Appendix C: Supplemental Information for Analyses in the Air Quality Chapter

This appendix describes methods, data sources, and assumptions for the air quality analyses presented in Chapter 4 of the main report. First is the information for the detailed analysis of children's health outcomes linked with exposure to fine particulate matter ($PM_{2.5}$) and ground-level ozone (O_3). Second is information required for the discussion of emerging literature linking wildfire smoke and fetal health outcomes.

Detailed Analysis of Air Quality and Children's Health

This section includes details of the air quality and children's health analysis: a summary of climate studies used in the analysis, a summary of air quality epidemiological studies used in the analysis, analysis steps, detailed results, and limitations of the approach.

SUMMARY OF CLIMATE STUDIES USED IN THIS ANALYSIS

This analysis considers pollutant sources linked to climate change that result in heightened levels of $PM_{2.5}$ and O_3. These include the following:

- *Climate penalty*, which refers to changes in air quality resulting from climate-induced changes in temperature humidity, precipitation, and wind patterns, which all increase the secondary formation of O_3 and $PM_{2.5}$.
- *Southwest dust*, which refers to changes in ambient dust levels associated with increasing aridity and is restricted to four southwestern U.S. states: Utah, Colorado, Arizona, and New Mexico.
- *Wildfires*, which herein refers to nationwide changes in pollutant concentrations and associated health impacts attributable specifically to wildfire activity in the western U.S.

The following studies are those used to quantify health effects in children, associated with these sources of pollutants:

CLIMATE PENALTY: FANN ET AL. (2021)[1]

Fann et al. estimated mortality risk associated with changing air quality; specifically, O_3 and $PM_{2.5}$ concentrations. The authors show that changes in climate increase the population-weighted O_3 and $PM_{2.5}$ concentrations throughout the U.S. This analysis uses the Fann et al. air quality surfaces (i.e., changes in concentrations of pollutants in response to changes in meteorology and emissions) to quantify health effects attributable to exposures to $PM_{2.5}$ and O_3. The underlying study modeled future pollutant concentrations using two GCMs (CanESM2 and GFDL-CM3) and two alternative simulated air pollutant emissions scenarios, one which uses a 2011 inventory that estimates pollution burden from all sources as of that year, and an alternative 2040 dataset that accounts for the implementation of a suite of regulatory policies on stationary and mobile emissions sources. The analysis completed in this EPA report considers the average of health impacts across both GCMs, under the 2011 emissions scenario. Health impacts associated with the alternative 2040 emissions inventory are estimated to be approximately 40% lower than health impacts associated with the 2011 inventory used in this analysis.

SOUTHWEST DUST: ACHAKULWISUT ET AL. (2019)[2]

Achakulwisut et al. estimated the health burden resulting from changes in fine and coarse airborne dust exposure due to climate change in the Southwest. They found that, by the end of the century, climate change could lead to fine dust levels increasing by 57%, and coarse dust levels increasing by 38%. This analysis used projected $PM_{2.5}$ concentrations for six GCMs (CanESM2, CCSM4, GFDL-CM3, GISS-E2-R, HADGEM2, and MIROC5) derived from a network of 34 monitors from the underlying study, spanning Arizona, Colorado, New Mexico, and Utah.

WILDFIRES: NEUMANN ET AL. (2021)[3]

Neumann et al. estimated health impacts from wildfire emissions of black carbon and organic carbon by modeling changes in wildfire activity for the western region of the contiguous U.S. They found that climatic factors increase wildfire pollutant emissions by an average of 0.40% to 0.71% per year, and these emissions result in spatially weighted wildfire $PM_{2.5}$ concentrations more than double for some climate model projections by the end of the 21st century. Future concentrations of $PM_{2.5}$ from western wildfires were projected for five GCMs (CanESM2, CCSM4, GISS-E2-R, HADGEM2, and MIROC5) and extend nationwide, as emissions associated with wildfires typically travel eastward across the country.

SUMMARY OF AIR QUALITY EPIDEMIOLOGY STUDIES USED IN THIS ANALYSIS

Numerous epidemiological studies document the relationship between degraded air quality and human morbidity or mortality. This analysis draws on evidence from seven studies that identify the magnitude of these relationships for children specifically (summarized below). These studies have been parameterized for use with the U.S. EPA's Environmental Benefits Mapping and Analysis Program (BenMAP, https://www.epa.gov/benmap), a tool that estimates the human health impacts of air quality changes at a refined spatial scale. BenMAP is used to determine the change in ambient air pollution based on user-specified air quality data and relates the change in pollution concentrations with certain health effects using concentration-response functions derived from epidemiology studies. BenMAP applies that relationship to the population experiencing the change in pollution exposure to calculate health impacts. Table 1 maps the studies described above to their risk measures and includes age groups, BenMAP surfaces, and pollutants. The studies described below are listed in the same order as they appear in Table 1. Note that these studies calculate outputs such as hazard ratios, rate ratios, relative risks, or odds ratios, which are alternative measures of association between an exposure (in this case, to air pollution) and the incidence of a specific adverse health effect. Some studies instead statistically estimate a regression function, where the relevant coefficient on the exposure variable provides the estimate of the association between exposure to air pollution and incidence.

INCIDENCE OF ASTHMA: TETREAULT ET AL. (2016)[4]

Tétreault et al. investigated the relationship between childhood asthma onset and long-term pollution exposure ($PM_{2.5}$, O_3, and NO_2). The authors followed a cohort of 1,200,000 children born in Quebec, Canada, from 1996 to 2011, from birth to approximately age 6, and mapped asthma incidence with residential exposures to air pollutants. The study defined the onset of asthma as a hospital-discharged diagnosis of asthma or two reports of asthma from two separate physicians within a two-year period. The authors used Cox proportional hazard models to estimate the association between asthma onset and pollution exposure, controlling for demographics and socioeconomic status. The coefficient and standard error for $PM_{2.5}$ were estimated from a hazard ratio of 1.33 (95% CI 1.31-1.34) for a 6.53 $\mu g/m^3$ increase in annual $PM_{2.5}$ concentration. The coefficient and standard error for O_3 were estimated from a warm-season hazard ratio of 1.07 (95% CI 1.06-1.08) for a 3.26 ppb increase in annual O_3 concentrations.

INCIDENCE OF HAY FEVER: PARKER ET AL. (2009)[5]

Parker et al. investigated the associations between long-term O_3 exposure and respiratory allergies (defined as hay fever or respiratory allergy symptoms) among 73,000 children nationwide aged 3-17, between 1999 and 2005. The analysis was conducted using logistic regression models, adjusted for demographic and socioeconomic factors. The coefficient and standard error for $PM_{2.5}$ are based on the odds ratio of 1.29 (95% CI 1.07-1.56) for a 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. The coefficient and standard error for O_3 are based on the odds ratio of 1.18 (95% CI 1.09-1.27) for a 10 ppb increase in warm-season daily mean O_3.

SCHOOL DAYS LOST: GILLILAND ET AL. (2001)[6]

Gilliland et al. examined the association between air pollution and school absenteeism among fourth grade children (aged 9-10) in twelve southern California communities in 1996. The relationship is applied here to all school-age children (aged 5-17). The authors used school records to collect daily absence data and parental telephone interviews to identify causes. Using an average length of absence at baseline, they determined how this could relate to limiting new absences in the future. The authors used 15- and 30-day distributed lag models to quantify the association between O_3 and school absences. O_3 levels were positively associated with all school absence measures. The coefficient and standard error are based on a percent increase of 16.3% (95% CI -2.6%-38.9%) associated with a 20 ppb increase in 8-hour average O_3 concentration.

EMERGENCY DEPARTMENT VISITS FOR ASTHMA: ALHANTI ET AL. (2016)[7]

Alhanti et al. studied the relationship between daily $PM_{2.5}$ concentrations and emergency department (ED) visits for asthma among residents of all ages (patient-level data) in Atlanta (1993–2009), Dallas (2006–2009), and St. Louis (2001–2007). The authors ran city-specific daily time-series

Poisson regression models by age group (0-4, and 5-18 were included in this analysis) and performed additional analyses stratified by race and sex. The coefficient and standard error for $PM_{2.5}$ are estimated from rate ratios of 1.01 (95% CI 1.00-1.02) and 1.02 (95% CI 1.01-1.04) associated with an 8 μg/m^3 increase in $PM_{2.5}$ concentration for children aged 0-4 and 5-18, respectively.

EMERGENCY DEPARTMENT VISITS FOR ASTHMA: MAR AND KOENIG (2009)[8]

Mar and Koenig studied the relationship between O_3 exposure and asthma hospitalizations in the Seattle area from 1998 to 2002. The authors used hospital data on daily asthma cases with local monitored O_3 concentrations to assess the association between asthma visits to the ED and air pollution. The coefficient and standard error are estimated from a relative risk of 1.11 (95% CI 1.02-1.21) for a 10 ppb increase in daily 8-hour maximum summer O_3 concentration.

HOSPITAL ADMISSIONS FOR RESPIRATORY ISSUES: OSTRO ET AL. (2009)[9]

Ostro et al. estimated the association between ambient $PM_{2.5}$ and respiratory diseases in children aged 5 to 19 in California. Hospital admission data was aggregated for all respiratory diseases to the county level to create a daily time series of admissions for each county. Authors analyzed data using a Poisson regression with time, day of the week, temperature, relative humidity, and pollutant as explanatory variables. They controlled for seasonality and time dependent effects by including a natural spline smoother for the daily time trend and meteorology. The coefficient and standard error are estimated from an excess risk of 4.1% (95% CI 1.8%-6.4%) for a 14.6 μg/m^3 increase in daily mean $PM_{2.5}$ concentration.

INFANT MORTALITY: WOODRUFF ET AL. (2008)[10]

Woodruff et al. examined the relationship between long-term exposure to $PM_{2.5}$ air pollution and postneonatal (i.e., from 28 days through the first year of life) infant mortality in 3,600,000 live births from 96 counties across the U.S. between 1999 and 2002. They used logistic regression models that incorporated generalized estimating equations to estimate odds ratios for all-cause and cause-specific postneonatal mortality as a result of exposure to air pollution. The coefficient and standard error are estimated from an odds ratio of 1.04 (95% CI 0.98-1.11) associated with a change of 7μg/m^3 in mean $PM_{2.5}$ exposure level.

ANALYSIS STEPS

Chapter 4 of this report quantifies the effects of pollutant exposures on children's health. This analysis relies on pollutant source information from Fann et al. (2021), Achakulwisut et al. (2019), and Neumann et al. (2021) and effect estimates from numerous epidemiological studies, as summarized above. Table 2 details the analytic steps, data sources, and assumptions used to project the various measures of children's health impacts resulting from air quality degradation linked to climate change. As described in the table, this analysis summarizes impacts by degree of global warming. For more information on how the analysis applies thresholds of degrees of global warming, see methods described in Chapter 2 of the main report and Appendix A. This analysis considers all geographies in the contiguous United States, except for the Southwest dust pollutant source, which is limited to four southwestern states (UT, CO, AZ, NM).

Table 1: Risk Measures, Studies, Age Groups, and BenMAP Surfaces Considered for Each Pollutant Source

Risk Measure	Study	Age Range	Pollutant Source			
			Climate Penalty		Southwest Dust ($PM_{2.5}$)	Wildfire ($PM_{2.5}$)
			$PM_{2.5}$	O_3		
Incidence of asthma	Tétreault et al. (2016)	0-17	x	x	x	x
Incidence of hay fever (rhinitis)	Parker et al. (2009)	3-17	x	x	x	x
School days lost, all cause	Gilliland et al. (2001)	5-17		x		
ED visits associated with asthma	Alhanti et al. (2016) Mar and Koenig (2009)	0-18	x	x	x	x
Hospital admissions for respiratory issues	Ostro et al. (2009)	0-18	x		x	x
Infant mortality	Woodruff et al. (2008)	0-0*	x		x	x

** Infant mortality estimated for postneonatal infants (i.e., those aged 28-365 days)*

Table 2: Analytic Steps in Climate Change Impacts on Air Quality and Children's Health Analysis

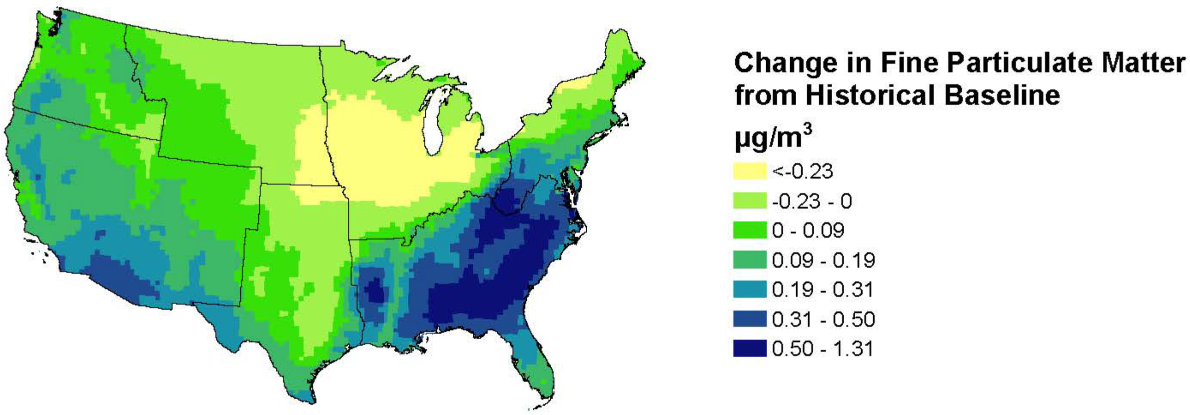
	Step	Data	Methods, Assumptions, Notes
Baseline Risks	1. Identify baseline incidence of health and well-being impacts under baseline climate and population	County- or national-level incidence by health effect obtained from BenMAP	This analysis used the finest scale data where available. Specifically, county-level baseline incidence data for lost school days, asthma ED visits, infant mortality, and respiratory hospital admissions were used. This analysis includes national-level baseline incidence data for new cases of asthma and incidence of hay fever (allergic rhinitis).
Future Climate Stressor	2. Utilize projected $PM_{2.5}$ and O_3 concentrations related to climate penalty, southwest dust, and wildfires	Present and future pollutant concentrations: • *Climate penalty:* Fann et al. (2021) • *Southwest dust:* Achakulwisut et al. (2019) • *Wildfires:* Neumann et al. (2021)	Pollutant data is available at different spatial scales and for different geographic regions. Different climate models are utilized within a set of six CMIP5 scenarios for each analysis, and results are binned based on 21st century arrival times for each GCM. • *Climate Penalty:* Nationwide analysis, using climate data at 36-km scale. Two GCMs: CanESM2, GFDL-CM3 • *Southwest dust:* Analysis limited to four southwestern states (UT, CO, AZ, NM). Baseline pollutant concentrations from 34 monitor sites. Six GCMs: CanESM2, CCSM4, GFDL-CM3, GISS-E2-R, HADGEM2, and MIROC5 • *Wildfires:* Nationwide analysis, using climate data at 0.25 x 0.25-(latitude/longitude) degree scale. Five GCMs: CanESM2, CCSM4, GISS-E2-R, HADGEM2, and MIROC5. $PM_{2.5}$ air quality outputs generated at 0.5 x 0.625 (latitude/longitude) degree grid scale.
Future Effects on Children	3. Estimate the increase in incidence of health effects associated with each degree-C increase in global mean temperatures	Health impact functions are derived from epidemiological studies described previously, parameterized in BenMAP See Chapter 2 of the main report and Appendix A for details on population methods and data sources used throughout the analysis.	The health impact functions used in this analysis are specific to children of different age ranges, presented in Table 1. These represent the best available studies with effects specific to children used in other EPA analyses. This analysis excludes health impacts to children outside of these age ranges (e.g., it does not quantify incidence of hay fever/rhinitis among those younger than three years old).

PROJECTIONS OF PM2.5 AND O3

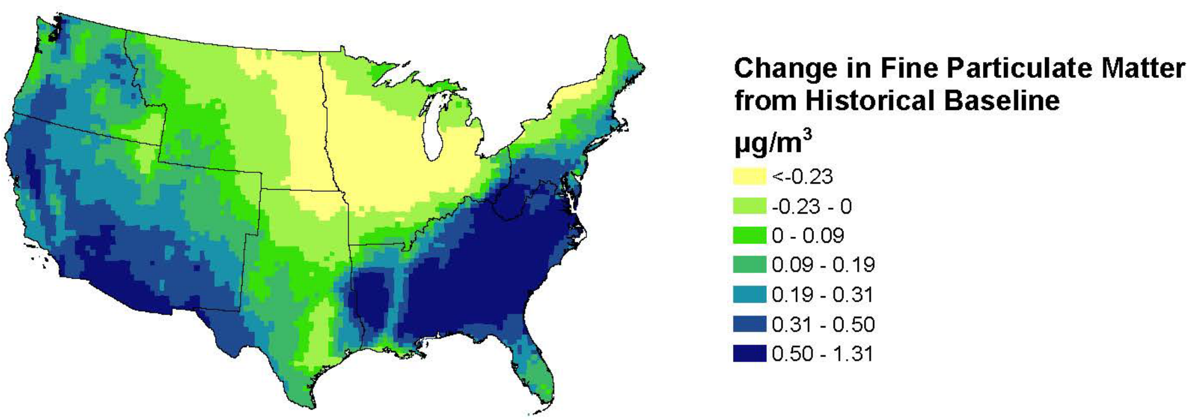
Figure 1 shows the change from 2000 baseline levels of $PM_{2.5}$ associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature, based on projections used in Fann et al. Figure 2 shows the change from 2000 baseline levels of O_3 associated with a 2°C (top panel) and 4°C (bottom panel) increase in global mean temperature, based on projections used in Fann et al.

Figure 1: Future $PM_{2.5}$ Concentrations at 2°C and 4°C Increase in Global Mean Temperature

2°C of Global Warming



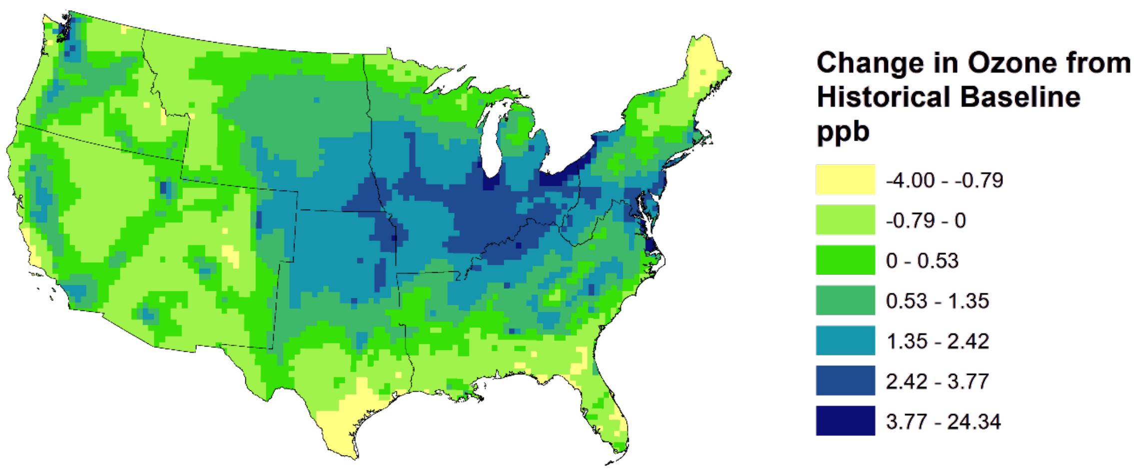
4°C of Global Warming



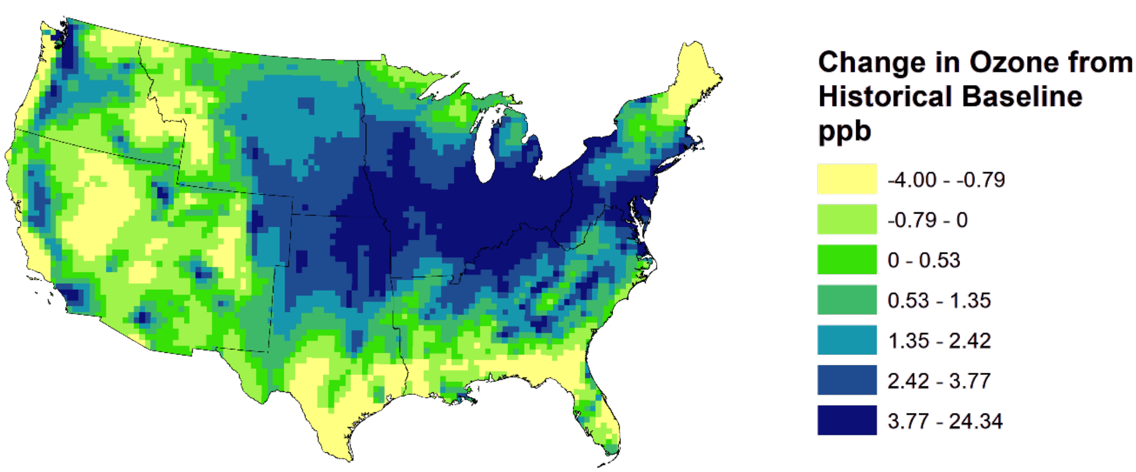
Source: USEPA (2021)[11]

Figure 2: Future O_3 Concentrations at 2°C and 4°C Increase in Global Mean Temperature

2°C of Global Warming



4°C of Global Warming



Source: Fann et al. (2021) and USEPA (2021)[12]

EFFECTS ON CHILDREN RESULTS

Table 3 presents the results of the analysis assuming population growth (see Chapter 2 and Appendix A). The analysis estimates additional health impacts attributable to climate change relative to the baseline period and sums the impacts for each health effect across the three pollutant sources (climate penalty, southwest dust, and wildfire). Table 4 provides the same estimates but assumes population remains constant at 2010 levels, isolating the influence of climate change specifically.

Table 3: Projected Annual Risks to Children's Health Associated with Future $PM_{2.5}$ and O_3 (with Population Growth)

Degree of Global Warming (°C)	(1) New Cases of Asthma (Aged 0-17)	(2) Incidence of Hay Fever/Rhinitis (Aged 3-17)	(3) School Days Lost from All Causes (Aged 5-17)	(4) ED Visits for Asthma (Aged 0-18)	(5) Hospital Admissions for Respiratory Illness (Aged 0-18)	(6) Infant Mortality (Aged 0-0)
1°C	19,200 *(14,400 to 24,800)*	126,000 *(92,000 to 159,000)*	1,270,000 *(960,000 to 580,000)*	3,450 *(2,560 to 4,370)*	173 *(117 to 224)*	4 *(2 to 6)*
2°C	34,500 *(27,900 to 42,800)*	228,000 *(179,000 to 276,000)*	2,240,000 *(1,850,000 to 2,630,000)*	6,240 *(5,210 to 7,330)*	332 *(230 to 430)*	7 *(4 to 10)*
3°C	57,900 *(51,400 to 66,600)*	367,000 *(318,000 to 418,000)*	3,590,000 *(3,570,000 to 3,610,000)*	10,300 *(9,930 to 10,800)*	537 *(292 to 782)*	11 *(5 to 16)*
4°C	89,600 *(74,100 to 108,000)*	554,000 *(447,000 to 662,000)*	5,480,000 *(5,170,000 to 5,790,000)*	15,800 *(14,500 to 17,200)*	785 *(353 to 1,220)*	15 *(6 to 25)*
5°C	134,000	771,000	7,630,000	22,400	1,160	24

Notes: All estimates presented in the table are incremental relative to baseline risks and convey impacts per year: (1) 841,000 new asthma cases, (2) 11.9 million incidences of hay fever/rhinitis, (3) 183 million school days lost from all causes, (4) 733,000 ED visits for asthma, (5) 429,000 hospital admissions for respiratory illness, and (6) 8,960 infant deaths. The table displays the average and range across climate models; a range for 5°C is not feasible because only one climate model reaches this temperature threshold before 2100. See Table 2 for analytic details.

Table 4: Projected Annual Risks to Children's Health Associated with Future $PM_{2.5}$ and O_3 (2010 Population)

Degree of Global Warming (°C)	(1) New Cases of Asthma (Aged 0-17)	(2) Incidence of Hay Fever/Rhinitis (Aged 3-17)	(3) School Days Lost from All Causes (Aged 5-17)	(4) ED Visits for Asthma (Aged 0-18)	(5) Hospital Admissions for Respiratory Illness (Aged 0-18)	(6) Infant Mortality (Aged 0-0)
1°C	18,600 *(13,700 to 23,400)*	112,000 *(81,900 to 141,000)*	1,150,000 *(867,000 to 1,440,000)*	3,180 *(2,340 to 4,010)*	143 *(95 to 187)*	6 *(3 to 8)*
2°C	32,200 *(25,500 to 39,000)*	194,000 *(152,000 to 235,000)*	1,950,000 *(1,600,000 to 2,300,000)*	5,510 *(4,550 to 6,470)*	258 *(178 to 338)*	11 *(7 to 15)*
3°C	49,300 *(43,600 to 55,100)*	294,000 *(255,000 to 333,000)*	2,940,000 *(2,930,000 to 2,960,000)*	8,460 *(8,210 to 8,710)*	393 *(204 to 586)*	17 *(8 to 25)*
4°C	72,900 *(60,200 to 85,500)*	431,000 *(351,000 to 510,000)*	4,360,000 *(4,160,000 to 4,560,000)*	12,600 *(11,600 to 13,500)*	561 *(231 to 890)*	24 *(9 to 38)*
5°C	100,000	585,000	5,880,000	17,100	840	36

Notes: See Table 3.

Figures 3 and 4 show the estimated change in childhood asthma diagnoses per 100,000 children aged 0-17 at 2°C and 4°C of global warming at the county level. For each figure, the top panel shows the combined impacts across pollution sources, which are split out by source below. The five states with largest impacts per 100,000 children are outlined in black for each pollutant source and listed below each map.

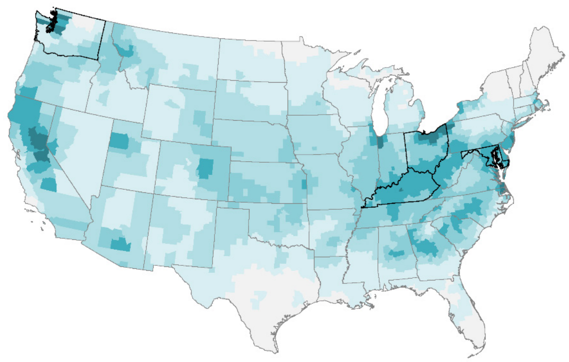
Tables 5 and 6 then follow with the number of cases per 100,000 children for each state at 2°C and 4°C of global warming specifically to provide perspective on the range of impacts across states, although there can be considerable heterogeneity within states (see Figures 3 and 4).

Figure 5 shows the change in total childhood asthma diagnoses for children aged 0-17 at 2°C and 4°C of global warming at the county level. Impacts are generally highest in areas with the large children's populations. The five states with largest total impacts are outlined in black and listed below each map. The relevant quantities or rates presented in each figure are provided in parentheses after the state name in the lists of top 5 states.

Figure 6 then shows the county-level impacts across pollutant sources for another impact of air quality on children's well-being: the number of annual school days lost. This additional endpoint demonstrates that the spatial distribution is fairly consistent across impacts considered in this analysis.

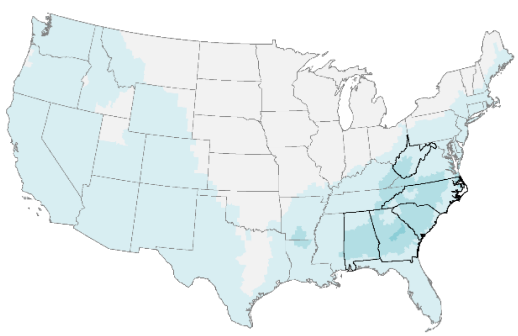
Figure 3: Estimated Change in New Annual Asthma Diagnoses Per 100,000 Children (Aged 0-17) at 2°C Global Warming (with Population Growth)

All Pollution Sources



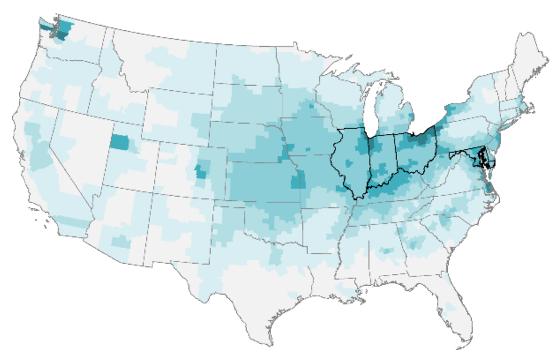
Top five states (rate/100,000 in parentheses): D.C. (90), OH (83), WA (81), KY (80), MD (80)

Climate Penalty, $PM_{2.5}$



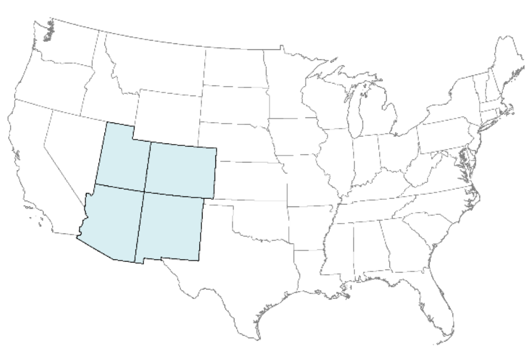
Top five states: SC (33), NC (31), GA (30), AL (29), WV (23)

Climate Penalty, O_3



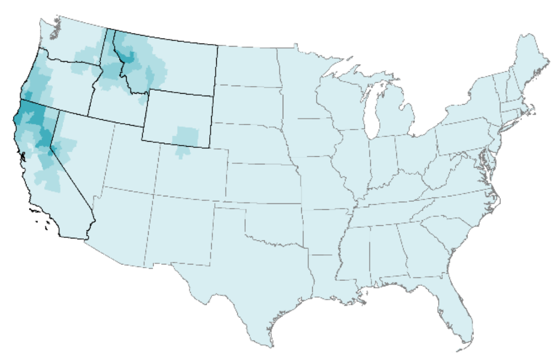
Top five states: IL (88), OH (87), D.C. (77), IN (73), MD (68)

Southwest Dust



Top four states: NM (13.0), AZ (13.0), UT (12.9), CO (12.9)

Wildfire



Top five states: MT (35), OR (31), ID (21), WY (19), CA (16)

Additional Asthma Diagnoses per 100,000 Children

<0 | 1 - 27 | 28 - 47 | 48 - 68 | 69 - 107 | 108 - 692

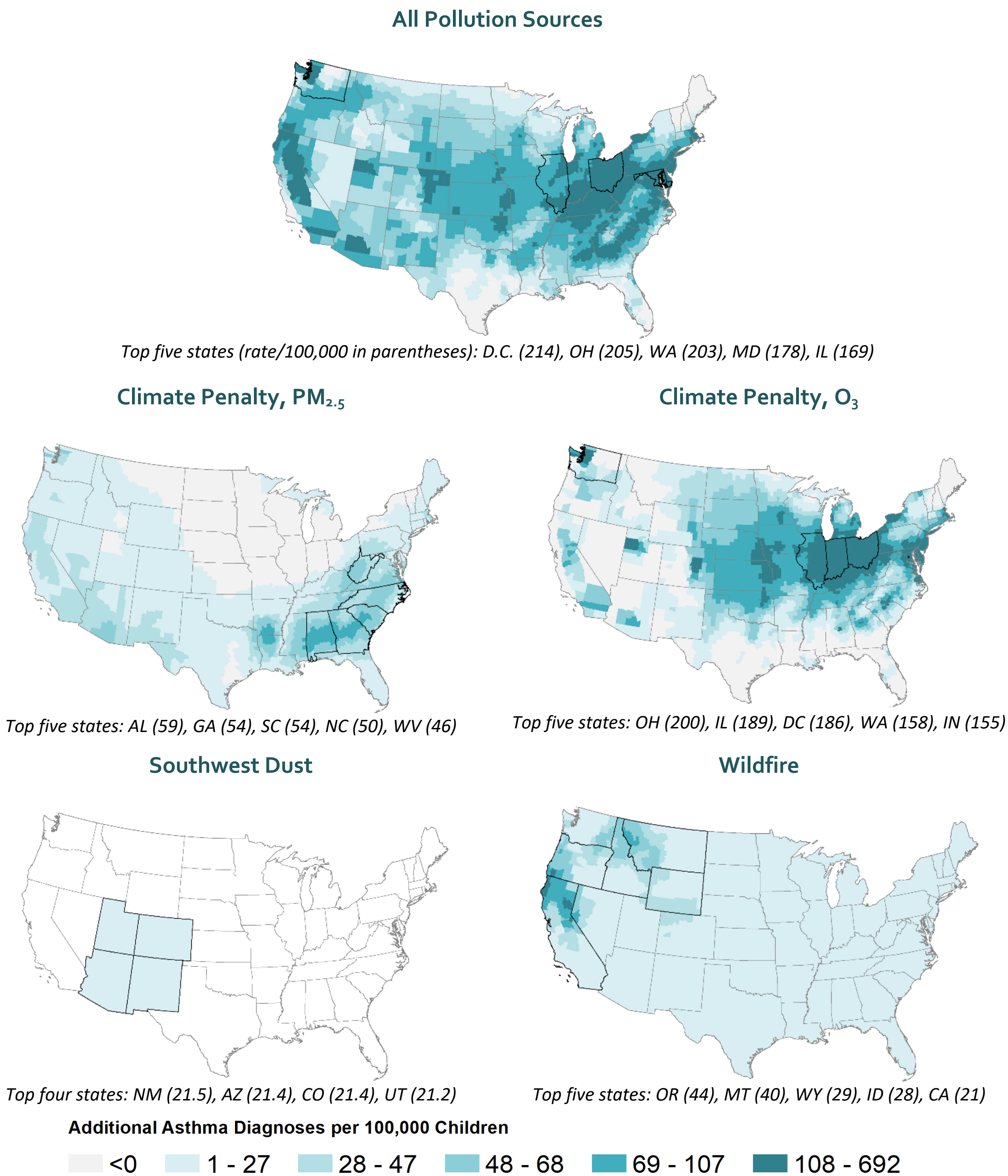
Note: These maps describe the projected change in new annual asthma diagnoses per 100,000 children at 2°C of global warming relative to the baseline (1986-2005). Darker shading conveys larger increases while lighter shading conveys small increases. The five states with the largest increases on average are outlined in black.

Table 5: Estimated New Annual Asthma Diagnoses Per 100,000 Children by State with 2°C Global Warming (with Population Growth)

State	Incidence Per 100,000 Children	State	Incidence Per 100,000 Children
Washington, DC	90	Rhode Island	40
Ohio	83	Alabama	40
Washington	81	Oregon	39
Kentucky	80	Wyoming	37
Maryland	80	Iowa	36
Virginia	77	Arkansas	36
West Virginia	76	Montana	34
Delaware	72	Connecticut	31
Colorado	70	New Mexico	30
Illinois	70	Nevada	29
New Jersey	65	South Dakota	29
Tennessee	61	Michigan	26
Indiana	61	Mississippi	25
North Carolina	60	Idaho	24
Pennsylvania	57	Wisconsin	24
Arizona	52	Minnesota	24
Kansas	52	Georgia	20
New York	51	Louisiana	13
South Carolina	50	North Dakota	10
Utah	48	Texas	8
Missouri	46	Florida	0
Nebraska	46	New Hampshire	-4
Massachusetts	46	Maine	-14
Oklahoma	46	Vermont	-16
California	45	--	

Notes: This table describes the projected new annual diagnoses per 100,000 children at 2°C of global warming using the methods described in Table 2 averaged to the state level. States are listed from largest to smallest impacts.

Figure 4: Estimated Change in New Annual Asthma Diagnoses Per 100,000 Children (Aged 0-17) at 4°C Global Warming (with Population Growth)



Note: These maps describe the projected change in new annual asthma diagnoses per 100,000 children at 4°C of global warming relative to the baseline (1986-2005). Darker shading conveys larger increases while lighter shading conveys small increases. The five states with the largest increases on average are outlined in black.

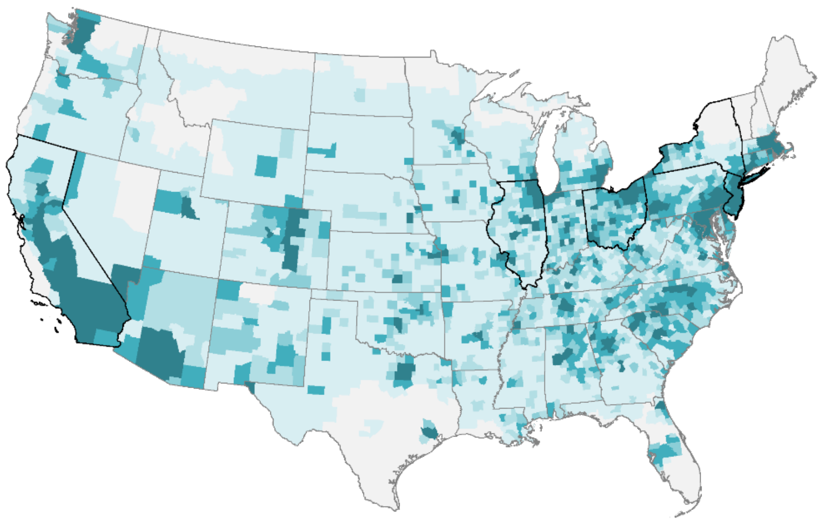
Table 6: Estimated New Annual Asthma Diagnoses Per 100,000 Children by State with 4°C Global Warming (with Population Growth)

State	Incidence Per 100,000 Children	State	Incidence Per 100,000 Children
Washington, DC	214	Michigan	91
Ohio	205	South Carolina	89
Washington	203	Georgia	88
Maryland	178	California	83
Illinois	169	Alabama	83
West Virginia	168	Iowa	74
Delaware	162	Arkansas	72
Virginia	162	Oregon	71
New Jersey	160	Wyoming	70
Kentucky	156	Wisconsin	68
Pennsylvania	143	Minnesota	65
Indiana	142	New Mexico	61
New York	141	South Dakota	58
Massachusetts	136	Mississippi	52
Colorado	133	Montana	47
Rhode Island	122	Idaho	43
Kansas	110	Nevada	40
Tennessee	109	Louisiana	39
North Carolina	106	North Dakota	32
Arizona	105	Texas	26
Missouri	100	New Hampshire	22
Utah	99	Florida	2
Connecticut	98	Vermont	-9
Nebraska	97	Maine	-11
Oklahoma	95	--	

Notes: This table describes the projected new annual diagnoses per 100,000 children at 4°C of global warming using the methods described in Table 2 averaged to the state level. States are listed from largest to smallest impacts.

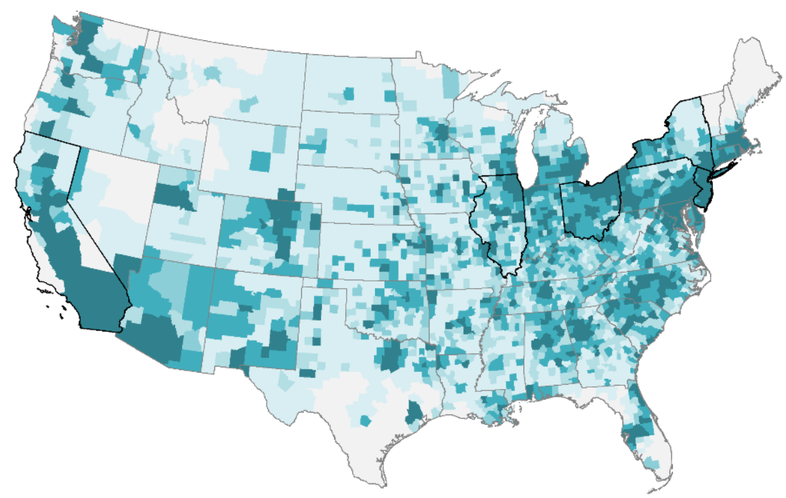
Figure 5: Estimated Change in Total New Annual Asthma Diagnoses Among Children Aged 0-17 (with Population Growth)

2°C of Global Warming



Top five states (excess diagnoses in parentheses): CA (3,640), NY (2,740), IL (2,570), OH (2,280), NJ (1,710)

4°C of Global Warming



Top five states: CA (9,490), NY (8,760), IL (7,050), OH (5,430), NJ (5,200)

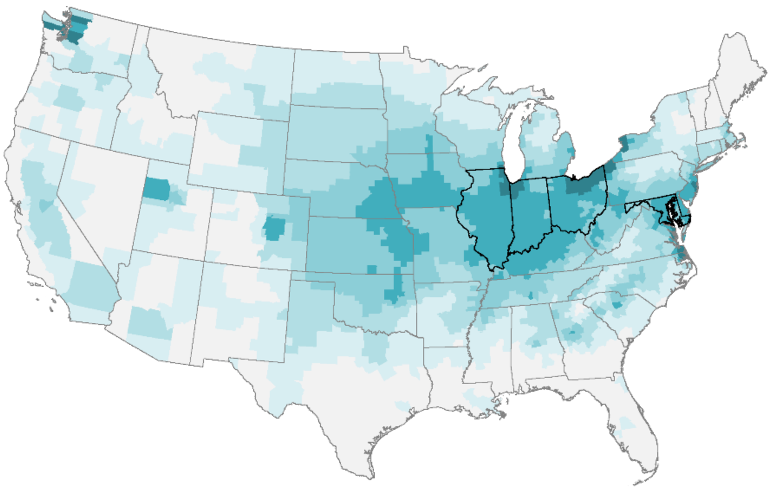
Total New Asthma Diagnoses

<0 | 1 - 3 | 4 - 6 | 7 - 9 | 10 - 30 | 31 - 3950

Note: These maps describe projected total change in new annual asthma diagnoses at 2°C and 4°C of global warming relative to baseline (1986-2005). The five states with the highest impacts are outlined in black. See Table 2 for analytic details.

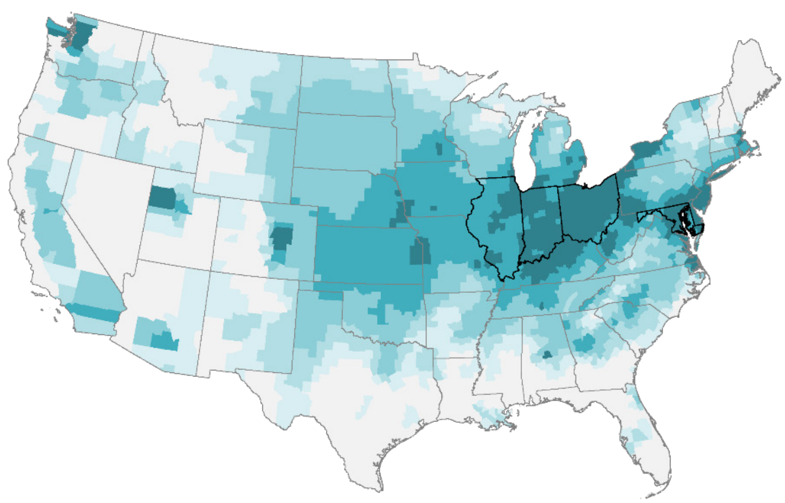
Figure 6: Estimated Change in Annual Lost School Days Due to Climate Change Per 100,000 Children (Aged 5-17) (with Population Growth)

2°C of Global Warming



Top five states, excess incidence in parentheses: IL (9,430), OH (9,350), D.C. (8,410), IN (7,950), MD (7,360)

4°C of Global Warming



Top five states: OH (20,800), IL (19,620), D.C. (19,550), MD (16,410), IN (16,390)

Annual School Days Lost

<0 | 1 - 2,000 | 2,001 - 4,200 | 4,201 - 6,300 | 6,301 - 10,000 | 10,001 - 60,000

Note: These maps describe projected change in annual school days lost due to climate change-induced changes in air quality at 2°C and 4°C of global warming relative to baseline (1986-2005). The five states with the highest impacts are outlined in black. See Table 2 for analytic details.

Figures 7 and 8 present the results of the social vulnerability analysis (see Chapter 2 and Appendix A for methods, data sources, and assumptions). These results are presented separately for $PM_{2.5}$ (Figure 7) and O_3 (Figure 8). The estimated risks for each socially vulnerable group are presented relative to each group's "reference" population, defined as all individuals other than those in the group analyzed. Positive numbers indicate the group is disproportionately affected by the referenced impact. Negative numbers indicate the group is less likely to live in the areas with the highest projected impacts.

Figure 7: Social Vulnerability Analysis Results for $PM_{2.5}$ and New Asthma Diagnoses Among Children

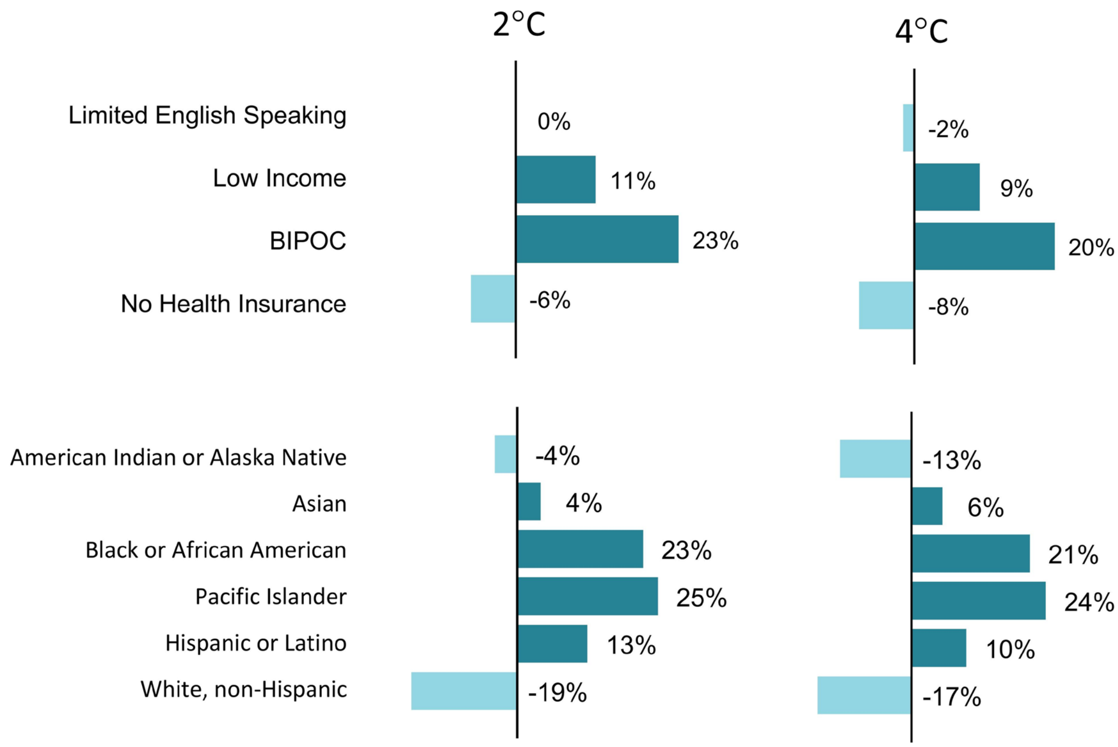
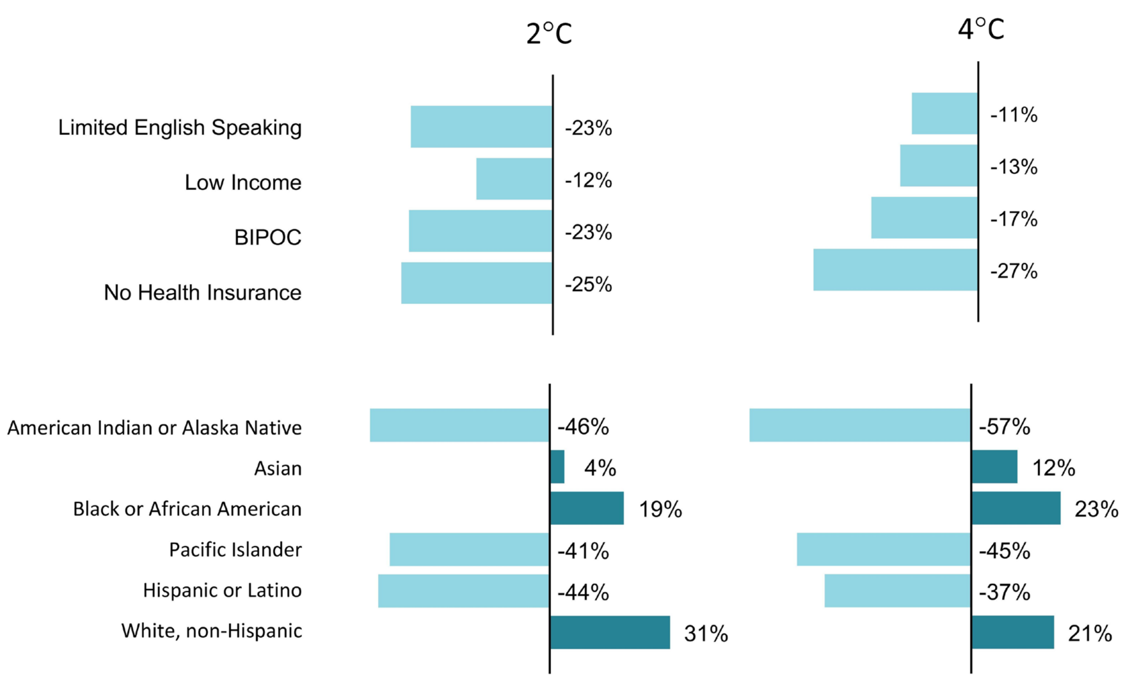


Figure 8: Social Vulnerability Analysis Results for O_3 and New Asthma Diagnoses Among Children



LIMITATIONS

Below are several limitations of the analysis. See Fann et al. (2021), Achakulwisut et al. (2019), and Neumann et al. (2021) for additional limitations of the underlying sectoral impact models.

1. ***There is limited epidemiological literature specifically on children's health effects of air pollution.*** This analysis relies on standard health functions used by the U.S. EPA for regulatory impacts analyses that are relevant to children. This set of functions focuses on respiratory morbidity effects, and mortality effects are restricted to the postneonatal population. Children are likely to experience additional morbidity and mortality effects that are not quantified by this analysis.
2. ***Impacts of coarse particulate matter on children's health are omitted from this analysis.*** The quantitative air quality analyses in this report focus on the impacts of $PM_{2.5}$ and O_3 on children's health. As noted in the main text of the report, additional impacts may be associated with other air pollutants. In particular, there is epidemiological evidence that exposure to coarse particulate matter (PM_{10}-$PM_{2.5}$) is associated with emergency department visits for asthma.[13] Coarse particle exposure among children is expected to increase as a result of both wildfire smoke exposure and increased levels of airborne fugitive dust. As described in Achakulwisut et al., while it is common to assume that impacts attributable to fine and coarse PM fractions are additive because there is technically no overlap in the diameter range of the two PM fractions, in practice, this issue is still up for debate owing to uncertainties in separating the health impacts attributable to fine and coarse PM in epidemiological studies. To avoid the potential for double-counting, we therefore omit quantitative consideration of coarse particulate matter on children's health – in the process we may underestimate the full impact of particulate matter of all size fractions on the health endpoints we assess.
3. ***The connection between climate change and air quality, particularly particulate matter, remains uncertain and is currently characterized by relatively few lines of evidence.*** As noted in the above-cited literature used in this report and in Dawson et al. (2014)[14], connections between climate change and air quality are complex, particularly with respect to particulate air quality. The modeling work utilized here (Fann et al. 2021) represents an important step forward in modeling finer scale meteorology which affects air quality, making use of state-of-the-art meteorological down-scaling and air quality models. The complexity of the relationship is illustrated by the finding in Fann et al. that some areas of the U.S. could experience improvements in air quality as a result of climate change, while most of the U.S. is expected to experience a decline in air quality. The Fann et al., work has not yet been supported by additional lines of evidence, and as a result may be subject to additional uncertainty.
4. ***Results of this analysis are available at the county level as the finest spatial scale.*** The BenMAP analysis was run using county-level baseline incidence and population data, which limits the geographic level to which health impacts associated with pollutant changes can be

specified. As a result, results may underrepresent the spatial precision of the gridded air quality data from underlying climate studies summarized at the beginning of this Appendix.

5. *This analysis does not capture fine-scale health effects of populations that may be at greater risk of exposure or disproportionate impacts, including BIPOC children, low income individuals, children with housing uncertainty, and children with various comorbidities.* This analysis estimates health effects at the county-level using 36-km-squared air quality concentrations and may not capture localized health effects experienced by fenceline and near-road children, who are likely disproportionately vulnerable.
6. *The airborne dust component of this analysis is limited to the southwestern region of the U.S.* While dust exposures are known to be large in the southwestern U.S., this analysis does not consider health effects from dust in other regions of the U.S., which are likely smaller than those in the Southwest but nonzero.
7. *Respiratory health may degrade for other climate-related reasons.* The health effects presented in this chapter are associated with changes in air quality linked with O_3 and $PM_{2.5}$. Respiratory health is likely to worsen among children for other climate-induced reasons, including changes and shift in plant pollen production (see Chapter 5 and Appendix D).

DATA SOURCES

Table 7: Summary of Data Sources Used in the Air Quality and Children's Health Analysis

Data Type	Description	Data Documentation and Availability
Climate modeling	*See Appendix A for data sources.*	
Air quality modeling	**Climate Penalty:** The Community Multiscale Air Quality (CMAQ) model estimated air quality over the conterminous US for five 11-year periods centered on 2000, 2030, 2050, 2075, and 2095. **Southwest Dust:** Seasonal mean concentrations of $PM_{2.5}$ measured at 35 monitoring sites and projected for 20-year periods centered on 2030, 2050, 2070, and 2090. **Wildfires:** Estimated $PM_{2.5}$ concentrations over the coterminous US for all years 2006-2100 using GEOS-Chem chemical transport model.	U.S. Environmental Protection Agency. (2020). CMAQ (Version 5.3.2). Available from https://doi.org/10.5281/zenodo.4081737 Climate penalty PM2.5 and O3 air quality results by degree of warming estimated from U.S. Environmental Protection Agency. 2021. "Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts." EPA 430-R-21-003. Achakulwisut, P., Anenberg, S.C., Neumann, J.E., Penn, S.L., Weiss, N., Crimmins, A., Fann, N., Martinich, J., Roman, H. and Mickley, L.J., 2019. Effects of increasing aridity on ambient dust and public health in the US Southwest under climate change. GeoHealth, 3(5), pp.127-144. https://doi.org/10.1029/2019GH000187

Data Type	Description	Data Documentation and Availability
		GEOS-Chem chemical transport model (Version 12.6). Available from http://acmg.seas.harvard.edu/geos/
Emissions inventory estimates	**Climate Penalty:** 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 • A 2040 emissions inventory which accounts for the implementation of a suite of Federal, state, and local air quality regulations on stationary mobile sources.	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-emissionsinventories/2011-national-emissions-inventorynei-data
Baseline health effect incidence rates	Mortality incidence rates projected from 2000 through 2060 were obtained from BenMAP-CE for one age group (postneonatal infants). Incidence rates for new cases of asthma were obtained from BenMAP-CE for three age groups (0-4, 5-11, and 12-17). Asthma prevalence rates were obtained from BenMAP-CE for two age groups (0-4 and 5-17). Asthma-related ED morbidity incidence rates were obtained from BenMAP-CE for one age group (0-17). Incidence rates for respiratory-related hospital admissions were obtained from BenMAP-CE for two age groups (0-1, 2-17, and 18-24). Prevalence rates of hay fever/rhinitis were obtained from BenMAP-CE for one age group (3-17). Baseline school days lost were obtained from BenMAP-CE for one age group (5-18).	U.S. EPA. (2023). Environmental Benefits Mapping and Analysis Program: Community Edition (BenMAP-CE) User Manual and Appendices. Washington, DC.
Future population of children	*See Appendix A for data sources*	
Demographics for social vulnerability analysis	*See Appendix A for data sources*	

Wildfire Smoke and Fetal Health

Chapter 4 features research on wildfire smoke exposure and risk of preterm births, a maternal health effect that may be exacerbated by climate change. This analysis estimates an additional 7,700 and 13,600 premature births per year at 2°C and 4°C of global warming, respectively, attributable to wildfire annually based on findings from Heft-Neal et al. (2022)[15], information on singleton births in 2010 from CDC[16], and population-weighted $PM_{2.5}$ concentrations associated with western wildfire smoke from Neumann et al. (2021).[17] Heft-Neal et al. estimated that 3.7% of preterm births in California were attributable to wildfire smoke exposure during the study period (2007-2012). This percentage is applied to the total number of singleton births in the continental U.S. from CDC in 2010 to estimate the number of births attributable to wildfire nationally in the baseline period. Total premature births associated with wildfire in the baseline period were multiplied by a ratio of change in wildfire-attributable $PM_{2.5}$ concentrations at 2°C and 4°C of global warming to estimate additional premature births associated with wildfire smoke with global warming. Finally, baseline wildfire-attributable premature births were subtracted from projected premature births to estimate the incremental number of premature births presented above and in Chapter 4.

DATA SOURCES

Table 8: Summary of Data Sources Used in the Wildfire Smoke and Fetal Health Analysis

Data Type	Description	Data Documentation and Availability
Number of premature births	National count of singleton births in 2010 and preterm singleton birth rate for 2010.	Centers for Disease Control and Prevention. 2012. "Births: Final Data for 2010." National Vital Statistics Reports (NVSS), 61(1). Available at: https://www.cdc.gov/nchs/data/nvsr/nvsr61/nvsr61_01.pdf
Future wildfire-attributable $PM_{2.5}$	Change in population-weighted wildfire-attributable $PM_{2.5}$ concentrations by degree used to scale the number of preterm births attributable to wildfire in the baseline period.	Neumann, J.E., Amend, M., Anenberg, S., Kinney, P.L., Sarofim, M., Martinich, J., Lukens, J., Xu, J.W. and Roman, H., 2021. Estimating PM2. 5-related premature mortality and morbidity associated with future wildfire emissions in the western US. Environmental Research Letters, 16(3), p.035019.
Wildfire-attributable preterm births	Baseline count of premature births estimated from percentage of premature births attributable to wildfire (2007-2012).	Heft-Neal, S., Driscoll, A., Yang, W., Shaw, G. and Burke, M., 2022. Associations between wildfire smoke exposure during pregnancy and risk of preterm birth in California. Environmental Research, 203, p.111872.

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