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Distinguishing between the Effects of Climate Change and Emission Mitigation on Ozone Concentration: Implications for Human Health

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Abstract

Distinguishing between the Effects of Climate Change and Emission Mitigation on Ozone Concentration: Implications for Human Health
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Introduction. Given the potential threat to human health, it is vital to gain better understanding of hazards associated with climate, emissions, and air quality. Combinations of representative concentration pathways (RCPs) and downscaling models provide finer-resolution estimates of ozone (O_3) effects on health at meaningful, local scales.

Methods. An empirical model using statistical downscaling methods was developed for RCP4.5 (low emissions) and RCP8.5 (high emissions) to isolate O_3 changes between 2001-2004 and 2055-2059 due to climate change. Parameters included temperature, relative humidity, planetary boundary layer, surface pressure, zonal/meridional wind speeds, precipitation, and stagnation. O_3 changes attributable to both emissions and climate were isolated using dynamical downscaling for the same pathways. Future O_3 concentrations from anthropogenic emissions were isolated using differences between the statistical and dynamical models. O_3 changes were then converted to excess mortality values by county and region.

Results. Climate change is expected to increase O_3 in across the U.S. with a national average of 0.30 ppb (SE: 0.01) and 0.65 ppb (SE: 0.01) under RCP4.5 and 8.5, respectively. O_3 contributions from a combination of climate and emissions could decrease by 2.6 ppb (SE: 0.02) under RCP 4.5 yet increase by 1.5 ppb (SE: 0.01) under RCP8.5. O_3 due to emissions alone is expected to decrease by 3.2 ppb (SE: 0.01) under the RCP4.5 scenario. However, despite the emission reduction of O_3 precursors planned under all pathways, O_3 is expected to increase by 0.6 ppb (SE: 0.10) under RCP8.5.

Discussion and Conclusions. This study demonstrates potential impacts of climate change, combined climate and emissions, and isolated emission changes on future O_3 levels. Even with reductions in precursor emissions across all pathways, O_3-related excess mortality may increase under RCP8.5. This indicates complications from methane emissions; expected to increase by 61% over 2005 levels by the 2050s under RCP8.5. This study has shown that substantial benefits may be achieved by mitigation of O_3 precursors regardless of changing climate. However, to achieve maximum prevention, it is important to continue or intensify mitigation of greenhouse gases and O_3 precursors (such as under RCP4.5) to avoid the cost to human health and quality of life.

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Introduction

Human-environment interactions can play significant roles in human health and continue to be explored as probable contributors to adverse health conditions. Recently, with the wave of interest in epigenetics and epigenetic epidemiology, environmental exposures are highlighted as main “tractable” sources of epigenetic change.[1] One interaction explored is the negative effects of ozone (O_3) on human health. Ozone is present in different layers of the atmosphere, but presence of ground-level O_3 is of particular concern since this is where the majority of human-environmental interactions occur. As a result, recognizing these interactions and the drivers of ground-level O_3 is important in understanding resultant health outcomes of O_3. Equally critical, is an understanding of factors that influence O_3 levels, providing insight into the development of policies for improving air quality and, therefore, human health in the future.

While O_3 levels have declined since the 1970 Clean Air Act, as of 2003, over 100 million people continued to live in areas where O_3 exceeds healthy standards.[2] Previous research has shown the influence of meteorological conditions on ground-level O_3 concentrations.[3-6] Ground-level O_3 is particularly sensitive to changes in climate due to enhanced chemical reactions of precursor chemicals under higher temperatures and changes in other climate variables.[7] Thus, accurate prediction models require reliable weather data to understand the influence of climatic conditions on O_3. Global climate models (GCMs) are a primary source of modeled climate data. To predict potential outcomes of environmental changes manifest in health, modeling techniques have been developed to link climate variables from GCMs with various pollutants such as O_3 that may be present in the ambient air.

The main drivers of ground-level O_3 generation have been well established in literature as anthropogenic emissions, presence of methane, and meteorological conditions.[8-10] In order to investigate the relationship that exists between O_3 concentrations and specific changes in these environmental influences, several studies have utilized both chemical transport and statistical models.[8,11-14] Using various combinations of models and approaches, these studies indicate that fluctuations in meteorology and escalating emissions are likely to increase the amount of ground-level O_3. Since O_3 changes due to meteorology are beyond our ability to control, understanding variations in climate and projecting emission changes may play a fundamental role in parsing out the portion of O_3 concentrations attributable to precursor emissions. Thus, future emission mitigation policies may rely heavily on modeled atmospheric concentrations to determine the correct course of action when setting proper emission limits and standards. This knowledge may be of particular importance on local-scales where adverse human health outcomes may be linked to changes in O_3 levels.

In addition to linking O_3 to potential drivers, other studies have demonstrated that elevations in O_3 levels could increase the likelihood of adverse health effects from air quality.[3,6,15,16] High O_3 concentrations have been associated with adverse health outcomes such as respiratory complaints, impaired lung function, asthma exacerbations, increased hospitalizations and premature death.[4,17-21] In a 50-city U.S. study, Bell et al. projected adverse effects due to such rises that may be present in the U.S. in 2050.[3] The results of the Bell et al. study suggest that hospital admissions due to respiratory complaint could increase by >5% and total mortality attributable to O_3 could increase by more than 1% by 2050. These associations were found to be more pronounced in sensitive populations (i.e. children, asthmatics). Additionally, Jerrett et al., utilizing data from the American Cancer Society Prevention Study, demonstrated that ozone exposure is significantly correlated with cardiopulmonary mortality.[22]

Given the potential threat to human health and anticipated climate shifts expected in the next century, it is imperative to more fully understand the dynamics associated with climate, precursor emissions, and air quality. Future atmospheric concentrations of O_3 can be more closely estimated from models designed to reflect a variety of emission scenarios. The most recent scenarios, the Representative Concentration Pathways (RCPs), were designed with support from the Intergovernmental Panel on Climate Change (IPCC). RCPs differ from other emission scenarios (i.e., Special Report on Emissions Scenario (SRES)) because the RCPs take into consideration current and intended air quality legislation for the projection of regional air pollutant emissions as well as atmospheric concentration of greenhouse gases (GHGs).[23-25] As a result, the RCP-based simulations reflect the impact of both climate change and emission control on air pollutant levels.

However, strictly using RCP projections alone in model development poses a problem since O_3 increases in the RCP scenarios are not separated into climatic and emission contributions. Under the parameters of the RCPs, most emissions of O_3 precursors (including carbon monoxide (CO), nitrogen oxides (NOx) and non-methane volatile organic compounds (NMVOCs)) are expected to decrease in the U.S.[23] This decrease is a result of planned legislative controls to reduce emissions of harmful gases and/or aerosols. In order to understand whether these planned controls will be effective, it is necessary to assess the health effects linked to future emission of O_3 precursors in the U.S. as planned and built into the RCP scenarios. Thus, any simulation based on these scenarios would include the effect of both changes in total GHG concentrations and air pollutant emissions. Assessments of O_3 changes under each RCP should, therefore, include methods to distinguish between changes due to GHG concentrations vs. those due to emissions. This segregated approach could aid in evaluations of O_3 changes solely from precursor mitigation.

As meteorological conditions can have a profound impact on O_3, any study examining future O_3 projections requires consideration of robust climate models to predict future conditions while accounting for the increased effects of climate change.[10,11,13,26,27] Global climate models (GCMs) generally exist on large, coarser global scales, while observed pollutant data and observed meteorological data are collected on finer, regional scales. In single pollutant studies (such as those involving O_3) the chosen climate model and its inherent spatial resolution can greatly affect the outcome of the research methods. In a study by West et al.

2013, the cobenefits of pollution mitigation for future air quality was quantified on a global scale. This study lays the foundation for studies such as our current study, however, it is an example of the detail that can be lost when conducting a global pollutant study on a coarse grid.[28]

In order to solve the issue involved with linking data from multiple data sources with differing spatial scales, to achieve finer spatial resolution, and to enhance the ability of analyses to benefit regional-scale climate policy, it is necessary to utilize methods of downscaling.[10,29-31] There are two major types of downscaling applied to address this spatial discrepancy. Dynamical downscaling utilizes output from a GCM as the initial and boundary conditions for regional models.[30] Using this approach, larger-scale GCMs can be used to produce higher-resolution models on regional scales. Statistical downscaling seeks to convert large-scale GCMs to finer-resolution regional models using purely statistical methods.[30,31] Dynamical downscaling, while known for its intensive computational requirements, is an effective way to link regional and global climate models and while also including atmospheric chemistry in the model. Dynamical downscaling uses initial and boundary conditions for both meteorology and chemistry from global models as inputs for regional models and also results in finer-resolution datasets.

In addition to the type of downscaling method used, spatial variation is a frequent concern when estimating climate change effects on health. With warmer and more variable conditions climate change may vary by space; causing changes in air quality attributable to these changes to vary in space as well.[21]

Spatially-resolved analyses of health impacts attributable to climate change and emission estimates are essential for developing effective adaptation strategies. Previous studies have examined the impact of climate change-induced O_3 change on health.[16,19,28] Post et al. modeled the impacts of ozone increases due to climate change on human health in the U.S. on a national and regional scale.[16] The regional scale was quite coarse with the entire U.S. broken into only 3 sub-regions for analysis. Additionally, Tagaris et al. sought to answer the same question; downscaling only to a 36km grid.[19] Finally, West et al. estimated the health effects of emission mitigation via air quality improvements (using RCP4.5) on a coarse global scale (2° x 2.5°).[28] These studies, while attempting to answer key questions in the field, were conducted at coarse resolutions which make it difficult to address community-level health outcomes.

In order to provide finer-resolution estimates of the effects of O_3 on human health, we developed a statistical downscaling model to evaluate future O_3 level changes due to climate change alone at the county level under both RCP 4.5 and RCP 8.5 in the continental U.S. Blending these estimations with our previous dynamical downscaling results (adding additional years to future predictions), we separated the impact of anthropogenic emissions from the impact of climate change on future ozone concentrations.[32] Additionally, we explored the projected ozone-related health impacts at county level using both emissions and climate change contributions and the spatial variability of the contributions of each potential driver. Building on previous studies, the purpose of this study is to produce better ozone models at higher regional resolutions, provide data parsed by contributing factors (climate change vs. anthropogenic emissions), and predict potential ozone health impacts in order to aid future emission mitigation policy.

Data and Methods

Climate Dataset Descriptions

NARR dataset: The National American Region Reanalysis climate dataset is produced by the National Centers for Environmental Protection and provides a wide range of observed climate parameters over North America on a 36 km x 36 km grid.[33] Data from this source was used for the base climate inputs for the years 2001-2004.

CESM/WRF dataset: The Community Earth System Model version 1.0 (CESM 1.0) is a global climate model developed by the National Center for Atmospheric Research (NCAR). The CESM model simulates conditions in Earth's atmosphere as well as in the oceans, land surfaces, and sea ice.[34] CESM-projected, coarse-resolution meteorological fields (12 km x 12 km) for both emissions scenarios RCP4.5 and RCP8.5 were used as the initial and boundary parameter inputs for the high-resolution Weather Research and Forecasting model (WRF) 3.2.1. [35] WRF is a regional climate model that lends the ability to simulate climate conditions with a defined set of input parameters.

WRF-CMAQ dataset: Future ozone concentrations from dynamical downscaling were obtained from the two-way coupled system called the WRF-CMAQ modeling system. This combines the WRF system described above and the

Community Multi-scale Air Quality Model. The combination of the two provides a well-defined atmospheric dynamic downscaling model.[36]

Parameters of Interest: Using daily meteorological data, we computed annual median values for temperature (TEMP), relative humidity (RH), wind speed and direction, planetary boundary layer height (PBL), surface pressure (PRSS) and total annual precipitation (PRSS) for each grid. Stagnant conditions (STG) were characterized by weak wind and no precipitation. In this study, a stagnant day was defined as having surface daily wind speed < 3.2 m/s, wind speed at 500 hPa < 13 m/s, and slight or no precipitation (< 0.1 mm/day).[37] We then calculated differences in the meteorological variables between baseline conditions (2001-2004, or 2000s) and future climate conditions (2055-2059, or 2050s) by grid.

Hourly surface temperature, surface relative humidity, precipitation, wind vectors (zonal (V) and meridional (U)), planetary boundary layer, and pressure were generated by the CESM/WRF model on 12 km x 12 km grids in the continental U.S. for the 2000s and 2050s. Details on model configuration and evaluation can be found in our previous study, Gao et al. (2012).[38]

Prediction of O_3 change:

Statistical Downscaling and Future O_3 from Climate Change Alone

In order to estimate changes in O_3 levels between the 2000s and 2050s caused by climate change alone, we first developed an empirical model to predict O_3 concentrations with meteorological variables. Daily NARR data in the 2000s (using the same variables as those simulated by WRF) were linked to the maximum daily 8-hour averaged O_3 (MDA8 O_3) measured by the U.S.

Environmental Protection Agency Air Quality System (USEPA-AQS). Among all the O_3 monitoring sites, those having at least two years of daily data were retained for model development (1,334 sites). We then matched the MDA8 O_3 concentrations with the NARR meteorological data by selecting the nearest NARR grid cell to the closest O_3 monitoring site. A total of 30 days of moving averaged data for all meteorological variables was used to smooth out short-term fluctuations and to focus on longer-term trends.

Multiple linear regression (MLR) models were developed to estimate the effects of meteorological variables on MDA8 O_3. Because O_3 concentration tends to erode over time, we included natural cubic splines of time (Julian day) to control for the long-term trend of O_3 concentration.[39] With the natural cubic splines, the coefficients of determination (R^2) for the model by site were much improved.[14] Additionally, we included day of the week as a categorical variable due to O_3 fluctuation and its relation to weekly human activity.[12,13] The basic form of the model is as below:

$$y = \beta_0 + \sum_{k=1}^{8} \beta_k x_k + ns(time) + DOW \qquad (1)$$

where y is a 30 day moving averaged MDA8 O_3 concentration; x_k is a 30 day moving averaged value of the meteorological variables; *ns(time)* is the natural cubic splines of time (Julian day: four degrees of freedom); and *DOW* is a categorical variable for day of the week (values from 0 to 6). The models were fitted for each site in order to obtain site-specific correlations between MDA8 O_3 and meteorological variables. Additionally, we used the estimated correlations

(β_k) of each meteorological variable to predict O_3 changes caused by future climatic change.

We matched the estimated regression coefficints (β_k) of the MLR model (equation 1) with the changes in meteorological variables between the 2000s and 2050s. The points closest to the each O_3 mornitoring site in the 12 x 12 km WRF-simulated data were selected. Based on the changes in the meteorological variables, we calculated means and variances of MDA8 O_3 changes by mornitoring site.

To obtain county-level O_3 changes, we interpolated the site-specific O_3 changes to changes for all 3,109 counties of the continental U.S. Changes in O_3 were predicted based only on the correlations of O_3 with meteorological variables and changing climate conditions under the two RCPs under the assumption that emmission conditions will remain static (using conditions in the 2000s). Hence, the predicted O_3 changes generated by the WRF-MLR were considerd attributable to climate change alone.

Dynamical Downscaling, Climate Change and Anthropogenic Emissions

To predict the MDA8 O_3 changes attributable to the combination of emission and climate change, the WRF-CMAQ (version 5.0) were used. The emission projection inputs for the WRF-CMAQ model simulations were based on the RCP database for both RCP 4.5 and RCP 8.5. Thus, the projected O_3 levels in the 2050s reflect the influence both of climate change and emission control on O_3 precursors as the RCP database is a set of new emission inventories reflecting planned air quality legislation and future GHG concentrations.[23]

Using calculated annual median values of MDA8 O_3 based on CMAQ-simulated O_3, we computed differences in MDA8 O_3 between the 2000s and the 2050s for each 12 km grid cell. We then aggregated values to the 3,109 counties to obtain county-level changes.

Additionally, to reduce the bias of model simulation, we calibrated the MDA8 O_3 levels using the concentrations measured by the USEPA-AQS. The closest CMAQ-simulated grid value to the USEPA-AQS sites was selected and matched with USEPA-AQS O_3 values. Ratios of annual averaged MDA8 O_3 for the 2000s were calculated for CMAQ-simulated and observed concentrations by site and interpolated to the county level. The five closest points to each population-weighted county centroid were identified and then the calibration ratios from each site were averaged to generate a single ratio for each county. Finally, we calculated calibrated CMAQ-simulated O_3 for the 2000s and the 2050s by multiplying the concentrations by the calibration ratios for each county.

Estimation O_3 change from Anthropogenic Emissions Alone

In order to isolate changes in O_3 concentration attributable to future anthropogenic emissions alone, we determined the differences between the concentrations generated by the previous two models. The dynamical downscaling model involving the CMAQ-simulated O_3 values represents the increase in future concentration attributable to both climate change and anthropogenic emissions. The statistical downscaling model, however, is an estimation of changes in concentration due to climate change alone. Thus, subtracting the statistical model (climate change only) from the dynamical model (climate change and emissions) we are left with an estimation of the contributions from emissions alone (see Equation 2).

$$\Delta Ozone_{climate\ change+emissions} - \Delta Ozone_{climate\ change} = \Delta Ozone_{emissions} \qquad (2)$$

Public Health Impact O_3 from Anthropogenic Emissions

Population and mortality rate estimates, as well as concentration response function (CRF) coefficients are required to estimate the excess mortality (EM) due to future changes in MDA8 O_3.[5,16] We used the four population projections developed by the Integrated Climate and Land-Use Scenarios (ICLUS) project; ICLUS-A1, B1, A2 and B2. ICLUS converts the global Special Report on Emissions Scenarios (SRES) settings into county-level projections.[40] The A1 storyline represents a scenario of rapid development, slow population growth, and high global interaction. In the U.S., the A1 assumes high migration both internationally and domestically. The B1 scenario assumes similar conditions to A1, but has a larger emphasis on sustainable economic growth which and lower domestic migrations than A1. The A2 storyline represents continued economic development with a more regional focus and slower economic convergence regionally. Thus, the A2 scenario is indicative of higher fertility rates than A1 and B1. The B2 scenario represents a more regionally-oriented future with moderate population growth, and much lower domestic migration.[40]

For the calculation of baseline mortality incidence, we used the predicted mortality rate for the year of 2050 at county level which is available at from the Environmental Benefits Mapping and Analysis Program Community Edition 1.0.8 (BenMAP-CE) developed by U.S. Environmental Protection Agency.[41] The

BenMAP-CE provides county-specific mortality rates derived from projected age-specific ratios of 2050 mortality rates to 2005 mortality rates.

We based CRFs on the association between non-accidental, all-cause mortality and short-term exposure to MDA8 O_3 as estimated by Bell et al., 2004 (RR = 1.0064 (95% CI: 1.0041-1.0092) per 15 ppb).[4] The estimations from Bell et al. are based on the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) dataset and cover 95 major U.S. cities. We estimated changes in EM at the county level using a health impact formula similar to methods that have previously used, as follows:[5,16]

$$\Delta y_i = POP_i \times MR_i \times \left[e^{\gamma \times \Delta C_i} - 1\right] \qquad (3)$$

where Δy is the expected number of deaths per year that may be attributed to changing air pollution levels (i.e., O_3) at county i; POP_i is population of county i; MR_i is population mortality rate, $POP_i \times MR_i$ indicates baseline mortality incidence (i.e., assuming no ozone change); γ is the concentration-response coefficient for MDA8 O_3; and ΔC_i is the difference in concentrations of MDA8 O_3 between future (2050s) and baseline (2000s) levels of MDA8 O_3.

After assessing O_3-related EMs due to both emission and climate changes and EMs due to climate change alone, we computed the health benefit of the emission changes of O_3 precursors. To evaluate the uncertainty of EM estimates attributable to the ranges of the CRF coefficients and mortality rates, we utilized Monte Carlo simulations. Random sampling and EM calculations were repeated 1,000 times for each county assuming a normal distribution of independent county-specific means, standard errors of the CRF coefficients, and mortality rates. We then estimated climate region and national level EM estimates by summing all the county-level EMs derived from the Monte Carlo simulation. We also estimated 95% confidence intervals (CIs) of the EMs based on the mean and standard deviation of the 1,000 simulations at both levels. The climate-region definitions are based on the divisions put forth by the National Climatic Data Center definition, dividing the continental U.S. into nine climate regions (Figure 1).[42]

Results

Prediction of O_3 change:

Figure 2 shows county-level changes in meteorological variables used in the model between the 2000s and the 2050s predicted by the WRF model. The changes in meteorological variables show wide spatial variations. Annual medians of the daily mean temperature were shown to increase by approximately 1.3 °C and 2.2 °C across the continental U.S. under RCP4.5 and 8.5, respectively; showing greater increases in the eastern area than in others. Overall, RH would increase annually by 0.9% under RCP4.5 and 1.6% under RCP8.5; with higher increases in the Central region. Daily total precipitation and mean pressure will increase by 0.1 mm/day and 1.1 hPa under both RCP4.5 and 8.5. Averages of PBL would decrease slightly by 17.0 m under RCP4.5 and 4.2 m under RCP 8.5. Meridional (N/S) wind speed will increase in most inland areas of the U.S. under both RCPs, while decreases are predicted in the Northwest region. Zonal (E/W) wind speed will decrease in much of the U.S with some increase seen in the West and Southwest regions.

For all 1334 USEPA-AQS O_3 monitoring sites, the MLR model performed well with relatively high R^2 for all sites. The average R^2 for all sites for predicting actual O_3 concentrations was R^2=0.76. MDA8 O_3 changes between the 2000s and the 2050s for the WRF-MLR model are shown in Figure 3 (A) and (B). Climate change alone (WRF-MLR) appears to cause an increase in MDA8 O_3 concentration in most of the continental U.S. except for some counties in the West and South regions. Overall, increases in MDA8 O_3 due to climate change is expected to be 0.30 ppb (SE: 0.01) and 0.65 ppb (SE: 0.01) under RCP4.5 and 8.5, respectively.

Using the WRF-CMAQ dataset (combination of both emissions and climate change included in the model), levels of MDA8 O_3 is expected to decrease by 2.6 ppb (SE: 0.02) nationally under RCP 4.5. Under RCP 8.5 concentrations are expected to increase more with national increases exceeding 1.5 ppb (SE: 0.01). See figure 3 (C) and (D).

According to the RCP4.5 emissions scenario, MDA8 O_3 due to emissions alone is expected to decrease by 3.2 ppb (SE: 0.01) in the future. Despite the emission reduction of O_3 precursors including CO, NOx and NMVOCs, MDA8 O_3 is expected to increase by 0.6 ppb (SE: 0.10) nationally in the 2050s under the RCP8.5 (see Fig 3 (E) and (F)). Although RCP 8.5 also assumes reduced CO, NOx and NMVOCs emissions, the pathway assumes 61% more emissions of methane in the 2050s than in 2005.[23,43]

Public Health Impact O_3 from Anthropogenic Emissions

Tables 1 and 2 provide the estimated O_3-related excess mortalities by region, population projection, and by RCP scenario projection. Under the highest population growth projection (ICLUS A2) and climate conditions under RCP 4.5, O_3-related EM due to climate change alone could increase by approximately 34 deaths/year nationally. However, the effect of emission reduction of O_3 precursors is poised to significantly offset the adverse health effects of the ozone due to climate change. Looking at mortality alone, estimated excess mortality from emissions only for RCP 4.5 showed a decrease in the EM by 1653 deaths/year in the 2050s. Consequently, the emission mitigation of O_3 precursors under RCP4.5 could avoid approximately 1619 (ICLUS-A2) premature deaths (0.11% of baseline mortality in the 2050s) with the largest benefits seen in the South and Southeast regions. A few counties in the West region are expected to increase in O_3-related EM even under RCP4.5, however, the statistics were not significant.

Under RCP8.5, the excess mortality from climate change alone could increase by 148 (4.5, 291.4, 95% CI) deaths/year (ICLUS-A2) nationally. Despite the planned emission reductions of major O_3 precursors built into the RCP pathways, EM from emissions would increase by 1252 (1019.3, 1484.8, 95% CI) deaths/year nationally under RCP8.5. Consequently, the net effect of emission changes under the RCP8.5 would reflect an increase in O_3-related EM by ~1400 (ICLUS-A2) deaths/year (0.10% of baseline mortality in the 2050s) under the

RCP8.5 scenario. The regions with the greatest negative impact are the West and the Northeast.

It is important to note that the estimated EMs attributable to O_3 changes under the RCPs vary by county within the same population projection; showing both negative and positive results by region, as seen in Tables 1 and 2. County-level O_3-related EM is high in counties with higher populations such as Los Angeles, California, Cook, Illinois, and Kings and Suffolk, New York; including some mortality under RCP4.5. However, generally, counties will only gain real benefits from emission changes under the RCP 4.5 scenario.

Discussion

The results of this study demonstrate that, while climate change alone can cause an increase in O_3 levels in the future, anthropogenic emission changes can also impact future O_3 concentrations. Potential increases in premature death and in adverse health effects of both climate change-induced and anthropogenic-induced O_3 increases may be substantially avoided by the emission reductions planned in the U.S. under RCP4.5.

Despite the emission reduction of CO, NOx and NMVOCs under RCP8.5, however, O_3-related EM may increase in the U.S. This increase may potentially be due to increases in methane emissions.[43] The methane emissions in RCP8.5 are significantly larger than in the other RCPs.[25] Differences between the RCPs in methane may actually have a stronger impact on O_3 level than the difference in NOx emissions.[44] Methane emission is predicted to increase by ~60% by the end of the 2050s across the U.S. under RCP8.5. The amount of increased methane could be especially high in cities with larger populations in the Northeast, East North Central, West and Northwest regions as addressed in van Vuuren et al.[25] Thus, this increase is may be expected to as the main contributing factor for increases in O_3 (Figure 3(D)) and O_3-related EM (Figure 5(F)) under the RCP8.5.

The distribution of ozone and related mortalities may be explained by the differential methane and GHG levels across counties in the future. CMAQ-simulated O_3 that reflects the effects of both emission and climate changes (particularly under RCP8.5) may increase in the western U.S. due to these increases in methane concentrations; while in the eastern US, the increase of methane concentrations may be offset by large decreases of NMVOC/NOx.[43] As a result, the net effect of O_3 precursor emissions changes on O_3-related EM (ECC-EM minus CC-EM) could increase in the South, Southwest, Northwest, and West regions under RCP8.5. This finding supports recent research that has linked future increases in methane concentrations to increased ozone concentrations and which has proposed that the control of methane emissions may be an efficient way to reduce both tropospheric ozone and radiative forcing.[10,28,45,46]

Ideally, to compare the effects of emission changes in O_3 precursors on O_3 level and their subsequent health effects, the use of the same model for scenarios with and without emission changes would more advantageous. However, we chose to use the MLR empirical model to analyze climate change-only effects and the CMAQ chemical transport model for both climate and emission change effects on O_3. The rationale for model choice is due to the RCP emission pathways. In the projected O_3 levels in the 2050s under the RCP, the emission projections of O_3 precursors were determined by emission database for the RCP and reflect the influence of both climate change and future emission control on O_3 precursors.[23] These precursors include GHGs, which inhibit a separation of emission and climate change from the WRF-CMAQ modeling process. Due to this limitation, we developed our model to assess the future climate change effect on O_3 using the WRF-simulated climate change; which has been shown to be effective at detecting the impact of climate change on ozone.

As with all predictions, there are many uncertainties in the estimation of the health impacts of ozone change under future climate and emission changes. These uncertainties generally lie in the estimation of the future mortality rate, CRF, population projection, and O_3 concentration predictions. We evaluated the uncertainty of EM estimates attributable to the ranges of CRF coefficients and mortality rates by applying the Monte Carlo simulation method.

This analysis of county-level spatial variations in EM due to climate change and emissions has added significantly by using a 12 km resolution prediction of meteorological variables and O_3 simulations based on WRF-CMAQ under RCPs. Using the relatively new RCP pathways, we have provided regional and county level estimates at finer spatial resolution for estimated future ozone concentrations and the potential impact. Additionally, this study has given two differing scenarios to compare some of the potential costs and/or benefits of following stricter emission control guidelines.

While climate change alone may cause some adverse health effects due to aggravation of air quality, substantial health benefits may be achieved by emission mitigation of O_3 precursors regardless of changing climate conditions. The effects of combined climate and emission changes on O_3-related mortality can vary spatially on regional, county, and local scales. This suggests that more regional and local level adaptations for mitigation may be more effective or appropriate than large scale environmental policies that have, thus far, proved inefficient.

However, even with the reduction of O_3 precursors, O_3-related excess mortality may still increase in the U.S., due to methane increases in the atmosphere. To prevent adverse health effects of this potential driver, it is important to continue to or even intensify mitigation efforts towards both GHGs and O_3 precursors in order to avoid the cost to human health and quality of life.

References

1. Mill J, Heijmans BT. From promises to practical strategies in epigenetic epidemiology. *Nature Reviews Genetics*. 2013;14(8):585-594.
2. (USEPA) USEPA. *The ozone report: measuring progress through 2003*. Research Triangle Park, North Carolina: EPA;2004.
3. Bell ML, Goldberg R, Hogrefe C, et al. Climate change, ambient ozone, and health in 50 US cities. *Climatic Change*. 2007;82(1-2):61-76.
4. Bell ML, McDermott A, Zeger SL, Samet JM, Dominici F. Ozone and short-term mortality in 95 US urban communities, 1987-2000. *Jama-Journal of the American Medical Association*. 2004;292(19):2372-2378.
5. Fann N, Lamson AD, Anenberg SC, Wesson K, Risley D, Hubbell BJ. Estimating the National Public Health Burden Associated with Exposure to Ambient PM2.5 and Ozone. *Risk Analysis*. 2012;32(1):81-95.
6. Knowlton K, Rosenthal JE, Hogrefe C, et al. Assessing ozone-related health impacts under a changing climate. *Environmental Health Perspectives*. 2004;112(15):1557-1563.
7. Aw J, Kleeman MJ. Evaluating the first-order effect of intraannual temperature variability on urban air pollution. *Journal of Geophysical Research-Atmospheres*. 2003;108(D12).
8. Dawson JP, Adams PJ, Pandis SN. Sensitivity of ozone to summertime climate in the eastern USA: A modeling case study. *Atmospheric Environment*. 2007;41(7):1494-1511.
9. Jacob DJ, Winner DA. Effect of climate change on air quality. *Atmospheric Environment*. 2009;43(1):51-63.

10. Nolte CG, Gilliland AB, Hogrefe C, Mickley LJ. Linking global to regional models to assess future climate impacts on surface ozone levels in the United States. *Journal of Geophysical Research-Atmospheres*. 2008;113(D14).

11. Weaver CP, Liang XZ, Zhu J, et al. A preliminary synthesis of modeled climate change impacts on U.S. regional ozone concentrations. *Bulletin of the American Meteorological Society*. 2009;90(12):1843-1863.

12. Camalier L, Cox W, Dolwick P. The effects of meteorology on ozone in urban areas and their use in assessing ozone trends. *Atmospheric Environment*. 2007;41(33):7127-7137.

13. Cheng CSQ, Campbell M, Li Q, et al. A synoptic climatological approach to assess climatic impact on air quality in South-central Canada. Part I: Historical analysis. *Water Air and Soil Pollution*. 2007;182(1-4):131-148.

14. Davis J, Cox W, Reff A, Dolwick P. A comparison of CMAQ-based and observation-based statistical models relating ozone to meteorological parameters. *Atmospheric Environment*. 2011;45(20):3481-3487.

15. Jackson JE, Yost MG, Karr C, et al. Public health impacts of climate change in Washington State: projected mortality risks due to heat events and air pollution. *Climatic Change*. 2010;102(1-2):159-186.

16. Post ES, Grambsch A, Weaver C, et al. Variation in Estimated Ozone-Related Health Impacts of Climate Change due to Modeling Choices and Assumptions. *Environmental Health Perspectives*. 2012;120(11):1559-1564.

17. Dockery DW, Pope CA. Acute Respiratory Effects of Particulate Air-Pollution. *Annual Review of Public Health*. 1994;15:107-132.

18. Strickland MJ, Klein M, Flanders WD, et al. Modification of the Effect of Ambient Air Pollution on Pediatric Asthma Emergency Visits Susceptible Subpopulations. *Epidemiology*. 2014;25(6):843-850.

19. Tagaris E, Liao KJ, Delucia AJ, Deck L, Amar P, Russell AG. Potential Impact of Climate Change on Air Pollution-Related Human Health Effects. *Environmental Science & Technology*. 2009;43(13):4979-4988.

20. Bell ML, Dominici F, Samet JM. A meta-analysis of time-series studies of ozone and mortality with comparison to the national morbidity, mortality, and air pollution study. *Epidemiology*. 2005;16(4):436-445.

21. Bernard SM, Samet JM, Grambsch A, Ebi KL, Romieu I. The potential impacts of climate variability and change on air pollution-related health effects in the United States. *Environmental Health Perspectives*. 2001;109:199-209.

22. Jerrett M, Burnett RT, Pope CA, et al. Long-Term Ozone Exposure and Mortality. *New England Journal of Medicine*. 2009;360(11):1085-1095.

23. (IIASA) IIfASA. RCP Database Version 2.0. 2013; http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=welcome. Accessed 8 August 2014.

24. Moss RH, Edmonds JA, Hibbard KA, et al. The next generation of scenarios for climate change research and assessment. *Nature*. 2010;463(7282):747-756.

25. van Vuuren DP, Edmonds J, Kainuma M, et al. The representative concentration pathways: an overview. *Climatic Change*. 2011;109(1-2):5-31.

26. Colette A, Granier C, Hodnebrog O, et al. Future air quality in Europe: a multi-model assessment of projected exposure to ozone. *Atmospheric Chemistry and Physics*. 2012;12(21):10613-10630.

27. Tolbert PE, Klein M, Peel JL, Sarnat SE, Sarnat JA. Multipollutant modeling issues in a study of ambient air quality and emergency department visits in Atlanta. *J Expo Sci Environ Epidemiol*. 2007;17:S29-S35.

28. West JJ, Smith SJ, Silva RA, et al. Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health. *Nature Climate Change*. 2013;3(10):885-889.

29. Caldwell P, Chin HNS, Bader DC, Bala G. Evaluation of a WRF dynamical downscaling simulation over California. *Climatic Change*. 2009;95(3-4):499-521.

30. Fowler HJ, Blenkinsop S, Tebaldi C. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*. 2007;27(12):1547-1578.

31. Mahmud A, Tyree M, Cayan D, Motallebi N, Kleeman MJ. Statistical downscaling of climate change impacts on ozone concentrations in California. *Journal of Geophysical Research-Atmospheres*. 2008;113(D21).

32. Kim YM, Zhou Y, Gao Y, et al. Spatially resolved estimation of ozone-related mortality in the United States under two representative concentration pathways (RCPs) and their uncertainty. *Climatic Change*. 2015;128(1-2):71-84.

33. PSD) NOaAAESRLPSDNOE. Nationla Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR). 2013; http://esrl.noaa.gov/psd/data/gridded/data.narr.monolevel.html. Accessed 20 Spetember 2013.

34. Gent PR, Danabasoglu G, Donner LJ, et al. The Community Climate System Model Version 4. *Journal of Climate*. 2011;24(19):4973-4991.

35. Skamarock WC, Klemp JB. A time-split nonhydrostatic atmospheric model for weather research and forecasting applications. *Journal of Computational Physics*. 2008;227(7):3465-3485.

36. Agency USEP. Atmospheric Modeling and Analysis Research: Coupled WRF-CMAQ Modeling System. http://www.epa.gov/amad/Research/Air/twoway.html. Accessed 16 October 2014.

37. JXL W, JK A. *Air Stagnation Climatology for the Uited States*. NOA/Air Resource Laboratory, Atlas No. 1;1999.

38. Gao Y, Fu JS, Drake JB, Liu Y, Lamarque JF. Projected changes of extreme weather events in the eastern United States based on a high resolution climate modeling system. *Environmental Research Letters*. 2012;7(4).

39. (USEPA) USEPA. *Integrated Science Assessment for Ozone and Related Photochemical Oxidants*. Research Triangle Park, NC2013.

40. Agency USEP. *Land-Use Scenarios: National-Scale Housing-Density Scenarios Consistent with Climate Change Storylines (Final Report)*. Washington, DC2009.

41. Agency USEP. *BenMap: Environmental Benefits Mapping and Analysis Program: User's Manual Appendices*. Research Trianle Park, NC: USEPA;2012.

42. (NOAA) NCDCNNOaAA. U.S. Climate Regions. 2013; http://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php. Accessed 21 September 2014.

43. Gao Y, Fu JS, Drake JB, Lamarque JF, Liu Y. The impact of emission and climate change on ozone in the United States under representative concentration pathways (RCPs). *Atmospheric Chemistry and Physics*. 2013;13(18):9607-9621.

44. Lamarque JF, Emmons LK, Hess PG, et al. CAM-chem: description and evaluation of interactive atmospheric chemistry in the Community Earth System Model. *Geoscientific Model Development*. 2012;5(2):369-411.

45. West JJ, Fiore AM. Management of tropospheric ozone by reducing methane emissions. *Environmental Science & Technology*. 2005;39(13):4685-4691.

46. West JJ, Fiore AM, Naik V, Horowitz LW, Schwarzkopf MD, Mauzerall DL. Ozone air quality and radiative forcing consequences of changes in ozone precursor emissions. *Geophysical Research Letters*. 2007;34(6).

Figures and Tables

Figure 1. *Climate regions of the continental U.S.*

Regions as defined by the National Climatic Data Center. Climate regions used to delineate like areas for analysis.

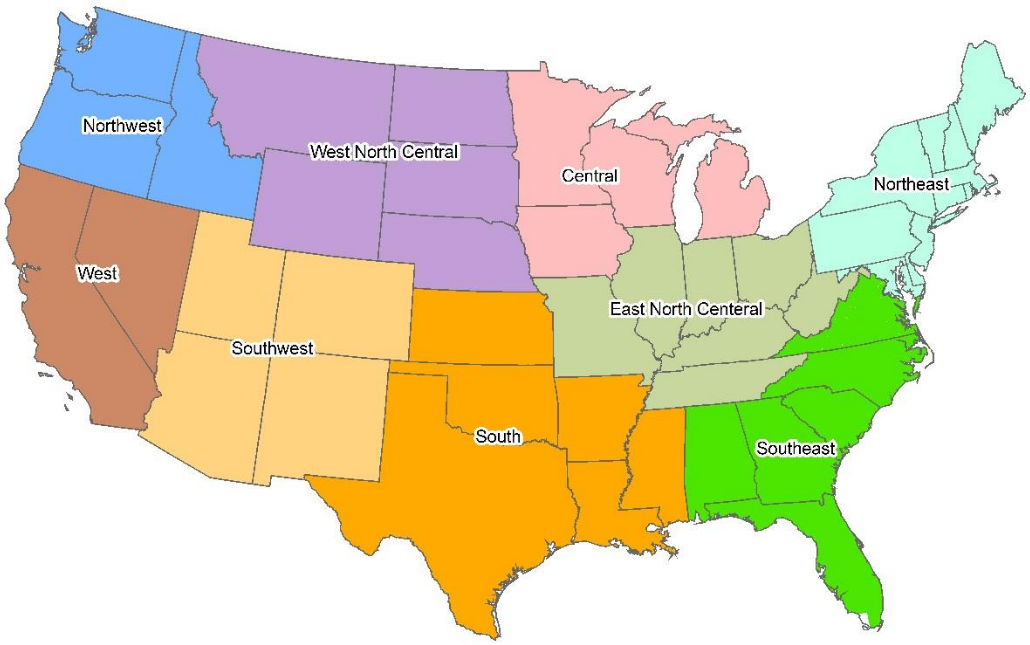

Figure 2. ***Changes in meteorological parameters.***

Differences between 2000s and 2050s in temperature, planetary boundary layer height, precipitation, relative humidity, surface pressure, and meriodonal and zonal wind speeds.

Figure 2.

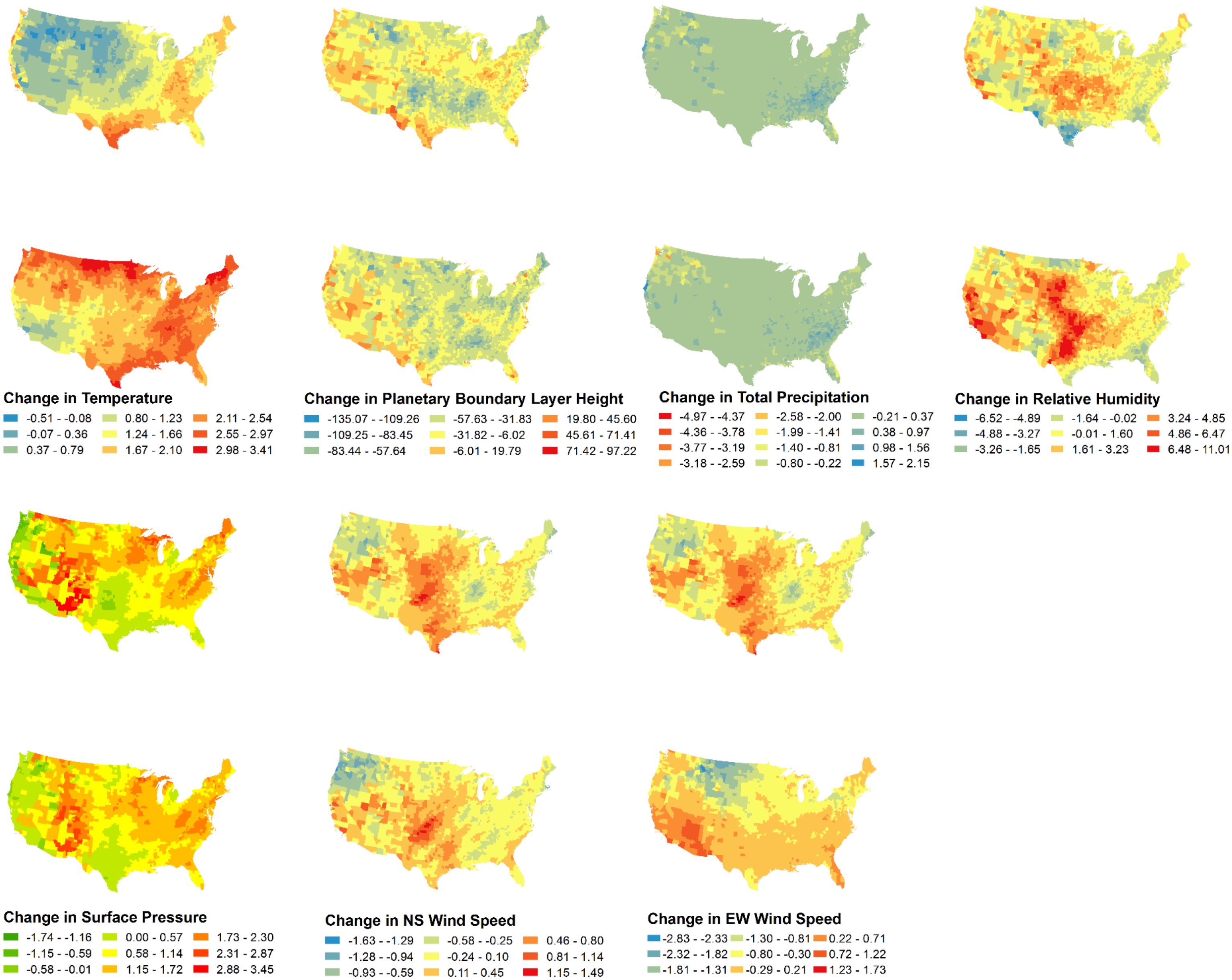
Change in Temperature
-0.51 - -0.08
-0.07 - 0.36
0.37 - 0.79
0.80 - 1.23
1.24 - 1.66
1.67 - 2.10
2.11 - 2.54
2.55 - 2.97
2.98 - 3.41
Change in Planetary Boundary Layer Height
-135.07 - -109.26
-109.25 - -83.45
-83.44 - -57.64
-57.63 - -31.83
-31.82 - -6.02
-6.01 - 19.79
19.80 - 45.60
45.61 - 71.41
71.42 - 97.22
Change in Total Precipitation
-4.97 - -4.37
-4.36 - -3.78
-3.77 - -3.19
-3.18 - -2.59
-2.58 - -2.00
-1.99 - -1.41
-1.40 - -0.81
-0.80 - -0.22
-0.21 - 0.37
0.38 - 0.97
0.98 - 1.56
1.57 - 2.15
Change in Relative Humidity
-6.52 - -4.89
-4.88 - -3.27
-3.26 - -1.65
-1.64 - -0.02
-0.01 - 1.60
1.61 - 3.23
3.24 - 4.85
4.86 - 6.47
6.48 - 11.01
Change in Surface Pressure
-1.74 - -1.16
-1.15 - -0.59
-0.58 - -0.01
0.00 - 0.57
0.58 - 1.14
1.15 - 1.72
1.73 - 2.30
2.31 - 2.87
2.88 - 3.45
Change in NS Wind Speed
-1.63 - -1.29
-1.28 - -0.94
-0.93 - -0.59
-0.58 - -0.25
-0.24 - 0.10
0.11 - 0.45
0.46 - 0.80
0.81 - 1.14
1.15 - 1.49
Change in EW Wind Speed
-2.83 - -2.33
-2.32 - -1.82
-1.81 - -1.31
-1.30 - -0.81
-0.80 - -0.30
-0.29 - 0.21
0.22 - 0.71
0.72 - 1.22
1.23 - 1.73

Figure 3. Changes in Ozone Concentrations.

Differences between 2000s and 2050s in ozone concentrations by RCP scenarios 8.5 and 4.5 and by model: (A) RCP 4.5 O_3 difference from climate change; (B) RCP 8.5 O_3 difference from climate change; (C) RCP 4.5 O_3 difference from combined climate change and emissions; (D) RCP 8.5 O_3 difference from combined climate change and emissions; (E) RCP 4.5 O_3 difference from emissions only; and (F) RCP 8.5 O_3 difference from emissions only.

Figure 3.

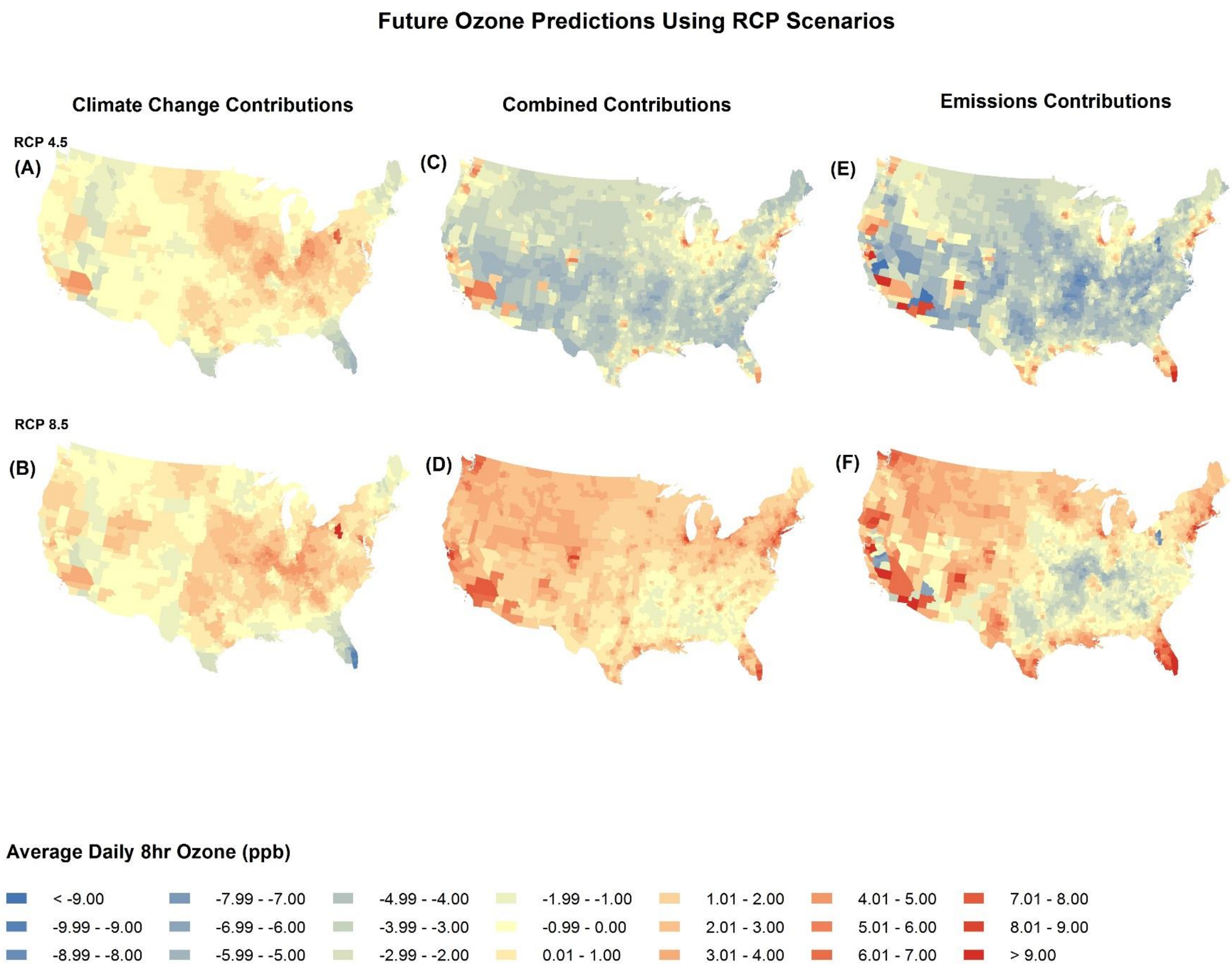
Future Ozone Predictions Using RCP Scenarios
Climate Change Contributions
Combined Contributions
Emissions Contributions
RCP 4.5
(A)
(C)
(E)
RCP 8.5
(B)
(D)
(F)
Average Daily 8hr Ozone (ppb)
< -9.00
-9.99 - -9.00
-8.99 - -8.00
-7.99 - -7.00
-6.99 - -6.00
-5.99 - -5.00
-4.99 - -4.00
-3.99 - -3.00
-2.99 - -2.00
-1.99 - -1.00
-0.99 - 0.00
0.01 - 1.00
1.01 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 6.00
6.01 - 7.00
7.01 - 8.00
8.01 - 9.00
> 9.00

Table 1. Excess Mortality under RCP 4.5.

Projected excess mortalities attributable to climate change only, anthropogenic emissions only, and combined effects of both climate change and emissions for 2050s from baseline 2000s by U.S. climatic region and by ICLUS population projection. Top values indicate projected values with 95% confidence intervals indicated below each estimate.

Table 1. Excess Mortality by Population Scenario: RCP 4.5

	CLIMATE CHANGE				EMISSIONS				COMBINED CLIMATE AND EMISSIONS			
REGION	ICLUS A2 RCP 4.5	ICLUS A1 RCP 4.5	ICLUS B2 RCP 4.5	ICLUS B1 RCP 4.5	ICLUS A2 RCP 4.5	ICLUS A1 RCP 4.5	ICLUS B2 RCP 4.5	ICLUS B1 RCP 4.5	ICLUS A2 RCP 4.5	ICLUS A1 RCP 4.5	ICLUS B2 RCP 4.5	ICLUS B1 RCP 4.5
National	34.2 -80.2, 148.6	3.2 -100.9, 107.4	82.5 -21.8, 186.8	4.9 -102.6, 112.4	-1652.8 -1861.1, -1444.5	-1394.0 -1587.6, -1200.4	-1495.8 -1683.6, -1308.0	-1414.8 -1610.3, -1219.3	-1667.2 -1870.1, -1464.3	-1435.8 -1624. -1246.8	-1433.8 -1618.4, -1249.2	-1346.8 -1545.6, -1148.1
Northeast	10.4 6.5, 14.3	7.2 2.8, 11.6	17.4 13.4, 21.5	-4.1 -117.1, -111.2	-163.5 -174.7, -152.4	-58.9 -72.4, -45.3	-34.5 -46.2, -22.8	-48.7 -64.3, -33.0	-108.0 -120.0, -96.1	-117.5 -131.5, -103.4	-132.2 -144.5 ,-119.9	-18.8 -22.7, -20.8
Southeast	-146.5 -149.6, -143.4	-115.0 -118.2, -111.8	-139.1 -141.6, -136.6	-114.2 -9.4, 1.2	-640.9 -643.9, -637.8	-575.9 -578.8, 573.0	-521.6 -523.8, 519.4	-518.1 -520.4, -515.8	-735.2 -738.5, -731.9	-659.3 -662.4, -656.1	-596.0 -598.5, -593.6	-573.5 -573.1, -570.8
East North Central	3.0 2.9, 3.1	3.0 2.9, 3.2	4.7 4.6, 4.8	5.4 5.2, 5.5	-76.0 -76.4, -75.6	-62.7 -63.0, -62.3	-84.5 -84.9, -84.1	-79.8 -80.1, -79.4	-77.1 -77.5, -76.7	-65.1 -65.4, -64.8	-85.9 -86.3, -85.6	-80.5 -80.8, -80.1
Central	133.4 132.9, 133.9	113.8 113.4, 114.2	143.0 142.6, 143.5	132.2 3.1, 3.3	-194.1 -195.1,- 193.1	-148.3 -149.0,- 147.5	-214.4 -215.3,- 213.4	-196.8 -197.7,- 195.9	-200.9 -201.9, 199.9	-172.6 -173.5,- 171.8	-225.6 -226.6,- 224.7	-211.2 -212.1,- 210.3

West North Central	3.8	3.1	3.4	3.2	-20.8	-16.8	-24.7	-22.7	-17.9	-14.4	-21.2	-19.4
	3.7, 3.8	3.0, 3.2	3.2, 3.5	-19.5, -19.4	-20.9, -20.7	-16.9, -16.8	-24.8, -24.5	-22.7, -22.6	-17.9 ,-17.9	-14.4, -14.3	-21.1, -21.2	-19.5, -19.4
South	15.3	13.8	10.0	9.4	-346.5	-307.4	-323.6	-308.7	-312.1	-278.9	-289.8	-282.9
	14.6, 15.9	13.2, 14.4	9.5, 10.5	-284.0, -281.9	-347.9, -345.1	-308.7, -306.1	-324.7 -322.4	-309.8, -307.5	-313.5, -310.8	-280.1, -277.7	-290.8, -288.8	-284.0, -281.9
Southwest	-26.1	-21.0	-15.4	-13.9	-168.5	-129.3	-119.4	-112.1	-116.6	-92.1	-94.6	-79.9
	-27.9, -24.3	-22.5, -19.6	-16.6, -14.2	-15.0, -12.9	-174.4, -162.5	-134.2, -124.4	-123.7, -115.1	-116.1, -108.1	-120.6, -112.6	-95.5, -88.7	-97.5, -91.6	-82.6, 77.1
Northwest	-10.4	-9.8	-8.8	-10.5	-9.7	-13.6	-16.1	-16.9	-21.4	-17.2	-22.9	-21.8
	-11.0, -9.8	-10.4, -9.1	-9.3 ,-8.2	-11.2, -9.9	-11.1, -8.3	-15.2, -12.1	-17.4, -14.7	-18.5, -15.4	-22.2 ,-20.6	-18.1, -16.2	-23.7, -22.1	-35.8 ,-1.8
West	114.9	52.5	77.3	81.2	-92.0	-104.5	5.1	-29.7	-57.9	-69.4	-54.4	-52.5
	81.4, 148.3	25.2, 79.8	46.4, 108.1	52.5, 109.9	-153.5 ,-30.5	-152.8, -56.3	-48.4, 58.6	-80.6, 21.3	-112.4, -3.4	-114.5, -24.2	-106.7 -2.0	-97.2, -7.9

* **Denotes a significant value**

Table 2. Excess Mortality under RCP 8.5.

Projected excess mortalities attributable to climate change only, anthropogenic emissions only, and combined effects of both climate change and emissions for 2050s from baseline 2000s by U.S. climatic region and by ICLUS population projection. Top values indicate projected values with 95% confidence intervals indicated below each estimate.

Table 2. Excess Mortality by Population Scenario: RCP 8.5

	CLIMATE CHANGE				EMISSIONS				COMBINED CLIMATE AND EMISSIONS			
REGION	ICLUS A2 RCP 8.5	ICLUS A1 RCP 8.5	ICLUS B2 RCP 8.5	ICLUS B1 RCP 8.5	ICLUS A2 RCP 8.5	ICLUS A1 RCP 8.5	ICLUS B2 RCP 8.5	ICLUS B1 RCP 8.5	ICLUS A2 RCP 8.5	ICLUS A1 RCP 8.5	ICLUS B2 RCP 8.5	ICLUS B1 RCP 8.5
National	148.0	91.6	220.2	66.1	1252.0	1289.5	1168.0	1272.3	1602.6	1268.0	1415.4	1435.2
	4.5, 291.4	-46.7, 229.9	85.2, 355.1	-81.3, 213.5	1019.3, 1484.8	1068.6, 1510.3	943.4, 1392.6	1033.8, 1510.9	1363.5, 1841.7	1043.8, 1492.2	(1185.4,1645.5)	(1191.0,1679.4)
Northeast	73.2	61.0	98.5	-5.7	491.0	474.2	427.0	512.8	545.8	575.8	533.4	477.8
	65.3, 81.0	51.6, 70.3	90.1, 106.8	-17.0, 5.6	476.4, 505.5	456.5, 492.0	412.0, 442.0	492.5, 533.0	530.0, 561.6	556.7, 594.8	517.0, 549.7	456.1, 499.5
Southeast	-156.5	-182.5	-173.7	-173.6	72.3	87.1	51.9	65.4	55.7	59.5	43.3	51.1
	-160.7, -152.3	-186.9, -178.1	-177.3, -170.2	-177.8, -169.4	69.3, 75.2	84.2, 90.0	49.4, 54.4	62.5, 68.3	53.7, 57.6	57.6, 61.5	41.6, 45.0	49.2, 53.0
East North Central	15.4	12.9	16.8	16.2	89.7	78.1	84.3	80.1	107.8	92.4	101.7	96.9
	15.2, 15.6	12.7, 13.1	16.6, 17.0	16.0, 16.4	77.6, 89.1	77.6, 78.6	83.8, 84.9	79.5, 80.6	107.2, 108.5	91.8, 92.9	101.1, 102.3	96.3, 97.4
Central	155.2	131.9	154.1	153.1	153.6	128.0	135.4	153.9	166.9	130.9	157.3	137.4
	154.6, 155.9	131.4, 132.5	153.5, 154.8	152.5, 153.6	152.2, 155.0	126.9, 129.1	134.0, 136.8	152.6, 155.2	165.4,168.5	129.6, 132.2	155.7, 158.9	136.0, 138.8

West North Central	5.7 5.6, 5.7	4.8 4.7, 4.9	5.8 5.8, 5.9	5.5 5.4, 5.6	10.3 10.2, 10.3	8.1 8.0, 8.1	11.7 11.6, 11.8	10.6 10.6, 10.7	12.3 12.2, 12.3	9.9 9.8, 9.9	14.0 14.0, 14.1	12.9 12.8, 12.9
South	44.3 43.6, 45.0	42.0 41.4, 42.6	38.5 37.9, 39.0	39.1 38.5, 39.7	10.4 9.4, 11.5	15.0 14.0, 16.0	8.2 7.3, 9.1	8.8 7.9, 9.8	27.4 26.6, 28.1	25.9 25.3, 26.5	15.5 14.8, 16.1	19.1 18.4, 19.7
Southwest	-8.6 -9.6, -7.5	-6.3 -7.2, -5.4	-4.4 -5.2, -3.7	-3.8 -4.6, -3.1	28.9 26.1, 31.7	29.9 27.6, 32.2	29.3 27.0, 31.6	34.1 32.0, 36.2	84.3 81.4, 87.2	71.4 68.9, 73.9	72.4 70.3, 74.6	65.4 63.3, 67.5
Northwest	-2.7 -3.4, -2.0	-3.7 -4.4, -3.0	-2.0 -2.7, -1.3	-2.6 -3.4, -1.8	83.7 81.9, 85.4	74.9 72.9, 76.8	82.6 80.8, 84.3	85.5 83.5, 87.5	80.8 78.8, 82.7	90.5 88.2, 92.7	82.5 80.5, 84.5	98.0 95.5, 100.4
West	98.0 63.1, 132.9	68.2 41.9, 94.5	102.0 70.4, 133.7	67.2 37.8, 96.5	373.9 300.7, 447.2	248.1 189.2, 307.0	379.8 311.7, 448.0	327.1 263.9, 390.4	391.9 307.0, 476.9	298.6 233.4, 363.9	460.6 382.5, 538.7	396.1 328.9, 463.3

* **Denotes a significant value**