Chen Chen
Hixon Center for Urban Ecology-Final Report for Hixon Fellowship 2018

Change in Air Pollution Exposure and Related Health Impact under Climate Change in U.S. Urban Centers

Chen Chen / Study Co-Investigators: Yang Zhang[1], Michelle L. Bell[2]
[1] North Carolina State University, Department of Marine, Earth, and Atmospheric Sciences
[2] Yale University, School of Forestry and Environmental Studies

Abstract

Introduction: Ambient air pollution is a top risk factor for human morbidity and mortality in the present day. Climate change can affect the distribution and composition of tropospheric air pollutants and magnify their health impact. Factoring air pollution related health considerations into the decision-making process is essential to optimize climate change mitigation and adaptation.

Methods: With emissions projected under the Representative Concentration Pathways (RCP) 4.5 and 8.5, air pollutant concentrations have been simulated using the North Carolina State University's modified online-coupled Weather Research and Forecasting Model with Chemistry, which downscaled their modified global Community Earth System Model. We estimated changes in exposure to $PM_{2.5}$ and ozone from levels in present-day (2001-2010) to levels for a future decade (2045-2054) in 196 major U.S. urban centers, including changes in: 1) decadal average concentrations; and 2) decadal total numbers of days that exceed U.S. Environmental Protection Agency health-based regulatory standards. A method was also developed to estimate the excess number of cardiovascular and respiratory hospital admissions attributable to $PM_{2.5}$ and ozone under climate change, taking population vulnerability, temporal change and seasonal variation of concentration-response function into consideration.

Results and Conclusions: In our preliminary results, for most U.S. urban centers in this study, we observed decreases in decadal average $PM_{2.5}$ concentrations from present-day to future decade under both scenarios, for this analysis which considers emissions changes only (i.e., not changes in population, etc.). We also observed decreases in decadal average ozone concentrations under RCP4.5 for most urban centers, while increases were observed under RCP8.5. More than half of urban centers in this study demonstrated decrease in total number of $PM_{2.5}$ and ozone exceedance days under both scenarios. However, we would still expect to observe adverse health outcomes associated with exposure to air pollutants in the future. We also observed spatial heterogeneity in change of concentrations between two pollutants.

Background

In 2015, 196 parties at the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change undertook ambitious efforts to adopt the Paris Agreement, aiming to mitigate and adapt to climate change, with 170 parties ratifying by 2016 [1]. How and to what extent climate change will influence human health deserves critical attention from researchers and policy makers [2]. Climate change can magnify health risk factors that already exist, including but not limited to extreme weather [3–6], under-nutrition from diminished food production [7], aeroallergens [8], and food-, water- and vector-borne diseases [9,10]. Climate change also could affect the distribution and composition of tropospheric air pollutions through atmospheric circulation, chemical reaction rates, deposition and altered natural emissions [11].

Ambient air pollution is a top risk factor for human morbidity and mortality in the present day. Two important urban pollutants, ambient $PM_{2.5}$ (particulate matter $\leq 2.5\mu m$) and ozone pollution, contributed to 4.2 and 0.2 million premature deaths globally in 2015, respectively [12]. An extensive literature also identified deleterious associations between exposure to $PM_{2.5}$ and ozone and adverse health endpoints like poor birth outcomes [13,14], respiratory and cardiovascular mortality [15–20] and morbidity [21–25]. Currently more than 23 and 107 million U.S. persons live in areas exceeding health-based standards for daily average $PM_{2.5}$ standard and 8-h ozone standard, respectively [26]. Accurate evaluation of health impacts from $PM_{2.5}$ and ozone under climate change is essential to estimate the health burden and marginal cost of climate change and to make informed decisions about mitigation and adaption policy of climate change. This is especially important as many U.S. cities already face high levels of harmful air pollutants.

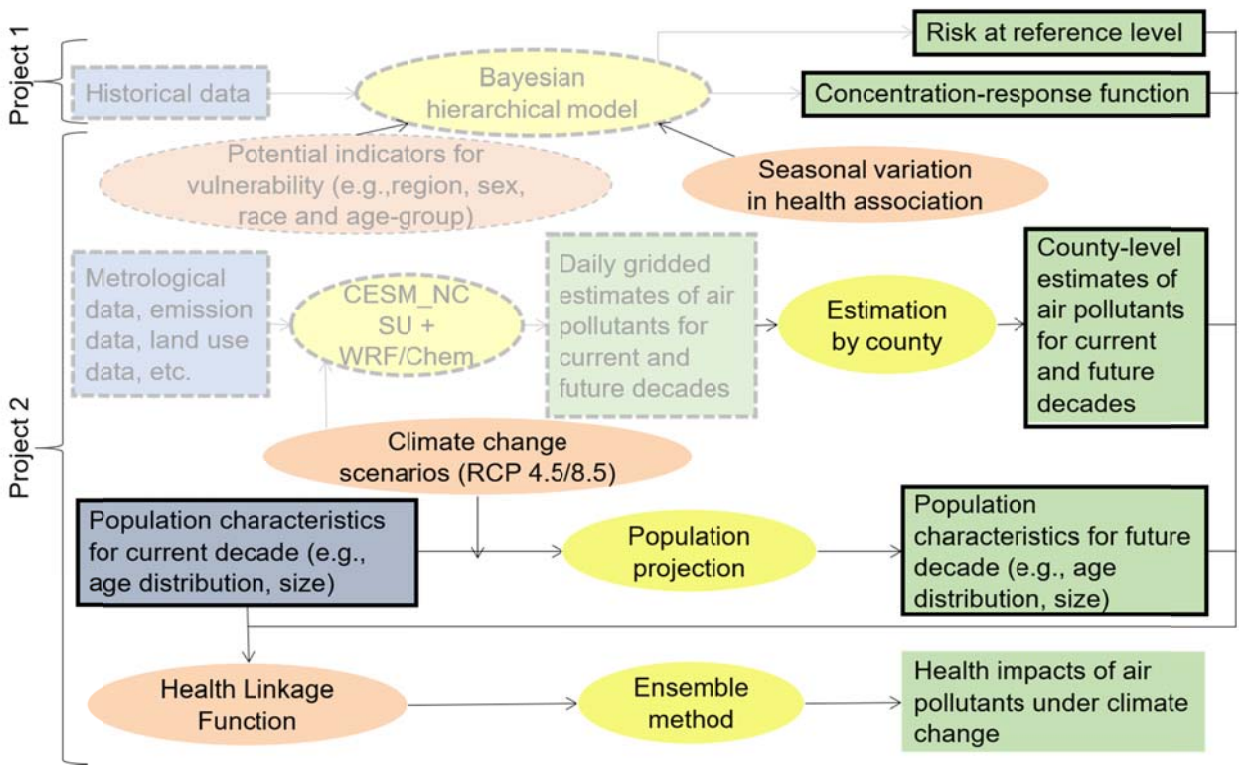

Figure 1. Diagram for conceptual model of this projected proposal and its relationship to my dissertation work

Literature on air pollution and health under climate change has grown rapidly in recent years. Two recent reviews reported that most studies projected increased mortality related to $PM_{2.5}$ and ozone as a result of climate change [27,28]. For example, *Silva et al. (2017)* projected positive change in air pollution related premature mortality attributable to climate change, under Representative Concentration Pathways (RCP) 8.5. However, few studies focused on other health outcomes, or considered vulnerability of sub-groups within the population, or adaptation in susceptibility over time [27,28]. For the U.S., a recent review by *Kinney (2018)* revealed consistently increasing ozone-related deaths in north-central and northeastern states, while PM-related deaths varied across studies and regions. Also, previous studies reported heterogeneity in the association between various health outcomes and air pollutants across sex, race, and age groups [31,32]. Moreover, changes in pollutant levels and associated health impacts at local scales are obscured by national or global assessments, and were not well explored by previous studies [33,34,27,28]. Temporal trend of association between particulate matter and adverse health outcomes was reported by researchers in the U.S. and Germany, which was confirmed by my preliminary results in Project 1 of my dissertation research (Figure 1) as well [35,36]. The observed seasonal variation in association between air pollution and risk of adverse health outcomes was not considered in previous climate change and air pollution studies, either [37]. Above studies highlighted the need to explore sensitive subpopulations by potential vulnerable indicators at both community (e.g., region, seasonality, and calendar year) and individual (e.g., sex, race, and age) levels. Further, the estimated changes in health impact from earlier work had a wide range, which highlights the need to acknowledge potential sources of uncertainties such as methodological choices and model assumptions [27,28]. We will attempt to address the knowledge gaps listed above in this study.

Objectives

In this study, we aim to estimate changes in $PM_{2.5}$ and ozone under different climate change scenarios in major U.S. urban counties. Specifically, we will estimate changes in exposure to two pollutants from levels in present-day (2001-2010) to levels estimated for a future decade (2045-2054) in 196 major U.S. urban counties. We plan to generate estimates and maps of these counties under climate change for changes in 1) decadal average $PM_{2.5}$ and ozone concentrations; and 2) decadal total of numbers of days that exceed U.S. Environmental Protection Agency (EPA) health-based standards for $PM_{2.5}$ and ozone. Given the limitation in time under this fellowship, we will only develop the method to estimate the excess number of cardiovascular and respiratory hospital admissions attributable to $PM_{2.5}$ and ozone under climate change, taking population vulnerability, temporal change and seasonal variation of concentration-response function (CRF) into consideration.

This study sponsored by Hixon Center for Urban Ecology is part of project 2 in my dissertation research (Figure 1). Project 1 of my dissertation research explores temporal trend in the association between $PM_{2.5}$ and risk of hospital admissions among elderly population. Project 2 combines CRF estimated in project 1 with estimated exposure changes and the method developed in this study, to further calculate changes in health impacts of $PM_{2.5}$ and ozone under different climate change scenarios. Results will reveal potential spatial and population heterogeneity in changes in air pollution related health impacts under climate change and identify critical groups and regions for mitigation and adaptation. This work will be beneficial to policy makers designing climate change policies, but also to communities interested in local climate adaptation measures and air quality.

Methods

Overview

We evaluated the impacts of $PM_{2.5}$ and ozone under climate change using three metrics in U.S. urban counties for changes in: 1) decadal average concentrations; 2) decadal total numbers of days that exceed current U.S. EPA health-based regulatory standards; and 3) decadal total excess number of hospital admissions related to exposure to air pollution. We selected 196 U.S. urban counties that have 1) sufficient pollutant monitoring data for CRF estimation; and 2) a population larger than 200,000 based on the U.S. Census Bureau 2010 decennial census.

With daily gridded air pollutant concentration simulations for present-day and future decades from state-of-the-science regional climate and air quality models, we calculated area-weighted county-specific changes in decadal averages of $PM_{2.5}$ and ozone concentrations, and the changes in decadal sum of days that exceed U.S. EPA health-based standards of $PM_{2.5}$ and ozone under different climate change scenarios. An exceedance day is any day during the study period with pollutant level higher than current National Ambient Air Quality Standards (NAAQS), namely with 8-hour daily maximum ozone concentration higher than 70 ppb, or with 24-hour average $PM_{2.5}$ concentration higher than 35 $\mu g/m^3$ [38]. This is different from the criteria for identifying non-attainment areas.

To quantify the health impact of air pollution, we used the excess number (EN) of hospital admissions due to air pollution, a metric used to describe the number of hospital admissions that could have been avoided if exposure was reduced to a reference level [39]. Compared with other health impact metrics pertaining to air quality management such as disability-adjusted life years, monetized impacts, and functional unit-based metric, EN yields the best interpretability and spatial resolution [40]. We considered cardiovascular and respiratory hospital admissions separately, each defined as a set of admission diagnoses. The calculation of ΔEN required four types of estimates as inputs, each of which contributes uncertainty: 1) distribution of air pollutants; 2) CRF for the association between short-term exposure to air pollutants and risk of hospital admissions; 3) health linkage function (HLF) connecting observed or projected air pollutant concentration and risk of hospital admissions; and 4) population characteristics such as size and age distribution. We estimated changes in EN under climate change as the difference in air pollutant related health impact between present-day decade and future decade following

Eq. 1, for each combination of health outcome, air pollutant and potentially vulnerable subgroup.

$$\Delta EN^{c} = \overline{Rate^{c,present-day}} \times \overline{Pop^{c,p}} \times HLF \qquad \text{Eq. 1}$$

where ΔEN^c denotes the change in excess number of hospital admissions due to air pollution (the future value minus the current value) in geographic area *c*; $Rate^{c, present\text{-}day}$ denotes the average risk (e.g., incidence rate) at current decade level for population *p* and area *c*; $Pop^{c,p}$ denotes the average population size for population *p* in geographic area *c*. In this study, area *c* could be a U.S. urban county; *HLF* denotes the health linkage function given the projected exposure levels for current and future decade and coefficients of CRF derived from epidemiological studies. Outputs from HLF represent the estimated percentage increase in risk of hospital admissions comparing to reference level of exposure.

We utilized the HLF derives from the population attributable fraction (PAF) concept, as described by *Murray and Lopez (1999)*. This is basically using the present-day population as the reference population and the future population as the *counterfactual* population with a different distribution of air pollutant concentration. As in most time-series analysis for environmental stressors, we treated the whole population as exposed and the derived HLF is shown in

Eq. 2.

$$HLF = \sum_{t=1}^{n} HL(Exposure_t^{c,p}, \beta(t)^{c,p}) = PAF^c = \frac{\sum_{t=1}^{n}(RR_t^c \times P_t^{c,present-day}) - \sum_{t=1}^{n}(RR_t^c \times P_t^{c,future})}{\sum_{t=1}^{n}(RR_t^c \times P_t^{c,present-day})}$$

$$= \frac{\sum_{t=1}^{n} e^{\beta(t)^{c,present-day} \times Exposure_t^{c,present-day}} - \sum_{t=1}^{n} e^{\beta(t)^{c,future} \times Exposure_t^{c,future}}}{\sum_{t=1}^{n_1} e^{\beta(t)^{c,present-day} \times Exposure_t^{c,present-day}}} \quad \text{Eq. 2}$$

where $Exposure_t^{c,\,future}$ denotes average air pollution level in time *t* of future decade for area *c*; $\beta(t)^{c,\,future}$ denotes the Bayesian area-specific estimate of association after pooling during time *t* of future decade.

Given the complexity of potential uncertainty for the inputs in the ΔEN calculation, we also quantified some potential uncertainties in calculation. Many studies approached this problem with an ensemble method by using extensive sensitivity analyses with different combinations of methodological choices [45,42,49,50]. We utilized a modified version of the Monte Carlo simulation method proposed by *Gasparrini and Leone (2014)*. We calculated county-specific change in health impact under climate change (ΔEN) 5000 times for each combination of RCF, pollutant and potentially vulnerable subgroups, using one randomly sampled set of parameters describing the population size distribution, one randomly sampled set of parameters describing CRF, and one randomly sampled set of parameters describing the risk at current decade level. These samples combined with other estimates (e.g., projected exposure level) were then utilized to empirically reconstruct the distribution of change in health impact and to compute uncertainty intervals. These uncertainty intervals describe the range of changes in air pollutant related health impact under climate change and provide information on how much uncertainty each component contributes to the overall estimate. Below we elaborated on proposed distributions and values for RCF, population characteristics and risk at current decade level.

<u>Ambient air pollutant concentration estimation</u>

Our collaborators, Prof. Yang Zhang and team at North Carolina State University (NCSU) in the Department of Marine, Earth, and Atmospheric Sciences, generated the daily gridded air pollutant concentration estimates for present-day and future decades using state-of-the-science regional climate and air quality model. They simulated air quality and climate with the online-coupled Weather Research and Forecasting Model with Chemistry (WRF/Chem) at a horizontal resolution of 36 km with 148 × 112 horizontal grid cells over the domain of continental U.S., and a vertical resolution of 34 layers for present-day (2001 to 2010) and future (2046 to 2055) decades. WRF/Chem was used to downscale NCSU's modified Community Earth System Model that generated the chemical and meteorological initial and boundary conditions at a horizontal resolution of 0.9° × 1.25° and a vertical resolution of 30 layers [52,53]. Projected emission of air pollutants and greenhouse gases for the future utilized in these models are from RCP 4.5 and 8.5, indicating projected radioactive forcing values of 4.5 and 8.5 W/m^2 for the year 2100 [54]. Based on consistent scenarios representative of current literature, RCPs represent a set of internally consistent potential development for emission, land use, and socio-economic scenarios [54]. RCP 8.5 assumed high population, relatively slow income growth, modest rate of technology development, and resulted in a high energy-intensive and high GHG emission scenario without specific climate change mitigation target [55]. RCP 4.5 assumed intermediate population, GDP growth and mitigation [56].

We used simulated air pollutant concentrations, daily average concentration for $PM_{2.5}$ and daily maximum 8-h concentration for O_3, from aforementioned models to estimate county-specific exposure for both present-day and future populations. We first generated weighted averages of daily air pollutant gridded model estimates, with weights assigned to grid cells by percentage of county area within each cell. Depending on the metrics of CRF, we aggregated these daily measurements to annual averages or decadal averages.

Concentration-response function from historical data

For associations between air pollution and adverse health, and risk for adverse health outcomes at a reference level, we utilized the Bayesian hierarchical model to generate county-specific estimates after pooling information across the urban counties [15,57]. Data utilized in this statistical model were hospital admission data of U.S. Medicare beneficiaries, U.S. EPA $PM_{2.5}$ monitoring data, and metrological data from National Oceanic and Atmospheric Administration. Model specification and data source are specified in project 1 of my dissertation research and not the main research question in this study.

To incorporate change of CRF over time into the calculation of ΔEN, we estimated three sets of CRFs for each combination of health outcome, air pollutant and potential vulnerable population: 1) CRF without temporal trend, and we assumed a normal distribution for this coefficient when sampled for the calculation of ΔEN; 2) CRF with non-linear temporal trend, and we assumed a multivariate normal distribution for these coefficients when sampled for calculation of ΔEN; and 3) season specific CRF [58], and we assumed a multivariate normal distribution for these coefficients when sampled for calculation of ΔEN. The assumptions of distributions here are consistent with the underlying assumptions of *TLNise* function, the algorithm utilized to derive these estimates from the Bayesian hierarchical model.

Since earlier researches indicate that $PM_{2.5}$ is unlikely to be a confounder for the ozone and morality relationship, estimation of CRFs were performed for $PM_{2.5}$ and ozone separately using the same set of equations [59]. To incorporate information of all study counties as well as to reduce variation in associations at individual county level, we used the Bayesian county-specific estimate of association after pooling. In this way, each urban county had their own risk estimates after incorporating information from all relevant counties in study. We also assessed the statistical significance of heterogeneity with Wald test or MANOVA before carrying out subset analyses.

Projected population characteristics

We obtained county-level population sizes and racial distributions for persons ≥65 years from the U.S. Census Bureau 2010 decennial census to represent present-day decade population distribution. For future decade, we combined information from multiple sources. We used county-level population projections by the U.S Integrated Climate and Land-Use Scenarios (ICLUS) for 2050 using Special Report on Emission Scenarios (SRES), the earlier version of climate change storyline produced by the Intergovernmental Panel on Climate Change [60]. RCP 8.5 is based on a revised version of SRES A2 scenario regarding demographics and economics trends, but the actual population projections of RCP 8.5 fall between SRES A2 and B2 scenarios [54,55]. Population assumptions in RCP 4.5 are based on scenarios of the Global Change Assessment Model with no corresponding scenario in SRES [56]. It employs the lowest population assumption among all RCPs and its population projections fall between SRES B1/A1 and B2 [54]. Since ICLUS projections lack age distribution of the population, we multiplied ICLUS county-level projections for the whole population by the ratio of elderly population to the whole population in 2050 projected by the U.S. Census National Population Projections to estimate the county-level population size and racial distribution for persons $\geq$65 years. For calculation of health impact, we assumed uniform distribution between projections of SRES A2 and B2 for RCP 8.5 related analysis, and uniform distribution among projections of SRES B1/A1, and B2 for RCP 4.5 related analysis.

Preliminary Results

As shown in Table 1, we observed decreases in decadal average concentrations and decadal sum of exceedance days for $PM_{2.5}$ and ozone under both climate change scenarios, except for change in ozone average concentration under RCP8.5. The interquantile ranges for both pollutants are also projected to decrease regardless of climate change scenario. Decadal average concentrations and decadal sum of exceedance days demonstrate spatial disparity between two pollutants but similar spatial pattern between two scenarios. For example, we projected highest increase in decadal average ozone concentration in counties of Midwest and Northeast under both RCP8.5 and RCP4.5 (Figure 2 and Figure 3), while we projected the smallest decrease in decadal average $PM_{2.5}$ concentrations in counties of West (Figure 4).

Table 1. Summary of county-specific exposure estimates for present-day and future dacades, and coresponding changes.

Scenarios	Present-day decade Median (Q1, Q3)	Future decade Median (Q1, Q3)	Change (future-present) Median (Q1, Q3)
Ozone decadal average concentration (ppb)			
RCP4.5	42.3 (39.5, 44.7)	39.5 (38.4, 41.3)	-2.9 (-4.4, -1.1)
RCP8.5	41.7 (38.3, 44.2)	43.7 (42.0, 45.5)	2.3 (0.8, 3.6)
$PM_{2.5}$ decadal average concentration (μg/m^3)			
RCP4.5	10.1 (7.2, 12.1)	5.7 (4.2, 6.7)	-4.0 (-5.8, -2.6)
RCP8.5	9.9 (6.9, 11.9)	4.2 (3.0, 5.2)	-5.5 (-7.4, -3.7)
Ozone decadal sum of exceedance days			
RCP4.5	138 (62, 222)	15 (10, 24)	-118 (-202, -44)
RCP8.5	105 (47, 190)	7 (3, 14)	-93 (-185, -32)
$PM_{2.5}$ decadal sum of exceedance days			
RCP4.5	8 (1, 33)	0 (0, 2)	-4 (-27, 0)
RCP8.5	10 (1, 33)	2 (0, 3)	-9 (-30, 0)

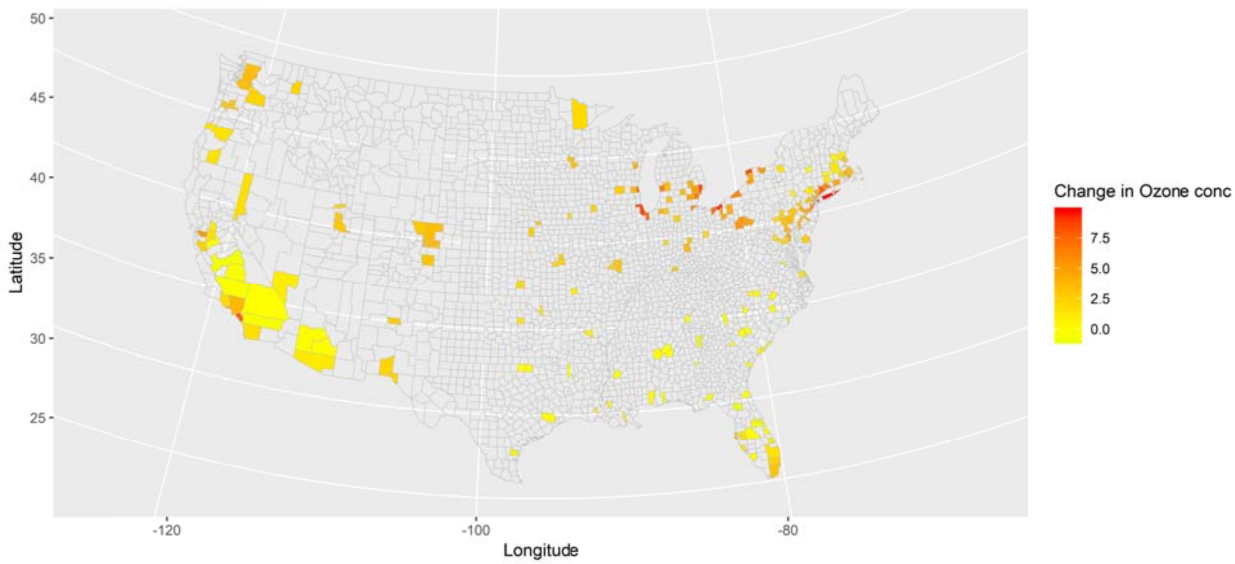

Figure 2. County-specific change in ozone (ppb) decadal average concentrations under RCP8.5 (future decade minus present-day decade).

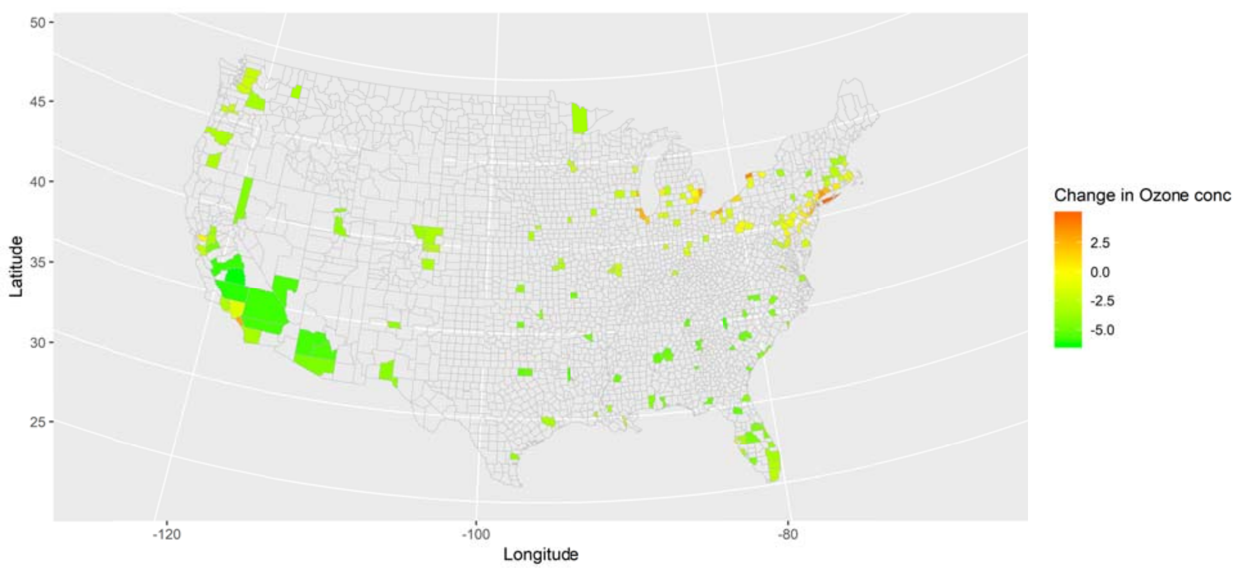

Figure 3. County-specific change in ozone (ppb) decadal average concentrations under RCP4.5 (future decade minus present-day decade).

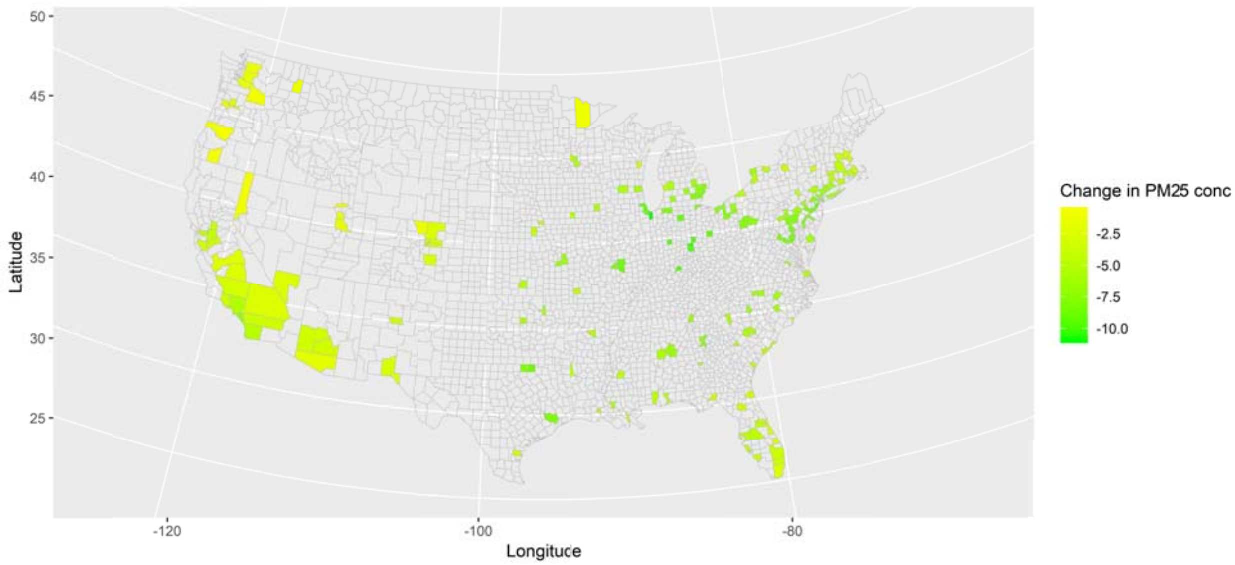

Figure 4. County-specific change in $PM_{2.5}$ ($\mu g/m^3$) decadal average under RCP8.5 (future decade minus present-day decade).

Conclusions, Study Strengths, and Limitations

For RCP4.5, the stabilization scenario with intermediate mitigation, we mostly observed decrease in $PM_{2.5}$ and ozone in urban centers. For RCP8.5, the high energy-intensive and high GHG emission scenario without specific climate change mitigation target, we observed a smaller decrease in $PM_{2.5}$ compared to RCP4.5 and generally an increase in ozone. Given the small differences in changes of air pollution levels between two climate change scenarios, as well as the spatial disparity in concentration change between pollutants, it is critical to calculate the air pollution related health impact in order to accurately evaluate any potential health co-benefits of climate change control policies projected in RCP4.5 versus RCP8.5. We also observed a general decrease in days with levels of air pollutant concentrations higher than NAAQS. However, fewer days in exceedance of NAAQS does not indicate a lack of health impact from exposure to $PM_{2.5}$ and ozone. Even at levels consistently below standards, exposure to $PM_{2.5}$ is still associated with elevated risk for hospital admissions [25]. We would still expect to observe adverse health outcomes associated with exposure to these air pollutants in the future.

In addition, the simulated air pollutant levels are not a perfect prediction of future urban center exposures. First, the model represents the best effort of the current research community but still has limitations. This simulation focused on change in projected emission of air pollutants and greenhouse gasses and assumed same land use/land cover over time [61(p1)]. Second, we estimated area weighted ambient air pollutant concentrations, which is a surrogate for average population exposure and is potentially subject to exposure misclassification.

The proposed method for change in excess number of hospital admissions due to air pollution is one of the first efforts to incorporate the influence of temporal trends and seasonal variation of CRF on the air pollution related health impact under climate change. It necessitates interdisciplinary research among climate change and air quality modeling, exposure assessment, and epidemiology, and thus incorporates the limitations and uncertainties of each.

First, this study only reveals a partial image for air pollution related health impact of climate change. We only evaluated the health impact related to short-term exposure to two single air pollutants, while long-term exposure to these pollutants and numerous other risk factors have deleterious human health impact and vary under climate change. Second, with CRF calculated by my analysis, we can account for uncertainty with Monte Carlo simulation, and to use health associations considering temporal trend and seasonal variation, at the county level, and specific to potential susceptible groups like age and sex. However, only using CRF estimated in one study does not take advantage of the collective knowledge accumulated in the epidemiology community. Third, the HLF we adopted incorporates the comparison of exposures between present-day and future populations and we can only change population characteristics simultaneous for both present-day and future population when estimating ΔEN. When future population characteristics were used, we applied the population characteristics of the future decade to the percentage change in excess number of hospital admission per projected change in air pollutant level. Thus, the resulting ΔEN is a comparison between the population with future characteristics and future air pollutant level, and the population with future characteristics and current air pollutant level. This is different from the direct comparison between the future and the current population, allowing both population characteristics and air pollution levels to differ.

Another widely used HLF is based on the health impact function from BenMAP, which compares average exposures between two periods and is less flexible in capturing temporal variation in exposures, thus not utilized here [33,42–44]. *Peng et al. (2011)* also proposed a new HLF for heat related mortality under climate change, which allows separate calculation of EN for present-day and future population and preserves the flexibility to apply different population characteristics simultaneously. However, applying this HLF to a continuous exposure requires calculation of risk at a pre-specified exposure level, where the adverse health impact of air pollutant should be minimized. Currently there is no consensus on this value for either $PM_{2.5}$ or ozone in the science community. The WHO utilized the theoretical minimum-risk exposure level (33.3 to 41.9 ppb for ozone and 2.4 to 5.9 μg/m^3 for $PM_{2.5}$), aiming to minimize the health impact by reducing air pollutant to a practically reasonable level [46]. While atmospheric scientists propose to use the policy relevant background level when all anthropogenic sources of emissions were removed [47,48]. Both reference levels are so low that little health impact assessment was conducted at this level, making it hard to derive a risk at reference level without extrapolating.

Next steps

In future work, we will leverage the above estimates to calculate the change in excess number of hospital admissions due to $PM_{2.5}$ and ozone under RCP4.5 and RCP8.5. These results will incorporate population heterogeneity in health response, projected population sizes, and projected change in ambient air pollution levels estimated above, which could provide insights in identifying critical groups and regions for mitigation and adaptation. We will also reach out to atmospheric scientists regarding these results for a more in-depth understanding of the observed changes in $PM_{2.5}$ and ozone exposures in order to better understand these results and follow-up on our preliminary findings.

Acknowledgements

This work was funded by the Yale Hixon Center for Urban Studies.

This research has been conducted under Assistance Agreement No. RD835871 awarded by the U.S. Environmental Protection Agency to Yale University. It has not been formally reviewed by EPA. The views expressed in this document are solely those of The Solutions for Energy, Air, Climate & Health (SEARCH) Center and do not necessarily reflect those of the Agency. EPA does not endorse any products or commercial services mentioned in this publication.

Many thanks to Prof. Michelle Bell, the Bell research group @ Yale, Prof. Yang Zhang, and Prof. Zhang's research team at NCSU.

Michelle L. Bell

17Jan2019

Bibliography

1. The Paris Agreement - main page. http://unfccc.int/paris_agreement/items/9485.php. Accessed December 7, 2017.
2. Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, eds. Summary for policymakers. In: *Climate Change 2014 Impacts, Adaptation, and Vulnerability*. Cambridge: Cambridge University Press; 2014:1-32. doi:10.1017/CBO9781107415379.003
3. Bobb JF, Peng RD, Bell ML, Dominici F. Heat-related mortality and adaptation to heat in the United States. *Environ Health Perspect*. 2014;122(8):811-816. doi:10.1289/ehp.1307392
4. Guo Y, Li S, Liu DL, Chen D, Williams G, Tong S. Projecting future temperature-related mortality in three largest Australian cities. *Environmental Pollution*. 2016;208(Part A):66-73. doi:10.1016/j.envpol.2015.09.041
5. Weinberger KR, Haykin L, Eliot MN, Schwartz JD, Gasparrini A, Wellenius GA. Projected temperature-related deaths in ten large U.S. metropolitan areas under different climate change scenarios. *Environment International*. 2017;107:196-204. doi:10.1016/j.envint.2017.07.006
6. Berman JD, Ebisu K, Peng RD, Dominici F, Bell ML. Drought and the risk of hospital admissions and mortality in older adults in western USA from 2000 to 2013: a retrospective study. *Lancet Planetary Health*. 2017;1(1):e17-e25. doi:10.1016/S2542-5196(17)30002-5
7. Ahmed SA, Diffenbaugh NS, Hertel TW. Climate volatility deepens poverty vulnerability in developing countries. *Environ Res Lett*. 2009;4(3):034004. doi:10.1088/1748-9326/4/3/034004
8. Breton M-C, Garneau M, Fortier I, Guay F, Louis J. Relationship between climate, pollen concentrations of Ambrosia and medical consultations for allergic rhinitis in Montreal, 1994-2002. *Sci Total Environ*. 2006;370(1):39-50. doi:10.1016/j.scitotenv.2006.05.022
9. Ebi KL, Mills DM, Smith JB, Grambsch A. Climate change and human health impacts in the United States: an update on the results of the U.S. national assessment. *Environ Health Perspect*. 2006;114(9):1318-1324. doi:10.1289/ehp.8880
10. Shuman EK. Global climate change and infectious diseases. *New England Journal of Medicine*. 2010;362(12):1061-1063. doi:10.1056/NEJMp0912931
11. Isaksen ISA, Granier C, Myhre G, et al. Atmospheric composition change: Climate–Chemistry interactions. *Atmospheric Environment*. 2009;43(33):5138-5192. doi:10.1016/j.atmosenv.2009.08.003
12. Forouzanfar MH, Afshin A, Alexander LT, et al. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The Lancet*. 2016;388(10053):1659-1724. doi:10.1016/S0140-6736(16)31679-8
13. Bell ML, Belanger K, Ebisu K, et al. Prenatal exposure to fine particulate matter and birth weight. *Epidemiology*. 2010;21(6):884-891. doi:10.1097/EDE.0b013e3181f2f405
14. Ebisu K, Bell ML. Airborne PM2.5 chemical components and low birth weight in the Northeastern and Mid-Atlantic regions of the United States. *Environ Health Perspect*. 2012;120(12):1746-1752. doi:10.1289/ehp.1104763
15. Dominici F, Samet JM, Zeger SL. Combining evidence on air pollution and daily mortality from the 20 largest US cities: a hierarchical modelling strategy. *J R Statist Soc A*. 2000;163(3):263-302. doi:10.1111/1467-985X.00170

16. Bell ML, McDermott A, Zeger SL, Samet JM, Dominici F. Ozone and short-term mortality in 95 US urban communities, 1987-2000. *JAMA*. 2004;292(19):2372-2378. doi:10.1001/jama.292.19.2372
17. Zeger SL, Dominici F, McDermott A, Samet JM. Mortality in the Medicare population and chronic exposure to fine particulate air pollution in urban centers (2000–2005). *Environ Health Perspect*. 2008;116(12):1614-1619. doi:10.1289/ehp.11449
18. Brook RD, Rajagopalan S, Pope CA, et al. Particulate matter air pollution and cardiovascular disease an update to the scientific statement from the American Heart Association. *Circulation*. 2010;121(21):2331-2378. doi:10.1161/CIR.0b013e3181dbece1
19. Krall JR, Anderson GB, Dominici F, Bell ML, Peng RD. Short-term exposure to particulate matter constituents and mortality in a national study of U.S. urban communities. *Environ Health Perspect*. 2013;121(10):1148-1153. doi:10.1289/ehp.1206185
20. Di Q, Wang Y, Zanobetti A, et al. Air pollution and mortality in the Medicare population. *New England Journal of Medicine*. 2017;376(26):2513-2522. doi:10.1056/NEJMoa1702747
21. Samet JM, Zeger SL, Dominici F, et al. The National Morbidity, Mortality, and Air Pollution Study. Part II: Morbidity and mortality from air pollution in the United States. *Res Rep Health Eff Inst*. 2000;94(Pt 2):5-70; discussion 71-79.
22. Dominici F, Peng RD, Bell ML, et al. FIne particulate air pollution and hospital admission for cardiovascular and respiratory diseases. *JAMA*. 2006;295(10):1127-1134. doi:10.1001/jama.295.10.1127
23. Zanobetti A, Franklin M, Koutrakis P, Schwartz J. Fine particulate air pollution and its components in association with cause-specific emergency admissions. *Environ Health*. 2009;8:58. doi:10.1186/1476-069X-8-58
24. Bell ML, Ebisu K, Leaderer BP, et al. Associations of PM2.5 constituents and sources with hospital admissions: analysis of four counties in Connecticut and Massachusetts (USA) for persons ≥ 65 years of age. *Environ Health Perspect*. 2014;122(2):138-144. doi:10.1289/ehp.1306656
25. Makar M, Antonelli J, Di Q, Cutler D, Schwartz J, Dominici F. Estimating the causal effect of low levels of fine particulate matter on hospitalization. *Epidemiology*. 2017;28(5):627–634. doi:10.1097/EDE.0000000000000690
26. US EPA O. Nonattainment Areas for Criteria Pollutants (Green Book). US EPA. https://www.epa.gov/green-book. Published April 14, 2016. Accessed August 28, 2017.
27. Madaniyazi L, Guo Y, Yu W, Tong S. Projecting future air pollution-related mortality under a changing climate: progress, uncertainties and research needs. *Environment International*. 2015;75(Supplement C):21-32. doi:10.1016/j.envint.2014.10.018
28. Orru H, Ebi KL, Forsberg B. The interplay of climate change and air pollution on health. *Curr Envir Health Rpt*. 2017;4(4):504-513. doi:10.1007/s40572-017-0168-6
29. Silva RA, West JJ, Lamarque J-F, et al. Future global mortality from changes in air pollution attributable to climate change. *Nature Climate Change*. 2017;7(9):647-651. doi:10.1038/nclimate3354
30. Kinney PL. Interactions of Climate Change, Air Pollution, and Human Health. *Curr Envir Health Rpt*. 2018;5(1):179-186. doi:10.1007/s40572-018-0188-x
31. Bell ML, Zanobetti A, Dominici F. Evidence on vulnerability and susceptibility to health risks associated with short-term exposure to particulate matter: a systematic review and meta-analysis. *Am J Epidemiol*. 2013;178(6):865-876. doi:10.1093/aje/kwt090

32. Bell ML, Zanobetti A, Dominici F. Who is more affected by ozone pollution? A systematic review and meta-analysis. *Am J Epidemiol*. 2014;180(1):15-28. doi:10.1093/aje/kwu115
33. Hubbell B, Fann N, Levy JI. Methodological considerations in developing local-scale health impact assessments: balancing national, regional, and local data. *Air Qual Atmos Health*. 2009;2(2):99-110. doi:10.1007/s11869-009-0037-z
34. Intergovernmental Panel on Climate Change, ed. Near-term climate change: projections and predictability. In: *Climate Change 2013 - the Physical Science Basis*. Cambridge: Cambridge University Press; 2014:953-1028. doi:10.1017/CBO9781107415324.023
35. Dominici F, Peng RD, Ebisu K, Zeger SL, Samet JM, Bell ML. Does the effect of PM10 on mortality depend on PM nickel and vanadium content? A reanalysis of the NMMAPS data. *Environ Health Perspect*. 2007;115(12):1701-1703. doi:10.1289/ehp.10737
36. Breitner S, Stölzel M, Cyrys J, et al. Short-term mortality rates during a decade of improved air quality in Erfurt, Germany. *Environ Health Perspect*. 2009;117(3):448-454. doi:10.1289/ehp.11711
37. Bell ML, Ebisu K, Peng RD, et al. Seasonal and regional short-term effects of fine particles on hospital admissions in 202 US counties, 1999–2005. *Am J Epidemiol*. 2008;168(11):1301-1310. doi:10.1093/aje/kwn252
38. US EPA O. NAAQS Table. US EPA. https://www.epa.gov/criteria-air-pollutants/naaqs-table. Published April 10, 2014. Accessed April 24, 2018.
39. Steenland K, Armstrong B. An overview of methods for calculating the burden of disease due to specific risk factors. *Epidemiology*. 2006;17(5):512-519.
40. Martenies SE, Wilkins D, Batterman SA. Health impact metrics for air pollution management strategies. *Environment International*. 2015;85:84-95. doi:10.1016/j.envint.2015.08.013
41. Murray CJL, Lopez AD. On the Comparable Quantification of Health Risks: Lessons from the Global Burden of Disease Study. *Epidemiology*. 1999;10(5):594-605.
42. Post ES, Grambsch A, Weaver C, et al. Variation in estimated ozone-related health impacts of climate change due to modeling choices and assumptions. *Environ Health Perspect*. 2012;120(11):1559-1564. doi:10.1289/ehp.1104271
43. Sujaritpong S, Dear K, Cope M, Walsh S, Kjellstrom T. Quantifying the health impacts of air pollution under a changing climate—a review of approaches and methodology. *Int J Biometeorol*. 2014;58(2):149-160. doi:10.1007/s00484-012-0625-8
44. US EPA O. Manual and Appendices for BenMAP-CE. October 2014. https://www.epa.gov/benmap/manual-and-appendices-benmap-ce. Accessed April 23, 2018.
45. Peng RD, Bobb JF, Tebaldi C, McDaniel L, Bell ML, Dominici F. Toward a quantitative estimate of future heat wave mortality under global climate change. *Environ Health Perspect*. 2011;119(5):701-706. doi:10.1289/ehp.1002430
46. GDB 2015 risk factors collaborators. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The Lancet*. 2016;388(10053):1659-1724. doi:10.1016/S0140-6736(16)31679-8
47. Emery C, Jung J, Downey N, et al. Regional and global modeling estimates of policy relevant background ozone over the United States. *Atmospheric Environment*. 2012;47:206-217. doi:10.1016/j.atmosenv.2011.11.012

48. Gong W, Builtjes P, Batchvarova E, Godowitch J, Timin B, Siljamo P. Regional and intercontinental modelling. In: *Air Pollution Modeling and Its Application XX*. NATO Science for Peace and Security Series C: Environmental Security. Springer, Dordrecht; 2010:109-280. doi:10.1007/978-90-481-3812-8_2
49. Schwartz JD, Lee M, Kinney PL, et al. Projections of temperature-attributable premature deaths in 209 U.S. cities using a cluster-based Poisson approach. *Environmental Health*. 2015;14:85. doi:10.1186/s12940-015-0071-2
50. Sun J, Fu JS, Huang K, Gao Y. Estimation of future PM2.5- and ozone-related mortality over the continental United States in a changing climate: An application of high-resolution dynamical downscaling technique. *J Air Waste Manag Assoc*. 2015;65(5):611-623. doi:10.1080/10962247.2015.1033068
51. Gasparrini A, Leone M. Attributable risk from distributed lag models. *BMC Med Res Methodol*. 2014;14:55. doi:10.1186/1471-2288-14-55
52. Glotfelty T, He J, Zhang Y. Impact of future climate policy scenarios on air quality and aerosol-cloud interactions using an advanced version of CESM/CAM5: Part I. model evaluation for the current decadal simulations. *Atmospheric Environment*. 2017;152:222-239. doi:10.1016/j.atmosenv.2016.12.035
53. Glotfelty T, Zhang Y. Impact of future climate policy scenarios on air quality and aerosol-cloud interactions using an advanced version of CESM/CAM5: Part II. Future trend analysis and impacts of projected anthropogenic emissions. *Atmospheric Environment*. 2017;152:531-552. doi:10.1016/j.atmosenv.2016.12.034
54. Vuuren DP van, Edmonds J, Kainuma M, et al. The representative concentration pathways: an overview. *Climatic Change*. 2011;109(1-2):5. doi:10.1007/s10584-011-0148-z
55. Riahi K, Rao S, Krey V, et al. RCP 8.5—A scenario of comparatively high greenhouse gas emissions. *Climatic Change*. 2011;109(1-2):33. doi:10.1007/s10584-011-0149-y
56. Thomson AM, Calvin KV, Smith SJ, et al. RCP4.5: a pathway for stabilization of radiative forcing by 2100. *Climatic Change*. 2011;109(1-2):77. doi:10.1007/s10584-011-0151-4
57. Dominici F, Daniels M, Zeger SL, Samet JM. Air pollution and mortality: estimating regional and national dose-response relationships. *J Am Stat Assoc*. 2002;97(457):100-111.
58. Peng RD, Dominici F, Pastor-Barriuso R, Zeger SL, Samet JM. Seasonal analyses of air pollution and mortality in 100 US cities. *Am J Epidemiol*. 2005;161(6):585-594. doi:10.1093/aje/kwi075
59. Bell ML, Kim JY, Dominici F. Potential confounding of particulate matter on the short-term association between ozone and mortality in multisite time-series studies. *Environ Health Perspect*. 2007;115(11):1591-1595. doi:10.1289/ehp.10108
60. US EPA O. Integrated climate and land-use scenarios. US EPA. https://www.epa.gov/iclus. Published January 30, 2015. Accessed October 11, 2017.
61. Yahya K, Wang K, Campbell P, et al. Decadal application of WRF/Chem for regional air quality and climate modeling over the U.S. under the representative concentration pathways scenarios. Part 1: Model evaluation and impact of downscaling. *Atmospheric Environment*. 2017;152:562-583. doi:10.1016/j.atmosenv.2016.12.029