IEc

Analysis of $PM_{2.5}$-Related Health Burdens Under Current and Alternative NAAQS

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EXECUTIVE SUMMARY

BACKGROUND AND RESEARCH OBJECTIVES

Air pollution is the greatest environmental health risk worldwide. Fine particle matter ($PM_{2.5}$) pollution is comprised of inhalable solid particles and liquid aerosols that are smaller than 2.5 microns in diameter. These fine particles can penetrate deep into the lungs and can enter the bloodstream, posing risks of cardiovascular, respiratory, and neurological diseases. In the United States, populations of color and those who experience low income bear a disproportionate burden of health impacts associated with $PM_{2.5}$ exposure. The United States Environmental Protection Agency (U.S. EPA) is required to use the best available science to set ambient air quality standards that are protective of human health, considering particularly vulnerable people within our communities.

Currently, the primary National Ambient Air Quality Standard (NAAQS) for annual mean $PM_{2.5}$ concentrations is 12 $\mu g/m^3$. EPA published its draft Policy Assessment (PA) for the Reconsideration of the National Ambient Air Quality Standards for Particulate Matter in October 2021, part of its periodic re-evaluation of the health protectiveness of the current standard. The draft PA evaluates the policy implications of available scientific research on the health and welfare effects of ambient PM and considers whether the current standards provide adequate public health protection. As our understanding of air pollution and its impacts on human health have developed through peer-reviewed epidemiological and toxicological research, EPA has made PM standards more protective of public health over time. In the recent draft PA, EPA concludes that currently available scientific evidence provides support for tighter standards:

> "When taken together, we reach the conclusion that the available scientific evidence, air quality analyses, and the risk assessment… can reasonably be viewed as calling into question the adequacy of the public health protection afforded by the combination of the current annual and 24-hour primary $PM_{2.5}$ standards" (p. 3-188).

Further, a variety of epidemiological studies presents strong evidence that historically disadvantaged groups, such as Black and Hispanic communities, are exposed to higher $PM_{2.5}$ concentrations than white and non-Hispanic populations, contributing to increased risk of PM-related adverse health effects (Mikati, 2018; Nachman and Parker, 2012; Basu, 2004).

In this report, we assess both the current health burden of $PM_{2.5}$ and potential benefits of achieving lower, more health protective $PM_{2.5}$ standards, making use of fine scale data that reflects spatial variance in air quality, population, and baseline health. Use of these fine-scale datasets enables us to assess the distribution of burden and potential benefits across racial and ethnic population subgroups, as well as those experiencing poverty. We highlight three specific research objectives addressed in this report:

- Characterize the $PM_{2.5}$-attributable health burden under the current $PM_{2.5}$ concentrations,

- Perform distributional analyses to estimate potential benefits from lower $PM_{2.5}$ NAAQS standards across racial and ethnic groups, and those experiencing poverty, and
- Assess the sensitivity of $PM_{2.5}$ estimates to the exposure model selected and the spatial scale of supporting demographic and health data.

CURRENT $PM_{2.5}$ EXPOSURE AND HEALTH BURDEN

Using EPA's BenMAP-CE program, we quantify the current $PM_{2.5}$-attributable health outcomes across racial and ethnic groups. First, we assess how different racial and ethnic groups are exposed to differing concentrations of $PM_{2.5}$ nationwide. Exhibit ES-1 shows the fraction of the Hispanic and non-Hispanic populations currently exposed to different $PM_{2.5}$ concentrations based on the 1 x 1 km air quality surface from Di et al. (2019). Concentrations above 10 µg/m^3 are highlighted to emphasize the differences in exposure by ethnicity.

EXHIBIT ES-1. PROPORTION OF POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 10 µg/m^3, ETHNICITY-STRATIFIED

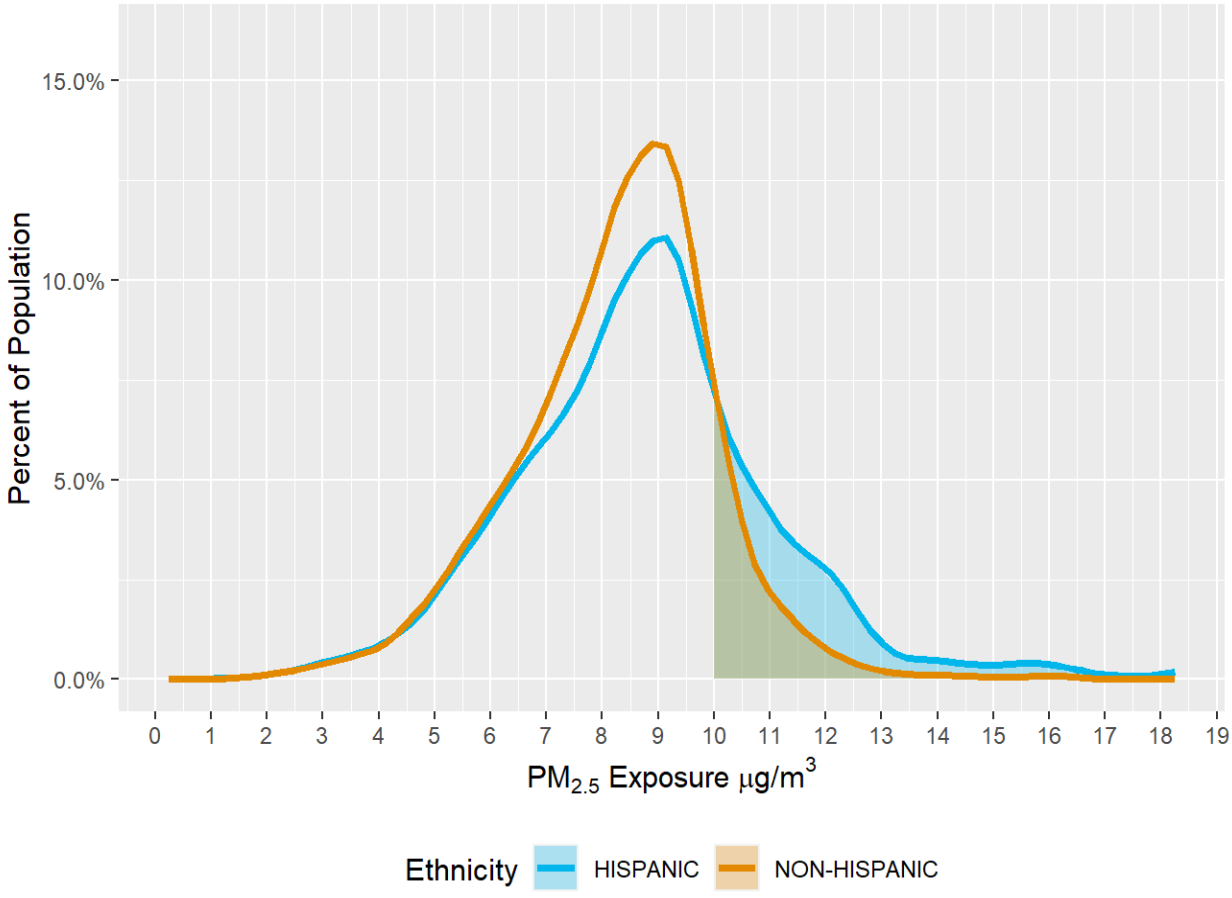


Exhibit ES-1 is clear: Hispanic Americans are consistently exposed to higher concentrations of $PM_{2.5}$ than non-Hispanic populations. These patterns are similarly present by race (not depicted); with the exception of Native Americans (45%), **a greater fraction of nonwhite Americans (67 to 74%) is exposed to $PM_{2.5}$ concentrations above 8 µg/m^3, compared to 59% of the white population.** Additionally, low-

income populations currently have 49% higher likelihood of living in areas that exceed 12 µg/m3 in comparison to wealthier populations. This difference drops to low-income populations having 5% higher likelihood of living in areas that exceed 8 µg/m3.

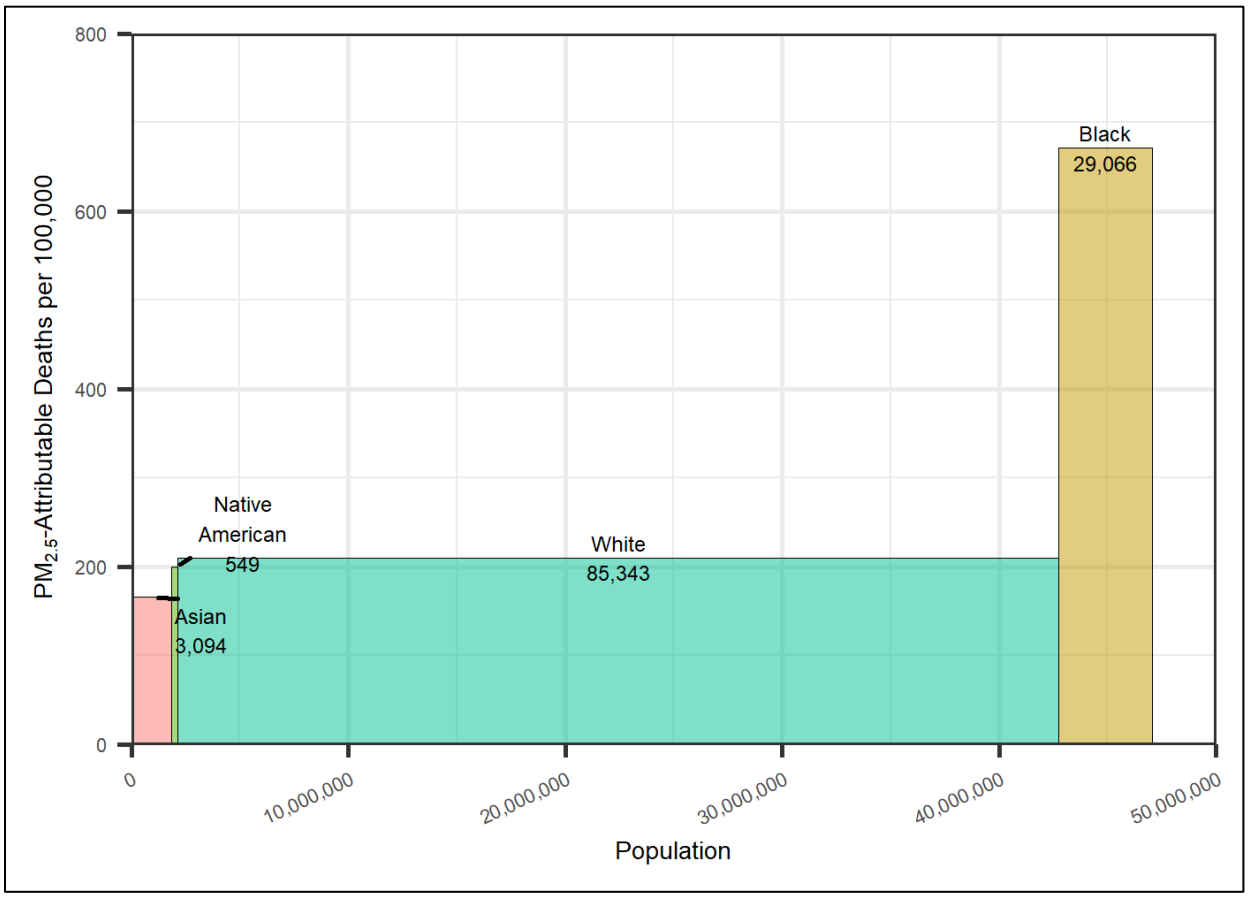
Next, we estimate PM-attributable mortality and morbidity and, where possible, stratify by race and/or ethnicity. We present PM-attributable mortality rates in Exhibit ES-2 using Di et al. (2017) race-specific concentration-response functions. On average, we estimate that among individuals ages 65 and up, 300 deaths per 100,000 population result from particulate matter exposure. This value varies significantly by race: Black populations experience a heightened PM-attributable mortality rate (670 deaths per 100,000) relative to other races (170 to 210 per 100,00). While not depicted, we also find a heighted mortality rate for Hispanic populations (260 deaths per 100,00).

EXHIBIT ES-2. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY RATE (PER 100,000)

RACE	PM-ATTRIBUTABLE MORTALITY (PER 100K)
Asian	170
Black	670
Native American	200
White	210
All	**300**

Exhibit ES-3 further depicts current $PM_{2.5}$-attributable mortality risk by race. The width of each rectangle indicates the total population of each race for the given geographic scale, and the height represents the $PM_{2.5}$-attributable mortality rate of each race, reported per 100,000 persons of each racial group. Thus, the area of each rectangle is representative of the current $PM_{2.5}$-attributable burden for each race, which is reported by racial group. The order of races in this figure represents increasing mortality burden per capita moving across the horizontal axis.

EXHIBIT ES-3. CURRENT NATIONAL $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN BY RACE



In total, we estimate roughly 110,000 deaths result from $PM_{2.5}$ exposure on an annual basis. These deaths are disproportionately borne by Black and Hispanic populations. **Black populations aged 65+ experience three times as many PM2.5-attributable deaths per capita compared to all other races.** In addition, we estimate significant PM-attributable burden of non-fatal health outcomes, displayed in Exhibit ES-4.

EXHIBIT ES-4. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN (ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION-RESPONSE FUNCTION	AGE GROUP	PM-ATTRIBUTABLE CASES
HOSPITALIZATIONS			
Non-fatal acute myocardial infarction (AMI)	Peters et al. (2001)	18-99	110,000
Non-fatal AMI	Pooling 5 Studies*	18-99	17,000
All Respiratory	Ostro et al. (2016)	0-18	9,900
Respiratory-1	Jones et al. (2015)	0-99	6,100
Respiratory-2	Bell et al. (2015)	65-99	2,100
Cardio-, Cerebro- & Peripheral Vascular Disease	Bell et al. (2015)	65-99	13,000
All Cardiac Outcomes	Talbott et al. (2014)	0-99	12,000
Alzheimer's Disease	Kioumourtzoglou et al. (2016)	65-99	27,000
Parkinson's Disease	Kioumourtzoglou et al. (2016)	65-99	4,500
EMERGENCY ROOM VISITS			
Respiratory	Krall et al. (2016)	0-99	75,000
Emergency Hospitalizations – Respiratory**	Zanobetti et al. (2009)	65-99	21,000
INCIDENCE			
Asthma	Tetreault et al. (2016)	0-17	260,000

Note: values are rounded to two significant figures
*Five AMI studies pooled together include: Pope et al., Sullivan et al., Zanobetti and Schwartz, and Zanobetti et al.
**Emergency Hospitalizations represent emergency department visits that result in a hospitalization.
Attributable burden assumes 100% reduction in fine PM and no threshold below which PM morbidity impacts are not observed.

Notably, the morbidity estimates presented in Exhibit ES-4 are not stratified by race or ethnicity due to data limitations. First, the incidence data commonly employed in these analyses (i.e., the default datasets in BenMAP-CE) are not stratified by race or ethnicity. Second, few epidemiological studies of non-fatal PM effects estimate separate concentration-response functions for these demographic variables. One exception, however, is Alhanti et al. (2016), which provides estimates of PM attributable pediatric asthma emergency department (ED) visits stratified by racial-ethnic groups. More specifically, the authors provide separate concentration-response relationships for (a) white, non-Hispanics and (b) non-White and/or Hispanic populations. Exhibit ES-5 presents asthma ED burden per capita (100,000) for these groups.

EXHIBIT ES-5. CURRENT $PM_{2.5}$-ATTRIBUTABLE ASTHMA ED BURDEN

RACE/ ETHNICITY	ASTHMA ED VISITS (PER 100K)
White, Non-Hispanic	10
White Hispanic or Non-white	58

The disparities in PM-attributable asthma ED burden appear even starker than those for mortality burden. More specifically, the Alhanti et al. effect coefficients result in a **six times higher asthma ED visit burden for non-white and white Hispanic populations (relative to white non-Hispanic populations)**.

BENEFITS OF ALTERNATIVE ANNUAL $PM_{2.5}$ STANDARDS

Next, we assess the potential benefits of lowering the annual $PM_{2.5}$ standard by examining the PM-attributable health burden associated with standards of 8 and 10 $\mu g/m^3$. Using the Di et al. (2019) 1 x 1 km air quality surface as a baseline, we model alternative standards using two complementary approaches. First, in areas modeled by EPA, we reduce $PM_{2.5}$ concentrations by the same proportion as in the PA. For example, in an area where EPA-modeled $PM_{2.5}$ concentrations dropped from 14 to 7 $\mu g/m^3$ (a 50% reduction), we would apply an identical relative reduction in concentrations of Di et al. modeled values in that area. Second, we conduct a simplistic "rollback to standard" in areas not modeled by EPA. For example, under a standard of 8 $\mu g/m^3$, all concentrations above the standard would be set to 8.

The potential benefits of lower $PM_{2.5}$ standards are sizable. **In total, we estimate roughly 4,800 avoided PM-attributable deaths associated with moving to a standard of 10 $\mu g/m^3$ and 19,600 avoided PM-attributable deaths associated with 8 $\mu g/m^3$**. Exhibit ES-6 presents these benefits stratified by race and normalized by population. The exhibit further distinguishes between the two standards and by the areas analyzed by EPA ("PA Areas") and areas outside of the EPA study area ("Non-PA Areas").

EXHIBIT ES-6. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS PER 100,000, BY ALTERNATIVE NAAQS

CONCENTRATION - RESPONSE RELATIONSHIP	RACE	ETHNICITY	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
			10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Hispanic	All	Hispanic	20	44	2	48	91	17
Total All Races	**All**	**All**	10	32	**1**	35	79	17
Asian	Asian	All	14	26	1	33	56	11
Black	Black	All	28	69	3	110	190	58
Native American	Native American	All	8	40	1	21	74	8
White	White	All	8	26	1	27	64	14

Note: Values are rounded to two significant figures. All values are expressed in terms of avoided PM-attributable deaths per 100,000 individuals ages 65+.

Several patterns emerge from Exhibit ES-6. First, unsurprisingly, the 8 $\mu g/m^3$ standard results in greater benefits relative to the 10 $\mu g/m^3$ standard – **the potential mortality risk reductions under the lower standard are roughly two to three times greater**. This relationship is heightened when looking at specific demographic groups. For example, **the 8 $\mu g/m^3$ standard results in three to four times greater mortality risk reductions than the 10 $\mu g/m^3$ standard for white and Black Americans, and in the non-PA areas the 8 $\mu g/m^3$ standard mortality risk reduction is over five times higher for all groups**.

Individuals experiencing poverty would see 30% higher mortality benefits per capita from more 8 µg/m^3 standard than a 10 µg/m^3 standard.

Non-PA areas experience a negligible share of per capita benefits across all groups at 10 µg/m^3 but comprise a meaningful share (50%) of per capita benefits when the standard is lowered to 8 µg/m^3. This pattern is highlighted further in Exhibit ES-7.

EXHIBIT ES-7. MORTALITY BURDEN UNDER CURRENT AND ALTERNATIVE PM NAAQS

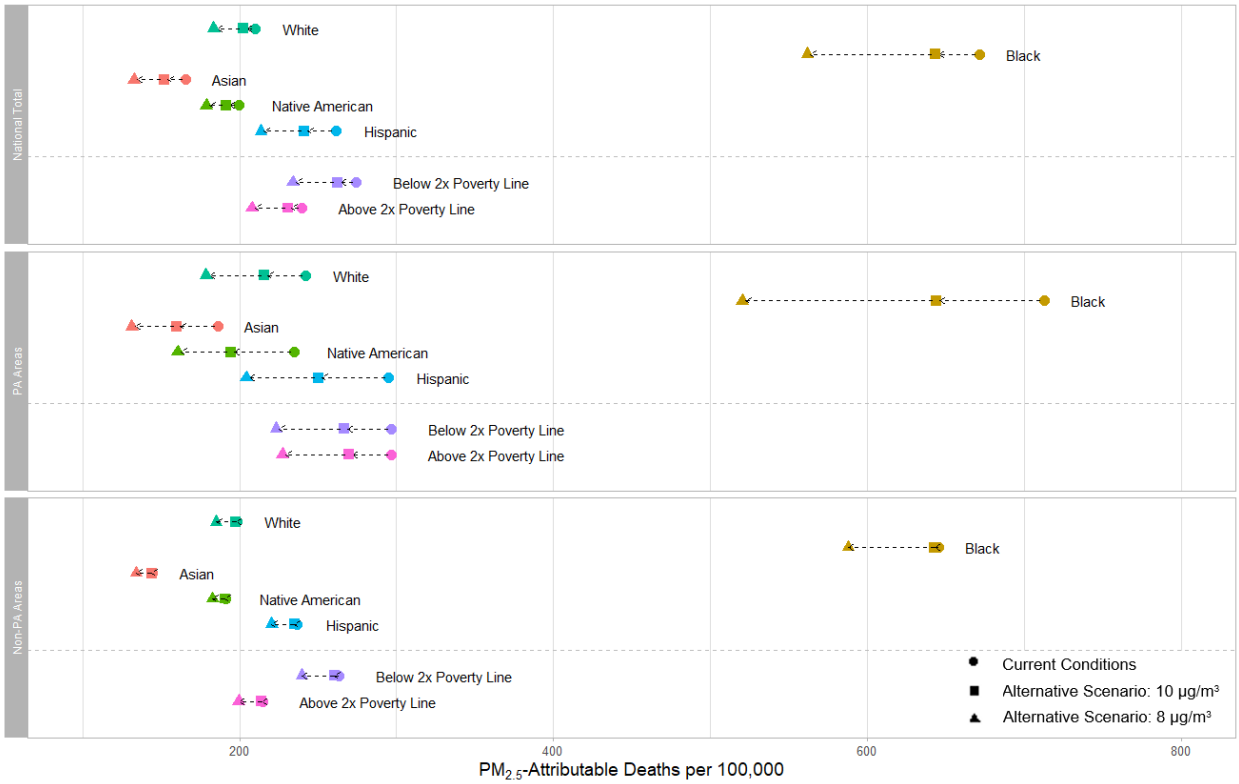


Exhibit ES-7 demonstrates that PA areas experience larger benefits from lowering the current NAAQS on an individual basis, compared to non-PA areas. This occurs because more of the high-exposure individuals live in the CBSA areas modeled in the PA. This supports the previous finding that while benefits are experienced in both PA and non-PA areas, as the NAAQS is lowered past 10 µg/m^3, PA areas potentially experience much higher risk reductions relative to non-PA areas, because of the significant portions of individuals, particularly minorities exposed to concentrations between 10 and 8 µg/m^3.

CONCLUSIONS

In this report, we used more finely resolved data sources for air quality, baseline health status, demographics, and risk to estimate the health burden of $PM_{2.5}$ exposures in the U.S., both in total and across races, ethnicities, and poverty status. We also estimated the potential benefits of more health protective $PM_{2.5}$ standards in the U.S. across these subgroups. Our results have provided insights into the distribution of health burdens and the potential to both improve public health generally and reduce discrepancies in risk across subgroups by adopting more protective annual NAAQS standards. Further,

the results suggest there is value to using analytical inputs at finer geographic scales and inputs particular to specific subpopulations to better understand variabilities in risks.

Overall, our results bolster the findings in EPA's most recent PA; current $PM_{2.5}$ concentrations result in significant premature mortality and morbidity nationwide, and these impacts are disproportionately borne by Black and Hispanic populations, and those living in poverty. Strengthening PM NAAQS would lessen both the overall social costs of air pollution and the disparities in health outcomes by race, ethnicity, and income levels. Nonetheless, we anticipate that significant disparities would persist under lower standards due to (1) higher age-specific baseline mortality incidence in non-White populations and (2) stronger PM-mortality response among these populations, as estimated by emerging epidemiological research. Further, this work provides valuable results that can be broken down across four axes: 1) the importance of spatial resolution of annual average $PM_{2.5}$ concentrations in understanding related health impacts; 2) the distribution of health impacts across groups as defined by race, ethnicity, and income; 3) expansion upon the important work done by EPA in their most recent PA, and 4) state-level application of our method.

CHAPTER 1 | INTRODUCTION

BACKGROUND

Air pollution is the greatest environmental health risk worldwide, with much of that risk due to exposures to fine particles (Health Effects Institute, 2020). Fine particulate matter ($PM_{2.5}$) pollution results from a variety of sources consists of a mixture of inhalable solid particles and liquid aerosols that are smaller than 2.5 microns in diameter, much smaller than a human hair. These fine particles are small enough to penetrate deep into the lungs and enter the bloodstream, making them particularly hazardous. Exposure to $PM_{2.5}$ causes heart, lung, and other diseases, which result in emergency department visits, hospitalizations, missed days of work and school, and even death. In the United States, populations of color and those who experience low income bear a disproportionate burden of health impacts associated with $PM_{2.5}$ exposure (Morello-Frosch et al., 2001; Morello-Frosch et al., 2002; Schweitzer and Zhou, 2010; Miranda et al., 2010; Sadd et al., 2011). The United States Environmental Protection Agency (U.S. EPA) is required to use the best available science to set ambient air quality standards to protect human health, including the health of particularly vulnerable people within our communities. The U.S. EPA publishes ambient standards on a daily and annual basis for $PM_{2.5}$.[1] Currently, the primary National Ambient Air Quality Standards (NAAQS) for these pollutants are:

- **Annual mean $PM_{2.5}$ standard:**[2] 12 $\mu g/m^3$
- **Daily mean $PM_{2.5}$ standard:**[3] 35 $\mu g/m^3$

As part of its periodic re-evaluation of the $PM_{2.5}$ NAAQS, the United States Environmental Protection Agency (EPA) published in October 2021 its draft Policy Assessment (PA) for the Reconsideration of the National Ambient Air Quality Standards for Particulate Matter. The draft PA evaluates the policy implications of available scientific research on the health and welfare effects of ambient PM and considers whether the current standards provide adequate public health protection. In doing so, EPA evaluates the potential benefits stemming from lower standards and discusses accompanying uncertainties.

As our understanding of air pollution and its impacts on human health have developed through peer-reviewed epidemiological and toxicological research, EPA has made PM standards more protective of

[1] EPA publishes both primary and secondary standards for PM: "Primary standards provide public health protection, including protecting the health of "sensitive" populations such as asthmatics, children, and the elderly. Secondary standards provide public welfare protection, including protection against decreased visibility and damage to animals, crops, vegetation, and buildings." See https://www.epa.gov/criteria-air-pollutants/naaqs-table. In this report, we focus on the primary annual mean standards for $PM_{2.5}$.

[2] The annual $PM_{2.5}$ standard is mean annual concentrations averaged over a 3-year window.

[3] The daily $PM_{2.5}$ standard is the 98th percentile of daily mean concentrations over a 3-year window.

public health over time. In the recent draft PA, EPA concludes that currently available scientific evidence provides support for tighter standards:

> "When taken together, we reach the conclusion that the available scientific evidence, air quality analyses, and the risk assessment… can reasonably be viewed as calling into question the adequacy of the public health protection afforded by the combination of the current annual and 24-hour primary $PM_{2.5}$ standards" (p. 3-188).

Further, a variety of epidemiological studies present strong evidence that historically disadvantaged groups, such as Black and Hispanic communities, are exposed to higher $PM_{2.5}$ concentrations than white and non-Hispanic populations, contributing to increased risk of PM-related adverse health effects (Mikati, 2018; Nachman and Parker, 2012; Basu, 2004). While EPA estimates considerable public health benefits from lowering the annual and 24-hour standards, the Agency notes some uncertainties regarding which alternative standard(s) are best supported by scientific research.

RESEARCH OBJECTIVES

In this report, we assess both the current health burden of $PM_{2.5}$ and potential benefits of achieving stronger $PM_{2.5}$ standards, making use of fine scale data that reflects spatial variance in air quality, population, and baseline health. Use of these fine-scale datasets enables us to assess the distribution of burden and potential benefits across racial and ethnic population subgroups, as well as those experiencing poverty. We highlight three specific research objectives addressed in this report:

- **Characterize the $PM_{2.5}$-attributable health burden under current conditions**. In doing so, we consider how exposure, deaths and other adverse $PM_{2.5}$ effects vary across racial and ethnic groups and across different income levels under $PM_{2.5}$ concentrations as currently experienced.
- Perform distributional analyses to estimate potential benefits from lower $PM_{2.5}$ NAAQS standards across racial and ethnic groups, and those experiencing poverty. Increased policy emphasis on environmental justice requires a better understanding of the air pollution-related health burdens experienced by historically underserved groups. A growing body of literature explores racial-ethnic disparities in air pollution exposure (Rosofsky et al., 2018; Tessum et al, 2019; Colmer et al, 2020; Tessum et al, 2021) and epidemiological studies such as Di et al. 2017 are reporting differential estimates of risk to different racial-ethnic groups for the same increment in $PM_{2.5}$ exposure. In this analysis, we assess risks to various racial groups and those experiencing poverty. By modeling more protective annual $PM_{2.5}$ standards of 8 and 10 $\mu g/m^3$, we also assess the potential benefits that may accrue to these groups and how the relative disparities in burden change under reduced fine particle standards.
- Assess the sensitivity of $PM_{2.5}$ estimates to the exposure model selected and the spatial scale of supporting demographic and health data. Hybrid exposure models that combine multiple data sources, including regulatory monitors, satellite-based estimates, photochemical modeling and other data, show promise for identifying exposure gradients at finer spatial scales We explore how applying finer-scale input data for air quality and for other relevant inputs in EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) tool can affect health burden or benefit estimates both in the aggregate and in terms of the distribution of health burdens across subpopulations of the United States.

GENERAL APPROACH

Broadly, IEc's assessment of lower annual $PM_{2.5}$ standards involves (1) characterizing the geographic distribution of baseline annual $PM_{2.5}$ concentrations corresponding to the current conditions under the existing standard and the distribution of these concentrations under more protective NAAQS alternatives; (2) estimating the changes in health effects attributable to a particular policy compared to the baseline; and (3) economic valuation of these effects. We estimate the impact of ambient $PM_{2.5}$ on health outcomes (e.g., premature mortality or morbidity endpoints) by assessing the difference in risk under a baseline and control scenario, where the latter represents improved air quality under more protective NAAQS. For this analysis, we use BenMAP-CE, an open-source program that allows users to estimate health and related economic impacts from changes in ambient air pollution. BenMAP-CE relies on epidemiological concentration-response functions to quantify the change in incidence of adverse health impacts stemming from changes in ambient pollutant concentrations. Additional detail on our technical approach can be found in Appendix E.

REPORT CONTENTS

This report applies a standard analytic framework for assessing environmental health benefits, but using some of the latest available input data to better characterize the distribution of benefits across subpopulations. This document is organized as follows:

- In Chapter 2, we characterize current $PM_{2.5}$ concentrations and estimate PM-attributable mortality and morbidity. We discuss the factors influencing disparities by race, ethnicity and income level, including $PM_{2.5}$ exposure, baseline incidence, and evidence from epidemiological research.
- In Chapter 3, we present air quality and health benefits modeling results for alternative standards of 8 and 10 $\mu g/m^3$.
- In Chapter 4, we provide a state-level case study on the impact of fine-scale morbidity incidence data using results from New Jersey.
- Finally, we summarize the results and discuss the implications of this work in Chapter 5.
- This report also has five appendices: Appendix A provides details regarding the air quality surfaces we used in this analysis; Appendix B presents additional graphics summarizing key inputs to the analysis; Appendix C presents supplemental graphics of exposures based on the fine scale air quality data; Appendix D includes supplemental results for health impacts, including state-level results; and Appendix E presents a memo describing the overall methodology for the analysis.

CHAPTER 2 | CURRENT $PM_{2.5}$-ATTRIBUTABLE HEALTH BURDEN

In this chapter, we estimate current $PM_{2.5}$-attributable health burdens related to $PM_{2.5}$ exposures nationwide using $PM_{2.5}$ air quality estimates from the year 2015. We analyze the impacts of increasingly fine scale data for air quality, health, and demographics to help us to better understand not only total health burden, but how those burdens are distributed across race, ethnicity, and poverty status.

We briefly review our approach to the current conditions analysis, then provide a characterization of the exposures experienced by different subpopulations based on spatial distribution. We investigate the implications of $PM_{2.5}$ exposures for mortality among different groups. We conclude this chapter by discussing the effect of applying fine scale modeling on $PM_{2.5}$ exposure and burden estimates and discuss three factors affecting the overall $PM_{2.5}$-attributable burden of each group: exposure, baseline mortality, and concentration-response relationships.

APPROACH OVERVIEW

Our approach applies the standard methods for air pollution health impact assessment used by EPA in its recent PA and in other regulatory analyses; using this standard framework, we conduct multiple model runs that vary in the data sets used to characterize variations in air quality, baseline health status, and the level of hazard posed by $PM_{2.5}$. We apply these different data sets to better model spatial variation (e.g., in air quality), variation across subpopulations (e.g., level of hazard), or both (e.g. baseline health status). We then compare across these runs to assess the impact of these alternative data sources on health burden or health benefit results. For example, we apply a 1 x 1 km air quality surface and compare to results generated using a 12 x 12 km resolution air quality surface (EPA, 2021). Appendices A, B, and E provide additional details of our framework and methodology in developing BenMAP-CE runs that estimate current burden.

The PA focuses on $PM_{2.5}$-attributable health burden for 47 core based statistical areas (CBSAs) expected to be most affected by changes in the PM NAAQS ("PA areas"), and its 12 x 12 km air quality surface is restricted to these areas, which cover many major population centers in the U.S. We expand on the geographic coverage of the PA to provide additional perspective regarding the potential magnitude of the PM mortality burden in the country, estimating health burden for three different geographic scales: (1) the contiguous United States ("Nation"), (2) PA areas, and (3) all areas not modeled in the PA ("non-PA areas"). This allows us to evaluate how estimates based on fine scale datasets compare to those that use datasets from the PA, while also providing a sense of the potential for health impacts in the rest of the country.[4].

[4] Not that our results, even those for PA areas, are not directly comparable to the published results in EPA's PA document. This reflects differences in the air quality conditions we use as baseline or reference conditions. We define the baseline as current $PM_{2.5}$ exposures from 2015, as a reflection of conditions under the current NAAQS. In the PA, EPA defines baseline as PM2.5 exposures under a hypothetical scenario modeled to

We evaluate improvements to the geographic scale and/or racial or ethnic specificity of the following key inputs to a health burden or health benefit analysis: 1) air quality; 2) demographics, including population and poverty status; 3) baseline health status (e.g. current mortality rates from all causes of death); and 4) measures of the effects of exposure to particles on mortality or emergency department visits.

Our selection of fine-scale and racially or ethnically stratified inputs is based on careful review and consideration of alternative models and datasets derived using current, peer-reviewed modeling techniques or obtained from reputable sources such as the Agency for Health Care Research and Quality's Healthcare Cost and Utilization Project (HCUP). Additional details of model considerations and rationale for data set selections can be found in Appendix E.

VARIATIONS IN CURRENT $PM_{2.5}$ EXPOSURE

Spatial variability in $PM_{2.5}$ concentration and where people live result in different exposure profiles for different groups. Exhibit 2-1 shows the fraction of each race's population currently exposed at each PM concentration in the contiguous U.S., based on the 1 x 1 km air quality surface from Di et al. (2019). Curves that are taller and shifted further to the right indicate higher levels of exposure for a particular group. Exhibits 2-1 and 2-2 use shading to emphasize populations exposed to $PM_{2.5}$ concentrations above 10 and 8 $\mu g/m^3$, respectively, and Exhibit 2-3 provides a tabular summary of these differences. We present assessments of the health impacts associated with exposure between the current and alternative NAAQS standards in Chapter 3. We present similar graphics that show the proportion of population exposed to $PM_{2.5}$ concentrations by ethnicity in Appendix C.

just meet the current NAAQS in which concentrations in some areas may be higher or lower than currently measured. EPA's approach is appropriate for the PA's policy evaluation objectives but is less well suited to our assessment of current burden. Thus, in order to facilitate a fairer comparison of our results with EPA's 12 km air quality-based results, we take EPA's approach in the PA an apply it to a separate baseline 12 km x 12 km 2015 current conditions air quality surface modeled by the agency and published in the PA docket (EPA, 2021).

EXHIBIT 2-1. PROPORTION OF POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS 10+ µG/M³

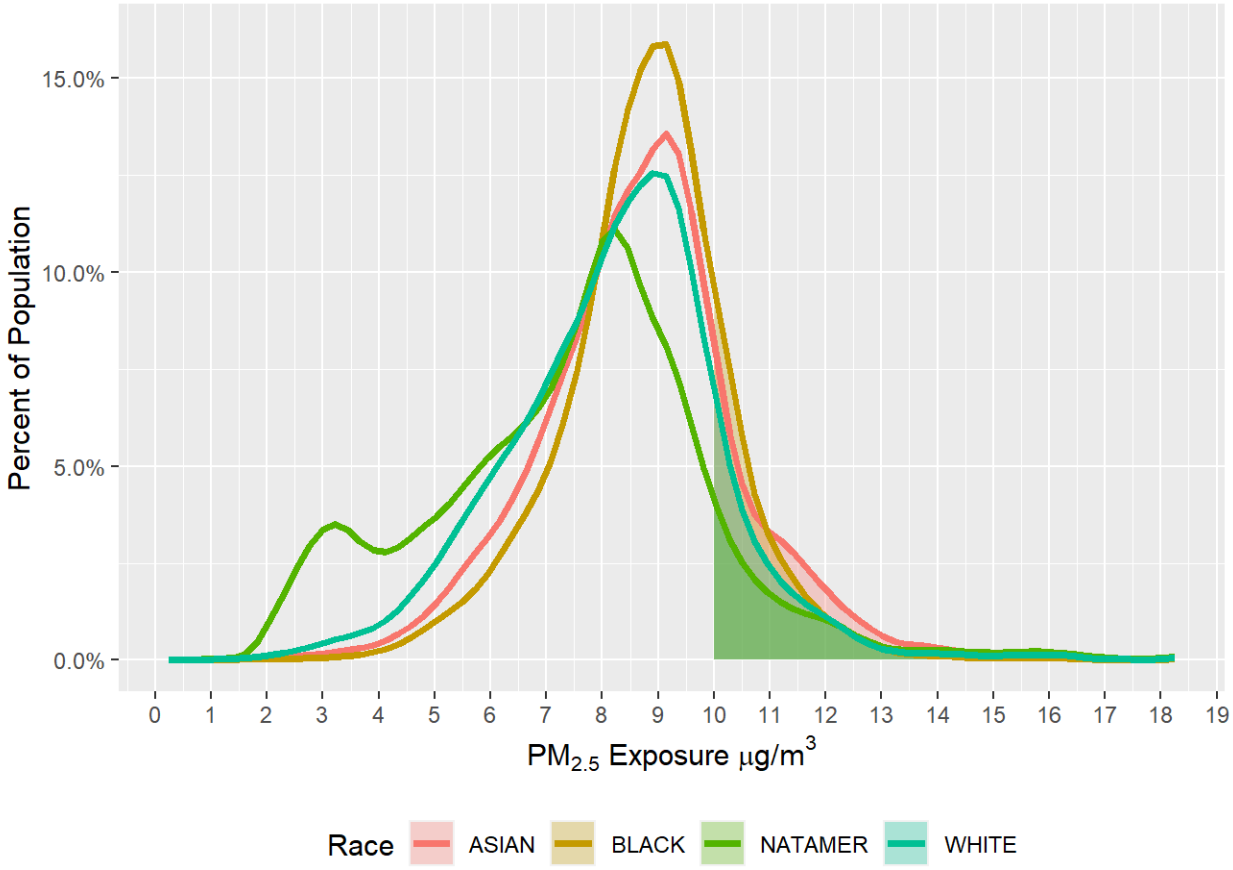


EXHIBIT 2-2. PROPORTION OF POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS 8+ µG/M³

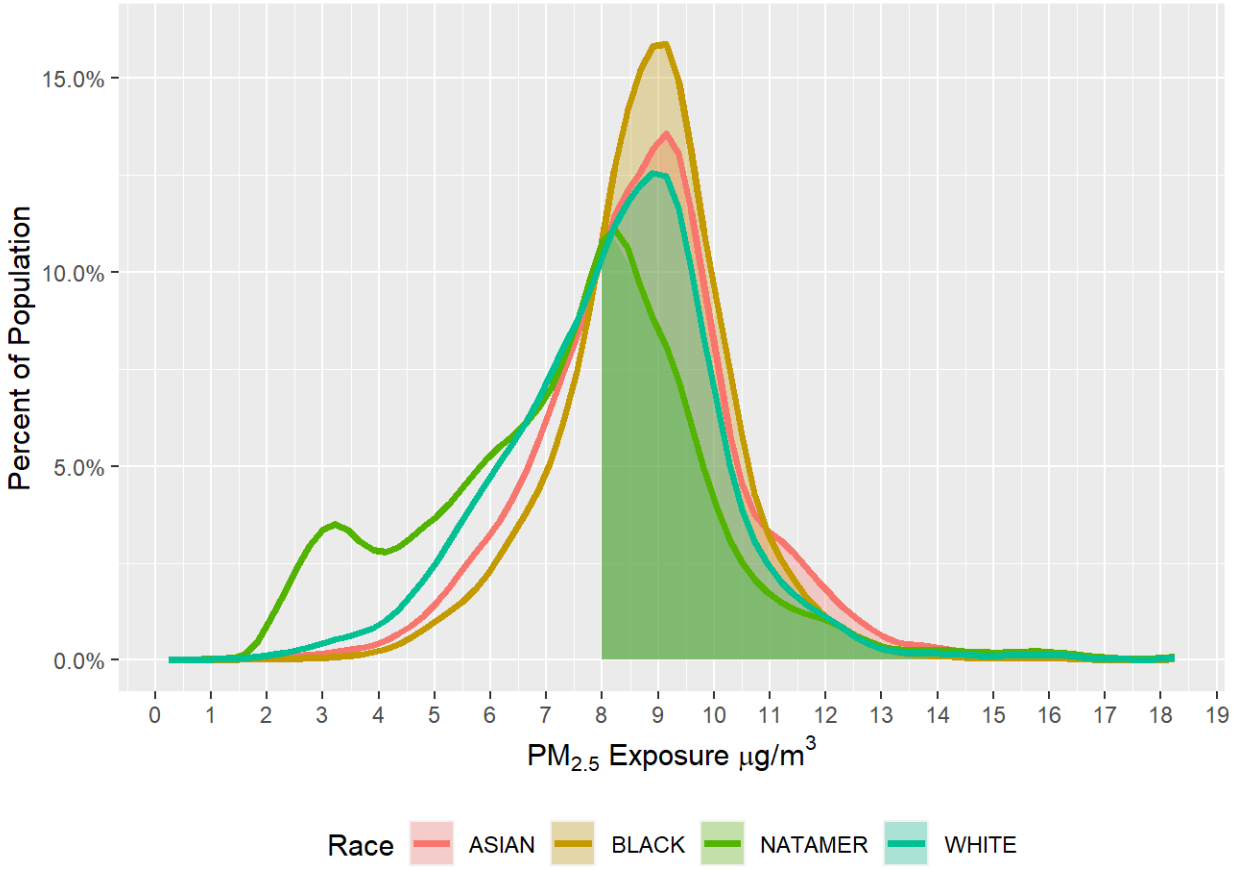


EXHIBIT 2-3. PROPORTION OF POPULATION AGED 0-99 EXPOSED AT VARIOUS $PM_{2.5}$ CONCENTRATIONS

RACE	ETHNICITY	PERCENT OF POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS: > 12 µg/m³	> 10 µg/m³	> 8 µg/m³	BETWEEN 10 & 12 µg/m³	BETWEEN 8 & 10 µg/m³
Asian	All	4%	19%	67%	15%	48%
Black	All	2%	18%	74%	16%	56%
Native American	All	3%	11%	45%	8%	34%
White	All	3%	14%	59%	11%	45%

Values do not sum across rows

As shown in Exhibits 2-1 through 2-3, Black Americans are consistently exposed to higher concentrations of $PM_{2.5}$ than white Americans. At concentrations between 8 and 10 µg/m³, 56% of Black Americans versus 45% of white Americans. When we include any concentrations over 8, Black and Asian Americans are much more likely to be exposed to these levels (74% and 67%, respectively than white Americans (59%), while Native Americans (45%) are less likely to be exposed at these levels.

75% of Black Americans are exposed to PM2.5 concentrations greater than 8 µg/m3 each year, compared to 59% of white Americans.

CURRENT (2015) $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN

We present below mortality burden attributable to $PM_{2.5}$ exposures under current conditions in the U.S., first presenting total numbers of attributable deaths for the nation as a whole and then exploring how this risk burden varies across, race, and poverty status.

TOTAL NATIONAL-LEVEL PM-ATTRIBUTABLE MORTALITY BURDEN

Exhibit 2-4 shows current (2015) $PM_{2.5}$-attributable mortality burden for all races and ethnicities at three geographic scales, estimated using a tract-level mortality incidence and air quality datasets of varying spatial scales. These estimates reflect current burden using incidence datasets that are not stratified by race and ethnicity.

EXHIBIT 2-4. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN USING FINE-SCALE INCIDENCE (TOTAL DEATHS, ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION – RESPONSE FUNCTION	AGE GROUP	NATION	PA AREAS		NON-PA AREAS
			1KM	12KM	1KM	1KM
All Cause Mortality	Turner et al. (2016)	30-99	120,000	43,000	40,000	83,000
	Di et al. (2017)	65-99	110,000	40,000	37,000	77,000
Note: values are rounded to two significant figures. Attributable burden assumes 100% reduction in fine PM and no threshold below which PM mortality impacts are not observed.						

We estimate current mortality burden nationally to be 120,000 across adults aged 30-99 using fine scale air quality and baseline incidence data, with the majority of this burden falling within the 65 to 99 age group (110,000). Applying the standard economic value from EPA's BenMAP tool for valuing cases of mortality (approximately $10 million per statistical case in 2020 dollars, assuming a 3% discount rate), the economic value of this health burden could be as high as $1.2 trillion dollars, not counting morbidity impacts. Current mortality burden estimated within the PA areas using the fine scale air quality surface is similar to but slightly less than the estimates generated using coarser air quality surface for the same year.

Exhibit 2-5 also shows the current (2015) $PM_{2.5}$-attributable mortality burden displayed in Exhibit 2-4 but with the use of a coarser, county-level, incidence dataset. When using the county-level incidence, we are also able to estimate the current $PM_{2.5}$-attributable mortality burden in infants.[5]

[5] The Woodruff et al. C-R function excludes neo-natal deaths (those occurring within the first 30 days after birth). Since the tract incidence dataset does not exclude neo-natal cases, we do not report tract incidence results for the Woodruff et al. study.

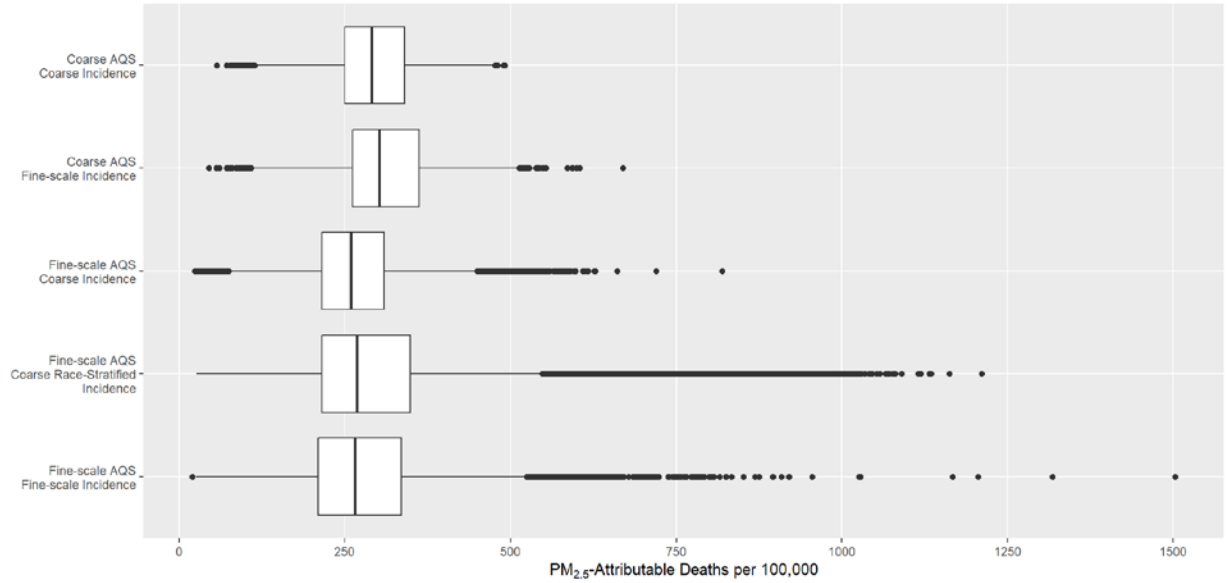
EXHIBIT 2-5. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN USING COARSE INCIDENCE (TOTAL DEATHS, ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION – RESPONSE FUNCTION	AGE GROUP	NATION	PA AREAS		NON-PA AREAS
			1KM	12KM	1KM	1KM
All Cause Mortality	Woodruff et al. (2008)	0-0	350	120	120	230
	Turner et al. (2016)	30-99	120,000	42,000	39,000	83,000
	Di et al. (2017)	65-99	110,000	38,000	36,000	76,000

Note: values are rounded to two significant figures. Attributable burden assumes 100% reduction in fine PM and no threshold below which PM mortality impacts are not observed.

For the adult mortality estimates, the use of more highly resolved tract-level baseline mortality incidence results in a slightly greater estimate of current burden than that estimated using county incidence, however, the aggregated estimates are largely in agreement with one another. To better understand the impact of these data set choices on variability in $PM_{2.5}$-attributable mortality, Exhibit 2-6 presents "box-and-whisker" plots that illustrate the spread and distribution of per-capita $PM_{2.5}$ mortality burden at the census tract level when using data of increased resolution or specificity. In each plot, the vertical line within the box represents the median; the lower and upper ends of the box represent the 25^{th} and 75^{th} percentiles, and the ends of the lines extending from the box represent the 5^{th} and 95^{th} percentiles.

EXHIBIT 2-6. CURRENT PM2.5-ATTRIBUTABLE MORTALITY BURDEN (PER 100,000) IN CENSUS TRACTS INCLUDED IN EPA'S PA ANALYSIS, USING VARYING COMBINATIONS OF INCIDENCE AND AIR QUALITY DATASETS



Note: See Appendix D for box-and-whisker plot values. The tracts analyzed are limited to the tracts within the PA areas due to the coarse air quality surface being limited to the PA areas.

Exhibit 2-6 shows an increase in variability in current per-capita $PM_{2.5}$ mortality rates when moving from a coarse spatial resolution of air quality to a finer air quality surface and when moving from coarse baseline mortality rate data ("incidence" in the graph) to a fine-scale air quality surface and fine-scale incidence dataset. The increasing spread, particularly of higher PM-attributable mortality rates as you move from the top to bottom of the graph illustrates the additional information that can be gained when using fine-scale datasets, even when there appears to be no significant differences in the aggregated national $PM_{2.5}$ impacts. (Exhibits 2-4 and 2-5). See Appendix D, Exhibits D-18 through D-21, for additional tract-level comparisons between the fine-scale and coarse datasets.

PM-ATTRIBUTABLE MORTALITY BURDEN STRATIFIED BY RACE

Exhibit 2-7 presents per capita current mortality burden using race- and ethnicity-stratified baseline mortality incidence rates and race- and ethnicity-stratified estimates of PM-attributable risk from Di et al. (2017), where the latter represent potential differences in hazard to different subgroups exposed to the same change in PM. These data sets better represent the variation in baseline health of these subpopulations and allows for the possibility of differential effects of PM exposure on mortality across races and ethnicities. Presenting these results as per capita estimates (current burden per 100,000 persons) allows us to compare current $PM_{2.5}$-related health burdens across different groups. Detailed mortality results for the Di et al. (2017) concentration-response function can be found in Appendix D.

EXHIBIT 2-7. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY RATE PER 100,000 INDIVIDUALS AGED 65-99, BY RACE

STRATIFIED RISK ESTIMATE	RACE	ETHNICITY	NATION	PA AREAS		NON-PA AREAS
			1KM	12KM	1KM	1KM
Hispanic	All	Hispanic	260	310	290	240
Total All Races	**All**	**All**	**300**	**330**	**300**	**230**
Asian	Asian	All	170	200	190	140
Black	Black	All	670	770	710	650
Native American	Native American	All	200	250	230	190
White	White	All	210	270	240	200

Note: values are rounded to two significant figures. Results based on risk estimates from Di et al., 2017.

Comparing per capita current mortality burden estimates across races provides useful takeaways. Black populations experience more than three times as many $PM_{2.5}$-attributable deaths per 100,000 persons compared to all other races, a result consistent with EPA's findings in the PA that Black Americans are disproportionately affected under the current NAAQS relative to other races. However, while the PA bases their findings on a hypothetical baseline scenario that assumes all areas meet the current standard but which allows air quality in some areas to worsen and in others to improve from current values, the gap we observe reinforces that the disparity is of similar magnitude when estimated analyzing current exposures.

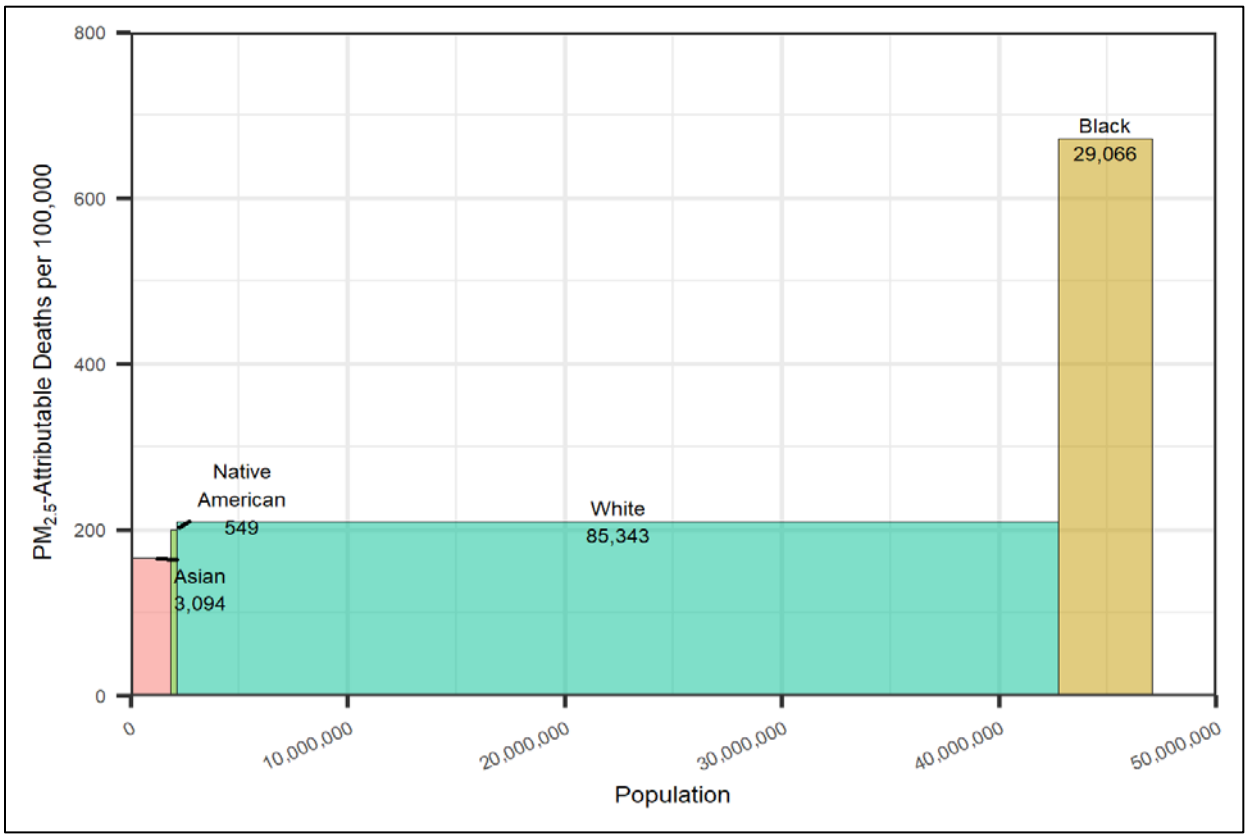
Current aggregated mortality burden estimates using the 1 x 1 km fine scale air quality surface are similar to estimates using coarser air quality. For example, across all races in PA areas for those aged 65-99, current mortality burden estimates are within 10 percent. Comparing current per capita health burden estimates across PA areas and non-PA areas, for each race, current burden is higher in PA areas than non-PA areas. This indicates that when we specify race-stratified concentration response functions, areas considered in the PA comprise the majority of current $PM_{2.5}$-attributable burden experienced by each group across the nation.

Black populations aged 65+ experience three times as many $PM_{2.5}$-attributable deaths per capita compared to all other races.

Exhibit 2-8 depicts the $PM_{2.5}$-attributable mortality rate per capita by race at the national level under current (2015) $PM_{2.5}$ exposures. This figure is based on the Di et al. (2019) 1 x 1 km $PM_{2.5}$ air quality surface, county-level race-stratified incidence rates, and Di et al. (2017) race-specific concentration-response functions for those aged 65 and up. The width of each rectangle indicates the total population of each race for the given geographic scale, and the height represents the $PM_{2.5}$-attributable mortality rate of each race, reported per 100,000 persons of each racial group. Thus, the area of each rectangle is representative of the current $PM_{2.5}$-attributable burden for each race, which is reported by racial group.

The order of races in this figure represents increasing mortality burden per capita moving across the horizontal axis.

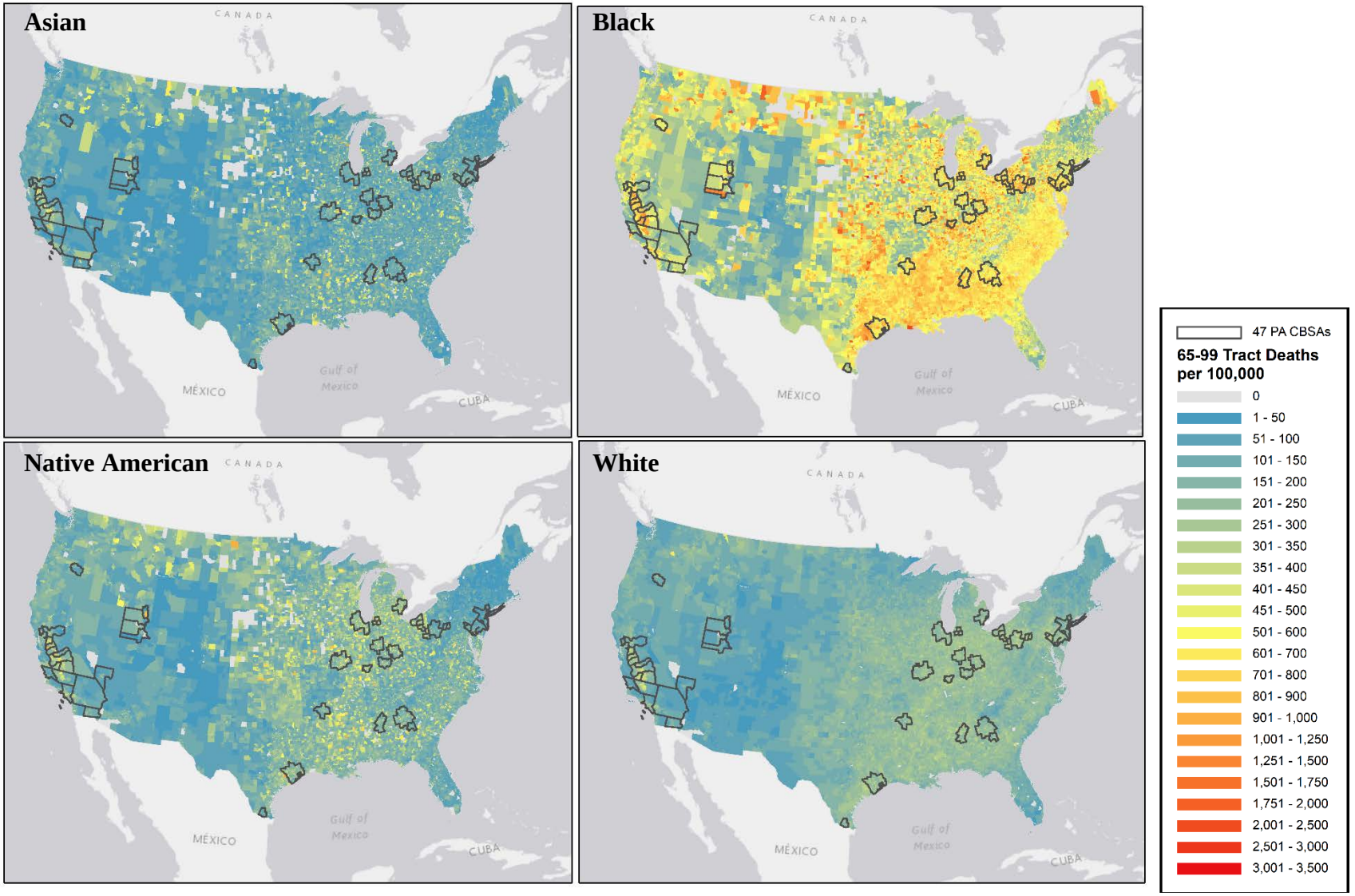
EXHIBIT 2-8. CURRENT NATIONAL $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN BY RACE, AGES 65-99



This exhibit illustrates that the results for total PM-attributable mortality burden and the risk per person can be quite different. Looking solely at total burden among those 65 and older, which is reflected above by the width of the rectangles, white Americans have the largest value in absolute terms, but this is driven in large part by the larger size of the white population in this age category. When looking on a per-person basis, illustrated by the height of the rectangles above, the story is quite different. Across the Nation, Black Americans have the highest risk of dying from $PM_{2.5}$ exposure on a per-person basis, with a rate more than triple that of white Americans.

Exhibit 2-9 maps our results for current $PM_{2.5}$-attributable mortality burden per capita by race at the census tract level to help visualize disparities across the Nation and identify areas where risks may be particularly severe. We find that increased per person risk of PM mortality among Black Americans is found consistently throughout the United States. The map also shows many locations where Asian and Native Americans experience higher risk on a per person basis than their white counterparts.

EXHIBIT 2-9. FINE SCALE $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN PER 100,000 FOR THOSE AGED 65-99, CENSUS TRACT LEVEL



PM-ATTRIBUTABLE MORTALITY BURDEN STRATIFIED BY POVERTY

Exhibit 2-10 illustrates the current per-capita $PM_{2.5}$ mortality burden for individuals whose income is less than two times the poverty line. Across the three study areas, individuals who experience low-income consistently experience higher rates of $PM_{2.5}$ mortality by 12% to 18%.

EXHIBIT 2-10. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY RATE (PER 100,000) BY INCOME FOR THOSE AGED 65-99

STRATIFIED RISK ESTIMATE	POVERTY STATUS	NATION	PA AREAS		NON-PA AREAS
		1KM	12KM	1KM	1KM
Combined Totals*	Below 2x Poverty Line	270	350	330	250
	Above 2x Poverty Line	240	310	280	220

Note: values are rounded to two significant figures
*We use the sum of the $PM_{2.5}$-attributable mortality below or above 2x the poverty line derived from the Di et al. (2017) race-specific concentration-response functions.

CURRENT $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN

$PM_{2.5}$ is also associated with numerous non-fatal health conditions or episodes of poor health. We present below national estimates for these morbidity impacts and then, for one non-fatal health impact for which we have race/ethnicity stratified risk information, we stratify these results along that metric to illustrate disparity in morbidity risks.

TOTAL NATIONAL-LEVEL PM-ATTRIBUTABLE MORBIDITY BURDEN

Exhibit 2-11 shows current $PM_{2.5}$-attributable morbidity burdens across three geographic areas using fine-scale air quality but incidence rates at the county level (or higher). Similar to the mortality results (presented in Exhibit 2-5), these estimates reflect current morbidity burden when using incidence datasets not stratified by race and ethnicity.

EXHIBIT 2-11. CURRENT NATIONAL $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN (ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION-RESPONSE FUNCTION	AGE GROUP	NATION	PA AREAS		NON-PA AREAS
			1KM	12KM	1KM	1KM
HOSPITALIZATIONS						
Non-fatal acute myocardial infarction (AMI)	Peters et al. (2001)	18-99	110,000	37,000	35,000	74,000
Non-fatal AMI	Pooling 5 Studies*	18-99	17,000	6,000	5,600	11,000
All Respiratory	Ostro et al. (2016)	0-18	9,900	3,900	3,700	6,200
Respiratory-1	Jones et al. (2015)	0-99	6,100	2,400	2,200	3,900
Respiratory-2	Bell et al. (2015)	65-99	2,100	750	700	1,400
Cardio-, Cerebro- & Peripheral Vascular Disease	Bell et al. (2015)	65-99	13,000	4,900	4,600	8,800
All Cardiac Outcomes	Talbott et al. (2014)	0-99	12,000	4,300	4,100	8,000
Alzheimer's Disease	Kioumourtzoglou et al. (2016)	65-99	27,000	8,200	8,100	19,000
Parkinson's Disease	Kioumourtzoglou et al. (2016)	65-99	4,500	1,600	1,500	3,000
EMERGENCY ROOM VISITS						
Respiratory	Krall et al. (2016)	0-99	75,000	27,000	26,000	49,000
Emergency Hospitalizations – Respiratory**	Zanobetti et al. (2009)	65-99	21,000	7,000	6,500	14,000
INCIDENCE						
Asthma	Tetreault et al. (2016)	0-17	260,000	97,000	92,000	160,000

Note: values are rounded to two significant figures
*Five AMI studies pooled together include: Pope et al., Sullivan et al., Zanobetti and Schwartz, and Zanobetti et al.
**Emergency Hospitalizations represent emergency department visits that result in a hospitalization.
Attributable burden assumes 100% reduction in fine PM and no threshold below which PM morbidity impacts are not observed.

For all morbidity endpoints, estimates generated using the fine scale air quality surface show minimal impacts on the total estimated values in the PA-modeled areas. We also find a substantial PM-attributable morbidity burden outside of the PA-modeled areas, potentially up to two-thirds of the total impacts.

ASTHMA EMERGENCY DEPARTMENT VISITS BY RACE/ETHNICITY

Exhibit 2-12 presents current morbidity burden per 100,000 persons for asthma Emergency Department (ED) visits using race-stratified baseline incidence and concentration-response estimates from Alhanti et al. (2016). Alhanti et al. (2016) provides estimates of PM attributable-risk for white, non-Hispanics and for all other race/ethnicity combinations.

EXHIBIT 2-12. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN FOR ASTHMA ED VISITS IN CHILDREN AGED 0-18 (PER 100,000, STRATIFIED BY RACE/ETHNICITY)

STRATIFIED RISK ESTIMATE ALHANTI ET AL., 2016	RACE/ ETHNICITY	NATION	PA AREAS		NON-PA AREAS
		1KM	12KM	1KM	1KM
White	White, Non-Hispanic	10	13	12	9
Total Non-white	**White, Hispanic Plus All Other Races, Ethnicities**	58	57	69	50

Risks of a PM-related asthma ED visit are substantially higher for non-white populations, with slightly higher rates in the PA-modeled areas. Use of the fine scale surface appears to show somewhat greater per-person rates compared with the coarser 12 km surface. In general, non-white Americans experience dramatically higher asthma ED visit burdens than white non-Hispanic Americans based on the Alhanti study, on the order of six times higher.

The burden of PM-attributable asthma ED visits for non-white Americans is six times higher compared to white Americans.

EFFECTS OF FINE SCALE MODELING OF AIR QUALITY AND BASELINE HEALTH INCIDENCE ON $PM_{2.5}$-ATTRIBUTABLE HEALTH BURDEN ESTIMATES

One key objective of this analysis is to explore the impacts (if any) of modeling at finer scales compared to what was specified in the PA. The PA specifies a 12 x 12 km air quality surface, and age-stratified county-level mortality incidence (not stratified by race or ethnicity). We build on the PA by assessing health burden with a 1 x 1 km modeled air quality surface from Di et al. (2019) and age-stratified census tract-level mortality incidence (not stratified by race or ethnicity) based on the U.S. Small-area Life Expectancy Estimates Project (USALEEP).

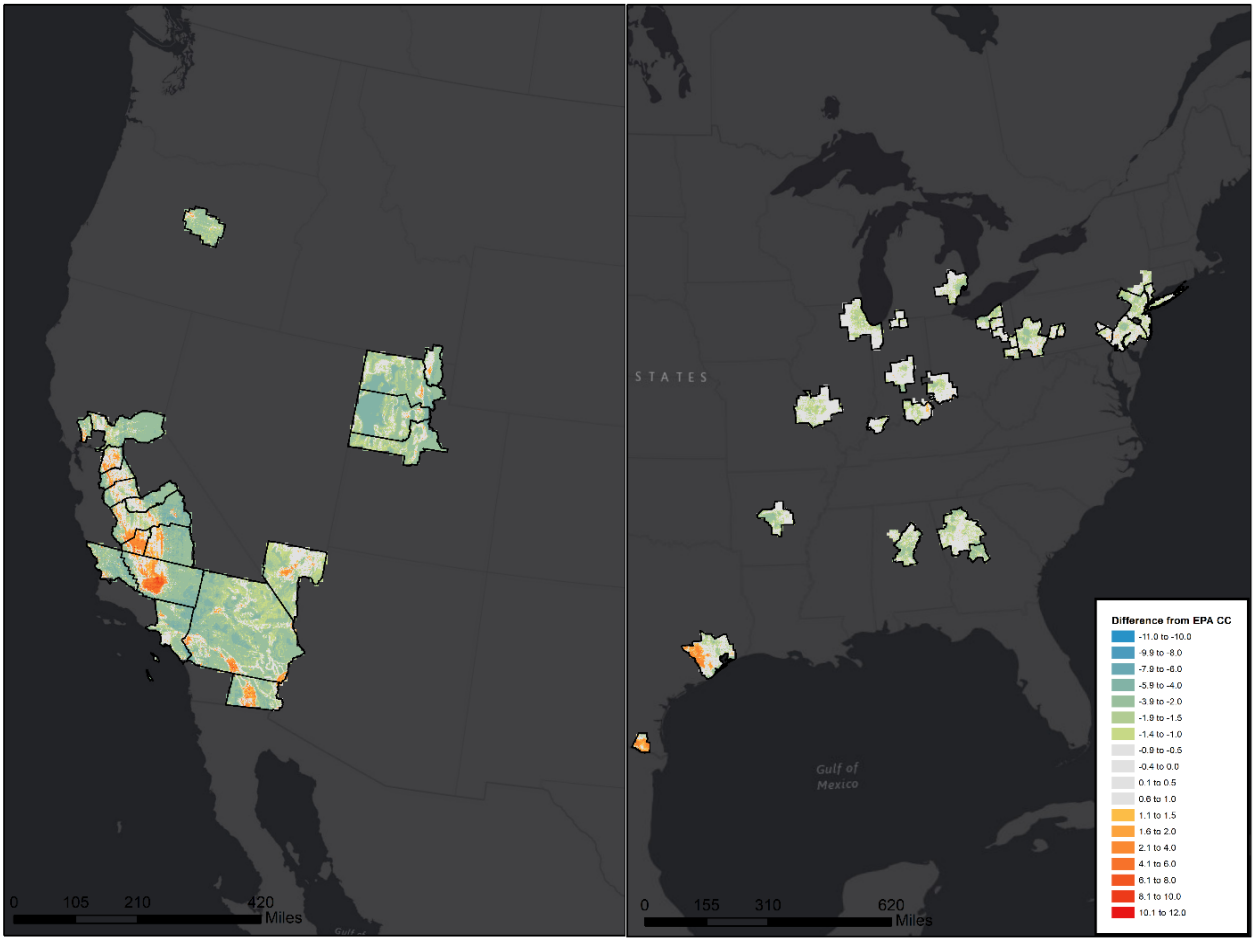
EFFECT OF APPLYING FINE-SCALE AIR QUALITY DATA

We estimate current $PM_{2.5}$-attributable mortality and morbidity burden (regardless of stratification by race and/or ethnicity) using the 1 x 1 km air quality surface (provide value) to be similar but less than estimates using the 12 x 12 km air quality surface (provide value) when summed across the Nation We evaluate whether current health burden differences are attributable to air quality by comparing exposures between both air quality surfaces across three metrics: (1) geographic resolution, (2) age, and (3) race/ethnicity.

Exhibit 2-13 displays the differences in magnitude of $PM_{2.5}$ exposure between the fine-scale 1 x 1 km air quality surface and the 12 x 12 km air quality surface within areas analyzed by EPA in the PA. In this

figure, red and orange regions indicate PA areas in which exposures within the fine scale air quality surface exceed those of the 12 x 12 km surface, while blue and green regions indicate PA areas where exposures within the 12 x 12 km surface exceed those of the fine scale air quality surface. Gray regions indicate PA areas in which $PM_{2.5}$ exposure across both air quality surfaces are within 0.5 µg/m^3 of each other.

EXHIBIT 2-13. DIFFERENCE IN CURRENT $PM_{2.5}$ EXPOSURE BETWEEN 1 X 1 KM AND 12 X 12 KM AIR QUALITY SURFACE



In the eastern United States, exposures within PA areas are relatively similar between both air quality surfaces, apart from two areas in Texas, which contain areas in which the fine scale air quality surface's exposures exceed that of the 12 x 12 km surface. In the western United States, there is a more noticeable difference in exposures between both surfaces, with many large differences concentrated in areas across central California. These wider variations in exposure could potentially be attributed to the wider spatial distribution in regulatory monitors across the western United States, as well as the uneven placement of regulatory monitors relative to the size of some PA areas.

Exhibits 2-14 and 2-15 compare population-weighted $PM_{2.5}$ exposure across race for those aged 65 and older using either (1) the 1 x 1 km model air quality surface or (2) the $PM_{2.5}$ concentration at the nearest

EPA regulatory monitor in 2015 to each 12 x 12 km cell. This comparison allows us to understand one of the variables, pollutant exposure, influencing our $PM_{2.5}$ mortality estimates and the differences we may see among the mortality estimates at the various geographic scales and when using the 1 x 1 km air quality surface versus the 12 x 12 km air quality surface.

EXHIBIT 2-14. DIFFERENCES IN 65-99 POPULATION WEIGHTED $PM_{2.5}$ EXPOSURE BETWEEN 1 X 1 KM AIR QUALITY SURFACE AND NEAREST EPA REGULATORY MONITOR (2015)

RACE	ETHNICITY	NATIONAL		PA AREAS		NON-PA AREAS	
		1 X 1 KM SURFACE	EPA 2015 NEAREST MONITOR	1 X 1 KM SURFACE	EPA 2015 NEAREST MONITOR	1 X 1 KM SURFACE	EPA 2015 NEAREST MONITOR
All	Hispanic	8.6	8.7	10	10	7.5	7.7
Asian	All	8.8	8.9	9.7	9.9	7.9	8.0
Black	All	8.8	8.8	9.7	10	8.3	8.1
Native American	All	7.3	7.7	9.8	10	6.7	7.1
White	All	8.1	8.2	9.4	9.7	7.6	7.7

Notes: All $PM_{2.5}$-exposures are population weighted using race-, ethnicity- and age-stratified population data from 2015. Values are rounded to two significant figures.

EXHIBIT 2-15. PERCENT DIFFERENCE BETWEEN $PM_{2.5}$ EXPOSURE IN PA AREAS VS. NON-PA AREAS FOR 1 X 1 KM SURFACE AND NEAREST EPA REGULATORY MONITOR (2015)

RACE	ETHNICITY	% INCREASE IN EXPOSURE IN PA AREAS VS. IN NON-PA AREAS	
		1 X 1 KM MODEL	EPA 2015 NEAREST MONITOR
All	Hispanic	35%	33%
Asian	All	23%	23%
Black	All	17%	24%
Native American	All	46%	41%
White	All	23%	25%

For results aggregated to large spatial scales, across all age categories and race/ethnicity groups, the fine-scale Di et al. (2019) based population-weighted $PM_{2.5}$ exposures in 2015 are very similar to those generated from the much coarser nearest monitor approach. In most cases, the fine scale estimates are slightly lower than exposures at the nearest EPA monitor from 2015. However, Black Americans experience the same exposure according with both methods nationally, and higher exposure outside of the PA-modeled areas. Results according to both air quality surfaces indicate Black and Asian populations experience the largest exposures. Across both air quality inputs, Native Americans experience the lowest population-weighted $PM_{2.5}$ exposure compared to all other races.

Similar to our comparison of health burden using fine-scale and 12 km model surfaces, the true benefit of using fine scale air quality inputs is less likely to be observed in results aggregated over large areas. Rather, as illustrated earlier in Exhibit 2-6, because these models better capture small-scale variation in exposure, the fine-scale air quality surfaces will produce an improved representation of variability in exposures across groups and may better detect unusually high-risk hot spots not otherwise identified.

APPLYING FINE SCALE MORTALITY INCIDENCE DATA

When we apply tract incidence when using all-race concentration-response functions from Di et al. (2017), as seen in Exhibit 2-4, we find that current mortality burden estimates are larger than when we apply county level mortality incidence.[6] For morbidity endpoints, we lack the detailed incidence data needed to explore the influence of local scale data nationally. However, we have conducted a state-level proof of concept analysis in the state of New Jersey, using zip-code level baseline incidence of ED visits stratified by race and ethnicity to evaluate morbidity burden estimates. Those case study findings are described in detail in Chapter 4.

CUMULATIVE EFFECT OF FINE SCALE MODELING ON CURRENT $PM_{2.5}$-ATTRIBUTABLE BURDEN

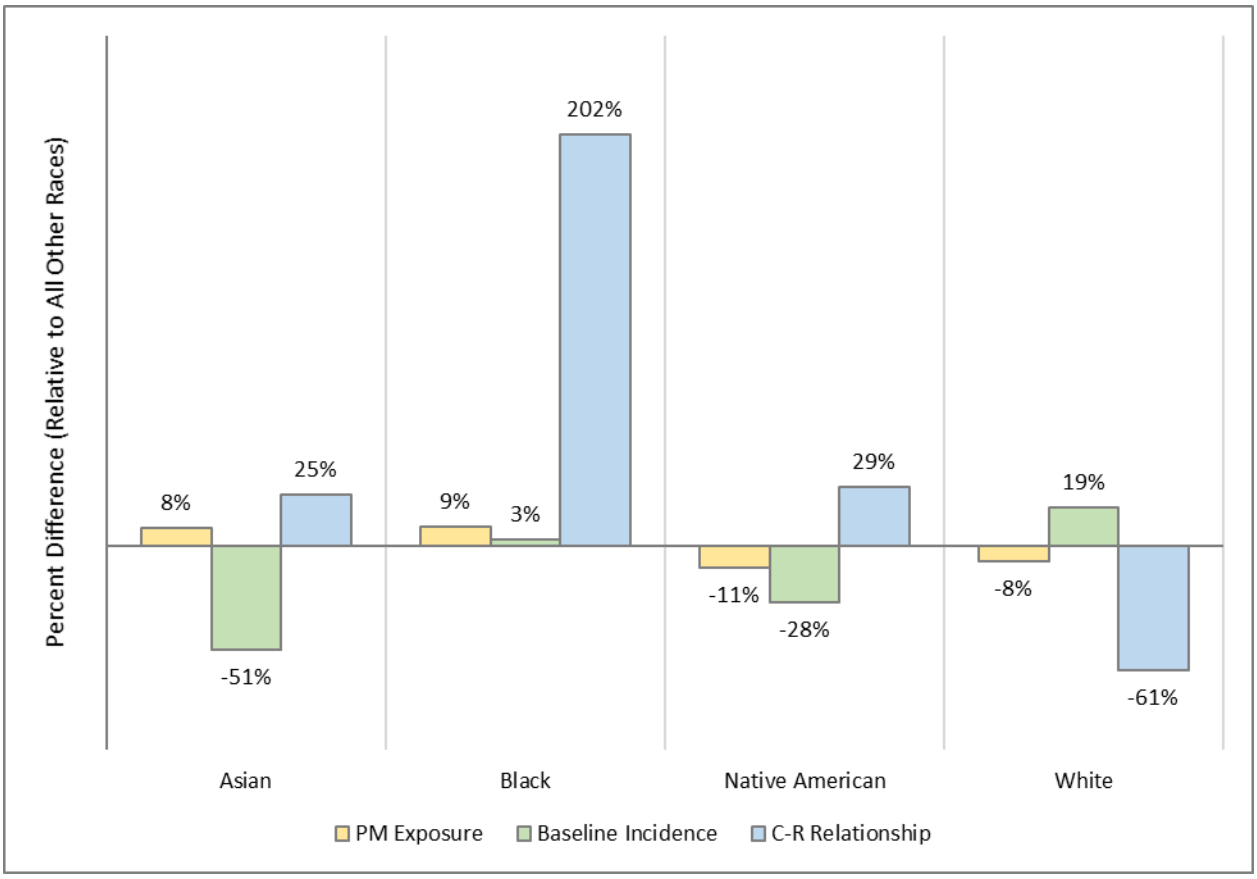
We use all-race current $PM_{2.5}$-attributable mortality burden estimates from Exhibit 2-5 to evaluate the cumulative effect of analyzing scenarios with both fine scale air quality and fine scale mortality incidence data. For the Di et al. (2017) all-race concentration-response function, when using the 12 x 12 km air quality surface and county-level mortality incidence, we estimate current $PM_{2.5}$-attributable mortality burden across PA areas to be 38,200 premature deaths. When we replace air quality with the 1 x 1 km air quality surface and use tract-level incidence, we estimate current mortality burden across PA areas to be 36,700 premature deaths. Thus, when we apply both fine scale air quality and mortality incidence, we find that current $PM_{2.5}$-attributable mortality burden decreases slightly, by 1,500. We find a similar difference when applying the Turner et al. (2016) all-race concentration-response function.. Due to data suppression issues, we are currently unable to evaluate the impact of combining fine-scale and race-specific baseline incidence rates simultaneously.

FACTORS INFLUENCING DIFFERENCES IN CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN

It is important to not only characterize disparities across different races, but also examine potential factors that explain these differences in current $PM_{2.5}$-attributable mortality. Exhibit 2-16 presents the factors explaining differences in $PM_{2.5}$-attributable mortality by race. These three factors include (1) $PM_{2.5}$ air quality exposure resolution, (2) baseline mortality rate resolution, and (3) concentration-response (C-R) relationships that define how mortality risk changes as a result of incremental changes in $PM_{2.5}$ exposure. In this figure, we show results for national-level BenMAP-CE scenarios using Di et al. (2019) 1 x 1 km $PM_{2.5}$ surface, county-level race-stratified incidence rates, and the Di et al. (2017) race-specific concentration-response functions for ages 65 and up.

[6] The USALEEP tract mortality incidence dataset is not stratified by race or ethnicity, so for our PA and national analysis, we are limited to comparing the impacts of utilizing fine scale mortality incidence data to all-race concentration-response functions.

EXHIBIT 2-16. FACTORS INFLUENCING RACE-SPECIFIC PM-ATTRIBUTABLE MORTALITY ESTIMATES



Notes: Results are specific to current $PM_{2.5}$-attributable mortality burden runs, including the use of county-level race-stratified incidence rates, Di et al. (2019) 1 x 1 km $PM_{2.5}$ surface, and the Di et al. (2017) race-specific concentration-response functions for ages 65 and up. Percent differences are relative to the population-weighted average values for all other races.

Overall, the race-specific Di et al. (2017) effect coefficients (i.e., slopes of the concentration-response functions) explain most differences in PM-attributable mortality by race. Effect coefficients range from 0.0061 (white) to 0.0189 (Black), representing a threefold difference in mortality impacts due to $PM_{2.5}$ exposure. In comparison, average $PM_{2.5}$ concentrations range from 7.28 $\mu g/m^3$ (Native American) to 8.83 $\mu g/m^3$ (Black) and 65+ baseline mortality incidence ranges from 2,117 deaths per 100,000 (Asian) to 4,352 (Black).[7] Across the three dimensions, Black Americans experience the highest $PM_{2.5}$ exposure, baseline all-cause mortality incidence, and $PM_{2.5}$-mortality response.

[7] Baseline mortality incidence for Black and White 65+ populations are relatively comparable nationwide; however, this takeaway may be misleading. Blacks experience significantly higher mortality incidence rates across all age groups; however, their 65+ population is, on average, younger than the White 65+ population. As such, the aggregate 65+ baseline incidence values appear comparable.

CHAPTER 3 | CHANGES IN $PM_{2.5}$ ATTRIBUTABLE HEALTH BURDEN UNDER ALTERNATIVE $PM_{2.5}$ STANDARDS

In this chapter, we explore how the health burdens we calculated in the previous chapter might change if EPA were to adopt a more protective NAAQS standards. For context, we first characterize the likelihood that socially vulnerable groups live in areas in which $PM_{2.5}$ exposures exceed certain concentration thresholds. We discuss how these likelihoods compare across groups and identify populations that may benefit from reducing the current $PM_{2.5}$ annual average NAAQS from 12 µg/m^3 to either 10 or 8 µg/m^3.[8] We then present mortality and morbidity risk reduction estimates under both alternative NAAQS scenarios and compare benefits across scenarios, geographic areas, and socially vulnerable groups. All analyses focus on reduction of the annual mean $PM_{2.5}$ NAAQS standard only and are based on 1) air quality surfaces either generated by EPA (for PA areas at 12 km scale) or 2) air quality surfaces reflecting changes at 1 km scale that are proportional to the changes reflected in EPA's air quality surfaces for an emissions reduction strategy focusing on primary $PM_{2.5}$ sources.

EXPOSURE ABOVE ALTERNATIVE STANDARDS

Before discussing health impacts, we first examine how $PM_{2.5}$ exposures are distributed among socially vulnerable groups experience above the standards we are assessing. We focus on two factors to identify socially vulnerable groups: 1) racial or ethnic groups that have been part of historical minorities;[9] and 2) those experiencing poverty. Within the minority subgroup, we assess impacts to Asian, Black, and Native American populations.[10] We assess exposure to Hispanic ethnicities separately where available.

Exhibits 3-1, 3-2, and 3-3 show the increased likelihood of these socially vulnerable groups to be exposed to $PM_{2.5}$ concentrations greater than the current NAAQS (12 µg/m^3) or greater than the two alternative standards assessed in this report (10 and 8 µg/m^3). The exposure likelihoods are assessed at three geographic scales: national, within PA areas, or non-PA areas. These graphics use race-specific populations at the census tract level distributed to 1 x 1 km grids by the proportion of the overall population within each 1 x 1 km grid (ages 65-99).[11]

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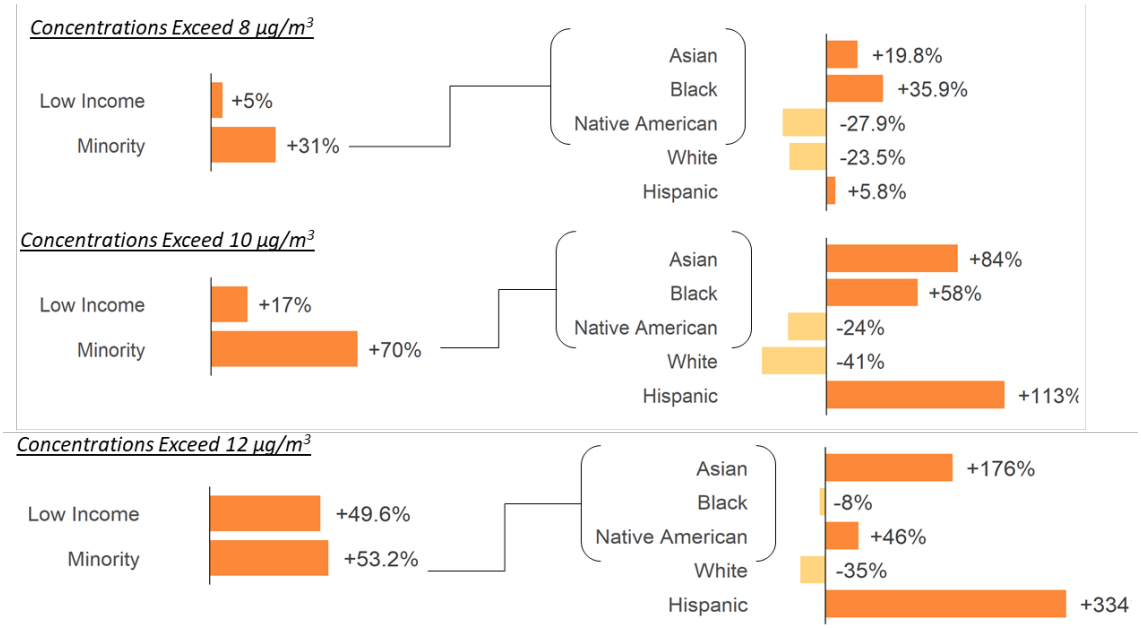
[8] Our analysis focuses exclusively on changes to the annual average NAAQS. Changes to the daily NAAQS may results in additional benefits in particular areas identified by EPA as more sensitive to changes in the daily standard, but that is outside of the scope of this analysis.

[9] This report adopts the term "minority" for consistency with U.S. census data. There are important differences in the social vulnerability of individual communities that are included under the "minority" umbrella. This report includes, where possible, results for individual racial and ethnic groups.

[10] We define "low income" or "impoverished" groups as those whose income is less than twice the federal poverty line.

[11] Race-specific populations within each census tract are distributed to each 1 x 1 km grid within a tract using the proportion of the total population, across all races, within each 1 x 1 km to the total population, across all races, within the respective tract. For example, a 1 x 1 km grid that contains 50 people and falls within a census tract containing 100 people will be assigned 50 percent of each races population from that

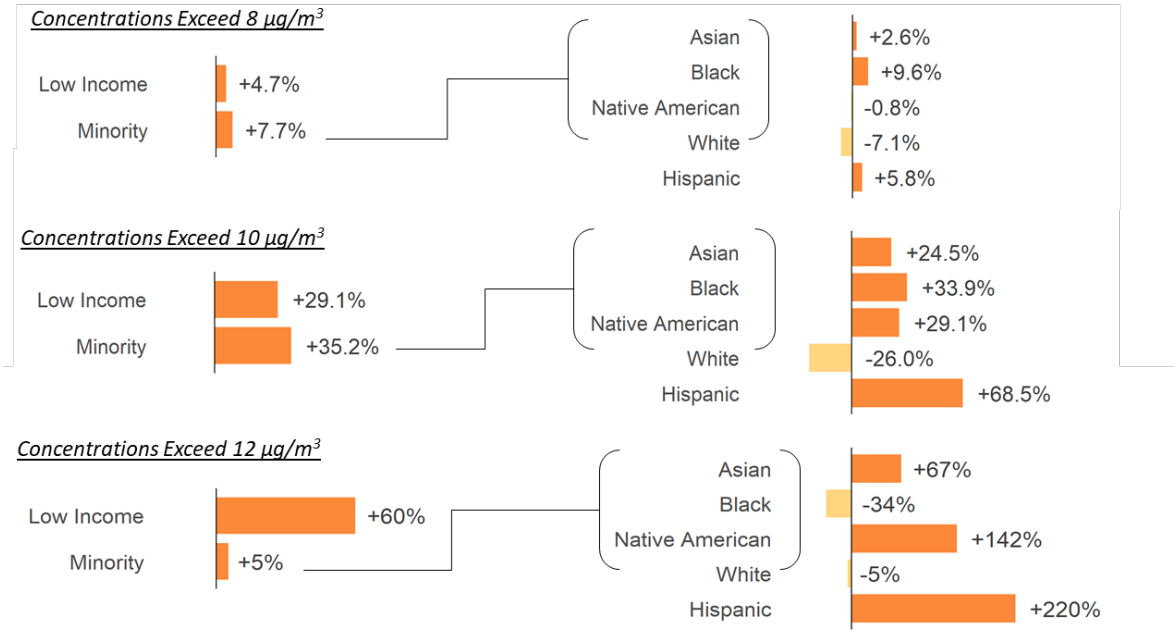
EXHIBIT 3-1. LIKELIHOOD OF LIVING WHERE $PM_{2.5}$ EXCEEDS SPECIFIED CONCENTRATIONS – NATION, 65-99



Note: The reference group for each race is all *other* races combined. Comparisons between individual race groups will vary.

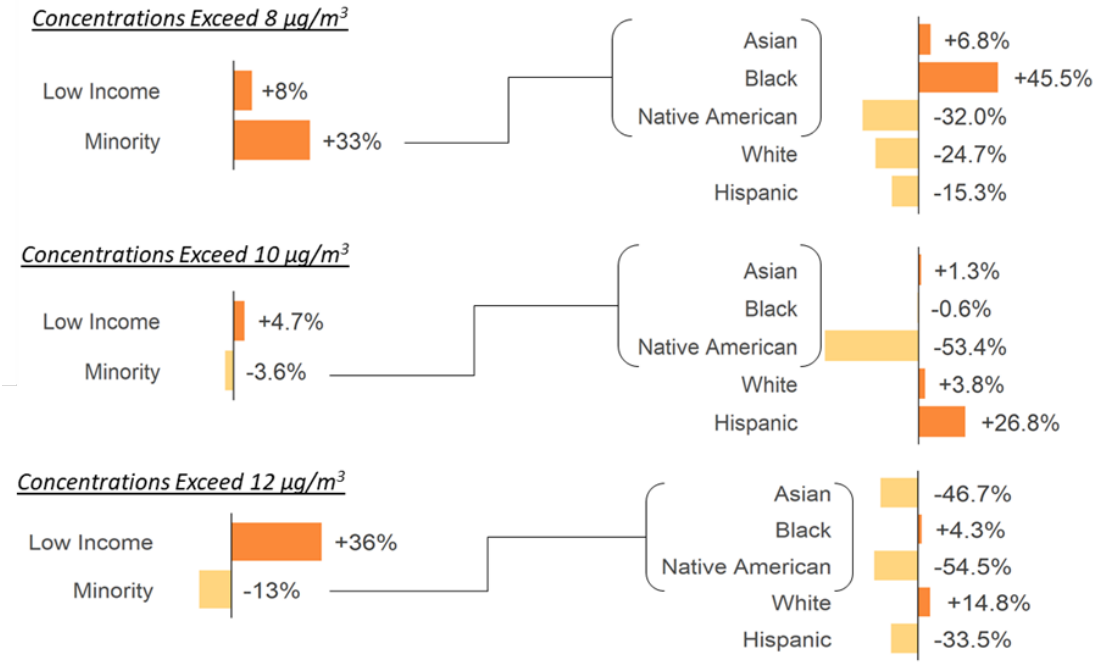
tract. This assumes that the distribution of the race-specific population within each 1 x 1 km grid is the same as the distribution of the race-specific population within the respective tracts.

EXHIBIT 3-2. LIKELIHOOD OF LIVING WHERE $PM_{2.5}$ EXCEEDS SPECIFIED CONCENTRATIONS – PA AREAS, 65-99



Note: The reference group for each race is all other races combined. Comparisons between individual race groups will vary.

EXHIBIT 3-3. LIKELIHOOD OF LIVING WHERE $PM_{2.5}$ EXCEEDS SPECIFIED CONCENTRATIONS – NON-PA AREAS, 65-99



Note: The reference group for each race is all other races combined. Comparisons between individual race groups will vary.

Aside from the non-PA areas, we consistently see increased likelihood of $PM_{2.5}$ higher exposure among low income and minority populations among the 65- to 99-year-old cohort. We also consistently see an increased likelihood in $PM_{2.5}$ exposure above the standards in the Asian, Black, and Hispanic populations, apart from some of the current NAAQS scenarios. However, unlike the other non-white groups, the Native American population typically displays a decrease in likelihood of exposure above the standards. These decreases are particularly dramatic in non-PA areas. Although it may appear from the fine scale air quality surface that Black Americans are less likely in general to live in areas where $PM_{2.5}$ exceeds 12 $\mu g/m^3$, they still are over four times more likely than white Americans to live in these high exposure areas.

MORTALITY RISK REDUCTION UNDER ALTERNATIVE $PM_{2.5}$ STANDARDS

Exhibit 3-4 shows the mortality risk reduction under two alternative $PM_{2.5}$ standards (10 $\mu g/m^3$ and 8 $\mu g/m^3$) across three geographic areas and air quality and incidence datasets of varying spatial scale. These estimates reflect avoided PM-attributable deaths when utilizing incidence datasets not stratified by race and ethnicity.

EXHIBIT 3-4. REDUCTION IN MORTALITY BURDEN BY ALTERNATIVE NAAQS (ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION-RESPONSE FUNCTION	AGE GROUP	10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
			NATION	PA AREA	NON-PA AREAS	NATION	PA AREA	NON-PA AREAS
COUNTY LEVEL INCIDENCE								
All-Cause Mortality	Woodruff et al. (2008)*	0-0	10	10	2	60	30	20
	Turner et al. (2016)	30-99	4,800	4,200	580	19,000	10,000	8,600
	Di et al. (2017)	65-99	4,400	3,800	550	17,000	9,300	8,000
Tract Level Incidence								
All-Cause Mortality	Turner et al. (2016)	30-99	4,900	4,300	580	19,000	11,000	8,700
	Di et al. (2017)	65-99	4,500	3,900	550	18,000	10,000	8,000

Note: values are rounded to two significant figures.
*The Woodruff et al. C-R function excludes neo-natal deaths (those occurring within the first 30 days after birth). Since the tract incidence dataset does not exclude neo-natal cases, we do not report tract incidence results for the Woodruff et al. study.

As with the current burden results in Chapter 2, the Turner et al. (2016) and Di et al. (2017) concentration-response functions produce higher risk reductions when using the tract-level incidence compared to the county incidence at the national scale and within PA areas. However, we see much closer, if not equal, results between the tract-level and county-level incidence within the non-PA areas. This suggests that the tract-level incidence provides additional context in areas where population densities are high, which may be useful in future fine-scale analyses. Interestingly, unlike in the total current burden results, the PA areas comprise more than 80 and 50 percent of the mortality risk reduction when assessing the 10 µg/m^3 and 8 µg/m^3 alternative standards, respectively.

Exhibit 3-5 presents per capita mortality risk reduction across the same geographies and air quality surfaces when using race-stratified incidence and a race-specific concentration-response function, from Di et al. (2017), for ages 65 to 99.

EXHIBIT 3-5. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS FOR THOSE AGED 65-99 BY ALTERNATIVE NAAQS (PER 100,000, STRATIFIED BY RACE)

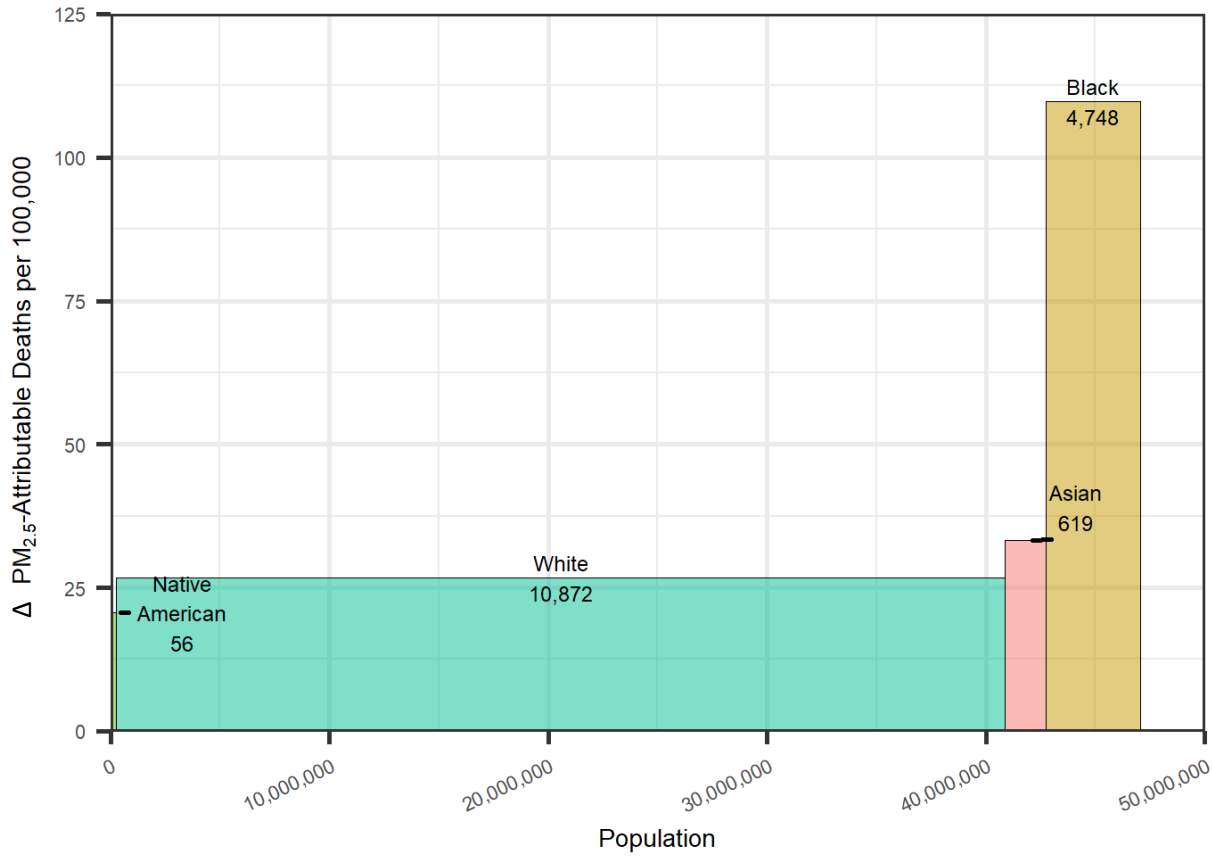
CONCENTRATION – RESPONSE RELATIONSHIP	RACE	ETHNICITY	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
			10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Hispanic	All	Hispanic	20	44	2	48	91	17
Total All Races	**All**	**All**	10	32	**1**	35	79	17
Asian	Asian	All	14	26	1	33	56	11
Black	Black	All	28	69	3	110	190	58
Native American	Native American	All	8	40	1	21	74	8
White	White	All	8	26	1	27	64	14

Note: values are rounded to two significant figures.

Not only do we observe much larger avoided PM-attributable deaths when comparing the 8 µg/m3 standard to the 10 µg/m^3 in Exhibit 3-4, but we can also see that the 8 µg/m^3 alternative standard reduces mortality risk at almost two to three times the rate of the 10 µg/m^3 alternative standard in the PA areas. When we compare the reduction in mortality risk at the national level, the 8 µg/m^3 standard becomes three to four times higher than the 10 µg/m^3 standard for white and Black Americans, and in the non-PA areas the 8 µg/m^3 standard mortality rate is over five times higher for all groups. Non-PA areas experience a negligible share of per capita benefits across all groups at 10 µg/m^3 but comprise a meaningful share of per capita benefits when the standard is lowered to 8 µg/m^3.

Exhibit 3-6 further illustrates the potential reductions in the $PM_{2.5}$-attributable mortality rate by race across the U.S under an alternative standard of 8 µg/m^3. This figure complements Exhibit 2-8 in Chapter 2; the width of each rectangle indicates the total population of each race for the given geographic scale, and the height represents the $PM_{2.5}$-attributable mortality rate of each race, reported per 100,000 persons of each racial group.

EXHIBIT 3-6. REDUCTION IN $PM_{2.5}$-ATTRIBUTABLE MORTALITY RATE UNDER AN ALTERNATIVE STANDARD OF 8 µG/M³ BY RACE



On average across the U.S., Black Americans stand to gain the highest reduction in per-capita mortality risk by reducing concentrations of $PM_{2.5}$ to 8 µg/m³ nationwide, while Native Americans' risk would fall the least. Unlike under the current $PM_{2.5}$ conditions, Asian Americans stand to experience greater per capita benefits in terms of mortality risk reduction than white Americans under an alternative standard of 8 µg/m³.

As shown in Chapter 2, a greater proportion of Black populations are exposed to $PM_{2.5}$ exposures between 8 and 10 µg/m³, relative to all other races. These findings are consistent with the findings above that these individuals experience larger benefits on a per-person basis when the current NAAQS is lowered to 10 and 8 µg/m³. When compared across races, the per-capita mortality risk reductions show that Black individuals benefit from more protective standards at two to three times the rate of all other races, with this difference in mortality rates increasing outside the PA areas and at a national scale. These results are consistent with the PA's findings that Black populations are disproportionately affected by $PM_{2.5}$ under current conditions relative to other races. However, our analysis provides additional context on the racial disparities outside of the PA areas assessed.

Individuals living in poverty will experience 30 percent higher mortality benefits per capita from more protective $PM_{2.5}$ NAAQS.

In addition to assessing differences across race and ethnicity, we estimate the per-capita mortality risk reduction for low-income individuals, presented in Exhibit 3-7. Although observed disparities are not as dramatic as those experienced by Black or Hispanic populations, individuals living below two times the poverty line stand to experience 30 percent higher benefits due to reduced mortality rates at alternative standards, compared to those with higher incomes.

EXHIBIT 3-7. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS FOR THOSE AGED 65-99 BY ALTERNATIVE NAAQS (PER 100,000)

CONCENTRATION – RESPONSE RELATIONSHIP	POVERTY STATUS	PA AREAS	NATION	NON-PA AREAS	PA AREAS	NATION	NON-PA AREAS
		10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Combined Totals*	Below 2x Poverty Line	38	12	3	91	42	22
	Above 2x Poverty Line	29	9	1	74	31	15

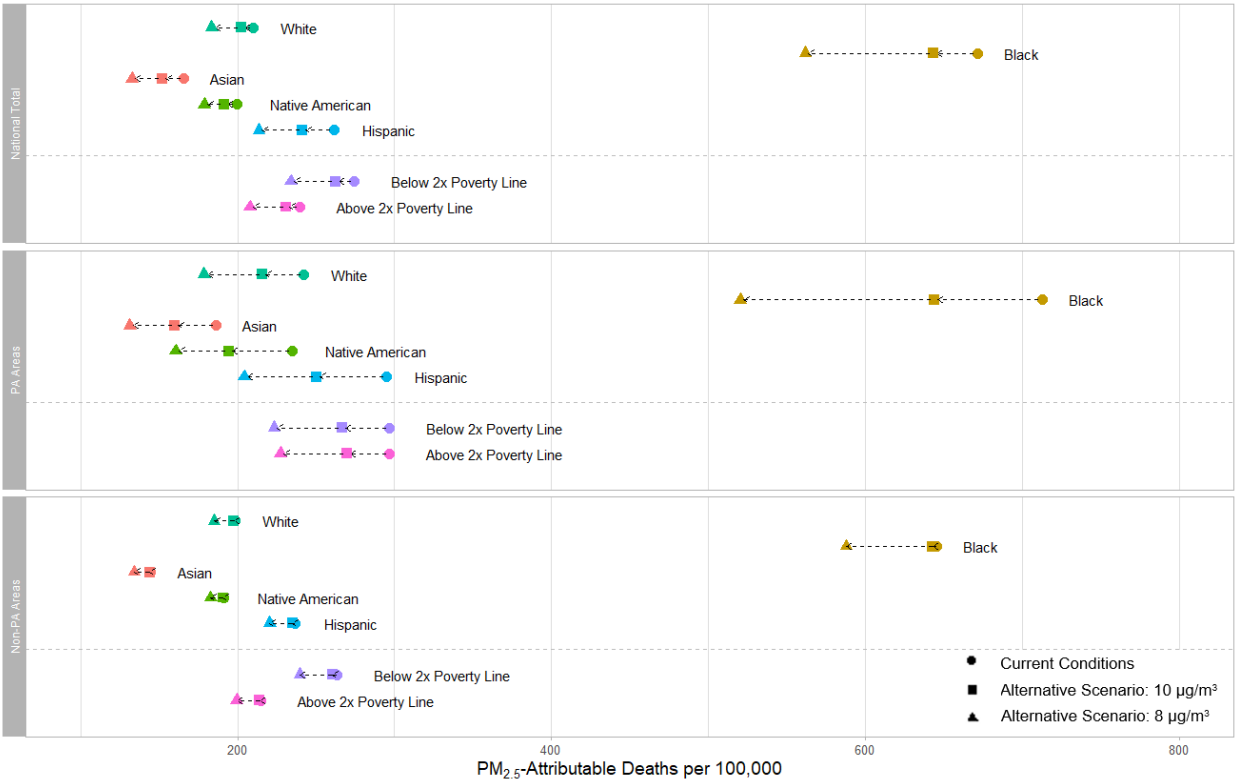
Note: values are rounded to two significant figures.
*We use the sum of the $PM_{2.5}$-attributable mortality below or above 2x the poverty line derived from the Di et al. (2017) race-specific concentration-response functions.

Exhibit 3-8 presents another view of the findings from Exhibit 3-6 and 3-7. It illustrates the disparities in mortality risk reduction across three spatial dimensions by race, ethnicity, and poverty status, starting from current mortality burden and ending at an alternative standard of 8 µg/m^3. As seen in the length of the connecting lines that demonstrate how per capita $PM_{2.5}$-attributable risks decrease from current conditions to each alternative standard, the risk benefits vary by group and with each incremental change in the standard. We find that Black Americans stand to gain the most in terms of reductions in per capita mortality risk from more protective annual NAAQS. However, even when NAAQS is set at 8 µg/m^3, Black populations still experience $PM_{2.5}$-attributable mortality risks that exceed that of all other races by a substantial margin. Our results also show that although Hispanic individuals do not benefit from the alternative standards at the same rate as Black individuals, their per-capita benefits are the second highest among all subpopulations. This suggests that Hispanic populations are also disproportionally affected by poor air quality.

Exhibit 3-8 shows that PA areas experience larger risk reduction benefits from lowering the current NAAQS *on an individual basis*, compared to non-PA areas. This occurs because more of the high-exposure individuals live in the CBSA areas modeled in the PA. As noted above, while benefits are experienced in both PA and non-PA areas, as the NAAQS is lowered past 10 µg/m^3, PA areas potentially

experience much higher risk reductions relative to non-PA areas, because of the significant portions of individuals, particularly minorities exposed to concentrations between 10 and 8 µg/m^3.[12]

EXHIBIT 3-8. MORTALITY RATES UNDER CURRENT AND ALTERNATIVE PM NAAQS, AGES 65-99



Exhibits 3-9 and 3-10 show the distribution of avoided PM-attributable deaths per 100,000 by race under the two alternative NAAQS scenarios, 8 and 10 µg/m^3. These maps show benefits from using the race-stratified Di et al. (2019) concentration-response function for ages 65-99. Non-PA areas with a zero value for deaths per capita reflect 1 x 1 km cells that contain current $PM_{2.5}$ exposure levels below the alternative NAAQS. For example, if a non-PA area has a current conditions $PM_{2.5}$ concentration of 9 µg/m^3, only the 8 µg/m^3 NAAQS scenario will model benefits within that area of reducing the baseline concentration of 9 µg/m^3 to 8 µg/m^3.[13] For the 10 µg/m^3 alternative NAAQS scenario, since the baseline $PM_{2.5}$ concentration is already below the alternative standard, no benefits are modeled.

As expected, a more protective standard of 8 µg/m^3 results in a higher rate of avoided PM-attributable deaths, particularly in areas not previously assessed by the PA. As seen by the greater density in coloring across non-PA areas for the 8 µg/m^3 scenario, lowering the NAAQS from 10 to 8 µg/m^3 captures a significant portion of benefits from non-PA areas that contain baseline $PM_{2.5}$ concentrations between 8 and 10 µg/m^3.

[12] Our analysis only evaluates EPA's air quality surface based on control of primary $PM_{2.5}$ emissions and does not consider control of secondary (area-source) $PM_{2.5}$ emissions

[13] Appendix E provides more detail into our modeling approach for estimating benefits under more stringent $PM_{2.5}$ NAAQS.

EXHIBIT 3-9. AVOIDED PM-ATTRIBUTABLE DEATHS PER 100,000 FOR 10 µG/M³ ALTERNATIVE NAAQS FOR AGES 65-99,1 X 1 KM AIR QUALITY SURFACE

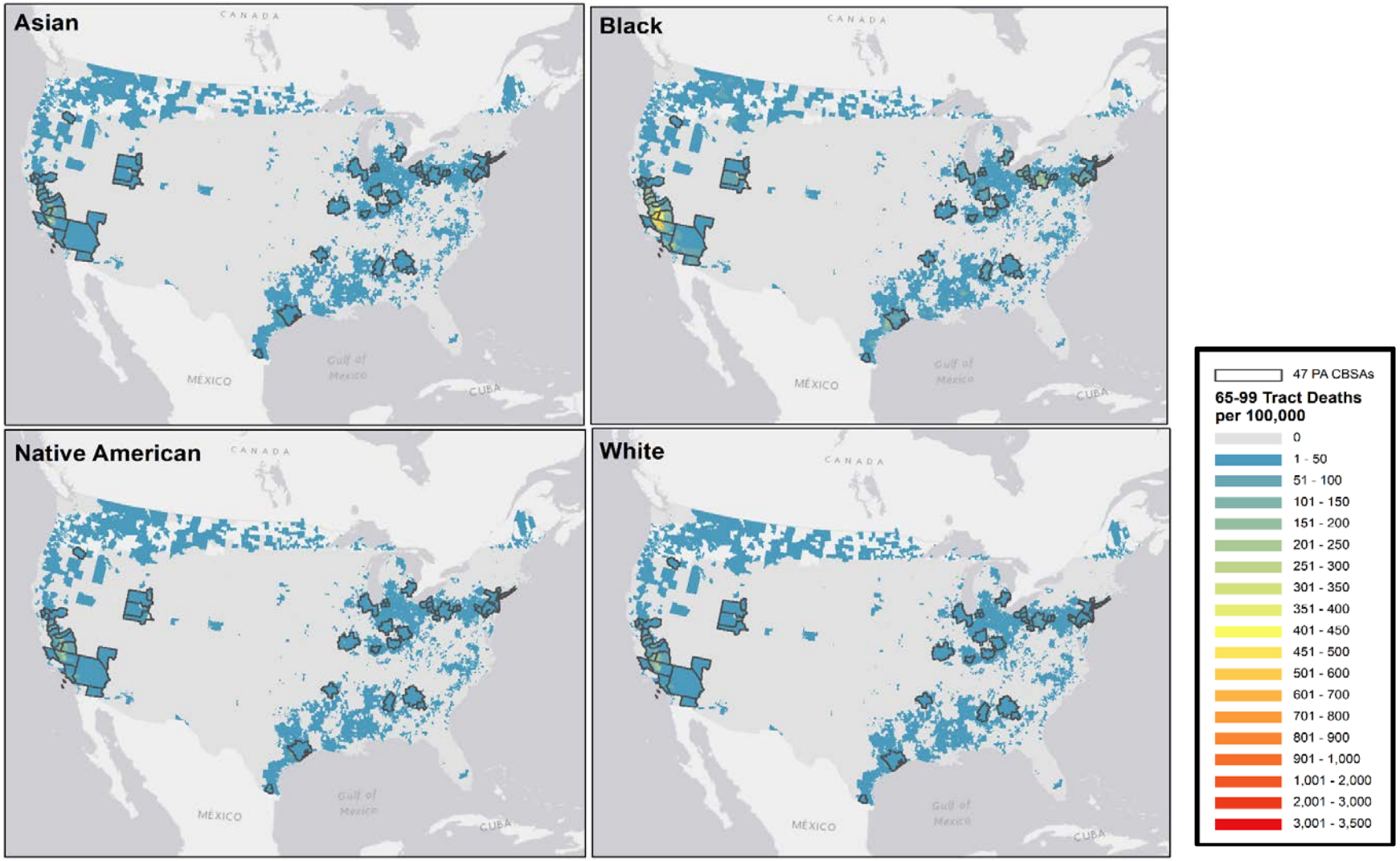
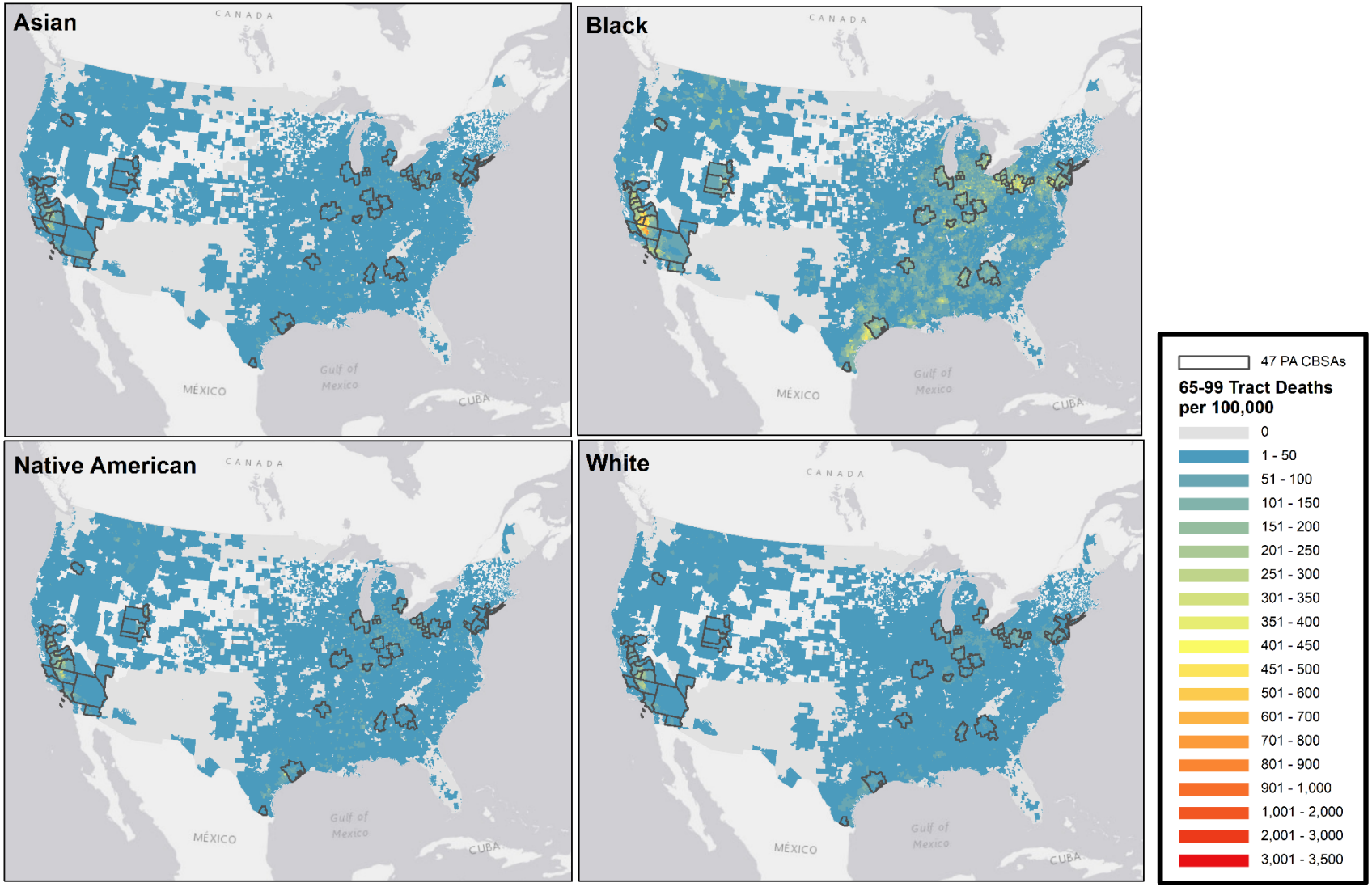


EXHIBIT 3-10. AVOIDED PM-ATTRIBUTABLE DEATHS PER 100,000 FOR 8 μG/M³ ALTERNATIVE NAAQS FOR AGES 65-99, 1 X 1 KM AIR QUALITY SURFACE



MORBIDITY RISK REDUCTION UNDER ALTERNATIVE $PM_{2.5}$ STANDARDS

Exhibit 3-11 shows the morbidity risk reduction under two alternative standards (10 µg/m^3 and 8 µg/m^3) across three geographies. These estimates reflect avoided hospitalizations, emergency department visits, and incidence of asthma and non-fatal acute myocardial infarctions (heart attacks) based on baseline rates of disease not stratified by race or ethnicity.

EXHIBIT 3-11. AVOIDED $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN (ALL RACE/ETHNICITY)

ENDPOINT	CONCENTRATION - RESPONSE FUNCTION	AGE GROUP	NATION	PA AREA	NON-PA AREAS	NATION	PA AREA	NON-PA AREAS
			10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
HOSPITALIZATIONS								
Non-fatal AMI	Peters et al. (2001)	18-99	4,600	4,000	510	18,000	10,000	8,000
Non-fatal AMI	Pooling 5 Studies*	18-99	670	590	74	2,700	1,400	1,200
All Respiratory	Ostro et al. (2016)	0-18	430	390	37	1,600	950	650
Respiratory-1	Jones et al. (2015)	0-99	250	230	30	1,000	560	440
Respiratory-2	Bell et al. (2015)	65-99	80	70	10	320	180	140
Cardio-, Cerebro- & Peripheral Vascular Disease	Bell et al. (2015)	65-99	550	480	62	2,100	1,200	920
All Cardiac Outcomes	Talbott et al. (2014)	0-99	470	420	53	1,900	1,000	850
Alzheimer's Disease	Kioumourtzoglou et al. (2016)	65-99	1,000	1,000	200	6,200	3,000	3,200
Parkinson's Disease	Kioumourtzoglou et al. (2016)	65-99	220	190	30	860	470	390
EMERGENCY ROOM VISITS								
Respiratory	Krall et al. (2016)	0-99	3,100	2,800	300	12,000	6,700	4,800
Emergency Hospitalizations – Respiratory**	Zanobetti et al. (2009)	65-99	780	690	90	3,100	1,700	1,500
INCIDENCE								
Asthma	Tetreault et al. (2016)	0-17	13,000	12,000	1,200	46,000	28,000	18,000

Note: values are rounded to two significant figures
*Five AMI studies pooled together include: Pope et al., Sullivan et al., Zanobetti and Schwartz, and Zanobetti et al.
**Emergency Hospitalizations represent emergency department visits that result in a hospitalization.

Overall, when we compare trends across scenarios and space, we find similar conclusions to our mortality benefits analysis. At an alternative standard of 10 µg/m^3, PA areas capture the vast majority of benefits compared to non-PA areas.

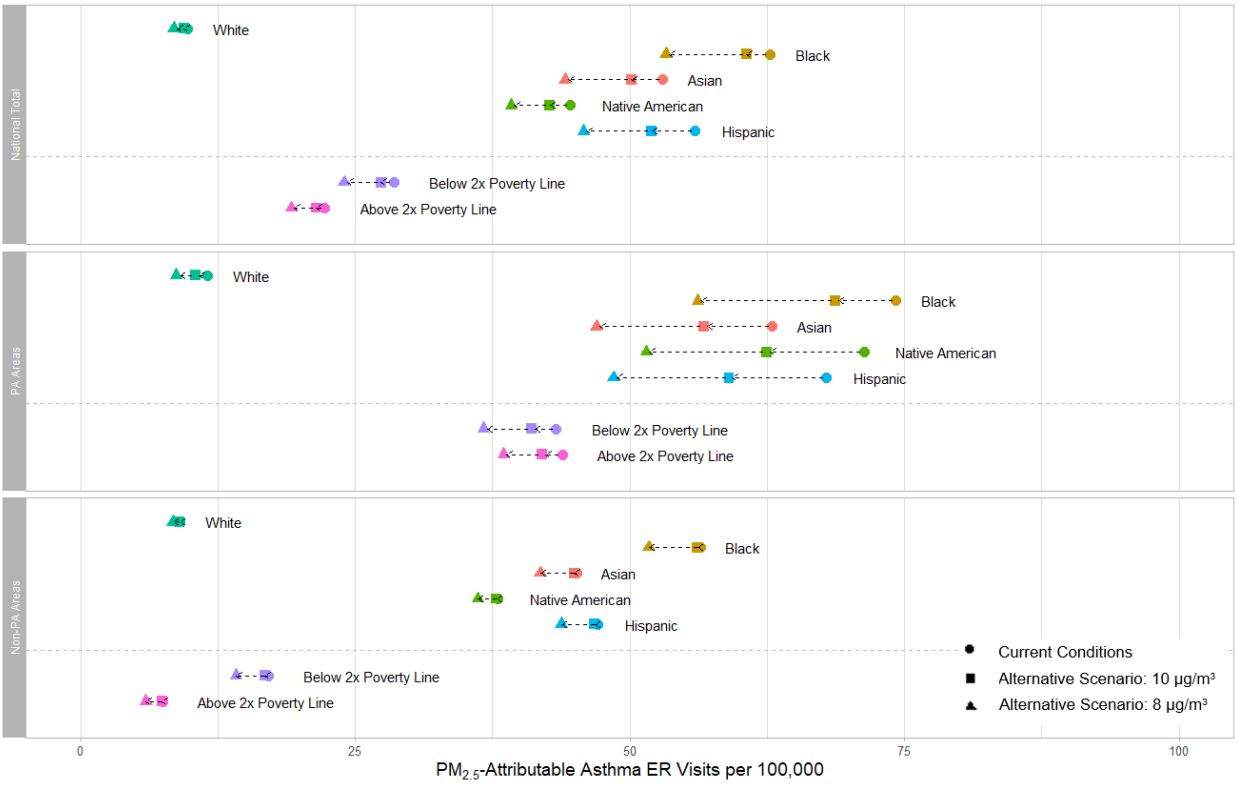
However, at an alternative standard of 8 μg/m^3, while PA area-attributed benefits more than double, non-PA area-attributed benefits increase at a much larger rate. For example, hospital admission reductions in non-PA areas attributed to non-fatal acute myocardial infarction (as estimated based on Peters et al. 2001) rise from 514 for the 10 μg/m^3 standard scenario to 8,434 for the 8 μg/m^3 scenario. This represents a more than 1,500 percent increase when moving from 10 to 8 μg/m^3. As such, under an alternative NAAQS of 8 μg/m^3, avoided $PM_{2.5}$-attributable morbidity burden in non-PA areas represent nearly half of all benefits. This indicates the potential benefits of moving past an alternative standard of 10 μg/m^3 to 8 μg/m^3 for non-PA area populations.

Exhibit 3-12a and 3-12b presents avoided asthma-related emergency room visits (per capita) for children ages 0 to 18 across the same geographies and alternative NAAQS scenarios but stratified by race and ethnicity based on estimates from the Alhanti et al study. We observe the same trends across alternative NAAQS scenarios and space as found in Exhibit 3-11 for morbidity endpoints not stratified by race or ethnicity. In general, the rates of potential benefits for non-white groups from more protective NAAQS are several times larger than those for white Americans.

EXHIBIT 3-12A. AVOIDED ASTHMA-RELATED EMERGENCY ROOM VISITS IN CHILDREN AGED 0-18 BY ALTERNATIVE NAAQS (PER 100,000, STRATIFIED BY RACE/ETHNICITY)

RACE/ ETHNICITY	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
	10 μG/M3 ALT NAAQS			8 μG/M3 ALT NAAQS		
White, Non-Hispanic	0.31	1.1	0.050	1.2	2.8	0.66
All White, Hispanic Plus All Other Races, Ethnicities	3.1	7.5	0.27	9.6	19	3.8

EXHIBIT 3-12B. AVOIDED ASTHMA-RELATED EMERGENCY ROOM VISITS IN CHILDREN AGED 0-18 BY ALTERNATIVE NAAQS (PER 100,000, STRATIFIED BY RACE/ETHNICITY AND POVERTY)



CHAPTER 4 | FINE SCALE MORBIDITY CASE STUDY: NEW JERSEY

In this chapter, we explore the sensitivity of morbidity results to the spatial scale and demographic stratification of incidence data. While previous chapters presented mortality data stratified by race and census tract, the morbidity incidence data that is publicly available for use in benefits analysis is, at best, aggregated at the county level typically is not stratified by race or ethnicity. As a proof-of-concept case study, we have explored the use of finer scale inputs, both in terms of spatial resolution and race- and ethnicity-stratification for a single state. We present below our approach and results for a calculation of PM-attributable asthma-related emergency department visits in New Jersey.[14]

DATA PROCUREMENT AND PROCESSING

To compare results across spatial scales and demographic compositions, we obtained and processed discharge-level emergency department visit data for New Jersey from 2016 to 2019 from the Healthcare Cost and Utilization Project's State Emergency Department Database (HCUP SEDD). Processing involved identifying all non-fatal visits to the emergency department in which the primary diagnoses was asthma (ICD-10 J45). These cases were aggregated to different levels of spatial and geographic aggregation. Exhibit 4-1 presents these two levels of aggregation for New Jersey incidence data.

EXHIBIT 4-1. AGGREGATION OF NEW JERSEY INCIDENCE DATA

ENDPOINT	AGES	SPATIAL SCALE	RACIAL/ETHNIC STRATIFICATION
Emergency Department Visits, Asthma	0-4, 5-18	ZIP code*	White Hispanic, white non-Hispanic, non-white
		ZIP3	Not stratified by race or ethnicity

Notes: *In instances where ZIP code and demographic stratified ED counts are below 11, we aggregate data from nearby ZIP codes to estimate a ZIP3-level rate. If cases are still <11, we aggregate further to the state level. The three racial/ethnic combinations are intended to match the categories in Alhanti et al. (2016). While further stratification is possible (e.g., by Black, Asian, and Native American), data suppression (i.e., instances where cases <11) results in more frequent use of imputation using rates at coarser geographic scales.

We produced two datasets: one for all race and ethnicity aggregated to the ZIP3 level, and one aggregated to the finer ZIP code level and stratified by white Hispanic, white non-Hispanic, and non-white. ZIP3s represent geographic aggregations of ZIP codes sharing the first three digits. There are 20 such areas in

[14] Our choice of endpoint and state were largely informed by data availability. Asthma ED visits are the only morbidity function for which we use race-specific effect coefficients (Alhanti et al. 2016). Further, we selected New Jersey because it is assessed in the PA (i.e., has relatively high $PM_{2.5}$ concentrations and available monitors) and provides the necessary data (ED counts) and data elements (race, ethnicity, zip code) upon purchase from the Healthcare Cost and Utilization Project State Emergency Department Database (HCUP-SEDD).

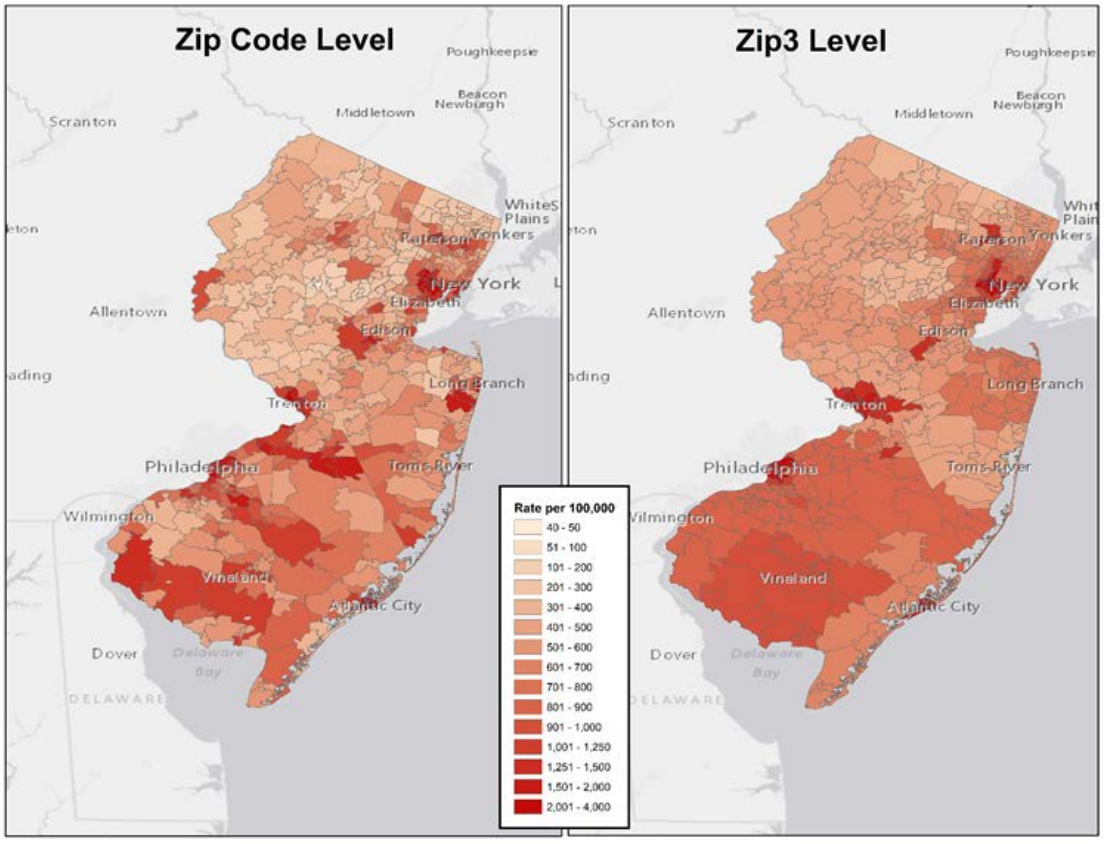
New Jersey, roughly equivalent to the number of counties (21).[15] We opted to compare these two datasets instead of using the default BenMAP-CE county-level incidence to minimize differences in datasets and data cleaning and processing.[16] Thus, the comparison presented below isolates the effects of geographic and demographic aggregation.

As expected, the resulting datasets characterize baseline asthma ED incidence with differing levels of variation across the state. Whereas the ZIP3 file includes 40 distinct incidence rates (20 per age group), the finely resolved dataset includes 1,336 unique values.

ANALYSIS

We investigate the impact of incidence datasets by assessing the current $PM_{2.5}$ burden statewide. Exhibit 4-2 shows the increased variance in baseline asthma ED visit rates in the state revealed when using zip code level data, and Exhibit 4-3 shows the impact of this difference on PM-attributable asthma ED visit burden. Exhibit 4-4 aggregates these results and shows the impact of applying finer scale incidence data on the asthma ED health burden estimates for the whole state, and health burdens stratified by race.

EXHIBIT 4-2. BASELINE INCIDENCE FOR ASTHMA ED VISITS IN NEW JERSEY AT ZIP CODE AND ZIP3 SCALES



[15] ZIP3s do not align with county borders. In at least one case (086), individual ZIP3s are split and do not represent one contiguous polygon.

[16] The differences between the BenMAP-CE and newly processed datasets include: (1) 2014 vs. 2016-2019 data, (2) medical coding of ICD-9 vs. ICD-10, and (3) processing for BenMAP-CE includes further imputation beyond state boundaries (e.g., regional datasets from HCUPnet).

EXHIBIT 4-3. PM-ATTRIBUTABLE ASTHMA ED VISITS IN NEW JERSEY AT ZIP CODE AND ZIP3 SCALES

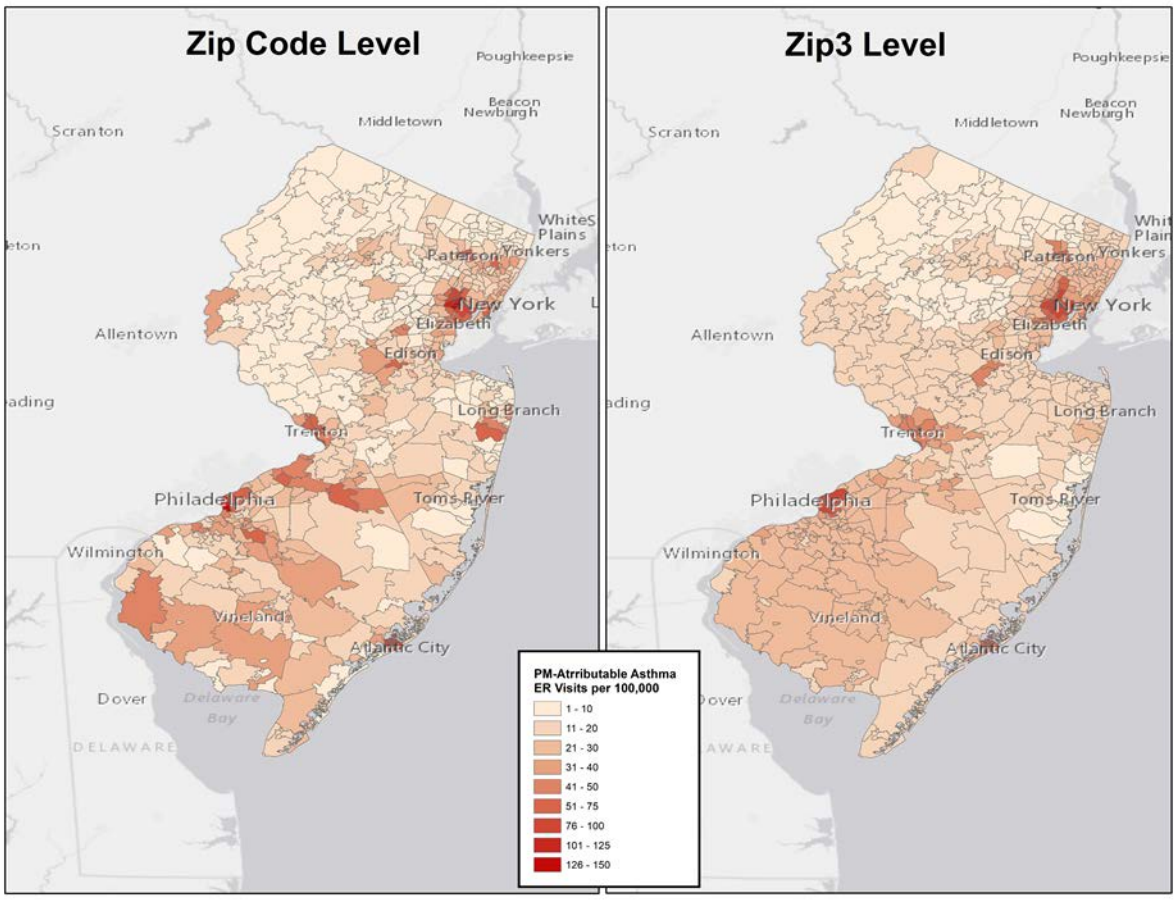


EXHIBIT 4-4. COMPARISON OF TOTAL $PM_{2.5}$-ATTRIBUTABLE ASTHMA ED VISITS IN NEW JERSEY USING ZIP CODE VERSUS ZIP3 INCIDENCE, BY RACE

RACE	ETHNICITY	TOTAL ED VISITS		DIFFERENCE (ZIP3 - ZIP CODE)	
		ZIP3 AGGREGATED	ZIP CODE & RACE/ETHNICITY	TOTAL	PERCENT
White	Non-Hispanic	7,600	5,400	-2,200	-29.0%
White	Hispanic	4,800	2,700	-2,100	-45%
Black	ALL	4,000	7,700	3,700	91%
Asian	ALL	1,600	2,000	370	23%
N. American	ALL	120	220	100	84%
Totals		18,000	18,000	0	0%

Statewide, the two incidence datasets produce comparable estimates overall. We estimate that ambient $PM_{2.5}$ results in an equivalent number of asthma ED visits each year, using either data set. The ZIP3 data, however, fails to reflect important differences in incidence by race and ethnicity.

Aggregated incidence rates overstate asthma ED incidence for white populations by 30% and understate incidence for other races by up to 90%.

By stratifying estimates by race, ethnicity, and zip code, we calculate $PM_{2.5}$-attributable cases that vary substantially from the aggregated incidence estimates for each race. In general, we find that aggregated incidence rates overstate incidence for white populations and understate incidence for other races. These differences are sizable. Employing finer scale and race/ethnicity stratified rates lowers white Hispanic estimates by 45 percent and increases Black estimates by 91 percent.

CONCLUSIONS

Baseline incidence represents a key data input for estimating air pollution attributable health effects. We demonstrate that coarse geographic resolutions (e.g., ZIP3, county)—such as those used in the PA for hospitalizations and emergency room visits—should accurately characterize overall incidence; however, these datasets do not facilitate the reliable estimation of race-specific effects. Health datasets are increasingly reporting rates at fine scales and by demographic factors relevant to distributional analyses. Finally, we note that while not illustrated in this chapter, fine scale incidence data is more suitable for assessing impacts at smaller scales. Aggregation to the state level masks this observation.

CHAPTER 5 | DISCUSSION

In this report, we used more finely resolved data sources for air quality, baseline health status, demographics, and risk to estimate the health burden of $PM_{2.5}$ exposures in the U.S., both in total and across races, ethnicities, and poverty status. We also estimated the potential benefits of more health protective $PM_{2.5}$ standards in the U.S. across these subgroups. Our results have provided insights into the distribution of health burdens and the potential to both improve public health generally and reduce discrepancies in risk across subgroups by adopting more protective annual NAAQS standards. Further, the results suggest there is value to using analytical inputs at finer geographic scales and inputs particular to specific subpopulations to better understand variabilities in risks. In this chapter, we present the main conclusions from our analysis, review limitations associated with our approach, and highlight areas for future research and analysis to further inform our understanding of the impact of fine-scale inputs on distributional health risk analysis.

CONCLUSIONS

Our results bolster the findings in EPA's most recent PA; current $PM_{2.5}$ concentrations result in significant premature mortality and morbidity nationwide, and these impacts are disproportionately borne by Black and Hispanic populations, and those living in poverty. Strengthening PM NAAQS would lessen both the overall social costs of air pollution and the disparities in health outcomes by race, ethnicity, and income levels.

This work provides valuable results that can be broken down across four axes: 1) the importance of spatial resolution of annual average $PM_{2.5}$ concentrations in understanding related health impacts; 2) the distribution of health impacts across groups as defined by race, ethnicity, and income; 3) expansion upon the important work done by EPA in their most recent PA, and 4) state-level application of our method.

We find that employing the fine scale air quality surface from Di et al., 2017 (at 1 x 1 km) has a bigger impact on characterizing variability in risks and identifying hot spots at the census tract level than on modifying large scale aggregations of results nationally. Use of this particular surface results in highly similar, but slightly lower estimates of total current health burden in areas modeled by EPA with 12 x 12 km air quality surfaces in the PA. However, the fine scale results identified a substantial number of census tracts with high per capita risk levels, many of which were in majority minority census tracts. This suggests that use of fine scale air quality data may be even more important for distributional analysis and neighborhood scale assessments. We also find that using fine scale (i.e., at the census tract level) baseline mortality incidence data tends to produce larger estimates of total current health burden compared to county-level mortality incidence, as these data may highlight people in more densely populated areas who experience poorer health generally and thus may be more susceptible to $PM_{2.5}$. These finer scale data can also help to better characterize distributions of health burden across disadvantaged groups in future analyses.

While finer scale spatial variability in air quality and baseline death rates explain some of the observed disparities in health outcomes, other factors play an important role as well. We estimate that Black Americans 65 and older experience three times as many PM-related deaths (per capita) as other racial groups at current air quality concentrations. This effect is primarily driven by the concentration-response relationship estimated by Di et al (2017) for Black Americans. Relative to other racial groups, Black Americans experience 9% higher $PM_{2.5}$ concentrations, 3% higher baseline mortality incidence rates, and a 202% higher PM-mortality risk.

Our broader geographic scope enables us to comment on existing disparities and potential benefits outside of the PA study areas. While concentrations outside of PA areas are notably lower on average, disparities in health outcomes are, in some cases, starker for regions not modeled by EPA. Although PM-attributable mortality and morbidity burden does not vary dramatically when stratified by poverty status within the PA areas, the pattern diverges significantly elsewhere. Outside of the PA areas, individuals living in poverty experience a 30 percent higher PM-attributable mortality rate relative to individuals with higher incomes. We note that the benefits of a 10 $\mu g/m^3$ annual standard represent a small fraction of total benefits outside of the PA areas where baseline concentrations tend to be lower; however, for a standard of 8 ug/m^3, non-PA areas could potentially comprise a substantial share of benefits. In addition to broadening the geographic scope to the national level, we provided a state-level case study in New Jersey to highlight the value of fine-scale morbidity incidence data. This application demonstrated that while aggregated datasets may facilitate the accurate estimation of total impacts, they may mischaracterize impacts by race, ethnicity, or fine-scale geography. While we employed data from the same set of databases used in the PA (HCUP SEDD), we note that many states do not make such data available and the states that do partner with HCUP do not always have the necessary data elements for these types of analyses (e.g., ZIP code, race, ethnicity).

LIMITATIONS

Our analysis is subject to the standard suite of uncertainties that accompany BenMAP-style health burden or health benefits analyses – uncertainties in concentration-response relationships between PM exposure and health outcomes; uncertainties in exposure assessment based on modeling of concentrations in locations distant from ground-level monitors; uncertainties in estimates of baseline health rates where data may need to be imputed or where available data must be used to approximate the population of interest; scenario uncertainty related to predicting future PM changes to meet alternative PM NAAQS; and in the economic values used to monetize these impacts. However, in addition to these there are some additional limitations particular to our approach and objectives.

First, we note that conclusions based on our use of fine scale modeling compared with EPA's 12 km model are limited by our use of a single air quality model for comparison; comparisons with additional hybrid air quality models would help make our findings more robust. Second, our use of ambient air quality estimates from the Di et al. model in non-PA areas, particularly outside of metropolitan areas, is subject to greater uncertainty than the results in the PA locations. We also direct readers to EPA's thorough discussion of ambient $PM_{2.5}$ exposure estimation in Chapter 2 of the PA. EPA comments on the heightened uncertainty in exposures in the western United States and in areas distant from monitors:

> "Excellent performance in cross-validation tests suggests that hybrid methods are reliable for estimating $PM_{2.5}$ exposure in many applications… However, there are also important limitations

> associated with the modeled fields… Performance evaluations for the [hybrid $PM_{2.5}$ modeling] methods are weighted toward densely monitored urban areas at the scales of representation of the monitoring networks. Predictions at different scales or in sparsely monitored areas are relatively untested. Second, studies have reported heterogeneity in performance with relatively weak performance in parts of the western U.S., at low concentrations, at greater distance to monitors, and under conditions where the reliability and availability of key input datasets (e.g., satellite retrievals and air quality modeling) are limited." (p. 2-61).

This discussion underscores our conclusion that modeling PM-attributable health effects outside of PA areas is accompanied by greater uncertainty. Additionally, we apply a simplistic approach to modeling air quality in the non-PA areas under an alternative NAAQS in lieu of conducting additional air quality modeling of changes to specific emissions source, and it may differ from the ultimate approaches pursued at the state and local level to achieve compliance as defined under the Clean Air Act. We believe our approach is likely to approximate the magnitude of benefits of air quality changes in areas currently exceeding a revised NAAQS; we also note that it would not reflect additional benefits of air quality management plans that would result from reducing emissions sources that would also affect $PM_{2.5}$ concentrations areas below proposed alternative NAAQS levels.

Second, our use of USALEEP-based mortality incidence data at the census-tract level reflects not only the uncertainties associated with the model used in that study, but also includes approximations of rates for the 85+ category, which were not reported in the USALEEP results. We are currently in the process of obtaining administrative data sets for a series of locations that we will use to provide some spot validations of these estimates.[17]

The race-specific concentration-response estimates applied in this study are derived from high quality peer-reviewed epidemiological literature and build off a substantial foundation of such studies conducted over decades that have found associations between fine particle exposures and mortality and morbidity. Nonetheless, the estimation of these race- and ethnicity-stratified risk estimates is a recent development in the evolution of this literature; additional studies in this area will help give us a fuller picture of the uncertainty and variability in effect modification of PM attributable mortality impacts by race and ethnicity. Our benefit results for NAAQS levels as low as 10 or 8 $\mu g/m^3$ presume that levels at or near these would still result in health impacts, and that the relationship would continue to be linear; this assumption continues to be supported by studies finding health impacts using studies of more recent air quality featuring lower mean concentrations (e.g., Pope et al, 2019, Wang et al. 2020, Wu et al., 2020). Further EPA notes in the PA that some studies report confidence in the linear relationship down as low as 5 $\mu g/m^3$ (2021).

Finally, our exploration of the use fine scale data was unable to address the impact of combined improvements in the geographic scale of inputs such as baseline health rates and improvements in the race-specificity of these data, due to extensive data suppression issues resulting from parsing of these data across both dimensions.

[17] Initial comparisons between USALEEP data and administrative data in Alameda County look promising. Using modeled USALEEP 0-99 incidence rates and observed death rates in the county, we calculate a Pearson correlation coefficient of 0.881 between values at the tract level.

AREAS FOR FUTURE STUDY

Given the limitations of the current study, we present several areas for future work. First, we opted to analyze two alternative standards. 8 and 10 μg/m^3. The magnitude and distribution of benefits varied in important respects for each alternative. Analysis of intermediate (e.g., 9 or 11 μg/m^3) and lower standards (e.g., 6 μg/m^3) may be warranted; however, epidemiological literature may be limited to a greater degree at lower concentrations.

Second, we demonstrated that benefits calculations are sensitive to the input data selected. Consideration of additional datasets, such as air quality models or epidemiological studies, may be needed to better understand the range of potential benefits. While we selected the best available datasets according to our judgment, these datasets are nonetheless associated with uncertainty, and exploration of additional datasets would help improve the robustness of these findings. For example, additional investigation and comparison of hybrid air quality model performance in the Western U.S. across models would be useful to better understand implications of these uncertainties on results in that portion of the country.

Finally, our understanding of the potential improvements resulting from more geographical- and population specific data would benefit from additional investigation into statistical methods for addressing the censored data sets that result when data are parsed across multiple dimensions. Evaluation of alternative approaches to improve our understanding of spatial or subpopulation variation; enhance reliability in results generated using these data sets; and protect individuals' privacy are key to further progress toward the objective of more locally tuned benefits analysis.

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APPENDIX A | AIR QUALITY INPUTS

CURRENT $PM_{2.5}$ CONDITIONS

We used two air quality surfaces to represent current conditions and estimate the current burden of $PM_{2.5}$. For comparison against the EPA's 2021 $PM_{2.5}$ Draft Policy Assessment, we used the EPA 12-km monitored air quality surface from the 2021 PA, which is limited to the 47 CBSAs assessed in the PA (Exhibit A-1). For the fine scale burden analysis, we used the 1 x 1 km Di et al., 2019 air quality surface which utilizes satellite and monitor data to model 2015 daily and annual $PM_{2.5}$ concentrations in the US (Exhibit A-2).[18] Unlike the EPA 12 x 12 km air quality surface, the Di 1 x 1 km air quality surface was not restricted to the 47 CBSAs assessed in the PA. We assessed the annual average $PM_{2.5}$ values of each air quality surface to estimate the baseline health burden associated with ambient pollution. These air quality surfaces also represented the control surfaces when assessing more protective $PM_{2.5}$ standards.

[18] We reviewed several model air quality surfaces for use in our benefit analysis. In total, we reviewed six studies against four criteria for inclusion: the model must incorporate satellite and monitor data; the model must have a spatial resolution less than $12km^2$; the model was generated tuned to the extent of the US (i.e., not a global model); and the model performed well (i.e., had a goodness-of-fit value greater than 0.75). Our review found that only two studies, Di et al., 2016 and Di et al., 2019, met all of our criteria requirements. Since the Di et al., 2019 study was a more recent version of the Di et al., 2016 study, we decided that only Di et al., 2019 model would be assessed.

EXHIBIT A-1. 2021 PA EPA 12 X 12 KM MONITORED AIR QUALITY SURFACE – LIMITED TO THE PA AREAS

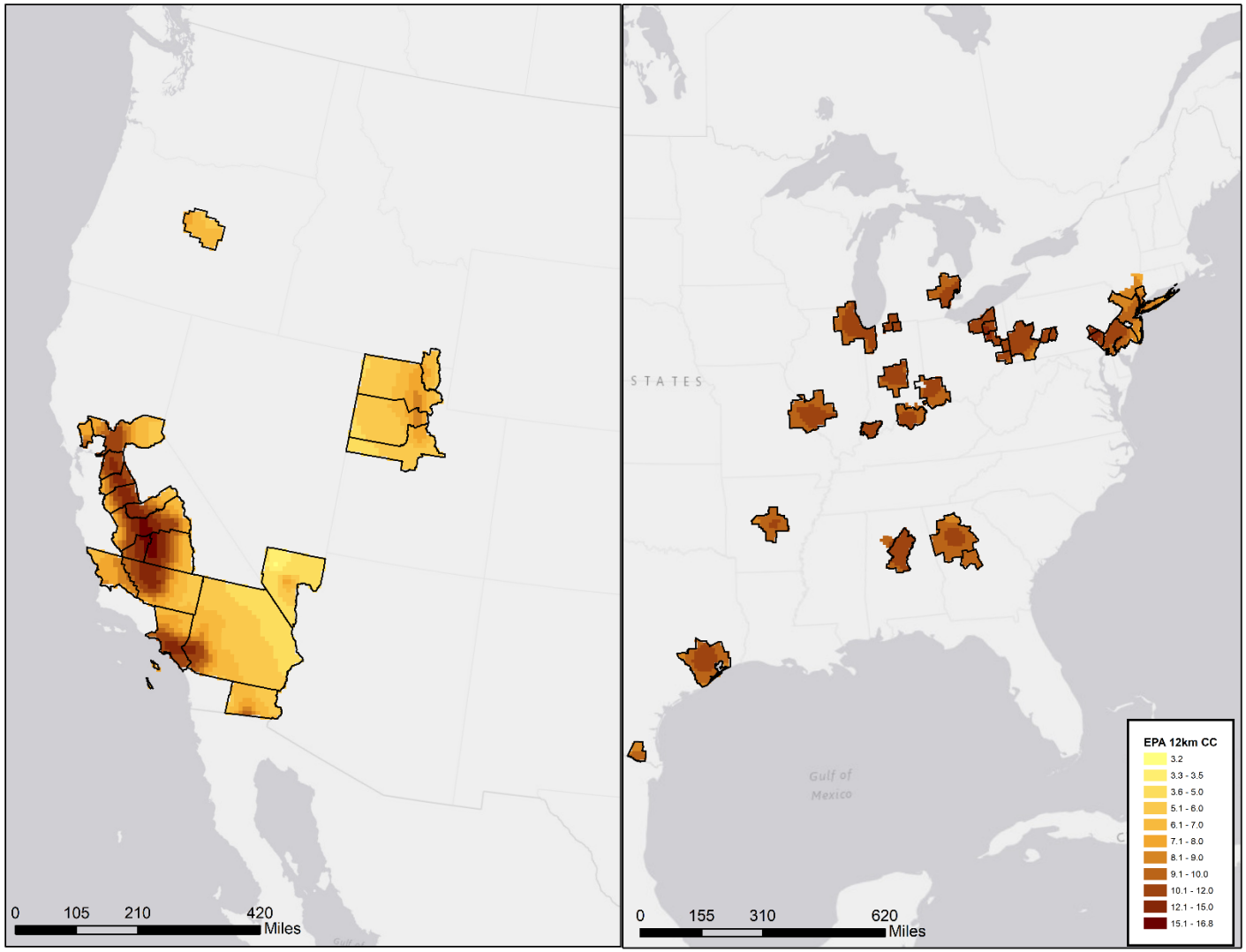
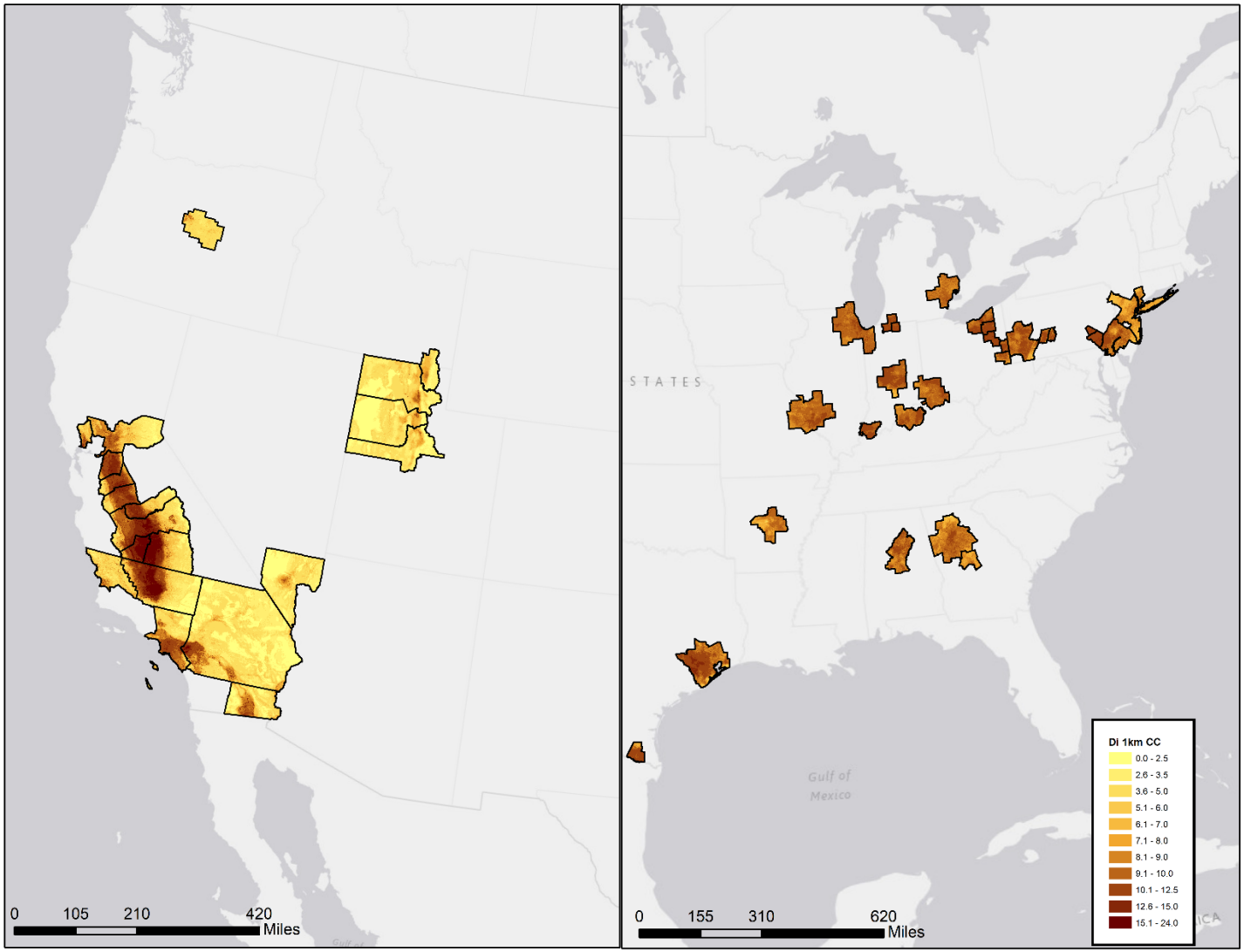


EXHIBIT A-2. DI ET AL. (2019) 1 X 1 KM 2015 ANNUAL $PM_{2.5}$ - RESTRICTED TO THE PA AREAS



ALTERNATIVE $PM_{2.5}$ STANDARDS

We evaluated the Di et al. (2019) air quality surface against two alternative standards, 8 µg/m^3 and 10 µg/m^3. To generate these air quality surfaces we treated grid cells within the PA areas differently from those outside of the PA areas. For grid cells within the PA areas, we applied an adjustment factor to each 1-km grid cell derived from the associated EPA modeled 12-km grid cell. That is, we will scale the baseline Di results proportionally based on the percentage change in the $PM_{2.5}$ concentration in EPA's alternative NAAQS control scenario relative to EPA's Current Conditions scenario.[19] For the remaining 1-km grid cells, we will apply a simplified "roll back" of air quality measurements for out of attainment cells to model benefits associated with just meeting the modeled standard (i.e., if a grid cell is above the standard it is set to equal the standard).

[19] Note that we deliberately do not compare the results against EPA's Baseline scenario in the draft PA, which estimates health burden assuming air quality degraded to a point where all areas modeled would just meet the current NAAQS. That is, the US would still be in compliance with the current, but concentrations in some areas would be higher than currently experienced. That scenario assumes conditions appropriate for a PA-type analysis which evaluates what conditions could be like if the standard remained unchanged. Our analysis focuses on assessing burden and benefits relative to current conditions as observed at monitors and estimated using state-of-the-art hybrid modeling.

APPENDIX B | DATA INPUTS

DATA INPUTS

See Appendix E Method Memorandum for details on input datasets and methods. This Appendix provides supplemental graphics of the datasets used in our analysis.

POPULATION

EXHIBIT B-1. PERCENTAGE OF TRACT POPULATION BY RACE

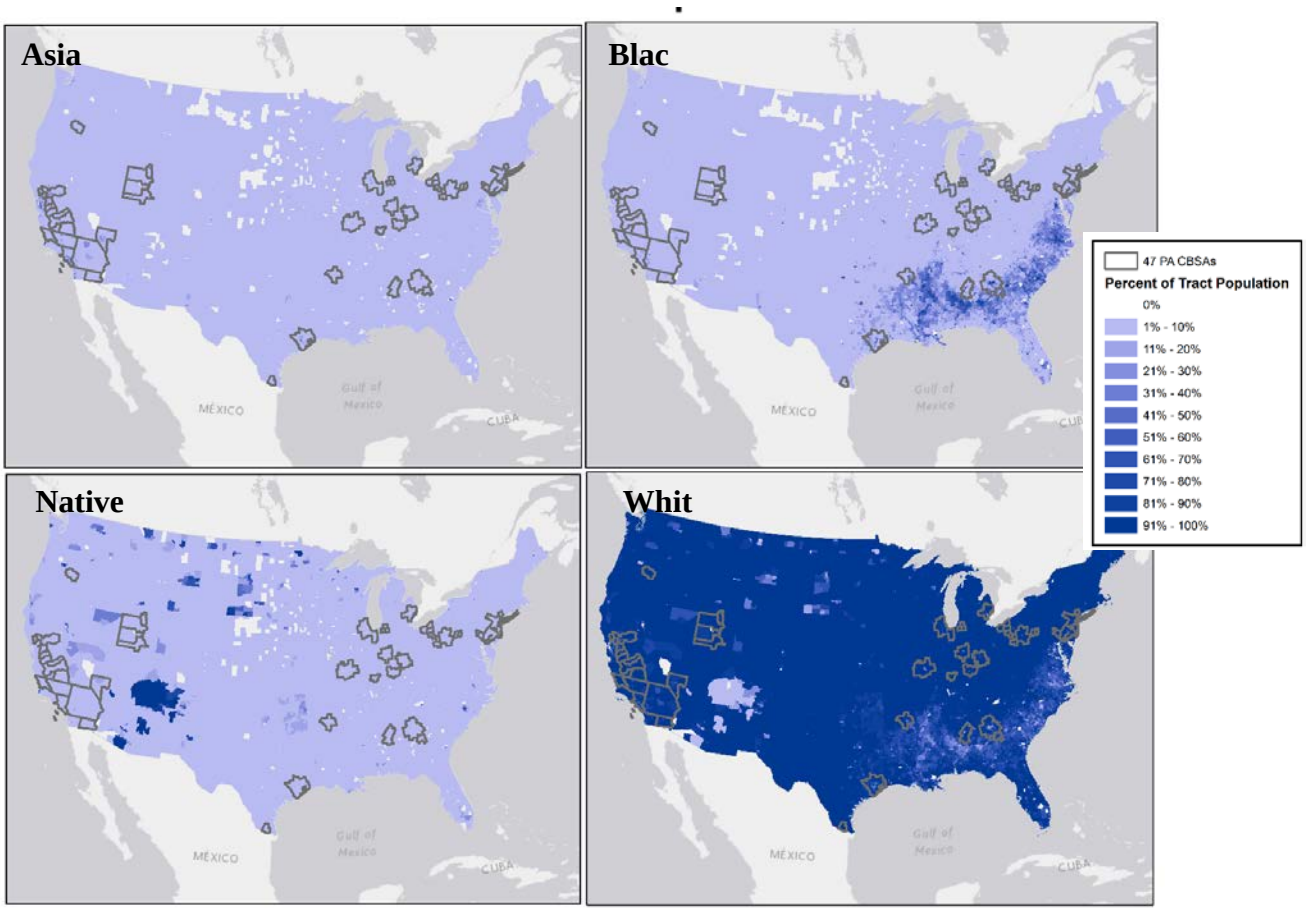
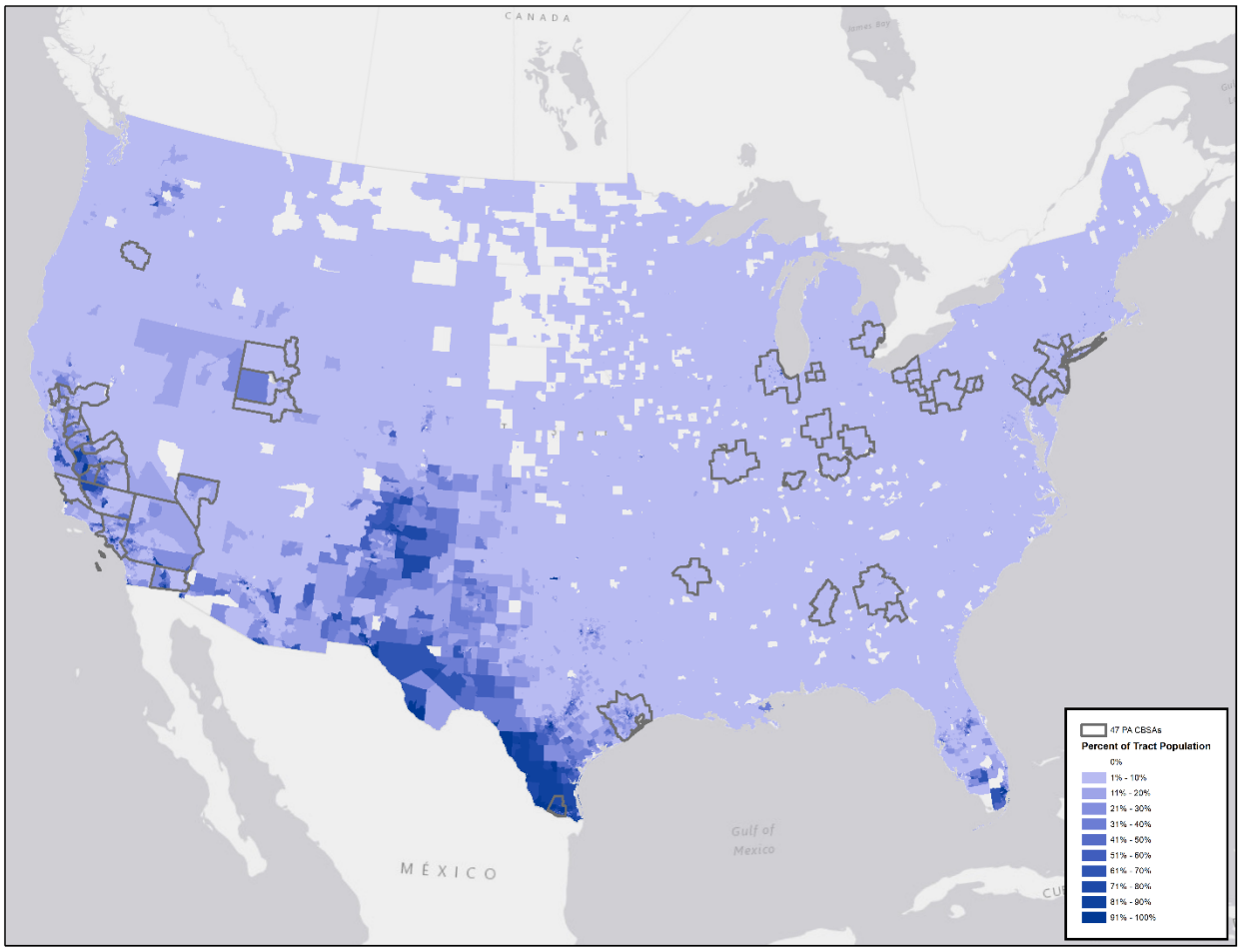
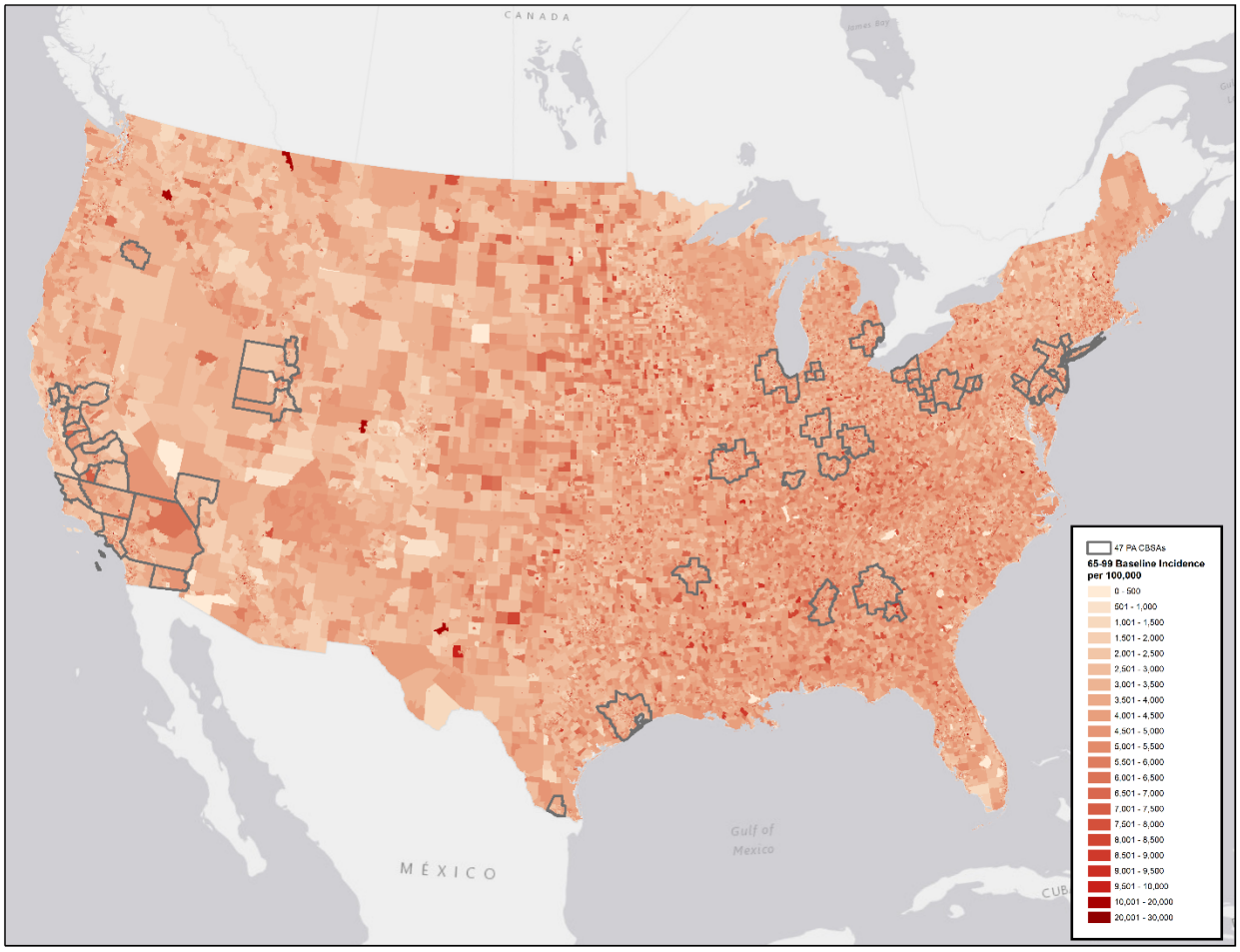


EXHIBIT B-2. PERCENTAGE OF TRACT POPULATION - HISPANIC



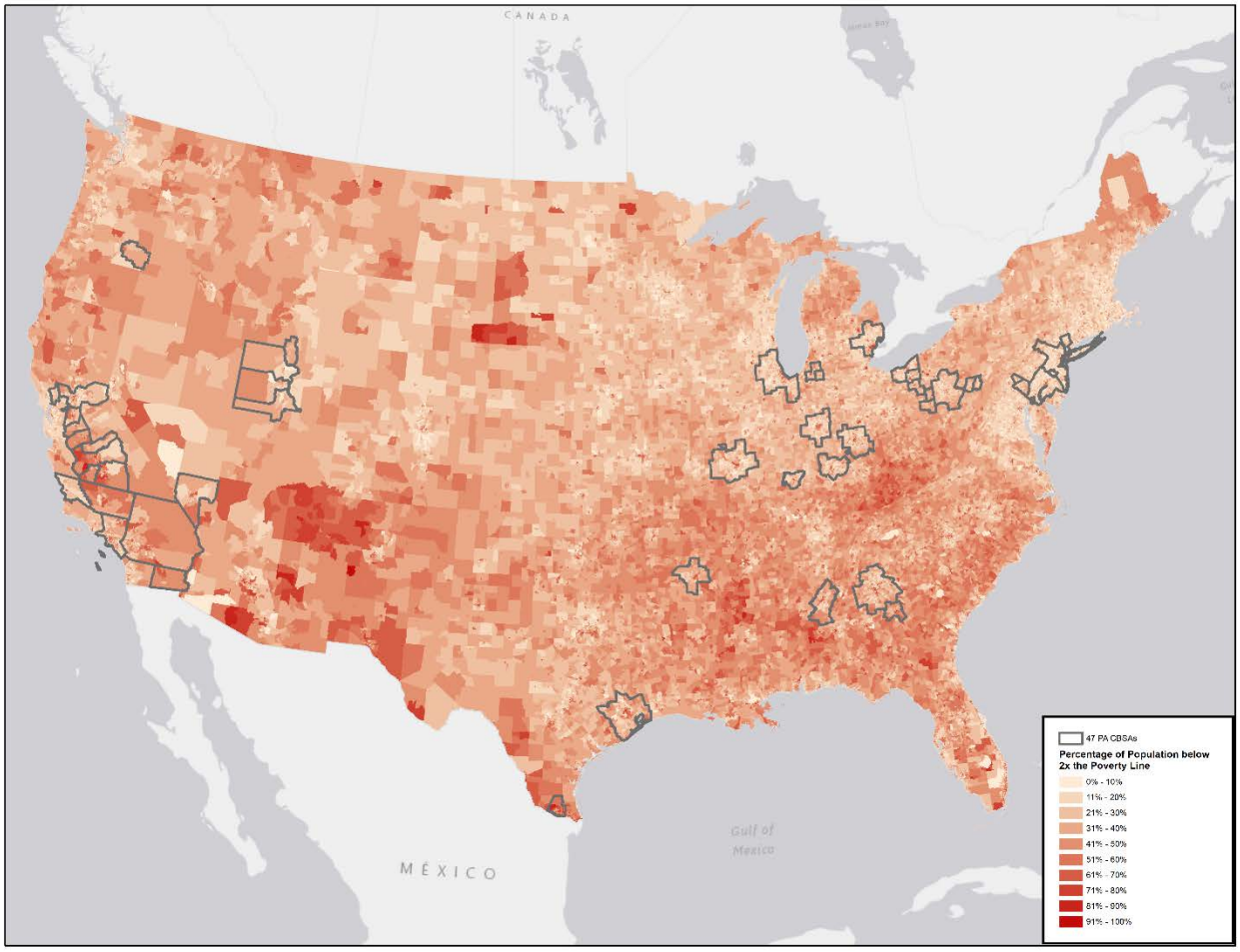
BASELINE MORTALITY INCIDENCE

EXHIBIT B-3. TRACT BASELINE MORTALITY INCIDENCE AGES 65-99 PER 100,000



POVERTY

EXHIBIT B-4. TRACT PERCENTAGE OF POPULATION BELOW TWO TIMES THE POVERTY LINE



APPENDIX C | SUPPLEMENTAL EXPOSURE GRAPHICS

EXPOSURE TO HISPANIC POPULATIONS

EXHIBIT C-1. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 10 µG/M³

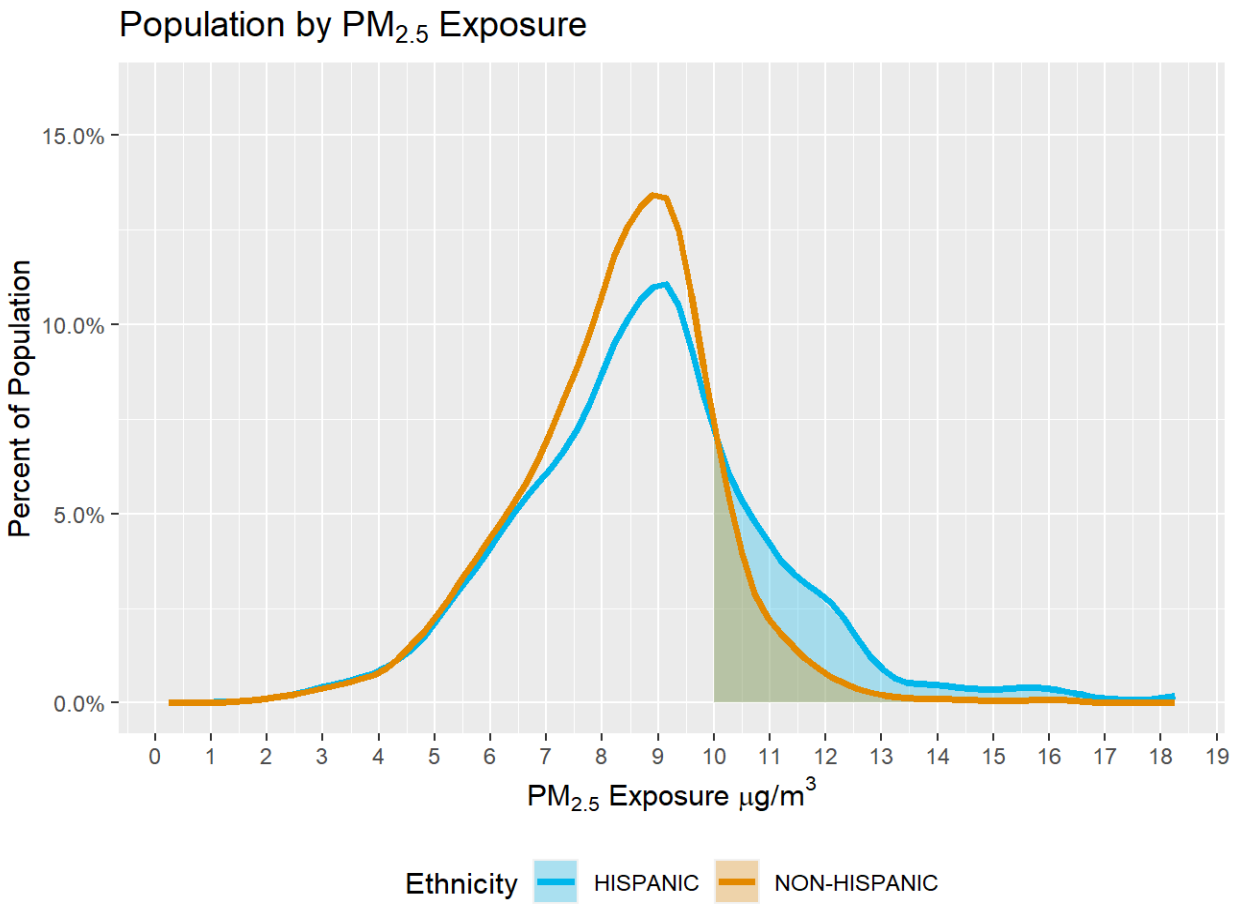


EXHIBIT C-2. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 8 µG/M³

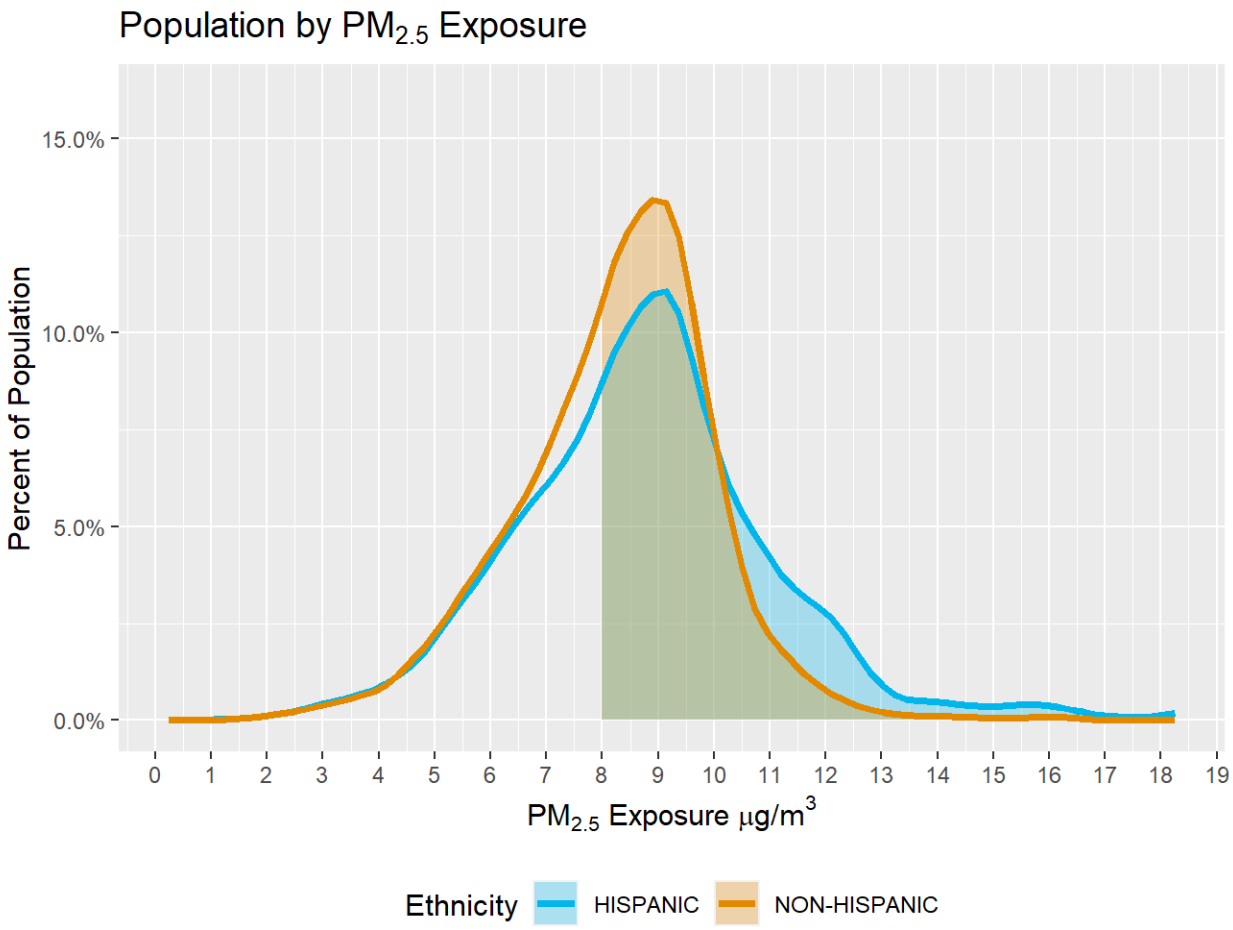


EXHIBIT C-3. PROPORTION OF 0-99 POPULATION EXPOSED TO VARIOUS $PM_{2.5}$ CONCENTRATIONS

RACE	ETHNICITY	PERCENT OF POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS:				
		> 12 µG/M³	> 10 µG/M³	> 8 µG/M³	BETWEEN 10 & 12 µG/M³	BETWEEN 8 & 10 µG/M³
All	Hispanic	7%	25%	65%	17%	40%
All	Non-Hispanic	2%	13%	60%	11%	48%

EXPOSURE BASED ON EPA 12 X 12 KM AIR QUALITY SURFACE – PA AREAS ONLY

EXHIBIT C-3. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 10 µG/M³ BY RACE

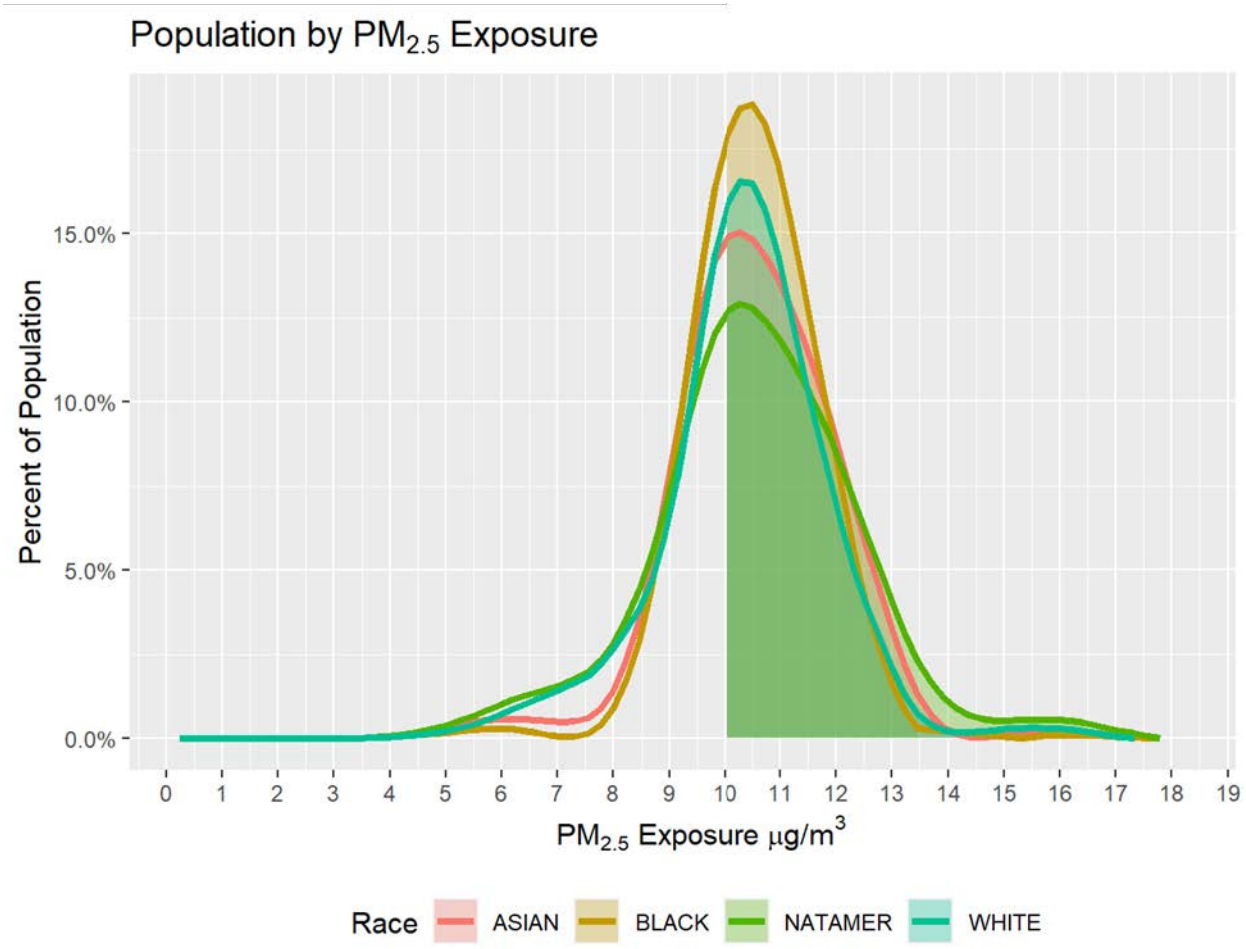


EXHIBIT C-4. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 8 µG/M³ BY RACE

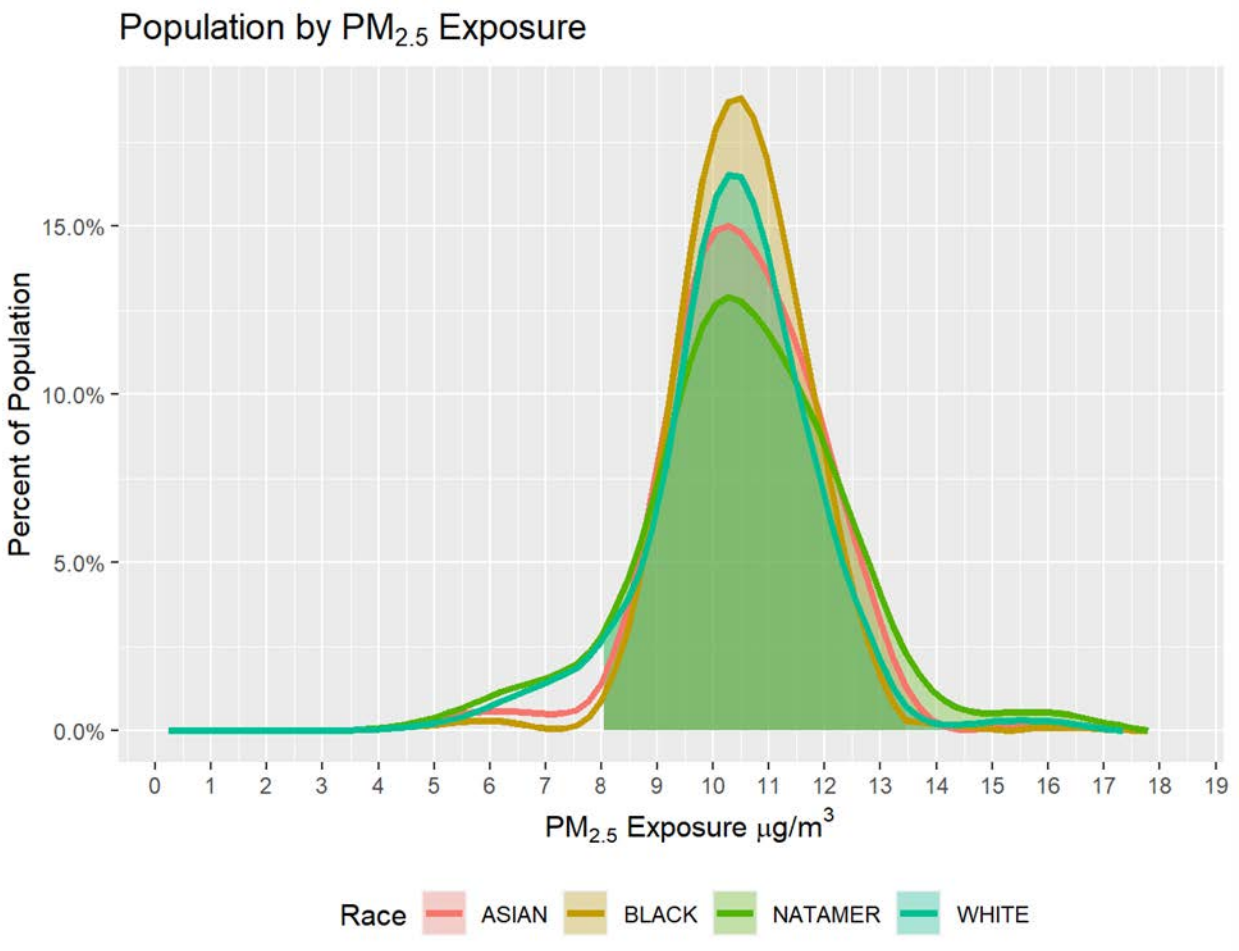


EXHIBIT C-5. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 10 µG/M³ BY ETHNICITY

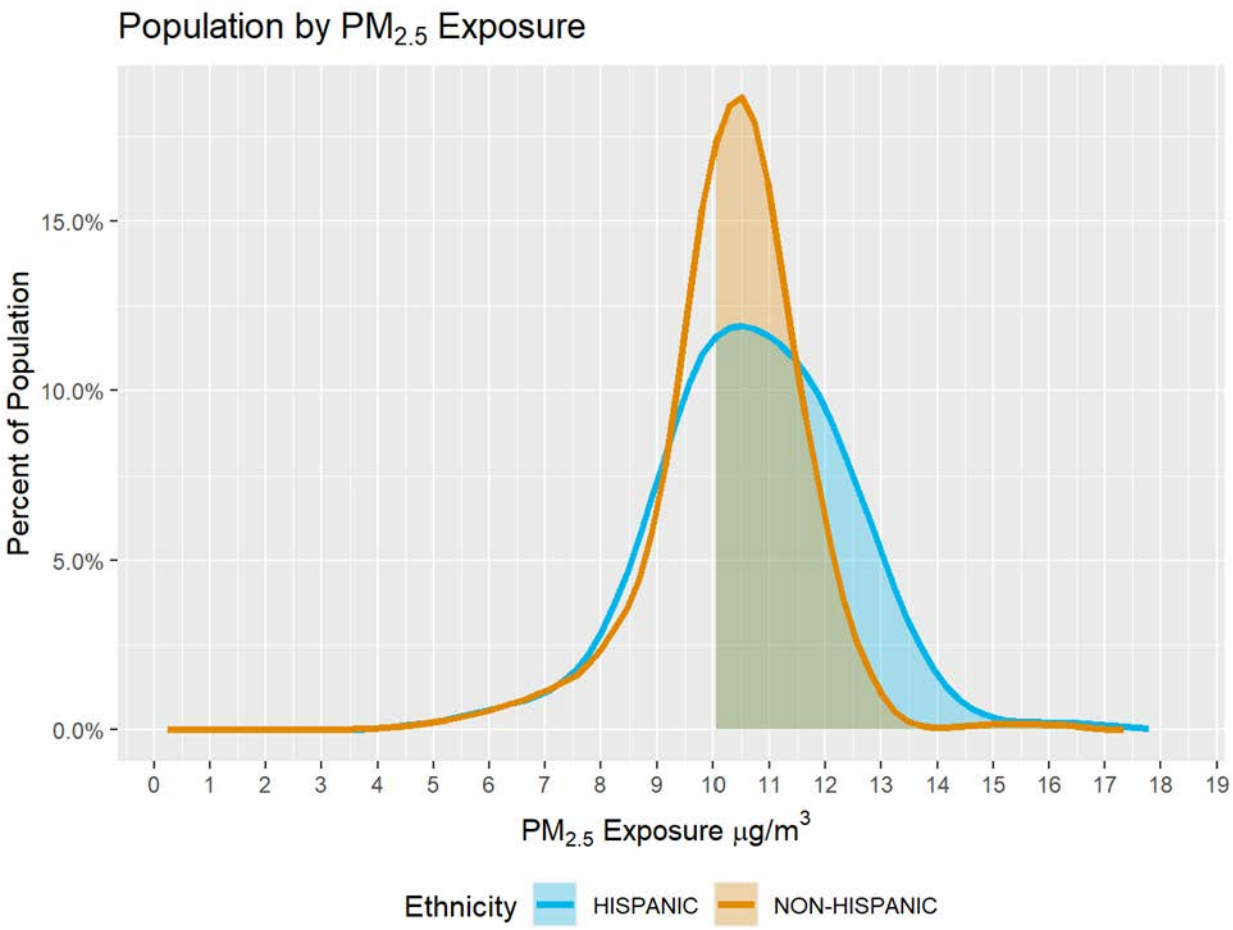
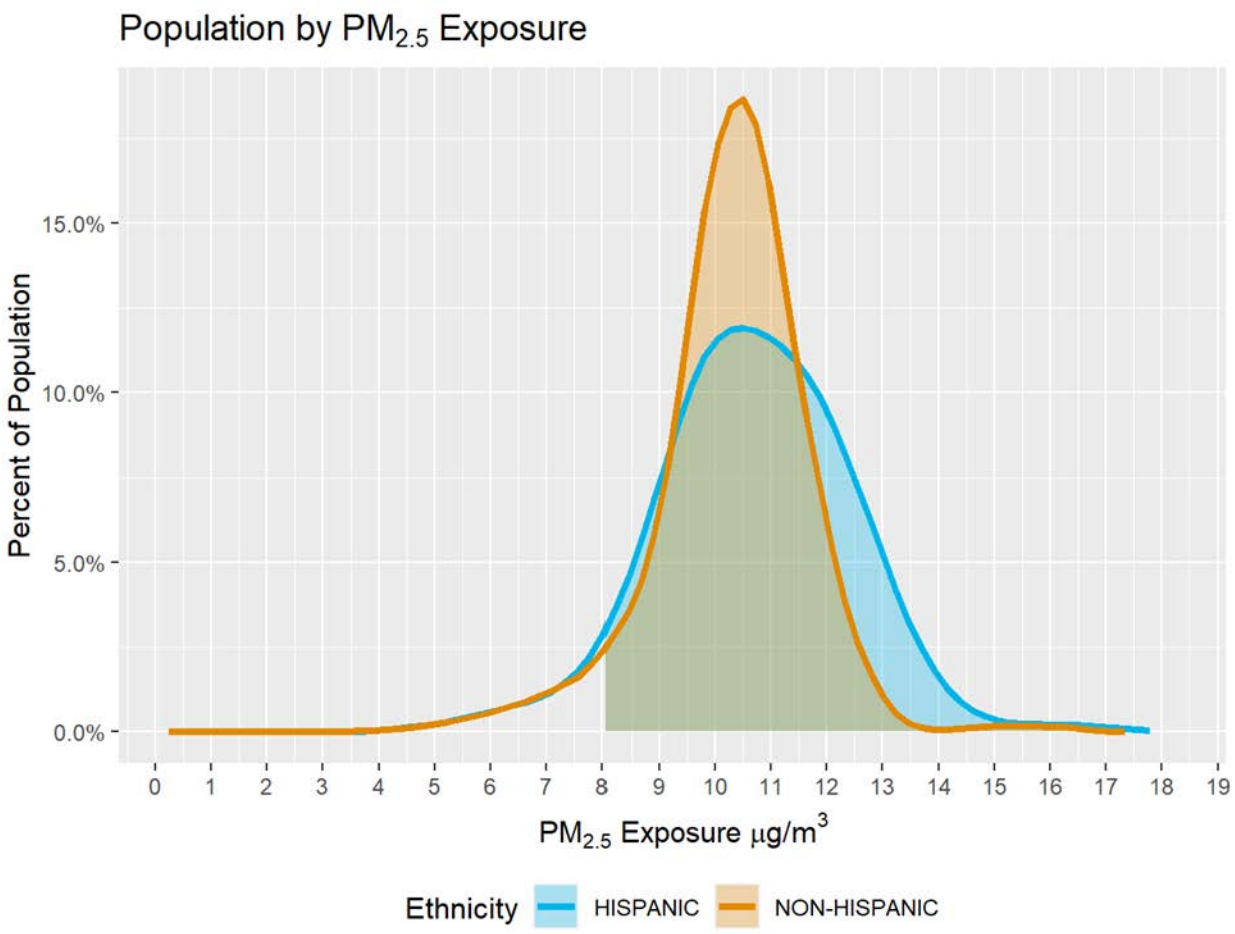


EXHIBIT C-6. PROPORTION OF 0-99 POPULATION EXPOSED TO $PM_{2.5}$ CONCENTRATIONS ABOVE 8 µG/M³ BY ETHNICITY



APPENDIX D | SUPPLEMENTAL HEALTH IMPACT RESULTS

This Appendix provides:

- The full estimates for health impact results reported as rates per 100,000 in Chapters 2 and 3;
- State and CBSA specific results by race and ethnicity for all-cause mortality (ages 65 to 99) and asthma-related emergency room visits (ages 0 to 18); and
- Additional graphics comparing tract-level results using coarse versus fine-scale datasets.

CURRENT $PM_{2.5}$-ATTRIBUTABLE HEALTH BURDEN

EXHIBIT D-1. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY

AUTHOR	CONCENTRATION – RESPONSE RELATIONSHIP	AGE GROUP	RACE	ETHNICITY	NATION	PA AREAS		NON-PA AREAS
					1KM	12KM	1KM	1KM
Di et al. (2017)	Hispanic	65-99	All	Hispanic	9,644	4,775	4,585	5,059
	Asian		Asian	All	3,101	1,883	1,765	1,336
	Black		Black	All	29,108	12,669	11,897	17,211
	Native American		Native American	All	551	126	120	431
	White		White	All	85,482	27,594	25,843	59,639

EXHIBIT D-2. CURRENT PM2.5-ATTRIBUTABLE MORTALITY BY POVERTY STATUS

AUTHOR	CONCENTRATION – RESPONSE RELATIONSHIP	AGE GROUP	POVERTY STATUS	NATION	PA AREAS		NON-PA AREAS
				1KM	12KM	1KM	1KM
Di et al. (2017)	Combined Totals	65-99	Below 2x Poverty Line	274	348	331	253
			Above 2x Poverty Line	240	314	282	223

EXHIBIT D-3. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORBIDITY BURDEN FOR PEDIATRIC ASTHMA ED VISITS (STRATIFIED BY RACE/ETHNICITY)

AUTHOR	CONCENTRATION - RESPONSE RELATIONSHIP	AGE GROUP	RACE	ETHNICITY	NATION	PA AREAS		NON-PA AREAS
					1KM	12KM	1KM	1KM
Alhanti et al. (2016)	White	0-18	White	Non-Hispanic	10	13	12	9
	Non-white		White	Hispanic	56	72	68	47
	Non-white		Asian	All	53	70	63	45
	Non-white		Black	All	63	80	74	56
	Non-white		Native American	All	45	76	71	38

EXHIBIT D-4. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN BY STATE (AGES 65+, STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
AL	2,718	8	1,125	7	1,578	11	1,143
AZ	1,441	26	112	34	1,269	254	485
AR	1,372	5	360	4	1,003	10	587
CA	12,520	1,638	2,067	98	8,716	3,038	4,049
CO	1,059	21	92	7	940	172	305
CT	1,220	14	190	1	1,015	67	306
DE	415	4	133	1	277	8	119
DC	418	3	369	1	46	7	137
FL	6,824	62	1,532	13	5,218	1,241	2,468
GA	4,149	40	1,958	5	2,145	47	1,654
ID	439	3	3	5	428	15	155
IL	5,616	116	1,657	10	3,832	275	1,845
IN	2,916	12	469	5	2,430	44	1,009
IA	1,133	5	39	2	1,088	11	333
KS	958	9	114	7	829	31	312
KY	1,932	6	283	2	1,641	9	754
LA	2,348	11	1,144	7	1,186	29	1,036
ME	384	1	4	1	378	1	116
MD	2,797	55	1,339	4	1,399	41	731
MA	1,758	36	188	1	1,532	60	420
MI	4,570	37	1,245	18	3,271	81	1,645
MN	1,365	19	81	10	1,255	13	359

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
MS	1,730	4	887	3	836	4	817
MO	2,534	14	523	7	1,990	22	893
MT	361	2	2	16	341	4	119
NE	583	3	46	3	531	12	182
NV	724	42	125	6	551	75	259
NH	305	2	3	-	300	2	66
NJ	3,470	110	877	3	2,479	297	897
NM	395	4	21	24	347	204	162
NY	6,928	241	2,023	10	4,653	771	2,169
NC	4,398	26	1,715	30	2,627	38	1,712
ND	171	-	1	5	164	1	46
OH	5,954	32	1,326	9	4,587	53	2,054
OK	1,441	12	225	83	1,121	29	565
OR	1,291	30	40	11	1,211	36	414
PA	6,924	65	1,299	4	5,556	120	2,120
RI	349	3	23	1	322	12	93
SC	2,240	9	1,026	4	1,201	16	893
SD	230	1	3	10	217	1	72
TN	2,832	12	772	5	2,043	16	1,118
TX	8,452	165	2,122	32	6,133	2,282	3,296
UT	479	11	10	3	455	33	137
VT	157	1	1	-	155	1	45
VA	3,182	62	1,180	6	1,933	51	958
WA	1,776	101	114	19	1,542	58	496
WV	850	2	56	1	791	2	331
WI	2,041	14	182	14	1,831	29	583
WY	89	-	1	1	86	5	25

EXHIBIT D-5. CURRENT $PM_{2.5}$-ATTRIBUTABLE PEDIATRIC ASTHMA ED VISITS BY STATE (STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
AL	345	11	209	4	80	42	148
AZ	393	23	42	26	50	253	169
AR	181	6	101	3	40	30	85
CA	3,780	568	393	70	238	2,511	1,492
CO	225	16	26	6	48	130	71
CT	296	31	81	3	67	115	98
DE	67	5	33	1	13	15	21
DC	60	2	45	-	4	9	22
FL	1,633	78	621	13	214	707	660
GA	915	61	531	7	134	181	361
ID	59	3	3	3	25	26	22
IL	1,155	105	358	12	215	466	419
IN	123	6	15	1	76	25	39
IA	84	7	15	1	39	22	28
KS	149	11	28	4	49	56	54
KY	202	11	78	1	82	30	82
LA	369	12	250	5	69	33	167
ME	-	-	-	-	-	-	-
MD	795	68	507	6	97	117	255
MA	274	38	67	3	68	98	92
MI	560	46	232	9	178	95	224
MN	205	40	57	7	60	40	65
MS	257	5	191	3	44	15	124
MO	291	18	113	4	114	42	108
MT	31	1	1	9	15	4	11
NE	61	4	13	2	19	23	23
NV	170	19	30	3	17	100	72
NH	41	5	3	-	25	7	9
NJ	839	116	267	8	122	326	286
NM	101	2	5	13	7	74	46
NY	2,759	334	1,011	45	266	1,102	1,201
NC	731	45	340	20	146	180	289
ND	21	1	2	5	11	3	7
OH	636	39	262	4	249	82	249
OK	250	14	52	57	58	69	105
OR	153	18	11	6	47	71	51
PA	1,099	99	384	9	362	244	409

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
RI	54	5	12	1	12	24	21
SC	304	9	198	3	56	38	129
SD	32	1	3	10	14	4	12
TN	288	14	135	2	87	50	119
TX	3,142	201	598	39	281	2,022	1,321
UT	50	5	3	2	18	23	16
VT	6	-	1	-	4	1	2
VA	545	74	226	5	121	119	152
WA	277	51	32	12	71	111	87
WV	55	2	10	-	38	5	21
WI	266	21	97	8	65	75	114
WY	10	-	1	1	5	4	3

EXHIBIT D-6. CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN BY 47 PA CBSAS (AGES 65+, STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Detroit-Warren-Dearborn, MI	2,286	25	950	5	1,306	37
New York-Newark-Jersey City, NY-NJ-PA	6,889	311	2,301	8	4,269	972
Logan, UT-ID	22	-	-	-	21	1
Ogden-Clearfield, UT	131	2	4	1	124	9
Prineville, OR	9	-	-	-	9	-
Chicago-Naperville-Elgin, IL-IN-WI	4,051	110	1,559	8	2,374	280
Cleveland-Elyria, OH	1,254	9	459	1	785	20
South Bend-Mishawaka, IN-MI	162	1	32	1	129	2
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	3,128	57	1,189	3	1,880	79
Akron, OH	417	2	92	1	323	1
Pittsburgh, PA	1,418	7	214	1	1,196	5
Elkhart-Goshen, IN	80	-	7	-	73	1
Salt Lake City, UT	192	7	5	1	179	17
Lebanon, PA	84	-	1	-	83	2
Altoona, PA	83	-	2	-	81	-
Johnstown, PA	93	-	4	-	89	1
Lancaster, PA	280	2	12	-	266	10
Canton-Massillon, OH	254	1	33	-	220	2

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Sacramento-Roseville-Folsom, CA	758	84	119	6	549	85
Napa, CA	60	3	2	-	54	6
Weirton-Steubenville, WV-OH	86	-	8	-	78	-
Provo-Orem, UT	68	1	1	-	66	3
Wheeling, WV-OH	90	-	4	-	87	-
Stockton, CA	337	42	57	3	235	73
Indianapolis-Carmel-Anderson, IN	807	5	209	1	592	6
Modesto, CA	230	10	14	3	204	53
Cincinnati, OH-KY-IN	935	6	210	1	718	3
Merced, CA	95	6	12	1	76	34
Madera, CA	52	1	6	1	44	20
St. Louis, MO-IL	1,406	10	443	2	950	9
Fresno, CA	453	39	55	6	354	152
Louisville/Jefferson County, KY-IN	583	3	149	1	431	4
Visalia, CA	194	7	9	2	175	79
Hanford-Corcoran, CA	59	3	7	1	49	23
Evansville, IN-KY	161	-	19	-	140	1
San Luis Obispo-Paso Robles, CA	77	2	2	1	72	8
Las Vegas-Henderson-Paradise, NV	536	36	117	3	380	63
Bakersfield, CA	330	16	40	5	269	108
Riverside-San Bernardino-Ontario, CA	1,295	80	224	12	978	403
Los Angeles-Long Beach-Anaheim, CA	4,555	749	989	28	2,789	1,308
Little Rock-North Little Rock-Conway, AR	315	1	100	1	213	2
Atlanta-Sandy Springs-Alpharetta, GA	2,057	31	1,012	3	1,012	32
El Centro, CA	47	1	3	1	42	51
Birmingham-Hoover, AL	656	2	316	1	337	3
Macon-Bibb County, GA	140	-	84	-	55	-
Houston-The Woodlands-Sugar Land, TX	2,216	91	821	8	1,297	359
McAllen-Edinburg-Mission, TX	192	1	3	-	188	257

EXHIBIT D-7. CURRENT PEDIATRIC $PM_{2.5}$-ATTRIBUTABLE ASTHMA ED VISITS BY 47 PA CBSAS (STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Detroit-Warren-Dearborn, MI	292	28	155	2	70	36
New York-Newark-Jersey City, NY-NJ-PA	3,085	396	1,098	46	258	1,286
Logan, UT-ID	1	-	-	-	1	1
Ogden-Clearfield, UT	10	1	1	-	4	4
Prineville, OR	1	-	-	-	-	-
Chicago-Naperville-Elgin, IL-IN-WI	933	91	283	10	124	425
Cleveland-Elyria, OH	136	7	73	1	35	21
South Bend-Mishawaka, IN-MI	2	-	1	-	1	-
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	679	79	320	5	132	143
Akron, OH	41	3	18	-	16	3
Pittsburgh, PA	143	12	53	1	68	9
Elkhart-Goshen, IN	-	-	-	-	-	-
Salt Lake City, UT	30	4	2	1	9	15
Lebanon, PA	14	1	2	-	5	6
Altoona, PA	7	-	1	-	5	-
Johnstown, PA	7	-	2	-	5	1
Lancaster, PA	53	4	9	1	22	18
Canton-Massillon, OH	20	1	7	-	11	2
Sacramento-Roseville-Folsom, CA	146	37	27	3	18	62
Napa, CA	5	1	-	-	1	3
Weirton-Steubenville, WV-OH	4	-	1	-	3	-
Provo-Orem, UT	5	-	-	-	3	2
Wheeling, WV-OH	4	-	1	-	3	-
Stockton, CA	126	24	15	2	8	76
Indianapolis-Carmel-Anderson, IN	20	1	3	-	13	3
Modesto, CA	74	7	5	1	7	54
Cincinnati, OH-KY-IN	109	8	46	1	42	12
Merced, CA	37	4	2	1	2	28
Madera, CA	241	8	13	9	10	200
St. Louis, MO-IL	174	11	90	1	56	16
Fresno, CA	85	11	8	2	4	60
Louisville/Jefferson County, KY-IN	111	7	56	1	32	16
Visalia, CA	81	4	4	2	4	68
Hanford-Corcoran, CA	4	-	-	-	-	3

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Evansville, IN-KY	5	-	1	-	3	-
San Luis Obispo-Paso Robles, CA	7	1	-	-	2	5
Las Vegas-Henderson-Paradise, NV	149	17	29	2	13	88
Bakersfield, CA	168	10	16	4	9	129
Riverside-San Bernardino-Ontario, CA	491	43	57	9	26	357
Los Angeles-Long Beach-Anaheim, CA	1,437	214	154	19	67	983
Little Rock-North Little Rock-Conway, AR	64	2	40	1	12	9
Atlanta-Sandy Springs-Alpharetta, GA	579	50	330	4	73	121
El Centro, CA	47	1	2	1	1	43
Birmingham-Hoover, AL	91	3	58	1	18	11
Macon-Bibb County, GA	21	1	16	-	3	1
Houston-The Woodlands-Sugar Land, TX	964	89	238	12	74	551
McAllen-Edinburg-Mission, TX	189	2	2	1	1	183

AVOIDED $PM_{2.5}$-ATTRIBUTABLE MORTALITY AND MORBIDITY UNDER ALTERNATIVE STANDARDS

EXHIBIT D-8. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS (STRATIFIED BY RACE)

AUTHOR	CONCENTRATION - RESPONSE RELATIONSHIP	AGE GROUP	RACE	ETHNICITY	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
					10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Di et al. (2017)	Hispanic	65-99	All	Hispanic	735	692	43	1,763	1,411	352
	Asian		Asian	All	254	248	7	619	521	98
	Black		Black	All	1,218	1,145	73	4,749	3,210	1,538
	Native American		Native American	All	22	21	1	57	38	19
	White		White	All	3,116	2,807	309	10,872	6,783	4,090

EXHIBIT D-9. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS

AUTHOR	CONCENTRATION – RESPONSE RELATIONSHIP	AGE GROUP	POVERTY STATUS	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
				10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Di et al. (2017)	Combined Totals	65-99	Below 2x Poverty Line	1,769	1,497	272	5,952	3,639	2,313
			Above 2x Poverty Line	2,842	2,724	118	10,345	6,913	3,433

EXHIBIT D-10. AVOIDED ASTHMA-RELATED PEDIATRIC ED VISITS IN CHILDREN BY ALTERNATIVE NAAQS

AUTHOR	CONCENTRATION – RESPONSE RELATIONSHIP	AGE GROUP	RACE	ETHNICITY	NATION	PA AREAS	NON-PA AREAS	NATION	PA AREAS	NON-PA AREAS
					10 µG/M3 ALT NAAQS			8 µG/M3 ALT NAAQS		
Alhanti et al. (2016)	White	0-18	White	Non-Hispanic	132	116	16	520	312	208
	Non-white		White	Hispanic	693	661	32	1,784	1,445	339
	Non-white		Asian	All	122	117	5	379	300	79
	Non-white		Black	All	261	242	19	1,158	787	371
	Non-white		Native American	All	19	18	1	55	40	15

EXHIBIT D-11. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS OF 10 µG/M³ BY STATE (AGE 65+, STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
AL	69	-	36	-	32	-	28
AZ	2	-	-	-	2	-	1
AR	10	-	4	-	6	-	4
CA	1,857	208	344	17	1,288	583	701
CO	4	-	1	-	3	2	2
CT	-	-	-	-	-	-	-
DE	23	-	8	-	14	1	6
DC	5	-	5	-	-	-	2
FL	-	-	-	-	-	-	-

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
GA	66	1	35	-	30	1	24
ID	3	-	-	-	3	-	1
IL	320	9	132	1	179	23	107
IN	163	1	44	-	117	4	58
IA	-	-	-	-	-	-	-
KS	-	-	-	-	-	-	-
KY	38	-	9	-	29	-	13
LA	14	-	5	-	9	-	5
ME	-	-	-	-	-	-	-
MD	29	-	12	-	17	-	7
MA	-	-	-	-	-	-	-
MI	263	3	112	1	147	4	100
MN	-	-	-	-	-	-	-
MS	13	-	7	-	6	-	7
MO	10	-	4	-	6	-	3
MT	10	-	-	-	9	-	3
NE	-	-	-	-	-	-	-
NV	15	1	3	-	10	2	6
NH	-	-	-	-	-	-	-
NJ	109	3	31	-	75	7	27
NM	-	-	-	-	-	-	-
NY	85	4	34	-	46	14	27
NC	14	-	6	-	8	-	5
ND	-	-	-	-	-	-	-
OH	306	2	98	-	206	3	109
OK	-	-	-	-	-	-	-
OR	12	-	-	-	12	-	4
PA	771	8	184	-	579	13	236
RI	-	-	-	-	-	-	-
SC	1	-	1	-	-	-	1
SD	-	-	-	-	-	-	-
TN	1	-	-	-	1	-	1
TX	255	9	91	1	153	66	102
UT	72	3	2	-	67	6	20
VT	-	-	-	-	-	-	-
VA	6	-	2	-	3	-	1
WA	7	-	-	-	6	-	2
WV	9	-	1	-	9	-	3
WI	5	-	-	-	4	-	1
WY	-	-	-	-	-	-	-

EXHIBIT D-12. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS OF 8 μG/M³ BY STATE (AGE 65+, STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
AL	381	1	174	1	205	2	161
AZ	23	1	3	-	20	5	8
AR	154	-	56	-	98	1	67
CA	3,276	407	618	28	2,223	967	1,176
CO	26	1	4	-	21	8	8
CT	36	-	7	-	28	3	10
DE	59	1	21	-	37	1	17
DC	73	-	66	-	6	1	25
FL	76	1	24	-	51	13	31
GA	573	7	300	1	265	7	222
ID	23	-	-	-	22	1	8
IL	1,134	25	400	2	707	66	378
IN	627	3	128	1	495	11	221
IA	39	-	2	-	37	1	12
KS	14	-	3	-	11	1	6
KY	291	1	56	-	233	2	106
LA	265	1	134	1	129	3	117
ME	-	-	-	-	-	-	-
MD	417	8	215	1	193	6	112
MA	5	-	1	-	3	-	1
MI	883	9	314	2	558	15	325
MN	9	-	3	-	5	-	4
MS	204	-	109	-	94	-	99
MO	251	2	81	-	168	2	82
MT	36	-	-	1	34	-	12
NE	13	-	3	-	10	-	5
NV	115	8	26	1	81	14	44
NH	1	-	-	-	1	-	-
NJ	601	19	164	1	416	55	155
NM	-	-	-	-	-	1	-
NY	897	42	369	1	485	147	291
NC	418	3	180	1	234	4	164
ND	-	-	-	-	-	-	-
OH	1,228	7	312	2	908	12	431
OK	37	-	7	2	27	1	15
OR	77	1	1	1	74	2	27

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC	BELOW 2X POVERTY LINE
PA	1,876	19	407	1	1,449	34	578
RI	3	-	-	-	3	-	1
SC	83	-	43	-	39	1	36
SD	5	-	-	-	4	-	1
TN	178	1	58	-	120	1	71
TX	1,149	31	352	4	762	344	465
UT	130	4	4	1	122	11	36
VT	1	-	-	-	1	-	-
VA	182	5	59	-	118	4	49
WA	82	4	4	1	72	3	27
WV	83	-	7	-	76	-	30
WI	124	1	13	1	109	3	35
WY	-	-	-	-	-	-	-

EXHIBIT D-13. AVOIDED PEDIATRIC ASTHMA ED VISITS BY ALTERNATIVE NAAQS OF 10 µG/M³ BY STATE (STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
AL	9	-	6	-	2	1	4
AZ	1	-	-	-	-	-	-
AR	2	-	1	-	-	-	1
CA	690	73	67	13	33	503	305
CO	2	-	-	-	-	2	1
CT	-	-	-	-	-	-	-
DE	4	-	2	-	1	1	1
DC	1	-	1	-	-	-	-
FL	-	-	-	-	-	-	-
GA	18	2	10	-	2	4	6
ID	-	-	-	-	-	-	-
IL	79	7	25	1	10	36	29
IN	4	-	1	-	3	1	1
IA	-	-	-	-	-	-	-
KS	-	-	-	-	-	-	-
KY	6	-	3	-	2	1	3
LA	2	-	1	-	1	-	1
ME	-	-	-	-	-	-	-
MD	7	-	4	-	1	1	2

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
MA	-	-	-	-	-	-	-
MI	32	3	17	-	8	4	14
MN	-	-	-	-	-	-	-
MS	2	-	1	-	-	-	1
MO	1	-	1	-	-	-	-
MT	1	-	-	-	-	-	-
NE	-	-	-	-	-	-	-
NV	4	-	1	-	-	2	2
NH	-	-	-	-	-	-	-
NJ	26	3	9	-	5	9	9
NM	-	-	-	-	-	-	-
NY	48	6	18	1	4	20	21
NC	3	-	1	-	-	1	1
ND	-	-	-	-	-	-	-
OH	32	2	16	-	10	4	13
OK	-	-	-	-	-	-	-
OR	1	-	-	-	-	-	-
PA	122	12	48	1	36	25	46
RI	-	-	-	-	-	-	-
SC	-	-	-	-	-	-	-
SD	-	-	-	-	-	-	-
TN	-	-	-	-	-	-	-
TX	107	9	24	1	7	66	45
UT	10	1	1	-	3	5	3
VT	-	-	-	-	-	-	-
VA	1	-	-	-	-	-	-
WA	1	-	-	-	-	-	-
WV	1	-	-	-	-	-	-
WI	1	-	-	-	-	-	-
WY	-	-	-	-	-	-	-

EXHIBIT D-14. AVOIDED PEDIATRIC ASTHMA ED VISITS BY ALTERNATIVE NAAQS OF 8 μG/M³ BY STATE (STRATIFIED BY RACE/ETHNICITY AND POVERTY STATUS)

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
AL	49	2	31	-	10	6	21
AZ	10	-	1	-	1	7	5
AR	26	1	17	-	5	3	12
CA	1,142	139	116	21	57	809	487
CO	10	-	1	-	1	7	4
CT	12	1	3	-	2	5	4
DE	10	1	5	-	2	2	3
DC	10	-	8	-	1	1	4
FL	19	1	8	-	2	7	8
GA	137	11	81	1	17	27	52
ID	2	-	-	-	1	1	1
IL	251	22	80	3	39	108	92
IN	23	1	3	-	14	5	7
IA	4	-	1	-	2	1	1
KS	3	-	1	-	1	1	1
KY	36	2	16	-	12	5	15
LA	40	1	27	-	8	3	18
ME	-	-	-	-	-	-	-
MD	121	10	79	1	13	18	40
MA	1	-	-	-	-	-	-
MI	110	10	52	1	30	17	45
MN	4	1	2	-	-	1	2
MS	29	-	22	-	5	2	14
MO	29	2	15	-	9	3	10
MT	3	-	-	1	2	-	1
NE	2	-	1	-	-	1	1
NV	32	4	6	-	3	19	14
NH	-	-	-	-	-	-	-
NJ	146	20	48	1	21	56	50
NM	-	-	-	-	-	-	-
NY	501	57	190	8	35	211	223
NC	78	5	38	1	14	20	31
ND	-	-	-	-	-	-	-
OH	130	8	56	1	48	17	52
OK	7	-	2	2	1	2	3
OR	8	1	-	-	2	4	3
PA	299	28	111	2	92	65	113

STATE	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC	BELOW 2X POVERTY LINE
RI	1	-	-	-	-	-	-
SC	12	-	8	-	2	1	5
SD	1	-	-	-	-	-	-
TN	19	1	9	-	5	3	8
TX	469	34	93	6	33	304	203
UT	17	2	1	-	5	8	5
VT	-	-	-	-	-	-	-
VA	35	6	11	-	8	9	8
WA	11	2	1	1	3	5	4
WV	6	-	1	-	4	1	2
WI	19	1	6	-	4	7	9
WY	-	-	-	-	-	-	-

EXHIBIT D-15. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS OF 10 µG/M³ BY 47 PA CBSAS (AGE 65+, STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Detroit-Warren-Dearborn, MI	254	3	111	1	140	4
New York-Newark-Jersey City, NY-NJ-PA	125	6	44	-	75	18
Logan, UT-ID	2	-	-	-	2	-
Ogden-Clearfield, UT	8	-	-	-	8	1
Prineville, OR	1	-	-	-	1	-
Chicago-Naperville-Elgin, IL-IN-WI	355	9	145	1	200	25
Cleveland-Elyria, OH	172	1	72	-	99	3
South Bend-Mishawaka, IN-MI	11	-	2	-	9	-
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	365	7	147	-	211	9
Akron, OH	34	-	8	-	26	-
Pittsburgh, PA	299	2	50	-	247	1
Elkhart-Goshen, IN	2	-	-	-	2	-
Salt Lake City, UT	62	2	2	-	57	6
Lebanon, PA	9	-	-	-	9	-
Altoona, PA	1	-	-	-	1	-
Johnstown, PA	5	-	-	-	5	-
Lancaster, PA	60	-	3	-	57	2
Canton-Massillon, OH	17	-	2	-	14	-

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Sacramento-Roseville-Folsom, CA	21	2	3	-	15	2
Napa, CA	2	-	-	-	1	-
Weirton-Steubenville, WV-OH	11	-	1	-	10	-
Provo-Orem, UT	1	-	-	-	1	-
Wheeling, WV-OH	2	-	-	-	2	-
Stockton, CA	63	8	12	1	43	14
Indianapolis-Carmel-Anderson, IN	90	1	26	-	64	1
Modesto, CA	59	2	4	1	52	14
Cincinnati, OH-KY-IN	52	-	13	-	38	-
Merced, CA	18	1	2	-	15	7
Madera, CA	12	-	2	-	10	5
St. Louis, MO-IL	13	-	4	-	8	-
Fresno, CA	162	14	22	2	124	54
Louisville/Jefferson County, KY-IN	32	-	9	-	23	-
Visalia, CA	87	3	5	1	78	36
Hanford-Corcoran, CA	35	2	4	1	28	14
Evansville, IN-KY	1	-	-	-	1	-
San Luis Obispo-Paso Robles, CA	5	-	-	-	4	-
Las Vegas-Henderson-Paradise, NV	15	1	3	-	10	2
Bakersfield, CA	178	8	23	3	143	59
Riverside-San Bernardino-Ontario, CA	345	22	65	3	254	113
Los Angeles-Long Beach-Anaheim, CA	834	140	198	5	492	249
Little Rock-North Little Rock-Conway, AR	9	-	3	-	6	-
Atlanta-Sandy Springs-Alpharetta, GA	64	1	33	-	30	1
El Centro, CA	10	-	1	-	9	11
Birmingham-Hoover, AL	64	-	34	-	30	-
Macon-Bibb County, GA	1	-	1	-	-	-
Houston-The Woodlands-Sugar Land, TX	212	9	84	1	119	35
McAllen-Edinburg-Mission, TX	1	-	-	-	1	2

EXHIBIT D-16. CHANGE IN AVOIDED PM-ATTRIBUTABLE DEATHS BY ALTERNATIVE NAAQS OF 8 μG/M³ BY 47 PA CBSAS (AGE 65+, STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Detroit-Warren-Dearborn, MI	649	7	282	1	358	10
New York-Newark-Jersey City, NY-NJ-PA	1270	58	468	2	743	194
Logan, UT-ID	4	-	-	-	4	-
Ogden-Clearfield, UT	26	-	1	-	24	2
Prineville, OR	2	-	-	-	2	-
Chicago-Naperville-Elgin, IL-IN-WI	999	25	405	2	567	71
Cleveland-Elyria, OH	336	2	139	-	194	6
South Bend-Mishawaka, IN-MI	36	-	8	-	29	-
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	869	16	348	1	505	22
Akron, OH	102	1	24	-	77	-
Pittsburgh, PA	507	3	84	-	420	2
Elkhart-Goshen, IN	17	-	2	-	15	-
Salt Lake City, UT	91	4	3	1	85	8
Lebanon, PA	23	-	-	-	23	1
Altoona, PA	17	-	1	-	17	-
Johnstown, PA	21	-	1	-	20	-
Lancaster, PA	102	1	5	-	96	4
Canton-Massillon, OH	58	-	8	-	50	-
Sacramento-Roseville-Folsom, CA	124	14	21	1	88	14
Napa, CA	12	1	1	-	11	1
Weirton-Steubenville, WV-OH	24	-	2	-	21	-
Provo-Orem, UT	10	-	-	-	9	-
Wheeling, WV-OH	19	-	1	-	18	-
Stockton, CA	101	13	18	1	69	22
Indianapolis-Carmel-Anderson, IN	215	1	61	-	152	2
Modesto, CA	78	3	5	1	69	18
Cincinnati, OH-KY-IN	208	1	53	-	153	1
Merced, CA	29	2	4	-	23	10
Madera, CA	17	-	2	-	14	7
St. Louis, MO-IL	272	2	95	-	174	2
Fresno, CA	209	18	28	3	161	69
Louisville/Jefferson County, KY-IN	135	1	38	-	96	1
Visalia, CA	105	4	5	1	95	43
Hanford-Corcoran, CA	41	2	5	1	34	16

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE	HISPANIC
Evansville, IN-KY	31	-	4	-	27	-
San Luis Obispo-Paso Robles, CA	18	1	-	-	17	2
Las Vegas-Henderson-Paradise, NV	114	8	26	1	79	14
Bakersfield, CA	211	10	27	3	170	70
Riverside-San Bernardino-Ontario, CA	476	31	89	4	351	156
Los Angeles-Long Beach-Anaheim, CA	1538	258	361	10	910	458
Little Rock-North Little Rock-Conway, AR	72	-	26	-	46	-
Atlanta-Sandy Springs-Alpharetta, GA	406	6	211	1	188	6
El Centro, CA	17	-	1	-	15	19
Birmingham-Hoover, AL	165	-	88	-	77	1
Macon-Bibb County, GA	27	-	17	-	10	-
Houston-The Woodlands-Sugar Land, TX	572	24	224	2	321	95
McAllen-Edinburg-Mission, TX	38	-	1	-	37	51

EXHIBIT D-17. AVOIDED PEDIATRIC ASTHMA ED VISITS BY ALTERNATIVE NAAQS OF 10 µG/M³ BY 47 PA CBSAS (STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Detroit-Warren-Dearborn, MI	31	3	17	-	7	4
New York-Newark-Jersey City, NY-NJ-PA	58	8	20	1	5	24
Logan, UT-ID	-	-	-	-	-	-
Ogden-Clearfield, UT	1	-	-	-	-	-
Prineville, OR	-	-	-	-	-	-
Chicago-Naperville-Elgin, IL-IN-WI	80	7	25	1	10	37
Cleveland-Elyria, OH	19	1	11	-	4	3
South Bend-Mishawaka, IN-MI	-	-	-	-	-	-
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	77	9	37	1	14	16
Akron, OH	3	-	1	-	1	-
Pittsburgh, PA	30	3	12	-	14	2
Elkhart-Goshen, IN	-	-	-	-	-	-
Salt Lake City, UT	10	1	1	-	3	5
Lebanon, PA	1	-	-	-	1	1
Altoona, PA	-	-	-	-	-	-
Johnstown, PA	-	-	-	-	-	-

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Lancaster, PA	11	1	2	-	4	4
Canton-Massillon, OH	1	-	-	-	1	-
Sacramento-Roseville-Folsom, CA	4	1	1	-	-	2
Napa, CA	-	-	-	-	-	-
Weirton-Steubenville, WV-OH	1	-	-	-	-	-
Provo-Orem, UT	-	-	-	-	-	-
Wheeling, WV-OH	-	-	-	-	-	-
Stockton, CA	23	4	3	-	1	14
Indianapolis-Carmel-Anderson, IN	2	-	-	-	1	-
Modesto, CA	18	2	1	-	2	14
Cincinnati, OH-KY-IN	6	-	3	-	2	1
Merced, CA	7	1	-	-	-	5
Madera, CA	63	2	3	2	2	53
St. Louis, MO-IL	2	-	1	-	-	-
Fresno, CA	30	4	3	1	1	20
Louisville/Jefferson County, KY-IN	6	-	3	-	2	1
Visalia, CA	36	2	2	1	2	30
Hanford-Corcoran, CA	2	-	-	-	-	2
Evansville, IN-KY	-	-	-	-	-	-
San Luis Obispo-Paso Robles, CA	-	-	-	-	-	-
Las Vegas-Henderson-Paradise, NV	4	-	1	-	-	2
Bakersfield, CA	90	5	9	2	5	69
Riverside-San Bernardino-Ontario, CA	135	12	16	2	7	98
Los Angeles-Long Beach-Anaheim, CA	264	38	29	4	11	182
Little Rock-North Little Rock-Conway, AR	2	-	1	-	-	-
Atlanta-Sandy Springs-Alpharetta, GA	17	2	10	-	2	4
El Centro, CA	10	-	-	-	-	9
Birmingham-Hoover, AL	8	-	6	-	2	1
Macon-Bibb County, GA	-	-	-	-	-	-
Houston-The Woodlands-Sugar Land, TX	92	9	23	1	7	53
McAllen-Edinburg-Mission, TX	1	-	-	-	-	1

EXHIBIT D-17. AVOIDED PEDIATRIC ASTHMA ED VISITS BY ALTERNATIVE NAAQS OF 8 μG/M³ BY 47 PA CBSAS (STRATIFIED BY RACE/ETHNICITY)

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Detroit-Warren-Dearborn, MI	81	8	43	1	19	10
New York-Newark-Jersey City, NY-NJ-PA	597	72	218	9	46	252
Logan, UT-ID	-	-	-	-	-	-
Ogden-Clearfield, UT	2	-	-	-	1	1
Prineville, OR	-	-	-	-	-	-
Chicago-Naperville-Elgin, IL-IN-WI	225	21	70	2	29	103
Cleveland-Elyria, OH	37	2	21	-	9	6
South Bend-Mishawaka, IN-MI	-	-	-	-	-	-
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	184	22	88	1	35	38
Akron, OH	10	1	5	-	4	1
Pittsburgh, PA	51	4	20	-	24	3
Elkhart-Goshen, IN	-	-	-	-	-	-
Salt Lake City, UT	14	2	1	-	4	7
Lebanon, PA	4	-	-	-	1	2
Altoona, PA	1	-	-	-	1	-
Johnstown, PA	2	-	-	-	1	-
Lancaster, PA	19	1	3	-	8	7
Canton-Massillon, OH	5	-	2	-	2	-
Sacramento-Roseville-Folsom, CA	24	6	4	-	3	10
Napa, CA	1	-	-	-	-	1
Weirton-Steubenville, WV-OH	1	-	-	-	1	-
Provo-Orem, UT	1	-	-	-	-	-
Wheeling, WV-OH	1	-	-	-	1	-
Stockton, CA	37	7	5	1	2	22
Indianapolis-Carmel-Anderson, IN	5	-	1	-	3	1
Modesto, CA	25	2	2	-	2	18
Cincinnati, OH-KY-IN	24	2	11	-	9	3
Merced, CA	11	1	1	-	1	8
Madera, CA	85	3	5	3	3	72
St. Louis, MO-IL	33	2	18	-	10	3
Fresno, CA	38	5	4	1	2	26
Louisville/Jefferson County, KY-IN	26	2	14	-	7	4
Visalia, CA	43	2	2	1	2	36
Hanford-Corcoran, CA	2	-	-	-	-	2

CBSA NAME	TOTAL	ASIAN	BLACK	NATIVE AMERICAN	WHITE - NON-HISPANIC	WHITE - HISPANIC
Evansville, IN-KY	1	-	-	-	1	-
San Luis Obispo-Paso Robles, CA	2	-	-	-	-	1
Las Vegas-Henderson-Paradise, NV	32	4	6	-	3	19
Bakersfield, CA	107	6	10	2	6	82
Riverside-San Bernardino-Ontario, CA	187	16	22	3	9	136
Los Angeles-Long Beach-Anaheim, CA	488	71	53	7	21	337
Little Rock-North Little Rock-Conway, AR	15	1	10	-	3	2
Atlanta-Sandy Springs-Alpharetta, GA	112	10	64	1	13	24
El Centro, CA	17	-	1	-	-	16
Birmingham-Hoover, AL	22	1	15	-	4	3
Macon-Bibb County, GA	4	-	3	-	-	-
Houston-The Woodlands-Sugar Land, TX	248	23	61	3	18	143
McAllen-Edinburg-Mission, TX	36	-	-	-	-	35

EXHIBIT D-18. RATIO OF $PM_{2.5}$-ATTRIBUTABLE DEATHS (PER 100,000) IN TRACTS WITH A MAJORITY NON-WHITE POPULATION

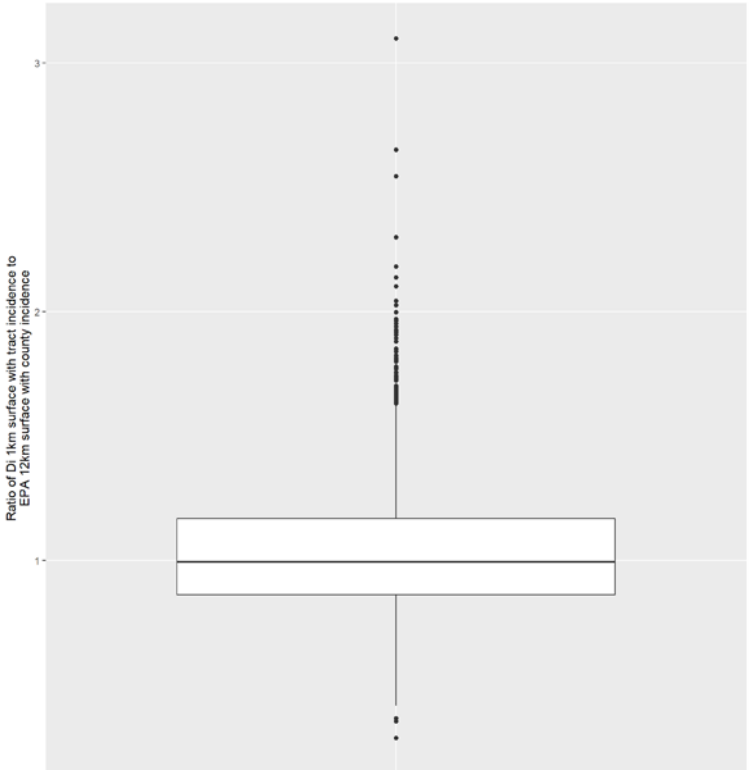


EXHIBIT D-19. RATIO OF $PM_{2.5}$-ATTRIBUTABLE DEATHS (PER 100,000) IN TRACTS WITH A MAJORITY WHITE POPULATION

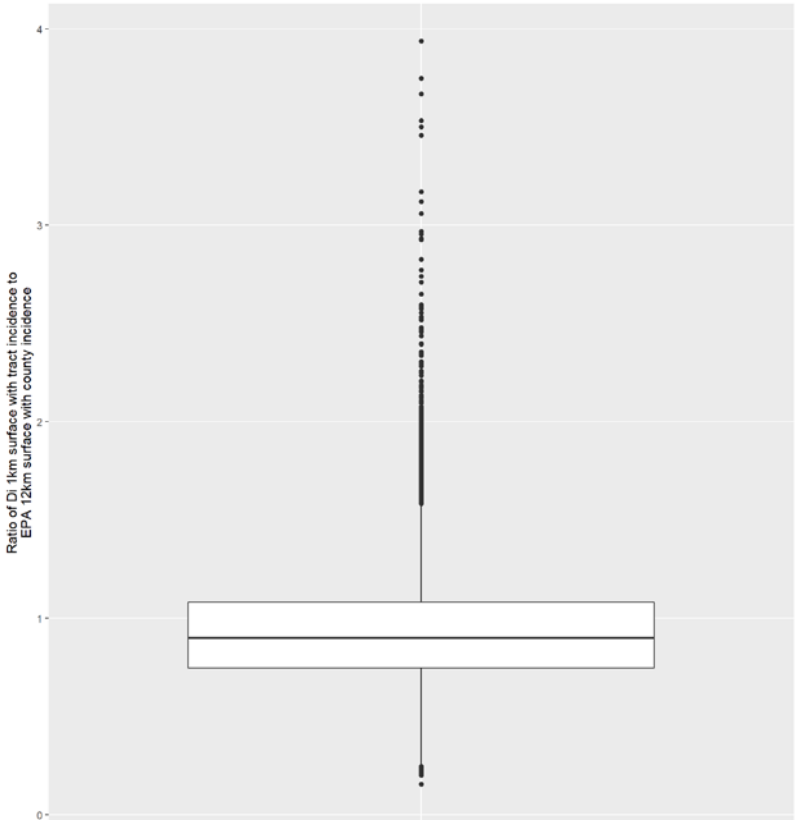


EXHIBIT D-20. BOX-AND-WHISKER PLOT VALUES FOR EXHIBIT 2-6: CURRENT $PM_{2.5}$-ATTRIBUTABLE MORTALITY BURDEN (PER 100,000) USING VARYING COMBINATIONS OF INCIDENCE AND AIR QUALITY DATASETS

INPUT	MEDIAN	LOWER IQR	UPPER IQR	5TH %	95TH %
12 x 12 km AQS; county-level incidence	291	250	340	114	476
12 x 12 km AQS; tract-level incidence	303	261	361	111	511
1 x 1 km AQS; county-level incidence	259	215	309	75	449
1 x 1 km AQS; county-level race-stratified incidence	268	215	348	26	548
1 x 1 km AQS; tract-level incidence	265	210	336	25	524

EXHIBIT D-21. BOX-AND-WHISKER PLOT VALUES FOR EXHIBITS D-18 AND D-19

INPUT	SUBSET	MEDIAN	LOWER IQR	UPPER IQR	5TH %	95TH %
1 x 1 km AQS with tract-level incidence & 12 x 12 km AQS with county-level incidence	All Tracts	0.9	0.8	1.1	0.3	1.6
	Tracts with a majority non-white population	1.0	0.9	1.2	0.4	1.6
	Tracts with a majority white population	0.9	0.7	1.1	0.3	1.6

APPENDIX E | METHODOLOGY MEMORANDUM

IEc

MEMORANDUM | April 15, 2022

SUBJECT Proposed Methodology for Assessing PM Health Burden and Estimating Benefits of a Lower Annual $PM_{2.5}$ Standard Using Finer Scale Inputs

INTRODUCTION

In October 2021, the United States Environmental Protection Agency (EPA) published its draft Policy Assessment (PA) for the Reconsideration of the National Ambient Air Quality Standards for Particulate Matter. The draft PA evaluates the policy implications of available scientific research on the health and welfare effects of ambient particulate matter (PM) and considers whether the current standards provide adequate public health protection. In doing so, EPA evaluates the potential benefits stemming from lower standards and discusses accompanying uncertainties.

EPA publishes ambient standards for two classes of particles: fine particles less than 2.5μm in diameter ($PM_{2.5}$) and particles less than 10μm (PM_{10}).[20] Currently, the primary National Ambient Air Quality Standards (NAAQS) for these pollutants are:

- **Annual mean $PM_{2.5}$:**[21] 12 μg/m^3
- **Daily mean $PM_{2.5}$ standard:**[22] 35 μg/m^3
- **Daily mean PM_{10} standard:**[23] 150 μg/m^3

These standards have changed over time based on the state of peer-reviewed research, such as toxicological and epidemiological studies on the effects of PM on public health. In the recent draft PA, EPA concludes that currently available scientific evidence provides support for more protective standards:

> "When taken together, we reach the conclusion that the available scientific evidence, air quality analyses, and the risk assessment… can reasonably be viewed as calling into question the adequacy of the public health protection afforded by the combination of the current annual and 24-hour primary $PM_{2.5}$ standards" (p. 3-188).

Further, EPA presents strong evidence that historically disadvantaged groups, such as Black and Hispanic communities, are exposed to higher $PM_{2.5}$ concentrations than white and non-Hispanic populations,

[20] EPA publishes both primary and secondary standards for PM: "Primary standards provide public health protection, including protecting the health of "sensitive" populations such as asthmatics, children, and the elderly. Secondary standards provide public welfare protection, including protection against decreased visibility and damage to animals, crops, vegetation, and buildings." See https://www.epa.gov/criteria-air-pollutants/naaqs-table. In this memorandum, we focus on the primary standards for $PM_{2.5}$.

[21] The annual $PM_{2.5}$ standard is mean annual concentrations averaged over a 3-year window.

[22] The daily $PM_{2.5}$ standard is the 98th percentile of daily mean concentrations over a 3-year window.

[23] The daily PM_{10} standard is not to be exceeded more than once per year, on average, over a 3-year window.

contributing to increased risk of PM-related adverse health effects. While EPA estimates considerable public health benefits from lowering the annual and 24-hour standards, the Agency notes some uncertainties regarding which alternative standard(s) are best supported by scientific research.

In this memorandum, we summarize our proposed approach for assessing both the current health burden of $PM_{2.5}$ and potential benefits of stronger $PM_{2.5}$ standards, making use of finer scale data that reflects spatial variance in air quality, population, and baseline health. Use of these fine-scale data sets will enable us to assess the distribution of burden and potential benefits across racial and ethnic population subgroups, as well as those experiencing poverty. We aim to supplement EPA's draft PA results with analyses that make use of cutting-edge data that enables us to characterize distributional health risks using a finer lens. In the following sections, we first present our research objectives and then outline the methods and data sources we anticipate employing for this analysis. We also provide examples of figures and statistics to serve as a template for the results of our work.

ANALYTIC DESIGN

In this section, we state our research objectives and outline our methodology for addressing these objectives. Attachment A (accompanying .xlsx file) provides additional detail on the BenMAP-CE runs planned to carry out this methodology.

RESEARCH OBJECTIVES

We aim to address three primary research objectives. First, we aim to **assess the sensitivity of $PM_{2.5}$ estimates to the exposure model selected and the scale of supporting demographic and health data.** Hybrid exposure models that combine multiple data sources, including regulatory monitors, satellite-based estimates, photochemical modeling and other data, show promise for identifying exposure gradients at finer spatial scales. EPA's draft PA employs a hybrid model at a 12 km x 12 km spatial scale in its risk assessment; we will explore how applying finer-scale input data for air quality and for other relevant inputs in EPA's BenMAP-CE tool can affect health burden or benefit estimates both in the aggregate and in terms of the distribution of health burdens across subpopulations of the US. We will also explore what these data can tell us about potential impacts throughout the contiguous US, in areas not modeled in the PA. In addition, we will explore the impacts of supplementing fine-scale air quality data with higher-resolution estimates of mortality rates and demographic variables such as poverty status.

Second, we aim to **characterize disparities in $PM_{2.5}$-attributable health burden under current conditions**. In doing so, we will consider how deaths and other adverse $PM_{2.5}$ effects are distributed across racial and ethnic groups and for those who experience poverty under current $PM_{2.5}$ concentrations. We will further assess geographic disparities by leveraging fine spatial scale datasets.

Third, we aim to **perform distributional analyses to estimate current burden and potential benefits from lower $PM_{2.5}$ standards across racial and ethnic groups, and those experiencing poverty**. Increased policy emphasis on environmental justice requires a better understanding of the air pollution-related health burdens experienced by historically underserved groups. A growing body of literature explores racial-ethnic disparities in air pollution exposure (Rosofsky et al., 2018; Tessum et al, 2019; Colmer et al, 2020; Tessum et al, 2021) and epidemiological studies such as Di et al. 2017 are reporting differential estimates of risk to different racial-ethnic groups for the same increment in $PM_{2.5}$ exposure. In this analysis, we focus specifically on Blacks, Hispanics, and those experiencing poverty. By modeling more protective annual $PM_{2.5}$ standards, we can assess the potential benefits to different racial and ethnic

groups and groups stratified by income related to the national poverty level. This objective builds upon EPA's existing model, which provides race-stratified benefits for alternative standards, by incorporating alternative datasets (e.g., fine-scale air quality modeling) that improve our ability to detect and characterize disparate impacts. We currently plan to assess the benefits of an 8 $\mu g/m^3$ standard and may consider either an intermediate standard (10 $\mu g/m^3$) or, if data allows, a more protective standard not evaluated in the draft PA (5 $\mu g/m^3$).

GENERAL APPROACH TO ASSESSING HEALTH IMPACTS

Broadly, IEc's assessment of lower annual $PM_{2.5}$ standards involves (1) characterizing the geographic distribution of baseline annual $PM_{2.5}$ concentrations corresponding to the current conditions under the existing standard and the distribution of these concentrations under more protective NAAQS alternatives; (2) estimating the changes in health effects attributable to a particular policy compared to the baseline; and (3) economic valuation of these effects. We estimate the impact of ambient $PM_{2.5}$ on health outcomes (e.g., premature mortality) by assessing the difference in risk under a baseline and control scenario, where the latter represents improved air quality resulting from policy changes.[24] For this analysis, we use BenMAP-CE, an open-source program employed by EPA for their regulatory impact analyses (RIAs). EPA relies on health impact functions to quantify the change in incidence of adverse health impacts stemming from changes in ambient pollutant concentrations. These functions can take multiple forms, but a common type for PM exposures is the following:

$$\Delta y = y_o \cdot \left(1 - e^{-\beta \cdot \Delta PM}\right) \cdot Pop$$

where Δy is the change in the incidence of the adverse health effect, y_o is the baseline incidence rate for the health effect, beta (β) is a coefficient derived from a relative risk (RR) estimate for a specific exposure change published in an epidemiological study, ΔPM is the change in concentration of fine particulate matter, and *Pop* is the exposed population.[25]

The health impact function highlights the datasets required for our analysis: two air quality surfaces per analysis, one baseline and one control; population, ideally stratified by age, race, and ethnicity; and baseline incidence rate of the health endpoint being evaluated (e.g, deaths from all causes per person per year), again ideally stratified by age, race, and ethnicity. These datasets, described in greater detail in Section 3, may be summarized at different spatial scales in BenMAP-CE. These model components are illustrated in Figure 1.

[24] In our analyses, the baseline and control scenarios will vary for each BenMAP-CE run. To assess the current burden of ambient $PM_{2.5}$, the baseline scenario will reflect current conditions and the control scenario will reflect a hypothetical "no pollution" scenario where $PM_{2.5}$ concentrations are set to either zero or a best estimate of non-anthropogenic background. To assess the benefits of more stringent standards, the baseline scenario will reflect current conditions and the control scenario will reflect hypothetical conditions under compliance with the more stringent standard. These differ somewhat from EPA's approach in the PA, in which EPA assumes a baseline scenario where all modeled areas are estimated to just meet the 12 $\mu g/m^3$ NAAQS.

[25] Based upon the functional form of the underlying concentration-response function, the functional form of the health impact function may differ.

FIGURE 1. BENMAP-CE DATASETS AND PROCESS

Following quantification of health effects, we value these outcomes using available economic research, including a mix of willingness to pay (WTP) and cost of illness (COI) estimates. Collectively, these values capture the welfare losses associated with $PM_{2.5}$-attributable death and disease.[26]

The scope of our PM burden and alternative NAAQS benefit analysis focuses on changes to the annual primary $PM_{2.5}$ standard (currently 12 $\mu g/m^3$). Fine particles are responsible for the majority of PM-related public health costs, and EPA notes that the annual standard is generally the "controlling" standard across much of the United States. We generally aim to assess impacts nationwide; however, we are limited to assessing impacts in the Continental United States based on the geographic scope of air quality surfaces, which are consistent with the analysis performed in EPA's draft PA. Additionally, select BenMAP-CE runs will be restricted to the 47 core-based statistical areas (CBSAs) evaluated in the PA. Finally, we will rely on data sources from 2015 to best characterize conditions, consistent with the approach taken by EPA in the draft PA analysis.

COMPARING HEALTH IMPACTS BASED ON AIR QUALITY DATA FROM DIFFERENT SOURCES

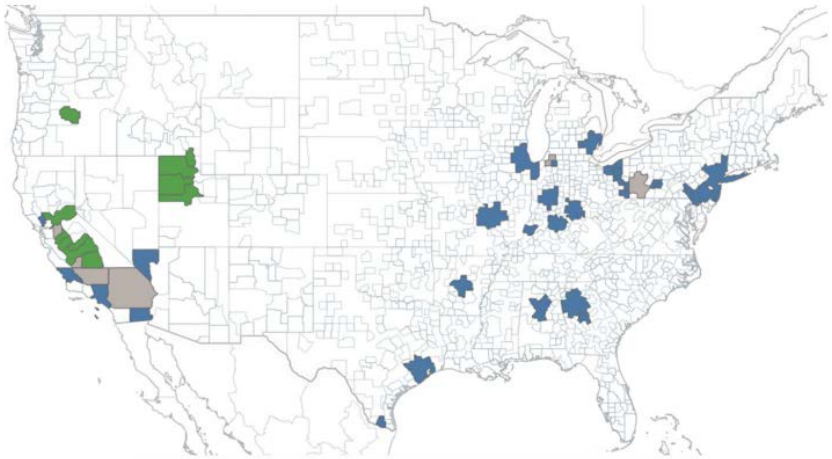
IEc will assess the sensitivity of $PM_{2.5}$-related health impacts to exposure estimates derived from 1) EPA's 12km air quality surface, which uses Bayesian downscaling to integrate monitor data with model data from a chemical transport model; and 2) Di et al. (2019)'s 1-km air quality surface for the contiguous US, which used an ensemble model that integrated $PM_{2.5}$ estimates from neural network, random forest, and gradient boosting algorithms based on satellite data, meteorological variables, land use variables, elevation, chemical transport model predictions, and reanalysis datasets (Di et al., 2019). It is important to note that the EPA 12-km air quality surface only provides $PM_{2.5}$ estimates for 47 core-based statistical areas (CBSAs, see Figure 2) across the US, which are defined by the Office of Management and Budget (OMB) to consist of the county or counties associated with at least one urban core of at least 10,000 people and the adjacent counties with a high degree of social and economic integration with the core area.[27] EPA performed the analysis within the 47 CBSAs based on the existence of $PM_{2.5}$ design values for 2014 to 2016 that are either close to or exceed the current annual and/or daily NAAQS. Further, these areas have readily available ground-based monitoring data and include a variety of regions across the US

[26] WTP represents the willingness of individuals to pay for a good or service, such as a reduction in the annual risk of illness or death. COI estimates include the direct medical costs and lost earnings associated with illness. Generally, we prefer valuing adverse health outcomes using high quality WTP estimates relative to high quality COI estimates because WTP is thought to incorporate the "pain and suffering" associated with these outcomes. For example, valuing non-fatal cardiovascular hospitalizations using only medical expenditures and lost productivity (i.e., a COI-based approach) would ignore the intangible costs (pain, discomfort, dread) associated with these events. Despite our preference for WTP-based estimates, economic valuation research is limited for many endpoints, resulting in the use (by EPA and others) of COI-based estimates for most non-mortality endpoints.

[27] US EPA. 2013. R2 Core Based Statistical Area (CBSA), 2013; TIGER/Lin Shapefile. https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7BE2C1506F-9E1C-4238-A3F9-0A620B06548A%7D

that may include a representative subset of the US population. We perform the comparison of health impacts based on the satellite surfaces both within these 47 CBSAs and nationwide using the Di et al. (2019) air quality surface.

FIGURE 2. CBSAS REPRESENTED IN US EPA'S 12KM AIR QUALITY SURFACE (FROM 2021 DRAFT PA)



Number of Urban Study Areas (CBSAs)	Controlling Standard	Population (≥30 years old)
30	Annual (Blue)	~50M
11	Daily (Green)	~4M
6	Mixed (Grey)	~5M
Total: 47		**~60M**

For comparison with EPA's 12-km downscaled surface based on the methods in Berrocal et al., 2012, we evaluated alternative hybrid air quality models by comparing them against the selection criteria described in Table 1.

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TABLE 1 AIR QUALITY MODEL SELECTION CRITERIA

MODELED AIR QUALITY SURFACE FEATURE	DESCRIPTION
Air quality data should be modeled at most finely resolved geographic scale	Analysts have been able to produce $PM_{2.5}$ estimates at the 12km, 10km, and 1km scale. We aim to use estimates at the most highly resolved geographic scale available that meets our other criteria.
Air quality data should be tuned to the extent of the contiguous US[28]	Analysts have tuned satellite surfaces globally, to North America, to the US, and to specific regions of the US based on their goals. We aim to use estimates that are tuned specifically to the contiguous US.
Satellite model performance analysis required.	Analysts must have completed a ten-fold cross validation analysis and achieved R^2 value of greater than .75 at the US extent.
Datasets should be publicly available.	Our analyses should be publicly available and therefore replicable by any user with appropriate software and analytical experience.

We compared satellite models described in draft PA Table 2-31, including Berrocal et al. (2012), Di et al. (2016), Hu et al. (2017), van Donkelaar et al. (2019), Di et al. (2019), and Hammer et al. (2020). From these, we have selected Di et al. (2019), modeled at the 1-km scale to produce daily and annual $PM_{2.5}$ values using a non-parametric neural network validated at the US extent with a ten-fold cross validation R^2 of 0.86 (daily) and 0.89 (annual). We will use the Di et al. (2019) 1km surface with annual average values for calendar year 2015 to estimate $PM_{2.5}$ concentrations both within EPA's 47 CBSAs and outside of those CBSAs within the contiguous US.[29]

The Di et al. 2019 modeled values closely align with the ground-based monitor values (R^2 for both daily and annual concentrations are greater than 0.86), these ground-truthing comparisons are most relevant for the areas near air quality monitors, which tend to be located in population centers. The accuracy of the Di et al. (2019) 1-km air quality grid is less well characterized in regions where monitor density is low and topography is variable (for example, the Appalachian and Rocky Mountain regions had lower R^2 values than more populous areas) (Di et al., 2019).

[28] Air quality model surfaces typically include the contiguous United States, exclusive of Alaska, Hawaii, and territories.

[29] We will obtain the data from the publicly available Di et al. (2019) air quality surface posted to the Socioeconomic Data and Applications Center (SEDAC) at Columbia University website. We will download and extract data for 2015 from the file named "Daily and Annual PM2.5 Concentrations for the Contiguous United States, 1-km Grids, v1 (2000–2016)."

We will use EPA's BenMAP-CE tool, described in Section 2.2, to calculate health impacts associated with the EPA 12-km surface within the 47 CBSAs and the Di et al. (2019) 1-km air quality surface nationwide. The health impacts calculated using the EPA 12-km surface will establish a comparison between the draft PA and our analyses; the Di et al. (2019) 1-km surface will allow comparison with the EPA 12-km surface within the 47 CBSAs and will provide a baseline value for the areas outside the CBSAs. We will use the same baseline incidence, population, and epidemiological effect estimates to calculate these health impacts, with air quality surfaces varying between analyses to isolate the effects of $PM_{2.5}$ estimates on the value and distribution of health impacts. We will run these analyses with finer scale baseline incidence data, as well, to isolate the impacts of fine scale demographic data on the value and distribution of health impacts.

We will produce maps that show baseline concentrations from each air quality surface (e.g., EPA 12-km surface and Di et al. 2019 1-km surface), as well as maps that show the differential between each pair of surfaces. We will also produce national level summary tables of incidence estimates and provide finer spatial scale results as appendices.

ASSESSING DISPARITIES

In addition to the effect of using finer scale hybrid air quality data on total health impacts, we are further interested in how these data affect estimates of the distribution of health risks across subpopulations. These risks may vary for several reasons: groups may be differentially exposed to $PM_{2.5}$ because of where they live relative to key emissions sources or pollutant transport patterns; their baseline health may be worse, rendering them more susceptible; and/or the proportional effect of a unit change in fine PM on mortality rates may be greater for some subgroups than others. Compliance with the NAAQS is analyzed at the county level; however, different neighborhoods within these counties may experience local emissions sources that expose some people or communities to very high concentrations of $PM_{2.5}$ while exposing other people or communities to much lower concentrations of $PM_{2.5}$ (below the NAAQS). We aim to assess whether these potential community differences fall along racial or economic lines; that is, are population-weighted $PM_{2.5}$ exposures different by racial-ethnic group or income relative to the national poverty level

To assess these potential disparities under current conditions and at alternative $PM_{2.5}$ NAAQS, we will analyze:

- Population-weighted $PM_{2.5}$ exposure at current conditions by racial-ethnic group and income relative to the national poverty level using census tract average exposure data from the EPA 12-km downscalar model within the 47 CBSAs; and[30]
- Population-weighted $PM_{2.5}$ exposure by racial-ethnic group and income relative to the national poverty level using census tract average exposure data from the Di et al. (2019) 1-km model within the 47 CBSAs and across the US.

We will produce summary maps, graphs, and tables that illustrate health impacts and relative distribution of burden by racial-ethnic group and by income relative to the national poverty level for each of these air quality scenarios. With information on the locations in exceedance of alternative standards and the populations who live there, we will produce figures that describe the likelihood that that members of

[30] IEc's assessments by racial-ethnic group will use the BenMAP definitions for race (White, Black, Asian, Native American) and ethnicity (Hispanic, Non-Hispanic).

socially vulnerable groups live in areas of higher exposure, using figures similar to those in the US EPA's 2021 report "Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts" (US EPA 2021).[31]

MODELING MORE PROTECTIVE $PM_{2.5}$ STANDARDS

We will evaluate the disparities associated with the $PM_{2.5}$-attributable health burden across groups characterized by 1) race and ethnicity and 2) income relative to the national poverty level at an alternative $PM_{2.5}$ NAAQS of 8 $\mu g/m^3$ and compare these results against those found by EPA in the draft PA. We will also observe the distribution of exposures at current conditions and determine if it will be necessary to additionally model disparities for either an intermediate standard (10 $\mu g/m^3$) or a more protective standard (e.g., 5 $\mu g/m^3$).

Similar to Section 2.3, we will conduct a set of runs that isolate the health impacts of either using fine scale air quality data or fine scale demographic data on racial-, ethnic- and income-related disparities at an alternative NAAQS.

US EPA estimates the health benefits of changing the current annual $PM_{2.5}$ standard of 12 $\mu g/m^3$ to 8 or 10 $\mu g/m^3$ using two alternative emissions scenarios for $PM_{2.5}$. The "primary" emissions scenario preferentially adjusts $PM_{2.5}$ emissions to be more localized around direct (or primary) emissions sources, while the "secondary" emissions scenario adjusts $PM_{2.5}$ emissions to be more evenly spread across their study area (as expected with secondary formation of $PM_{2.5}$). For the purposes of this analysis, we focus on simulating the "primary" emissions scenario; this is consistent with EPA's decision to only model potentially at-risk populations using the "primary" scenario.

While US EPA models benefits from moving from the current PM NAAQS standard to a modeled alternative standard, we will model benefits from moving from current conditions to a modeled alternative standard. To estimate benefits from moving from current air quality conditions to 8 $\mu g/m^3$, we will use the Di et al. 2019 1-km air quality surface to estimate baseline air quality. We will assign a "control" air quality surface that reflects air quality under an alternative $PM_{2.5}$ standard of 8 $\mu g/m^3$, relative to current conditions.

The manner in which the "control" air quality surface is developed depends on whether each modeled fine-scale grid cell is within one of the 47 CBSAs in EPA's air quality surface. For grid cells within these CBSAs, we will start with the Di et al (2019) surface and apply an adjustment factor to each 1-km grid cell derived from EPA's modeling results for the 12-km EPA grid cell within which that 1-km cell falls. That is, we will scale the baseline Di results proportionally based on the percentage change in the $PM_{2.5}$ concentration in EPA's alternative NAAQS control scenario relative to EPA's Current Conditions scenario.[32] Since the spatial resolution of the EPA-modeled surface (12-km) is different from the Di et al. 2019 surface (1-km), we will apply the same proportional scaling factor for all Di et al. cells within each EPA 12-km cell.

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[31] An example "likelihood" figure is shown in Figure 3.2 of US EPA's report with the title "Likelihood that those in socially vulnerable groups currently live in areas with the highest projected increases in annual premature deaths from climate-driven effects on $PM_{2.5}$."

[32] Note that we deliberately do not compare the results against EPA's Baseline scenario in the draft PA, which estimates health burden assuming air quality degraded to a point where all areas modeled would just meet the current NAAQS. That is, the US would still be in compliance with the current, but concentrations in some areas would be higher than currently experienced. That scenario assumes conditions appropriate for a PA-type analysis which evaluates what conditions could be like if the standard remained unchanged. Our analysis focuses on assessing burden and benefits relative to current conditions as observed at monitors and estimated using state-of-the-art hybrid modeling.

For the entire nation (including cells outside the CBSAs), we will apply a simplified nation-wide "roll back" of air quality measurements in BenMAP-CE for out of attainment cells to model benefits associated with just meeting the modeled standard. Available resources and time do not allow for rigorous photochemical transport modeling of alternative emissions change scenarios resulting in compliance with alternative NAAQS standards. As an alternative, we assume a more basic "what if" scenario where all grid cells where baseline air quality concentrations are above 8 $\mu g/m^3$ under current conditions will be reduced to 8 $\mu g/m^3$ in the control scenario and all areas starting below the alternative standard will be unmodified. Since we only model out of attainment areas to just meet the modeled standard, outputs for these runs reflect the lower bound of the range of potential benefits to historically excluded and currently marginalized groups for meeting the $PM_{2.5}$ standard, as strategies for meeting the alternative NAAQS would likely reduce $PM_{2.5}$ concentrations more broadly.

For both modeling scenarios (EPA-based proportional reduction, nation-wide rollback to the standard), we will estimate the change in mortality from meeting an alternative standard of 8 $\mu g/m^3$ in two ways: 1) using county-level incidence data stratified by race and ethnicity, and 2) using either zip-code or census tract level mortality incidence data not stratified by race and ethnicity.

We will stratify monetized and unmonetized results by CBSA or non-CBSA designation, to reflect the different modeling approaches used in those areas and the associated implications for levels of uncertainty in results. For CBSA areas, we will compare results from both modeling scenarios and discuss observed differences. For each modeled standard, we will present both total count and change in baseline mortality and morbidity by race and ethnicity and stratified by income relative to the national poverty level. We will stratify monetized benefits from the more protective standards in a similar format.

We will also present mortality and morbidity results at the national level. Our results will indicate the potential benefits of just meeting more protective $PM_{2.5}$ standards to different racial and ethnic groups and to groups experiencing poverty. In addition to results presented at broad geographic levels (47 CBSAs, Nation), we will provide EDF with the associated .csv outputs from BenMAP-CE at finer geographic resolutions (e.g., tracts), should EDF wish to undertake its own analyses of these data.

DATA INPUTS

Table 2 provides a summary of the chosen data inputs for this work. Several inputs are novel to this study relative to EPA's draft PA, including the baseline fine-scale air quality surface and tract-level all-cause mortality incidence rates. We will also use several morbidity and mortality health impact functions that were not considered in the draft PA.

Section A.1 in the Appendix provides detailed information on all air quality surfaces considered for the analysis, as well as the rationale for choosing the Di et al. 2019 surface to represent the baseline air quality scenario. Section A.2 details all chosen health impact functions and endpoints, which include both mortality and morbidity outcomes.

Sections A.3 and A.4 detail all chosen incidence and valuation functions, and Section A.5 specifies additional data inputs, specifically tract-level income related to the national poverty level.

TABLE 2. DATA INPUTS SUMMARY

DATA INPUT CATEGORY	DATA INPUT(S)	SPECIFIC TO IEC STUDY? (RELATIVE TO DRAFT PA)
Baseline Air Quality Surface	Di et al., 2019 neural network air quality surface (1-km resolution)	Yes
Health Impact Functions	EPA Standard Health Functions for mortality and morbidity from EPA's BenMAP-CE tool, plus additional race-stratified health impact functions extracted from 2019 $PM_{2.5}$ Integrated Science Assessment for mortality	Morbidity impacts not included in 2021 draft PA. Pope et al, 2019 function added for race-stratified mortality endpoint.
Baseline Incidence	Tract-level all-cause mortality incidence rates for ages 30-99. County-level race-stratified all-cause mortality incidence rates for ages 30-99. Mix of county-level and national-level incidence data for morbidity endpoints.	Yes
Valuation Functions	EPA Standard Valuation Functions for mortality and morbidity endpoints from EPA's BenMAP-CE tool.	No
Population	Census tract-level population data for the entire United States	Yes
Other	Census-tract level poverty estimates	Yes

NEW JERSEY SUPPLEMENT

The national analyses described above will incorporate datasets with a mix of sub-county spatial scales, including 1-km air quality data, Census tract and/or zip code level mortality incidence data, and Census tract population. Morbidity incidence rates, however, are all currently estimated at the county or national levels in BenMAP-CE. We aim to explore the sensitivity of results to the spatial scale of these data by conducting a case study in New Jersey with newly developed morbidity incidence data at the zip code level.

IEc will purchase discharge-level emergency room and hospitalization data from the Healthcare Cost and Utilization Project (HCUP) for 2016-2019 for the State of New Jersey, from which we will develop a zip-code level dataset of baseline incidence rates for the state. We aim to compare resulting county-level and zip code-level results from these data for a subset of morbidity outcomes (e.g., respiratory hospitalizations) whose incidence can be estimated based on hospital admissions or emergency department visit data. Additionally, we will explore whether these data allow us to meaningfully stratify incidence rates by race and ethnicity, subject to data suppression constraints.[33]

[33] Per the HCUP data use agreement, any summary values less than 10 must be suppressed to address privacy concerns; in such cases rates for the specific subgroup for that zip code would be imputed from rates at a larger geographic scale for which data are not suppressed. If substantial proportion of zip code level values will require imputation for a given health endpoint, IEc will consult with EDF to determine whether or not to proceed with a stratified analysis for that endpoint.

APPENDIX A: DATA INPUTS

A.1 AIR QUALITY

We reviewed multiple fine-scale $PM_{2.5}$ air quality surfaces for use in assessing the baseline health burden associated with ambient pollution. Since we are using the EPA 12-km monitored surface from the 2021 PA, our review focused only on model air quality surfaces. The air quality surfaces and the benefits and limitations of each are described below. The air quality surfaces and the benefits and limitations of each are described below.

Baseline Model Surface(s)

We reviewed model air quality surfaces as they can often provide pollutant measures at finer resolutions in areas where the monitoring network is less dense. Model surfaces can incorporate meteorological and geographical variables that fill in these gaps and potentially better characterize the spatial distribution of pollutants than the nearest monitors could. However, in areas with robust monitoring networks, the monitor data best represents ground-level ambient concentrations. For this reason, we focused our review of model surfaces on hybrid models which incorporate both the accuracy of monitor data with the spatial coverage of model data.

In addition to the hybrid model criteria for air quality surfaces, we assessed model surfaces against three criteria:

- Spatial resolution – since the goal of our health burden and potential benefits analysis is to perform distributional analyses to assess fine scale benefits of stronger $PM_{2.5}$ standards across racial, ethnic, and income-based groups, we prioritized models at the most highly resolved geographic scale available that meets our other criteria;
- Model extent – we prioritized models that were derived for the Contiguous US, our study area, over a global scale or continent-wide model;
- Model performance – we prioritized models with high goodness-of-fit values, greater than 0.75, when cross-validated

We used the EPA's 2021 $PM_{2.5}$ Draft Policy Assessment as a starting point for gathering high quality hybrid model surfaces. The 2021 draft PA discussed four hybrid models: Berrocal et al. 2021, Di et al. 2016, Hu et al. 2017, and van Donkelaar et al. 2019. After reviewing these studies, we discovered a more recent publication of the Di et al. 2016 method, Di et al. 2019, as well as the Hammer et al. 2020 study. Table A.1 contains the details of the six criteria for each model, while Table A.2 presents a matrix of the criteria met by each study.

TABLE A.1. MODEL SURFACE STUDY DETAILS

AUTHOR	MODEL YEAR	SPATIAL SCALE	TEMPORAL SCALE	MODEL EXTENT	HYBRID MODEL METHOD	MODEL PERFORMANCE (RMSE UNIT $\mu G/M^3$)
Berrocal et al., 2012	2002	12km	Daily	Eastern US	Bayesian downscaler – fuse EPA Air Quality System (AQS) monitoring network with the CMAQ modelled data	No R^2 provided; RMSE of 12
Di et al., 2016	2000-2012	1km	Daily	US	Neural network – using EPA AQS monitoring network, and a variety of satellite measures (MAIAC AOD, GEOS-Chem, NDVI, etc.)	R^2 of 0.84; RMSE of 2.94
Hu et al., 2017	2011	12km	Daily	US	Random forest – using EPA AQS monitoring network as well as AOD data, meteorological fields, and land use variables	R^2 of 0.80; RMSE of 2.83
van Donkelaar et al., 2019	2000-2016	1km	Monthly	North America	Ground weighted regression (GWR) – using EPA AQS, Canada's National Air Pollution Surveillance (NAPS), CASTNET and IMPROVE monitoring data, satellite and AOD data, and GEOS-Chem data	R^2 of 0.70; No RMSE provided
Di et al., 2019	2000-2015	1km	Daily/ Annual	US	Neural network - using EPA AQS, IMPROVE, and CASTNET monitoring network, and a variety of satellite measures (MAIAC AOD, GEOS-Chem, NDVI, etc.)	R^2 of 0.86; RMSE of 2.79
Hammer et al., 2020	1998-2018	1km	Annual	Global	GWR of residuals – using World Health Organization (WHO) Global	R^2 of 0.81 (globally) RMSE of 6.8 (globally) & 1.78 (North

AUTHOR	MODEL YEAR	SPATIAL SCALE	TEMPORAL SCALE	MODEL EXTENT	HYBRID MODEL METHOD	MODEL PERFORMANCE (RMSE UNIT $\mu G/M^3$)
					Ambient Air Quality Database monitoring data satellite and AOD data, and simulation data (GEOS-Chem)	America, High Income)

TABLE A.2 MODEL SURFACE CRITERIA ASSESSMENT

AUTHOR	INCORPORATES SATELLITE AND MONITOR DATA (HYBRID MODEL)	FINE SCALE RESOLUTION (<12KM)	TUNED TO THE EXTENT OF THE US	MODEL PERFORMANCE R^2 >0.75
Berrocal et al., 2012	Yes	No	No	No
Di et al., 2016	Yes	Yes	Yes	Yes
Hu et al., 2017	Yes	No	Yes	Yes
van Donkelaar et al., 2019	Yes	Yes	No	No
Di et al., 2019	Yes	Yes	Yes	Yes
Hammer et al., 2020	Yes	Yes	No	Yes

Our review of the studies found that only two studies, Di et al., 2016 and Di et al., 2019, meet all of our criteria requirements. Since the Di et al., 2019 study is a more recent version of the Di et al., 2016 study, we have decided that only Di et al., 2019 model will be assessed. Although the Hu et al., 2017 study does not meet the fine scale resolution criteria, we have decided to also include this study in our analysis as our monitor baseline surface is the same resolution (12km) and it meets all other criteria requirements. As part of our analysis, we will perform spatial comparisons between the EPA 12km air quality surface and the two model surfaces to better understand differences between the monitor and satellite model data.

Baseline Monitor Surface(s)

As mentioned previously, we will be assessing $PM_{2.5}$ health impacts using the EPA's 12km air quality surface as our baseline 'monitor' surface. This surface uses a Bayesian downscaling method to calibrate the CMAQ chemical transport model predictions, simulated from the EPA AQS monitoring data. Although this surface is not solely monitor based, it does not incorporate the satellite data and variables used by the model baseline surfaces. As a result, and mentioned above, our monitor surface provides the lowest spatial resolution of the $PM_{2.5}$ surfaces assessed and may limit our ability to assess the spatial distribution of health impacts across racial, ethnic, and income-based groups.

Rollback Grids

As discussed in Section 2.5, for the entire contiguous United States, we will develop "roll back" air quality grids to estimate health impacts of just meeting each alternative $PM_{2.5}$ standard. If a grid cell's

baseline $PM_{2.5}$ concentration is greater than the specified alternative standard, then we will roll back its air quality to 8 $\mu g/m^3$. If the grid cell's baseline $PM_{2.5}$ concentration is less than the specified alternative standard, its air quality remains unchanged.

Thus, the outputs for these areas represent the potential benefits of just meeting each alternative $PM_{2.5}$ standard, assuming areas already in attainment do not become out of attainment after the more protective $PM_{2.5}$ standard is enforced.

HEALTH IMPACT FUNCTIONS

To estimate risk of all-cause mortality associated with long-term $PM_{2.5}$ exposure, we used health impact functions from Di et al. (2017) and Turner et al. (2016). EPA selected these studies for long-term mortality analyses in the draft PA, and they are among the EPA Standard Health Functions that are available in BenMAP-CE. Consistent with the draft PA, we used Di et al. (2017) for all-cause mortality analyses stratified by race and ethnicity, which provided functions for Asian, Black, Hispanic, Native American, and White populations.

In addition to mortality, we chose to assess the set of morbidity endpoints for which both county-level incidence data and at least one EPA Standard Health Function were readily available in BenMAP-CE. We also included asthma incidence in children, despite having limited spatial resolution in baseline incidence, because evidence suggests disparities in asthma prevalence have been growing in the 2000s, particularly among non-Hispanic blacks and Hispanics of Puerto Rican descent, as well as those of multiple race, American Indians, or Alaska Native persons (Bhan et al, 2015 and CDC, 2012).

Table A.3 contains a summary of the selected health impact functions and corresponding endpoints.

TABLE A.3 SELECTED HEALTH IMPACT FUNCTIONS AND CORRESPONDING ENDPOINTS

ENDPOINT	HEALTH IMPACT FUNCTION	AGE RANGE (YEARS)
Mortality, All-Cause	Turner et al. 2016[1] Di et al. 2017[1,2] Woodruff et al. 2008[1]	30-99 65-99 0-0
Acute Myocardial Infarction, Nonfatal	Peters et al. 2001[1] Sullivan et al. 2005[1] Pope et al. 2006[1] Zanobetti and Schwartz 2006[1] Zanobetti et al. 2009[1]	18-99 18-99 18-99 18-99 18-99
Emergency Hospital Admissions, All Respiratory	Zanobetti et al. 2009[1]	65-99
Emergency Room Visits, Asthma	Alhanti et al. 2016[1,3]	0-18
Emergency Room Visits, All Cardiac Outcomes	Ostro et al. 2016[1]	0-99
Emergency Room Visits, Respiratory	Krall et al. 2016[1]	0-99
Hospital Admissions, All Cardiac Outcomes	Talbott et al. 2014[1]	0-99
Hospital Admissions, All Respiratory	Ostro et al. 2009[1]	0-18
Hospital Admissions, Alzheimer's Disease	Kioumourtzoglou et al. 2016[1]	65-99
Hospital Admissions, Cardio-, Cerebro- and Peripheral Vascular Disease	Bell et al. 2015[1]	65-99
Hospital Admissions, Parkinson's Disease	Kioumourtzoglou et al. 2016[1]	65-99
Hospital Admissions, Respiratory-1 (ICD-9 466,480-486, 490-493)	Jones et al. 2015[1]	0-99
Hospital Admissions, Respiratory-2 (ICD-9 464-466, 480-487, 490-492)	Bell et al. 2015[1]	65-99
Incidence, Asthma	Tetreault et al. 2016[1]	0-18

[1] EPA Standard Health Functions (2021) available in BenMAP-CE 1.5.8
[2] Race-stratified functions available for Asian, Black, Hispanic, Native American, and White populations
[3] Race-stratified functions available for Asian, Black, Hispanic White, Native American, and Non-Hispanic White populations

POPULATION

For the analyses of the EPA current conditions 12-km surface we will rely on the 2015 12-km population within the BenMAP-CE database. These data are disaggregated by age, gender, race, and ethnicity. (see the BenMAP-CE User Manual for Appendix J for detailed methods).[34]

For the analyses of the 1-km air quality surfaces, we will rely on the 2010 Census tract population data, disaggregated by age, gender, race and ethnicity. We will use the Woods and Poole (2015) county-level forecasts, developed by age, gender, race and ethnicity, to project the census tract population for 2015 (see the BenMAP-CE User Manual for details on the Woods and Poole (2015) methods).

[34] The USEPA BenMAP-CE User Manual can be found here: https://www.epa.gov/sites/default/files/2015-04/documents/benmap-ce_user_manual_march_2015.pdf

BASELINE INCIDENCE

Baseline incidence refers to the number of new cases in a given population over a specified time period. In BenMAP-CE, incidence rates are typically summarized per person per day or per year at a specified geographic scale. The program includes a set of county- and national-level mortality and morbidity incidence rates, described below, that we plan to supplement with finer resolution datasets.

Mortality Incidence

We will rely on a mix of mortality incidence inputs to characterize the baseline numbers of deaths by cause, age, geography, and in some cases, race and ethnicity. First, we will use tract-level all-cause mortality incidence rates recently developed by IEc using data from the CDC's US Small-area Life Expectancy Estimates Project (USALEEP) study. [35] These rates provide a fine-scale representation of deaths for all US Census tracts using 2015 data. We will validate the geographic variability of these rates by comparing them with any public and freely available tract-level mortality rates constructed from administrative data (i.e., death records). Additionally, we will employ county-level race-stratified and ethnicity-stratified mortality incidence rates. These data are currently available in BenMAP-CE and were developed by IEc in 2021. The data represent deaths over the period of 2007 to 2016. Sub-county data are not currently available for deaths stratified by race and ethnicity. Additional detail on these data are available in the BenMAP-CE user manual.[36]

Morbidity Incidence

BenMAP-CE includes a set of county-level incidence rates for the period 2012-2014 for emergency room visits and hospitalizations. These data are supplemented by national-level rates for other morbidity endpoints, including incident asthma. Additional information on the default incidence rates is available in the BenMAP-CE user manual.

As discussed in Section 4 (New Jersey Case Study), the BenMAP-CE morbidity rates are not stratified by race or ethnicity. IEc is exploring whether HCUP data will allow for finer scale benefits estimation, and how estimates may differ when processed at finer spatial scales and by race and/or ethnicity.

OTHER DATA INPUTS

We use data from the American Community Survey (ACS) to provide Census tract-level summaries of income related to the national poverty level. These data represent 5-year average ACS estimates from 2015 to 2019 for the fraction of the total population in the tract that falls below the federal poverty line and the fraction of the tract population below 200% of the poverty line.

All estimates are generated at the Census tract level for 72,538 tracts in the contiguous United States. For each estimate, we generate a coefficient of variation (CV) equal to the ratio of the standard error to the point estimate. For tracts with a CV greater than 0.3, we impute the tract-level estimate with a county-level estimate following Census guidance, which defines any estimate with a CV greater than 0.3 as low reliability and to be used with extreme caution. In cases of counties with a CV greater than 0.3, we impute with a state-level estimate.

[35] https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html

[36] https://www.epa.gov/benmap/benmap-ce-manual-and-appendices

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