight using high resolution models e.g Goto et al. (2016), Yuqiang Zhang et al. (2017), Yang Zhang et al. (2017), Kumar et al. (2018), Zhu et al. (2019), Amnuaylojaroen et al. (2022). Some e.g Fenech et al. (2021) combine a health impacts assessment with an investigation into the underlying chemical changes and what this suggests about the sectoral drivers. Liu et al. (2016) do not estimate health impacts but, in addition to modelling RCP impacts on $PM_{2.5}$ in China, they analyse seasonal changes, the likely sectors responsible and the impacts on radiative forcing. Seasonality is also considered by Yang Zhang et al. (2017) who recommend that US states consider different seasonal responses, demonstrating that wintertime O_3 responses may differ in different states due to the VOC/NO_x regimes, but do not make it clear whether this effect is also expected in summer.

As outlined previously, some studies prioritise separating the impacts of climate and emissions change. Some go further, e.g Bhattarai et al. (2024) consider the air quality impacts of global land use change. Some focus on separating out the impacts of different sectors or regions, e.g Yuqiang Zhang et al. (2017), who also consider health, economic impacts and separating out emissions and climate change impacts touch on this; focusing on a single scenario (RCP4.5) and analysing in greater depth the drivers behind the impacts. They find that residential emissions are the most impactful for driving future US air quality and that 15% the reduction of $PM_{2.5}$ and 62% of the reduction of O_3-related deaths in their simulations were attributable to greenhouse gas mitigation outside the US.

1.8 Thesis Aims and Structure

The primary aims of this thesis are to:

- Quantify the change in major air pollutant concentrations in Europe following climate mitigation scenarios and analyse whether a certain level of climate mitigation is needed to get air quality co-benefits. Understand where the changes are greatest.

- Analyse why the emissions changes in different sectors assumed by climate mitigation do this, considering air quality chemistry. Identify key sectors for mitigation based on this.

- Quantify the health effects from air quality change of climate change mitigation scenarios in Europe.

- Understand whether the health benefits or costs of following different scenarios disproportionately affect different populations.

-Understand the separate impacts of emissions and climate change on air quality and the dominant pathways of secondary pollutant formation.

The project design of this thesis is based on enhancing the existing literature. Some of the

initial methodological parameters of the project include:

- Use of the SSPs as the basis for the modelling study:

At project commencement, use of the SSPs for air quality research was limited; to my knowledge only Markandya et al. (2017) and Turnock et al. (2018) were available at the time. This is a fast-moving field; most of the literature has been published while this project is ongoing. Using the SSPs allows for better representation of the socioeconomic conditions resulting in different climate endpoints than the RCPs.

The different assumptions of socioeconomic development within the SSPs change the balance of different emissions species, e.g trajectories of NH_3 emissions differ strongly in the SSPs than they do in the comparable RCPs - usually assuming a more gradual change over the century as opposed to RCPs, which assume more immediate mitigation. Similarly, the input of socioeconomic changes into the SSPs results in different patterns than the RCPs, e.g SSP1-2.6 will have a greater difference from SSP2-4.5 than RCP2.6 and RCP4.5 as the latter only considers emissions stringency as opposed to detailed analysis of the changes in emissions caused by socioeconomic changes. For example, SSP2-4.5 assumes a greater increase in global NH_3 emissions than RCP-4.5. As shown above, the balance of NO_x, NH_3 and VOCs including CH_4 matter considerably for the chemical processes that govern air quality, especially for O_3.

-Using the regional model WRF-Chem if possible:

A key objective of this thesis is to provide better representation and understanding of the atmospheric chemistry responsible for governing future air quality than the existing research and to do so at a finer spatial scale. To understand why air quality responds the way it does to emissions changes, especially secondary air quality, the methodology needs to be able to represent a large range of complex chemical processes and to do so at a reasonably fine resolution. Much of the existing research uses models that operate at 100+ km spatial scales, whereas several meaningful chemical processes that govern air quality do so on a local scale. At coarser resolutions, the impacts of these local processes get averaged over large areas, thus hampering the abilities of coarser models to represent air quality. Similarly, some pollutants are emitted at much greater concentrations in urban regions and result in highly elevated urban

pollution. This too, gets averaged out using coarser models. Considering the proportion of the population of Europe that live in urban regions, using a finer-resolution model is important for health impact estimation and understanding the impacts.

WRF-Chem is a detailed chemical transport model and is well suited to modelling complex chemistry and at resolutions capable of capturing elevated urban concentrations. This potentially allows for a better exploration of local-to-regional air quality impacts than existing research. It has a history of being used for modelling future air quality, albeit Europe was not the focus.

-Europe as the domain focus:

Europe is my focus due to the importance of climate leadership in achieving climate goals. Richer countries are argued to have "moral responsibility" to lead on climate mitigation, and mitigate financial costs as they are demonstrably responsible for a greater proportion of current climate change extremes even considering only recent emissions (Schöngart et al. 2025), with arguments about whether for climate mitigation, the "polluter pays principle" or "historical polluter pays principle" should apply (Tilton, 2016). Some projections suggest that climate change mitigation could be more impactful in developing countries albeit largely due to developed countries "exporting" emissions elsewhere (Wei et al. 2012). European Climate leadership is currently seen to have had some success, but in a changing world there are calls for advancement of this, particularly as an EU collective (Oberthür & Dupont, 2021), although perceptions of its efficacy can vary across the continent (Schwerhoff, 2016). Europe has a high density of governments, often with different understandings and ambitions around environmental mitigation policy, e.g Buzogány & Ćetković (2021) note that MEPs from Central and Eastern European countries are more likely to be resistant to ambitious mitigation.

Europe has a lot to gain from air quality mitigation; Europe has a disproportionately high per capita mortality rate from air pollutant exposure, most likely due to highly dense and urbanised population meaning a greater proportion of the population are exposed to the region's most polluted areas (Lelieveld et al. 2019a). By demonstrating that relatively near-term and local benefits (e.g improvements in air quality, ideally on a country by country scale) can be achieved by climate mitigation there is greater incentive for more ambitious "climate leadership" in Europe, as being the one to "pay" for climate mitigation is not necessarily a cost.

Europe has rarely been considered as a "collective" when considering future air quality, except when separated as a region in global studies. Thus far, the only future air quality co-benefits study covering most of Europe using RCPs is Colette et al. (2013). Pisoni et al. (2023) focus specifically on the impacts of the EU "fit for 55" policy package. Others focus on individual countries, particularly the UK (Pannullo et al. 2017; Fenech et al. 2021; Macintyre et al. 2023). To my knowledge, future European air quality specifically following the SSPs, has only been investigated as a small aspect of global studies using CMIP6 models, or by Ingole et al. (2022) who project air quality solely in Barcelona.

Following the above criteria and assessment of the literature, 3 Chapters are presented:

Paper 1 "The $PM_{2.5}$ and O_3 co-benefits of a low-carbon economy in Europe"
paper 2: "Reducing inequities in the future air pollution over Europe"
Paper 3 "Heatwave Impacts on UK Air Quality Mitigation"

The goals of paper 1 were to introduce and validate a regional atmospheric chemistry model setup designed to simulate the air quality implications of following the SSPs and to understand to what degree air quality in Europe changes following different emissions scenarios, and crucially, why they do so. This would include analysis of $PM_{2.5}$ components and O_3 precursors to establish which are drivers of change. By understanding the change in $PM_{2.5}$ precursors (and primary components) and O_3 precursors, the mechanisms that control their influence on air quality (for example, the importance of the balance of NO_x and NH_3 to $PM_{2.5}$ outlined by Clappier et al. (2021)) and the sectors which are the greates contributors to emissions of each, this paper could indicate which sectors need to be prioritised to achieve air quality co-benefits of climate mitigation scenarios.

Paper 2 is an "impacts" paper designed for greater policy relevance. The goals of this paper is to estimate the changes in mortality from $PM_{2.5}$ and O_3 that can be expected based on the emissions changes in each scenario. This is targeted at a policy audience and will hopefully present the potential improvements to human health that can be gained through additional mitigation and demonstrate the costs of failing to do so. Then, the chapter explores whether, on a regional scale, the air quality benefits of emissions reductions are more impactful in more developed or less developed areas of Europe, thus investigating whether current climate mit-

igation pathways are equitable. Another goal of this paper is to understand why - analysing the correlation between development and mortality rates in European subregions with different characteristics (e.g rural/urban, coastal/inland, Northern/Central/Southern Europe etc). When combined with the understanding gained from paper 1 in terms of dominant air pollutant sources and chemical processes, this chapter aims to explain why inequity changes in response to the emissions changes in each scenario the way they do.

Paper 3 is designed to answer the question of to what degree climatic conditions "penalise" emissions change; that is how much the impacts of climate change on meteorological conditions alter the overall change in air quality on top of emissions changes. As demonstrated by the literature, the climate itself has and will continue to have strong impacts on secondary air quality through pathways such as triggering increased isoprene emissions, thus increasing the availability of VOCs or through increased NO_x availability from PAN decomposition at higher temperatures. In this paper, I aim to explore these pathways and understand which are most impactful for the climate penalty to emissions change in Europe.

Paper 3 uses an exploratory methodology - considering using meteorological data from the heatwave season of 2022 as an indicator for conditions under future climate change. A secondary aim of this paper is to examine how the "climate penalty" generated using this indicator compares to methodologies in which future climate model output is used. This can explore whether this method is a suitable compromise for factoring in climate change to allow for use of models better optimised for air quality modelling.

The following sections discuss some of the most important methodological tools for these papers. Beyond that, the Chapters representing each paper are inserted with a short preface.

1.9 WRF-Chem

Papers 2 & 3 of this thesis describe work directly using chemical transport model data. Paper 2 does not directly use modelling, but is still based on the model output from paper 1.

This thesis uses the "Weather Research and Forecasting Model with Chemistry" or WRF-Chem version 4.2 (Grell et al. 2005). WRF-Chem is based on the WRF model (Skamarock et al. 2008), designed for regional weather forecasting. WRF-Chem is modular and can be compiled in setups with a range of schemes within the model that affect how it operates. In this thesis, WRF-

Chem was compiled using a set of automated scripts known as "WRFotron". By focusing on specific regions, WRF-Chem can be run at higher resolutions and with more detailed, "online-coupled" chemical schemes than GCMs. This means chemistry and meteorology can interact and feedbacks more effectively represented (Grell et al. 2005). WRF-Chem is an Eulerian model, in which chemical and meteorological parameters are calculated on a grid within the domain at a default timestep of one hour. The finer possible resolutions improve representation of the concentration of air pollutant gradients of emissions and across different land surface types (Crippa et al. 2017). This comes with the tradeoff of higher computational expense and time taken for simulations.

Figure 1.8 (Peckham et al. 2017) demonstrates the structure of the WRF-Chem modelling system, which can be summed up in three parts: 1) the WPS pre-processing, which initialises boundary conditions and schemes necessary for the model to run, the "ARW" model in which the chemical and meteorological inputs are read in and the model simulates, and postprocessing in which the hourly data for 600+ variables are produced. From each hourly output file, the chosen variables can be extracted, concatenated, regridded and turned into a single netcdf file per variable per month for analysis.

Table 1.2 (adapted from an abridged version in paper 2) shows the inputs, chemical and physical schemes used for the model simulations as part of this thesis:

Parameter	**Scheme Used**	**Source**
Chemical Scheme	MOZART-MOSAIC 4-bin Aerosol w/Aqueous Chemistry	Hodzic & Knote, 2014
Biogenic Emissions	MEGAN v2.0.4	Guenther et al. (2006)
Fire Emissions	FINNv1.5	Wiedinmyer et al. (2011)
Natural Dust Emissions	GOCART	Chin et al. (2000), Ginoux et al. (2001), Zeng et al. (2020)
Meteorological Boundary Conditions	ECMWF ERA5	Hersbach et al. (2020)
Chemical Boundary Conditions	CESM2-WACCM CMIP6 Simulations	Danabasoglu (2019)
Dry Deposition	Weseley	Weseley (2007)
Cloud microphysics	Morrison 2-moment scheme	Morrison et al. (2005)
Long & Shortwave Radiation	Rapid Radiative Transfer Model	Iacono et al. (2008)
Cumulus Parameterisation	Grell 3-D	(Grell & Dévényi, 2002)
Planetary Boundary Layer	Mellor-Yamada-Nakanishi-Niino 2.5	(Nakanishi & Niino, 2006)
Land-surface model	NOAH	Ek et al. (2003)
Land Use	MODIS	Sulla-Menasche & Friedl (2019)

Table 1.2: Model parameters used and sources.

A number of the schemes used in these simulations are the "defaults" in the WRFotron setup. Where possible, I chose to use default schemes and inputs due to the anthropogenic emissions and chemical boundary conditions coming from sources not designed for use with WRF-Chem.

Biogenic emissions from the Model of Emissions of Gases and Aerosols from Nature (MEGAN) version 2.0.4 (Guenther et al. 2006) is one of these "defaults". This "online" scheme uses

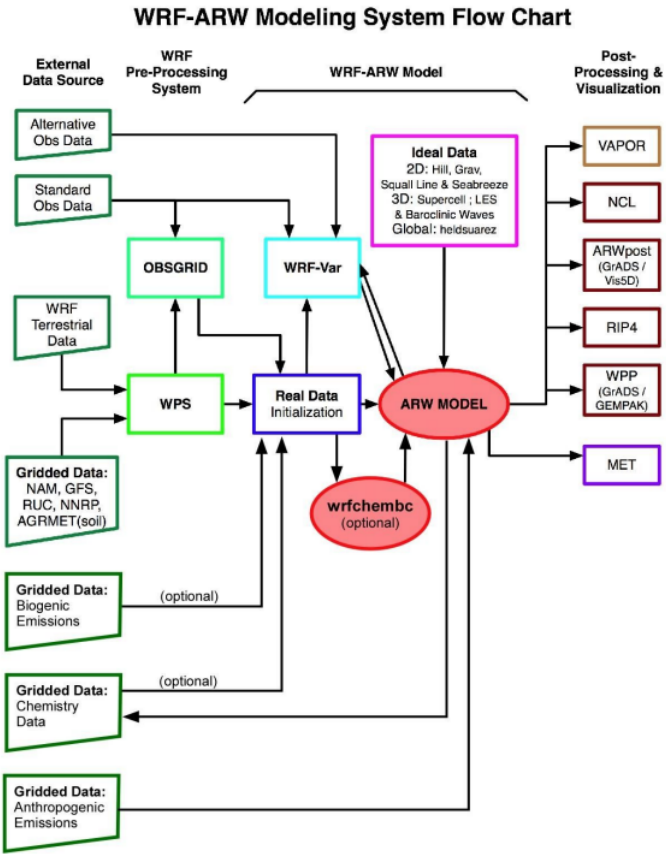


Figure 1.8: Structure of the WRF-Chem model from Peckham et al. (2015) demonstrating the stage of the process at which each input or scheme is applied

vegetation-specific standard emissions rates of isoprene and monoterpenes which respond to sunlight, temperature, leaf area index, leaf age and soil moisture (DiMaria et al. 2023). MEGAN categorises "plant function types" at 1km resolution (e.g Needle Evergreen Tree or Shrub) each of which has its own isoprene emissions factor. MEGAN is the recommended biogenic scheme for use with the chemistry scheme (Hodzic & Knote, 2014).

Land use data from MODIS contains 18 land use classes at 1km resolution, including 7 different tree and shrubland classes and 2 cropland classes.

The chemistry scheme used is MOZART-MOSAIC (Hodzic & Knote, 2014). This combines the Model of Ozone and Related Tracers gas phase chemistry scheme (Emmons et al. 2010) and the MOSAIC aerosol scheme. This scheme uses an updated version of MOZART with detailed treatment of monoterpene and aromatics and improved representation of isoprene oxidation. MOZART includes 85 gas-phase species, 157 gas-phase reactions and 39 photolysis reactions. The Model for Simulating Aerosol Interactions and Chemistry scheme (MOSAIC)

handles aerosols. Aerosols are split into four size bins up to 10 um in diameter. SOA is generated through a system simulating oxidation of a range biogenic and anthropogenic precursors in which gas phase/solid phase volatility considers total organic load and temperature. The GOCART dust scheme from Zeng et al. (2020) is optimised for use with MOSAIC aerosols; it consists of a measure of substrate erodability for sand, silt and clay and uses the model wind speed, soil moisture and soil characteristics to modify quantity emitted (Ginoux et al. 2001).

FINN fire emissions v.1.5 (Wiedinmyer et al. 2011) are created from retrospective satellite observations of fires at 1km resolution. For all simulations in all Chapters, fires from 2014 are used. This is one potential limitation of my research - biomass burning emissions consistent with the SSPs do exist (Van Marle et al. 2017) but I use present-day fires. This was to avoid added computational difficulty and uncertainty that could occur trying to run the model with additional inputs designed for GCMs. This means that the impacts of fire projections are not considered in my simulations. FINN assumes that all fires are $1km^2$ and modifies this based on the vegetation classification within MODIS for the area and fuel loadings are based on the classification. The fire_emiss preprocessor within WRFotron regrids the FINN emissions, applies a diurnal cycle and maps the relevant chemical species to the MOSAIC aerosols, thus an entirely new preprocessor would be needed for the van Marle et al. (2017) emissions. FINN does not include combustion of biofuels or waste, these will therefore not be "double counted" from their inclusion within CMIP6 anthropogenic emissions. Similarly, agricultural burning is included within FINN, but is not included within the anthropogenic emissions for CMIP6. This means that agricultural burning emissions in the simulations are all at present day levels.

1.9.1 Meteorological inputs

Meteorology in WRF-Chem can be "free-running" or "nudged". The initial and boundary conditions are used to define the conditions at the start of the simulation and at the boundaries of the model domain. Where the model is nudged, meteorological parameters are periodically adjusted to once again match the initial and boundary conditions. In my simulations, nudging took place 6-hourly within and above the boundary layer. The meteorological inputs were extracted from reanalysis data from ECMWF ERA5 (Hersbach et al. 2020), for 2014 (paper 1) along with 2022 (paper 3 only), meaning that every 6 hours, meteorology was forced to products designed to represent real-world weather conditions in these years.

The ERA5 reanalysis is a global 31 km resolution 3D grid product with 137 levels up to 80km in the atmosphere. Almost 350 variables can be extracted from this dataset with minimum 3-hourly temporal resolution between January 1940 and the present day (Copernicus Climate Data Store, 2024). To create this, observation data from both satellite and ground-based observations are used with a numerical model to provide a gridded product representative of the Earth's atmosphere; for given time windows, systems designed to select the most appropriate land, sea and atmosphere observations are used to bias correct the ERA5 model output (Hersbach et al. 2020). This product is frequently updated and representations of real-world conditions are usually available as a final product 2-3 months after realitime.

ERA5 reanalysis data was used due to its existing compatibility with WRF-Chem using the WRF-Chem system. The implications of using ERA5 is that this thesis does not factor in the impacts of climate change itself on air quality. Paper 3 aims to quantify the potential impact this could have had on the results by comparing air quality for both the present day and 2050 following SSP3-7.0 using meteorology from both 2014 and 2022, which had record breaking heat waves in most of Europe. Using elevated heat periods as an analogue for climate change is a method described previously by Yule et al. (2024). While using future meteorological conditions may be the preferable method, this was not feasible in the time frame of the thesis for reasons described below:

1.9.2 Anthropogenic emissions and chemical boundary conditions

The anthropogenic emissions used are gridded CEDS emissions consistent with the CMIP6 and ScenarioMIP intercomparison projects; that is Hoesly et al. (2018) for historical emissions and Feng et al. (2020) for projections consistent with the SSPs. For the "present day" simulations, 2014 emissions were used as this was the final year of non-projected emissions consistent with CMIP6. 2050 emissions were used from Feng et al. (2020) consistent with SSP1-2.6, SSP2-4.5 and SSP3-7.0. As standard, these provide gridded emissions of CO, CH_4, NH_3, NO_x, SO_2, NMVOCs, BC, OC and CO_2.

The historical CMIP6 emissions (Hoesly et al. 2018) are available from 1750-2014. These are produced using a combination of existing emissions inventories, emissions factors and driver data to produce annual country and sector specific time series. Emissions estimates are used for emissions pre-1960 and for countries where emissions inventories were not available. Emissions

for 221 surface regions are quantified/estimated along with a global region to cover aircraft and shipping. These are split into 8 different fuels and 55 specific sectors. Where necessary to estimate emissions (e.g regions without reliable emissions reporting, emissions pre-1960 etc), "emissions drivers" which include population and energy use are considered. These are gridded onto a 50km horizontal resolution grid using population grids and spatial proxy distributions and monthly fractions from the ECLIPSE project are applied to provide monthly emissions. The sectoral and regional emissions from Hoesly et al. (2018) are used as the basis of emissions projections as described by Gidden et al. (2019). Effectively, the IAM output for the SSPs is aggregated over larger regions and a downscaling process is used to generate country-level emissions from these; they use linear downscaling for biomass burning, so that the fraction of regional emissions from each country remains constant. Emissions from other sectors factor in GDP and population projections in determining the total from each country. Planned policies specific to countries are not factored in. These pathways provide annual emissions, but the original models produced data for 2015, 2020 and every ten years until 2100. Emissions data between the model years is interpolated The emissions pathways from Gidden et al. (2019) are used to generate gridded emissions by Feng et al. (2020). Gridded emissions are only available from years in which interpolation was not used. Feng et al. (2020) use the same methodology as Hoesly et al. (2018) to turn country-specific emissions time series into grids, but the 2014 spatial grids from Hoesly et al. (2018) are used as the spatial proxy. This means that the location of emissions from Feng et al. (2020 are consistent with the historical emissions and remain static in the future, aside from considering projections in the change in spatial distribution of international shipping.

The emissions files I used were obtained from a JASMIN repository of CMIP6/ScenarioMIP emissions used for Turnock et al. (2020). As these emissions files were setup for use with GCMs, the files were not used directly in the WRF-Chem simulations. The default setup in WRFotron uses EDGAR-HTAPv2 emissions (described by Huang et al. 2017). To ensure that the model would accept emissions representative of the SSPs, I created emissions files in the structure of EDGAR-HTAPv2 using the CMIP6 emissions data and used standard bilinear regridding to ensure they were at the appropriate resolution. The namelist within WRF-Chem was set to read the total emissions of each species without sectoral refinement. Aside from aviation emissions, all emissions are assumed to be emitted at the surface. Aviation emissions were distributed in three vertical levels to match EDGAR-HTAPv2 emissions. No unit conversion was necessary.

A similar principle to creating the emissions files was used to create chemical initial and boundary conditions for the simulations. The data for these was obtained from 6-hourly WACCM data (see Marsh et al. 2013 for a description of WACCM) specifically obtained from CESM2-WACCM simulations from Danabasoglu (2019) for the ScenarioMIP project.CESM2-WACCM is a parameterisation of the Community Earth System Model 2 with the Whole Atmosphere Community-Climate model used for simulating the atmosphere (Marsh et al. 2013; Gettelman et al. 2019; Danabasoglu et al. 2020) The MOZART-MOSAIC scheme is capable of running with WACCM chemical initial and boundary conditions. The relevant variables were extracted by Daniel Marsh and converted into single initial/boundary condition files by Ailish Graham. More information about CESM2-WACCM is provided in the appendix, section 1.1.

1.10 Concentration-Response Functions

Three concentration-response functions were used for the analysis in paper 2. These are:

-eSCHIF-Fusion for $PM_{2.5}$(Weichenthal et al. 2022)

-the GEMM, also for $PM_{2.5}$ (Burnett et al. 2018)

-The Global Burden of Disease 2019 function for O_3 mortality (Murray et al. 2020).

The analysis primarily focused on eSCHIF-Fusion for $PM_{2.5}$-attributable mortality. I did not solely use this function because it is a recently created function and its use is somewhat exploratory at the time of writing. The GEMM on the other hand has been widely used for health impacts estimations since its introduction, including for future mortality estimates (Ingole et al. 2022; Im et al. 2023; Turnock et al. 2023; Reddington et al. 2023).

The eSCHIF-Fusion function is a combination of two functions; the extended Shape Constrained Health Impact Function (eSCHIF) (Brauer et al. 2022) covering low $PM_{2.5}$ concentrations and the Fusion model Burnett et al. (2022) for higher concentrations, up to 83 μg m^3. The Fusion model was designed specifically as an alternative to the GEMM due to limitations in its ability to extrapolate expected mortality at more extreme concentrations (Burnett et al. 2022). Fusion has lesser uncertainty at higher $PM_{2.5}$ concentrations than GEMM and is recommended for use instead of GEMM by teams led by Richard T. Burnett, who produced both functions (Burnett et al. 2022). The combination of the eSCHIF function with Fusion is designed to operate

well across the concentration range; at low concentrations, where Fusion does not operate as effectively, the exposure-response function from eSCHIF, which is derived from a Canadian cohort and designed to accurately represent mortality at lower $PM_{2.5}$ concentrations, is used. The functions for determining relative risk are shown in paper 2.

The relative risk curves for eSCHIF-Fusion are shown in figure 1.9:

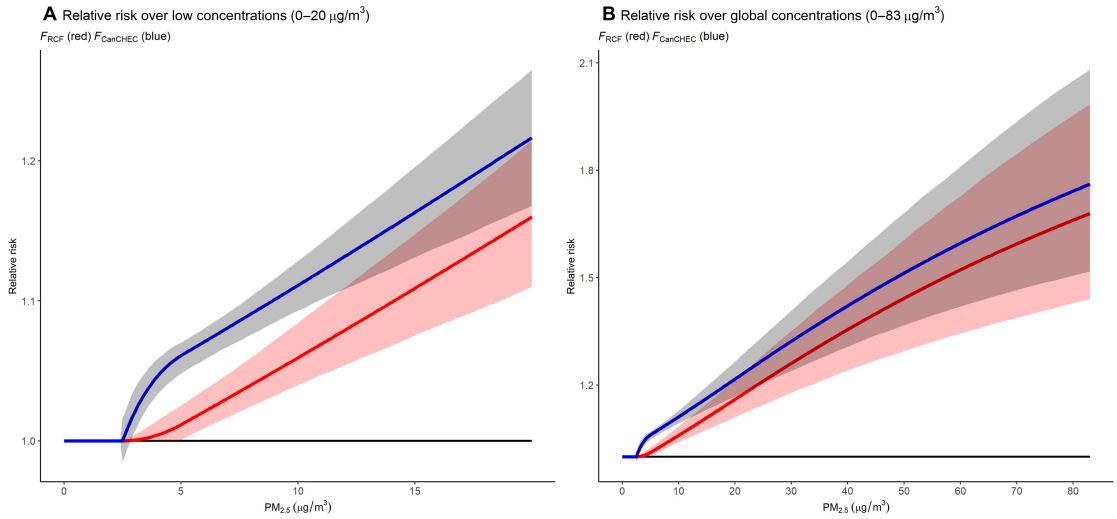


Figure 1.9: risk curves for eSCHIF-Fusion up to 20 μg m^3 (left) and up to 83 μg m^3 (right). Figure from Weichenthal et al. (2022). In these, the blue lines and shaded areas represent the refined function used in my work and the red line refers to a previous function the authors provide as comparison, demonstrating the higher response to concentrations at lower $PM_{2.5}$ concentrations using eSCHIF-Fusion

No excess mortality is assumed below 2.4 μg m^3. In reality, $PM_{2.5}$ is a "non-threshold pollutant" meaning that no safe level of exposure has been identified (Krewski et al. 2009). For all functions, zero air pollution-attributable mortality is assumed under the age of 25. This leads to the possibility that mortality could be underestimated.

The eSCHIF-Fusion and GEMM approaches correlate $PM_{2.5}$ exposure with all NCD and LRI mortality. The GEMM can estimate death per age group, whereas eSCHIF-Fusion is not set up for this.

The GEMM function uses the same range of population exposures (2.4-83 μg m^3). It includes 41 cohorts - 15 of these were independently analysed in greater detail and a non-linear function was assumed. For 26 further cohorts for which the authors had less information, a linear relationship between $PM_{2.5}$ and mortality was estimated. The combined hazard ratio makes up the GEMM. The combined hazard ratio curve is shown in figure 1.10.

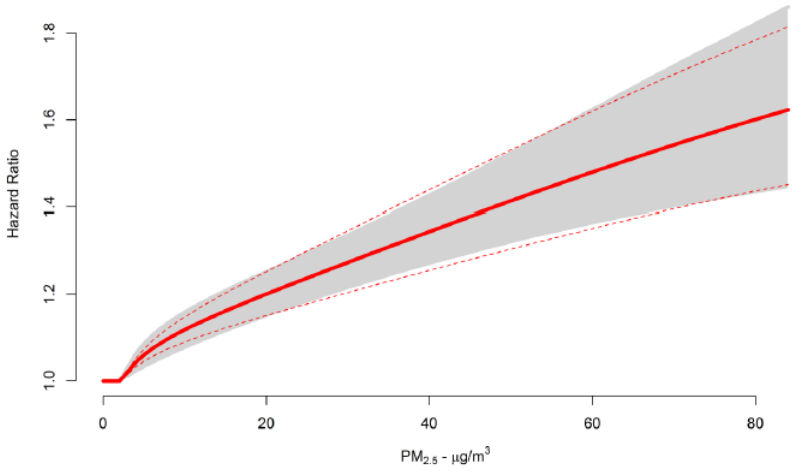


Figure 1.10: Hazard ratio curves for GEMM up to 83 μg m^3 (right). Figure from Burnett et al. (2018)

The function used for O_3 mortality was a simple linear function consistent with the global burden of disease study (Murray et al. 2020). This uses a linear hazard ratio function for COPD mortality based on 6-monthly-mean daily maximum 8-hour O_3 (6mDM8h O_3) as the O_3 exposure value. The relative risk used to generate the attributable fraction ranges from 1.03 to 1.05 per 10ppb increase in 6mDM8h O_3. A mixing ratio of 35.7 ppb was used corresponding to the 5th percentile value of Turner et al. (2016) as the counterfactual, below which, no associated mortality is assumed.

Other assumptions to note regarding health impact functions, particularly for $PM_{2.5}$ are that while it is generally recognised that there is different toxicity of different $PM_{2.5}$ species, there is limited ability to factor this in in the standard health impacts functions used. Few studies try to assess differential toxicity between particulate species, however Lelieveld et al. (2015) report that if carbonaceous aerosol is considered to be five times as toxic as inorganic particles, the sectoral drivers behind overall air quality mortality in some regions (including Europe) may differ.

A source of uncertainty in estimating future mortality is the use of population projections. In some research, the population has been shown to have had a greater impact on changes in $PM_{2.5}$ mortality than changes in air pollutant concentrations (Vohra et al. 2021). A basic description of the population and baseline mortality projections used is in paper 2. More information about these is provided in the appendix section 1.3.

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Chapter 2

The Co-benefits of a Low-Carbon Future on Air Quality in Europe

2.1 Preface

This is the first primary research Chapter of the thesis. The goal of this Chapter was to present and validate the model setup using CMIP6 emissions in WRF-Chem and then present the air quality changes following SSP1-2.6, SSP2-4.5 and SSP3-7.0, examining how the emissions themselves could drive the trends seen. This is because analysis of the initial research showed that at the time, very little air quality research used the then-new SSPs as inputs, and these represented a big step forward from the RCPs in representing societal developments that lead to future radiative forcings in the emissions themselves. Similarly, the prevalent use of GCMs meant there was little regional refinement. $PM_{2.5}$ was a particular focus of this paper because the advantage of this method was the model's better representation of aerosol chemistry and concentration gradients meant I could analyse $PM_{2.5}$ components and discuss which sectors and processes were likely responsible for this. I also worked in this Chapter to ensure that impacts were communicated in a potentially policy-relevant manner, hence displaying results on a country-by-country level.

Considerable trial and error was needed to develop the method for this project. The non-negotiables were the European domain, use of WRF-Chem and use of the SSPs. This posed a lot of challenges, including managing disk space, building a stable model and particularly, deciding how best to manage future meteorology. Several methods were tested, including the

NCRM-Chem setup described by Kumar et al. (2018) - perhaps the obvious choice for using WRF-Chem to model future air quality. This was not used because:

-The ability to consider GHG forcing does not fix the problem of lack of available projected meteorological inputs representative of the SSPs.
-The existing available GHG pathways did not cover a "sustainable" scenario (e.g forcings leading to radiative forcing endpoint of 2.6 W $m^{-}2$. The objective of this research is to demonstrate the benefits of climate change mitigation in Europe more so than highlight the consequences of climate change.
-A version of NRCM-Chem was compiled but testing with forcings different to the RCP forcings innate in the build showed this version to be very unstable.
-The benefit of NRCM-Chem is that it allows for climatic conditions over long periods of time to be simulated. This would necessitate long simulations, e.g 10 years. Doing this would be very computationally expensive and time-consuming, requiring tradeoffs such as modelling fewer scenarios and/or reducing the chemical timestep, such as the method used by Kumar et al. (2018)

I chose to keep meteorology constant at 2014 levels following the method of Fenech et al. (2021) and using the justification of considerably higher contribution of emissions change compared to climate change (Chemel et al. 2014; Doherty et al. 2017). The implications of this and whether or not this "trade-off" was worthwhile became an important theme of my thesis. Thus, I include some comparison with GCM output in this paper. Paper 3 directly led on from this theme, examining what the impacts of this choice may be.

From below, this Chapter is a reproduction of the following paper, with minor formatting changes and a few clarifications based on corrections asked for post-viva:

Clayton, C. J., Marsh, D. R., Turnock, S. T., Graham, A. M., Pringle, K. J., Reddington, C. L., Kumar, R., and McQuaid, J. B.: The co-benefits of a low-carbon future for $PM_{2.5}$ and O_3 air pollution in Europe, Atmos. Chem. Phys., 24, 10717–10740, https://doi.org/10.5194/acp-24-10717-2024, 2024.

2.2 Abstract - Paper 1

There is considerable academic interest in the potential for air quality improvement as a co-benefit of climate change mitigation. Few studies use regional air quality models for simulating future co-benefits, but many use global chemistry–climate model output. Using regional atmospheric chemistry could provide a better representation of air quality changes than global chemistry–climate models, especially by improving the representation of elevated urban concentrations. We use a detailed regional atmospheric-chemistry model (WRF-Chem v4.2) to model European air quality in 2050 compared to 2014 following three climate change mitigation scenarios. We represent different climate futures by using air pollutant emissions and chemical boundary conditions (from CESM2-WACCM output) for three shared socioeconomic pathways (SSP1-2.6, SSP2-4.5 and SSP3-7.0: high-, medium- and low-mitigation pathways respectively).

We find that in 2050, following SSP1-2.6, mean population-weighted $PM_{2.5}$ concentrations across European countries are reduced by 52% compared to 2014. Under SSP2-4.5, this average reduction is 34%. The smallest average reduction is 18%, achieved following SSP3-7.0. Maximum 6-monthly-mean daily-maximum 8h (6mDM8h) ozone (O_3) is reduced across Europe by 15% following SSP1-2.6 and by 3% following SSP2-4.5, but it increases by 13% following SSP3-7.0. This demonstrates clear co-benefits of climate mitigation. The additional resolution allows us to analyse regional differences and identify key sectors. We find that the mitigation of agricultural emissions will be key for attaining meaningful co-benefits of mitigation policies, as evidenced by the importance of changes in NO_3^- aerosol mass to future $PM_{2.5}$ air quality and changes in CH_4 emissions to future O_3 air quality.

2.3 Introduction

Air pollution is a major public-health issue worldwide. The health impacts are usually attributed to two air pollutants: $PM_{2.5}$ (any airborne non-gaseous particle under 2.5µm in diameter), which can be both a primary or secondary air pollutant, and ozone (O_3), which is a secondary pollutant. Primary sources of $PM_{2.5}$ include a range of natural and anthropogenic sources. As a secondary pollutant, it can be formed from emissions of species such as ammonia (NH_3), sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Tropospheric O_3 is a secondary pollutant formed by photochemical reactions involving volatile organic compounds (VOCs), including methane (CH_4), nitrogen oxides (NO_x) and carbon monoxide (CO), in the presence of sunlight.

Air pollution has wider consequences than just mortality, such as the economic cost (Vandyck et al., 2020) and reduced crop yields (Lobell et al., 2022). Both $PM_{2.5}$ and O_3 are linked with climate change; many sources of primary $PM_{2.5}$ and O_3 precursors are also sources of long-lived greenhouse gases. Additionally, air pollutants themselves have an impact on climate forcing through several pathways, including by directly affecting the radiative balance of the atmosphere, modifying the albedos of clouds and glaciers, and increasing the cloud lifetime (von Schneidemesser et al., 2020; Peace et al., 2020).

Exposure to air pollution contributes to about 6.7 million deaths per year (World Health Organisation, 2022), 4.2 million of which are from ambient outdoor air pollution. In Europe, an estimated 368000 deaths per year are attributable to air pollution according to Juginovic et al. (2021), approximately 90% of which were attributable to $PM_{2.5}$, and the annual mean mortality rate from air pollution in Europe of 133 deaths per 100000 people exceeds the global mean of 120 deaths per 100000 (Lelieveld et al., 2020). Additionally, the European Environment Agency (2022) reported that in 2022, 96% of Europe's urban population was exposed to $PM_{2.5}$ concentrations above the World Health Organisation's guideline value of $5\mu g/m^3$ (World Health Organisation, 2021).

Improving air quality in Europe is feasible: primary air pollution responds quickly to air pollutant emissions reductions, potentially resulting in lower population exposure. Notably, some secondary air pollutants such as O_3 can worsen depending on the emissions reductions in some circumstances, but reducing emissions largely leads to an overall air quality benefit. Due to reductions in anthropogenic emissions of air pollutants, the $PM_{2.5}$ air quality in most of Europe has improved over the past half-century; between 1960 and 2009, population-weighted $PM_{2.5}$ concentrations in the European Union decreased by 55.3% (Butt et al., 2017). Similarly, the responsiveness of air pollution to emissions changes was demonstrated by the changes in $PM_{2.5}$ air quality from national to global scales during the COVID-19 pandemic (Jephcote et al., 2021; Venter et al., 2021; Putaud et al., 2023). The speed of this response to changes in emissions indicates that considerable improvements in air quality can be achieved when air pollutant emissions are reduced. Conversely, O_3 concentrations in Europe have increased in the latter half of the 20th century and early 21st century (Turnock et al., 2020) despite considerable reductions in local anthropogenic O_3 precursor emissions. This is potentially due to increased intercontinental transport of O_3 precursors (Guerreiro et al., 2014). Despite improving trends

in $PM_{2.5}$, O_3 concentrations may increase because reduced NO_x emissions result in the reduced titration of O_3 (Miyazaki et al., 2021). A different approach may therefore be required to reduce exposure to O_3.

Greenhouse gas mitigation policies may also result in lower air pollution emissions and subsequent improved air quality (Turnock et al., 2020; Vandyck et al., 2020). This cobenefit is often suggested as a motivator to encourage faster and stronger climate mitigation from policymakers, including at the regional level, because it turns the concept of climate change mitigation from a diffuse, global-scale requirement to something that can provide measurable near-term local benefits (von Schneidemesser et al., 2020). Existing research suggests that air quality co-benefits of climate mitigation could occur in Europe. For example, Turnock et al. (2020) find that across Europe, $PM_{2.5}$ concentrations would decrease by the middle of this century for a range of future scenarios and be lower in scenarios with greater mitigation. Reddington et al. (2023) find that reductions in $PM_{2.5}$ across Europe following a sustainable scenario (SSP1-1.9) could improve health across the continent. Fenech et al. (2021) find similar when focusing on the UK. This may not be true for all pollutants and all scenarios. Findings differ for O_3, for which Turnock et al. (2020) project an increase in Europe following scenarios with limited climate change mitigation, and Fenech et al. (2021) project an increase compared to the present in all scenarios.

The interactions between air quality and climate change mitigation policies are complicated and non-linear (von Schneidemesser et al., 2015). Surface-level O_3, for example, may worsen following NO_x reductions, as discussed previously (Miyazaki et al., 2021). Complexity is also added by climatic impacts of surface-level O_3 (Archibald et al., 2020) and secondary organic aerosol (Scott et al., 2018; Raes et al., 2010). Climate change will also affect the prevailing meteorological conditions and impact the dispersion of air pollutants, thereby affecting human exposure (Graham et al., 2020). It is also not a given that all climate mitigation strategies will reduce emissions of primary air pollutants as it depends on the mitigation strategy used. Modelling is therefore needed to understand how climate change mitigation and air quality might interact when considering differing strategies for climate mitigation.

Previous research into the linkages between climate change and air quality largely uses the air pollutant emissions associated with CMIP5 as model input (e.g. Silva et al., 2016; Kumar et al., 2018; Fenech et al., 2021), which are linked with the representative concentration pathways

(RCPs) (van Vuuren et al., 2011). RCPs are pathways of greenhouse gas concentrations over the 21st century that result in different radiative-forcing endpoints in 2100. Some more recent research (e.g. Rao et al., 2017; Turnock et al., 2020 Turnock et al., 2023; Reddington et al., 2023) uses the CMIP6 (the successor to CMIP5) emissions, which work with the shared socioeconomic pathways (SSPs) (O'Neill et al., 2017). The SSPs expand the range of pathways and also provide different narratives of socioeconomic development, meaning they factor in the role of socioeconomic development in more detail than the RCPs. They also further expand on the link between pollution and climate, describing how air pollution control progresses when following the narratives, which is then fed into the air pollutant emissions used in CMIP6 (Rao et al., 2017), and so the SSPs used in CMIP6 will provide a better assessment (Coelho et al., 2023). Using scenarios for research in this way does have disadvantages: the RCPs and SSPs are optimised for climate modelling, not air quality modelling, and an over-reliance on them in the literature may reduce the use of more specific scenarios.

The difficulty of modelling air quality and climate simultaneously makes modelling air quality and climate mitigation co-benefits challenging. Many studies using the SSPs use the output from global climate models and/or Earth system models, such as Turnock et al. (2020), or "reduced-form" models that generalise over large regions (Rao et al., 2017). These types of models may have less detailed chemistry schemes than regional air quality models. They also tend to have a coarser horizontal resolution than regional air quality models. This is important for air quality research to simulate chemical processes that impact on air pollutants at local and urban scales (Adedeji et al., 2020; Fenech et al., 2018; Goto et al., 2016). Despite this, global chemistry–climate models have tended to be used for future projections of air quality due to prohibitive computational requirements for running multi-decadal simulations with regional air quality models. Some studies using CMIP6 output (Turnock et al., 2023; Reddington et al., 2023) are making progress in improving the representation and resolution of present-day air quality by combining CMIP6 output with observational and reanalysis data; however, the approaches taken by these studies still use a coarser grid for future simulations.

Some regions are over-represented in regional air quality and climate mitigation co-benefits studies, notably China and India (von Schneidemesser et al., 2020). Examples include Kumar et al. (2018) and Chowdhury et al. (2018) for India and Cheng et al. (2021) and Conibear et al. (2022) for China. We chose to focus our domain on Europe as it is an under-represented region

in the literature. Although studies that focus on Europe or subregions of European countries exist, they largely use CMIP5 emissions instead of CMIP6 (e.g. Fenech et al., 2021 and Sa et al., 2016) or have the primary focus of quantifying the impacts of climate change itself on air quality as opposed to emissions changes (Tainio et al., 2013; Tarin-Carrasco et al., 2019).

2.4 Method

Here, we explore the potential mid-century air quality impacts in Europe following the emissions changes from three up-to-date SSPs (SSP1-2.6, SSP2-4.5 and SSP3-7.0) using a state-of-the-art regional atmospheric-chemistry model. This aims to help us understand the implications of these updated emissions changes on a sub-regional scale in the European domain.

2.4.1 Model description

We use the Weather Research and Forecasting coupled with Chemistry (WRF-Chem) model version 4.2. This is an Eulerian, grid-based atmospheric chemistry model. Grell et al. (2005) provide a general model description. We use WRF-Chem at 30km horizontal resolution with 38 vertical levels up to 50 hPa and a domain of 100×100 grid boxes with latitudes ranging from 32 to 60°N and longitudes ranging from 22°W to 30°E in the north of the domain but narrowing to 13°W to 19°E in the Mediterranean (Fig. A.4). Note that the model domain does not cover all of Europe, and for the purpose of this study, we define "Europe" as 13 countries: Germany, the UK, France, Spain, Italy, the Netherlands, the Czech Republic, Hungary, Poland, Slovakia, Ireland, Slovenia and Portugal. These countries have a combined population of approximately 380 million and represent a range of sources of primary air pollutants and environmental conditions that will affect air quality. We chose the model, resolution and domain in order to capture the changes at the regional and country level; while the resolution is not fine enough to fully represent the chemistry at city scale, it is sufficient to demonstrate urban peaks or elevated concentrations of air pollutants near some power stations. We chose Europe as a domain in part due to the fewer studies in this area but also due to the concentration of national and regional administrative areas, thereby improving the policy relevance of our work. A 30km horizontal resolution allows a compromise between global- and local-scale models by allowing us to increase our domain size to cover most of Europe while also representing air quality in smaller regions more realistically than global models.

We simulate a present-day air quality control with gridded 2014 emissions used in CMIP6 (Hoesly et al., 2018) and perform simulations with anthropogenic emissions representing 2050 for each of SSP1-2.6, SSP2-4.5 and SSP3-7.0 (Feng et al., 2020). These emissions are created based upon the SSPs, meaning they include similar assumptions; for example, the projected land-use changes factor into the emissions. The model parameters are shown in Table 2.1. For all scenarios, the meteorology was fixed at 2014 conditions using meteorological initial and boundary conditions from ECMWF ERA5 (Hersbach et al., 2020). The aerosol–radiation feedback is switched on in the model; however, as the simulations are frequently nudged to the meteorology, there is no meaningful meteorological difference between the scenarios. It is well established that in Europe, the impact of emissions changes on future $PM_{2.5}$ air quality is likely to far eclipse the impact of climate change (Colette et al., 2013; Chemel et al., 2014; Doherty et al., 2017). Additionally, in Europe, even O_3 pollution may not be sensitive to changes in climate (Zanis et al., 2022); thus, we are confident that not factoring in meteorological changes is a worthwhile trade-off to allow us to use a detailed model in WRF-Chem at a relatively fine resolution.

2014 was chosen as this is the most recent year of historical emissions data from the emissions inventory used in CMIP6. We also use CMIP6 output from CESM2-WACCM (Danabasoglu, 2019) simulations to provide initial and chemical boundary conditions. To simulate the chemistry, a scheme described by Hodzic and Knote (2014) is used that combines MOZART-4 gas-phase chemistry, which includes 85 gas-phase species, 157 gas-phase reactions and 39 photolysis reactions (this scheme and the included reactions are provided by Emmons et al., 2010) with the MOSAIC aerosol-chemistry scheme described initially by Zaveri et al. (2008). This provides detailed chemistry for a range of aerosol species, including nitrate from ammonium nitrate (NO_3^-), sulfate (SO_4^{2-}), organic carbon (OC), black carbon (BC), ammonium from other sources (NH_4^+), sodium and chloride, all in four size bins up to 10µm in diameter. The combined scheme described by Hodzic and Knote (2014) enhances these by including aqueous chemistry, improving the treatment of monoterpenes and hydrocarbons, and updating the mechanism for calculating secondary organic aerosols. In the model, $PM_{2.5}$ is the sum of the total dry aerosol mass in the three smallest size bins (up to 2.5µm in diameter) of the above aerosol components and "other inorganics" (OIN), which largely consists of dust. The full range of model inputs are shown in Table 2.1.

Parameter	Scheme Used	Source
Chemical Scheme	MOZART-MOSAIC 4-bin Aerosol w/Aqueous Chemistry	Hodzic & Knote, (2014)
Biogenic Emissions	MEGAN v2.0.4	Guenther et al. (2006)
Fire Emissions	FINNv1.5	Wiedinmyer et al. (2010)
Natural Dust Emissions	GOCART	Chin et al. (2000), Ginoux et al. (2001)
Meteorological Boundary Conditions	ECMWF ERA5	Hersbach et al. (2020)
Chemical Boundary Conditions	CESM2-WACCM CMIP6 Simulations	Danabasoglu, (2019)

Table 2.1: Model parameters used and sources.

2.4.2 Emissions associated with CMIP6

We simulated three different emissions scenarios. SSP1-2.6 represents a scenario with accelerated mitigation of greenhouse gases and sustainable societal development. SSP2-4.5 is a "middle of the road" scenario in which the trajectory of greenhouse gas mitigation does not accelerate or decelerate strongly and there are no great changes in the uptake of sustainable behaviours. SSP3-7.0 is a scenario in which regional rivalry hampers greenhouse gas mitigation and sustainable development. The assumptions for air pollutant controls mirror the trajectories of greenhouse gas emissions in each scenario, with some non-linearity or deviations in particular species to match the scenario narrative. These are explained by Rao et al. (2017); in summary, SSP1 assumes an acceleration of pollution control progress, SSP3 assumes a deceleration, and SSP2 assumes neither a notable acceleration nor deceleration from present-day controls. Figure 2.1 shows how the emissions of key species change in future scenarios compared to the present day, demonstrating how the narrative scenarios translate to emissions data. Here, the non-methane VOCs are grouped. We see that SSP1-2.6 has considerably lower emissions of all pollutant species compared to the present day. Compared to SSP1-2.6, SSP2-4.5 and SSP3-7.0 have lower reductions in emissions overall and notably differing trajectories for NH_3 emissions, which increase compared to the present in both scenarios. The NH_3 emissions increases are largest in rural regions, including most of France and Spain and northern Poland. Both scenarios have NH_3 emissions decreases in Paris, the Rhine-Ruhr region, and coastal parts of Spain and Italy. There are differences between SSP3-7.0 and SSP2-4.5 for CH_4 emissions, which are mitigated following SSP2-4.5 but worsen following SSP3-7.0, and for CO, which is heavily mitigated following SSP1-2.6 and SS2-4.5 but reduces only minimally following SSP3-7.0.

Table 2.2 shows the European total emissions of air pollutants assumed for the present-day scenario in 2014 and those in 2050 following the simulated scenarios, as taken from the input emissions files from Hoesly et al. (2018) for the present day and Feng et al. (2020) for the future scenarios. All the emissions files were at 50 km horizontal resolution. The emissions were then

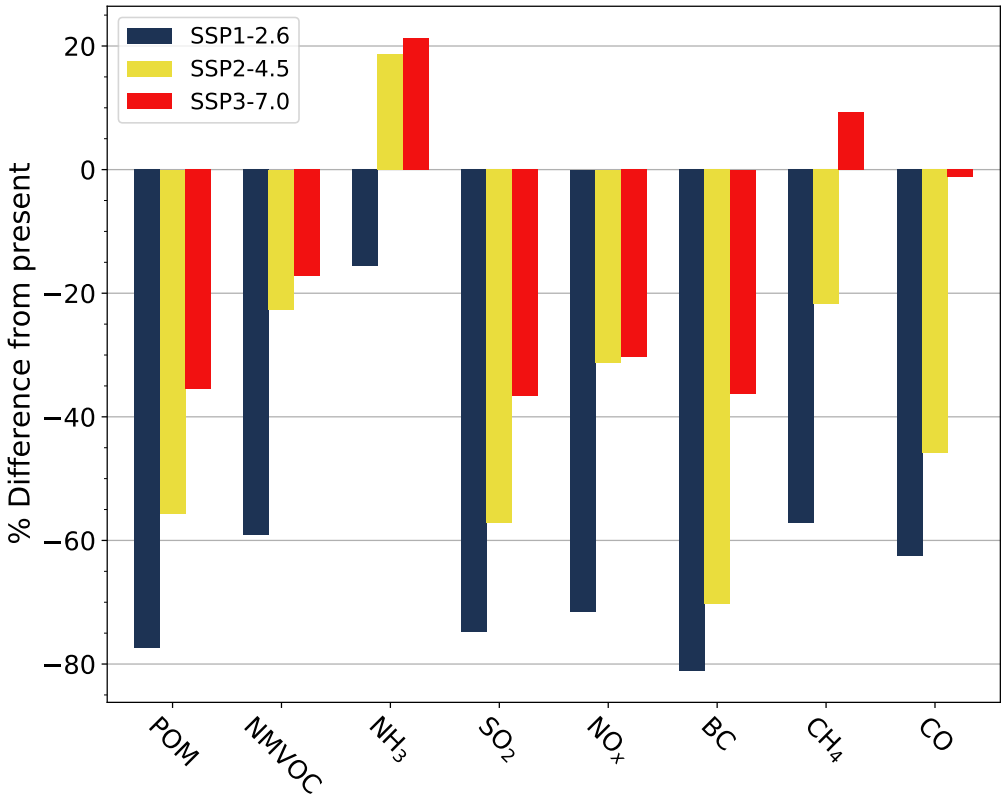


Figure 2.1: Relative change of model domain annual mean emissions (averaged over the entire domain) from 2014 to each of the future scenarios in 2050.

regridded to 30 km using a standard bilinear regridding method.

Pollutant	**2014 emissions**	**SSP1-2.6 (2050)**	**SSP2-4.5 (2050)**	**SSP3-7.0 (2050)**
Black Carbon	0.37	0.07	0.11	0.24
CO	24	9	13	23.7
NH_3	4.9	4.1	5.8	5.9
NO_x	12.9	3.4	8.9	9
SO_2	4.56	1.2	2	2.9
POM	1.74	0.39	0.77	1.12
NMVOC	8.1	3.3	6.3	6.7
CH_4	22.5	9.7	13	24.5

Table 2.2: European (domain defined above) total emissions of air pollutants in 2014 from CMIP6 and 2050 from ScenarioMIP SSP1-2.6, SSP2-4.5 and SSP3-7.0, all expressed in Mt/yr. OC converted to POM by a 1,4 scaling factor as in fig 2.1

As the CMIP6 emissions do not include a component of inorganic $PM_{2.5}$ or PM_{10} directly emitted as anthropogenic dust (as required for WRF-Chem), we created files to simulate this fraction as follows. We use linear regression to calculate the relationship between carbon monoxide and anthropogenic $PM_{2.5}$ and PM_{10} in EDGAR-HTAPv2 (Janssens-Maenhout et al., 2015). We

then apply this same relationship to the carbon monoxide emissions within CMIP6 to estimate emissions from anthropogenic $PM_{2.5}$ and PM_{10}. This methodology has been used previously by Kumar et al. (2018) and Wu et al. (2019). These input files are referred to in the rest of the text as anthropogenic dust emissions. To generate emissions of individual non-methane VOC (NMVOC) chemical species, we used scaling factors derived from ratios of individual NMVOCs to total NMVOCs in the EDGAR-HTAPv2 emissions inventory (Huang et al., 2017). This provided a greater spectrum of speciated VOCs than the scaling factors used by Hoesly et al. (2018) and Feng et al. (2020).

2.4.3 Model output

We use hourly output from each of the year-long WRF-Chem simulations for each species (O_3, CO, CH_4, SO_2, NO_2, nitrogen oxide (NO), NH_3, $PM_{2.5}$ dry aerosol mass and separate files for the individual $PM_{2.5}$ components, NO_3^-, NH_4^+, SO_4^{2-}, OC, BC, sodium and chloride). All air pollutant output was analysed only at surface level. For some of the analysis, we weighted $PM_{2.5}$ and O_3 by population using the formula outlined in Abdul Shakor et al. (2020). We used time-varying gridded population projections for each SSP from Jones and O'Neill (2016). To represent the present-day population, the SSP2 population projection for 2020 was used. This was to allow for a consistent source of all population data as there were no data for 2014.

2.4.4 Model validation

The present-day simulation for 2014 was validated against $PM_{2.5}$, O_3 and other aerosol component observations (as detailed in Table 3) from the European Monitoring and Evaluation Programme (EMEP) as this features sites for a range of species across Europe. Sites with an altitude above 1 km were excluded as the measurement and modelling of air quality in complex terrain is challenging and frequently less accurate (Giovannini et al., 2020). We used spatial linear interpolation to extract data from our gridded model output to compare to the locations of the observation sites. The sites used are shown in Fig. A.4.

Comparisons of modelled and observed O_3 and $PM_{2.5}$ are shown in Figs. 2.2 and 2.3. Figure 2.2 shows observed and simulated monthly mean $PM_{2.5}$ (a) and O_3 (b) colour coded by the observation station. Simulated monthly O_3 data show a slight underestimation (the mean absolute bias compared to observations was -3.40 $\mu g/m^3$) overall. This underestimation is generally larger in the observation sites in Germany (Schmucke, Neuglobsow and Waldhof); however,

an overestimation is seen in sites closer to the Mediterranean (Saint-Nazaire and Barcarrota). There were no available O_3 observations for Vredepeel, Cabauw Wielsekade, Guipry and Melpitz. $PM_{2.5}$ showed an overestimation compared to observations, with a mean absolute bias of 7.98 $\mu g/m^3$. The sites with the largest overestimation were Cabauw Wielsekade, Harwell and Vredepeel. The overestimation was smaller in sites such as San Pablo de los Montes, Barcarrota and Penausende. The eastern European observation sites all showed a bias lower than the average. As all the observation sites use different monitoring technologies and all overestimate $PM_{2.5}$, we expect this to be an artefact of the model.

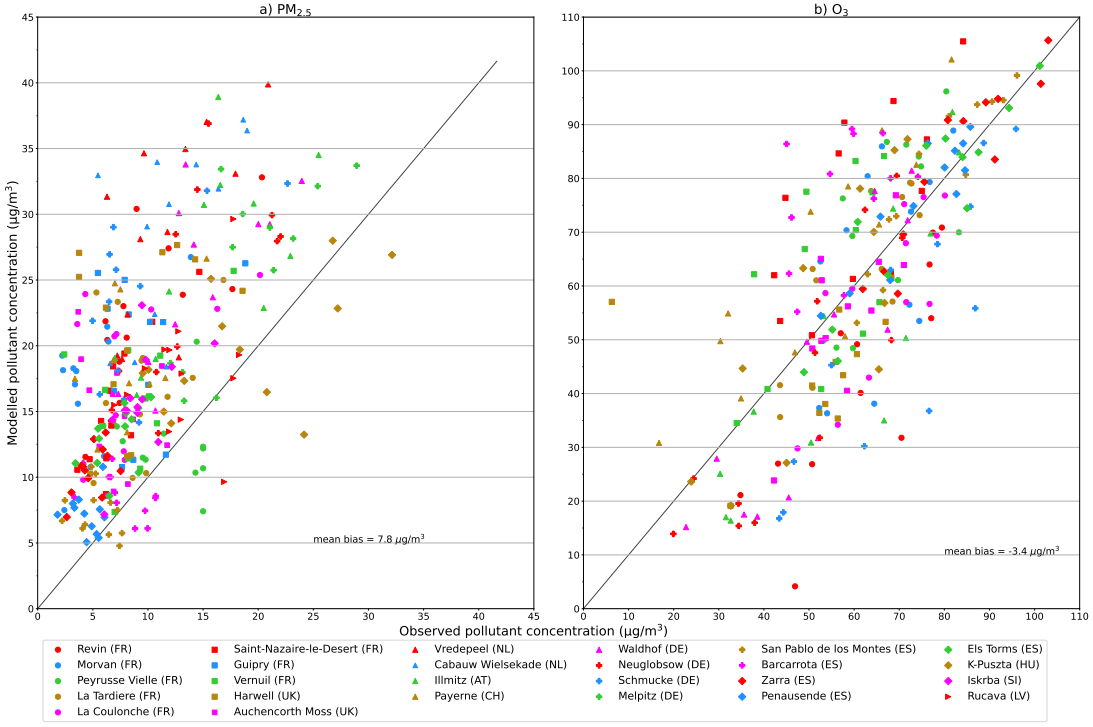


Figure 2.2: Comparison of modelled $PM_{2.5}$ (a) and O_3 (b) to ground-based Observations. Monthly means are used for both species and the units are $\mu g/m^3$. Model data is interpolated from the latitude and longitude coordinates of the observation site. The middle line on each plot represents what the data would look like if observations and model were equal.

Figure 2.3 is a comparison of modelled monthly-mean data with observations (averaged over all sites). The model presents a seasonal cycle, with higher $PM_{2.5}$ in spring and autumn, matching when the emissions peaked. The overestimation of $PM_{2.5}$ by the model was larger in spring and autumn and smaller in summer. The simulated O_3 showed seasonal biases: the model underestimated in winter and spring but overestimated during summer and autumn.

Turnock et al. (2020) reported an underestimation of $PM_{2.5}$ compared to observations in Europe in a similar period (2005–2014). This is likely because of the additional emission source of $PM_{2.5}$

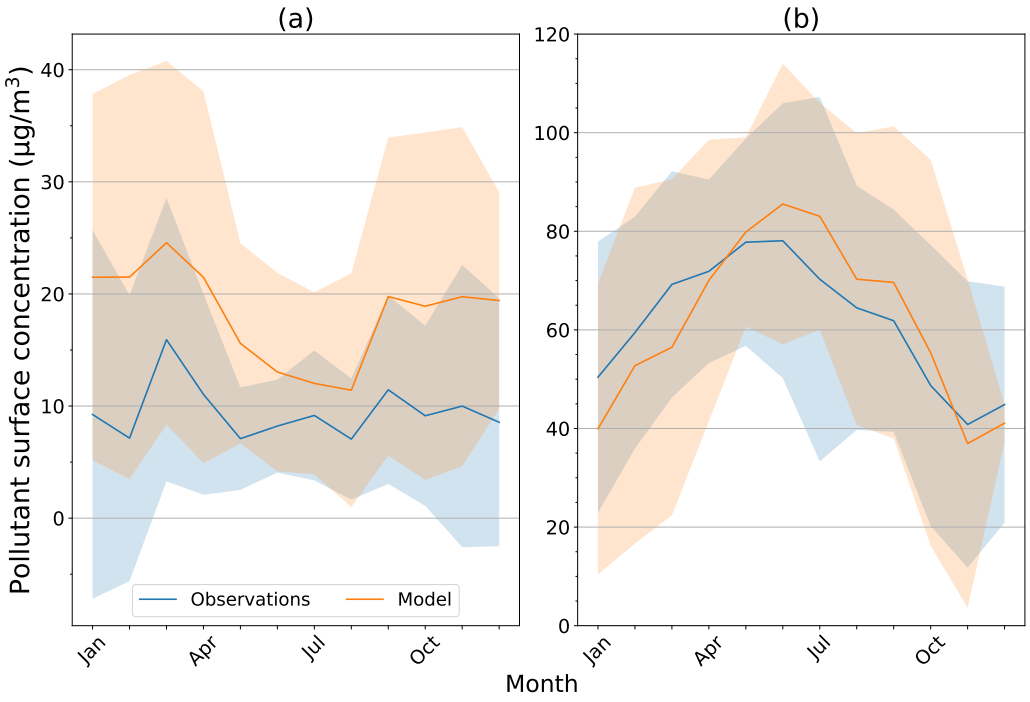


Figure 2.3: Seasonal cycle in 2014 of a) $PM_{2.5}$ and b) O_3 comparison of monthly mean modelled data to observations (average of all sites). Number of sites = 26 for $PM_{2.5}$ and 21 for O_3. Both pollutants are measured in $\mu g/m^3$. The shaded areas represent variation from the mean across sites as 2* standard deviation.

in our simulations and the coarse resolution used by Turnock et al. (2020). Conversely, $PM_{2.5}$ overestimations have been seen in other studies that used CMIP6 emissions to drive regional models, such as Cheng et al. (2021), who found that nitrate, sulfate and ammonium $PM_{2.5}$ were overestimated by 30%–60% compared to observations when simulating over China.

Further validation of $PM_{2.5}$ components (a comparison of modelled values with ground-based observations) was conducted to diagnose the difference between the model and observations. This is shown in Table 2.3. The total bias in $PM_{2.5}$ is greater than the combined bias of the individual aerosol species. Although not every observation site measured each species and therefore the proportions cannot be assumed to be the same at each site, this implies that a different source may account for much of the bias. A large proportion of the bias likely comes from the OIN (dust) component. This agrees with previous research: Im et al. (2014) find that WRF-Chem setups using GOCART over-produce dust when the MOSAIC aerosol scheme is used. Similarly, when validating WRF-Chem over Cyprus, Georgiou et al. (2018) show that WRF-Chem simulations with MOSAIC aerosols can result in a significant overestimation of $PM_{2.5}$, largely driven by the dust scheme. Additionally, some of the overestimation in the OIN component is likely the result of the derived anthropogenic dust emissions as this is calculated

from the CO emissions, which would explain the larger overall $PM_{2.5}$ overestimation in polluted urban regions.

Table 2.3 shows that the model overestimates NO_3^- aerosol by 2.7 $\mu g/m^3$ and underestimates SO_4^{2-} aerosol by -2.1 $\mu g/m^3$ when compared to the observation sites. The overestimation of NO_3^- aerosol matches the findings of other WRF-Chem studies, including Cheng et al. (2021) and Balzarini et al. (2015); however, both of these studies found an SO_4^{2-} overestimation as opposed to underestimation. The NO_3^- overestimation may be the result of high NH_3 emissions over much of the year for the emissions used in CMIP6 in comparison to other emissions inventories. When compared to EDGAR-HTAPv3 (Crippa et al., 2023), CMIP6 NH_3 emissions were lower during February, March and April but higher for the rest of the year. Similarly, the CMIP6 emissions of nitrogen oxides (NO_x) are generally higher than EDGAR-HTAPv3 in urban regions, which may also contribute to the overestimation of NO_3^- aerosols.

Pollutant	**N (sites)**	**Model Mean ($\mu g/m^3$)**	**Obs Mean ($\mu g/m^3$)**	**Bias (model-obs) ($\mu g/m^3$)**	**Root Mean Square error ($\mu g/m^3$)**
$PM_{2.5}$	26	17.9	10.1	7.8	9.1
Nitrate (NO_3^-)	14	5.8	3.1	2.7	4
Ammonium (NH_4^+)	10	1.5	1.2	0.3	0.6
Organic Carbon (OC)	24	3	2.9	0.1	1.5
sulfate (SO_4)	10	1.3	3.4	-2.1	2.5
Black Carbon	13	0.8	0.4	0.4	0.6
Chloride	13	1.4	0.2	1.2	1.5
Sodium	14	1.9	0.2	1.7	1.9

Table 2.3: Mean difference between annual mean model output and annual mean ground-based observations for different $PM_{2.5}$ components across monitoring sites in Europe

2.5 Results

2.5.1 Changes in $PM_{2.5}$

Table 2.4 shows the whole domain annual mean $PM_{2.5}$ in the present day and the change from this in the future scenarios. In general, the annual mean $PM_{2.5}$ reduced in all future scenarios compared to the present day. The future reduction in European annual mean $PM_{2.5}$ of 38% in SSP1-2.6 was far greater than the 11% following SSP3-7.0. There are differences in the pattern when population weighting is applied (notably this applies only to the 13 countries mentioned

		Change from present-day in $\mu g/m^3$ (% in brackets)		
Domain statistic	**Present day concentration ($\mu g/m^3$)**	**SSP1-2.6**	**SSP2-4.5**	**SSP3-7.0**
Minimum	4.9	-1.5 (-31)	-0.61 (-13)	-0.1 (-2)
Mean	19.4	-7.3 (-38)	-4.2 (-21.6)	-2.1 (-10.8)
Maximum	44.4	-21.3 (-48)	-17.6 (-40)	-5.6 (-12.6)
Population-weighted mean	17.5	-8.6 (49)	-5.2 (30)	+0.9 (5)

Table 2.4: Annual mean $PM_{2.5}$ whole domain change statistics for each future scenario in 2050 compared to the present day baseline (the left-hand column). For future scenarios, the raw change for each of these is shown in $\mu g/m^3$ followed by the percentage change in brackets. Population-weighted mean is for only the 13 countries identified as Europe previously.

previously); overall, population exposure to $PM_{2.5}$ increases slightly following SSP3-7.0 despite the domain-wide decrease. This suggests that the majority of the increases in $PM_{2.5}$ are in highly populated areas.

Spatially, we see greater reductions in $PM_{2.5}$ in urban and industrial regions than the domain average (Fig. 2.4 shows percentage changes between the present and future scenarios, while Fig. A.5 shows the absolute changes). Both industrial (for example, the Po Valley in Northern Italy and the Rhine-Ruhr in north-western Germany) and urban regions see strong $PM_{2.5}$ reductions under SSP1-2.6 and SSP2-4.5 (although these are far larger following SSP1-2.6). Conversely, under SSP3-7.0, only urban regions see considerable $PM_{2.5}$ reductions. This could be explained by a larger reduction in industrial $PM_{2.5}$ emissions following SSP2-4.5 than SSP3-7.0 (-56% compared to -47%) and a larger reduction in OC emissions (-72% compared to -65%). Both SSP2-4.5 and SSP3-7.0 have small percentage increases in industrial NO_x and SO_2 emissions and relatively consistent NH_3 emissions when compared to the present day, suggesting that it is not differences in the NO_x and NH_3 ratio that cause the differences between SSP2-4.5 and SSP3-7.0 in industrial regions.

Additionally, under SSP3-7.0, localised areas of worsening air quality are seen, including around East Yorkshire in the UK (worsening up to 4 $\mu g/m^3$) and Zeeland and South Holland in the Netherlands (worsening up to 2 $\mu g/m^3$). Some of these localised increases correspond with the locations of major combustion power plants, including Drax (North Yorkshire, UK) and Belchatow (central Poland). This is because the emissions scenarios assume that power generation emissions increase up to mid-century compared to the present day following SSP3-7.0; they drop following SSP2-4.5, but this is approximately half the reduction that is predicted following SSP1-2.6. All scenarios show slightly worsening $PM_{2.5}$ air quality of up to 2 $\mu g/m^3$ near Gijon, on the northern coast of Spain. This reflects worsening NO_x emissions in all scenarios at this location.

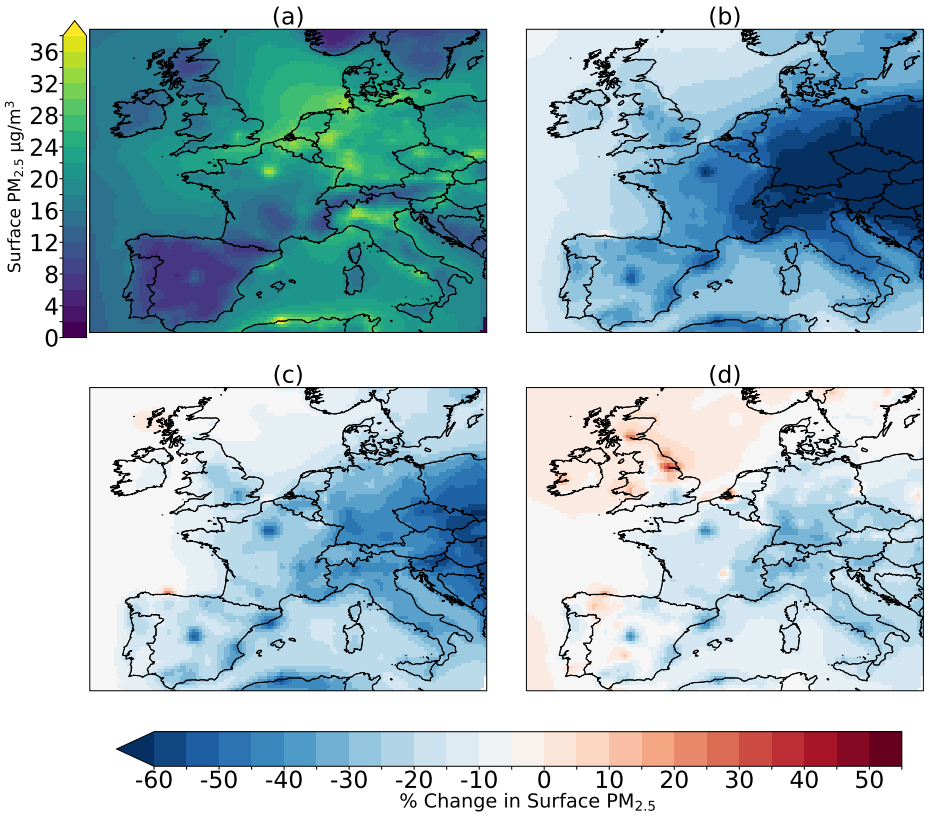


Figure 2.4: (a) Modelled annual mean $PM_{2.5}$ ($\mu g/m^3$) using 2014 emissions. (b),(c) and (d) are the percentage change from (a) the annual mean $PM_{2\cdot5}$ ($\mu g/m^3$) simulated using 2050 emissions for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

The $PM_{2.5}$ reductions in SSP1-2.6 are larger across most of the domain compared to the other scenarios. This is most notable across central and eastern Europe (e.g. Germany, Poland, the Czech Republic and Austria). This is potentially because these regions have a larger proportion of anthropogenic $PM_{2.5}$ sources than natural sources. Smaller improvements are projected in countries such as Portugal and Ireland, where natural sources of $PM_{2.5}$ dominate. In the regions where the reductions in SSP1-2.6 compared to SSP2-4.5 and SSP3-7.0 are the largest (such as central and eastern Germany), the size of the reduction is likely the result of the combined reduction in NH_3 and NO_x emissions in SSP1-2.6 (-25% and -70%, respectively, domain-wide).

Across the domain, SSP2-4.5 and SSP3-7.0 have increases in NH_3 emissions (both approximately 20%) and reductions in NO_x (both approx. -30%) (Fig. 2.1). Where only NO_x is reduced, in some regions (usually NO_x-abundant regions), the increased oxidising capacity of the atmosphere can result in increased formation of secondary organic aerosol, thus limiting the efficacy of emissions reductions. This impact can be mitigated by joint reductions of both NO_x and NH_3 (Clappier et al., 2021). This is supported by the near-universal decreases of over 60% in NO_3^- $PM_{2.5}$ following SSP1-2.6, which are the result of a domain-wide reduction of 18% of agricultural NO_x emissions and 7% of agricultural NH_3 emissions. Following SSP2-4.5 and SSP3-7.0, NO_3^- $PM_{2.5}$ does decrease universally; however, the reductions are much larger in urban than in rural regions. Notably, both of these scenarios have approximately 20% increases in agricultural NH_3 emissions and increases in agricultural NO_x emissions (41% following SSP2-4.5; 10% following SSP3-7.0). This suggests that the difference in agricultural emissions will be a large driver of the extra reductions in $PM_{2.5}$ following SSP1-2.6, and the mitigation of emissions in this sector will be key to achieving improved air quality in Europe. It should, however, be noted that some rural regions (e.g. western France, Scotland, Wales and most of Spain) do still have overall NH_3 emissions increases following SSP1-2.6. This may explain the smaller reductions in $PM_{2.5}$ in these regions (Figs. A.6 and A.7).

Reductions in SO_2 emissions also contribute to the reduced $PM_{2.5}$. The countries that tend to see the largest decreases in $PM_{2.5}$ concentrations following the future scenarios are central/eastern European countries. These countries, particularly the urban areas of them, usually have a higher contribution from SO_x aerosol (including SO_4^{2-}, which will cover much of this aerosol in the chemistry scheme) to $PM_{2.5}$ (Zauli-Sajani et al., 2024). SO_x aerosol is formed by reactions between SO_2 and NH_3. For example, atmospheric sulfuric acid is formed when SO_2

reacts with OH radicals. The sulfuric acid can then react with NH_3 to form SO_4^{2-} particulates (Clappier et al., 2021). Unlike for NH_3 and NO_x, there is limited non-linearity of SO_4^{2-} $PM_{2.5}$ reductions resulting from the mitigation of SO_2 emissions (Clappier et al., 2021). This means that SO_2 emissions reductions retain efficacy in reducing SO_4^{2-} $PM_{2.5}$ regardless of trends in NH_3 and NO_x emissions. SO_2 emissions reduce in all scenarios – by approximately 30% for both SSP2-4.5 and SSP3-7.0 and by approximately 75% following SSP1-2.6 (Fig. 1). This may explain why $PM_{2.5}$ reductions are most consistently seen in central and eastern Europe in all the future scenarios: in this region, reductions in SO_2 emissions (see Fig. A.8) lower the $PM_{2.5}$ in the sulfate fraction to a greater degree than in western Europe. In western Europe, following SSP2-4.5 and SSP3-7.0, the reductions in NO_x in the absence of NH_3 hamper $PM_{2.5}$ reductions. This impact is reduced in eastern Europe, where NH_3 and NO_x provide a lesser contribution to $PM_{2.5}$ compared to SO_2, meaning that eastern Europe has larger $PM_{2.5}$ reductions following SSP2-4.5 and SSP3-7.0.

All countries show overall decreases in population-weighted $PM_{2.5}$ (Fig. 2.5). The magnitude of this varies greatly based on the scenario. Following SSP1-2.6, the percentage decrease ranges from 22.7% in Ireland to 68.6% in Hungary. Other countries with decreases in population-weighted mean $PM_{2.5}$ of greater than 50% following SSP1-2.6 include Slovenia, Slovakia and Germany. These countries also see the greatest reductions in $PM_{2.5}$ following the other scenarios; for example, the largest reduction following SSP3-7.0 is in Slovenia, at nearly 25%. This may be due to reductions in residential emissions, which see the greatest reduction as a proportion of total emissions in Slovenia and are reduced in all scenarios. This is in keeping with literature that identifies the importance of reducing residential-sector emissions to improve $PM_{2.5}$ concentrations in Europe, especially eastern Europe (Zauli-Sajani et al., 2024). For most countries in the domain, the agricultural sector contributes most to total air pollutant emissions.

In addition to benefiting the least following SSP1-2.6, Ireland benefits the least following SSP2-4.5, with a reduction of 5%. Similar to Ireland, Portugal and Spain do not benefit as much from the emissions changes compared to others. Ireland even shows an increase in population-weighted $PM_{2.5}$ following SSP3-7.0 of nearly 4%, which is also seen in the UK. What this suggests is that the benefits are concentrated in countries where anthropogenic sources dominate $PM_{2.5}$ concentrations in the present day. As coastal-island countries, Ireland and the UK likely have a greater proportional quantity of natural sea salt aerosol making up $PM_{2.5}$ – previous literature

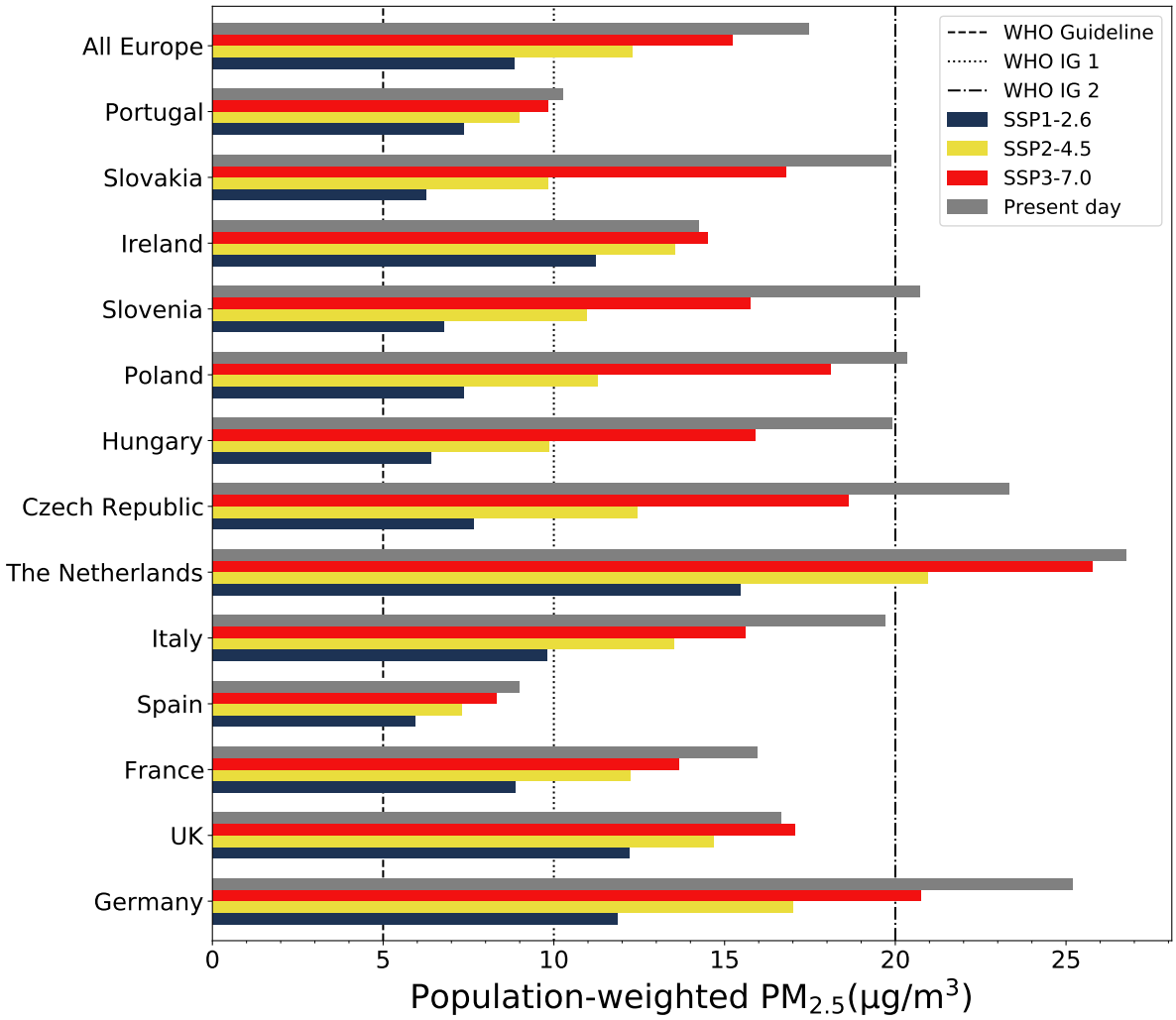


Figure 2.5: Population-weighted $PM_{2.5}$ in a selection of European countries following different scenarios compared to WHO guideline values. The lines labelled with "IG" are WHO interim guidelines. All Europe refers to a combined population-weighted mean of the 13 countries on the Figure

suggests that sea salt $PM_{2.5}$ can reach up to 300 km inland and produce up to 5 $\mu g/m^3$ of $PM_{2.5}$ (Manders et al., 2010). Spain and Portugal are likely to have large proportions of natural dust $PM_{2.5}$ due to their proximity to North Africa.

Figure 2.5 also compares the population-weighted mean to the World Health Organisation annual mean $PM_{2.5}$ guideline value of 5 $\mu g/m^3$ (World Health Organisation, 2021). It suggests that following SSP1-2.6, many countries could see $PM_{2.5}$ exposure reduce below interim target values (guidelines the WHO suggest as targets to aim for before reaching the guideline value), representing a significant potential benefit for human health. Even the emissions reductions from SSP1-2.6 do not result in annual mean population-weighted $PM_{2.5}$ concentrations under this guideline, but when factoring in the average overestimation of $PM_{2.5}$ from our model, they are

likely to be achievable in some locations. Notably, while countries where $PM_{2.5}$ is dominated by natural sources see less improvement, these have among the lowest $PM_{2.5}$ population exposure in the present day. This means that the benefits of the emissions changes are primarily seen in the countries that most need them. The whole-domain average also moves below the WHO interim target 1 of 10 $\mu g/m^3$ following SSP1-2.6, after a reduction of almost 50%.

Figure 2.6 shows the seasonal cycle of $PM_{2.5}$ components averaged across the entire model domain. SSP1-2.6 has a much lower contribution of anthropogenic $PM_{2.5}$ than SSP2-4.5 and SSP3-7.0, driven by the emissions reductions shown in Figure 2.1. Figure 2.6 also shows that it is the change in these anthropogenic species, particularly in NO_3^- and OC, that drive the differences between the future scenarios, with NO_3^- alone reducing the total $PM_{2.5}$ following SSP1-2.6 by over 5 $\mu g/m^3$ throughout much of the year. The importance of NO_3^- aerosol in the future scenarios to determining the total $PM_{2.5}$ implies that NH_3 and NO_x emissions reductions will be key to improving future air quality. All future scenarios show overall reductions in NO_x emissions, which can limit the formation of NO_3^- and NH_4^+ particulates (Pusede et al., 2016); however, it is only SSP1-2.6 that shows a significant reduction in NO_3^- aerosol, likely because it is the only scenario where NH_3 emissions reduce compared to the present day. This suggests that agriculture will be a key sector for attaining air quality co-benefits as agriculture is a major source of NH_3 emissions. The reduction in OC concentrations is proportionally far larger under SSP1-2.6 than the other scenarios, potentially due to the trajectories of power sector OC emissions.

Our findings are in agreement with other work in the area in that we find that air quality co-benefits of climate mitigation are likely for $PM_{2.5}$. When compared to Fenech et al. (2021) (who used CMIP5 emissions and focused on the UK) for example, we see that both studies project that strong mitigation will result in air quality co-benefits in terms of $PM_{2.5}$ for the UK. The reductions we project for the most comparable scenarios (SSP1-2.6 and RCP2.6) are larger (-7.3 as opposed to -2.2 $\mu g/m^3$ or approximately 38% vs 25%). We see a diverging trend for the most pessimistic scenarios - while they see reductions in $PM_{2.5}$ concentrations following RCP8.5, we see worsening $PM_{2.5}$ following SSP3-7.0.

Notably, our model simulated high present-day $PM_{2.5}$ in urban regions (e.g. Paris, Madrid and London) compared to surrounding areas. It also produced elevated $PM_{2.5}$ in heavily industrial regions of Europe such as the Po Valley and the Rhine-Ruhr (Fig. 2.4a). It is the changes in

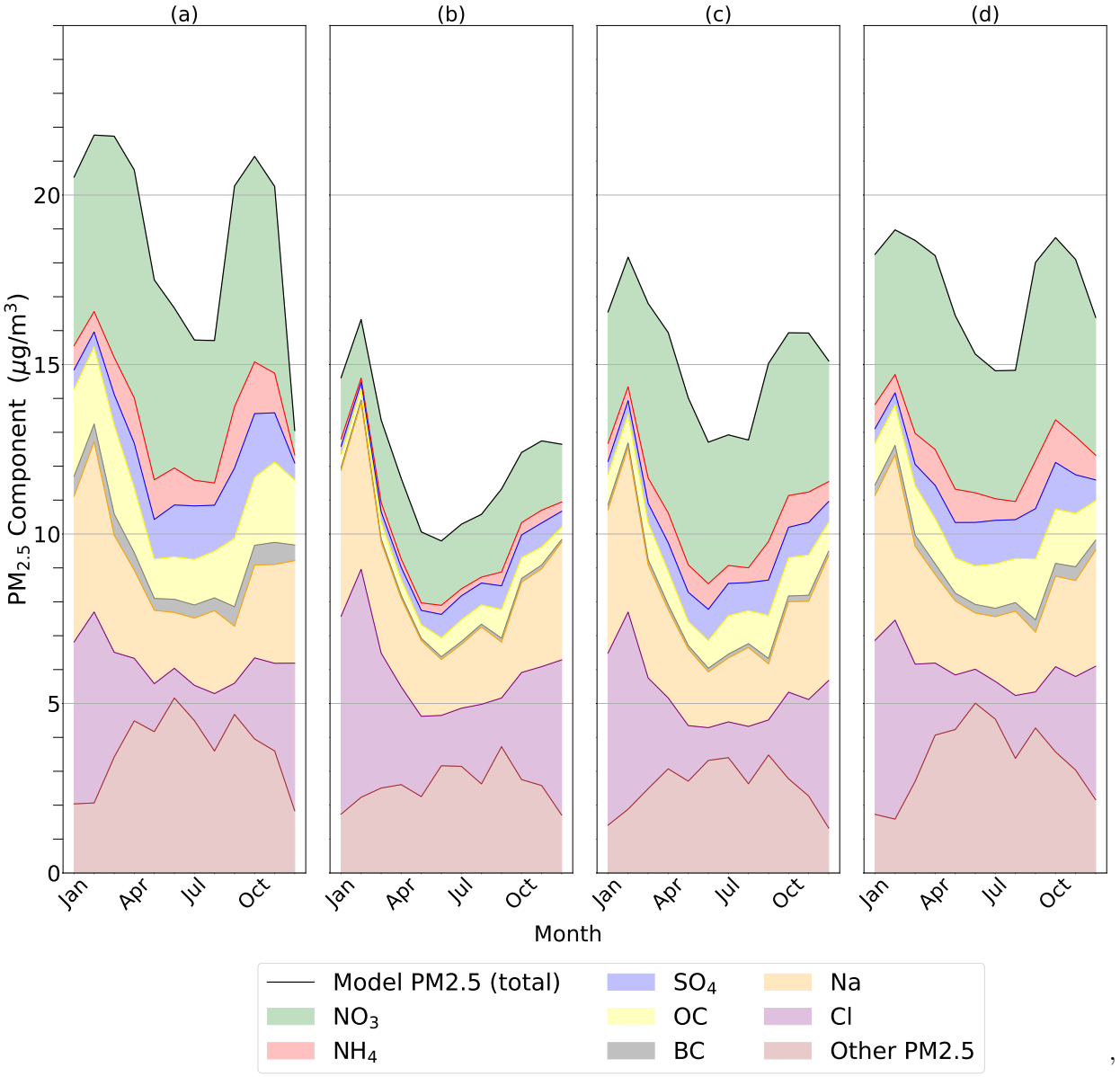


Figure 2.6: Seasonal cycle of domain average $PM_{2.5}$ over each simulation by component, (a) is the 2014 simulation, (b),(c) and (d) are 2050 from each of SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

these regions that stand out in the other panels of Fig. 2.4. What this suggests is that our methodology allows us to better represent changes on a local level than work using climate model output. This can be shown when our work is compared to Turnock et al. (2020) (who used CMIP6 output for a global domain) in Fig. 2.7, which shows the difference in the change between the present and 2050 following SSP3-7.0 for both $PM_{2.5}$ and O_3. Figure 7 shows that we see similar spatial changes except for different trends in $PM_{2.5}$ across the Iberian Peninsula and most of the British Isles. This comparison shows how the finer spatial resolution allows us to see localised elevated concentrations of pollution, whereas pollutants are distributed more

evenly over the coarser resolution of global models. We also see greater improvements in $PM_{2.5}$ overall than Turnock et al. (2020); for example, for SSP1-2.6, our domain improvement of 7 $\mu g/m^3$ is more than double theirs (approximately 3 $\mu g/m^3$). This highlights that using air pollutant concentrations from global model simulations may underestimate the extent of future changes in air quality.

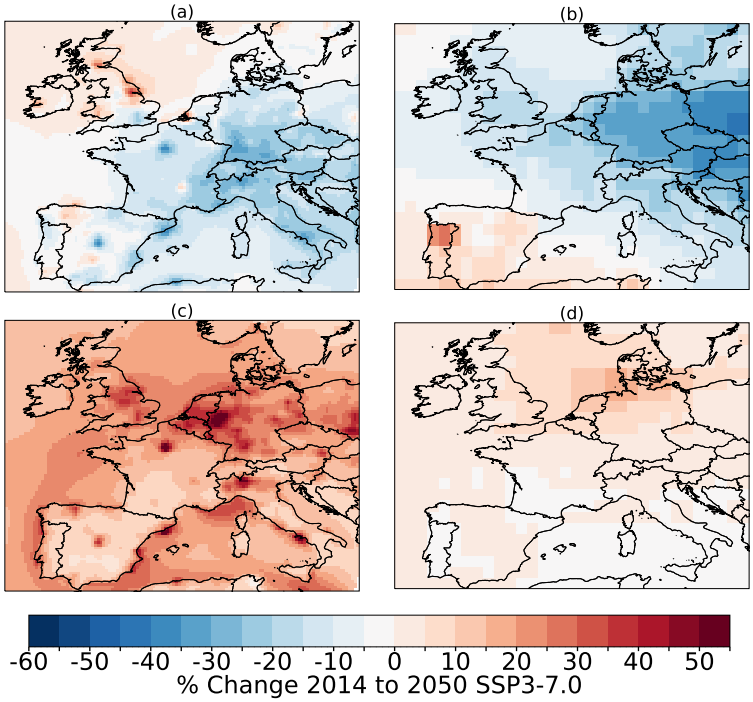


Figure 2.7: a) Percentage change annual mean $PM_{2.5}$ between present day and 2050 following SSP3-7.0 from our simulations with WRF-Chem b) The same from Turnock et al. (2020) using CMIP6 multi-model output. c) and d) Same as the above, but O_3 compared. Note that this is annual mean O_3 and thus, c) differs from panel d) of Figure 2.8

Geographically, the reductions in European $PM_{2.5}$ are lower than those in more polluted regions in other studies. Cheng et al. (2021) find a reduction in population-weighted mean $PM_{2.5}$ in China between 2020 and 2050 following SSP1-2.6 of between 20 and 25 $\mu g/m^3$ (from approximately 42 $\mu g/m^3$ in the present-day scenario). However, this reduction is similar to the average relative reduction of 52% across European countries that we find. Studies on future air quality in India also find that scenarios with a greater focus on sustainability result in reductions in surface air pollution (Chowdhury et al., 2018; Kumar et al., 2018), although methodological differences make direct comparisons with these studies challenging. What these comparisons suggest is that Europe could see similar relative air quality co-benefits to other regions following future sustainability scenarios.

		Change from present-day in $\mu g/m^3$ (% in brackets)		
Domain Statistic	**Present day concentration ($\mu g/m^3$)**	**SSP1-2.6**	**SSP2-4.5**	**SSP3-7.0**
Minimum	23.9	+6.4 (+26.7)	+8.3 (+34.7)	+12.3 (+51.5)
Mean	66.2	-9.8 (-15)	+1.7 (+2.6)	+8.7 (+13.1)
Maximum	97.4	-13.3 (-24)	-0.6 (0.6)	+7.6 (+7.8)
Population-weighted mean	52.7	-3 (-7)	+5.3 (+10)	+8.8 (+16.7)

Table 2.5: Annual mean O_3 whole domain change statistics for each future scenario compared to the present day baseline (the left-hand column). For future scenarios, the absolute change for each of these is shown in $\mu g/m^3$ followed by the percentage change in brackets. Population-weighted mean is for only the 13 countries identified as Europe previously.

2.5.2 Changes in O_3

The maximum 6-monthly-mean daily-maximum 8h (6mDM8h) O_3 shows marginally higher concentrations in Mediterranean regions, including Italy, southern Spain and the French Riviera, which get more sunlight (Fig. 2.8 shows percentage changes between the present and future simulations, while Fig. A.9 shows the absolute changes). In the simulations using future scenarios, O_3 strongly reduces following SSP1-2.6 (a mean reduction of approximately 15%), whereas SSP2-4.5 shows variation across the domain. While the mean change is a reduction of approximately 3%, increases are seen in most of England, the Benelux region and north-western Germany. 6mDM8h O_3 increases across most of the domain following SSP3-7.0 (a mean increase of approximately 13%). This is not universal; small decreases of up to 5% are seen in most of the Mediterranean regions with high present-day O_3. Despite the lack of peaks in the present-day simulation, in the future simulations, O_3 pollution does not reduce as much in urban regions as it does in much of the rest of the domain following SSP1-2.6. The same regions show increases following SSP2-4.5 (and some regions, such those as around Barcelona and Naples, show increases following SSP1-2.6), whereas much of the rest of the domain has reductions in surface level O_3, and the increases are higher than in surrounding areas following SSP3-7.0.

The differing trends in emissions of CH_4, CO and NO_x (Fig. 2.1) between the scenarios may explain the difference in O_3. It is well established in the literature that in urban areas, reductions in NO_x emissions can cause increases in surface-level O_3, including within Europe (Lee et al., 2020; Finch and Palmer, 2020). This is due to decreased titration of O_3, in which reduced NO concentrations due to the reductions in NO_x emissions result in less destruction of O_3 molecules (Monks et al., 2015). This is supported by our results, as the largest O_3 increases are seen in the urban areas with the largest reductions in NO_2, such as Naples (Italy) and Barcelona (Spain) (Fig. A.10). This effect is likely to be amplified in autumn and winter, when emissions

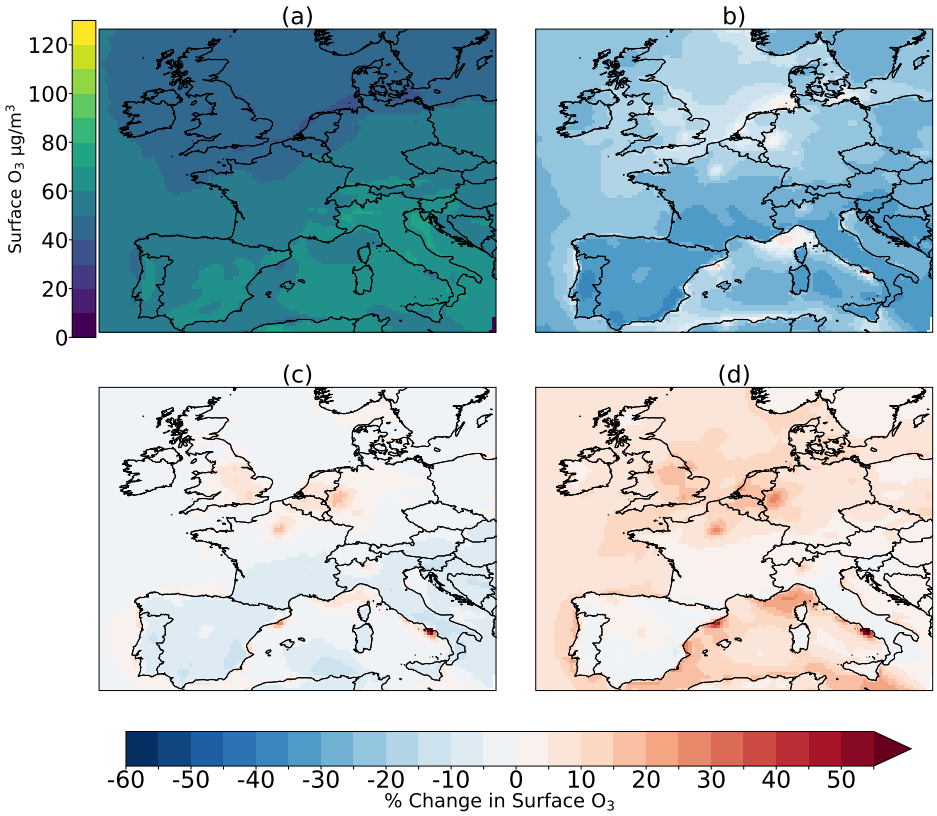


Figure 2.8: 6mDM8h O_3 calculated as the highest 6-month mean of the highest rolling 8-hour O_3 in 24-hour periods in the O_3 output for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

reduction policies are likely to have the most impact. Figures A9–A12 support this, showing that the O_3 increases are largest during the winter months. This is why the annual mean O_3 concentration changes (Fig. A.11) follow a different pattern to 6mDM8h O_3.

Reductions in NMVOCs could be having similar effects to the NO_x reductions in some regions. In all scenarios, reductions in NO_x emissions are stronger than NMVOC emissions; however, following SSP2-4.5 and SSP3-7.0, the proportional gap is much larger. This suggests that in VOC-limited regimes (which are generally urban areas), where reductions in NO_x are more likely to exacerbate O_3, we may see a larger O_3 response. Notably, the emissions changes may cause different patterns in NO_x and VOC-limited regimes that may impact on the O_3 response; for example, Liu et al. (2022) find that in Europe following SSP3-7.0, the percentage of VOC-limited areas drops from nearly 80% to 27% in winter and from 37% to under 3% in summer. If our simulations have a similar change in sensitivity, this could suggest that a different precursor, such as CH_4, primarily drives the increases in O_3 following SSP3-7.0, which suggests that agriculture will be a key sector for determining future O_3 pollution.

In SSP1-2.6, this impact of reduced NO_x emissions causing O_3 increases is masked by O_3 increases from another source, likely much stronger decreases in CO and CH_4 emissions than in SSP2-4.5 and SSP3-7.0. What this means is that while all scenarios assume increased pollution control, the additional focus given to climate mitigation (e.g. reducing CH_4 emissions) and the more sustainable socioeconomic development in SSP1-2.6 and SSP2-4.5 have potential air quality co-benefits by outweighing any impacts on O_3 from reduced NO_x. O_3 is considerably more impactful on health during the peak season due to the high thresholds needed to affect population health on a large scale, so most parts of Europe will see a reduced impact of O_3 pollution following both SSP1-2.6 and SSP2-4.5.

We find a considerably higher percentage increase in annual mean O_3 in 2050 following SSP3-7.0 compared to that found for Europe by Turnock et al. (2020) (Fig. 2.7). Once again, the difference in resolution is clear here, as we see much larger increases in O_3 around certain urban regions, whereas Turnock et al. (2020) show a smaller trend distributed over larger areas. As with $PM_{2.5}$, the finer resolution we use could prove valuable, especially for understanding health impacts and trends in urban areas. As shown by the contrasting trends in urban and rural areas for O_3 pollution following some scenarios, being able to represent these changes is valuable.

Compared to studies focusing on regions outside of Europe, our findings are similar to those reported by Zhang et al. (2017), who use WRF-CMAQ to simulate the impact of RCPs on air pollutants over the USA. They find overall small decreases in 6mDM8h O_3 (up to 2 ppb) except in some large urban areas following RCP4.5, where they report increases of up to 10 ppb. Following SSP2-4.5, we see a similar trend (an average reduction of -1.5 ppb but localised increases around some cities and industrialised areas).

2.6 Limitations

There are limitations of this study to be considered. Primary among these is the overestimation of $PM_{2.5}$ concentrations in the present day. While these are mostly systemic, they should be taken into account when considering the absolute concentrations reported, especially when compared to air quality guideline values. It is likely that the percentage changes we see would be less drastic had the model not overestimated $PM_{2.5}$. As the model overestimates NO_3^- and underestimates SO_4^{2-} $PM_{2.5}$, we may overestimate the impacts on changes in NH_3 and NO_x emissions on future air quality, particularly in the agricultural sector compared to other sectors

such as industry.

The resolution that we use is designed for the region or country scale and not the urban scale. A horizontal resolution of 30 km is unlikely to faithfully capture atmospheric chemistry at the city scale. Although we can represent the locations of urban and industrial peaks, be aware that the model may not simulate chemistry at this scale as effectively as a finer-scale model.

We also do not control for the impacts of population change in the future scenarios in Table 2.4, Fig. 2.5 or Table 2.5.

2.7 Summary

We use emissions data for three SSPs (SSP1-2.6, SSP2-4.5 and SSP3-7.0), representing very different climate futures, to simulate air quality in Europe in 2050 compared to the present day. This work uses WRF-Chem v4.2, with a much more detailed chemistry scheme and finer grid resolution than much of the previous work using SSPs, to provide a more detailed assessment of potential air quality co-benefits on a regional scale.

We show that while $PM_{2.5}$ is expected to reduce compared to the present day across most of Europe in all future scenarios, it shows by far the biggest reductions in scenarios with a greater focus on sustainability and therefore more stringent emissions reductions. We find that in 2050, following SSP1-2.6, mean population-weighted $PM_{2.5}$ concentrations across European countries reduce by 52% compared to 2014. Under SSP2-4.5, this average reduction is 34%. The smallest average reduction was 18%, obtained following SSP3-7.0. The additional benefits we see following SSP1-2.6 are likely due to emissions reductions in the agricultural and industrial sectors.

We also show the sign of O_3 change differs across the scenarios: in the more sustainable scenario, SSP1-2.6 (and, to a lesser extent, SSP2-4.5), much of Europe will see reduced 6mDM8h O_3 concentrations, whereas 6mDM8h O_3 will worsen following SSP3-7.0. This is likely driven by a combination of reduced NO_x and increased CH_4 emissions. This demonstrates the importance of reducing CH_4 alongside other O_3 precursor species to avoid reducing the efficacy of overall air pollutant controls, which is caused by focusing entirely on $PM_{2.5}$ and NO_x without also considering the impacts on O_3, as is evident from the increases in O_3 concentrations during the COVID-19 lockdowns, where large reductions in NO_x emissions occurred with a smaller or no

effect on CH_4 (Jephcote et al., 2021; Miyazaki et al., 2021).

We find that using a regional atmospheric-chemistry model provides us with the ability to analyse in more detail where air quality in Europe could change in response to the scenarios and that the patterns in air quality changes obtained using this methodology differ from what you get using climate model output. From that, we can make a more informed hypothesis as to why air pollutants respond the way they do, based on sector-specific emissions changes. We demonstrate the value that can be added by using this methodology; for example, it can provide country-specific population-weighted mean changes, which may be more useful to regional and national policymakers. This demonstrates the importance of a combined approach to modelling air quality co-benefits using both global and regional models.

To conclude, our results suggest that air quality co-benefits will be seen if society follows a pathway in which environmental sustainability is a priority, particularly in terms of mitigating climate change. This implies there are potential public-health benefits, although the results of this may differ from those of other studies, so further studies to calculate the health benefits are important.

2.8 Data Availability

Data is available on an online repository at Zenodo (DOI: 10.5281/zenodo.10781398). Data can alternatively be accessed by contacting Connor Clayton. The emissions data is pubicly available on the Input4MIPs website (https://aims2.llnl.gov/search/input4mips/)

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Chapter 3

Reducing Inequities in the Future Air Pollution Health Burden Over Europe

3.1 Preface

This paper directly leads on from paper 1 and indeed uses many of the same inputs (albeit with $PM_{2.5}$ bias correction, which is discussed in this paper and with more detail included in the appendix). As discussed, this thesis was designed with policy-relevance in mind. To achieve this, I decided that analysis of the public health impacts of the results of paper 1 would be more effective for communicating the benefits of stringent mitigation. However, I chose to enhance this with analysis of health equity changes. This is for several reasons; some were more practical, e.g. I did not feel that solely running the output from paper 1 through a health impacts function was enough to warrant a separate piece of research and by the time this was in progress, a considerable quantity of research examining future health impacts of air quality had been recently published. Health equity is a personal interest that I had been keen to examine in the project from the beginning and is a growing focus in environmental and public health policy. At the time of writing, the only work I was aware of examining health equity of future air quality was Reddington et al. (2023). I felt that this way I could not only improve the policy relevance of my work, but I could utilise the benefits provided by a regional model due to the fine spatial scale at which deprivation changes.

I also chose to join the growing body of research utilising the more recent eSchif-Fusion health function from Weichenthal et al. (2022) as opposed to the GEMM (Burnett et al. 2018). eSCHIF-Fusion is becoming more commonly used in future health impacts research following a paper from Burnett et al. (2022) which suggests that researchers move away from GEMM. I present results using both functions for comparison.

To best consider health and equity, further data inputs to represent these were required. Deeper discussion than in the paper of the data used for future population, baseline mortality rates and human development index (along with why I chose HDI as the equity metric) is available in the appendix.

Below this, this Chapter is a recreation of the following paper with formatting changes so as to meet University of Leeds requirements and a few clarifications based on corrections asked for post-viva.

Clayton, C.J., Turnock, S.T., Marsh, D.R., Graham, A.M., Reddington, C.L., Vohra, K., Mcquaid, J.B., 2025. Reducing Inequities in the Future Air Pollution Health Burden Over Europe. Earth's Future 13.. https://doi.org/10.1029/2024ef005404

3.2 Abstract

The strategies that policymakers take to mitigate climate change will have considerable implications for human exposure to poor 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 analyse 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 analyse 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.

3.3 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

3.4 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.

3.5 Intro

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; Vohra et al. 2021; Juginovic 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 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 standardisation 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 modelling 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 towards 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 (Fenech et al. 2021; Turnock et al. 2020; Clayton et al. 2024).

A weakness of using RCPs and SSPs for future air quality co-benefit analysis is that the inputs are not optimised for regional air quality models, which have higher horizontal resolution (often 50km by 50km 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 (Markandya et al. 2018; Ingole et al. 2022).

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 hour 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 100km scale or greater, and thus may miss regional trends and lack some relevant chemistry, e.g 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, e.g some works use scenarios more specific to expected trajectories or policies implemented in individual countires. For example work by Macintyre et al. (2023) use scenarios designed for the UK with a model optimised 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 optimised 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 neighbourhoods 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 decarbonisation 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 decarbonisation, 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 analysing 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.

3.6 Methods

3.6.1 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 30km 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 (Hoesly et al, 2018; Feng et al. 2020). We use 2014 as the present-day control year for the model simulations because this is the final year con-

sidered 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 towards air pollutant concentrations in Europe (Jonson et al. 2018; 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 $\mu g/m^3$ 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 is 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 (ECMWF, 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. 2014). 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.

3.6.2 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. (2022), 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 is 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 1000 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 5μg m^{-}3 as described by Weichenthal et al. (2022).

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:

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

For the above, z represents annual mean $PM_{2.5}$, z_cf 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 μg m$^-$3 is as follows:

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

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 modelled 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 (Murray et al. 2020) which uses a hazard ratio function for COPD mortality. We input maximum 6-monthly-mean daily maximum 8-hour 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 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 & O'Neill, 2016). These are gridded products, which we used at a 0.125°x 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.

3.6.3 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 analyse. The NUTs-2 subregions ranked in deciles (to match with other studies) of subnational HDI is shown in Figure (3.1). This demon-

strates 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.

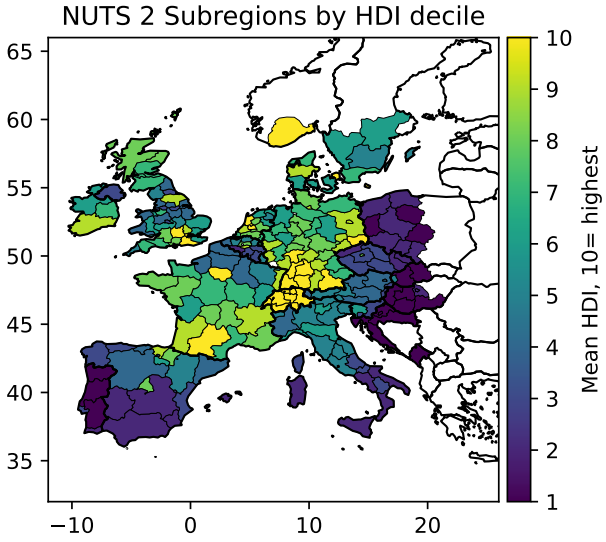


Figure 3.1: Choropleth map of European NUTS 2 regions in the domain split into 10 categories based on the average subnational HDI of grid cells within the region

We chose subnational HDI as opposed to similar products, such as gridded gross domestic product projections for the SSPs from Wang & Sun, 2021) (the metric used by Reddington et al. (2023)) or the Global Gridded Deprivation Index (CIESIN, 2022) as we found that HDI data provided a more realistic indication of socioeconomic 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 human development index consistent with the SSPs have been published. More detailed discussion on HDI and why it was used is available in the appendix, section 1.4.

3.7 Results

The present and future $PM_{2.5}$ concentrations for each scenario are shown in Figure (3.2). 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 scenarios, surface $PM_{2.5}$ reduces with the largest reductions in Central Europe (particularly South-West Germany) and some urban centres, such as Paris. These reductions are highest following SSP1-2.6, e.g over 90% reductions in SW Germany and in Paris. SSP1-2.6 also shows a larger generalised 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.

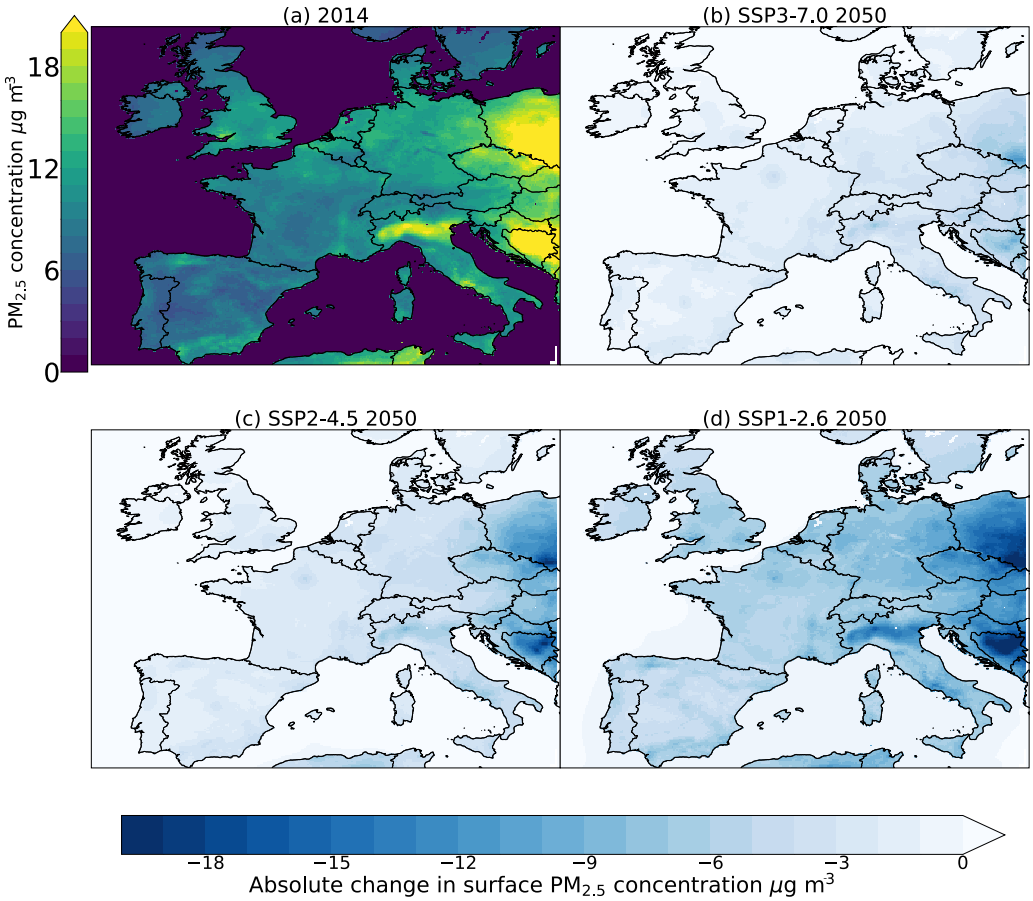


Figure 3.2: a) annual mean $PM_{2.5}$ from the Van Donkelaar reanalysis in 2014, b) absolute change in $PM_{2.5}$ from the present in the scaled VD reanalysis for SSP3-7.0 in 2050, c) SSP2-4.5 d) in 2050 SSP1-2.6 in 2050

3.7.1 Population exposure in comparison to guideline values

Figure 3.3 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 3.3a) and 10 μg m^{-}3 for NO_2 (Figure 3.3c) (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 3.3b).

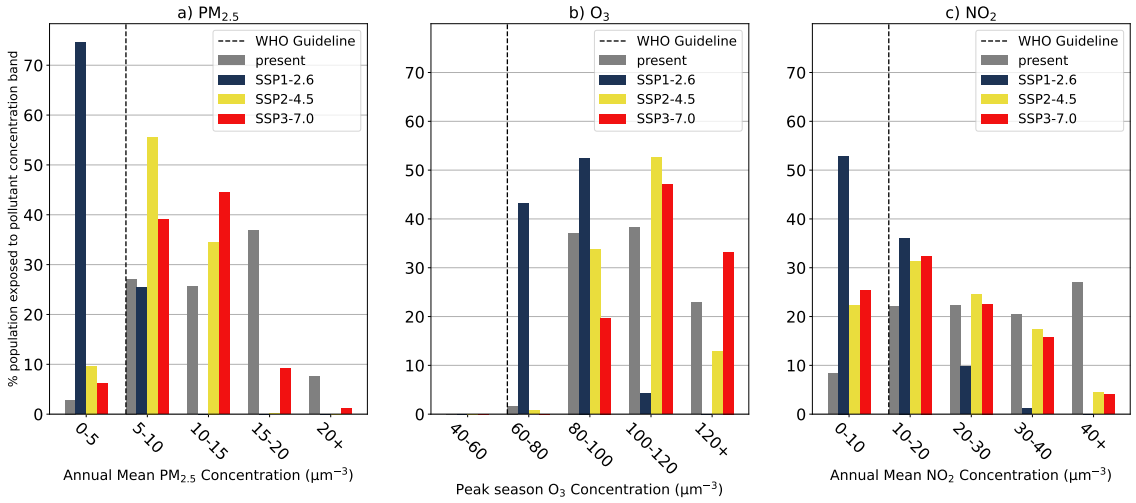


Figure 3.3: The proportion of the population of Europe exposed to different bands of exposure to a) annual mean $PM_{2.5}$, b) peak season O_3, c) annual mean NO_2 (e.g the bars closest to the y-axis of a) represent the percentage of the population whose annual exposure is between 0 and 5μg/m^3). The vertical lines on each figure represent WHO guideline values

3.7.2 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 3.1 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 119,000 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-.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 3.4 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 rate 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 rate 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 rate reduces by over 80% across parts of Central Europe. With this and the results in Table 3.1, 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 3.2 as these reductions do not outweigh the increases in overall mortality caused by population change.

Table 3.1: Summed $PM_{2.5}$ mortality in each scenario and mean mortality rate per 100,000 population using both Fusion-eSCHIF and GEMM. 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 (* = Juginovic et al., 2021; ** = European Environment Agency, 2023). Where the mortality is for a particular age group, GEMM has been used.

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 (1000s) 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 (0.28-0.40)
Age 30-34	1.2 (1-1.4)	0.21 (0.17-0.24)	0.53 (0.44-0.60)	0.56 (0.46-0.66)
Age 35-39	2.1 (1.7-2.5)	0.37 (0.30-0.44)	0.97 (0.8-1.1)	1.0 (0.83-1.2)
Age 40-44	3.9 (3.2-4.5)	0.64 (0.53-0.76)	1.72 (1.4-2.0)	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 (4.9-7.0)
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)

Notes: Mortality ($PM_{2.5}$)* $\approx$ 400,000. Mortality ($PM_{2.5}$ + O_3)** $\approx$ 320,000. *Juginovic et al. (2021); **European Environment Agency (2023).

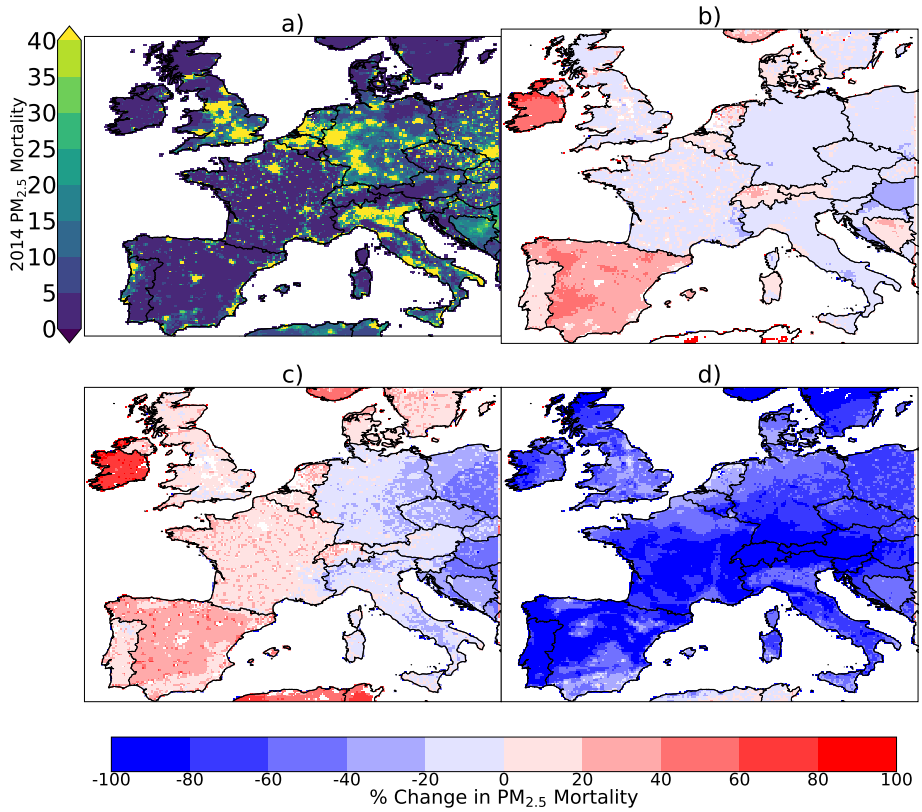


Figure 3.4: a) Annual $PM_{2.5}$ mortality rate in 2014, b) $PM_{2.5}$ mortality rate % change from the present day in 2050 following SSP3-7.0 c) as b) following SSP2-4.5 d) as b) following SSP1-2.6

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 3.2). We see that overall O_3 mortality rate 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 (figure 3.5). 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 com-

pared 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).

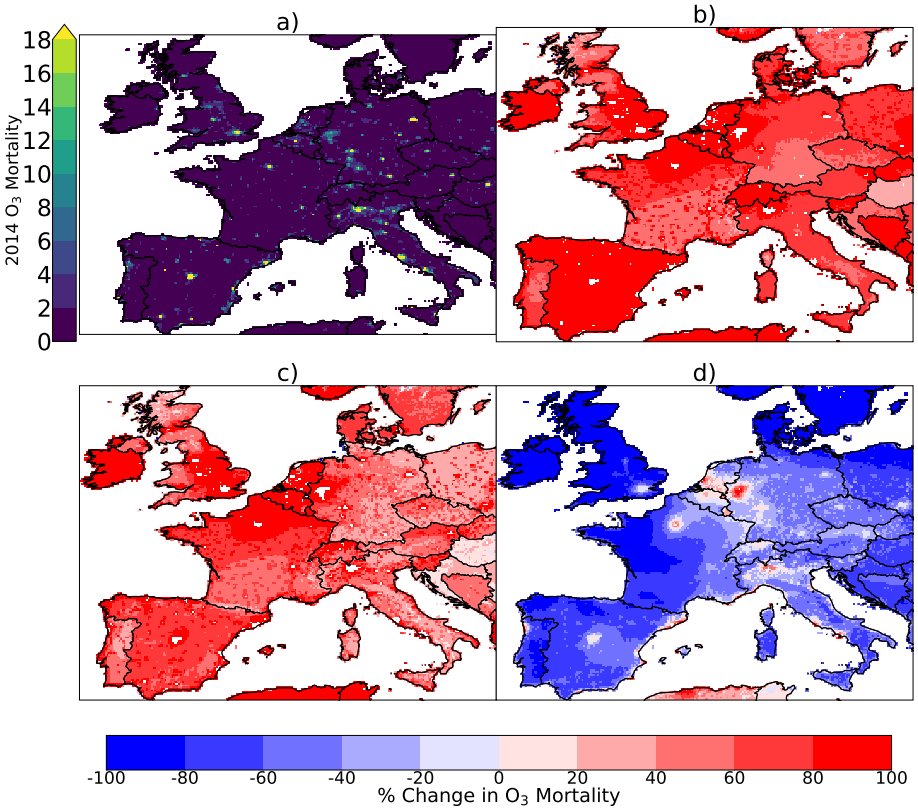


Figure 3.5: a) Annual O_3 mortality rate in 2014, b) Annual O_3 mortality rate % change from the present day in 2050 following SSP3-7.0 c) as b) following SSP2-4.5 d) as b) following SSP1-2.6

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 e.g Juginovic 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 Tarin-Carrasco et al. (2019) do for $PM_{2.5}$ 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

Table 3.2: 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 (0.015-0.020)	0.020 (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 (0.075-0.10)
Age 50-54	0.25 (0.21-0.29)	0.067 (0.056-0.078)	0.19 (0.16-0.22)	0.20 (0.17-0.24)
Age 55-59	0.50 (0.42-0.58)	0.15 (0.13-0.18)	0.43 (0.36-0.50)	0.46 (0.39-0.54)
Age 60-64	0.91 (0.77-1.10)	0.30 (0.25-0.35)	0.86 (0.72-0.99)	0.93 (0.78-1.10)
Age 65-69	1.48 (1.24-1.71)	0.54 (0.45-0.63)	1.53 (1.29-1.78)	1.65 (1.40-1.92)
Age 70-74	2.13 (1.80-2.47)	1.06 (0.89-1.24)	3.06 (2.58-3.56)	3.28 (2.77-3.80)
Age 75-79	3.25 (2.74-3.78)	1.79 (1.50-2.10)	5.12 (4.31-5.93)	5.44 (4.59-6.30)
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 (7.5-10.3)	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)

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 ageing, 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. 2021) and could worsen the $PM_{2.5}$ 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 centres. 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 Tables 3.1 and 3.2 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 towards 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 (<3000 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 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, e.g 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 (Garcia-Leon 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 Garcia-Leon 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 emphasises the importance of ensuring that air quality improves to mitigate other population health pressures that will emerge in Europe over the coming century.

3.7.3 Equity in reductions in air quality-related mortality

Figure 3.6 shows the average subnational human development index 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 (3.6a). Figures (3.6b), (3.6c) and (3.6d) 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 (in comparison to the rest of the domain, not globally) 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 decarbonisation; we instead find that more deprived groups get increased benefits from decarbonisation overall, but that this varies by scenario. In scenarios with smaller emissions reductions, e.g. 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 decarbonisation on a global scale may not be replicated in Europe.

Table (3.3) 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 the supporting information; see Appendix Figures A.16 - A.23. 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 (Appendix Figure A.17). In contrast, in rural regions, there is far greater clear inequity in $PM_{2.5}$ mortality rate in all scenarios (Appendix figure A.16). 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 3.3 that population change is not the driving factor in the more equitable $PM_{2.5}$ exposure across the continent following SSP2-4.5 than SSP1-2.6. When the population is kept consistent, we see a similar trend in equity to when it is not (Appendix Figure A.23).

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 (Appendix Figure A.19) and those in Northern Europe (Appendix Figure A.20). 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 $PM_{2.5}$ (Fig 3.2). 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 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 $PM_{2.5}$.

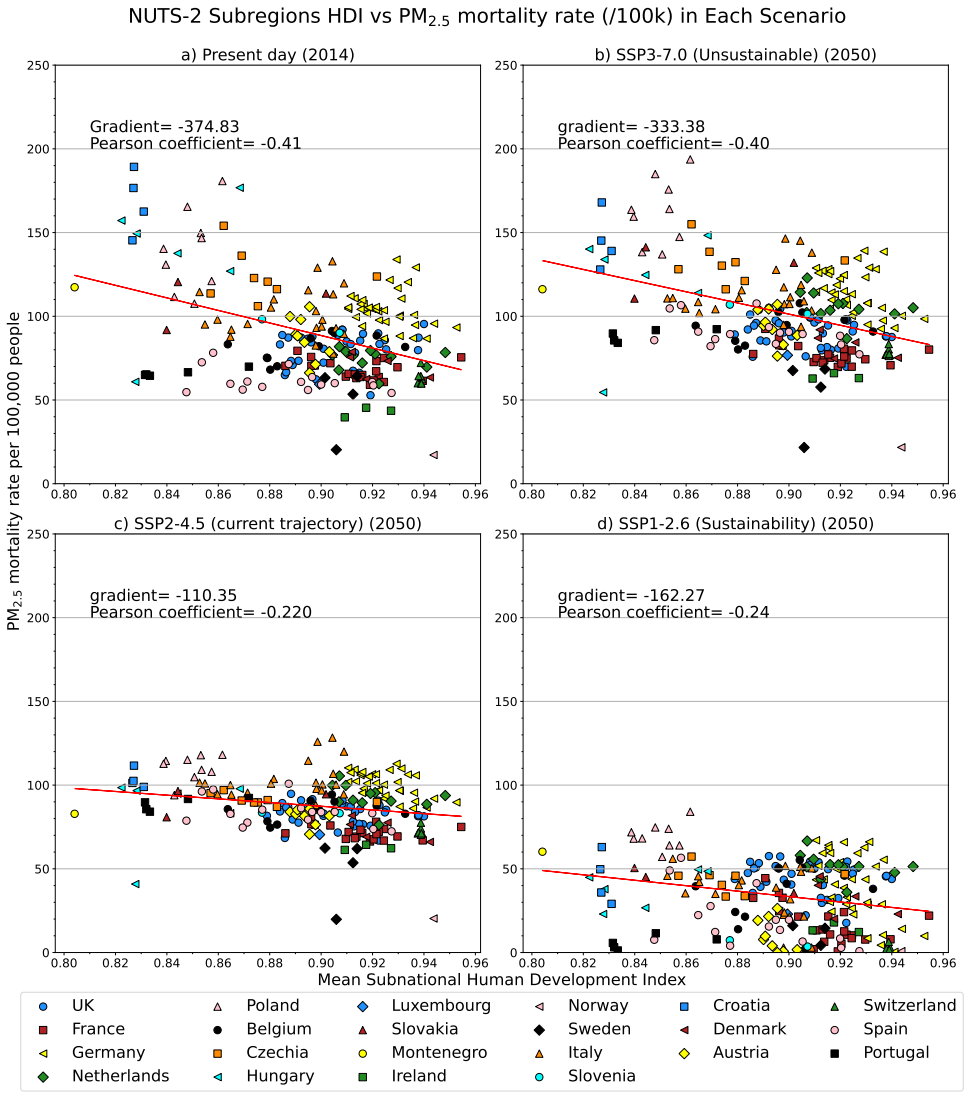


Figure 3.6: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in. The r-value of the correlation 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.

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 EEA, (2023). Notably, however, The EEA, (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

	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**

Table 3.3: 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). 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.

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 centres, 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 3.7, which is the same format as Figure 3.6, 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 3.4) compared to when it is not (Figure 3.7).

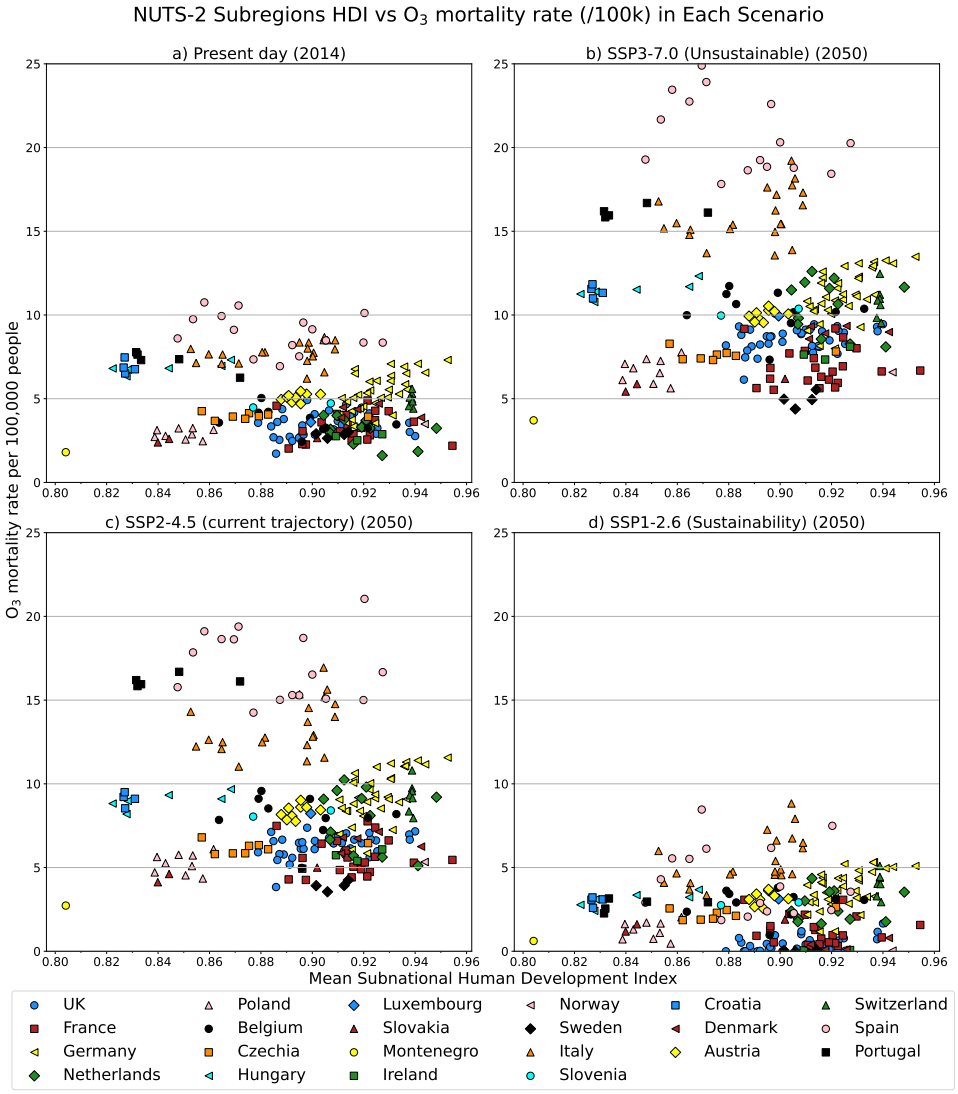


Figure 3.7: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in NUTS 2 subregions in a) the present day b)SSP3-7.0 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the sub-region is in. The r-value of the correlation and the gradient of the linear regression line (the change in O_3 mortality rate per 0.1 increase in HDI) are also provided.

	Pearson coeficcient (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

Table 3.4: 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). 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 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 (Appendix Figures A.28, A.29, A.30) 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 3.4).

The predominant differences between SSP2-4.5 and SSP3-7.0, in terms of emissions, that may explain these trends are that there are significantly larger increases in CH_4 emissions assumed following SSP3-7.0 compared to the present day than following SSP2-4.5. This 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 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 (Appendix Figure A.24). This may be why the reductions in O_3 mortality are smaller in 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 3.4; Appendix Figure A.31) suggesting that the distribution of population change is a considerable factor towards this trend.

3.8 Conclusion

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 subregions 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 maximise 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.

3.9 Contributions

Connor J. Clayton: Performed model simulations, transformed emissions files to work with WRF-Chem, wrote the bias correction code, developed methodology for assessing equity and performed this analysis. Did the majority of the writing and created the figures and tables.

James B. McQuaid, Daniel R. Marsh and Steven T. Turnock: Assisting with project conceptualisation, supervising project and advising on developing methodology, writing, and interpreting results. CESM2-WACCM boundary conditions were developed and provided by Daniel R. Marsh. Steven T. Turnock assisted with testing different methodologies of bias correction.

Ailish M. Graham: Helped setup the model simulations this work is based on and provided code for getting the chemical boundary conditions to work with WRF-Chem. Providing guidance on bias correction of $PM_{2.5}$ using the Van Donkelaar reanalysis.

Carly J. Reddington: Developed the python code used for all health functions in this paper. Provided advice on using and interpreting mortality output. Contributed towards describing the uncertainty in the mortality functions.

Karn Vohra: Providing guidance on using Fusion-eSCHIF and contributing towards writing the section describing the mortality functions

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3.11 Data

The data on which this article is based are available at (Clayton, 2024a) and (Clayton, 2024b)

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Chapter 4

Heatwave Impacts on UK Air Quality Mitigation

4.1 Preface

As discussed in the paper 1 preface, the impacts of keeping meteorology at present-day levels was a key limitation/ theme in my thesis. This discussion formed a large part of my 1st-year transfer and featured in the review comments for both published papers. Despite previous research indicating that climate penalties to air quality are likely to be limited (Bhattarai et al. 2024; Zanis et al. 2022) and that emissions changes dominate (Chemel et al. 2014; Doherty et al. 2017), this limitation was something I clearly needed to address. Like paper 1, this meant that an experimental methodology needed to be used to factor in future meteorology in the WRF-Chem simulations.

As discussed previously, no external meteorology files compatible with WRF-Chem that represent the SSPs are available to my knowledge. I first tried to create these; using a similar principle to creating the emissions files for paper 1. I created a multi-model mean for key meteorological parameters from CMIP6 output and modified present-day ERA5 reanalysis data to include the future mean meteorology, however WRF-Chem did not function with these inputs. Simultaneously, this project was affected by the decommissioning of the Arc4 high-performance computing system at the Uni of Leeds. This placed a stringent timeline on producing results and considerably lowered the available computing resources. This meant I needed an alternative method requiring considerably less computing resource than paper 1 had and had limited time

to test methodologies. The method I used here, with a smaller domain (the UK), constrained time periods and using a summer notable for excess heatwaves as a climate change analogue, inspired by work by Yule et al. (2024) was primarily designed to meet this restriction.

The heatwave method does however have advantages. Firstly, it allowed me to compare the impact of this to existing climate penalty research to investigate whether this is an effective method. It also could potentially allow me to increase the policy relevance, as the impact of heat and heatwaves on UK public health is a key policy priority of the UK Health Security Agency, who have recently begun publishing Adverse Weather Plans for which heatwaves form a large part (UKHSA, 2023) and participating in research on UK heat health impacts e.g Murage et al. (2024). The constrained time period also aided with being able to consider short-term air quality changes as the result of emissions change (which forms very little part of existing research using SSPs) and the heatwaves.

Below is the draft of paper 3 although this is not yet submitted.

4.2 Abstract - Paper 3

In Europe, poor climate change mitigation efforts have been widely shown to exacerbate air pollution. Heatwaves also may result in air pollution events and are expected to become more common as the climate changes. Due to difficulty modeling air quality, weather and climate change simultaneously, few studies demonstrate the combined impacts of these environmental issues. In this study, we use a detailed atmospheric chemistry model focused on the UK to estimate summer concentrations of $PM_{2.5}$ and O_3 air quality with CMIP6 emissions representative of the year 2014 and 2050 following a scenario with little climate change mitigation (SSP3-7.0) and 2014 meteorology. We compare this to model simulations where meteorology from a year with a notable heatwave (2022) has instead been used. This allows us to test whether conditions that will become much more frequent in a low-mitigation future cause air pollution episodes in the UK.

We demonstrate that a summer with frequent heatwaves has limited impact on $PM_{2.5}$ concentrations in the UK (ranging from a decrease of -0.22 $\mu g/m^3$ in the North West to maximum of 1.53 $\mu g/m^3$ increase in London). Although these changes are small, the increased number

of days in most UK regions that see elevated $PM_{2.5}$ concentrations exceed the decreases they would see if only emissions changes from a weak mitigation scenario were considered resulting in a net increase of up to 7 days of elevated population exposure in Wales and South-West England.

This effect is amplified for O_3 concentrations, which are considerably elevated in the heatwave conditions (maximum of 14.15 increase $\mu g/m^3$ in the East Midlands). We find that the increases in O_3 in these periods can considerably exacerbate the worsening O_3 air quality seen in the UK from following a weak climate mitigation scenario, to a degree larger than the impacts of the emissions change itself. Regions of the UK can see up to 22 more days with elevated O_3 concentrations (in Wales) where both emissions and heatwave conditions are considered compared to a maximum increase from emissions alone of 12 days (London). This emphasises the potential co-benefits of stringent mitigation of anthropogenic emissions associated with climate change and air quality; stringent mitigation scenarios will not only have reduced long-term air pollutant concentrations, but less frequently see heatwave conditions that cause considerably elevated short-term O_3 concentrations.

4.3 Introduction

Much existing research establishes that different climate mitigation "futures", usually represented by the Shared Socioeconomic Pathways (O'Neill et al. 2017) will have varying implications for air quality (Clayton et al. 2024; Turnock et al. 2020; Reddington et al. 2023). Specifically, in Europe, SSP3-7.0, which is widely considered a "worst-case scenario" was found by Clayton et al. (2025) to result in an increase of 12,000 deaths per year from $PM_{2.5}$ and 27,000 from O_3 by 2050 (when population change is factored in). Globally, Turnock et al (2023) found $PM_{2.5}$-attributable deaths increased by over 9 million and O_3-attributable deaths by 1.21 million.

The methods used by the above vary, notably Clayton et al. (2025) and Clayton et al. (2024) considered only the impacts of emissions change, whereas Reddington et al. (2023) and Turnock et al. (2023) used output from the Coupled Model Intercomparison Project 6 (CMIP6). These techniques have advantages and disadvantages; using only emissions and forcing the model to present-day meteorology means that models with better representation of local to regional scale

air quality processes can be used, but the impact of climate change is not considered. Climate change itself can affect the formation of secondary pollutants (Silva et al.2017; Doherty et al. 2017) and thus there is widely expected to be a climate penalty on the efficacy of future emissions mitigation due to feedbacks (Von Schneidemesser et al.(2020); Zanis et al. (2022).

Meteorology changes associated with climate change for O_3 may have non-linear impacts on surface concentrations. Elevated temperatures have been shown to speed up the rate of both O_3 production and destruction (Doherty et al. 2017) and have impacts on O_3 precursors, notably peroxyacetyl nitrates (PAN). PAN is destroyed faster at higher temperatures to form NO_x, thereby increasing availability of species needed to form O_3 and subsequently increasing surface O_3. Higher temperatures can also result in increased emissions of biogenic volatile organic compounds from plants (Scott et al. 2018; Zanis et al. 2022) and increase CH_4 in wetland environments (Doherty et al. 2017). Both are O_3 precursors and can result in increased surface O_3. It has been suggested that the increase of O_3 through climate change could affect the ability of forests to drawdown carbon, further worsening climate change (Cheesman et al. 2024).

Notably, humidity may alter the response of surface O_3 to temperature, for example in more humid, less-polluted environments increased water vapour availability may result in increased O_3 destruction and lower overall surface O_3, but this effect is mostly only present in low-NO_x environments (Doherty et al. 2017, Zanis et al. 2022). However, the response of humidity to climate change is uncertain. It is well understood that warmer air can hold more moisture, and climate change is attributable to increasing global water vapour availability in the lower troposphere - an increase of approximately 1% every 10 years (Allan et al. 2022).

$PM_{2.5}$ concentrations also have a non-linear response to temperature increases; increased temperature can cause $PM_{2.5}$ reductions due to increased evaporation of ammonium nitrate, however the increased BVOC emissions may increase $PM_{2.5}$ concentrations, as it could accelerate the rate of production of organic aerosol and sulphate (Megaritis et al. 2014). Where humidity increases, $PM_{2.5}$ may increase due to nitrate being increasingly partitioned to the aerosol phase (Megaritis et al. 2014).

Both $PM_{2.5}$ and O_3 concentrations could also be affected by the dynamical impacts of climate change beyond chemistry e.g climate change-related reductions in wind speed have been observed globally over the 20th century (Roderick et al. 2007; McVicar et al. 2012). Such trends are expected to continue as the climate changes further based on the scenarios used for CMIP5

and CMIP6 (Wohland et al. 2021; Shen et al. 2022), although research suggests that land use changes contribute more to the existing trend than physical changes caused by increased greenhouse gas concentrations (Zhang et al. 2019; Wohland et al. 2021). Low wind environments means reduced dispersal of pollutants. There is evidence, however, that wind speed change is non-linear and wind speeds have increased since the McVicar study was published (Zeng et al. 2019) so there is uncertainty in how important this will be in future. Similarly, and linked with the effects on humidity, climate change affects precipitation; e.g Robinson et al. (2021) find that rainfall extremes have been more frequent in recent years in Europe than would have been expected under a stationary climate. This could increase wet pollutant deposition. Going into the future, Trancoso et al. (2024) claim that Northern Europe precipitation is expected to increase, but reduce in Southern Europe.

An omission from much of the existing research is the impact of weather extremes, such as heatwaves on future air quality. Heatwaves are defined as 5 or more consecutive days of prolonged heat in which the daily maximum temperature is higher than the average maximum temperature by 5°C or more (World Health Organisation). Climate change is expected to have increased the incidence of heatwaves over the late 20th Century and the 21st century, and this trend is expected to continue into the future (Robinson et al. 2021; Marx et al. 2021). This is already having an impact on public health; 37% of ambient temperature-related premature deaths between 1991 and 2018 have been estimated to be attributable to the impacts of anthropogenic climate change (Vicedo-Cabrera et al. 2021). Even using climate models, the impacts of heatwaves are poorly understood; it has been found that CMIP5 and CMIP6 have reasonably poor representation of the processes that lead to heatwaves (van Oldenborgh et al. 2022).

Heatwaves can worsen air quality episodes through a range of pathways. Heatwaves often form when high temperatures coincide with high atmospheric pressure. This can result in low wind speed and pollutants building up near the surface (Wu et al. 2019). As described previously, heat may amplify the formation of O_3 and $PM_{2.5}$ (Zanis et al. 2022, Megaritis et al. 2014). Heatwaves may also increase the incidence and severity of wildfires (Spracklen et al. 2009; Jones et al. 2020) which also worsen local air quality. This can lead to compound effects where local populations are exposed to health risks from heat and severe increases in air pollution.

4.3.1 2022 European heatwaves

In 2022 a group of heatwaves over Europe was calculated to have resulted in over 60,000 deaths from heat stress (Ballester et al. 2022). The heatwaves and the accompanying drought affected countries across Europe in June, July and August. These heatwaves were notable for the length of time for which temperatures between 35 and 40 degrees C were recorded in many countries, as opposed to an exceptional number of individual days above 30 degrees or 35 degrees over the entire summer (Copernicus Climate Change Service (CCCS), 2022). Some temperature records were broken, for example, the UK recorded its first temperature above 40 degrees C in history at Coningsby, Lincolnshire (CCCS, 2022). In the UK, 5 particular periods in this time were designated as "heat episodes" (UK Health Security Agency, 2022). These were the 16-19 June, 11-25 July, 30 July-5 August, 10-17 August and 23-25 August.

Temperature anomalies were most extreme in France (particularly Southern France), Northern & Central Spain, Northern Italy and Western Germany with compound effects from the heat and drought most severe in localised parts of Southern & Western France, South-West England, North-West Italy and Northern & Central Spain (Tripathy & Mishra, 2023).

While the 2022 European heatwaves broke records, they were notably not outside the expectations set by climate change projections. Analysis suggests that following climate change scenarios, temperature extremes like those seen in the Mediterranean regions during the 2022 heatwaves could be expected approximately every seven years in the same region following SSP2-4.5 (Tejedor et al. 2024). Kendon et al. (2023), writing for the State of the UK Climate 2022 Report are even more pessimistic, claiming that following a medium climate-mitigation scenario (RCP4.5) in the UK, the conditions observed in the UK during the 2022 heatwave would be representative of an average year, or even a cool year by 2100.

4.3.2 Modelling challenges

The impacts of climate change are expected to be considerably lower than those of emissions changes (Doherty et al. 2017), however, the absence of climate change impacts reduces how representative emissions-only studies are likely to be for future air quality. On the other hand, CMIP6 models are designed for modelling climate change and long simulations, but to do this have coarse grid resolution and less detailed chemistry schemes than the atmospheric chemistry models usually used in emissions-only studies. Finer resolution is advantageous for modelling

air quality (especially when calculating mortality) as it results in better representation of the physical and chemical processes in urban areas (Fenech et al. 2018). A comparison of these methods made by Clayton et al. (2024) demonstrates the potential implications of using a finer resolution, showing that emissions-only simulations show much larger changes in air quality around urban regions when comparing the present-day and Shared Socioeconomic Pathways in 2050 than the results of Turnock et al. (2020) which use coarse resolution global climate models. While this suggests that there are advantages to using regional atmospheric chemistry models, lacking any representation of the impact of climate change itself is a clear tradeoff. Similarly, there is limited capacity to factor in climate change to these studies due to the extreme computational expense of running regional atmospheric chemistry models long enough to capture climate variability. In addition to the lack of availability of appropriate meteorological data representative of future climate change in the required format and temporal/spatial resolution for these models.

To combat this issue, a range of techniques have been considered. Chen et al. (2023) for example use climate model output to establish the global air quality impacts of following SSPs, but downscale the results to local resolution using machine learning and a reanalysis product. A similar approach is used for considering the air quality impacts of different emissions scenarios in India by Miinalainen et al. (2023), who argue that it allows for much more flexible use of global climate models. Some studies also correct to global reanalysis products developed from observations (Reddington et al. 2023). Others, such as Kumar et al. (2018) and Wu et al. (2019) use a version of WRF-Chem with greenhouse gas concentrations perturbed to levels consistent with CMIP5 scenarios and allow meteorology to run free over 10-year simulations. This method may be more effective but would come with significant computational expense that may not be realistic for many research teams. Kumar et al. (2018) note that they reduce the model timestep to producing 6-hourly data to achieve this, which is a compromise that could affect how well the model represents some chemical processes, especially for considering O_3. More recently, the MUSICA model (Schwantes et al. 2022) has been developed with multi-scale meteorology and chemistry, which may be better able to handle both long-term climate and regional scale chemistry, but this model is still in exploratory usage. Similarly, Fritz et al. (2022) develop a version of GEOS-Chem (another air quality model) embedded within the CESM2 climate model, but this is also exploratory.

In this study we explore an alternative; the use of a present-day heatwave period as an "analogue" for climate change conditions. Climate change has resulted in more frequent heatwave conditions and will continue to do so (Robinson et al. 2021; Marx et al. 2021). Thus, it is possible that when choosing a present-day meteorology year for "emissions only" co-benefits of climate mitigation studies, such as Clayton et al. (2024), Macintyre et al. (2023) and Fenech et al. (2021) that using a year in which there were heatwave episodes may be more representative of a future climate. Past heatwave analogues have been used before to consider the impact of future heatwaves (Yule et al. 2024) but, to our knowledge, heatwave meteorology has yet to be used as an analogue for climate change and how it relates to air quality.

4.4 Methodology

Four 3 month-long regional air quality model simulations, covering the months of June, July and August were performed using WRF-Chemv4.2 to simulate heatwave summer time conditions and assess the impacts on air quality and whether the meteorological effects exceed the impacts of emissions changes from a weak mitigation scenario. These simulations were at 15km horizontal resolution and covered the British Isles. Table 4.1 (also from Clayton et al. 2024) shows the model configuration used in this study.

Parameter	**Scheme Used**	**Source**
Chemical Scheme	MOZART-MOSAIC 4-bin Aerosol w/Aqueous Chemistry	Hodzic & Knote, 2014
Biogenic Emissions	MEGAN v2.0.4	Guenther et al. (2006)
Fire Emissions	FINNv1.5	Wiedinmyer et al. (2010)
Natural Dust Emissions	GOCART	Chin et al. (2000), Ginoux et al. (2001)
Meteorological Boundary Conditions	ECMWF ERA5	Hersbach et al. (2020)
Chemical Boundary Conditions	CESM2-WACCM CMIP6 Simulations	Danabasoglu, (2019)

Table 4.1: Model parameters used and sources.

The simulations covered the following scenarios:

. 2014 Meteorology and 2014 emissions from CMIP6 henceforth referred to as CTRL_PD

. 2014 Meteorology and 2050 emissions from CMIP6 following the SSP3-7.0 scenario henceforth referred to as CTRL_FUT

. 2022 Meteorology and 2014 emissions from CMIP6 henceforth referred to as HEAT_PD

. 2022 Meteorology and 2050 emissions from CMIP6 following the SSP3-7.0 scenario henceforth referred to as HEAT_FUT

2014 emissions are from Hoesly et al.(2018). Future emissions are described by Gidden et al. (2019) & Feng et al. (2020). These are modified for use with WRF-Chem as per Clayton et al. (2024) with one exception; Clayton et al. (2024) generated anthropogenic $PM_{2.5}$ and PM_{10} emissions via a linear regression from the carbon monoxide emissions. We do not use this as it caused a considerable overestimation in $PM_{2.5}$ concentrations in their study.

One of the processes with the strongest response to temperature changes and is very meaningful for air quality is the emission of BVOCs. BVOC emissions in our configuration are generated by MEGAN version 2.0.4 (Guenther et al. 2006). This scheme uses vegetation-specific standard emissions rates of isoprene which factor in sunlight, temperature, leaf area index, leaf age and soil moisture (DiMaria et al. 2023). MEGAN categorises plant types "plant function types" (e.g Needle Evergreen Tree or Shrub) by default as opposed to specific species. Each function type has its own emissions factor for isoprene and monoterpenes. We use the default vegetation cover in MEGAN for each scenario. MEGAN is thought to overestimate isoprene emissions in a range of landscapes, including in Europe so this may result in high additional production of O_3 as temperatures increase (Jiang et al. 2019; Kota et al. 2015; Wang et al. 2017).

We calculated a "heatwave penalty" for some of the results; this refers to the increase in an air pollutant concentration as a result of the difference in meteorology after the impact of emissions changes is factored in. To do this, we first calculated population-weighted daily mean $PM_{2.5}$ and population-weighted daily maximum O_3 aggregated by each region of the UK for each scenario. Then this formula was applied with:

EMIS_ONLY_CHNG = CTRL_FUT - CTRL_PD (thus working out the strength of the emissions change without future meteorology.

EMIS_MET_CHNG = HEAT_FUT - CTRL_PD (the strength of the change if both meteorology and emissions are considered)

Heatwave penalty = EMIS_MET_CHNG - EMIS_ONLY_CHNG

For some of the following results, we use a seasonal mean heatwave penalty, some it is expressed daily and some is the mean of only the 6 "elevated heat" periods.

4.5 Results and Discussion

WRF-Chemv4.2 using the ECMWF-ERA5 reanalysis as meteorological initial and boundary conditions showed a difference in meteorological conditions between the scenarios consistent with heatwave conditions being present in 2022 and not 2014. Figure 4.1 shows the subsequent model output of key meteorological paramaters averaged over the land surface within the domain. Figure 4.1a shows the daily maximum hourly temperature at 2m average. This was similar in the simulations using 2014 and 2022 for most of June, but on 11th and 12th July, the 2022 simulations showed high peaks in temperatures up to 29 degrees C. August temperatures were consistently at least 2 degrees C higher in the 2022 simulations than the 2014 simulations until late August, where the 2014 simulation also showed elevated temperatures. Wind speed did not differ as much between the two years, but 2022 had higher wind speed in June. Late July, mid-August and the end of August 2022 had periods of high surface pressure (Figure 4.1c), suggesting stagnant, low wind speed environments. Absolute humidity - the total availability of water vapour (Figure 4.1d) (calculated here from temperature at 2m and relative humidity using the Magnus-Tetens equation) was similar in both simulation periods, although 2022 was unexpectedly more humid (in terms of water vapour availability, not necessarily precipitation) than 2014 in late August.

Figure 4.2 shows the population-weighted daily mean $PM_{2.5}$ concentrations over the full simulation in each statistical region of the UK. It demonstrates that overall, neither emissions nor meteorology caused significant changes to overall $PM_{2.5}$ concentrations. As demonstrated by Clayton et al. (2024), 2050 following SSP3-7.0 results in similar or slightly elevated $PM_{2.5}$ concentrations for much of Europe, so this result was expected. Figure 4.2 does suggest some heatwave impacts on $PM_{2.5}$ air quality, for example for several regions of the UK, elevated $PM_{2.5}$ concentrations are seen in the simulations using 2022 meteorology between approximately 10th-20th August. This coincides with a long period of persistently elevated temperatures and high pressure shown in Figure 4.1. Most regions show elevated $PM_{2.5}$ concentrations on approximately 12/13th July. This is observable on all simulations, regardless of meteorology year, however the peaks are higher where 2022 meteorology is used. This could be due to the influ-

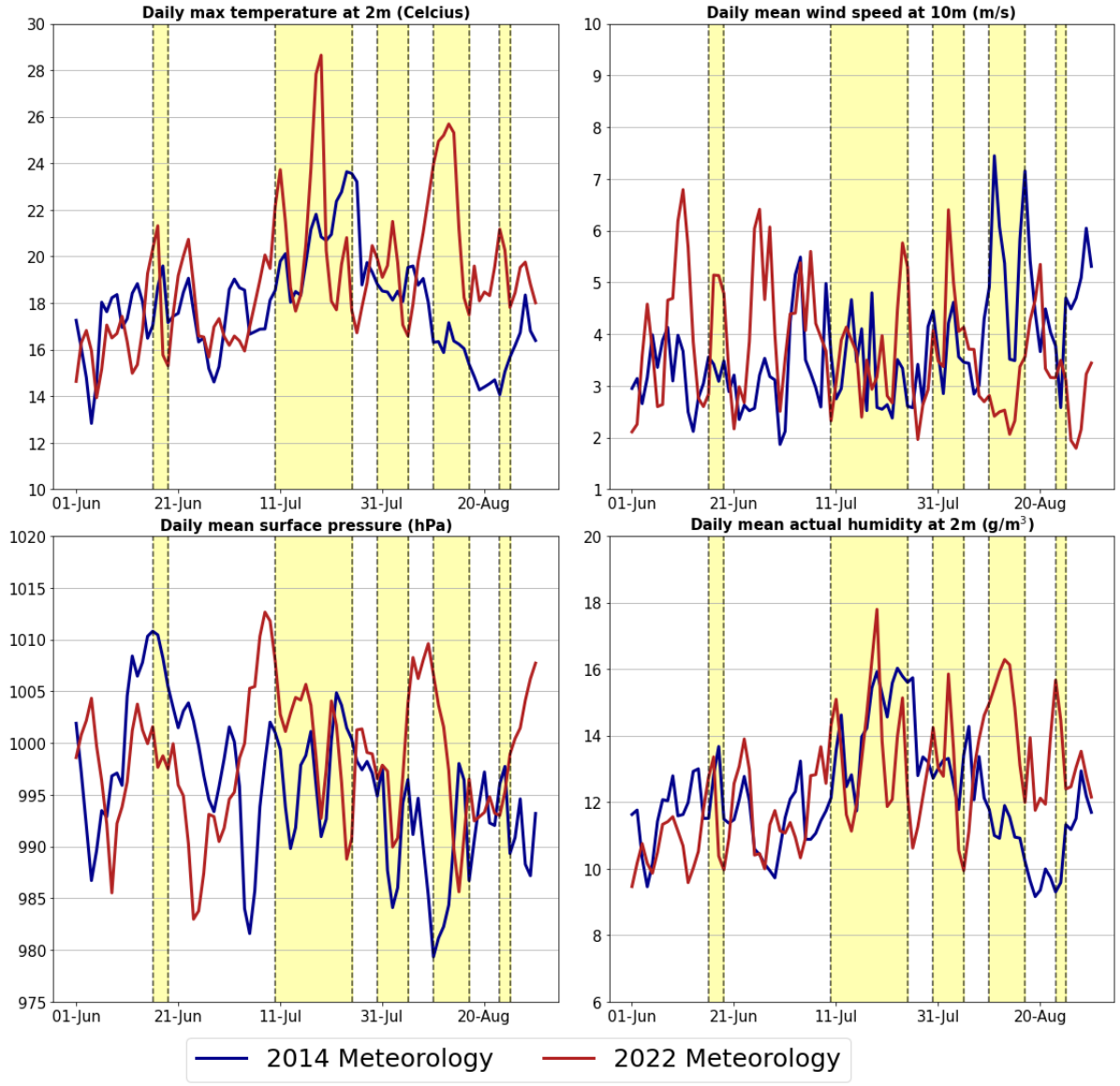


Figure 4.1: Time series plots showing how key meteorological parameters averaged over the land surface of the UK evolved over the scenarios when using 2014 vs 2050. This uses model output as opposed to the meteorological initial and boundary condition data. Elevated heat periods (as defined by the UKHSA) are shaded in yellow

ence from elevated surface temperatures and low wind speed seen at this period in both 2022 and 2014. The added influence of higher pressure in 2022 could cause the higher $PM_{2.5}$ peak in the 2022 meteorology simulations. While low wind speeds result in anti-cyclonic conditions and increase ambient $PM_{2.5}$, it is not a given that higher wind speeds reduce $PM_{2.5}$ concentrations - in the UK, Easterly and South-Easterly winds are associated with increased ambient $PM_{2.5}$ due to increased transport from continental Europe (Graham et al. 2020).

Table 4.2 shows how the changes in $PM_{2.5}$ concentrations in each scenario may affect exposure to air pollution concentrations above guideline values. It demonstrates that on a day-to-day

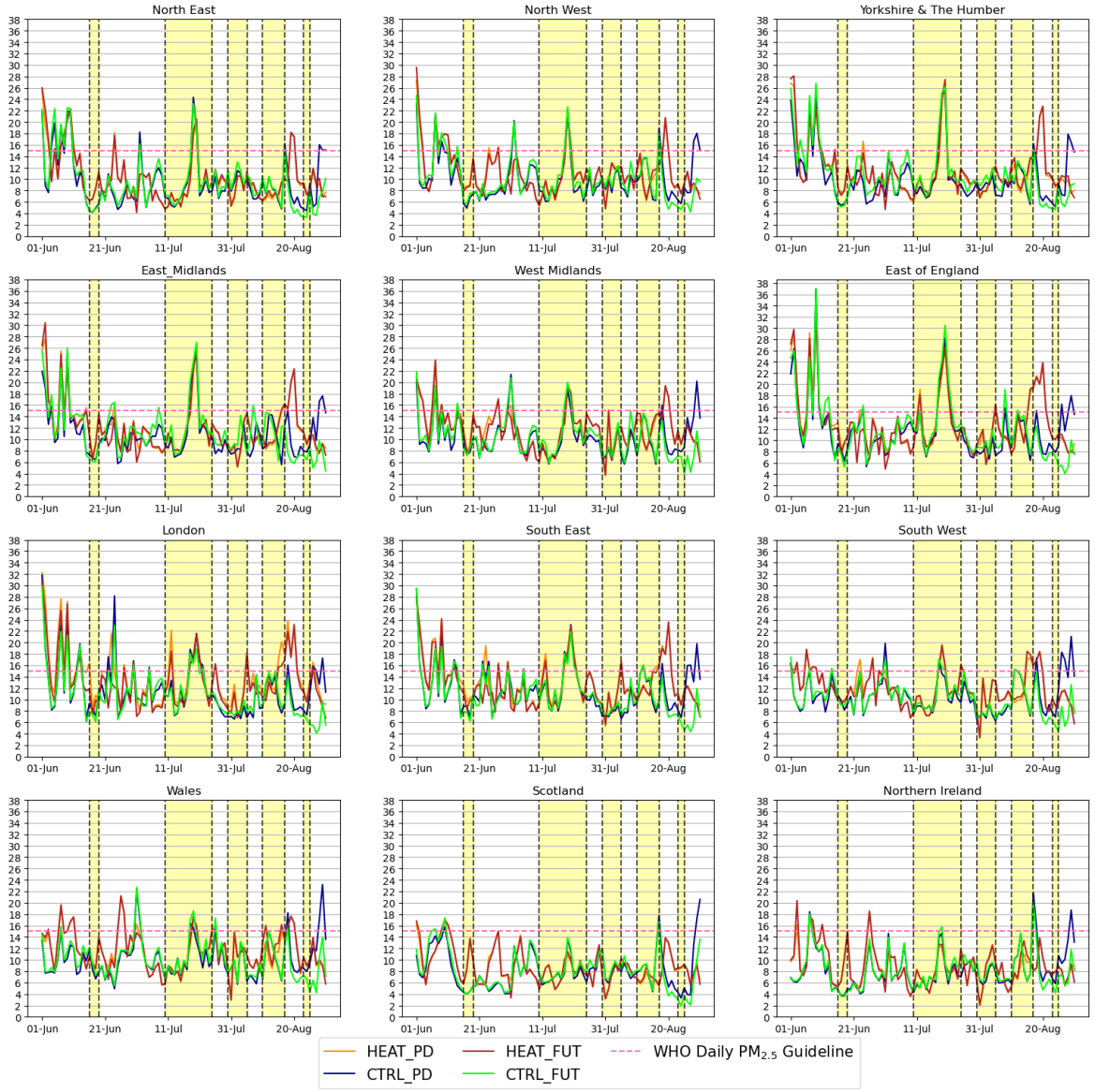


Figure 4.2: Daily mean population-weighted $PM_{2.5}$ concentrations in $\mu g/m^3$ for each simulation in each statistical region of the UK. The WHO daily mean $PM_{2.5}$ exposure guideline is included as a comparison. Elevated heat periods (as defined by the UKHSA) are shaded in yellow

Region	CTRL_PD	CTRL_FUT	HEAT_PD	HEAT_FUT	emissions-attributable change	heatwave-attributable change	combined impact
North East England	13	11	14	14	-2	1	1
North West England	9	9	12	12	0	3	3
Yorkshire and the Humber	11	12	12	12	1	1	1
East Midlands	11	12	15	14	1	4	3
West Midlands	10	10	14	12	0	4	2
East of England	18	17	21	19	-1	3	1
London	19	12	27	24	-7	8	5
South East England	18	15	22	19	-3	3	1
South West England	9	10	19	16	1	10	7
Wales	9	7	15	16	-2	6	7
Scotland	4	4	4	5	0	0	1
Northern Ireland	4	3	5	5	-1	1	1

Table 4.2: Number of days that exceed the WHO $PM_{2.5}$ guideline of 15 $\mu g/m^3$ by simulation

basis, the impacts of weather on $PM_{2.5}$ exceed those of changes from SSP3-7.0 emissions. In fact in some regions, the impact of the weather results in overall increases in excessive $PM_{2.5}$ exposure despite the impacts of emissions alone suggesting that population exposure to $PM_{2.5}$ would reduce over the summer. This is especially notable in London, which would see 7 fewer days over the summer period with elevated air pollution following SSP3-7.0 but instead sees an overall increase of 5 days with elevated air pollution if a heatwave year is used along with the emissions change. The increase attributable to weather conditions are greatest in London and South West England, however it is Wales and the South West that see the largest combined change in elevated air pollution days, both of which have 7 extra days of elevated $PM_{2.5}$ over the 92-day summer period when both weather and emissions change are considered. What this means is that for the UK, future climate change impact could be more important for short-term $PM_{2.5}$ air quality than emissions change in a weak mitigation scenario.

The maximum population-weighted daily rolling 8-hour mean O_3 concentrations in each region of the UK through each simulation are shown in Figure 4.3. This figure demonstrates stronger temperature dependence - all regions of the UK saw periods of elevated O_3 concentrations in O_3 throughout August. These correlate with increases in surface temperatures. Notably, in Wales, Scotland and the South-West, late July in the 2014 simulations see higher daily maximum O_3 concentrations than the 2022 simulations. The spatial distribution of the increased concentrations in the South West for both $PM_{2.5}$ and O_3 may be explained by the distribution of the changes in meteorology, which are shown in Figure 4.1. While overall trajectory of change for each of the meteorological conditions tends to be the same across the country in each month, the South of England sees the greatest increase in August temperatures compared to the 2014 baseline.

Table 4.3 shows the days exceeding the WHO O_3 guideline values following each simulation. It shows that short-term O_3 exposure has a stronger response than $PM_{2.5}$. In part, this is because

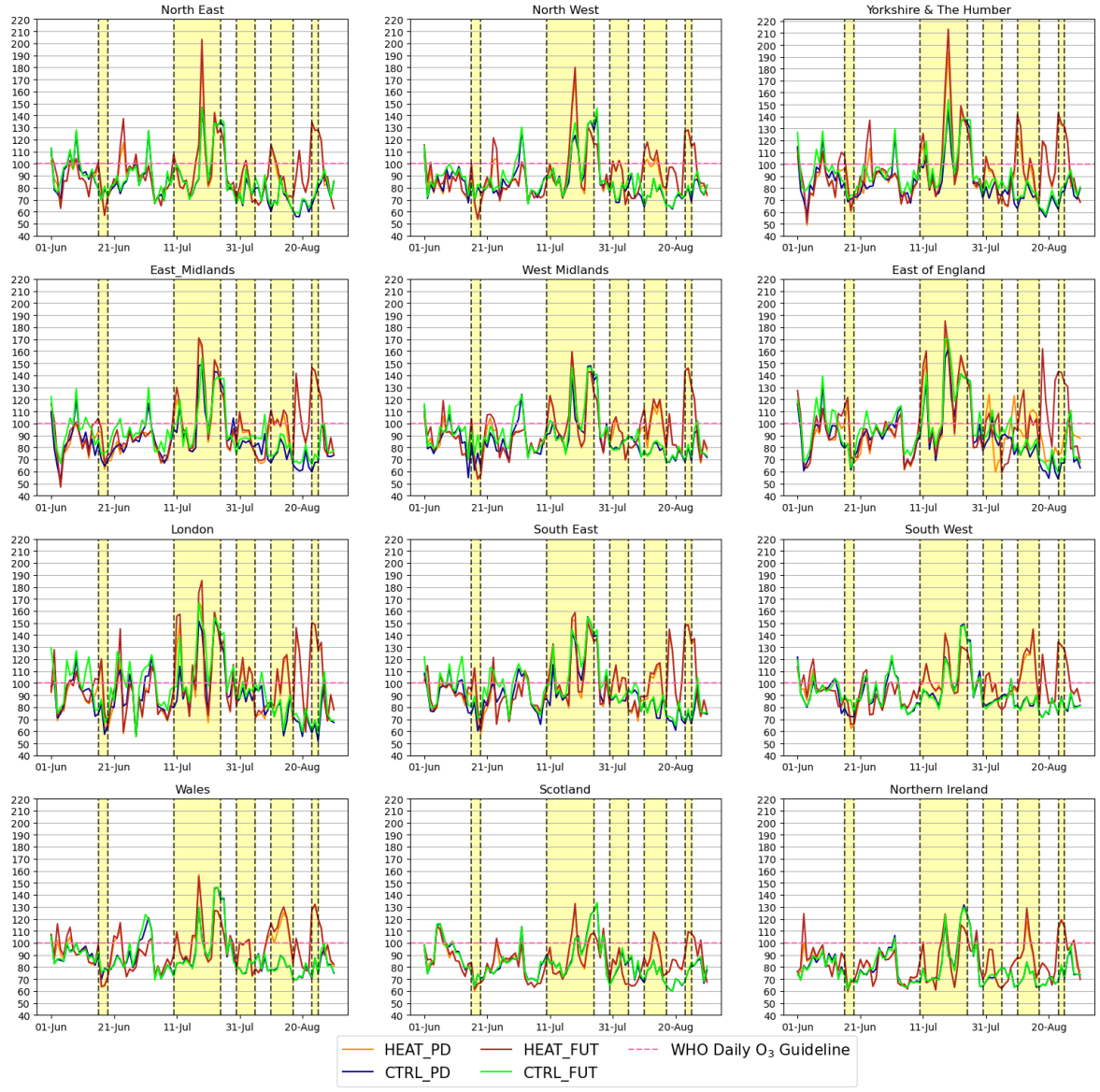


Figure 4.3: Daily maximum 8-hour population-weighted mean O_3 concentrations in $\mu g/m^3$ for each simulation in each statistical region of the UK. The WHO daily 8-hour population-weighted mean O_3 exposure guideline is included as a comparison. Elevated heat periods (as defined by the UKHSA) are shaded in yellow

Region	CTRL_PD	CTRL_FUT	HEAT_PD	HEAT_FUT	emissions-attributable change	heatwave-attributable change	combined impact
North East England	11	12	22	24	1	11	13
North West England	10	13	21	24	3	12	14
Yorkshire and the Humber	12	15	23	27	3	11	15
East Midlands	13	17	22	27	4	9	14
West Midlands	12	15	22	29	3	10	17
East of England	19	30	24	37	11	5	18
London	23	35	32	34	12	9	11
South East England	20	29	32	33	9	12	13
South West England	19	22	28	33	3	9	14
Wales	13	16	35	35	3	22	22
Scotland	12	12	16	18	0	4	6
Northern Ireland	7	7	13	14	0	6	7

Table 4.3: Number of days that exceed the WHO O_3 daily maximum 8-hour rolling mean guideline of 100 $\mu g/m^3$ by simulation

O_3 exposure increases following CTRL_FUT compared to CTRL_PD for O_3 as opposed to $PM_{2.5}$ in which it is a mixed picture. For O_3 HEAT_FUT demonstrates that for all regions except for London and the East of England, the impacts of the weather considerably exacerbate worsening O_3 caused by emissions change, usually by greater degrees than the emissions change itself. This effect is most pronounced in Wales, in which HEAT_FUT has 22 more days above the guideline value than CTRL_PD. This demonstrates that even if over a year, the O_3 response is low and long-term health impacts are small, the impact of heatwave conditions can considerably alter short-term O_3 exposure and put public health at risk.

The different response in London could be a result of the assumptions inherent in SSP3-7.0. While it is a weak mitigation scenario it does assume reductions in NO_x emissions of over 20%. As London is an entirely urban region, NO_x reductions from mitigation are likely proportionally larger than other regions. With this being a VOC-limited regime, the resulting increases here may simply outweigh the impact of the heatwave, especially as an entirely urban region may have lesser emissions of BVOCs, which are a key biogenic climate feedback resulting in increased O_3 production. The potential reasons for the stronger response to emissions change than climate in the East of England is less clear, however, this region sees a low heatwave impact in comparison with the rest of England in conjunction with a comparatively high increase from emissions change. This is potentially because the agricultural nature of this area could mean assumed increases in CH_4 emissions following SSP3-7.0.

The O_3 trends can in part be explained by the changes seen in important precursors; Figure 4.4 shows how daily maximum isoprene, PAN and NO_2 (here used as an indicator of NO_x) averaged over the land surface with both 2014 and 2022 meteorology change through the simulations. The output for these in CTRL_FUT and HEAT_FUT are shown in this figure. It shows that daily maximum isoprene concentrations largely follow the surface temperature trends throughout the

simulations and are higher in the 2022 simulation when 2022 temperatures are higher and vice-versa, resulting in daily maximum isoprene concentrations being on average 0.12 ppb higher in the HEAT_FUT than CTRL_FUT. The large spike in temperature seen in the 2022 simulation on 12th/13th July is also represented in the isoprene concentrations. Isoprene is a BVOC demonstrated to have a strong response to hot and dry conditions in the UK (Ferracci et al. 2020) and is well established as a precursor that has meaningful impacts on tropospheric O_3 at both a local and continental level (Lee et al. 2006; Squire et al. 2015). This means there is a potential biogenic feedback on climate change even when anthropogenic emissions are kept constant; O_3 is a greenhouse gas and can be transported to the upper atmosphere, thus accelerating climate change and potentially resulting in yet more isoprene emissions. This is not linear though due to the ability of O_3 to damage or kill plants, which limits isoprene formation (Cheesman et al. 2024).

Isoprene's ability to impact on O_3 is heavily tied to NO_x availability and is much reduced where NO_x availability is lower (Curci et al. 2009). In other words, its impact is tied to the concentrations of anthropogenic precursors. This suggests that in more polluted regions than the UK, the penalty this causes to O_3 could worsen. This may explain the relatively small heatwave impacts in Scotland, Northern Ireland and the East of England compared to more densely populated regions. It does also mean that stronger NO_x controls could be able to reduce the biogenic O_3 feedback from BVOCs, provided that anthropogenic VOCs are also mitigated.

PAN concentrations were almost universally lower through HEAT_FUT than with CTRL_FUT, by an average of 0.05ppb. This does suggest that the increased temperatures overall are increasing the destruction of PAN and thereby increasing NO_x availability, however surface temperatures were not universally higher in 2022 than 2014, suggesting that other influences from the meteorology may be affecting PAN concentrations. NO_2 concentrations showed some response to changes in meteorology (an average daily maximum increase of 6.41 ug/m^3 increase in 2022), particularly in August and following the same peaks observed in the isoprene concentrations that correspond to especially hot days. The combination of lower wind speeds and higher temperatures may result in the higher NO_2 concentrations in HEAT_FUT in most of August - heatwave conditions have been observed previously to cause overall increases in NO_x concentrations in the UK by a range of mechanisms, including reactions with BVOCs, and impacting on the partitioning of NO_x as NO and NO_2, with the ratio favouring NO_2 at warmer

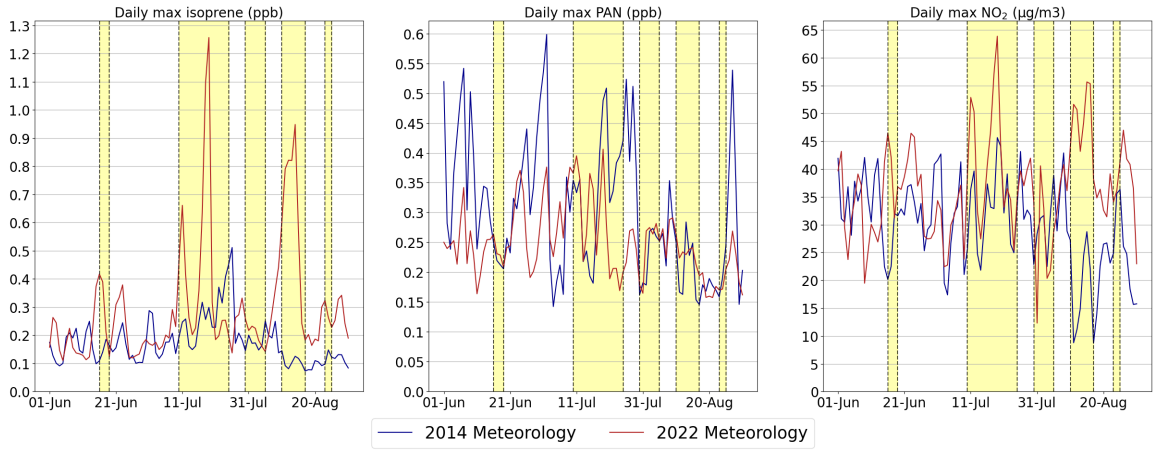


Figure 4.4: Average of UK overland daily maximum concentrations for key O_3 precursors when using 2014 meteorology compared to 2022 meteorology. Simulations both use 2050 emissions.

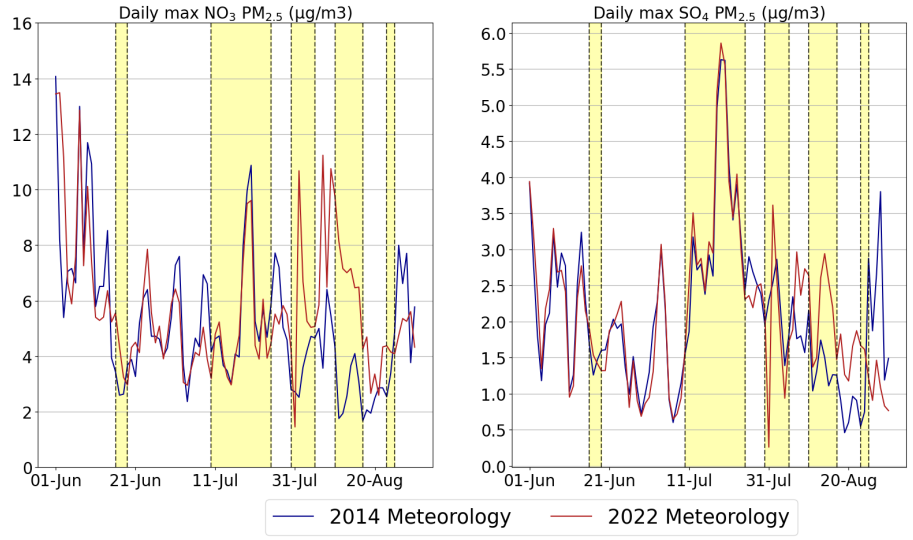


Figure 4.5: Average of UK overland daily maximum concentrations for key $PM_{2.5}$ components when using 2014 meteorology compared to 2022 meteorology. Simulations both use 2050 emissions.

temperatures although these are complicated by competing chemical mechanisms, such as NO_x depletion as excess O_3 is formed (Kalisa et al. 2018; Ryan et al. 2023).

The differences in isporene shown in Figure 4.4 could also contribute to the $PM_{2.5}$ penalty as increased isoprene emissions are associated with increased formation of secondary organic aerosol (Bartik et al. 2024). There may be some reductions in certain types of SOA however as some volatile aerosols may be partitioned more to the gas phase during high heat events (Doherty et al. 2017). Isoprene output is used as the indicator as opposed to SOA due to SOA $PM_{2.5}$ not being available in the model output used for analysis. This partitioning is also

expected to reduce NO_3^- concentrations with higher temperatures, and this could contribute to some of the trends shown in Figure 4.5. Daily maximum NO_3^- is marginally higher in the 2014 meteorology simulation than the 2022 simulation over most of the three month period, before being considerably lower in early-mid August, which results in an overall average increase in NO_3^- $PM_{2.5}$ in 2022 of 0.59 $\mu g/m^3$. This elevated period coincides with the period of stronger wind speeds in 2014 than in 2022 and higher temperatures in 2022. Based on the overall $PM_{2.5}$ trend showing decreased $PM_{2.5}$ in CTRL_FUT in this period, this is likely the result of greater dispersion from wind in 2014 compared to stagnant conditions in 2022.

There is little difference in SO_4^{2-} $PM_{2.5}$ concentrations between the simulations (higher daily maximum SO_4^{2-} $PM_{2.5}$ in 2022 of 0.05 $\mu g/m^3$), suggesting that while increased oxidation to SO_4^{2-} aerosol may be a factor in climate impacts on $PM_{2.5}$ aerosol (Doherty et al. 2017), this is not represented by the model used. Once again, SO_4^{2-} $PM_{2.5}$ is lower in early August following the 2014 simulation, suggesting a physical driver of concentrations, such as precipitation (which could be indicated by the higher relative humidity in 2014 shown in Figure 4.1) as opposed to a chemical driver.

The overall heatwave penalty as defined in the methodology to $PM_{2.5}$ and O_3 for each region of the UK is shown in Figure 4.6. It shows that the maximum penalty for $PM_{2.5}$ is 1.9 $\mu g/m^3$ in London. For regions in the North and East of the UK, the penalty does not exceed 1 $\mu g/m^3$, suggesting that a larger penalty is found in regions with higher base $PM_{2.5}$ concentrations. This indicates that for the UK warmer summers result in higher $PM_{2.5}$ concentrations but this impact is small. There is still an additional risk to health – $PM_{2.5}$ is a non-threshold pollutant and guideline values are low e.g the WHO guideline is 5 $\mu g/m^3$. As the heatwave conditions trigger little enhancement of $PM_{2.5}$ in the summer months this is unlikely to cause large changes in annual mean $PM_{2.5}$, the common metric used for health impact calculations such as eSCHIF-Fusion (Weichenthal et al. 2022) and the Global Exposure Management Model (Burnett et al. 2018). This suggests that the meteorological phenomena expected to become more frequent from climate change are unlikely to vastly change the health outcomes of $PM_{2.5}$ modelling scenarios in low-air pollution environments such as the UK. This supports the hypothesis that for studies where emissions scenarios are used to consider impacts of future air quality, it may be appropriate to ignore the impacts of meteorology where it allows for modelling strategies that improve resolution to capture peak $PM_{2.5}$ concentrations.

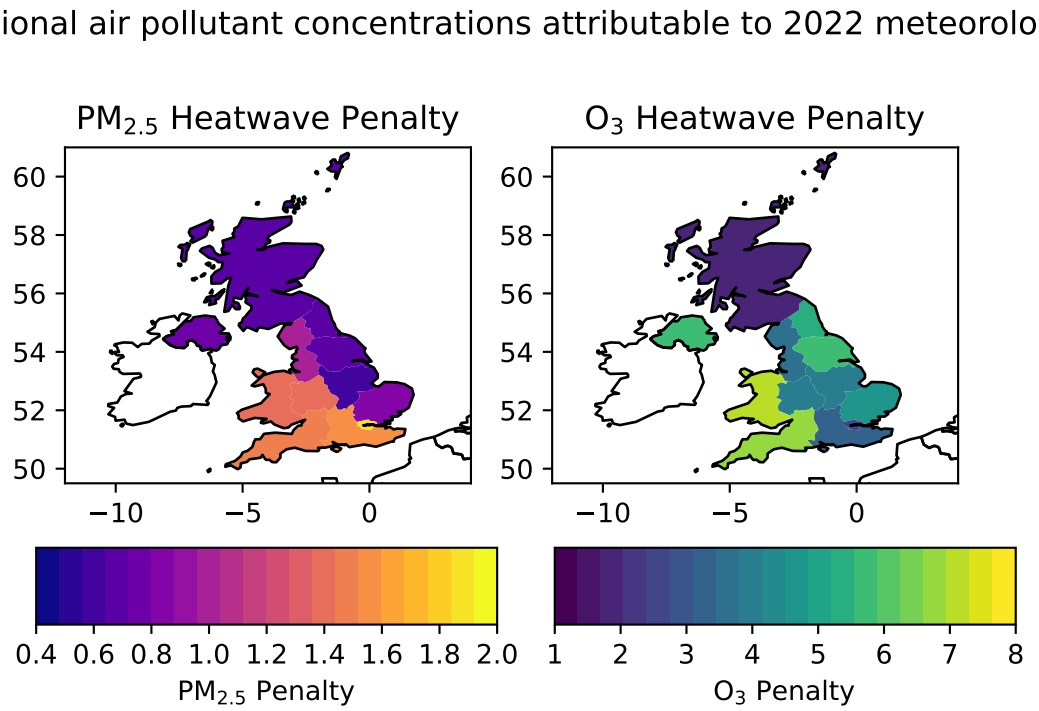


Figure 4.6: Additional pollutant concentrations (in $\mu g/m^3$) over the length of the simulations attributable to heatwave conditions by UK region. O_3 penalty is in terms of daily maximum and $PM_{2.5}$ in daily mean. Both simulations used to show this use 2050 emissions i.e this is the impact of temperature on top of the change already caused by emissions.

For O_3, the penalty is larger, up to 7 $\mu g/m^3$ in Wales and the South-East. O_3 notably also sees larger penalties in some predominantly rural areas (e.g North-East England and Northern Ireland) compared to $PM_{2.5}$. Unlike $PM_{2.5}$, the O_3 penalty indicated could have a impact on the outcome of health impacts functions; this is because common O_3-related mortality functions such as Turner et al. (2016) use a function that considers only O_3 in the 6 months of the year with the greatest concentration, so while this is still a long-term function, the short term elevation is less likely to "average out". More notable however is the clear difference in short-term O_3 events; Table 4.4 demonstrates that the O_3 penalty predicted when only the 5 time periods with heatwave conditions are considered, the predicted penalty can up to double.

The sensitivity of O_3 to meteorology in comparison to $PM_{2.5}$ is shown in table 4.4, which compares the heatwave penalties shown in Figure 4.6 with the same calculation when only the 5 "elevated periods" of heat described by the UKHSA (2022) are used. It demonstrates that when these periods are isolated, the penalty to $PM_{2.5}$ is actually lower in all regions of the UK (albeit by less than 1 $\mu g/m^3$ in each region), whereas for O_3 it can reach over 10 $\mu g/m^3$ higher. Heatwave conditions have a clear, short-term impact on O_3 concentrations and

	Heatwave Penalty ($\mu g/m^3$)					
	Whole Summer		Heatwaves Only		Change heatwave-summer	
Region	PM2.5	O3	PM2.5	O3	PM2.5	O3
North East England	0.68	5.45	-0.22	10.82	-0.9	5.37
North West England	1.01	3.79	0.63	10.7	-0.38	6.91
Yorkshire and the Humber	0.66	5.56	0.34	14.13	-0.32	8.57
East Midlands	0.58	4	0.31	14.15	-0.27	10.15
West Midlands	1.4	4.1	1.18	11.37	-0.22	7.27
East of England	0.85	4.54	0.77	12.92	-0.08	8.38
London	1.85	2.69	1.53	12.52	-0.32	9.83
South East England	1.55	3.1	1.27	10.15	-0.28	7.05
South West England	1.45	6.86	1.41	13.31	-0.04	6.45
Wales	1.41	7.22	1.07	13.9	-0.34	6.68
Scotland	0.7	1.71	0.08	3.8	-0.62	2.09
Northern Ireland	0.74	5.74	0.28	8.96	-0.46	3.22
Mean	1.07	4.56	0.72	11.39	-0.35	6.83

Table 4.4: Comparison of heatwave penalty over the whole summer and when focusing on 6 "elevated heat" periods in each UK region

modify the surface concentrations considerably. Conversely, the impacts on $PM_{2.5}$ are limited. The result of a lower penalty in the 5 "elevated periods" than over the whole summer was unexpected, suggesting that the hot, stagnant conditions in these periods were not the sole driver of the difference in $PM_{2.5}$ and there are likely other factors at play that drive the overall penalty. 2014 was notable for a comparatively rainy August, but was somewhat dry during July (Kendon et al. 2015). 2022 on the other hand, had little precipitation throughout the summer (Kendon et al. 2023). Thus, it is plausible that there is increased deposition of pollutants via precipitation in August 2014, which would explain the consistently higher $PM_{2.5}$ in most of August in HEAT_PD and HEAT_FUT shown in Figure 4.2. Conversely, as the long heatwave period in July has relatively similar $PM_{2.5}$ in the HEAT simulations to the CTRL simulations, the penalty to $PM_{2.5}$ concentrations could appear lower when just factoring in these periods as opposed to when the excess precipitation in the summer of 2014 is captured.

The overall penalty is compared to those identified in other literature in table 4.5. This demonstrates that there is still considerable uncertainty in both $PM_{2.5}$ and O_3 climate penalties, especially in the case of $PM_{2.5}$. Compared with other studies, we project an O_3 penalty higher than the majority of existing penalty estimates. This may be in part due to a slightly different metric, we use daily maximum O_3 as opposed to a daily mean 8hr maximum. Regardless, this result is not outside the range of estimates we see from existing literature. This suggests that focusing on extreme heat periods can produce a high approximate penalty in O_3 in comparatively

	PM2.5 penalty ($\mu g/m^3$)	O3 penalty ($\mu g/m^3$)	domain	year	Notes
This Study	1.07	4.56	United Kingdom	2022	Using heatwaves instead of climate change
Silva et al. (2017)	3.2	0.7	global	2100	Using RCP8.5 - a more pessimistic scenario, results are population-weighted and a multi-model mean Both metrics annual mean
Zanis et al. (2022)	N/A	-0.2	Europe	2050	SSP3-7.0 multi-model 10-year JJA mean.
Bhattarai et al (2024)	up to 5	N/A	global	2050	SSP3-7.0. Penalty far lower (<1) in Europe. Uses climate model (CESM2)
Im et al. (2022)	uncertain	up to 1.5	Europe	2050	Review paper summarising a range of previous research. O_3 in ppb mostly annual means
Nolte et al. (2018)	"-1 to 1"	up to approximately 4	USA	2030	Also using CESM2. O_3 in ppb. also annual means
Murray et al. (2024)	"-2 to 0"	<6	global	2090-2095	Specific numbers not available. O_3 in ppb and seasonal maximum 8-hour average, All averaged over decades uses a chemical transport model
Fann et al. (2021)	0.1	0.7	USA	2040	Using CESM2 output for RCP 8.5. summer season means of the maximum daily 8-hour mean O_3
Hong et al. (2019)	up to 9	"2-8"	China	2046-2050	Using RCP4.5 and a downscaling of CESM. Average PM2.5 penalty is considerably lower than 9, but unclear O_3 metric is Apr-Sep average of daily 1-hr maximum
Liu et al. (2021)	1.43	N/A	Eastern China	2050	Uses RCP8.5 and WRF-CMAQ with modified climate model output for meteorology

Table 4.5: Long-term climate penalties calculated in a range of studies. $PM_{2.5}$ penalties are all annual means, but the metric varies for O_3

low-pollution environments. The uncertainty in $PM_{2.5}$ penalty estimates provides a challenge in assessing how robust use of a heatwave penalty as an alternative to a climate penalty is due to the lack of clear consensus on the approximate climate penalty that is expected.

To diagnose the drivers of the overall penalty, the penalties were correlated with each of the potential meteorological drivers shown in Figure 4.1 and with each related "precursor" shown in figures 4.4 and 4.5. The resulting correlation matrix is shown in Figure 4.7. In this figure, the squares with bold labeled numbers have a statistically significant correlation (labels are excluded when a variable is correlated against itself). The number corresponds to the r-value of the correlation.

Figure 4.7 shows some unexpected outcomes; primarily that the only meteorological or chemical driver that has a statistically significant link with the $PM_{2.5}$ penalty is pressure at the surface. This relatively weak linkage suggests that as the difference in surface pressure between 2022 and 2014 increases, the $PM_{2.5}$ penalty decreases. This implies that higher surface pressure results in a lower $PM_{2.5}$ penalty, an unexpected result considering higher surface pressure would indicate meteorological stagnation. Similarly, the lack of linkage between $PM_{2.5}$ penalty and wind speed suggests that even though increased $PM_{2.5}$ concentrations are observable during a period of stagnation in HEAT_FUT, over the course of the summer this is not a strong predictor of the strength of the climate impact on $PM_{2.5}$. It is possible that the influence of transboundary $PM_{2.5}$ on overall concentrations is high enough that the reduced influx of $PM_{2.5}$ in stagnant conditions outweighs the increased trapping of pollutants near the surface. This counter-intuitive potential

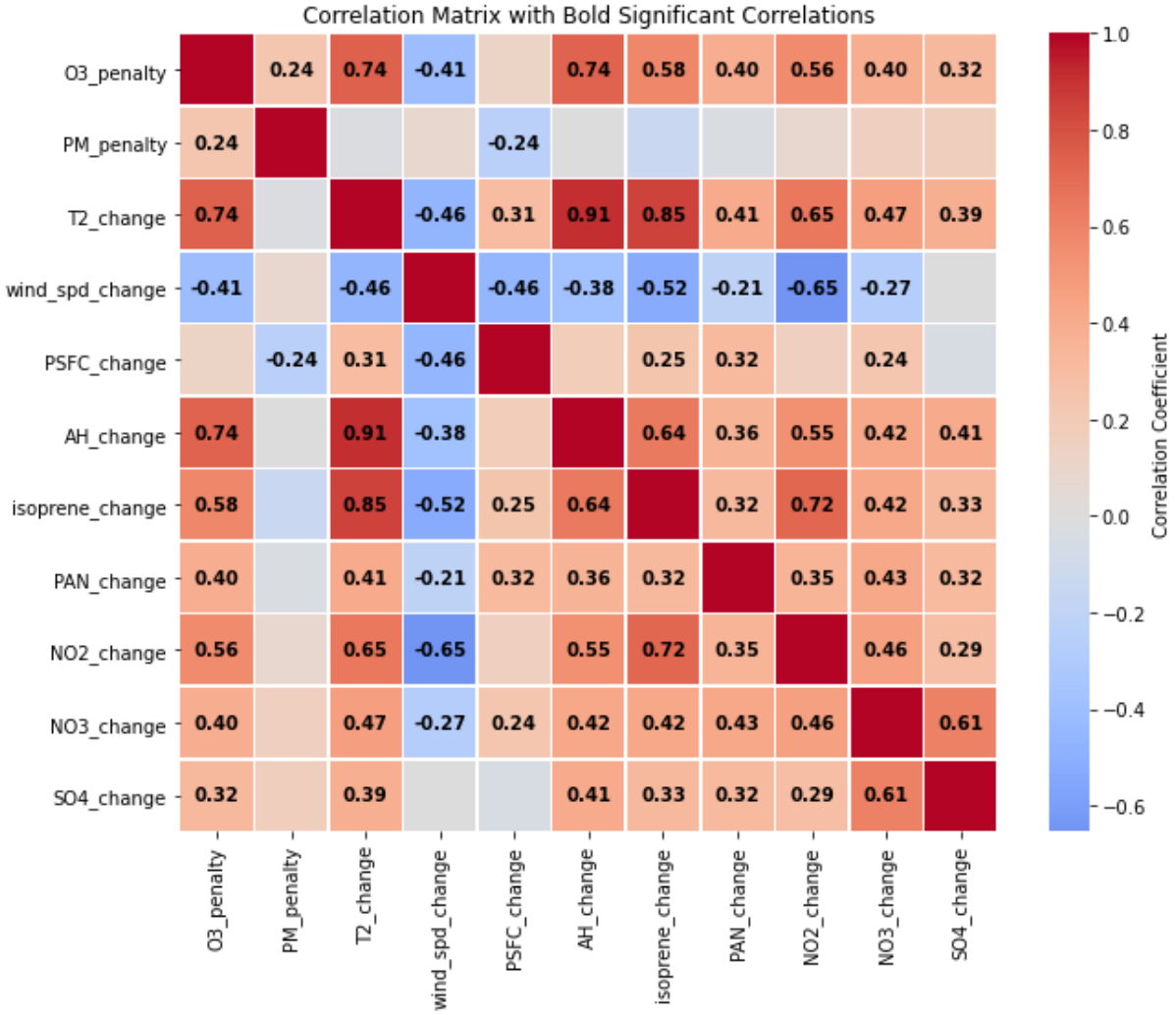


Figure 4.7: Correlation matrix between heatwave penalty to $PM_{2.5}$ and O_3 concentrations and different meteorological conditions and precursors.

mechanism is similar Graham et al.(2020)'s suggestion that higher wind speeds can increase $PM_{2.5}$ in the UK if the winds come from Continental Europe. Similarly, and perhaps more plausibly, there could be a missing driver of change, such as precipitation. Alternatively, it could be that the change in meteorology between 2014 and 2022 triggers several small and conflicting changes to $PM_{2.5}$ through physical and chemical mechanisms, meaning that an overall penalty can not be clearly linked to individual factors. This is supported by there being statistically significant linkages between temperature and the differences in NO_3^-/SO_4 concentrations when just meteorological change is considered but not in the $PM_{2.5}$ penalty where the influence of emissions change is also factored in.

There is a far clearer response to meteorology when considering the O_3 penalty. This penalty is correlated strongly with change in surface temperature and there are clear potential pathways to explain this, with strong correlations between change in isoprene concentrations and change in surface temperature (and between isoprene and the O_3 penalty) also found. We also see that increased availability of NO_2 is strongly associated with the O_3 penalty. We also see that lower wind speeds are significantly associated with the O_3 penalty, suggesting that stagnation also plays a strong role in determining the strength of the penalty. Humidity also correlates well - where humidity increases, O_3 penalty is larger. This is perhaps counterintuitive considering the potential destruction of O_3 in more humid conditions suggested by Doherty et al. (2017). In our simulations, the absolute humidity tracks temperature at 2m very well, i.e higher temperatures coincide with higher humidity, especially in late August, which drives much of the overall O_3 penalty. It is likely that the strong response of O_3 to temperature simply outweighs any additional destruction as a result of added absolute humidity or that the reasonably high NO_x concentrations in the UK stop this from taking place.

4.6 Conclusions

We find that extreme heat conditions which are likely to occur with much greater frequency as the climate changes could exacerbate the air quality impacts of failing to implement stringent emissions policies in the UK. The impacts of meteorological change on $PM_{2.5}$ is limited, however when a heatwave year is used, we demonstrate that there can be short-term daily maximum O_3 increases of over 10 $\mu g/m^3$ for most regions of the UK during extreme periods compared to a less extreme summer. The increases in temperature can explain this, with likely pathways such

as increasing the availability of isoprene and NO_x due to PAN destruction.

The implications of this are that elevated O_3 events should be expected to be much more common in climate futures where there is limited co-ordinated efforts to mitigate climate change. It is well established that climate change mitigation can improve long-term air quality exposure; this result demonstrates that stringent climate mitigation is needed to avoid considerably increasing the frequency of short-term air quality events.

We show that the "penalty" to $PM_{2.5}$ and O_3 air quality over the course of the summer when comparing 2022 and 2014 is within the ranges of climate penalties predicted by other research. This suggests that there is an argument for using an "extreme" year to represent pessimistic climate mitigation scenarios. The penalty to long-term air quality concentrations for both pollutants is small over the UK. This suggests that in studies considering long-term air quality impacts in environments similar to the UK, it is reasonable to only consider emissions change. If considering short-term air quality, especially O_3, and/or studying domains in which future meteorological changes are expected to be more extreme, it may be more prudent to use a model capable of representing these changes.

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Chapter 5

Discussion & Conclusions

5.1 Synthesis of Results

In this section, I explore some of the overarching themes and conclusions of the research presented in papers 1, 2 and 3. I also discuss the potential limitations of my research and suggest directions for future research.

The underlying aim of this thesis to understand to what degree air pollution in Europe could be mitigated alongside climate change, specifically representing different "futures" using the recently released SSPs and the WRF-Chem chemical transport model. This was a very exploratory project without a clearly defined method or set of desired outputs at project commencement. Primarily, this was intended as an "impact-focused" research project as opposed to a deep investigation of underlying chemical or climatic processes - this kind of work would likely benefit better from an established model setup; however, the research question was designed to have significant scope for developing my own aims through the project.

As the work developed, further project goals were identified including:

. Creating and validating a regional model capable of using CMIP6 emissions.

. Understand what mitigation strategies or sectors are the most impactful for improving European air quality.

. As more health co-benefits studies are published, what further air quality-related co-benefits of climate mitigation can be identified?

. Investigate the impact of considering only emissions change and whether or not the weakness of regional modelling in representing future climate change can be mitigated.

These aims informed the Chapters presented. Paper 1 (Chapter 2 in this thesis) presents and validates WRF-Chem simulations over Europe using CMIP6 emissions. To my knowledge, it was, and remains, the only published work to use this method. In this, I also take advantage of the increased representation of $PM_{2.5}$ components in WRF-Chem compared to GCMs and assess what the trends in these, and the trends in emissions suggest about key target sectors for achieving air quality co-benefits in the future.

Paper 2 leads on from this work, but focuses on policy-relevance and demonstrating the impacts. At the time of undertaking this work, the number of studies estimating health impacts of climate mitigation via air quality co-benefits was rapidly increasing, thus I felt it was important not to solely focus on this. I took inspiration from Reddington et al. (2023) in considering equity impacts, using the advantages of the improved model resolution and constrained domain to communicate these at more policy-relevant scales.

Like paper 1, paper 3 was also experimental. This was designed to investigate firstly whether it is possible to address the weakness of regional modelling in representing future meteorology. Secondly, what the implications of including future meteorology could be. I also investigate short-term air pollution events following SSPs, which, to my knowledge is not studied following SSPs in prior research.

5.2 Key Findings

5.2.1 Stringent mitigation is required for whole-continent co-benefits

The papers I present here clearly demonstrate that the benefits of stringent mitigation for air quality far outstrip the potential benefits of a medium mitigation scenario for most of Europe.

Paper 1, for example demonstrates that domain mean $PM_{2.5}$ reduces by 38% following SSP1-2.6, close to double the 21.6% improvement projected from following SSP2-4.5. Similarly, SSP2-4.5 sees a small domain average O_3 increase, whereas SSP1-2.6 shows a 15% domain average decrease. As demonstrated in paper 1, the lack of progress in mitigating O_3 precursors aside from NO_x likely drives increasing O_3 concentrations for many locations in the domain. In terms of impact, this means that when combined with the impact of population and baseline mortality change, only a stringent mitigation scenario is expected to reduce the burden of either $PM_{2.5}$ or O_3-related mortality across the whole domain. This is not a simple trend - notably, following SSP2-4.5, $PM_{2.5}$ mortality decreases in much of the domain, but marginally increases in much of Western Europe, notably regions which had relatively low pollution to start with e.g Spain, France and Ireland. This is driven by a couple of things: the much readier response to emissions changes in Central and Eastern Europe than in Western Europe means the air quality there improves. In the West, following this scenario, air quality remains somewhat stagnant and the increases in population likely drive the $PM_{2.5}$-attributable mortality increases.

Interestingly, this has a slightly different pattern from other global regions. Figure 5.1 from Turnock et al. (2020) demonstrates how for some regions of the world, following SSP2-4.5 does result in significant reductions in $PM_{2.5}$ concentrations by midcentury, particularly in Asia. This demonstrates a similar trend that I discuss when considering the equity implications in paper 2; in less developed economies, where solid fuel burning, especially for heating and fuel constitute a greater proportion of $PM_{2.5}$ emissions, even moderate mitigation improves particulate air quality. In regions that have already seen historic reductions in air pollutant emissions, different strategies are needed to improve air quality, strategies not assumed in SSP2-4.5.

There are implications of this for the climate leadership & polluter pays or historic polluter pays debates. The "historical polluters" in Europe expected to show climate leadership appear to only get air quality co-benefits when following a stringent mitigation scenario. This could be interpreted optimistically or negatively; on the one hand, this provides a clear incentive for richer countries to aim for stringent mitigation by demonstrating that non-ambitious methods will not provide many local or immediate benefits. Conversely, it could discourage any mitigation if stringent mitigation measures are not considered achievable by policymakers.

Encouragingly, work by Pisoni et al. (2023) modelling the potential air quality benefits of the EU-55 policy package by 2030 shows similar relative changes - suggesting that $PM_{2.5}$ air

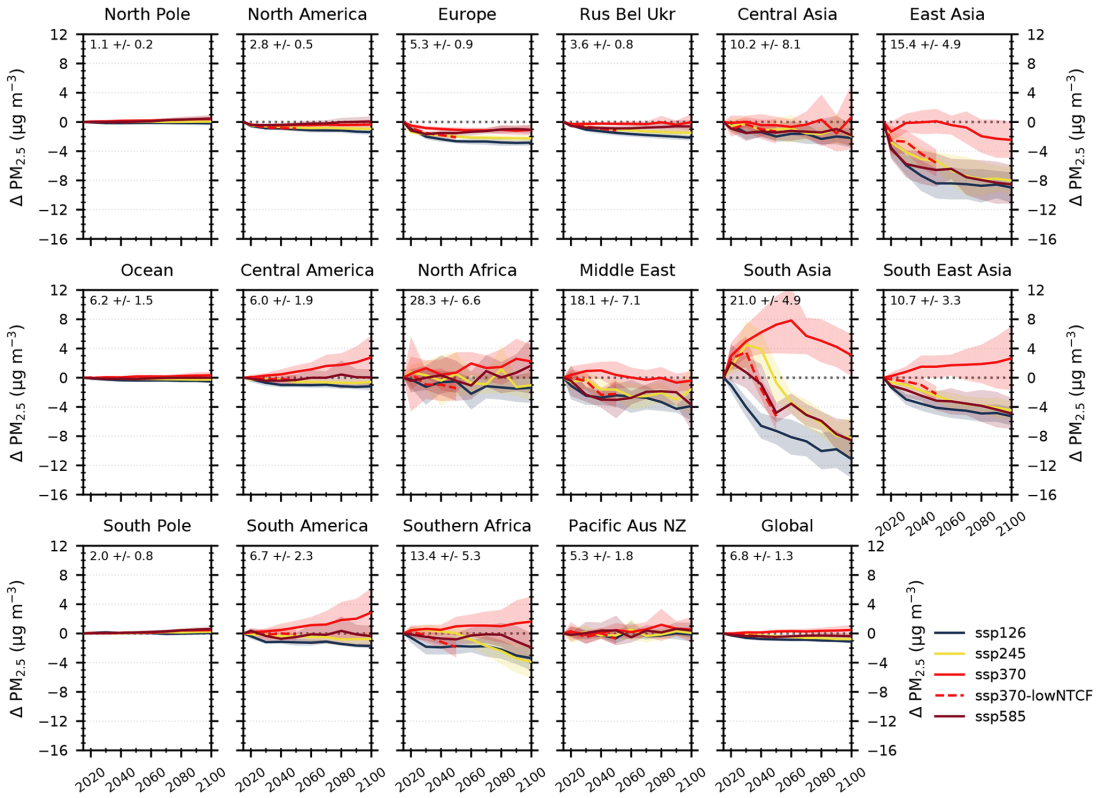


Figure 5.1: Projected changes in surface $PM_{2.5}$ around the globe by Turnock et al. (2020) following the same scenarios as this thesis with the additions of a low-NTCF version of SSP3-7.0 and SSP5-8.5

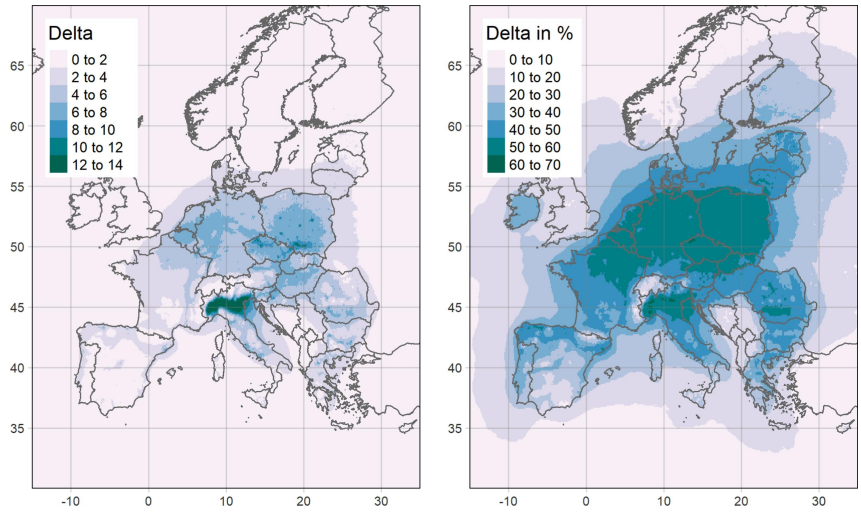


Figure 5.2: Projected changes in surface $PM_{2.5}$ in 2030 relative to 2015 as a result of the EU-55 mitigation package from Pisoni et al. (2023)

quality could drop by 60/70% over much of Central Europe (albeit using an offline model using less detailed chemistry) - this is shown in figure 5.2. This implies that current climate change mitigation policy could be sufficient to achieve air quality co-benefits. In some ways, the work by Pisoni et al. (2023) is more optimistic than the results of this thesis; the EU-55 set of policies has little in the way of mitigation of ammonia emissions, which my results suggest are vital to improving air quality in the future.

While paper 3 does not directly demonstrate the benefits of stringent mitigation, it supports the argument by demonstrating that failing to mitigate climate change could cause an increase in the frequency of short-term elevated air pollution events, particularly for O_3. Following SSP3-7.0 which assumes some, but limited mitigation of $PM_{2.5}$, changes in the climate itself may exacerbate $PM_{2.5}$ exposure enough to undo any gains made by the limited mitigation (see paper 3, table 4.2).

5.2.2 Agriculture as a key sector

Following on from the need for stringent mitigation to mitigate air quality across Europe, my research demonstrates that the difference in emissions associated with agriculture are likely the driver of the difference between SSP1-2.6 and SSP2-4.5. This being because they a larger driver of air quality in the West than East and are the key source of ammonia emissions, which drives the additional reduction in NO_3^- aerosol seen comparing SSP1-2.6 and SSP2-4.5.

Agriculture being important for European air quality is well known; As mentioned previously,

Lelieveld et al. (2015) estimate it to be the largest source of $PM_{2.5}$ mortality across the continent, and analysis of $PM_{2.5}$ sources finds that even in major UK cities such as London and Birmingham, the contribution of NH_3 to $PM_{2.5}$ exceeds that of local city sources (Kelly et al. 2023). Studies that estimate the impacts of NH_3 reductions consistently demonstrate that they could reduce $PM_{2.5}$ mortality in Europe by 50%+ in places (Giannakis et al.2019 Giannadaki et al.2018)

In terms of the policy implications of this, I reinforce the common calls for greater consideration of agriculture to improve European air quality. There has been a considerable challenge in engaging policymakers with agricultural emissions reductions, particularly in the case of NH_3 (Brunekreef et al. 2015). There are still policies that cover NH_3, e.g signatories to the National Emissions Ceilings Directive are expected to reduce agricultural emissions by 19% relative to 2005 levels by 2030 and by 6% of this by 2020 (EEA, 2016), however historically, legislative tools designed for NH_3 emissions reductions have considerably lagged behind those for NO_x and SO_2 in ambition (Brunekreef et al. 2015). Even with this in mind, nine EU countries failed to meet the 6% target and two thirds are not meeting the 2030 target as of 2024 (European Environment Agency, 2024). Agricultural emissions mitigation is not always enshrined into policy, for example in the UK, information given to farmers about NH_3 emissions appears to be through non-legislative guidance (the Code of Good Agricultural Practice - DEFRA, 2024) as opposed to specific legislation. There are many factors as to why agricultural emissions of both NH_3 and CH_4 may be challenging to mitigate; concerns about food security, economic viability for farms, competitiveness of trade and ability to ensure compliance can hamper how palatable implementing more stringent controls on emissions for this sector can be for policymakers (Guthrie et al. 2018; Leahy et al. 2020). Agriculture is also of course, a sector for which emissions cannot be eliminated. This is especially true of scenarios such as SSP2-4.5 which assume that agricultural production will increase considerably to meet the demands of a quickly growing population (Fricko et al. 2017). This explains the emissions changes shown in Figure 2.1 (paper 1) in which NH_3 emissions in Europe increase by nearly 20% across Europe, despite legislative requirements for emissions reductions. I note that the importance of agricultural emissions to future air quality is meaningful for the strength of the "co-benefits" argument. Reducing NH_3 emissions is a major driver for reducing $PM_{2.5}$, but NH_3 does not have as direct a role in climate change. Agricultural emissions from fertilisers (usually associated with NH_3) have a complex relationship with the climate, as emissions from agriculture

often occur alongside emissions of N_2O, which is a powerful greenhouse gas. Conversely, the $PM_{2.5}$ associated with NH_3 emissions contributes to the aerosol cooling effect and increasing cloud lifetimes (Beaudor et al. 2025). Reducing agricultural production could reduce bulk NH_3 emissions and a switch to more vegetable-based diets could also reduce emissions as livestock are a larger source of ammonia emissions than crops (Wyer et al. 2022). This uncertainty in the impact of NH_3 emissions on climate means that it is arguable that a large proportion of the additional $PM_{2.5}$ reductions driven by this following SSP1-2.6 are not a co-benefit of climate mitigation as the underlying assumptions that cause the projected NH_3 emissions reductions are pollution control rather than climate mitigation.

There is a stronger argument for mitigation of agricultural emissions to reduce emissions of CH_4. CH_4 is a far more powerful greenhouse gas than CO_2 (Badr et al. 1991) and its global warming potential as an NTCF have been well studied (Turnock et al. 2023). Similarly, research clearly demonstrates that mitigation of CH_4 is also strongly beneficial in reducing O_3 pollution - especially notable here is the result of Staniaszek et al. (2022) that suggests that O_3 would be lower following SSP3-7.0 with CH_4 emissions eliminated than SSP1-2.6. The failure to mitigate CH_4 as effectively in SSP2-4.5 and its active worsening SSP3-7.0 are likely drivers of the worsening O_3 concentrations in these scenarios. The dominance of CH_4 in determining O_3 concentrations in Europe demonstrates just how important mitigation of it should be considered to effectively achieve air quality co-benefits of climate mitigation policy.

A switch in agricultural systems reducing the proportion of livestock farming is likely the most meaningful shift for achieving air pollution co-benefits of mitigation, due to livestock slurry being a large source of both NH_3 and CH_4 (Wyer et al. 2022). This means that improving agriculture-sourced particulate air quality could still be a co-benefit of climate change mitigation, but it depends on specific policies. SSP1-2.6 does represent changes in agricultural patterns; back in Chapter 1, I present figure 1.6, which demonstrates that in the OECD, livestock production falls by approximately 10% between 2020 and 2050 in the OECD, despite an increase in population. Ultimately, for countries which in the present day have better air quality and have already significantly mitigated sources such as fossil fuel production and transport, it is successfully mitigating emissions in the "uncomfortable" sectors, for both pollution and climate that make the difference. Without agriculture emissions mitigation, only the current and not the historic polluters in Europe achieve significant co-mitigation. Thus, it is important to demonstrate to

the historic polluters that local co-benefits can ease the costs of climate mitigation and it is worthwhile targeting more difficult sectors.

5.2.3 Importance of O_3 mitigation

Strongly linked with the demonstrated importance of agriculture, this work also supports the suggestion that O_3 mitigation needs to be factored more into air pollution and climate mitigation policy. We see that following SSP2-4.5, which assumes no faster trajectory in emissions mitigation than historic trajectories and a lack of innovation in targeting CH_4 and NH_3 emissions, that much of Europe sees worsening O_3 concentrations, and when combined with population increases, all of it sees worsening O_3 mortality. O_3 also doubles its contribution to overall air quality-related mortality in all future scenarios from approximately 5% to approximately 10%. Also of note is the wider impacts of O_3; it is also associated with ancillary impacts of air quality such as ecosystem and vegetation impacts (Tai et al. 2014), which implies that if not adequately controlled, O_3 could also impact on food security (Ramya et al. 2023) and the wellbeing benefits of ecosystem services (Mills et al. 2013).

Current air pollutant mitigation strategies in Europe do not tend to consider O_3 mitigation as the primary target, however several do target precursors. Vieno et al. (2020) assess the nature of mitigation policies across Europe, find that these primarily consist of road traffic controls, aimed at reducing NO_x emissions. NO_x is of course, an O_3 precursor, however it is well documented that NO_x reductions can be counter-productive in controlling O_3 in urban areas without also mitigating VOCs (Real et al. 2024). Viana et al. (2020) note that emerging policies include targeting woodburning stoves, construction/demolition and shipping, notably all of which would primarily reduce NO_x or particulate emissions. The risk to health from O_3 is recognised by the European Commission (2008) who have an O_3 daily maximum limit values of 120 $\mu g/m^3$ 8-hour mean. These are notably higher than the daily maximum guideline values recommended by the WHO of 100 $\mu g/m^3$ and thus questions should be asked of whether the level of ambition is suitable to adequately protect public health from this growing issue (although the EU has since designated 100 $\mu g/m^3$ as a "target value" in the revised Ambient Air Quality Directive of 2024). Perhaps alarmingly, I do however show in Paper 2, figure 3.3 that meeting WHO guideline values (albeit, in this case I use the 60 $\mu g/m^3$ 6-month average 8-hour maximum guideline) may not be achievable in Europe, even following SSP1-2.6.

This thesis, particularly when examining the SSP2-4.5 results, also demonstrates how certain "easier" or "common" policies can exacerbate O_3 due to the response of O_3 to NO_x reductions in VOC-limited regimes, which cover much of Europe, particularly urban areas (Real et al. 2024). This is likely a driver of the increase in O_3 concentrations shown in paper 1, particularly in dense areas of Northern Europe. Paper 2 reinforces this, demonstrating that O_3 mortality would worsen following SSP2-4.5 and SSP3-7.0, even when population and baseline mortality are kept constant. Paper 3 also emphasises why O_3 needs to be factored in to mitigation policy more than it is currently. Heatwave conditions, like in 2022 will become more common, no matter which scenario real-world mitigation and societal development follows most closely, but this increase can be lessened with stringent, immediate climate change mitigation. This thesis shows that these conditions result in a notable increase in O_3 concentrations, resulting in increases of up to 20 days with elevated concentrations even in a relatively mild climate such as the UK. Ultimately, while it may pose a policy challenge, a whole-system approach to air quality and climate change mitigation may be needed, with increased cooperation between policymakers and organisations with specific remits to avoid focusing too much on certain sectors when mitigation efforts would be better served elsewhere.

Interestingly, the increasing O_3 concentrations I simulate following SSP2-4.5 diverge from the trends found in CMIP6 output by Turnock et al. (2020), see figure 5.3. They find that SSP2-4.5 sees decreasing O_3 in Europe by 2050, rather than the mixed picture I simulate which leads to a small overall increase in concentrations. There could be a number of drivers of this. For example, the large increases in O_3 my simulations show tend to be in heavily urban areas, perhaps driven by NO_x reductions, for example the Rhine-Ruhr, Naples and Paris. The urban concentration gradients leading to these highly elevated areas may not be represented as well by the GCMs. Conversely, the better representation of the climate system in the GCMs than in WRF-Chem may allow for some long-term processes that my simulations will not capture e.g Zanis et al. (2022) find that in less-polluted environments, increased water vapour can cause increased O_3 destruction, potentially resulting in an overall small benefit to O_3 concentrations. Following SSP2-4.5 where most pollutant concentrations will be marginally lower than the present day, GCMs could potentially also be showing an O_3 benefit as opposed to a penalty. Figure 5.3 also demonstrates that in different regions, the response to the scenarios is different; for example SSP2-4.5 suggests O_3 will increase by midcentury in South Asia. This raises the question of whether the large concentration increases I see in urban O_3 would be even more stark had I

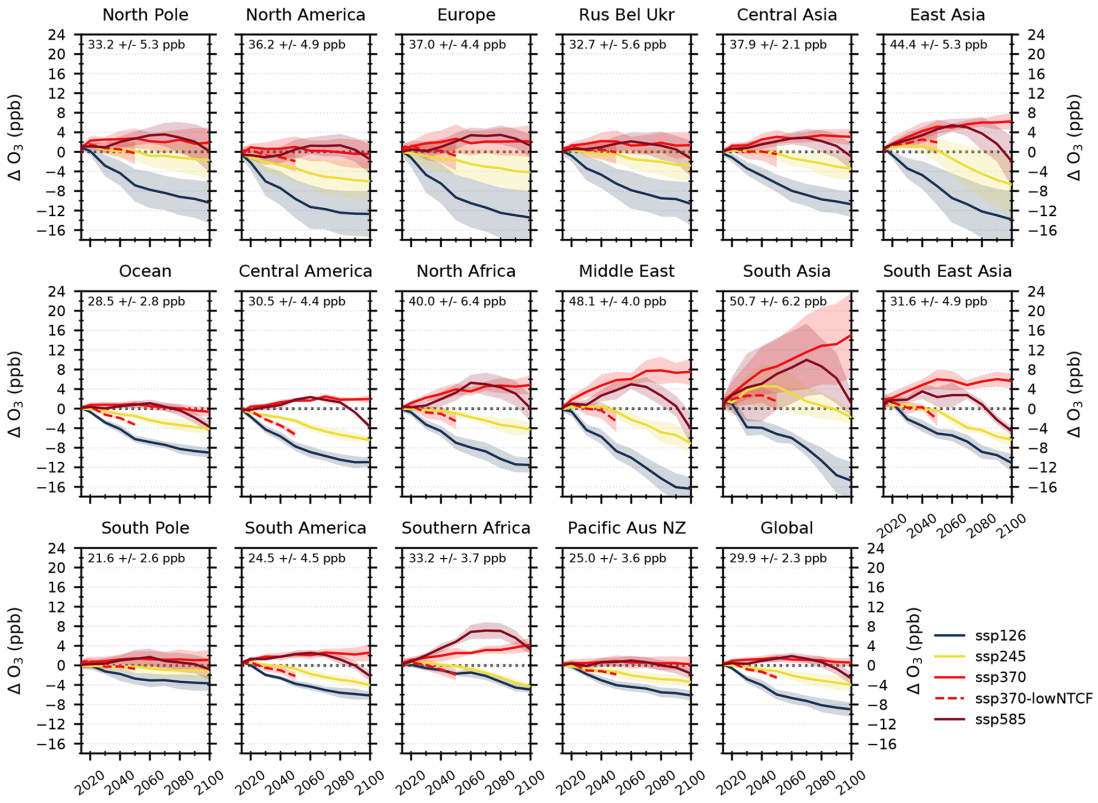


Figure 5.3: Projected changes in surface O_3 around the globe by Turnock et al. (2020) following the same scenarios as this thesis with the additions of a low-NTCF version of SSP3-7.0 and SSP5-8.5

used South Asia as a domain. Similarly, the result I showed in paper 3 that future extreme heat events could outweigh small reductions in emissions in the UK could be stronger in areas in which heatwaves will be more common and intense.

5.2.4 Air quality changes most in polluted regions

While arguably an obvious conclusion, this work clearly demonstrates that it is the regions of Europe which, in the present day, suffer the worst from poor air quality that see the greatest co-benefits of climate mitigation. This also ties in with the discourse surrounding current and historical polluters. Figure 2.5 in paper 1, for example, shows that the countries that see the greatest overall $PM_{2.5}$ reductions include Slovakia, Slovenia and Hungary. Subregions of these countries also tend to have a higher mortality rate from $PM_{2.5}$ exposure in the present day. In these higher polluting, lower HDI countries there is less of a need for extremely stringent mitigation; Poland, for example sees annual population-weighted $PM_{2.5}$ reduce by nearly half following SSP2-4.5. population-weighted $PM_{2.5}$ in Slovenia reduces by approximately 5 $\mu g/m^3$ even following SSP3-7.0. Germany is somewhat of an outlier here, achieving large air quality

improvements even with lesser mitigation scenarios despite having a high HDI.

As discussed, this is likely due to the higher prevalence of fossil fuel burning for energy and residential heating in central Europe. The implications of this are that, while agriculture is clearly an important sector for air quality improvements as a whole, there is still considerable improvement to be made in air quality from more "traditional" mitigation policies that target NO_x and BC/OC provided these are implemented in the right places. As found by Buzogány & Ćetković (2021) policymakers in Central/Eastern Europe are generally more resistant to stringent mitigation efforts. This finding shows that the economic concerns in these countries may be assuaged by the clear air quality improvements that could be achieved locally in these countries. Similarly, unlike countries such as the UK, Central/Eastern European countries can improve air quality through more "traditional" policies targeting fossil fuels and road transport, or by taking inspiration from wood-burning interventions such as that of DEFRA (2025). This reduces the political risk of implementing potentially more contentious and harder to achieve emissions reductions in the agricultural sector. The most polluted countries do not have the same "all-or-nothing" response to emissions change to countries such as the UK and benefit even if mitigation falls short of the levels that provide continent-wide improvements. While there is a risk that this could hamper ambition despite stringent mitigation clearly being superior, this demonstrates that there is little risk of "wasted cost" health wise in the most polluted regions.

Similarly, as shown in figure 2.4 and figure 2.8, it is urban regions that have the most drastic changes in air quality following the different scenarios. This is true of both improvements in air quality and deterioration in air quality. The strongest reductions in $PM_{2.5}$ in all scenarios are in regions such as Paris, Madrid and Northern Italy. Even following SSP3-7.0, where countries like Spain and the UK see marginally increased $PM_{2.5}$ across much of the countries, there are still reductions near Madrid, Barcelona and London. Conversely, these same regions benefit the least in terms of surface O_3 changes following SSP1-2.6 and have more drastic increases in O_3 concentrations in the more pessimistic scenarios. What this could show is that the additional gains from SSP1-2.6 that drive the drastic domain-wide reductions in mortality are due to reduced "baseline" levels of $PM_{2.5}$ and O_3 driven by emissions of NH_3 (which comes from rural sources) and CH_4 (which has a long enough atmospheric lifetime that it affects air quality beyond just around the emissions source). This suggests that there is still a place for urban-focused emissions control policies like low emissions zones; they can still be very impactful in improving

local health. These should just not be relied on alone as background concentrations must also be considered, especially for O_3 for which failing to mitigate the "background" precursor results in counterproductive responses to NO_x emissions controls that are particularly strong in urban areas. Similarly, paper 3 demonstrates that the penalty to $PM_{2.5}$ from elevated heat in the UK is largest in London, further demonstrating that limiting climate change could be of particular importance to urban areas.

5.2.5 Impact of short-term air quality and extreme events

To my knowledge, the future air quality during extreme weather conditions have very little consideration in the existing literature base. Largely, where the impacts of climate change itself on air quality are considered, the results are often expressed as a long-term climate penalty over a year or the summer season (e.g Bhattarai et al. 2024; Im et al. 2022; Silva et al. 2017). In paper 3, I demonstrate how these conditions can considerably modify exposure to elevated air pollutant conditions in the short despite the overall long-term "climate signal" being small. While the health impact functions I used do not represent this, it is well known that short-term elevated $PM_{2.5}$ and O_3 during air pollution events can cause impacts to health (Katsouyanni et al. 1996; Brunekreef & Holgate, 2002). This has been shown in various studies around the globe to increase hospital admissions (Requia et al. 2023; Singh et al. 2024). This can have its own issues, such as increased short-term pressure on local health services. In paper 3, I show how weather conditions that will be more common with climate change cause elevated air pollution more frequently and for O_3, this can be compounded if emissions mitigation efforts are poor. It is also well known that short-term air quality events and the health impacts of elevated heat can impact eachother, e.g O_3 exposure may be more likely to impact health in individuals already under the impacts of heat stress (Kalisa et al. 2018; Gao et al. 2025). Extreme events is a topic that existing research using future scenarios do not frequently cover and warrants further investigation. This is especially true in regions which have worse air quality and/or experience more extreme weather events.

5.2.6 Advantages of regional modelling

My research shows that while some effort is required to use regional chemical transport models for future climate scenarios, this technique can allow for insights that may not be as accessible using global climate models. Being able to examine $PM_{2.5}$ components, e.g as in figure 2.6.

Many GCMs, including those used as inputs for CMIP6 lack nitrate chemistry (Turnock et al. 2020) - considering that NO_3^- $PM_{2.5}$ is such an important driver of the efficacy of pollution control in Europe, models better able to capture this may be more appropriate in certain regions. Notably, as I demonstrated in figure 2.7 from paper 1, urban concentration gradients are more stark when using the regional model than aggregated CMIP6 output. I have also captured that the co-benefits will be most keenly observed in urban areas.

Equity research also benefits greatly from a regional focus. To consider equity of the changes on a global level would require a very different approach and come with a lot of caveats and assumptions. This is not to say that such work is impossible or not useful. Reddington et al. (2023) is a great example of how global equity can be considered; they split each grid cell into one of four GDP quartiles and compare how air quality changes differ for each quartile. This method gives a good overview of how improved equity of air pollutant exposure could be a global co-benefit of climate mitigation, but with limited refinement. Firstly, as my study was regional, I could choose the data source to represent equity that most effectively represented Europe and considered more than just the economic dimension. Deprivation also changes on very small spatial levels, even the level I consider deprivation is aggregated at a much coarser level than would normally be used if working at a country level (e.g Gray et al. 2023).

In my literature review, I asserted that regional modelling studies could be of greater interest to local up to country level policymakers that global studies. I believe that I have successfully demonstrated that this methodology allows me to represent how countries and smaller regions can expect different outcomes from mitigation. For example, in figure 3.5 from paper 1 I show that in the UK and Ireland following SSP3-7.0 actually worsens population-weighted $PM_{2.5}$ concentrations, yet in countries such as Slovakia, Slovenia, Hungary and Germany, even this pessimistic scenario could improve population-weighted exposure by up to 5 $\mu g/m^3$. In papers 2 and 3, I present a lot of the data at subnational level, allowing me to be able to separate the mortality rate changes between urban and rural subregions of specific countries - which allowed me to demonstrate the importance of mitigating rural emissions to achieve health improvements for all. In paper 3, I am able to separate out where in the UK faces the greatest compounding impacts of emissions and climate change e.g demonstrating that London could see a greater $PM_{2.5}$ penalty than the rest of the country, which could be very meaningful for public health. This could support existing research demonstrating the increasing importance of the urban heat

island effect to future public health as the climate changes by Heaviside et al. (2017). While regional modelling in this way comes with many limitations, that are addressed in the next section, the potential benefits of this method are clear.

5.3 Limitations

While using WRF-Chem is one of the key differentiators between my work and the existing research base, and this brings a lot of strengths in capturing urban pollution and simulating chemistry, it also brings weaknesses. Put simply, much of this thesis uses WRF-Chem with inputs not designed for it, to answer questions that are very challenging to address with a chemical transport model. To ensure compatibility with WRF-Chem, only future emissions and chemical initial/boundary conditions were used for the model simulations. Biomass burning, land use and meteorology were all kept at present-day levels. This means that none of my simulations are "true" representations of the full sets of conditions projected in the SSPs, adding uncertainty.

Lack of future meteorology is likely the key limitation here. Although in paper 3 I go some way to demonstrating that the impact to long-term air quality from meteorological conditions expected to be more common as climate change progresses is limited, it is not negligible either, especially in the case of O_3, where I demonstrate that over a warm summer, UK concentrations could increase by 4.56 $\mu g/m^3$ on average. This could be amplified in other parts of Europe with higher emissions of O_3 precursors or more extreme summer temperatures. As discussed below, the methodology I used to investigate (using a heatwave season as a climate change analogue) was unorthodox and chosen out of necessity. Using single years means I cannot account for meteorological variability, but it does mean I can discuss what implications the meteorological years I chose have for air quality.

Another limitation of WRF-Chem as a basis is that the extreme computational expense, vast quantities of data produced and time required to use it results in a need to be very selective in scenario choice. Ensemble modelling (a generally recommended technique for future modelling as a way of mitigating uncertainty - see Sokhi et al. 2022) is not feasible without considerable computing resources. Similarly, there is limited ability to run sensitivity simulations. In terms of how this affected this thesis, is that for papers 1 & 2, I ran only four scenarios and was unable to test the impacts of using different meteorology years or eliminating emissions from

specific sectors. Much of the analysis is through examining output of specific parameters and extrapolating how the emissions changes may have affected them, but I had limited opportunity to run specific, targeted tests to examine how certain air pollutants respond. Paper 3 was in some ways similarly affected; this work would benefit from testing how the meteorology changes would affect scenarios with stronger mitigation too. Similarly, at the time of performing the simulations for paper 3, the ARC4 high-performance computing system was being decommissioned. This meant that its computing power was reduced and I had a very limited time frame to perform simulations. The smaller domain and constrained simulation lengths of paper 3 were out of necessity and the method for this paper could be improved with a greater number of scenarios (e.g examining the heatwave impacts on SSP1-2.6) and also considering the air quality implications of a mild winter.

WRF-chem is a complex model and considerable trial and error was required to develop a model setup that functioned using CMIP6 emissions and chemical boundary conditions. While it is almost certainly possible to develop versions of the model that can use CESM2-WACCM for meteorological boundary conditions and include CMIP6-consistent biomass burning emissions, this would require more time or technical expertise than I had access to, or a research group, rather than sole researcher focus. An example of how this meant that the methodology needed to be adapted was in choosing how to represent future meteorology for paper 3. My original plan had been to calculate 10-year averages of key meteorological parameters for 2045-2055 (so as to capture meteorological variability), and edit the present-day meteorological boundary conditions to match these averages. This did not work and due to the time taken in testing this and the need to consider long simulation times, I had to choose an alternative method, choosing to nudge to present-day meteorology. Similarly, there was limited time or opportunity to run sensitivity tests establishing the best method for producing anthropogenic $PM_{2.5}$ and PM_{10} emissions. Had I had more time, I may have not proceeded with the simulations giving me overestimated $PM_{2.5}$ for paper 1 and may have been able to find an alternative.

The bias correction method itself may be a limitation; while it is clearly preferable to considerably overstating $PM_{2.5}$-attributable mortality, it does have implications. For example, I used summed percentage change in NO_3^-, NH_4^+, SO_4^{2-}, OC and BC to avoid including the generated $PM_{2.5}$ component, but this also means I am not factoring any changes in SOA in the mortality estimations. Also, in some regions (parts of France than Spain) the modelled results are lower

than the VD reanalysis, meaning the scaling factor will actually increase $PM_{2.5}$. The spatial distribution of $PM_{2.5}$ not being the same as the modelled present-day $PM_{2.5}$ means the paper 2 results are not a 1-1 representation of the health implications of paper 1.

The CMIP6 inputs also come with their own sets of limitations. A key one here is the 50km resolution of the emissions files. My work aims to provide a good representation of the pollutant concentration gradient around urban regions. The resolutions I use (30km and 15km) are better for this than work using GCMs, but at the very least the 30km resolution is still relatively coarse for representing these gradients. I maintain that the regional modelling method I use has advantages for representing this over work with GCMs (and comparative disadvantages regarding meteorology and SSP inputs as described above). The ability to show urban gradients better is demonstrated in Figure 3.7 in paper 1, however, there is a limit to how well the concentration gradient can be represented when the emissions themselves are at a coarse resolution. This means that there is a limitation to how well the elevated air quality mortality in urban regions is represented.

5.4 Future Research

Paper 3 demonstrates some potential opportunity for future research; I demonstrate here that long-term impacts of climate change on air quality are not the whole story. The changing in climate extremes are also likely to impact on air quality extremes. Studies usually frame air quality using annual or seasonal means. There is value in demonstrating how different climate scenarios could affect short-term exposure to elevated air quality around the world, especially if this can factor in future meteorological conditions.

The different results I report for Europe compared to more polluted regions (i.e that only stringent mitigation achieves meaningful benefits for most of the continent due to reducing agricultural emissions) demonstrates how different regions of the world can respond to the assumptions in the scenarios. Notably, some regions are considerably understudied e.g Shindell et al. (2022) is the only study I know of using the SSPs or RCPs for estimating future air quality in Africa with a health focus (as opposed to the biogenics focus of Brown et al. 2022). Similarly, studies considering Asia tend to focus on India and Eastern China. The unique situations of different regions around the world could have different implications for how they respond to mitigation scenarios. For example, how would the very different trajectories in oil

production in the scenarios affect regions such as the Niger Delta where this forms a large basis of the economy? How would the scenarios affect areas such as the Middle East, which may have greater natural dust emissions?. Could research such as that by Brown et al. (2022) modelling O_3 responses to climate scenarios in the tropics to investigate impact on forests also shed light on the public health impacts of air quality in tropical cities? Bearing in mind for example, that the less optimistic scenarios assume continuing deforestation (Popp et al. 2017), and forest loss reduces precipitation in the tropics (Smith et al. 2023), could this change air pollutant exposure? Or in the Arabian Peninsula, where climate change is expected to increase precipitation (Rao et al. 2024). Going beyond the changes in pollutant concentrations alone, work such as the equity assessment I conducted for paper 2 could also vary by region. For example, the differing pattern in urban deprivation in Europe compared to much of the rest of the world necessitated careful selection of tools. The equity implications may differ in regions where cities are generally less deprived. Some of these examples would require different techniques to the method I used; the expected meteorological changes would not show when using present-day meteorology.

While I have emphasised the challenges of regional modelling of future air quality, I agree with the assessment of Sokhi et al. (2022) that bridging the regional and global scales to facilitate this is a necessary next step. There are clear benefits to being able to represent regional changes in future air quality. To facilitate the above, I would recommend further work to identify a consistent methodology and set of inputs for using the SSPs with regional chemical transport models. As MUSICA (Schwantes et al. 2022) develops, it is likely that the academic community will move away from WRF-Chem. MUSICA's development is led by the same institution and research group as WRF-Chem (NCAR). NCAR has announced that WRF-Chem is no longer being developed (NCAR, 2025). This means that regional modelling using NCAR tools is currently in a transitional period; MUSICA is not well distributed and its use is currently exploratory, but any tools built to facilitate regional chemistry models from NCAR will use MUSICA as the intended tool and not WRF-Chem. I believe that facilitating the use of future scenarios should be a key consideration for MUSICA's development. To my understanding it is a priority, and that the structure of MUSICA (meteorology on a 100km global grid tapering into higher resolution chemical transport modelling over selected regions) will facilitate the use of CESM2-WACCM meteorological and chemical boundary conditions. The CMIP6 simulations using CESM2-WACCM (Danabasoglu, 2019) could potentially be used here. What I would like to see along with these is for MUSICA to be built to be compatible with CMIP6 anthropogenic

emissions, or a consistent methodology developed to translate CMIP6 emissions into a format compatible with MUSICA. Ability to include other CMIP6 inputs such as biogenic emissions and land use could mitigate some of the limitations I identify in my work.

5.5 Summary

To summarise, there are clear air quality co-benefits of a low-carbon economy in Europe. The difference between stringent mitigation scenarios and the current trajectory of emissions change are so stark that failure to mitigate climate change represents an enormous wasted opportunity in terms of public health. However, if stringent mitigation is achieved, hundreds of thousands of deaths per year could be avoided and the current inequitable mortality rate could be mitigated, demonstrating that aiming to achieve a low-carbon economy in Europe is worth it. This does not mean that achieving air quality co-benefits will be straightforward. While more "traditional" emissions mitigation options will improve air quality in Central and Eastern Europe, to improve air quality further in Western Europe will require targeting sectors such as agriculture that are more difficult to mitigate and this may require lifestyle change. Without coordinating efforts between countries to ensure stringent mitigation in all relevant sectors, increasing O_3 concentrations driven by complex emissions responses and changes in the climate itself threaten to counteract the reductions in $PM_{2.5}$ concentrations, wasting taxpayer's money and policy-maker's effort. A coordinated response will also be required to better understand how policies at all spatial levels will affect secondary air pollution, particularly O_3 as it becomes a much greater proportional health concern in the future.

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Appendix A

Appendix

A.1 Additional Information About Inputs

A.1.1 CESM2-WACCM

CESM2-WACCM is a parameterisation of the Community Earth System Model 2 with the Whole Atmosphere Community-Climate model used for simulating the atmosphere (Marsh et al. 2013; Gettelman et al. 2019; Danabasoglu et al. 2020). The current version used in CMIP6 uses CESM2 (Danabasoglu et al. 2020) as a base earth system model with WACCM 6 (Gettelman et al. 2019) as the atmospheric modelling component, although CESM2 can alternatively be run with CAM6 as the atmospheric component. Figure A.1 from Danabasoglu et al. (2019) shows the constituent components that make up CESM2.

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The WACCM6 component is of greatest relevance to this thesis as it was from this that the chemical initial and boundary conditions were developed. WACCM6 is a"whole atmosphere" model, meaning that unlike chemical transport models it is capable of atmospheric simulations beyond the troposphere. WACCM6 is optimised for capturing processes in the middle atmosphere (stratosphere and mesosphere) of vital importance to the climate system, such as stratospheric aerosol loading and climatology of water vapour and O_3 (Gettelman et al. 2019). WACCM6 runs at approximately 100km horizontal resolution and at 70 atmospheric levels from surface up to 6×10^{-6} hPa ($\sim$ 140 km).

WACCM6 has more detailed tropospheric chemistry than the CAM6 alternative, including a

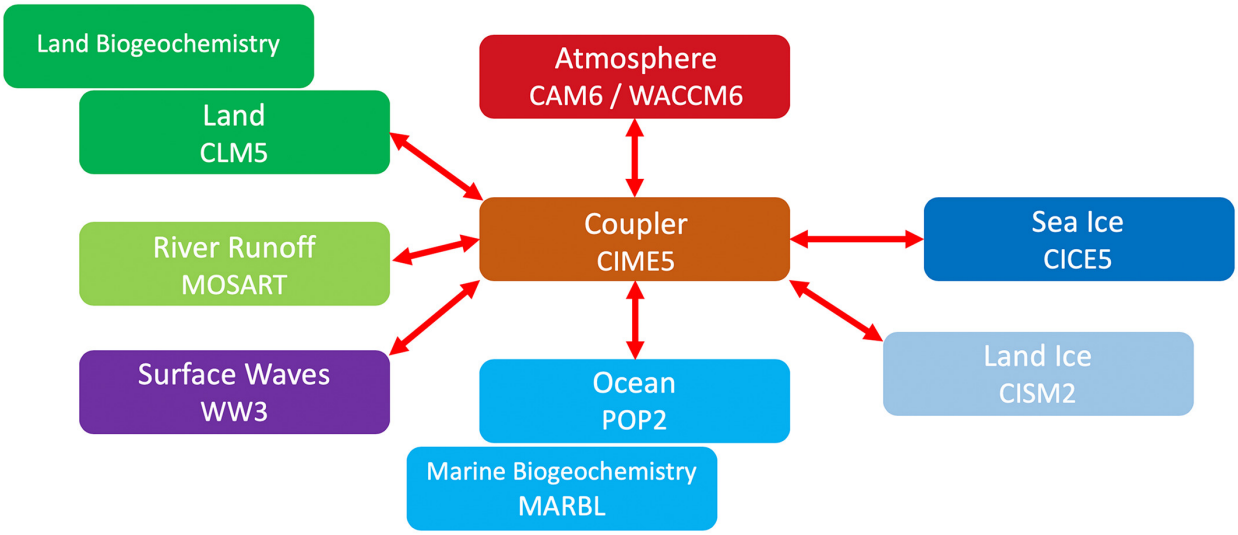


Figure A.1: A diagram showing the component models within CESM2 (Danabasoglu et al. 2020)

total of 231 solution species, 583 chemical reactions broken down into 150 photolysis reactions, 403 gas-phase reactions, 13 tropospheric, and 17 stratospheric heterogeneous reactions (Gettelman et al. 2019). This includes reasonably detailed representation of aerosol chemistry in comparison with other CMIP6 models; the Modal Aerosol Model 4 (Liu et al. 2016). This includes representation of aerosol-cloud interactions and also provides a detailed SOA scheme developed by Hodzic et al, (2016) to represent aerosol chemistry. Notably however, the NO_3 chemistry scheme has some limitations as it simulates NO_3 in the gas phase, but not in the aerosol phase. Biogenic emissions are considered similarly to in WRF-Chem, using MEGAN v 2.1 (Guenther et al. 2012).

The simulations used for boundary conditions are CESM2-WACCM simulations for the ScenarioMIP project from Danabasoglu, 2019). As these simulations are also designed for scenarioMIP, they use many of the same inputs e.g emissions from Hoesly et al. (2018) and Feng et al. (2020). Unlike our simulations, CESM2-WACCM considers greenhouse gas forcings consistent with the SSPs. This mean that effectively the chemistry from outside the boundary feeding into our simulations considers climate change, whereas within the domain it does not. This could be a limitation of this work

A.1.2 $PM_{2.5}$ reanalysis

To improve representation of $PM_{2.5}$-attributable health impacts for paper 2, I applied a scaling methodology, using a global gridded $PM_{2.5}$ reanalysis from van Donkelaar et al. (2021) (which

I refer to as the VD reanalysis). The VD Reanalysis data for 2014 is taken as the present day $PM_{2.5}$ and scaling based on the anthropogenic $PM_{2.5}$ simulated in future scenarios is applied to this to represent future $PM_{2.5}$. This method has been used previously for projections by Turnock et al. (2023) and Reddington et al. (2023). The VD reanalysis has also been used for non-projected bias correction, e.g in the air quality stripes described by Pringle et al. (2025). The scaling method is described in paper 2. The bias from paper 1 was not uniform across the domain and appeared to be larger in urban regions, in some parts of the domain (mostly Spain and Poland) VD reanalysis $PM_{2.5}$ was higher than the modelled $PM_{2.5}$. This is shown in figure 2.6. This is likely a better way of handling the bias than applying a strict factor uniformly across the domain that could cause artificially low $PM_{2.5}$ in areas the overestimation was less of a problem as it corrects both under and over-predictions.

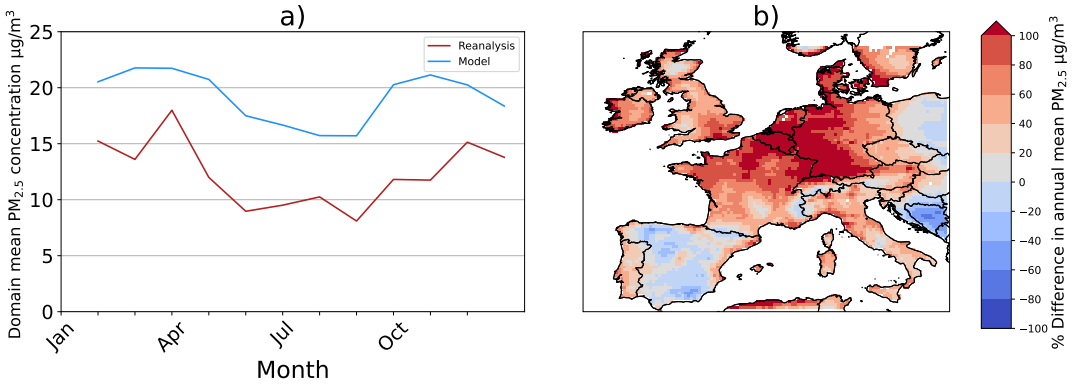


Figure A.2: Left: Time series of modelled surface $PM_{2.5}$ across the domain vs the VD reanalysis. Right: The spatial difference between annual mean $PM_{2.5}$ of the model compared to the VD reanalysis

The VD reanalysis is a hybrid product advancing on previous techniques which relied primarily on annual satellite observations of aerosol optical depth (AOD). While these still form a major part of the VD reanalysis, this product also uses ground observations and chemical transport modelling and can provide monthly gridded data at both 1km and 10km resolutions. The basis are monthly means of five daily satellite AOD observations which are combined with simulated AOD to create an AOD "best estimate" with the contribution of each satellite product weighted by its agreement with the AERONET remote sensing observations network. To generate $PM_{2.5}$ concentrations, the global GEOS-Chem model is used to calculate a relationship between AOD and $PM_{2.5}$ concentrations. The relationship is then applied to the gridded satellite product and adjusted based on selected ground-based observations to produce the final, monthly reanalysis product (van Donkelaar et al. 2021).

	SSP1 Sustainability	**SSP2 Middle of the Road**	**SSP3 Regional Rivalry**	**SSP4 Inequality**	**SSP5 Fossil-fueled Development**
High fertility (pop growth)	Low	Medium	High	High	Low
Other Low Fertility (pop growth)	Low	Medium	High	Medium low	Low
Rich Low Fertility (pop growth)	Medium	Medium	Low	Medium low	High
Urbanization (High Income)	Fast	Central	Slow	Central	Fast
Urbanization (Medium Income)	Fast	Central	Slow	Fast	Fast
Urbanization (Low Income)	Fast	Central	Slow	Fast	Fast

Table A.1: Expected population and urbanisation per income/fertility category of countries, adapted from Jones & O'Neill (2016)

A.1.3 Population and baseline mortality data

A source of uncertainty in estimating future mortality is the use of population projections. Population has been demonstrated in some research to have had a bigger impact on changes in $PM_{2.5}$ mortality than changes in air pollutant concentrations in some populations (Vohra et al. 2022).

The population growth projections consistent with the SSPs over the period of 2010 to 2100 are generated by grouping countries by fertility and income into 3 categories: high fertility, low fertility and high income with low fertility (which effectively represents the OECD and therefore countries within the model domains considered in this thesis) (Samir & Lutz, 2017). The SSPs also have urbanisation projections which are based entirely on the income each storyline projects (Samir & Lutz, 2017). Table (A.1) adapted from Jones & O'Neill et al. (2016) demonstrates the population growth and urbanisation expected up to 2100 in each category of country by SSP.

What table 2.2 demonstrates is that within European countries, following SSP1-2.6, population will increase, and greater population would be expected to move to urban regions where pollution may be higher. Following SSP2-4.5, similar population growth would be expected, but a lower proportion would be expected to live in urban areas. Following SSP3-7.0, population growth will be smaller than the other scenarios and little urbanisation is expected, meaning that

demographic trends would be unlikely to modify exposure to air pollutants much compared to the present day. Migration assumptions are made on national level projections for each SSP and modify a present-day matrix of migration based on assumptions including conflict and politics (Jones & O'Neill, 2016).

To translate the projections to an approximately 14 km grid, Jones & O'Neill (2016) use a "gravity type" model. This uses the country-level population and urbanisation projections and scales a "base year" gridded population, for which the authors use the "Gridded Population of the World" (GPW)(NASA, 2025) dataset for the year 2000. Each grid cell is given an "urban population potential surface" and a "rural population surface" and the projected population increase for each country at each 10-year time interval is distributed across each grid cell within that country, with the balance of growth in rural/urban potential cells determined by the urbanisation projections. This allows for rural cells to become urban cells based on the classification criteria used. As the MODIS land surface model within WRF-Chem remains static for all simulations, some cells may not have an "urban" land designation during the simulations, but do have an elevated population when estimating health impacts. While land surface can impact on $PM_{2.5}$ concentrations, Bhattarai et al. (2024) demonstrate that the land use changes within the SSPs alone do not greatly alter $PM_{2.5}$ concentrations. The gridded anthropogenic emissions themselves also do not factor in spatial changes in land use or population and are based on static, present-day locations (Feng et al. 2020), meaning that population increases designed to represent growing urban areas may occur without representation of the increased urban emissions.

The baseline mortality data and population age structure (for GEMM) are taken from projections by the Frederick S. Pardee Centre for International Futures (2021). These projections are created for each country and 5-year age groups using a process called "Distal Drivers"; this combines regression curves for various causes of death identified in the early Global Burden of Disease project and social indicators for each country (primarily GDP, education and technological progress) to estimate how these will change over time (Pardee Wiki, 2018). The future projections of baseline mortality do not change with SSP scenario, and thus this may not represent different progress in health protection assumed in different scenarios.

A.1.4 Deprivation data

In paper 2, I assess the impacts of the future scenarios on health equity. To do this, I needed a consistent measure of deprivation/ development across Europe. Deprivation can vary greatly across very small spatial scales, and this variation may not be represented when larger spatial scales are varied (Cebrecos et al. 2018) so I wanted to ensure that I could use data with the finest consistent spatial scale possible. As "Europe" is not a single entity politically and the EU reports most data, there was not to my knowledge, an official measure of deprivation that included every country within the domain available at a less than national scale. Similarly, many metrics, even from the EU were not reported at a consistent scale across different countries. To mitigate this, I looked for deprivation indices that were available on a global grid. This would allow me to aggregate the data at a spatial scale of my choosing. Numerous potential data sources were available:

-the Global Gridded Relative Deprivation Index (GGRDI) (Center for International Earth Science Information Network (CIESIN), 2022)

-Gridded projections of Gross Domestic Product consistent with the SSPs (Wang & Sun, 2021)

-Gridded subnational Human Development Index (HDI) (Kummu et al. 2018)

Deprivation/development is a multi-faceted issue that spreads beyond finance; dedicated measures of deprivation, such as the Index for Multiple Deprivation (IMD) used in the UK tend to combine a range of indicators. In the case of the IMD, this includes indicators of household income, employment, health, education, crime, living environment and barriers to services (Ministry of Housing, Communities & Local Government, 2019). GDP on the other hand is a measure of the economic output of a country, and therefore does not factor in wider indices of deprivation or income distribution within a country. It is therefore generally not seen as an effective measure of living standards in a country, even when expressed on a per-capita level. While it can be an effective indicator for broadly splitting regions by wealth, e.g use of GDP projections in the work by Reddington et al. (2023), as the focus of my thesis was on a more

local/regional spatial scale, I chose to use a better representation of current living standards with the trade-off of not projecting changes in deprivation.

HDI and the GGRDI both consider a more multi-faceted set of metrics; HDI combines metrics: gross national income per capita, life expectancy at birth, expected and mean years of schooling. It is usually reported at country level (United Nations, 2025). To create HDI grids, Kummu et al. (2018) use compiled subnational HDI datasets from a range of sources to scale national HDI data, using a ratio of population-weighted subnational HDI and reported subnational HDI. This is provided at an approximately 9.2km horizontal resolution, and I used the grid for 2015 HDI. The GGRDI uses 6 components to determine deprivation at a 1km grid. These are: subnational HDI, child dependency ratio, infant mortality ratio and satellite observations of built-up area and nighttime lights. The GGRDI actually uses the subnational HDI grids from Kummu et al. (2018) as an input. Despite the greater number of factors, I chose not to use GGRDI because of the impact of the night-time lights and the built-up areas used to generate the gridded product. This causes the GGRDI to heavily associate urban areas with lesser deprivation. Although it is true that globally, rural areas tend to experience higher multidimensional deprivation than urban areas (Castaneda et al. 2018), this may not hold in Europe. Figure 2.5 demonstrates this by comparing the GGRDI (left) and subnational HDI grids (right - taken from the final figure used in the published version of paper 2, Clayton et al. (2025)) aggregated by National Unit of Territorial Statistics level 2 regions. Please note that for HDI a higher value indicates better living standards, whereas a higher GGRDI indicates higher relative deprivation. The GGRDI figure therefore suggests that regions such as Scotland, Southern Ireland and Southern Norway are amongst the most deprived in Europe, whereas industrial regions in Poland and Hungary are amongst the least deprived. CIESIN (2022) do identify the less clear trends in urban population and deprivation in higher-income countries as a limitation of the GGRDI. As the subnational HDI data did not show this effect to the same degree, I used it instead of the GGRDI.

A.2 Paper 1 supplementary figures

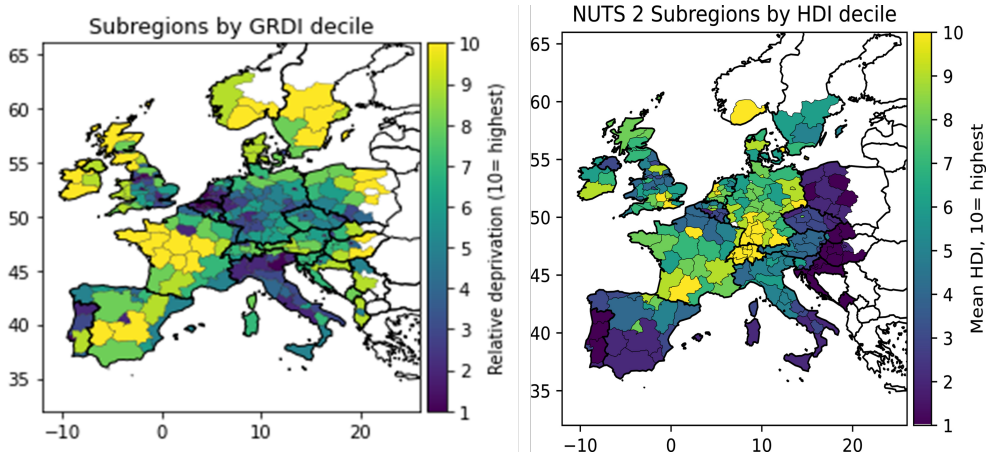


Figure A.3: Comparison of GGRDI (left) and Subnational HDI (right) (from Clayton et al. (2025)). Note that a yellow area on the left plot is the most deprived decile and on the right is the least deprived (or most developed) decile

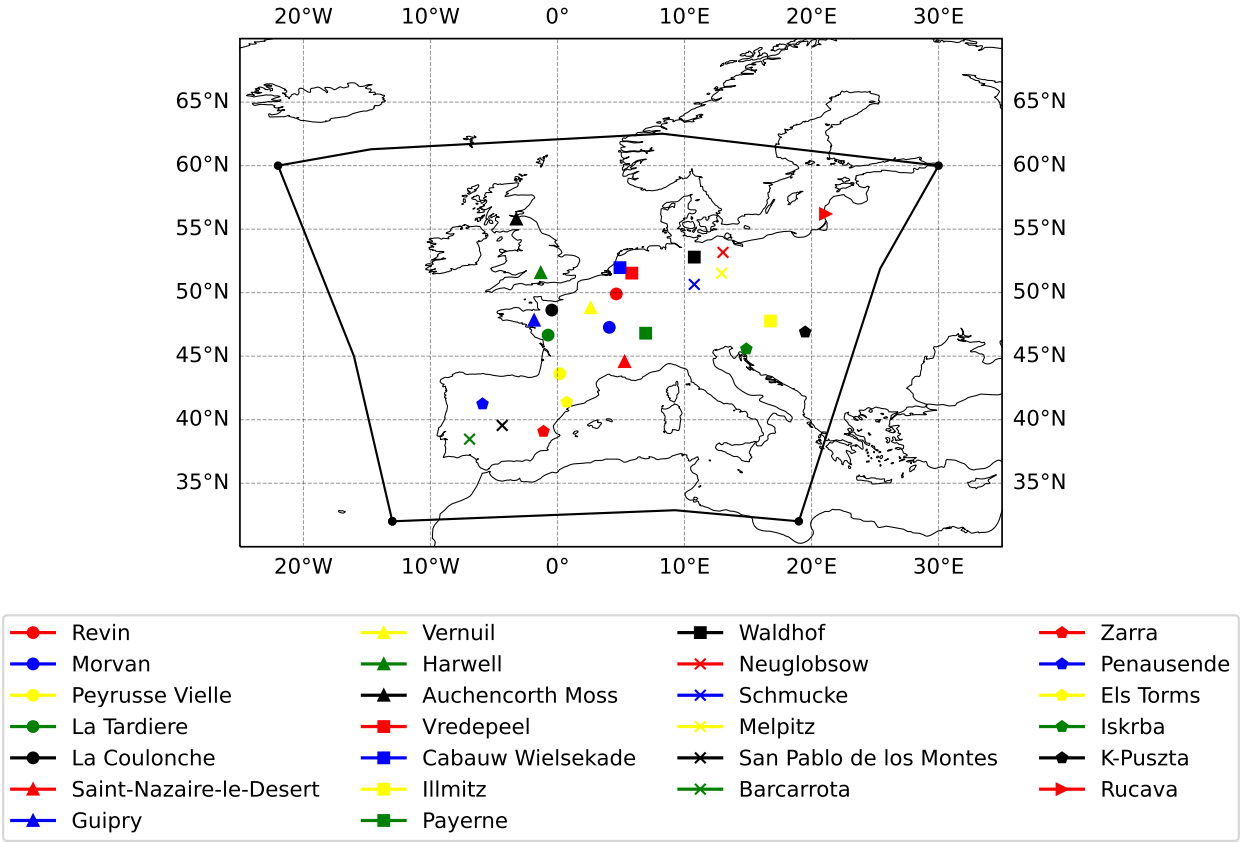


Figure A.4: The domain input into WRF-Chem v4.2 for our simulations at 30 km resolution. The observation sites used for model validation are also shown. The colours and shapes represent nothing other than to allow each site to have a unique symbol/colour to identify their place on the map.

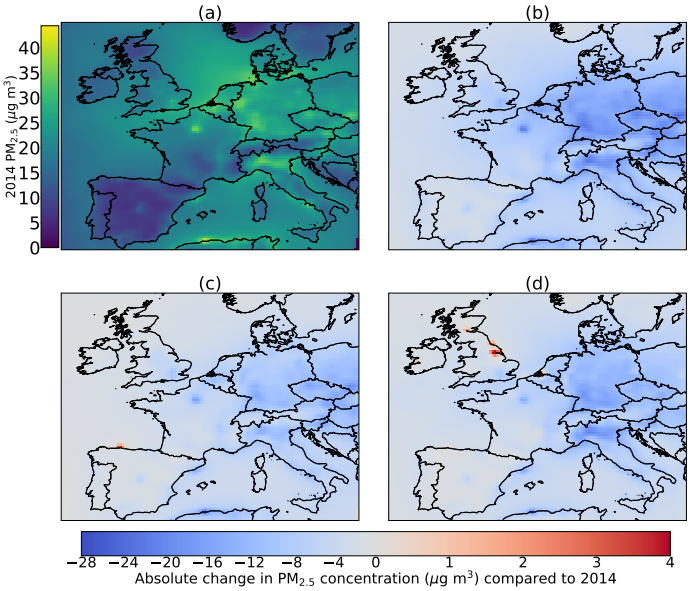


Figure A.5: Annual mean $PM_{2.5}$ for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the absolute change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

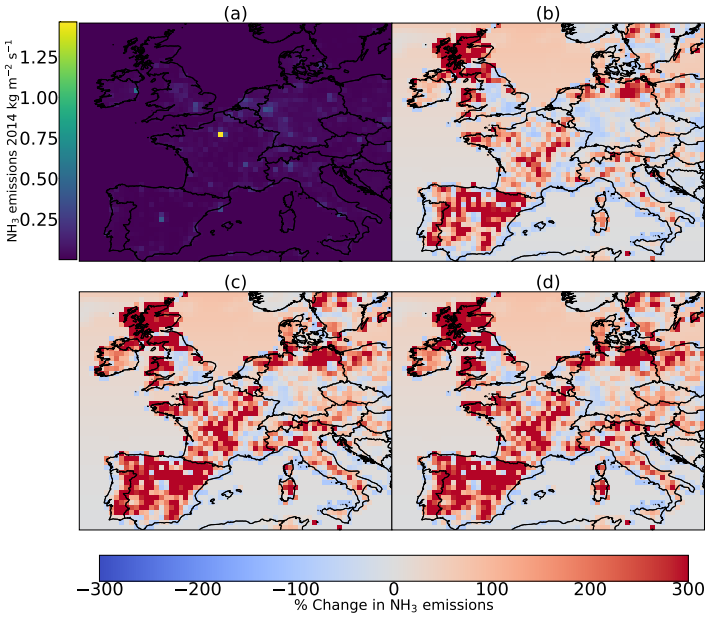


Figure A.6: Annual mean NH_3 emissions for each scenario. (a) shows this metric for 2014. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 in 2050 respectively.

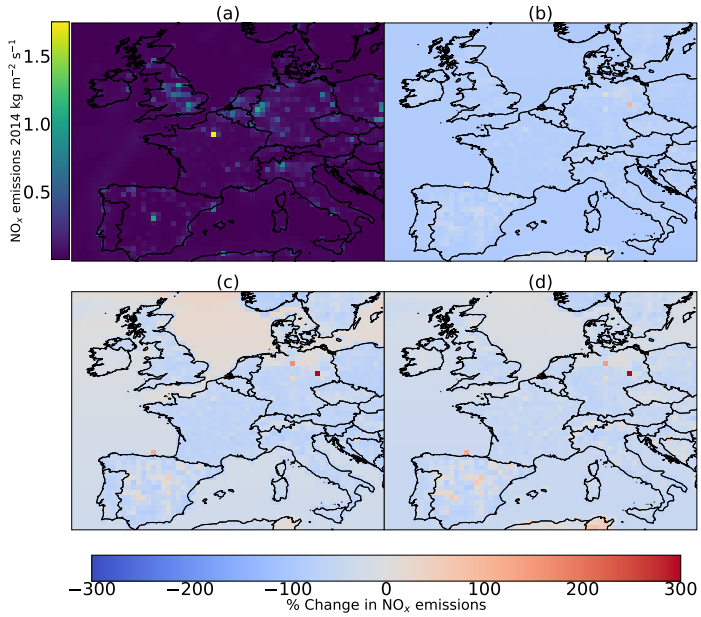


Figure A.7: Annual mean NO_x emissions for each scenario. (a) shows this metric for 2014. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 in 2050 respectively.

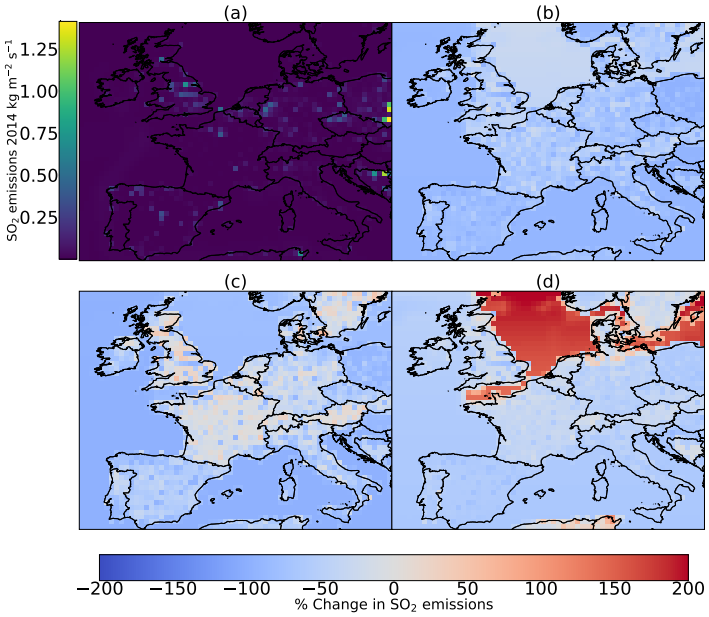


Figure A.8: Annual mean SO_2 emissions for each scenario. (a) shows this metric for 2014. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 in 2050 respectively.

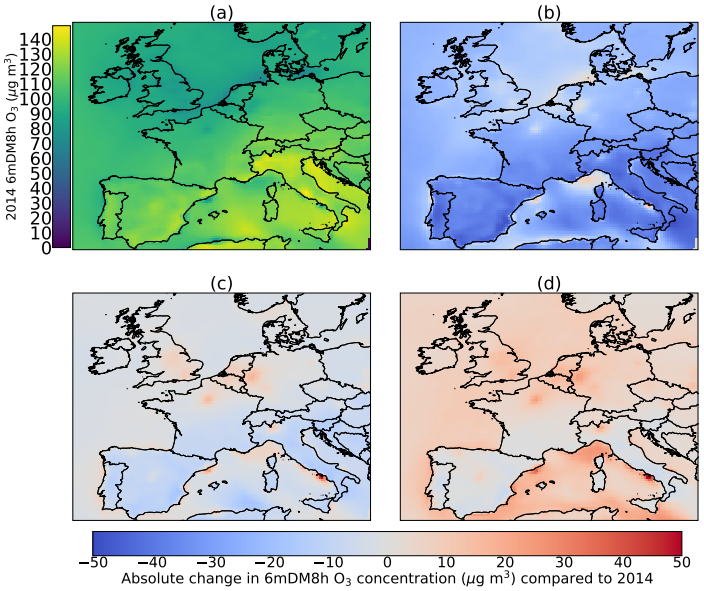


Figure A.9: 6mDM8h O_3 for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the absolute change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

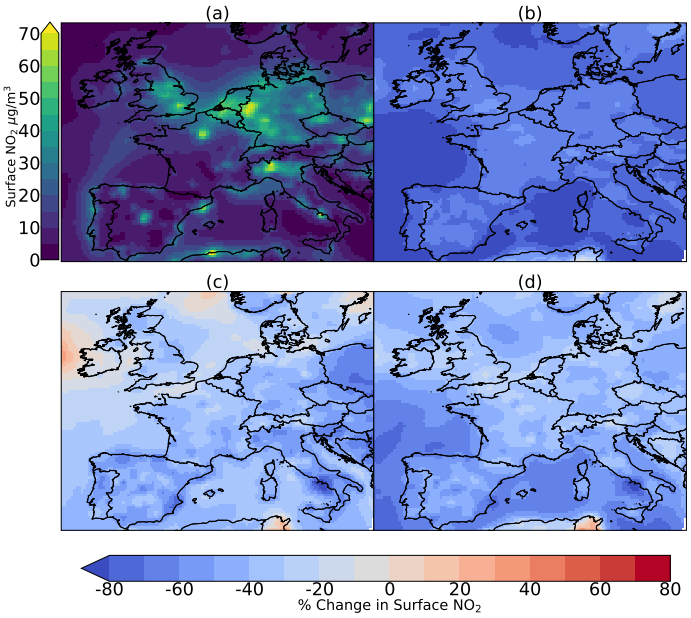


Figure A.10: Annual mean NO_2 for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

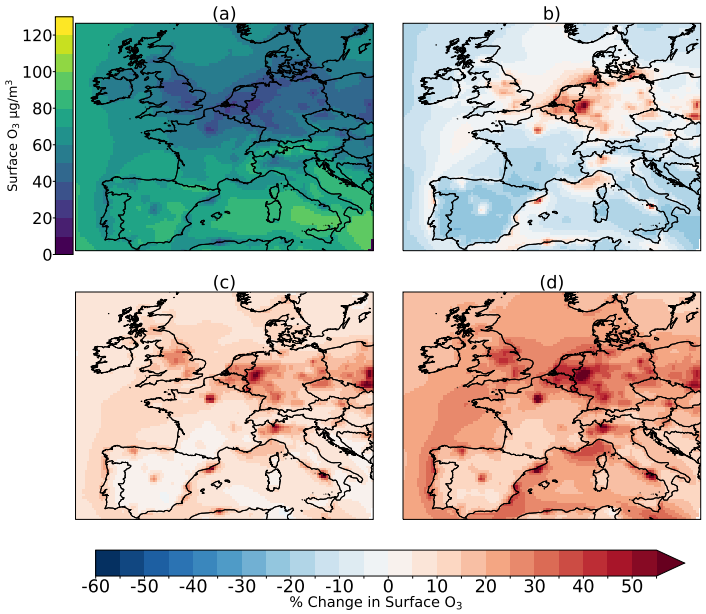


Figure A.11: Annual mean O_3 for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

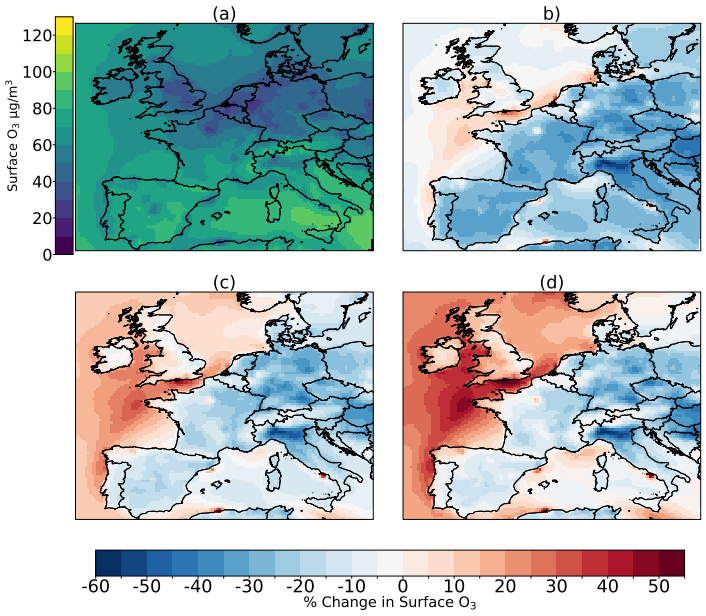


Figure A.12: Mean O_3 in January, February and December for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

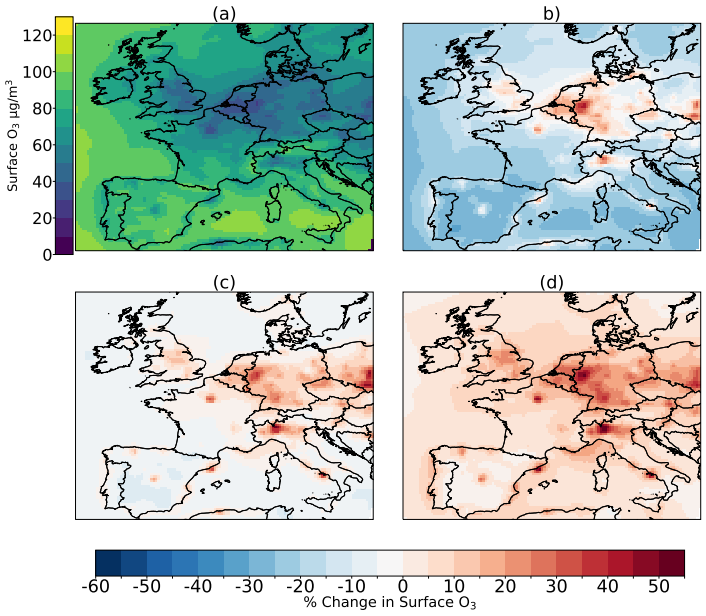


Figure A.13: Mean O_3 in March, April and May for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

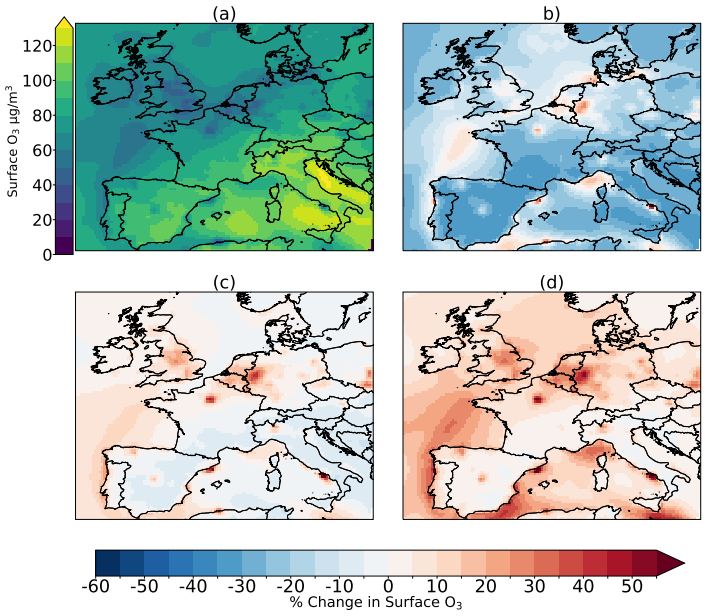


Figure A.14: Mean O_3 in June, July and August for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

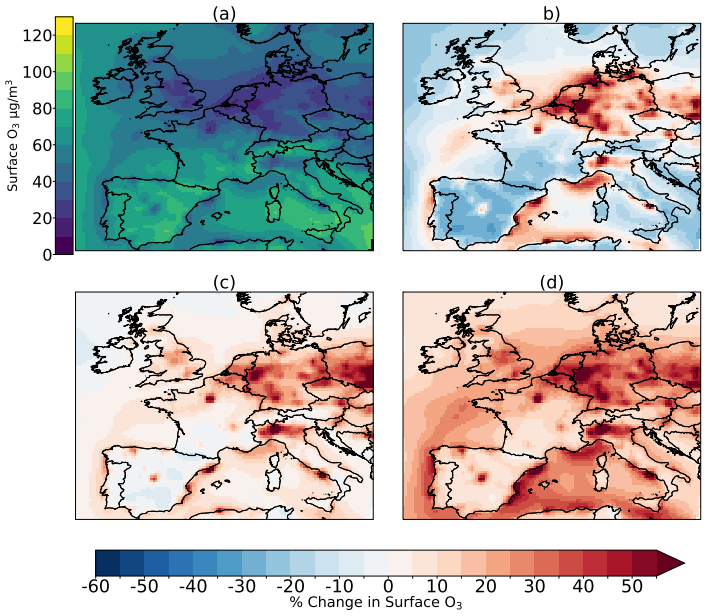


Figure A.15: Mean O_3 in September, October and November for each scenario. (a) shows this metric for the CMIP6 2014 simulation. (b),(c) and (d) show the percentage change from this for SSP1-2.6, SSP2-4.5 and SSP3-7.0 respectively.

A.3 Paper 2 Supplementary Figures

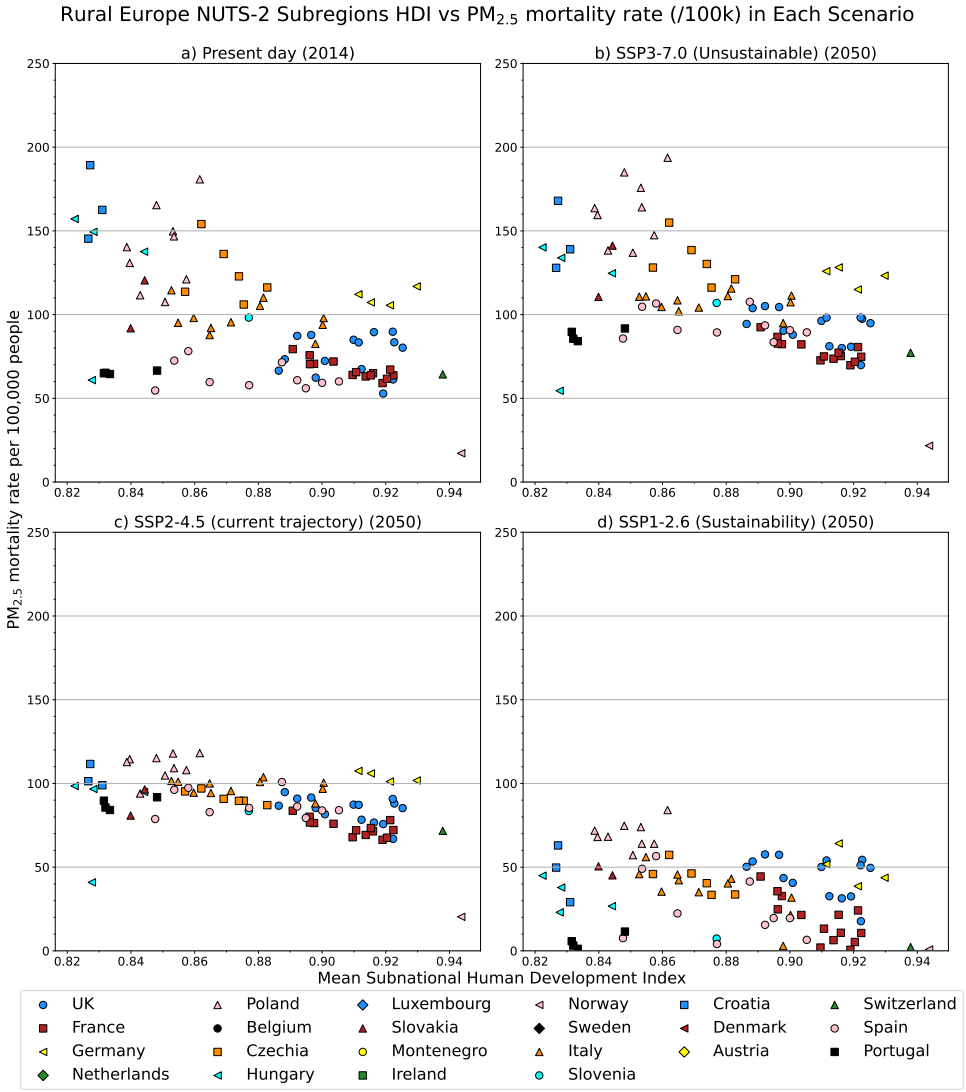


Figure A.16: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in rural NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

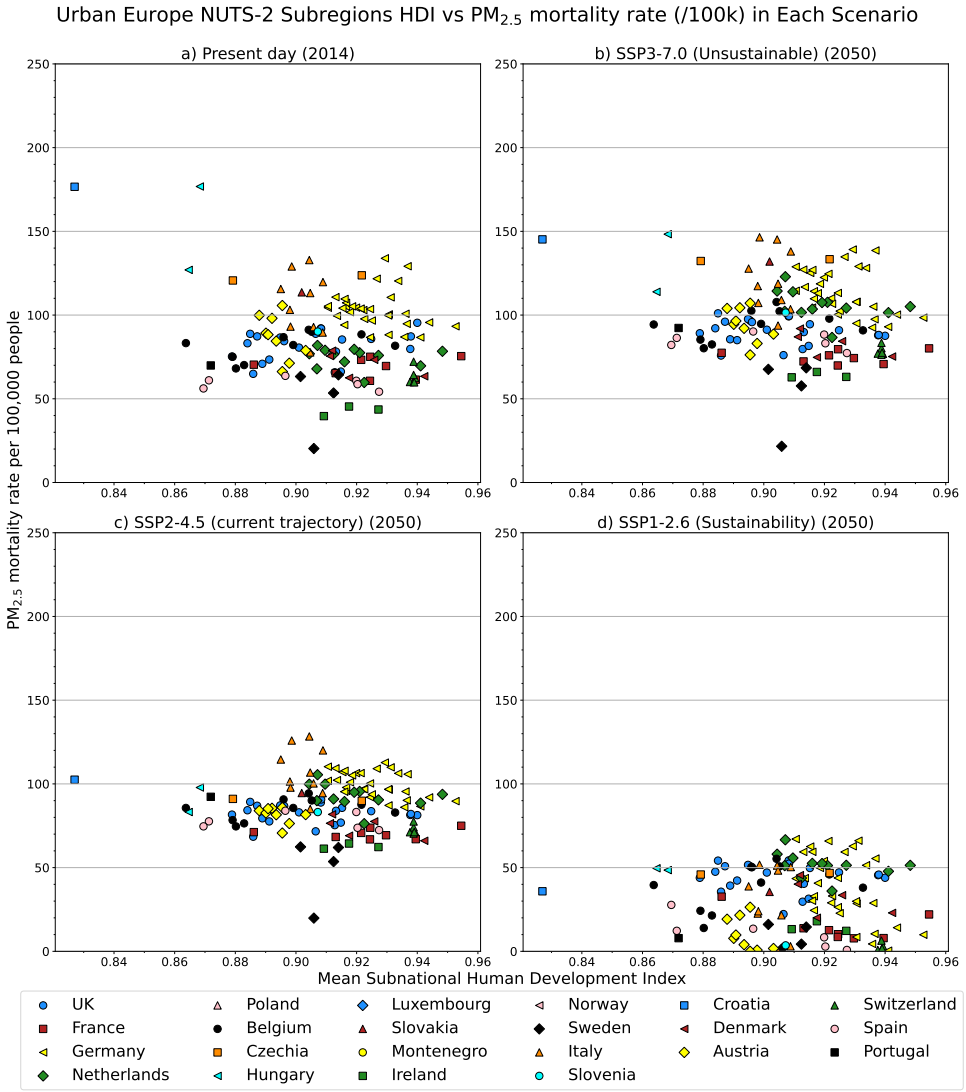


Figure A.17: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in urban NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

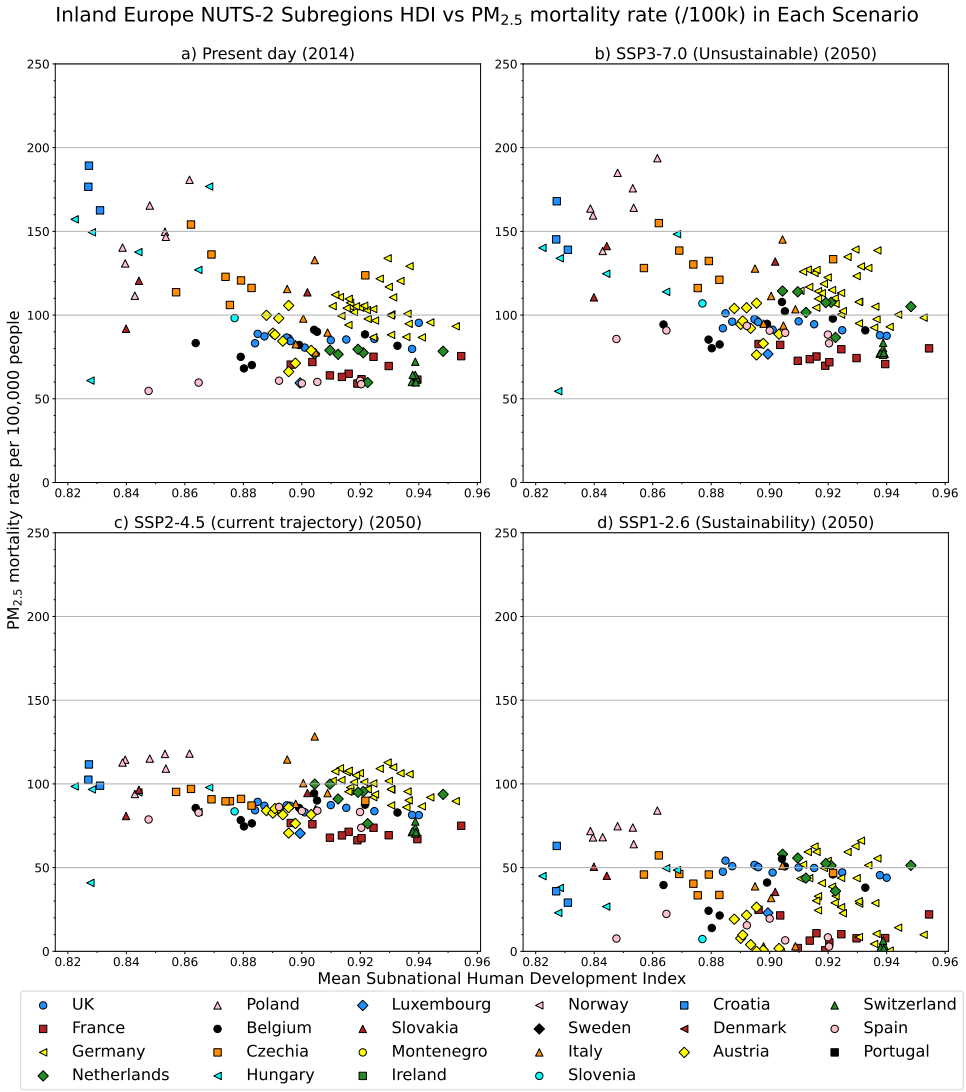


Figure A.18: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in inland NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

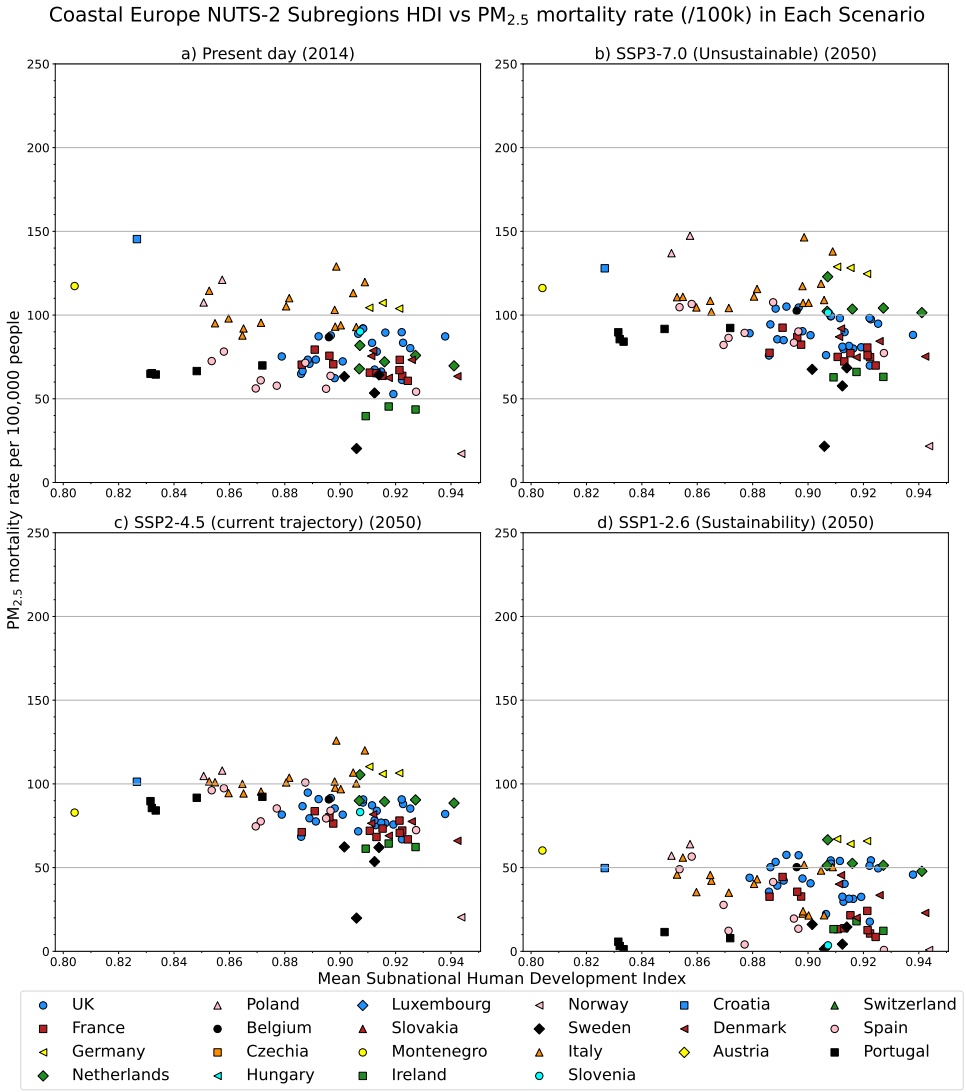


Figure A.19: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in coastal NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

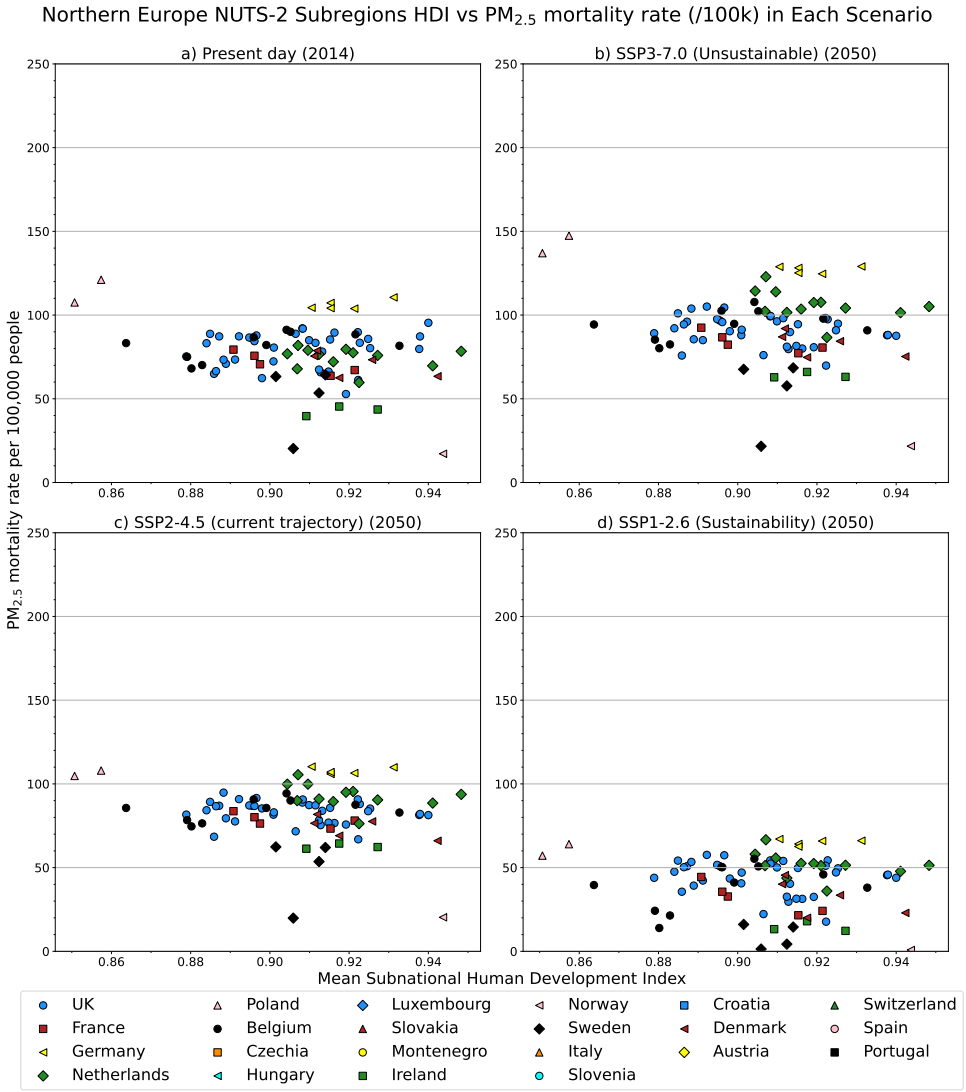


Figure A.20: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in Northern European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

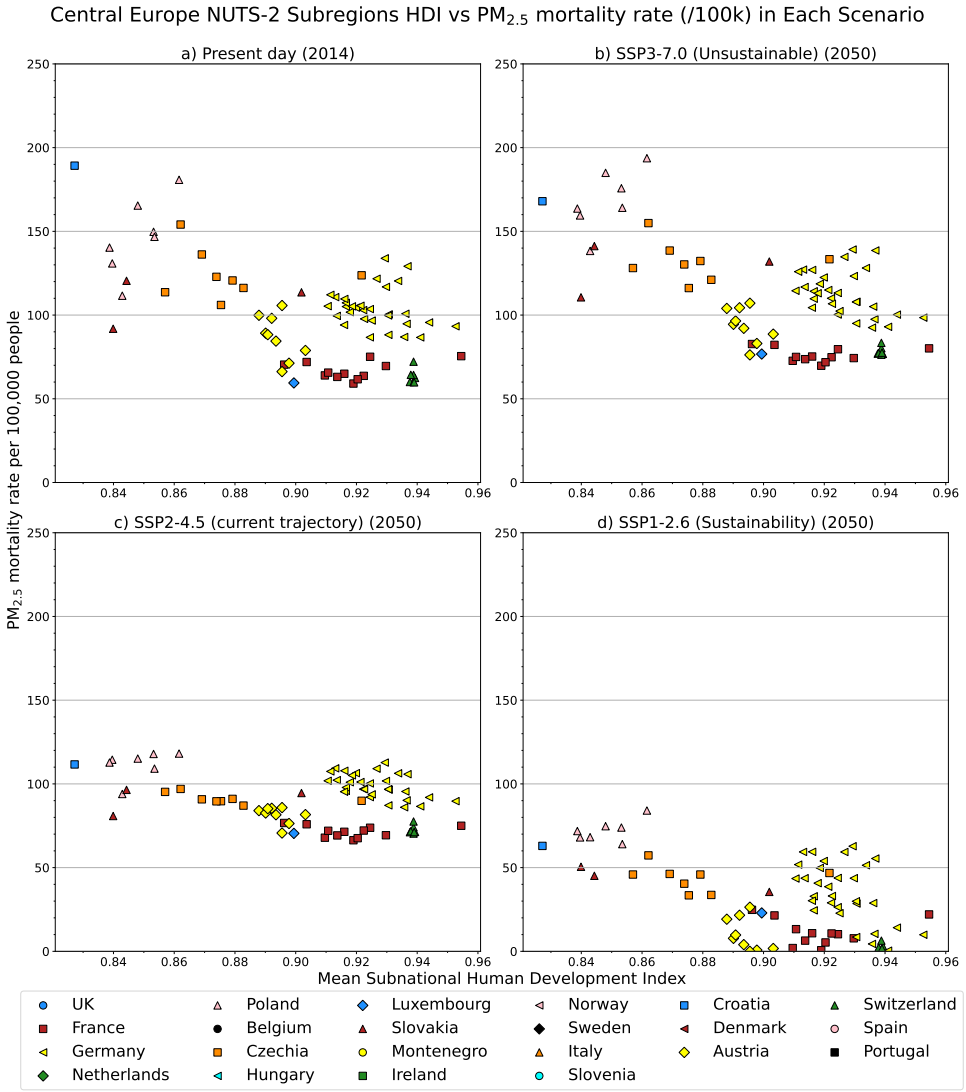


Figure A.21: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in Central European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

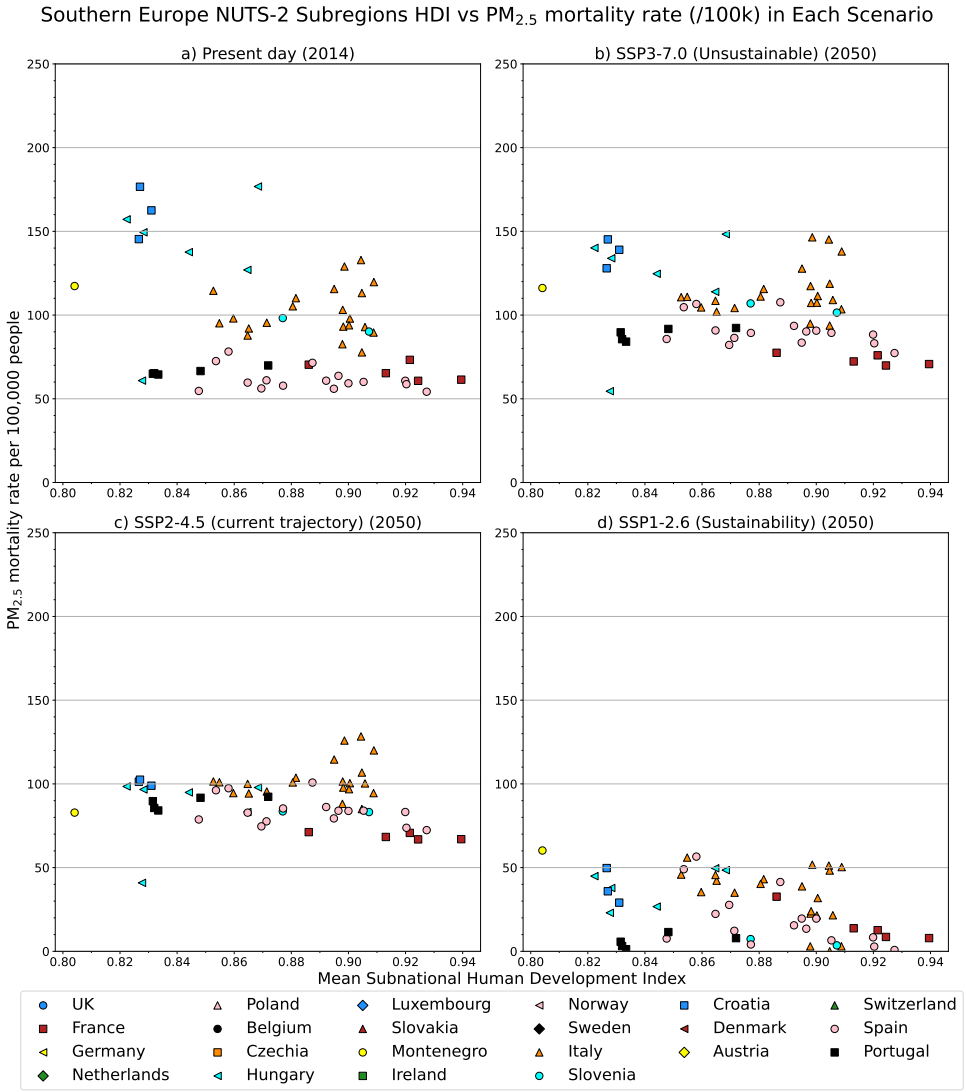


Figure A.22: Scatter plot of $PM_{2.5}$ mortality rate (air quality deaths per 100,000 population vs mean HDI in Southern European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

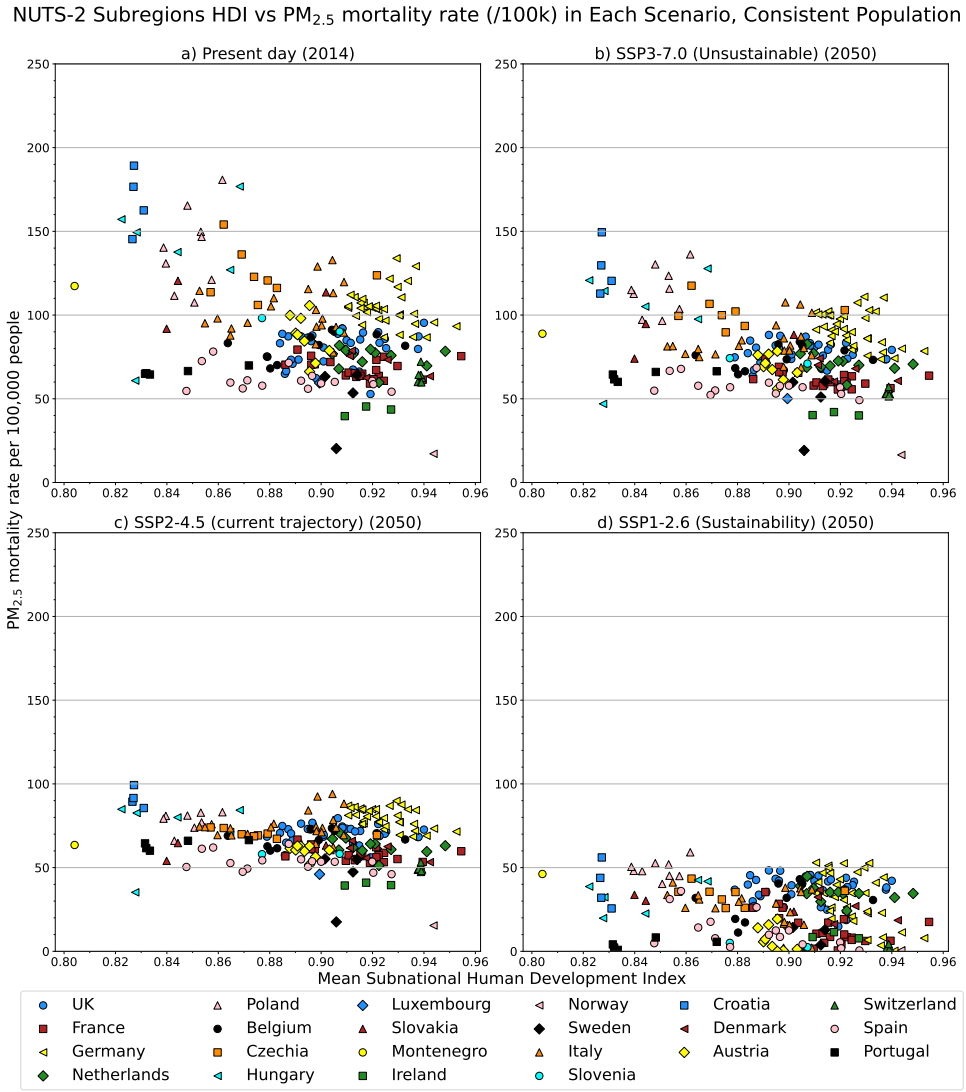


Figure A.23: Scatter plot of $PM_{2.5}$ mortality rate when population change is not factored into the exposure-response function (air quality deaths per 100,000 population vs mean HDI in NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

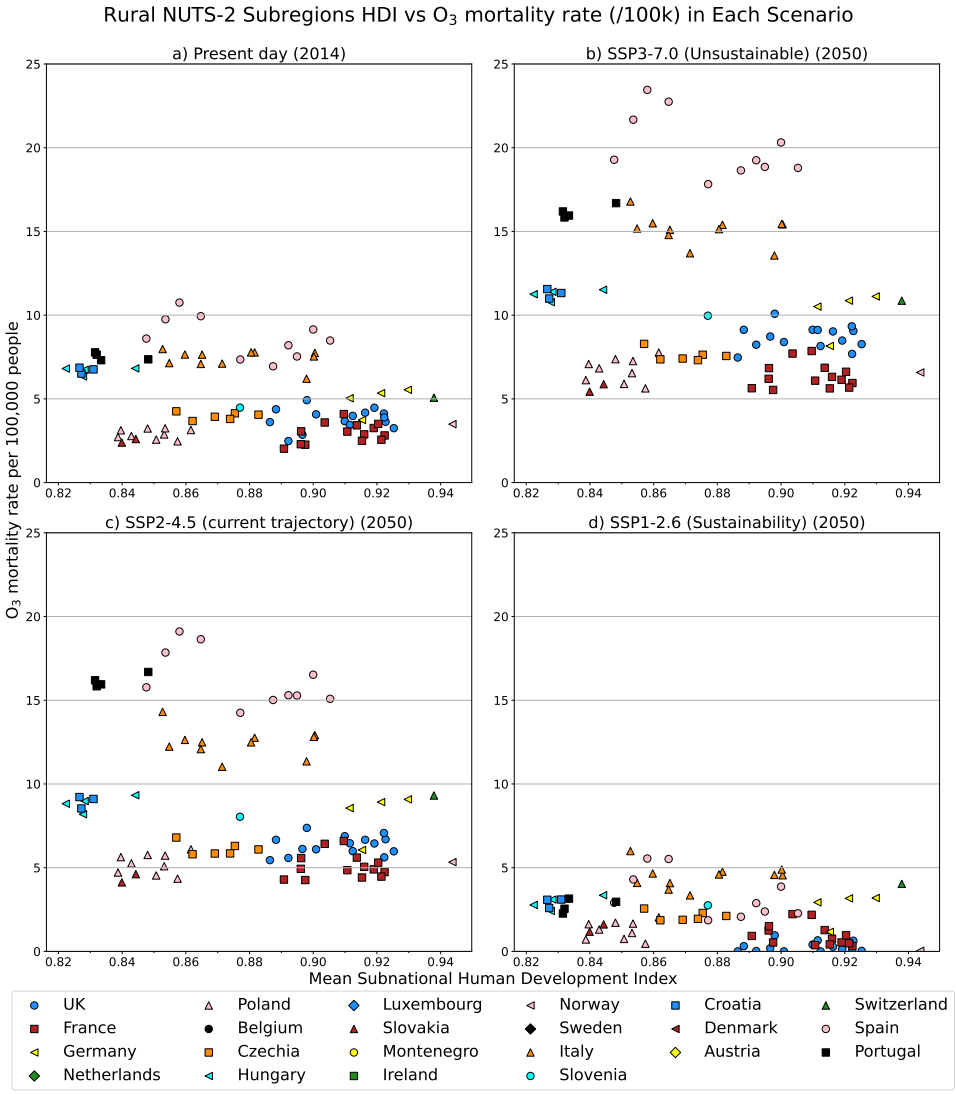


Figure A.24: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in rural NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

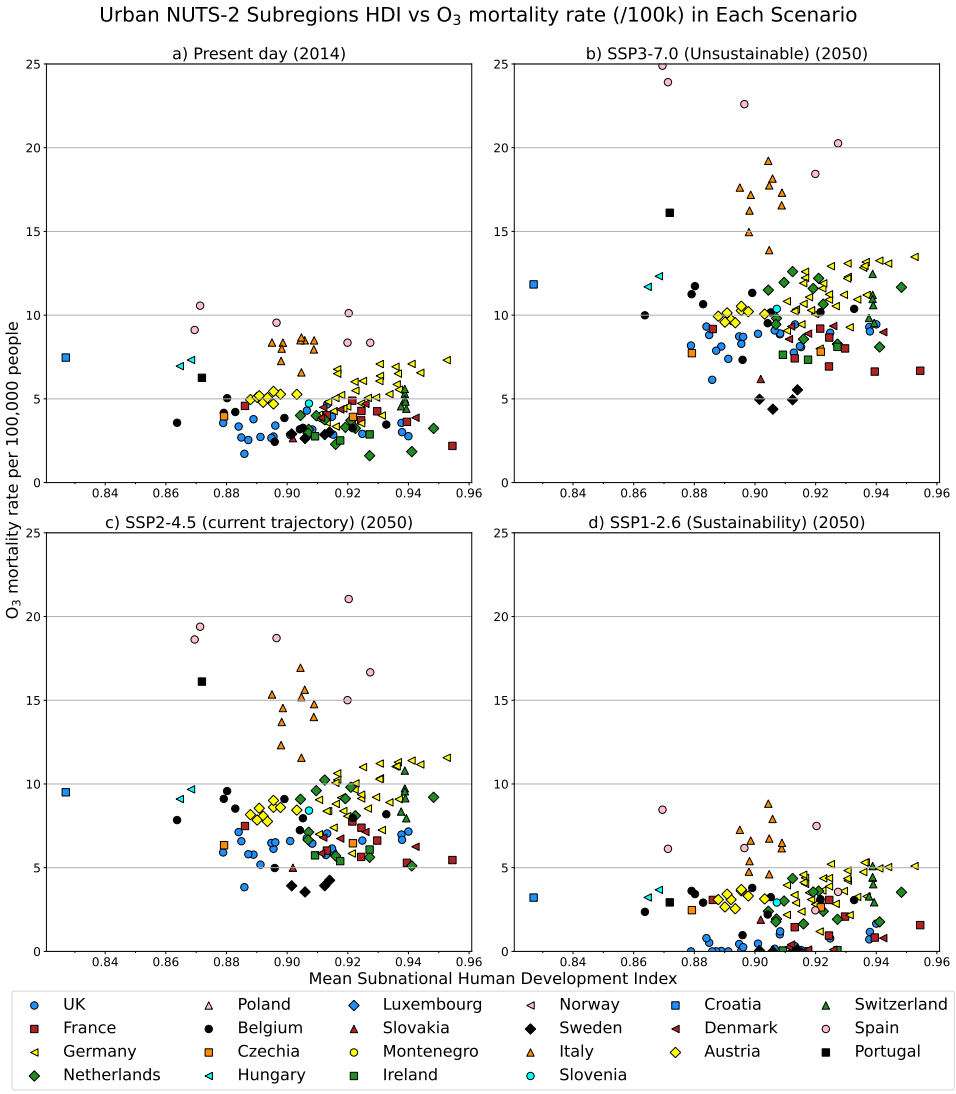


Figure A.25: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in urban NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

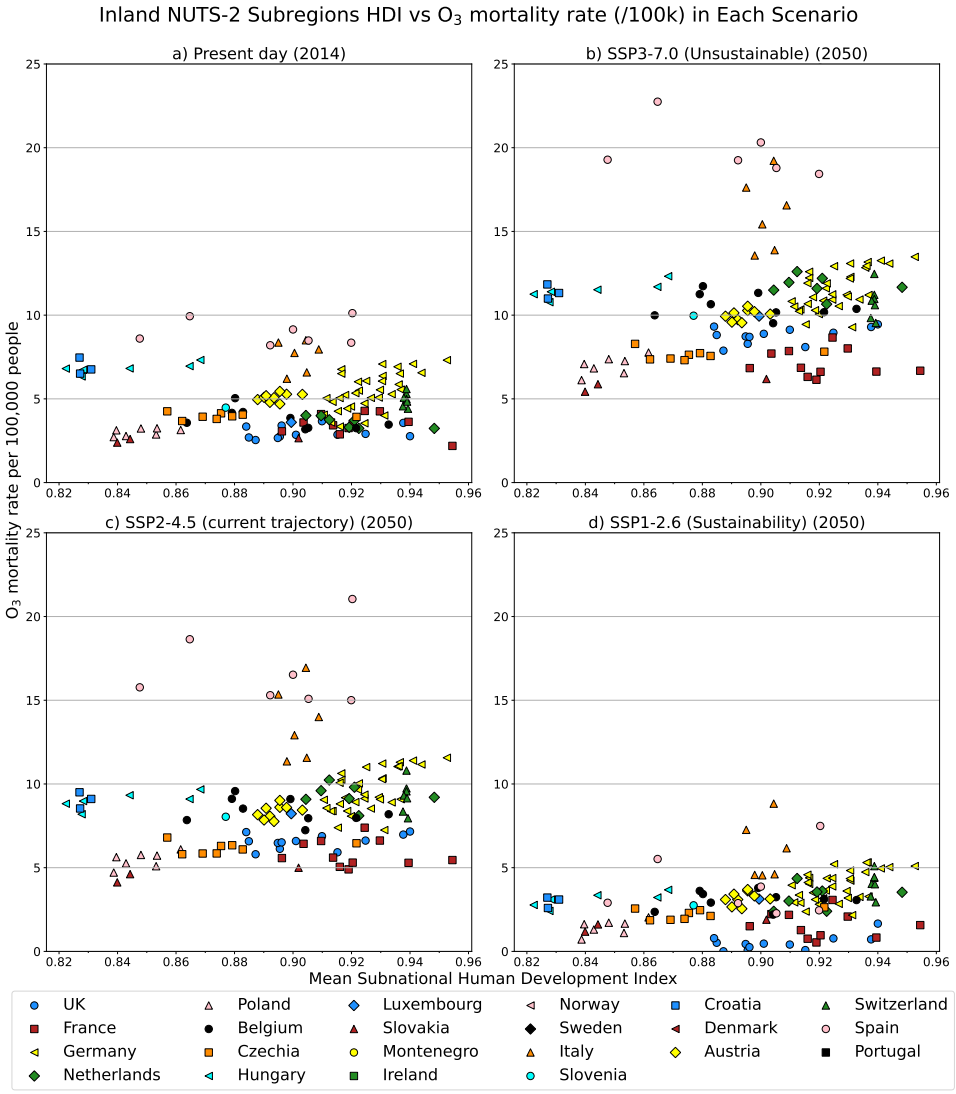


Figure A.26: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in inland NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

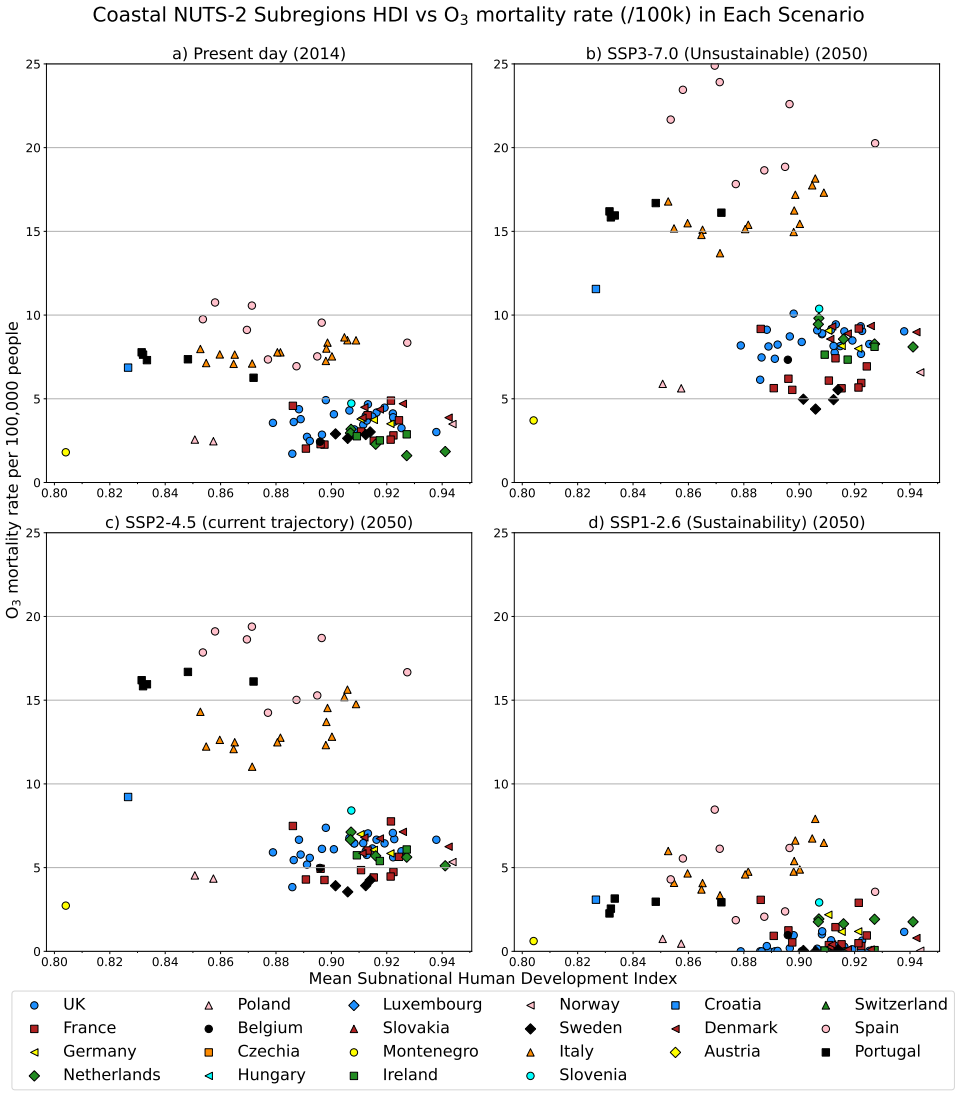


Figure A.27: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in coastal NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

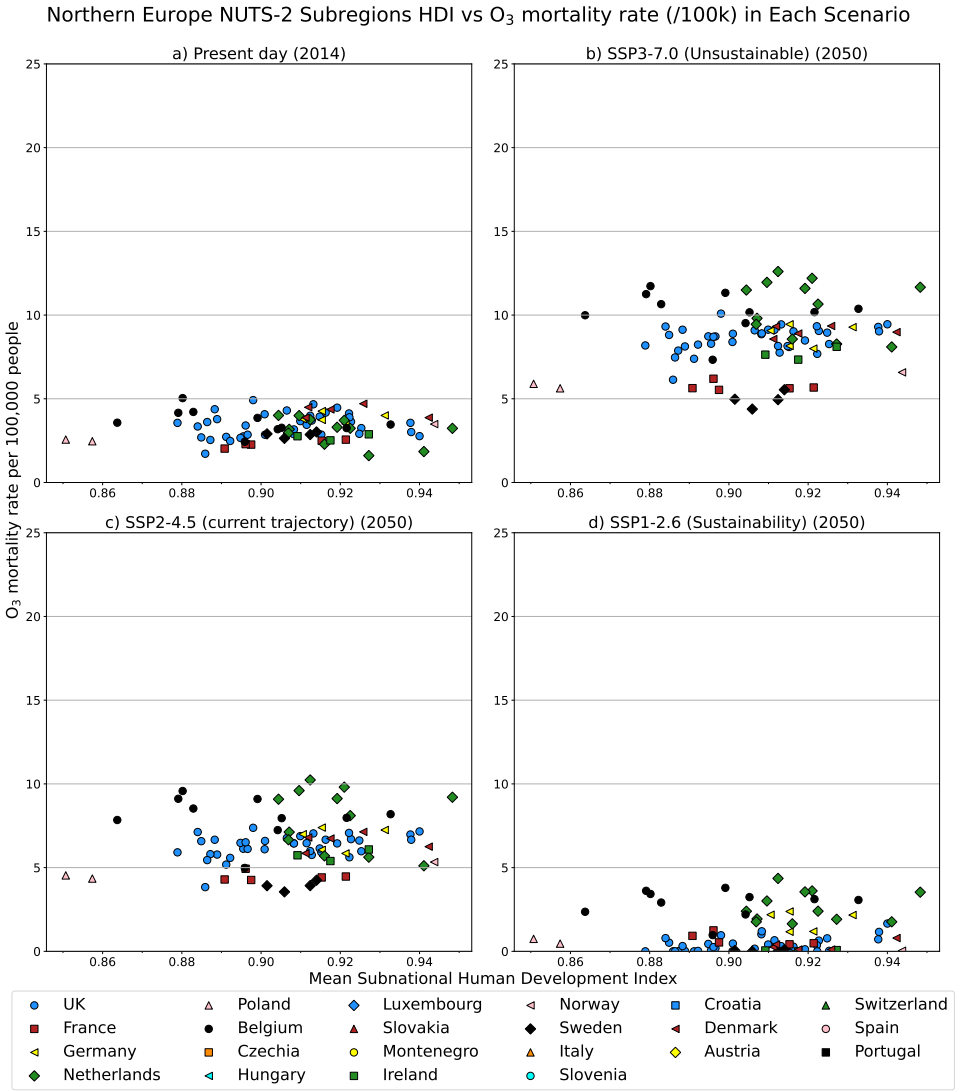


Figure A.28: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in Northern European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

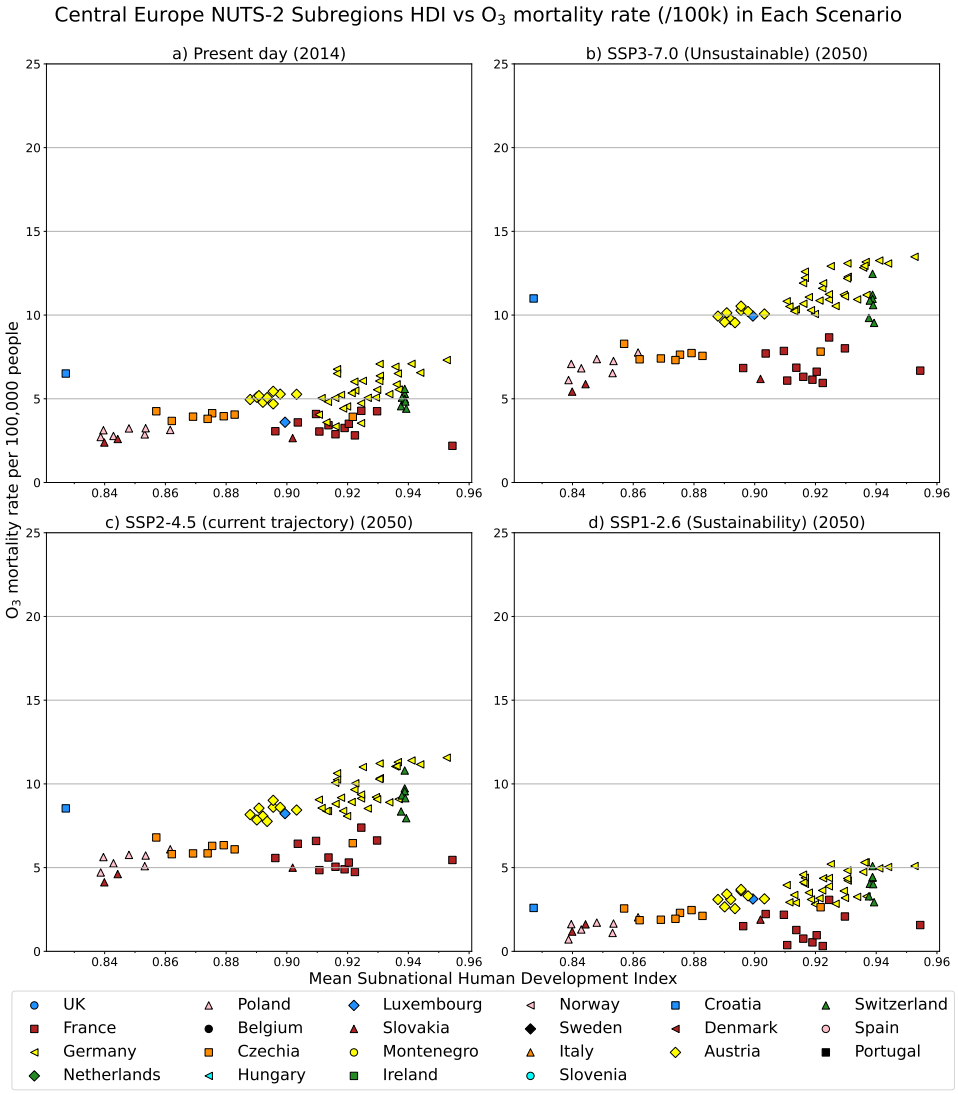


Figure A.29: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in Central European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

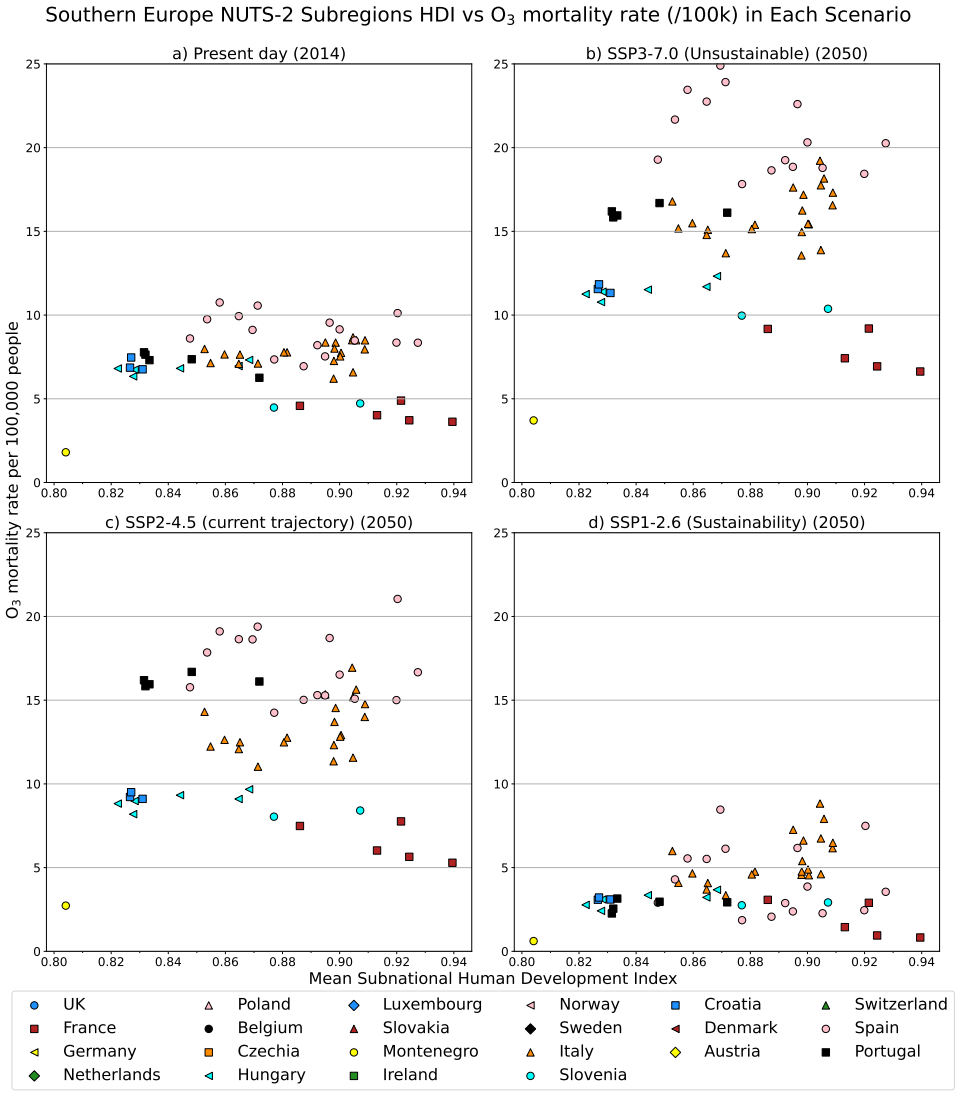


Figure A.30: Scatter plot of O_3 mortality rate (air quality deaths per 100,000 population vs mean HDI in Southern European NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

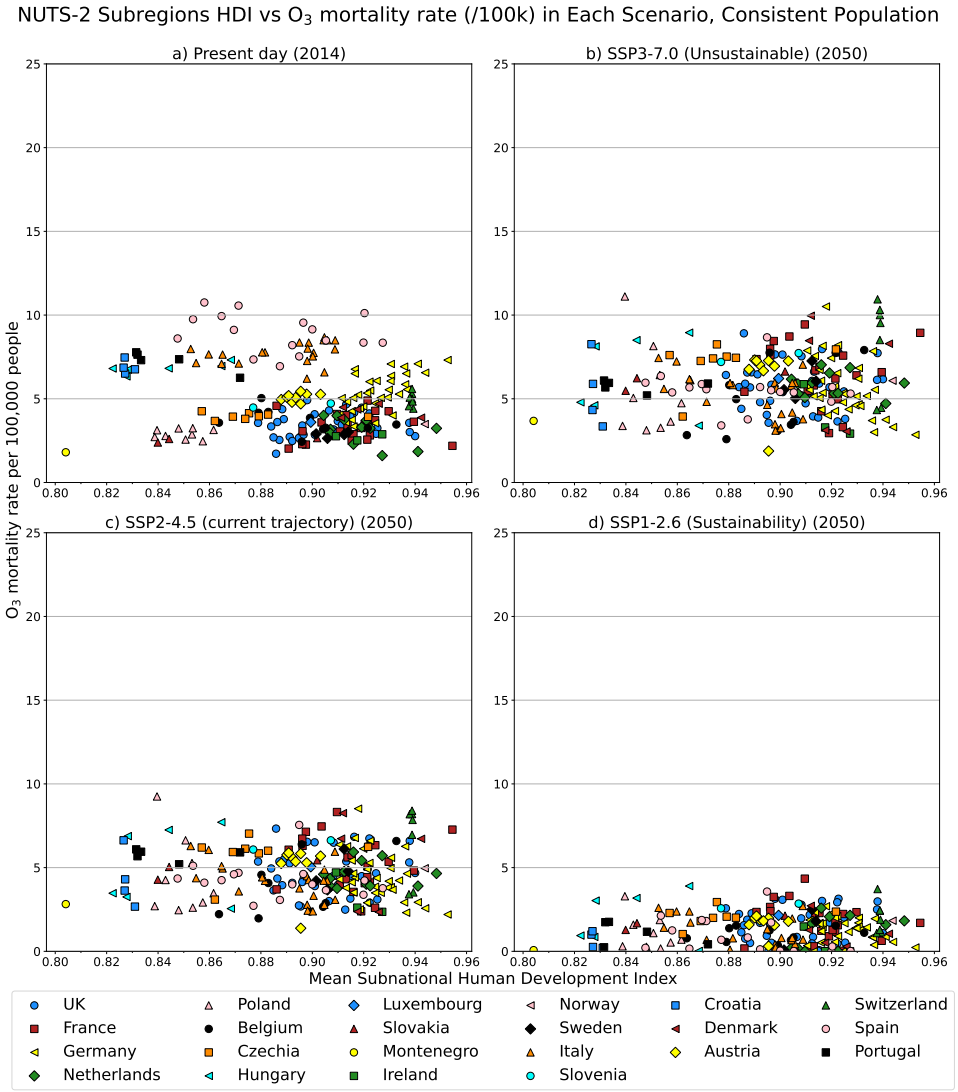


Figure A.31: Scatter plot of O_3 mortality rate when population change is not factored into the exposure-response function (air quality deaths per 100,000 population vs mean HDI in NUTS 2 subregions in a) the present day b)SSP1-2.6 2050, c)SSP2-4.5 2050 and d) SSP3-7.0. Each point on the plot is colour-coded by the Country the subregion is in.

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