Air pollution and associated human mortality: the role of air pollutant emissions, climate change and methane concentration increases from the preindustrial period to present

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Abstract. Increases in surface ozone (O\textsubscript{3}) and fine particulate matter (≤ 2.5 µm aerodynamic diameter, PM\textsubscript{2.5}) are associated with excess premature human mortalities. We estimate changes in surface O\textsubscript{3} and PM\textsubscript{2.5} from pre-industrial (1860) to present (2000) and the global present-day (2000) premature human mortalities associated with these changes. We extend previous work to differentiate the contribution of changes in three factors: emissions of short-lived air pollutants, climate change, and increased methane (CH\textsubscript{4}) concentrations, to air pollution levels and associated premature mortalities. We use a coupled chemistry-climate model in conjunction with global population distributions in 2000 to estimate exposure attributable to concentration changes since 1860 from each factor. Attributable mortalities are estimated using health impact functions of long-term relative risk estimates for O\textsubscript{3} and PM\textsubscript{2.5} from the epidemiology literature. We find global mean surface PM\textsubscript{2.5} and health-relevant O\textsubscript{3} (defined as the maximum 6-month mean of 1-h daily maximum O\textsubscript{3} in a year) have increased by 8 ± 0.16 µg m\textsuperscript{-3} and 30 ± 0.16 ppbv (results reported as annual average ± standard deviation of 10-yr model simulations), respectively, over this industrial period as a result of combined changes in emissions of air pollutants (EMIS), climate (CLIM) and CH\textsubscript{4} concentrations (TCH4). EMIS, CLIM and TCH4 cause global population-weighted average PM\textsubscript{2.5} (O\textsubscript{3}) to change by +7.5 ± 0.19 µg m\textsuperscript{-3} (+25 ± 0.30 ppbv), +0.4 ± 0.17 µg m\textsuperscript{-3} (+0.5 ± 0.28 ppbv), and 0.04 ± 0.24 µg m\textsuperscript{-3} (+4.3 ± 0.33 ppbv), respectively. Total global changes in PM\textsubscript{2.5} are associated with 1.5 (95% confidence interval, CI, 1.2–1.8) million cardiopulmonary mortalities and 95 (95% CI, 44–144) thousand lung cancer mortalities annually and changes in O\textsubscript{3} are associated with 375 (95% CI, 129–592) thousand respiratory mortalities annually. Most air pollution mortality is driven by changes in emissions of short-lived air pollutants and their precursors (95% and 85% of mortalities from PM\textsubscript{2.5} and O\textsubscript{3} respectively). However, changing climate and increasing CH\textsubscript{4} concentrations also contribute to premature mortality associated with air pollution globally (by up to 5% and 15%, respectively). In some regions, the contribution of climate change and increased CH\textsubscript{4} together are responsible for more than 20% of the respiratory mortality associated with O\textsubscript{3} exposure. We find the interaction between climate change and atmospheric chemistry has influenced atmospheric composition and human mortality associated with industrial air pollution. Our study highlights the benefits to air quality and human health of CH\textsubscript{4} mitigation as a component of future air pollution control policy.
1 Introduction

Human activities since preindustrial time have resulted in large increases in air pollution (IPCC, 2001). Measurements at various sites in the Northern Hemisphere indicate an increase from the 1860s to 2000s in surface ozone (O$_3$) of approximately a factor of 4 (from about 10 to 50 ppbv) (Gros, 2006; Marenco et al., 1994). Sulfate aerosol concentrations in Greenland ice cores suggest a factor of 3–4 increase from the mid-1860s to the present (Dösch et al., 1995; Fischer et al., 1998). Over the same period, European high-alpine glaciers indicate an increase in carbonaceous aerosols of a factor of 3 (Lavanchy et al., 1999), while Greenland ice cores show little change (Lamarque et al., 2010). Sulfate and carbonaceous aerosols are key components of fine particulate matter (≤2.5 µm aerodynamic diameter, PM$_{2.5}$), which, along with O$_3$, are pollutants that adversely impact human health (Bell et al., 2004; Jerrett et al., 2009; Krewski et al., 2009; Levy et al., 2005; Pope et al., 2002; Pope and Dockery, 2006). Here, we apply simulations of a global atmospheric chemistry-climate coupled model to investigate changes in O$_3$ and PM$_{2.5}$ from the preindustrial era to the present and their associated effects on premature mortality.

O$_3$ is a secondary air pollutant that is formed in the troposphere by catalytic photochemical reactions of nitrogen oxides (NO$_x$ = NO + NO$_2$) with carbon monoxide (CO), methane (CH$_4$) and other volatile organic compounds ( VOCs). PM$_{2.5}$, including sulfate, nitrate, organic carbon (OC), black carbon (BC), secondary organic aerosol (SOA), fine dust and sea salt, is either directly emitted from various sources or produced via chemical reactions between directly-emitted gas-phase precursors (including SO$_2$, NO$_x$, NH$_3$, biogenic VOCs etc.) and atmospheric oxidants (i.e., OH, H$_2$O$_2$, O$_3$). Changes in O$_3$ and PM$_{2.5}$ concentrations from the preindustrial period to the present (1860–2000) are difficult to quantify because of sparse and uncertain preindustrial measurements, spatial heterogeneity of these species, uncertainties in estimating preindustrial emissions, and the nonlinear dependence of O$_3$ and PM$_{2.5}$ on their precursor emissions (Horowitz, 2006).

Changes in surface O$_3$ and PM$_{2.5}$ concentrations are largely controlled by changes in emissions of their precursors. Consequently, many recent studies have applied chemical transport models (CTMs) to estimate changes in tropospheric O$_3$ and aerosol concentrations from the preindustrial era to the present (Grenfell et al., 2001; Horowitz, 2006; Lamarque et al., 2005; Mickley et al., 2001; Tsigaridis et al., 2006; Wang and Jacob, 1998). Anenberg et al. (2010) used preindustrial and present simulations from one of these CTM modeling studies (Horowitz, 2006) to estimate the effect of anthropogenic O$_3$ and PM$_{2.5}$ on present premature human mortality. However, these studies, which usually apply different emissions of short-lived species but use the same meteorological driver for preindustrial and present day simulations, do not take into account the interaction between climate and air pollution (Jacob and Winner, 2009; Isaksen et al., 2009; Fiore et al., 2012). Some short-lived species are radiatively active; therefore, they perturb climate and meteorology from regional to global scales (Naik et al., 2013; Levy et al., 2008; Shindell et al., 2008). As a result, quantifying the impact of their emission changes on air quality using CTM simulations driven by the same meteorology neglects the feedbacks between short-lived species and climate. Conversely, studies have shown that climate change can affect surface O$_3$ and PM$_{2.5}$ concentrations and thus indirectly affect human mortality (Bell et al., 2007; Fang et al., 2013; Tagaris et al., 2009). Additionally, CH$_4$ concentration changes (from 800 ppbv in 1860 to 1750 ppbv in 2000) not only give a direct radiative forcing of +0.42 W m$^{-2}$ (calculated as in Ramaswamy et al., 2001), but also contribute to increasing O$_3$ concentrations which indirectly changes climate (Shindell et al., 2009). To understand changes in surface O$_3$ and PM$_{2.5}$ over the industrial period (defined here as 1860–2000), we need to consider the effects of changing emissions of short-lived species, climate and CH$_4$ concentrations on surface air quality and allow feedbacks between chemistry and climate to take place.

In this paper, we utilize the Geophysical Fluid Dynamics Laboratory (GFDL) Atmospheric Model, version 3 (AM3), a newly developed global 3-D model that fully couples atmospheric chemistry and climate. Our goal is to understand changes in O$_3$ and PM$_{2.5}$ from the preindustrial era to the present (“industrial” or “historic” period) and their associated effects on premature mortality. We further attribute the changing PM$_{2.5}$ and O$_3$ concentrations over this period to three factors: (1) changes in direct emissions of their constituents and precursors; (2) climate change induced changes in surface concentrations, and (3) the influence of increasing CH$_4$ concentrations on tropospheric chemistry. For each factor, we estimate the associated impact on human health. The GFDL AM3 model and our simulations are described in Sect. 2. We evaluate simulated surface O$_3$ and PM$_{2.5}$ concentrations in Sect. 3. Changes in surface air quality are attributed to specific factors in Sect. 4. In Sect. 5, we calculate the changes in premature mortality associated with the simulated changes in air quality. Findings and conclusions are presented in Sect. 6.

2 Methods

2.1 Model description

The AM3 model (Donner et al., 2011) is the atmospheric component of the GFDL atmosphere-ocean coupled climate model CM3. AM3 is designed to address key emerging issues in climate science, including aerosol-cloud interactions and chemistry-climate feedbacks. It is GFDL’s first global atmospheric model to include the indirect effects of cloud-aerosol interactions (with 16 interactive aerosol species) and
Table 1. Model simulation configurations. All simulations are run for 11 yr with the first year used for spin-up (SST: sea surface temperature; SIC: sea ice; WMGG: well-mixed greenhouse gases; ODS: ozone-depleting substances).

<table>
<thead>
<tr>
<th>Simulations</th>
<th>SST and SIC</th>
<th>WMGG</th>
<th>ODS</th>
<th>CH$_4$ (tropospheric chemistry)</th>
<th>Anthropogenic and biomass burning emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 1860$^b$</td>
<td>1860</td>
<td>1860</td>
<td>1860</td>
<td>1860</td>
<td>1860</td>
</tr>
<tr>
<td>5 1860ALL2000EM</td>
<td>1860</td>
<td>1860</td>
<td>1860</td>
<td>1860</td>
<td>2000</td>
</tr>
</tbody>
</table>

$^a$ The concentrations of ODS in the 1860 simulation are set to pre-1950 levels.

$^b$ Simulations run for the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP).

2.2 Simulations

To investigate the change in concentrations of O$_3$ and PM$_{2.5}$ (including simulated sulfate, nitrate, small dust, small sea salt, OC, BC, SOA) during the industrial period, we use AM3 time-slice simulations for “1860” and “2000”. Results from these simulations were contributed to the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP) (Lamarque et al., 2012). We also analyze three additional sensitivity simulations. The five simulations used are summarized in Table 1 and described briefly below.

We use the “1860” and “2000” simulations to quantify the change in air quality during the industrial period. These simulations use prescribed mean climatological sea surface temperature (SST) and sea ice cover (SIC) for the decade 1860–1869 and 1995–2004, respectively, taken from one member of the 5-member ensemble historical simulation of the GFDL CM3 model conducted in support of the Intergovernmental Panel on Climate Change-Fifth Assessment Report (IPCC-AR5). Well-mixed greenhouse gases (WMGG), including CO$_2$, N$_2$O, CH$_4$ and CFCs, are specified for the years 1860 and 2000 according to the database (http://www.iiasa.ac.at/webapps/IntRcpDb/dsd?Actionhtmlpage\&page=welcome) developed in support of the IPCC-AR5 (Meinshausen et al., 2011). Global mean CH$_4$ concentration is specified at the surface at 1860 and 2000 levels, respectively, as lower boundary conditions for tropospheric chemistry calculations. Anthropogenic emissions (including from energy production, industry, land transport, maritime transport, aviation, residential and commercial sectors, solvents, agriculture, agriculture waste burning on fields, and waste) and biomass burning emissions (including from open vegetation fires in forests, savanna and grasslands) of short-lived air pollutants (i.e., NO$_x$, CO, SO$_2$, NMVOCs, BC and OC, etc.) for 1860 and 2000 are from the emission inventory of Lamarque et al. (2010). Anthropogenic emissions for 2000 were constructed by aggregating existing regional and global emission inventories for 40 world regions and 10 sectors. Anthropogenic emissions for 1860 were generated based on extrapolation of the historical EDGAR-HYDE emission inventory from 1890 backwards to 1850 using global fossil fuel consumption estimates from Andres et al. (1999) and regional scale data for population from the HYDE dataset (Goldewijk, 2005). Biomass burning emissions in 2000 are from the GFED2 emission inventory (van der Werf et al., 2006); the 1900–2000 biomass burning emission trend is taken from RETRO (1960–2000, Schultz et al., 2008) and GICC (1900–1950, Mieville et al., 2010) inventories; no trend is assumed between 1850 and 1900 as suggested by ice-core and charcoal records (Marlon et al., 2008; McConnell et al., 2007). The 1860 and 2000 anthropogenic and biomass burning emissions used are summarized in Table S1 of the Supplement. As described by Naik et al. (2013), all natural emissions except those that depend on the simulated meteorology (lightning NO$_x$, dimethyl sulfide (DMS), sea salt and dust emissions), are the same for both simulations. Ozone-depleting substances (ODS) are set to pre-1950 levels in the 1860 simulation and to 2000 levels in the 2000 simulation. All simulations were run for 11 yr with the first year used as spin-up.

We define the difference in PM$_{2.5}$ and O$_3$ concentrations between the AM3 2000 and 1860 simulations as “industrial” air pollution, which reflects the total changes in air pollution levels between the start of the industrial period and 2000. Our definition of “industrial” pollution includes not only the effect of changes in short-lived air pollutant emissions, but also the effect of changes in climate, CH$_4$ and ODS
concentrations. It differs from the “anthropogenic” pollution defined in Anenberg et al. (2010), which was estimated as the difference between two CTM simulations with different emissions and, therefore, solely reflected the impact of emission changes on air pollution in a system that did not allow feedbacks between chemistry and climate.

To isolate the individual impacts of changes in emissions, climate, and CH$_4$ concentrations on surface concentrations of O$_3$ and PM$_{2.5}$, we analyze three additional AM3 simulations (simulations 3, 4 and 5 in Table 1). Briefly, simulation 2000CL1860EM is the same as the 2000 simulation except it uses 1860 emissions of short-lived species; simulation 1860CL2000EM is also the same as the 2000 simulation but its SST, SIC, WMGG and ODS concentrations (applied in stratospheric chemistry and radiative forcing calculations) are set to 1860 levels; simulation 1860ALL2000EM is the same as 1860CL2000EM, but its global mean CH$_4$ concentration is specified at 1860 levels for tropospheric chemistry calculations. Impacts of (1) changing emissions of short-lived species, (2) changing climate and (3) changing CH$_4$ concentrations on air quality are estimated in our study as 2000-2000CL1860EM, 2000-1860CL2000EM, and 1860CL2000EM-1860ALL2000EM, respectively. In order to distinguish signals, driven by changing emissions, CH$_4$ and climate, from internal model variability, we use annually-invariant SST, SIC and air pollutant emissions to drive 11-yr model simulations and analyze averages of the last 10 yr of each simulation. To indicate the significance of a result, relative to the inter-annual variability due to internal model variability, we report a mean (average of all 10 yr) along with the standard deviation (root mean square of variance over the 10 yr) in the following sections (as mean ± std).

2.3 Adverse health impacts

We analyze the effect of changes in air pollution concentrations during the industrial period (∼ 1860 to ∼ 2000) on premature mortality using health impact functions that relate changes in air pollutant concentrations to changes in mortality. We further evaluate the relative importance of changes in emissions of air pollutants, climate change and increased CH$_4$ concentrations on air pollution concentrations and the associated incidence of premature mortalities.

To obtain estimates of the excess mortalities (ΔMort) attributable to air pollution changes during the industrial period, we use health impact functions for O$_3$ and PM$_{2.5}$. These functions are based on log-linear relationships between relative risk and concentration derived from the American Cancer Society (ACS) cohort studies for adults aged 30 and older (Jerrett et al., 2009; Krewski et al., 2009; Pope et al., 2002). We apply

\[ ΔMort = POP \times Frac \times Mort_{base} \times (1 - e^{-\beta \Delta C}) \]  

(1)

in each of the AM3 surface grid cells and separately calculate changes in mortality associated with changes in PM$_{2.5}$ and O$_3$. We use the population (POP), baseline mortality (Mort$_{base}$), and, consistent with the ACS study, the fraction of the population (Frac) ≥ 30 yr of age in each grid cell. Changes in O$_3$ and PM$_{2.5}$ concentrations (ΔC) from specific factors (changes in short-lived emissions, climate, and CH$_4$) from preindustrial to present day are obtained as the exposure indicators from the difference between two simulations as described in Sect. 2.2. The appropriate concentration-mortality response factor (β) is used for each pollutant. For PM$_{2.5}$, β is obtained from Krewski et al. (2009), which provides the latest reanalysis of the ACS study (Pope et al., 2002). They found a 10 μg m$^{-3}$ increase in PM$_{2.5}$ concentrations was associated with 6% (95% confidence interval, CI, 4–8%), 13% (95% CI, 10–16%) and 14% (95% CI, 6–23%) increase in all-cause, cardiopulmonary, and lung cancer mortality, respectively. For O$_3$, we use (β) from Jerrett et al. (2009), for which, a 10 ppb increase in O$_3$ is associated with a 4% (95% CI, 1.3–6.7%) increase in respiratory disease mortality. We use population distribution (CIESIN, 2005), fraction of adults aged 30 and older (WHO, 2003), baseline mortality for the year 2000 for lung cancer, cardiopulmonary disease, and respiratory disease mortality (WHO, 2003), as summarized in Table 2. We assume the ACS cohort studies conducted in the United States are valid globally, as relative risks characterized in US based time series studies are similar to those found in various time-series studies in Europe (Levy et al., 2005) and Asia (HEI, 2010) and no cohort studies have yet been conducted in developing countries. However, we recognize that differences exist in PM$_{2.5}$ composition, health status, lifestyle, age structure, and medical attention available around the world, which could substantially affect our results.

3 Model evaluation

Various simulated physical and chemical parameters in AM3 have been evaluated by Donner et al. (2011) and Naik et al. (2013). Here we evaluate the ability of our 2000 AM3 simulation to reproduce observed surface O$_3$ and PM$_{2.5}$ concentrations around the world in order to increase confidence in our estimates of the excess mortalities attributable to air pollution.

We evaluate surface O$_3$ in our 2000 simulation against surface O$_3$ data from observational networks in the United States (Clean Air Status and Trends Network-CASTNet) and in Europe (European Monitoring and Evaluation Programme-EMEP). Sites in these two networks are well suited for evaluating global models as they represent regional O$_3$ concentrations rather than urban plumes. A comparison between the simulated and observed seasonal cycle of O$_3$ over twelve regions spanning the US and Europe is shown in Fig. 1. In general, like in Naik et al. (2013), the AM3 2000 simulation reproduces the observed seasonal cycle of surface O$_3$ concentrations over most regions (r > 0.7 and...
Table 2. Regional statistics for population and mortality rates. Population aged 30 and older (unit: million), cardiopulmonary, lung cancer and respiratory mortality rates (unit: % per year) for regions used in this study.

<table>
<thead>
<tr>
<th>Regions</th>
<th>POP (≥30)(^a)</th>
<th>Cardiopulmonary mortality rate(^b)</th>
<th>Lung cancer mortality rate(^b)</th>
<th>Respiratory mortality rate(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>North America</td>
<td>218</td>
<td>0.609</td>
<td>0.079</td>
<td>0.092</td>
</tr>
<tr>
<td>South America</td>
<td>135</td>
<td>0.496</td>
<td>0.025</td>
<td>0.083</td>
</tr>
<tr>
<td>Europe</td>
<td>359</td>
<td>0.997</td>
<td>0.073</td>
<td>0.080</td>
</tr>
<tr>
<td>Africa</td>
<td>238</td>
<td>0.667</td>
<td>0.017</td>
<td>0.122</td>
</tr>
<tr>
<td>South Asia</td>
<td>469</td>
<td>0.744</td>
<td>0.025</td>
<td>0.132</td>
</tr>
<tr>
<td>Southeast Asia</td>
<td>163</td>
<td>0.588</td>
<td>0.035</td>
<td>0.139</td>
</tr>
<tr>
<td>East Asia</td>
<td>711</td>
<td>0.612</td>
<td>0.047</td>
<td>0.179</td>
</tr>
<tr>
<td>Middle East</td>
<td>97</td>
<td>0.868</td>
<td>0.039</td>
<td>0.071</td>
</tr>
<tr>
<td>Rest of Asia</td>
<td>65</td>
<td>1.364</td>
<td>0.064</td>
<td>0.093</td>
</tr>
<tr>
<td>Australia</td>
<td>11</td>
<td>0.440</td>
<td>0.065</td>
<td>0.058</td>
</tr>
</tbody>
</table>

\(^a\) CIESIN, 2005; \(^b\) WHO, 2003.

Fig. 1. Comparison of simulated monthly mean surface O\(_3\) in GFDL AM3 “2000” simulation (red line) with measurements from various regions in the United States (a–f, results from CASTNet, http://www.epa.gov/castnet/) and Europe (g–l, results from EMEP, http://www.nilu.no/projects/ccc/emepdata.html). Observed values (black dots) represent the average of climatological monthly mean surface O\(_3\) concentrations for each site (grey lines) within each region (Table S1 in Naik et al., 2013). Vertical black lines denote standard deviation across the sites.
bias < 20 ppbv, except in the Northwest United States). Naik et al. (2013) attribute the strong positive bias of O₃ in the Northwest US to the model failure to capture the influence of maritime air masses on sites close to the ocean. Over populated areas, such as the Eastern United States, South California and Europe, surface O₃ bias range from 4 ppbv to about 15 ppbv. Despite this positive bias, simulated O₃ seasonal cycles follow observed cycles with correlation coefficients greater than 0.95 over all 6 European regions and greater than 0.7 elsewhere, indicating that the model is generally capturing the seasonal cycle of O₃.

The optical characteristics of aerosols simulated in AM3 were evaluated in Donner et al. (2011). They found that simulated AOD was within a factor of 2 of AERONET observations. However, annual mean surface PM₂.₅ mass concentrations simulated by AM3, which is directly associated with human mortality responses, has not yet been evaluated. Here, we evaluate annual mean PM₂.₅ concentrations (or its major component, sulfate, where long-term PM₂.₅ observations are not available) for the 2000 simulation with observations over the United States (the US Air Quality System, USAQS), Europe (EMEP) and East Asia (Acid Deposition Monitoring Network in East Asia, EANET). Measured concentrations are averaged over corresponding model grids for 1997–2003 and 1995–2004 for the USAQS (PM₂.₅) and EMEP (sulfate) datasets, respectively. Asian sulfate observations are collected from Liu et al. (2009a) and Zhang et al. (2011). Figure 2 shows a consistent underestimate of total PM₂.₅ over the United States. However, the bias for dust (Donner et al., 2011) and sulfate over Europe and East Asia is much smaller (Fig. 2a). The greater underestimate of total PM₂.₅ than dust or sulfate in the AM3 2000 simulation is likely related to the simulation of SOA. AM3 SOA production is scaled directly from terpene emissions and butane oxidation (Donner et al., 2011); therefore, it may underestimate SOA away from terpene and butane sources. Additionally, AM3 does not consider SOA produced by oxidation of isoprene and does not include in-cloud mechanisms for SOA production and thus likely underestimates total SOA production. Despite the systematic PM₂.₅ underestimate of more than 20%, AM3 captures the global spatial distribution of PM₂.₅ well, with a correlation coefficient above 0.9.

4 Surface PM₂.₅ and O₃ concentration changes

We first quantify the increase in surface concentrations of PM₂.₅ and O₃ due to “industrial pollution” from preindustrial time (year 1860) to the present (year 2000) (denoted as TOTAL, Sect. 4.1). In the following subsections, we analyze the causes of these changes and attribute them to three factors: changes in emissions of air pollutants (denoted as EMIS, Sect. 4.2), climate (denoted as CLIM, Sect. 4.3) and CH₄ concentrations (denoted as TCH4, Sect. 4.4).

4.1 Total changes from 1860 to 2000

Distributions of annual mean surface PM₂.₅ and health-relevant O₃ (defined as the maximum 6-month mean of 1-h daily maximum O₃ in a year, denoted as H-O₃) in year 2000 are shown in Fig. 3a and b. Global population-weighted concentrations of PM₂.₅ and H-O₃ are 13 ± 0.15 μg m⁻³ and 61 ± 0.20 ppbv (Table 3). Both PM₂.₅ and H-O₃ show maximum concentrations near source regions in East Asia, eastern United States, India and central Africa. High concentrations of PM₂.₅ (ranging from 20 to 40 μg m⁻³) over

![Fig. 2. (a) Scatter plot of AM3 “2000” simulated and observed annual mean concentrations of PM₂.₅ (black squares, corresponding to the US observations) and sulfate (green triangles, corresponding to Asian and European observations). 1:1 line is shown in red. (b) Map of the relative difference (i.e., (model-obs)/obs) in PM₂.₅ (squares) or sulfate (triangles). PM₂.₅ observations over the United States are from the US Air Quality System (AQS) Database (1997–2003 average, http://www.epa.gov/tnn/airs/airsaqs/); sulfate observations over Europe are from the European Monitoring and Evaluation Programme (EMEP, 1995–2004, http://www.emep.int/); sulfate observations over East Asia are from the Acid Deposition Monitoring Network in East Asia (EANET, http://www.eanet.cc/product/index.html), collected from Liu et al. (2009a) and Zhang et al. (2011).](image-url)
northern Africa and the Middle East are associated with strong dust emissions. Present-day tropospheric air mass-weighted OH and H$_2$O$_2$ concentrations, and their changes from 1860 to 2000 driven by all changes (TOTAL), changes in emissions of short-lived reactive pollutants (EMIS), changes in climate (CLIM), and changes in tropospheric CH$_4$ concentration (TCH$_4$). Results are reported for 10-yr model simulations as annual average ± standard deviation.

<table>
<thead>
<tr>
<th>Atmospheric species</th>
<th>2000</th>
<th>TOTAL</th>
<th>EMIS</th>
<th>CLIM</th>
<th>TCH$_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM$_{2.5}$ (µg m$^{-3}$)</td>
<td>13 ± 0.15</td>
<td>8 ± 0.16</td>
<td>7.5 ± 0.19</td>
<td>0.4 ± 0.17</td>
<td>0.04 ± 0.24</td>
</tr>
<tr>
<td>H$_2$O$_3$ (ppbv)</td>
<td>61 ± 0.20</td>
<td>30 ± 0.16</td>
<td>25 ± 0.30</td>
<td>0.5 ± 0.28</td>
<td>4.3 ± 0.33</td>
</tr>
<tr>
<td>OH (10$^{10}$ molecules cm$^{-3}$)</td>
<td>1.19 ± 0.01</td>
<td>−0.11 ± 0.01</td>
<td>0.13 ± 0.01</td>
<td>−0.02 ± 0.01</td>
<td>−0.24 ± 0.01</td>
</tr>
<tr>
<td>H$_2$O$_2$ (10$^{10}$ molecules cm$^{-3}$)</td>
<td>1.95 ± 0.01</td>
<td>0.84 ± 0.01</td>
<td>0.41 ± 0.02</td>
<td>0.15 ± 0.03</td>
<td>0.35 ± 0.02</td>
</tr>
</tbody>
</table>

Year 2000 global population-weighted annual mean surface PM$_{2.5}$ and H$_2$O$_3$ (health-relevant O$_3$, defined in Sect. 2), tropospheric mean mass-weighted OH and H$_2$O$_2$ concentrations, and their changes from 1860 to 2000 driven by all changes (TOTAL), changes in emissions of short-lived reactive pollutants (EMIS), changes in climate (CLIM), and changes in tropospheric CH$_4$ concentration (TCH$_4$). Results are reported for 10-yr model simulations as annual average ± standard deviation.
Fig. 3. Annual PM$_{2.5}$ (left, unit: µg m$^{-3}$) and H-O$_3$ (right, unit: ppbv) surface concentration in 2000 (row 1, a and b), their total changes from preindustrial to present day (“2000” minus “1860” simulations) (row 2, c and d), and changes over that time interval due to anthropogenic air pollutant emissions only (“2000” minus “2000CL1860EM” simulations) (row 3, e and f), due to climate change only (“2000” minus “1860CL2000EM” simulations) (row 4, g and h), and due to the impact of CH$_4$ increases on tropospheric chemistry only (“1860CL2000EM” minus “1860ALL2000EM” simulations) (row 5, i and j). Dotted areas indicate changes significant at the 95% confidence level as assessed by student t-test.

short-lived pollutant emissions (Fig. 3e) is strongly correlated ($R = 0.99$) with the pattern of the total changes resulting from all three factors between 1860 and 2000 (Fig. 3c).

Emission changes applied in this study include both anthropogenic and biomass burning emissions, both of which were influenced by human activity during the industrial period. Anthropogenic emissions increase during the industrial period almost everywhere while changes in biomass burning emissions driven by human activities vary in sign depending on location. For example, from 1860 to 2000, sulfate concentrations increase everywhere, especially in the Northern Hemisphere mid-latitudes, driven by enhanced emissions of anthropogenic precursors (e.g. a factor of 18 increase in sulfur dioxide emissions, Table 2 in Naik et al., 2013). However, BC and OC decrease over the US while increasing over central Africa and tropical South America. This is driven by a decrease in biomass burning in the United States and an increase in the tropics between 1860 and 2000 (Fig. 8 in Naik et al., 2013). According to Mieville et al. (2010), in boreal regions, burnt surface area and biomass burning emissions have decreased over the past one to two centuries as a result of human-induced land-use change and fire suppression policy. In contrast, over central Africa, central South America and Indonesia, biomass burning emissions have increased over the past few decades due to human pressure and the
use of fire for deforestation as part of agriculture expansion (Mieville et al., 2010).

We found that increases in \( \text{O}_3 \) precursor emissions from preindustrial time to the present lead to 45% and 40% increases in the photochemical production and loss of \( \text{O}_3 \), respectively, leading to a 21% increase in the tropospheric \( \text{O}_3 \) burden. As a result, the global mean population-weighted \( \text{H-O}_3 \) increases by 25 ± 0.30 ppbv (Table 3). Although the distribution of emission-driven changes in \( \text{H-O}_3 \) (Fig. 3f) correlates well with that of the total change in \( \text{H-O}_3 \) from 1860 to 2000 (Fig. 3d, \( R = 0.99 \)), the emission-driven increase of \( \text{H-O}_3 \) accounts for only 83% of the total increase (30 ± 0.16 ppbv), indicating that other factors also influence changes in \( \text{H-O}_3 \) concentrations. We show in Sects. 4.3 and 4.4 that changing climate and increased \( \text{CH}_4 \) concentrations drive the rest of the \( \text{H-O}_3 \) increase.

Due to increases in emissions of short-lived species, aerosols become more abundant in the atmosphere and are associated with decreased precipitation in the AM3 model (Donner et al., 2011). In our study, feedbacks from increased concentrations of short-lived species lead to global precipitation decreases of 0.03 mm day\(^{-1}\) with large decreases (about 1 mm day\(^{-1}\)) over source regions such as East Asia. As a result, sulfate lifetime to wet deposition increases from 6.4 days in 1860 to 6.9 days in 2000. Increases in emissions of short-lived species also cause a net negative all-sky radiative forcing (\(-1.43 \text{ W m}^{-2}\), including both direct and indirect radiation), cooling the atmosphere and reducing chemical reaction rates (although this effect varies locally depending on the location and type of aerosols).

### 4.3 Impact of historical climate change

Historical climate change indirectly affects surface \( \text{PM}_{2.5} \) and \( \text{O}_3 \) by modifying transport patterns, precipitation, water vapor, and temperature-dependent reaction rates. Here we estimate the effect of historical climate change on surface \( \text{PM}_{2.5} \) and \( \text{O}_3 \) by comparing the 2000 simulation with a simulation with emissions of short-lived species set at 2000 levels but with year 1860 SST, SIC and WMGG (1860CL2000EM). The global average \( \text{CH}_4 \) concentration in 2000 is applied as the lower boundary condition for tropospheric chemistry calculations in both simulations. This allows us to isolate the role of climate change on air quality from the impact of \( \text{CH}_4 \) on tropospheric chemistry. The two simulations analyzed here have different ODS concentrations (Table 1), therefore, the impact of historical climate change also includes the effects of stratospheric \( \text{O}_3 \) depletion caused by anthropogenic ODS emissions over the period. Our historical climate change does not include the climate change induced effect on emissions of biogenic hydrocarbons, such as isoprene and terpenes that are air pollutant precursors. If a biogenic air pollutant precursor emission response to the changing climate were included, it would likely increase our estimate of the changes in \( \text{PM}_{2.5} \) and \( \text{O}_3 \) concentrations described below.

#### 4.3.1 \( \text{PM}_{2.5} \)

From 1860 to 2000, our simulation indicates that climate change caused global population-weighted \( \text{PM}_{2.5} \) concentrations to increase by 0.4 ± 0.17 µg m\(^{-3}\) (Table 3), accounting for 5% of the total increase over this period. The spatial distribution of \( \text{PM}_{2.5} \) change driven by climate change and that driven by all factors together are loosely correlated (\( R = 0.3 \)). Changes in \( \text{PM}_{2.5} \) driven by climate change show a complicated pattern (Fig. 3g): modest increases (up to 2 µg m\(^{-3}\)) occur over East Asia, South and South-east Asia, west Africa and Central Europe; significant decreases (up to 1.5 µg m\(^{-3}\)) occur over the United States, central Asia, and central and western Australia. Significant decreases over central and western Australia are driven by lower concentrations of sea salt and dust (not shown), two \( \text{PM}_{2.5} \) components with emissions dependent on meteorology. Increases that are statistically significant over Asia, India and central Europe are driven by increases in BC, sulfate and OC, with OC accounting for a majority of the enhanced \( \text{PM}_{2.5} \). Increases in the concentration of these species is driven by reductions in large-scale precipitation, the major driver of wet deposition (Fig. 4, Fang et al., 2011). Increases also result from higher \( \text{H}_2\text{O}_2 \) concentrations (+0.15 ± 0.03 × 10\(^{10}\) molec cm\(^{-3}\), Table 3) that increase the aqueous phase production of sulfate. Decreases in \( \text{PM}_{2.5} \) over the United States and central Asia are driven by stronger large-scale precipitation/wet deposition close to their \( \text{PM}_{2.5} \) precursor source regions (Fig. 4). While changes in \( \text{PM}_{2.5} \) driven by climate change are statistically significant over most continental regions, 10-yr simulations are likely too short to generate a robust signal for precipitation distinguishable from noise on a regional scale (Naik et al., 2013). Figure 4 shows that simulated differences in large-scale precipitation is significant at the 95% confidence level over part of East Asia, north India and Central Europe and many ocean regions, but is not significant elsewhere. If we lower the confidence level to 90%, regions with statistically significant differences in precipitation become larger over Asia and India (see Supplement, Fig. S1). We realize that the spatial distribution of \( \text{PM}_{2.5} \) responses to historical climate change can be highly variable and uncertain, because of inconsistencies associated with changes in regional precipitation, precipitation frequencies and regional ventilation, as suggested in Jacob and Winner (2009). Future studies applying similar simulations as ours from various models in the ACCMIP project will help to further evaluate the robustness of \( \text{PM}_{2.5} \) response to historical climate change.

#### 4.3.2 \( \text{O}_3 \)

As a result of historical climate change and stratospheric \( \text{O}_3 \) depletion, the global population-weighted \( \text{H-O}_3 \)
concentration increases by 0.5 ± 0.28 ppbv (Table 3), accounting for less than 2% of the total historical H-O\textsubscript{3} change. Despite the small contribution, the spatial distribution of H-O\textsubscript{3} changes driven by climate change follows that driven by all factors with a correlation coefficient of 0.71. Historical climate change leads to increases in O\textsubscript{3} over polluted areas and at high-latitudes in the Northern Hemisphere, while decreasing O\textsubscript{3} over remote regions and oceans (Fig. 3h). This pattern, similar to that of surface O\textsubscript{3} responses to a warmer future climate (Fang et al., 2013; Liao et al., 2006; Murazaki and Hess, 2006), is mainly associated with the tropospheric chemistry of O\textsubscript{3} under a warmer and wetter atmosphere. O\textsubscript{3} decreases over remote oceanic regions is largely driven by an increase in water vapor (total column water vapor increases by 3% from preindustrial times), which leads to increases in HO\textsubscript{x} (HO\textsubscript{x} = OH + HO\textsubscript{2}) concentrations (+3.6 ± 0.1 × 10\textsuperscript{6} molec cm\textsuperscript{-3}). Reaction with HO\textsubscript{x} is the primary sink of O\textsubscript{3} at low NO\textsubscript{x} concentrations. However, surface O\textsubscript{3} increases by up to 3 ppbv over regions with large NO\textsubscript{x} emissions such as south China, north India, northeast United States, central Europe and central Africa. Factors contributing to O\textsubscript{3} increases over these regions include: (1) increased O\textsubscript{3} production due to higher water vapor leading to more abundant HO\textsubscript{x} which leads to increased O\textsubscript{3} production at high NO\textsubscript{x} concentrations; (2) increased global average temperature (+0.5°C) from 1860 to 2000, increases photochemistry rates and decreases net formation of peroxyacetyl nitrate (PAN, CH\textsubscript{3}C(O)OO\textsubscript{2}), a reservoir species for NO\textsubscript{x}, leaving more NO\textsubscript{x} available over source regions which promotes local O\textsubscript{3} production; and (3) increased lightning that increases production of lightning NO\textsubscript{x} (+3%). While lightning NO\textsubscript{x} is mostly formed in the upper free troposphere and contributes to stronger tropospheric O\textsubscript{3} production, its contribution to surface O\textsubscript{3} is small, most likely over regions where subsidence brings lightning-affected air masses to the surface, such as the southwestern United States (Fang et al., 2010).

Since 1950, anthropogenic emissions of ODS have caused stratospheric O\textsubscript{3} depletion. Stratospheric O\textsubscript{3} depletion and the associated changes in photochemical reaction rates in the troposphere, combined with changes in transport between the stratosphere and troposphere, also affects tropospheric O\textsubscript{3}. To estimate this effect on surface O\textsubscript{3}, we first evaluate changes in the cross-tropopause O\textsubscript{3} fluxes, and find the net flux decreases by almost 15% relative to its level in the 1860 simulation. To estimate the stratospheric O\textsubscript{3} contribution to surface O\textsubscript{3}, we analyze a tracer of stratospheric O\textsubscript{3} implemented in these simulations (O\textsubscript{3S}). This tracer, as described in Lin et al. (2012), is defined as O\textsubscript{3} above the World Meteorological Organization (WMO) thermal tropopause at each model time step. Once mixed into tropospheric air, O\textsubscript{3S} is subject to the same transport and loss as tropospheric O\textsubscript{3}. Surface O\textsubscript{3S} shows an annual global mean reduction of 0.7 ppbv, resulting from both stratospheric O\textsubscript{3} depletion leading to less O\textsubscript{3} transport from the stratosphere to troposphere, and stronger O\textsubscript{3} destruction in the troposphere. Surface O\textsubscript{3S} change has distinctive seasonal variations, with smaller decreases (−0.2 ppbv) in winter than in summer (−1.3 ppbv), consistent with projections that stratospheric-tropospheric exchange of O\textsubscript{3} increases in winter months in a warming climate (Collins et al., 2003; Liao et al., 2006; Zeng and Pyle, 2003). The decrease in O\textsubscript{3S} concentration at the surface suggests that historical changes in stratospheric O\textsubscript{3} trends to decrease surface O\textsubscript{3} concentrations. However, this surface O\textsubscript{3S} change likely overestimates changes in the stratospheric contribution to surface O\textsubscript{3} since any O\textsubscript{3} above the thermal tropopause is instantly labeled as “stratospheric” regardless of its actual origin (Lin et al., 2012).

### 4.4 Impact of increased CH\textsubscript{4} concentration

The simulated change in H-O\textsubscript{3} and PM\textsubscript{2.5} due to climate change explored in Sect. 4.3 does not allow changes in CH\textsubscript{4} concentration to affect tropospheric chemistry (Table 1). Although this configuration intentionally isolates the role of climate change, increases in CH\textsubscript{4} concentrations from 1860 to 2000 also affect tropospheric chemistry and hence surface O\textsubscript{3} and PM\textsubscript{2.5} concentrations. We estimate the effect of increased CH\textsubscript{4} concentrations on O\textsubscript{3} and PM\textsubscript{2.5} concentrations by taking the difference between the 1860CL2000EM and 1860ALL2000EM simulations (Fig. 3i and j). Both simulations are identical except that the global mean CH\textsubscript{4} concentrations applied in the tropospheric chemistry calculations are set to year 2000 (1750 ppbv) and 1860 (800 ppbv) levels, respectively.

Tropospheric CH\textsubscript{4} perturbs the concentrations of oxidizing agents in the atmosphere, which in turn affect PM\textsubscript{2.5} and O\textsubscript{3} concentrations. In addition, CH\textsubscript{4} is a precursor of tropospheric ozone. Reaction with CH\textsubscript{4} is
a primary sink of atmospheric OH. Higher CH4 concentrations in 2000 than 1860 result in an OH decrease of 0.24 ± 0.01 × 10^9 molec cm^{-3} and an increase of 0.35 ± 0.03 × 10^{10} molec cm^{-3} in H2O2 (Table 3). As OH and H2O2 are associated with the gas-phase and in-cloud production of sulfate, changing CH4 thus indirectly influences PM2.5. Compensating changes in OH and H2O2 lead to a small and insignificant global change in PM2.5 (global population-weighted PM2.5 decreases by 0.04 ± 0.24 µg m^{-3}, Table 3). The spatial pattern of PM2.5 changes driven by the impact of increased CH4 concentration is also not correlated with its total change during the industrial period.

CH4 increases (from 800 ppbv in 1860 to 1750 ppbv in 2000) result in an increase in the global population-weighted H-O3 concentration of 4.3 ± 0.33 ppbv (Table 3, TCH4), accounting for almost 15 % of the total H-O3 produced during the industrial period. The fraction that CH4 contributes to total H-O3 produced during the industrial period is much higher (22 % over land) if it is weighted by area. The distribution of surface O3 enhancement driven by increased CH4 is significant everywhere in the world and is approximately 5–10 ppbv in the Northern Hemisphere and 2–5 ppbv in the Southern Hemisphere (Fig. 3)). A spatial correlation of 0.7 between changes in surface H-O3 driven by increased CH4 and that driven by all factors supports total O3 changes being partly driven by CH4. Although the impact of CH4 on O3 has been discussed in previous literature (Dentener et al., 2005; Fiore et al., 2002, 2008; West et al., 2006), most of these studies focus on the potential benefit of future CH4 mitigation while our study examines the total change in O3 resulting from historic increases in CH4. However, the magnitude of CH4 impact on O3 in those studies is consistent with ours: for example, Fiore et al. (2008) estimate that anthropogenic CH4 emissions contribute 5 ppbv to global mean surface O3; West et al. (2006) and Anenberg et al. (2009) find that a 20 % reduction in anthropogenic CH4 and a 20 % reduction in global CH4 mixing ratio lead to approximately a 1 ppbv decrease in global mean surface O3.

5 Premature mortalities associated with industrial air pollution

5.1 Estimate of premature mortalities associated with changes in PM2.5 and O3 concentrations during the industrial period

We estimate excess mortalities attributable to industrial air pollution separately for O3 and PM2.5, using population and baseline mortality rates at present (2000) along with concentration changes in O3 and PM2.5 from 1860 to 2000. Globally, in 2000, industrial PM2.5 is associated with 1.53 (95 % CI, of 1.03–1.98) million cardiopulmonary mortalities and 95 (95 % CI, 44–144) thousand lung cancer mortalities per year (Table 4); while industrial O3 is associated with 0.37 (95 % CI, 0.13–0.59) million respiratory mortalities per year (Table 4). Our estimates suggest that about 1.5 million cardiopulmonary and 95 thousand lung cancer mortalities associated with PM2.5 exposure, and 0.37 million respiratory mortalities associated with O3 exposure would have been avoided in 2000 if surface PM2.5 and O3 had remained at 1860 levels (i.e., anthropogenic and biomass burning emissions of air pollutants, CH4 and climate had all remained the same in 2000 as they were in 1860). Our estimated mortalities associated with industrial PM2.5 and O3 are considerably lower than those in Anenberg et al. (2010), which is consistent with differences between our emission scenarios and calculated surface concentrations and theirs, as discussed in Sect. 4.1. If we apply a low concentration threshold (LCT) of 5.8 µg m^{-3} PM2.5 and 33.3 ppbv O3 (the lowest values in the ACS studies), premature mortalities associated with industrial PM2.5 and O3 are 15 % and 11 % lower, respectively. These relative differences are smaller here than in Anenberg et al. (2010) (33 % and 28 %, respectively for mortalities associated with PM2.5 and O3) because our preindustrial emissions and hence simulated preindustrial O3 and PM2.5 are higher than theirs (see Sect. 4.1 and Table S1). As differences with and without use of the LCT are relatively small in our study, we hereafter only report mortalities without the LCT.

We separate the world into 10 regions as in Liu et al. (2009b) and Fang et al. (2013) to estimate the regional mortalities associated with industrial air pollution. The regional distribution of premature mortality associated with industrial PM2.5 and O3 is shown in Fig. 5. Eastern China and northern India are hotspots for air pollution mortalities, driven by their large increases in surface PM2.5 and O3 concentrations and their large populations. East Asia accounts for 43 % (56 %) of the global cardiopulmonary (lung cancer) mortalities associated with industrial PM2.5 and 50 % of the global respiratory mortalities associated with industrial O3. South Asia is second, accounting for 27 % (16 %) of the global cardiopulmonary (lung cancer) mortalities associated with industrial PM2.5 and 19 % of the global respiratory mortalities associated with industrial O3. None of the other regions contribute over 15 % to the global mortalities associated with industrial air pollution.

5.2 Attribution of premature mortalities associated with industrial air pollution to changing emissions of short-lived pollutants, climate and methane concentrations

In Sect. 4, changes in surface O3 and PM2.5 from 1860 to 2000 are attributed to changes in air pollutant emissions, climate and CH4 concentrations. Here, we estimate the mortality responses using Eq. (1) with concentration changes driven by each factor separately. We further evaluate the relative importance of each factor to total air pollution mortalities in 2000 by comparing the mortality response associated with
The 95 % confidence intervals are shown in brackets. 3 million respiratory mortalities associated with O\textsubscript{3} could have been avoided. 92 (95 % CI, 43–140) thousand lung cancer mortalities as-
ersions in year 2000 had remained at 1860 levels, 1.49 \(2000CL1860EM\), EMIS). We find that if air pollutant emis-
sions are the same as in 1860, about 91 (95 % CI, 71–110) thousand cardiopulmonary mortalities, 5 (95 % CI, 2–8) thousand lung cancer mortalities associated with PM\textsubscript{2.5} exposure and 7 (95 % CI, 2–12) thousand respiratory mortalities associated with O\textsubscript{3} exposure could have been avoided.

We next estimate the global mortality response associated with industrial PM\textsubscript{2.5} and O\textsubscript{3} pollution resulting from changes in air pollutant emissions only (2000 – 2000CL1860EM, EMIS). We find that if air pollutant emissions in year 2000 had remained at 1860 levels, 1.49 (95 % CI, 1.18–1.79) million cardiopulmonary mortalities, 92 (95 % CI, 43–140) thousand lung cancer mortalities associated with PM\textsubscript{2.5} exposure and 0.33 (95 % CI, 0.11–0.52) million respiratory mortalities associated with O\textsubscript{3} exposure could have been avoided.

We finally assess the relative importance of each factor to air pollution mortality regionally and globally. Figure 6 shows NMC for each region. Due to the non-linearity in the health impact function, chemistry, and chemistry-climate system, the value of each bar in Fig. 6 is close to, but not exactly, 1.

Global premature mortality associated with industrial PM\textsubscript{2.5}, is dominated by increased emissions of reactive air pollutants (∼95 %), however, climate change is influential with a global NMC of ∼5 %. Regionally, contributions of climate change to cardiopulmonary and lung cancer mortality associated with industrial PM\textsubscript{2.5} can be as high as 14 % with the highest values over Europe and Australia. The

### Table 4. Premature mortalities in 2000 associated with industrial air pollution. Values are calculated as in Eq. (1), using ACS health impact functions, concentration difference in annual PM\textsubscript{2.5} and H-O\textsubscript{3} between “1860” and “2000” simulations, WHO baseline mortality rate and population in the year 2000. The 95 % confidence intervals are shown in brackets.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Change in Premature mortalities (1000s deaths)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PM\textsubscript{2.5} mortality (Chronic, cardiopulmonary)</td>
</tr>
<tr>
<td>World</td>
<td>1532 (1214, 1832)</td>
</tr>
<tr>
<td>North America</td>
<td>38 (30, 46)</td>
</tr>
<tr>
<td>South America</td>
<td>15 (12, 18)</td>
</tr>
<tr>
<td>Europe</td>
<td>125 (99, 152)</td>
</tr>
<tr>
<td>Africa</td>
<td>77 (61, 93)</td>
</tr>
<tr>
<td>South Asia</td>
<td>417 (331, 499)</td>
</tr>
<tr>
<td>Southeast Asia</td>
<td>108 (86, 130)</td>
</tr>
<tr>
<td>East Asia</td>
<td>661 (527, 788)</td>
</tr>
<tr>
<td>Middle East</td>
<td>52 (41, 63)</td>
</tr>
<tr>
<td>Rest of Asia</td>
<td>29 (23, 35)</td>
</tr>
<tr>
<td>Australia</td>
<td>0.7 (0.5, 0.8)</td>
</tr>
</tbody>
</table>
impact of increased CH\textsubscript{4} concentrations on PM\textsubscript{2.5} and associated premature mortality globally is insignificant (Table 3).

The global premature respiratory mortality associated with industrial O\textsubscript{3} is also dominated by increased emissions of short-lived air pollutants (more than 85 \%). However increases in CH\textsubscript{4} are also influential with a global NMC of 13 \%. Regionally, NMC of increased CH\textsubscript{4} to O\textsubscript{3} ranges from 10 to 33 \% with the largest increases in excess mortalities in regions where increases in short-lived air pollutant emissions are relatively low (i.e., Australia, South America and Africa). Thus respiratory mortalities from industrial O\textsubscript{3} over those relatively clean regions are more affected by rising global background CH\textsubscript{4} concentrations than other regions. The contribution of climate change is small with a global NMC of about 1 \%.

6 Discussion and conclusions

In this study, we apply the GFDL Atmospheric Model version 3 (AM3), a global chemistry-climate model, to examine changes in surface O\textsubscript{3} and PM\textsubscript{2.5} from the preindustrial period to the end of the 20th century and associated changes in premature mortality. Simulated global population-weighted PM\textsubscript{2.5} and H-O\textsubscript{3} (health-related O\textsubscript{3}, defined as the maximum 6-month mean of 1-h daily maximum O\textsubscript{3} in a year) concentrations increase by 8 \pm 0.16 \mu g m\textsuperscript{-3} and 30 \pm 0.16 ppbv, respectively, from the preindustrial period to the present (1860 to 2000). We quantify excess mortalities attributable to industrial air pollution and find that around year 2000, industrial PM\textsubscript{2.5} is associated with 1.53 (95 \% CI, 1.21–1.83) million cardiopulmonary disease and 95 (95 \% CI, 44–144) thousand lung cancer; industrial O\textsubscript{3} is associated with 0.37 (95 \% CI, 0.13–0.59) million annual respiratory mortalities.
India and China suffer most from industrial air pollution mortality as they have experienced strong increases in air pollution levels and have large exposed populations.
effective method of reducing local premature mortalities associated with O₃ exposure. Our study highlights the benefits of controlling CH₄ emissions as part of air quality policy.

Many opportunities to mitigate CH₄ are available (UNEP, 2011). Anenberg et al. (2012) examined potential measures and showed that, relative to the 2030 reference scenario and population, implementing available CH₄ measures would avoid around 70 thousand deaths due to respiratory disease associated with O₃ exposure. We estimate industrial O₃ respiratory mortalities to be approximately 375 thousand in the year 2000 (Table 3). This suggests that, with currently available CH₄ mitigation measures, respiratory mortalities associated with industrial O₃ pollution could be reduced by nearly 20%.

Modeling estimates of industrial air pollution and associated excess mortalities strongly depend on emission changes applied during this period, as reflected by differences between this study and Anenberg et al. (2010). They also depend on simulated physical, dynamical and chemical processes in the atmosphere. To evaluate the robustness of our results, similar studies using different chemistry-climate models could be conducted. Many of the simulations applied in this study were conducted under the ACCMIP Project. Multiple modeling groups have participated in this project, all of which use the same emission inventories and run simulations for preindustrial (1860) and present (2000) (http://www.giss.nasa.gov/projects/accmip/specifications.html). Further analysis of the ACCMIP simulations (http://www.atmos-chem-phys-discuss.net/special_issue176.html) could reduce uncertainties in modeling estimates of industrial air pollution and associated mortalities.

Supplementary material related to this article is available online at: http://www.atmos-chem-phys.net/13/1377/2013/acp-13-1377-2013-supplement.pdf.

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