# Significant human health co-benefits of African emissions mitigation

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**Abstract.** Future African aerosol emissions, and therefore air pollution levels and health outcomes, are uncertain and understudied. Understanding the future health impacts of pollutant emissions from this region is crucial. Here, this research gap is addressed by studying the range in the future health impacts of ~~African~~aerosol emissions from Africa in the Shared Socioeconomic Pathway (SSP) scenarios ~~is studied~~, using the UK Earth System Model version 1 (UKESM1) along with human health concentration-response functions. The effects of Africa following a high-pollution aerosol pathway are studied relative to a low-pollution control, with experiments varying aerosol emissions from industry and biomass-burning. Using present-day demographics, annual deaths within Africa attributable to ambient particulate matter are estimated to be lower by 150,000 ($5^{th}$ – $95^{th}$ CI: 67,000 – 234,000) under stronger African aerosol mitigation by 2090, while those attributable to $O_3$ are lower by 15,000 ($5^{th}$ – $95^{th}$ CI: 9,000 – 21,000). The particulate matter health benefits are realised predominantly within Africa, with the $O_3$-driven benefits being more widespread – though still concentrated in Africa – due to the longer atmospheric lifetime of $O_3$. These results demonstrate the important health co-benefits from future emissions mitigation in Africa.

## 1 Introduction

Anthropogenic emissions of aerosols, their precursors, and reactive gases have substantial impacts on the climate. These impacts include a general aerosol cooling and, to a lesser extent, warming due to tropospheric $O_3$ (Thornhill et al., 2021; Smith et al., 2020), as well as shifts in circulation patterns such as monsoons (Kasoar et al., 2018; Shawki et al., 2018; Wang et al., 2016; Liu et al., 2018). In addition to their climate effect, aerosols contribute to fine particulate matter air pollution, termed $PM_{2.5}$ to denote particles with diameters less than 2.5µm (Turnock et al., 2020). Reactive gases also modify concentrations of $O_3$, another important climate forcer and air pollutant (von Schneidemesser et al., 2015). Due to their relatively short lifetimes, the effects of aerosols on the climate and human health depends on their emission location (Persad and Caldeira, 2018), with the health impact being particularly localised (Shindell et al., 2018). Since these species are co-emitted with greenhouse gas emissions, general climate change mitigation policies can lead to health co-benefits via reduced air pollution (Shindell et al., 2018).

GlobalThe continent of Africa features a complex mix of air pollutant sources, both natural – such as dust from e.g. the Sahara – and anthropogenic, with continent-specific complexities such as imported second-hand high-emission vehicles (Abera et al., 2021).  There is a broad range of possible future African pollutant emissions pathways (Abera et al., 2021), some of which involve drastic increases in pollutants in key regions (Turnock et al., 2020). Recent and likely future dynamics of urbanisation can also be expected to drive enhanced exposure to air pollutants (Abera et al., 2021; Katoto et al., 2019). Reducing air pollution impacts in developing countries is a key component of the Sustainable Development Goals (Coker and Kizito, 2018).

The wide range of potential future African air pollutant emissions suggests concurrently disparate possible air pollution impacts over the continent. Despite this, studies assessing the human health impact of air pollution over Africa are sparse, especially those focused on outdoor air pollution (Abera et al., 2021), inhibiting the creation of appropriate concentration-response functions (CRFs) (Chen and Hoek, 2020 , Abera et al., 2021; Katoto et al., 2019; Coker and Kizito, 2018). Observational data of air pollution in Africa is sparse (Coker and Kizito, 2018), with issues on data availability (Pinder et al., 2019) and structural barriers to reliable data collection (Pinder et al., 2019; Katoto et al., 2019). Strong intra-regional disparities in research persist, with two reviews finding over half of all studies measuring outdoor air pollution impacts in sub-Saharan Africa focusing on a single country (South Africa), and large areas entirely unstudied (Katoto et al., 2019; Coker and Kizito, 2018).

This study, while recognising the inadequacy of extant exposure research to effectively assess the effect of air pollutants in Africa, utilises recent CRFs (e.g. (Burnett et al., 2018; GBD 2019 Risk Factors Collaborators, 2020)), which incorporated high air pollution cohort studies from the Global South. This allows for a more accurate investigation of the effect of air pollution on human health in Africa than previously possible.

Global annual average PM$_{2.5}$ concentrations have increased 15-20% since the pre-industrial era to $6.9 \pm 1.5$ µg m$^{-3}$ (Turnock et al., 2020) , and are thought to still be slightly increasing in recent decades by 0.2% yr$^{-1}$, particularly over Asia and southern Africa (Gliß et al., 2021). The average concentration experienced by humans is much higher than this global average due to the co-location of anthropogenic sources with population centres; 69% of people are estimated to be exposed to PM$_{2.5}$ concentrations higher than 10 µg m$^{-3}$ (Lelieveld et al., 2013), with an average population-weighted PM$_{2.5}$ exposure of 38 µg m$^{-3}$, reducing to just 11 µg m$^{-3}$ when excluding fossil fuel emissions (Vohra et al., 2021). The World Health Organisation recommends limiting long-term exposure to less than 5 µg m$^{-3}$ (World Health Organisation, 2021), lowered in 2021 from their previous threshold of 10 µg m$^{-3}$, though there is no known safe level of PM$_{2.5}$ concentrations (Silva et al., 2013). Present-day human health impacts of PM$_{2.5}$ are substantial but uncertain, with estimates varying from 2.37 (1.33 – 2.93) million deaths yr$^{-1}$ (Partanen et al., 2018) to the more recent finding of 8.7 (-1.8 – 14.0) million deaths yr$^{-1}$ (Vohra et al., 2021). In other studies, 3.61 (2.96-4.21) million deaths yr$^{-1}$ have been attributed to fossil-fuel PM$_{2.5}$ alone (Lelieveld et al., 2019), and the Global

Burden of Disease 2019 (hereafter: GBD2019) estimated $PM_{2.5}$-attributable deaths to be 4.14 (3.55 – 4.80) million deaths $yr^{-1}$ (GBD 2019 Risk Factors Collaborators, 2020).

70  Anthropogenic activity has also increased annual average surface concentrations of $O_3$, by 11.7ppb to the present-day levels of 29.9ppb (Turnock et al., 2020). $O_3$'s lifetime is longer than that of $PM_{2.5}$, but its effects are still strongly co-located with anthropogenic activity, with a population-weighted maximum 6-month average 1-hr daily maximum concentration of around 57ppb (Anenberg et al., 2010). Impacts of $O_3$ on premature mortality have been estimated to be 0.7 ± 0.3 million deaths $yr^{-1}$ (Anenberg et al., 2010) and 0.38 (0.12 – 0.73) million deaths $yr^{-1}$ (Silva et al., 2016), using the same concentration-response

75  functions (CRFs) (Jerrett et al., 2009). Using more recent CRFs (Turner et al., 2016) 0.6 ± 0.1 million deaths $yr^{-1}$ were attributed to $O_3$-linked respiratory causes (Shindell et al., 2018), and GBD2019 attributed 0.365 (0.175-0.504) million deaths $yr^{-1}$ to $O_3$, purely from Chronic Obstructive Pulmonary Disease (COPD) (GBD 2019 Risk Factors Collaborators, 2020). Note that $O_3$ concentrations presented in this study are annual average of the daily maximum 8-hour mean concentration, to be consistent with the CRFs used.

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Future impacts of air pollutants will depend on both emissions and demographic changes. The reduced air pollution from measures targeting the direct lowering of carbon emissions rather than relying on negative emissions technologies would prevent 93 ± 41 million deaths from $PM_{2.5}$ and 60 ± 18 million deaths from $O_3$ over the 21st century (Shindell et al., 2018). Measures compatible with 2oC2°C warming are projected to reduce life-years lost due to $PM_{2.5}$ by 0.7 million yr $yr^{-1}$ in Europe

85  by 2050 compared to a business-as-usual scenario, despite population increases (Schucht et al., 2015). Air pollutant emissions decrease into the future in all the CMIP5-era Representative Concentration Pathway (RCP) scenarios, with reduced future air pollution-linked mortality (Silva et al., 2016). However, the range in aerosol emissions between the different RCP scenarios is far smaller than that covered by the newer Shared Socioeconomic Pathways (SSPs)(Gidden et al., 2019), which extend the RCP framework to include different socioeconomic and demographic trends, and are projected to have substantially different

90  air pollution impacts on human health (Im et al., 2023). Thus, the future range of possible human health impacts of air pollution is larger under more recent, less explored, scenarios.

Several previous studies have investigated the human health impacts of changes in global emissions, but predominantly consider the global response. The effect of the newer SSPs on human health has also yet to be studied in detail, with the latest

95  CRFs. The continent of Africa features a complex mix of air pollutant sources, both natural and anthropogenic, with a broad range in future emissions pathways, some of which involve drastic increases in pollutants in key regions(Turnock et al., 2020). The wide range in potential future African air pollutant emissions suggests concurrently disparate possible air pollution impacts over the continent. Despite this, Africa has been historically understudied, especially in exposure-response cohort studies(Chen and Hoek, 2020). Nevertheless, the recent inclusion of high air pollution cohort studies from the Global South in recent CRFs

100 (e.g. (Burnett et al., 2018; GBD 2019 Risk Factors Collaborators, 2020)), allows for a more accurate investigation of the effect of air pollution on human health in Africa than previously possible with the latest CRFs.

The current study investigates the potential future impacts of African emissions on air pollution, both within and beyond the continent. A strong mitigation control scenario (Shared Socioeconomic Pathway SSP119; see Section 2 and Figure S1) is
105 compared to three experiments with a subset of African aerosol and reactive gas emissions substituted for those from a weak mitigation scenario (SSP370). These three experiments use in turn emissions of aerosol and reactive gas from the weak mitigation scenario from three different sources: biomass burning (BB), non-BB, and all sources. The experiments are named for the emissions which are substituted from SSP370, and are thus termed AerBB, AerNonBB, and AerAll respectively. AerNonBB features higher African non-BB emissions than the control, while BB emissions from Africa in AerBB are
110 relatively reduced (Figure S1). N.B. the terminology non-BB is used in this paper to refer to the non-biomass burning emissions themselves (i.e. those from fossil fuels and biofuels), which are changed in both AerAll and AerNonBB, and so the effects of changed non-BB emissions are found under both experiments. BB similarly refers to biomass burning emissions, changed in both AerAll and AerBB. NonBB emissions are purely anthropogenic, while those from biomass burning are complexly related to human activity, particularly over Africa (Bauer et al., 2019), driving the counterintuitive increase in BB emissions in the
115 stronger mitigation scenario. The UK Earth System Model 1 (UKESM1) is used to simulate the climate response to each emissions scenario. Ten control experiments are used, identical in their emissions but driven with different initial conditions to explore the internal variability (see Section 2); seven realisations of each of the three additional scenarios are simulated. The current study addresses these gaps using the SSPs to investigate the potential future impacts of African emissions on air pollution, both within and beyond the continent. Using the UK Earth System Model version 1 (UKESM1), a strong mitigation
120 scenario was compared to three alternative emissions scenarios, each substituting a subset of pollutant emissions over Africa for a weak mitigation equivalent.
Pollutant concentrations are not bias-corrected here, in order to determine the specific estimation in UKESM1 and due to the sparse observations over Africa. The focus is therefore on the relative impact of the scenarios, while also contextualising the magnitudes in relation to prior studies.
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The control scenario thus depicts a global future with strong climate mitigation policies, leading to relatively low greenhouse gas emissions and consequently low air pollutant levels. Each of the alternative scenarios represents a future in which Africa instead follows a weak mitigation scenario in its emissions of air pollutant precursors, allowing for an exploration of the health impacts of such a range in future trajectories. Present-day population and
130 baseline mortality rates are used throughout, to isolate the effect of changing air pollutants (see Section 2).

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## 2 Methods

### 2.1 Earth System Model and Experiments

This study uses the UK Earth System Model version 1 (UKESM1), a fully-coupled global climate model used in the CMIP6
model intercomparison exercise. UKESM1 couples the ocean module NEMO to its atmospheric module GA7.1 and the land
module GL7, with further couplings to earth system components such as the biogeochemical scheme (Sellar et al., 2019). Its
horizontal resolution is $1.875° \times 1.25°$, with 85 vertical levels. The atmospheric scheme features interactive chemistry, with
291 reactions and 84 species (Archibald et al., 2020). This is coupled to the GLOMAP-mode aerosol scheme, which simulates
the concentrations of Black Carbon (BC), Organic Carbon (OC), Sulfate, sea salt, Primary Marine Organic Aerosol (PMOA),
and Secondary Organic Aerosol (SOA) in five lognormal modes, four soluble and one insoluble (Bellouin et al., 2013; Mulcahy
et al., 2020). GLOMAP-mode is a 2-moment scheme, calculating both aerosol mass and number concentration, allowing
different processes to impact these independently; it simulates both aerosol direct and indirect effects (Mann et al., 2010),
with broader semi-direct effects enabled via the coupling to the dynamical atmosphere. Dust is treated separately within
UKESM1 via the older 1-moment (mass only) CLASSIC scheme (Bellouin et al., 2011).

UKESM1's representation of surface $PM_{2.5}$ and $O_3$ has been evaluated in relation to observations and other models (Turnock
et al., 2020) (in particular, Figures 3-8 in (Turnock et al., 2020)). In areas that are well-sampled with surface $PM_{2.5}$
measurements, UKESM1 is consistent with other CMIP6 models, exhibiting a low-bias in $PM_{2.5}$ in Eastern Europe and North
America by around 2-10µg m$^{-3}$. Over oceans $PM_{2.5}$ is also systematically low, but the picture over other land areas is mixed,
compared to MERRA reanalysis. In the multi-model mean, $PM_{2.5}$ concentrations over Northwest Africa are too low (Turnock
et al., 2020), while those over East and Southern Africa are too high, by around 2-15 µg m$^{-3}$ between models. Concentrations
over Asia are also generally too high, with all bias patterns roughly similar between DJF and JJA. UKESM1 is typical in its
$PM_{2.5}$ bias across most regions, including northern Africa. In Sub-Saharan Africa, however, it exhibits a stronger seasonal
cycle than other models, with the main biomass burning seasons featuring substantially higher $PM_{2.5}$ concentrations than other
models and the observational best estimate. Simulated $PM_{2.5}$ concentrations are up to 50% higher than the multi-model and
observational means in July and January, though they still lie close to the wide observational range. The areas of high biases
in CMIP6 are areas with high background $PM_{2.5}$ and large ranges in simulated concentrations across CMIP6, with inter-model
standard deviations of over 20µg m$^{-3}$ in the most polluted areas of northern and central Africa.

CMIP6 models generally exhibit high-biases in surface $O_3$, overestimating North American, European, and East Asian
concentrations by around 10ppb in DJF and JJA compared to surface observations (Turnock et al., 2020). UKESM1 has typical
biases in JJA (i.e. high), but overestimates the amplitude of the seasonal cycle becoming the only one of five CMIP6 models
studied by (Turnock et al., 2020) to exhibit a low bias over Northern Hemispheric land. As for $PM_{2.5}$, the areas with the largest

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concentrations and inter-model standard deviations are the high emissions regions in Africa and Asia. UKESM1's
representation of $O_3$ over Sub-Saharan Africa is much closer to the multi-model mean; the lack of local surface observations
precludes a full evaluation, though the sole observational station in South Africa closely tracks the models' regional averages
(Figure 4 in (Turnock et al., 2020)).

Aerosol Optical Depth (AOD) in UKESM1 is consistent with satellite observations in low-AOD areas, but is low-biased over
some areas with strong aerosol emissions such as West Africa (Mulcahy et al., 2020).

**2.2 Experiments**

This study uses the Shared Socioeconomic Pathway (SSP) emissions trajectories to estimate the future health impact of
different African emissions pathways. The SSPs are denoted SSPx-y, with x an integer referring to one of five socioeconomic
narrative pathways, to explore different non-climate societal evolutions, and y denoting the top-of-atmosphere (TOA) radiative
forcing in 2100 under a particular mitigation scenario (O'Neill et al., 2017). The SSPs therefore explore a range of future
possible trajectories covering both socioeconomic and mitigation trends. This project uses SSP119 as a control scenario.
Designed to be roughly consistent with strong mitigation under the Paris agreement, this follows socioeconomic trajectory 1 –
"sustainability" (van Vuuren et al., 2017) – along with broad emissions reductions to approximately reach 1.9 W m$^{-2}$ radiative
forcing in 2100. To test the effect of weaker mitigation in Africa for different sets of emissions, three experiments are
simulated, switching out the SSP119 aerosol and reactive gases emissions over Africa for their SSP370 equivalent. SSP370
follows the socioeconomic trends in narrative 3 – "regional rivalry" (Fujimori et al., 2017) – coupled with weak mitigation,
leading to a TOA radiative forcing of 7 W m$^{-2}$ in 2100. The three experiments performed are named after the SSP370 emissions
subset which is substituted over Africa, and are; the full set of experiments is:

AerAll
AerNonBB
AerBB
Control: SSP119 globally
AerAll: Control, with African aerosol emissions from SSP370
AerNonBB: Control, with African non-biomass burning aerosol emissions from SSP370
AerBB: Control, with African biomass burning aerosol emissions from SSP370

AerAll indicates that all aerosol and reactive gas emissions over Africa are substituted with SSP370, while emissions over all
other areas, and for other climate forcers such as well-mixed GHGs over Africa, are kept at their SSP119 values as in the
control. AerBB then switches out just the biomass-burning (BB) components of aerosols and reactive gases, and AerNonBB
changes only the non-BB emissions (i.e. fossil fuel and biofuel) over Africa. N.B. the terminology non-BB is used in this paper

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to refer to the non-biomass burning emissions themselves (i.e. those from fossil fuels and biofuels), which are changed in both AerAll and AerNonBB, and so the effects of changed non-BB emissions are found under both experiments. BB similarly refers to biomass burning emissions, changed in both AerAll and AerBB. NonBB emissions are purely anthropogenic, while those from biomass burning are complexly related to human activity, particularly over Africa (Bauer et al., 2019), driving the counterintuitive increase in BB emissions in the stronger mitigation scenario. Pollutant concentrations are not bias-corrected here, in order to determine the specific estimation in UKESM1 and due to the sparse observations over Africa. The focus is therefore on the relative impact of the scenarios, while also contextualising the magnitudes in relation to prior studies.

The control scenario thus depicts a global future with strong climate mitigation policies, leading to relatively low greenhouse gas emissions and consequently low air pollutant levels. Each of the alternative scenarios represents a future in which Africa instead follows a more "pessimistic" scenario in its emissions of air pollutant precursors, allowing for an exploration of the health impacts of such a range in future trajectories.

The aerosol emissions changed are BC and OC, and the reactive gases are $C_2H_6$, $C_3H_8$, CO, dimethyl sulfide (DMS), HCHO, $Me_2CO$, MeCHO, $NH_3$, NO, lumped non-methane volatile organic compounds (NVOC), and $SO_2$. In UKESM1, all these emissions species have both BB and non-BB components except for $SO_2$, which has only a non-BB component. All are emitted from the surface except a subset of BB BC and OC representing large fires, which are injected vertically uniformly from the surface to 3km, and aircraft NO emissions which are injected in a 3D grid. It should be noted that, since the aerosol and $O_3$ precursors are co-emitted with greenhouse gases, these scenarios changing emissions subsets are not realistic future scenarios. Instead, the purpose is to investigate the range of plausible human health impacts between scenarios, which are driven by the species altered in these experiments.

Multiple ensemble members were simulated for each experiment, each initiated in 2015 with slightly different atmospheric and ocean conditions to explore the internal climate variability. Ten ensemble members of SSP119 are used for the control – five simulated for this study and five taken from the UKESM1 CMIP6 experiments, and seven of each of the other experiments are simulated. All simulations run the length of the SSP scenarios, i.e. 2015-2100. The analysis of the health impacts here focuses on the effects in 2090. For the $O_3$ impacts, the five UKESM1 CMIP6 control members didn't output the concentrations hourly, so only the five control experiments simulated for this project were used for the control concentrations. The local and remote climate impacts of these emissions scenarios, plus additional scenarios changing $CO_2$ emissions similarly, are explored in a separate paper(Wells et al., 2023).

Figure S1 indicates the time evolution of the aerosol and $SO_2$ emissions over Africa and globally in the control (black) and experiments (red), with total and BB carbonaceous aerosol shown. Also shown is maps of the emissions differences for carbonaceous aerosol and $SO_2$. Total carbonaceous aerosol emissions over Africa decline quickly in the SSP119 control,

consistent with general emissions mitigation, whereas they remain roughly flat in SSP370. This acts to dampen the general global decrease in emissions, though they still almost halve at the global level through the 21st century as the rest of the world follows SSP119. The BB emissions subset, however, shows the opposite (and weaker) trend, with emissions remaining
235 approximately constant in SSP119 but declining in SSP370, while global emissions decline in each case. This is inconsistent with the general emissions reductions in SSP119, and is reflective of the more complex link between anthropogenic activity and BB emissions than between human actions and non-BB emissions. Different IAMs were used to produce the emissions pathways for the different scenarios (IMAGE for SSP1 and AIM/GCE for SSP3 (Fujimori et al., 2017; van Vuuren et al., 2017)); this makes a clear understanding of the differences between complex emissions sources difficult, but it likely relates
240 to different land-use activity in the scenarios. Non-BB emissions still dominate the carbonaceous aerosol emissions change, as indicated by the larger overall carbonaceous emissions in SSP370 than SSP119 over Africa. The $SO_2$ emissions change features a complex pattern, with higher emissions across most of the continent in SSP370 than SSP119, but relatively lower over southern Africa (except South Africa). In both cases, emissions drop overall substantially, and the differing spatial changes over Africa approximately cancel ~~to drive~~, resulting in little overall emissions difference between the scenarios. As with the
245 BB aerosol changes, the specific cause of the differing trends in $SO_2$ emissions is hard to discern, though it is driven by stronger industrial $SO_2$ emissions in SSP119 (Gidden et al., 2018), indicating a projected faster industrialisation in SSP119 than SSP370 in southern Africa.

**2.~~2~~3 Health Impact Analysis**
250 Many studies utilise a common methodology to estimate the human health impact of a given concentration, or change in concentration, of pollutants (e.g. (Anenberg et al., 2010; Shindell et al., 2018)). Cohort studies, tracking a large population over many years, are used to produce empirically-determined concentration-response functions (CRFs), linking background air pollutant concentrations to the change in the Relative Risk (RR) of dying from a particular Cause Of Death (COD). The RR at zero concentration is one by definition, and increases monotonically above a Low Concentration Threshold (LCT). The
255 form of RR is constrained by the fit used to derive the function. Early studies used exponential fits (Pope III et al., 2002), while others use linear relationships or power laws (Pope III et al., 2009; Ezzati et al., 2004), while more recent studies use more complex functional forms (Burnett et al., 2014, 2018).

While various cofounding factors are controlled for – such as lifestyle and income level – it is not necessarily valid to generalise
260 a RR from a single cohort to the global scale. This issue especially applies to the extrapolation of pollutant concentrations to levels outside those experienced by the cohort population. In particular, a large American Cancer Society cohort study was used to generate earlier RR curves, but the highest $PM_{2.5}$ concentrations this cohort was exposed to were less than 30 µg m$^{-3}$, lower than the global population-weighted average of 38 µg m$^{-3}$ found by (Vohra et al., 2021). This gap can be bridged using data from active smoking, but this assumes a short, high exposure burst – from smoking individual cigarettes – has the same
265 health effect as a lower, continuous background concentration (Smith and Peel, 2010; Pope III et al., 2009). More recent studies

use multiple cohort studies across a range of ambient exposures, significantly mitigating this issue (Burnett et al., 2018; GBD 2019 Risk Factors Collaborators, 2020), and rendering such CRFs more applicable to highly-polluted regions than prior estimates. At the other end of the exposure range, the assumed LCT below which the RR is one (i.e. pollutant concentrations below this have no human health effect) has decreased in consecutive studies, as cohorts in ever cleaner environments still exhibit significant effects of air pollution; there is no biological justification for a threshold, and more recent CRFs, including that used here, use a statistical distribution to represent the LCT (GBD 2019 Risk Factors Collaborators, 2020).

The "Attributable Fraction" (AF) estimates the fraction of deaths – of a particular COD – attributable to the air pollutant exposure (Mansournia and Altman, 2018):

$$AF = (RR - 1)/RR = 1 - (1/RR). \qquad (1)$$

Given a COD-specific RR curve, and common grids of surface concentrations of the pollutant (either $PM_{2.5}$ or $O_3$), baseline population (Pop), and mortality for a specific COD (y0), the number of deaths attributable to the pollutant can be estimated as

$$Deaths = y0 * Pop * AF. \qquad (2)$$

Equation 2 is applied at each gridcell to determine the estimated annual deaths within the cell.

The Concentration-Response Functions used in this study are taken from the Global Burden of Disease 2019 (hereafter: GBD2019) (GBD 2019 Risk Factors Collaborators, 2020) for $PM_{2.5}$, and from (Turner et al., 2016) for $O_3$. While studies prior to GBD2019 imposed functional forms of varying complexity on their CRFs, GBD2019 uses a Bayesian Meta-Regression method to provide the fit, with only the assumption that the CRF should be monotonic. Due to the uncertainties regarding the existence and level of safe low concentrations of $PM_{2.5}$, GBD2019 suggests the use of a uniform distribution from 2.4-5.9 µg m$^{-3}$ for the LCT, representing the lowest and the 5th percentile concentrations found in the background concentrations – this threshold is used in this study. The GBD2019 dataset provides 1000 "draws" of the fit for each COD-age pair, with no threshold; an LCT from the suggested uniform distribution was then randomly selected for each draw to complete the distribution. These 1000 draws represent the uncertainty in the CRF; the median, 5th, and 95th percentile impacts using these draws are calculated here to explore this uncertainty.

GBD2019 provides CRFs for six CODs for $PM_{2.5}$: Lung Cancer (LC), Chronic Obstructive Pulmonary Disease (COPD), Lower Respiratory Infection (LRI), Type 2 Diabetes (T2DM), Stroke, and Ischemic Heart Disease (IHD). The latter two are age-dependent, on 5-year brackets; T2DM applies only to populations over 25 years; and the other CODs are applied to the total population. The CRFs for $PM_{2.5}$ apply to annual average $PM_{2.5}$ concentrations.

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Following prior studies (Malley et al., 2017; Shindell et al., 2018; GBD 2019 Risk Factors Collaborators, 2020), the CRF for $O_3$ in this study was taken from (Turner et al., 2016) for respiratory mortality, which includes COPD, LRI, upper respiratory infections, asthma, pneumoconiosis, interstitial lung disease, pulmonary sarcoidosis, and other chronic respiratory diseases. This CRF applies to populations over 30, and applies to the annual average of the daily maximum 8-hour mean concentration.

305 An LCT of 26.7ppb, the minimum concentration found in the cohort studies used by (Turner et al., 2016) is applied here, with a sensitivity test carried out applying an LCT of 31.1ppb, representing the 5th percentile in the underlying cohort data.

This study uses the following approximation for $PM_{2.5}$:

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$$PM_{2.5} = OC + BC + SO_4 + 0.25 * SS + 0.1 * Dust. \quad (3)$$

i.e. all carbonaceous and sulfate aerosol contributes to $PM_{2.5}$, but only 25% of sea salt and 10% of dust are assumed to be less than 2.5µm in diameter. This approximation is used in AerChemMIP (Turnock et al., 2020) and other studies (e.g. (Allen et al., 2021)).

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Single years of pollutant concentrations, averaged across the ensembles, were utilised in this study – 2015, 2050, and 2090. There are several reasons for the choice to use single years rather than e.g. averaging over a decade to smooth out interannual variability. The present-day value needed to be ~~centred~~centered around 2015, the start of the scenarios, since this is where the emissions start to diverge. All simulations were initialised from 2015, so it wouldn't have been possible to use a larger window

320 to average around 2015. If data past 2015 had been used, e.g. 2015-2025 for the present day, this would have introduced other issues: since the emissions scenarios diverge from 2015, the choice of scenario to take the data from would affect the results, and this wouldn't represent the present-day in the other scenarios; in addition, the rapid decrease in emissions from 2015 in all scenarios would mean the 2015-2025 average would be significantly lower than the concentrations in 2015, and therefore not closely represent the conditions experienced by the 2015 population distributions present-day concentrations.

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Population numbers from the SSPs in 2015 – equal between scenarios since the SSPs only diverge after 2015 – were used to ensure consistency across the methodology (Lutz et al., 2018). Equation 2 is applied in each model grid-cell level, using the pollutant concentrations output from UKESM1, so the country-level population data was re-gridded to the $1.875° \times 1.25°$ UKESM1 grid. To approximately preserve present-day within-country population distributions, a high resolution ($0.25° \times$

330 $0.25°$) present-day population file was used (CIESIN, 2018), and a country name was assigned to each cell within this grid using a global shapefile (Sandvik, 2008). The present-day population distribution within each country was then scaled to create the correct total for each age-year pair, and these distributions were then re-gridded to the UKESM1 grid resolution. Baseline

mortality data for each COD-age pair was applied at the country-level (IHME, 2020), and re-gridded to the UKESM1 grid using the global shapefile.

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Present-day populations were used for the analysis for two reasons. First, to isolate the effect of changes in emissions on human health. Second, while the SSPs include population projections, they do not include future baseline mortality estimates, and present-day mortality rates cannot be assumed constant while populations and other social factors change significantly, and differently between scenarios.

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## 3 Results

### 3.1 Air Pollution Impact

Africa is a continent with a major presence of key pollutants compared to the global average, as seen in Figure S2. Based on our UKESM1 simulations, the organic carbon (OC) contribution to $PM_{2.5}$ is generally highest in the tropical biomass burning regions, peaking in Africa; this is also true for atmospheric dust. The distribution of $O_3$ is smoother than that of $PM_{2.5}$, owing to its longer lifetime, with the concentrations again being higher than average near the main emissions regions, in the low latitudes in Africa.

The changes in surface $PM_{2.5}$ and $O_3$ over Africa near the end of the century (2090) for all simulations, split into contributions from each component, are shown in Figure 1. Figure S3 shows the corresponding timeseries of simulated pollutants for Africa, its sub-region west Africa, neighbouring region Europe, as well as for the whole globe. The simulations explore the change in pollution levels in scenarios where the whole globe follows a strong mitigation pathway, while Africa follows a more "pessimistic" policy pathway in terms of its biomass burning aerosols (AerBB simulation; though as discussed in Section 2 these emissions are higher in the control), non-biomass burning aerosols (AerNonBB) and all aerosols combined (AerAll) (see Section 2). The carbonaceous aerosol increases under AerNonBB are near the main non-biomass burning emission regions, especially in West and East Africa, while reductions under AerBB are ~~centred~~centered on the biomass burning regions North and South of the Equator. AerAll then exhibits features of both. Sulfate shows weaker changes, with the North African non-BB increased emissions contrasting with the reduced emissions south of the Equator. Changes in dust are significant, with a substantial decrease in areas with high background dust emissions. This decrease in dust emissions is ultimately due to the impact of the aerosol emissions on local surface winds, which drives the emission of dust (See Figure S4 in the Supplement). $O_3$ follows a similar pattern to the $PM_{2.5}$ changes, as its concentration is modified by the reactive gases co-emitted with the anthropogenic aerosol species.
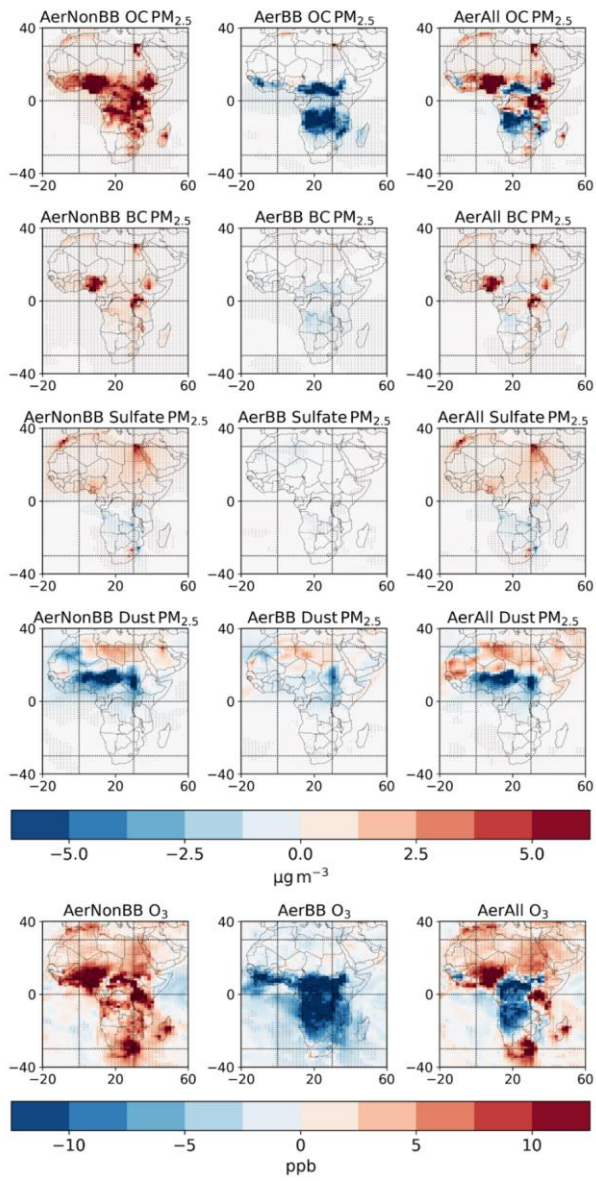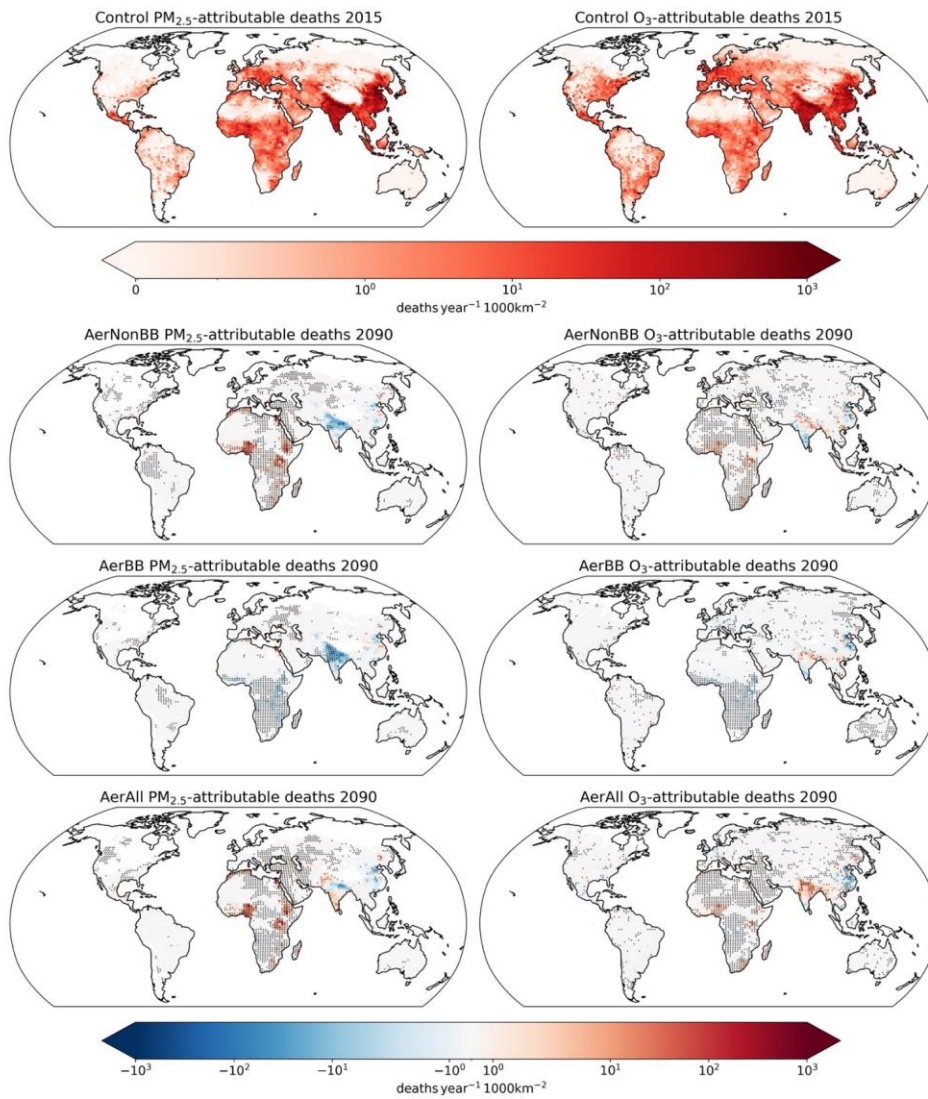
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Figure 1: The change in the organic carbon (OC), black carbon (BC), sulfate, and dust aerosol contributions to surface $PM_{2.5}$, and $O_3$, under each emissions scenario relative to the SSP119 control in 2090 over Africa. Stippling indicates areas where the ensemble mean change is greater than one intra-ensemble standard deviation away from zero.

**3.2 Health Impact**

The estimated deaths in 2015 from $PM_{2.5}$ (6 Causes of Death (CODs), see Section 2) and $O_3$ (respiratory illnesses only) per $1000km^2$ are shown in the top row of Figure 2. Table 1 indicates global and regional totals. The control SSP119 experiment is used for the air pollutant concentrations in 2015, an arbitrary choice as the SSP emissions diverge only after this year.

Globally, 2.76 (2.11 – 3.48) million annual deaths are attributed to $PM_{2.5}$, with Ischemic Heart Disease (IHD) the largest COD followed by Stroke, and 2.28 (1.73 – 2.70) million to $O_3$. Deaths are highest in areas where population densities and pollutant concentrations are high: in East and South Asia, and in tropical Africa. The highest number of deaths attributable to $PM_{2.5}$ and $O_3$ exposure occur in Asia; Africa experiences large impacts too – 12% and 7.4% of the global total for $PM_{2.5}$ and $O_3$ respectively.

Control PM$_{2.5}$-attributable deaths 2015 · Control O$_3$-attributable deaths 2015 · AerNonBB PM$_{2.5}$-attributable deaths 2090 · AerNonBB O$_3$-attributable deaths 2090 · AerBB PM$_{2.5}$-attributable deaths 2090 · AerBB O$_3$-attributable deaths 2090 · AerAll PM$_{2.5}$-attributable deaths 2090 · AerAll O$_3$-attributable deaths 2090

deaths year$^{-1}$ 1000km$^{-2}$

380

14

The methodology of this study is not directly comparable to comprehensive estimates of the present-day impact of air pollution, since only one model with no bias correction is used here; the focus of the analysis is on the differences between scenarios instead. However, the magnitude of the estimated impacts can be contextualised against prior studies to explore the effect of these methodological differences. Our estimate for total present-day $PM_{2.5}$-related deaths is generally lower than prior studies; its central estimate is lower than some (Lelieveld et al., 2019; Vohra et al., 2021; IHME, 2020; Im et al., 2023; Bauer et al., 2019), and higher than at least one other(Partanen et al., 2018). GBD2019 found higher impacts than those found here, using the same CRFs but different $PM_{2.5}$ concentrations, and also including neonatal deaths (IHME, 2020). The number of present-day respiratory deaths attributed here to $O_3$ exposure is generally higher than found in previous studies, e.g. (Anenberg et al., 2010; Silva et al., 2016) which both used an earlier, smaller CRF (Jerrett et al., 2009) than that used here. Studies utilising the CRFs used in this study (Turner et al., 2016) also find lower numbers of deaths than estimated here (Shindell et al., 2018; GBD 2019 Risk Factors Collaborators, 2020; Malley et al., 2017), likely due to higher $O_3$ concentrations in UKESM1 (see Section 2).

The uncertainty in deaths due to the CRF (Table 1) is far larger than that from intra-ensemble pollutant variations for both $PM_{2.5}$ and $O_3$, consistent with prior studies determining the CRF to be the largest source of uncertainty (Turnock et al., 2016; Johnston et al., 2012; Li et al., 2016; Shindell et al., 2018).
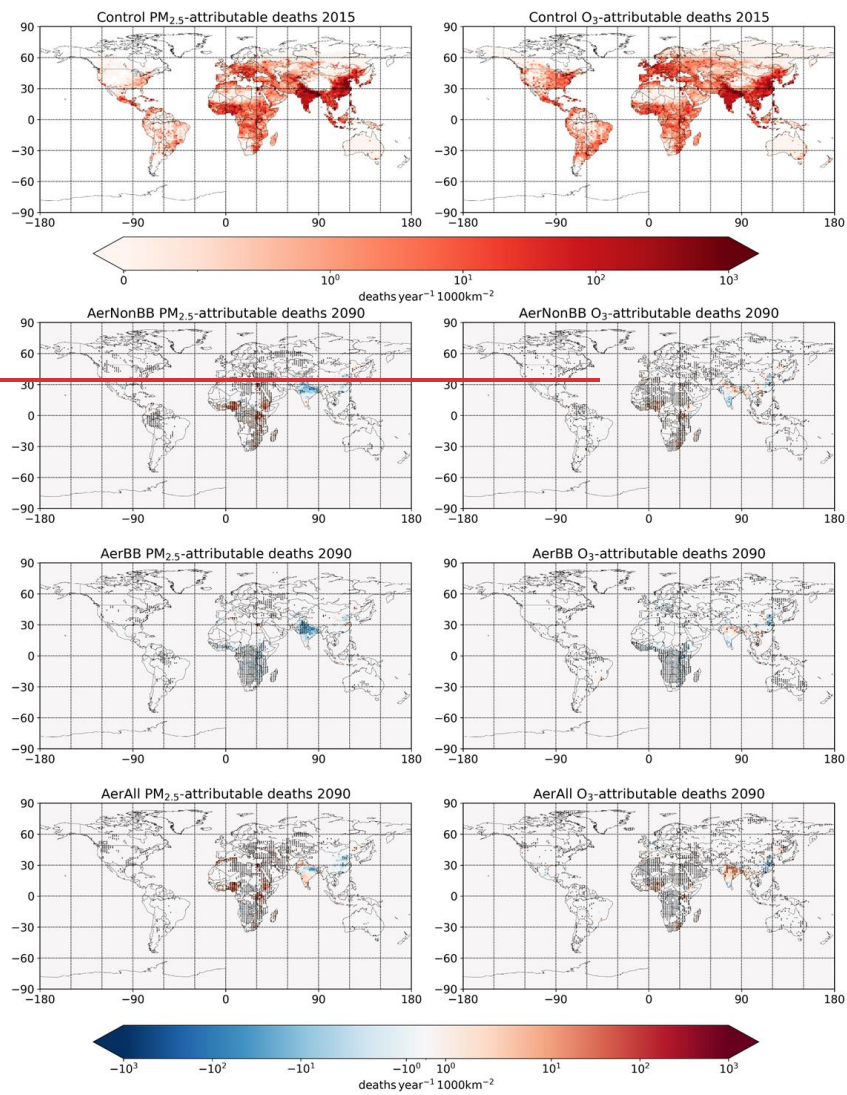
Figure 2: Top row: annual deaths per 1000km$^2$ attributable to air pollution for all CODs for PM$_{2.5}$ and respiratory illnesses for O$_3$ in 2015. Subsequent rows: impact of each scenario on 2090 deaths per 1000km$^2$ attributable to PM$_{2.5}$ and O$_3$ exposure relative to the SSP119 control, using 2015 spatial and age-based population distributions. Stippling indicates areas where the change is greater than one intra-ensemble standard deviation away from zero.

| Species | Region | COD | ~~Mean~~Middle RR (thousand deaths/yr) | Low RR (thousand deaths/yr) | High RR (thousand deaths/yr) |
|---|---|---|---|---|---|
| PM$_{2.5}$ | Global | All | 2760 ± 30 | 2110 ± 30 | 3480 ± 30 |
| | | COPD | 310 ± 4 | 245 ± 4 | 377 ± 4 |
| | | IHD | 920 ± 10 | 697 ± 9 | 1190 ± 10 |
| | | LC | 196 ± 3 | 148 ± 3 | 247 ± 3 |
| | | Stroke | 870 ± 10 | 690 ± 10 | 1060 ± 10 |
| | | T2DM | 197 ± 1 | 145 ± 1 | 254 ± 1 |
| | | LRI | 264 ± 6 | 184 ± 5 | 361 ± 8 |
| PM$_{2.5}$ | Africa | All | 340 ± 10 | 250 ± 10 | 430 ± 10 |
| | Europe | | 58 ± 6 | 22 ± 3 | 111 ± 9 |
| | Asia | | 2180 ± 30 | 1730 ± 20 | 2660 ± 30 |
| | ~~Central~~ West Africa | | 12~~1~~43 ± 92 | 9~~3~~33 ± 28 | 15~~0~~54 ± 102 |
| O$_3$ | Global | Resp | 2280 ± 30 | 1730 ± 30 | 2700 ± 30 |
| | Global 31.1ppb | | 2160 ± 30 | 1630 ± 30 | 2570 ± 40 |
| | Africa | | 169 ± 3 | 125 ± 3 | 204 ± 4 |
| | Europe | | 139 ± 5 | 100 ± 3 | 172 ± 5 |
| | Asia | | 1680 ± 30 | 1290 ± 20 | 1970 ± 30 |
| | ~~Central~~ West Africa | | 46~~2~~9 ± 1 | 34~~2~~2 ± 1 | 55~~3~~4 ± 1 |

Table 1: Annual of deaths (in thousands) in 2015 attributable to PM$_{2.5}$, shown globally in total and for each COD separately, and the total across several regions (definitions in Figure S2), and those attributable to respiratory illnesses caused by O$_3$ exposure globally and in several regions. Also shown is the effect of using a Low Concentration Threshold (LCT, above which no harm is assumed; see Section 2) of 31.1ppb on global deaths for O$_3$, instead of the 26.7ppb used for the main results. Values are shown using the central CRF estimate and the 5$^{th}$ and 95$^{th}$ percentile CRF estimates~~s~~, all from GBD2019 for PM$_{2.5}$ and Turner et al. (2016) for O$_3$. The uncertainty given for each estimate is the estimated ~~5-95~~5$^{th}$ – 95$^{th}$ percentile range across the

ten control ensemble members, calculated as the standard deviation multiplied by 1.6449. The region definitions are shown in Figure S2.

The 2nd to 4th rows of Figure 2 show the effect on annual deaths per 1000 km$^2$ in 2090 of the different emissions scenarios, relative to the SSP119 control scenario, for both PM$_{2.5}$ and O$_3$. Population distributions from 2015 are used here to isolate the effect of the changed pollutants. The spatial pattern of human health impacts is broadly consistent with the emissions changes, modulated by the population distribution. AerNonBB features higher deaths across Africa than in the control, particularly in the highly populated West and East regions, due to future increases in fossil-fuel emissions. The decrease in dust emissions in the southern Sahara leads to an overall reduction in PM$_{2.5}$ ~~(and hence deaths)~~ – and therefore lower health impacts – in this region~~, indicating that~~ (See Figure S4). This indicates that the indirect effects of pollutant emissions on atmospheric circulation – and therefore natural dust emissions – can have a substantial influence on their overall impact, as also noted by e.g. (Bauer et al~~,~~ (2019) and Yang et al (2017). The lower future African biomass burning emissions in the AerBB experiment compared to the control result in significantly lower deaths across central and southern Africa. Still, the co-location of fossil fuel emissions with population centres causes these emissions to dominate the overall impact in AerAll.

Some remote impacts of the changed emissions are visible, with Southern Europe and the Middle East exhibiting consistent changes with those found in North Africa. The impact in each scenario relative to the control on global and African PM$_{2.5}$ and O$_3$ annual deaths in 2090 is shown in Table 2, and the total deaths are shown in Figure 3 over Africa and globally, with additional regions in the Supplement. Overall, Africa following SSP370 rather than SSP119 emissions leads to around 150,000 (5th – 95th CI: 67,000 – 234,000) additional annual deaths across Africa from PM$_{2.5}$, and 15,000 (5th – 95th CI: 9,000 – 21,000) from O$_3$, when the background populations are held constant ~~(1st column of Table 2).~~. In Africa, air pollutant trends are consistent with the impact changes (Figure S3). O$_3$ is projected to approximately match PM$_{2.5}$ in its health impacts by 2090 in these scenarios, due to the weaker decline in O$_3$ levels than in PM$_{2.5}$ (Figure 3). The short pollutant lifetime, coupled with internal variability, causes the impacts outside Africa to be noisier than those within the continent; note that only one year (2090) was used for the analysis, as discussed in Section 2.3.

435

| | PM$_{2.5}$ (Thousands of deaths in 2090) | | O$_3$ (Thousands of deaths in 2090) | |
|---|---|---|---|---|
| Experiment | Global | Africa | Global | Africa |
| AerNonBB | **130** | **154** | **23** | **24** |
| AerBB | **-44** | -2 | **-22** | -18 |
| AerAll | **151** | **152** | **25** | 15      440 |

Table 2: Effect of each scenario, relative to the control, in thousands of annual PM$_{2.5}$ and O$_3$ deaths in 2090 globally and just over Africa, using 2015 populations and the central CRF. Values are bolded when they are more than one intra-ensemble standard deviation away from zero. The Africa region definition is shown in Figure S2.

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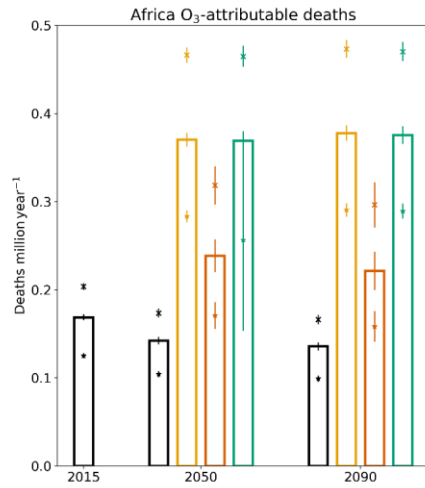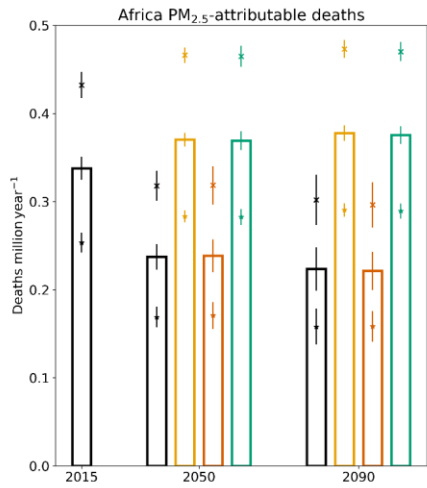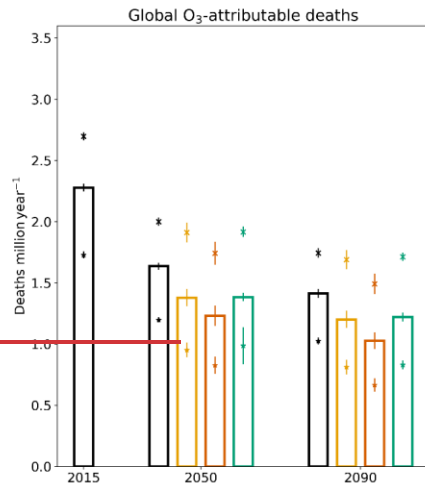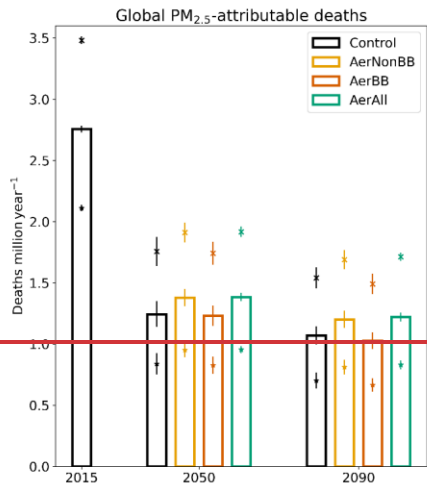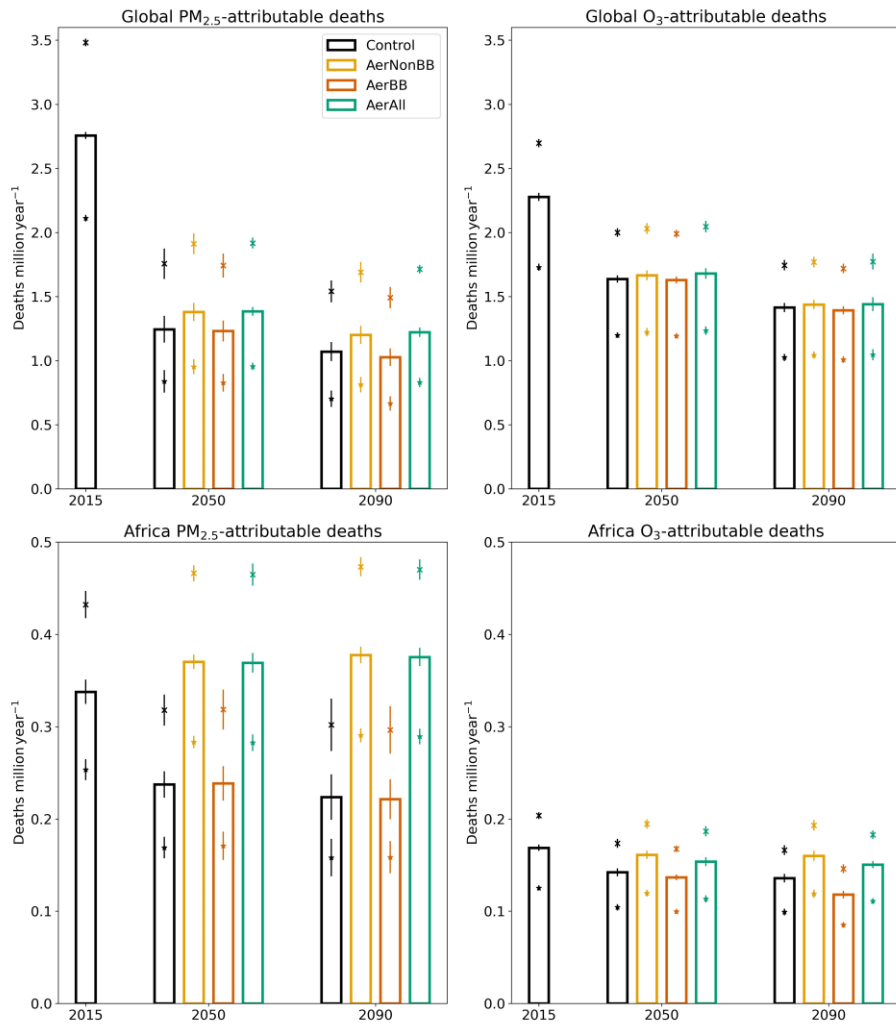
Figure 3: Annual PM$_{2.5}$- and O$_3$-attributable deaths in the control in 2015, and each scenario in 2050 and 2090, globally and over Africa, using 2015 spatial and age-based population distributions. The bars indicate the estimated deaths using the central

CRF estimates; the crosses and stars use the 95th and 5th percentile CRF values respectively. For each CRF value, the (much smaller) uncertainty due to intra-ensemble variation in pollutant concentrations is indicated with vertical error bars. This intra-ensemble variation is defined as the estimated 5 955th – 95th percentile range across the ten control ensemble members, calculated as the standard deviation multiplied by 1.6449. The Africa region definition is shown in Figure S2.

**4 Discussion and Conclusions**

This study used the Earth System Model UKESM1 to explore the range of impacts from future African pollutant emissions on air quality and premature mortality. The strong mitigation SSP119 scenario was compared to three alternative emissions scenarios, each substituting a subset of pollutant emissions over Africa for their (weak mitigation) SSP370 equivalent. Compared to SSP119, SSP370 has much higher fossil fuel and biofuel emissions, but lower African biomass burning emissions; the reasons for this are unclear and reflect methodological challenges within the SSP framework. The increase in non-biomass emissions far outweighs the decrease in biomass emissions, particularly over population centres. To evaluate the human health impacts of the future emissions, CRFs were used from the recent GBD2019 study (GBD 2019 Risk Factors Collaborators, 2020) for six CODs for $PM_{2.5}$, and (Turner et al., 2016) for $O_3$ Respiratory impacts. Estimates were calculated using present-day demographics, to isolate the effect of changes in pollutants on a given population.

The methodology of this study is not directly comparable to comprehensive estimates of the present-day impact of air pollution, since only one model with no bias correction is used here; the focus of the analysis is on the differences between scenarios instead. However, the magnitude of the estimated impacts can be contextualised against prior studies to explore the effect of these methodological differences. Our estimate for total $PM_{2.5}$-related deaths in 2015, of 2.76 (2.11 – 3.48) million, is generally lower than prior studies; its central estimate is lower than some (Lelieveld et al., 2019; Vohra et al., 2021; IHME, 2020; Im et al., 2023; Bauer et al., 2019) , and higher than at least one other (Partanen et al., 2018). GBD2019 found higher impacts than those found here, using the same CRFs but different $PM_{2.5}$ concentrations, and also including neonatal deaths. The dominance of the uncertainties in CRF over those in $PM_{2.5}$ concentrations is consistent with prior research (Shindell et al., 2018).

The number of present-day respiratory deaths attributed here to $O_3$ exposure (2.28 (1.73 – 2.70) million) is generally higher than found in previous studies, e.g. (Anenberg et al., 2010; Silva et al., 2016) which both used an earlier CRF reflecting weaker associations between $O_3$ and health impacts (Jerrett et al., 2009) than that used here. Studies utilising the CRFs used in this study (Turner et al., 2016) also find lower numbers of deaths than estimated here (Shindell et al., 2018; GBD 2019 Risk Factors Collaborators, 2020; Malley et al., 2017) , likely due to higher $O_3$ concentrations in UKESM1 (see Section 2.1), but sparse observations preclude a full evaluation. The estimated $O_3$ impacts were not very sensitive to changes in the LCT. The uncertainty In deaths due to the uncertainty within each CRF (Table 1) is far larger than that from intra-ensemble pollutant

variations for both $PM_{2.5}$ and $O_3$, consistent with prior studies determining the CRF to be the largest source of uncertainty (Turnock et al., 2016; Johnston et al., 2012; Li et al., 2016; Shindell et al., 2018).

The effect of Africa following SSP370 rather than SSP119 is estimated to result in 150,000 additional annual deaths from $PM_{2.5}$, and 15,000 from $O_3$, across Africa in 2090, when using 2015 populations. Due to the large decrease in aerosol emissions in SSP119, annual $PM_{2.5}$ deaths could be similar to those due to $O_3$ by the end of the century. However, this result may also be affected by the $O_3$ biases.

Correcting for model biases in $PM_{2.5}$ and $O_3$ concentrations in a CMIP6 model with low-biased concentrations was found to substantially affect estimated health impacts (Im et al., 2023), though this effect was strongest over high emissions regions, and dampened when using more recent non-linear CRFs. The results of the scenarios in this study should therefore be primarily interpreted relative to each other, as the substantial differences between scenarios are less affected by the model biases.

Present-day populations were used in this study to isolate the effect of changes in air pollutants alone, and because of the difficulties in projecting changes in mortality rates. Increasing and ageing future populations will lead to higher estimated deaths, and hence larger reductions in deaths upon emissions mitigation. In SSP1, the present-day African population of 1bn increases to around 1.7bn by 2070, before declining slightly; in SSP3, it increases throughout the century, reaching 4bn by 2090 (Lutz et al., 2018). Projected urbanisation (Jiang and O'Neill, 2017) will increase the co-location of population centres and emissions, increasing the human health impacts of air pollution (Silva et al., 2017). This co-location is already dampened by the coarse model grid, which reduces the estimated impacts (Li et al., 2016; Likhvar et al., 2015), an effect which will be more pronounced for $PM_{2.5}$ than for ozone (Malley et al., 2017). Prior work has found changes in populations play a comparable role to those in emissions in the SSPs (Im et al., 2023), though this estimate assumed the persistence of present-day baseline mortality rates.

Relatively higher non-BB aerosol south of the Sahara weakened the local surface circulation, reducing dust emissions sufficiently to reduce overall $PM_{2.5}$ levels (and hence deaths) in some areas, demonstrating the importance of accounting for natural aerosols and circulation impacts when estimating the impacts of emissions changes (Bauer et al., 2019; Yang et al., 2017). This effect will likely vary substantially between models, due to differing aerosol impacts and parameterisations of dust emissions.

The CRFs used in this study are generated by combining multiple cohort studies (GBD 2019 Risk Factors Collaborators, 2020). The more recent CRFs used here cover a wider range of air pollutant concentrations than those in earlier studies, but there are still limitations in the representativeness of the input data. In particular, used to generate the CRFs, stemming from structural and historic challenges in air pollution research in Africa is underrepresented in cohort studies (Chen and Hoek, 2020). (Abera

23

et al., 2021; Katoto et al., 2019; Coker and Kizito, 2018; Pinder et al., 2019). Further research characterising appropriate CRFs for use in disparate regions is essential to generate more reliable estimates of air pollution impacts. If BC has a higher toxicity (Lelieveld et al., 2015; Coker and Kizito, 2018), future air pollutant impacts per unit concentration change of $PM_{2.5}$ would be reduced as BC's share of $PM_{2.5}$ declines, and the effect of $PM_{2.5}$ mitigation therefore enhanced.

UKESM1's horizontal resolution is coarser than the relevant scales for localised air pollutants from different sources, as the distinction between rural/urban and emissions from vehicles, factories, and domestic fuel is dampened by averaging across the model gridcells. Global models are incapable of resolving these distinctions, which are of relevance for policy and behavioural considerations. Models of this resolution still clearly resolve distinctions between high and low air pollutant regions (Figure 1), and this method has been applied in many prior studies, often at coarser resolutions, to generate understandings of the global mortality impact of air pollution (Shindell et al., 2018; Lelieveld et al., 2019, 2013; Vohra et al., 2021; Silva et al., 2016; Partanen et al., 2018; Anenberg et al., 2010; Silva et al., 2017).

Pollutant concentrations from single years were used to estimate the health impacts (see Section 2). While the intra-ensemble mean was used, the variation in the concentrations manifests in large variations in the projected impacts over heavily populated regions which had no emissions change in our experiments, such as in Asia.

The effect of different future African emissions pathways on human health is large: reductions of anthropogenic African aerosol emissions through climate mitigation within the range of the SSPs can reduce annual deaths by 150,000 for $PM_{2.5}$, and 15,000 for $O_3$, compared to a more polluted pathway, using present-day demographics. These values can be expected to be larger under future increasing and ageing populations. These results are focused on 2090, but the rapid emissions drop in SSP119 suggests that significant benefits would occur much faster under such a scenario. Substantial near-term localised reductions in the impacts of air pollution could therefore be obtained as co-benefits of climate change mitigation in Africa.

**Data availability**
Reasonable requests for model output and the data used for figures in this manuscript are available from the corresponding author.

**Author contributions**
AV and CDW conceived and designed the experiments. CDW carried out the analysis with assistance from MK and ME and led the preparation of the paper. All authors provided discussion of the analysis and reviewed the paper.

**Competing interests**
The authors declare that they have no conflict of interest.

24

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765