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http://dx.doi.org/10.1289/ehp.1104271

Online 12 July 2012

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Running title: Climate Change Impacts on Human Health via Ozone

Keywords: climate change, mortality, ozone, population projections, sensitivity analysis

Acknowledgements/Disclaimer

Support for this analysis was funded through U.S. EPA Award RD-83337301-0. Additional support, provided by Abt Associates Inc., was funded through U.S. EPA Contract EP-D-08-100. The views expressed in this document are solely those of the authors and do not represent official U.S. EPA policy.

CFI Statement: ESP, JH and HM are employed by Abt Associates Inc., Bethesda, MD. L-YL is employed by Pacific Northwest National Labs, Richland, WA. None of the authors has any actual or potential competing financial interests to declare.

Abbreviations and Definitions

BenMAP	Environmental Benefits Mapping and Analysis Program
C-R	concentration-response
ER	emergency room
ES	exponential smoothing
GNM	Georgia Institute of Technology, the Northeast States for Coordinated Air Use Management, and the Massachusetts Institute of Technology
ICLUS	Integrated Climate and Land-Use Scenarios
IPCC	Intergovernmental Panel on Climate Change
MDA8	Maximum Daily 8-Hour Average Ozone Concentration (in ppb)
NAAQS	National Ambient Air Quality Standard
NCHS	National Center for Health Statistics
NERL	National Exposure Research Laboratory
NRC	National Research Council
RIA	Regulatory Impact Analysis
SRES	Special Report on Emissions Scenarios

Abstract

Background: Future climate change may cause air quality degradation via climate-induced changes in meteorology, atmospheric chemistry, and emissions to air. Few studies have explicitly modeled the potential relationships between climate change, air quality, and human health, and fewer still have investigated the sensitivity of estimates to the underlying modeling choices.

Objectives: Our goal was to assess the sensitivity of estimated ozone-related human health impacts of climate change to key modeling choices.

Methods: Our analysis included seven linked climate change/air quality modeling systems, five population projections, and multiple concentration-response functions. Using the Environmental Protection Agency (EPA)'s Environmental Benefits Mapping and Analysis Program (BenMAP), we estimated future O_3-related health effects in the U.S. attributable to simulated climate change between 2000 and c. 2050, given each combination of modeling choices. Health effects and concentration-response functions were chosen to match those used in EPA's 2008 O_3 National Ambient Air Quality Standards (NAAQS) Regulatory Impact Analysis (RIA).

Results: Different combinations of methodological choices produced a range of estimates of national O_3-related mortality from roughly 600 deaths avoided as a result of climate change to 2500 deaths attributable to climate change (though the large majority produced increases in mortality). The choice of climate change/air quality model reflected the greatest source of uncertainty, with the other modeling choices having lesser but still substantial effects.

Conclusions: Our results highlight the need to use an ensemble approach, rather than relying on any one set of modeling choices, to assess the potential risks associated with O_3-related human health effects resulting from climate change.

Introduction

There is a substantial and growing literature on the potential impacts of climate change in the absence of efforts to mitigate the atmospheric accumulation of greenhouse gases due to global emissions and other factors. The recent Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report found that "warming of the climate system is unequivocal" and that "most of the observed increase in globally averaged temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations" (IPCC 2007). Of particular importance for the U.S. EPA's mission to protect human health and the environment is the potential for future climate change to cause air quality degradation via climate-induced changes in meteorology and atmospheric chemistry, posing challenges to the U.S. air quality management system and the effectiveness of its pollution mitigation strategies (IPCC 2007; NRC 2004; Jacob and Winner 2009; Isaksen et al. 2009). In this context, the Global Change Research Program in EPA's Office of Research and Development, in partnership with EPA's Office of Air and Radiation, began soliciting research targeted at climate change impacts on air quality in 1999 (U.S. EPA 2009a; Weaver et al. 2009).

To move from a consideration of environmental impacts to an explicit assessment of human health risks, the demographics and size of the exposed population, whether now or in the future, is a critical input. Therefore, EPA has concurrently been developing high-resolution, spatially explicit population projections for the U.S. These projections, from the Integrated Climate and Land-Use Scenarios (ICLUS) project (U.S. EPA 2009b), have been developed to be consistent with the underlying assumptions of the IPCC Special Report on Emissions Scenarios (SRES) social, economic, and demographic storylines (Nakicenovic et al. 2000).

Our work builds on these two efforts by examining the potential indirect impacts of climate change on the health of a hypothetical future U.S. population (c. 2050) via its direct impact on tropospheric O_3 concentrations. We input both the climate change/air quality modeling results and various population projections into BenMAP, EPA's air pollution benefits analysis model, to estimate the changes in adverse health effects resulting from the changes in ambient O_3 concentrations simulated by the climate-air quality modeling systems. Our analysis considers the health impacts associated with O_3 changes induced only by future climate change; the air quality modeling simulated the response of O_3 to global climate change alone, without changes in anthropogenic emissions of O_3 precursors (e.g., due to future air quality management efforts and/or future economic growth; as described in EPA 2009a and Weaver et al. 2009). Knowlton et al. (2004), Bell et al. (2007), Hwang et al. (2004), West et al. (2007), Tagaris et al. (2009), and Sheffield et al. (2011) all modeled the health impacts of climate change-induced changes in O_3. All of these studies found that simulated climate change produced increases in O_3-related mortality. Tagaris et al. (2009) also found the potential for additional $PM_{2.5}$-related mortality due to climate change. However, few studies have investigated the sensitivity of their estimates to the underlying modeling choices. For example, each of the references cited used a single climate/air quality modeling system as the basis for their analysis, though Tagaris et al. (2009) did provide a useful estimate of the uncertainty surrounding their O_3-related health findings based on the range of results reported in Weaver et al. (2009). Similarly, only West et al. (2007) considered population growth in their analysis. Therefore, instead of developing a quantitative estimate of future human health impacts of climate-induced O_3 changes, our goal, building on this previous work, was to assess the sensitivity of such estimates to key modeling assumptions and choices. Our purpose is to explore the uncertainty space surrounding assessment of these climate-related health impacts and to sketch out the envelope of health risks that society must begin to consider.

Methods

Our study was designed to assess the sensitivity of modeled future O_3-related human health impacts in the U.S. to modeling and methodological choices for (1) climate-induced changes in future meteorological conditions, (2) the changes in O_3 concentrations resulting from those meteorological changes, (3) the size as well as age and geographic distributions of the affected population, and (4) the concentration-response (C-R) relationships linking O_3 levels to specific health outcomes.

There is substantial uncertainty surrounding each of the inputs to our analysis, particularly because it focuses so far into the future. Much of this uncertainty cannot be assessed quantitatively. Even assigning probabilities to the different models (representing our subjective assessments about the relative accuracy with which each approximates a future reality) is premature. Instead, we present our analysis as a series of sensitivity analyses or “what if” scenarios designed to assess the impact of the various assumptions and modeling approaches on the results. Figure 1 illustrates the basic structure of the analysis.

Climate Change/Air Quality Modeling Systems

Our analysis includes seven modeling efforts of six research groups (Harvard University; Carnegie Mellon University (CMU); Washington State University (WSU); EPA’s National Exposure Research Laboratory (NERL); the Georgia Institute of Technology, the Northeast States for Coordinated Air Use Management, and the Massachusetts Institute of Technology

(GNM) joint effort; and the University of Illinois, which considered two different SRES scenarios (denoted Illinois-1 and Illinois-2) but otherwise used identical setups. The Harvard and CMU simulations used global-scale (e.g., 2o x 3o grids) atmospheric chemistry models. The remaining simulations used regional air quality models, which necessitates downscaling Global Climate Model data to fine scales (e.g., 36 km grids). These modeling efforts are described in detail elsewhere (U.S. EPA 2009a; Weaver et al. 2009); we summarize the key characteristics in Tables 1 and 2. Briefly, each modeling group explored the potential impacts of climate change on O_3 concentrations in the U.S. using two linked models. First, a climate model was used to simulate meteorological conditions in the U.S. for future years (under climate change) and the present. This modeled meteorology was then input to an air quality model to simulate the ambient O_3 concentrations that would result. Anthropogenic emissions were held constant between the base case and the climate change case, but climate-sensitive biogenic and evaporative emissions were allowed to change in response to changes in climate. Baseline emissions were similar, though not identical, across modeling efforts (e.g., for the U.S., based largely on 1999 or 2001 EPA emissions inventory data), as described in the individual publications about these simulations. Some modeling groups used dynamical downscaling (with a regional climate model) to further regionalize the global climate model simulation outputs. Choice of downscaling model and methodology is an additional source of uncertainty, but systematically separating out this additional source was not feasible for this analysis.

The modeling groups produced from 3 to 10 summers' worth of Maximum Daily 8-Hour Average Ozone Concentrations (MDA8) approximately centered on the years 2000 ("present") and 2050 ("future"). MDA8 was computed by taking rolling 8-hour averages for a 24-hour period and then taking the maximum. This was done for all days in the modeled O_3 seasons.

Although different models used different grids, for consistency the air quality grids for all of the models were remapped to a 30 km x 30 km grid for this analysis. Further adjustment of modeled air quality is described in the Supplemental Material (see Supplemental Material, page 3).

Population Projections to a Future Year

All of the BenMAP runs used populations projected to 2050. To explore the sensitivity of our results to assumptions about what this future population would look like, we selected five population projections for input into our analysis. One of these is simply the 2000 Census population – i.e., we assumed no change from the 2000 Census population by 2050 to show the risk associated with climate change in the absence of changes in populations exposed. A second population projection is extrapolated from the Woods & Poole population projections for the year 2030 already in BenMAP (Woods & Poole Economics Inc. 2007), using a set of exponential smoothing (ES) forecasting methods (for details see Supplemental Material pages 3-4). Finally, we selected three of the ICLUS population projections – A1, A2, and the base case (BC) – to provide the lower and upper bound ICLUS total population projections, as well as an intermediate case. The basis for the ICLUS population projects and the underlying assumptions are described in detail elsewhere (U.S. EPA 2009b) and more briefly in the Supplemental Material (page 4).

Concentration-Response Relationships and Health Impact Functions

We followed the selection of health effects, studies, and C-R functions EPA used in the benefits analysis for the O_3 NAAQS RIA completed in 2008 (U.S. EPA 2008). The C-R functions are taken from epidemiological studies, and we assume they are applicable to any year, though this assumption entails additional uncertainties. The suite of health effects included mortality from all causes ("all-cause mortality"), non-accidental mortality, hospital admissions for respiratory illnesses, emergency room (ER) visits for asthma, school loss days; and minor restricted activity days (see Supplemental Material, Table S1, for study details). For several health effects, two or more C-R functions were pooled (see Supplemental Material pages 4 -5 for details on pooling and Table S4 for the pooled estimates).

Most of the studies in the air pollution epidemiological literature have estimated exponential (log-linear) C-R functions in which the natural logarithm of the health effect is a linear function of the air pollutant:

$$y = Be^{\beta x}, \qquad [1]$$

where x is the ambient air pollutant (e.g., O_3) level, y is the incidence of the health effect at O_3 level x, β is the coefficient of ambient O_3 concentration, and B is the incidence at x=0.

The "health impact function" – the relationship between a change in the pollutant concentration ($\Delta x = x_1 - x_0$) and the corresponding change in incidence of the health effect in the population ($\Delta y = y_1 - y_0$) – derived from the log-linear C-R function is

$$\Delta y = y_0[e^{\beta \Delta x} - 1], \qquad [2]$$

where x_1 and x_0 represent the model-simulated summertime O_3 levels c. 2050 and c. 2000, respectively, while y_1 and y_0 represent the health effect incidence in the with- and without-climate-change (baseline) scenario, respectively. The baseline incidence (y_0) is the product of the baseline incidence rate and the exposed population. The measure of O_3 concentration available from the climate change/air quality models is the O_3 season average MDA8. The C-R functions relate the MDA8 to health effects, and we applied this O_3 season average MDA8 to each day. Since the health impact functions are nearly linear, this application of a seasonal average to each day in the season provides a good approximation to the result we would get if we had individual daily 8-hour maxima for each day in the O_3 season. In many cases, the C-R function used an O_3 metric other than the MDA8 (e.g., the 24-hour mean) (see Supplemental Material, Table S1); the coefficients from these functions were converted to coefficients for the MDA8 (see Abt Associates Inc. 2010, Appendix G, for methods). This conversion would be expected to add only a small amount of uncertainty to the results.

Baseline Incidence Rates

A detailed description of the estimation of baseline incidence rates c. 2050 is given in the Supplemental Material (pages 5 – 7). Briefly, we calculated cause-specific death counts at the county level for selected age groups from individual-level mortality data for years 2004-2006 obtained from the Centers for Disease Control, National Center for Health Statistics (NCHS), for the entire United States. The county-level death counts were then divided by the corresponding county-level population to obtain the mortality rates. We used three years (2004-2006) of mortality and population data to provide more stable estimates. We then extrapolated these county-level mortality rates to 2050 using the U.S. Census Bureau national mortality life tables (U.S. Census Bureau 2010).

Regional rates for hospitalizations and asthma ER visits were calculated from year 1999 regional hospitalization and year 2000 ER visit counts obtained from NCHS' National Hospital

Discharge Survey and National Hospital Ambulatory Medical Care Survey, respectively (CDC 2008; CDC 2010) (Supplemental Material, pages 6 – 7). We applied the regional rates to every county in a region. Hospitalization rates are cause-specific, with causes defined by those combinations of ICD codes that were used in the selected epidemiological studies. We were unable to project hospitalization and ER visit rates to 2050, however, because, unlike for mortality rates, there are no reliable projections of hospitalization or ER visit rates or trends into the future.

Defining the "O_3 Season"

The climate change/air quality models used in this analysis generally defined the O_3 season as June, July, and August, i.e., climatological summer in the Northern Hemisphere. Though most air pollution epidemiology studies focusing on O_3 have defined the season more broadly (e.g., May through September), we use the more conservative June-August definition for consistency with the O_3 simulations. Modeling results summarized in Weaver et al. (2009) indicate similar magnitudes of climate-induced O_3 increases in fall and spring, suggesting that the health impacts we report here are more conservative than if we considered a more standard, longer O_3 season.

Estimation of Human Health Impacts

BenMAP calculated the change in each adverse health effect within each grid cell of the air quality grid by combining the appropriate C-R function coefficient (β), baseline incidence (y_0), and simulated change in O_3 due to climate change (Δx) in the health impact function (equation [2]). While BenMAP uses the same "national" C-R function coefficient (β) in all grid cells, population estimates and baseline incidence rates in the health impact function are as location-specific as possible. The grid cell-specific changes in health effects are then summed across grid cells to produce county-level, state-level, and national estimates of health impacts.

Results

Using the 7 climate change/air quality models and 5 population projections, we produced 35 potential "answers" to the question: How many O_3-related cases of a given health effect (e.g., non-accidental mortality) may be attributable to climate change in the conterminous United States in a future year? We also considered more than one C-R function for some health effects, further increasing the number of potential "answers."

National Results

Estimates of annual national O_3-related non-accidental mortality c. 2050 ranged from over 600 deaths avoided because of climate change to over 2500 deaths attributable to climate change, depending on the climate change/air quality model, population projection, and C-R function used (Table 3). Estimates for all-cause mortality follow similar patterns according to climate change/air quality model and population projection (Supplemental Material, Table S2). The broad patterns seen for mortality across the different modeling choices are largely mirrored for the morbidity effect estimates as well, though for some health outcomes the numbers of cases are much larger, for example in the hundreds of thousands or millions for minor restricted activity days (Supplemental Material, Tables S3 - S7).

Figure 2 summarizes the influence of the climate change/air quality model and population projection on estimates of future O_3-related non-accidental deaths attributable to climate change, using the Bell et al. (2004) C-R function. The C-R function is itself a source of substantial uncertainty. Had we instead used the Ito et al. (2005) C-R function, for example, the numbers would have generally been over 4 times larger (e.g., 2560 attributable deaths compared with 570 based on Illinois-1 and ICLUS_A1), although the basic pattern according to climate change/air quality model and population projection is the same (see Table 3).

Our analysis is one of the first to account for population growth and associated changes in age and geographic distributions, and we found that considering these factors has a substantial influence on the estimates of health impacts. The assumption that the population c. 2050 will be exactly what it was in the year 2000 (i.e., by using Census 2000 population estimates) produces estimates that are consistently lower than those based on population projections, all of which assume at least some increase in population size relative to the year 2000, in addition to changes in the age distribution of future populations., as is easily seen in Figure 2 and Table 3 (and proposed in Tagaris et al. 2009).

The choice of methods to project future age and geographic distributions can also influence results. For example, although the ICLUS_A2 population projection for 2050 is, in total, greater than the ICLUS_A1 projection (424.8 million vs. 386.7 million), ICLUS_A1 is skewed more towards the older age groups (with about 26 percent projected to be age 65 or older in 2050 versus only about 21 percent based on ICLUS_A2; see Supplemental Material, Figure S1). Since older people have substantially higher baseline incidence rates for mortality (and other adverse health effects) than younger people, the same increase in O_3 concentration would result in more deaths among an older population than a younger one as the estimated change in the outcome is a function of the baseline incidence, which is the product of the baseline incidence rate and the population size. This is reflected in the slightly higher numbers of O_3-

related deaths for ICLUS_A1, despite the overall smaller population. If age group-specific mortality C-R functions were available, their application would likely accentuate the importance of age distribution, since older people may be more vulnerable to air pollution.

The importance of the age distribution of the affected population is particularly apparent when we consider morbidity effects that focus on specific age subgroups in the population, such as O_3-related school days lost (ages 5 – 17) or respiratory hospital admissions among those age 65 and older (see Supplemental Material, Tables S3, S4, S6, and S7). For example, estimates of O_3-related respiratory hospital admissions among infants attributable to climate change c. 2050 based on the ICLUS_A1 population projection are uniformly smaller in magnitude than the corresponding estimates based on ICLUS_A2, regardless of the climate change/air quality modeling system used (see Supplemental Material, Table S3). This is because ICLUS_A2 projects that a greater percentage of the population (and a larger total population) will be under 1 year of age, and that a smaller percentage of the population will be 65 and older, relative to ICLUS_A1 (see Supplemental Material, Figure S1).

Across all of these dimensions, the source of the greatest uncertainty, for both non-accidental and all-cause mortality, appears to be the projections of future climate change-induced meteorological changes and corresponding air quality changes, which are determined by the climate change/air quality modeling system used. This is shown clearly in the results of an analysis of variance, which decomposes the total variability in estimated mortality into the variability due to the chosen climate change/air quality model, population projection, epidemiological study (C-R function) used, and interactions between these modeling choices, respectively (see Table 4). The different impacts across model choices are magnified to a greater or lesser degree by study choice/C-R function (see Supplemental Material, Figure S2).

Regional Estimates

Because national estimates can mask very different regional changes, we delineated three broad regions for additional analysis: the Northeast (defined as east of 100 degrees west longitude and north of 36.5 degrees north latitude); the Southeast (defined as east of 100 degrees west longitude and south of 36.5 degrees north); and the West (defined as everything west of 100 degrees west longitude). These three regions account for the entire continental U.S. Finer-scale regional breakdowns, while possible, would have been an over-interpretation of our results given the various uncertainties.

Figure 3 shows national and regional estimates of O_3-related non-accidental mortality using the C-R function from Bell et al. (2004) and the ICLUS_A1 population projection, and it illustrates this national-level masking of differing regional trends. For example, the modest net change in nation-wide O_3-related non-accidental mortality based on the WSU climate change/air quality model represents the sum of highly variable regional estimates (i.e., 275 avoided deaths in the Northeast, plus 369 additional deaths in the Southeast, plus 54 additional deaths in the West). With the exception of Illinois-1 and Illinois-2, none of the driving climate/air quality scenarios produces regional health impact estimates that are all in the same direction – i.e., increases in O_3 estimated concentrations attributable to climate change in some regions are accompanied by decreases in other regions (due, for example, to factors such as differences in circulation patterns and increases in cloud cover, as discussed in Weaver et al. 2009). While the WSU climate/air quality simulation estimates suggest large decreases in O_3-related deaths in the Southeast and large increases in the Northeast, the GNM and NERL model estimates show regional effects in just the opposite directions. These same general patterns are evident for all-cause mortality and for different C-R functions for either type of mortality.

Discussion

We have attempted to assess the sensitivity of estimated O_3-related human health impacts of climate change to the following key modeling assumptions and choices: climate-induced changes in meteorological conditions and the corresponding changes in O_3 concentrations; projections regarding the size, and age and geographic distributions of the affected population; and the concentration-response relationships linking O_3 levels to specific health outcomes.

Looking across all combinations of modeling choices (including climate change/air quality model, population projection, and C-R relationship), estimates of national O_3-related mortality and morbidity attributable to climate change by mid-century span a wide range – e.g., from roughly 600 cases of non-accidental mortality avoided as a result of climate change to roughly 2500 cases attributable to climate change.

The source of the greatest uncertainty at the national level appears to be the climate change/air quality scenario used, with choice of C-R function and population projection also important, though less influential in this analysis. Not only is the total population exposed to O_3 in a future year important, but assumptions regarding the age distribution of that population are also important for estimating O_3-related adverse health effects. The variability of these estimates represents the true extent of uncertainty in the problem, however, only to the extent that our choices (seven simulations, five population projections, a few alternative C-R specifications, and a single unchanging set of emissions to air) span the full range of possibilities in their respective dimensions. Our estimates thus may understate the plausible range of potential future outcomes.

National results can mask important regional differences. Estimates for the Northeast region generally indicated adverse health impacts and were the most consistent across the 7 climate/air quality scenarios of the 3 regions. In contrast, estimated health impacts for the Southeast showed substantial variation. The West generally showed the smallest impacts, largely due to the relatively smaller projected populations.

The wide range of estimated O_3-related mortality and morbidity attributable to climate change resulting from different methodological choices highlights the need to consider an ensemble of estimates, rather than relying on any one modeling system or set of assumptions. Despite this range, however, the large preponderance of the estimates is in the direction of climate-induced increases in O_3 leading to adverse health impacts. This is illustrated in Figure 4, which shows that population-weighted climate-induced O_3 concentration changes estimated using the different climate/air quality simulations indicate that 50-90% of the future U.S. population would be subject to increases in O_3 exposure, all other factors remaining constant.

Finally, as Tagaris et al. (2009) suggested, climate change may have even greater health impacts associated with other air pollutants like $PM_{2.5}$. The combined health effects of O_3 and these other pollutants, along with other factors such as increased heat waves, should be explored using multi-pollutant models.

Conclusion

At this stage in the development of a scientific understanding of climate change and air pollution-related human health, it would be unwise to rely on any one model, epidemiological study, or population projection. This is perhaps the most important "take away" message of our analysis. Different combinations of methodological choices and model assumptions produce widely varying results, particularly at regional scales, and can produce fundamentally different conclusions about the overall impact of climate change on O_3-related health effects. The goal of this study was therefore not to develop any best guess as to the most likely future human health impacts of climate-induced O_3 change, but instead to explore the uncertainty space surrounding assessment of these impacts and to begin to define the envelope of future risk. This also highlights the need to develop decision-making frameworks and tools capable of managing the uncertainty such ensembles represent (e.g., see Lempert et al. 2004; Johnson and Weaver 2009).

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Table 1. Summary of global climate and O_3 modeling systems used in this analysis

Model	Harvard	CMU
Simulation Period	5 summer/falls	10 summers/falls
GCM	GISS III	GISS II′
Resolution	$4^{o} \times 5^{o}$	$4^{o} \times 5^{o}$
GHG Scenario	A1b	A2
GCTM	GEOS-Chem	GISS II′
Climate Sensitive Emissions	BVOCs; Lightning and soil NO_x	BVOCs; Lightning and soil NO_x

Abbreviations:

BVOC	biogenic volatile organic compounds
GCM	General Circulation Model
GCTM	Global Chemical Transport Model
GEOS	Goddard Earth Observing System
GHG	Greenhouse Gas
GISS	Goddard Institute for Space Studies
NOx	Nitrogen oxides

Table 2. Summary of regional climate and O_3 modeling systems used in this analysis

Model	NERL	Illinois 1	Illinois 2	WSU	GNM
Simulation Period	5 JJAs	4 JJAs	4 JJAs	5 Julys	3 JJAs
GCM	GISS III	PCM	PCM	PCM	GISS III
Global Resolution	4º × 5º	2.8º × 2.8º	2.8º × 2.8º	2.8º × 2.8º	4º × 5º
GHG Scenario	A1b	A1Fi	B1	A2	A1b
RCM	MM5	CMM5	CMM5	MM5	MM5
Regional Resolution	36 km	90/30 km	90/30 km	36 km	36 km
Convection Scheme	Grell	Grell	Grell	Kain-Fritsch	Grell
RAQM	CMAQ	AQM	AQM	CMAQ	CMAQ
Chemical Mechanism	SAPRC99	RADM2	RADM2	SAPRC99	SAPRC99
Climate Sensitive Emissions	BVOCs; Evaporative	BVOCs; Evaporative	BVOCs; Evaporative	BVOCs; Evaporative	BVOCs; Evaporative

AQM	Air Quality Model
BVOC	biogenic volatile organic compounds
CMAQ	Community Multiscale Air Quality Model
CMM5	University of Illinois Climate extension of the Penn State/NCAR Mesoscale Model version 5
GCM	General Circulation Model
GEOS	Goddard Earth Observing System
GHG	Greenhouse Gas
GISS	Goddard Institute for Space Studies
JJA	June, July, August
MM5	Penn State/NCAR Mesoscale Model version 5
PCM	Parallel Climate Model
RADM2	Regional Atmospheric Deposition Model (2nd generation)
RAQM	Regional Air Quality Model
RCM	Regional Climate Model
SAPRC	Statewide air pollution research center

Table 3. Estimated changes in national summertime (June-August) O_3-related non-accidental mortality due to simulated climate change between 2000 and c. 2050 [a]

Climate Change/ Air Quality Model	Study	Population Projection				
		ICLUS_A1	ICLUS_A2	ICLUS_BC	Woods & Poole	Census_ 2000
Illinois-1	Bell et al. (2004)	570	520	510	440	170
	Ito et al. (2005)	2560	2340	2280	1970	780
	Schwartz (2005)	860	790	770	670	270
Illinois-2	Bell et al. (2004)	530	480	480	420	160
	Ito et al. (2005)	2390	2180	2160	1870	710
	Schwartz (2005)	810	730	730	640	250
CMU	Bell et al. (2004)	480	430	430	350	150
	Ito et al. (2005)	2180	1950	1920	1570	690
	Schwartz (2005)	730	660	650	540	240
Harvard	Bell et al. (2004)	240	220	230	200	80
	Ito et al. (2005)	1090	1000	1030	890	380
	Schwartz (2005)	370	340	350	300	130
GNM	Bell et al. (2004)	40	30	20	10	-20
	Ito et al. (2005)	180	140	80	50	-80
	Schwartz (2005)	60	50	30	20	-30
NERL	Bell et al. (2004)	10	10	-10	-50	-20
	Ito et al. (2005)	50	20	-40	-240	-100
	Schwartz (2005)	20	10	-20	-80	-40
WSU	Bell et al. (2004)	-150	-140	-110	-60	0
	Ito et al. (2005)	-650	-630	-480	-240	0
	Schwartz (2005)	-220	-210	-160	-90	0

[a] Numbers rounded to the nearest 10

Table 4. Analysis of variance results for estimates of national summertime (June-August) O_3-related non-accidental mortality due to simulated climate change between 2000 and c. 2050

Source	DF	ANOVA SS	Percent of Total SS
Model	6	24271499	48%
Population Projection	4	2108558	4%
Study	2	9055636	18%
Model*Study	12	10495284	21%
Model*Population Projection	24	2641882	5%
Study*Population Projection	8	921745	2%
Model*Study*Population Projection	48	1165135	2%
Total	104	50659739	100%

Figure Legends

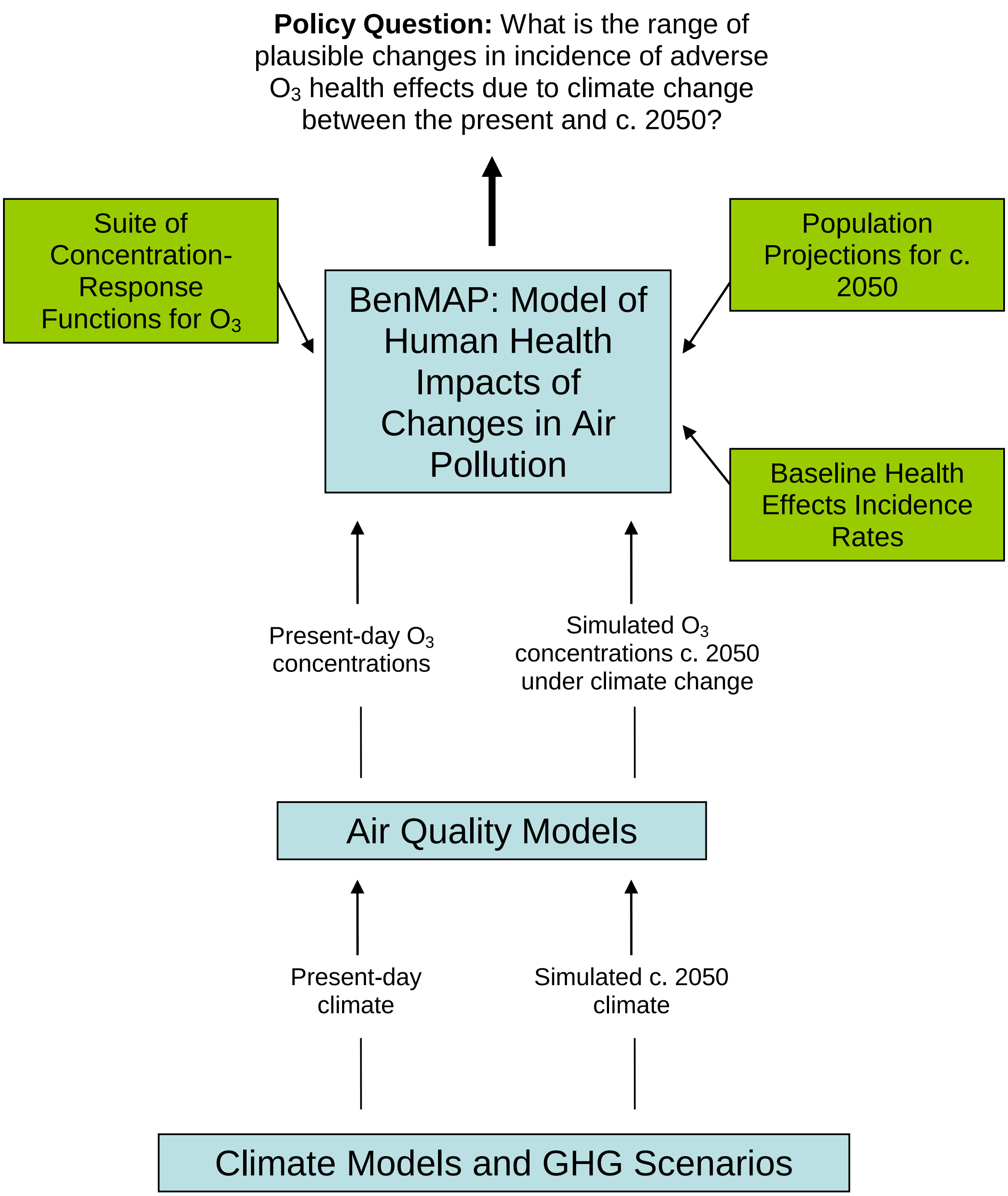
Figure 1. The structure of the analysis of O_3-related impacts on human health attributable to climate change

Figure 2. Estimated national summertime (June-August) O_3-related non-accidental mortality due to simulated climate change between 2000 and c. 2050 (C-R function from Bell et al. 2004) (Note: -0.6 deaths were estimated based on the WSU climate change/air quality model and Census_2000 population data.)

Figure 3. Estimated national and regional summertime (June-August) O_3-related non-accidental mortality due to simulated climate change between 2000 and c. 2050 (C-R function from Bell et al. 2004; ICLUS_A1 population projection)

Figure 4. Cumulative probability density functions of national population-weighted summertime O_3 concentration changes between 2000 and c. 2050 from the seven sets of climate-air quality modeling results (ICLUS_A2 population projection; other population projections yield similar results)

Figure 1. The structure of the analysis of O_3-related impacts on human health attributable to climate change



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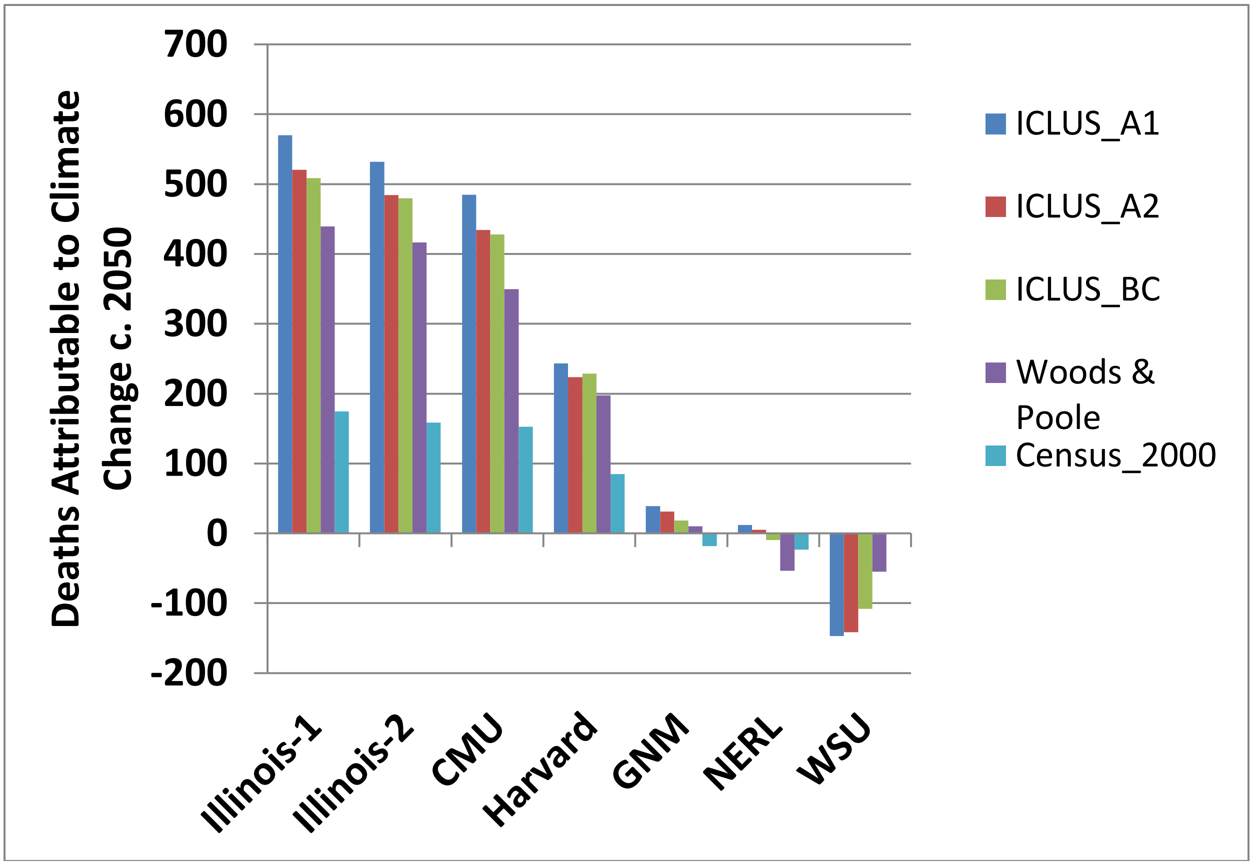
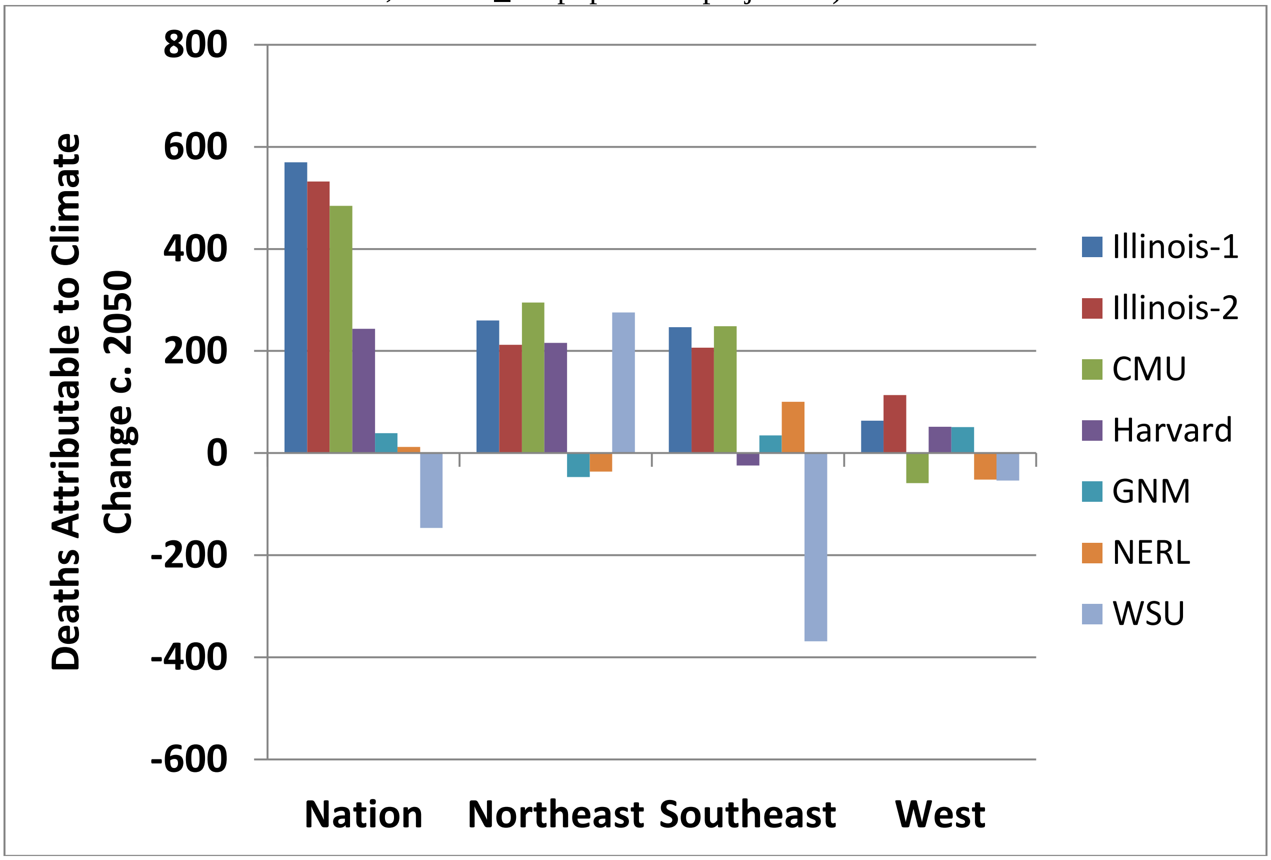


Figure 3. Estimated national and regional summertime (June-August) O_3-related non-accidental mortality due to simulated climate change between 2000 and c. 2050 (C-R function from Bell et al. 2004; ICLUS_A1 population projection)



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