Appendix D. Air Quality

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1. Introduction

Climate change impacts human health in many ways. One of these impacts is through increasing concentrations of ambient air pollutants, including fine particulate matter ($PM_{2.5}$) and ground-level ozone, which have significant impacts on respiratory and cardiovascular morbidity and mortality health effects.[1] Changes in climate, including changes in temperature, humidity, precipitation, and other meteorological factors, create conditions in which secondary formation of $PM_{2.5}$ and ozone are better supported, increasing the magnitude and broadening the distribution of human exposures to these pollutants.[2]

The relationship between exposure to air pollution and socially vulnerable populations has been examined over the last forty years in the U.S.[3,4] Vulnerability has been defined by the U.S. EPA as the "differential exposure, differential preparedness, and differential ability to recover."[5] It is well understood that environmental hazards are inequitably distributed, with poor people and people of

[1] Crimmins A, Balbus J, Gamble JL, Beard CB, Bell JE, Dodgen D, Eisen RJ, Fann N, Hawkins M, Herring SC, Jantarasami L, Mills DM, Saha M, Sarofim MC, Trtanj J, Ziska L. 2016. Executive Summary. The impacts of Climate Change on Human Health in the United States: A Scientific Assessment. U.S. Global Change Research Program, Washington, DC, 24 pp. http://dx.doi.org/doi:10.7930/JOOPOWXS

[2] Nolte CG, Dolwick PD, Fann N, Horowitz LW, Naik V, Pinder RW, Spero TL, Winner DA, and Ziska LH. 2018. Air Quality. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller DR, Avery CW, Easterling DR, Kunkel KE, Lewis KLM, Maycock TK, and Stewart BC, (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 512–538. doi: 10.7930/NCA4.2018.CH13

[3] Mahaffey KR, Annest JL, Roberts J, Murphy RS. National estimates of blood lead levels: United States, 1976-1980: association with selected demographic and socioeconomic factors. *N Engl J Med*. 1982 Sep 2;307(10):573-9. doi: 10.1056/NEJM198209023071001. PMID: 7110203.

[4] Hoek G, Krishnan RM, Beelen R, Peters A, Ostro B, Brunekreef B, and Kaufman JD. 2013. Long-Term Air Pollution Exposure and Cardio-Respiratory Mortality: A Review. *Environmental Health* 12(43).

[5] U.S. Environmental Protection Agency. 2003. Framework for Cumulative Risk Assessment. Washington, D.C.

color consistently bearing more than their share of the burden of environmental pollution.[6] Policies may contribute to disproportionate impacts on these socially vulnerable.[7,8] Federal agencies are directed to identify and address disproportionately adverse human health or environmental effects of policies on "minority and low-income populations," which define the "socially vulnerable" that are analyzed in this document.

This chapter analyses the extent to which future changes in climate will degrade air quality and disproportionately burden the health of socially vulnerable individuals. Specifically, it analyzes where the hazards of increased $PM_{2.5}$ and ozone concentrations expose populations made particularly vulnerable by a series of demographic and socioeconomic factors, leading to increased health risks.

Section 2 describes motivation and background for investigating these factors. Section 3 lays out the methods employed to perform the analysis, while Section 4 provides the results of the analysis. Section 5 summarizes results into the broader conclusions and describes important next steps.

2. Differential Exposure to Air Pollutants by Socially Vulnerable Populations

There is a growing body of literature that finds evidence of increased exposure to air pollution among socially vulnerable populations.[9] The supporting literature generally focuses on four determinants of social vulnerability to adverse health impacts from air pollution, including income measures, race and ethnicity, educational attainment, and age. While these characteristics have individual impacts on air pollution exposure and resulting adverse health effects, they are often observed and analyzed in conjunction with one another.

Evidence of the Relationship between Social Vulnerability Determinants and Air Pollutant Exposures

Studies have found that health hazards, including air pollution exposure, are significantly different between communities with varying educational attainment and income characteristics. Many studies use educational attainment as an indicator in assessing environmental justice communities.[10,11,12]

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[6] Cole LW, Foster SR. 2001. *From the Ground Up: Environmental Racism and the Rise of the Environmental Justice Movement*. New York and London. New York University Press.

[7] U.S. EPA. 2015. Guidance on Considering Environmental Justice During the Development of Regulatory Actions.

[8] In an aim to address the unequal distribution of environmental hazards, President Biden issued Executive Order 14008 on January 27, 2021, which created an Interagency Council tasked with developing "a strategy to address current and historic environmental injustice." Sec. 220 of Executive Order 14008 amended Executive Order 12898 issued by President Clinton in 1994. Executive Order 14008 - Executive Order on Tackling the Climate Crisis at Home and Abroad, 2021. Executive Order 12898 - Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations, 1994.

[9] Ebi KL, Balbus JM, Luber G, Bole A, Crimmins A, Glass G, Saha S, Shimamoto MM, Trtanj J, and White-Newsome JL. 2018. Human Health. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller DR, Avery CW, Easterling DR, Kunkel KE, Lewis KLM, Maycock TK, and Stewart BC, (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 539–571. doi: 10.7930/NCA4.2018.CH14

[10] Fann N, Roman HA, Fulcher CM, Gentile MA, Hubbell BJ, Wesson K, and Levy JL. 2011. Maximizing Health Benefits and Minimizing Inequality: Incorporating Local-Scale Data in the Design and Evaluation of Air Quality Policies. *Risk Analysis*, *31*(6), 908–922. http://doi.org/10.1111/j.1539-6924.2011.01629.x

[11] Alexeeff GV, Faust JB, August LM, Milanes C, Randles K, Zeise L, and Denton J. 2012. A screening method for assessing cumulative impacts. *International Journal of Environmental Research and Public Health*, *9*(2), 648–659. http://doi.org/10.3390/ijerph9020648

[12] Kershaw S, Gower S, Rinner C, and Campbell M. 2013. Identifying inequitable exposure to toxic air pollution in racialized and low-income neighbourhoods to support pollution prevention. *Geospatial Health*, *7*(2), 265–78. http://doi.org/10.4081/gh.2013.85

Kershaw et al. (2013) found significant differences in educational attainment between Census tracts hosting toxic air pollution emitters compared with those that do not. Schweitzer and Zhou (2010) studied concentrations of pollutants within neighborhoods in 80 metro areas in the U.S., and found that population exposures to ozone and $PM_{2.5}$ are greater in neighborhoods with higher poverty rates, as well as in neighborhoods with more African American and Asian households. The authors found poverty to be an important predictor of air pollution exposures in people over age 65.[13] Miranda et al. (2011) assessed whether the Clean Air Act and its Amendments have been equally successful in ensuring clean air in both advantaged and disadvantaged communities. The study authors found that low-income communities tend to have greater sources of environmental hazards, including greater ambient air pollution concentrations than their higher income counterparts. In addition, Miranda et al. (2011) ranked U.S. counties with sufficient air quality data by the number of poor air quality days for daily ozone, daily $PM_{2.5}$, and annual $PM_{2.5}$ concentrations. Using these rankings, authors were able to identify the top twenty percent of counties with the best air quality and lowest twenty percent of counties with the poorest air quality by pollution metric. Study authors found that non-Hispanic Black individuals consistently reside in communities with the poorest air quality (for both $PM_{2.5}$ and ozone), and Hispanic individuals consistently reside in communities with poor air quality (for $PM_{2.5}$).[14]

Studies of health risks of those in disadvantaged communities consistently find that race plays an explanatory role in describing risk, even after controlling for other socioeconomic and demographic factors like income, housing value, and education status.[15,16, 17] Research on $PM_{2.5}$ exposure and effects on mortality rates found that community-level socioeconomic status variables modified the association, with increasing estimates for areas with high proportions of residents and families in poverty; Black residents; and population without a high-school degree; lower estimates were found for increasing median household income and proportion of white residents.[18] Another U.S.-based study of $PM_{2.5}$ exposures related to electricity generation found that related health impacts are highest for Black individuals, and when analyzed by income status, pollutant exposures are higher for lower-income than higher-income people.[19] Similarly, Rosofsky et al. (2018) examined $PM_{2.5}$ and nitrogen dioxide trends across Massachusetts over eight years and found that non-Hispanic Black individuals and Hispanic individuals lived in areas with higher pollutant concentrations than non-Hispanic white individuals, and that inequalities between racial and ethnic groups were greater compared to groups distinguished by income and educational attainment.[20] Additional research indicates that increased air pollution-related

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[13] Schweitzer L, and Zhou J. 2010. Neighborhood-Air Quality, Respiratory Health, and Vulnerable Populations in Compact and Sprawled Regions. *Journal of the American Planning Association*, 76:3, 363-371, DOI: 10.1080/01944363.2010.486623.

[14] Miranda ML, Edwards SE, Keating MH, Paul CJ. Making the Environmental Justice Grade: The Relative Burden of Air Pollution Exposure in the United States. *Int J Environ Res Public Health.* 2011 Jun; 8(6): 1755-1771.

[15] Morello-Frosch R, Pastor Jr M, Porras C, Sadd J. 2002. Environmental Justice and Regional Inequality in Southern California: Implications for Future Research. *Environ Health Perspectives*. 110(2): 149-154.

[16] Sadd JL, Pastor M, Morello-Frosch R, Scoggins J, Jesdale B. 2011. Playing It Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California. *Int J Environ Res Public Health*. 8: 1441-1459.

[17] Morello-Frosch R, Pastor M, and Sadd J. 2001. Environmental Justice and Southern California's 'Riskscape': The Distribution of Air Toxics Exposures and Health Risks among Diverse Communities. *Urban Affairs Review* 36(4): 551–78.

[18] Kioumourtzoglou, M-A, Schwartz J, James P, Dominici F, Zanobetti A. $PM_{2.5}$ and mortality in 207 US cities: Modification by temperature and city characteristics. *Epidemiology*. 27(2):221-227.

[19] Thind MPS, Tessum CW, Azevedo IL, Marshall JD. Fine particulate Air Pollution from Electricity Generation in the US: Health Impacts by Race, Income, and Geography. *Environmental Science and Technology*. 2019. 53(23), 14010-14019.

[20] Rosofsky A, Levy JI, Zanobetti A, Janulewicz P, Fabian MP. 2018. Temporal trends in air pollution exposure inequality in Massachusetts. *Environmental Research*. 161: 76-86.

health risks associated with race and ethnicity are associated with social, historical, healthcare, and institutional disparities between groups.[21]

Another recent paper uses Census block-level demographic data with fine-scale spatial resolution satellite-based $PM_{2.5}$ data to assess differences in ambient pollutant exposures between non-Hispanic Black individual and non-Hispanic white individuals in the U.S. [22] The authors analyzed how these exposure differences may have changed over time. Between 2000 and 2015, pollution concentrations decreased significantly due to implementation of Clean Air Act policies, though Black individuals consistently live in the most polluted areas. Currie et al. (2020) found that with Black individuals moving out of urban settings, thus decreasing their exposures, and White populations moving into urban settings, thus increasing their exposures, the disparity in $PM_{2.5}$ concentrations experienced between the two racial groups has decreased. Another recent study analyzed concentrations of $PM_{2.5}$ between 1981 and 2016 at the Census tract level across the country.[23] Similar to the findings of Currie et al. (2020), authors found that absolute disparities in concentrations between more and less polluted Census tracts have decreased, though relative disparities between these groups persist. This decrease in disparities is due to the implementation of Clean Air Act policies that address air pollution in the most polluted areas.

Climate Change, Air Pollution, and Exposure of Socially Vulnerable Groups

While the relationship between air pollution exposure and socially vulnerable populations is clear, studies have not specifically analyzed the correlations between air pollution caused by climate change and these groups in the U.S. Recent studies have drawn a link between climate change impacts and increased air pollution concentrations, specifically for $PM_{2.5}$ and ozone, which have the greatest adverse influence on human health.[24] The U.S. EPA's 2015 report on acknowledges and quantifies a 'climate penalty' on air quality.[25,26] The climate penalty, as defined by Fann et al. (2021), is the excess risk to human health associated with climate-induced changes in air quality.[27] Changes in temperature, humidity, precipitation, and wind patterns increase secondary formation of ground-level ozone and $PM_{2.5}$,[28] and longer warm seasons increase the number of days with poor air quality.[29] Increased wildfire and windblown dust events associated with climate change also result in higher $PM_{2.5}$ emissions,

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[21] Jones CP. "Why Racism, Not Race, Is a Risk Factor for Dying of COVID-19." Interview by Claudia Wallis. *Scientific American*, June 12, 2020. https://www.scientificamerican.com/article/why-racism-not-race-is-a-risk-factor-for-dying-of-covid-191/

[22] Currie J, Voorheis J, and Walker R. 2020. What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and Satellite-based measures of air quality. NBER Working Paper No. 26659.

[23] Colmer J, Hardman I, Shimshack J, Voorheis J. 2020. Disparities in $PM_{2.5}$ air pollution in the United States. *Science* 369, 575-578.

[24] Nolte CG, Dolwick PD, Fann N, Horowitz LW, Naik V, Pinder RW, Spero TL, Winner DA, and Ziska LH. 2018. Air Quality. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 512–538. doi: 10.7930/NCA4.2018.CH13

[25] U.S. EPA. 2015. Climate change in the United States: Benefits of global action. U.S. Environmental Protection Agency, Office of Atmospheric Programs, EPA 430-R-15-001.

[26] Garcia-Menendez F, Saari RK, Monier E, and Selin NE. 2015. U.S. air quality and health benefits from avoided climate change under greenhouse gas mitigation. *Environmental Science and Technology*. DOI: 10.1021/acs.est.5b01324.

[27] Fann NL, Nolte CG, Sarofim MC, Martinich J, Nassikas NJ. 2021. Associations between simulated future changes in climate, air quality, and human health. *JAMA Network Open*. 4(1). Doi:10.1001/jamanetworkopen.2020.32064.

[28] Fann NL, Nolte CG, Sarofim MC, Martinich J, Nassikas NJ. 2021. Associations between simulated future changes in climate, air quality, and human health. *JAMA Network Open*. 4(1). Doi:10.1001/jamanetworkopen.2020.32064.

[29] Garcia-Menendez F, Saari RK, Monier E, and Selin NE. 2015. U.S. air quality and health benefits from avoided climate change under greenhouse gas mitigation. *Environmental Science and Technology*. DOI: 10.1021/acs.est.5b01324.

increasing ambient $PM_{2.5}$ concentrations. Warmer temperatures may also increase emissions of $PM_{2.5}$ from increased energy use for cooling systems.[30] The CIRA report analyzes the benefits of global greenhouse gas mitigation efforts in 2100, indicating an estimated 57,000 fewer premature deaths from poor air quality related to greenhouse gas mitigation in that year. By projecting increased maximum daily temperatures through 2095, Fann et al. (2021) found that compared with the baseline year 2000, the climate penalty on $PM_{2.5}$ under a higher emissions scenario can cause an additional 21,000 premature deaths in 2095 alone and 4,100 premature deaths from ozone.

3. Methods for Assessing Social Vulnerability Dimensions of Climate Change-Related Changes in Air Pollution

The four determinants of social vulnerability assessed here describe the specific factors that lead to systemic social inequalities and a historical lack of social capital.[31,32] For example, individuals may experience systemic social inequalities by encountering differential opportunities. They may also have to deal with a historical lack of social capital, where those social inequalities have been in play for generations, impacting not just the current scenario but also baseline health status and ability to avoid and mitigate harmful climate-related air pollution exposures. Exposure to air pollutants may impact these socially vulnerable groups in different ways. In this analysis, three dimensions of air pollution impacts are assessed that may lead to disproportionate effects on socially vulnerable populations. The first acknowledges that changes in air pollution may be geographically concentrated in areas with people who are more socially vulnerable; i.e., the analysis quantifies how changes in air pollution may be geographically concentrated in areas with higher or lower social vulnerability. The second recognizes that there are elevated baseline morbidity and mortality rates among particularly vulnerable subgroups, and that these people are at greater risk for death attributable to air pollution than their less vulnerable counterparts who experience the same changes in air pollution. Effects among subgroups with elevated baseline morbidity and mortality rates are analyzed. The third focuses on effect modification by attribute, where socially vulnerable populations may be at higher risk of adverse health consequences stemming from air pollution.[33] The analysis evaluates the potential disparity across socially vulnerable populations using effect coefficients specific to at-risk populations from select epidemiological studies.

This analysis used U.S. EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) to build upon recent work by Fann et al. (2021), which assessed $PM_{2.5}$- and ozone-attributable mortality over the 21st century.[34] BenMAP-CE quantifies health impacts resulting from changes in air pollution concentrations. To estimate air quality effects under a full range of future

[30] Garcia-Menendez F, Saari RK, Monier E, and Selin NE. 2015. U.S. air quality and health benefits from avoided climate change under greenhouse gas mitigation. *Environmental Science and Technology*. DOI: 10.1021/acs.est.5b01324.

[31] Morello-Frosch R, Pastor Jr M, Porras C, Sadd J. 2002. Environmental Justice and Regional Inequality in Southern California: Implications for Future Research. *Environ Health Perspectives*. 110(2): 149-154.

[32] Study authors define social capital as "social networks, cohesion, and a community's ability to mobilize politically."

[33] Effect modification occurs when an exposure (to air pollution, for example) has a different effect among different subgroups (such as socially vulnerable populations) compared to a reference group.

[34] Fann NL, Nolte CG, Sarofim MC, Martinich J, Nassikas NJ. 2021. Associations between simulated future changes in climate, air quality, and human health. *JAMA Network Open*. 4(1). Doi:10.1001/jamanetworkopen.2020.32064.

temperatures, Fann et al. (2021) estimated changes in mortality under a high GHG scenario (RCP8.5)[35] using two global climate models, CESM and CM3, and two simulated air pollutant emissions inventories, a 2011 dataset based on the base case (EI11) from the National Emissions Inventory (NEI) and a 2040 dataset projected from the NEI (EI40). The 2011 emissions dataset estimated the pollution burden from all sources with no further restrictions, while the 2040 dataset accounts for the implementation of a suite of regulatory policies on stationary and mobile emissions sources.

This analysis estimated health impacts using concentration-response (C-R) functions employed in similar studies, including functions parameterized in BenMAP-CE that are specific to at-risk populations.[36] All-cause mortality disaggregated by race is analyzed using C-R function information from Di et al. (2017); new incidence of asthma as a chronic condition is analyzed using C-R functions from Tétreault et al. (2016); emergency room (ER) visits due to asthma for white and non-white groups are analyzed using C-R functions from Alhanti et al. (2016).[37,38,39] Di et al. (2017) and Alhanti et al. (2016) were selected from Chapter 12 of the most recent Particulate Matter Integrated Science Assessment (ISA), which assesses the weight of epidemiological evidence demonstrating adverse risk of exposure-related mortality and morbidity for sensitive groups.[40] Tétreault et al. (2016) has been used to estimate avoided new incidence of asthma in EPA's recently released Regulatory Impact Analysis (RIA) on the Cross-State Air Pollution Rule.[41]

All C-R functions selected are listed in Table 1 below. Differential mortality burden due to higher incidence rates among some populations is evaluated using race-stratified mortality incidence rates (the second dimension mentioned above).[42] In addition, two studies provide C-R functions specific to white and non-white populations, which were used to analyze excess risk to these subgroups compared to the general population (the third dimension mentioned above). Total health impacts by Census tract were summed within each health endpoint.

[35] RCP8.5 was selected to assess a wide range of future climates, but this does not imply a judgment regarding the likelihood of that scenario. As shown in this section, air quality impacts stemming from specified discrete levels of future warming are derived from this trajectory of radiative forcing.

[36] Zanobetti A, and Schwartz J. 2008. Mortality displacement in the association of ozone with mortality: an analysis of 48 cities in the United States. *American Journal of Respiratory and Critical Care Medicine* 117(2):184-189.

[37] Di Q, Wang Y, Zanobetti A, Wang Y, Koutrakis P, Choirat C, Dominici F, Schwartz JD. 2017. Air Pollution and Mortality in the Meidcare Population. *The New England Journal of Medicine* 376(26):2513-2522.

[38] Tétreault L-F, Doucet M, Gamache P, Fournier M, Brand A, Kosatsky T, Smargiassi A. 2016. Childhood Exposure to Ambient Air Pollutants and the Onset of Asthma: An Administrative Cohort Study in Quebec. *Environmental Health Perspectives* 124(8):1276-1282.

[39] Alhanti BA, Chang HH, Winquist A, Mulholland JA, Darrow LA, Sarnat SE. 2016. Ambient air pollution and emergency department visits for asthma: a multi-city assessment of effect modification by age. *Journal of Exposure Science & Environmental Epidemiology* 26(2):180-188.

[40] U.S. EPA. 2019. Integrated Science Assessment for Particulate Matter. Retrieved from Research Triangle Park, NC: U.S. Environmental Protection Agency, Office of Research and Development, National Center for Environmental Assessment-RTP Division.

[41] U.S. EPA. 2021. Regulatory Impact Analysis for the Final Revised Cross-State Air Pollution Rule (CSAPR) Update for the 2008 Ozone NAAQS. Retrieved from Research Triangle Park, NC: U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division.

[42] Incidence data for new cases of asthma and ED visits are not disaggregated by race and do not allow for this type of analysis.

Table 1. Selected Health Endpoints for Vulnerable Populations

POLLUTANT	ENDPOINT	STUDY	SOURCE	AT-RISK POPULATION	VULNERABILITY DIMENSIONS
$PM_{2.5}$	All-cause mortality	Di et al. (2017)	PM ISA	Non-white	1, 2, 3
	Incidence, asthma	Tétreault et al. (2016)	U.S. EPA, 2021	N/A	1
	ER visits, asthma	Alhanti et al. (2016)	PM ISA	Non-white	1, 3
Ozone	All-cause mortality	Zanobetti & Schwartz (2008)	Fann et al.	N/A	1, 2

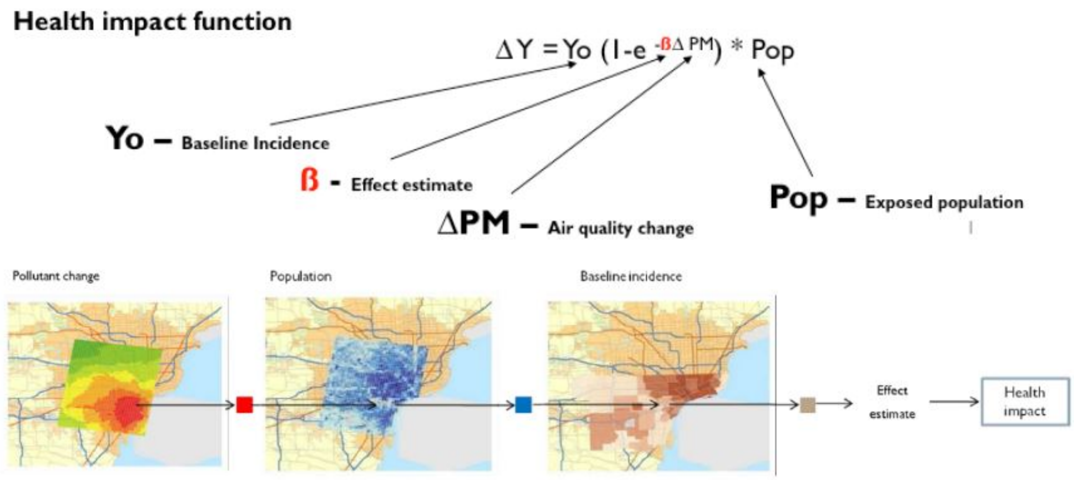
In conjunction with the functions listed in Table 1, additional standard data inputs for BenMAP-CE analyses were employed. This analysis used the same air quality surfaces employed by Fann et al. for 2030, 2050, 2075, and 2095 relative to the baseline year of 2000 (these define the first dimension of social vulnerability, that is, differential exposure). The Fann et al. work estimates impacts for four eras for both pollutants ($PM_{2.5}$ and ozone), two climate models (CESM and CM3), and two emissions inventories (2011 dataset and 2040 dataset), for a total of 32 scenarios. This analysis used BenMAP-CE with mortality incidence (2007-2016) stratified by white and non-white populations, and with non-stratified morbidity incidence and prevalence – see table 2 for a summary of the data used to estimate $PM_{2.5}$ mortality.[43] Population information comes from the 2010 U.S. Census and is available at the county level disaggregated by age, race, and ethnicity. The relation of these components is presented in Figure 2 below.

Table 2. Selected Baseline Incidence Data – All-Cause PM Mortality for the Di et al. (2017) Study

SUBPOPULATION	AGES 65-99	AGES 65-69	AGES 85-89
All populations	0.0401	0.0186	0.1164
White Non-Hispanic	0.0412	0.0187	0.1165
Hispanic White	0.0321	0.0163	0.1059
Black	0.0402	0.0204	0.1249
Asian-American	0.0309	0.0158	0.1082
Native American	0.0353	0.0199	0.1208

[43] For new cases of asthma, morbidity incidence from 2006-2008 is used for one of the two arguments in the epidemiological function, and for the second argument, 2018 prevalence is used, which matches the method used in EPA's 2021 Regulatory Impact Analysis for the Final Revised Cross-State Air Pollution Rule. For asthma ED visits, morbidity incidence from 2014 is used.

Figure 2. Components of Health Impacts Analysis Performed in BenMAP-CE



Each era, pollutant, model, and emissions inventory combination scenario is processed and applied to the C-R functions using BenMAP-CE to generate estimated health effects for the vulnerable populations of interest.

To further understand the health impacts from $PM_{2.5}$ and ozone exposures associated with degrees Celsius increases in global mean temperature, this analysis uses the health effect estimates calculated using BenMAP-CE and follows the four steps outlined in Figure 3 and further described below.

Step 1: Estimate the health impacts associated with each degree Celsius increase in global mean temperature (from BenMAP results). This analysis estimates health impacts associated with increased ambient pollutant exposures due to increasing global mean temperature, including $PM_{2.5}$-related premature mortality, $PM_{2.5}$-related childhood asthma emergency department (ED) visits, and ozone-related premature mortality using BenMAP-CE and methods originally described in Fann et al. (2021). For more on the climate projection methods, see Appendix C.

Step 2: Categorize Census tracts into three groups: high, medium, and low health impacts per person per year. Output from Step 1 is used to categorize Census tracts into three evenly sized groups, or terciles. The high impact group comprises of Census tracts with the most health impacts (by health endpoint); the low impact group includes Census tracts with the least health impacts (by health endpoints). This analysis focuses on the composition of populations found in the high impact tercile.

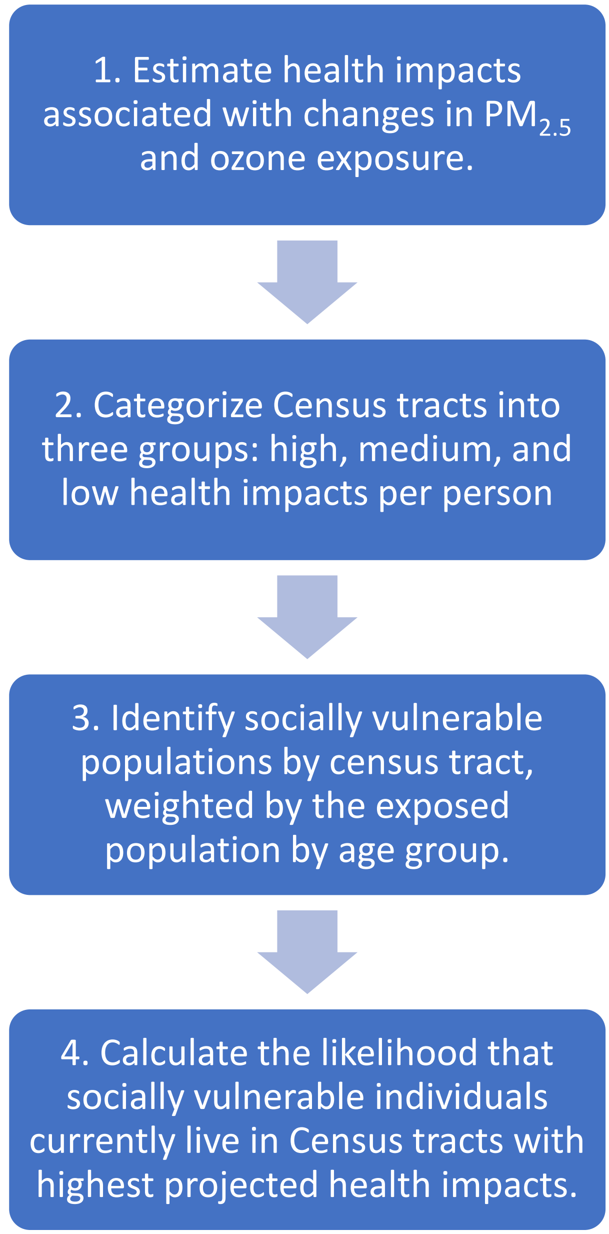
Step 3: Identify socially vulnerable populations by Census tract. Comprehensive data do not exist on exactly which individuals both experience these air pollution exposure-related health impacts and are socially vulnerable. Instead, this analysis relies on data from the American Community Survey (2014-2018) at the Census tract level to (1) count the number of individuals in socially vulnerable groups relative to non-socially vulnerable groups then (2) weight the proportions by the total population within each age group being analyzed.[44] This analysis assesses (1) premature deaths associated with $PM_{2.5}$

[44] The air quality modeling in the Fann et al. (2021) study is conducted at 36 km grid cell resolution. The air quality model produces 16,280 grid cells covering the contiguous U.S. and beyond, but there are less than 2,500 grid cells that make up the contiguous U.S. Demographic and social

*c*exposure for those aged 65 and up (Di et al., 2017, for both race and ethnicity-stratified and non-stratified C-R functions), (2) new cases of asthma as a chronic condition associated with $PM_{2.5}$ exposure for children aged 0 to 17 (Tétreault et al., 2016), (3) asthma ED visits associated with $PM_{2.5}$ exposure for children aged 0 to 18 (Alhanti et al., 2016), and (4) premature deaths associated with ozone exposure for those aged 0 to 99. The measures of social vulnerability included in this analysis are: individuals in low income households; Black and African American, American Indian and Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals; and individuals with no high school diploma.[45,46] Because the two age classes analyzed in this chapter are children and those aged 65 and up (see Section 4 for details on the ozone analysis), 'over 65' is not a separate determinant of social vulnerability as it is in other chapters of this report.

Step 4: Calculate the likelihood that socially vulnerable individuals currently live in Census tracts with highest projected health impacts. These likelihoods are expressed relative to the non-socially vulnerable population and are calculated at the national and regional level. The likelihood measures are separately calculated for each social vulnerability metric. These likelihood metrics can be interpreted as the degree to which the health impacts of changes in ambient $PM_{2.5}$ and ozone concentrations associated with increases in global mean temperature disproportionately affect socially vulnerable groups relative to non-socially vulnerable groups.

Figure 3. Four Steps for Assessing Health Impacts on Socially Vulnerable Populations



vulnerability data available at the Census tract level is used. There are 72,761 Census tracts in the analysis, with an average of 29 tracts per AQ grid cell. Higher resolution Census tracts are used to identify meaningful differences in the locations of socially vulnerable populations. It is possible that the differential in geographic precision leads to either under- or over-attributing disparities in air pollution exposure. The results presented in Section 4 are consistent with the identification of a disproportionate burden of air pollutant exposures of socially vulnerable populations described in the literature review in Section 2.

[45] Individuals in low income households are defined as those who earn less than two times the federal poverty limit in income each year. Further details on the specific American Community Survey data used in this analysis can be found in Appendix C.

[46] No high school diploma refers to individuals who have not attained a high school diploma or its equivalent.

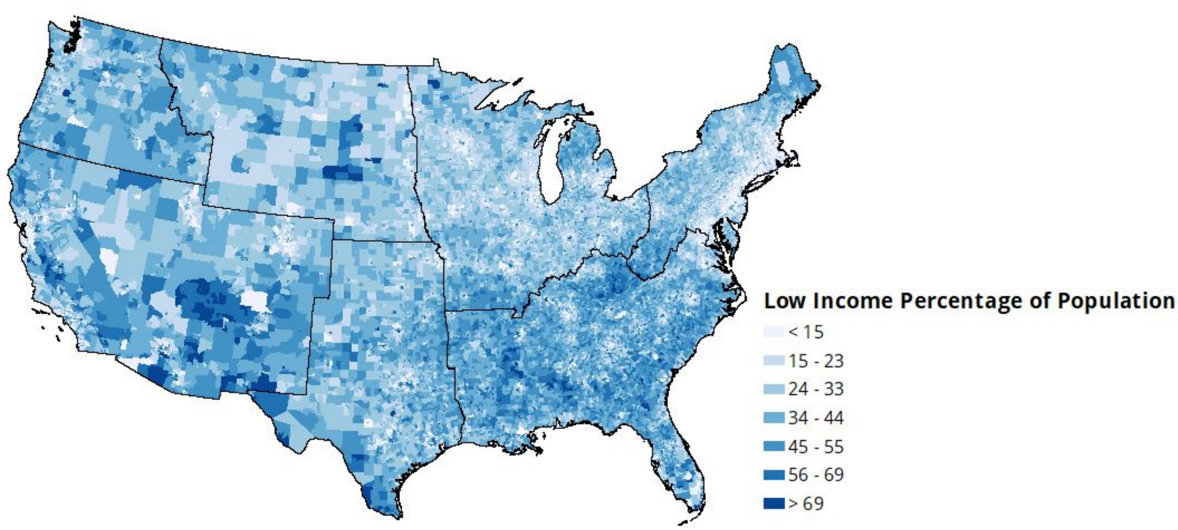
4. Results and Discussion

Section 4 describes the results of the analytic methods described in Section 3. The first set of results show the top health impact terciles and the national level likelihood of health impacts by social vulnerability factors. Regional level likelihoods of health impacts are presented by social vulnerability factors, supported by maps of these impacts by Census tract, and maps that show social vulnerability factors by Census tract. Generally, the analyses of four social vulnerability factors that relate to air pollutant exposure indicate that southern regions of the U.S. are both more socially vulnerable and experience greater health impacts than northern regions.

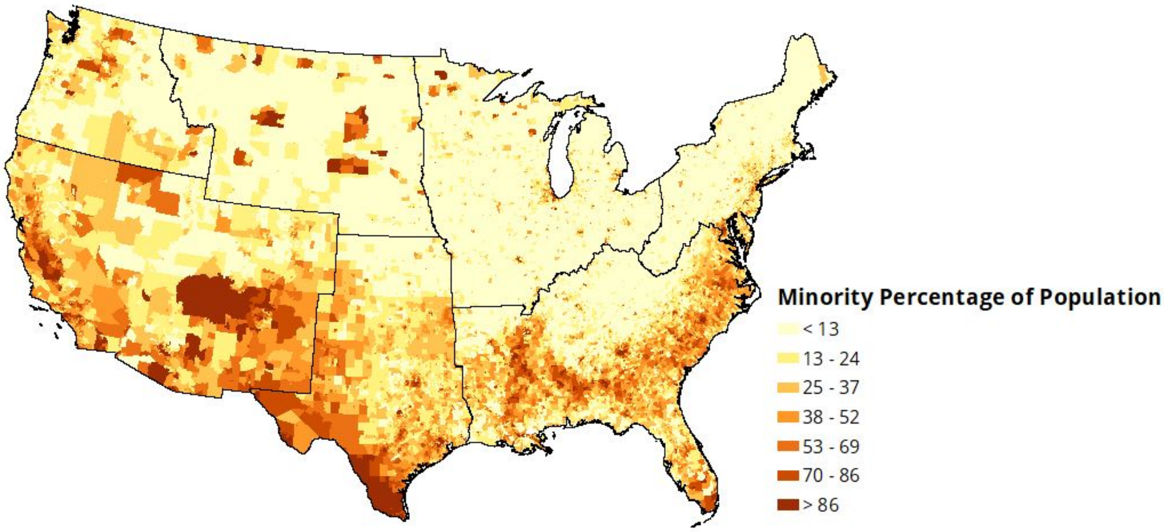
Figure 4 shows the proportion of socially vulnerable individuals by low income, minority, and education status. These maps show proportion of socially vulnerable individuals within Census tracts, which this analysis assumes does not change in relation to increase in global mean temperature. These maps are consistent and applicable across analyses of mortality and morbidity health impacts related to $PM_{2.5}$ and ozone exposure.

Figure 4. Maps of Proportion of Population who are Socially Vulnerable by Income, Minority, and Education Factors by Census Tract

A



b



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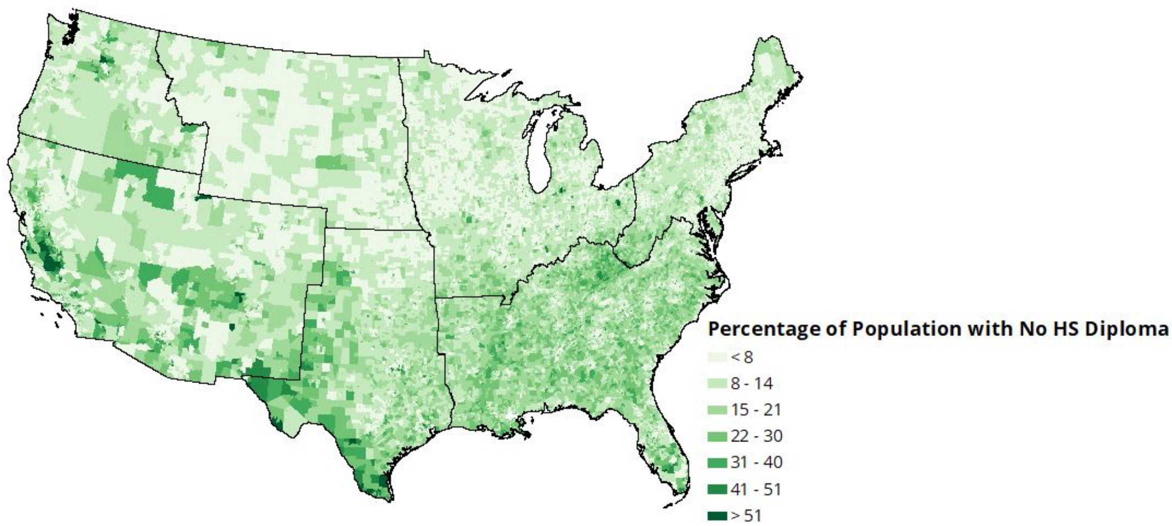


Figure 4a shows Census tracts that have high proportions of people with low income concentrated in the Southeast and Southwest. The Northeast has a distribution of Census tracts with both high proportions of individuals who experience low income and low proportions of individuals who experience low income. The proportion of these socially vulnerable individuals in the Midwest is lower than in other regions.

Figure 4b shows Census tracts with high proportions of people who identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino. Regions in the southern U.S. have more Census tracts with higher proportions of Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals than northern regions.

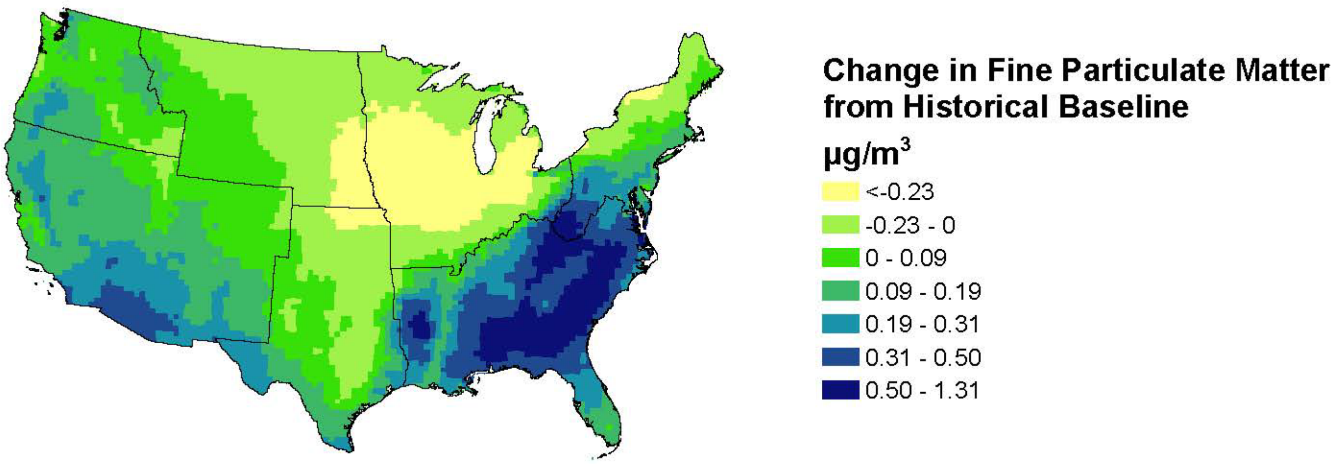
Figure 4c shows the percentage of the population with no high school diploma. The southern regions have greater proportions of population who have no high school diploma compared with other regions.

As in Fann et al. (2021), health impacts associated with anthropogenic air pollutant emissions were analyzed using two inventories – the 2011 National Emissions Inventory (NEI) and a projected 2040 inventory. This section focuses on results associated with the 2011 NEI, because that year more closely matches the time period of the American Community Survey (ACS) data used to characterize socially vulnerable populations. The 2040 projection accounts for the implementation of federal, state, and local air quality regulations on stationary and mobile sources. The estimates of air quality health impacts associated with the 2040 projection are consistently smaller in absolute terms than those associated with the 2011 NEI, but when examined for potentially disproportionate impact on socially vulnerable populations, the results are identical to those for the 2011 NEI. Consequently, this section presents results only for the 2011 NEI dataset.

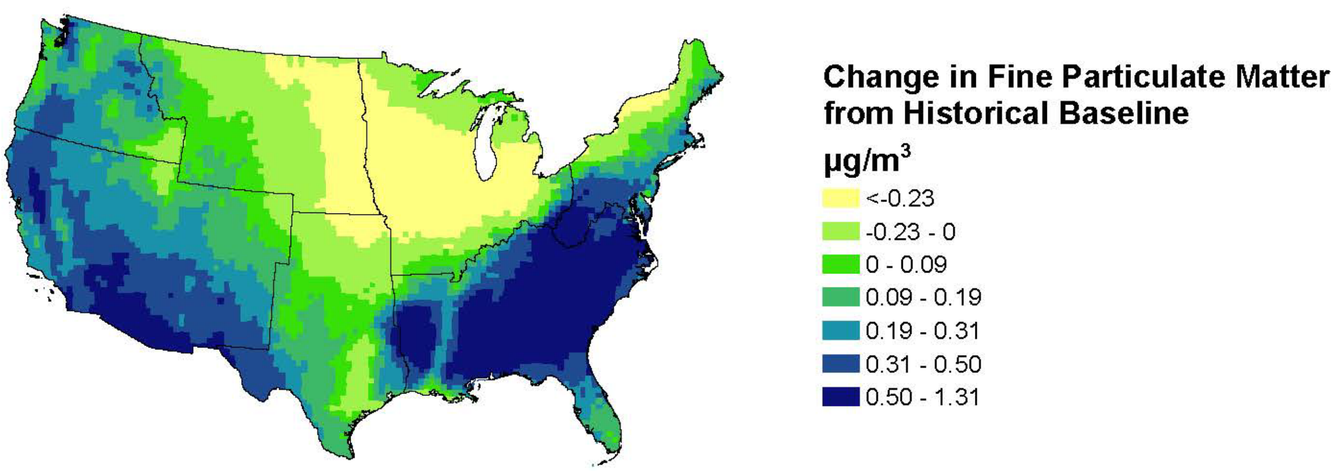
Figure 5 shows the change from 2000 baseline levels of $PM_{2.5}$ associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature (relative to 1986-2005). The maps show that the largest increases in particulate matter concentrations occur in the Southeast region. $PM_{2.5}$ concentrations also increase in the Southwest and Northwest regions. $PM_{2.5}$ concentrations decrease in portions of the Midwest, Northern Great Plains and Southern Great Plains for both 2°C and 4°Cof global mean temperature increase.

Figure 5. Map of Change in $PM_{2.5}$ Concentration from Historical Baseline at 2°C and 4°C Increase in Global Mean Temperature by Census Tract, using 2011 Anthropogenic Emissions Inventory

2°C of Global Warming



4°C of Global Warming



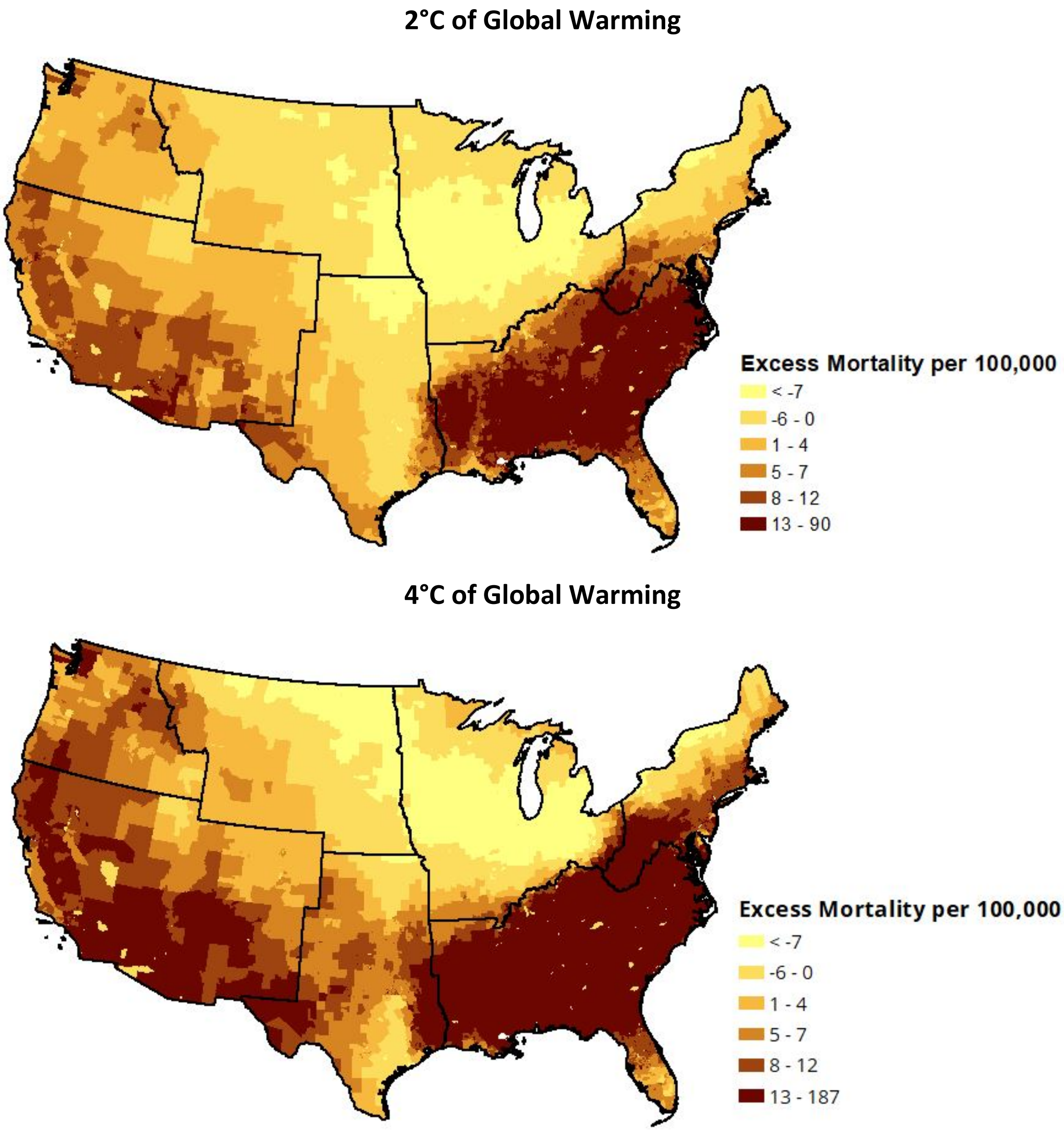
Premature Mortality Associated with $PM_{2.5}$ Exposure in those Age 65 and up

The analysis begins by analyzing premature mortality impacts associated with $PM_{2.5}$ exposure in those age 65 and up, where different C-R functions were used to calculate impacts as stratified by race and ethnicity, in accordance with Di et al. (2017).[47]

Figure 6 shows a map of $PM_{2.5}$-related deaths in those age 65 and older associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature (relative to 1986-2005). The units are excess mortality (above baseline) per 100,000 individuals over age 65.

[47] This analysis applied stratified concentration-response functions from Di et al. (2017) for race and ethnic groups including white, Black, American Indian or Alaska Native, Asian, and Hispanic individuals. Health impacts were assessed using non-race and ethnic group stratified C-R functions from both Di et al. (2017) and Krewski et al. (2009), as well, but the focus in this appendix is on the race and ethnic group stratified functions to achieve more race and ethnicity-specific results.

Figure 6. Map of $PM_{2.5}$-related excess mortality impacts in those age 65 and older at 2°C and 4°C increase in global mean temperature by Census tract, using 2011 anthropogenic emissions inventory



The majority of premature deaths are projected to occur in the Southeast region at both 2°C and 4°C. The Northeast and Southwest are also projected to experience a disproportionate burden of premature mortality impacts, increasing from 2°C to 4°C of warming.

Figure 7 shows the distribution of $PM_{2.5}$-related premature deaths across Census tracts by low, medium, and high impact tercile.

Figure 7: Distribution of Projected $PM_{2.5}$-Related Premature Deaths Per Person Per Year for those Aged 65 and Older By Census Tract (Nationally) Associated with Degree Celsius Increases in Global Mean Temperature. Excess Premature Mortalities are Shown as the Count Per 100,000. Beige, Yellow, and Orange Colors Represent the Low, Medium, and High Impact Tercile of Census Tracts, Respectively.

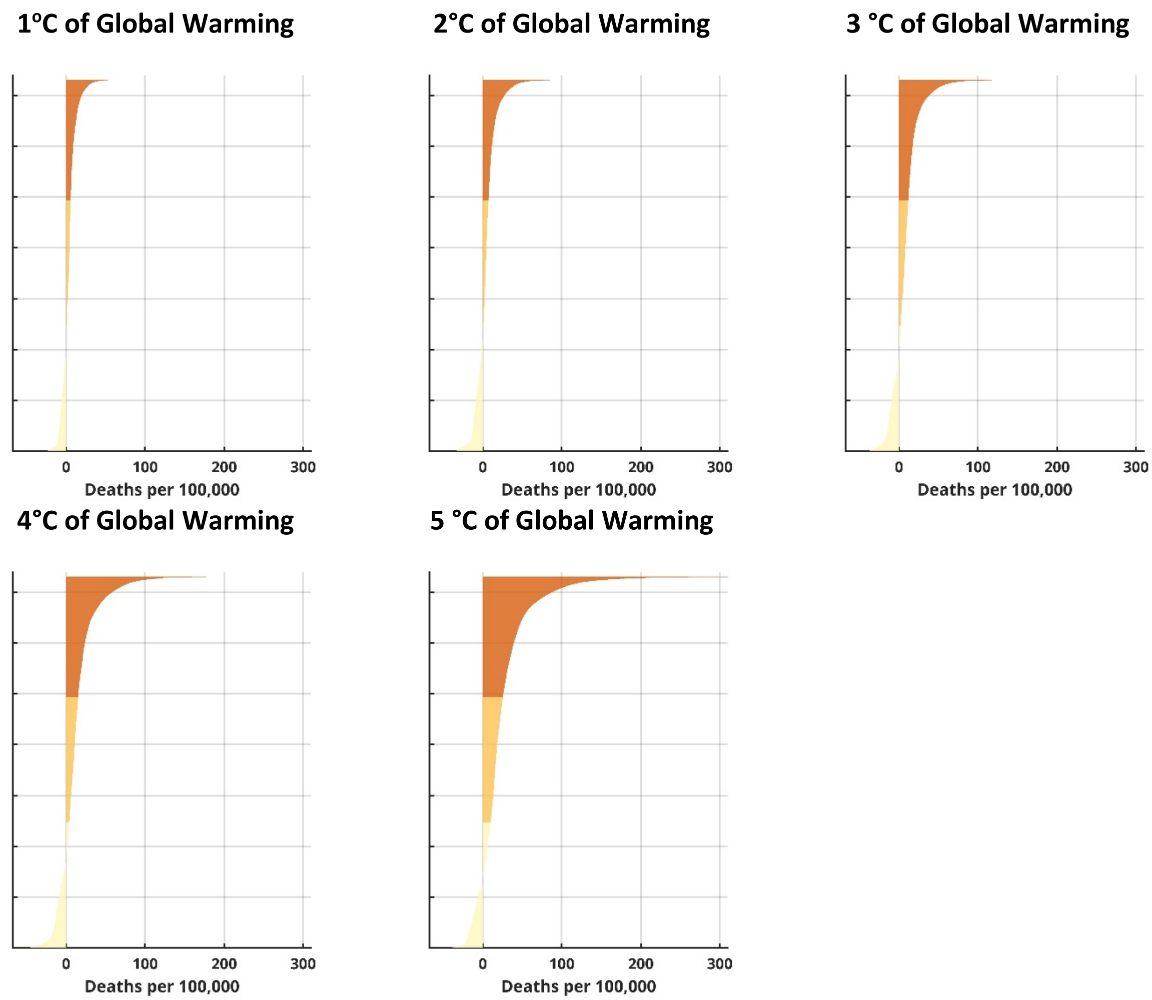


Figure 7 shows similar shaped distributions of excess premature deaths across degrees of warming with higher mortality rates for increased warming. At an increase of 5°C global mean temperature, the most impacted Census tracts experience an annual excess mortality risk of more than 300 per 100,000 individuals.

Figure 8 presents the distribution of Census tracts by national impact tercile with 2°C and 4°C of warming (relative to 1986-2005). The highest impact terciles nationally are concentrated in the Southeast and Southwest regions at both levels of global warming.

Figure 8. National Distribution of Census Tracts by Premature Mortality Impact Tercile (low, medium, and high)

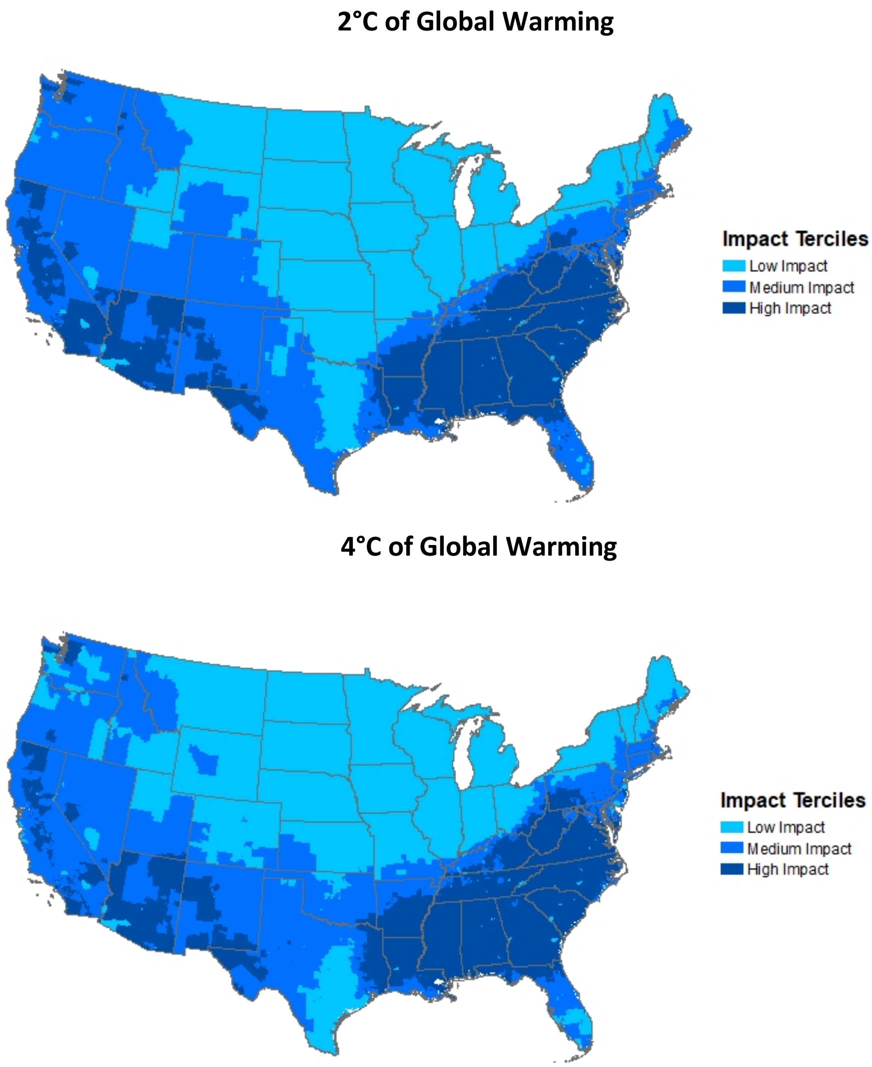


Table 3 shows the range of deaths by tercile nationally at both 2°C and 4°C increases in global mean temperature.

Table 3. National Distribution of Census tracts by Premature Mortality Impact Tercile (low, medium, and high)

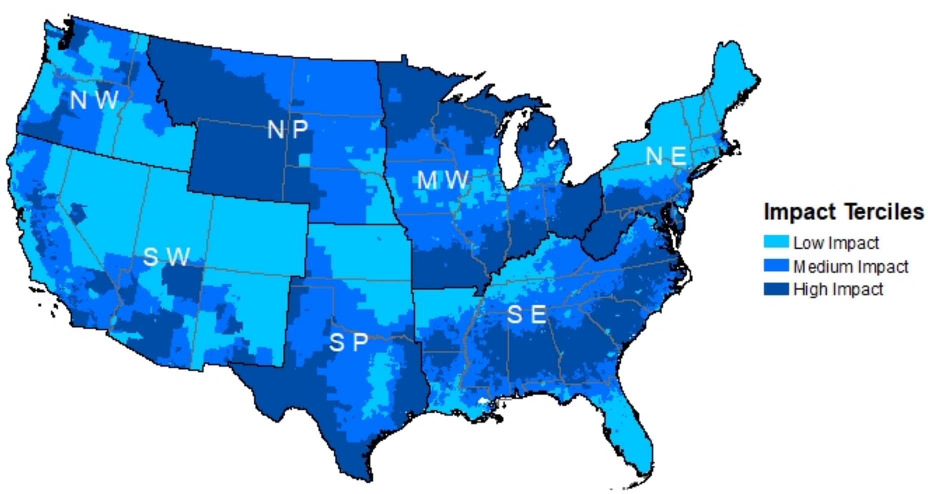
IMPACT TERCILE	MORTALITY PER 100,000	
	2°C	4°C
Low	-52 - 0	-67 - 4
Medium	0 - 7	4 - 15
High	7 - 90	15 - 187

In the lowest tercile of impacts a protective effect may exist. At the high end of impacts, the increase in mortality risk ranges from 7 to 90 excess deaths per 100,000 at 2°C to 15 to 187 excess deaths per 100,000 at 4°C global mean temperature increase.

Figure 9 shows the regional distribution of Census tracts by impact tercile (calculated by determining the distribution of impacts within each region, as opposed to nationally as in Figure 8.) By calculating highest impact terciles regionally, this analysis can identify relatively high-risk Census tracts within each region. In the Northeast, for example, the highest impact terciles are within West Virginia and Maryland; the most southern states of the region. In the Southern Great Plains, highest impact terciles are along the Mexican border. In the Midwest, highest impact terciles are in the northernmost and southernmost tracts. The highest impact tercile Census tracts remain similar between 2°C and 4°C increased global mean temperature.

Figure 9. Regional Distribution of Census Tracts by Premature Mortality Impact Tercile (low, medium, and high)

2°C of Global Warming



4°C of Global Warming

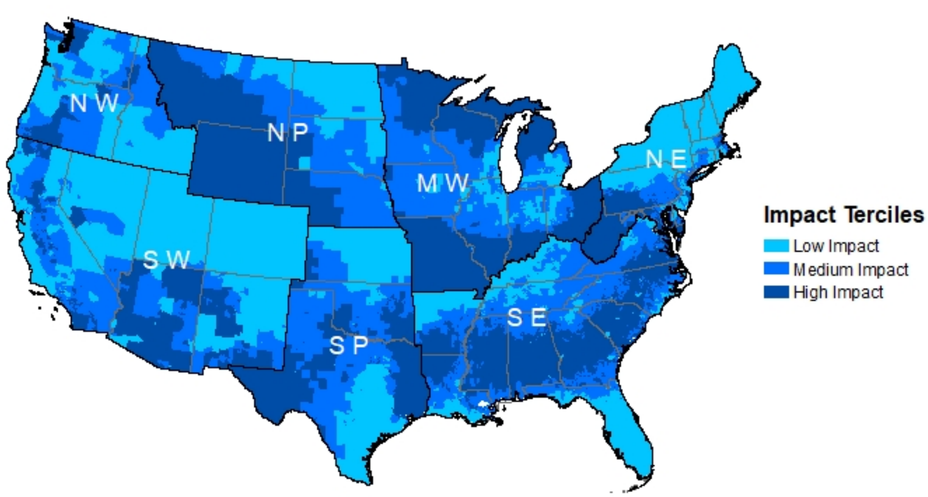


Table 4 shows the range of mortality rates by tercile across each region at both 2°C and 4°C increases in global mean temperature (relative to 1986-2005).

Table 4. Regional Distribution of Census Tracts by Premature Mortality Impact Tercile (low, medium, and high)

REGION	IMPACT TERCILE	MORTALITY PER 100,000	
		2°C	4°C
Midwest	Low	-52 - -11	-67 - -14
	Medium	-11 - -7	-14 - -7
	High	-7 - 26	-7 - 53
Northeast	Low	-26 – 3	-31 – 10
	Medium	3 – 6	10 – 14
	High	6 – 52	14 - 108
Northern Great Plains	Low	-35 - -9	-21 - -8
	Medium	-9 - -3	-8 - -2
	High	-3 – 5	-2 - 9
Northwest	Low	-6 – 2	-3 – 5
	Medium	2 – 5	5 – 10
	High	5 – 22	10 – 50
Southeast	Low	-3 – 9	-9 – 18
	Medium	9 - 19	18 – 41
	High	19 – 90	41 - 187
Southern Great Plains	Low	-25 - -2	-11 – 4
	Medium	-2 – 2	4 – 7
	High	2 – 29	7 - 112
Southwest	Low	-7 – 6	-5 – 12
	Medium	6 – 9	12 – 17
	High	9 – 26	17 - 47

Table 4 shows the range of distribution in tercile impact categories across regions. In the Midwest, the high impact tercile ranges from a mortality risk of -7 to 26 per 100,000 at 2°C and -7 to 53 per 100,000 at 4°C, while the Southeast high impact tercile ranges from 19 to 90 per 100,000 at 2°C and 41 to 187 per 100,000 at 4°C. The lowest impact tercile in the Southeast experiences rates of mortality more similar to medium and high impact terciles in other regions. However, details about excess mortality nationally and within regions only tells part of the story; the other important consideration is the proportion of socially vulnerable individuals living in these areas.

For both 2°C and 4°C global mean temperature increases, the analysis assesses the likelihood that socially vulnerable individuals currently live in Census tracts projected to experience the highest burden of premature mortality associated with $PM_{2.5}$ exposure in those aged 65 and up, relative to their reference populations. Figure 10 shows the difference in likelihood of socially vulnerable people living in highly impacted Census tracts compared with their reference populations.

Figure 10. Likelihood that socially vulnerable individuals experience highest risk of $PM_{2.5}$-related premature mortalities in those age 65 and up relative to reference populations, nationally

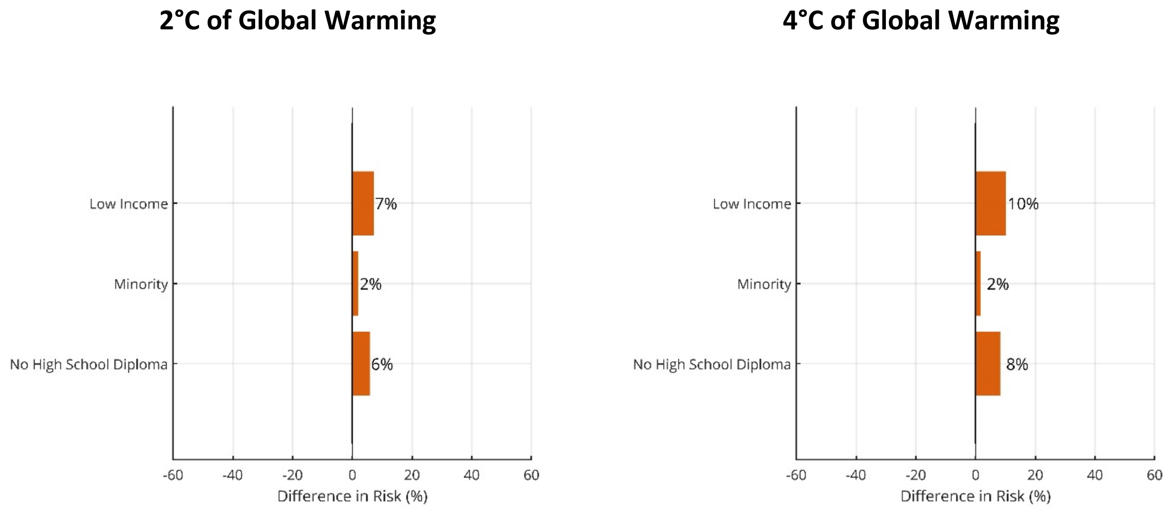
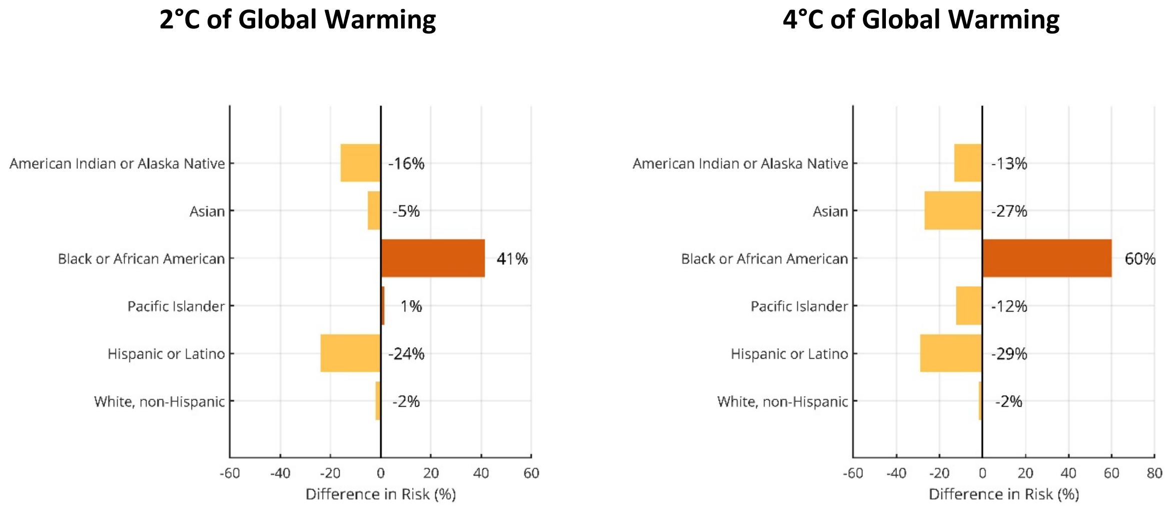


Figure 10 shows the same pattern of increased likelihood that socially vulnerable individuals aged 65 and up live in areas with highest risk of $PM_{2.5}$-related premature mortality across 2°C and 4°C increases in global mean temperature nationally. Those who experience low income have an estimated 7% increased likelihood of $PM_{2.5}$-related premature mortality at a 2°C increase in global mean temperature and 10% increased likelihood at a 4°C increase. People who identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino experience an estimated 2% increase in likelihood of premature mortality at both 2°C and 4°C increase in global mean temperature. Those with no high school diploma experience 6% and 8% greater likelihood of $PM_{2.5}$-related premature mortality at the 2°C and 4°C increases in global mean temperature, respectively. This analysis focuses on 2°C and 4°C increases in temperature to assess these likelihoods on the regional scale.

Figure 11 provides specific details by race and ethnicity regarding the change in likelihood of premature mortality for Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino populations demonstrated in Figure 10.

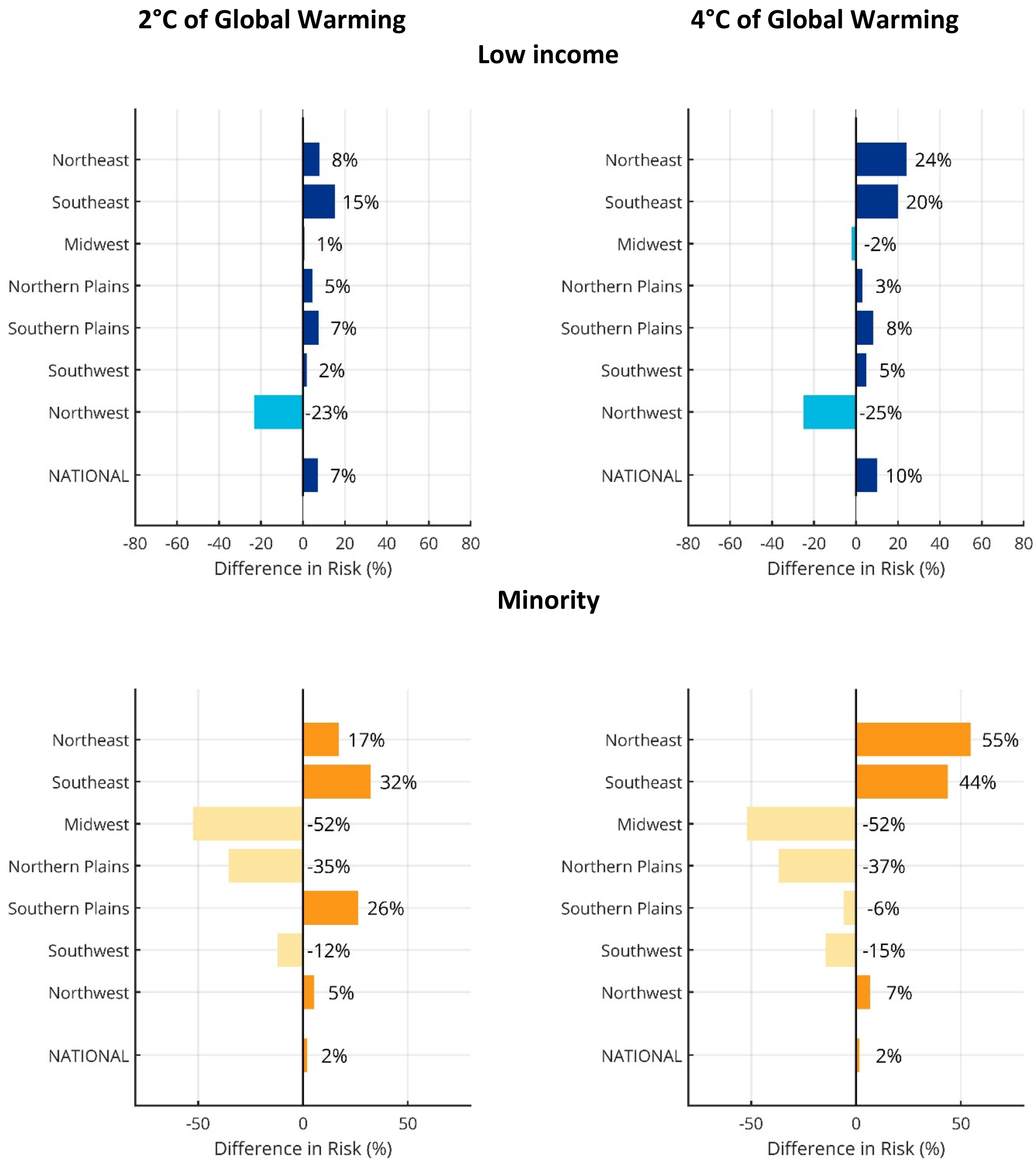
Figure 11. Likelihood that Individual Racial and Ethnic Groups Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-related premature mortalities in those age 65 and up relative to their reference populations, nationally



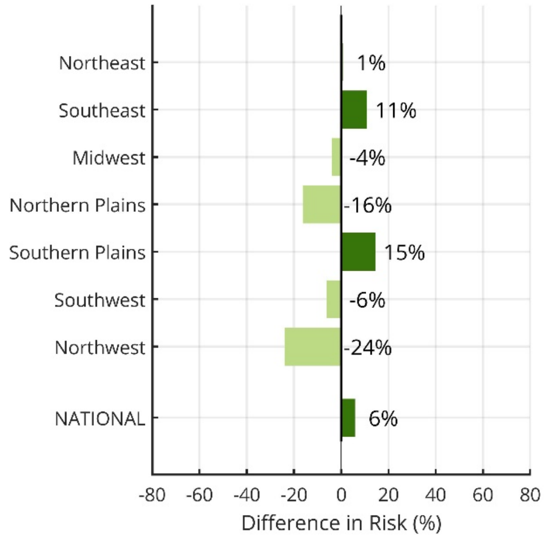
While Figure 10 shows that minorities have only a 2% higher likelihood of living in high-impact areas relative to non-minorities, Figure 11 shows the results for the individual racial and ethnic groups comprising the minority population. At 2°C and 4°C increase in global mean temperature, Black and African American individuals are 41% and 60% more likely than non-Black and non-African American individuals to live in areas with the highest projected increases in $PM_{2.5}$-related premature mortality.

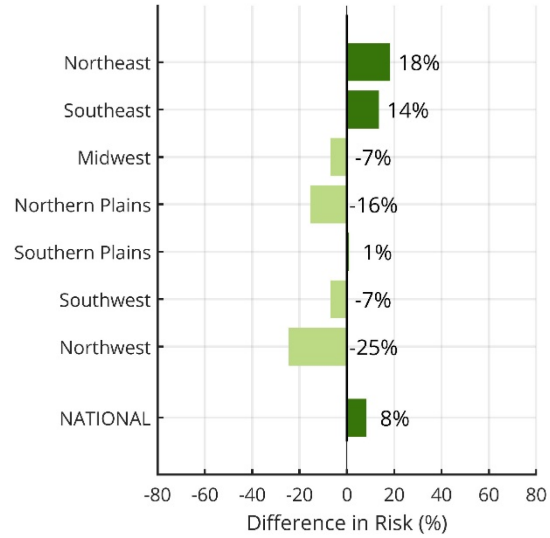
Figure 12 shows the likelihood that socially vulnerable individuals live in areas with the highest projected increases in of $PM_{2.5}$-related premature deaths relative to their reference populations across geographic regions within the contiguous U.S.

Figure 12. Likelihood that Socially Vulnerable Individuals Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Premature Mortality Relative to Their Reference Populations, at the Regional Level



No High School Diploma





Individuals who experience low income are more likely to live in areas with the highest $PM_{2.5}$-related mortality impacts in those age 65 and up in the Northeast, Southeast, and Southern Great Plains at both 2°C and 4°C (including an increase of up to 24% in the Southeast at 4°C); those living in the Midwest, Northern Great Plains, and Southwest experience minimal or no difference in likelihood based on their income status. Interestingly, those in the Northwest experience an opposite pattern at both 2°C and 4°C and experience a decrease in likelihood of living in areas the highest projected impacts. Individuals who experience low income in the Northeast and Southeast regions may experience disproportionately high risk due to the heterogeneous distribution of population who experience low income in those regions, as seen in Figure 4a. However, lower percentages of the population in the Northeast experience low income when compared with those in the Southeast.

Individuals who identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino experience an increased likelihood of living in the high impact Census tracts in the Northeast (a 17% increase at 2°C; 55% at 4°C) and Southeast (32% increase at 2°C; 44% at 4°C), while those in the Midwest, Northern Great Plains, and Southwest experience a decreased likelihood of living in the most impacted Census tracts. In the Southern Great Plains, these socially vulnerable individuals experience an increase at 2°C and a decrease at 4°C.

As seen in Figures 4b, 10, and 12, Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals in the Southeast region are more likely to live in a Census tract that is highly impacted by $PM_{2.5}$-attributable premature mortality than white non-Hispanic individuals. Conversely, even though Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals in the Northeast region are also more likely to live in a Census tract that is highly impacted by premature mortality attributable to $PM_{2.5}$ than white non-Hispanic individuals, there are fewer Census tracts that have high proportions of Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals. As a result, the health risk differences in the Northeast are greater for Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals, while health risks and

Census tracts with greater proportion of Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino individuals in the Southeast are both high.

People without a high school diploma or its equivalent experience an increased likelihood of living in the most impacted Census tracts in the Southeast at both 2°C and 4°C, but most of these individuals in other regions experience either a decrease in likelihood of impacts or no difference compared with individuals who received a high school diploma or higher education. Figure 4c shows the percentage of the population with no high school diploma. The Southeast region has greater disproportionality between those with at least a high school diploma and those without when compared with other regions. The Northwest region experiences the opposite relationship, with those who have less than a high school diploma experiencing a decrease in likelihood of living in Census tracts with high health impacts. In the Northwest, fewer Census tracts have high proportions of the population with no high school diploma. Higher health impacts are concentrated in western Washington, though that area does not have increased social vulnerability related to education.

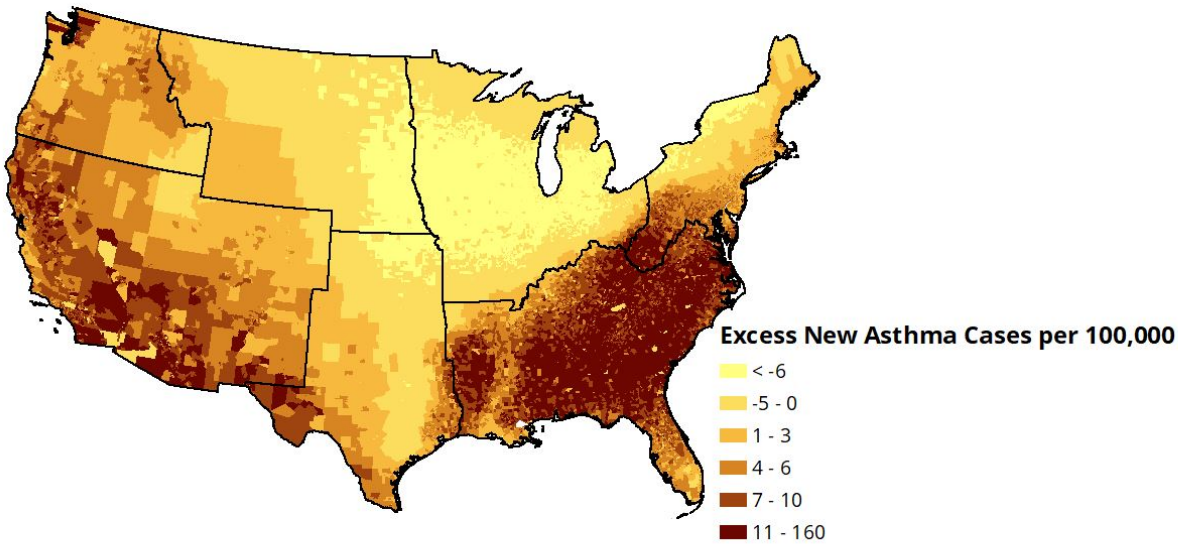
New Incidence of Asthma Associated with $PM_{2.5}$ Exposure in Children Age 0 to 17

New cases of asthma as a chronic condition ("asthma cases") associated with $PM_{2.5}$ exposure are analyzed in children age 0 to 17 using a C-R function based on risk model information from Tétreault et al. (2016). Figure 5 shows the change in $PM_{2.5}$ concentrations at 2°C and 4°C increases in global mean temperature. Increases in $PM_{2.5}$ concentrations lead to increased incidence of asthma in children.

Figure 13 shows a map of $PM_{2.5}$-related asthma cases in children age 0 to 17 associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature. The units are excess incidence of asthma (above baseline) per 100,000 individuals age 0 to 17.

Figure 13. Map of $PM_{2.5}$-Related Incidence of Asthma in those Age 0 to 17 at 2°C- and 4°C Increase in Global Mean Temperature by Census Tract, using 2011 Anthropogenic Emissions Inventory

2°C of Global Warming



4°C of Global Warming

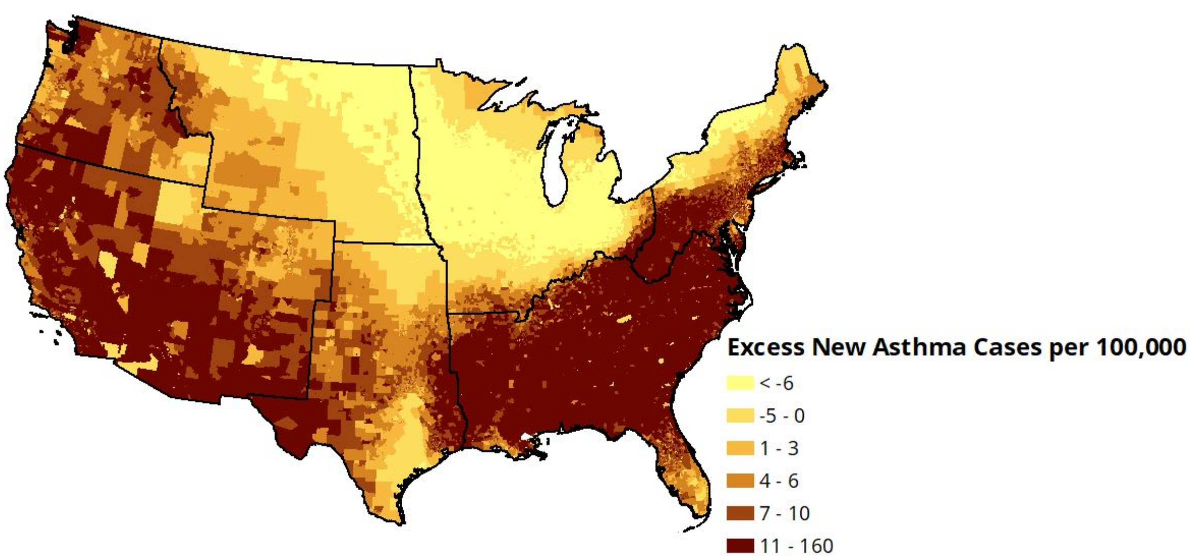


Figure 13 shows excess new asthma cases centralized in the Southeast and Southwest regions at 2°C increase in global mean temperature. At 4°C increase, high impact areas expand north from the Southeast into the Northeast and both north and east from the Southwest into the Northwest and Southern Great Plains regions. Compared to $PM_{2.5}$-related premature mortality impacts shown in Figure 6, the western regions are more impacted by childhood asthma cases at 2°C of warming. Differences in premature mortality and asthma cases impacts are driven by multiple factors, including the spatial distribution of age-specific populations and differing baseline incidence rates. Further, the premature mortality C-R function is race-stratified while the asthma cases C-R function is not.

Figure 14 shows the distribution of $PM_{2.5}$-related asthma cases across Census tracts by low, medium, and high impact tercile. With each degree increase in global mean temperature, asthma cases per 100,000 increases across terciles.

Figure 14. Distribution of Asthma Cases per 100,000 in Children Aged 0 to 17 Per Child Per Year by Census Tract (nationally) Associated with Degree Celsius Increases in Temperature

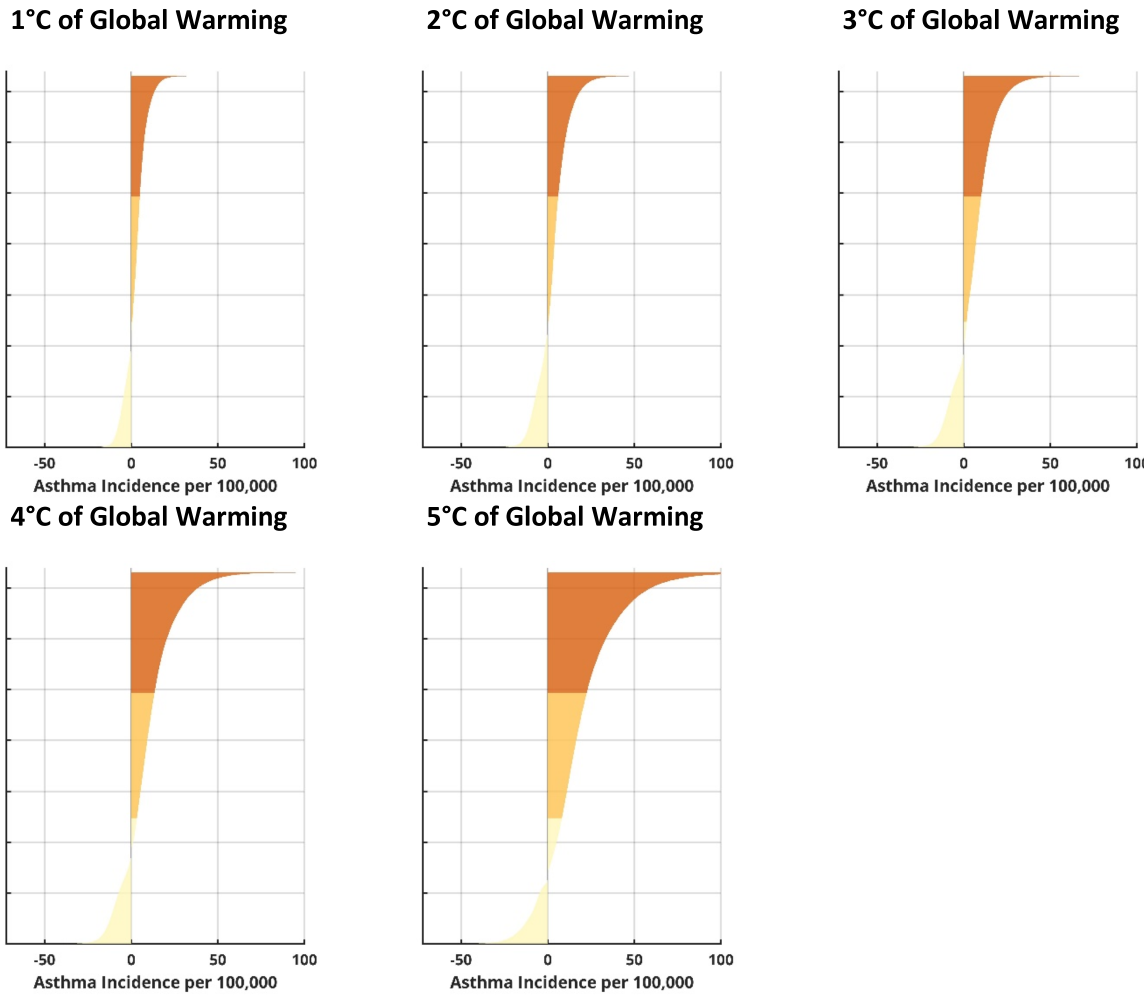
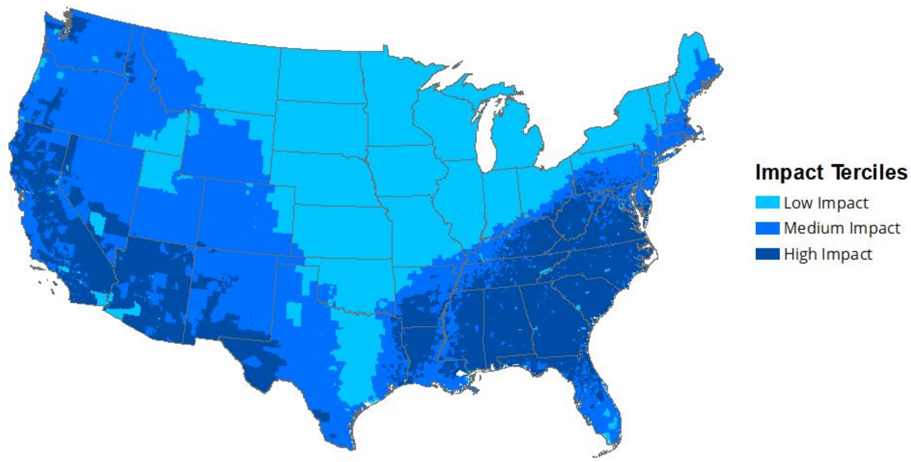


Figure 15 presents the distribution of Census tracts by national impact tercile with 2°C and 4°C increase in global mean temperature. Nationally, the highest impact terciles are focused in the Southeast and Southwest regions and remain largely the same at 2°C and 4°C increases in global mean temperature.

Figure 15. National Distribution of Census Tracts by Asthma Cases-Related Impact Tercile (low, medium, and high)

2°C of Global Warming



4°C of Global Warming

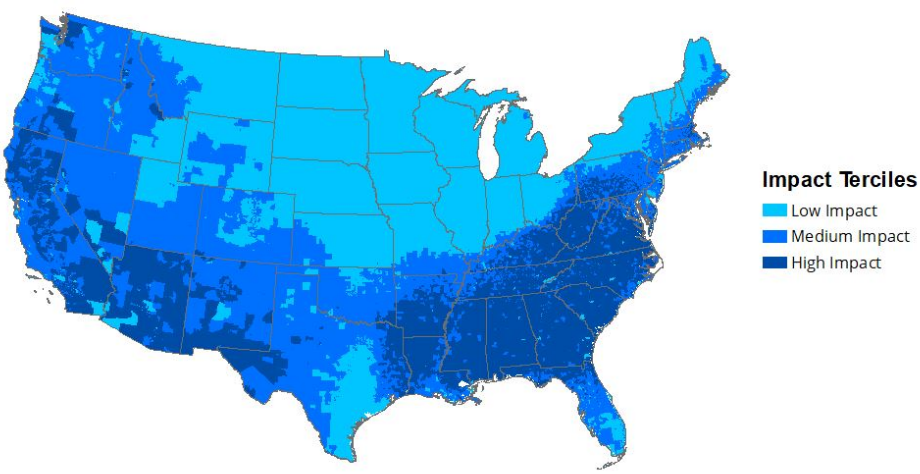


Table 5 shows the range of childhood asthma cases impacts by tercile nationally at both 2°C and 4°C increased global mean temperature.

Table 5. National Distribution of Census Tracts by Asthma Cases Impact Tercile (low, medium, and high)

IMPACT TERCILE	ASTHMA CASES PER 100,000	
	2°C	4°C
Low	-41 – 0	-57 – 3
Medium	0 – 6	3 – 13
High	6 – 65	13 - 160

The lowest tercile of impacts finds a decrease in asthma cases with both 2°C and 4°C increase in global mean temperature. In the highest tercile of impacts, the increase in asthma cases in children ranges from 6 to 65 new cases per 100,000 at 2°C and 13 to 160 new cases per 100,000 at 4°C increase in global mean temperature.

Figure 16 shows the regional distribution of Census tracts by impact tercile (calculated by determining the distribution of impacts within each region, rather than nationally as in Figure 15.) By calculating highest impact terciles regionally, this analysis identifies relatively high-risk Census tracts within each region. The highest impact terciles for asthma cases are distributed similarly to those for mortality impacts, shown in Figure 9; in the Northeast, high impact Census tracts are concentrated among the southern states in the region. In the Southeast, high impact terciles are distributed throughout the region (excluding much of Florida.) In the Southern Great Plains, highest impact terciles occur near the Mexican border. In the Midwest, highest impact terciles occur in the northernmost and southernmost tracts. In the Northwest, high impact Census tracts are distributed across the region, while in the Northern Great Plains, high impact Census tracts are across Montana and Wyoming. The highest impact tercile Census tracts by region remain similar between 2°C and 4°C increased global mean temperature.

Figure 16. Regional Distribution of Census Tracts by Asthma Cases Impact Tercile (low, medium, and high)

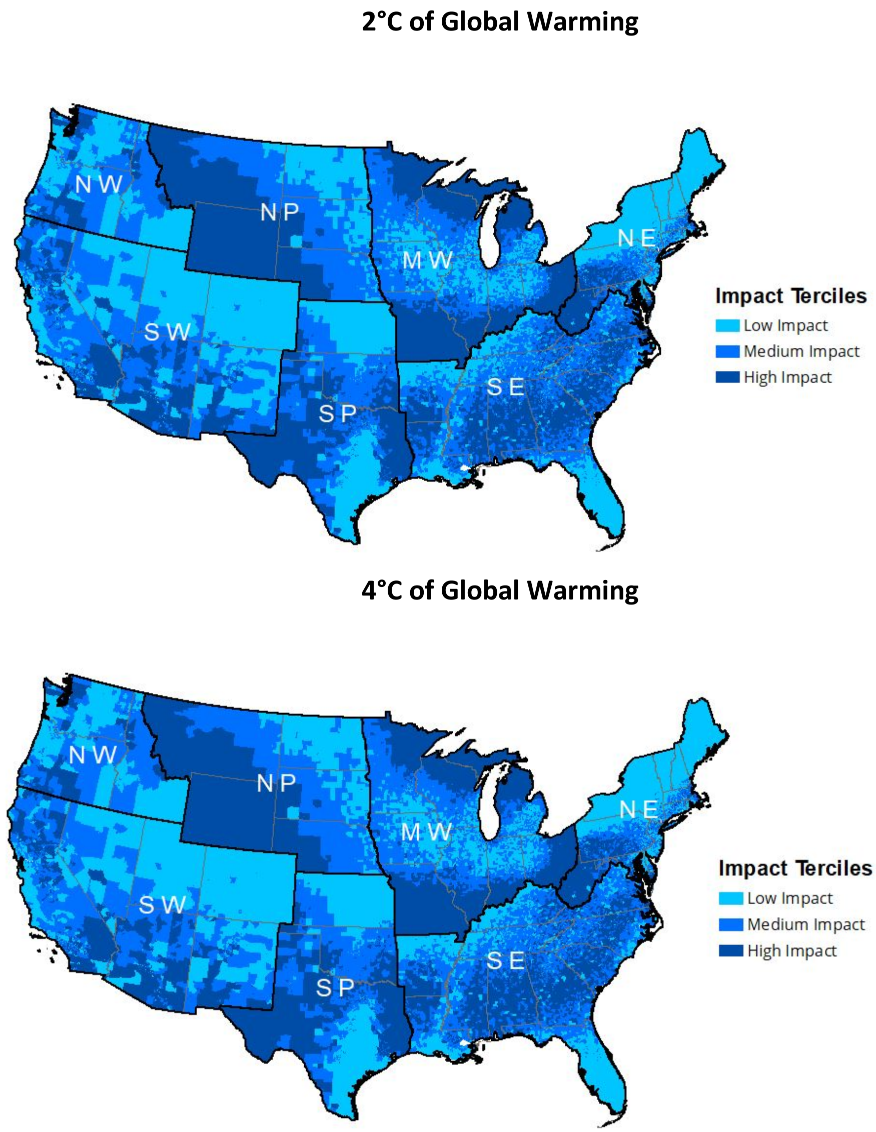


Table 6 shows the range of asthma cases by tercile across each region at both 2°C and 4°C increase in global mean temperature. At the low end in the Midwest, the high impact tercile ranges from a risk of -6 to 28 new cases of asthma per 100,000 at 2°C °C and -6 to 58 new cases per 100,000 at 4°C. At the high end in the Southeast, the high impact tercile ranges from a risk of 13 to 65 new cases per 100,000 at 2°C and 28 to 160 new cases per 100,000 at 4°C of warming. Details about excess risk of childhood asthma cases nationally and regionally only tells part of the story; the other important consideration is the proportion of socially vulnerable individuals living in these areas.

Table 6. Regional Distribution of Census Tracts by Asthma Cases Impact Tercile (low, medium, and high)

REGION	IMPACT TERCILE	ASTHMA CASES PER 100,000	
		2°C	4°C
Midwest	Low	-41 - -10	-57 - -12
	Medium	-10 - -6	-12 - -6
	High	-6 – 28	-6 – 58
Northeast	Low	-32 – 2	-56 – 8
	Medium	2 – 5	8 – 13
	High	5 – 62	13 - 128
Northern Great Plains	Low	-32 - -9	-30 - -7
	Medium	-9 - -3	-7 - -2
	High	-3 – 8	-2 – 16
Northwest	Low	-5 – 2	-3 – 6
	Medium	2 – 5	6 – 11
	High	5 – 54	11 – 127
Southeast	Low	-6 – 7	-2 – 14
	Medium	7 – 13	14 – 28
	High	13 – 65	28 – 160
Southern Great Plains	Low	-21 - -2	-10 – 3
	Medium	-2 – 1	3 – 6
	High	1 – 25	6 – 66
Southwest	Low	-9 – 5	-5 – 10
	Medium	5 – 9	10 – 17
	High	9 – 46	17 - 95

This analysis assesses the likelihood that socially vulnerable individuals currently live in the Census tracts projected to experience the highest increases in the rate of new asthma diagnoses associated with $PM_{2.5}$ exposure in children under the age of 18, relative to their reference populations. Figure 17 shows the results at the national level.

Figure 17. Likelihood that Socially Vulnerable Children Live in Areas with the Highest Projected Increases in New Asthma Diagnoses from Climate-Driven Changes in $PM_{2.5}$ Relative to Their Reference Populations

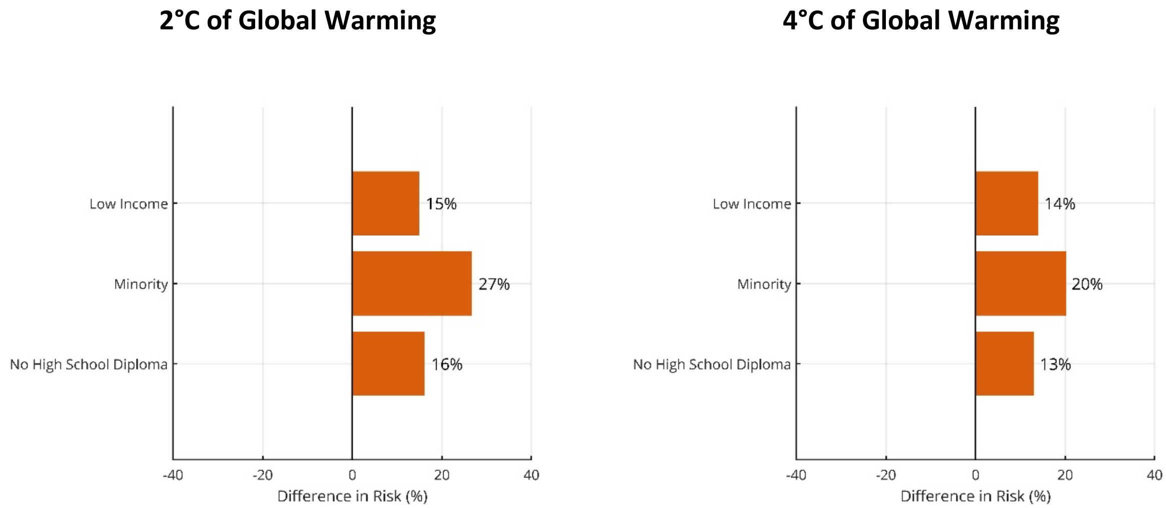
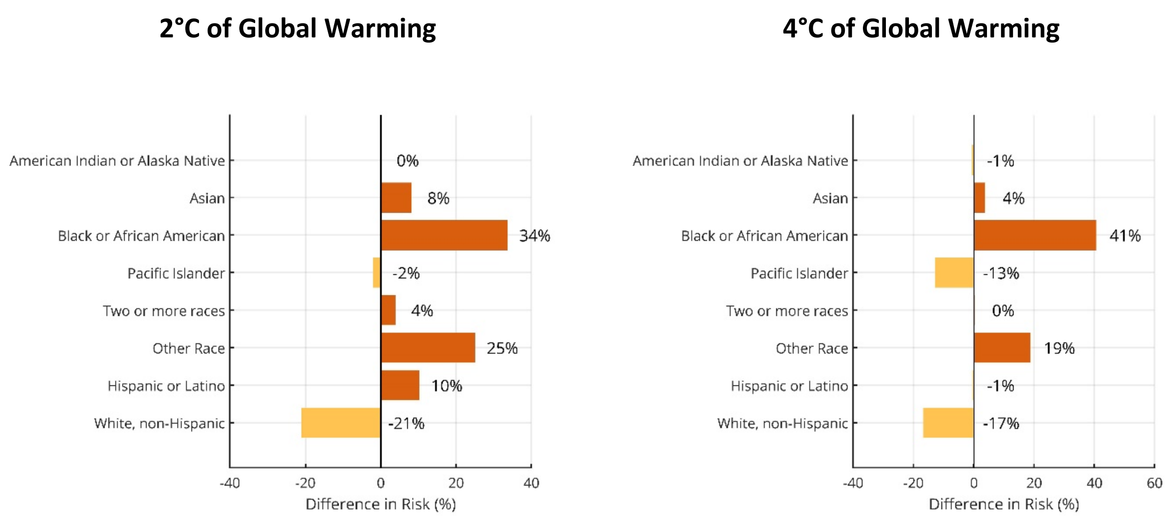


Figure 17 shows that minorities are 20-27% more likely than non-minorities to live in high-impact areas. Low income individuals and individuals with no high school diploma are also more likely than their reference populations to live in high-impact areas.

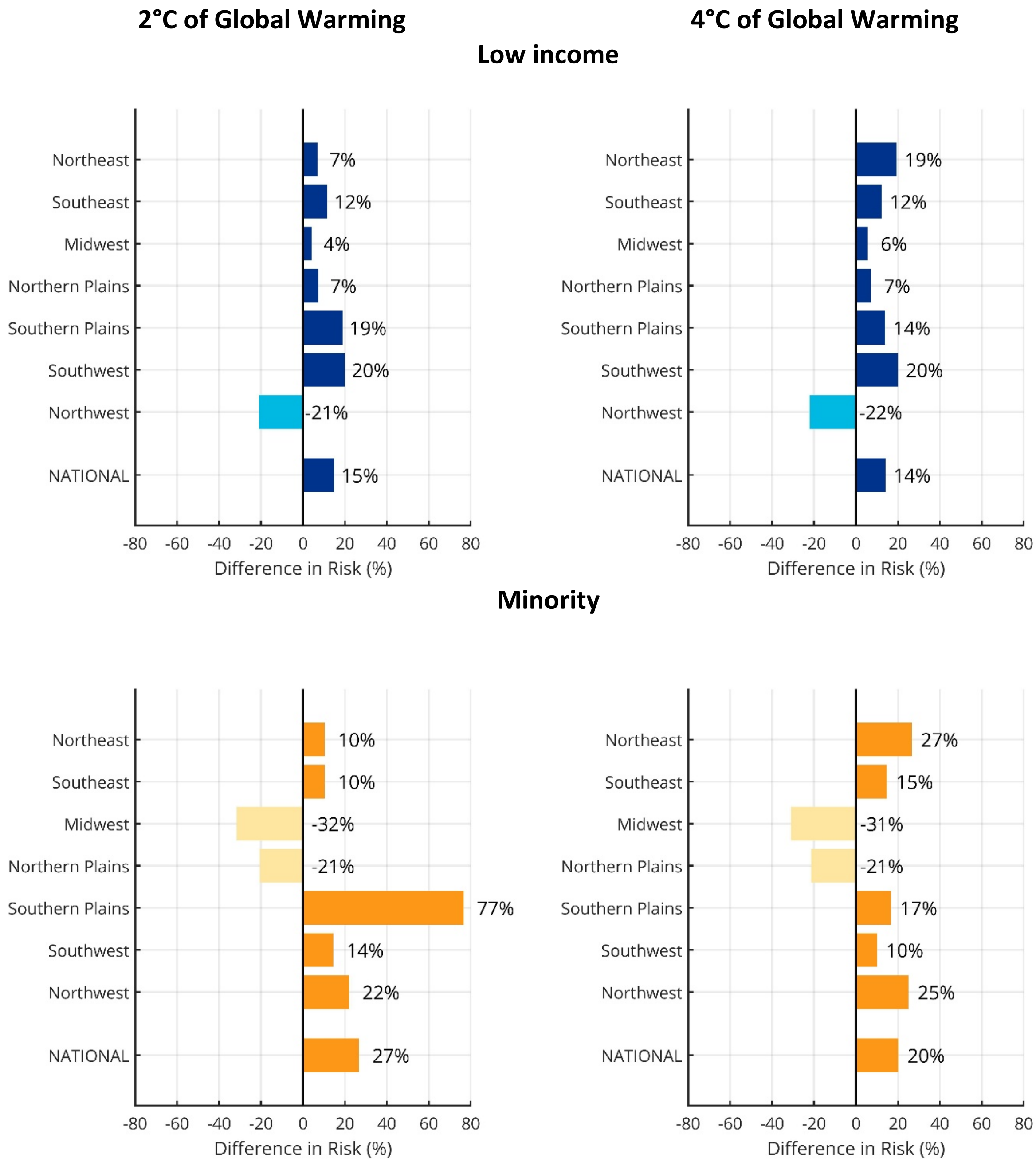
Figure 18 presents results for individual racial and ethnic groups. As shown, Black and African American individuals are 34-41% more likely than their reference population to live in areas with the highest projected increases in asthma diagnoses from climate-driven changes in $PM_{2.5}$.

Figure 18. Likelihood that Individuals from Specific Racial and Ethnic Groups Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Asthma Diagnoses, Relative to their Reference Populations

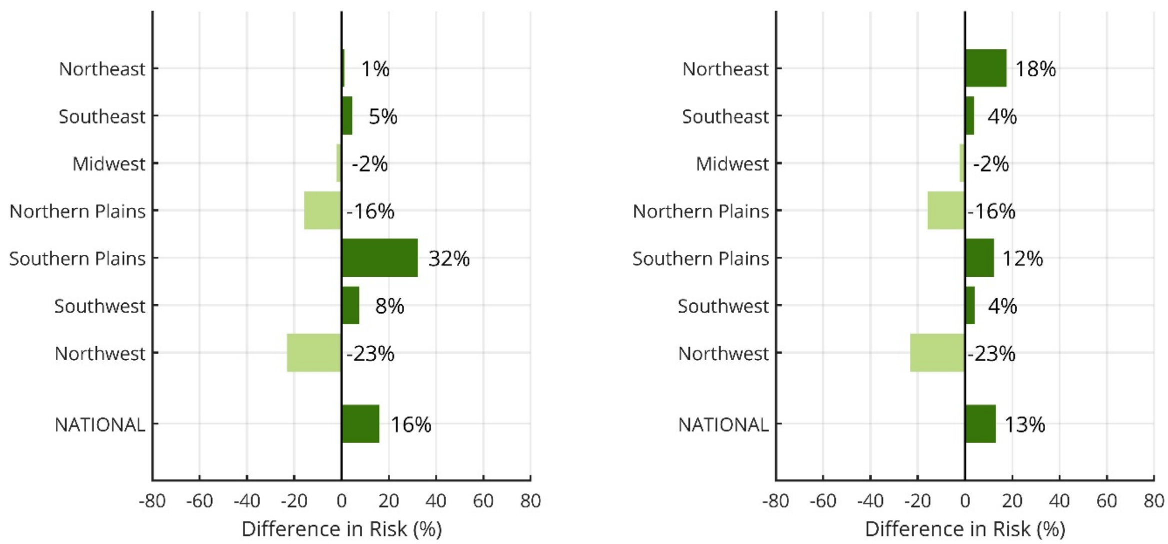


To further investigate the patterns seen at the national level, Figure 19 shows results at the regional level.

Figure 19. Likelihood that Socially Vulnerable Children Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Asthma Diagnoses, Relative to their Reference Populations



No High School Diploma



Children who are part of low income families have an increased likelihood of living in Census tracts with greatest risk of $PM_{2.5}$-attributable asthma cases across regions at 2°C and 4°C (20% increase in the Southwest) with the exception of the Northwest, at both 2°C and 4°C of warming. Vulnerable individuals in the Southwest experience slightly greater risk compared to other regions, which corresponds to the high percentage of individuals who experience low income in parts of the Southwest, as seen in Figure 4a. A large portion of health impacts occur in this region, shown in Figure 13.

Children in households that identify as Black and African American, American Indian or Alaska Native, Asian, Pacific Islander, or Hispanic/Latino are more likely to experience the highest $PM_{2.5}$-related risk of asthma cases in the Northeast, Southeast, Southern Great Plains, Southwest, and Northwest, with the greatest increase of 77% occurring in the Southern Great Plains. Children of the same vulnerable populations in the Midwest and Northern Great Plains are less likely to live in Census tracts with the highest risk of new cases of asthma at 2°C and 4°C of warming. The Southern Great Plains experiences an increase in risk over 50% greater than the next highest region at 2°C of warming, which can be explained by the highest rates of new asthma cases occurring in the same areas with high percentages of minority populations, notably near the border between Texas and Mexico (See Figure 4b and Figure 13).

Children whose parents have no high school diploma experience an increased likelihood of living in the most impacted census tracts in the Northeast, Southeast, Southern Great Plains, and Southwest, with the greatest increase of 32% in the Southern Great Plains at 2°C of warming. Again, the southernmost Census tracts of Southern Great Plains have both high health impacts and high percentages of individuals with no high school diploma, as seen in Figures 4c and 13. The distribution of these vulnerable populations and $PM_{2.5}$-attributable asthma cases among children explains the high disproportionality seen in the Southern Great Plains.

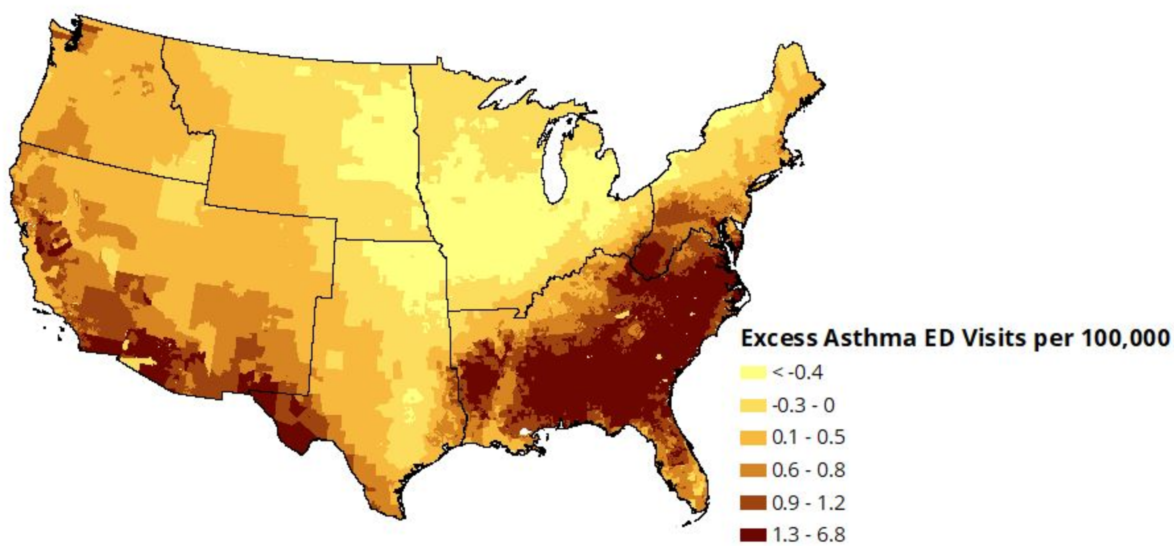
Asthma Related ED Visits Associated with $PM_{2.5}$ Exposure in Children Age 0 to 18

Asthma-related ED visits are analyzed in children aged 0 to 18 associated with $PM_{2.5}$ exposure using the C-R function described by Alhanti et al. (2016).

Figure 20 shows a map of $PM_{2.5}$-related asthma ED visits in children age 0 to 18 associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature. The units are excess asthma ED visits above baseline per 100,000 children age 0 to 18.

Figure 20. Map of Projected $PM_{2.5}$-Related Asthma ED Visits in Children Age 0 to 18 at 2°C and 4°C Increase in Global Mean Temperature by Census Tract, Using 2011 Anthropogenic Emissions Inventory

2°C of Global Warming



4°C of Global Warming

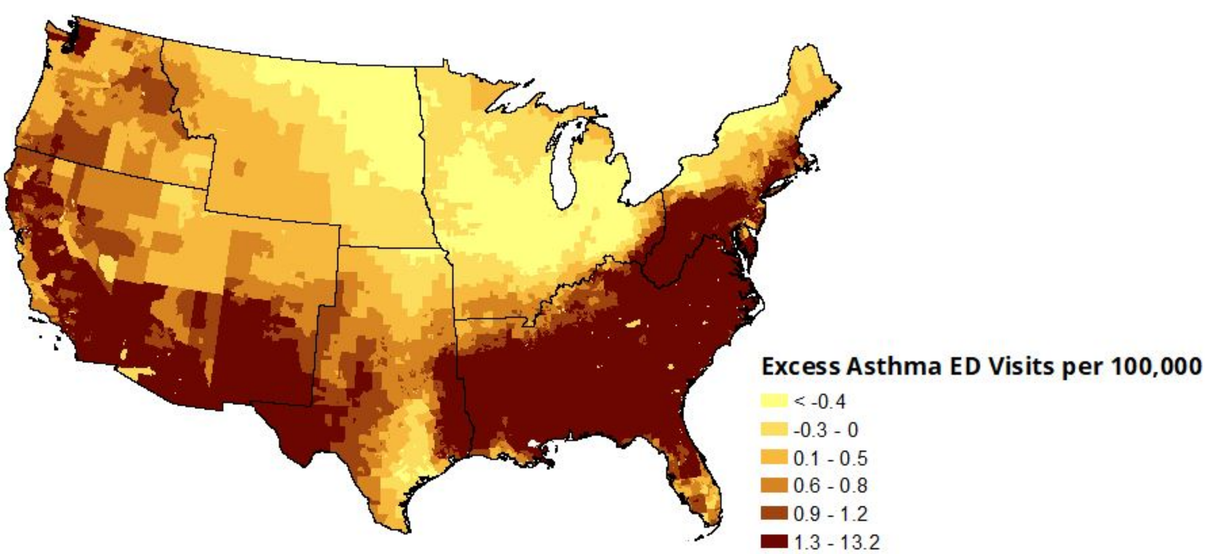


Figure 20 shows high impact areas across the southern U.S., including most of the Southeast region, and in the Southwest within California's Central Valley and along the Mexican border. The western U.S. experiences more $PM_{2.5}$-related asthma ED visits than the Midwest, with high impacts into the southern Northeast, as well.

Figure 21 shows the distribution of asthma-related ED visits in children age 0 to 18 per child per year by Census tract at the national scale using the 2011 anthropogenic emission inventory.

Figure 21. Distribution of Asthma-Related ED Visits in Children Aged 0 to 18 Per Child Per Year by Census Tract (nationally) Associated with Degree Celsius Increases in Temperature

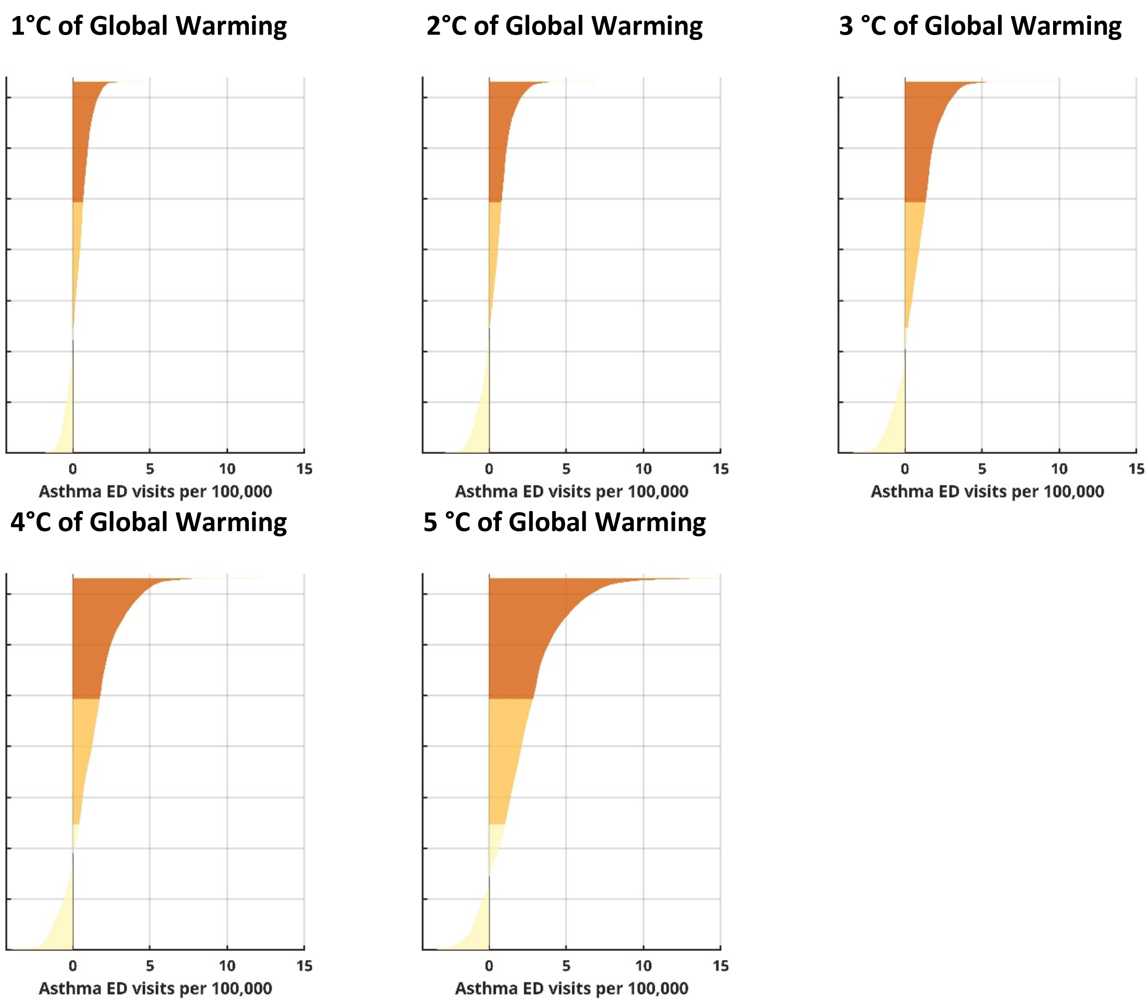
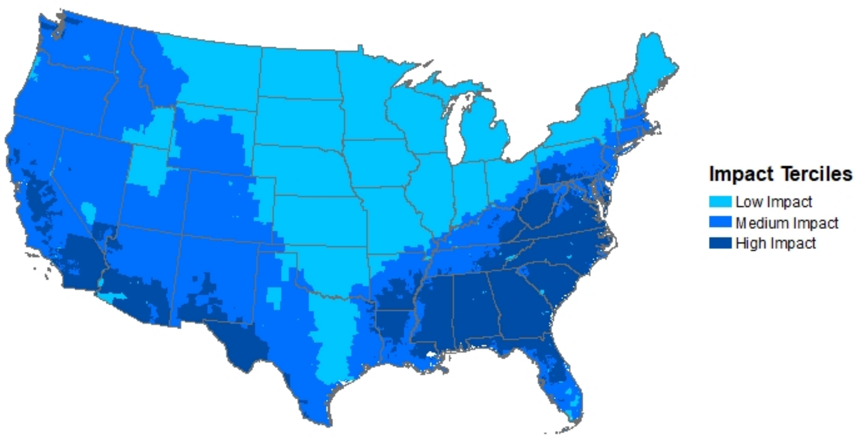


Figure 21 shows that maximum impact tercile values at 1°C increase in global mean temperature are projected to be less than five asthma-related ED visits per 100,000, while maximum impact tercile values at 5°C increase in global mean temperature are less than 25 asthma-related ED visits per 100,000. Based on the relatively small range in impacts, this section continues to analyze global mean temperature increases for 2°C and 4°C.

Figure 22 presents the distribution of Census tracts by national impact tercile with 2 and 4°C of Global Warming of warming. The highest impact terciles nationally are concentrated in the Southeast and in the Southwest along the Mexican border at both 2°C and 4°C increase in global mean temperature. Increasing global mean temperature from 2°C to 4°C pushes higher impact Census tracts further south.

Figure 22. National Distribution of Census Tracts by Asthma-Related ED Visit Impact Tercile (low, medium, and high)

2°C of Global Warming



4°C of Global Warming

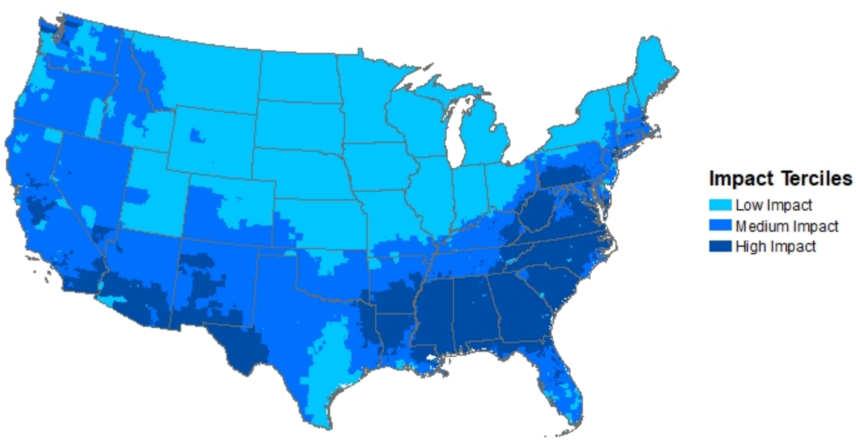


Table 7 shows the range of asthma-related ED visit impacts by tercile nationally at both 2°C and 4°C increased global mean temperature.

Table 7. National Distribution of Census Tracts by Asthma-Related ED Visit Impact Tercile (low, medium, and high)

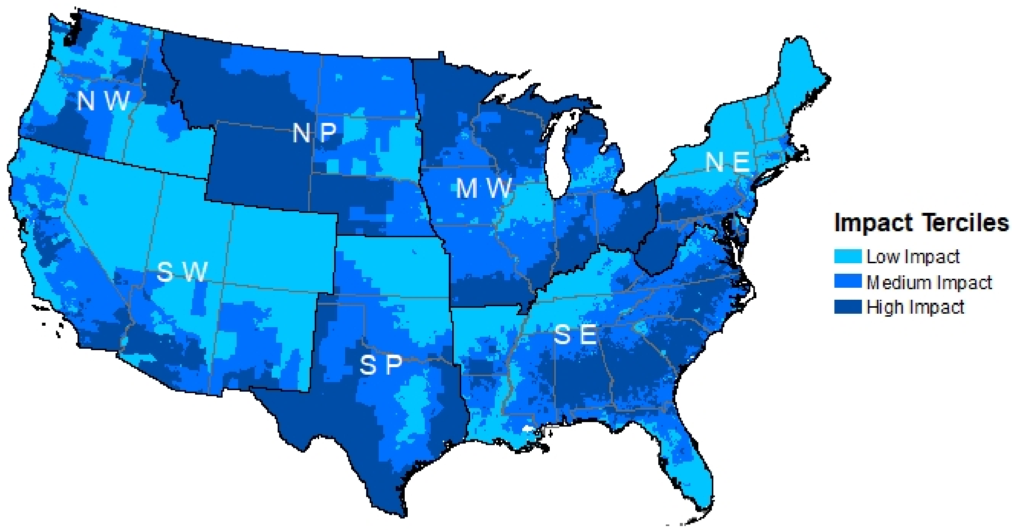
IMPACT TERCILE	ASTHMA ED VISITS PER 100,000	
	2°C	4°C
Low	-3.1 – 0	-4.3 – 0.4
Medium	0 – 0.8	0.4 – 1.7
High	0.8 – 6.8	1.7 – 13.2

In the lowest tercile of impacts a protective effect may exist, whereby climate change at a national level reduces the number of asthma ED visits per 100,000 individuals. At the high end of impacts, the increase in risk of asthma-related ED visits in children ranges from 0.8 to 6.8 visits per 100,000 at 2°C to 1.7 to 13.2 visits per 100,000 at 4°C global mean temperature increase.

Figure 23 shows the regional distribution of Census tracts by impact tercile (calculated by determining the distribution of impacts within each region, as opposed to nationally as in Figure 22.) By calculating highest impact terciles regionally, this analysis can identify relatively high-risk Census tracts within each region. The same pattern within regions for asthma-related childhood ED visits occurs for premature mortality, shown in Figure 9. The highest impact tercile Census tracts by region remain similar between 2°C and 4°C increased global mean temperature.

Figure 23. Regional Distribution of Census Tracts by Asthma-Related ED Visit Impact Tercile (low, medium, and high)

2°C of Global Warming



4°C of Global Warming

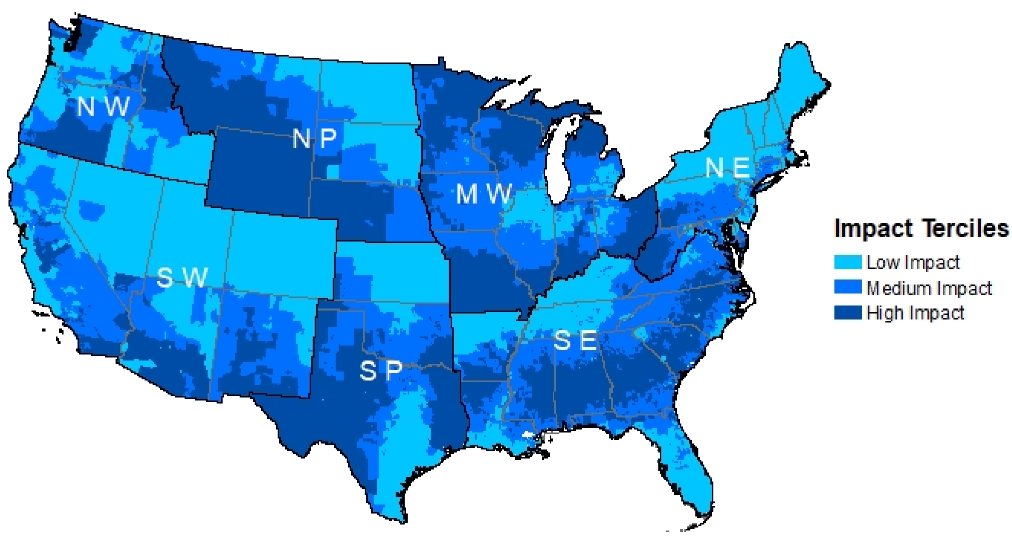


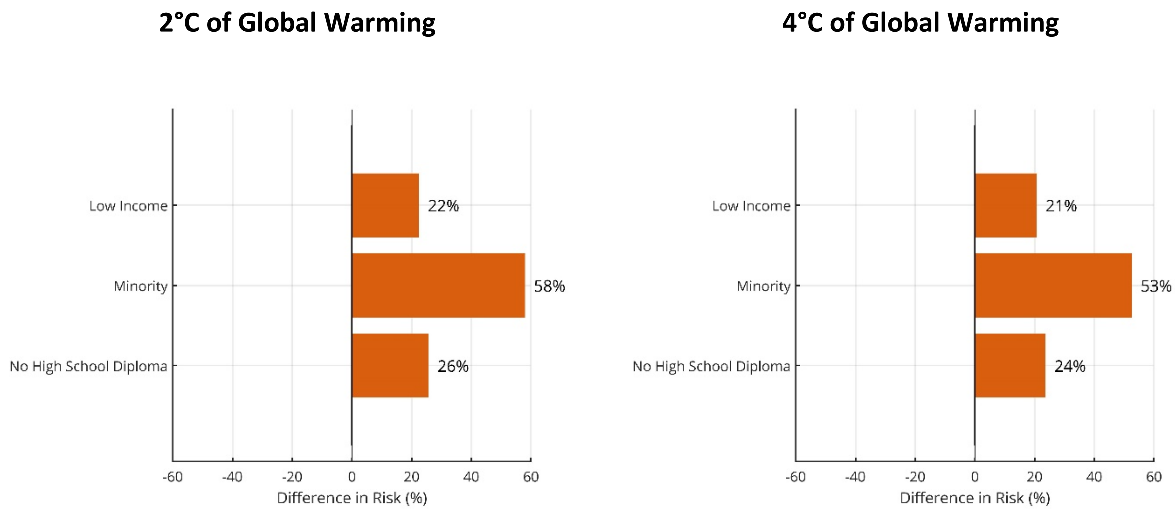
Table 8 shows the range of distribution in tercile impact categories across regions at both 2°C and 4°C increase in global mean temperature. Notably, the Midwest, Northeast, Northern Great Plains have climate-driven protective effects of asthma-related childhood ED visits even in the highest tercile of impacts at 2°C increase in global mean temperature. In other words, climate change at a national level is projected to reduce the number of asthma ED visits per 100,000 individuals. Excess impacts (i.e., increases in premature deaths) occur in the highest impact tercile at 4°C increase in global mean temperature in the Midwest, Northeast, Northeast, Southeast, and Southern Great Plains. Details about excess risk of asthma-related childhood ED visits nationally and within regions only tells part of the story; the other important consideration is the proportion of socially vulnerable individuals living in these areas.

Table 8. Regional Distribution of Census Tracts by Asthma-Related ED Visit Impact Tercile (low, medium, and high)

REGION	IMPACT TERCILE	ASTHMA ED VISITS PER 100,000	
		2°C	4°C
Midwest	Low	-3.1 - -1.0	-4.3 - -1.2
	Medium	-1.0 - -0.4	-1.2 - -0.4
	High	-0.4 – 1.2	-0.4 – 2.5
Northeast	Low	-1.5 – 0.4	-2.4 – 1.2
	Medium	0.4 – 0.8	1.2 – 2.1
	High	-0.8 – 2.6	2.1 – 5.4
Northern Great Plains	Low	-1.4 - -0.6	-1.5 - -0.5
	Medium	-0.6 - -0.2	-0.5 - -0.1
	High	-0.2 – 0.4	-0.1 – 0.7
Northwest	Low	-0.5 – 0.2	-0.3 – 0.5
	Medium	0.2 – 0.4	0.5 – 0.8
	High	0.4 – 1.9	0.8 – 4.4
Southeast	Low	-0.2 – 0.8	-0.3 – 1.6
	Medium	0.8 – 1.6	1.6 – 3.3
	High	1.6 – 6.1	3.3 – 13.2
Southern Great Plains	Low	-1.4 - -0.2	-0.7 – 0.4
	Medium	-0.2 – 0.2	0.4 – 0.7
	High	0.2 – 2.0	0.7 - 4.8
Southwest	Low	-0.3 – 0.6	-0.1 – 1.1
	Medium	0.6 – 1.0	1.1 – 1.8
	High	1.0 – 6.8	1.8 – 12.1

This analysis considers the likelihood that socially vulnerable individuals live in the Census tracts projected to experience the highest burden of asthma-related ED visits associated with $PM_{2.5}$ exposure in children age 0 to 18. Figure 24 shows the difference in likelihood of children experiencing an asthma-related ED visit within socially vulnerable individuals compared with non-socially vulnerable individuals nationwide.

Figure 24. Likelihood that Socially Vulnerable Children Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Asthma ED Visits Relative to their Reference Populations, Nationally



In Figure 24, results project an increased likelihood of living in areas with the highest asthma-related ED visit impacts for children who experience low income (22% increase), children in households that identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino (58% increase), and children whose parents have an education of less than high school diploma or its equivalent (26% increase). These relationships are consistent between the 2°C and 4°C increases in global mean temperature.

Figure 25 provides results by race and ethnicity.

Figure 25. Likelihood that Individual Racial and Ethnic Groups Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Asthma ED Visits Relative to Their Reference Populations, Nationally

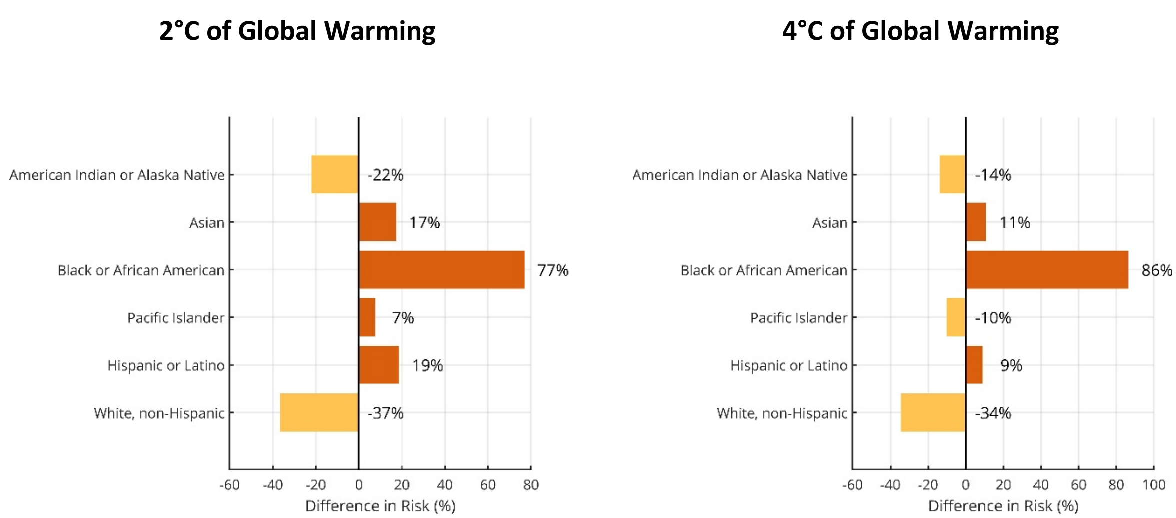
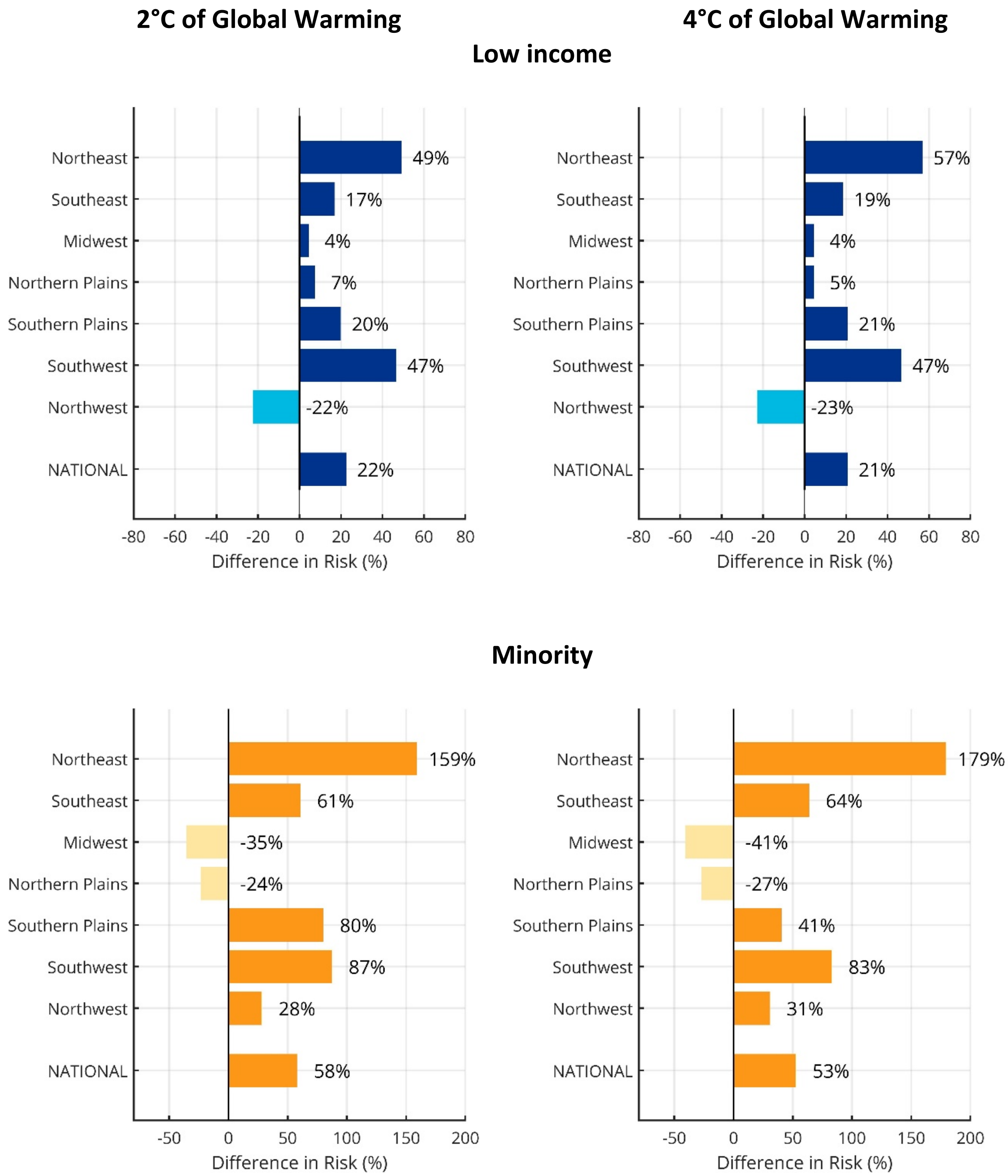


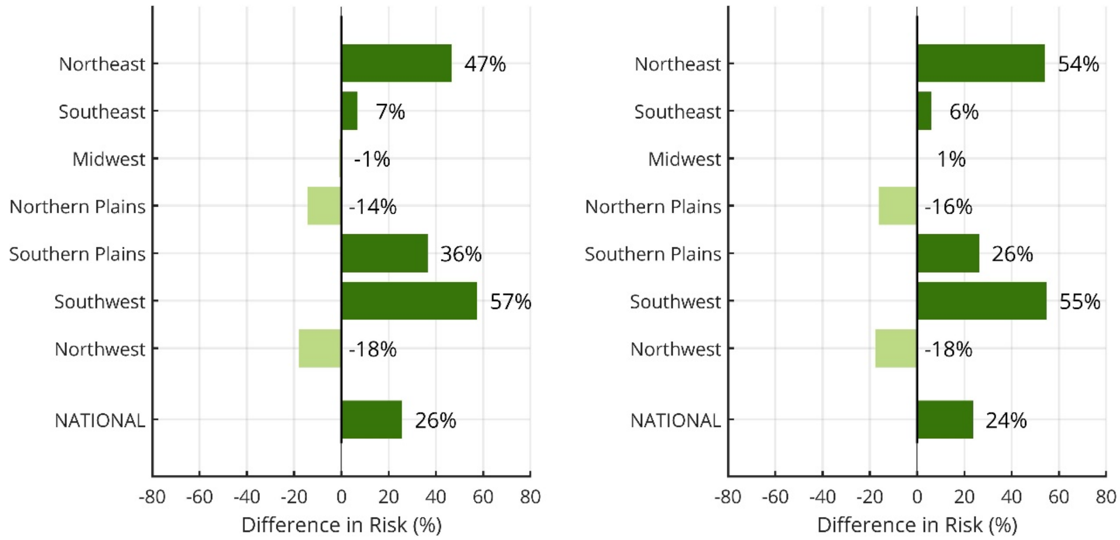
Figure 25 shows that Black and African American individuals are 77- 86% more likely than their reference population to currently live in areas with the highest projected impacts.

To better understand the patterns seen at the national level, Figure 26 shows results at a regional level.

Figure 26. Likelihood that Socially Vulnerable Children Currently Live in Areas with the Highest Projected Increases in $PM_{2.5}$-Related Asthma ED Visits Relative to their Reference Populations, Regionally



No High School Diploma



Children who experience low income consistently experience an increase in likelihood of living in Census tracts with greatest risk of $PM_{2.5}$-attributable asthma-related ED visits across regions (of up to 57% increased likelihood in the Northeast), with the exception of the Northwest, at both 2°C and 4°C increase in global mean temperature. When considering the socially vulnerable populations shown in Figure 4a, results show that while many of the health impacts are concentrated in the Southeast and many areas in the Southeast experience low income, disproportionate impacts are not projected for individuals who experience low income in that region compared with individuals who do not experience low income. Higher disproportionality occurs in the Midwest and Southwest, even though the Midwest experiences fewer asthma-related ED visits overall.

Similarly, children in households that identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino consistently experience an increase in likelihood of living in Census tracts with greatest risk of $PM_{2.5}$-attributable asthma-related ED visits across regions (of up to a remarkably high 179% in the Northeast), with the exception of the Midwest and Northern Great Plains, who experience a decrease in likelihood. These patterns are consistent at both 2°C and 4°C increase in global mean temperature. In Figure 4b, results show a greater proportion of Census tracts with higher percentages of Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino people in the southern regions, but not in the Northeast. Most Census tracts experience higher health risks in southern regions, while socially vulnerable Census tracts in the Northeast experience higher health impacts than non-socially vulnerable Census tracts in the Northeast.

Children whose parents have less than a high school diploma experience an increase in likelihood of living in Census tracts with greatest risk of $PM_{2.5}$-attributable asthma-related ED visits in the Northeast, Southeast, Southern Great Plains, and Southwest (of up to 57% in the Southwest). Those in the Northern Great Plains and Northwest experience the opposite. These patterns are consistent at both 2°C and 4°C increase in global mean temperature. Figure 4c shows the percentage of individuals (over age 25) with no high school diploma. Children whose parents have less than a high school diploma experience an increase in likelihood of living in Census tracts with greatest risk of $PM_{2.5}$-attributable asthma-related ED visits in the Northeast and Midwest, though these regions do not include large proportions of the population with no high school diploma. Results show increased vulnerability in the Southern Great Plains and Southwest, where more people do not have a high school diploma, and greater proportions of the population experience greater health risk.

The direction of the trends relating socially vulnerable populations and ED visits for asthma shown in Figure 26 is the same as those for incidence of asthma in children, though generally larger in magnitude for asthma ED visits. In part, this reflects the precision of race-stratified effect estimates, which were available for asthma ED visits but not for incidence of asthma.

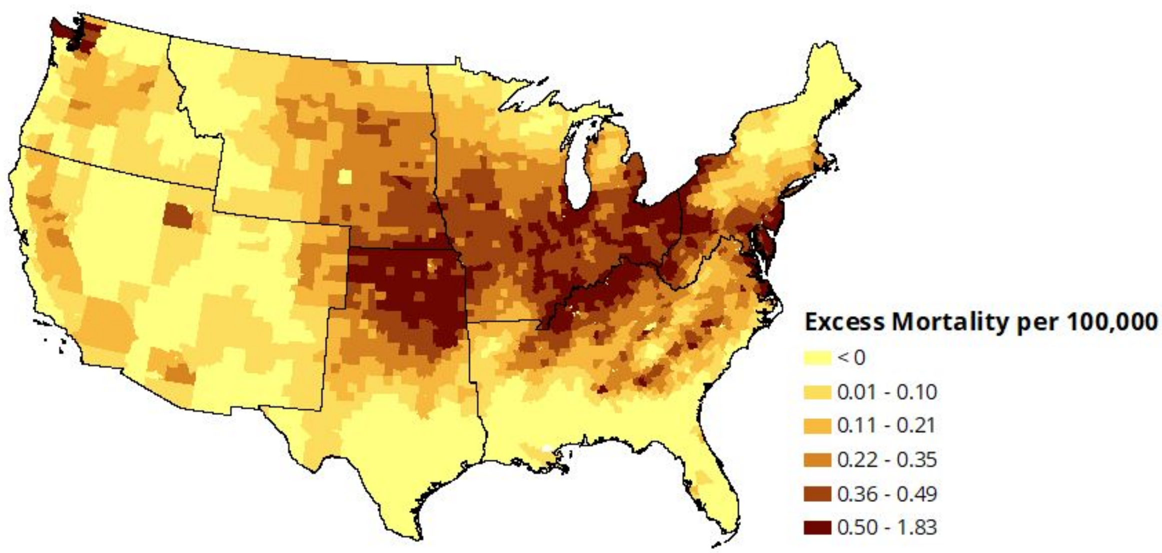
Premature Mortality Associated with Ozone Exposure Across All Ages

Premature mortality associated with ozone exposure is analyzed using a C-R function described by Zanobetti and Schwartz (2008) in those aged 0 to 99.

Figure 27 shows a map of ozone-related premature mortality impacts in those age 65 and older associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature. Units are excess mortality above baseline per 100,000 individuals aged 0 to 99.

Figure 27. Map of Ozone-Related Premature Mortality Impacts in those Ages 0 to 99 at 2°C and 4°C Increase in Global Mean Temperature by Census Tract, using 2011 Anthropogenic Emissions Inventory

2°C of Global Warming



4°C of Global Warming

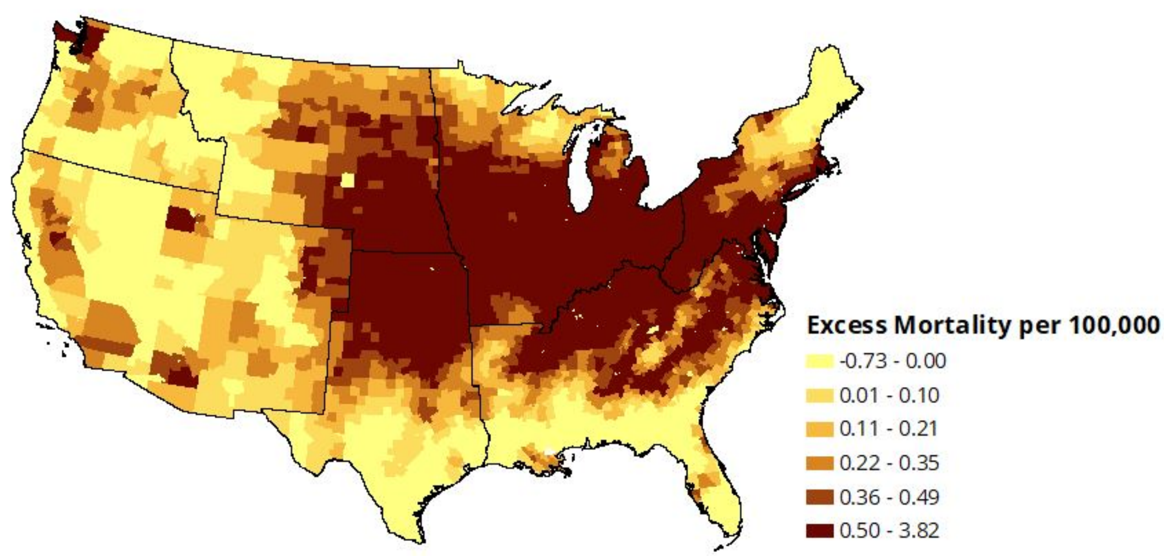


Figure 27 shows that ozone-related premature mortality impacts are most pronounced in the central U.S., including most of the Midwest region, the northern portions of the Southern Great Plains and Southeast, and in the southern portions of the Northern Great Plains.

Distribution of premature mortality impacts associated with ozone exposure is shown in Figure 28.

Figure 28. Distribution of Ozone-Related Premature Mortalities in those Aged 0 to 99 Per Person Per Year by Census Tract (nationally) Associated with Degree Celsius Increases in Temperature. Premature Mortalities are Shown as the Count Per 100,000.

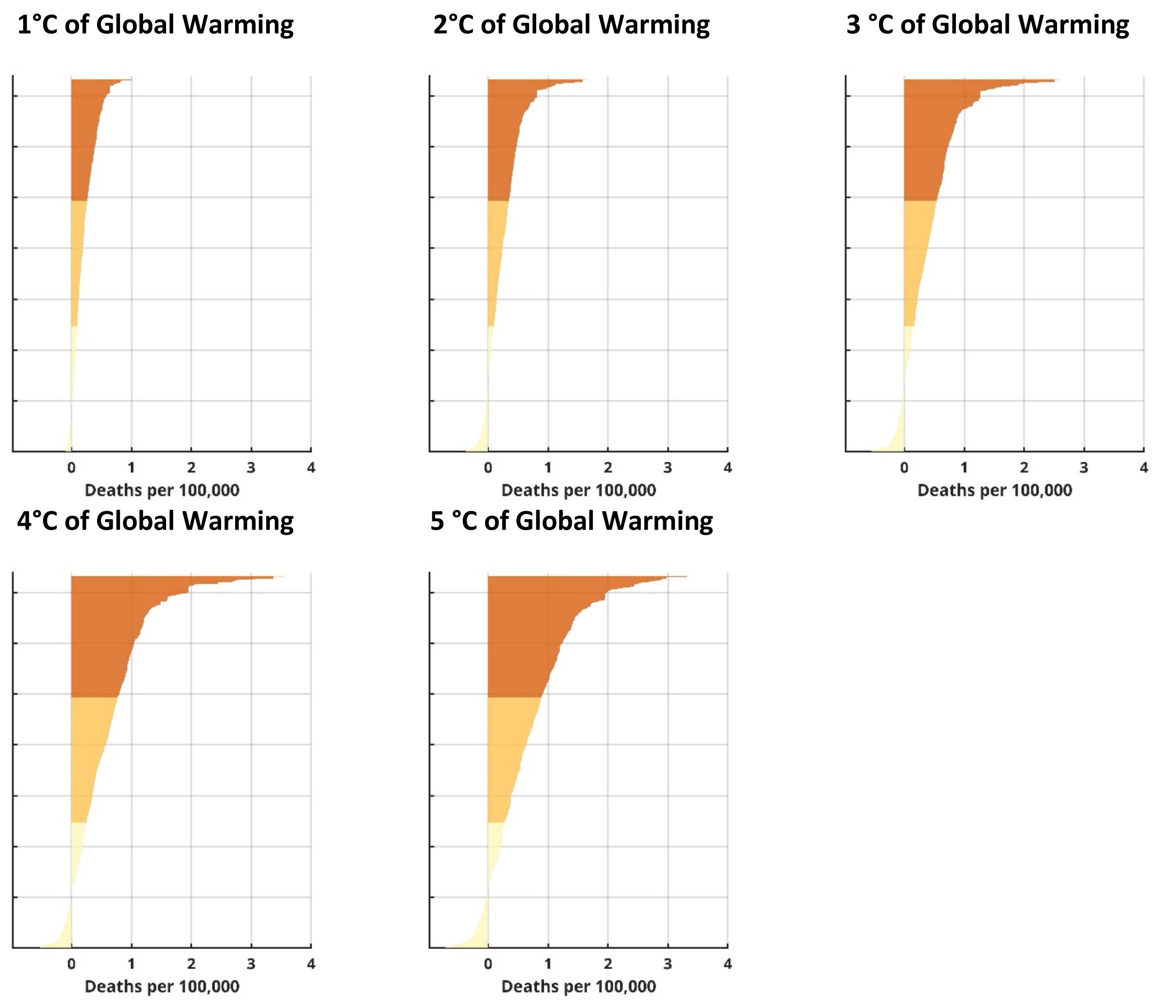
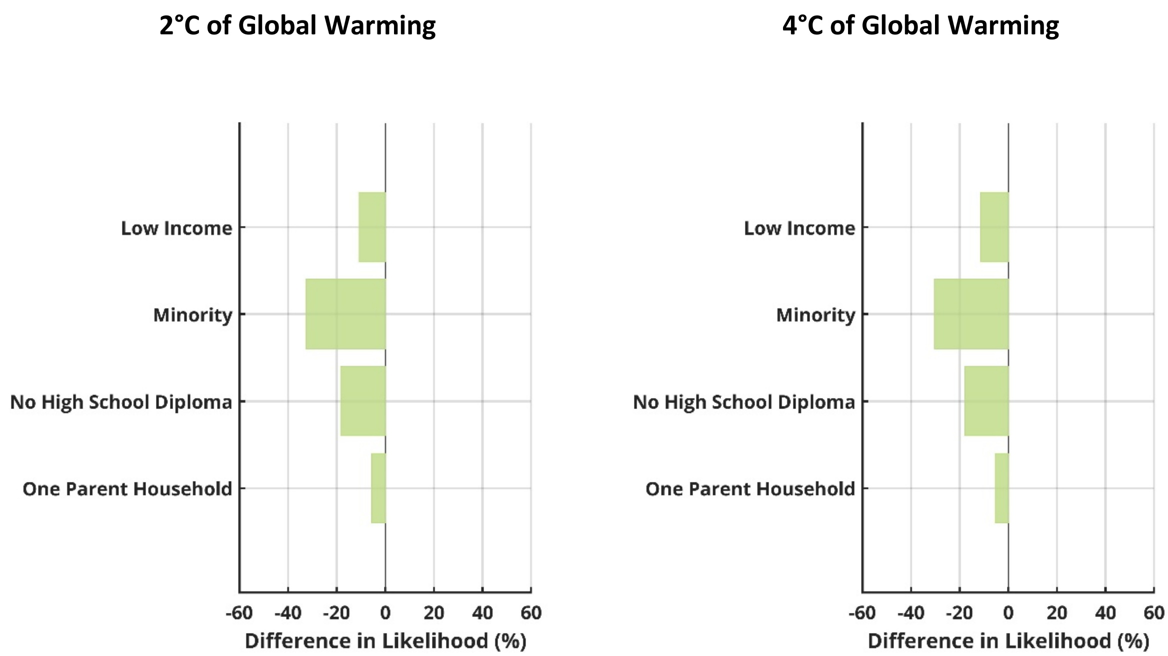


Figure 28 shows similar impacts associated with the top tercile of health impacts for ozone-related premature mortalities at degree increases in global mean temperature between 1°C and 5°C. Maximum projected values from 1°C to 5°C increases range from one to three deaths per 100,000. As such, this section analyzes only the 2°C and 4°C increases in global mean temperature.

For both 2°C and 4°C global mean temperature increase, this section assesses the likelihood that socially vulnerable individuals live in Census tracts projected to experience the highest burden of premature mortality associated with ozone exposure in those aged 0 to 99. Figure 29 shows the difference in likelihood of socially vulnerable individuals living in highly impacted Census tracts compared with non-socially vulnerable individuals nationally.

Figure 29. Likelihood that Socially Vulnerable Individuals Experience Highest Risk of Ozone-Related Premature Mortality in those Ages 0 to 99 and up Relative to Non-Socially Vulnerable Individuals, Nationally



In Figure 29, results show decreased likelihood of ozone-related mortality across all ages in socially vulnerable individuals. The results indicate that while socially vulnerable individuals have decreased likelihood of the highest ozone-related mortality impacts for those ages 0 to 99, less socially vulnerable populations have increased likelihood of experiencing higher risks. This pattern indicates that premature mortality for those ages 0 to 99 is not informative for further disproportionality consideration of ozone-related impacts by degree Celsius increase in global mean temperature. Ozone atmospheric chemistry is complex – for example, ozone formation in urban areas may be limited by volatile organic compound (VOC) concentrations, while ozone formation in rural or non-urban areas may be limited by concentrations of nitrogen oxides (NOx). In some vegetated areas, increases in temperature due to climate change lead to increased emissions of biogenic VOCs. In areas that are already NOx-limited, additional biogenic VOCs may impact $PM_{2.5}$ formation but may not significantly impact ozone formation because the air is already saturated with the maximum amount of nitrogen oxides that can react to form additional ozone. Overall, because the disproportionality analysis is performed at the national and regional level rather than on a finer scale, it is not possible to disentangle the roles or interactions among ozone precursor emissions components in modeled ozone concentrations.

5. Analysis Limitations

The analysis represents a high level description of how socially vulnerable populations may disproportionately experience $PM_{2.5}$-attributable premature mortalities for those age 65 and older, ozone-attributable premature mortalities for those ages 0 to 99, $PM_{2.5}$-attributable asthma cases for children ages 0 to 17, and $PM_{2.5}$-related asthma ED visits for children ages 0 to 18. The findings, however, are subject to several key limitations.

- The BenMAP-CE analysis was run using county-level incidence and population data and then apportioned to the Census tract-level for likelihood estimates. The likelihood results underrepresent the spatial precision of the 36-km grid air quality surfaces and overrepresent the spatial precision of the county-level health effect estimates.
- As the analysis estimates health effects at the county-level using 36-km square air quality concentrations, the results may not capture the more pronounced health effects experienced by fence line and near-road communities, which are likely disproportionately socially vulnerable.
- $PM_{2.5}$-attributable premature mortality is analyzed only for those age 65 older and is not representative of the whole population. The results do not capture $PM_{2.5}$-attributable premature mortality for socially vulnerable individuals below the age of 65.
- The analysis does not use race- or ethnicity-stratified morbidity incidence for $PM_{2.5}$-related new cases of asthma or asthma ED visits as these data are not available.
- The likelihood estimates may be influenced by factors beyond the determinant of social vulnerability, such as population density. For counties with very low populations of individuals who identify as Black and African American, American Indian or Alaska Native, Pacific Islander, Asian, or Hispanic/Latino, the estimated health impacts are not representative of a large population and may have higher associated error or uncertainties.

6. Data Sources

DATA TYPE	DESCRIPTION	DATA DOCUMENTATION AND AVAILABILITY
Climate modeling	The RCP8.5 scenario from two global climate models (CESM and CM3) was dynamically downscaled to 36-km resolution over North America using the Weather Research and Forecasting (WRF) model.	Community Earth System Model (CESM) available at https://www.cesm.ucar.edu/models/?ref=hp Geophysical Fluid Dynamics Laboratory Coupled Model version 3 (CM3) https://www.gfdl.noaa.gov/coupled-physical-model-cm3/ Weather Research and Forecasting Model available from https://www.mmm.ucar.edu/weather-research-and-forecasting-model
Air quality modeling	The Community Multiscale Air Quality (CMAQ) model estimated air quality over the coterminous US for five 11-year periods centered on 2000, 2030, 2050, 2075 and 2095.	U.S. Environmental Protection Agency. (2020). CMAQ (Version 5.3.2). Available from https://doi.org/10.5281/zenodo.4081737
Emissions inventory estimates	CMAQ was run using two emission inventory estimates: • the 2011 National Emissions Inventory which estimates the level and distribution of pollutants emitted from all sources and	US Environmental Protection Agency. 2011 National Emissions Inventory, Version 2: Technical Support Document. US Environmental Protection Agency; 2015. Available from https://www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data

DATA TYPE	DESCRIPTION	DATA DOCUMENTATION AND AVAILABILITY
	• a 2040 emission inventory projection which accounted for the implementation of a suite of federal, state, and local air quality regulations on stationary and mobile sources.	
Baseline health effect incidence rates	Race-stratified baseline incidence rates (2007-2016) were obtained from BenMAP-CE for eleven age groups (ages 0-0, (infants under age 1), 1-4, 5-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and 85-99). 2014 asthma-related emergency department morbidity incidence rates were obtained from BenMAP-CE for nine age groups (ages 0-17, 18-24, 25- 34, 35-44, 45-54, 55-64, 65-74, 75-84, and 85-99). 2006-2008 incidence rates for new cases of asthma as a chronic condition were obtained from BenMAP-CE for four age groups (ages 0-4, 5-11, 12-17, and 18-34). 2018 asthma prevalence rates were obtained from the National Health Interview Survey for two age groups (ages 0-4 and 5-17).	U.S. EPA. (2018). *Environmental Benefits Mapping and Analysis Program: Community Edition (BenMAP-CE) User Manual and Appendices*. Washington, DC.
Population	2010 US census population data was obtained from BenMAP-CE at the county level, disaggregated by age, race, and ethnicity.	U.S. EPA. (2018). *Environmental Benefits Mapping and Analysis Program: Community Edition (BenMAP-CE) User Manual and Appendices*. Washington, DC. U.S. Census Bureau, cited 2017: Population Estimates Program. Available online at https://www.census.gov/programs-surveys/popest.html